Multi-Sensor Detection Coalition Solving Based on Improved Whale Algorithm

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ABSTRACT

In order to solve the problem of low accuracy and premature falling into local optimal solution when multi-sensor is measuring accurate targets. In this paper, a mathematical model of multi-sensor detection coalition is proposed and established , and a mathematical model of the improved whale algorithm is formed . The improved whale algorithm uses a random or optimal seeking agent, combined with a forbidden algorithm to avoid falling into a local optimal solution prematurely. And then the air combat environment is simulated and the detection coalition after the improved whale algorithm is used to solve the problem . Under the same conditions , the comprehensive evaluation of the solution to both the gray wolf algorithm and the ant colony algorithm is inferior to that of the improved whale algorithm , and the effect of the number of painless whales on the solution results are also compared . Finally , the simulation results show that the improved whale algorithm has a simple mechanism , few parameters , strong optimization capability , and can substantially improve the convergence speed and avoid the system from falling into the local optimum solution too early , while maintaining good stability.

Keywords: Improve the whale algorithm; taboo algorithm; multi-sensor detection alliance; optimal solution

1. INTRODUCTION

Since the 20th century, the application of science and technology in the military has developed in spurts , and various cutting-edge scientific technologies have been used on the modern battlefield , and the shape of modern warfare has changed dramatically . Modern warfare is developing in the form of information technology , and information warfare has become one of the main postures of warfare , especially through multi-sensor data integration technology , which can identify , link , compare , evaluate and process information about / on different sources , so as to conduct more accurate status assessment , target classification and comprehensive threat assessment . Making full use of the functions and performance of multi-sensors , adapting to the complex and changing operational environment of air types , and optimizing the multi-sensor detection capabilities of the coalition is important to our overall command of the modern battlefield .

The challenge to multi-target distribution management is usually solved by the establishment of Multisensor Detection Alliance (MDA). In the literature [1] , the concept of Multi sensor crossed prompting technology was systematically proposed and also applied to target screening , which significantly improved the speed , accuracy and reliability of detection . The literature [2] describes the application of multi-sensor crosses / crossed prompting technology in MDA and proposes a sensor management structure of prediction and update . The literature [3] used a multi-sensor asynchronous communication information weighted calculation method. Improve multi-sensor asynchronous communication information classification algorithm. The multi-sensor asynchronous communication information classification process is combined with the multi-sensor asynchronous information classification process . In the literature [4] the scheme optimizes the objective function of MDA so that the tracking bee selects the head bee by two-way roulette , thus solving the situation that the algorithm seeks a local optimal solution and improving the convergence speed ; in the literature [5] , an improved Hybrid leapfrog scheduling algorithm is proposed to optimize the sensor configuration , which leads to a large improvement in the convergence of the algorithm . In the literature [6] , a genetic algorithm (Genetic algorithm) modelled is proposed and the stability of the algorithm is verified .

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From the above literature , it can be seen that currently in the formation of MDA , although the stability , robustness and similarity of the algorithm are good , the solution quality of the algorithm needs to be further improved , there is a weak optimization effort , and there may also be parameter redundancy leading to increased uncertainty . Lack of real-time and efficiency and other shortcomings . In order to improve these shortcomings and optimize the algorithm , we propose to establish the Improved Whale Algorithm (IWOA) based on the Improved Whale Algorithm to solve the MDA optimal solution to achieve the purpose of rapid response and identification of enemy targets in future warfare .

2. MODELING

2.1 Establishment of MDA model

Let there be a total of *m* sensors in a Multi-sensor Alliance, denoted as $O_m = \{x_1, x_2, \ldots\ldots, x_m\}$, and *n* targets at any moment. The Multi-sensor Alliance formed for target *a* at time *t is* denoted as $Y_a = \{y_1, y_2, \ldots\ldots, y_n\}$.

Let the detection union *O* be an 0-1 matrix of order *m* × *n. It* follows that

$$o_{ij} = \begin{cases} 0, & \text{The sensor does not join a} \\ & \text{dynamic alliance to the target} \\ 1, & \text{Sensors join a dynamic alliance to the target} \end{cases}$$

The detection accuracy B of the sensor to the target is a matrix of order m × n, where b_{ij} is the detection accuracy of the sensor y_i to the target . a_j

Sensor y_i To target a_j Detection accuracy b_{ij} Calculated from equation(1)

$$b_{ij} = \frac{q_{ij} \times a_{ij}}{Q \times T} \tag{1}$$

Eq.

q_{ij} is the number of targets detected by y_i for the target a_j at a given moment.

a_{ij} is the effective time at which the target a_j is detected by y_i at a given moment.

Q is the total number of targets to be detected by the coalition . a_j

T Total time for the target a_j campaign.

2.2 Alliance energy consumption calculation model

When using the sensor y_i for target detection, the energy consumption is

$$\mathrm{dep}(\mathrm{y_i}) = e^{-\frac{\mathrm{g}(\mathrm{y_i})}{\alpha_1 \times \mathrm{d}(\mathrm{y_i}) + \beta_1}} \tag{2}$$

Eq.

α_1 and β_1 are constants, taken from $\alpha_1 = 0.01$, $\beta_1 = 0.1$.

$\mathrm{g}(\mathrm{y_i})$ is the number of targets that can be detected simultaneously at y_i .

$\mathrm{d}(\mathrm{y_i})$ is the maximum detection distance of y_i .

2.3 Objective function

In determining the objective function of the MDA model, the requirements of maximum detection accuracy B of the MDA joint O and minimum total energy consumption Dep of the alliance should be satisfied. From this, the objective function (3) can be obtained

$$\begin{cases} \max B = \max \sum_{i=1}^{n} b_j \\ \min Dep = \min \sum_{i=1}^{n} \mathrm{dep}\ a_j \end{cases} \tag{3}$$

2.4 Constraints

The case discussed in this paper implies that the sensor can detect multiple targets at the same time, but in practice, the number of targets detected by the sensor y_i at the same time n_i must be smaller than the maximum number of targets detected by the sensor N_i at the same time. At the same time, the number of sensors in the established MDA $\mathrm{n_j}$ must be greater than or equal to 0. The constraint is thus: $\begin{cases} n_i \le N_i \\ n_j \ge 0 \end{cases}$.

2.5 Evaluation function

The Rating Criteria for MDA is defined as the value of the optimal solution for MDA, i.e., the fitness value. The fitness value discussed in this paper should be proportional to the total target detection accuracy B and inversely proportional to the maximum total energy consumption Dep. We use $\psi(\mathrm{X})$ to denote the optimal fitness value of the MDA.

$$\psi(\mathrm{X}) = \frac{1 - \prod_{j=1}^{m} o_{ij}(1 - b_j)}{\sum_{j=1}^{n} o_{ij} \times \mathrm{dep}\ a_j} \tag{4}$$

3. IWOA FORMATION METHOD

The WOA (Whale of Algorithm), like most metaheuristic algorithms, is still relatively easy to fall into local optimal solutions and converge slowly, so we improve on the basic WOA in order to get better results. We improve the WOA in the following two aspects: (i) using BP (Back Propagation) neural network algorithm to improve the diversity of the initial position of the whale; (ii) using parameter nonlinearization to make the WOA enter the local optimal search phase and taboo algorithm as early as possible to avoid the WOA from falling into the local optimal too early.

Surrounding the prey

Since the whale's exploration area corresponds to a space of global solutions, prey must be located so that the whale surrounds them. Because the location of the optimal design at the time of exploration is a priori agnostic, WOA considers the current optimal candidate solution to be the target prey or the prey that is closest to the target i.e., close to the optimal solution. After artificially specifying the best Search agent, other Search agents try to update their positions as the best Search agent. This phase behavior is represented by the following equations (5) and (6).

$$S = |\vec{U} \cdot \vec{X}'(t) - \vec{X}(t)| \tag{5}$$

$$\vec{X}(t+1) = \vec{X}'(t) - \vec{Z} \cdot S \tag{6}$$

Eq.

t indicates the number of current iterations.

$\vec{U}$ and $\vec{Z}$ are the coefficient vectors.

$\vec{X}'(t)$ is the position vector of the best solution obtained so far.

$\vec{X}(t)$ is the position vector.

And if a better solution exists, then $\vec{X}'(t)$ should be updated in each iteration, where the vectors $\vec{Z}$ and $\vec{U}$ are computed as follows.

$$\vec{Z} = 2b \times \vec{r}_1 - b \tag{7}$$

$$\vec{U} = 2 \times \vec{r}_2 \tag{8}$$

$\vec{r}_1$ with $\vec{r}_2$ being a random vector in [0,1].

Throughout the iteration the value of b decreases from 2 to 0. The expression is

$$b = 2 - \frac{2t}{t_{\max}} \tag{9}$$

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

Bubble netting for hunting

Whale hunting consists of two main mechanisms: encircling prey and bubble net hunting. When using bubble netting for hunting, the position update between the whale and the prey is represented by logarithmic spiral equations (10) and (11).

$$\vec{X}(t+1) = L' \times e^{KF} \times \cos(2\pi F) + \vec{X}'(t) \tag{10}$$

$$L' = |\vec{X}'(t) - \vec{X}(t)| \tag{11}$$

Eq.

L' denotes the distance of the exploring individual from the current optimal solution.

K denotes the spiral shape parameter.

F denotes a random number whose value range is [-1,1] are distributed.

And since there are two types of hunting behavior in the process of approaching the prey, thus IWOA selects bubble net hunting or shrink encirclement according to the probability p. The position updates Equation (12).

$$\vec{X}(t+1) = \begin{cases} \vec{X}'(t) - F \cdot \vec{Z},\ p \le 0.5 \\ L' \times e^{KF} \times \cos(2\pi F) + X'(t),\ \ p \ge 0.5 \end{cases} \tag{12}$$

Eq.

p denotes the probability of the trapping mechanism, a random number with the value range [0,1].

In as the number of iterations *t* increases. The parameter *F* and the convergence factor *K* gradually decrease if $|F| < 1$, then the whale gradually surrounds the current optimal solution, which belongs to the local optimization-seeking stage in WOA.

Exploration of prey

To ensure that all whales can fully explore in the solution space, IWOA updates the position according to the whales' distance from each other for the purpose of random exploration. Therefore, when $|\vec{U} \ge 1|$, the exploring individuals swim to random whales, see Eqs. (13) and (14).

$$L'' = |\vec{U} \cdot \vec{X}_{rand}(t) - \vec{X}(t)| \tag{13}$$

$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{Z} \cdot S \tag{14}$$

Eq.

L'' denotes the distance between the explored individual and the random individual.

$\vec{X}_{rand}(t)$ Indicates the individual position of the current location.

3.1 Parameter optimization

In WOA, $\vec{Z}$ and $\vec{U}$ directly affect the refreshing of individual whale positions, while b directly affects the change of $\vec{Z}$. The value of b in the algorithm is set to a linear change range between 2 and 0, so to some extent it cannot obviously reflect the individual search process of the algorithm, which leads to local exploration of WOA at a later stage, thus increasing the convergence time of the algorithm. is changed so that it varies nonlinearly, and the formula is as follows.

$$b = 1 - \arcsin(\frac{t}{t_{\max}}) \tag{15}$$

Eq.

t denotes the number of iterations.

From Eq. (14), we can see that the nonlinear change can make the value of b decreases rapidly in the initial stage, which achieves our purpose of entering the local exploration this morning and improves the convergence speed of WOA.

3.2 Avoid falling into local optimum using the forbidden algorithm

In the parameter optimization process, we change the parameter b so that WOA enters the local optimum exploration phase as early as possible, but we do not want the algorithm to fall into a local optimum and arrive at a local optimum solution, so we use the forbidden algorithm to avoid it; the basic idea is to put a marker on the local optimum solutions we have obtained earlier so that we can avoid these local optimum solutions in the next iteration.

The main parameters of the forbidden algorithm are designed as follows.

Neighborhood structure

Facing the characteristics of the model in this paper, we use Random disturbance (RDT) neighborhood structure. Numerous experiments have shown that the standard unit vector is the most suitable as the Random disturbance vector. Set up 2n unit perturbation vectors.

$\pm(1,0,0,0,\ldots,0,\ldots)^T$

$\pm(0,1,0,0,\ldots,0,\ldots)^T$

$\pm(0,0,1,0,\ldots,0,\ldots)^T$

$\pm(0,0,0,1,\ldots,0,\ldots)^T$

……

$\pm(0,0,0,0,\ldots,1,\ldots)^T$

……

$\pm(0,0,0,0,\ldots,0,\ldots,1)^T$

Adaptation value function

$$\psi(\mathrm{X}) = \frac{1 - \prod_{j=1}^{m} o_{ij}\ (1 - b_j)}{\sum_{j=1}^{n} o_{ij}\,\mathrm{dep}\, a_j} \tag{16}$$

Taboo table setting

The forbidden objects are all elements of the forbidden table i.e. randomly scrambled operations.

Taboo length (TabuL)

TabuL is the term of the taboo object in the taboo table, and the taboo object is unbanned only when its term is 0. Assume that the initial TabuL = 7.

Size and selection of candidate solution set

The optimum is generally selected in the neighborhood of the previous state. The scale is 9.

Taboo algorithm flouting guidelines

The algorithm uses a criterion based on the exploration direction: if an object that has been tabooed makes a change in the fitness value during the last taboo, and the fitness value of the corresponding candidate solution of the tabooed object is currently better than the current solution, then this tabooed object can be unbanned.

Exploration strategy

Adopt a diversity exploration strategy, i.e., broaden the exploration area, especially the unknown area.

Taboo algorithm termination guidelines

A termination criterion with a given maximum number of no-improvement iterations is used. The maximum number of no-improvement iterations is 20.

4. SIMULATION AND RESULTS ANALYSIS

Suppose in an air interdiction operation, the enemy incoming targets are 6, while our sensors involved in the detection mission are 8. Table 1 gives the capability of each sensor to detect enemy targets.

Table 1. Sensor to target detection accuracy table.

	target1	target2	target3	target4	target5	target6	Impor-tance factor	Test-ing Capa-bility	Energy consump-tion value
S1	0.9829	0.0324	0.4135	0.3862	0.9872	0.6585	0.05	8	0.03
S2	0.4391	0.8652	0.5458	0.4714	0.2595	0.5479	0.11	6	0.03
S3	0.1716	0.1961	0.9696	0.9870	0.0715	0.8013	0.08	5	0.02
S4	0.0082	0.2321	0.0747	0.1639	0.0158	0.0367	0.21	8	0.04
S5	0.2762	0.0921	0.0475	0.9448	0.4997	0.6481	0.15	10	0.02
S6	0.4462	0.9145	0.2753	0.4624	0.2129	0.2361	0.12	8	0.03
S7	0.0413	0.1639	0.6174	0.9427	0.8025	0.6559	0.07	12	0.04
S8	0.0581	0.3544	0.3973	0.3306	0.5697	0.9167	0.06	12	0.02

Table 2. IWOA solving.

Objectives	Programs	Adaptability	Energy consumption
1	1, 3, 5	26.0563	0.08
2	2	30.54	0.03
3	6, 8	34.168	0.05
4	5, 7	34.198	0.07
5	8	31.13	0.06
6	3, 5, 8	45.88	0.02

4.1. IWOA obtains the optimal solution of the detection federation scheme

The optimal solutions of MDA were calculated using WOA and IWOA, and the results obtained after 100 Monte Carlo experiments are shown in Figure 1, and the optimal solutions of the coalition are shown in Table2.

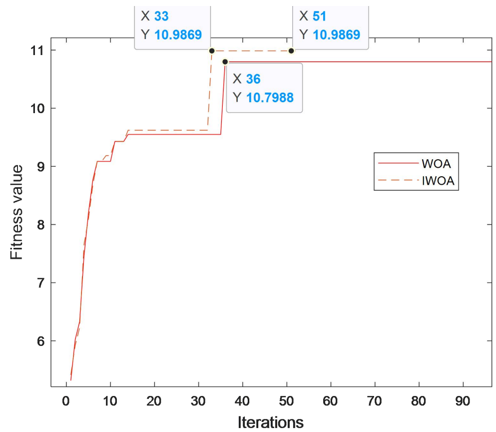

Figure 1. Comparison before and after the improvement of whale algorithm.

Table 3. Effect of different quantitieson the algorithm solution.

Objectives	Sensors	
	The number of whales is 70 heads	The number of whales is 100 heads
1	1, 2, 3, 4, 6, 7	3, 5, 6, 7
2	2, 4, 5, 8	4, 5, 6
3	4, 6, 8	3, 4
4	1, 5	5, 8
5	1, 3, 4, 5, 8	1, 6, 7
6	1, 2, 3, 5, 6, 7, 8	1, 4, 5, 8

From Figure 1, it is known that WOA and IWOA can solve the optimal solution of MDA effectively. The fitness value of 10.7988 is obtained and reaches the steady state after 36 iterations using WOA, while the fitness value of 10.9869 is obtained and reaches the steady state after 33 iterations using IWOA, and the convergence speed is significantly improved by introducing the forbidden algorithm.

4.2 The effect of whale population on the optimal solution of the MDA scheme

In the study of IWOA, the number of whales is considered to have an impact on the optimal solution of MDA, for which we conducted 100 Monte Carlo experiments for 70 and 100 numbers of whales, respectively, and the results are shown in Figure 2, and the optimal solution scheme obtained is shown in Table 3.

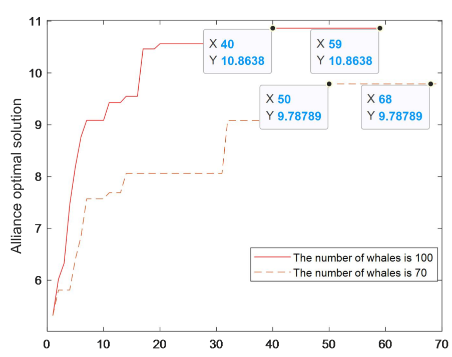

Figure 2. Effect of different number of whales on the solution.

It can be seen from Fig. 2 that when the number of whales is 70, the algorithm is stable after 51 iterations, and the optimal solution of MDA is 9.787; when the number of whales is 100, the adaptation value is stable after 40 iterations, and the optimal solution is 10.863. It is obvious that increasing the number of whales can improve the convergence of the algorithm, and can get a higher adaptation value and a better The optimal solution of the multi-sensor detection coalition system.

4.3 Effect of different algorithms on the optimal solution of the MDA scheme

In the study of IWOA, we compared IWOA with Gray Wolf algorithm and Ant Colony algorithm under the same conditions, and the results are shown in Fig. 3 and Fig. 4.

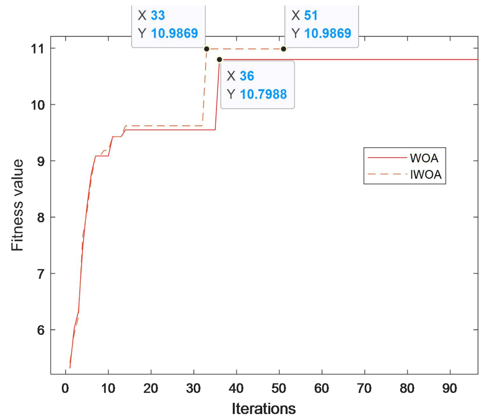

Figure 3. Comparison of different algorithms to find the optimal solution.

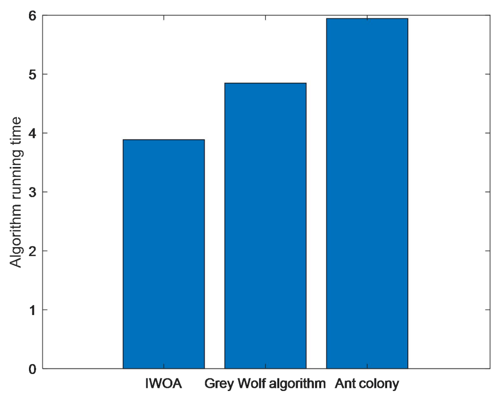

Figure 4. Running time of different algorithms to find the optimal solution.

From Fig. 3 , Fig. 4, it can be seen that all three different algorithms reached stability, the ant colony algorithm obtained the fitness value of 8.89843 after 49 iterations and took the longest time; the gray wolf algorithm obtained the fitness value of 9.57873 after 40 iterations; and the improved whale algorithm obtained the fitness value of 10.8269 after 34 iterations and took the shortest time. It is easy to see that there is relatively high solution quality and relatively fast convergence in the IWOA-based MDA scheme for finding the optimal solution.

5. CONCLUSION

In this paper, we mainly propose IWOA-based MDA to find the optimal solution. Firstly, we establish the MDA model and propose the objective function of MDA as well as the evaluation function, etc. Secondly, we compare the basic WOA with IWOA to find the optimal solution of MDA and discuss the influence of the number of whales on the solution. Finally we compare IWOA with gray wolf algorithm and ant colony algorithm. The results of simulation experiments show that IWOA has significantly improved the degree of finding the optimal solution for MDA. After comprehensive analysis, we conclude that IWOA has the ability to find the best coalition adaptation scheme in a short period of time, substantially improve the convergence speed and avoid falling into the local optimal solution prematurely, while maintaining good stability, in addition to the simple mechanism, few parameters and strong optimization ability.

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