Modified Communication Parallel Compact Firefly Algorithm and Its Application

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***Abstract*—Coverage is an important indicator to measure the monitoring quality of Wireless Sensor Network (WSN). As a NP-hard problem, it is a mainstream method to introduce swarm intelligence algorithm to solve it. After analyzing the traditional Firefly Algorithm (FA), aiming at the defects of this algorithm, this paper proposes Modified Communication Parallel Firefly Algorithm (MCPFA) family algorithm, which improves the performance of the algorithm to a certain extent. On this basis, the compact optimization method is introduced and the Modified Communication Parallel Compact Firefly Algorithm (MCPCFA) family algorithm is proposed to further improve the overall function of traditional FA. The proposed algorithm is tested by several classical functions in CEC2013 test function set to verify the performance of the algorithm. Finally, a WSN node deployment scheme based on MCPCFA family algorithm is proposed to improve the network coverage. Through simulation experiments, compared with the traditional Partial Swarm Optimization (PSO), FA, Parallel FA (PFA) and Compact FA (CFA), MCPCFA family algorithm shows the best performance in WSN network layout.**

***Index Terms*—firefly algorithm, modified parallel strategy, compact optimization method, WSN, coverage optimization**

I. Introduction

Swarm intelligence algorithm is an optimization method proposed by researchers based on the research of biological group behavior and physical phenomena in nature. In recent decades, many scholars at home and abroad have proposed a variety of swarm intelligence algorithm. These algorithms are inspired by biological evolution or natural biological habits. Therefore, each algorithm has its own rules and characteristics. Yang Xin-she simulated the living habits of fireflies and proposed FA in [1]. As a swarm intelligence algorithm, it can also be free from the nature of optimization problems. These algorithms or their variants are used to solve optimization problems in various fields. Like other swarm intelligence algorithms, FA and its variants are used to solve optimization problems in a variety of domains.

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Internet of things and big data are hot research and application fields in the intelligent era. As the core infrastructure of Internet of things and big data, WSN have been widely studied and deeply developed in recent years [2]. At present, WSN have been integrated into life and widely used in various fields [3]. Node deployment is one of the basic problems that must be properly solved for any type of WSN application to achieve the expected quality of service. Therefore, the research on the layout of WSN is particularly important. The traditional 2D coverage research is not enough to meet the actual needs, so the coverage research in 3D environment has attracted extensive attention of researchers. As a NP-hard problem, the introduction of evolutionary algorithm solves some problems to a certain extent.

The 3-D curved surface deployment problem is a special situation in the three-dimensional space deployment. It is closer to the application scenarios in the real world, such as volcano monitoring, building structure monitoring, and disaster rescue monitoring. Sensors can only be placed on the surface of the three-dimensional terrain, and cannot be arbitrarily deployed in the air or in the mud. The research on the area coverage of 3-D curved surface is to monitor the area of the mouth mark on the terrain surface such as the mountain surface and the building surface. Due to the complex shape of the terrain surface and the changeable environment, it is very difficult to monitor the events or important parameter information of the three-dimensional surface. Therefore, the research on the deployment of 3D surface nodes has very important practical application value.

In this paper, our goal is to analyze the shortcomings of FA and make corresponding improvements, so as to improve the performance of the algorithm. Because the traditional FA has the problem of poor convergence performance and the algorithm is easy to fall into the local optimum, this paper proposes three modified communication parallel strategy. Then, FA has the problem of high time complexity. For this problem, this paper proposes a compact scheme combined with the FA to reduce the time complexity of the algorithm. And combined with the parallel FA family algorithms, the proposed compact scheme is introduced into each group, and the MCPCFA family algorithms are proposed, which further improves the overall performance of FA. Using the improved version of FA proposed in this paper, MCPCFA family algorithm optimizes the node deployment strategy of WSN and finds the node layout mode with the maximum coverage. The main contributions of this paper are summarized as follows.

- MCPFA family algorithm is proposed, and the population number of MCPFA is updated to further improve the performance of FA.
- The performance of the proposed MCPFA is analyzed. In order to use less memory to simulate the operation of MCPFA, the compact idea is added, and the MCPCFA is proposed to improve the overall function of FA.
- In this paper, CEC2013 test function set is used to test and analyze the performance of the proposed MCPCFA family algorithm, which verifies our theory. The data results show that compared with other comparison algorithms, MCPCFA shows strong ability.
- This paper introduces the traditional WSN coverage model, 0-1 model. At the same time, MCPCFA family algorithm was used to optimize the model. Through the analysis of simulation results, it is confirmed that the optimization ability of the proposed method is better than other methods. The superiority and applicability of MCPCFA in this field are also verified.

The rest of the arrangements are as follows. The second part reviews the FA algorithm and proposes the MCPCFA algorithm. The third part analyzes the experimental performance of the proposed MCPCFA algorithm. Section IV introduces the 0-1 coverage model of WSN. Section V discusses the application of MCPCFA in WSN coverage in detail. Finally, the work of this paper is summarized.

II. Modified Communication Parallel Compact Firefly Algorithm

A. Firefly Algorithm

FA simulated the biological behavior of fireflies and assumed that each firefly was always glowing. In order to simulate the luminous behavior of fireflies, assuming that all fireflies no gender distinction, each a firefly is likely to be attracted to other individuals. In addition, the bright fireflies will attract darker fireflies, and their brightness is directly proportional to the fitness function value with its location. The specific steps of FA are as follows.

First of all, each a firefly in the fitness function value is calculated, and according to the results of this decision direction of movement of each individual.

Then, their individual attractiveness was calculated by (1).

$$\beta = \beta_0 \times e^{-\gamma r_{ij}^2} \tag{1}$$

Finally, each firefly moves its position according to the rules of (2).

$$x_{id}\left(t+1\right) = x_{id}\left(t\right) + \beta\left(x_{jd}\left(t\right) - x_{id}\left(t\right)\right) + \alpha \tag{2}$$

Where, I_0 is the maximum brightness of firefly individual. γ is the light intensity absorption coefficient. r_{ij} is the spatial distance between firefly i and j. β_0 is the maximum attraction. α is the step factor, which is a constant on $[0, 1]$.

B. Modified Communication Parallel Firefly Algorithm

Although the traditional FA has stronger global search ability than other algorithms, like most swarm intelligence algorithm, FA still has the disadvantage that it is easy to fall into the local optimal solution, resulting in the premature convergence of the algorithm in the running process. Therefore, aiming at this problem, based on the traditional parallel strategy [4], this paper proposes MCPFA family algorithm. Next, the new ideas proposed in this paper will be explained in detail.

Firstly, it is assumed that there are pop firefly individuals in the population, and the maximum number of iterations is $iter_{\max}$. Before the algorithm starts to run, the whole firefly population is clustered, and the population is divided into g groups. Then there will be pop/g particles in each group after clustering. In addition, it is also necessary to set up an information exchange mechanism to exchange information every time the number of iterations t of the algorithm reaches an integer multiple of R, and the exchange strategy will be divided into two parts according to the different search stages of the algorithm. After this operation, the population will return to the optimization state at the position after information exchange to continue the optimization work. The communication strategies in the two different search stages are explained below. It is worth mentioning that two different search stages will be distinguished when $t = \frac{iter_{\max}}{2}$, the first stage before and the second stage after. That is, when $t < \frac{iter_{\max}}{2}$, the algorithm is considered to be in the first stage, while when $t \geq \frac{iter_{\max}}{2}$, the algorithm is considered to be in the second stage.

a) Communication strategy in the first stage: Like most swarm intelligence algorithm, FA also has some disadvantages, such as poor convergence and easy to fall into local optimality. Therefore, in this part of the work, we will improve FA to improve the convergence and accuracy of the algorithm. In addition to the different communication strategies used, MCPFA family algorithm will use the same grouping method and preparations before communication. The specific operations are as follows.

- Modified Communication Parallel Firefly Algorithm-Best (MCPFA-B) After the grouping operation, all particles have entered the parallel working state. Every time the number of iterations t reaches R, the action of information exchange will occur. Before that, the particles in each group will be sorted according to the size of fitness function value, and the arranged population will be divided into A and B parts. Among them, A represents the particles whose fitness function value is in the first half. Then, the particle order after the A part is $x_{Abest}\left(x_{A1}\right) > x_{A2} > x_{A3} > \ldots > x_{Aworst}\left(x_{A\frac{pop}{2}}\right)$. The B part represents the particles whose fitness function value is in the last half. Then, the particle order after the B part is $x_{Bbest}\left(x_{B1}\right) > x_{B2} > x_{B3} > \ldots > x_{Bworst}\left(x_{B\frac{pop}{2}}\right)$. Among them, it is worth noting that the fitness function value of x_{Aworst} is better than that of x_{B1}. The reason for this is that the algorithm itself has the disadvantage of poor convergence. Using the best particle to replace the worst particle can speed up the convergence speed of the algorithm to a certain extent and make the algorithm find the global optimal solution faster.

$$\begin{aligned} x_{Abest}\left(x_{A1}\right) &\rightarrow x_{Aworst}\left(x_{A\frac{pop}{2}}\right) \\ x_{Bbest}\left(x_{B1}\right) &\rightarrow x_{Bworst}\left(x_{B\frac{pop}{2}}\right) \end{aligned} \tag{3}$$

Where x_{A1} and x_{B1} represent the position of the particle with the best fitness function value in A and B respectively. x_{Aworst} and x_{Bworst} represent the position of the particle with the worst fitness function in A and B respectively. $\rightarrow$ expresses the meaning of substitution. After information exchange, the replaced particles will be optimized again in the updated position. When the number of iterations t reaches an integral multiple of R again, information exchange will be carried out again until the end of the first search phase. Fig. 1 shows a schematic diagram of this optimization scheme.

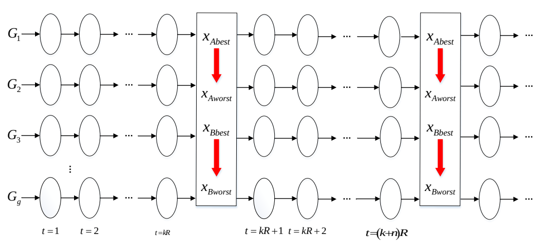


Fig. 1. Communication strategy of the first stage of MCPFA-B.

- Modified Communication Parallel Firefly Algorithm-Average (MCPFA-A) Like MCPFA-B, the algorithm performs grouping operation first, and then all particles enter the optimization state. When the number of iterations $t = kR$, the particles are sorted according to the fitness function value. However, different from the previous method, MCPFA-A will use the average value of the current population for information exchange in the operation of information exchange. As shown in (4), the average value of the position of the particles in A and B is calculated and recorded as x_{Aave} and x_{Bave}.

$$\begin{aligned} x_{Aave} &= \frac{x_{A1}+x_{A2}+\ldots+x_{Aworst}}{\frac{pop}{2g}} \\ x_{Bave} &= \frac{x_{B1}+x_{B2}+\ldots+x_{Bworst}}{\frac{pop}{2g}} \end{aligned} \tag{4}$$

After getting the average, the algorithm will replace the worst value in the part A with the average value in the part A. Part B is the same as part A. The specific operation is shown in (5).

$$\begin{aligned} x_{Aave} &\rightarrow x_{Aworst} \\ x_{Bave} &\rightarrow x_{Bworst} \end{aligned} \tag{5}$$

Where x_{Aave} and x_{Bave} represent the average position of all particles in part A and B respectively. Fig. 2 shows the schematic diagram of MCPFA-A optimization scheme in the first stage.

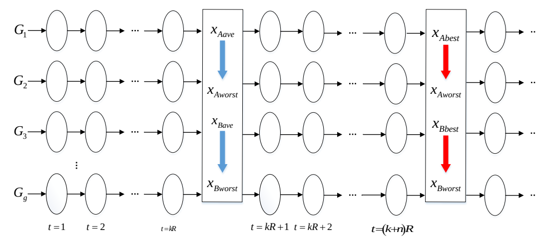


Fig. 2. Communication strategy of the first stage of MCPFA-A.

- Modified Communication Parallel Firefly Algorithm-Rand (MCPFA-R) Similar to the methods of MCPFA-B and MCPFA-A, MCPFA-R also needs to sort the fitness function values of fireflies in each group before information exchange, and divide the particles in each group into two parts: Part A and B. Then, MCPFA-R randomly selects one particle x_{Arand} and x_{Brand} in A and B respectively. These two particles are used to replace the worst fitness particles x_{Aworst} and x_{Bworst}. The specific operation is shown in (6).

$$\begin{aligned} x_{Arand} &\rightarrow x_{Aworst} \\ x_{Brand} &\rightarrow x_{Bworst} \end{aligned} \tag{6}$$

Where x_{Arand} and x_{Brand} represent the positions of randomly selected particles in parts A and B respectively. For ease of understanding, Fig. 3 shows the schematic diagram of MCPFA-R optimization scheme in the first stage.

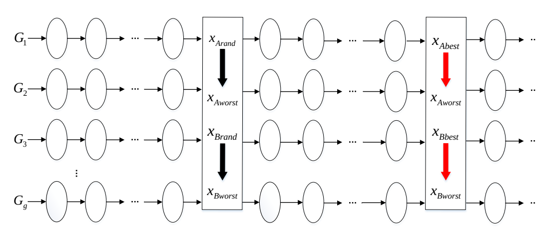


Fig. 3. Communication strategy of the first stage of MCPFA-R.

b) Communication strategy in the second stage: In the second stage, FA begins to enter the convergence stage, that is, the whole population begins to approach the global optimal solution. At this stage, the operation of information exchange still needs to be carried out. However, since the possibility of a better position in the solution space is relatively small, and the algorithm is in the convergence stage, the information exchange operation in the second stage will only use the optimal value in each group. At the same time, in order to improve the convergence speed of the algorithm, when the number of iterations reaches an integral multiple of M, the previously divided g group population is fused. The so-called fusion processing means that after each fusion, The number of groups of the population will be reduced to half of the previous one. At the same time, the latter half of the particles with relatively poor fitness function value in the fused group should be discarded and only the first half of the particles should be retained. In this way, the number of firefly individuals in the whole population will continue to decrease until there is only one group left, and the fusion operation will be stopped. The exchange of information will not be stopped until the end of the algorithm. The schematic diagram of the proposed idea in this stage is shown in Fig. 4.

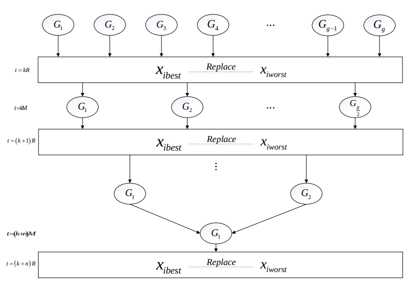


Fig. 4. Communication strategy of the second stage of MCPFA.

To sum up, MCPFA family algorithm proposed in this paper adds a modified parallel strategy on the basis of traditional FA, divides the population into g groups and optimizes at the same time. When the algorithm is in the first stage, whenever the number of iterations t reaches an integral multiple of R, three communication strategies are used to replace the position of the worst fitness function value particle x_{worst} in the group, so as to improve the global search ability of the algorithm. When the algorithm is in the second stage, in order to improve the convergence of the algorithm, the particle x_{best} with the best fitness function value in the group is used to replace x_{worst}. At the same time, whenever t reaches an integer multiple of M, the packets are fused. For example, the first group and the second group are fused, the third group and the fourth group are fused, and the latter half of the particles with relatively poor fitness function value are discarded to improve the computer memory occupied by the algorithm and improve the efficiency of the algorithm. In practical application, R and M will be set in advance.

C. Compact optimization method

This paper proposes MCPFA family algorithm, which improves the performance of the algorithm to a certain extent, but MCPFA family algorithm still has room to improve. For example, the traditional FA occupies too much computer memory space, and MCPFA is also troubled. In order to solve this problem, compact optimization idea is introduced in this study. This optimization method simulates the population behavior of the algorithm by establishing a population distribution probability. The most essential feature of compact method is that it has no actual population, but uses virtual population instead. The virtual population is a probability model, and they are encoded in a data structure, represented by the disturbance vector PV [5], [6].

$$PV = [\mu, \delta] \tag{7}$$

Where, μ and δ are two parameters, which are expressed as the mean and standard deviation of the PV vector respectively, t indicates the number of iterations of the current program μ and δ will vary in the Gaussian probability density function PDF and are limited to the region of $[-1, 1]$. At the same time, PDF is normalized so that its area is 1, and it is a uniform distribution of complete shape [7].

$$PDF_{\mu_i,\sigma_i}(x) = \frac{e^{-\frac{-(x-\mu_i)^2}{2\sigma_i^2}}\sqrt{\frac{2}{\pi}}}{\sigma_i\left(erf\left(\frac{\mu_i+1}{\sqrt{2}\sigma_i}\right)\right) - erf\left(\frac{\mu_i-1}{\sqrt{2}\sigma_i}\right)} \tag{8}$$

$$\mu_i(t+1) = \mu_i(t) + \frac{1}{N_p}(winner_i - loser_i) \tag{9}$$

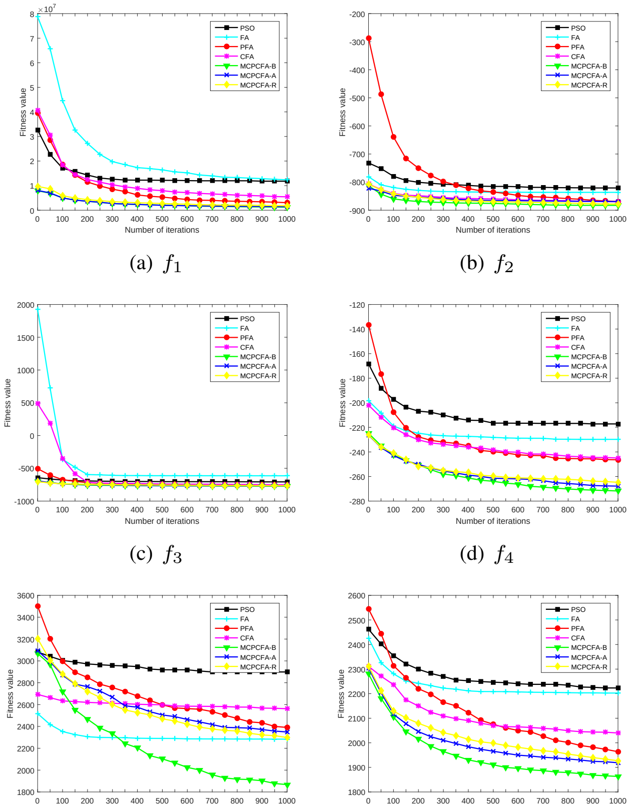
$$\begin{aligned}\sigma_i^2(t+1) = (\sigma_i(t))^2 + (\mu_i(t))^2 - (\mu_i(t+1))^2 \\ + \frac{1}{N_p}\left(winner_i^2 - loser_i^2\right)\end{aligned} \tag{10}$$

Finally, the time complexity of MCPCFA is theoretically analyzed to better introduce the MCPCFA algorithm proposed in this paper. the time complexity of the compression strategy FA is O($g\times d$), the time complexity of updating the optimal value is O(1), and the time complexity of the FA algorithm using the parallel strategy is O($g\times g$). So the above calculation complexity is max(O($g\times d$), O(1), O($g\times g$))=O($g\times d$), std. $d>g$. The computational complexity of the entire algorithm is O($time_{max}\times g\times d$), that is, the time complexity of MCPCFA is O($time_{max}\times g\times d$).

III. Test experiments to verify the performance of the proposed algorithm

In order to verify the advantages of MCPCFA family algorithm proposed in this paper, several classical test functions from CEC2013 test function set will be used to test the performance of the algorithm in MATLAB2015b. At the same time, comparative experiments were carried out with PSO, FA, PFA and CFA. In order to ensure the fairness of the experimental results, the parameter settings of each algorithm will be set uniformly. Each test function will be run 30 times and the results will be averaged and compared. The population number of all algorithms is set to 80 and the maximum number of iterations itermax is set to 1000. In PFA and MCPCFA family algorithm, the population was divided into 8 groups. In addition, make all teams exchange information every 20 iterations.

CEC2013 test function set includes Unimodal Functions, Basic Multimodal Functions and Composition Functions. We select two classical test functions from each category to test the performance of the algorithm. The results of this test are shown in Tab. I and Fig. 5.



(a) f_1 (b) f_2

(c) f_3 (d) f_4

(e) f_5 (f) f_6

Fig. 5. The results of test experiment

Through the above test experiments, we can clearly see that the MCPCFA family algorithm proposed in this study show better performance in these three types of problems. This also verifies the superiority of the improvement scheme proposed in this study.

To better illustrate the advantages of memory usage after introducing the parallel compression optimization method, we analyze the memory situation of MCPCFA and FA. A comparison of memory costs is shown in the Tab. II. The number of variables for the FA and MCPCFA algorithms can be obtained from the above update equations. In the Tab. II, the algorithm update equation consists of Eq. (1-2) and Eq. (7-10). Assuming that the number of particles is n, and n is a positive integer. The population size of MCPCFA is n. So the time complexity is 6×n×T×Iterations. Similarly, we can get the time complexity of FA as 2×N×T×Iterations. Although the update equation of MCPCFA is larger than that of FA, it has only n individuals and n is much smaller than N. So it consumes less memory than the original algorithm.

IV. 3D 0-1 Coverage model of Wireless Sensor Network

The node deployment problem of WSN is necessary [9]. The traditional coverage problem is usually studied based on 2D plane, but if the sensor nodes are placed on 2D plane, the simulation experiment will be obviously different from the actual situation. Therefore, in this study, the sensor nodes are placed on the 3D terrain, and the terrain elements such as high and low-lying are added to the three-dimensional terrain, so as to more truly simulate the actual coverage problem. To sum up, the 3D 0-1 model and the terrain model proposed in this study will be described in detail below.

In general, the sensing model of sensor nodes is usually simplified to 0-1 model, that is, when a point in the area is covered by sensor nodes, it is recorded as 1. If it is not overwritten, it is recorded as 0. The most commonly used 0-1 sensing model is the sensing disk model. All points within the radius of a disk with a fixed length r centered on a sensor node are considered to be covered by the node. Assuming that the coordinate of a node i in the detected area is (x_i, y_i, z_i), the communication radius is r and the coordinate of the target pixel j is (x_j, y_j, z_j), the distance between the node i and the target pixel j is as follows.

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{11}$$

Use $O_{i,j}$ to represent the perception quality of node i to pixel j. When the position of the pixel j to be concerned is within the circle of the sensing range r of node i, it is considered that the perception quality of node i to pixel j is 1, that is, the perception of node i to pixel j is 1. Otherwise, when pixel j is outside the sensing range of node i, the perception of node i to pixel j is 0, Therefore, the mathematical expression is as follows.

$$O_{i,j} = \begin{cases} 1, d_{i,j} \le r \\ 0, otherwise \end{cases} \tag{12}$$

The traditional 2D coverage model ignores the factors in the actual terrain. Although the problem is simplified, it can not be applied in practice. Therefore, during the experiment, the terrain elements of high and low-lying are added to the terrain, so that the model can more truly simulate the actual scene. The next simulation experiment will also use the model.

V. Application of MCPCFA family algorithm in WSN 3D coverage optimization

To solve the coverage problem is essentially to find the optimal deployment strategy. Different strategies have a significant impact on coverage, especially on 3D terrain. By optimizing the parameters of FA, using modified parallel strategy and introducing compact idea, this paper proposes MCPCFA family algorithm to improve the performance of FA. MCPCFA family algorithm performs well in solving basic multimodal functions, and the 0-1 coverage of WSN belongs to

TABLE I
COVERAGE OF DIFFERENT NUMBER OF NODES

Function	f_1	f_2	f_3	f_4	f_5	f_6
PSO	11806088	-820.806	-706.818	-217.204	2898.773	2223.218
FA	12371935	-836.479	-614.059	-229.762	2283.462	2202.544
PFA	3051820	-869.359	-755.468	-246.415	2390.835	1963.838
CFA	5453586	-870.054	-750.4	-244.972	2562.319	2039.94
MCPCFA-B	1234468	-882.79	-773.23	-271.77	1867.24	1863.02
MCPCFA-A	1434183	-869.116	-768.149	-267.83	2349.067	1918.792
MCPCFA-R	1778181	-878.305	-766.806	-264.703	2298.769	1927.079

TABLE II
THE TIME COMPLEXITY OF THE TWO ALGORITHMS

Algorithm	Particle	Memory Size	Computing Complexity	Use Equations
MCPCFA	n	6×n	6×n× T× Iteration	(1)(2)(7)(8)(9)(10)
FA	N	2× N	2× T× N× Iteration	(1)(2)(3)

this kind of problem. Therefore, the 0-1 coverage problem of WSN is effectively solved by the MCPCFA family algorithm.

The sensor node is set on the ground, so you only need to know the two coordinate values of a point to calculate the coordinates of the point. Therefore, the algorithm can optimize the deployment strategy by optimizing the location of any 2D sensor nodes. Each particle of the algorithm represents a deployment strategy.

Each individual updates their own location and calculates the fitness function value according to (13).

$$R\left(t\right)=\frac{1}{Z}\sum_{j=1}^{Z}\left(\sum_{i=1}^{P}O_{i,j}\right) \tag{13}$$

Where, $R\left(t\right)$ is the coverage at iteration t, p represents the number of sensor nodes, and Z represents the number of pixels in the simulation model made in this study. The purpose of this experiment is to find a node deployment strategy with the largest network coverage under the condition of existing hardware facilities.

The proposed algorithm is applied to the WSN 3D coverage model by using MATLAB 2015b simulation tool to verify the applicability of the proposed MCPCFA family algorithm in this field. Firstly, the sensor nodes are randomly distributed in this 3D terrain. In order to fully prove the performance of the proposed algorithm in 3D coverage, PSO, FA, PFA and CFA are used for comparative experiments. The number of sensor nodes is set to 30-55. The communication radius r of each node is set to 5-10m. The size of the monitoring area is 100m*100m. Sensor nodes are randomly distributed in the 3D terrain. The simulated 3-D terrain is shown in Fig. 6. The maximum number of iterations $iter_{\max}$ of the algorithm is set to 30. The initial population of pop is 80. Information exchange is conducted every three iterations of the program. At the same time, $t \leq 15$ is the first stage of the algorithm, and $t > 15$ enters the second stage of the algorithm. In other words, from $t = 18$, the firefly population will be fused between groups. Make the program fuse once every three iterations.

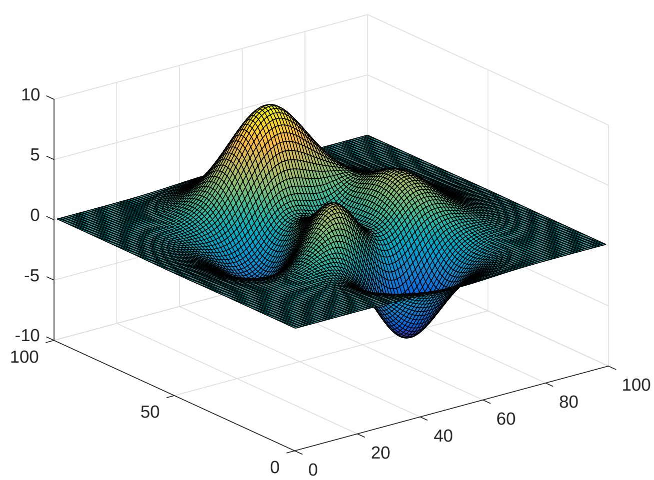


Fig. 6. Random deployment of sensor nodes on 3-D topographic maps

It is worth noting that MCPCFA family algorithm starts the fusion operation between groups when the number of iterations is $t = 18$, while $g = 8$ and $M = 3$ are set in this experiment, that is, the fusion action between groups occurs when $t = 18$, 21 and 24 respectively. Since then, the number of groups has been gradually fused from 8 groups to 1 group, there is no need for fusion operation. Next, the results of the two groups of simulation experiments will be summarized and analyzed.

A. Simulation experiment when the total number of sensor nodes is different

In this part, we will experiment with different number of sensor nodes. For fairness, we guarantee that other parameters remain unchanged. The total number of sensor nodes is set to

30, 35, 40, 45, 50 and 55 respectively, and the communication radius is uniformly set to 5m. The experimental results optimized by different algorithms are recorded in Tab. III.

TABLE III
COVERAGE OF DIFFERENT NUMBER OF NODES

Nodes	30	35	40	45	50	55
PSO	0.4611	0.5082	0.5541	0.5959	0.6359	0.6657
FA	0.4637	0.5176	0.5608	0.598	0.6389	0.6707
PFA	0.4688	0.5203	0.5642	0.6046	0.6434	0.6752
CFA	0.4697	0.5233	0.5647	0.6095	0.6462	0.6763
MCPCFA-B	0.4952	0.5432	0.5939	0.6354	0.6784	0.7612
MCPCFA-A	0.4891	0.5341	0.5845	0.6233	0.6658	0.6937
MCPCFA-R	0.4897	0.5408	0.5881	0.6289	0.6663	0.7008

It can be seen from the results in Tab. III that with the increase of the number of sensor nodes, the coverage of WSN is also improving. At the same time, when the number of nodes is 50, compared with traditional PSO, FA, PFA and CFA, the coverage optimized by MCPCFA-B is increased by 4.52%, 3.95%, 3.5% and 3.22% respectively. When the number of nodes is other values, the coverage has also been significantly improved. It can be seen that no matter how many sensor nodes are, mcpcfa finds the node deployment mode with the highest coverage through optimization.

B. *Simulation experiment with different communication radius*

In this part, we will experiment with different communication radius of sensor nodes. Similarly, for fairness, the total number of sensor nodes is uniformly set to 30, and other parameters are consistent. We set the communication radius as 5m, 6m, 7m, 8m, 9m and 10m respectively. The experimental results are recorded in Tab. IV.

TABLE IV
COVERAGE OF DIFFERENT COMMUNICATION RADIUS

Radius	5m	6m	7m	8m	9m	10m
PSO	0.4611	0.605	0.7265	0.8341	0.8996	0.9433
FA	0.4637	0.6234	0.7537	0.8463	0.9145	0.9587
PFA	0.4688	0.6301	0.7597	0.8513	0.9202	0.9628
CFA	0.4697	0.6323	0.7632	0.8534	0.9266	0.9683
MCPCFA-B	0.4952	0.6672	0.7988	0.8931	0.9562	0.9881
MCPCFA-A	0.4891	0.6432	0.7787	0.8762	0.9398	0.9766
MCPCFA-R	0.4897	0.6587	0.7853	0.8861	0.9437	0.9802

It can be seen from the experimental results in Tab. IV that the coverage increases with the increase of communication radius. Through comparison, it can be seen that the performance of MCPCFA-B is the best. Compared with traditional FA, when the communication radius is 7m, the coverage optimized by MCPCFA family algorithm is improved by 4.51%, 2.5% and 3.16% respectively. When the communication radius is other values, the trend of the results is also consistent. Therefore, the effectiveness of mcpcfa proposed in this study and the applicability of this method in solving the WSN coverage optimization problem can be more determined.

VI. CONCLUSION

Aiming at the defects of traditional FA, MCPFA family algorithm is proposed in this paper to improve the problem that the algorithm is easy to fall into local optimal and run slowly. Meanwhile, due to the high time complexity of MCPFA family algorithm, this paper proposes MCPCFA family algorithm by introducing compact optimization method. Through the test experiments of several classical test functions in CEC2013, MCPCFA family algorithm shows superior performance compared with other methods. In the study of WSN, it is very important to maximize network coverage by effective node deployment under limited conditions. In order to solve this problem, the proposed MCPCFA family algorithm is applied to the 3D coverage research of WSN in this paper. The applicability of the proposed algorithm in this field is verified by simulation.

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