Cooperative search approach for UAVs via Pigeon-inspired Optimization and Markov moving targets

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***Abstract*—To solve the problem of repeated search, static targets and low efficiency in cooperative search for multi-UAVs, a method based on pigeon-inspired optimization (PIO) and Markov is proposed. Firstly, a honeycomb environmental model similar to the sensor detect region is established to reduce repeated search for the area. Secondly, Markov chain with the Gaussian distribution is used to represent dynamic movement of targets. Thirdly, the Cauchy mutation and Gaussian mutation are introduced into the map and compass operator and the landmark operator of PIO, respectively. Meanwhile, simulated annealing (SA) mechanism is exploited to reserve the worse individual, so as to effectively reduce the problem that PIO is easy to fall into local optimum. Finally, the algorithm is compared with other swarm intelligence algorithms through simulation experiments. The results show that the new method is effective and available.**

Keywords—multi-UAVs cooperative search, honeycomb model, Markov chain, Cauchy mutation, Gaussian mutation, pigeon-inspired optimization

I. INTRODUCTION

The intelligent unmanned development in the military field is an important part of accelerating the development of military intelligence and also a key area for military intelligence to move from person to object. Unmanned Aerial Vehicle(UAV) has the features of being strong continuous working capacity and low life-cycle cost, and have unique advantages in terms of size, speed and maneuverability[1], and become the power of the times that affect the future information war. Since single UAV can carry a relatively small mission payload and has limited ability to perform tasks, the capability of the multi-UAVs can be complemented and coordinated by actions, thereby improving the overall system performance. Therefore, the application style of UAVs has gradually evolved from a single platform to a multi-platform of swarm intelligence.

Multi-UAVs cooperative search means that multiple UAVs minimize the uncertainty of the environment in an unknown area according to certain search rules and discover the target as much as possible. H. Peng et al.[2] simulated and analyzed several typical cooperative target search strategies. Such as, Random Search(RS), Greedy Search(GS), Rolling Horizon Control (RHC) search, etc. Due to the decentralization, interaction and distribution, and overall self-organization of swarm intelligence individual behaviors, there has conjunctions with the requirements of localization, distribution and robustness of UAV cooperative search. As a result, multi-UAVs cooperative search for swarm intelligence has become a hot topic. Reference [3] set up an environment model based on search information map, and used local Particle Swarm Optimization (PSO) to construct UAV subgroups in real time to realize distributed search for multiple static targets. F. Yang et al.[4] proposed a multi-UAVs cooperative search method based on improved Ant Colony Optimization(ACO) algorithm in uncertain environment, it used the behavior rules of the improved ACO to determine the transfer of waypoints and updated based on pheromone map. However, the ACO algorithm, the PSO algorithm and the Artificial Bee Colony(ABC) algorithm have the problem of low search efficiency and slow convergence. H. B. Duan et al.[5] proposed the Pigeon-inspired Optimization (PIO) algorithm to effectively overcome the above problems, and has achieved research results in many aspects[6]. C. Li et al.[7] proposed an edge potential function and improved PIO method to accomplish the image target detection task. But the above algorithms have limitations in two aspects:(i) Completing the cooperative search for static targets; (ii) The swarm intelligence algorithms are easy to fall into local optimum. In this study, the hybrid model of moving target model and mutation simulated annealing pigeon-inspired optimization (MSAPIO) algorithm is proposed to accomplish the Multi-UAVs cooperative search.

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II. SYSTEM MODELING

Multi-UAVs cooperative search is a complex dynamic process. The influencing factors of its performance are search environment, UAV's own characteristics, target motion and so on.

A. Environment Information Map

Environment information map is the response of UAVs to environmental uncertainty during the search process. Reference [3,8] used a rectangular grid to discretize the search area, but the sensor's detection of the surrounding environment is closer to the circular domain, so this paper uses hexagons to construct a honeycomb search environment, which can reduce the search of duplicate regions, thereby improving search efficiency. The search area L is discretized into $L_x \times L_y$ grids, and each UAV is considered as a particle in the grid, so that the multi-UAVs collaborative search problem can be converted into the coordination of the grid positions between the UAVs. The construction of the environmental information model is shown in Fig. 1.

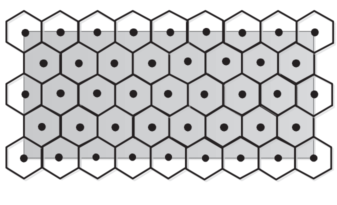


Fig. 1. Environmental information model

In Fig. 1, the gray shaded portion is the search area. Assume that the area is represented by two-dimensional coordinates (x, y), the detection radius of the sensor is r, the increase Δx of the abscissa x is r, and the increase Δy of the ordinate y is $3r/2$.

In time t, suppose that the probability of target existence of grid (x, y) is $p(x, y, t)$, $p(x, y, t) \in [0,1]$; $ud(x, y, t)$ is the uncertainty of the environmental information. It can be described by the entropy of the target existence probability $p(x, y, t)$. $ud(x, y, t)$ is defined as

$$ud(x,y,t)=\begin{cases}0 & p(x,y,t)=0\ or\ 1\\ H[p(x,y,t)] & otherwise\end{cases} \tag{1}$$

$$\begin{aligned}H[p(x,y,t)]=&-p(x,y,t)\log_2 p(x,y,t)-\\&(1-p(x,y,t))\log_2(1-p(x,y,t))\end{aligned} \tag{2}$$

B. UAV Movement Model

Assuming that all UAVs are at the same flight altitude, the status information $x_i(t)$ of UAV$_i$ at time t is

$$x_i(t)=[pos_i(t)\,or\,O_i(t)] \tag{3}$$

Where $pos_i(t)=(x_i(t),y_i(t))\in\{1,2,\cdots,L_x\}\times\{1,2,\cdots,L_y\}$ is the spatial position of UAV$_i$, direction $O_i(t) \in \{0,1,2,3,4,5,6,7\}$ as shown in Fig.2, 8 numbers represent 8 directions. UAV can only reach the adjacent three positions during the flight due to the limitation of the minimum turning diameter, namely straight, left and right. Which is

$$O_i(t+1)\in\{O_i(t)-1,O_i(t),O_i(t)+1\}\bmod 8 \tag{4}$$

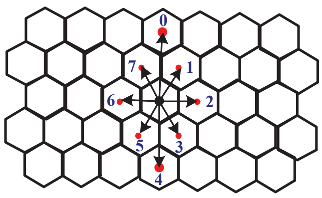


Fig. 2. UAVs motion model diagram

C. Target Information Map

The target information map reflects the probability of the existence of a specific grid target, and its priori information is provided by the intelligence and monitoring platform. As the search progresses, the target information map is constantly updated. Suppose that the target existence probability of the grid (x, y) at time t is $p(x, y, t)$, and the update method is

$$p(x,y,t+1)=\begin{cases}\dfrac{p_d p(x,y,t)}{p_f+(p_d-p_f)p(x,y,t)} & ,\delta(t)=1\\[2ex] \dfrac{(1-p_d)p(x,y,t)}{1+p_d p(x,y,t)-p_f(1-p(x,y,t))} & ,\delta(t)=0\end{cases} \tag{5}$$

Where $\delta(t) = 1$ means that the target in the grid (x, y) was found, and $\delta(t) = 0$ means that it was not found. Besides, p_d and p_f represent the detection probability and the false alarm probability, respectively.

D. Digital Pheromone Map

The digital pheromone graph [9] is an extended potential field method with implicit coordination mechanism. This paper defines two basic pheromones of attractive pheromone and repulsive pheromone to realize the dynamic cooperative behavior of UAVs.

Firstly, define the parameters for the corresponding grid pheromone concentration

1) $r_A(x, y, t)$ and $r_R(x, y, t)$ are constants. Denoting the number of attractive pheromone and repulsive pheromone released by the grid (x, y) at time t.

2) $t_A(x, y, t)$ and $t_R(x, y, t)$ represent the number of attractive pheromone and repulsive pheromone transmitted by the grid (x, y) at time t.

3) e_A and e_R represent the evaporation coefficients of attractive pheromone and repulsive pheromone.

4) p_A and p_R represent the propagation coefficients of the attractive pheromone and repulsive pheromone.

Suppose that the attractive pheromone s_A of the grid (x, y) at time t is defined as

$$\begin{aligned}s_A(x,y,t)=&(1-e_A)[(1-p_A)(s_A(x,y,t-1)+\\&\lambda^{\frac{1}{f(x,y)}}r_A(x,y,t)+t_A(x,y,t))]\end{aligned} \tag{6}$$

Where $\lambda\in(0,1)$ is regulatory factor. $f(x, y)$ is the number of time periods from the last time the grid (x, y) was accessed to the current time, defined as

$$\begin{aligned}f(x,y)&=\frac{t(x,y)}{T_c}\\ t_A(x,y,t)&=\sum_{(x',y')\in Nei(x,y)}\frac{p_A}{N(x',y')}(s_A(x',y',t-1)+r_A(x',y',t))\end{aligned} \tag{7}$$

Where $t(x, y)$ is the last time the grid (x, y) is accessed to the current time, T_c is the pheromone update period, and $Nei(x, y)$ is the adjacent grids of grid (x, y), and $N(x', y')$ is a normalized form of $Nei(x, y)$.

Similar to the attractive pheromone, the repulsive pheromone of the grid (x, y) at time t is defined as

$$\begin{aligned}s_R(x,y,t)=&(1-e_R)[(1-p_R)(s_R(x,y,t-1)+\\&\lambda^{f(x,y)}r_R(x,y,t)+t_R(x,y,t))]\end{aligned} \tag{8}$$

The update method of $t_R(x, y, t)$ is

$$t_R(x,y,t)=\sum_{(x',y')\in Nei(x,y)}\frac{p_R}{N(x',y')}(s_R(x',y',t-1)+r_R(x',y',t)) \tag{9}$$

Therefore, the pheromone concentration of the grid (x, y) at time t is defined as the difference between the attractive pheromone and repulsive pheromone.

$$s(x,y,t)=s_A(x,y,t)-s_R(x,y,t) \tag{10}$$

III. TARGET MOTION MODEL AND FITNESS FUNCTION

A. Target Motion Prediction

Markov chain is a special Markov process with discrete time and state. It has no posterior features. The relevant definitions are as follows.

Definition 1: Markov chain. Assume that the discrete random sequence of the state space $\{S(i), i = 0,1,2,...,n\}$ is I, for m non-negative integers $n_1,n_2,\ldots,n_m(0 \le n_1 < n_2 <\cdots< n_m)$ and for all $t > 0,i_1, i_2,\ldots, i_m, i_{m+t} \in I$, there is

$$\begin{aligned} P\{S(n_{m+t}) = i_{m+t} \mid S(n_1) = i_1, S(n_2) = i_2, \cdots, \\ S(n_m) = i_m\} = P\{S(n_{m+t}) = i_{m+t} \mid S(n_m) = i_m\} \end{aligned} \tag{11}$$

Where $\{S(i), i = 0,1,2,\cdots,n\}$ is a Markov chain whose one-step transition probability is $P\{S(n+1)= j \mid S(n)= i\}$, can be abbreviated as p_{ij}.

In multi-UAVs collaborative search process, since the future motion state of the target is only related to the current state, and is independent of the past motion state, the motion state of the UAV can constitute a typical Markov chain. When time is discrete, whether the next moment of the target moves to a neighboring grid or stay in the current grid is determined by the transition matrix of motion state.

The state transition probability of the target motion depends on the characteristics of the target motion. According to experience, the target usually moves to a grid with a higher environmental uncertainty for UAVs, and the one-step state transition probability is defined as

$$p_{ii} = \frac{ud(x_i, y_i)}{\sum_{j\in L} ud(x_j, y_j) + ud(x_i, y_i)} \tag{12–1}$$

$$p_{ij} = \begin{cases} \dfrac{ud(x_j, y_j)}{ud(x_j, y_j) + ud(x_i, y_i)}, & j \in L \\ 0, & j \notin L \end{cases} \tag{12–2}$$

Where L is the target motion area, $ud(x_i,x_i)$ and $ud(x_j,xj)$ are the uncertainty of the grids (x_i,x_i) and (x_j,x_j) respectively, p_{ii} is the probability of staying still, p_{ij} is the probability of moving to an adjacent grid.

In addition, the accuracy of the target motion prediction depends largely on the estimation of the initial position of the target. From a statistical point of view, the target motion is usually assumed to follow a certain distribution, such as normal distribution or Beta distribution[10]. Since the Beta distribution has the cost of the prediction step, this paper uses a two-dimensional normal distribution to represent the initial position of the target, if the initial center position of the target is (x_0,y_0), $(x, y)$is the adjacent position, the variance is σ_0^2, then the joint probability density function for the position of the target is

$$f(x, y) = \frac{1}{2\pi\sigma_0^2} e^{-\frac{(x-x_0)^2+(y-y_0)^2}{2\sigma_0^2}} \tag{13}$$

Consequently, the distribution of the position of target at the initial time can be defined as

$$p_0(x, y, 0) = \int_{x-x_0-\frac{1}{2}}^{x-x_0+\frac{1}{2}} \int_{y-y_0-\frac{1}{2}}^{y-y_0+\frac{1}{2}} f(x, y)dxdy \tag{14}$$

B. Fitness Function Design

Multi-UAVs cooperative search mainly considers three factors: minimizing environmental uncertainty, finding as many targets as possible, and improving search efficiency as much as possible. So, the fitness function should include three items: environmental uncertainty profit, target discovery profit and cooperation profit.

(1) Environmental uncertainty profit

$$f_e(x, y, t+1) = ud(x, y, t+1) - ud(x, y, t)$$

(2) Target found profit

According to (5) and (14), the position distribution of the target at time t is obtained, where the target found profit is defined as the distribution probability of the target position

$$f_t(x, y, t+1) = p(x, y, t+1)$$

(3) Cooperation profit

$$f_c(x, y, t+1) = s(x, y, t+1)$$

Using linear weighted sum, the above three profits are integrated to form a fitness function

$$fitness(t) = \omega_1 f_e(x, y, t) + \omega_2 f_t(x, y, t) + \omega_3 f_c(x, y, t) \tag{15}$$

In the formula, ω_1, ω_2, and ω_3 reflect the importance of environmental uncertainty profit, target found profit, and cooperation profit separately, and $\omega_1+\omega_2+\omega_3=1$.

IV. PIGEON-INSPIRED OPTIMIZATION ALGORITHM AND IMPROVED MODEL

A. PIO

The PIO algorithm is a new bio-inspired swarm intelligence optimizer inspired by homing behaviors of pigeons. Aiming at pigeons to use different navigation tools at different stages of finding targets, two different operators are used: map and compass operator, landmark operator.

Initialize the pigeon's position X_i and speed V_i in the multidimensional search space

$$X_i = [x_{i1}, x_{i2}, \cdots, x_{iD}] \qquad V_i = [v_{i1}, v_{i2}, \cdots, v_{iD}]$$

Where i is the i-th pigeon, $i \in \{1,2, \ldots,N\}$, N is the total number of pigeons, D is the problem solving dimension. Each pigeon updates its position and speed according to (16)

$$\begin{aligned} V_i(t) &= V_i(t-1)e^{-R\times t} + rand(X_{gbest} - X_i(t-1)) \\ X_i(t) &= X_i(t-1) + V_i(t) \end{aligned} \tag{16}$$

R is the map and compass factor, which can reduce the speed of the pigeons as the iteration proceeds, the random number $rand \in [0,1]$, t is the current number of iterations,

X_{gbest} is the global optimal position obtained by t-1 iterations. Suppose the maximum number of iterations of the map and compass operator is $Nc1$. When $t > Nc1$, stop the map and compass operator and enter the landmark operator.

Landmark operator. The number of pigeons per iteration is halved, and the center position of the remaining pigeons is X_c, which is used as a landmark, the reference direction of flight. Center position X_c and the position of remaining pigeons is updated as shown in (17)

$$X_c(t-1) = \frac{\sum_{i=1}^{N_p} X_i(t-1) \cdot fitness(X_i(t-1))}{N_p \sum fitness(X_i(t-1))}$$
$$X_i(t) = X_i(t-1) + rand \cdot (X_c(t-1) - X_i(t-1)) \tag{17}$$

Where N_p is the number of pigeons halved by t-1 iterations, fitness(•) is the fitness function of each pigeon, and its definition is different for different solving problems. As shown in (18)

$$fitness(X_i(t-1)) = \begin{cases} \dfrac{1}{fitness(X_i(t-1)) + \varepsilon}, & for \min optimization \\ fitness(X_i(t-1)), & for \max optimization \end{cases} \tag{18}$$

Suppose the maximum number of iterations of the landmark operator is $Nc2$, and when $t > Nc2$, the landmark operator is stopped. Recording the optimal position for each iteration and representing it with X_p

$$X_p = \max(X_g(1), X_g(2), \cdots, X_g(t))$$

B. Improved PIO Model

The standard PIO algorithm has the advantages of fast convergence and high search efficiency, but only considers the global optimality of all pigeons in the search process, so it is easy to fall into local optimum.

In order to the utmost extent avoid the algorithm falling into local optimum, this paper introduces the Cauchy factor, Gauss factor and Simulated Annealing (SA)[11] mechanism into the standard PIO model to improve the performance of the algorithm. In evolutionary computational theory, Gaussian mutation and Cauchy mutation are two popular mutation techniques. Cauchy mutation has the advantage of jumping out of local optimum, while Gaussian mutation performs better in local convergence[12]. Therefore, the Cauchy mutation can be introduced into the map and compass operator of the standard PIO algorithm, and the Gaussian mutation introduces the landmark operator, which can avoid the premature convergence and fall into the local optimal problem, and can ensure that the landmark operator finds the global optimal solution.

Convenient for describing the mutation mechanism, when searching for the maximum of the goal function, the position of each dimension $\overline{x}_i$ is regarded as 1, that is $\overline{x}_i = x_i$, then the position after the mutation is $\overline{x}_i' = x_i' = x_i + \Delta r \cdot X$, Δr is the mutation step size and X is a random variable. If Gaussian mutation is used, the X is a random variable that satisfies the Gaussian mutation $X = N(\mu, \sigma^2)$, and its probability density function is shown in (19)

$$f_N(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, x \in (-\infty, +\infty) \tag{19}$$

If Cauchy mutation is used, the X is a random variable that satisfies the Cauchy mutation X=C, and its probability density function is shown in (20)

$$f_C(x) = \frac{1}{\pi}\left(\frac{a}{a^2 + x^2}\right), x \in (-\infty, +\infty) \tag{20}$$

As a result, after the introduction of Cauchy mutation into the map and compass operator, the position and velocity update of the new generation of pigeons is shown in (21)[13]. The timing of mutation is the absolute value of the globally optimal fitness function in the most recent K_1 iteration is less than the threshold e_1, then the Cauchy mutation operation is performed on the global optimal position.

$$V_i(t) = V_i(t-1)e^{-R\times t} + \{X_{gbest} + a \times \tan[\pi(rand - \frac{1}{2})] - X_i(t-1)\} \tag{21}$$
$$X_i(t) = X_i(t-1) + V_i(t)$$

Since the landmark operator is a fine search for the target, the step size at the initial mutation can be slightly larger, but the step size of the mutation should be gradually reduced as the iteration proceeds. The log sig(•) function happens to have nonlinear drop feature from 1 to 0. Consequently, this paper introduces the log sig(•) function to represent the mutation step size, and its position update is shown in (22). The timing of mutation is the absolute value of the change of each dimension of center position X_c in the recent K_2 iteration is less than the threshold e_2, then the Gaussian mutation operation is performed on center position X_c.

$$X_c'(t-1) = X_c(t-1) + \log sig\left(\frac{Nc_2/2 - t}{k}\right) N(\mu, \sigma) \tag{22}$$
$$X_i(t) = X_i(t-1) + rand \cdot (X_c'(t-1) - X_i(t-1))$$

In addition, the standard PIO algorithm always finds the global optimal solution in the search process, and it is easy to fall into the local optimum. Therefore, the worse individual should be reserved with a certain probability. The Simulated Annealing(SA) algorithm proposed in the 1980s can solve this problem. It is assumed that the worse individual is reserved by the probability P_r, and The difference between the fitness of the individual X_{ig} after adding Gaussian mutation and the individual X before mutation is Δf, and the probability P_r is defined as

$$P_r = \exp(\Delta f / T) \tag{23}$$

Where T is the annealing temperature, and the value gradually decreases as the iteration proceeds. Moreover, if the initial annealing temperature is higher and the annealing rate is lower, the improved model will be more helpful to jump out of the local optimum.

The above ideas are integrated into the standard PIO algorithm, and the Mutation Simulated Annealing Pigeon-inspired Optimization (MSAPIO) algorithm model is obtained. The algorithm implementation process is described as follows

Step1: Create search map. Establishing target information map according to (5) and (14), and establishing environmental information map according to (1).

Step2: Initialize parameters. Initialize parameters of MSAPIO algorithm, such as the total number of pigeons N, the maximum number of iteration $Nc1$, $Nc2$ of the two operators, as shown in Table 1, and the initial position and velocity of each pigeon in the pigeon group and so on.

Step3: Estimate the fitness of pigeons. Evaluate the position of each pigeon using the fitness function of (15).

Step4: Update map and compass operator. The position and velocity of each pigeon is updated by (16). For each iteration, if the fitness of pigeon is better than X_{gbest}, X_{gbest} is replaced by the position of the current pigeon , if the Cauchy mutation is met, utilize (21) to jump out of the local optimum, continue to perform this step operation until the number of iteration reaches $Nc1$.

Step5:Update landmark operator. The position of each pigeon and center position is updated by (17).For each iteration, if the new generation $X_c(t)$ is better than the old generation $X_c(t\text{-}1)$, then replace the old generation $X_c(t\text{-}1)$ with the new generation $X_c(t)$. If the Gaussian mutation is met, use (22) for local adjustment. If the center position after the Gaussian mutation is next to the position before the mutation, calculate the difference, and use (23) to determine P_r. Then, compare the random number rand with P_r, rand$\in(0,1)$. If rand $< P_r$, reserve the worse individual, otherwise, return to the pre-mutation state and continue to perform this step operation until the number of iteration reaches $Nc2$, and the algorithm converges.

The standard PIO and MSAPIO parameters are selected as shown in Table 1

TABLE I. SET OF PARAMETERS FOR PIO AND MSAPIO

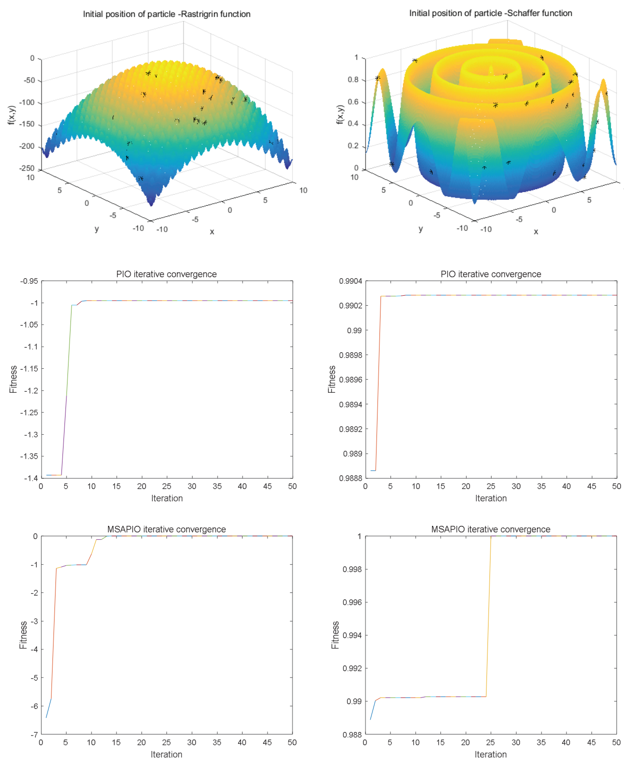
Parameter	Description	Value	Application
$Nc1$	Map and compass operator iterations	15	PIO and MSAPIO
$Nc2$	Landmark operator iterations	5	
N	Number of pigeons	50	
R	Map and compass factor	0.3	
a	Cauchy distribution probability density parameter	1	MSAPIO
μ	The mean of the Gaussian distribution	0	
σ	The variance of the Gaussian distribution	1	
K_1	Cauchy mutation condition of map and compass operator	3	
K_2	Gaussian mutation condition of landmark operator	2	
e_1	Map and compass operator mutation threshold	0.1	
e_2	Landmark operator mutation threshold	0.01	
T	The annealing temperature	1000	

V. EXPERIMENTAL RESULTS AND ANALYSIS

First, the classical fitness function is used to verify the superiority of the proposed algorithm to the standard PIO algorithm. Then, the performance of Multi-UAVs cooperative search is measured from two aspects: search coverage and number of discovery targets.

A. Algorithm Performance Comparison

The proposed algorithm uses the mutation and simulated annealing mechanism, which is easy to jump out of the local optimum relative to the standard PIO algorithm. Multimodal fitness evaluation functions are used for testing, Fig. 3(a) uses the Rastrigrin function, which is at x = (0, 0, ..., 0) takes the minimum of 0; Fig. 3(b) uses the Schaffer function, which is at x = (0, 0) , ..., 0) takes the maximum of 1. It is not difficult to find from the figure that the algorithm can effectively avoid falling into local optimum.

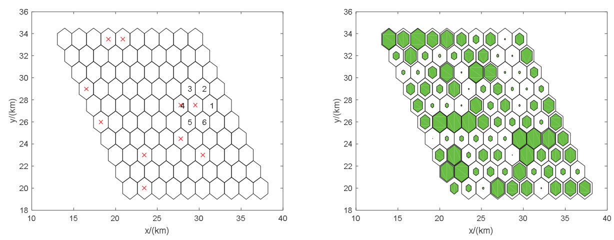


(a) Rastrigrin function (b) Schaffer function

Fig. 3. Diagram of optimal value convergence

B. Search Range Coverage

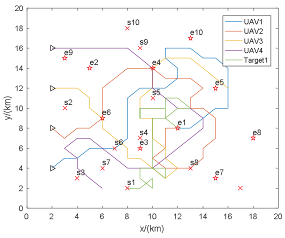
Assume that the search area L is divided into 10×10 grids. Fig. 4(a), the red "×" are randomly generated target initial position, and the number "1, 2, 3, 4, 5, 6" is a possible moving position at the next moment of the target. Fig. 4 (b) is the initial environmental uncertainty generated randomly, and the shaded green part is proportional to the uncertainty.



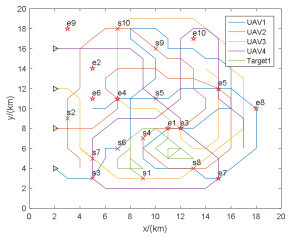
(a) Position of initial targets (b) Initial uncertainty map

Fig. 4. Initial state

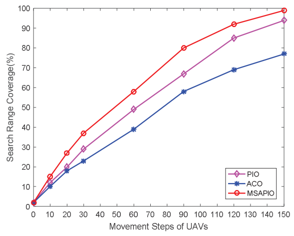
In order to verify the superiority of the algorithm, Fig. 5 shows the motion tracks and search range coverage of 4 UAVs in different simulation steps. It is convenient to observe the movement, (a) and (b) only the motion tracks of UAVs and target 1 in 30 and 60 steps are given, and (c) is the change of search range converge under the guidance by the different algorithms. The 20km*20km search area is divided into 20*20 grids, the initial positions of the four UAVs are represented by "▷"; "×" is the randomly generated dynamic target, and "s_i" is the starting position of the i-th target. "e_i" is the end position after the movement of the Markov chain. According to the figure analysis, UAVs can achieve as many targets as possible with the minimum number of steps, and the search coverage expands with the increase of the number of search steps.



(a) The tracks of UAVs in 30 steps



(b) The tracks of UAVs in 60 steps

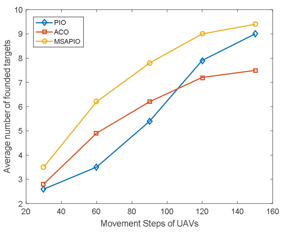


(c) The rate of converage

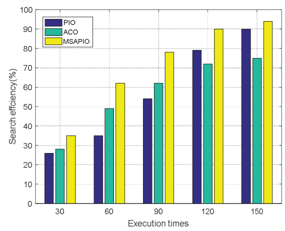
Fig. 5. The movement tracks and coverage of UAVs

C. *Search Target Efficiency*

Fig. 6 compares the 3 algorithms of standard PIO, ACO and MSAPIO from the validity of search targets, and (a) and (b) show the average of search targets and the effectiveness of the search strategy respectively. It is not difficult to find out from the simulation results that since the algorithm uses digital pheromone to complete the cooperation between UAVs, which relative to other algorithms can find more targets and greatly improve the effectiveness of the search .



(a) Average of targets



(b) Effectiveness of the search strategy

Fig. 6. Effectiveness evaluation of collaborative search

VI. Conclusion

A multi-UAVs cooperative search method is proposed based on improved PIO and dynamic target motion model. Firstly, the environmental information map, target information map and pheromone map were constructed, and the target motion model in line with Markov chain was established to realize multi-UAVs cooperative search modeling. Then, the improved PIO algorithm is used to complete the optimization solution. Although the PIO algorithm has the advantages of fast convergence and high search efficiency, it is easy to fall into local optimum. Therefore, this paper adds the Cauchy and Gaussian mutation to the two operators of the PIO algorithm, and uses the SA mechanism to reserve the worse individuals and avoid falling into local optimum.

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