DOI: 10.13009/EUCASS2019-424

A Multi-UAV Collaborative Real-time Path Planning Method Under Time-space Constraints

Quan Zhao, Ke Li*, Peipei Liu*, Haotian Shi*, Chen Niu**, Kun Zhang**
**Northwestern Polytechnical University*
Xi'an 710072, China, and kunzhang029@gmail.com
***Xi'an JiaoTong University*
Xi'an 710061, China, and kunzhang029@gmail.com

Abstract
This paper presents a multi-UAV 3D path planning method based on sparse A* algorithm. Firstly, the UAV performance constraints model is established. Secondly, the improved three-dimensional sparse A* path planning algorithm is proposed. Thirdly, the collaborative path planning correction mechanism under a dynamic environment is designed, which uses an established correlation-impact degree model. Finally, based on an assumed battlefield environment, the method is simulated. The results show that the algorithm can carry out multi-UAV path planning and meet the time-space coordination, the collaborative path planning correction mechanism can effectively deal with the sudden threat.

1. Introduction

Traditional path planning algorithms include A* algorithm and its variants [1-2], GA (Genetic Algorithm)[3-4], Ant colony optimization algorithm [5] and other evolutionary algorithms, as well as geometric methods such as Bubins [6-7]. Evolutionary algorithms usually have slower computation speed, and their performance is highly dependent on the initial seeds. The traditional geometric method has a small amount of computation, but the planned path cannot guarantee optimality, and in a complex environment, the complexity of the algorithm will increase accordingly. The more commonly used algorithm in UAV path planning is A* algorithm and its variants, which has a faster calculation speed and can consider the path cost factors.
Sparse A* algorithm (SAS) is a common variant of A* algorithm [8]. The SAS algorithm was first used to solve the single path planning problem in the two-dimensional environment, which can well handle the constraints such as the minimum segment length, the maximum horizontal angel, and the maximum path length. The two-dimensional SAS algorithm uses a sparse expansion method when expanding nodes, which greatly reduces the search space. Using a similar method, some studies [9-10] combine the maximum climb/dive angle constraints to make the sparse expansion in three-dimension, and propose the 3D version of the SAS algorithm. The 3D SAS algorithm combines the minimum segment length, maximum horizontal angle variation, maximum pitch angle variation, path length constraint, flight height constraint, and fixed target attack direction into the algorithm. When expanding a node, the SAS algorithm does not traverse each location unit in the area, but only considers several of the branches, usually dividing the horizontal direction and the vertical direction. The distance between these nodes and the current node is segment length which should be greater than minimum segment length.
This work presents a multi-UAV 3D path planning method based on sparse A* algorithm. The method is proposed to solve the problem of multi-UAV collaborative real-time path planning under the influence of sudden threats with time-space coordination.
Firstly, the UAV performance constraints model is established based on the UAV motion model and some tactical requirements. The UAV performance constraints model includes pitch angle variation constraint, horizontal angle variation constraint, minimum segment length constraint, whole path length constraint, height constraint, and so on.
Secondly, the improved three-dimensional sparse A* path planning algorithm is proposed. And a planned path length coordination factor calculation model and a cooperative anti-collision constraint model for multi-UAV path planning are established. The planned path length coordination factor is used to meet time coordination, and the cooperative anti-collision constraint is used to satisfy spatial coordination. The sparse A* algorithm process is modified and extended for multi-UAV cooperation. The cost function is composed of threat factor, path length factor, required angle factor and multi-UAV path coordination factor, etc.

DOI: 10.13009/EUCASS2019-424

Thirdly, the correlation-impact degree model of the multi-UAV path with a sudden threat is established, then the collaborative path planning correction mechanism under a dynamic environment is designed. When a sudden threat occurs, the current state of each UAV and the correlation-impact degree on the multi-UAV path are obtained. Re-execution timings of the improved sparse A* algorithm is determined by the obtained information.
Finally, the simulation is carried out based on an assumed battlefield environment, which is established with traditional terrain, radar, and some other threat models. The simulation results show that the improved sparse A* algorithm can reasonably and effectively carry out multi-UAV path planning and meet the time-space coordination, the collaborative path planning correction mechanism under a dynamic environment can effectively deal with the sudden threat in the planning environment.

2. UAV Performance Constraints Model

In the problem of flight path planning, it is necessary to comprehensively consider the maneuvering performance constraints of UAV. The UAV performance constraints include the maximum pitch angle variation constraint, the maximum horizontal angle variation of the UAV in a certain range, the flying height constraint, and the whole path length constraint, etc. Considering that the SAS algorithm is planned according to the step with a segment length, it is also necessary to consider the minimum segment length constraint. If the performance constraints of the UAV are taken into account, it can be guaranteed that the final planned waypoints is flyable. The planned flight path can be generated according to the planned waypoints, it can be provided for actual control of the UAV.

2.1 Minimum Segment Length Constraint

The minimum segment length constraint is the shortest distance that the UAV must fly directly before changing the current attitude. Usually, the distance of 1s when the UAV at the cruising speed is taken. The running step length of the SAS algorithm should not be smaller than this value. Otherwise, the planned path is not suitable for the actual situation. If the minimum segment length $L_{\text{min\_step}}$ is set, the UAV needs to satisfy the following formula when changing the attitude:

$$L_{\text{step}} \geq L_{\text{min\_step}} \tag{1}$$

Where L_{step} is the length of the path segment between two adjacent waypoints. A fixed segment length is usually used in the SAS algorithm to make it greater than or equal to the minimum segment length. What’s more, in using of the algorithm results, for example, during further smoothing process, the value of L_{step} may change.

2.2 Maximum Pitch Angle Variation Constraint

The maximum pitch angle variation constraint contains two parts, the maximum climb angle constraint and maximum dive angle constraint. They must be considered when planning a path of a fixed-wing UAV. The main factors affecting the maximum climb angle or the maximum dive angle include the UAV’s engine performance, weather conditions, flight altitude and UAV’s airfoil structure. The climb angle and the dive angle should not be too large, otherwise it may cause stall. The maximum climb angle and maximum dive angle can be directly analyzed by the performance of the UAV as its basic parameter.
Note that the maximum climb angle is $\gamma_{\text{min\_climb}}$ and the maximum dive angle is $\gamma_{\text{min\_dive}}$. Under normal conditions, the dive angle γ_{dive} and the climb angle γ_{climb} are approximately equal to the pitch angle. When calculating, selecting stronger conditions and ignoring the possible large maneuver of the UAV, the angular relationship between the waypoint $P_i : (x_i,y_i,z_i)$ and the waypoint $P_{i+1} : (x_{i+1},y_{i+1},z_{i+1})$ should satisfy the following formula:

$$\begin{cases} \tan\gamma_{\text{climb}} = \dfrac{z_{i+1}-z_i}{\sqrt{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}} \leq \tan\gamma_{\text{max\_climb}}, & z_i - z_{i-1} > 0 \\ \tan\gamma_{\text{dive}} = \dfrac{z_{i+1}-z_i}{\sqrt{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}} \leq \tan\gamma_{\text{max\_dive}}, & z_i - z_{i-1} < 0 \end{cases} \tag{2}$$

DOI: 10.13009/EUCASS2019-424

2.3 Maximum Horizontal Angle Variation Constraint

The maximum horizontal angle constraint means that the steering capability of the UAV in the horizontal direction is limited between two adjacent segments in path. Normally, the maximum horizontal angle variation constraint needs to consider the factors of cruise speed and segment length. Two adjacent segments have three waypoints $P_i : (x_i,y_i,z_i)$, $P_{i+1} : (x_{i+1},y_{i+1},z_{i+1})$, and $P_{i+2} : (x_{i+2},y_{i+2},z_{i+2})$, and their angular relationship should satisfy as:

$$\left|\tan\Delta\psi\right| = \left|\frac{(y_{i+2}-y_{i+1})-(y_{i+1}-y_i)}{(x_{i+2}-x_{i+1})-(x_{i+1}-x_i)}\right| \le \tan\Delta\psi_{\max} \tag{3}$$

$\Delta\psi$ is the horizontal angle variation between two adjacent segments, and $\Delta\psi_{\max}$ is the maximum horizontal angle variation.

2.4 Height Constraint

The flight height constraint includes two aspects. First, the UAV is generally considered to have a maximum flying height that cannot be exceeded. In addition, the UAV must ensure a certain height from the ground to avoid a crash. Let $P_t : (x_t,y_t,z_t)$ be a waypoint that passes during the flight of the UAV, and the following relationship needs to be satisfied:

$$\begin{cases} z_t - z_{\text{terrain}}(x_t, y_t) \ge \Delta z_{\min} \\ z_t \le z_{\max} \end{cases} \tag{4}$$

Where $\Delta z_{\min}$ is the minimum ground clearance height, $z_{\text{terrain}}(x_t,y_t)$ is the terrain height corresponding to (x_t,y_t), and $z_{\max}$ is the maximum flight altitude. During the SAS algorithm planning process, $P_t : (x_t,y_t,z_t)$ can be the point between the two waypoints.

2.5 Whole Path Length Constraint

Since the energy carried by the UAV is generally limited, the maximum flight length of the UAV exists. During calculating, the maximum path length of the UAV is generally set to the straight line distance from the planned start waypoint to the planned target waypoint. Let the maximum path length to $L_{\text{max\_path\_length}}$, the planned waypoints are P_1, P_2, …, P_r, and P_s is one of candidate waypoint expanded by P_r. If P_{target} is the planned target waypoint, the following condition must be met:

$$\left\|P_s - P_r\right\| + \left\|P_{\text{target}} - P_s\right\| + \sum_{i=1}^{r-1}\left\|P_{i+1} - P_i\right\| \le L_{\text{max\_path\_length}} \tag{5}$$

3. Improved Three-dimensional Sparse A* Path Planning Algorithm

3.1 Planned Path Length Coordination Factor

In the process of multi-UAV path planning using sparse A* algorithm, the whole path length of each UAV from the start waypoint to the planned target waypoint is unknown, but the estimated total length of each UAV can be calculated. It equals the sum of the planned path length and the straight-line distance from the current planned node to the target waypoint. In the case where the performance of the UAV (mainly judged by the cruising speed) is close to or the same, if the values of the estimated total length of the different UAVs can be close to each other, the UAVs have similar time-consuming when arriving at their target. If the performance of the UAV has a certain difference, it can be corrected by multiplying the estimated total length of the path by a certain coefficient. Let the maximum path length to

DOI: 10.13009/EUCASS2019-424

$L_{\text{max\_path\_length}}$, the planned waypoints are P_1, P_2, … , P_r, and P_s is one of candidate waypoint expanded by P_r. If P_{target} is the planned target waypoint. The estimated total length of path $L_{\text{estimated\_total\_length}}$ is calculated as follows:

$$L_{\text{estimated\_total\_length}} = \left\| P_s - P_r \right\| + \left\| P_{\text{target}} - P_s \right\| + \sum_{i=1}^{r-1} \left\| P_{i+1} - P_i \right\| \tag{6}$$

When there are k UAVs, the planned path length coordination factor of $R_{\text{cooperate},\, i}$ of the i-th UAV in candidate waypoint P_s is:

$$R_{\text{cooperate},i} = \mathrm{C}_{\text{cooperate}} \left(\operatorname*{Max}_{k} L_{\text{estimated\_total\_length},k} - L_{\text{estimated\_total\_length},i} \right) \tag{7}$$

Where $\mathrm{C}_{\text{cooperate}}$ is a coefficient can be adjusted. The planned path length coordination factor of $R_{\text{cooperate},\, i}$ can be used in the calculation process, so as to meet time coordination. When the performance is insufficient, a recommended cruising speed of the UAV is given according to the length of the final planned path.

3.2 Cooperative Anti-collision Constraint Model

Spatial coordination mainly refers to when UAVs are flying, each UAV must be at a safe distance, which is related to the maneuverability of UAVs. Let a certain time t during the flight of the i-th UAV pass $P_{t,i}$: ($x_{t,i}$,$y_{t,i}$,$z_{t,i}$), and the same time t during the flight of the j-th UAV pass $P_{t,j}$: ($x_{t,j}$,$y_{t,j}$,$z_{t,j}$), then it must satisfy the following relationship:

$$\left\| P_{t,i} - P_{t,j} \right\| \geq \Delta L_{\text{min\_safe}} \tag{8}$$

Where $\Delta L_{\text{min\_safe}}$ is the minimum safety distance. When the planning targets of UAVs are very close, the position of each UAV will inevitably approach when the planning is about to end. Therefore, when each planning process approaches the planned target waypoint, $\Delta L_{\text{min\_safe}}$ may change to a smaller value.

The relationship described in equation (8) has different implementation methods in the planning process. For the simple condition, it is possible to calculate line spacing between the flight path segments generated by the current planning and the last several segments of the existing other UAV's path, then we can make sure whether the minimum safe distance is met, and the difference of possible recommended cruise speeds between different UAVs needs to be considered. Therefore, the parameter of the algorithm is a process of gradually iterative adaptation. Generally, the space coordination constraint needs to be stronger.

3.3 Cost Function

The basic cost function of the A* algorithm is in the form of:

$$f(n) = g(n) + h(n) \tag{9}$$

Where n is the current planning node, $f(n)$ is the total cost function, $g(n)$ is the actual cost function, and is related to the planned path, and $h(n)$ is the estimated cost function, and is related to the predicted path. Variants of A* algorithms usually have optimization and refinement of the cost function. For the improved multi-UAV three-dimensional sparse A* algorithm described in this paper, the cost function includes the following costs:

(1) Height threat cost: Height threat cost is an actual cost. In general, considering that UAVs can use terrain to hide themselves, the higher the flight, the more likely it is to be captured by the enemy radar, the greater the likelihood to be damaged. Therefore, the flying height of the UAV is taken as one of the cost factors. Let P_t : (x_t,y_t,z_t) be a waypoint that passes during the flight of the UAV, the height threat value at P_t is:

DOI: 10.13009/EUCASS2019-424

$$R_{\text{height}}(P_t)=\begin{cases}1-\dfrac{(z_t-z_{\max})^4}{z_{\max}^4}, & z_{\text{terrain}}(x_t,y_t)+\Delta z_{\min}\le z_t\le z_{\max}\\ 1, & z_t>z_{\max}\end{cases} \tag{10}$$

The height threat value from the start waypoint to the planning waypoint P_t : (x_t,y_t,z_t) is numerically integrated and multiplied by a coefficient to obtain the height threat cost $g_{\text{height}}(P_t)$.

(2) Terrain threat cost: The cost of terrain threat is an actual cost. Terrain threats mainly refer to peaks and highlands that may cause obstacles to UAVs at a certain flight altitude. The influence of peaks or highlands on the horizontal direction is only considered. The terrain threat cost varies according to the terrain modelling, and there are different ways. The terrain threat value from the start waypoint to the planning waypoint P_t : (x_t,y_t,z_t) is numerically integrated and multiplied by a coefficient to obtain the terrain threat cost $g_{\text{terrain}}(P_t)$.

(3) Task threat costs: the mission threat costs are actual costs. Three types, including enemy radar threats, enemy missile threats and atmospheric threats (referring to a certain range of climatic conditions that are not conducive to UAV flight) are considered. Depending on the environment modeling, the mission threat costs come in different forms. Each mission threat value from the start waypoint to the planning waypoint P_t : (x_t,y_t,z_t) is numerically integrated and multiplied by a coefficient, then they were accumulated to the mission threat cost $g_{\text{task\_threat}}(P_t)$.

$$g_{\text{task\_threat}}(P_t)=g_{\text{radar}}(P_t)+g_{\text{missile}}(P_t)+g_{\text{climate}}(P_t) \tag{11}$$

(4) Target attack angle cost: The target attack angle cost is an estimated cost. The target attack angle refers to a given three-dimensional pose that the UAV should satisfy when it reaches its target. The target attack angle cost is designed according to the deviation of the current planned waypoint position from the direction of the target attack angle, as shown in the following figure:

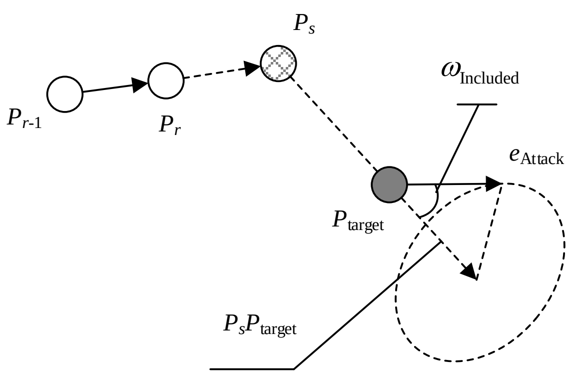

Figure 1: target attack angle cost

Where the current planning waypoint is P_s, the target waypoint is P_{target}, ω_{Included} is direction deviation, and e_{Attack} is the direction vector of the target attack angle, then the target attack angle cost of the current planning waypoint is:

$$h_{\text{attack}}(P_s)=\begin{cases}0, & \|P_{\text{target}}-P_s\|\ge k_{\text{a}}L_{\text{start\_target}}\\ k_{\text{b}}\omega_{\text{Included}}, & \|P_{\text{target}}-P_s\|<k_{\text{a}}L_{\text{start\_target}}\end{cases} \tag{12}$$

Where $L_{\text{start\_target}}$ is the straight line distance from the start waypoint to the target waypoint, and k_{a}, k_{b} are coefficients, usually, $k_{\text{a}}=1.0$, $k_{\text{b}}=1/\pi$.

(5) Planned path length cost: The planned path length cost is actual cost. If the planned waypoints are P_1, P_2, … , P_r, and P_s is one of candidate waypoint expanded by P_r, the planned path length cost is:

DOI: 10.13009/EUCASS2019-424

$$g_{\text{planned\_length}}(P_s) = \mathrm{C}_{\text{planned\_length}}\left(\left\|P_s - P_r\right\| + \sum_{i=1}^{r-1}\left\|P_{\text{i+1}} - P_i\right\|\right) \tag{13}$$

(6) Estimated path length cost: The estimated path length cost is estimated cost. The straight line distance from the current planned waypoint to the target waypoint is used as the estimated path length. If the planned waypoints are P_1, P_2, … , P_r, and P_s is one of candidate waypoint expanded by P_r, the estimated path length cost is:

$$h_{\text{estimated\_length}}(P_s) = \mathrm{C}_{\text{estimated\_length}}\left\|P_{\text{target}} - P_s\right\| \tag{14}$$

In summary, if the planned waypoints are P_1, P_2, … , P_r, and P_s is one of candidate waypoint expanded by P_r, then cost function of the improved multi-UAV three-dimensional sparse A* planning is:

$$\begin{aligned} f(P_s) = \quad & g_{\text{planned\_length}}(P_s) + g_{\text{height}}(P_s) + g_{\text{terrain}}(P_s) + g_{\text{task\_threat}}(P_s) \\ & + h_{\text{attack}}(P_s) + h_{\text{estimated\_length}}(P_s) + R_{\text{cooperate}}(P_s) \end{aligned} \tag{15}$$

3.4 Method Of Three-dimensional SAS Algorithm Node Expansion

As shown in the following figure, in the vertical plane, the angles in the range of -$\gamma_{\text{max\_dive}}$ to $\gamma_{\text{max\_climb}}$ are equally divided to generate branches of optional P_s.

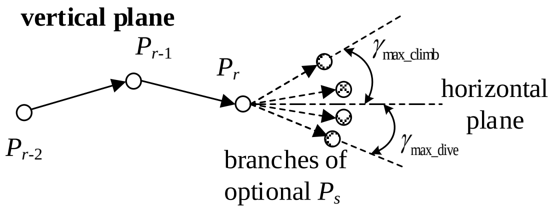

Figure 2: Angel partition in the vertical plane

On the horizontal plane, the angles in the range of -$\Delta\psi_{\max}$ to $\Delta\psi_{\max}$ are equally divided to generate branches of optional P_s.

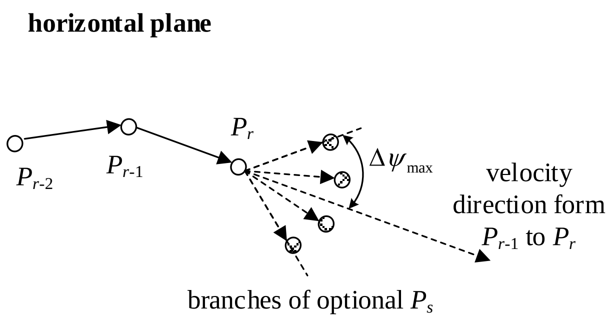

Figure 3: Angel partition in the horizontal plane

DOI: 10.13009/EUCASS2019-424

By integrating the nodes to be extended within the maximum pitch angle variation and the maximum horizontal angle variation constraint, a set of nodes to be expanded can be generated for subsequent constraints judgment and cost function value calculation. The option selected from this set that satisfy the constraints and has the lowest cost function value is (r+1)-th waypoints. Since the candidate extension nodes generated by the algorithm are discrete, the calculated path may have certain twists and turns, and the number of branches is appropriately selected (for example, an odd number of branches are selected), and additional join the branch with the same velocity direction with the upper path segment can make the path planning result smoother.

3.5 The Improved Multi-UAV Three-dimensional Sparse A* Algorithm Process

The improved multi-UAV three-dimensional sparse A* algorithm is based on the single UAV three-dimensional sparse A* path planning algorithm, transforming its process into multiple UAV simultaneous operation planning, and introducing the planned path length coordination factor and cooperative anti-collision constraint, makes it possible to satisfy time coordination and spatial coordination.
The 3D sparse A* route planning algorithm is shown below:

Table 1: The three-dimensional sparse A* path planning algorithm

Algorithm 1 :The three-dimensional sparse A* path planning algorithm
Put the start waypoint as a node into the OPEN list ;
do while (OPEN !=NULL)
Get the node with the lowest total cost function value from the OPEN list as $P_{\min}$;
if ($\lVert P_{\min}- P_{\text{target}} \rVert <0.5L_{\text{step}}$)
Return successful running, output waypoints;
else
Put $P_{\min}$ to the CLOSED list ;
According to the node $P_{\min}$ to expand optional nodes, generate the set of nodes to be selected as S ;
Traversing nodes in S to determine whether it satisfies the performance constraints of UAV;
if (Exist node(s) in S that satisfy constraints)
Calculate the total cost function value of node(s) that satisfy constraints in S;
Put node(s) in S that satisfy constraints to the OPEN list ;
Sort the OPEN list ;
end if
end if
loop
Return failed running ;
Comments : A node is a data structure that contains parent and child node indexes and information of a waypoint.

The improved multi-UAV three-dimensional sparse A* algorithm is shown below:

Table 2: The improved multi-UAV three-dimensional sparse A* path planning algorithm

Algorithm 2 :The improved multi-UAV three-dimensional sparse A* path planning algorithm
Set parameters and coefficients in the algorithm;
Set the count of planned waypoints (abbreviated as CPW) for all UAVs to be 1;
Set the collaborative required count of waypoints (abbreviated as CPCW) to be 2 ;
do while (all UAVs' computing state are not complete)
Find the UAV with the smallest CPW as the current extending UAV, if there are multiple minimum values, choose one randomly among them;
do while (OPEN of the current extending UAV != NULL)
Get the node with the lowest total cost function value from the OPEN list of the current extending UAV as $P_{\min}$;
if ($\lVert P_{\min}- P_{\text{target,the current extending UAV}} \rVert <0.5L_{\text{step,the current extending UAV}}$)
Set the current extending UAV 's computing state to be complete and successful ;
break;
else
Put $P_{\min}$ to the CLOSED list of the current extending UAV;
According to the node $P_{\min}$ to expand optional nodes, generate the set of nodes to be selected as S ;

DOI: 10.13009/EUCASS2019-424


```
        Traversing nodes in S to determine whether it satisfies the performance constraints of the current extending UAV (includes the anti-collision constraint);
        if (Exist node(s) in S that satisfy constraints)
          Calculate the total cost function value of node(s) that satisfy constraints in S (The total cost function includes the planned path length coordination factor );
          Put node(s) in S that satisfy constraints to the OPEN list of the current extending UAV;
          Sort the OPEN list of the current extending UAV;
          (CPW of the current extending UAV)++;
        end if
        if  (CPW of the current extending UAV equals CPCW)
          break ;
        end if
      end if
      if (All of the CPWs are equal to CPCW)
        CPCW++ ;
      end if
    loop
    if (OPEN of the current extending UAV == NULL)
      Set the current extending UAV 's computing state to be complete and failed;
      Set the mark that the current extending UAV no longer participates in the calculation;
    end if
loop
Output the waypoints of all successfully planned UAVs;
Compute the recommended cruising speed that based on the path length of all successfully planned UAVs;
```

Comments : When a UAV 's computing state to be set as complete and successful, it still participates in the judgment of constraints if other UAVs need.

4. Collaborative Path Planning Correction Mechanism

4.1 Correlation-impact Degree Model Of Multi-UAV Path Based On Sudden Threat

During the flight of the UAV in accordance with the planned path, unpredictable threats may occur on its path, which requires the planning system to have a faster calculation speed and be able to handle sudden threat situation. Therefore the mechanism for planning corrections to existing paths is proposed. When a sudden threat occurs, information about the sudden threat can be obtained. Compared with the planned paths, the degree of impact of the sudden threat on the multi-UAV paths can be obtained. Based on this, the collaborative path planning correction mechanism is proposed. The process of calculating the correlation-impact degree is shown as follows:

1: Obtain the current real-time location of each UAV;
2: Add a sudden threat to the threat information set;
3: Traverse the threat information set, at same time traverse each UAV from the current location to the last waypoint, and calculate whether the sudden threat has an impact on the planned paths (including the sudden threat has no effect, the sudden threat has generated a threat zone, and the sudden threat has generated a no-fly zone, etc.. In case of the impact exist, when traversing waypoints of paths, the location of the specific affected section can also be calculated, and the estimated time contact to the threat can be obtained.

4.2 Using Of Correlation-impact Degree Model

After the correlation-impact degree of sudden threat is obtained, different path correction mechanisms can be designed according to the degree of impact. Different correction mechanisms can be adopted under different impact situations. Three path correction mechanisms are proposed as follows:

CASE 1: The sudden threat has no impact on the paths, and each UAV should fly in accordance with its planned path.

CASE 2: The sudden threat affects paths. If the estimated time contact to the threat is greater than a certain multiple of the time of re-planning calculation. The current real-time location of each UAV is used as a start waypoint to add a sudden threat to the threat information set. Carry out re-planning calculation;

CASE 3: The sudden threat affects paths. If the estimated time contact to the threat is smaller than a certain multiple of the time of re-planning calculation. The current real-time location of each UAV is used as a start waypoint to add a sudden threat to the threat information set. It needs to geometrically design the path to bypass the threat or start from the location close to the threat, then plan and integrate existing paths to form new paths and fly according to new paths.

DOI: 10.13009/EUCASS2019-424

5. Experimental Results And Conclusions

5.1 Comparison Between Different Minimum Safety Distance

As shown in the following Figure 4, the left one is the condition with minimum safety distance equals 0.5km, the right one is 1.5km. There are a total of 39 mountain peaks, 7 radars, 6 enemy missiles, and 4 atmospheric threats in the environment. The environment size is 130km×130km.

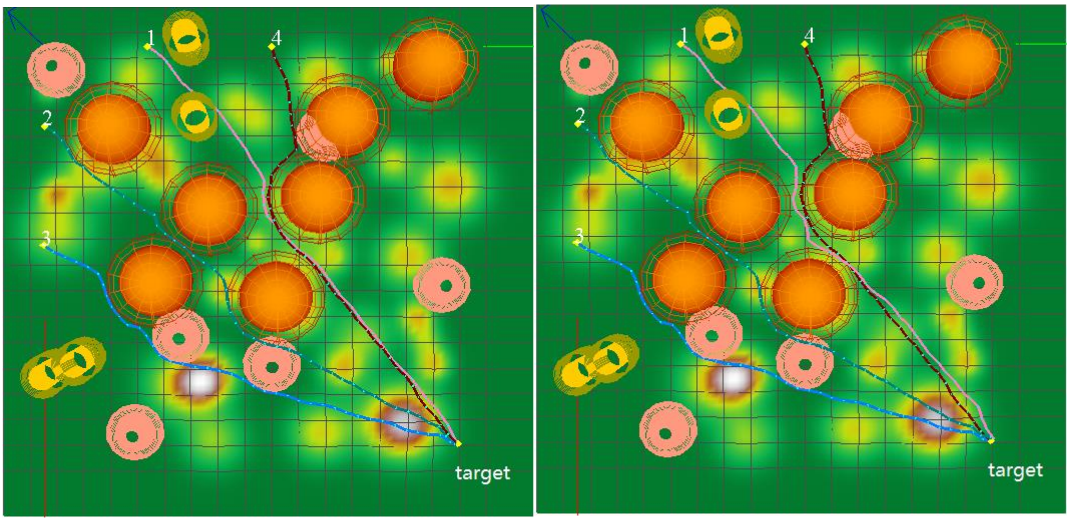

Figure 4: Angel partition in the horizontal plane

As shown in Figure 4, the cooperative anti-collision constraint has the effect it should have.

5.2 Comparison Between Different Planned Path Length Coordination Factor And Environments

As shown in the following Table 1, Case 1 has the environment with no peak, radar or missile, Case 2 has a total of 4 mountain peaks, 3 radars, 1 enemy missile, and 1 atmospheric threat in the environment, Case 3 has a total of 39 mountain peaks, 7 radars, 6 enemy missiles, and 4 atmospheric threats in the environment. The environment size is 130km× 130km. In three cases, the start waypoint of the 4 UAVs remains unchanged, and the target waypoint takes random value within range [75km~100km, 75km~100km, minimum permissible height]. The data presented were obtained from at least 40 simulations. The simulations calculated the variance of count of segments divided by average number of count of segments as an indicator of coordination.

Table 3: Variance of count of segments divided by average number of count of segments

	Case 1	**Case 2**	**Case 3**
$C_{cooperate}$=0.0	9.5051	7.2217	3.4494
$C_{cooperate}$=0.01	9.5014	7.1091	3.9270

The results show that when the environment is not too complex (in Case 2), the time coordination has the best performance. Too complicated environment will make the time coordination performance worse. It is because other factors in the complex environment mask the performance of the planned path length coordination factor.

DOI: 10.13009/EUCASS2019-424

5.3 Scenario With Sudden Threat Occurs

As shown in the following Figure 5, the figure shows the scenario sudden threats were added from outside at two moments. There are a total of 4 mountain peaks, 3 radars, 1 enemy missile, and 1 atmospheric threat in the environment. The environment size is 130km×130km.

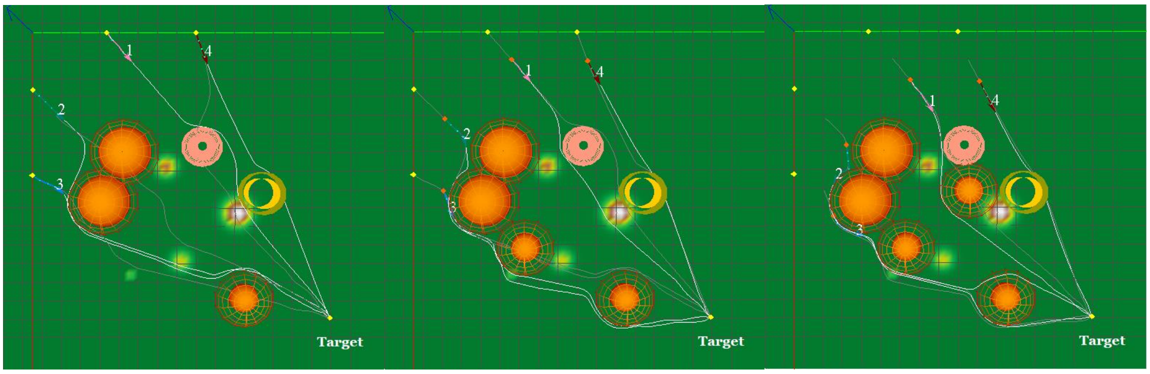

Figure 5: Scenario with sudden threat occurs

The results show that the collaborative path planning correction mechanism under a dynamic environment can effectively deal with the sudden threat in the planning environment.

5.4 Conclusions

In this paper, a multi-UAV three-dimensional path planning method based on sparse A* algorithm is proposed. By comparing with the simulation without the planned path length coordination factor, the simulation results show that the improved sparse A* algorithm can reasonably and effectively carry out multi-UAV path planning and meet the time-space coordination. And the collaborative path planning correction mechanism under a dynamic environment can effectively deal with the sudden threat in the planning environment, so that the UAV can change the path in real time and normally perform the task when possible sudden threat occurs.
The A* algorithm has a wide application in UAV path planning. The cooperative anti-collision constraint and the planned path length coordination factor proposed in this paper is working in the space-time coordination of multi-UAV path planning, but there is still a lot of room for optimization. The idea of achieving time coordination through path length coordination, can further directly use the flight time so that it can be closer to real situation, and can do this by making certain adjustments to the existing processes and architectures. What's more, how to cooperate with the further modification and smoothing of the planned path to make the results of the algorithm more close to the actual application is also the key direction of the future work.

6. Acknowledgment

This work was supported by the Key Laboratory Project Foundation (6142504190105), the Innovative Talents Promotion Plan in Shaanxi Province (2017KJXX-15), the Science and Technology on Avionics Integration Laboratory and Aeronautical Science Foundation (20155153034).

References

[1] Kim Y, Gu D W, Postlethwaite I. 2008. Real-time path planning with limited information for autonomous unmanned air vehicles. *J. Automatica*. 44(3):696–712.
[2] Daniel K, Nash A, Koenig S, et al. 2014, Theta*: Any-Angle Path Planning on Grids. *J. Journal of Artificial Intelligence Research*. 39(1):533–579.
[3] Peng JL, Sun XX, et al. 2008, 3-D Path Planning with Multi-constrains. In: *2008 Chinese Control and Decision Conference*.3301–3305.
[4] Lu N, Gong Y, Pan J. 2016. Path planning of mobile robot with path rule mining based on GA. In: *28th Control & Decision Conference. IEEE*.1600–1604.

DOI: 10.13009/EUCASS2019-424

[5] Jie Chen, Fang Ye, Tao Jiang. 2017, Path Planning under Obstacle-Avoidance Constraints Based on Ant Colony Optimization Algorithm. In : *17th International Conference on Communication Technology, IEEE*. 1434–1438.
[6] Shanmugavel M , Tsourdos A , White B , et al. 2010. Co-operative path planning of multiple UAVs using Dubins paths with clothoid arcs. *J. Control Engineering Practice*. 18(9):1084–1092.
[7] Lin Y, Saripalli S. 2014, Path planning using 3D Dubins Curve for Unmanned Aerial Vehicles. In : *2014 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE*. 296–304.
[8] Shuai Guo, Shumei Yu. 2016, A strategy to escape from local traps for sparse A* algorithm. In : *2016 International Conference on Robotics and Biomimetics, IEEE*. 1802–1807.
[9] Carsten J, Ferguson D, Stentz A. 2007, 3D Field D*: Improved Path Planning and Replanning in Three Dimensions. In : *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*. 3381–3386.
[10] Hrabar S. 2008, 3D path planning and stereo-based obstacle avoidance for rotorcraft UAVs. In : *IEEE/RSJ International Conference on Intelligent Robots & Systems*. 807–814.
[11] Tansel Uras， Sven Koenig. 2015, An Empirical Comparison of Any-Angle Path-Planning Algorithms. In: *Proceedings of the Eighth International Symposium on Combinatorial Search*. 206–210.
[12] Dolgov D , Thrun S , Montemerlo M , et al. 2010, Path Planning for Autonomous Vehicles in Unknown Semi-structured Environments. *J. The International Journal of Robotics Research.* 29(5):485-501.
[13] Edin Dolicanin, Irfan Fetahovic, Eva Tuba, et al. 2018, Unmanned Combat Aerial Vehicle Path Planning by Brain Storm Optimization Algorithm. *J. Studies in Informatics and Control*. 27(1): 15-24.