



Multi sensor and multi task allocation based on improved whale optimization algorithm

Binlin YUAN^{1, 2}, Shifeng ZHANG¹, Boxuan WANG³, Kun ZHANG^{3, *}

¹College of Aerospace Science and Engineering, National University of Defense Technology, Changsha, China;

²Sichuan Tengden Technology Co., Ltd., Chengdu, China;

³School of Electronic and Information, Northwestern Polytechnical University, Xi'an, China.

*Corresponding author

Abstract

In response to the collaborative detection problem of unmanned aerial vehicle (UAV) formations in dual aircraft formation cluster operations, this paper constructs an optimization model with detection benefits and detection costs as the objectives based on task priority, and designs an improved whale optimization algorithm to solve the model. Firstly, an elite population initialization based on multiple constraint conditions was proposed, and secondly, an improved method for updating whale individual positions was proposed by combining model characteristics. Subsequently, a local search strategy was designed to enable the algorithm to escape from local optima. Finally, the effectiveness of the proposed algorithm in solving task allocation problems was verified through simulation experiments. Compared with the Harris Eagle algorithm, the improved whale optimization algorithm obtains a higher quality non dominated solution set, indicating that the algorithm has certain advantages.

Keywords: sensor collaboration, task allocation, improving the whale algorithm

1. Introduction

In recent years, with the continuous development of military technology, the concept of systematic joint operations has emerged. Through the effective collaboration of different combat platforms and various combat elements, it is possible to enhance situational understanding and prediction capabilities, and achieve comprehensive management of detection, fusion, and attack and defense. In systematic joint operations, drone clusters equipped with high-precision sensors have been used to carry out target detection tasks. However, the rapidly changing combat environment and the increasing concealment of enemy targets pose significant challenges to target detection. In order to achieve rapid and accurate target detection, the reasonable allocation of drones and sensors is crucial for leveraging the collaborative detection advantages of the cluster [1,2]. In the collaborative detection scenario of unmanned aerial vehicle (UAV) formations in cluster operations, due to the large number of detection tasks and limited detection resources, it is not possible to effectively ensure the detection of all tasks by UAV formations. At the same time, there are also situations where tasks cannot be executed by certain sensors. It is necessary to coordinate and allocate tasks as a whole based on the battlefield environment and task requirements, while considering the detection efficiency and rationality of tasks, and allocate tasks to appropriate sensor platforms.

The purpose of task allocation is to optimize the model through reasonable task allocation and achieve a reasonable match between detection tasks and detection resources. When establishing the model, both the detection performance of sensors and tactical applications should be considered. Currently, numerous researchers have proposed methods and models for task allocation. Nash proposed a sensor target allocation method for tracking targets using linear programming techniques in 1977, and first applied optimization techniques to sensor management. In 2010, Hitchings et al. proposed a stochastic control approximation algorithm based on rolling time domain control [4]. In recent years, intelligent optimization algorithms such as particle swarm optimization [5,6], ant colony algorithm [7], genetic algorithm [8,9], auction algorithm based on market mechanism [10], contract network algorithm [11] have become the most commonly used methods for solving task allocation problems. Most research on sensor allocation methods focuses on the efficiency elements of sensor

targets [12], with maximizing efficiency as the objective function. A task allocation optimization model is proposed in reference [13], which establishes a comprehensive detection efficiency evaluation index system based on spatial occupancy, detection accuracy, and threat characteristics. The traditional contract network algorithm is improved to make it suitable for sensor target allocation on multiple platforms; Reference [14] proposed a quantitative evaluation model for sensor information perception ability based on the performance characteristics of sensors, and achieved the maximization of sensor detection perception ability through particle swarm optimization algorithm. At present, the methods for assigning collaborative targets to sensors have limitations such as a single configuration, relatively static styles, and weak coupling between collaborative efficiency indicators and actual scenarios. Therefore, this article focuses on the problem of multi sensor collaborative multi target allocation on heterogeneous platforms. From various factors such as sensor performance, battlefield situation, and resource consumption, a comprehensive detection efficiency evaluation index system is constructed for both regional detection and target detection tasks. The whale fish algorithm [15] is improved to improve its convergence speed and make it suitable for task allocation on multiple platforms and sensors.

2. Task Analysis

2.1 Task Assignment Description

In this article, two unmanned aerial vehicle platforms carry three types of sensors: radar, optoelectronic, and electronic warfare (ESM). They mainly constitute eight task execution modes: radar single machine detection, radar collaborative detection, optoelectronic single machine detection, optoelectronic collaborative detection, ESM single machine detection, ESM collaborative detection, radar high gain electronic support (HGESM) single machine detection, and HGESM collaborative detection. Among them, radar can be further divided into modes based on radiation conditions and transmission and reception conditions. Through radiation conditions, it can be divided into LPI detection, burst detection, and continuous radiation, while transmission and reception conditions can be divided into four types: transmission and reception separation, single transmission and multiple reception, multiple transmission and multiple reception, and spontaneous self reception. At the same time, there are also three specific radar situations. Collaborative detection mode. According to the above division, a total of 48 sensor execution modes are formed, and these 48 modes are sequentially encoded with [0-48] integers. The drone platform receives detection tasks from the base for centralized task allocation. Multiple sensors carried by the drone platform use corresponding execution modes to independently or collaboratively execute corresponding tasks based on the task allocation results. The detection tasks assigned by the base have the following attributes:

- Task quantity: The number of tasks issued by the base;
- Task types: mainly including two types of tasks, area detection task is to search for a certain airspace, and target detection task is to track and locate a certain target;
- Task Priority: Each task has different priorities during task execution due to its type, tactical status, and battlefield situation. The priority is ranked from high to low as 1, 2, 3 and so on;
- Task radiation level requirements: Radiation levels are divided into 5 levels, sorted from high to low as 5, 4, 3, 2, and 1. Different sensors can be used to perform tasks at different radiation levels.
- Task assignment situation: Task assignment is executed by a certain platform;
- Target/airspace center position: the position coordinates of the target or airspace center in the Local Cartesian coordinates coordinate system;
- Airspace radius: Airspace is the radius of a cylinder in space that is horizontally projected;
- Starting altitude of airspace: the coordinate value of the lowest horizontal plane in the airspace in the sky direction in the Local Cartesian coordinates coordinate system;
- End altitude of airspace: The coordinate value of the highest horizontal plane in the airspace in the sky direction in the Local Cartesian coordinates coordinate system.

The results of sensor task allocation can be represented by the following table:

Table 1 List of sensor task allocation results

	Task 1	Task 2	...	Task n
Radar A	1	2	0	0

Radar B	0	3	0	0
Photoelectricity A	0	0	0	41
Photoelectricity B	0	0	40	42
ESM A	0	0	0	0
ESM B	0	0	0	0
HGESM A	0	0	0	0
HGESM B	0	0	0	0

According to the sensor task allocation result table, it can be described as a matrix with k rows and n columns:

$$X = [x_{ij}]_{k \times n} \quad (1)$$

$$x_{ij} \in [0, 48]$$

In the formula, k represents the number of sensors, n represents the number of tasks, and each row in the matrix represents a sensor. Among them, each column represents a task, and x_{ij} represents the mode in which sensor i participates in executing task j. $x_{ij} = 0$ is not involved in executing the task. If there are two $x_{ij} \neq 0$ in a column, it indicates that the task is executed through the collaboration of two sensors.

2.2 Task Executable Matching

After assigning tasks to the drone platform, each task has certain task requirements, and due to these requirements, not all sensor execution methods can perform these tasks. Based on these task requirements, this article conducts preliminary screening and generates a task executable matching list as follows:

Table 2 Task executable matching list

	Task 1	Task 2	...	Task n
Radar A	1	1	0	1
Radar B	1	1	0	1
Radar collaboration	0	1	0	1
Photoelectricity A	0	0	1	1
Photoelectricity A	0	0	1	1
Photoelectricity collaboration	0	0	1	1
ESM A	0	0	1	0
ESM B	0	0	1	0
ESM collaboration	0	0	1	0
HGESM A	0	1	1	0
HGESM B	0	1	0	0
HGESM collaboration	0	1	0	0

According to the above table, the task executable matching matrix is:

$$Y = [y_{ij}]_{m \times n} \quad (2)$$

$$y_{ij} \in [0, 1]$$

In the formula, m represents the number of sensor execution methods, n represents the number of tasks, y_{ij} is 0 represents task execution method i cannot execute task j, y_{ij} is 1 represents task execution method i cannot execute task j.

The task requirements mainly include the following:

- Task radiation level requirements: Due to the ability to use different sensors at different radiation levels, the corresponding relationship between task radiation level and sensor usage is shown in Figure 1 and Figure 2.

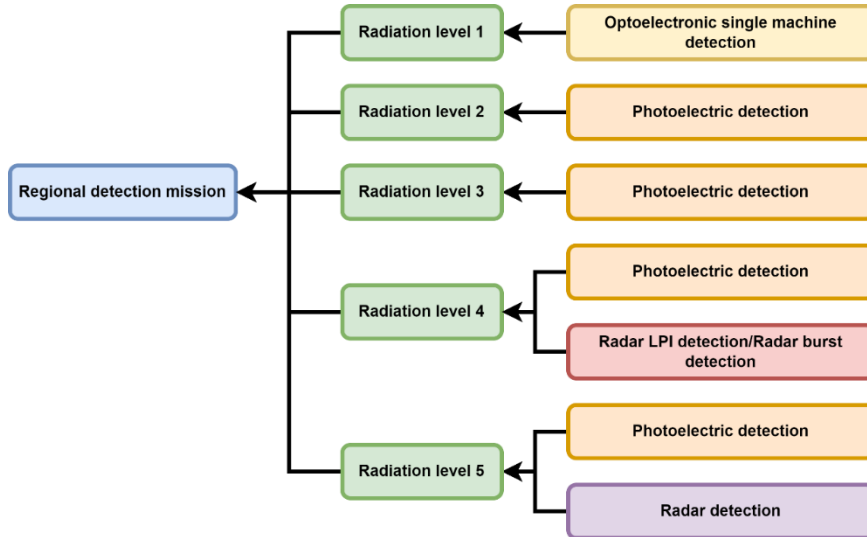


Figure 1 Relationship diagram between radiation level and sensor mode for regional detection tasks

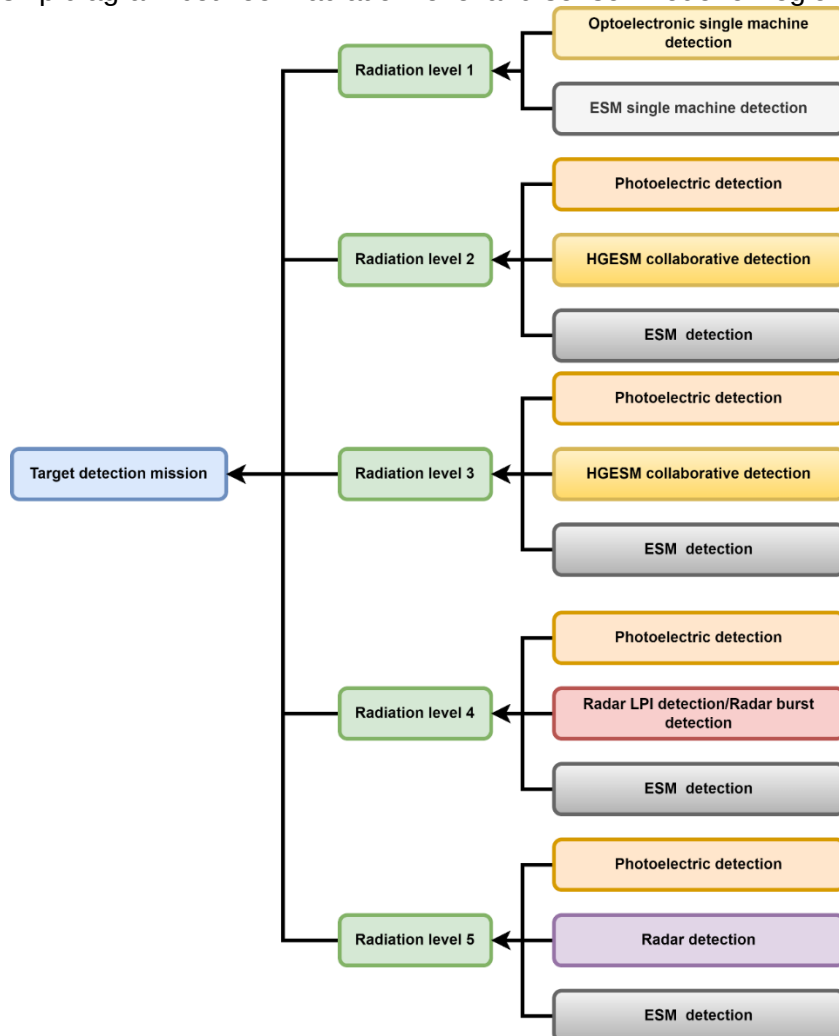


Figure 2 Diagram of the Corresponding Relationship between Radiation Level and Sensor Mode in Target Detection Tasks

- Task type requirement: Regional detection tasks cannot be executed through ESM and HGESM; The target detection task cannot be executed by HGESM alone.
- Task specification requirement: When there is a task execution platform or task execution mode specified in the task attribute, the task can only be executed through the specified platform or mode.
- Sensor detectable requirement: The target is required to be within a certain angle and distance range of the sensor.

3. Establishment of Detection Efficiency Model

3.1 Analysis of Detection Efficiency Indicators

For regional detection tasks, the detection efficiency indicators that are concerned include detection distance, detection angle, detection accuracy, detection dwell time, detection resource consumption, etc; For target detection tasks. The detection efficiency indicators of concern include detection distance, detection angle, detection accuracy, detection resource consumption, etc. During the execution of detection tasks, sensor collaboration can expand the detection range and improve detection accuracy, achieving a "1+1>2" effect. Quantitatively analyze and model the detection benefits and costs for different detection tasks and sensor collaboration methods, in order to form a complete detection efficiency indicator system.

3.1.1 Detection Revenue Modeling

- Detection distance advantage: Each sensor has its corresponding detection distance threshold. Under the same azimuth conditions, the farther the target is relative to each other, the poorer the ranging accuracy.

$$g_2(i, j) = 0.2 + 0.8e^{-\frac{\min\{\rho, \rho_d\}}{1000}} \quad (3)$$

In the formula, i, j represents the sensor number and task number, ρ represents the relative distance of the target, and ρ_d represents the critical value of the detection distance range determined by the sensor's capability and operating mode.

- Detection angle advantage: Due to the fact that under the same distance conditions, the target usually has the highest accuracy when facing a single sensor detection beam or falling on the midpoint of the connection between two sensors.

$$g_1(i, j) = 0.2 + 0.8e^{-\frac{\min\{\theta, \theta_a\}}{\pi/9}} \quad (4)$$

In the formula, i, j represents the sensor number and task number respectively, θ is the relative azimuth angle of the target, and θ_a is the critical value of the detection azimuth range determined by the sensor's capability.

- Detection dwell time advantage: There is only a detection dwell time advantage for regional detection tasks, and the detection dwell time is estimated based on the size of the target airspace and beam scanning speed.

This article defines the search area Φ as follows:

$$\Phi = \begin{bmatrix} \Phi_{\min}^A & \Phi_{\max}^A \\ \Phi_{\min}^P & \Phi_{\max}^P \end{bmatrix} \quad (5)$$

$\Phi_{\min}^A, \Phi_{\max}^A$ represents the starting range of the azimuth direction, and $\Phi_{\min}^P, \Phi_{\max}^P$ represents the starting range of the pitch direction. So the search time T can be expressed as

$$T = \text{ceil}\left(\frac{\Phi_{\max}^A - \Phi_{\min}^A}{\phi}\right) \times \text{ceil}\left(\frac{\Phi_{\max}^P - \Phi_{\min}^P}{\phi}\right) \times \tau \quad (6)$$

Among them, $\text{ceil}()$ represents an upward rounding function, ϕ is the beam width of the sensor, and τ is the residence time of each beam during scanning.

After normalizing the search time, the advantage function of detection dwell time can be obtained as follows:

$$g_3(i, j) = \begin{cases} T, \text{Single machine detection} \\ \max(T_1, T_2), \text{Collaborative detection} \end{cases} \quad (7)$$

Among them, T is the search time calculated during single machine detection, T_1 is the search time calculated by platform 1 during collaborative detection, and T_2 is the search time calculated by platform 2 during collaborative detection.

For regional detection tasks, the detection benefit function is as follows:

$$g(i, j) = \sum_{s=1}^3 c_s(i, j) g_s(i, j) \quad (8)$$

In the formula, $c_s(i, j)$ is the weight coefficient, satisfying both $c_s(i, j) > 0$ and $\sum_{s=1}^3 c_s(i, j) = 1$.

For target detection tasks, the detection benefit function is as follows:

$$g(i, j) = \sum_{s=1}^2 c_s(i, j) g_s(i, j) \quad (9)$$

In the formula, $c_s(i, j)$ is the weight coefficient, satisfying both $c_s(i, j) > 0$ and $\sum_{s=1}^2 c_s(i, j) = 1$.

3.1.2 Detection Cost Modeling

- Detection resource consumption: The number of tasks that a single sensor can perform simultaneously is limited. The more sensors used, the more resources spent, and the less remaining resources left for other tasks at the same time.

$$h_1(i, j) = \frac{n_{\text{sensor}}}{N_{\text{uav}}} \quad (10)$$

In the formula, n_{sensor} represents the number of sensors performing the task and N_{uav} represents the number of drone platforms.

- Sensor error: Quantify the detection accuracy of single sensor detection and collaborative detection based on the detection performance of the sensor.

$$h_2(i, j) = \begin{cases} p_{rd}, \text{Radar single machine detection} \\ \alpha * p_{rd}, \text{Radar collaborative detection} \\ p_{oe}, \text{Photoelectricity single machine detection} \\ 0.8 * p_{oe}, \text{Photoelectricity collaborative detection} \\ p_{esm}, \text{ESM single machine detection} \\ 0.8 * p_{esm}, \text{ESM collaborative detection} \\ p_{hgesm}, \text{HGESM single machine detection} \\ 0.8 * p_{hgesm}, \text{HGESM collaborative detection} \end{cases} \quad (11)$$

In the formula, $p_{rd}, p_{oe}, p_{esm}, p_{hgesm}$ represents detection error coefficient caused by using radar, optoelectronics, ESM, and HGESM for detection, and α represents the accuracy coefficient of the sensor in different modes.

For regional detection tasks and target detection tasks, the detection cost function is as follows:

$$h(i, j) = \sum_{s=1}^2 b_s(i, j) h_s(i, j) \quad (12)$$

In the formula, $b_s(i, j)$ is the weight coefficient that satisfies $b_s(i, j) > 0$ and $\sum_{s=1}^2 b_s(i, j) = 1$.

3.1.3 Establishment of Detection Efficiency Function

For the allocation relationship between all sensors and tasks, the overall detection efficiency function is obtained by integrating the detection benefit function and the detection cost function.

$$f(i, j) = A \times g(i, j) - B \times h(i, j) + C \times \frac{1}{P_j} \quad (13)$$

In the formula, let A, B, and C be undetermined coefficients greater than 0, which can be selected according to different characteristics of the task, reflecting the relative importance of different indicators such as detection accuracy, coverage range, and formation load balancing. P_j represents the priority of the task.

Considering the independent or pairwise combination of m sensors within a formation to complete the detection task of n enemy targets, there are $m + C_m^2 = \frac{m(m+1)}{2}$ different combinations of sensors.

At this point, the detection efficiency function between all sensor combinations and all targets can

be written as a matrix $F(i, j)$ of $\frac{m(m+1)}{2}$ rows and n columns. Achieving optimal overall detection efficiency means extracting an element from each row of the matrix to maximize their algebraic sum.

3.2 Constraint Establishment

In the task allocation process of formation detection sensors, it is necessary to consider various constraints such as task radiation level, maximum executable task of sensors, etc. When the allocation result does not meet these constraints, it will cause the sensors to be unable to execute the assigned task, resulting in invalid allocation results. The constraint conditions constructed in this article are as follows:

Task executable constraints: In task executable matching, a task executable matching matrix is constructed based on task radiation level, task type, and task assignment, indicating whether the task can be executed through a certain sensor. Some constraints are first processed. The task executable constraint associates the task executable matching matrix with the sensor task allocation matrix, which can be expressed as:

$$\begin{aligned} x_{(\lfloor i/4 \rfloor * 3 + i \% 4)j} &= 0, \text{ if: } y_{ij} = 0, i = 0, 1, 3, 4, 6, 7, 9, 10 \\ x_{(\lfloor i/4 \rfloor * 3)j} &= 0, x_{(\lfloor i/4 \rfloor * 3 + 1)j} = 0, \text{ if: } y_{ij} = 0, i = 2, 5, 8, 11 \end{aligned} \quad (14)$$

In the formula, x_{ij}, y_{ij} represents the task allocation result matrix and the task executable matching matrix, respectively.

Sensor maximum executable task constraint: Each type of sensor has an upper limit for executing tasks.

$$\begin{aligned} \sum_{j=0}^{j=n} x_{ij} &< N_{rd}, i = 0, 1 \\ \sum_{j=0}^{j=n} x_{ij} &< N_{oe}, i = 2, 3 \\ \sum_{j=0}^{j=n} x_{ij} &< N_{esm}, i = 4, 5 \\ \sum_{j=0}^{j=n} x_{ij} &< N_{hgesm}, i = 6, 7 \end{aligned} \quad (15)$$

In the formula, $N_{rd}, N_{oe}, N_{esm}, N_{hgesm}$ represents the maximum number of executable tasks for radar, optoelectronic, ESM, and HGESM, respectively.

4. Design of Multi Sensor and Multi Task Allocation Algorithm

4.1 Overview of Whale Optimization Algorithm

The Whale Optimization Algorithm is a metaheuristic optimization algorithm that simulates the hunting behavior of whales by randomly or optimally searching for agents chasing prey, as well as using a spiral to simulate the bubble net attack mechanism of humpback whales. According to Hof and Van Der Gucht's research, certain areas of the whale brain have a type of cell similar to humans called spindle cells, whose function is to judge movement and human social behavior. The most unique aspect of whale social behavior is their unique hunting method: bubble net foraging. They like to prey on a group of krill or small fish near the water surface. According to observations, this foraging is accomplished by creating unique bubbles on a circular or 9-shaped path as shown in Figure 3.

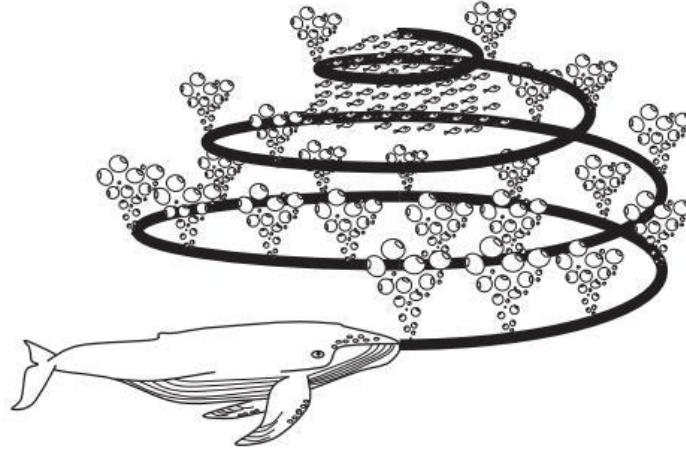


Figure 3 Bubble net feeding behavior of humpback whales

The whale optimization algorithm adopts three predation methods: wandering for food, encirclement contraction, and spiral predation. Firstly, generate a random number p for policy selection, with a value between $[0, 1]$. Among them, at $p < 0.5$, the predation method is to choose between wandering foraging and encirclement contraction predation. The selection of predation method is based on the relationship between the generated coefficient vector $|A|$ and 1, and its formula is as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (16)$$

Among them, $\vec{a}$ is generated by a function that continuously changes with the number of iterations, decreasing from 2 to 0, and $\vec{r}$ is the $k \times n$ matrix of a random number, $\vec{r}_{ij} \in [0, 1]$. When $|\vec{A}| < 1$, choose the hunting method of wandering and foraging, otherwise choose the hunting method of encircling and contracting. When $p > 0.5$, the hunting method of whales is spiral hunting. The population is mainly updated based on the following three predatory methods:

- Wandering and foraging:

Search for any individual in the whale population to find food, and the individual update formula is as follows.

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \times \vec{D} \quad (17)$$

Among them, $\vec{X}(t+1)$ represents the updated individual, and $\vec{X}_{rand}$ represents the randomly selected whale individual in the population. The formula for parameter $\vec{D}$ is as follows.

$$\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}| \quad (18)$$

Among them, X represents the current whale individual, and the formula for the coefficient vector X is as follows.

$$\vec{C} = 2 \cdot \vec{r} \quad (19)$$

- Surrounding contraction:

The formula for updating the position of searching for the optimal individual to find food in a whale population is as follows:

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (20)$$

Among them, $\vec{X}^*(t)$ represents the current optimal individual, and the formula for parameter $\vec{D}$ is as follows.

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}| \quad (21)$$

- Spiral predation:

Searching for the optimal individual to find food in a whale population, whales prey on things along a logarithmic spiral trajectory, and their position update formula is as follows.

$$\vec{X}(t+1) = \vec{D}' \cdot e^l \cdot \cos(2\pi l) + \vec{X}^*(t) \quad (22)$$

Among them, l takes a random number of $[-1, 1]$, and the formula for parameter $\vec{D}'$ is as follows.

$$\vec{D}' = \left| \vec{X}^*(t) - \vec{X} \right| \quad (23)$$

4.2 Improved Whale Optimization Algorithm Process Design

In the improved whale algorithm for multi-sensor and multi task allocation, the sensor task allocation matrix is used as the individual of the population. Due to the fact that the whale optimization algorithm can only perform individual updates for continuous variables, it is not suitable for the two-dimensional discrete individual updates of the model. In this paper, the Boolean matrix is used as an intermediate matrix to transform the task allocation matrix into a Boolean matrix. The calculation of whale algorithm updates is carried out through the Boolean matrix, and the elements in the obtained matrix are rounded to the nearest whole number. The position update of whale individuals is achieved through the Boolean matrix. Then, based on the traditional whale algorithm, this article adds a local search strategy based on greedy algorithm. Compare the individual Boolean matrices before and after the update, and assign the value of the corresponding position in the original sensor task allocation matrix to the position where the median of the matrix has not changed; If the median value of the matrix changes, read the position in the task executable matching matrix, obtain the feasible mode of the sensor for the task, seek the task allocation result with the best efficiency in different modes for the same sensor, and assign the mode with the best efficiency.

The steps to improve the whale optimization algorithm are as follows:

Step 1: Initialize a population of X , which is the sensor task allocation matrix.

Step 2: Calculate the fitness value of the sensor task allocation matrix based on the fitness function and find the optimal solution.

Step 3: Update the required parameters p and A for each iteration, and convert the individual task allocation matrix into a Boolean matrix.

Step 4: Determine the size of p and 0.5. If $p < 0.5$, proceed to step 5; Otherwise, proceed to step 6.

Step 5: Determine the relationship between $|\vec{A}|$ and 1. If $|\vec{A}| < 1$, select the current optimal solution and update the population through the bounding contraction mechanism; Otherwise, randomly select an individual to update the position of the walking and foraging mechanism.

Step 6: Select the current optimal individual and update it through a spiral predation strategy.

Step 7: Conduct a local search based on greedy algorithm for the changing positions in individuals and assign values to the patterns.

Step 8: Calculate the fitness value of the current task allocation scheme to select the optimal individual and determine whether the maximum number of iterations has been reached. If the number of iterations has not been reached, execute step 3; otherwise, the iteration will stop.

The algorithm flowchart of the whale optimization algorithm is shown in the following figure:

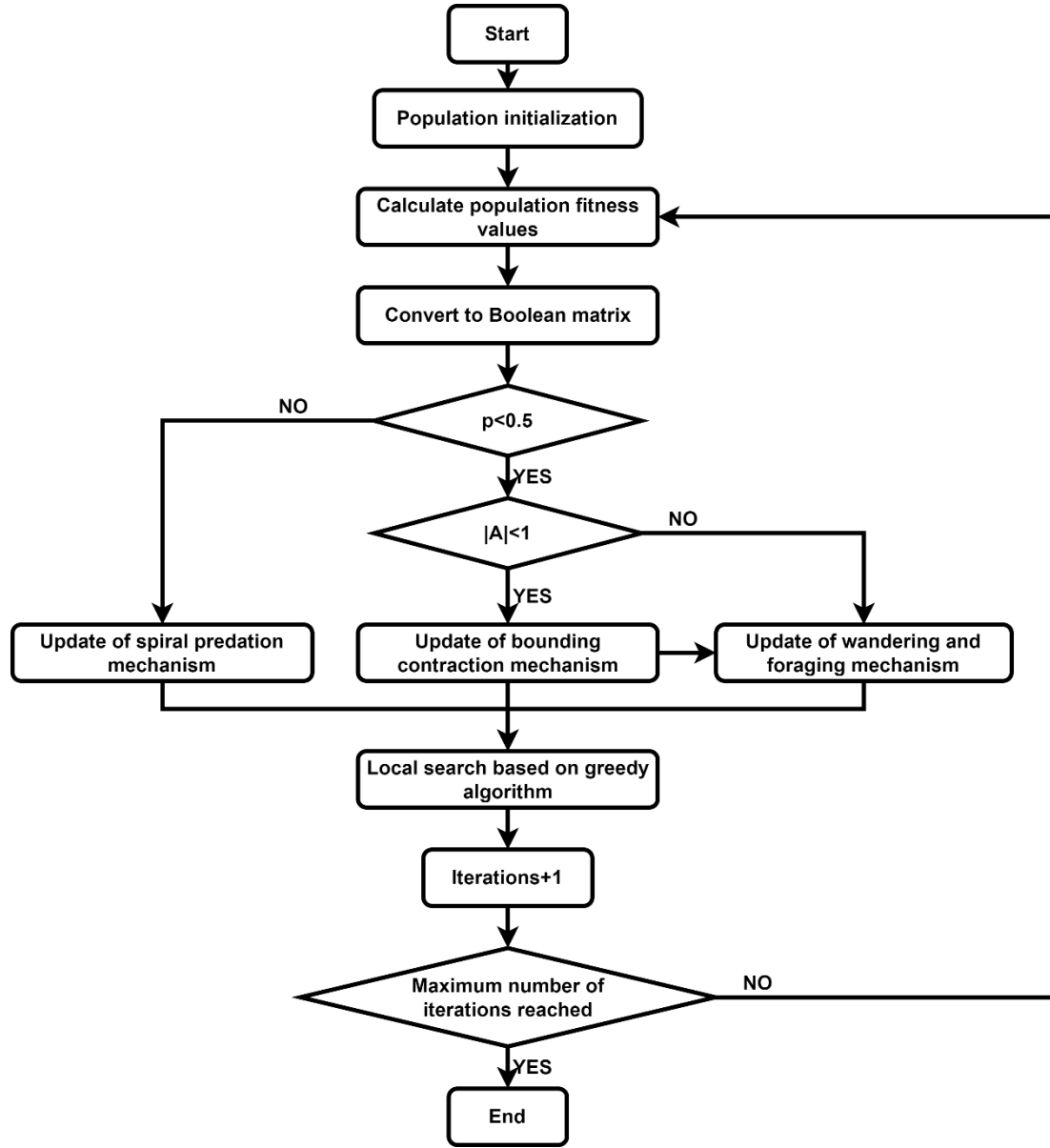


Figure 4 Improved whale optimization algorithm flowchart

5. Simulation Analysis

5.1 Simulation Scene Settings

Our formation consists of two drones with initial positions (X, Y, and Z axis coordinates) located at UAV1 (60000, 7000050000) m and UAV2 (60000, 7000040000) m, respectively. Each drone carries three types of sensors, including radar, optoelectronics, and ESM, and can achieve four detection task execution modes. The base can carry out several tasks to detect targets or airspace in the battlefield. The following are the parameter settings for the simulation case.

The data settings for the execution mode of drone platform detection tasks are shown in Table 3.

Table 3 Data list of drone platform detection task execution methods

Detection execution method	Detection distance (km)	Detection angle range (°)	Maximum number of detections	Beam width (°)	Detection error coefficient
Radar detection	200	± 60	2	3	0.1
Photoelectric detection	120	± 30	3	2	0.25
ESM detection	120	360	4	1	0.4
HGESM detection	100	± 60	4	3	0.25

Based on typical scenarios, construct 5 tasks and task attributes as shown in the table below.

Table 4 Typical Task Setting List

Task Number	Task type	Task priority	Task specific information	Mission objective/airspace center coordinates (m)	Mission airspace radius (m)	Task radiation level	Starting height	Termination height
1	Target detection mission	1		[120000,6000,1000]		1		
2	Regional detection mission	2	Designated Platform 2	[150000,5000,4000]	2000	2	3000	7000
3	Target detection mission	3	Designated Platform 1	[1000,6000,13000]		3		
4	Regional detection mission	4		[4000,4000,14000]	2000	4	3000	5000
5	Target detection mission	5		[140000,4000,4000]		5		

5.2 Simulation Result

With the above simulation settings, the following results can be obtained.

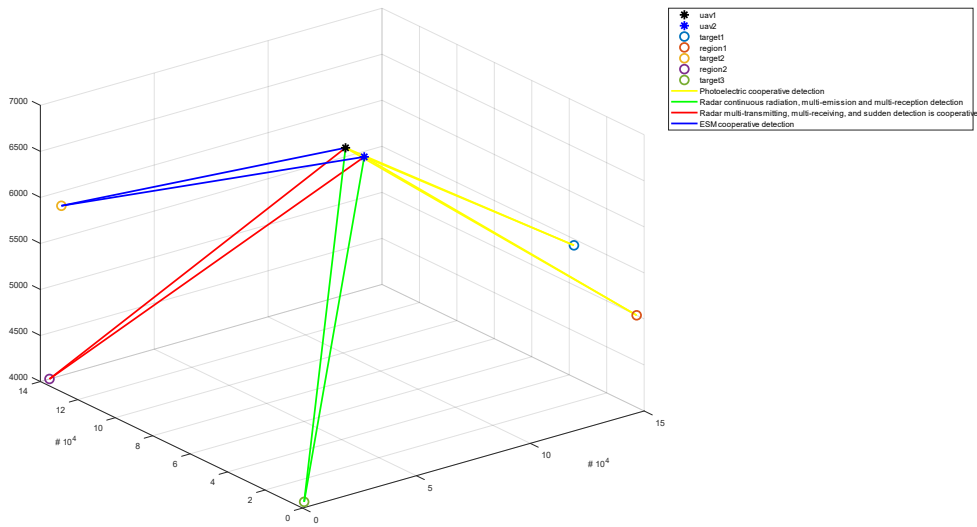


Figure 5 Simulation Case Results of Sensor Task Allocation

From the above figure, it can be seen that Task 1 is a target detection task with the highest priority and radiation level of 1. It can only perform ESM and photoelectric collaborative detection. Due to the high accuracy of photoelectric sensors, photoelectric collaborative detection is adopted; Task 2 is a regional detection task with a radiation level of 2. ESM, optoelectronic, and HGESM detection can be used. However, due to the highest precision of optoelectronic collaborative detection and the moderate beam width of the optoelectronic sensor, it will not cause too long residence time. The optoelectronic sensors of both drone platforms can detect the area in Task 2 and meet the maximum number of detections. Therefore, optoelectronic collaborative detection is used to execute Task 2; The target of Task 3 is not on the same side as the targets of Task 1 and Task 2, and the photoelectric sensor cannot cover the target of Task 3. Therefore, ESM and HGESM can only be used for detection. Task 3 is a target detection task, and residence time does not need to be considered. Comparing the accuracy, it can be concluded that collaborative detection through ESM is better for Task 3; Task 4 is a regional detection task with a radiation level of 4. It can use radar for burst detection. The radar has the maximum beam width, which makes the dwell time shorter and the

accuracy higher. Therefore, radar multi transmitter multi receiver burst collaborative detection is adopted; The radiation level of Task 5 is 5, and radar continuous radiation detection can be used, which has higher detection accuracy than burst detection. Therefore, radar multi transmitter multi receiver continuous radiation collaborative detection is adopted.

Through the above simulation cases, it can be seen that the improved whale algorithm can be used to solve the problem of multi-sensor and multi task allocation, and a relatively optimal result can be obtained. The Harris Eagle Algorithm (HHO) is a new heuristic algorithm proposed by Heidari et al. [16] in 2019, which has strong optimization ability. This article designs a performance comparison experiment between the improved Whale Algorithm and the Harris Eagle Algorithm, comparing the running time, convergence iteration times, and optimal performance of the two algorithms under different task quantities.

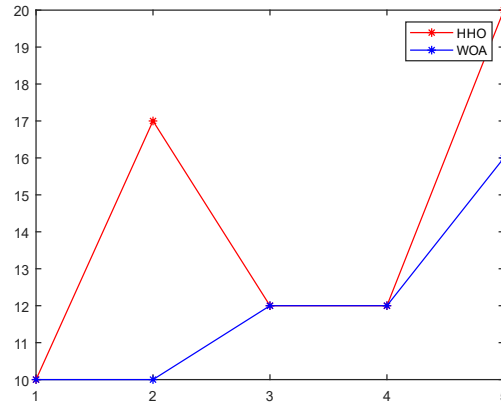


Figure 6 Comparison curve of algorithm iteration times

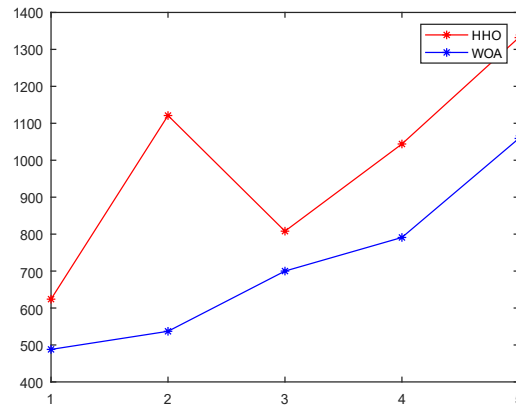


Figure 7 Comparison curve of algorithm running time

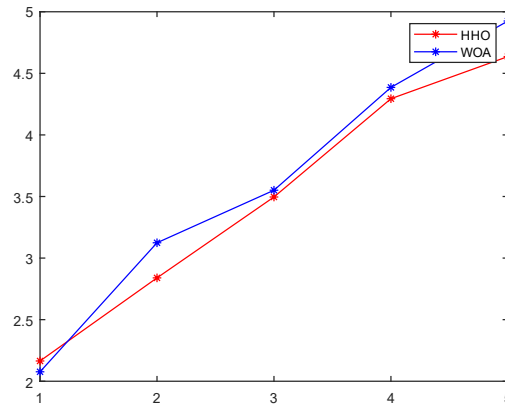


Figure 8 Comparison curve of optimal detection efficiency of algorithms

From Figures 6, 7, and 8, it can be seen that the improved whale algorithm outperforms the Harris eagle algorithm in terms of convergence iteration times, algorithm running time, and optimal computational efficiency. This indicates that the improved whale optimization algorithm has certain

advantages over the Harris eagle algorithm in solving multi-sensor and multi task allocation problems, and can consume less detection costs to obtain higher detection benefits, making high priority tasks easier to be assigned.

6. Conclusion

This article studies the problem of collaborative detection sensor task allocation in unmanned aerial vehicle (UAV) formations in dual aircraft formation cluster operations. By combining sensor collaborative detection with intelligent algorithms, various information elements in typical combat scenarios are comprehensively considered, and a sensor task allocation efficiency function for detection benefits and detection costs is established; Aiming at the problem of sensor task allocation in multi-mode, an improved whale algorithm was proposed, and the effectiveness of the algorithm for sensor task allocation was verified through simulation experiments. The algorithm performance was compared with the Harris Eagle algorithm, proving its certain superiority.

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8. Contact Author Email Address

kunzhang@nwpu.edu.cn

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