INTERNATIONAL JOURNAL OF CIRCUITS, SYSTEMS AND SIGNAL PROCESSING
DOI: 10.46300/9106.2022.16.65 Volume 16, 2022

An Improved Intrusion Weed Optimization Algorithm for Node Location in Wireless Sensor Networks

Shihui Li

School of Electro-Mechanical and Informaiton, Yiwu Industrial & Commercial College, Yiwu, Zhejiang 322000, China

Received: July 12, 2021. Revised: December 12, 2021. Accepted: January 12, 2022. Published: January 14, 2022.

Abstract—**The distribution optimization of WSN nodes is one of the key issues in WSN research, and also is a research hotspot in the field of communication. Aiming at the distribution optimization of WSN nodes, the distribution optimization scheme of nodes based on improved invasive weed optimization algorithm(IIWO) is proposed. IIWO improves the update strategy of the initial position of weeds by using cubic mapping chaotic operator, and uses the Gauss mutation operator to increase the diversity of the population. The simulation results show that the algorithm proposed in this paper has a higher solution quality and faster convergence speed than IWO and CPSO. In distribution optimization example of WSN nodes, the optimal network coverage rate obtained by IIWO is respectively improved by 1.82% and 0.93% than the IWO and CPSO. Under the condition of obtaining the same network coverage rate, the number of nodes required by IIWO is fewer.**

***Keywords*—improved invasive weed optimization algorithm, wireless sensor networks, node location, CPSO, IWO**

I. INTRODUCTION

The wireless sensor network(WSN) is a multihop wireless network combined by a set of sensor nodes which are static or moving in the form of self-organization. It has the advantages of strong invulnerability and rapid deployment, and also has an extensive application prospect in civilian and military use. In recent years, it has become a research hotspot both at home and abroad[1-2]. The research shows that the reasonable arrangement of sensor nodes is beneficial to improve the comprehensive performance of WSN, but the phenomenon of channel disturbance and information redundancy is also prone to appear, which will cause the energy waste. Therefore, how to reasonably deploy sensor nodes and optimize network performance has become one of the key technologies of WSN.

For the problem of the distribution optimization of WSN nodes, many scholars at home and abroad use artificial intelligence algorithm to deal with it. However, almost all intelligent algorithms are easy to fall into the problems of local optimum [3-5], premature convergence and slow later convergence. Therefore, scholars have proposed using other operators to improve the original algorithm in order to improve its performance of searching optimization. For example, Rani[6] and others combine the differential evolution operator with the ABC algorithm and put forward a DABC algorithm to solve the distribution optimization problem of WSN node. Bishan[7] and others, according to the node dormancy strategies, divide the node distribution phase, and use the power law to update the component of glowworm swarm optimization(GSO) to get the optimal coverage of WSN. Saravanan and others[8] use the data aggregation operator to improve the ant colony algorithm(ACO) to maximize the effective coverage area of WSN and put forward an optimized mechanism of WSN node distribution based on DAACO algorithm.

Invasive weed algorithm (IWO) is widely used in multi-objective optimization problems[9-10], but is seldom used in the research of the distribution optimization of WSN nodes. Like other algorithms, the basic IWO algorithm also has the problems of premature convergence and low convergence accuracy. Aiming at the above problems, this paper proposes an improved IWO (IIWO) to effectively avoid the phenomenon of algorithm premature, and the Gaussian mutation operator is introduced to select a certain number of weed seeds to produce variation individuals, which will ensure the diversity of population in this paper through the standard function test and WSN simulation example.

II. MATHEMATICAL PROBLEM DESCRIPTION

If there are n WSN nodes in the whole area, the region A can be discretized into the $s \times s$ grid and the area of each grid is 1. For any net point p_j ($j = 1, 2, \cdots, m \times n$), the distance between it and s_i is

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (1)$$

There are two types of the measurement model of the WSN node[10]: the first one is the binary measurement model; the second one is the probabilistic model. This paper uses a common probabilistic measurement model to calculate its coverage.

$$C_{ij} = \begin{cases} 1, & d_{ij} \le R - R_e \\ \exp(\dfrac{-\lambda_1 \alpha_1^{\varepsilon_1}}{\alpha_2^{\varepsilon_2} + \lambda_2}), & R - R_e < d_{ij} < R + R_e \\ 0, & \text{else} \end{cases} \qquad (2)$$

In the formula, $R_e (0 < R_e < R)$ is the effective measuring radius of the sensor, $\alpha_1 = R_e - R + d_{ij}$, $\alpha_2 = R_e + R - d_{ij}$,other quantities are measured parameters.

If all nodes are detected and they are independent events, then according to the probability that the point p_j is detected by a single node, the synthetic probability that it can be detected by all nodes can be obtained simultaneously.

$$C_j = 1 - \prod_{i=n} (1 - C_{ij}) \qquad (3)$$

In the formula, if C_j is greater than or equal to a particular threshold C_t , then the point p_j is considered that can be detected by the node; on the contrary, if C_j is less than the C_t , then p_j is considered that can't be detected. Through many experiments, this paper chooses $C_t = 0.75$.

Then, through the synthetic probability that p_j is detected, we measure the coverage rate of each grid. That is, through the formula(3), the detected probability of each grid point can be calculated. We take the proportion of the number of the grid points that are detected in the total number of grid as the coverage rate of WSN. The specific mathematical description is

$$C_s = \frac{\sum_{j=1}^{m \times n} C_j}{m \times n} \qquad (4)$$

Therefore, the distribution optimization problem can cover the whole target area through the optimization algorithm. That is, this problem can be converted to the maximization problem of equation (5), that also is

$$\max \left(\frac{\sum_{j=1}^{m \times n} C_j}{m \times n} \right) \qquad (5)$$

III. IMPROVED INVASIVE WEED ALGORITHM

A. Description of IWO

IWO is a simulation of weed cloning, land occupation, growth and reproductive behavior. The algorithm consists of five steps, that is population initialization, growth and propagation, spatial expansion, eliminate through competition and stopping criterion [11]. Each weed individual corresponds to an objective function value that is the WSN area coverage rate. The specific steps are as follows.

Step1. Population initialization. The location of weed i is randomly generated from the following formula

$$\boldsymbol{X}_i = \boldsymbol{X}_L + rand(0,1) \cdot (\boldsymbol{X}_U - \boldsymbol{X}_L) \qquad (6)$$

In the formula, $\boldsymbol{X}_i = [x_{i1}, x_{i2}, \cdots, x_{iD}]$ ($i = 1, 2, \cdots, P_I$), D is the dimension of the solution vector, P_I is the number of initial population scale. $\boldsymbol{X}_U$ and $\boldsymbol{X}_L$ are respectively the upper limit and lower limit of $\boldsymbol{X}_i$.

Step2. Growth and propagation. The fitness value $f(\boldsymbol{X}_i)$ of each weed seed is calculated. Each individual produces the number of seeds based on the maximum fitness value $f_{\max}$ and minimum fitness value $f_{\min}$ of the population, and the better individual of the population, the more the number of the produced seeds. For the maximum optimization problem, the number of seeds P_s produced by each individual can be computed by the following formula[12]

$$P_s = \frac{f(\boldsymbol{X}_i) - f_{\min}}{f_{\max} - f_{\min}} (S_{\max} - S_{\min}) + s_{\min} \qquad (7)$$

In the formula, $S_{\max}$ and $S_{\min}$ are respectively the maximum and minimum number of seeds.

Step3. Spatial expansion. Seeds produced by weeds are randomly distributed in the neighborhood of their parent weeds by the normal distribution $N(0, \sigma_{iter}^2)$. In the algorithm iteration process, the law of the variation of the standard deviation can be described as

$$\sigma_{iter} = \sigma_F + \left(\frac{iter_{\max} - iter}{iter_{\max}} \right)^w (\sigma_I - \sigma_F) \qquad (8)$$

In the formula, w is the nonlinear adjustment factor; σ_I and σ_F are respectively the initial standard deviation and final standard deviation of seed sowing; σ_{iter} is the standard deviation of the iter th generation. It should be pointed out that through the above search mechanism, the distribution position of seeds will be closer to their parent individuals as the increase of the number of iterations, so as to realize searching optimization.

Step4. Elimination through competition. After several iterations, when the number of the population exceeds the maximum population size $P_{\max}$, all individuals should be sorted in order of the fitness value. The first $P_{\max}$ individuals with the high fitness value are reserved.

Step5. Stopping criterion. Steps (2)~(4) are repeated. The individual with the best fitness value of each generation population is recorded. Until the number of iterations reaches the maximum number of iterations $\mathrm{iter}_{\max}$, the algorithm stops, then the optimal solution of iteration is output.

B. Design of IWO

In the IWO, the initial location of random weeds may lead to uneven location distribution. The characteristics of the randomness and regularity of chaotic operators and the traversing any state in a certain scope without repetition should be considered. According to the document [13], this paper uses cubic mapping chaotic operator to improve the initialization of weed position in a chaotic model. A chaotic sequence is generated, and the search of weed initial position is realized by using chaotic characteristics.

Step1. $\boldsymbol{Y}=(y_1,\cdots,y_d)$ is generated randomly, $y_i \in[-1,1]$, $1\le i\le d$.

Step2. We use the formula (10) to make the $M-1$ times iterations for $\boldsymbol{Y}$ dimension by dimension, then the rest of $M-1$ individuals are generated.

Step3. The generated chaotic variable is mapped to the search space of the solution according to formula (9)

$$x_{id}=x_L+(1+y_{id})\frac{x_U-x_L}{2} \tag{9}$$

In the formula, x_{id} is the position of weed i in d dimension. y_{id} is the generated d th dimension values of weed i by using the formula(9). x_U and x_L are respectively the upper limit and lower limit of the value of x_{id}.

This paper selects a certain number of weed seeds at random after step (3), and uses Gauss mutation operator to operate it. The individual $\boldsymbol{V}_i$ after mutation can be obtained.

$$\boldsymbol{V}_i=\boldsymbol{X}_i+e(\boldsymbol{X}_B-\boldsymbol{X}_i) \tag{10}$$

In the formula, e represents the Gaussian distribution with a mean value of 0 and a variance of 1. $\boldsymbol{X}_B$ is the individual with the highest fitness value in the current population. For variation individuals, there is a random interference which obeys the Gauss distribution between the parent and the current optimal individual [14], which may lead to the location of the variation individuals out of the search scope of the algorithm. Therefore, when the value of the variation individual $\boldsymbol{V}_i$ is not within the range of the search, the position is searched again through the following formula

$$\boldsymbol{V}_i=\boldsymbol{X}_L+e(\boldsymbol{X}_U-\boldsymbol{X}_L) \tag{11}$$

The cubic chaotic operator and Gauss mutation operator are introduced to improve the traditional IWO, and an improved IWO is generated. The pseudo-code for the IIWO is shown below.

```
Weed position is generated randomly by cubic chaotic operator
For iter=1 to iter_max
  f_max and f_min of the population are calculated
For each weed individual
Determine the number of seeds produced by each weed
Seeds are generated by the random distribution
The fitness value of seeds is calculated
New individuals are generated by using Gauss mutation operators
                    End
Individuals are sorted in ascending order according to fitness values
If P_s > P_max
Select the first P_max individuals with high fitness value
                    End
   iter=iter+1
                    End
```

IV. SIMULATION

A. Standard Function Test

This paper uses four standard test functions proposed by document[15] to test, and compares it with CPSO(chaotic PSO, CPSO for short) and IWO. The global minimum of the four functions is 0, and the number of iterations is 500 times. Then 30 independent tests of each test function are made through each algorithm. The table1 gives the statistical results of the test, including mean value(Mean) and standard deviation(SD).

Table 1. Standard function test results

Function	Index	IWO	CPSO	IIWO
Sphere	Mean	1.65e-20	1.52e-58	5.95e-60
	SD	4.21e-20	884e-58	8.03e-60
Ackley	Mean	1.93e-07	8.32e-12	1.24e-15
	SD	2.03e-06	1.28e-13	2.34e-15
Rastrigin	Mean	3.28e-16	1.48e-25	4.25e-29
	SD	2.29e-16	4.65e-25	8.51e-30
Griewank	Mean	5.32e-04	1.59e-16	2.24e-16
	SD	8.41e-03	1.54e-16	1.38e-16

From the table, we can see that when CGSO is in Sphere, Ackley and Rastrigin functions, the mean value and standard deviation of it are superior to the IWO and CPSO, and the both have obvious increase of orders of magnitude. For example, the IIWO in Sphere function is respectively improved by 40 and 2 orders of magnitude than IWO and CPSO. Although the performance of IIWO in the Griewank function is lower than that of CPSO, the mean value and standard deviation of them are at the same order of magnitude. This shows that, compared with the other two algorithms, IIWO can fully develop the information of the object that is searched, and has high quality of solution.

B. Simulation Example of WSN

To test the validity of IIWO in dealing with the problem of distribution optimization of WSN nodes, the effective monitoring range of WSN of this simulation is the square area 100m × 100m, the perception radius R of each sensor node is 7m and 100 WSN nodes are distributed randomly in the range of monitoring. IWO, CPSO and IIWO are iterated for 500 generations, and operated 30 times repeatedly. The best solution should be recorded. In addition, the number of the population of the three algorithms is set as 20. The other parameters are shown in Table 2.

Table 2. Parameter settings for three algorithms

Algorithm	Parameter setting
IWO	$S_{max}=10$, $S_{min}=0$, $\sigma_I=1$, $\sigma_F=0.01$
CPSO	$c_1=c_2=2$, $W=0.8$
IIWO	$S_{max}=10$, $S_{min}=0$, $\sigma_I=1$, $\sigma_F=0.01$

From Table 3, we can see that the success probability of WSN distribution optimization dealt by the IWO which is improved by chaotic operator and Gauss mutation operator is increased greatly. The average coverage rate of WSN that is obtained through IIWO is 2.8% and 13.3% higher than the other two algorithms respectively.

Table 3. Comparison of the results of three algorithms

	IWO	CPSO	IIWO
The covering times over 80%	41	47	50
The covering times over 90%	38	43	48
Average coverage rate	84.2 %	94.8%	97.5%

The iterative curves that three algorithms deal with the optimal solution of the coverage of network nodes are shown in Figure 1.

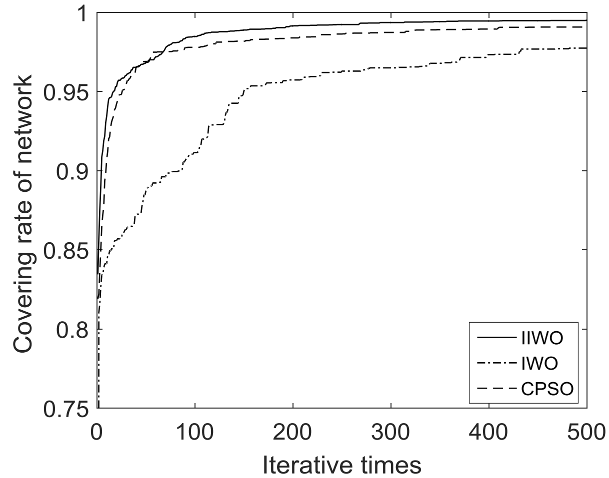

Figure 1. The iterative curve of three algorithms

From Figure 1, we can see that the IWO and CPSO begin to converge after 479 and 197 iterations respectively, while IIWO begins to converge after the 95 iteration. The optimal rate of IIWO is 99.28%, and the CPSO and IWO are 98.88% and 97.05% respectively. This shows that the IIWO has the fast convergence speed.

The population size is respectively set as Table 4. Each of them is iterated for 300 generations. The final obtained network coverage rate of each algorithm is recorded, which is shown in table 4. From the table 4, we can see that IIWO has strong robustness.

Table 4. Comparison of the three algorithms

Algorithm	Population size		
	10	20	30
IWO	67.6%	81.6%	83.5%
CPSO	82.6%	90.3%	93.1%
IIWO	90.0%	92.1%	96.9%

The simulation of the network coverage rate based on the number of different nodes is designed. The curves of the network coverage rate of the three algorithms as the change of node density are shown in Figure 2. From the figure, we can see that in order to achieve more than 95% coverage rates, CPSO and IWO need to respectively arrange 150 and 200 nodes, while IIWO only needs to arrange 125 nodes. This shows that, compared with the other two algorithms, IIWO has strong ability to mine the global information.

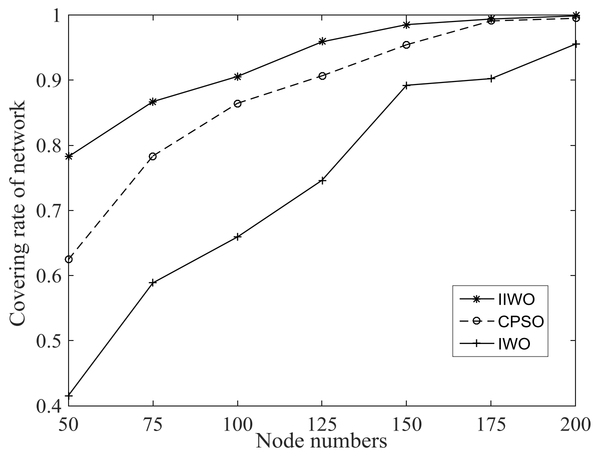

Figure 2. Network coverage comparison diagram

From Figure 3, we can see that the nodes with chaotic initial state can be distributed evenly and have relatively small overlap coverage rate after the optimal arrangements of IIWO. Therefore, the distribution optimization strategy of WSN nodes based on IIWO proposed by this paper can reasonably solve the problem of network coverage optimization and can effectively improve the network coverage rate.

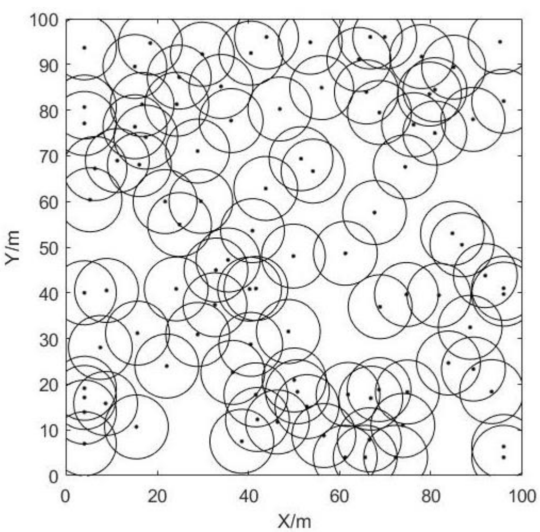

Figure 3. Node distribution graph of initial time

V. Conclusion

The performance of improved invasive weed optimization algorithm (IIWO) and its application for coverage optimization in wireless sensor networks are discussed in this paper. Firstly, on the premise that connectivity among nodes was guaranteed, we established a mathematical model to achieve the coverage of objective area with wireless sensor networks. And this problem was transformed into function optimization based on this algorithm. Then, the invasive weed optimization algorithm was used to search the optimal deployment with the strong search performance. The cubic mapping chaotic operator was introduced to enhance the ability of local search and robustness, and the gauss mutation operator was used to keep the diversity of population. Lastly, the proposed algorithm had been verified through the numerical benchmark functions and coverage simulation. All the results showed that our proposed algorithm had fast convergence speed, nice robustness and strong ability of data mining. Hence, it had the ability to solve the problem of deployment problem in wireless sensor networks.

In future, IIIWO can be widely used in multi-objective optimization problems. The Gaussian mutation operator is introduced to select a certain number of weed seeds to produce variation individuals, which will ensure the diversity of population.

References

[1]Hussain S, Matin A W, Islam O. Genetic Algorithm For Hierarchical Wireless Sensor Networks. *Journal of Networks*, 2017, 2(5), pp.87-97.

[2]Kuila P, Jana P K. Energy Efficient Clustering And Routing Algorithms For Wireless Sensor Networks: Particle Swarm Optimization Approach. *Engineering Applications of Artificial Intelligence*, 2014, 33, pp. 127-140.

[3] Ozturk C, Karaboga D, Gorkemli B. Probabilistic dynamic deployment of wireless sensor networks by artificial bee colony algorithm. *Sensors*, 2019, 11(6), pp. 6056-6065.

[4] Mehrabian A R, Lucas C. A Novel Numericaloptimization Algorithm Inspired From Weed Colonization. *Ecological Informatics*, 2016, 1(4), pp. 355-366.

[5] Öztürk C, Karaboğa D, GÖRKEMLİ B. Artificial Bee Colony Algorithm For Dynamic Deployment Of Wireless Sensor Networks. *Turkish Journal of Electrical Engineering & Computer Sciences*, 2012, 20(2), pp. 255-262.

[6] Rani D S, Subrahmanyam N, Sydulu M. Multi-Objective Invasive Weed Optimization–An Application To Optimal Network Reconfiguration In Radial Distribution Systems. *International Journal of Electrical Power & Energy Systems*, 2015, 73, pp. 932-942.

[7] Bishan W. Optimized model of energy industry chain considering low carbon development mechanism. *Energy Sources*, Part A: recovery, utilization, and environmental effec decision tree. 2020, 42 (21), pp.1686-1702.

[8] Saravanan B, Vasudevan E R, Kothari D P. Unit Commitment Problem Solution Using Invasive Weed Optimization Algorithm. *International Journal of Electrical Power & Energy Systems*, 2018, 55, pp. 21-28.

[9] Zheng Zhixue. Research on fault monitoring of cloud computing cluster based on improved decision tree algorithm. *Information Recording Materials*. 2021, 22 (05), pp.171-172.

[10] T. Santhi Vandanna, S. Venkateshwarlu, K. Viswanath, Robust and Highly Secure Technique for Wireless Body Sensor Network using Sequence of ECG Data, WSEAS Transactions on Information Science and Applications, Volume 17, 2020, pp. 138-145.

[11] Khushboo Jain, Anoop Bhola, An Optimal Cluster-Head Selection Algorithm for Wireless Sensor Networks, WSEAS Transactions on

Communications, Volume 19, 2020, pp. 1-8.

[12] Dick O E, Glazov A L. Estimation of the synchronization between intermittent photic stimulation and brain response in hypertension disease by the recurrence and synchrosqueezed wavelet transform. *Neurocomputing*. 2021, 455, pp.315-327.

[13] Bandyopadhyay K S, Pramanik S, Ghosh R, et al. A New Combinational Technique in Image Steganography. *International Journal of Information Security and Privacy*, 2021, 15(3), pp. 93-104.

[14] Hsien-Chu W, Wen-Li F, Chwei-Shyong T, et al. An image authentication and recovery system based on discrete wavelet transform and convolutional neural networks. *Multimedia Tools and Applications*. 2021,122, pp.233-241.

[15] Hutchison Z L, Gill A B, Sigray P, et al. A modelling evaluation of electromagnetic fields emitted by buried subsea power cables and encountered by marine animals: Considerations for marine renewable energy development. *Renewable Energy*. 2021, 177, pp. 572-585.