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# Wireless Sensor Network Coverage Optimization based on Whale Group Algorithm

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**Abstract.** For all of types of applications in wireless sensor networks (WSNs), coverage is a fundamental and hot topic research issue. To monitor the interest field and obtain the valid data, the paper proposes a wireless sensor network coverage optimization model based on improved whale algorithm. The mathematic model of node coverage in wireless sensor networks is developed to achieve full coverage for the interest area. For the model, the idea of reverse learning is introduced into the original whale swarm optimization algorithm to optimize the initial distribution of the population. This method enhances the node search capability and speeds up the global search. The experiment shows that this algorithm can effectively improve the coverage of nodes in wireless sensor networks and optimize the network performance.

**Keywords:** wireless sensor network, coverage optimization, whale swarm algorithm, reverse learning

## 1. Introduction

Wireless sensor network (WSN) is a distributed network system which composed of a large number of sensor nodes in the form of self-organization. The scope of wireless sensor network applications has been expanding beyond its original military purposes. It is also used for social purposes, for example, disaster intervention, ecological environment and habitat monitoring [1], status identification for production equipment, emergency search-and-rescue, and medical care, etc.

For the application of wireless sensor network, how to improve network coverage through effective deployment of nodes is a research hotspot in wireless sensor network filed.

Node deployment algorithm can be classified as deterministic deployment and random deployment [2]. Deterministic deployment mode is defined as selectively deciding the locations of the nodes to achieve one or more deployment objectives for the networks. Random deployment is a sub-optimal method as it causes unbalanced deployment and requires sensors in excess of the planned deployment to achieve the same level of coverage. To achieve maximum coverage with a limited number of sensors, deterministic deployment is a preferred choice. Node deployment can also be classified as continuous space-based deployment and grid-based deployment. Due to a variety of advantages, such as flexibility, extendibility, implementability, it has become an active branch of sensor deployment for WSNs. This paper investigates deterministic deployment and grid-based deployment.

The basic requirement of node deployment is to guarantee enough coverage and connectivity properties, where coverage is to ensure that each detection area is monitored by at least one node, and connectivity is to guarantee that any node can communicate with each other [3]. Meanwhile, to complete node deployment, energy consumption of the network should be considered, and it is necessary to cover all targets areas with a minimum of nodes. So, how to balance the energy consumption of the network while ensuring the maximum coverage of the monitoring area, reduce the number of the network activity nodes and prolong the life-time of the network has become an important problem in the field of wireless sensor network [4].

In recent years, scholars have proposed some meta-heuristic algorithms (Genetic Algorithms [5], Particle Swarm Optimization [6], Simulated Annealing [7], etc.) which have good effects in coverage optimization of wireless sensor networks. In [8], it considers a probabilistic sensing model that provides different sensing capabilities in terms of coverage range and detection quality with different costs. A sensor deployment problem for a planar grid region is formulated as a combinatorial optimization problem [9] with the objective of maximizing the overall detection probability within a given deployment cost. C Zhao came up with a genetic algorithm for integer planning optimally and deployed the relay nodes so as to obtain the optimal energy efficiency by minimizing the average path length. Literature proposed a target coverage scheduling scheme based on genetic algorithm [10].This algorithm uses improved global search technology to monitor all targets and to find the best coverage set and extend the network lifecycle. Literature proposed a new normalization method on the basis of genetic algorithm [11], which reduces the complexity of the algorithm and the number of sensor nodes by designing an evaluation function based on Monte Carlo method [12].

In addition, ant colony optimization (ACO) is also used for sensor deployment in [13]. They formulate coverage requirements of the sensor network as a minimum-cost connectivity guaranteed point k-coverage problem. An improved ant colony algorithm (EasiDesign) is proposed to achieve the approximate solution to this optimization problem. The authors made modifications in the convergence strategy and the ant state transition rule of the general ant colony optimization, but the large searching range of the algorithm insults in lots of inferior solutions and slow convergence. A grid-based deployment approach ACO–greedy is proposed on the basis of ACO with a greedy migration mechanism for deployment cost minimization [14].

Particle swarm optimization is also applied in wireless sensor network coverage optimization. In [15], an adaptive particle swarm optimization algorithm is proposed to add the degree of aggregation and evolution of particle swarm to the inertia coefficient, which enhances its self-adaptive ability, reduces the overlapping of particles in the search process and effectively improves Wireless Sensor Network Coverage and Convergence Rate. Literature provides an improved particle swarm optimization (PSO) algorithm by changing the basic form of PSO and introducing disturbance (d-PSO) [16].This algorithm provides a good-coverage solution with a satisfying coverage rate in a short time.

Considering the disadvantages of the above algorithms, this paper proposes an improved algorithm based on whale swarm algorithm [17], which is applied to the coverage optimization of wireless sensor networks. By using the excellent global searching ability and the capability of dealing with multi-objective optimization problems of the whale swarm algorithm, the optimal coverage scheme in the network coverage area can be found, the energy consumption reduced as much as possible [18].

The remainder of this paper is organized as follows. In section 2, we describe the problem that how to maximize coverage wireless sensor deployment, then the node sensing model and coverage model are introduced respectively. In section 3, the whale swarm algorithm is proposed and improved. In section 4, the parameters of wireless sensor network node deployment and whale swarm algorithm are listed at first, then presents the effectiveness of the improved whale swarm algorithm through experimental results, and conclusions are given in section 5.

## 2. Wireless Sensor Network Coverage Model

### 2.1. Description of the Problem

In wireless sensor networks, it is assumed that the monitoring area is a two-dimensional plane. And the nodes are randomly deployed in the interest field. In order to reduce energy consumption and prolong the life cycle of the network, how to use the least number of nodes to achieve the maximum network coverage has become the research focus. For simplicity, it is assumed that:

1) The location of each sensor node can be obtained by GPS positioning devices. The real-time location information of the node can be obtained by GPS system.

2) Boolean perception model and Boolean communication model are adopted uniformly by all nodes. The Boolean perception model transforms the coverage problem into point coverage problem, and nodes within a node-aware scope can communicate with each other.

3) Each node is either in working or dormant states. This type of work and dormant states can reduce energy consumption and resource waste.

4) The sensing radius of a node is r, and the maximum communication radius is R=2r.

### 2.2. Node Sensing Model

As shown in the node coverage model in Fig.1, the monitoring area is made from some pixels.

Each pixel is a monitoring unit (pixels in yellow, nodes in blue and nodes in node). If a pixel is covered by the sensor node, the coverage rate is X/N*M. Let the wireless sensor network node set as S=(S1,S2,S3... Sn).

The coordinates of each node is $S_i(X_i, Y_i)$ $(i=1,2...n)$ .

Set the coordinates of pixels as $(j=1,2...n)$.

Sensor node to pixel distance $d(S_i, X)=\sqrt{(x_j-x_i)^2+(y_j-y_i)^2}$ .

The probability formula that the pixel X is perceived is expressed as:

$$P(s_i,X)=\begin{cases}1 & d(s_i,X)\le R\ -r\\ \exp\left(\dfrac{-\lambda_1\alpha_1^{\beta_1}}{\alpha_2^{\beta_2}+\lambda_2}\right) & R\ -r < d(s_i,X) < R\ +r\\ 0 & \text{otherwise}\end{cases}\quad . \tag{1}$$

Where $\alpha_1 = r_e - R_s + d(s_i,H)$ , $\alpha_2 = r_e - R_s + d(s_i,H)$ $\lambda_1$ , $\lambda_2$ , $\beta_1$ , $\beta_2$ are the measurement parameters related to sensor node characteristics [18], $r_e(0<r_e<Rs)$ is the reliability of the sensor node measurement parameters [19].

Therefore, according to a method proposed by reference [20] for simultaneous measurement of multiple sensor nodes, the probability that the pixel $X$ is jointly detected by the sensor nodes in the entire monitoring area is:

$$P(s_{all},X) = 1-\prod_{i=n}[1-P(s_i,X)] \quad . \tag{2}$$

Let each wireless sensor network pixel can be joint detection probability $P_{th}$, then the sensor node is detected by the definition of the conditions:

$$\min_{x_j,y_j}\{P(s_{all},X)\} \ge P_{th} \quad . \tag{3}$$

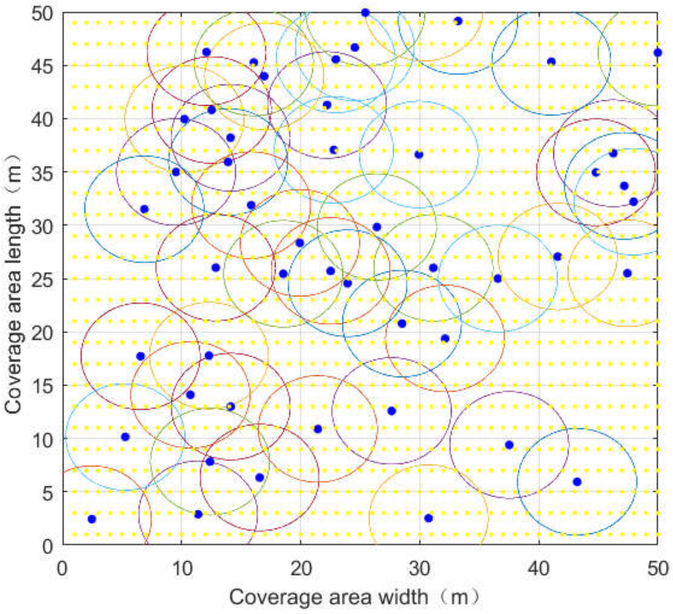


**Fig. 1.** Node coverage model

### 2.3. Coverage Model

In this paper, the coverage of wireless sensor networks is defined as the ratio of the area of pixels covered by all nodes to the total monitored area [21], that is:

$$f_1 = \frac{\sum_{x_i=1}^{M}\sum_{y_i=1}^{N} P(s_{all}, X)}{M*N} \quad . \tag{4}$$

Let |S'| be the total number of sensor nodes in the monitoring area and |S'| be the number of sensor nodes in operation. Then, node utilization $f_2$ is defined as

$$f_2 = \frac{|S| - |S'|}{|S|} \quad . \tag{5}$$

Energy consumption is an important index to evaluate the performance of wireless sensor network. Therefore, the larger the energy balance function $f_3$, the more unbalanced energy consumption, and vice versa, the more balanced energy consumption[22].

$$f_3 = \frac{Max(E_i) - Min(E_i)}{\frac{1}{n}\sum_{i=1}^{N} E_i} \quad . \tag{6}$$

Coverage optimization is a multi-objective optimization problem in wireless sensor network. When the network coverage meets the requirements, the number of working nodes is reduced as much as possible, and the redundant nodes are set up into a dormant state to achieve the energy balance effect. The above function $f_1$, $f_2$, $f_3$ are weighted to obtain the coverage optimization model $f$ .

$$f = w_1 f_1 + w_2 f_2 + w_3(1 - f_3) \quad . \tag{7}$$

Where $w_1$, $w_2$, $w_3$ is the weighted values, and $w_1$+$w_2$+$w_3$=1.

In order to improve the overall network performance (coverage, node utilization, energy consumption), this paper uses the whale swarm optimization algorithm to give the solution for equation (7).

## 3. Wireless Sensor Network Optimization Strategy based on Whale Swarm Algorithm

### 3.1. Algorithm Introduction

Whales are mammals that grow in the ocean and have strong group communication ability and high IQ. Whale size is relatively large, and usually dominated by the community. In seawater, they can make a variety of melodious sounds, and the spread of a very wide range. Social whales use ultrasound to communicate with their peers to complete prey, migration and other activities. When a whale discovers food, it will sound to inform the whales about the amount of food and other information. As a result, each whale receives a large amount of information from nearby whales and then opts to move to the nearest and most food-bearing spot. The predatory behavior of whales in this vocal communication inspired scholars to develop a new target optimization algorithm [23]. In this paper, we use the characteristics of optimization of whale swarm optimization algorithm and apply it in wireless sensor network coverage optimization.

### 3.2. Find the Optimal Solution

When it preys, the whale moves aggressively to the optimal one if it is close to optimal distance. If the distance is long, the whale moves slowly toward it.

From this kind of motion rule based on ultrasonic decay, a new formula is obtained, which makes the algorithm not get trapped in local optimum prematurely, and also helps to find multiple global optimal solutions. The random movement of whale $X$ under the guidance of optimal whale Y is expressed by the following formula [24]:

$$x_i^{t+1} = x_i^t + rand(0, \rho_0 \cdot e^{-\eta \cdot d_{X,Y}}) * (y_i^t - x_i^t) \quad . \tag{8}$$

Where $x_i^t$ and $x_i^{t+1}$ are the $i$ element of $X$ iteration position in the step $t$ and step $t+1$, respectively; $y_i^t$ is the iteration position of step $t$ for the $i$ element of X; $d_{X,Y}$ is the distance between $X$ and $Y$; $rand(0, \rho_0 . e^{-\eta . d_{X,Y}}) * (y_i^t - x_i^t)$ represents random number from 0 to $\rho_0 . e^{-\eta . d_{X,Y}}$; $\rho_0$ represents distribution intensity.

Whales in the water exchange information by ultrasonic. But the intensity of ultrasonic sign decay quickly. So the distance from the wave source $d$ and propagation intensity $\rho$ can be expressed as:

$$\rho = \rho_0 \cdot e^{-\eta d} \quad . \tag{9}$$

$$\eta = -20 \cdot \ln(0.25) / d_{max} \quad . \tag{10}$$

Where $\rho_0$ represents wave source intensity, $d_{max}$ represents the maximum distance between any two whales in the search area, $\eta$ represents the attenuation factor (depending on the physicochemical properties of the medium and the nature of the ultrasound). When $\eta$ is constant, $\rho$ decreases exponentially with increasing $d$, which means that the transmission range of the ultrasonic wave is limited. If the signal source is out of the propagation range, the message carried by it may be distorted. According to a large number of experiments, the $\rho_0$=2 is the most suitable value.

### 3.3. Whale Group Optimization Algorithm Improvement

It can be seen from the basic whale swarm algorithm that the size of the population and the initialization of the individual whale position have a great influence on the speed of solving the whale swarm algorithm and the accuracy of the solution. If a whale is located far from other whales in the population, it will move very slowly during optimization and iteration, which will increase the solution time and slow down the solution speed; at the same time, it is easier to fall into the local optimum during the searching.

In order to solve this problem, this paper improves on the original algorithm and introduces the backward learning algorithm [25] to initialize the whale population position, which can effectively avoid generating poorly positioned individuals. The initialization process is as follows:

1）Randomly initialize whale populations, $N=\{X_{ij}\}$, $i=1,2,3...S_n$，$j=1,2,3...P$, $S_n$ represents the number of whales, and $P$ is the dimension which represents the optimal solution.

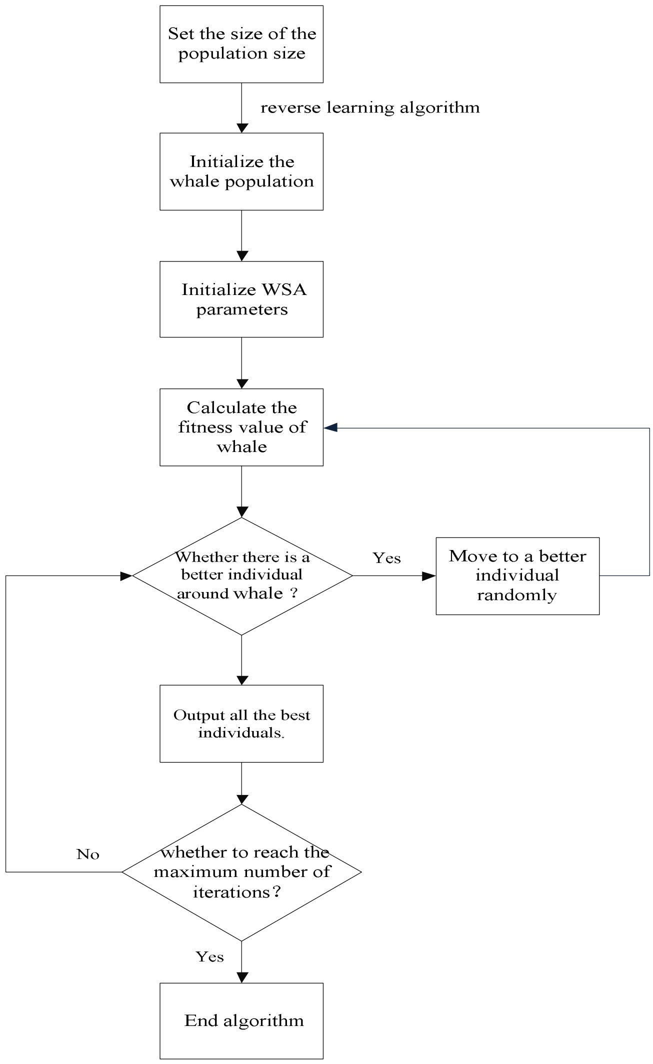


**Fig. 2.** Flowchart of the whale swarm optimization algorithm

2）Calculate the reverse population $N' = \{ X_{ij}^{'} \}$, $X_{ij}^{'} = X_{\min,j} + X_{\max,j} - X_{ij}$, where $X_{\max,j}$ and $X_{\min.j}$ represent the maximum an minimum values in the jth element of the population.

3）To calculate the fitness of the whale position, select a $S_n$ species population with a smaller fitness for the initial whale population in $\{ N = \{ X_{ij} \} | N' = \{ X_{ij}^{'} \}$.

As be seen in Fig.2, the algorithm steps can be described as follow:

Step1: Set the size of the population size (the number of sensor nodes), the use of reverse learning algorithm to initialize the whale population;

Step2: Initialize WSA parameters, the number of iterations, attenuation factor, etc;

Step3: Calculate the fitness value of each whale individual, and record the best individual with the smallest fitness value;

Step4: Determine whether there is a better (nearest and better) individual around each whale individual, and if so, move to a better individual randomly according to Eq. (8); otherwise, continue to recycle;

Step5: If the termination condition is satisfied, that is, all the optimal solutions of WSN coverage are found, then all the best individuals are output, otherwise, the procedure returns to step 4;

Step6: Judge whether to reach the maximum number of iterations, if not reached the maximum number of iterations, then return to step 3 to continue the loop, if the maximum number of iterations, the algorithm ends.

We give the improvement WSA algorithm. The pseudo-code is shown in Table 1.

**Table 1.** Node optimization pseudocode

| Improve the WSA algorithm |
|---|
| Set the size of the population, use the reverse learning algorithm to initialize the whale position; WSA initialization of parameters<br>Evaluation of whales Calculate its fitness $U_{(i)}$）<br>  while meet the number of iterations do<br>   for i=1 to N do<br>     Find better Y near $U_{(i)}$;<br>     if Y exist then<br>       $U_{(i)}$ move to Y according to formula 8;<br>     Evaluate $U_{(i)}$;<br>     end if<br>    end for<br>  end while<br>return global optimal solution |

# 4. Simulation Experiment

## 4.1. Experimental Procedure

The simulation experiment is divided into two parts. First, in order to verify the effectiveness of the whale algorithm in solving wireless sensor network coverage optimization problem, the basic whale algorithm is used to optimize the coverage of the wireless sensor network simulation. Then, in order to verify the improved whale algorithm Compared with the superiority of the original algorithm, the improved whale swarm algorithm is used to optimize the coverage simulation in the same environment. The experimental parameters are shown in Table 2.

**Table 2.** Parameters Table

| Parameter name | Parameter value | Parameter name | Parameter value |
|---|---|---|---|
| Monitoring area | 50m×50m | $P_{th}$ | 0.8 |
| Number of nodes | 50 | $\beta_2$ | 1.5 |
| Node perceived radius r | 5m | The number of iterations T | 200 |
| Node communication radius R | 10m | Attenuation factor ρ | 2 |
| $\lambda_1$ | 1 | $\beta_1$ | 1 |
| $\lambda_2$ | 0 | $w_1$ | 0.6 |
| $w_3$ | 0.1 | $w_2$ | 0.3 |

## 4.2. Experimental Results and Analysis

**Comparison between WSA and RWSA.** Fig. 3 shows the node coverage pattern of the basic whale algorithm after 200 iterations.

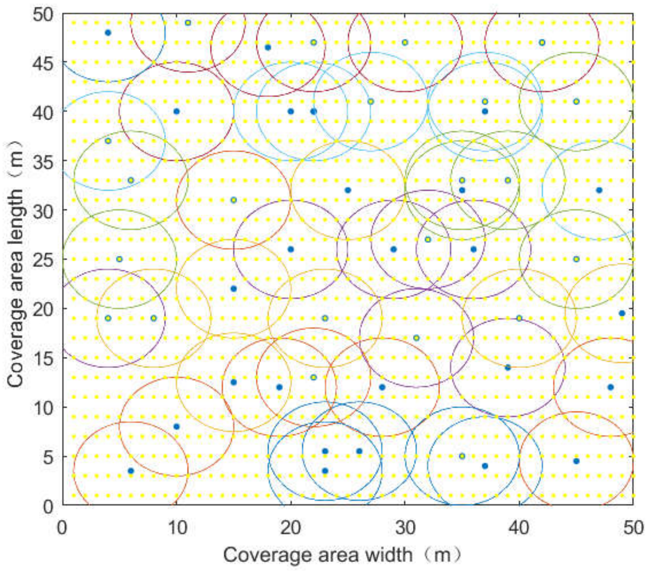


**Fig. 3.** Basic whale algorithm after 200 iterations

As can be seen from the coverage results of Fig. 3, after 200 iterations of the whale algorithm, sensor nodes can basically cover most areas, but there are still blind areas, which can effectively achieve coverage optimization of the wireless sensor network node and improve network coverage optimization rate.

Fig. 4 shows the node coverage pattern of the improved whale algorithm after 200 iterations.

Fig. 5 shows the relations between the number of iterations and network coverage of the basic whale algorithm and the improved whale algorithm.

Fig. 5 shows that in the same initial conditions, network coverage of the basic whale algorithm no longer increases and reaches the optimal coverage after 150 iterations, whereas network coverage of the improved whale algorithm reaches the optimal coverage after 122 iterations. It means that the improved whale algorithm can jump out of local optimum quickly and accelerate the convergence speed.

After 20 simulations, the average network coverage rate, node utilization rate and energy balance coefficient of the two algorithms proposed in this paper are shown in Table 3.

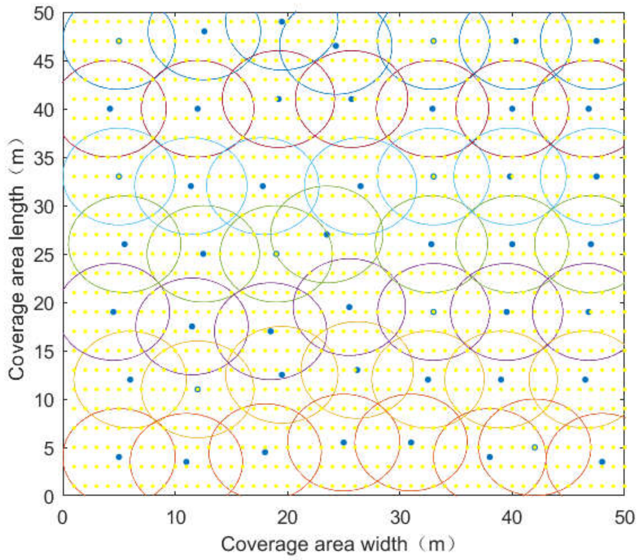


**Fig. 4.** Improved whale algorithm after 200 iterations

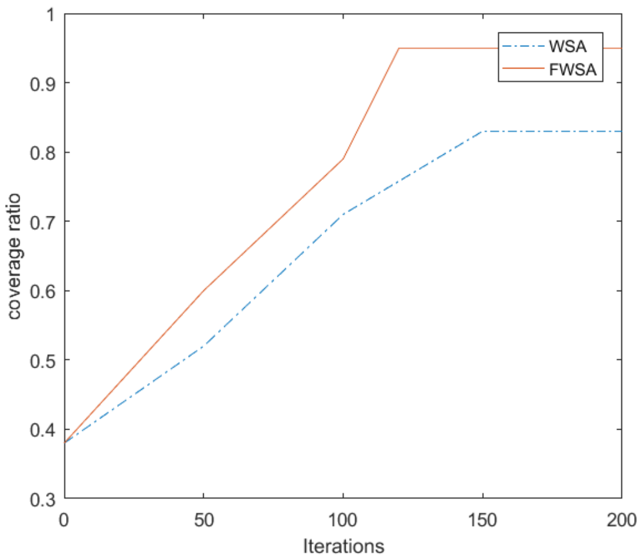


**Fig. 5.** The number of iterations

From Table 3, it can be seen that compared with the basic whale algorithm, the node utilization rate of the improved whale algorithm is increased by 15.1% and the energy balance coefficient is reduced by 1.3%, which further explains that the network coverage model optimized by the improved whale algorithm has fewer overlapped areas and lower energy consumption of sensor nodes. And it indicates that the improved whale algorithm in finding the optimal solution can quickly jump out of the local optimal solution to reduce energy waste and speed up the solution speed.

**Table 3.** Algorithm Comparison

| Optimization algorithm | Whale group algorithm | Improved whale swarm algorithm |
|---|---|---|
| Network coverage | 83.2% | 95.8% |
| Node utilization | 40.6% | 55.7% |
| Energy balance coefficient | 6.75% | 6.42% |

**Comparison with Other Algorithms.** The comparison of network coverage performance between the basic whale swarm algorithm used in this paper and the improved whale swarm algorithm based on the reverse learning theory, the clustering particle swarm optimization (CCPSO) algorithm, the standard particle swarm optimization (PSO) algorithm based on the collision theory in Literature[26], the basic artificial fish swarm algorithm (FSA), and improved artificial fish swarm algorithm (IFSA) proposed in Literature [27] can be seen in Table 4.

**Table 4.** Coverage Comparison

| Optimization algorithm | Coverage |
|---|---|
| WSA(basic whale swarm algorithm ) | 83.2% |
| RWSA(improved whale swarm algorithm) | 95.8% |
| PSO(standard particle swarm optimization0 | 64% |
| CCPSO(clustering particle swarm optimization) | 94% |
| FSA(basic artificial fish swarm algorithm) | 76.9% |
| IFSA(improved artificial fish swarm algorithm) | 94.3% |

From Table 4, it can be seen that the coverage rate of the basic whale-swarm algorithm is 19.2% higher than that of the standard particle swarm optimization algorithm, which is 6.3% higher than that of the traditional artificial fish swarm algorithm but 9.8% lower than that of the clustering particle swarm optimization algorithm and 10.1% lower than that of the improved artificial fish swarm algorithm. It can indicates that basic whale swarm algorithm has some optimization effects in the network coverage, but still has disadvantages. Other than the improved whale swarm algorithm has higher network coverage than other algorithms.

## 5. Conclusions

In this paper, we studied the network coverage problem in wireless sensor network. Firstly, the node sensing model is analyzed and the regional area monitoring is transformed into point monitoring by discrete method. Then we studied the network coverage model, add node utilization and energy utilization in network coverage by the inertial weight method. Thus, the optimization problem of wireless sensor network coverage is transformed into multi-objective optimization problem. In the node deployment issues, this paper proposes a new whale swarm optimization algorithm. By combining with the reverse learning algorithm, this algorithm makes the initial population distribution more reasonable, and solves the problem of negative movement of the nodes in the adjacent distant nodes. So that the searching ability of the node is enhanced. Finally, the experiment proves that the algorithm can improve network coverage effectively. Compared with other algorithms, FWSA algorithm can reduce the number of iterations and reach higher coverage.

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