Multi-UAV cooperative Route planning based on decision variables and improved genetic algorithm

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Abstract. In order to reduce the threat cost of multi-UAV coordination, improve the effective flight time and the mission success rate, a path planning model was designed for the effectiveness and real-time performance of multi-UAV track coordination. In this paper, based on the path planning model under the condition of non-interference, the model of minimum cost flight path of multi-UAV based on time synergy is given, and a time-sequence-space coordination model is proposed to meet the requirements of electronic jamming, mission confusion and radar illumination. The decision variables of range and threat are introduced into the collaborative function of track cost, and by adjusting the cost functions and collaborative variables in real time, the path planning model was optimized for unmanned support aircraft in coordination with multiple unmanned aircraft mission, at the same time, the genetic algorithm is improved by combining the adaptive crossover rate and mutation rate, and the optimization of track collaborative solution process is realized. Finally, the effectiveness of track coordination model of multi-UAV based on decision variables and improved genetic algorithm is verified by semi-physical simulation.

1. Introduction

Facing the increasingly complex task environment of target detection, target tracking, precision strike, many tasks usually need multi-UAV to have it accomplished, the multiplicity and complexity of the task put forward higher request to the effective flight time and the success rate of the task of multi-UAV. In order to increase the probability of mission success, the UAV must carry out redundant configuration, realize mutual support and complementary capabilities [1]. Some scholars have put forward relevant path planning algorithms, for example, based on voronoi diagram and probabilistic road map hierarchical decomposition[2], multi-UAV path planning is realized, and Wolf Swarm Algorithm and fuzzy recognition are used to solve the problems of complex terrain, numerous threats and short flight path[3-5], but most of the algorithms are confined to a limited model in a specific situation, and cannot realize the multi-UAV multi-stage mission integrated route planning. Therefore, path planning, optimal path planning and formation coordination must be considered to improve the operational efficiency of multi-UAV, and multi-UAV cooperative path planning has become one of the core technologies of multi-UAV cooperative mission planning [6]. One of the current cooperation methods is the cooperation between the operational UAV and supported UAV [7]. The supported UAV can form a mixed formation with the operational UAV outside the threat area to jam the radar in
the threat area, to help the UAV to get the shortest track and reach the target area safely, so as to make full use of the cooperative advantages of the supported UAV and the operational UAV. Therefore, the point of how to use the improved genetic algorithm to coordinate the optimal arrival time of each UAV is the key research content of route planning [8].

2. Description of multi-UAV route cooperative planning
Assuming a formation consisting of M UAV carries out a mission to a target area, the goal of multi-UAV cooperative route planning is to plan a route for each UAV to ensure that the UAV can reach their target points at the same time, reduce the process threat, improve the survival rate and mission success rate. The track generated in this way is not necessarily optimal for a single UAV, but is approximately optimal for the whole UAV formation. Firstly, the influence of range and threat weight coefficient should be considered in multi-UAV cooperative planning [9], the different flight paths can be realized by adjusting range and threat weight coefficient, if the weight coefficient of the range is large, the route is the best, and if the weight coefficient of the threat is large, the route is the best. Secondly, compared with single aircraft multi-path planning, multi-aircraft cooperative path planning needs to generate multiple paths for UAV with different tasks, multi-UAV path planning needs to meet the superimposition requirements of time and space coordination among UAV, which is also a process of optimization [10].

3. Track coordination mode of multi-UAV
The track coordination of multi-UAV mainly includes time coordination and space coordination [11]. It is necessary to guarantee the minimum radar detection probability and the acceptable mission duration, and to coordinate the UAVs to carry out reconnaissance, jamming and attack on the target at the same time.

3.1. Time synergy
At present, there are three main methods in time coordination of multi-UAV, one is to use the time of velocity variation, the other is to use the time of velocity control and trajectory planning to calculate the time of coordination, and the other is to use the method of short trajectory maneuver track segment maneuver[12]. In this paper, Scheduled Arrival Time (SAT) is used to coordinate the flight path of multi-UAV to reach the target area of the mission with the least total cost. In order to effectively carry out time-based cooperative route planning, information is exchanged and shared through air-ground and air-to-air communication, and the model of time-based cooperative algorithm is optimized to obtain the minimum cooperative cost.

The arrival time t of route planning is regarded as a time co-variable, the $T^S$ of time domain is regarded as a co-space, and the flight path and speed are determined strictly according to the variable t, the algorithm model of collaborative variable must satisfy the requirement of collaborative route planning. Defines $y_{ia}$ as the current position of the i UAV, $y_{ib}$ is defined as the target position of the i UAV, and Y is defined as the set of all positions in the planned track area, then $y_{ia} \in Y, y_{ib} \in Y$. $x_i$ is defined as any flight path from $y_{ia}$ to $y_{ib}$, $X_i$ is the set of all flight paths, then $X_i(y_i) = \{x_i | x_i: y_{ia} \times y_{ib}\}$. The synergetic space $T^S$ contains a global synergetic variable and several local synergetic variables, which are denoted by $t_i$. The function $f_i: X_i \rightarrow IR^S$ is defined as a mapping from the set of flight paths $X_i$ to the cooperative space $T^S$. Let the i UAV fly from $y_{ia}$ to $y_{ib}$, according to $f_i$, the local cooperative variable set of the i UAV is $T_i(x_i) = \bigcup_{x_i \in X_i(y_i)} f_i(x_i)$, where $T_i \subset T^S$, the minimum local cooperative variable of the i UAV is $t_i^* = \min(T_i(y_i))$, if the route planning algorithm and the cost evaluation function $\emptyset$ have been determined, then we can determine a flight path $x_i^* = f_i(x_i^*)$ for the UAV i is determined accordingly.
3.2. Temporal-spatial synergy

When the multi-UAV carry out a specific mission to the same target, the track coordination mainly belongs to the calculation of the time coordination model, according to the different flight paths of $R$ and $Z$, at the same time of time coordination, the space cooperative flight paths should be established according to the time sequence, and the two subtasks $K_{i,j}, K_{i,j+1}$ of the task $K_i$ are the arrival of the support aircraft and the arrival of the mission aircraft in the specified airspace, therefore, the space coordination problem based on time series can be expressed as $(K_{i,j} < K_{i,j+1}, \Delta t_{j,j+1})$, that is, the unmanned mission aircraft must arrive in the designated airspace to execute the Space Mission $K_{i,j+1}$ within the time of $\Delta t_{j,j+1}$, the sequence is shown in figure 1(a). When the UAV reach the designated airspace, they must complete the submission $K_{i,j}$ to the target area, such as electronic jamming, task confusion, and so on, so that the UAV formation can effectively evade the target threat, execute the mission $K_{i,j+1}$, as shown in figure 1(b), the stars represent the target points of the UAV's trajectory.

![Time series synergy](image1)

![Space synergy](image2)

Figure 1. Multi-UAV space coordination based on time series synergy.

As can be seen from the time sequence diagram, the time $t$ for the UAV to reach the designated airspace must be between $t_k$ and $t_{k+1}$. In this way, the unmanned support aircraft can play an effective role in space coordination on the basis of time sequence, so as to provide support for the execution of $K_{i,j+1}$ missions. Only the spatial cooperation which satisfies the time sequence constraint is the real multi-UAV cooperation.

4. Construction of collaborative route planning model

4.1. Decision variables and collaborative function design

The goal of cooperative route planning is to find the least cost flight path based on time and space collaboration, that is, the route planning should achieve high integrated mission efficiency. The cost of route planning has two aspects: one is the range cost of the UAV, the other is the threat cost of the UAV. The track cost function is $J_k = \omega H_k + (1 - \omega) W_k$. Where $J_k$ represents the track cost of the UAV $k$, $H_k$ is the range cost, then $H_k = \sum_{i=1}^{n} h_{k,i}$, $h_{k,i}$ is the $i$-track distance of the UAV $k$, therefore, the flight time of the UAV in the target airspace can be reduced and the fuel consumption can be saved by shortening the total travel distance of the track.

Let $W_k$ be the threat cost, and let $W_k = \sum_{i=1}^{n} t_{k,i}$, $t_{k,i}$ is the $i$-track threat level of the UAV $k$, therefore, the decision-making is made to avoid the threat by planning the route away from the area where the threat is stronger. $\omega$ is the weight coefficient, by adjusting the size of $\omega$ to choose whether to reduce the track travel directly through the threat airspace. $n$ is the number of track segments. The number of threats to be considered in each segment is $Q$, the threat degree of each point on the track is calculated by integral calculation, and the threat intensity $D_{rm}^i$ of the $r$ threat on the $m$ split point in the $i$-track is obtained, and the distance $h_{rm}^i$ of the $r$ threat on the $m$ split point in the $i$-track is obtained. The shortest distance between two nodes in the route is selected and the distance from each node to the
threat source is obtained, the threat cost is \( t_{k,i} = \sum_r \sum_{m=1}^Q d_{r,m} \left( \frac{1}{h_{r,m}} + \frac{1}{d_{r,\alpha}} + \frac{1}{d_{r,\beta}} \right) \). In order to shorten the calculation time, we need to calculate the radar threat value at \( h_{i/5}, h_{i/2}, 4h_{i/5} \) of the segment separation distance, then the threat cost model with decision variable \( X_{i,r} \) is as follows:

\[
t_{k,i} = \sum_r \sum_{m=1}^Q X_{i,r} d_{r,m} \left( \frac{1}{h_{r,m}} + \frac{1}{d_{r,\alpha}} + \frac{1}{d_{r,\beta}} \right)
\]

The decision variable \( X_{i,r} \) represents the threat decision, \( X_{i,r} = 1 \) indicates that radar \( r \) is a threat to \( i \)-track and \( X_{i,r} = 0 \) indicates that radar \( r \) is not a threat to \( i \)-track. The schematic diagram is shown in figure 2.

![Figure 2. Schematic diagram of threat cost calculation model.](image)

We think that the value of decision variable \( X_{i,r} \) can be judged by the distance between track point and radar, then the value of decision variable under interference is:

\[
\begin{align*}
X_{i,r} &= 1, d_{r,\alpha} > R_r \\
X_{i,r} &= 0, d_{r,\alpha} \leq R_r
\end{align*}
\]

\( R_r \) is the detection range of the radar \( r \), which is determined by the radar range of the UAV, and is divided into short-range decision-making and long-range decision-making, the long-range decision variables for track coordination of UAV are:

\[
\begin{align*}
X_{i,r} &= 1, d_{r,\alpha} \leq R_{min} \\
X_{i,r} &= 1, R_{min} \leq d_{r,\alpha} \leq R_{max} \\
X_{i,r} &= 0, d_{r,\alpha} > R_{max} \\
X_{i,r} &= 0, R_{min} \leq d_{r,\alpha} \leq R_{max}
\end{align*}
\]

Among them, \( R_{min} \) is the minimum operating range and \( R_{max} \) is the maximum operating range. The short-range decision variables for track coordination of UAV are:

\[
\begin{align*}
X_{i,r} &= 1, d_{r,\alpha} \leq R_r \\
X_{i,r} &= 0, d_{r,\alpha} > R_r
\end{align*}
\]

Considering the total cost of flight path, multi-UAV path planning needs to realize cooperative flight path, so it is necessary to give the model of cooperative variable and cooperative function. If the velocity range of multi-UAV is \( v = [V_{min}, V_{max}] \), then the coordination variable model is \( t_k \in \left[ \frac{H_k}{V_{max}}, \frac{H_k}{V_{min}} \right] \). That is, the time range of UAV \( k \) flying along a certain flight path to reach the target point, that is the optimal flight path to reach the time. Define the synergetic function model as follows:

\[
J_k = e_i w_k t_k \frac{H_k}{H_k}
\]

Then the cost function model of multi-UAV is \( J = \min \sum_{k=1}^M J_k(t_k) \). The synergetic function \( J_k \) shows how the flight cost of UAV varies with the synergetic variables. For each track path, its flight time and track point is different, the \( J_k \) cost function also changes, the relationship between the cost function \( J_k \) and the co-variable \( t_k \) is shown in figure 3. It can be seen that by optimizing the
collaborative variables and collaborative functions in the collaborative route planning model, the collaborative route optimization can be achieved with the least amount of data transmission and operation. Because the co-operation function is an increasing function, the optimal track arrival time $t_k$ appears in the low-end region, and the UAV fleet has the minimum threat cost sum. For a particular flight path, let the value of the optimal trajectory arrival time $t_k$ be $t_a$, both $t_k$ and threat cost $W_k$ will increase when the speed of the UAV decreases. When the flight path is different, the increase of the flight path will be beneficial to the threat avoidance of the UAV, when the threat cost $W_k$ is reduced, the optimal track arrival time $t_k$ will increase.

Figure 3. Curve of multi-UAV cooperation function.

4.2. Genetic algorithm model for collaborative route planning

4.2.1. Coding mode. The track coordinate coding method uses polar coordinate system to mark the track of multi-UAV, sets A and B as the starting point and the target point of the track planning, (1,2, ... , m) as the track section points of UAV, and has m-1 track sections altogether. By polar coordinate coding, the polar diameter of track segment is $(1\sigma, 2\sigma, \cdots, m\sigma)$. The genes encoded by chromosomes are calculated using multiples of track-adjusted angle $\Delta \varphi_0$, and the maximum track-adjusted angle is $\Delta \varphi_{max}$, then there is and $\Delta \varphi_i = s_i \Delta \varphi_0$, and there is $|\Delta \varphi_i| \leq \Delta \varphi_{max}$. If the population size is $M = \Delta \varphi_{max}/\Delta \varphi_0$, then the value of each locus of the trace chromosome is $s_i \epsilon [-M, \cdots, -1, 0, 1, \cdots, M]$. 

4.2.2. Fitness function model of track chromosome. If the track is C and the locus chromosome fitness evaluation function is composed of the track cost and the threat cost, the fitness model is:

$$f_{cost}(C) = J_{c,k} + \sum_{i=1}^{2} \omega_i s_i(C)$$  \hspace{1cm} (6)

By using this model, the adaptability of a single UAV whose flight path distance is greater than the maximum range is adjusted, at the same time, the trajectory planning of a single UAV whose trajectory terminal adjustment angle exceeds the maximum trajectory adjustment angle is transformed into the problem of the minimization of the trajectory chromosome fitness.

4.2.3. Genetic operator model. In the model of genetic algorithm, genetic operators adopt adaptive crossover rate and chromosome mutation rate, because genes need to be in the range of value when chromosome is encoded, the real value of chromosome mutation must be restricted in $[-M, M]$, then the adaptive crossover rate model is:

$$P_z = \begin{cases} P_{z1} - \frac{(P_{z1} - P_{z2})(f' - f_{avg})}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ P_{z1}, & f' < f_{avg} \end{cases}$$ \hspace{1cm} (7)

And the adaptive mutation rate model of chromosome is:

$$P_b = \begin{cases} P_{b1} - \frac{(P_{b1} - P_{b2})(f'' - f_{avg})}{f_{max} - f_{avg}}, & f'' \geq f_{avg} \\ P_{b1}, & f'' < f_{avg} \end{cases}$$ \hspace{1cm} (8)
Among them, $f_{avg}$ is the average fitness rate of chromosome evolution, $f_{max}$ is the maximum fitness rate, $f'$ is the larger value of cross-individual fitness, $f''$ is the variant individual fitness.

5. Simulation of cooperative route planning

In this paper, the decision variables and the collaborative function model proposed by collaborative route planning are simulated in an improved genetic algorithm. In the integrated environment of Matlab, the parameters of the improved genetic algorithm are set as follows: population size 100-500, max evolutionary algebra 200, adaptive crossover rate $P_{x1} = 0.95$, $P_{x2} = 0.55$, adaptive mutation rate $P_{m1} = 0.02$, $P_{m2} = 0.002$, the UAV adopts mid-low air track, altitude is 2000m to 3000m, terrain scale is 100km×100km, multi-circle area represents different threat range.

![Figure 4. Track planning simulation.](image1)
![Figure 5. Simulation of cooperative route planning.](image2)
![Figure 6. Simulation diagram of mixed formation route planning.](image3)

(1) Figure 4 shows the two UAVs starting from the coordinates (12,12) and (12,90), and there are no unmanned support aircraft. The UAV are visible from the figure and have reached the target range of 94.8 km and 92.3 km respectively. The target point can be executed at the same time by adjusting the track coordination variable $t_k$. (2) Figure 5 shows the flight path of the unmanned mission aircraft in coordination with the unmanned support aircraft. As shown in figure 5, the UAV divides the radar threat area on the top left and bottom left of the map into two separate parts, this is of great significance to the mission success rate and the survival rate of the unmanned mission aircraft. (3) Figure 6 is the simulation result of route planning for a single UAV after adjusting the range cost
coefficient. Figure a is a route map for route planning with a range cost factor $H_k = 0.3$, and figure b is a route map for route planning with a range cost factor $H_k = 0.8$, and figure c shows that after adjusting the range cost coefficient, the unmanned mission aircraft and the unmanned support aircraft carry out the mission track in coordination. By the coordination of the unmanned support aircraft, the threat cost is greatly reduced, thus providing a wider airspace area for the mission.

6. Conclusions
Aiming at the effectiveness of multi-UAV cooperative path planning, a model of cooperative path planning is presented, and the decision variables are introduced into the time-coordination, time-sequence-space coordination model of track cost, meanwhile using the improved genetic algorithm to solve the optimization process of flight path coordination, and then the real-timeness and validity of flight path coordination are solved.

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