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Research Article

A Joint Optimization Method for Cooperative Detection Resources Based on Channel Capacity

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Aiming at the resource optimization problem in the cooperative detection task, the objective function is constructed based on the channel capacity, and the artificial bee colony (ABC) algorithm is improved to realize the joint optimization of the UAV swarm trajectory and radiation power. Firstly, a multiple input multiple output (MIMO) cooperative detection model is constructed. Then, based on the perspective of information theory, the channel capacity of the cooperative detection model is derived and used as the objective function for optimizing the detection resources of UAV swarm. Then, the factors affecting the objective function are sorted out and analyzed one by one, and the constraints are clarified. Aiming at the shortcomings of ABC algorithm, its search strategy and parameter optimization method are improved. A joint optimization process of UAV swarm trajectory and radiated power based on improved ABC algorithm is constructed. Finally, through simulation verification and algorithm comparison, it shows that the algorithm in this paper can improve the perception ability of cooperative detection of UAV swarm.

1. Introduction

In the future battlefield, realize the advantage of one-way transparency of the battlefield. That is to say, we can grasp the enemy's dynamics, and it is difficult for the enemy to understand our state. It can realize the discovery, decision-making, and action before the enemy and grasp the initiative of the battlefield [1–3]. This requires us to have significantly better situational awareness than the enemy. This ability not only is limited to the perception of spatial position but also requires the perception of electromagnetic and energy dimensions. And realize the prediction of each dimension of the opponent, so as to identify and predict the intention of the opponent. With the rapid development of UAV technology and information technology, the capabilities of unmanned platforms have gradually improved, and in some fields, there has been a state and trend that surpasses humans [4–6]. In particular, UAV swarm [7–10] has emerged functions that are not available on single platforms due to their quantity effect and scale effect. It has become the main combat platform and confrontation style of the future war.

UAV swarms can flexibly adjust their spatial position and radiation power to improve their awareness of battlefield situations in a distributed manner. How to optimize the detection resources of UAV swarm has become the core problem restricting the performance of collaborative detection.

Cooperative detection is mainly based on the multiple input multiple output (MIMO) radar system. Because MIMO radar has the characteristics of space diversity and frequency diversity, it can realize the coordination at signal levels, thereby significantly improving the detection efficiency and greatly reducing the probability of being interfered. In order to further improve the efficiency of collaborative detection, scholars have carried out research from two aspects of signal processing and radiation strategy. Signal processing mainly focuses on improving the array signal processing method [11–13] and improving the space-time adaptive algorithm [14, 15]. Such research is not relevant to this paper and will not be discussed here.

In terms of optimizing radiation strategy, scholars designed the objective function related to detection or used and improved some detection criteria to optimize parameters [16, 17]. Literatures [18, 19] used the Cramer-Rao lower bound (CRLB) of target estimation as the objective function. The literature [18] studied the optimization method of radiated power under the condition of setting error. The literature [19] optimized the scheduling strategy and radiation power control method of the optimal detection. The literature [20–23] improved the detection accuracy of MIMO based on information theory. Among them, the literature [20] optimized the Bayesian Fisher information matrix (BFIM) and then obtained the optimal beam selection and power control strategy. The literature [21, 22] further extended it to the extrapolation of the track of target tracking and used cooperative game theory to solve it, realizing the joint optimization of radar coordinates and power. The literature [23] further quantified the amount of information in track extrapolation, used it to correct BFIM, and obtained the optimal power control strategy. Based on the perspective of game theory, the literature [24–27] regarded detection as a game process between the detector and the target and then optimized the radiation parameters. The literature [24] studied the corresponding radiation power optimization methods under different game strategies. Literatures [25, 26] found the Nash equilibrium point and used it to optimize the radiation strategy. The literature [27] was based on the concept of zero-sum game, adjusting MIMO radar signal in real time, thereby weakening the enemy's electromagnetic interference. Literatures [28, 29] realized the joint optimization of radar radiation power and signal parameters based on intelligent algorithms. Literature [30, 31] were based on the theory of compressed sensing, by minimizing the correlation of each receiver, to achieve the purpose of synchronous optimization of the detection beam and the radiation strategy.

It can be seen from the above discussion that the current research on cooperative detection mainly focuses on two aspects. One is to improve the accuracy of collaborative detection by improving the signal processing method. The other is to improve the detection performance by optimizing the deployment positions of different collaborative detection platforms or optimizing the radiation power. However, there are few literatures on joint optimization of detection resources at this stage. The joint optimization of parameters will break down barriers in multiple dimensions such as time, space, and energy. This kind of research jointly optimizes detection resources from multiple dimensions, which can better improve the efficiency of collaborative detection.

Aiming at the above two problems, based on the perspective of information theory, this paper constructs a joint optimization model of trajectory and power for cooperative detection of UAV swarm and uses the improved artificial bee colony algorithm to optimize it.

The main contribution of this paper is to convert the problem of improving detection ability into a standard optimization problem through modeling, which is convenient for solving related problems and carrying out follow-up research. And a model for joint optimization of multidimensional detection resources is constructed. At the same time, the research in this paper has a positive effect on improving the combat effectiveness of UAV swarm and our ability to perceive the battlefield.

Therefore, the joint optimization of multidimensional detection resources will be studied in the following sections. The MIMO detection model is constructed, the relationship between the transmitted signal and the echo signal is deduced, and the channel capacity of the cluster detection is obtained in Section 2. Constructing objective functions and constraints for optimizing UAV swarm trajectories and radiated power are discussed in Section 3. Improve the Artificial Bee Colony algorithm (ABC) algorithm in Section 4. A joint optimization process of cooperative detection resources based on improved ABC algorithm is constructed in Section 5. Through simulation verification and algorithm comparison, the advantages of the method are reflected in Section 6. Finally, got the conclusion in Section 7.

2. Collaborative Detection Model of UAV Swarm

2.1. MIMO Detection Model. UAV swarm is used to collaboratively detect targets, and the spatial distribution is shown in Figure 1.

As shown in Figure 1, it is assumed that at time t, the number of our drones is M. The coordinates and velocities of each UAV are $P_i = [x_i^t, y_i^t]$ and $v_i = [v_{xi}^t, v_{yi}^t]$, respectively, where $i = 1, 2, \cdots, M$. There are U targets in the air, and the corresponding coordinates are $T_u = [x_{Tu}^t, y_{Tu}^t]$, where $u = 1, 2, \cdots, U$.

The advantages of MIMO radar can be seen intuitively from Figure 1. Assuming that among our M UAVs, M_t UAVs transmit detection signals, the echo signal of the target is received by each UAV. This means that every target is detected $M \times M_t$ times. Compared with the single-input single-output radar that only detects a target once, the received signal is increased by M times. From the perspective of information theory, it can be seen that this detection method significantly improves the information obtained from the target, thus improving the detection performance.

2.2. Channel Capacity of MIMO Detection. For ease of explanation and analysis, a set of receiving and transmitting forms is constructed to introduce the channel capacity, as shown in Figure 2.

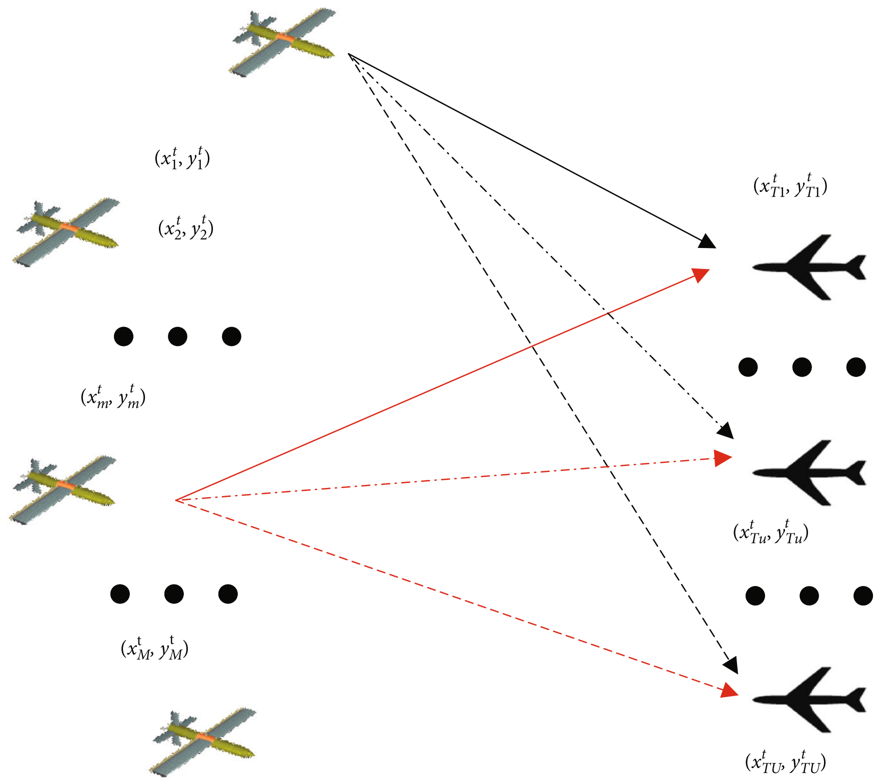
Assuming that at time t, the positions of the transmitter, the detected target and the receiver in the UAV swarm are

$$P_{fm} = \left[x_{fm}^t, y_{fm}^t\right], T_u = \left[x_{Tu}^t, y_{Tu}^t\right], P_l = \left[x_l^t, y_l^t\right].. \quad (1)$$

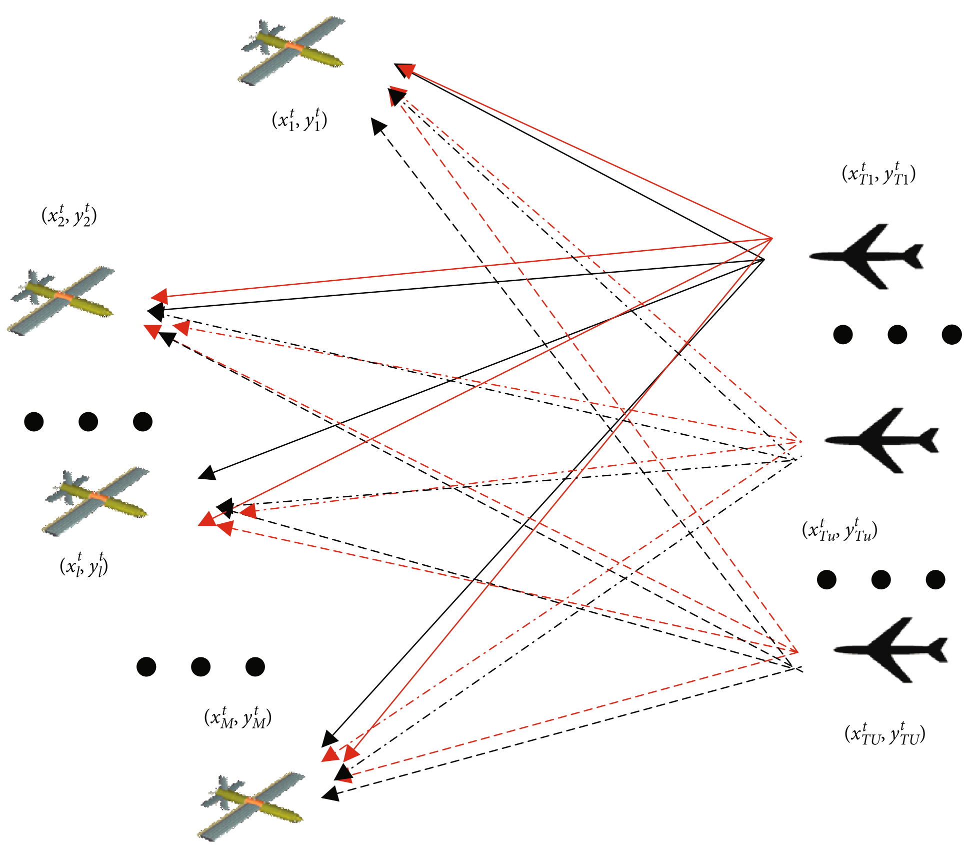
As shown in Figure 2, the distance between the transmitter and the target is D_{mu}, and the distance between the target and the receiver is D_{lu}. D_{mu} and D_{lu} are calculated from the coordinates. Then, the propagation time τ_{ml} of the signal is

$$\tau_{ml} = \frac{1}{c}\left(D_{mu} + D_{lu}\right) \quad (2)$$

where c is the speed of light.



(a) Transmit detection signal



(b) Receive echo signal

Figure 1: Schematic diagram of MIMO detection.

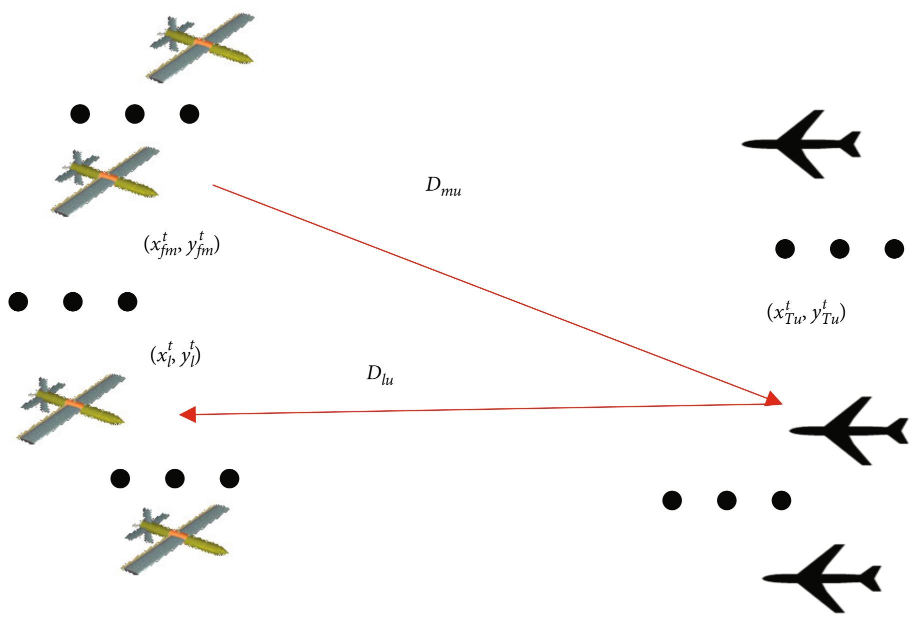


Figure 2: Schematic diagram of single detection.

Assuming that the detection signal transmitted by the transmitter is $s_m(t)$, the echo signal can be expressed as

$$y_{ml} = \sqrt{\frac{P_m \beta}{D_{mu}^2 D_{lu}^2}} \alpha_{ml} s_m(t - \tau_{ml}) + n, \quad (3)$$

where Pm represents the equivalent detection power of the m-th UAV radar, which is the product of the radar power and the antenna gain. β represents the attenuation constant, and $P_m \beta / D_{mu}^2 D_{lu}^2$ represents the received power attenuated by the atmosphere. α_{ml} represents the RCS of the target during the process that the m-th UAV transmits the detection signal and the l-th UAV receives the signal. α_{ml} will be introduced and analyzed in detail later. τ_{ml} represents the time difference between the received signal and the transmitted signal. n represents the received noise. This paper assumes that the noise mainly comes from the thermal noise of the receiver. Therefore, n is regarded as Gaussian white noise obeying a normal distribution.

Assuming that the u-th target is detected, the set of signals transmitted by the transmitter is **PF**, the channel is **H**, and the dimension of the channel is $M \times M_t$. The received signal is denoted **Y**, and the noise is **N**. Then for a detection system with M_t transmitters and M receivers, the relationship between the transmitted signal and the received signal can be expressed as

$$\mathbf{Y} = \mathbf{H} \times \mathbf{PF} + \mathbf{N}. \quad (4)$$

The covariance matrices of the transmitted signal, noise, and received signal are $\mathbf{R_{PF}}$, $\mathbf{R_N}$, and $\mathbf{R_Y}$, respectively, namely,

$$\mathbf{R_{PF}} = E\left[\mathbf{PF} \times \mathbf{PF}^H\right], \quad (5)$$

$$\mathbf{R_N} = \sigma_n^2 \mathbf{I}_M, \quad (6)$$

$$\mathbf{R_Y} = \mathbf{H R_{PF} H}^H + \mathbf{R_N}, \quad (7)$$

where $\mathbf{I}_M$ is the identity matrix. $\mathbf{PF}^{\mathrm{H}}$ represents the Hermite matrix of **PF**.

Then according to the definition of channel capacity, the channel capacity C between the transmitted signal and the received signal can be expressed as

$$C = \log_2\left(\frac{|\mathbf{R_Y}|}{|\mathbf{R_N}|}\right) = \log_2\left(\frac{|\mathbf{R_N} + \mathbf{H R_{PF} H}^H|}{|\mathbf{R_N}|}\right) = \log_2\left(\left|\mathbf{I_M} + \mathbf{H R_{PF0} H}^H\right|\right), \quad (8)$$

where $\mathbf{R_{PF0}}$ represents the normalized matrix, that is,

$$\mathbf{R_{PF0}} = \frac{E\left[\mathbf{R_{PF} R_{PF}^H}\right]}{\sigma_n^2}. \quad (9)$$

In summary, the channel capacity model between the transmitted signal and the received signal is constructed.

2.3. Applicability of Channel Capacity Model. The concept of channel capacity comes from information theory and is an important indicator to measure the information transmission efficiency and channel performance in the communication process. In this paper, the channel capacity is used as the objective function for analyzing and optimizing cooperative detection, mainly for the following three reasons.

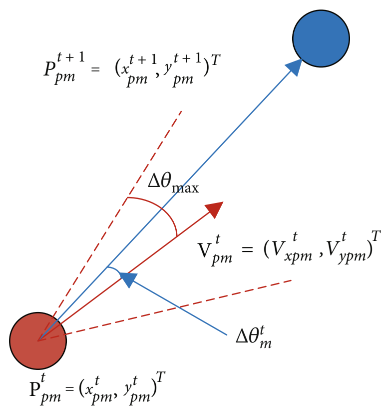


Figure 3: Schematic diagram of motion constraints.

First of all, this paper considers that the problem of target detection is a problem of obtaining information about targets. This view is widely used in radar array signal processing and radar antenna design and has many research results. The detection problem is transformed into a problem of obtaining more accurate information about target, and the method in information theory is used as an index to evaluate the detection ability, and then, the detection resources are optimized. This research model is completely feasible.

Secondly, the channel capacity is essentially the correlation coefficient between the transmitted signal and the received signal. If no echo signal is received, there will only be clutter at the receiver. Then, the correlation coefficient between the echo signal and the transmitted signal is 0; correspondingly, no target is detected. When the correlation is weak, the echo signal is received. However, due to the fading of the signal in the atmosphere and the interference of noise, the features of the echo signal are weakened a lot, and the features of the target that can be extracted from the echoes are much less, resulting in a weakening of the ability to estimate the target state. When the correlation is strong, the echo signal has a little attenuation, which can be used to detect the state of the target well.

Finally, the channel capacity can be understood as the upper limit of the ability to obtain target information, similar to the CRLB for parameter estimation, or the maximum accuracy of our detection. Just like the definition of channel capacity, if the upper limit of capacity is exceeded, it is difficult for the channel to ensure effective and stable information transmission. Similarly, once the channel capacity is determined during the detection process, it means that the total amount of target information we can obtain is determined accordingly. And when the amount of information mastered is certain, there is an upper limit to the degree of understanding it can be. Only when new nonredundant information is obtained, can the detection ability of the target be further improved.

Therefore, this paper regards the channel capacity as the objective function to optimize the detection performance of UAV swarm. In this way, the position and radiation power of the UAV are jointly optimized, thereby improving the detection efficiency.

3. Optimization Model

3.1. Objective Function. On the basis of the previous article, the channel capacity of our UAV swarm to detect U targets is obtained, and the objective function is also

$$Q = \arg\max \sum_{u=1}^{U} \omega_u C_u = \arg\max \sum_{u=1}^{U} \omega_u \log_2\left(\left|\mathbf{I_M} + \mathbf{H}_u \mathbf{R_{PF0}} \mathbf{H}_u^H\right|\right), \tag{10}$$

where ω_u represents the importance of the u-th objective.

There are many ways to determine the importance of targets, such as expert systems and methods of subjectively determining weights. An objective method was used to determine weights by calculation based on information entropy or rough set theory. And the method was used to jointly determine the weights subjectively and objectively. There are many research results in this direction, but it is not the focus of this paper, so it will not be expanded here. If the importance of the objective is not considered, it is only necessary to delete ω_u in the objective function of formula (10).

In summary, the construction of the cooperative detection objective function is completed.

3.2. Constraints

3.2.1. Constraint on Motion. Suppose the motion state of the UAV [32–34] at two adjacent moments is shown in Figure 3.

As shown in Figure 3, the position and speed of m-th UAV at time t are $\mathbf{P}^t_m = [x^t_m, y^t_m]$ and $\mathbf{v}^t_m = [v^t_{xm}, v^t_{ym}]$. By optimizing it, the position and speed at the next moment are obtained as $\mathbf{P}^{t+1}_m = [x^{t+1}_m, y^{t+1}_m]$ and $\mathbf{v}^{t+1}_m = [v^{t+1}_{xm}, v^{t+1}_{ym}]$. The corresponding relationship is shown in the red and blue dots in Figure 3. Assuming that the time difference between the two moments is Δt, it satisfies

$$\begin{cases} \mathbf{P}^{t+1}_m = \mathbf{P}^t_m + \mathbf{v}^t_m \Delta t, \\ \left\|\mathbf{P}^{t+1}_m - \mathbf{P}^t_m\right\|_2 \le \left\|\mathbf{v}^t_m\right\|_2 \Delta t. \end{cases} \tag{11}$$

$\|\|_2$ means to take the 2 norms. The relationship between the two speeds can be expressed as

$$\mathbf{v}^{t+1}_m = \mathbf{v}^t_m + \Delta\mathbf{v}^t_m. \tag{12}$$

Among them, $\Delta\mathbf{v}^t_m$ is the speed change amount, and the speed $\mathbf{v}^{t+1}_m$ at the next moment should satisfy

$$\begin{cases} \left\|\Delta\mathbf{v}^t_m\right\|_2 \le \Delta v_{\max}, \\ v_{\min} \le \left\|\mathbf{v}^{t+1}_m\right\|_2 \le v_{\max}. \end{cases} \tag{13}$$

That is, the adjustment amount of the speed and the speed at the next moment cannot exceed the allowable range.

According to the relationship between the velocity vectors at the two moments, the direction change amount of the UAV can be obtained. That is, the amount of heading angle change $\Delta\theta_m^t$, which should satisfy

$$\left|\Delta\theta_m^t\right| \le \Delta\theta_{\max}, \tag{14}$$

where | | represents the absolute value.

The above are the motion constraints that the UAV should meet and also the parameters that need to be optimized. In this paper, the cooperative detection capability of the UAV swarm is improved by optimizing the UAV track.

3.2.2. Constraint on Radiated Power. According to formula (5), it can be seen that $\mathbf{H}$ is related to the degree of power attenuation $P_{mu}\beta/D_{mu}^2 D_{lu}^2$ and the RCS α_{ml} of the target. The degree of power attenuation is related to the radiated power P_{mu} allocated to detect the u-th target and the distance between the transmitter and the target and the target and the receiver. The distance can be calculated using coordinates.

At the same time, the radiated power should meet

$$\sum_{u=1}^{U} P_{mu} \le P_m. \tag{15}$$

That is, the sum of the radiation power used by a single UAV to detect multiple targets cannot exceed its upper power limit.

3.2.3. Constraint on Channel Capacity. In the process of detecting the u-th target, the channel capacity C_u needs to satisfy

$$C_u \ge C_{\min}. \tag{16}$$

Among them, $C_{\min}$ represents the minimum channel capacity requirement that can realize the target detection.

Because in the process of optimizing the detection resources, a situation is likely to occur. All drones are very close to one or several targets and will continue to approach. The closer the distance is, the greater the channel capacity will be, so that the sum of the channel capacities will be greater. This will lead to the realization of the objective function getting bigger and bigger. But obviously, this is not the optimal solution for multiple target detection. At the same time, it is difficult to get out of this situation. Because if the drone is forced to gradually move away from the target, it will bring about a decline in the objective function. When the drone is far away from the target, as the constraints are reduced, it will return to the state where multiple drones are approaching a target. A situation similar to oscillation is formed, falling into a local optimum.

Therefore, the constraints of formula (16) need to be set. Only in this way can each target be effectively detected, and parameters can be optimized under this premise, thereby improving the overall detection performance.

4. Improved ABC Algorithm

The optimization of UAV swarm detection resources studied in this paper is a typical NP-Hard problem. It is difficult to have an explicit solution for such problems, and the solution forms are not the same due to the different environment and task requirements. Therefore, this section realizes the optimal solution to this problem by improving ABC.

4.1. Artificial Bee Colony Algorithm. The artificial bee colony algorithm is an intelligent optimization method based on the biological characteristics of bees. The core framework of the algorithm can be summarized as

First, the employed bees conduct a wide-area search to obtain the general location of the nectar source, that is, the key area where the optimal solution may exist. The information on the employed bees is then aggregated to the guard bees. The guard bees further screen the nectar sources that may have the optimal solution and search them precisely to further improve the quality of the optimal solution. However, if the guard bees search the key area for a period of time, the quality of the optimal solution does not improve significantly, or after other guard bees search for better optimal solutions. The guard bee will be converted into an employed bee, and the wide-area search will be repeated.

The algorithm flow can be expressed as follows.

Step 1. The first step is population initialization.

Assuming that the number of populations is PN and the spatial dimension to be optimized is R, the first-generation population with dimension $\mathrm{PN} \times R$ can be generated:

$$P_{op}^1 = \begin{bmatrix} x_{1,1}^1 & x_{1,2}^1 & \cdots & x_{1,R}^1 \\ x_{2,1}^1 & x_{2,2}^1 & \cdots & x_{2,R}^1 \\ \vdots & \vdots & \ddots & \vdots \\ x_{PN,1}^1 & x_{PN,2}^1 & \cdots & x_{PN,R}^1 \end{bmatrix} \tag{17}$$

The corresponding solution vector in formula (17), which is also the target solution to be optimized, is $\mathbf{X}_i^1 = [x_{i,1}^1\, x_{i,2}^1 \cdots x_{i,R}^1]$. The parameter $x_{i,j}^1$ corresponding to the j-th attribute of the i-th particle is generated using formula (18), where $i = 1, 2, \cdots, \mathrm{PN}$, $j = 1, 2, \cdots, R$.

$$x_{i,j}^1 = x_{\min,j} + r\left(x_{\max,j} - x_{\min,j}\right), \tag{18}$$

where $x_{\max,j}$ and $x_{\min,j}$ are the maximum and minimum values in the feasible solution space of the j-th attribute. r is a random number that obeys a uniform distribution between (0, 1).

Step 2. The employed bees search globally.

Use formula (19) to generate candidate solutions after the $(n+1)$-th search.

$$v_{i,j}^{n+1} = x_{i,j}^n + \phi\left(x_{i,j}^n - x_{k,j}^n\right), \tag{19}$$

where k is a uniformly distributed positive integer in [1, PN]. ϕ is a random number between (-1, 1) that obeys a uniform distribution. The feasible solution vector generated by formula (19) is $\mathbf{V}_i^{n+1} = \left[\, v_{i,1}^{n+1} \quad v_{i,2}^{n+1} \quad \cdots \quad v_{i,R}^{n+1} \,\right]$.

Then, calculate the fitness functions $\mathbf{V}_i^{n+1}$ and $\mathbf{X}_i^n$ corresponding to $F(\mathbf{V}_i^{n+1})$ and the original feasible solution $F(\mathbf{X}_i^n)$. Compare the two fitness functions, and select the better solution for subsequent iterations.

Step 3. The guard bees determine the nectar source.

Guard bees often use the roulette method in formula (20) to determine the exact nectar source to search.

$$P_i^n(\mathbf{X}_i^n) = \frac{F(\mathbf{X}_i^n)}{\sum_{i=1}^{PN} F(\mathbf{X}_i^n)}, \tag{20}$$

where $P_i^n(\mathbf{X}_i^n)$ represents the probability that the guard bee chooses $\mathbf{X}_i^n$. The purpose of using the roulette method is to ensure that functions with high fitness can be selected with a high probability, which is also more worthy of subsequent accurate searches, and more bees will search for it.

Step 4. The guard bee is converted into employed bee.

If the i-th guard bee performs a certain number of searches, its fitness function does not change significantly. Then, it will be converted into an employed bee and return to Step 1 to search again. This ensures that the bees can jump out of the local optimum. This operation will eliminate some local optimal solutions, making the ABC algorithm more likely to search for the global optimal solution.

The above is the algorithm flow and key operations of the ABC algorithm. Since the ABC algorithm has a clear division of labor for the bees, it can better avoid the contradiction between speed and accuracy in the optimization algorithm. It also provides a new idea for the improvement of intelligent algorithms.

But the ABC algorithm itself also has some shortcomings. Therefore, this paper improves it and applies the improved algorithm to the resource optimization of cooperative detection of UAV swarm.

4.2. Improved Strategy

4.2.1. Improved Search Strategy. When the ABC algorithm performs iterative update search, the search direction of the bee is determined by the positive or negative of ϕ in formula (19). While the positive and negative values of ϕ have strong randomness, which weakens the search efficiency. Therefore, some scholars have improved the previous formula (19) as

$$v_{i,j}^{n+1} = x_{i,j}^n + \sigma_{i,j}^n \left|\phi_{i,j}^n\right| \left|x_{i,j}^n - x_{k,j}^n\right|, \tag{21}$$

where $\sigma_{i,j}$ are just property symbols; that is, the value is -1 or 1. $|\phi|$ represents the step size of the search. Other parameter definitions are the same as formula (19). The improved method has been verified in the relevant literature to have good results. It can ensure that the search direction is directed towards the direction of improving the fitness function.

However, when the bees are trapped in the local optimum, the improved strategy will cause the bees to oscillate. For the convenience of introduction and understanding, this paper uses formula (22) to describe it in detail:

$$y = (2 + x) \sin (2\pi x). \tag{22}$$

The corresponding function curve is shown in Figure 4.

Figure 4 is the form of a typical amplitude modulated signal. Using the above search method, the minimum value of the function is searched in the interval of [0.4]. It can be seen that the global optimal solution is the point corresponding to the red dotted circle. While when the bee searches for the point corresponding to the black circle, it falls into a local optimum. According to the search mode of formula (21), when searching in a certain direction, its fitness function will decrease. At this time, the improved algorithm corresponding to formula (21) will make the bees search in the opposite direction. But it can be seen from Figure 4 that when the bees are trapped in the local optimum, it is difficult to jump out of the local optimum when searching in any direction. That is, at time k, the bee is in the local optimum shown by the black circle. The bees are near the local optimum point at time $k + 1$. It returns to the local optimum point at time $k + 2$. In the end, the bees oscillate near the local optimum.

Therefore, this paper further improves the search strategy on its basis. The search strategy still adopts the model of formula (21). But compare the fitness functions corresponding to the three solutions of $v_{i,j}^{n+1}(+)$, $v_{i,j}^{n+1}(-)$, and $x_{i,j}^n$. Among them, $v_{i,j}^{n+1}(+)$ and $v_{i,j}^{n+1}(-)$ are the corresponding solutions when the value of $\sigma_{i,j}^n$ is ± 1.

When the fitness function of $v_{i,j}^{n+1}(\pm)$ is better, the better one of the two is selected for parameter update. When the performance of $v_{i,j}^{n+1}(\pm)$ is weaker than that of $x_{i,j}^n$, set the step size to 2 times and recalculate to obtain the new candidate solution. Also select better one to update. If the performance is still weaker than $x_{i,j}^n$, let the step size be $3|\phi_{i,j}^n|$ and recalculate the new solution. By repeatedly increasing the multiple of the step size, the conversion conditions in Step 4 of the ABC algorithm are met. If there is still no better solution, let $F(\mathbf{X}_i^n)$ be the local optimum, and keep this value as a candidate for the global optimum.

The above is the improvement of the search strategy.

4.2.2. An Improved Population Generation Method Based on Chaotic Sequence. Both Step 1 and Step 4 of the ABC algorithm involve the generation of bee populations. The purpose of initialization is to hope that the bees can explore a larger area in Step 1 or jump out of the local optimal solution obtained by the search in Step 4. The more uniform the distribution of particles, the more comprehensive the search. In other words, the area that the bees explore is preferably an area that the bees have not searched before. The population generated in this way is more beneficial to improve the search efficiency. But judging from the corresponding formula of population generation in the ABC algorithm, it does not have this kind of performance. Therefore,

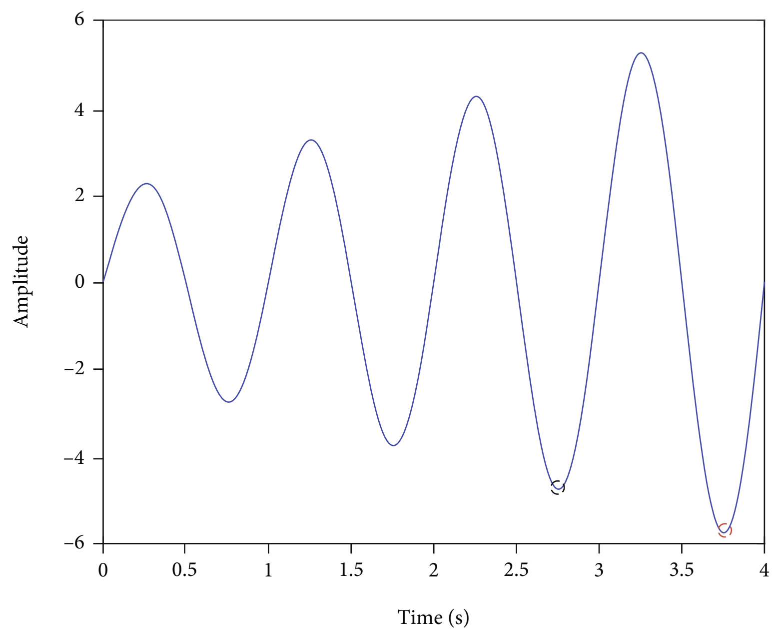


Figure 4: Example function curve.

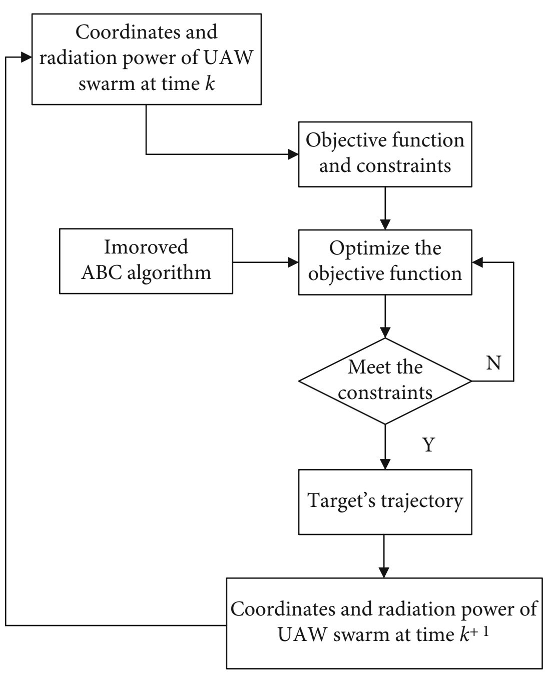


Figure 5: Detection resource optimization process based on the improved ABC algorithm.

this paper reconstructs the population generation strategy in Step 1 and Step 4 based on the chaotic sequence.

Chaotic systems are random and ergodic. Randomness ensures that the population is independent of each other and has a relatively uniform distribution when it is initialized. Ergodicity ensures that as new populations are generated, the corresponding search space is also traversed step by step, thereby ensuring the integrity of the search space exploration.

In formula (18), the random number r only needs to obey a uniform distribution. Therefore, this paper improves it so that it is generated by chaotic sequence and has more randomness and ergodicity.

Typical chaotic sequences include Logistic, Circle, and Tent sequences. When the sequence is long enough, the Tent sequence can traverse all states within the bounded space. Using it to improve the random number r in the ABC algorithm can improve the diversity of the population and the possibility of the space being traversed. At the same time, a new population generated by Tent chaotic sequence is also used in Step 4. Initialize the position of the newly converted bee so that it can jump out of the local optimum. And it can search the space that has not been searched with a higher probability.

The Tent chaotic sequence is generated by recursive iteration, and its process can be described as follows.

Step 1. Take any initial value x_0 in the range of (0, 1), but $x0 \neq 0.2,0.4,0.6,0.8$.

Step 2. Use formula (23) to generate a recursive sequence:

$$x_{i+1} = \begin{cases} 2x_t, & 0 \le x_i \le 0.5, \\ 2(1 - x_t), & 0.5 \le x_i \le 1. \end{cases} \tag{23}$$

Perform Bernoulli shift operation on x_{i+1}:

$$x_{i+1} = (2x_i) \bmod 1, \tag{24}$$

where $(a) \bmod (b)$ means that after dividing a by b, the part of a that is not divisible by b. Then, formula (24) indicates that only the fractional part of x_{i+1} is reserved, which also satisfies the requirement that r should take a value between (0, 1).

Step 3. If x_{i+1} is one of {0, 0.25, 0.5, 0.75}, or $x_{i+1} = x_{i+1-k}$, k is one of {1, 2, 3, 4}. Then, let $x_{i+1} = x_{i+1} + \alpha$, where α is a random number that obeys a uniform distribution between (-1, 1).

Step 4. Determine whether the termination condition is reached. The general termination condition is that the number of recurrences is reached or the required sequence length is generated. If the termination condition is reached, output the generated sequence; otherwise, execute Step 5.

Step 5. Determine whether x_{i+1} meets the conditions of Step 3. If it is satisfied, return to Step 3, and regenerate x_{i+1}; otherwise, return to Step 2, and use the recursive formula to generate the subsequent sequence.

Through the above operations, the improvement of Step 1 and Step 4 in the ABC algorithm is completed, that is, using the Tent sequence to generate the initial population and optimize the position of the converted bees. Thus, the possibility of bees traversing the search space is improved, and the possibility of falling into a local optimum is also reduced.

5. Joint Optimization Process of Cooperative Detection Resources Based on Improved ABC Algorithm

In order to improve the detection ability of the UAV swarm to the target, combined with the objective function, constraints, and the corresponding optimization algorithm constructed, the construction of the detection resource optimization process is shown in Figure 5.

The flow in Figure 5 can be described as follows.

Step 1. Obtain the position and radiation power of each UAV in swarm at time k. At the same time, combined with the characteristics of the objective parameters, the objective function to be optimized is constructed.

Step 2. Combine the UAV performance parameters to construct constraints.

Step 3. Use the improved ABC algorithm to jointly optimize the detection resources. The optimized spatial position and radiated power are obtained.

Step 4. Determine whether the optimization result satisfies the constraints in Step 2. If not, return to Step 3 to reoptimize; otherwise, execute Step 5.

Step 5. Update the position and radiated power of the UAV at the next moment with the optimization results. Return to Step 1, and reoptimize until the final optimization moment K is reached.

The above is the optimization process of UAV swarm detection resources.

6. Simulation Verification and Algorithm Comparison

6.1. Comparison of Detection Method. In order to verify and compare the performance of the algorithm constructed in this paper, the algorithm in this paper is compared with the trajectory optimization algorithm based on the Bayesian Fisher optimization algorithm, the posterior Fisher information is optimal, and the fixed configuration only optimizes the radiation power.

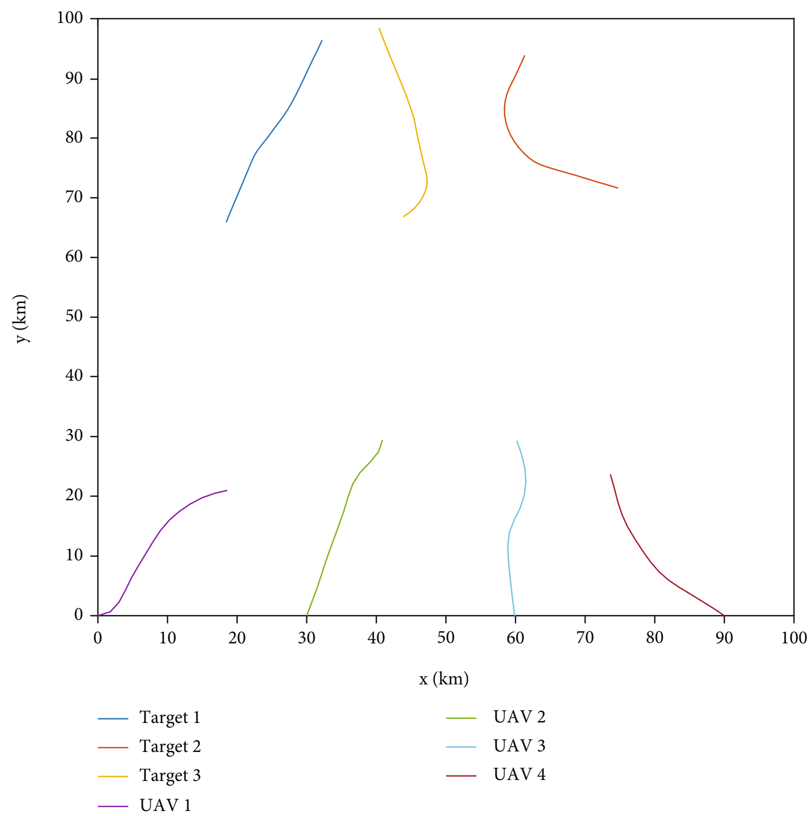
Suppose four UAVs detect the target. The target is three aircrafts, and the movement mode adopts the method of constant velocity, constant acceleration, and constant turn rate alternately. The above four methods are used for optimization, and the trajectory comparison is obtained as shown in Figure 6.

It can be seen qualitatively from Figure 6 that all four detection methods can ensure that the UAV swarm is flying towards the target group. With the shortening of the distance, the positioning accuracy of the target is gradually improved. Comparing the three figures in Figures 6(a)–6(c), it can be seen that UAV swarm in Figure 6(a) is obviously more flexible than the other two methods in terms of position transformation. This is because the detection performance is effectively quantified by using the channel capacity. Therefore, there will be a movement state where UAVs often adjust their positions and the trajectory changes significantly. The method in this paper is more beneficial to improve the detection effect of the target.

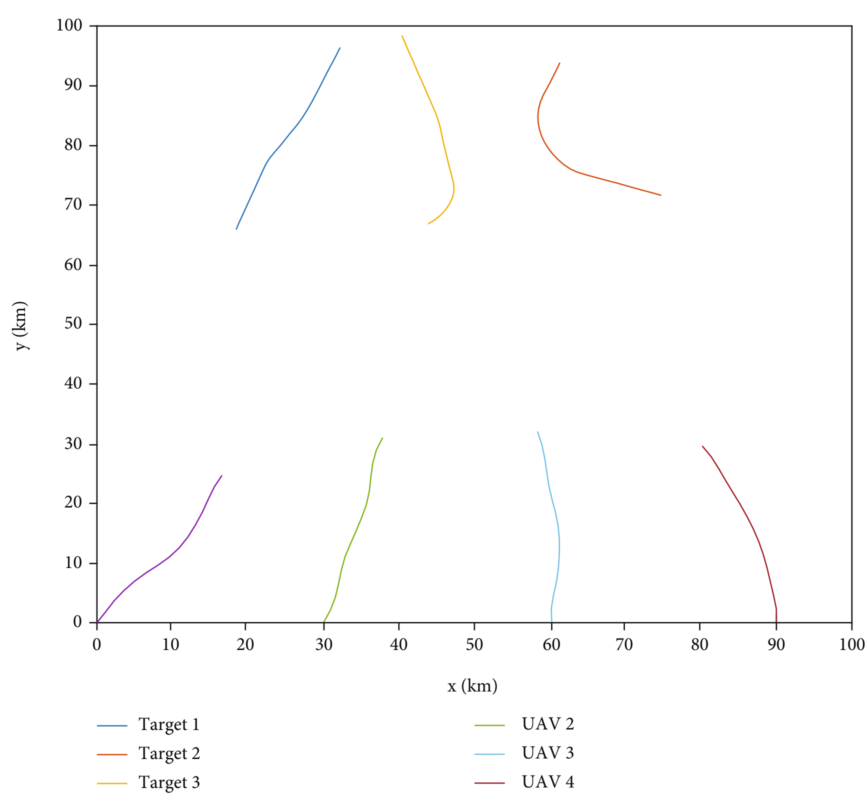
In order to further quantify and compare the performance of the four methods, this paper conducts 50 Monte Carlo simulation experiments for the above four methods, respectively. The average of the results of each step is taken to obtain the mean square error (MSE) comparison curve of positioning, as shown in Figure 7.

From the average MSE in Figure 7, it can be seen that the algorithm in this paper outperforms other algorithms. This is because the performance of both Bayesian Fisher and posterior Fisher methods relies heavily on the estimation of the probability distribution of target locations. The more accurate the estimation of the probability distribution of the target position, the better the detection effect. While when the target state changes in a short time, the performance of such methods is limited. This also reflects the better performance of the algorithm in this paper for the detection of maneuvering targets in the air.

At the same time, it can be seen from Figure 7 that the performance of the algorithm that only optimizes power is not significantly different from those of other algorithms. As can be seen from Figure 6(d), the UAVs flew towards the target group in a fixed configuration. This will continue to shorten the distance between the UAV swarm and the target, helping to improve detection accuracy. Secondly, power optimization will further ensure the detection performance. Finally, it is due to the number effect of the UAV swarm and the split mode of transmitter and receiver in the MIMO system. These will result in a nonlinear increase in detection performance as the number of UAVs increases. This is also an emergent feature of swarm, and this advantage applies to all swarm detection methods.

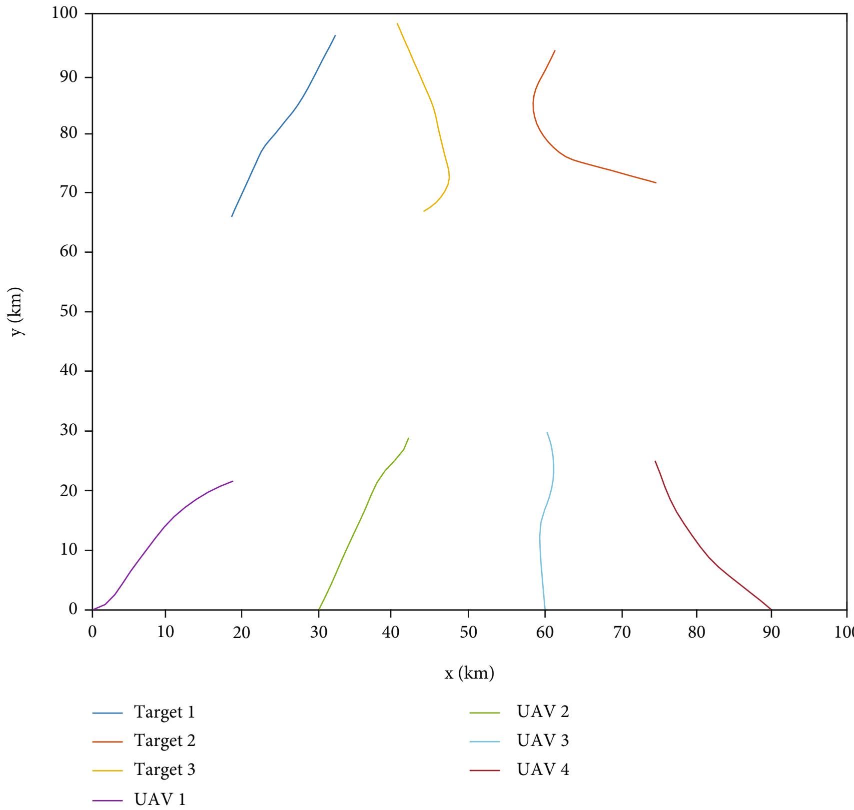


(a) The optimization results of the algorithm in this paper

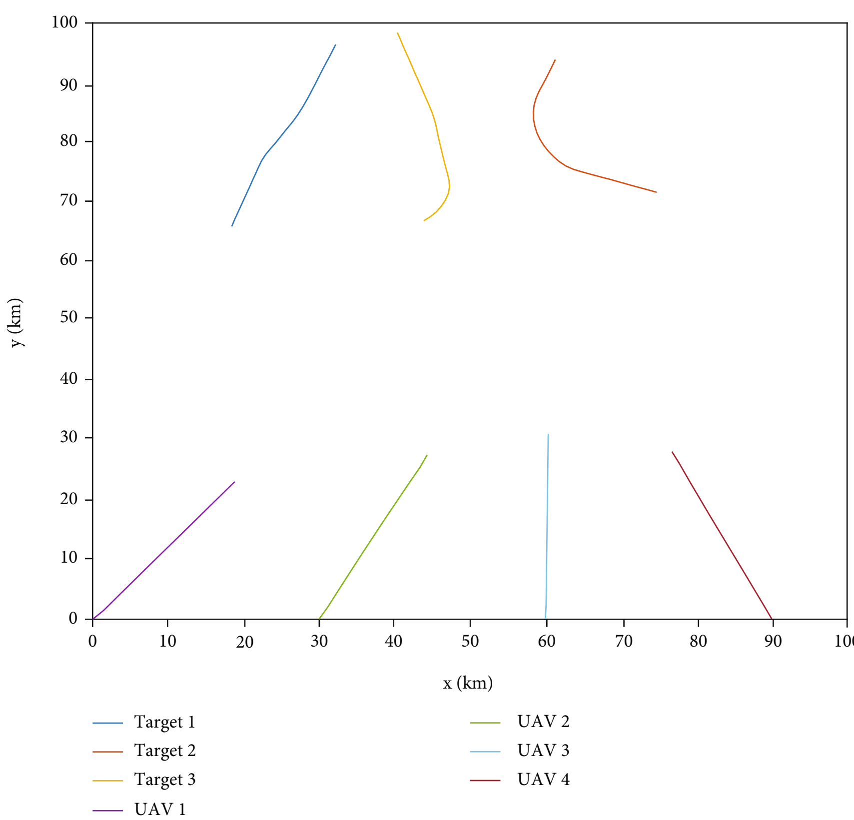


(b) The optimization results of Bayesian Fisher algorithm

FIGURE 6: Continued.



(c) The optimization results of posterior Fisher Information algorithm



(d) The optimization results of fixed configuration

Figure 6: Comparison of the results of different optimization algorithms.

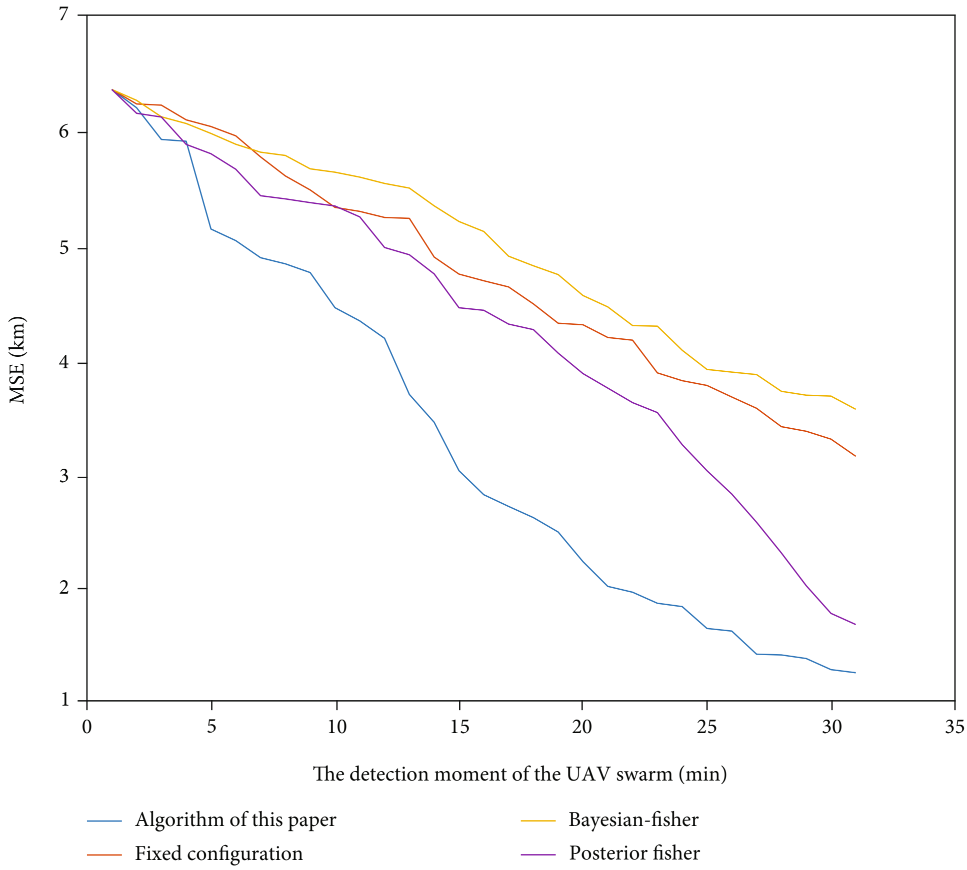


Figure 7: MSE comparison of different detection algorithms.

6.2. Comparison of Optimization. In order to further measure the performance of the improved ABC algorithm in this paper, the advantages of this algorithm are highlighted. The improved ABC algorithm in this paper, the ABC algorithm with improved search direction, and the improved Particle Swarm Optimization (IPSO) algorithm are used for comparison.

In the optimization process, only the optimization algorithm used in the process in Figure 5 is changed, and other processes are exactly the same. The above three algorithms are used to optimize the trajectory and radiation power of the UAV, and the results are shown in Figure 8.

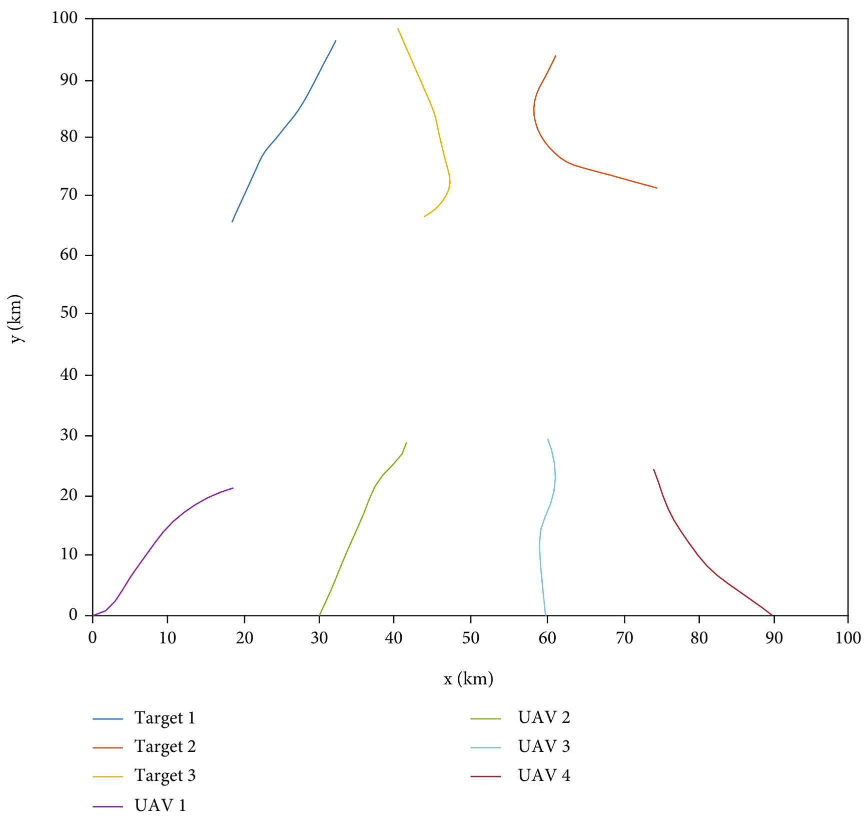
It can be seen from Figure 8 that the ABC algorithm and the IPSO algorithm can also achieve good optimization of the trajectory and radiated power. But compared with Figure 6(a), there is a difference in performance.

Comparing Figures 8(a) and 6(a), it can be seen that the trajectory of the UAV in Figure 8(a) is more tortuous. Compared with the improved algorithm, the ABC algorithm does not fully explore in the search space, resulting in a local optimum. This is shown in Figure 8(a) as oscillations around the local optimum, that is, where there are obvious bends in the UAV3's trajectory. Because the particles are trapped in a local optimum, this causes the drone to both want to approach the target and to return to the optimum point. Thus, there is an obvious bending process. Obviously, this process is not only difficult to obtain good detection results. At the same time, due to this obvious change of motion state, the stability of the UAV will also be reduced.

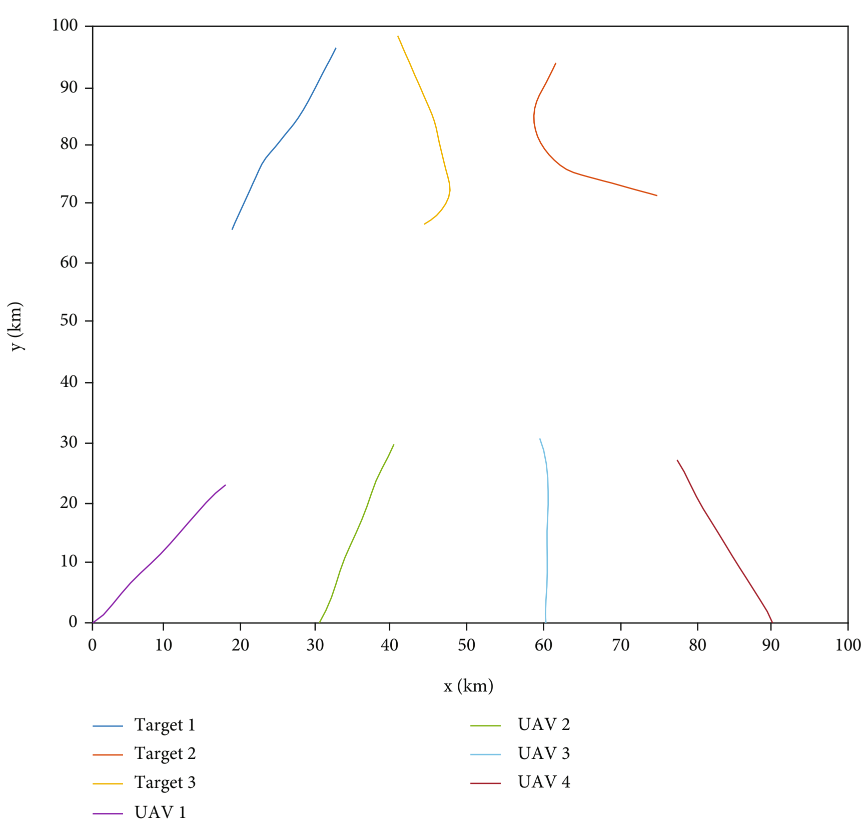
Comparing Figures 8(b) and 6(a), it can be seen that the trajectory of IPSO is more direct. This is due to the fact that the PSO algorithm and its improved algorithm retain the characteristics of the high-speed optimization of the PSO algorithm itself. However, when the optimization problem is more complicated, it is difficult for the particles to obtain the global optimal solution. This is also the contradiction between the optimization speed and the precision that the intelligent algorithm is always difficult to overcome. And obviously, the IPSO algorithm focuses on the speed of the algorithm. This leads to the performance of the IPSO algorithm being worse than that of the algorithm in this paper.

To further compare the performance of the three optimization algorithms, using the above three optimization algorithms, 30 Monte Carlo simulation experiments were carried out, respectively. The optimization results are averaged for comparison, as shown in Figure 9.

As can be seen from Figure 9, the performance of the improved ABC algorithm has been significantly improved. This is because the improvement of the ABC algorithm in this paper will significantly reduce the possibility of falling into a local optimum. The performance will not be inferior to the ABC algorithm with improved search direction. And due to the improved population generation method, with the increase of the number of optimization iterations, the probability of the improved algorithm to search and obtain the global optimum is higher than that of the ABC algorithm with improved search direction.



(a) The optimization results of ABC



(b) The optimization results of IPSO

Figure 8: Comparison of the results of different algorithms.

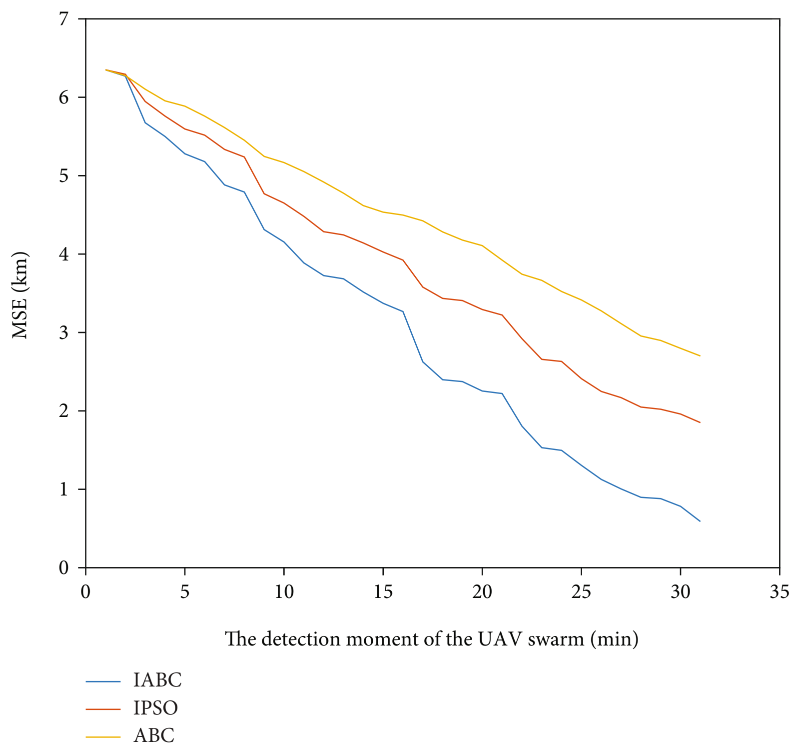


Figure 9: MSE comparison of different optimization algorithms.

At the same time, it can be seen that the performance of the improved ABC algorithm is better than that of the improved PSO. This is also because for more complex problems, the ABC algorithm can compromise the speed of the algorithm performance and the quality of the search. Compared with the PSO algorithm that focuses on the optimization speed, with the improvement of the dimension and difficulty of the optimization problem, the advantages of the algorithm in this paper will gradually become prominent.

7. Conclusion

(1) In order to improve the situational awareness of the UAV swarm, this question is converted into a problem of improving the channel capacity between the transmitter and the receiver. The cooperative detection model is constructed, and the optimization solution process is given to realize the optimization of detection resources

(2) This paper deduces the quantitative representation equation of channel capacity. And use it as the objective function to optimize the cooperative detection resources. At the same time, constraints are constructed with the characteristics of the UAV. The problem of improving the detection ability is converted into a typical optimization problem, and the optimization solution process is given

(3) In view of the shortcomings of the ABC algorithm, the search direction of the individual is improved, and the chaotic sequence is used to construct a population generation method, thereby improving the efficiency of the ABC algorithm

(4) This paper constructs a resource optimization method for UAV swarm cooperative detection based on the improved ABC algorithm. And through simulation verification and algorithm comparison, the performance and advantages of the algorithm are highlighted. This research has a positive effect on improving the combat effectiveness of UAV swarm and the ability to perceive the battlefield

(5) In the actual combat process, the situation of the enemy and the enemy changes drastically in a short period of time. The time for us and the enemy to make decisions and optimize is extremely short. Therefore, it is planned to improve and optimize the architecture in the future to realize real-time decision-making

Data Availability

The data used to support the findings of this study are included within the supplementary information file(s).

Conflicts of Interest

The authors declare no conflict of interest.

Supplementary Materials

Supplementary 1. The trajectories of the three targets in Figure 6 are in "Figure 6 target's trajectory.txt."

Supplementary 2. The data of the trajectory of the UAV obtained by the algorithm in this paper in Figure 6(a) are in "Figure 6(a) the optimization results of the algorithm in this paper.txt."

Supplementary 3. The data of the trajectory of the UAVs obtained by Bayesian Fisher algorithm in Figure 6(b) are in "Figure 6(b) the optimization results of Bayesian Fisher algorithm.txt."

Supplementary 4. The data of the trajectory of the UAVs obtained by posterior Fisher Information algorithm in Figure 6(c) is in "Figure 6(c) the optimization results of posterior Fisher Information algorithm.txt".

Supplementary 5. The data of the trajectory of the UAVs obtained by fixed configuration in Figure 6(d) are in "Figure 6(d) the optimization results of fixed configuration.txt."

Supplementary 6. The data of the MSE comparison of different detection algorithms in Figure 7 are in "Figure 7 MSE comparison of different detection algorithms.txt."

Supplementary 7. The data of the MSE comparison of different optimization algorithms in Figure 8 are in "Figure 8 MSE comparison of different optimization algorithms.txt."

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