Multi-Strategy Enhanced Coot Algorithm for Coverage Optimization in Wireless Sensor Networks

Weibin Kong, Yi Du, Xiaoyu Zhang, Baomin Jia ✉, Zhongqing Fang, Qiong Liang and Xue Du

College of Information Engineering, Yancheng Institute of Technology, Yancheng, China

✉ Email: jiaycit@sina.com

An improved coot optimization algorithm is proposed for wireless sensor networks (WSNs) coverage optimization. To monitor the interest field and obtain the valid data, a wireless sensor network coverage model is established. The population is initialized with cubic map and opposition-based learning strategy. The leader population is reversely learned dimension by dimension, so as to improve the diversity of the population and the global optimization ability of the algorithm. The simplex method is introduced to optimize the local exploration of the population. The experimental results show that the enhanced coot optimization algorithm for coverage optimization in wireless sensor networks can reduce energy consumption and improve network coverage.

Introduction: In recent years, people's research on the IoT technology has been deepening. The WSNs as the core part of the IoT has become one of the important research objects. WSNs are widely used due to their advantages of diverse integration functions and wide range of coverage. However, in a designated area, it will lead to node redundancy and cause a large waste of energy and materials if excessive sensor nodes are thrown. Therefore, the reasonable deployment of sensor node locations is of great significance to optimize its performance. Zhu et al. [1] proposed the mixed strategy weed algorithm to improve network coverage. Cao et al. [2] intended to improve the HWSN coverage rate by an enhanced social spider optimization algorithm, which can reduce energy consumption. In paper [3], the grey wolf optimizer with enhanced hierarchical structure was applied to solve the WSNs coverage optimization problem and achieved good results.

In this letter, a coverage optimization method for wireless sensor networks based on the improved coot optimization algorithm is proposed. To increase the diversity of the population, the cubic map and opposition-based learning strategy (COBL) is used during initialization phase. Combined with the simplex method to update the position of the follower to help the algorithm jump out of the local optimum. Carrying out dimension-by-dimensional opposition-based learning on the leader population to strengthen the global search ability of the algorithm. Experimental results show that this method can effectively reduce node redundancy and increase network coverage in WSNs coverage optimization problems.

WSNs Coverage Model: In a WSN, assuming that the monitoring area is a two-dimensional plane and N sensor nodes are randomly deployed. Each sensor node has the same sensing radius R and communication radius R_C, and $R_C=2R$. The set of nodes can be expressed as $\boldsymbol{S}=\{s_1,s_2,s_3,\cdots,s_n\}$, and the monitoring area is $\boldsymbol{M}=\{m_1,m_2,m_3,\cdots,m_n\}$. In this letter, the Boolean perception type is used as the sensor node perception model. The perception range is a circular area with the node as the center and R as the radius. As long as the monitoring area is within the sensing radius, it can be considered as covering the node. The two-dimensional plane is discretized into $m\times l$ pixels. For any fixed point $p=(x_i,y_i)$, the sensor node's perception probability $p_{cov}(s_i,m_j)$ is defined as follows:

$$p_{cov}(s_i,m_j)=\begin{cases}1, d(s_i,m_j)\le R\\ 0, else\end{cases} \tag{1}$$

$$d(s_i,m_j)=\sqrt{(x-x_i)^2+(y-y_i)^2} \tag{2}$$

where $d(s_i,m_j)$ is the Euclidean distance from the sensor node to the target point p.

When monitoring with a detector, each pixel may be sensed by multiple nodes. So the joint sensing probability distribution of a pixel by sensor nodes is expressed in Eq.(3).

$$p(\boldsymbol{S},m_j)=1-\prod_{i=1}^{n}\left[1-p_{cov}(s_i,m_j)\right] \tag{3}$$

The total coverage rate R_{cov} of the detection area is as follows:

$$R_{cov}=\frac{\sum_{j=1}^{m\times l}p(\boldsymbol{S},m_j)}{m\times l} \tag{4}$$

Therefore, the WSN coverage optimization is transformed into finding the optimal solution a for R_{cov} described in Eq. (5).

$$f(a)=Max\left[R_{cov}(a)\right] \tag{5}$$

Enhanced Coot Optimization Algorithm: To address the issues of slow convergence and susceptibility to local optima in the original algorithm, COOT algorithm based on simplex method and dimension-by-dimension opposition-based learning (SDO-COOT) was proposed. And it is used to optimize the coverage of WSNs. The optimization process of SDO-COOT is compared to the process of finding the best node in the WSN. The improvement method is as follows:

(1) Initialization of COBL

By combining the Cubic map and opposition-based learning, a new strategy COBL is proposed, with the mathematical model as Eqs.(6-7).

$$Z_{i+1}=\rho Z_i(1-Z_i^2) \tag{6}$$

$$X'_{i,j}=lb_j+ub_j-Z_i\times(ub_j-lb_j) \tag{7}$$

where $Z_i\in(0,1)$. ρ is a control parameter with a value of 2.595, and $X'_{i,j}$ is the j th-dimensional component of the opposition position of the i th individual.

(2) Simplex Method

The simplex method[4] is a polytope search algorithm that has strong local search capabilities. In this letter, it is introduced into the chain search phase to enhance the local search capability of the algorithm and help it escape local optima. It performs four operations including reflection, compression, expansion and contraction. The specific steps are as follows:

Step 1 Compute the fitness of all follower coots, find the optimal point X_G with the minimum fitness value, the second-best point X_B , and the worst point X_S , and calculate the centroid by Eq.(8).

$$X_C=(X_G+X_B)/2 \tag{8}$$

Step 2 To perform the reflection operation according to Eq.(9).

$$X_R=X_C+\alpha(X_C-X_S) \tag{9}$$

where α is the reflection coefficient with a value of 1.

Step 3 If $f(X_R)<f(X_G)$, then perform an expansion operation as follows:

$$X_E=X_C+\gamma(X_R-X_C) \tag{10}$$

where γ is the reflection coefficient which takes a value of 2.

Step 4 If $f(X_R)>f(X_G)$, then perform a compression operation by Eq.(11).

$$X_W=X_C+\beta(X_S-X_C) \tag{11}$$

where β is the reflection coefficient which takes a value of 0.5.

Step 5 If $f(X_S)>f(X_R)>f(X_G)$, then perform a contraction operation as shown in Eq. (12).

$$X_T=X_C+\beta(X_C-X_S) \tag{12}$$

(3) Dimension-by-dimension Opposition-based Learning

During the leader movement phase, the position is updated according to dimension-by-dimension opposition-based learning as follows:

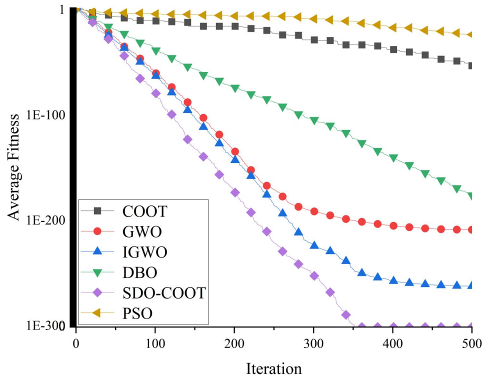
$$Temp(i)=ub(i)+lb(i)-Temp(i)\times rand \tag{13}$$

where $Temp(i)$ represents the current position of the leader population, $ub(i)$ and $lb(i)$ are the upper and lower bounds of the current dimension.

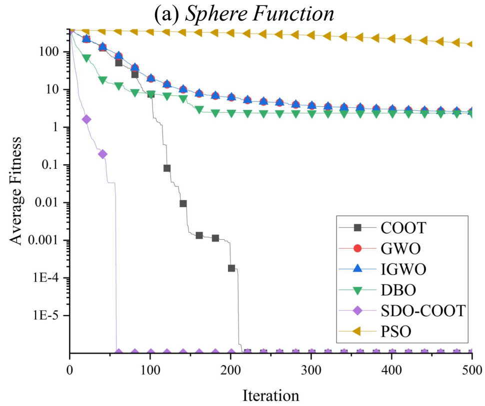
The value of a certain dimension is combined with the values of other dimensions to form a new solution after opposition-based learning. The new solution is evaluated according to the fitness. If the quality of the current solution can be improved, the update result of opposition-based learning in this dimension is retained, otherwise the original information is retained. This update to the next dimension will be carried out using this elite retention method until each dimension is updated.

This method effectively suppresses the mutual influence between dimensions and improves the convergence efficiency and optimization capability of the algorithm.

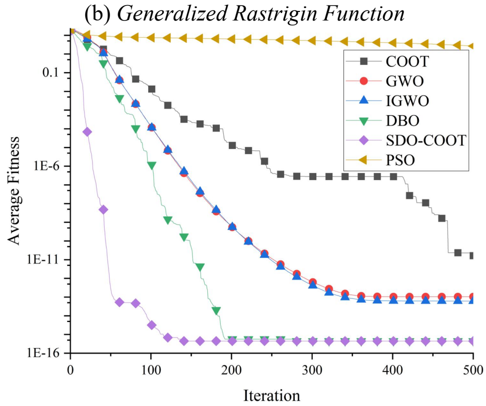
Results: In order to verify the improvement of SDO-COOT, other 5 algorithms were compared with it. Including Coot Optimization Algorithm (COOT) [5], Grey Wolf Optimization Algorithm (GWO) [6], Improved Grey Wolf Optimization Algorithm (IGWO) [7], Dragonfly Optimization Algorithm (DBO) [8] and the classical Particle Swarm Optimization Algorithm (PSO) [9]. Each algorithm was set with the same parameters, including a population size of 30, a maximum iteration of 500 and 30 independent runs to obtain the average value. The experiments were conducted on both the unimodal Sphere Function and the multimodal including Generalized Rastrigin Function and



(a) *Sphere Function*



(b) *Generalized Rastrigin Function*



(c) *Ackley's Function*

Fig. 1 *Iteration curves of 6 algorithms on test functions*

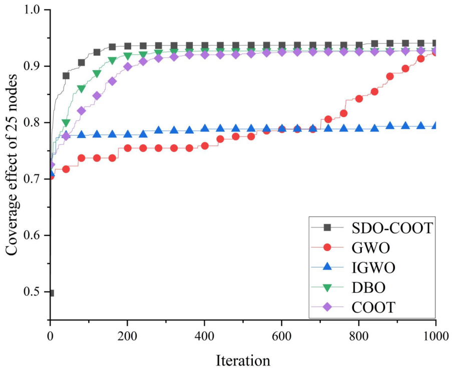
Ackley's Function with a dimension of 30. The iteration curves of the test results are shown in Figure 1.

From Figure 1, it can be seen that whether it is a unimodal function or a multimodal function, SDO-COOT has higher optimization accuracy, faster convergence speed and superior performance than the other five algorithms.

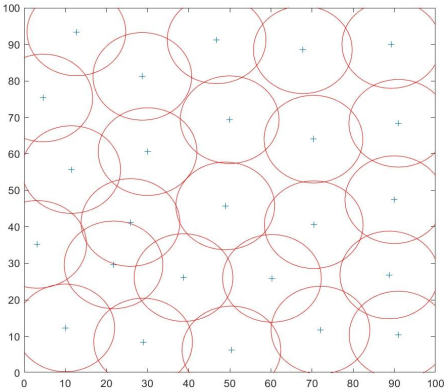
Table 1. Results of five algorithms for WSNs coverage optimization

algorithm	coverage	
	25 nodes	30 nodes
COOT	92.74%	96.69%
GWO	92.42%	97.95%
IGWO	79.33%	86.55%
DBO	92.71%	96.84%
SDO-COOT	**94.08%**	**98.09%**

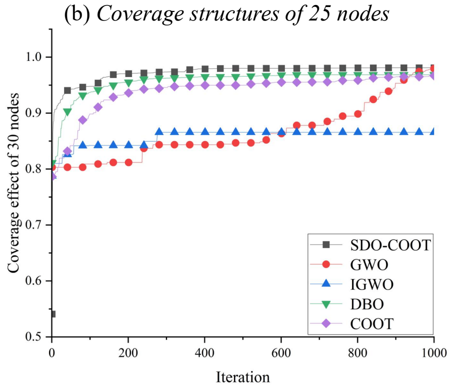
To verify the performance of SDO-COOT in WSNs node coverage, a simulation example is conducted. The



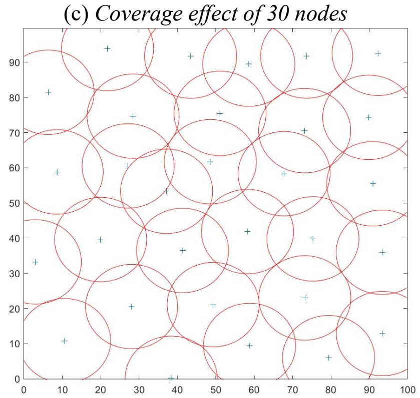
(a) *Coverage effect of 25 nodes*



(b) *Coverage structures of 25 nodes*



(c) *Coverage effect of 30 nodes*



(d) *Coverage structures of 30 nodes*

Fig. 2 *Coverage effect and coverage structures for different nodes*

simulation area is set to 100m*100m and the number of sensor nodes is 25. Set the population size to 30, the number of iterations to 1000 and $R = 6m, R_c = 12m$. The coverage rate curves of COOT, GWO, IGWO, DBO and SDO-COOT algorithms are shown in Figure 2, and the coverage results are shown in Table 1.

From the results in Figure 2 and Table1, it can be seen that the proposed method is superior to several other algorithms in terms of coverage, which proves the superiority of the proposed method. In addition, the results show that the more the number of nodes is set, the higher the coverage.

Conclusion: In this letter, a Coot optimization algorithm based on simplex method and dimension-by-dimension opposition-based learning is proposed to optimize the coverage of WSNs. The effectiveness of SDO-COOT is verified by COBL, simplex method and dimension-by-dimension opposition-based learning strategy into the coot optimization algorithm. Then the SDO-COOT is further applied to the coverage optimization problem of WSNs. The experimental results show that the improved algorithm has faster convergence speed and higher precision, which reduces the node redundancy in the coverage optimization process of wireless sensor network and improves the coverage.

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Conflict of interest: The authors have no conflict of interest to declare.

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