Research on Wireless Sensor Network Localization Based on An Improved Whale Optimization Algorithm

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Abstract

DV-HOP algorithm for wireless sensor network (WSN) has the disadvantage of large node positioning error and low accuracy. Firstly, the node localization model is elaborated, secondly, Fuch chaotic opposition learning is used in the initialization of the whale optimization algorithm population to improve the initial position diversity, an adaptive strategy is used for the parameters in the encircling predation behavior to avoid the algorithm falling into local optimum prematurely, Gaussian perturbation is used to update the individual positions during the iterative search to improve the global search capability, and finally IWOA is solved for the optimal value of the node localization objective function. The performance of IWOA algorithm is verified in simulation experiments, and the solution accuracy and solution quality are improved in different degrees. The IWOA algorithm demonstrates good localization results in terms of comparative data results of node localization unknown nodes, reference nodes, node density, communication radius aspects and area of the region.

Keywords: Node localization, Fuch chaos, Adaptive strategy

1 Introduction

With the increasing maturity of wireless communication technologies as well as computer software, the cost of embedded devices with functions such as sensing targets, processing data and communication has been greatly reduced, and the application scenarios and scales have been expanded, facilitating the rapid development of WSNs [1]. In WSNs, how to perform node localization has been one of the important research directions in wireless sensing networks. In recent years, better results have been achieved using metaheuristic algorithms for node localization, such as the Ant Colony Optimization (ACO) [2], Particle Swarm Optimization (PSO) [3], Artificial Fish Swarm Algorithm (AFSA) [4], Artificial Bee Colony (ABC) [5], etc. In 2016, an Australian scholar, Mirjalili Seyedali, constructed a new algorithm-Whale Optimization Algorithm (WOA) [6], which consists of three parts: encircling predation, bubble attack, and foraging. In the algorithm, the humpback whale is set as a candidate solution of the optimization problem in the search space, and the global optimal solution of the optimization problem is determined by updating the candidate solution through continuous optimization of the humpback whale. The WOA has a simple structure and has good results in dealing with multipeaked low-dimensional functions. However, the algorithm, like all metaheuristics, has the disadvantage of easily falling into a local optimum and converging quickly. In this paper, new solution strategies are proposed. Strategy 1: To address the problem of lack of diversity in the population, this paper uses Fuch chaos in the WOA initialization, which can better initialize the individuals of the algorithm and maximize the diversity of the solutions. Strategy 2: The parameter setting in the spiral position update of WOA causes the individual humpback whales to easily fall into the local optimum. In order to solve this problem, this paper uses an adaptive strategy method to cause the individual humpback whales to swim in a more reasonable way, thus avoiding the algorithm falling into the local optimum. Strategy 3: In order to improve the global search ability of the algorithm, the introduction of Gaussian perturbation method idea in this paper can effectively avoid this situation, which can improve the quality of the global solution of the humpback whale.

This paper is organized as follows: In section 1, the current problems of node localization and metaheuristic algorithms are described. Section 2 describes the current research work. Section 3 describes the node localization model. Section 4 describes the node localization strategy based on the improved whale algorithm. Section 5 simulates the experiments. Section 6 offers the conclusions reached in this paper.

2 Related Work

Range-Based and Range-Free localization are two types of methods that have been studied by researchers. Therefore, our study starts with the DV-HOP algorithm for node localization without ranging, and the DV-Hop localization algorithm is divided into three steps.

Step 1: Record the minimum number of hops between the beacon node and the unknown node. All anchor nodes transmit their position information and initial hop number (initial hop number is 0) to all nodes within their communication radius, and the receiving node records the hop number from each beacon node and compares the hop number size, and only keeps the data group from the beacon

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node with the minimum hop number, adds 1 to the hop number and forwards it to other nodes.

Step 2: Obtain the distance between the anchor node and the unknown node. The anchor node uses the position information and minimum hop count of other anchor nodes obtained in step 1 to calculate its own average distance per hop and transmits this information to the network by broadcasting. The unknown node receives and records the average distance per hop from the first anchor node and then rejects such information from other anchor nodes. The unknown node calculates the distance to each beacon node from the existing hop count information and the average distance per hop information.

Step 3: The unknown node calculates its own position. The unknown node calculates its own position by using the known distance to the anchor node and using the coordinates of 3 or more beacon nodes.

S. Kumar et al. [7] proposed an optimized DV-Hop algorithm for wireless sensing networks, simulation results show that the algorithm outperforms the DV-Hop algorithm and the improved DV-Hop algorithm in all considered scenarios; Y. Hu et al. [8] proposed a threshold-based DV-HOP algorithm and uses the weighted average hop distance within the threshold to estimate the position of the node, simulation experiments illustrate that this algorithm has better localization effect compared to the traditional DV-Hop; S. Tomic et al. [9] proposes three DV-Hop node localization algorithms, simulation experiments illustrate that the third algorithm has better results; P. Wang et al. [10] proposed a multi-objective DV-Hop localization algorithm based on NSGA-II, simulation experimental results illustrate that this algorithm is better than other algorithms in terms of localization effect; X. Chen et al. [11] proposed a weighted approach to the average hop distance to improve the localization accuracy of unknown nodes, simulation experiments illustrating the effectiveness of this method; S. Kumar et al. [12] proposed better localization accuracy by minimizing the error term of the estimated distance between the anchor node and the unknown node in the DV-Hop algorithm; Q. Qian et al. [13] proposes a DV-Hop localization algorithm based on the optimal node, simulation experiments illustrate the improved localization effect of this algorithm.

V. Kanwar [14] and S. P. Singh et al. [15] proposed using different optimized particle swarm optimizations for node localization and improved the node localization effect by these optimized algorithms; Z. H. Cui et al. [16] and X. Yu et al. [17] used different optimized cuckoo search algorithms for node localization in DV-Hop, and simulation experiments illustrated that the cuckoo search algorithm has better results; Y. Liu [18] proposed the use of different optimized bat algorithms for node localization in DV-Hop; their simulation experiments show that the algorithm shows more significant advantages compared to DV-Hop; J. Li et al. [19] proposed the use of the cat colony algorithm for node localization. By optimizing the cat swarm algorithm to different degrees, the improved cat swarm algorithm achieves better results in node localization; R. Rajakumar et al. [20] proposes a node localization model based on the grey wolf algorithm. This uses the grey wolf algorithm to optimize the node positions in the DV-Hop algorithm and simulation experiments show that the algorithm achieves better results in the metrics of node localization. S. Arora et al. [21] proposes a node localization algorithm based on the butterfly optimization algorithm.

Among these methods, some of them improve the localization accuracy but increase the hardware cost and energy consumption at the same time, and some of them use metaheuristic algorithms that have the disadvantage that the algorithm is easy to fall into local convergence, leading to the reduction of algorithm performance, which can improve the node localization accuracy but the improvement effect is not enough. In this paper, we introduce WOA in the node localization of DV-HOP algorithm to improve the localization accuracy because WOA is a relatively new metaheuristic algorithm that has been widely used in recent years, and in addition, we optimize three aspects of WOA to improve the algorithm performance and can play a better role in node localization.

3 Node Positioning Model

DV-Hop is a widely used and adopted non-ranging algorithm with the advantages of simple implementation and high localization accuracy. It mainly uses the least squares method to calculate the unknown node coordinates, but the positioning accuracy is affected by the cumulative error factors. In this paper, we take the two-dimensional plane as an example to study, establishing the node positioning model, and analysing the generated errors. Setting (x, y) as the unknown node coordinates, (x_i, y_i) as the reference node coordinates, and the corresponding distance between the unknown node and the reference node as d_i, the expression is as follows.

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 = d_2^2 \\ \quad \cdots \\ (x_n - x)^2 + (y_n - y)^2 = d_n^2 \end{cases} . \quad \textbf{(1)}$$

Subtracting the first n - 1 equations from the last equation gives the following equation:

$$\begin{cases} 2(x_1 - x_n)x + 2(y_1 - y_n)y = x_1^2 - x_n^2 + y_1^2 - y_n^2 - d_1^2 + d_n^2 \\ 2(x_2 - x_n)x + 2(y_2 - y_n)y = x_2^2 - x_n^2 + y_2^2 - y_n^2 - d_2^2 + d_n^2 \\ \quad \cdots \\ 2(x_{n-1} - x_n)x + 2(y_{n-1} - y_n)y = x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 - d_{n-1}^2 + d_n^2 \end{cases} . \quad \textbf{(2)}$$

Using a linear system of equations to represent $QL = b$

$$Q = \begin{bmatrix} 2(x_1 - x_n)\ 2(y_1 - y_n) \\ 2(x_2 - x_n)\ 2(y_2 - y_n) \\ \cdots \\ 2(x_{n-1} - x_n)\ 2(y_{n-1} - y_n) \end{bmatrix}. \tag{3}$$

$$L = \begin{bmatrix} x \\ y \end{bmatrix}. \tag{4}$$

$$b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_1^2 - d_n^2 \\ x_2^2 - x_n^2 + y_2^2 - y_2^2 + d_2^2 - d_n^2 \\ \cdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_{n-1}^2 - d_n^2 \end{bmatrix}. \tag{5}$$

In the actual environmental process, there are some definite error factors ε, which bring a great deal of disturbance to node positioning. Thus, the above linear equation system must be considered to be modified to $QL + \varepsilon = b$, which is expressed by the least squares method as follows.

$$L = (Q^T Q)^{-1} Q^T b. \tag{6}$$

From Eq. (6), it is found that the parameter b is the key to solving for L, while the factor affecting the parameter b is d_n. When the value of d_n is relatively large, the least squares method used to calculate the coordinates of specific nodes cannot be applied [22]. To address this problem, the localization problem in an error-laden environment is converted to an optimization problem with functional constraints, and the distance measurement error between nodes is expressed as follows.

$$| r_i - d_i | < \varepsilon_i. \tag{7}$$

ε_i is the ranging error between the nodes, while r_i is the actual distance between the reference node and the unknown node in the wireless sensing network, $i \in [1, n]$, so the optimization problem is converted to the following expression.

$$\begin{cases} d_1^2 - \varepsilon_1^2 \le (x - x_1)^2 + (y - y_1)^2 \le d_1^2 + \varepsilon_1^2 \\ d_2^2 - \varepsilon_2^2 \le (x - x_2)^2 + (y - y_2)^2 \le d_2^2 + \varepsilon_2^2 \\ \cdots \\ d_n^2 - \varepsilon_n^2 \le (x - x_n)^2 + (y - y_2)^2 \le d_n^2 + \varepsilon_2^2 \end{cases}. \tag{8}$$

We let $f_i = \sum_{i=1}^{n} \sqrt{(x - x_i)^2 + (y - y_i)^2 - d_i^2}$, with f_i denoting the measurement error between the unknown node and the reference node and therefore defining the objective function $f(x, y)$ as

$$f(x, y) = \sum_{i=1}^{n} \sqrt{(x - x_i)^2 + (y - y_i)^2 - d_i^2}, \tag{9}$$

where a smaller value of $f(x, y)$ means that the solved coordinate value is closer to the actual value. Therefore, the node localization problem in wireless sensing networks is converted into a multidimensional constrained optimization equation, and the properties of the metaheuristic algorithm to find the optimal value are used to solve the obtained node-specific location, gradually iterating to the minimum difference value until the best value is obtained.

4 Node Localization Based on Improved Whale Optimization Algorithm

4.1 Whale Optimization Algorithm

The WOA is a metaheuristic intelligent optimization algorithm that imitates the prey-hunting activity of cetaceans in the natural ocean, and its core idea consists of three main behaviours: encircling predation, bubble attack, and prey finding. In the whale algorithm, the size of the whole whale population is set as N, and the optimal solution is searched in the D-dimensional search space. The position of the ith whale in the D-dimensional space is denoted as $X_i = (X_i^1, X_i^2, \ldots\ldots, X_i^D)$, $i = 1, 2, \ldots, N$, and the position of the prey is the global optimal solution of the corresponding problem.

4.1.1 Encircle and Prey

In the initial stage of the algorithm, the whales are able to identify the location of the prey and surround it, but the algorithm does not set the global optimal location in advance, so the optimal location in the current population is set as that of the prey to be captured, and the other individuals whales in the population are guided to approach the current optimal individual to hunt, using Equation (10) to update the location of individuals:

$$X(t+1) = X_p(t) - A \times | C \times X_p(t) - X(t) |, \tag{10}$$

where t is the number of current iterations, $X_p(t) = (X_p^1, X_p^2, \cdots X_p^D)$ is the local optimal solution, $A \bullet | C \bullet X_p(t) - X(t) |$ is the enclosing step, and the parameters A and C are expressed as follows:

$$A = 2a \times rand_1 - a, \tag{11}$$

$$C = 2 \times rand_2, \tag{12}$$

where $rand_1$ and $rand_2$ denote random numbers between (0, 1) and a is a convergence factor whose value decreases linearly from 2 to 0 along with the gradual increase in the number of iterations. a is expressed as

$$a = 2 - 2t/t_{\max}, \tag{13}$$

where $t_{\max}$ is the maximum number of iterations.

4.1.2 Bubble Attack

The whale is able to achieve the goal of localized whale advantage seeking by contracting the envelope and spiral to update the position to simulate the behaviour of whales hunting and spitting out bubbles to catch food.

(1) Contraction encirclement mechanism

According to Eqs. (11) and (13), the whales are simulated to perform shrinkage encirclement, and when $|A|<1$, the individual whale approaches another individual whale located at the current optimal position, and the larger the value of $|A|$, the greater the swimming pace of the individual whale; otherwise, the pace decreases.

(2) Spiral update position

The individual whale calculates the distance between it and the whale at the current optimal position to search for prey in a spiral way, and the expression of the spiral wandering method is shown as follows:

$$X(t+1) = D^{'} \times e^{lb} \times \cos(2\ \ l) + X_p(t), \tag{14}$$

where $D^{'} = |X_p(t) - X(t)|$ denotes the distance between the ith individual whale and the whale at the optimal position, b denotes the constant used to bound the logarithmic spiral shape, and l denotes a random number with the value [-1, 1]. The probability of choosing the shrinkage envelope mechanism and the spiral position update in the optimization process are the same, both taking the value of 0.5.

4.1.3 Prey Hunting

The above behaviours are all ways in which the whale can perform a local range of solution finding; in fact, the whale algorithm can also randomly find the current individual whale for global optimization with the expression

$$X(t+1) = X_{rand}(t) - A|C \times X_{rand}(t) - X(t)|, \tag{15}$$

where $X_{rand}(t)$ is the location of a randomly selected individual whale in the current population.

4.2 Improved Whale Optimization Algorithm

Like most metaheuristic algorithms, the whale algorithm suffers from the disadvantages of being prone to local optima and slow convergence. In order to better improve the effectiveness of the whale algorithm in node localization. The algorithm is improved in the following three aspects: using Fuch chaotic opposition learning to improve the diversity of whale initial locations; avoiding the algorithm from falling into local optimum too early by a nonlinear strategy; and mitigating the decay of whale location diversity by Gaussian perturbation for individual screening.

4.2.1 Population Initialization

In this paper, we propose an optimization strategy based on the Fuch chaotic opposition initialization. The purpose of the redundant chaos idea in the metaheuristic algorithm is to exploit the characteristics of periodicity and non-repetition of chaotic variables so as to search the entire solution space and avoid the traditional random search relying on probability, thus producing uniformly distributed individuals and improving the quality of the initialized solution. The literature [23] illustrates that Fuch mapping is superior to Logistic and Tent mappings having stronger chaotic properties, therefore, in this paper, Fuch mapping is used as the mapping function for chaotic search with the following mathematical expressions.

$$c_{i+1} = \cos(1/c_i^2), \tag{16}$$

where c_i is the chaotic variable.

Set $x^i = (x_1^i, x_2^i, ..., x_D^i)$ to denote the vector waiting to be optimized, D to denote the dimension, $x_k^i \in [x_k^{\min}, x_k^{\max}]$, $x_k^{\min}$ and $x_k^{\max}$ to denote the minimum and maximum values of the dimension, respectively, so that the chaotic individual is represented as follows.

$$x_{new}^i = x_k^{\min} + (x_k^{\max} - x_k^{\min})(c_k^{i+1} + 1)/2. \tag{17}$$

To further ensure that more of the better solutions are retained in the search space maximally and evenly distributed in the search space when searching for the current and the opposing solutions. We used the opposition learning [24] strategy in our initialization. We used the following mathematical model of dyadic learning.

$$OP^i = \begin{cases} -X^i + (X^{\max} - X^{\min})/2, X^i \geq 0 \\ -X^i - (X^{\max} - X^{\min})/2, X^i < 0 \end{cases}. \tag{18}$$

In Equation (18), X^i denotes the current initial solution, $X^{\min}$ and $X^{\max}$ denote the minimum and maximum values of the initial solution, respectively.

The steps for using chaos and dyadic learning in the initialization of the population are as follows.

Step 1: Chaos generation of chaotic vector sequence using Eq. (16)

Step 2: Load the chaotic vectors into the original solution space using Equation (17) to generate the initial solution X^i

Step 3: Calculate the initial solution X^i according to Equation (18) and the corresponding opposing solution OP^i

Step 4: The initial solution X^i and the opposing solution OP^i are ranked according to the fitness value, and the top N solutions are selected as the population initialization solutions.

4.2.2 Parameter Optimization

In the whale algorithm, parameters A and C determine the update of individual whale positions, while another parameter a directly determines the change in value of A. Since the value of parameter a in the algorithm is set to a linear change range between 2 and 0, it cannot effectively reflect the process of individual search of the algorithm to a certain extent, which easily leads to the local search of the algorithm at a later stage and prolongs the search time of the algorithm. To cause the individual to enter the local search phase as soon as possible, a nonlinearly varying strategy is proposed for the parameter a, with the following equation.

$$a = 1 - \sin(\frac{t}{t_{\max}}). \qquad \textbf{(19)}$$

From Formula (19), it is found that the nonlinear change strategy can cause the value of parameter a to decrease rapidly in the early stage of the algorithm, which causes the individual whale to enter the local search phase as early as possible and improves the algorithm solution accuracy and convergence rate, while the other parameter C is just a (0, 2) random number in the whale algorithm. According to the inspiration of the particle swarm algorithm about the position update, the optimization parameter C in the global phase of the whale can reduce the search uncertainty, make the individual whale position update adaptive, and better maintain the ability of regional search and local exploration. Therefore, in this paper, the following optimization is performed for the parameter C.

$$C = \begin{cases} C_{\min} + f_{\min}/f_{ave} & f \le f_{ave} \\ C_{\max} - f_{\max}/f_{ave} & f > f_{ave} \end{cases}, \qquad \textbf{(20)}$$

where $C_{\min}$ and $_{\max}$ denote the minimum and maximum values of the parameters, respectively, f denotes the current fitness value of the individual whale, and $f_{\min}$ and f_{ave} denote the minimum and average values of the fitness values, respectively.

4.2.3 Individual Update Based on Gaussian Perturbation

In the later stage of the search, the WOA algorithm is prone to the problem of group aggregation, which causes the algorithm to fall into the local extreme value in the later stage. Reference [25] shows that the use of Gaussian perturbation algorithm in the bat algorithm can strengthen the global search ability of the algorithm and improve the accuracy of understanding. Since both the bat algorithm and the whale optimization algorithm are multi-swarm algorithms, Gaussian disturbance is used in the whale optimization algorithm in this paper. The probability density function of the Gaussian distribution is expressed as follows:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{(x-\mu)^2}{2\sigma^2}). \qquad \textbf{(21)}$$

In formula (21), the larger the value of σ, the smaller the probability value of the position x, which means that the smoother the curve, the more scattered the probability distribution, on the contrary, when the value of σ is smaller, the curve is steeper, then It shows that the probability distribution is relatively concentrated. Therefore, we take σ value of 1 here, which can ensure that the algorithm can solve efficiently and avoid premature convergence, so the update of the individual is as follows:

$$X(t+1) = X_p(t) + X_p(t) \times f(t). \qquad \textbf{(22)}$$

In formula (22), A represents a random number with a mean of 0 and a variance of 1 obeying a Gaussian distribution

4.2.4 Algorithm Step

Step 1: Establish the correspondence between the node location in the wireless sensor network and the whale algorithm. That is, the whale algorithm treats each solution in the node localization problem as a whale individual. In each iteration of the whale algorithm, the quality of the current whale is judged by the set fitness function, and finally the optimal whale individual is found to obtain the best node positioning. The expression of the fitness function of the whale algorithm adopts formula (9);

Step 2: Initialize the relevant parameters of the whale algorithm and the relevant parameters of node positioning, and set the maximum number of iterations;

Step 3: According to Section 4.2.1, use Fuch-based chaotic oppositional learning population initialization;

Step 4: According to the formula (19-20) in Section 4.2.2, the formula (10-11) is updated for the encircling and preying behavior;

Step 5: Execute the bubble attack behavior;

Step 6: Perform individual update according to Section 4.2.3;

Step 7: Determine whether the optimization has reached the maximum number of iterations, and if so, find the optimal whale individual, which is the approximate value of the optimal position of the node to be tested, otherwise go to Step 4, and add 1 to the number of iterations.

5. Simulation Experiments

To further verify the effectiveness of the IWOA in node localization accuracy, ACO, PSO and WOA are selected for comparison in this paper. The hardware platform chosen contains a Core I5 CPU, 16 GB DDR4 memory, 2T hard disk, MATLAB 2012 simulation software, and Win10 operating system. The number of iterations is set to 1000.

5.1 Algorithm Performance Comparison

In this paper, six benchmark test functions in CEC2017 (Table 1) are selected to judge the performance of the algorithms in this paper, and four indicators of minimum, maximum, mean and standard deviation are chosen. The parameters of the four algorithms are shown in Table 2, and the simulation results are shown in Table 3.

Table 1. Benchmark test function

No	Function name	Benchmark function
F1	Sphere	$f(x)=\sum_{i=1}^{n} x_i^2$
F2	Schwefel 1.2	$f(x)=\sum_{i=1}^{n}(\sum_{j=1}^{i} x_j)$
F3	Rosenbrock	$f(x)=\sum_{i=1}^{n-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$
F4	Ackley	$f(x)=20\exp(-\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2})-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))$
F5	Rastrigin	$f(x)=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10)$
F6	Schewfel 2.21	$f(x)=\max(abs(x_i))$

Table 2. Main parameters of the 4 algorithms

Algorithm	Description
ACO [2]	The pheromone is set to 0.01, the volatility coefficient is set to 0.01, and the path selection probability is set to 0.5
PSO [3]	The inertia weight is set at 0.1, and the learning factor is 2.
WOA [6]	a is [2, 0] linearly non-decreasing
IWOA	a is [2, 0] linearly non-decreasing, the b value is 1.5, and c is 1

Table 3 shows the test results of the four algorithms under four metrics with different dimensions of the six classical test functions. From the numerical results of these metrics tests, the algorithms in this paper achieve better numerical results in all the classical functions, which shows that the improved strategies are effective. Therefore, we believe that these six test functions have well tested the algorithm of this paper. In test functions F1-F3, IWOA has better results compared with the other three algorithms in testing the standard index results, and the advantage of data testing is very obvious, especially in the F1-F4 functions. When the value of dimension is 2, the minimum value of this paper's algorithm is 0, which shows that this paper's algorithm has good solution quality. This indicates that the IWOA performs better overall. Through the above results, it is found that this algorithm has better results in the test function compared with the other three algorithms (especially the WOA algorithm). It shows better results in different dimensions, which also shows that the performance of the algorithm in this paper is indeed significantly improved by the Fuch chaotic population initialization, adaptive strategy and Gaussian perturbation improvement, and the solution quality effect is further enhanced.

Table 3. Optimization results of the four algorithms in different benchmark functions

Function	Dimension	Algorithm	Minimum value	Maximum value	Mean	Standard deviation
F1	2	ACO	0.0205	16478.500	1990.67892	4985.5318
		PSO	6.1472E-11	0.0042617	0.000140519	0.0004011
		WOA	1.4521E-14	2.824E-07	1.3141E-07	4.4852E-07
		IWOA	**0**	1.1368E-67	2.6216E-69	1.7134E-68
	5	ACO	0.3706	30482.1835	4561.47157	8649.6718
		PSO	0.0034	4.1852	1.01395105	1.3256
		WOA	2.1561E-08	5.3161E-03	5.912E-04	1.1831E-03
		IWOA	3.9718E-55	8.2136E-41	1.9561E-42	1.2528E-41
	30	ACO	27124.2624	134125.416	70170.8017	35173.8124
		PSO	1452.3613	6299.0228	3637.5227	1211.7122
		WOA	2.649E-03	1.041E+01	1.8021E+00	2.221E+00
		IWOA	5.6743E-43	1.7644E-31	4.9137E-33	2.6423E-32
F2	2	ACO	0.211709	89.1365	9.28170	25.3572
		PSO	4.6115E-07	0.0099	0.0010	0.0011
		WOA	1.9131E-07	5.807E-03	3.915E-04	9.2271E-04
		IWOA	**0**	5.187E-42	3.272E-43	1.1521E-42
	5	ACO	0.847483	16849.7207	798.049	2888.386
		PSO	0.0049	1.3204	0.2272	0.2597
		WOA	1.3171E-04	1.8182E-01	3.8121E-02	3.9022E-02
		IWOA	1.2781E-32	6.7831E-26	2.3462E-27	1.0281E-26
	30	ACO	44550.64	1.6697E+20	3.4185E+18	2.3659E+19
		PSO	15.0176	67.9770	33.4899	11.0343
		WOA	1.2381E-01	8.9183E+00	3.2161E+00	3.0819E+00
		IWOA	3.2393E-28	2.5221E-21	2.2287E-22	5.6991E-22
F3	2	ACO	0.0322	270.422	38.92631	88.32911
		PSO	4.0806E-11	0.0017	9.8150E-05	0.0003
		WOA	6.7901E-11	2.2252E-04	2.1898E-05	3.7841E-05
		IWOA	**0**	3.7892E-10	3.6754E-11	7.0909E-11
	5	ACO	0.021984	1018.44312	96.20109	271.8118
		PSO	9.3079E-11	0.0014	0.0002	0.0003
		WOA	8.4593E-07	3.381E-03	2.7712E-04	5.1443E-04
		IWOA	1.2137E-12	5.9615E-09	5.9052E-10	1.2255E-09
	30	ACO	0.1603	13059.0257	761.43718	2834.95721
		PSO	8.9233E-11	0.0416	0.0021	0.0061
		WOA	3.7177E-05	9.5211E-02	1.3132E-02	1.8931E-02
		IWOA	4.5790E-11	2.8173E-07	2.8142E-08	5.0604E-08
F4	2	ACO	0.15782	98.8934	40.9021	43.4112
		PSO	2.3389E-05	0.1167497	0.0079	0.01815393
		WOA	9.1739E-07	2.3493E-01	1.9032E-02	4.2301E-02
		IWOA	**0**	3.7892E-15	1.4087E-16	5.1258E-16
	5	ACO	3.9816	98.9013	77.0836	28.6501
		PSO	0.0517	4.4858	0.8580	0.8908
		WOA	2.9321E-02	7.4451E-01	2.1729E-01	1.3387E-01
		IWOA	2.3214E-13	3.0698E-02	1.2890E-03	4.8835E-03
	30	ACO	86.1713	99.7146	97.1821	2.7163
		PSO	15.8714	39.9832	26.7036	4.8160
		WOA	6.4403E-01	1.7071E+00	1.3721E+00	2.2463E-01
		IWOA	3.7050E-02	6.2034E-01	4.3133E-01	1.5607E-01
F5	2	ACO	71231.1722	79962.92	7491773.86	22744721.52
		PSO	4.5371E-07	7.80186	0.345358	1.191631
		WOA	7.9036E-08	2.3132E+00	7.9053E-02	3.3269E-01
		IWOA	7.1633E-11	4.5806E-04	1.6821E-05	6.7930E-05
	5	ACO	18.8482	12.7512	10.0172	9.1782
		PSO	1.73915	1732.363	167.49165	360.13007
		WOA	8.2972E-01	6.5381E+00	3.8721E+00	1.3091E+00
		IWOA	1.6695E-03	3.0681E+00	9.7833E-01	8.4284E-01
	30	ACO	51342.0331	77689.3512	14453.2914	27245.4923
		PSO	13718.400	29065.250	84826.368	63480.300
		WOA	2.922E+01	9.806E+02	2.946E+02	2.602E+02
		IWOA	2.7621E+01	2.8936E+01	2.9186E+01	4.0376E-01
F6	2	ACO	0.03691920	16748.3712	1670.5606	4641.1354
		PSO	2.2516E-10	0.00458124	0.00036729	0.00089128
		WOA	5.704E-10	9.926E-04	6.431E-05	1.951E-04
		IWOA	1.4320E-14	6.0278E-08	4.7190E-09	1.2007E-08
	5	ACO	0.9832	0.9268	0.7122	0.7732
		PSO	0.0004	12.3665	1.1243	2.1209
		WOA	8.9971E-04	2.9293E-01	4.1243E-02	4.7751E-02
		IWOA	1.3182E-07	2.5106E-02	9.6304E-03	4.8154E-02
	30	ACO	2.1263	9.8212	7.9713	2.1209
		PSO	1364.9936	7575.0923	3644.1280	1313.5267
		WOA	1.7143E+00	1.3154E+01	4.183E+00	2.131E+00
		IWOA	3.1915E-01	2.6013E+00	1.4156E+00	6.1832E-01

5.2 Comparison of Localization Metrics

To test the localization effect of the algorithm in this paper, two other improved whale optimization algorithms, namely, the Chaotic whale optimization algorithm (CWOA) [26] and Levy whale optimization Algorithm (LWOA) [27], are selected in this paper. The main contents of the experimental comparison are unknown node localization, reference node ratio, node density, communication radius and area in a total of six aspects. The environment-related parameters in the wireless sensing network are shown in Table 4.

Table 4. Simulation environment parameters

Parameter name	Parameter values
Area size/m×m	10×10
Total number of nodes/pc	50
Number of reference nodes/pc	20
Communication radius/m	30
Node distribution	Random distribution

The error results are averaged in the simulation experiments to compare the advantages and disadvantages of the performance of the three positioning algorithms, and the average positioning error equation is as follows.

$$E_{average} = \frac{\sum_{i=1}^{N}\sqrt{(\overline{x}_i - x_i)^2 + (\overline{y}_i - y_i)^2}}{N \times R}. \quad \textbf{(23)}$$

where $(\overline{x}_i, \overline{y}_i)$ is the estimated coordinate, (x_i, y_i) is the actual coordinate, N is the number of unknown nodes, and R is the communication radius.

(1) Effect of unknown node localization

Figure 1 shows the results of the average localization error variation of the three algorithms with different numbers of unknown nodes. As the number of unknown nodes gradually increases, all three algorithms show dramatic fluctuations, which indicates that the number of unknown nodes has a greater influence on node localization, but from the values of the whole curve, IWOA has a smaller average localization error range than CWOA and LWOA. This indicates that IWOA plays a better role in solving node localization compared with CWOA and LWOA with improvements of 10.8% and 8.38%, respectively.

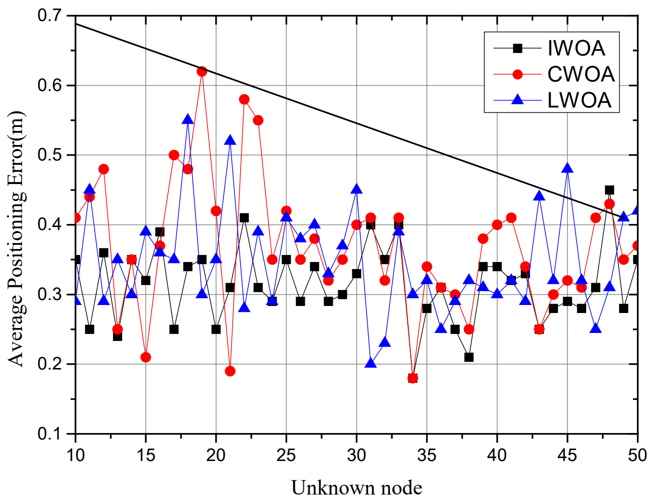

Figure 1. Comparison of unknown node positioning errors

(2) Effect of reference node ratio

Figure 2 shows the effect of the change in the average positioning error of the three algorithms at different reference node ratios. This shows the importance of the number of reference nodes in wireless sensing networks. From the results of the curves in the figure, the curve of IWOA decreases faster than the other two curves, especially under the same proportion of reference nodes. The localization accuracy of IWOA has a significant advantage compared with the CWOA algorithm and LWOA algorithm by 13.03% and 9.6%, respectively.

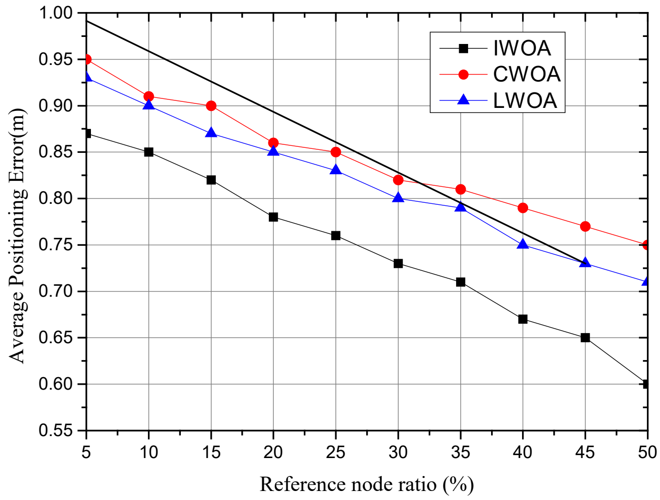

Figure 2. Comparison of reference node scale positioning error

(3) Effect of node density

Figure 3 shows the effect of localization error changes of the three algorithms at different node densities. With the gradual increase of node density, the errors of the three localization algorithms are reduced by different degrees, and the localization accuracy of the IWOA algorithm is improved by 10.2% and 9.24% compared with the CWOA and LWOA algorithms, respectively. In particular, the IWOA algorithm error decreases most significantly when the proportion of nodes is between 5% and 30%. When the proportion of nodes increases to 40%, the localization error does not decrease significantly, and the curve stabilizes, which is mainly due to the increase in node density. This increases the mutual communication between nodes, but the energy consumption of nodes also increases, so the selection of the number of nodes to reduce the error according to the actual situation is a factor that should not be ignored. Especially in the case of low node density, the IWOA algorithm still has a good localization effect, which indicates that the IWOA algorithm is more stable than the other two algorithms. The IWOA algorithm can effectively improve the localization accuracy in terms of node density.

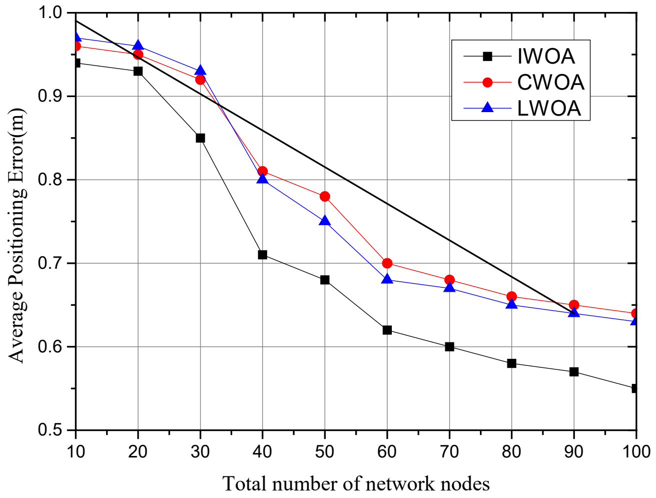

Figure 3. Comparison of positioning error under node density

(4) Effect of communication radius

Figure 4 shows the effect of the three algorithms on the variation in node localization error under different communication radii of nodes, from which it is found that the average node localization error of the three algorithms shows a decreasing trend as the communication radius of nodes gradually increases. When the communication radius is between [10, 20], the decrease in the curves of the three algorithms is faster, and when the communication radius is between [20, 30], the decrease in the curves of the three algorithms is gentler, which shows that the gradual increase in the communication radius has little effect on the three algorithms to relieve the localization error in node localization. However, from the whole process, the IWOA still has obvious advantages over the CWOA algorithm and LWOA algorithm. The localization accuracy of the IWOA is improved by 9.1% and 7.1% compared with the CWOA and LWOA algorithms, respectively.

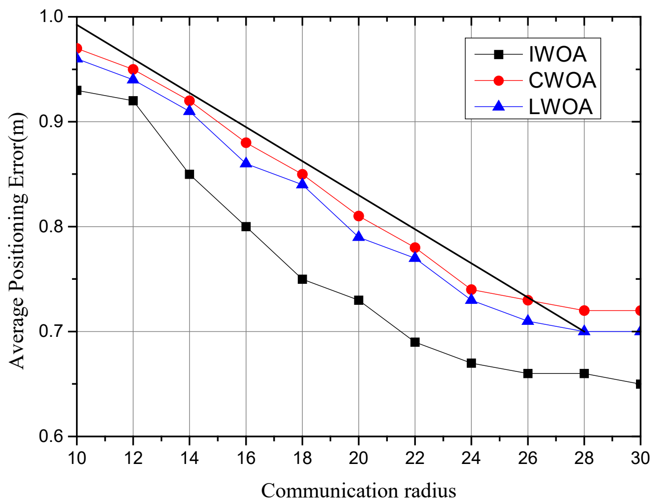

Figure 4. Comparison of positioning error with communication radius

(5) Effect of area

Figure 5 shows the effect of the three algorithms on the variation of the localization error under different areas. With the gradual expansion of the area, the average localization error of the three algorithms increases to different degrees because the expansion of the area affects the accuracy of node localization. This shows that the IWOA can effectively adapt to an environment with a larger localization area and broaden the application area of node localization. IWOA is improved by 15.3% and 8.2% compared with the CWOA and LWOA algorithms, respectively.

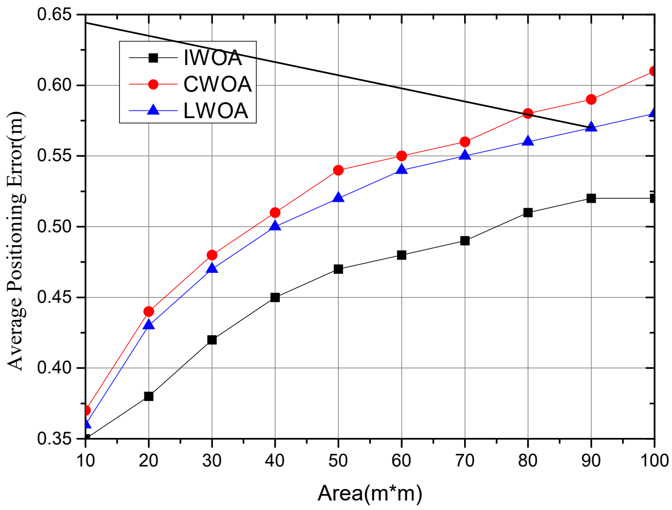

Figure 5. Comparison of positioning error under different areas

(6) Effect of the number of nodes

Figure 6 shows the effect of the change of localization error of the three algorithms at different numbers of nodes. The IWOA algorithm has a 7.1% and 7.3% reduction compared to CWOA and LWOA, respectively. This shows that the number of nodes has little influence on the algorithm of this paper.

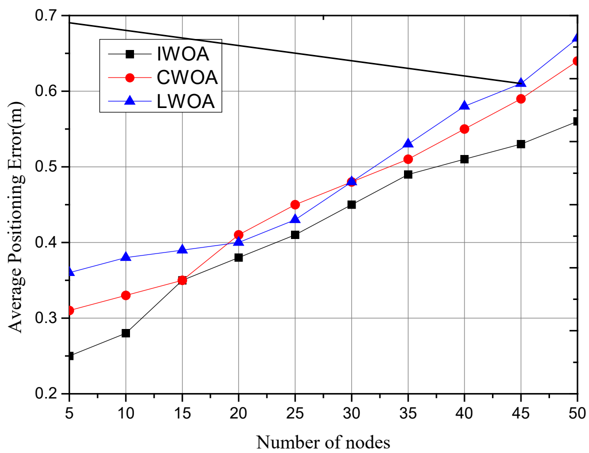

Figure 6. Comparison of positioning error with different number of nodes

6. Conclusion

Aiming at the shortcomings of large error and low accuracy of least-squares node localization in wireless sensing networks, this paper proposes an IWOA algorithm combining a node localization model and an improved whale algorithm, Fuch chaotic opposition learning is used in the initialization of the whale optimization algorithm population to improve the initial position diversity, an adaptive strategy is used for the parameters in the encircling predation behavior to avoid the algorithm falling into local optimum prematurely, Gaussian perturbation is used to update the individual positions during the iterative search to improve the global search capability, and finally achieves a better position search effect. In the simulation experiments, the algorithm is able to achieve better results in terms of the node localization index.

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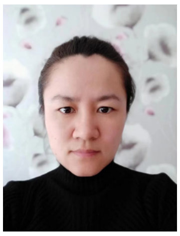

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