Optimal search for moving targets with sensing capabilities using multiple UAVs

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Abstract: This paper studies the problem of using multiple unmanned air vehicles (UAVs) to search for moving targets with sensing capabilities. When multiple UAVs (multi-UAV) search for a number of moving targets in the mission area, the targets can intermittently obtain the position information of the UAVs from sensing devices, and take appropriate actions to increase the distance between themselves and the UAVs. Aiming at this problem, an environment model is established using the search map, and the updating method of the search map is extended by considering the sensing capabilities of the moving targets. A multi-UAV search path planning optimization model based on the model predictive control (MPC) method is constructed, and a hybrid particle swarm optimization algorithm with a crossover operator is designed to solve the model. Simulation results show that the proposed method can effectively improve the cooperative search efficiency and can find more targets per unit time compared with the coverage search method and the random search method.

Keywords: unmanned air vehicle (UAV), moving target search, model predictive control, path planning, hybrid particle swarm optimization.

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1. Introduction

With the continuous development of unmanned air vehicle (UAV) technology, in recent years, the application of the UAV for military and civilian target search has gradually increased. UAV path planning methods for target search have become an important research direction. According to the target's moving ability, the target search can be divided into stationary target search and moving target search. In the stationary target search, UAV path planning is usually performed beforehand to maximize the coverage of the mission area. However, the moving target search is much more complex. Because the target's position is

changing over time, the UAV path planning must be real-time during the search process.

Based on the existing literature, the solving process of searching for the moving target is usually as follows. First, an environment model is constructed based on the search map [1–5] (also known as probability map [2], uncertainty map [3,4], and pheromone map [5]), which is a grid map that reflects the target and environment information. Second, the search map is updated using certain rules during the UAV search process. Third, the UAV path is planned based on the updated search map so as to maximize the probability of finding the targets. Hu et al. [2] divided the update of the probability map into three parts. The first part used the Bayesian rule and consensus-based map fusion. The second part was based on the detection probability model and the false alarm probability model. The third part considered the environmental changes. Then a new three-dimensional coverage control method was proposed to plan the UAV path. Xiao et al. [3] divided the mission area into certain area and uncertain area, and updated the uncertain map based on an uncertainty diffusion model. Then a combination of the virtual force method and the receding horizon method was presented to optimize the UAV path. Ru et al. [5] combined the probability map, uncertainty map, and pheromone map into a cognitive information map, where the probability map was first updated based on the detection information of UAV sensor and further updated based on the target transition probability predicted with the Gaussian distribution. Then the UAV path planning was conducted by using the distributed cooperative control method. Sun et al. [6] used a heuristic strategy to update the probability map. First, the target existence probability of the adjacent grids was updated by an uncertainty propagation step. Then, the probability map was updated based on the Bayesian rule and Kalman filter. Finally, a decentralized search algorithm was used to plan the UAV path.

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In addition to the search map method, some other methods were also proposed to solve the problem of searching for moving targets. Kassem et al. [7] presented a Bayesian filtering algorithm to update and predict the probability density function of target state, and used the Kuhn–Tucker conditions to obtain the optimal search strategy. Riehl et al. [8] introduced a cooperative graph-based model predictive search algorithm to solve the problem of searching for moving targets in a closed, bounded region. Royset et al. [9] proposed a convex mixed-integer nonlinear model to search for moving targets, and solved this model based on the cutting-plane method and the linearization. Altshuler et al. [10] proposed an improved geometrical method to search for moving targets capable of escaping from UAVs in a pre-conditioned environment. Detienne et al. [11] proposed a two-stage method based on 0-1 linear model to search for intelligent moving targets which can counter-detect sensors and learn the searcher's behavior. Alpern et al. [12] combined the zero-sum game theory and the rendezvous search theory to solve a new type of search problem for static or moving target which may be cooperator or evader.

Based on the studies mentioned above, this paper considers the problem of searching for moving targets with sensing capabilities: targets move within the mission area in a Markovian fashion. There are a number of sensing devices installed in the mission area. Once a UAV passes over a sensing device, the device can find the UAV and will send the UAV's position information to all targets. At the same time, the UAV can also sense the device. When obtaining the UAV's position, each target will perform appropriate movement to increase the distance between itself and the UAV.

This paper proposes a novel cooperative search method to search for moving targets with sensing capabilities (CSMMSC). First, an environment model is constructed using a search map, and the search map is updated based on the detection information and motion prediction of moving targets. Then a multi-UAV search path planning optimization model based on the model predictive control (MPC) method is established with the objective function of maximizing the cumulative probability of target discovery. Next a hybrid particle swarm optimization (HPSO) algorithm is proposed to solve the model. Results of the simulation confirm that the proposed method is effective.

The contributions of this paper are as follows: (i) with focus on the target's sensing capabilities, this paper extends the traditional updating method of search map, based on which the UAVs can plan their paths to reduce the risk of exposure of their positions; (ii) weight factors are introduced into the objective function of the multi-UAV search

path planning optimization model to enhance the search performance; (iii) an HPSO algorithm with a crossover operator for solving multi-UAV search path planning optimization model is provided, and this algorithm can solve the problem effectively.

The remaining part of this paper is organized as follows. Section 2 describes the problem. Section 3 defines the search map and proposes its update method. Section 4 presents a search path planning optimization model of the UAVs. The HPSO algorithm is introduced in Section 5. The simulation experiments are used to verify the effectiveness of the proposed method in Section 6. Finally, the overall work is summarized in Section 7.

2. Problem description

Assume N_V UAVs equipped with detection sensors search for N_T moving targets within a mission area E . E is divided into $L \times W$ grids, where each grid is expressed as (m, n) ($m \in \{1, 2, \dots, L\}; n \in \{1, 2, \dots, W\}$) representing the square area of $[m, m+1) \times [n, n+1)$. The length of each grid is c . Fig. 1 shows a 10×10 sized mission area, with the black square representing grid (8,9).

Fig. 1 Three possible heading deflection angles of UAV in the mission area

There are N_B sensing devices with fixed positions within the mission area. When a UAV flies into the grid covered by a sensing device, the device can find the UAV and will send the UAV's position information to all targets. Without the UAV's position information, each target randomly moves to any grid adjacent to its current grid. Once acquiring the UAV's position, each target will take an appropriate action to avoid the UAV. Specifically, each target will move for a time step toward the direction of maximizing the distance between itself and the UAV and then return to the random Markovian motion.

The flying speed of each UAV is v , and the path of each UAV depends on the heading angle, which refers to the an-

gle between the flight direction of the UAV and the x axis. Path planning is performed every ΔT time to select the heading deflection angle of the next time interval. Limited to its dynamic characteristics, the UAVs cannot turn in any random direction. As indicated in Fig. 1, they can only select one of the following three directions as the heading deflection angle at time $t_k (k = 0, 1, 2, \dots, K) : \{-\alpha, 0, \alpha\}$.

Referring to [1], this paper assumes the following: (i) when a UAV flies into a grid, the UAV can only detect this grid; (ii) communications between the UAVs are ideal and there is no communication delay; (iii) there is at most one target in a grid at one time.

Based on these conditions, planning the optimal search path for each UAV is required to achieve the goal of finding as many targets as possible in a given time period.

3. Definition of search map

Environment information is expressed using a search map [1–5]. $p_{mn}(t_k) \in [0, 1]$ denotes the target existence probability, which represents the probability of a target locating in a grid (m, n) at time t_k . Then the search map at time t_k can be defined as

$$SMP(t_k) = \{p_{mn}(t_k) | m \in \{1, 2, \dots, L\}, n \in \{1, 2, \dots, W\}\}. \quad (1)$$

In the process of the search mission, all UAVs share one search map to indicate current environment information, and the search map is updated over time. The updating process is composed of two steps: updating the search map based on the detection information and updating the search map based on the prediction of target motion. Based on the information provided by the search map, each UAV can plan an optimal search path.

3.1 Search map updating based on detection information

In the process of the search mission, the UAVs use the detection sensors to detect the targets and thereby update the search map by the detection information. The basic update model was provided in previous works [1–5]. In this paper, we consider that there are several sensing devices in the environment, and UAVs need to avoid the sensing devices after being detected at a given position so as to avoid being detected again during the subsequent search process. For this reason, the previous updating method of the search map is extended by classifying the update conditions at time t_k into five types as follows.

(i) UAV searches the grid (m, n) and finds a target but not any sensing device:

$$p_{mn}(t_{k+1}) = \frac{p_d p_{mn}(t_k)}{p_f + (p_d - p_f) p_{mn}(t_k)}. \quad (2)$$

(ii) UAV searches the grid (m, n) and finds a target and a sensing device:

$$p_{mn}(t_{k+1}) = \tau_2 \times \frac{p_d p_{mn}(t_k)}{p_f + (p_d - p_f) p_{mn}(t_k)}. \quad (3)$$

(iii) UAV searches the grid (m, n) and finds neither target nor sensing device:

$$p_{mn}(t_{k+1}) = \frac{(1 - p_d) p_{mn}(t_k)}{1 - p_f + (p_f - p_d) p_{mn}(t_k)}. \quad (4)$$

(iv) UAV searches the grid (m, n) and finds a sensing device without any target:

$$p_{mn}(t_{k+1}) = \tau_2 \times \frac{(1 - p_d) p_{mn}(t_k)}{1 - p_f + (p_f - p_d) p_{mn}(t_k)}. \quad (5)$$

(v) UAV does not search the grid (m, n) :

$$p_{mn}(t_{k+1}) = \tau_1 p_{mn}(t_k). \quad (6)$$

As in (2)–(6), p_d is the detection probability indicating the probability of UAV finding a target when the target is within the current grid. p_f is the false alarm probability indicating the probability of UAV finding a target but no target is actually within the current grid. $\tau_1, \tau_2 \in [0, 1]$ are dynamic information factors.

3.2 Search map updating based on target motion prediction

As the target's motion law is unknown, in order to reduce the uncertainty during the search, this paper uses the target motion prediction model proposed in [13,14] to further update the search map. First the target motion within the time period $t_k \rightarrow t_{k+1}$ is predicted at time t_k based on the Gauss-Markov motion model, and then the search map is updated to guide the UAV path planning.

Assume that the position of target is independent in the x and y directions and that its estimated speed is v_0 . The target position at time t_k is (x_k, y_k) , and the target position at time t_{k+1} is (x_{k+1}, y_{k+1}) . Let $t_{k+1} - t_k = a_k \Delta t = \Delta T$, in which Δt is a time step and a_k is the number of time steps within the time range $t_k \rightarrow t_{k+1}$. The acceleration of target is assumed to form the Gaussian white noise sequences ε_n with the same variance ζ . Thus, after time ΔT , the target positions in the x and y directions at time t_{k+1} are x_{k+1} and y_{k+1} , which are consistent with Gaussian distributions with means of μ_x and μ_y , and variance of σ^2 , respectively. μ_x, μ_y and σ^2 are expressed as follows:

$$\begin{aligned} \mu_x &= x_k + \frac{x_{k+1} - x_k}{\sqrt{(x_{k+1} - x_k)^2 + (y_{k+1} - y_k)^2}} v_0 a_k \Delta t \\ \mu_y &= y_k + \frac{y_{k+1} - y_k}{\sqrt{(x_{k+1} - x_k)^2 + (y_{k+1} - y_k)^2}} v_0 a_k \Delta t \end{aligned}$$

$$\sigma^2 = \frac{4a_k^3 - a_k}{12} \xi \Delta t^4. \quad (7)$$

In this way, after time ΔT , the transition probability density function from the position (x_k, y_k) to the position (x_{k+1}, y_{k+1}) is as follows:

$$p\{(x_{k+1}, y_{k+1})|(x_k, y_k)\} = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{1}{2\sigma^2}[(x_{k+1} - \mu_x)^2 + (y_{k+1} - \mu_y)^2]\right\}. \quad (8)$$

According to the function above, assume that the target is in the grid (l, w) at time t_k , so at time t_{k+1} , the probability of the target moving to the grid (m, n) is as follows:

$$H((l, w), (m, n), \Delta T) = \frac{1}{2\pi\sigma^2} \int_{Y_n - \frac{\epsilon}{2}}^{Y_n + \frac{\epsilon}{2}} \int_{X_m - \frac{\epsilon}{2}}^{X_m + \frac{\epsilon}{2}} \exp\left\{-\frac{1}{2\sigma^2}[(x_{k+1} - \mu_x)^2 + (y_{k+1} - \mu_y)^2]\right\} dx_{k+1} dy_{k+1} \quad (9)$$

where (X_m, Y_n) is the central point of the grid (m, n) .

At the same time, all targets cannot move beyond the grids of the mission area, so we have

$$\sum_{l=1}^L \sum_{w=1}^W H((l, w), (m, n), \Delta T) = 1. \quad (10)$$

Furthermore, the target existence probability of the grid (m, n) at time t_{k+1} is

$$p_{mn}(t_{k+1}) = \sum_{l=1}^L \sum_{w=1}^W (H((l, w), (m, n), \Delta T) p_{mn}(t_k)). \quad (11)$$

From the analysis above, the update of the search map at time t_k based on the detection information and the prediction of target motion is summarized as follows.

(i) UAV searches the grid (m, n) and finds a target without any sensing device:

$$p_{mn}(t_{k+1}) = \sum_{l=1}^L \sum_{w=1}^W \left(H((l, w), (m, n), \Delta T) \frac{p_d p_{mn}(t_k)}{p_f + (p_d - p_f) p_{mn}(t_k)} \right). \quad (12)$$

(ii) UAV searches the grid (m, n) and finds a target and a sensing device:

$$p_{mn}(t_{k+1}) = \sum_{l=1}^L \sum_{w=1}^W$$

$$\left(H((l, w), (m, n), \Delta T) \tau_2 \frac{p_d p_{mn}(t_k)}{p_f + (p_d - p_f) p_{mn}(t_k)} \right). \quad (13)$$

(iii) UAV searches the grid (m, n) and finds neither target nor sensing device:

$$p_{mn}(t_{k+1}) = \sum_{l=1}^L \sum_{w=1}^W \left(H((l, w), (m, n), \Delta T) \frac{(1 - p_d) p_{mn}(t_k)}{1 - p_f + (p_f - p_d) p_{mn}(t_k)} \right). \quad (14)$$

(iv) UAV searches the grid (m, n) and finds a sensing device without any target:

$$p_{mn}(t_{k+1}) = \sum_{l=1}^L \sum_{w=1}^W \left(H((l, w), (m, n), \Delta T) \tau_2 \frac{(1 - p_d) p_{mn}(t_k)}{1 - p_f + (p_f - p_d) p_{mn}(t_k)} \right). \quad (15)$$

(v) UAV does not search the grid (m, n) :

$$p_{mn}(t_{k+1}) = \sum_{l=1}^L \sum_{w=1}^W (H((l, w), (m, n), \Delta T) \tau_1 p_{mn}(t_k)). \quad (16)$$

4. UAV search path planning

Multi-UAV cooperative searching for moving targets is a dynamic process. The MPC method is suitable for modeling and solving dynamic problems [15–17]. Therefore, this paper uses the MPC method to construct an UAV path planning model.

4.1 MPC method

According to the method of MPC, multi-UAV are considered as a control system [5]. Let the state of the overall system at time t_k to be $x(t_k) = \{x_1(t_k), x_2(t_k), \dots, x_{N_v}(t_k)\}$, and the control input at time t_k is $u(t_k) = \{u_1(t_k), u_2(t_k), \dots, u_{N_v}(t_k)\}$, then the state model of the multi-UAV system can be recorded as $x(t_{k+1}) = f(x(t_k), u(t_k))$, in which f is the state transition function of the system. The search path planning process of multi-UAV at time t_k is divided into the following two steps:

Step 1 Predict the system state. The system state for the next q steps is

$$X(t_k) = \{x(t_k|t_k), x(t_{k+1}|t_k), \dots, x(t_{k+q-1}|t_k)\}$$

which is predicted based on the current system state $x(t_k)$.

Step 2 Calculate the optimal heading deflection angle. According to the predicted system state for the next q

steps, the optimal search performance is used to determine the optimal control input sequence of the next q steps.

$$U^*(t_k) = \{u(t_k|t_k), u(t_{k+1}|t_k), \dots, u(t_{k+q-1}|t_k)\}.$$

Then the first item of the sequence $u(t_k|t_k)$ is set as the optimal heading deflection angle at time t_k .

Specifically, the state of UAV i at time t_k is $\mathbf{x}_i(t_k) = [xp_i(t_k) \ \vartheta_i(t_k)]^T$ ($i = 1, 2, \dots, N_V$), in which $xp_i(t_k)$ is the position of UAV i at time t_k and $\vartheta_i(t_k)$ is the heading angle of UAV i at time t_k . Then the state model of UAV i at time t_{k+1} can be presented as

$$\mathbf{x}_i(t_{k+1}) = f(\mathbf{x}_i(t_k), u_i(t_k)) = \begin{bmatrix} xp_i(t_{k+1}) \\ \vartheta_i(t_{k+1}) \end{bmatrix} = \begin{bmatrix} xp_i(t_k) + v\Delta T S(\vartheta_i(t_k) + \Delta\vartheta_i(t_k)) \\ \vartheta_i(t_k) + \Delta\vartheta_i(t_k) \end{bmatrix}. \quad (17)$$

As in (17), $S(\vartheta_i(t_k) + \Delta\vartheta_i(t_k))$ is a trigonometric function. Set $\vartheta_i(t_k) + \Delta\vartheta_i(t_k) = *$, then $S(*) = [\cos(*) \ \sin(*)]^T$. According to (17), the state of UAV i on the search map will be updated after the heading deflection angle $\Delta\vartheta_i(t_k)$ is determined.

4.2 Objective function

The objective function is defined as the sum of target discovery probability of the grids covered by the pre-planned q steps of search path of each UAV [1], which is defined as

$$J(t_k) = \sum_{i=1}^{N_v} \sum_{(m,n) \in A_i} \{(p_d - p_f)p_{mn}(t_k) + p_f\} \quad (18)$$

where $(p_d - p_f)p_{mn}(t_k) + p_f$ denotes the target discovery probability of the grid (m, n) at time t_k .

Considering that only the first step of search path is actually conducted by UAV, the weight factors are introduced into the objective function. The sum of target discovery probability of the grids potentially covered by the first step of the search path is given a relatively high weight. The objective function is defined as

$$J'(t_k) = w_1 \sum_{i=1}^{N_v} \sum_{(m,n) \in B_i} \{(p_d - p_f)p_{mn}(t_k) + p_f\} + w_2 \sum_{i=1}^{N_v} \sum_{(m,n) \in (A_i - B_i)} \{(p_d - p_f)p_{mn}(t_k) + p_f\}. \quad (19)$$

As in (18) and (19), A_i stands for the grids covered by the pre-planned q steps of search path of UAV i , B_i stands for the grids covered by the first step of search path of UAV i , w_1 and w_2 are weights. $w_1 > w_2$ and $w_1 + w_2 = 1$.

4.3 Search path planning optimization model

In summary, with focus on the moving targets with sensing

capabilities, in this paper, a search path planning optimization model based on MPC method is shown as

$$\begin{aligned} U^*(t_k) &= \max J'(t_k) \\ J'(t_k) &= w_1 \sum_{i=1}^{N_v} \sum_{(m,n) \in B_i} \{(p_d - p_f)p_{mn}(t_k) + p_f\} + \\ &w_2 \sum_{i=1}^{N_v} \sum_{(m,n) \in (A_i - B_i)} \{(p_d - p_f)p_{mn}(t_k) + p_f\} \\ &\text{s.t.} \\ &\left\{ \begin{aligned} &H((l, w), (m, n), \Delta T) = \frac{1}{2\pi\sigma^2} \int_{Y_n - \frac{c}{2}}^{Y_n + \frac{c}{2}} \int_{X_m - \frac{c}{2}}^{X_m + \frac{c}{2}} \\ &\exp \left\{ -\frac{1}{2\sigma^2} [(x_{k+1} - \mu_x)^2 + (y_{k+1} - \mu_y)^2] \right\} \\ &dx_{k+1} dy_{k+1} \\ &\mathbf{x}_i(t_{k+z+1}) = f(\mathbf{x}_i(t_{k+z}), u_i(t_{k+z})) = \\ &\begin{bmatrix} xp_i(t_{k+z+1}) \\ \vartheta_i(t_{k+z+1}) \end{bmatrix} = \\ &\begin{bmatrix} xp_i(t_{k+z}) + v\Delta T S(\vartheta_i(t_{k+z}) + \Delta\vartheta_i(t_{k+z})) \\ \vartheta_i(t_{k+z}) + \Delta\vartheta_i(t_{k+z}) \end{bmatrix} \\ &\mathbf{x}_i(t_k|t_k) = \mathbf{x}_i(t_k) \\ &u_i(t_k|t_k) = u_i(t_k) = \{\Delta\vartheta_i(t_k)\} \\ &\Delta\vartheta_i(t_{k+z}|t_k) \in \{-\alpha, 0, \alpha\} \\ &\lceil xp_i(t_k) \rceil \neq \lceil xp_j(t_k) \rceil, \quad i \neq j \\ &i, j = 1, 2, \dots, N_V \\ &z = 0, 1, \dots, q-1 \\ &l = 1, 2, \dots, L \\ &m = 1, 2, \dots, L \\ &w = 1, 2, \dots, W \end{aligned} \right. \end{aligned} \quad (20)$$

where $\lceil xp_i(t_k) \rceil \neq \lceil xp_j(t_k) \rceil$ ($i \neq j$) means that UAV i and UAV j will not be in the same grid at any time t_k , $u_i(t_k|t_k) = u_i(t_k) = \{\Delta\vartheta_i(t_k)\}$ represents the optimal heading deflection angle of UAV i at time t_k , based on which the search path of UAV i is planned.

5. Solution algorithm

5.1 HPSO algorithm

The key to solve this model is to find an optimal control input of the MPC system, which is a nonlinear optimization problem. The PSO algorithm provides special advantage in solving nonlinear optimization problems [18,19]. It is a kind of intelligent optimization algorithm inspired by the behavioral characteristics of the biological population. In PSO, each potential solution can be imaged as a “bird” in the search space, and extracted as a “particle” without mass and volume. Each particle flies in the search space at a certain speed, and the speed is dynamically adjusted

according to its own flying experience and that of its fellow particles. Every particle has an adaptive value that is determined by the objective function. All particles know the best position ever found so far and their own current positions, which is considered as their flying experience. In addition, each particle knows the best position for all the particles found so far in the entire population, which is seen as the flying experience of its fellow particles. The next movement of the particle is determined through its own flying experience and the best flying experience of its fellow particles.

Previous works [19–22] combined PSO with other optimization algorithms, such as the genetic algorithm, differential evolution algorithm, simulated annealing algorithm, and local searching, to form HPSO algorithms. Experiments showed these HPSO algorithms had faster convergence speed and greater search accuracy than PSO and they produced better results for some nonlinear optimization problems [20–22].

In this paper, a crossover operator of the genetic algorithm is introduced into the PSO algorithm to form a new HPSO algorithm. In the new algorithm, the particles not only update the speeds and positions, but also perform pairwise crossover operations with a certain probability to generate the offspring particles and then replace the current particles with the offspring particles. Crossover operation makes the offspring particles inherit the parent particles' advantages. The offspring particles constitute a part of the populations in the new generation, which increases the population's diversity and enhances the search efficiency of the algorithm as well.

5.1.1 Encoding

Each particle is encoded by a 2×1 dimensional matrix $\begin{bmatrix} x_i(t_k) \\ v_i(t_k) \end{bmatrix}$, where the first line of elements represents the position of the particle and the second line of elements represents the speed of the particle. The control input of UAV i at time t_k is $u_i(t_k) = \{\Delta\vartheta_i(t_k)\}$. In order to facilitate encoding, the position of particle i satisfies $x_i(t_k) \in \{-1, 0, 1\}$. After decoding, -1 corresponds to $-\alpha$, 0 corresponds to 0 , and 1 corresponds to α . Namely, the particle position $x_i(t_k)$ corresponds to the heading deflection angle $\Delta\vartheta_i(t_k)$ of UAV i . If $x_i(t_k) < -1$, let $x_i(t_k) = -1$. Moreover, the speed of particle i satisfies $v_i(t_k) \in \{-1, 0\}$. Using the encoding method, the decoded particle corresponds to the heading deflection angle of UAV at different time, making the calculation easy and efficient.

5.1.2 Steps of the HPSO algorithm

Set the position of particle i as x_i and its speed as v_i . The best position of this particle itself is p_i , and the best po-

sition among all particles is p_g . The steps of the HPSO algorithm are as follows.

Step 1 Initialize the speed of each particle v_i as a random integer ranged $[-1, 0]$ and the position of each particle p_i as a random integer ranged $[-1, 1]$.

Step 2 Based on the best position of each particle, calculate the adaptive value of each particle according to (21), and then select the particle position which corresponds to the maximum adaptive value from all particles as p_g .

$$fit(t_k) = w_1 \sum_{j=1}^{N_v} \sum_{(m,n) \in B_j} \{(p_d - p_f)p_{mn}^i(t_k) + p_f\} + w_2 \sum_{j=1}^{N_v} \sum_{(m,n) \in (A_j - B_j)} \{(p_d - p_f)p_{mn}^i(t_k) + p_f\} \quad (21)$$

where A_j stands for the grids covered by q steps of pre-planned path of UAV j . B_j denotes the grids covered by the first step of the pre-planned path of UAV j . $p_{mn}^i(t_k)$ indicates the target existence probability of the grid (m, n) at time t_k by decoding the position of particle i .

Step 3 Update the position and speed of each particle using (22) and (23).

$$v_i = wv_i + c_1r_1(p_i - x_i) + c_2r_2(p_g - x_i) \quad (22)$$

$$x_i = x_i + v_i \quad (23)$$

Equation (22) stands for the speed update of particle i , in which c_1, c_2 are positive constants referred as learning factors; w is the inertial factor; r_1, r_2 are random numbers within $[0, 1]$. Equation (23) is the position update of particle i .

Step 4 For particle i , compare its current adaptive value with the adaptive values experienced in history positions and then select the particle position corresponding to the maximum adaptive value to replace p_i .

Step 5 Compare the adaptive value of current all p_i with p_g , and select the particle position corresponding to the maximum adaptive value to replace p_g .

Step 6 Perform pairwise crossover operation of selected particles at crossover probability p_c to generate offspring particles. The crossover operator is as follows:

$$\begin{cases} child_1(x_i) = r \times parent_1(x_i) + (1-r) \times parent_2(x_i) \\ child_2(x_i) = r \times parent_2(x_i) + (1-r) \times parent_1(x_i) \end{cases} \quad (24)$$

$$\begin{cases} child_1(v_i) = \frac{parent_1(v_i) + parent_2(v_i)}{|parent_1(v_i) + parent_2(v_i)|} |parent_1(v_i)| \\ child_2(v_i) = \frac{parent_1(v_i) + parent_2(v_i)}{|parent_1(v_i) + parent_2(v_i)|} |parent_2(v_i)| \end{cases} \quad (25)$$

where r is a random number within $[0, 1]$. For particle i , $child_1(x_i)$ and $child_2(x_i)$ stand for the positions of two offspring particles after crossing over the positions of two

parent particles $parent_1(x_i)$ and $parent_2(x_i)$. $child_1(v_i)$ and $child_2(v_i)$ represent the speeds of two offspring particles after crossing over the speeds of two parent particles $parent_1(v_i)$ and $parent_2(v_i)$.

Step 7 Return to Step 2, repeat the above process till reach the maximum number of iterations, then output the solution p_g .

5.2 Solving process

To sum up, the solving process of the multi-UAV search path planning optimization model based on MPC method is shown in Fig. 2.

Fig. 2 Solving process

6. Simulation experiments

Simulation experiments are performed in Matlab. The computer configuration is as follows: Intel Core i5-2400, CPU @3.10 GHz, 3.10 GHz, memory 2.00 GB. The operating system is Windows 7.

Divide the mission area E into 40×40 square grids. The initial target existence probability of each grid is 0.5, set $c = 1$ km, $v = 0.2$ km/s, $\alpha = 45^\circ$, $v_0 = 0.2$ km/s, $\xi = 12.5$, $\Delta T = \Delta t = 5$ s, $a_k = 1$. Four sensing de-

vices are placed at (4, 6), (20, 8), (40, 30), and (27, 15), respectively. Let $pc = 0.9$.

Fig. 3 shows 100 steps of search paths for four UAVs searching for ten moving targets. The UAVs are initially located at four corners of the mission area. The targets move randomly within the grids. The search paths of the four UAVs are indicated in Fig. 3.

Fig. 3 Search paths for four UAVs searching ten moving targets

The following five experiments are conducted: parameter sensitivity analysis; comparison of updating methods of the search map; comparison of objective functions; comparison of HPSO algorithm with PSO algorithm; comparison of the CSMMSC method with random search method and coverage search method. Each experimental data is the average of ten simulation results. The steps of simulation are set to 1 000. Let $q = 10$.

6.1 Parameter sensitivity analysis

Firstly, we test the sensitivity of the weights: w_1 and w_2 . To save the paper length, here we show four groups of results among many experiments in Table 1.

Table 1 Average numbers of targets found under different w_1 and w_2

w_1	w_2	Number of targets found
0.825	0.175	2.7
0.625	0.375	3.7
0.575	0.425	3.2
0.375	0.625	1.9

As shown in Table 1, the group of $w_1 = 0.625$ and $w_2 = 0.375$ provides the best search performance. Therefore, we set $w_1 = 0.625$ and $w_2 = 0.375$ in the subsequent experiments.

Secondly, the sensitivity of dynamic information factor τ_2 on search results is tested with a total of four groups of

experiments. The value of τ_2 in each experiment and the average numbers of targets found are listed in Fig. 4.

Fig. 4 Average numbers of targets found under different τ_2

As indicated in Fig. 4, $\tau_2 = 0.65$ provides the best performance, with an average number of 3.7 targets found. According to the results, the following parameters are used in the following experiments: $w_1 = 0.625$, $w_2 = 0.375$, $\tau_2 = 0.65$ and $q = 10$.

6.2 Comparison of updating methods of the search map

To search for moving targets with sensing capabilities, we extend the updating method of the search map by adding the dynamic information factor τ_2 . Thus the UAVs can be as far as possible to avoid the sensing devices, and the positions of the UAVs would not be exposed more than once. The updating method of the search map proposed in this paper is compared with previously method in [1] and the results are presented in Table 2.

Table 2 Comparison of updating methods for the search map

Number of targets	4 UAVs		6 UAVs	
	$\tau_2 = 0.65$	no τ_2	$\tau_2 = 0.65$	no τ_2
10	3.7	3.4	4.2	3.9
15	5.4	4.8	6.4	5.9
20	7.1	6.2	7.6	6.4

The experimental data in Table 2 indicates that our modification for the search map updating method is effective in helping the UAVs find more targets. We add the dynamic information factor τ_2 to our search map model. When an UAV flies into a grid covered by a sensing device, the target existence probability of the grid will decline by $1 - \tau_2$. Then the UAV will plan its next path to avoid flying into the grid again, which reduces the risk of exposing its position to the sensing device.

6.3 Comparison of objective functions

The objective function in previous work [1] is modified to facilitate searching for moving targets with sensing capabilities. The modified objective function as in (19) is compared with the previous objective function as in (18). The results of the experiments are shown in Table 3.

Table 3 Comparison of the objective functions

Number of targets	4 UAVs		6 UAVs	
	(19)	(18)	(19)	(18)
10	3.7	2.5	4.2	2.7
15	5.4	3.4	6.4	4.2
20	7.1	5.1	7.6	6.5

From Table 3, we can draw a conclusion that our modification for the objective function is effective. The previous objective function is the sum of target discovery probability in the grids covered by the q steps of the search path. Because only the first step of the search path is actually conducted by the UAVs, we introduce the weight factors w_1 and w_2 into the objective function to highlight the importance of the first step of the search path. This modification increases the probability of the UAVs finding targets.

6.4 Comparison of HPSO algorithm with PSO algorithm

The HPSO algorithm is used for solving the multi-UAV search path planning optimization model in this paper. By incorporating the crossover operator into the PSO algorithm, the offspring particles can inherit the advantages of the parent particles, which increases the population's diversity and enhances the search efficiency of the algorithm as well. In the following experiments, the HPSO algorithm is compared with the PSO algorithm and the results are given in Table 4 and Fig. 5.

Table 4 Comparison of the HPSO algorithm with the PSO algorithm

Number of targets	4 UAVs		6 UAVs	
	HPSO	PSO	HPSO	PSO
10	3.7	3.1	4.2	3.5
15	5.4	4.1	6.4	4.4
20	7.1	5.7	7.6	6.5

Fig. 5 Comparison of HPSO algorithm with PSO algorithm under different simulation steps

As shown in Table 4, the HPSO algorithm finds more targets than the PSO algorithm under the same condition. In the HPSO algorithm, the particles not only update the speeds and positions, but also perform pairwise crossover operations with a certain probability to generate the offspring particles and then replace the current particles with

the offspring particles. This increases the population's diversity and enhances the search efficiency of the algorithm.

Fig. 5 shows the average numbers of targets found under different simulation steps by the HPSO algorithm and the PSO algorithm in a scenario including four UAVs and ten targets.

As depicted in Fig. 5, the HPSO algorithm always finds more targets than the PSO algorithm under different simulation steps. Therefore, the HPSO algorithm is more suitable for solving this kind of problem.

Table 5 Comparison of the CSMMSC method with the random search method and the coverage search method

Number of targets	4 UAVs			6 UAVs		
	Random search	Coverage search	CSMMSC	Random search	Coverage search	CSMMSC
10	1.5	1.1	3.7	2.3	1.3	4.2
15	1.8	2.3	5.4	2.9	2.6	6.4
20	3.1	2.4	7.1	5.5	3.3	7.6

Table 5 shows that the CSMMSC method finds more moving targets than the random search method and the coverage search method. The random search method performs poorly due to its random mode and the coverage search method is more suited to searching the stationary target.

Fig. 6 shows the average numbers of finding targets under different simulation steps by the CSMMSC method, the random search method, and the coverage search method in a scenario with four UAVs and ten targets.

Fig. 6 Comparison of the CSMMSC method with the random search method and the coverage search method under different simulation steps

According to Fig. 6, the numbers of targets found of the three methods are almost the same at the beginning. However with the simulation steps increasing, the CSMMSC method outperforms the random search method and the coverage search method. The main reason is that in the CSMMSC method the UAVs acquire more information about the targets with the simulation steps ongoing by keeping updating the search map. This is beneficial for the UAVs to precisely plan their paths.

7. Summary

A new type of moving target search problem is consi-

6.5 Comparison of the CSMMSC method with random search method and coverage search method

The CSMMSC method proposed in this paper is compared with the random search method and the coverage search method. In the random search method, the heading angle of each UAV is randomly selected within a certain range. In the coverage search method, the UAVs search the moving targets in the mission area by scanning back and forth. The results of the experiments are shown in Table 5.

dered in this paper. The target has the searcher's position aware capability as well as the moving capability, which increases the difficulties for searching. We propose a multi-UAV cooperative search method to address the problem. First, the extended search map model based on detection information and target movement prediction is used to describe and update the target existence probability in the environment. Then, the multi-UAV search path planning optimization model is constructed and weight factors are introduced to improve the conventional objective function to maximize the target discovery probability. Finally, an HPSO algorithm is designed to solve the model with improved efficiency. The simulation results show that the CSMMSC method can better solve the problem of searching for moving targets with sensing capabilities than the random search method and the coverage search method.

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