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Retraction

Retracted: Study of Node Distribution and Density Optimization in Mobile Sensor Network 3D Space

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Gu, C. Gao, J. Lyu, W. Fan, and L. You, "Study of Node Distribution and Density Optimization in Mobile Sensor Network 3D Space," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 6978812, 7 pages, 2021.

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Research Article

Study of Node Distribution and Density Optimization in Mobile Sensor Network 3D Space

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Mobile sensor network is applied in information collection in emergencies. As the mobile sensor network in real environment is widely deployed with different height and the redundancy of the sensor node needs to be as low as possible, therefore, it is necessary to effectively deploy mobile sensor nodes in the 3D space to have reasonable layout and optimized density. To this end, we established the optimization model of mobile sensor network deployment and solved the model with chemical reaction optimization (CRO). The experimental results have shown that compared with traditional particle swarm optimization (PSO), CRO algorithm can achieve reasonable deployment more rapidly and enhance the network performance evaluation value effectively. The reasonable deployment of mobile sensor network node is very significant to information collecting, postperiod decision-making, and rapid rescuing work in emergencies.

1. Introduction

In recent years, advances in technology have made it possible to achieve compact and low-cost mobile sensors, and more and more people are beginning to focus on mobile sensor networks. In this chapter, we study a wireless sensor network in which each mobile node has some maneuvering capabilities of traditional static nodes; besides, it is composed of all the enhanced nodes with controllable mobility. For some traditional, wireless sensor network deployment methods will be very difficult or even invalid if they are used in hazardous areas and dynamic environmental objects such as disaster sites and emergency rescue. With the mobile sensor network composed of mobile sensor nodes, the problem can be solved. Related sensor's mobile node can be automatically deployed on site, according to predetermined procedure to obtain an appropriate node distribution density and then network coverage timely return real-time monitoring data. The issue of wireless sensor network node distribution and density optimization is one of focuses of the wireless sensor network study [1], mainly concerning deployment environment, node sense model and deployment algorithm [2], etc.; full coverage of sensor network can be achieved after comprehensive consideration of many factors. Compared with the deployment of conventional 2D plane environment, it is more complex to achieve the deployment of 3D plane environment, which is much closer to practical application environment; therefore, the research work is more of practical meaning.

Due to the limited energy of sensor node and inaccessibility of its application area, in order to improve the surveillance quality and network reliability of the wireless sensor network, generally, the sensor nodes are deployed in the target area of interest extensively and densely, causing the coverage area of large amounts of nodes in the network to overlap with each other. This coverage redundancy directly leads to redundancy of collecting and transmitting data, thus resulting in unnecessary energy consumption. To address the coverage redundancy of the sensor network node, we study the density optimization of node distribution in the 3D space of mobile

sensor network in this paper. The model is built in 3D space, considering the coverage and connectivity of wireless sensor network and forming a composite evaluation function. In order to reduce the difficulty of solving this function, we use geometric weighting method to transform the multiobjective constraint optimization function into an equivalent single constraint optimization function and use a relatively new chemical reaction optimization (CRO) algorithm to solve this function.

In the study of mobile sensor network, the deployment of mobile node is an important research branch, which concerns how to put limited node into the surveillance area reasonably to achieve maximum network surveillance performance. Many scholars discussed the self-organizing of mobile sensor network node; literature [3] proposed a 3D self-deployment (3DSD) algorithm, which maintains the connectivity of the network by adopting the negotiation strategy and used the density control method to balance the distribution of nodes.

The algorithm can achieve more rapid and more uniform node automatic deployment in a 3D space with obstacles. Literature [4] holds that although the full coverage is very important to the surveillance and control of wireless sensor network, however, as it is inevitable to cover voids for various reasons, the paper applies hollow circle attribute evaluation method to identify the covered voids that occurred. Based on the node density, literature [5] applies distributive coverage blind area repair algorithm to solve the deployment issue caused by node death in the directed sensor network. Literature [6] proposed the node deployment reinforced algorithm based on constraint artificial fish swarm in the directed sensor network; in this algorithm, we set up 2D plane node model, introduced "perceptual centroid" as artificial fish, and simulated consistent foraging of fish swarm to find the optimal solution in the solution space. In literature [7], genetic algorithm and simulated annealing algorithm are used to improve the coverage algorithm, and a deployment enhancement algorithm for multimedia directed sensor network is proposed, which can improve the coverage and reduce the number of iteration calculation.

This paper focuses on the study of mobile sensor network node deployment and density optimization used for information collection in emergencies. In the detailed application above, in general cases, in order to guarantee the surveillance quality of the network, the sensor nodes need to be randomly deployed with high density in the target surveillance area. The network model used in this paper is based on the following assumption:

(1) The sensor network consists of one base station and large amounts of sensor nodes in the 3D space; each of the nodes has unique identification

(2) All sensor nodes stay still after optimal deployment

(3) The energy of sensor node is limited, while the energy of base station is infinite

(4) By means of satellite positioning technology, all sensor nodes can obtain their own position information

(5) Time synchronization technology can be applied to achieve synchronization of sensor node and base station

The sensor node monitors the target periodically; in every monitoring period, all nodes can directly communicate with one another, sending the collected data information to the node of base station.

2. Problem Description

In building up the wireless sensor network, the network coverage is one of standard issues of the wireless sensor network, which is how to deploy sensor network node. Under the condition of ensuring certain service quality (QOS), the network node should be used as few as possible to achieve maximum network coverage scope. In the optimization of network coverage [8–12] for mobile sensor networks, we need to consider both node coverage and regional coverage.

Suppose the monitoring 3D region A is digitally discretized into $m \times n \times h$ pixels, and the number of mobile sensor nodes with the same parameters is n, the coordinates of each node are known, and the sensing radius is r, and the communication radius is R. The equation $\mathrm{Si} = (x_i, y_i, z_i, r)$ represents the sensor node i, whose coordinate is $\{x_i, y_i, z_i\}$, and its monitoring radius is r. Suppose the coordinates of the target pixel are (x, y, z), then the distance between the target pixel and the sensor node is

$$d(s_i, p) = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2}. \tag{1}$$

The node coverage can be defined as the event that the target pixel is covered by the mobile sensor node i is defined as r_i; then, the probability $P_{\mathrm{cov}}(x, y, z, s_i)$ of the event is the probability that the coordinate point (x, y, z) is covered by the sensor node s_i. The sensor node coverage model presents a probability distribution of certain characteristics in practical application, that is

$$P_{\mathrm{cov}}(x, y, z, s_i) = \begin{cases} 1 & d(s_i, p) \le r \\ 0 & \text{otherwise} \end{cases}. \tag{2}$$

The average probability of all points on the road being detected is taken to represent the coverage performance of the sensor network. As long as there is one node coverage point (x, y, z), the coordinate (x, y, z) is regarded to be covered by node set. The coverage of the node set can be calculated with the formula (3):

$$P_{\mathrm{cov}}S = 1 - \prod_{i=1}^{N} (1 - P_{\mathrm{cov}}(x, y, z, s_i)). \tag{3}$$

There are $m \times n \times h$ pixels in the monitoring area A and whether each pixel is covered can be represented by the joint measurement probability $P_{\mathrm{cov}}(S)$. Area coverage $R_{\mathrm{area}}(S)$ can

be defined as the ratio of the coverage area $A_{\text{area}}(S)$ of node set S to the total area A_s of monitoring area A, as shown in formula (4) below:

$$R_{\text{area}}(S) = \frac{A_{\text{area}}(S)}{A_S} = \frac{\sum P_{\text{cov}}(S)}{m \times n \times h}. \tag{4}$$

In order to analyze network performance, the probability model is used as the communication model of wireless sensor node S_i, reflecting the communication quality of internode in practical network environment.

$$T(s_i, s_j) = \begin{cases} 1 & 0 \le d(s_i, s_j) \\ 0 & d(s_i, s_j) > R \end{cases}. \tag{5}$$

In the formula, $T(s_i, s_j)$ is the communication strength of sensor node s_i and s_j. R is effective communication scope, supposing $R = 50$ m.

The communication intensity of the network is used to indicate the communication performance of the network. This value can be obtained by calculating the average communication intensity of all mobile sensor nodes. According to the node communication model formula in formula (5), we can conclude that the network communication intensity is

$$\text{Trans} = \frac{\sum_{i=1}^{N} T(S_i, S_j)}{2N}. \tag{6}$$

3. Methodology

3.1. Optimization Model of Mobile Sensor Network Deployment. By optimizing the position of each mobile sensor node, the coverage and connectivity of the network are optimized. In order to achieve the optimal coverage and connectivity at the same time, it is necessary to solve the multiobjective constraint optimization problem. We transform the multiobjective optimization problem into an equivalent single constraint optimization problem by geometric weighting method.

The nonconstraint optimization issue equivalent to the constraint optimization issue above is

$$f = \min\left[\max\left(\frac{1 - \prod_{i=1}^{N}(1 - P_{\text{cov}}(x, y, zs_i))}{m \times n \times h}\right)\omega_1 \times \max\left(\frac{\sum_{i=1}^{N} T(s_i, s_j)}{N}\right)\omega_2\right]. \tag{7}$$

ω_1 and ω_2 represent the weights of their respective functions in the overall function.

The constraint conditions are

$$s.t. R_{\text{area}}(S) \ge 0.95. \tag{8}$$

Firstly, according to the usual coverage standard, the network coverage $R_{\text{area}}(s)$ needs to be greater than or equal to 95% to ensure that the entire network is effectively covered by the sensor node set.

$$\begin{aligned} g_i(X) &\le 0, i = 1, 2, \cdots, n, \\ h_j(X) &\le 0, j = 1, 2, \cdots, m. \end{aligned} \tag{9}$$

In the formula, $g_i(X)$ and $h_j(X)$ represent the connectivity of the network and the constraint conditions determined by the need of network coverage and connection.

Secondly, in the connectivity requirement, the following conditions should be met: the number of adjacent nodes of any mobile sensor node is not 0, and the network island is not formed.

Due to the complexity of the problem model, we adopted a relatively new intelligent optimization algorithm—chemical reaction optimization algorithm (CRO) [13–15] to solve it. This algorithm is a swarm intelligence algorithm based on the collision and energy conversion of molecules in the process of chemical reaction. It is searched by the collision of molecules and the chemical reaction after the collision to lead the molecules to the lowest possible energy state.

3.2. Chemical Reaction Optimization Algorithm. The CRO algorithm simulates the change and migration of molecules in a chemical reaction system. In the chemical reaction, each molecule has kinetic energy KE and potential energy PE. After the invalid collision of single molecule, a new molecular structure ω' is obtained, which satisfies the inequality:

$$\begin{aligned} PE_\omega + KE_\omega &\ge PE_\omega, \\ KE_\omega{}' &= \left(PE_\omega - PE_\omega{}' + KE_\omega\right) \times \alpha. \end{aligned} \tag{10}$$

α represents the kinetic energy KE loss rate. The kinetic energy $\text{KE}_\omega{}'$ is stored in the central energy buffer to support the Decomposition and Synthesis of molecules, which is also a feature of the CRO, while the other part of the kinetic energy $(PE_\omega - PE_{\omega'} + KE_\omega) \times (1 - \alpha)$ is consumed in the reaction system.

Basic chemical reactions can be broken down into four categories: On-wall Ineffective Collision, Decomposition, Intermolecular Ineffective Collision, and Synthesis. The specific principle of each basic chemical reaction is as follows:

(1) *Intermolecular Ineffective Collision*. The Intermolecular Ineffective Collision can be regarded as the collision reaction of two molecules, because the energy conversion involved in the exchange reaction is small; the two molecules exchanged a small amount of energy during the collision, and the energy loss can be ignored. So ω_1 and ω_2 are the two molecules that are involved in the collision, and you can get two new molecules by the collision reaction, and the molecular structure is ω_1' and ω_2'

(2) *On-Wall Ineffective Collision*. In the process, the properties of the molecule change, the structure of the molecule changes, and a new molecule are created. Because the impact force is not large, the structure of the new molecule is similar to the structure of

the original molecule. The original molecular structure is ω, and the new molecular structure is ω'

(3) *Synthesis*. When two molecules collide with each other, the two molecules combine into one molecule due to the fierce and powerful impact, and the energy is transferred. So the two molecules before the collision are ω_1 and ω_2, and the new molecules after the collision are ω'. In the synthesis reaction, molecules collide with each other with great strength and energy conversion, resulting in two molecules combining into one molecule. This new molecular structure ω' is greatly different from that of the two original molecules

(4) *Decomposition*. The collision force in the decomposition reaction is very large; one molecule ω is decomposed into two new molecules ω_1' and ω_2'; the new molecules are greatly different from the original molecule. This mechanism enables CRO algorithm to jump out of local minimum value

The flow diagram of CRO algorithm is shown in Figure 1. The main steps of the algorithm are:

Step 1. In the initialization phase, we initialized the molecular set; the target function is set to be PE of molecule. Initialized KE of every molecule is set to be InitialKE value.

Step 2. In every iteration, different molecular combination types are chosen based on whether it is uni-molecular reaction or intermolecular reaction. When it is uni-molecular, we choose On-wall Ineffective Collision or Decomposition. When it is an intermolecular reaction, we choose the Intermolecular Ineffective Collisions or Synthesis.

Step 3. Calculate the value of target function and test whether it is new minimum value.

Step 4. When the termination condition is met, the iteration process is stopped. We output the present optimal solution.

Condition of termination. The program will be stopped when the iteration number reaches the predetermined maximum iteration number.

4. Results and Discussion

4.1. Experimental Environment and Parameter Setting. In order to verify the effect of the algorithm designed in this paper on the sensor network deployment optimization problem, the experimental platform is Win10/MATLAB (R 2012a); the computer hardware is Inter(R) Core (TM) i5-3230m CPU, 8 GB RAM. The CRO algorithm is designed, and the simulation results are compared with those of particle swarm optimization (PSO) [16, 17] intelligent algorithm.

In order to simulate the three-dimensional deployment environment, the sensor node is randomly deployed in the 500 m × 500 m × 500 m space, as shown in Figure 2. The main test criterion is the adaptive value of the optimization function. In this space, the number of sensor nodes is 200. After repeated experiments, the control parameters are set to be the communication distance of node is $R_1 = 50$ m, the sensing radius of node is $r = 50$ m, the weight value of network coverage is $\omega_1 = 0.5$, and the weight value of network communication intensity is $\omega_2 = 0.3$.

4.2. Network Connectivity and Deployment Testing. Figure 3 is the neighbor relation diagram between nodes, which is mainly used to test the connectivity of the network to see whether there is a network island. In the figure, the red circle is the sensor node, and the blue line is the analog communication connection between nodes. If two nodes can communicate with each other, a blue line is established between them and their neighbors. As can be seen from the following figure, all nodes can interconnect with each other and communicate with each other, so there are no isolated nodes and information islands.

Figure 4 shows the regional deployment coverage diagram of the node. We should try our best to make each node strengthen the coverage, but no information island can appear. In the figure below, the red asterisk is the sensor node, the blue sphere is the monitoring coverage of the node, and the area inside the blue sphere is the area that the node can perceive and detect. We will use the CRO algorithm to enable the node to be better deployed to cover the vast majority of the area without having an information island.

Figure 5 is a schematic diagram of CRO algorithm. The energy change process of chemical reaction can be reflected from the change of potential energy. It is inspired by the interaction between molecules in chemical reactions to find the lowest potential energy phenomena in the potential energy surface. The four primary reactions are Intermolecular Ineffective Collision, Decomposition, On-wall Ineffective Collision, and Synthesis. The result of a chemical reaction is the product of a chemical reaction. The change of the chemical reaction product is expressed by the system potential energy. The whole reaction process is a process in which the reaction potential energy gradually decreases. At the end of the reaction process, the system potential energy reaches the minimum, and the state tends to be stable. It can be seen that CRO algorithm is an optimization process to seek the minimum system potential energy.

4.3. Comparison between CRO Algorithm and PSO Algorithm. Figure 6 is the relation schema of iteration number-perception radius; in the simulation experiment, we applied CRO algorithm and PSO algorithm to make comparison. The perception radius of node is from 8 m to 10 m; the step length is 0.05 m; when the constraint conditions of formula (8) are met, record the number of iterations taken. The program will continue to run until the preset conditions are met or the number of iterations reaches the preset number. To prevent the program from running invalid for a long time, we set the maximum number of iterations to 700. Through Figure 5, we can discover that CRO algorithm can reach the constraint condition of the system with different perception radius and small number of iteration, which means that the regional coverage is higher than 95%, and

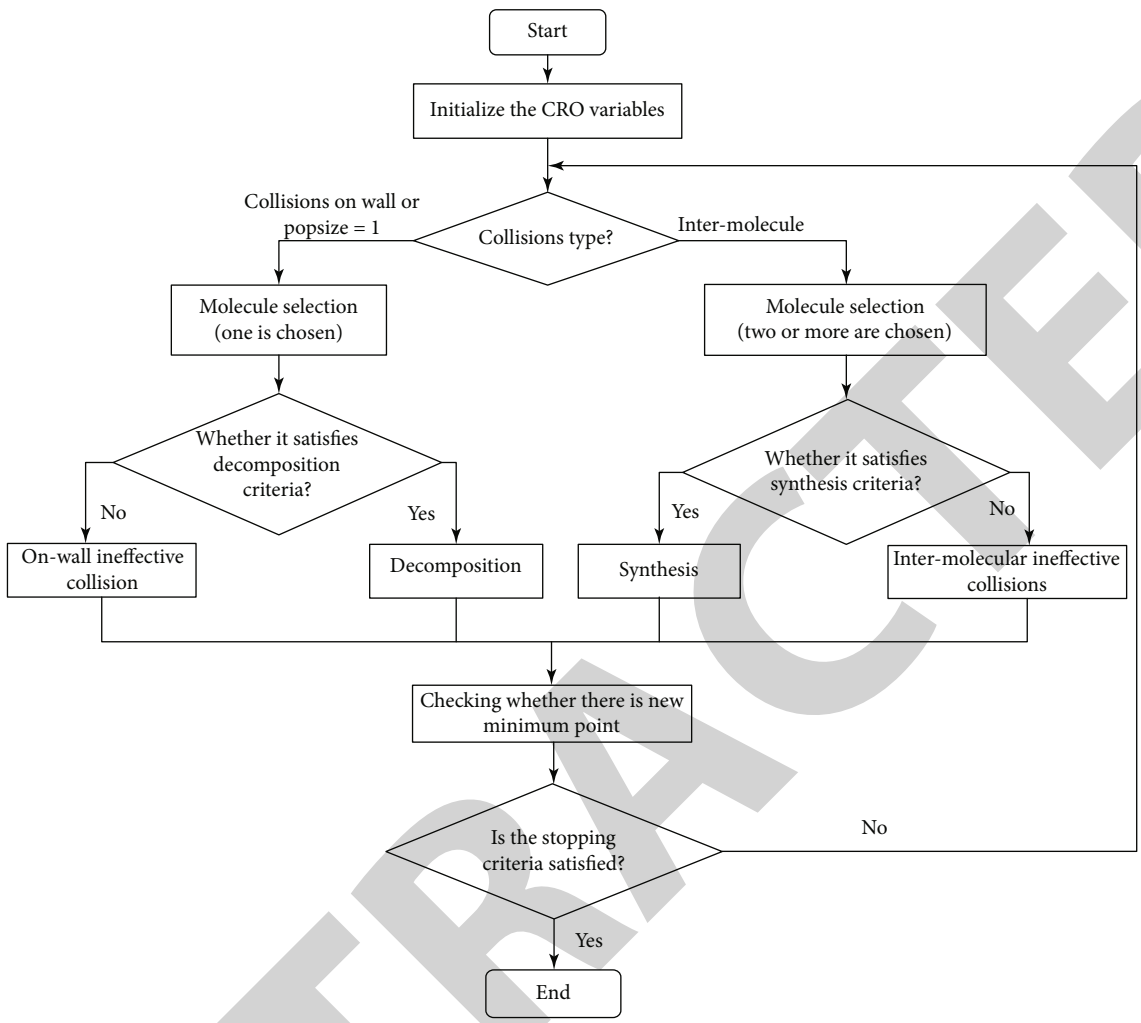

Figure 1: The flow diagram of CRO algorithm.

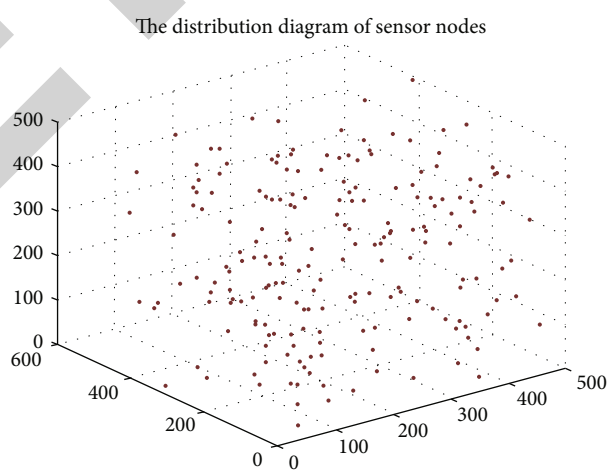

Figure 2: The distribution diagram of sensor nodes.

communication can be made between any two nodes, and no island occurred. From this, we know that CRO algorithm is more effective than PSO algorithm.

Table 1 is the comparison table of the optimal value of fitness function. CRO algorithm and PSO algorithm are used to solve the function model, and the final value of the fitness

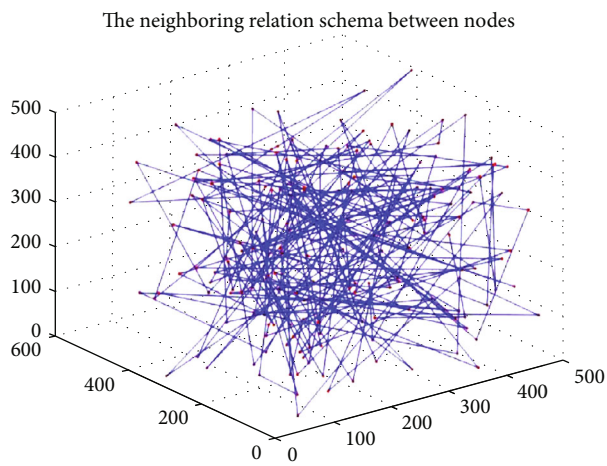

Figure 3: The neighboring relation schema between nodes.

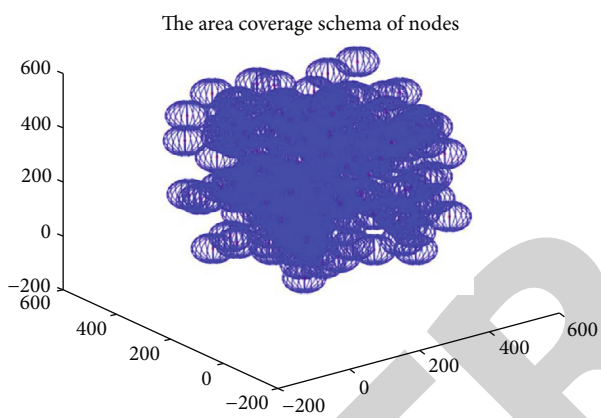

Figure 4: The area coverage schema of nodes.

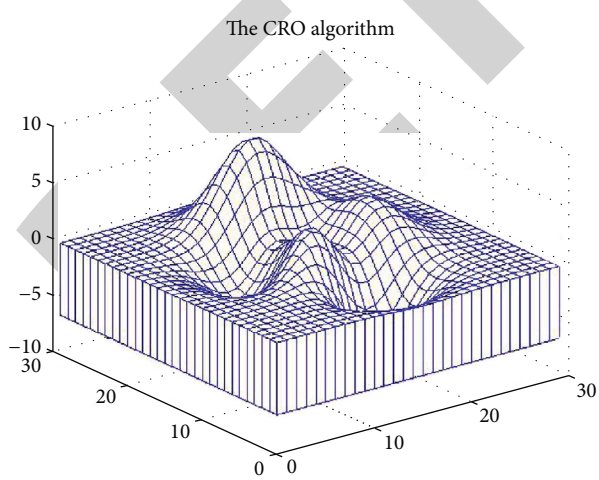

Figure 5: Sketch map of chemical reaction optimization algorithm.

function obtained in 5 simulation experiments is recorded. According to the following table, the average value of the function obtained by CRO algorithm is 11.24, while the average value of the function obtained by PSO algorithm is 9.864. Through comparison, it is found that the average value of the function obtained by CRO algorithm is 1.376 higher than that obtained by PSO algorithm. The reason for this phenomenon is that CRO algorithm is a comprehensive algorithm, which has a variety of operators such as Decomposition and Synthesis, which can help the program to change the position of node coordinates greatly, so as to better and faster jump out of the local optimal solution and find the global optimal value.

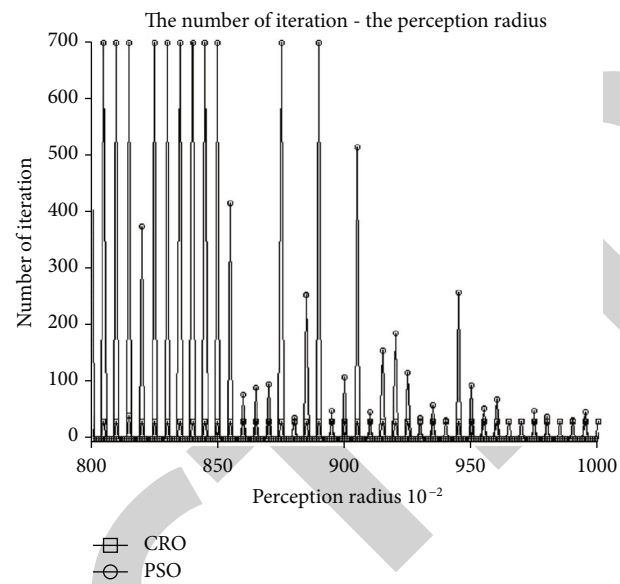

Figure 6: Relation schema of number of iteration-perception radius.

Table 1: Comparison table of optimal value of fitness function.

Experiment no.	PSO	CRO
Experiment 1	9.94	11.19
Experiment 2	9.85	11.26
Experiment 3	10.01	11.17
Experiment 4	9.77	11.27
Experiment 5	9.75	11.31

5. Conclusion

To address the reasonable deployment of mobile sensor, the mobile sensor network deployment optimization model is established for information collecting of emergencies and solved with CRO algorithm. The experimental results have shown that CRO algorithm is more suitable for solving the mobile sensor network deployment optimization of information collecting in emergencies than PSO algorithm, which can effectively optimize network layout, enabling the comprehensive evaluation value of network performance to improve by 13.95%; CRO algorithm can obtain better mobile sensor network deployment by improving the disadvantage of PSO algorithm easily engaged in optimal local value.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request. (Jingjing Lyu :lvjingjing@cdu.edu.cn).

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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