International Journal of Multimedia and Ubiquitous Engineering
Vol.9, No.8 (2014), pp.241-250
http://dx.doi.org/10.14257/ijmue.2014.9.8.21

The WSN Coverage Optimization of the Diversified AFSA Based on Chaos Learning Strategy

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Abstract

WSN coverage optimization is an important problem. Considering that the artificial fish algorithm is easy to fall into local optimum and of slow convergence, an improved algorithm has been proposed in this paper. The chaos strategy is used to carry out the initialization of the foraging behavior, which makes the fish swarm evenly distributed in space, to avoid the randomness of the initialized individual. At the same time, the concept of diversity is introduced in the swarm behavior, which makes its avoidance of congestion further improved. Through standard test functions and simulated network coverage testing, the algorithm presented in this paper improves the WSN network node coverage, which effectively reduces the network cost and further improves the network coverage optimization.

Key words*: chaos; AFSA; diversity; wireless sensing*

1. Introduction

Wireless Sensor Network (WSN) is a new information technology developing with the progress of communication technology and embedded technology. Coverage optimization has always been an important aspect of the wireless sensing. The quality of the optimized result directly influences whether the network resource is used reasonably. It is a key problem in wireless sensing how to reasonably keep the network coverage and extend the network life cycle.

Wireless sensing is mainly made up of multiple separate nodes, and these nodes are divided into static and dynamic nodes. Between the nodes, the environmental interactions are implemented through sensing and controlling parameters. The static nodes are usually deployed artificially and suitable for some safe zones, because this way can be adjusted according to the position of the scene, which can realize good coverage. The dynamic node way is to deploy randomly, easy to form some blind areas and overlapping areas. At present, the research on WSN has made some achievements. The reference [1] presents an optimizing strategy based on the particle swarm algorithm, and effectively prevents the algorithm from falling into the premature trap through introducing the disturbance factor, which accelerates the algorithm convergence. It is verified by simulation experiments that the optimization algorithm can effectively improve the performance of network coverage. In addition, it is compared with the latest algorithm. The reference [2] presents a three-dimensional particle swarm algorithm (3D - PSO), which can improve the execution efficiency and positioning accuracy of the algorithm. It limits the searching space of particles, to speed up the convergence rate of the positioning results. The simulation results show that the algorithm has better robustness and higher positioning precision. The reference [3] constructs a probability Voronoi model from the perspective of multiple sensors collaborative monitoring, trying to solve the above problems. And the validity of the model has been verified with the biggest breakthrough path algorithm based on the probability Voronoi model. The model is put forward for the first time and worth

ISSN: 1975-0080 IJMUE

popularizing in practice. The reference [4] puts forward a kind of WSN coverage optimization algorithm based on genetic PSO. The maximum coverage of the wireless sensor is used as the objective function. By using the genetic algorithm with self-adaptive crossover and variation factor, search the solution space. The strong global search capability of PSO is used to increase the search scope, to make particle coverage more efficient and to strengthen the optimum searching ability of the algorithm. It improves the coverage of nodes and solves the problem of premature. The simulation results show that the method can effectively realize the WSN coverage optimization. The reference [5] describes the solution of the problem that the current coverage algorithm consumes too much energy on nodes and is poor in monitoring accuracy when used in monitoring spatially continuous distribution of physical quantity. In this paper, a new WSN coverage algorithm based on the dynamic nested grid technology in combination with the numerical analysis of hydromechanics (DNGCA), and the simulation results show that the algorithm is improved much on the main coverage indicators compared to other algorithms. The reference [5] puts forward a WSN coverage algorithm of particle swarm. It uses the maximum coverage of the wireless sensor as the objective function, with several particle swarms independently searching the solution space, to increase the search area of the particles and reduce the possibility of local optimum. The evolutionary particle is used to make the particle coverage more efficient, which improves the optimum searching capability of the algorithm, effectively avoids the “premature” problem easy to occur in the standard particle swarm algorithm and improves the stability of the algorithm. The reference [7] argues to optimizing the WSN nodes by using AFSA and particle swarm algorithm. Due to their shortcomings, the particle swarm algorithm is easy to fall into local optimum, which is difficult to achieve the global convergence; the genetic algorithm in different wireless sensing structure has to determine the methods of genetic manipulation, so the solving process is very complex; the ant colony algorithm is strong in local search, but because of its low speed in solving in the early stage, it covers the timeliness of optimization.

AFSA (AFSA) [6] is a new intelligent and bionic algorithm presented by simulating the foraging and living activities of fish, which is easy to implement but slow in convergence and easy to be premature. On the basis of this, an improved AFSA is proposed in this paper. In the initialization phase of artificial fish, the chaos reverse learning strategy is used, which enables the fish swarm initialized to be evenly distributed in space, to speed up the global convergence of the algorithm. The simulation experiment shows that compared with the AFSA, the algorithm of this paper has a high accuracy of optimum searching and a high speed of convergence.

2. The Network Coverage Model

2.1. Node Coverage Description

In the model, set a target area, which is divided into $M \times N$ grids. In this area, place a set number of fixed nodes and mobile nodes and set the coordinate of each node. The perception radius and the communication radius of a node is set as r and R, respectively. The node collection of the sensor is represented as $C = \{c_1, c_2 \ldots\ldots c_n\}$, and $c_i = \{x_i, y_i, r\}$ means that the circle center is (x_i, y_i) and the radius is r.

2.2. The Description of Coverage

If the coordinate of the node C_i in the sensor network is (x_i, y_i), and the coordinate of any node T_j in the area is (x_j, y_j), the distance between the network node and the target node is as follows:

$$L(C_i, T_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

Wherein, λ_1 and λ_2 are the input parameters and the measured probability from node C_i to the target node T_j is:

$$P_{(C_i, T_j)} = \begin{cases} 0 & R_s + R_e \prec L(C_i, T_j) \\ e^{\frac{-2\lambda_1 \alpha}{\lambda_2 \beta}} & R_s - R_e \le L(C_i, T_j) \le R_s + R_e \\ 1 & R_s - R_e \ge L(C_i, T_j) \end{cases} \quad (2)$$

3. A Brief Introduction of the AFSA

The AFSA (AFSA) is a kind of intelligent algorithm, which is set in the search space and uses n artificial fish. The state of number i artificial fish is represented as the vector $X_i = (X_{i1}, X_{i2}, X_{i3}, \ldots\ldots X_{iN})$, and the current food density of the artificial fish is represented as $Y = T(x)$. In the artificial fish swarm, the distance between a fish and another is expressed as: $d_{ij} = \| x_i - x_j \|$ and the step length in the artificial fish swarm is represented as $step$. The view range of the artificial fish swarm is $Range$, and $Number$ is used to represent the individual number of the fish swarms. In the algorithm, the state of each artificial fish is a solution. Substitute X_i into the optimization function, to judge the quality of each fish by the value of the function. The basic behavior of the artificial fish swarm is described as follows.

3.1. Foraging Behavior

If the current state of the AFSA is x_i, according to the formula (3), randomly select a state x_j, with the food density meeting the condition of $T(x_i) < T(x_j)$, and then calculate by the formula (4). If the food density meets $T(x_i) \ge T(x_j)$, in the visible range, randomly select a state, where $rand$ represents a random number.

$$x_j = x_i + e^{\frac{x_j}{x_i}} \quad (3)$$

$$x_j = x_i + rand \cdot \sum_{i=1}^{n} (X_i - \overline{X}_i)^2 \quad (4)$$

3.2. Swarm Behavior

The swarm behavior is used to avoid congestion. It is to search the number of partners currently in the visible range n and the center position x_c. When the food density is $T(x_i) < T(x_c)$, it shows that there is higher food density at the partner's location. And then use the formula (3) to replace x_i with x_c to go to the partner's location.

3.3. Rear-ended Behavior

The rear-ended behavior means that the fish swarm explores the optimal artificial fish in the visible area, and when the state is $T(x_i) < T(x_{max})$ it shows that at the location of x_{max} there is a high density of food. With formula (4), use x_{max} to replace x_i. After judging, it will continue to implement the foraging behavior.

4. The Improved AFSA

4.1. The Chaos Learning Strategy

The foraging behavior of AFSA is very important. The quality of foraging behavior initialization directly influences the algorithm's speed of global convergence and the quality of the corresponding solutions. Usually, due to the lack of some information, the random initialization method is often used to generate the initial solution of the algorithm. The reference [8] presents a chaos initialization method on the basis of the research on particle swarm algorithm and uses the strategy to initialize the AFSA, with the specific steps shown as follows:

$for\ i = 1\ to\ N\ do$

$T_j \in (1, 2)$

$for\ k = 1\ to\ j\ do$

$y_{i,k} = 1 - 3 \times y^3_{i,d} + 2 \times y^2_{i,d}$

$endfor$

$x_j = x_i + y_{i,j} * rand$

$endfor$

$endfor$

4.2. The Dynamic Self-adaptive Swarm

In the swarm behavior, the swarm will gather at the location with high food density, which is easy to cause certain blocking situations. In settling the problem of WSN coverage, it will cause local optimum. To solve such problems, an updating strategy is presented in reference [9] in this paper. This strategy introduces the concept of diversity to the formula [4], to improve the searching ability of the algorithm.

Set the number of fish swarms in the AFSA as N and the number j individual in the number i group of artificial fish x_i as $x_{ij} = (x_{ij1}, x_{ij2}, \ldots\ldots x_{ijn})$, in which n is the number of dimensions, and the optimal position of the number j generations of individual artificial fish swarm is $y_i = (y_{j1}, y_{j2}, \ldots\ldots y_{jn})$. Join the current position of the fish swarm with the generations of optimal positions, written as $z_j = (x_{ij1}, x_{ij2}, \ldots\ldots x_{ijn}, y_{j1}, y_{j2}, \ldots\ldots y_{jn})$. All the individuals z_j in the AFSA forms an $N \times n$ matrix z, which is normalized to get the following matrix z'

$$z' = \frac{\sum_{i=1}^{n} (X_{\max} - \overline{X}_{\min})^2}{\sum_{i=1}^{n} X_{\max} Y_{\min}} \quad (5)$$

The diversity of the fish swarm is represented as follows:

$$F = \frac{\sum_{i=n+1}^{N} Q(i)}{\sigma_i} \quad (6)$$

So the improved formula is

$$x_j = x_i + r_{ij}(k) \cdot rand \cdot \sum_{i=1}^{n} (X_i - \overline{X}_i)^2 \quad (7)$$

4.3. Steps for Coverage Optimization

Step 1: initialize the WSN, according to the scale of the network, to set the size of the artificial fish swarm as N , the biggest mobile step length as $step$, visible range as $Visual$ and the iteration as $number$.

Step 2: Calculate the food density of the current positions of individual fish swarms, choose those with high food density to show on the bulletin board

Step 3: In the foraging behavior, adopt chaos learning strategy proposed in this paper to carry out initialization

Step 4: As for the rear-ended behavior and swarm behavior of the artificial fish simulated fish swarm, in swarming the improved formula is used to select a new location.

Step 5: After one traversal of the artificial fish swarm, compare the food density in the current position with that shown on the bulletin board. If the comparison result is the former is greater than the latter, the position of the fish swarm shown on the bulletin board will be replaced.

Step 6: If it meets the end condition, input the $T(x)$ value in the bulletin board, which is the optimal scheme of WSN coverage.

5. Analysis of the Algorithm Results

To test the performance of this algorithm, there are two parts of tests in this paper, one of which is to test the performance of the algorithm and the other of which is to test the network coverage optimization.

5.1. Algorithm Performance Test

This algorithm selects three benchmark functions to test, C# of Visio Studio.Net 2007 as the test platform, and Windows XP as the operation system. The three functions are as follows:

(1) $f1(z) = \sum_{i=1}^{D} [z_i^2 - 10\cos(2\pi z_i) + 10]$, which is a multimodal function which minimizes when $z_i = 0 (i = 1, 2, ...D)$.

(2) $$f2(z)=\frac{\sum_{i=1}^{n}\cos^4(x_i)-2\prod_{i=1}^{n}\cos^2(x_i)}{\sqrt{\sum_{i=1}^{n} ix_i^2}}$$ is also a multimodal function which reaches the global minimum value 0 when $z_i = 0(i = 1, 2, ...D)$.

(3) $$f3(z)=418.9283\times D-\sum_{i=1}^{D} x_i \sin([x_i]^{1/2})$$ is a uni-modal function which reaches the global minimum value 0 when $z_i = 1(i = 1, 2, ...D)$.

On the three functions mentioned above, the Particle Swarm Algorithm, the AFSA and the algorithm presented in this paper are compared. In the AFSA, let the scale of the artificial fish swarm be M = 20, $visual$ 2.85, $step$ 2.5, d 0.618, $L\max$ 40 and the dimension of the test function be 2. In the Particle Swarm Algorithm, let w be 0.5, and $c1, c2$ are also 0.5. Table 1 shows the results of the three algorithms.

Table 1. The Optimum Searching Results of the Four Algorithms

Function	Algorithm	Average Minimum Value
f1	Particle Swarm Optimization	0.027421
	AFSA	0.021623
	The Algorithm of this paper	0.005211
	The Reference [4] Algorithm	0.010417
f2	Particle Swarm Algorithm	0.061241
	AFSA	0.052374
	The Algorithm of this paper	0.021478
	The Reference [4] Algorithm	0.034752
f3	Particle Swarm Algorithm	0.085413
	AFSA	0.068741
	The Algorithm of this paper	0.031785
	The Reference [4] Algorithm	0.057412

It can be seen from the results of Table 1 that the average minimum values and minimum values of the algorithm of this paper are better than that of the other three algorithms, and the test effect is ideal.

5.2. Analysis of the Results

5.2.1. Wireless Sensing Coverage Test

Set the environment of simulation experiment as: the network detection area is 10m*10m. For the nodes of each wireless sensor, the perception radius is 0.5 m, and the communication radius is 2m. Under the environment of Matlab7.0, use the Core i3 computer the frequency of which is 2.2GHZ to carry out the simulated network coverage optimization. Let the number of artificial fish swarms be $Number$ =200, the $Range$ of artificial fish swarms be 5, the largest iteration be N = 500, to compare the algorithm of this paper with the basic particle swarm algorithm, artificial fish algorithm and the reference [4] algorithm and make analysis. As shown in Figure 1-2.

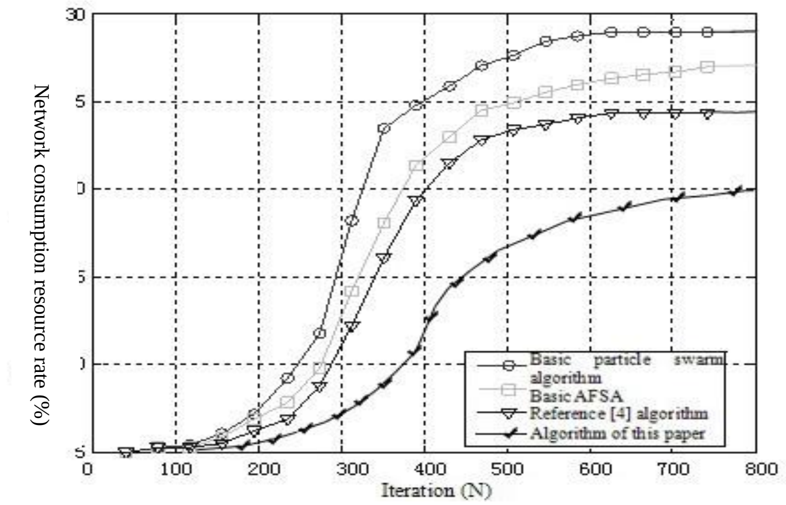

Figure 1. The Comparison of the Network Resources Consumed by the Four Algorithms

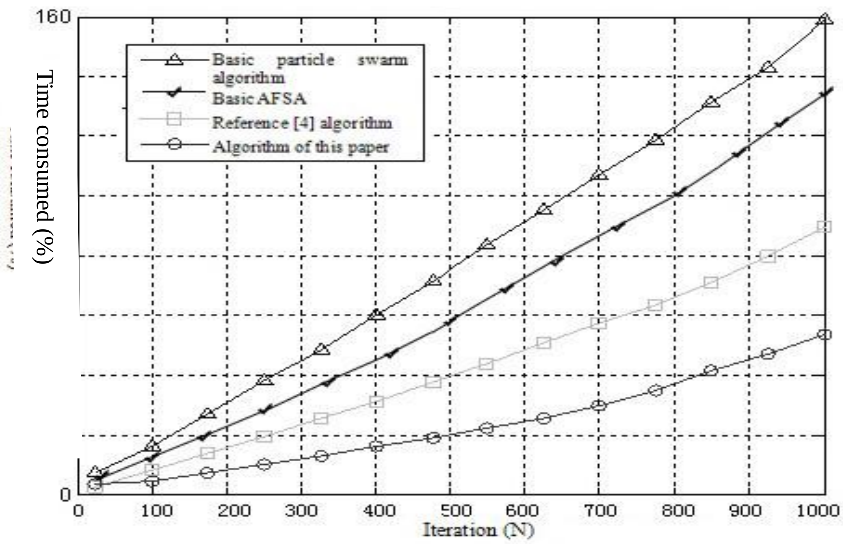

Figure 2. The Comparison of the Time Consumed by the Four Algorithms

It can be seen from Figure 1-2 that the algorithm in this paper is better than the other three algorithms in the consumption of time and network fees, and it is found that the response time tends to be flat with the increase of the iteration, which suggests that by improving the artificial fish algorithm, the convergence has been accelerated and the optimal solution can be found by fewer iterations. Compared with other algorithms, its response time is shortened, and the aspects like stability are improved substantially.

5.2.2. The Comparison of Other Coverage Optimization Algorithm

In the same simulation environment, the method of random distribution is adopted to compare the Particle Swarm Algorithm, Ant Colony Algorithm, AFSA and the algorithm of this paper by experiments. The comparison results are shown in Figure 3.

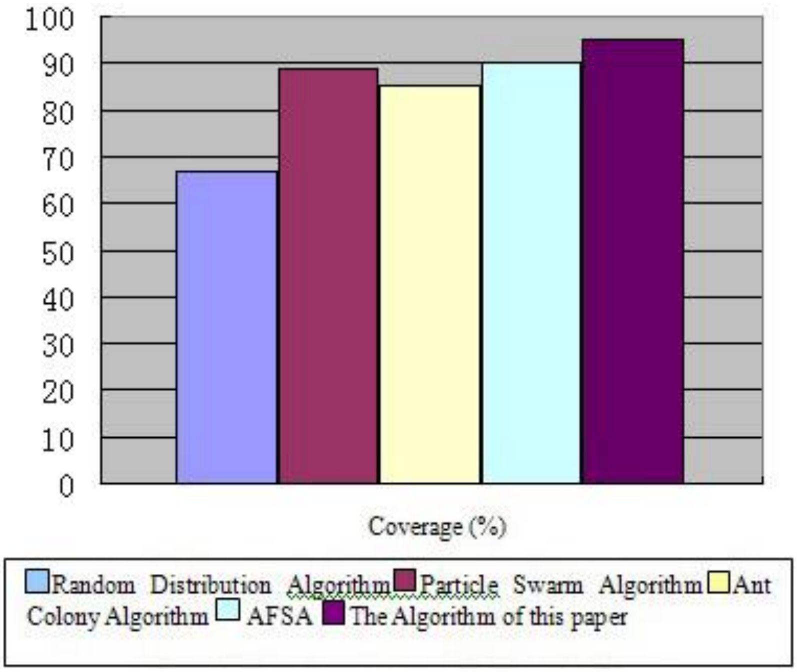

Figure 3. The Node Coverage of Different Algorithms

From Figure 3, it can be seen that the coverage of the Random Distribution Algorithm is around 70%, which cannot meet the actual needs of the WSN. The node coverage of the Particle Swarm Algorithm and the Ant Colony Algorithm ranges from 80% to 90%. The node coverage of the modified AFSA reaches more than 90%, which realizes the coverage optimization in WSN and can keep high network coverage in a relatively long period to extend the network life circle, with a good practical application effect.

6. Conclusion

Network coverage is the key problem in sensor networks. As the AFSA is easy to fall into local optimum and has a low rate of convergence, to better optimize, based on the original research results, in this paper, the chaos reverse learning initialization is introduced into the algorithm. It prevents the algorithm from falling into local optimum, and at the same time introduces the concept of diversity into the improved algorithm, to accelerate the convergence rate. Through the test of the standard functions, this algorithm is better than the AFSA in each aspect. The simulation experiment shows that the improved AFSA can get the optimal coverage node at a little expense, to reduce the network delay, improve the coverage of the nodes and decrease the number of mobile nodes. It has great significance for the actual application.

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