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3D Multi-UAV Collaboration Based on the Hybrid Algorithm of Artificial Bee Colony and A*

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Abstract: Multi-UAV cooperative operation has more advantages in penetrating enemy defense systems, detecting targets and attacking missions. Firstly, a 3D multi-UAV track planning method based on the hybrid algorithm of artificial bee colony and A* is presented. Theoretical and simulation researches have shown that the hybrid algorithm has better performance in avoiding threats and smaller track cost compared to A* algorithm. Secondly, the adaptive time collaboration under the 3D multi-UAV collaborative track planning based on the hybrid algorithm is studied. According to the time arrange, the adaptive time coordination state is divided into simultaneous arrival, sequential arrival, and uncoordinated arrival. In the case of sequential arrival, we focus on the iterative selection of the arrival time difference instead of specified time intervals, which can maximize the possibility of the multi-UAV sequential arrival and enhance the ability of coordinated attack.

Key Words: Hybrid algorithm, 3D multi-UAV track planning, Adaptive time collaboration

1 Introduction

With the rapid development of the aviation technology and artificial intelligence, unmanned aerial vehicles (UAVs) have broad application prospects in civil fields and military investigations due to their flexible operation and low cost. The cooperative combat of multiple UAVs in military missions has more advantages than the single UAV in penetrating enemy defense systems, detecting targets, and attacking missions [1]. Track planning and multi-UAV collaboration have become the focus of current research.

The algorithm is the core part of the UAV's autonomous track planning [2]. Classical algorithms include A* algorithm, mixed integer linear programming (MILP) [3], distributed algorithms and so on. In these algorithms, A* algorithm has many researches and applications [4~6]. It is a classical heuristic search algorithm, which runs fast and can quickly solve and get the shortest path, but it is not ideal for avoiding threats and the track cost is relatively large compared with other algorithms; The intelligent algorithms include genetic algorithm (GA) [7, 8], particle swarm optimization (PSO), and artificial bee colony algorithm (ABC) and so on. Among them, the ABC algorithm simulates bee foraging, and has good global and local optimization ability. After iterative optimization, the ideal path can be obtained and the obstacle avoidance ability becomes strong. Reference [9] solved the UAV track planning in 3D environment with the ABC algorithm. The ABC algorithm requires a great number of bees and iterations to generate a reliable path with multiple track points. However, too many track points will complicate the calculation, too few makes the track uncertain. Due to the limitations of a single algorithm, improvement of algorithm and mix of multiple algorithms become common solutions. Reference [10] introduced the covariance to improve the ABC algorithm, and reference [11] proposed a mobile robot track planning algorithm based on the combination of ABC and RRT. In this paper, a hybrid algorithm combining ABC and A* is proposed to carry out three-dimensional UAV track planning. First, we determine a few number of track points and use the ABC algorithm to generate the initial planning to reduce the computational complexity and expect local and global optimality, the initial track is not certain due to too few track points; Then the adjacent initial track points are inserted track points which are planned with the A* algorithm to obtain the final certain track.

Multi-UAV collaboration is also one of the popular researches. Researches on multi-UAV collaboration include coordinated attacks [1, 5, 12, 13], UAV formation control [14], cooperative information collection [15], task assignment [16] and so on. Time coordination goal is one of the main tasks in multi-UAV coordinated attack. Considering the increasing effectiveness and power of combat, most of the time coordination focuses on arriving at the same time. But when the time cannot satisfy the simultaneous arrival constraint, arriving sequentially which has a similar attack effect can be taken into account.

Sequential arrival can also reduce the chance of exposure to enemy in air defense facilities at the time of investigation and evaluation. Reference [12] and reference [13] introduce the multi-UAV coordinated track planning of arriving at the same time and arriving sequentially with specified time intervals when not meet the simultaneous arrival requirements. Reference [17] proposed a method of track planning based on Laguerre diagram and closed-loop speed control to achieve multi-UAV sequential arrival with

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specified time intervals. However, it is difficult to achieve the sequential arrival when specify the time intervals. This paper considers searching adaptive time intervals by iterative judgment of the time difference of arrival to maximize the probability of multi-UAV sequential arrival to improve the multi-UAV attack effectiveness.

Based on the above, the rest of this paper is as follows: The second part introduces the track cost model; The third part studies the ABC algorithm, A* algorithm and the process of UAV track planning with the hybrid algorithm based on ABC and A*; The fourth part introduces the multi-UAV adaptive time coordination with the iteration of time difference; The fifth part is the simulation results and discussion; The sixth part is the research summary.

2 Track Cost Model

The track cost in UAV track planning is one of the track evaluation criteria. Track cost is as follows:

$$\mathrm{J} = (1-\beta)(J_{fule} + J_{height}/2) + \beta J_{threat} \quad (1)$$

Where β is the threat cost coefficient, $1-\beta$ is the fuel and height cost coefficient, $0 \leq \beta \leq 1$; J_{fule} is the fuel consumption cost, which is proportional to the path length in 2D and 3D track planning; J_{height} is the height cost which is equal to zero in 2D track planning and related to the height difference between adjacent track points on the minimum threat surface in 3D track planning; J_{threat} is the threat cost, the centre points of threatening mountains are accounted as the threat points and the threat range is the circular domain. The threat cost of a point is sum of the reciprocal of the fourth power of the distance between threat points and this point. When the track segment within the threat range, the track threat cost is the integral of the point threat cost along the track segment [18]; when the track segment is out of the threat range, the track threat cost is equal to zero. In order to simplify the calculation, the track threat cost is approximately equal to the sum of the threat cost at $1/10, 3/10, 5/10, 7/10$ and $9/10$ of the track segment instead of the integral of the point threat cost along the track segment.

3 Track Planning Algorithm

3.1 ABC Algorithm

The ABC algorithm [9~11, 19, 20] is a bionic intelligent algorithm. It divides bees into hiring bees, following bees and exploring bees. Hiring bees are responsible for finding the source of honey and share the information of the found honey source with the following bees through their dance. Following bees select the appropriate honey source to collect honey according to “roulette”. When the honey source cannot be updated to the maximum number of times, we need to abandon the original honey source and avoid being trapped in local optimum. At this time, the exploring bees are responsible for finding a new honey source instead of the original honey source. The ABC algorithm has good searching ability and can jump out of the local optimum. Within a certain range, the more the population of bees and the number of iterations, the better the track, but the spatial complexity and calculation time are multiplied, moreover, the local search ability of the ABC algorithm is weakly convergent.

3.2 A* Algorithm

The A* algorithm [4~6] is a classical heuristic search algorithm whose track cost formula is as follows:

$$\mathrm{f(n)} = \mathrm{g(n)} + \mathrm{h(n)} \quad (2)$$

n represents the current track point, $\mathrm{f(n)}$ represents the track cost, $\mathrm{g(n)}$ represents the track cost of the current point to the starting point, and $\mathrm{h(n)}$ represents the track cost of the current point to the end point, which is taken as the length between the two points.

The A* algorithm iteratively finds each track point to get the final path. Each track point has minimum track cost, which is searched from the nine-square grid points centered on the current track point. Due to the simple selection of track cost, the A* algorithm runs fast, but it also leads to insufficient optimization ability of the algorithm.

3.3 Track Planning with Hybrid Algorithm Based on ABC and A*

The flow chart of the hybrid algorithm is shown in Fig. 1. First, the initial track is obtained by ABC algorithm with fewer population of bees and fewer track points. The track between two adjacent track points is further planned by the A* algorithm to obtain more track points so that we can get a certain track. Proceed as follows:

1) Combine the actual environment with the threat model as the basic topography, and conduct the terrain smoothing and curvature limits to meet the UAV’s constraints, including climbing and diving angle, turning angle and minimum ground clearance to generate the minimum threat surface [21, 22]. Since 3D ABC optimization requires a large amount of computation and has a large spatial complexity, firstly, we convert the 3D track planning into a 2D track planning to simplify the operation. Projecting the 3D fusion topography onto the 2D plane, retaining the threat information and performing 2D track planning with the hybrid algorithm of this paper. The 2D and 3D track costs need to be applied to determine the optimal 2D track, and then the optimal 2D track points are projected back onto the 3D minimum threat surface to obtain a 3D track. This method can reduce the spatial complexity and calculation amount of searching directly in 3D space [21, 23].

2) The ABC algorithm optimizes the initial track points: In order to guarantee the operation speed, the fewer number of track points are preset (10 in the algorithm comparison simulation part and 5 in the multi-UAV collaboration simulation part). To ensure the excellent path and eliminate

the abnormal search situation, we need multiple operations to obtain multiple optimal paths and select one path with the lowest 3D track cost from them as the initial track.

3) A* algorithm optimizes the track: Select the adjacent track points in the initial track as the starting point and the end point respectively, and use the A* algorithm to conduct the second planning to obtain the track points between the initial track points, then get the final 2D track points.

4) Restore the height information of the optimal 2D track, which means project the 2D track points onto the minimum threat surface to obtain the 3D track points, and the 3D path is determined after the connection.

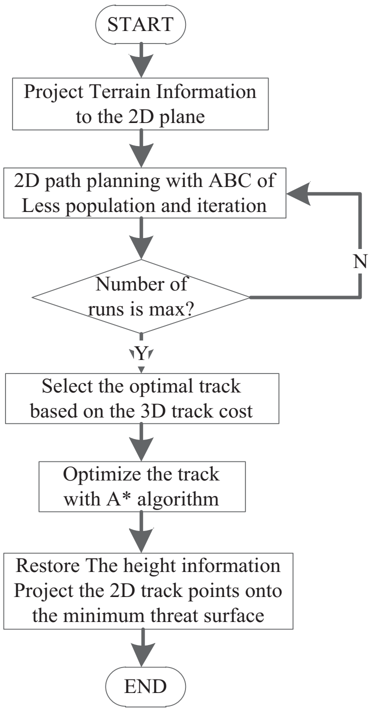


Fig. 1: Track planning with hybrid algorithm flow chart

4 Multi-UAV Collaboration——Adaptive Time Collaboration

In this paper, taking three UAVs as an example, the track length of each UAV obtained by the hybrid algorithm is Li, $i = 1,2,3$, and the flight speed range of the three UAVs is v, $v \in [100m/s, 150m/s]$. The flight time range of each UAV is Ti, $Ti \in [Li/150, Li/100]$, $i = 1,2,3$.

When these three Ti have a common intersection, the three UAVs can arrive at the same time; When there is no intersection, iterate over the time difference of arrival (Δt) and select the minimum Δt to make the three UAVs sequential arrival; If there is no Δt satisfy the condition, it is considered that the three UAVs cannot cooperate and the track needs to be re-planned. Finally, the speed of each UAV is calculated according to the arrival time.

The flow chart of adaptive time coordination of three UAVs is shown in Fig. 2. The iteration condition of Δt, time coordination state and the schematic diagram are shown in Table 1.

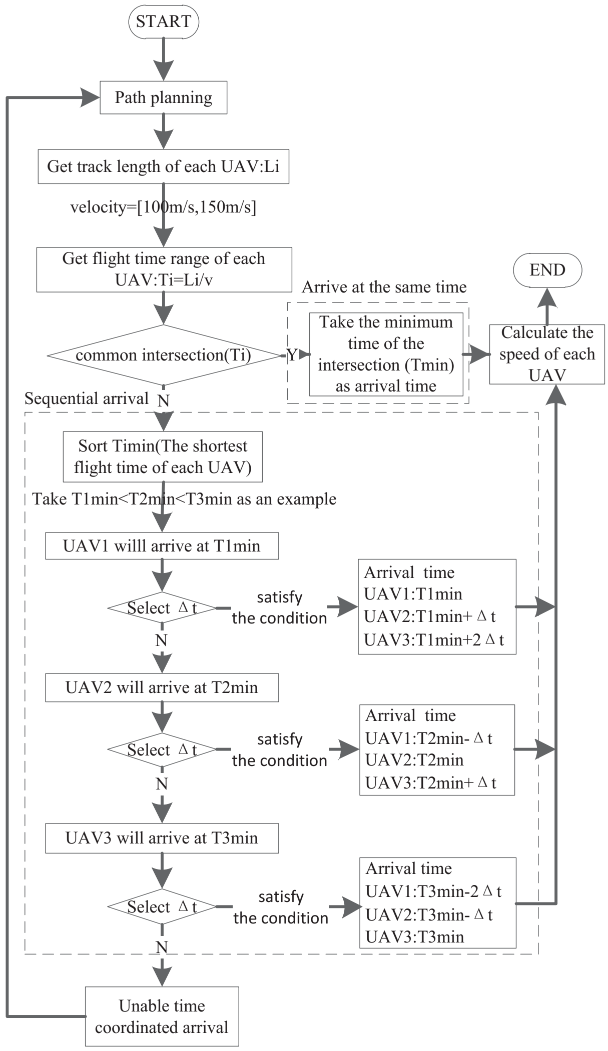
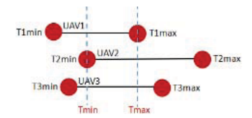
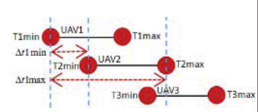
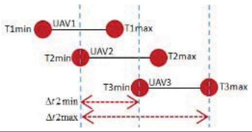
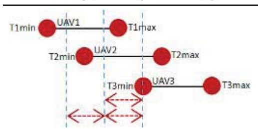


Fig. 2: Adaptive time constraint flow chart

Table 1: Adaptive time coordination condition

Schematic Diagram	Iteration Condition	State
	$\Delta t = 0$	Simultaneous Arrival
	$UAV1$ $will$ $arrive$ at $T1\min$ $\begin{cases} \Delta t \in [\Delta t1\min, \Delta t1\max] \\ T1\min + 2\Delta t \in [T3\min, T3\max] \\ \Delta t \in [0s, 600s] \end{cases}$	Sequential Arrival
	$UAV2$ $will$ $arrive$ at $T2\min$ $\begin{cases} \Delta t \in [\Delta t2\min, \Delta t2\max] \\ T2\min - \Delta t \in [T1\min, T1\max] \\ \Delta t \in [0s, 600s] \end{cases}$	Sequential Arrival
	$UAV3$ $will$ $arrive$ at $T3\min$ $\begin{cases} T3\min - \Delta t \in [T2\min, T2\max] \\ T3\min - 2\Delta t \in [T1\min, T1\max] \\ \Delta t \in [0s, 600s] \end{cases}$	Sequential Arrival

The iteration of Δt can make the UAV arrive as fast as possible with a small Δt. Compared with arriving sequentially with a specified Δt, the iterative process increases the possibility that the UAVs can satisfy the sequential arrival condition. In this paper, $\Delta t \in [0s, 600s]$ is required. The range of Δt can be set as needed in practical applications. In the future, we will consider the event-triggered control to save energy [24, 25].

5 Simulation

5.1 Topography Simulation

The Daxinganling area is selected from the geospatial data cloud (http://www.gscloud.cn/), and the Global Mapper software is used to intercept the area of 12.6km×12.6km and convert the topography data into .grd format for MATLAB reading. Set the interval to 30 meters, sampling and smoothing to get the basic topography simulation map as shown in Fig. 3.

Set the threat model and equivalent it to the peak model as equation (3). The fusion topography of the basic topography and threat model is as shown in equation (4).

$$z_2(x,y) = z_0 \sum_{i=1}^{n} z_i \exp[-\left(\frac{x-x_{0i}}{x_{si}}\right)^2 - \left(\frac{y-y_{0i}}{y_{si}}\right)^2 \quad (3)$$

$$z(x,y) = \max(z_1(x,y), z_2(x,y)) \quad (4)$$

Where z_0 is the topography reference height, x, y are the horizontal coordinate points, $z_1(x,y)$ is the basic topography height, $z_2(x,y)$ is the height of the threat model which is equivalent to the peak model, n is the number of peaks, and z_i is the highest height of the i-th peak, x_{0i} and y_{0i} represent the horizontal coordinates at the highest point of the i-th peak. x_{si} and y_{si} are slope parameters of the threat model.

Parameters: $z_0 = 6$, $n = 3$. The horizontal coordinates of the center points of the three threat models are $[50,100; 200,400; 350,100]$, the vertical coordinates corresponding the highest points are $[400; 450; 530]$, the slope parameters of the three threat models are set to $[200,130; 200,170; 110,160]$.

The fusion topography is shown in Fig. 4.

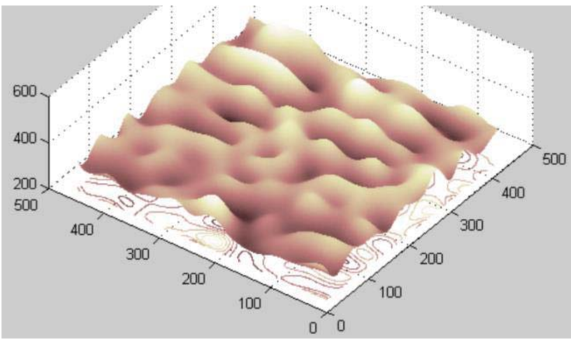


Fig. 3: Basic topography

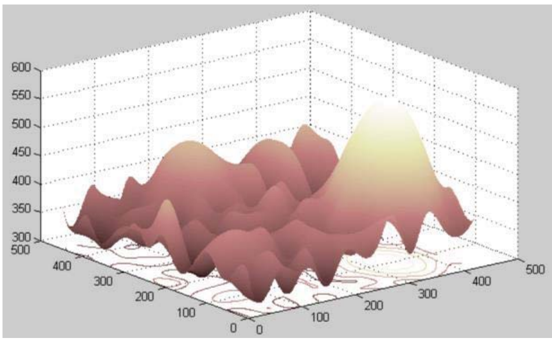


Fig. 4: Fusion topography

5.2 Comparison of Hybrid Algorithm and A*

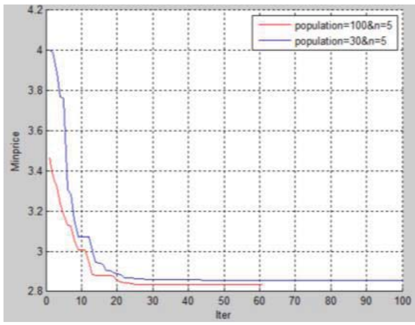


Fig. 5: ABC—Iterative of different population

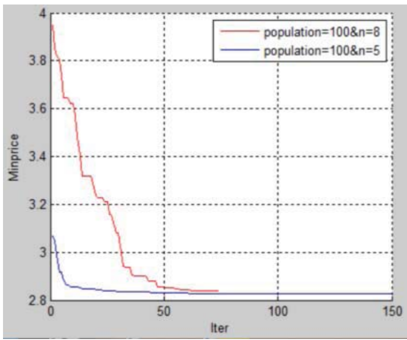


Fig. 6: ABC—Iterative of different track points numbers

Fig. 5 are the curves of the track cost to the number of iterations with 5 track points in population of 100 and 30 respectively. We can observe the change of the population has little effect on the final iteration convergence value and the number of iterations, but the run time from the start to the 60th generation is reduced from 33.43s of population 100 to 7.02s of population 30 in simulation. The result shows the population reduction can significantly shorten the iterative convergence time.

Fig. 6 are the curves of the track cost to the number of iterations with population 100 in track points of 5 and 8 respectively. We can observe the change of the number of track points has significant effect on convergence speed, with track points of 8, it requires more iterations to converge to the optimal value.

Fig. 7 and Fig. 8 are the simulation diagrams of the track planning by a single UAV using the A* algorithm and the hybrid algorithm respectively, the horizontal coordinate of the starting point is $(10,12.6)$ and the horizontal coordinate of the destination point is $(400,370)$, the maximum climbing angle is $60°$, curvature is 0.1.

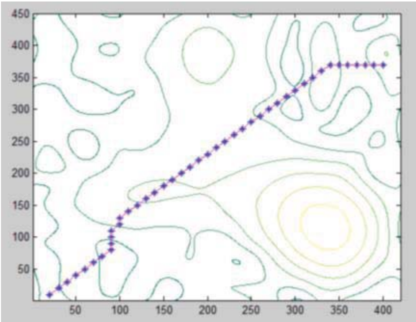


Fig. 7: Track planning with A*

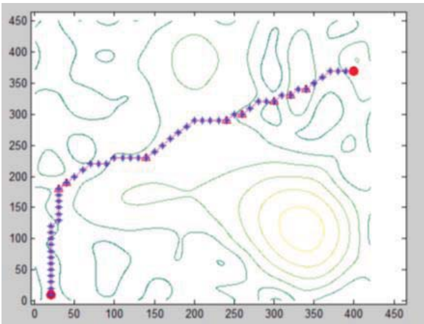


Fig. 8: Track planning with hybrid algorithm

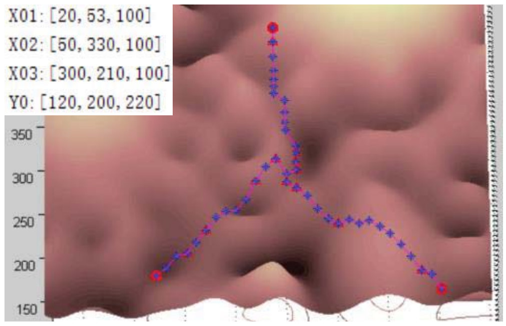
Table 2: Track costs comparison of two algorithms

Algorithm	Fuel and height cost	Threat cost	3D total cost
A*	178.1802	581.3259	480.5394
Hybrid	215.1557	124.7718	147.3678

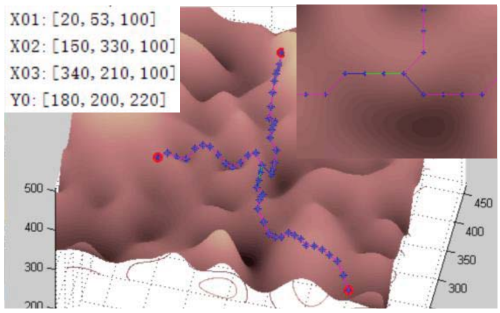
Table 2 shows the track costs comparison of two algorithms. The fuel consumption and height cost of hybrid algorithm related to the total length of the track is 215.1557, which is slightly larger than the 178.1802 of the track of the A* algorithm. However, the threat cost corresponding to the obstacle avoidance effect is reduced from 581.3259 of the A* algorithm to 124.7718 of the hybrid algorithm, showing a strong obstacle avoidance capability of the hybrid algorithm.

5.3 Multi-UAV Collaboration Based on the Hybrid Algorithm

The multi-UAV collaboration simulation is shown in Fig. 9. The population of the ABC is 50, the number of the preset track points is 5, and the number of iterations is 60. The UAV parameters refer to the multi-UAV cooperation part of Section 4 in this paper. X_{0i} indicate the coordinates of the starting points of the three UAVs, Y_0 indicates the coordinates of the destination points of the three UAVs.



(a) Simultaneous arrival



(b) Sequential arrival

Fig. 9: Multi-UAV adaptive time collaboration result

Fig. 9(a) shows the simultaneous arrival of the three UAVs. The running result shows there is an intersection of the three Ti, which is $[7363.9s, 9950.2s]$, Δt is $0s$, and $7363.9s$ is selected as the time when the three UAVs reach the destination point at the same time. The speed of each UAV is $137.04m/s$, $135.12m/s$ and $150m/s$; Fig. 9(b) shows the sequential arrival of the three UAVs, the running result shows there is no intersection of the three Ti, Δt is $393.3s$, and the arrival time of the three UAVs is $8059.6s$, $8452.9s$ and $8846.2s$, the speed of each UAV is $100.0014m/s$, $120.2346m/s$ and $150m/s$; The partial view inserted in the upper right corner near the destination point shows the sequential arrival. Three UAVs flew along the pink track until the first UAV arrived at the destination point, and then the two UAVs flew along the blue track. After the Δt time, the second UAV reached the destination point. The last UAV flew along the green track to the destination point after the Δt time again, and the three UAVs completed the sequential arrival.

6 Conclusion

This paper present a hybrid algorithm based on the ABC and A* to realize the 3D multi-UAV track planning. Simulation shows that the hybrid algorithm has smaller threat cost and smaller total 3D cost, which means the hybrid algorithm has better performance than A*. Then, the multi-UAV adaptive time collaboration is studied. UAVs can judge the time coordination state by the time ranges, and the time ranges are calculated by the track lengths and the speed range. When the state is simultaneous arrival, the multi-UAV should select the shortest arrival time. When the state is sequential arrival, the iteration process of arrival time difference is adopted, which can maximize the possibility of the multi-UAV sequential arrival and enhance the effectiveness of coordinated attack. When the state is uncoordinated arrival, the re-track planning is required. In the future, we can further study the multi-UAV mission assignment, increase the diversity of missions and strengthen the ability of UAVs to complete tasks.

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