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Distributed intelligent self-organized mission planning of multi-UAV for dynamic targets cooperative search-attack

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Abstract This article studies the cooperative search-attack mission problem with dynamic targets and threats, and presents a Distributed Intelligent Self-Organized Mission Planning (DISOMP) algorithm for multiple Unmanned Aerial Vehicles (multi-UAV). The DISOMP algorithm can be divided into four modules: a search module designed based on the distributed Ant Colony Optimization (ACO) algorithm, an attack module designed based on the Parallel Approach (PA) scheme, a threat avoidance module designed based on the Dubins Curve (DC) and a communication module designed for information exchange among the multi-UAV system and the dynamic environment. A series of simulations of multi-UAV searching and attacking the moving targets are carried out, in which the search-attack mission completeness, execution efficiency and system suitability of the DISOMP algorithm are analyzed. The simulation results exhibit that the DISOMP algorithm based on online distributed down-top strategy is characterized by good flexibility, scalability and adaptability, in the dynamic targets searching and attacking problem.

1. Introduction

With the development of the automation technology, the Unmanned Aerial Vehicle (UAV) system is becoming increasingly complex and powerful. The UAVs are expected to gradually enter the air force's main battle weapon and will partly replace some of the jet fighters and bomber, to account for most of the air defense and strike missions. According to the observe-orient-decide-act model, the Air Force Research Laboratory divided the UAV's autonomy capability into 10 levels.[1] Nowadays, the UAVs gradually rose from the tactical level to the strategic level. The multi-UAV cooperative control techniques play an important role, which include the task assignment,[2] path planning and replanning,[3] mission planning,[4] formation and reconfiguration,[5] communication network[6] and so on. In addition, the development of multi-UAV cooperative control techniques was investigated to promote further research.[7]

The centralized control architecture and the distributed control architecture are two types of the cooperative control

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architectures for multi-UAV.[8] Along with the improvement of UAV's performance, the distributed control architecture with superiorities of higher reliability, less computation and communication has been a research focus.[4–6] Therefore, the distributed control architecture is utilized in this paper. The specific strategies for the cooperative mission planning problem are mainly divided into two kinds: top-down scheme and down-top scheme. Although the top-down scheme based on the hierarchical decomposition strategy can effectively reduce the difficulty and complexity of the problem, it will consume large computation and communication costs when the battlefield situation changes dynamically. In contrast, the down-top scheme based on the self-organized strategy emphasizes each individual's dynamic response to the environment, and thus is more reliable and flexible. Several self-organized down-top schemes with simple calculation and good robustness have been presented based on the swarm intelligence. Ref.[9] surveyed the heterogeneous flying self-organized networks structure, and presented a variety of distributed gateway-selection algorithms. Ref.[10] proposed a fast and coupled solution for cooperative mission planning of multi-UAV with a distributed genetic algorithm.

Therefore, this work aims to solve the cooperative search-attack mission planning problem of multi-UAV in the dynamic environment with moving targets, and a novel self-organized down-top method is proposed. Different from the results in the literature, the main contributions are as follows.

(1) The multi-UAV cooperative search-attack integration problem for the dynamic targets in an uncertain environment is investigated, which has not been well addressed in the literature. Refs.[11–18] investigated the multi-UAV cooperative search-attack problem with stationary targets. Ref.[19] studied the cooperative search planning and task allocation of the multi-UAV for the moving targets. Ref.[20] and Ref.[21] mainly focused on the search task for moving targets. Ref.[22] developed a new cooperative network platform of multi-UAV surveillance, and carried out some experiments of recognition and tracking of multiple moving targets. Furthermore, the practical constraints of UAV's maneuverability, collision avoidance and threat avoidance are considered in this search-attack integration problem, and this is what many references ignore or do not research thoroughly.

(2) For the cooperative search-attack mission planning problem, a Distributed Intelligent Self-Organized Mission Planning (DISOMP) algorithm is originally presented in this paper. For the cooperative search problem, there are some algorithms presented, such as optimal search theory,[15] grid based search algorithm,[16] probabilistic decision making scheme,[12,17,19] heuristic algorithm,[11,13,18,20–22] and predictive algorithm.[14] The proposed DISOMP algorithm is constituted by a search module designed by the distributed Ant Colony Optimization (ACO) algorithm, an attack module designed by the Parallel Approach (PA) guidance method, a threat avoidance module designed based on the Dubins Curve (DC) scheme, and a communication module for information exchange among the multi-UAV system. This combinatorial optimization scheme can effectively solve the search-attack integration mission planning problem in the uncertain dynamic environment. Furthermore, the mission completeness, mission execution efficiency and multi-UAV system suitability of the DISOMP algorithm are deeply investigated. All above contribute to the practical applications of the DISOMP algorithm.

The rest of this paper is organized as follows. In Section 2, the multi-UAV cooperative search-attack mission planning problem is described. In Section 3, the DISOMP algorithm composed of a search module, an attack module, a threat avoidance module and a communication module is proposed. In Section 4, simulations are conducted to verify the effectiveness of the DISOMP. Finally, a conclusion is given in Section 5.

2. Cooperative search-attack problem description

In this section, the search-attack mission in uncertain environment will be modeled, the search-attack mission planning problem will be defined, and the constraints of search-attack mission planning model will be given.

2.1. Search-attack mission in uncertain environment

The illustration of the search-attack mission in uncertain environment is given in Fig. 1.

(1) Mission area discretization

Discretize and rasterize the mission area $L \times W$ in a two-dimensional plane. There is a cooperative multi-UAV system including some isomorphic UAVs, targets (such as moving ground or air vehicles) and threats (such as environmental obstacles, enemy radars and fire points) in the mission area. The UAVs move between the grids in the discrete space with the constraints of maneuverability, collision avoidance and threat avoidance.

(2) UAV's property and motion parameters

Assume that the UAVs in a multi-UAV system are isomorphic, and each UAV takes the same search sensors and attack weapons, and can execute the search and attack missions. There are N_u UAVs. Let the projection radius of UAV

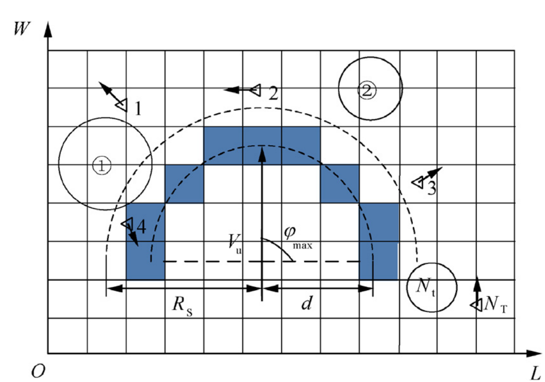


Fig. 1 Illustration of search-attack mission area.

detection range in the mission area be R_S, the maximal turning angle of UAV be φ_{max}, the speed of UAV be V_u, and the step displacement of UAV be d. The detection range and the next possible positions of the UAV are illustrated in Fig. 1, noted by a semi-circle and some deep color grids.

(3) Dynamic targets and threats

There are N_T dynamic moving targets and N_t threats in the mission area, noted by the triangles and the circles in Fig. 1, respectively (Labelled as 1,2,...,N_t/N_T). The targets move in straight lines or curves with random directions, with the speed of V_T. The radius of the threat is R_t. All above information is unknown in advance for the multi-UAV system. The task of the multi-UAV system is to search and attack these targets and guarantee that UAVs do not enter the threatened area.

2.2. Search-attack mission planning problem

The multi-UAV cooperative search-attack integration mission for dynamic targets can be transformed to be a mission planning problem.

Definition 1 (Target search mission). When a target is in the detection range of UAV, the target is considered to be searched, which is described as

$$0 \le r \le R_S \tag{1}$$

where R_S is the detection range, and r is the distance between the UAV and the target. The surveillance coverage rate is calculated as the ratio of grids which have been searched to all the grids in mission area, and is expressed by

$$P = \sum_{x=1}^{L}\sum_{y=1}^{W} \mathrm{node}_{x,y}/(LW) \qquad \mathrm{node}_{x,y} \in \{0,1\} \tag{2}$$

where $\mathrm{node}_{x,y} = 0$ means that the grid (x,y) has not been searched, while $\mathrm{node}_{x,y} = 1$ means that the grid (x,y) has been searched. The search mission goal is to increase the coverage of the mission area in order to find more targets, and therefore, the surveillance coverage rate is taken as the search benefit J_S, that is

$$J_S = P \tag{3}$$

Definition 2 (Target attack mission). When a UAV seeks out a target, it will fly to track the target. When the target is in its attack range, the target is considered to be attacked, which is described as

$$0 \le r \le R_A \tag{4}$$

where R_A is the attack range. The attack benefit is calculated as the total value of the targets which have been attacked, and is calculated by

$$Q = \sum_{l=1}^{N_{T0}} \mathrm{value}_l \tag{5}$$

where N_{T0} is the total number of targets which have been attacked and value $_l$ is the value of the l-th target. The attack mission goal is to maximize the attack benefit, that is

$$J_A = Q \tag{6}$$

Definition 3 (Centralized search-attack mission planning model). Suppose that there is a central processor to make decision for the search-attack mission, then the mission planning model can be defined as deciding the UAVs' flight paths to search and attack the moving targets, by maximizing the following performance index function:

$$\begin{aligned} &U^* = \arg\max_U (\omega J_S + (1-\omega)J_A) \\ &\text{s.t.} \quad C \le 0 \end{aligned} \tag{7}$$

where $\omega \in \{0,1\}$, $\omega = 1$ indicates that the UAV is performing a search mission, $\omega = 0$ indicates that the UAV is performing an attack mission, U is the decision input which represents the UAV's position at the next time instant, and C is a constraint set of the mission planning model.

Definition 4 (Distributed search-attack mission planning model). Suppose that each UAV is an independent individual with a separate processor to build its own solution, then the centralized search-attack mission planning model can be transformed to be a distributed model. The distributed search index Eq. (3) and attack index Eq. (6) are respectively decomposed as

$$\begin{cases} J_S = \sum_{i=1}^{N_u} \mu_i J_{Si} \\ J_A = \sum_{i=1}^{N_u} \mu_i J_{Ai} \end{cases} \tag{8}$$

where μ_i is the weight coefficient of the i-th UAV. Then the centralized optimization model Eq. (7) can be decomposed as

$$\begin{aligned} &U_i^* = \arg\max_{U_i} \left(\omega_i J_{Si}(X_i, \tilde{X}_j) + (1-\omega_i) J_{Ai}(X_i, \tilde{X}_j)\right) \\ &\text{s.t.} \quad \begin{cases} \tilde{X}_j = \left\{X_j | j \in T^i_{\mathrm{adjoin}}\right\} \\ G_i \le 0 \quad i = 1,2,\cdots,N_u \end{cases} \end{aligned} \tag{9}$$

where X_i is the state vector of the i-th UAV, T^i_{adjoin} is the set of UAVs which communicate with the i-th UAV, and C_i is the constraint set of the i-th UAV, which will be given in the next subsection.

2.3. Constraints of search-attack mission planning model

The constraints of the mission planning model for multi-UAV mainly include the maneuverability constraints C_m, collision avoidance constraints C_c and threat avoidance constraints C_t. Then the constraints set C_i in Eq. (9) can be expressed as $C_i = \{C_m, C_c, C_t\}$.

(1) Maneuverability constraints. The maximum turning angle φ_{max} of each UAV which limits its turning radius and rate is considered and expressed by

$$C_m : \varphi_i(k) - \varphi_{max} \le 0 \quad i = 1,2,\cdots,N_u \tag{10}$$

where $\varphi_i(k)$ is the turning angle of the i-th UAV at time k.

(2) Collision avoidance constraints. A safe distance d_{min} between two UAVs is considered to avoid the collision, which is expressed by

$$C_c : d_{min} - d_{ij}(k) \le 0 \quad i,j = 1,2,\cdots,N_u; i \ne j \tag{11}$$

where $d_{ij}(k)$ is the distance between the i-th UAV and the j-th UAV at time k.

(3) Threat avoidance constraints. A safe distance R_{min} from the threat (such as obstacle, fire and radar) to the UAV is considered. The distance between the UAV and the threat's center should not be shorter than the radius of the threat, which is expressed by

$$C_{\mathrm{t}}: R_{\min} - d_{il}(k) \leq 0 \quad i = 1, 2, \cdots, N_{\mathrm{u}}; l = 1, 2, \cdots, N_{\mathrm{t}} \quad (12)$$

where $d_{il}(k)$ is the distance between the i-th UAV and the l-th threat.

3. Design of DISOMP for cooperative search-attack problem

The mission will be accomplished by online planning the flight paths of multi-UAV through the information interaction between the UAVs and the battlefield environment. This section will design the DISOMP algorithm for the dynamic targets cooperative search-attack problem.

3.1. Configuration of DISOMP

Each UAV in the multi-UAV system is equipped with a separate processor to deal with its local tasks, which contain targets search mission, attack mission and communication with other adjacent UAVs. The configuration of the DISOMP algorithm is shown in Fig. 2, which is composed of a search module, an attack module, a threat avoidance module and a communication module. Design details of the modules are given in the following.

3.2. Search module based on ACO

All UAVs take the same search sensors to search the mission area, according to Definition 1. When a target is in the detection range of UAV, the target is considered to be discovered. ACO is an intelligent optimization algorithm with global optimization performance, versatility characteristics.[23] Based on the ACO algorithm, the waypoint of each UAV is online generated by maximizing the distributed search-attack mission planning performance index Eq. (9) with the constraints Eqs. (10)–(12).

(1) Simulative relation between ant agent and UAV. In the search module, an UAV is simulated as an ant agent, and thus the ant agent is assumed to have the positioning, perception, memory, movement, combat, communication and self-renewal capabilities as the UAV platform, while being subject to the UAV's performance constraints. The UAV flying is simulated as the ant agent moving. An iteration of the ACO

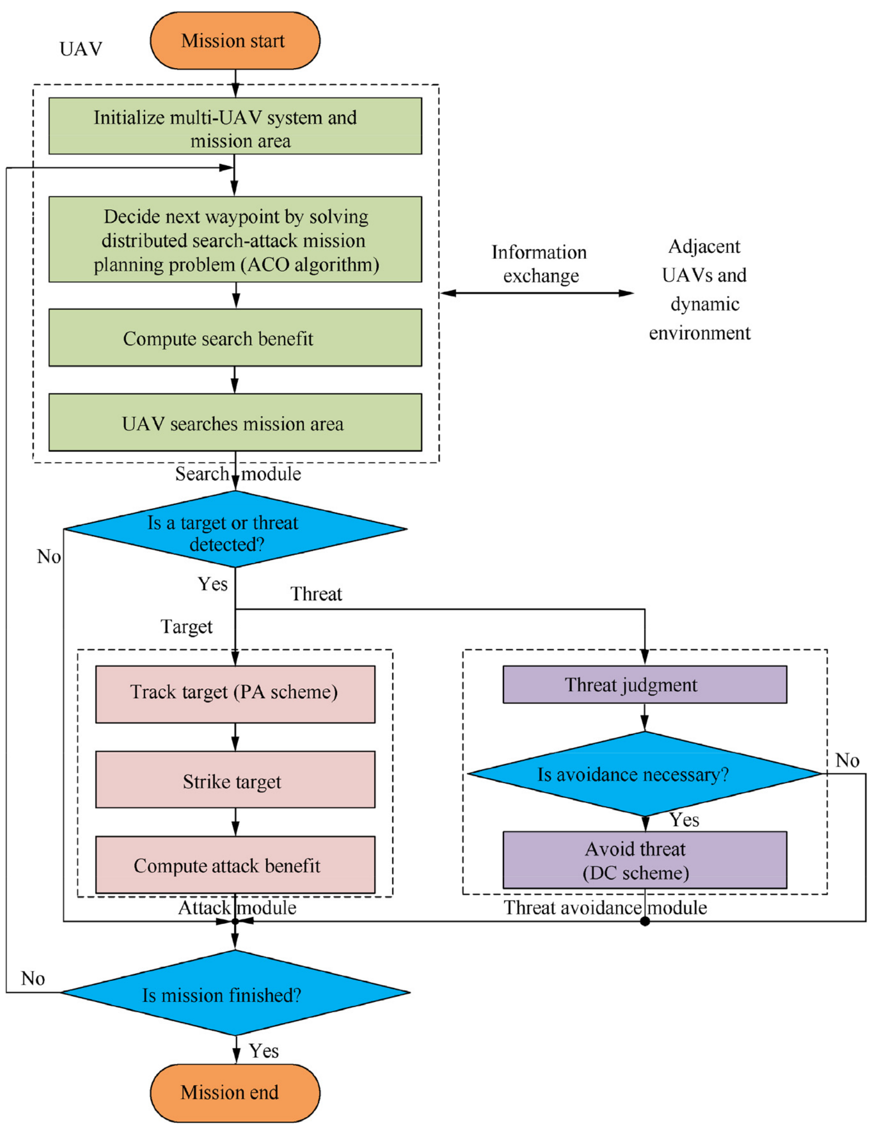


Fig. 2 Configuration of DISOMP algorithm.

algorithm is equal to a decision of the UAV for mission planning, and also equal to a flight step of the UAV. The cooperative search mission problem is simulated as the distributed optimal path searching problem.

(2) Local pheromone update mechanism. When the ant agent completes a state transition, it needs to update the pheromone concentration according to the position distribution of the whole ant colony. The pheromone concentration of grids which have been searched should be reduced to avoid excessive search of a certain area. The information of the j-th ant agent at time k_j as is known to the i-th ant agent can be expressed as

$$\mathrm{Info}_j(k_j) = \{(x_j(k_j), y_j(k_j)), \mathrm{PSI}_j(k_j)\} \qquad k_j \le k \tag{13}$$

where $(x_j(k_j), y_j(k_j))$ is the position of the j-th ant agent, and $\mathrm{PSI}_j(k_j)$ is the movement direction of the j-th ant agent. The information of the j-th ant agent at time k predicted by the i-th ant agent is

$$\mathrm{Info}_j(k_j) = \{(x_j(k_j), y_j(k_j)), \mathrm{PSI}_j(k_j)\} \qquad k_j \le k \tag{14}$$

Then the local pheromone update mechanism of the i-th ant agent is described by

$$\begin{cases} \tau^i_{x,y}(k+1) = \tau^i_{x,y}(k) - \Delta\tau^i_{x,y}(k) \\ \Delta\tau^i_{x,y}(k) = \sum_{j=1}^{N_u} \Delta\tau^{(i,j)}_{x,y}(k) \end{cases} \tag{15}$$

$$\Delta\tau^{(i,j)}_{x,y}(k) = \begin{cases} \Delta\tau_{l0} \frac{R^4 - d^4\left((x,y),\left(x^*_j(k), y^*_j(k)\right)\right)}{R^4} & d\left((x,y),\left(x^*_j(k), y^*_j(k)\right)\right) \le R \\ 0 & d\left((x,y),\left(x^*_j(k), y^*_j(k)\right)\right) > R \end{cases} \tag{16}$$

where $\tau^i_{x,y}(k)$ is the pheromone concentration of the grid (x,y) in the local pheromone structure of the i-th ant agent, $\Delta\tau^{(i,j)}_{x,y}(k)$ is the pheromone decrement caused by the j-th ant agent, $\Delta\tau_{l0}$ is the local pheromone attenuation coefficient, and $d\left((x,y),\left(x^*_j(k), y^*_j(k)\right)\right)$ is the distance between (x,y) and $\left(x^*_j(k), y^*_j(k)\right)$. Therefore, the local pheromone in the searched area is updated by Eq. (16).

(3) Global pheromone update mechanism. Due to the uncertainty of the environment, such as new target appearing in the area which has been searched, a global enhancement of the pheromone is needed after some intervals. The global pheromone update mechanism is described by

$$\tau^i_{x,y}(k+1) = \tau^i_{x,y}(k) + F\Delta\tau_{g0} \tag{17}$$

where $F \in (0,1)$ is the uncertainty coefficient and $\Delta\tau_{g0}$ is the global pheromone update coefficient.

(4) State transition rule. The transition rule of the ant agent is designed as

$$\mathrm{grid}^*(k+1) = \arg \max_{\mathrm{GRID}(k+1)} \left(\tau^\alpha(\mathrm{GRID}(k+1))\eta^\beta(\mathrm{GRID}(k+1))\right) \tag{18}$$

where α and β denote the importance factors of pheromone concentration and heuristic visibility, respectively. The heuristic is represented as the surveillance coverage rate, and hence $\eta = P$. GRID$(k + 1)$ is the set of candidate grids at the next time, and grid$^*(k + 1)$ is the decided grid from the candidate grid set according to the transition rule.

(5) Optimal path generation procedure. The movement of the ant agent is influenced by its own state and the states of the adjacent ant agents. First, the ACO parameters and the mission area are initialized. Second, the local pheromone of the searched area is updated according to Eqs. (13)–(16), and the global pheromone of the mission area is updated according to Eq. (17). Third, the ant agent moves according to the state transition rule Eq. (18), and the optimal flight path is obtained by the ACO algorithm.

(6) Convergence analysis. Different from the convergence definition of the classical ACO algorithm, the convergence of the DISOMP is defined as the ant's surveillance coverage rate. If the surveillance coverage rate can finally reach a stable level with certain iterations, the distributed ACO algorithm is considered to be convergent.[11] If the ant agent is surrounded by the searched grids, it will fall into excessive local searching. Correspondingly, for the DISOMP algorithm, when the coverage rate keeps invariant for the iteration threshold I_t, the ant agent should move to the nearest unsearched area. This scheme ensures that the coverage rate of the mission area can always reach to 100%. Therefore, the DISOMP algorithm is convergent.

3.3. Attack module based on PA

Based on the PA guidance method, the UAV can track and strike the moving target, according to Definition 2. The attack mission is divided into two steps: target tracking and target striking.

(1) Target tracking. As shown in Fig. 3, the target line azimuth q is the angle of target line and the baseline, σ_u is the angle between UAV's velocity vector and the baseline, σ_T is the angle between the target's velocity vector and the baseline, ψ_u is the angle between the target line and the UAV's velocity vector, and ψ_T is the angle between the target line and the target's velocity vector. The PA guidance method requires that the target line of sight should be kept moving in parallel along the given direction during the guidance process, and thus the azimuth velocity of the target line is controlled to be zero. Therefore, the PA guidance method is expressed by

$$\begin{cases} V_u \sin\psi_u = V_T \sin\psi_T \\ \psi_T = q - \sigma_T \end{cases} \tag{19}$$

Then the guide command of the UAV is computed by

$$\psi_u = \arcsin[(V_T \sin\psi_T)/V_u] \tag{20}$$

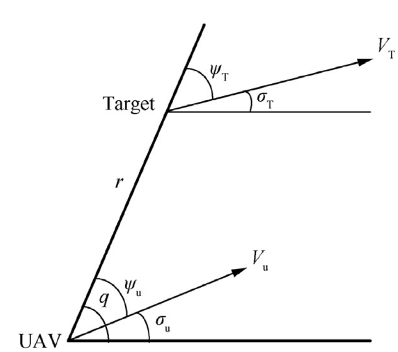


Fig. 3 Illustration of parallel approach scheme.

(2) Target striking. From the PA guidance law Eq. (20), it is found that when the target is in a linear motion, the UAV can attack the target in any direction and the straight trajectory can be obtained as long as the velocity ratio V_u/V_T is constant. When the target is in a complex maneuver, ψ_u needs dynamic change.

3.4. Threat avoidance module based on DC

When a threat is detected by the UAV, the UAV performs the mission to avoid the threat, which includes two steps: one is the threat judgment and the other is the safe path generation based on DC.

(1) Threat judgment. When the threat is discovered by the UAV, the UAV will judge whether it is necessary to avoid the threat, according to the relative distance and direction between the UAV and the threat. The UAV moves forward and simultaneously detects the environment to continue the mission. Judge whether the candidate grid can successfully avoid the threat. If it is possible to enter the threatened area in the next step, that is $d \geq d_{il} - \lambda R_T$, then the UAV will generate a safe path based on the DC, as shown in Fig. 4.

(2) Safe path generation based on DC. The Dubins Curve was originally proposed by Dubins in 1961 and has been widely used in aircraft path planning.[24] There are normally four types of paths generated by the DC: two circumscribed paths and two inscribed paths. The shortest one will be chosen as the optimal path. As shown in Fig. 5, P_S (x_s,y_s) is the initial position with velocity V_s, P_F (x_f,y_f) is the final position with velocity V_f, R_s is the radius of the initial circle, R_f is the radius of the final circle, the dotted line is the inscribed path and the solid line is the circumscribed path. Then the solution γ of DC scheme can be expressed as $P_S(x_s, y_s, \psi_s) \xrightarrow{\gamma} P_F(x_f, y_f, \psi_f)$. According to the Euclidean geometry method, the safe path can be obtained by the following steps[8]: (A) Figure out the center coordinates of the initial circle O_s (x_{cs},y_{cs}) and the final circle O_f (x_{cf},y_{cf}); (B) Draw a circle, when it is the inscribed DC, the radius of the cycle is $R_f + R_s$; when it is the circumscribed DC, the radius of the cycle is$|R_f - R_s|$; (C) The tangent point on the final circle is the exit point P_N of the optimal path, and the tangent point on the initial circle is the entry point P_X; (D) Finally draw an arc from P_S to P_X with the center O_s, connect P_X and P_N, draw an arc from P_N to P_F with the center O_f, and then the safe optimal path is generated.

3.5. Communication module

The communication module runs throughout the entire mission process, which is responsible for the information exchange of the UAV's moving positions and directions. Each UAV needs to communicate with the adjacent UAVs at set intervals, as shown in Eqs. (15) and (16). The exchanged information mainly includes its own state information used for the collision avoidance and the cooperative control. Moreover, there also exits information exchange between the dynamic environment and the UAVs, as shown in Eq. (17).

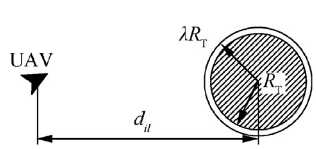


Fig. 4 UAV threat detection diagram.

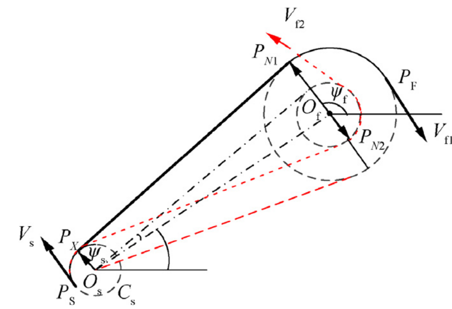


Fig. 5 Circumscribed and inscribed DC.

4. Simulation study

In order to verify the effectiveness of the DISOMP algorithm for the dynamic target cooperative search-attack problem, the numerical simulations are carried out based on the MATLAB R2014b software with the computer processor Intel(R)Xeon (R)CPU E3-1230 v5@3.40 GHz, RAM 8.00 GB, and 64-bit WINDOWS 10 operating system.

4.1. Search-attack mission scene and parameters

(1) Mission area and target information. Divide the mission area 20 km × 20 km into the discrete grids 1000 × 1000. There are 9 targets moving in the area, whose initial positions, values and moving directions are given in Table 1 and Fig. 6, and the moving speeds of the targets are 20 m/s (1 grid distance per unit time). However, the information of the targets is unknown in advance for the UAVs.

(2) UAV motion parameters. Two homogenous UAVs are sent to the mission area. The first UAV (UAV1) is initially located at position (8, 12) km and the second UAV (UAV2) is initially located at position (8, 8) km, respectively. The UAV's maximum turning angle $\varphi_{max} = 45°$, the moving speed V_u = 200 m/s (10 grids per unit time), and the detection radius R_s = 600 m (30 grids).

(3) ACO algorithm parameters. The number of the ant agent is equal to the number of the UAVs. The description and value of important system parameters are given in Table 2.

(4) DISOMP algorithm steps. According to the configuration of DISOMP algorithm shown in Fig. 2, the steps are described in the following:

Table 1 Target information.

Target label	Starting coordinate (km)	Value	Moving direction (°)
1	(3,3)	20	0
2	(3,5)	50	90
3	(6,5)	40	45
4	(6,12)	20	−30
5	(12,5)	20	60
6	(12,12)	30	45
7	(18,5)	30	150
8	(18,12)	20	180
9	(19,12)	20	150

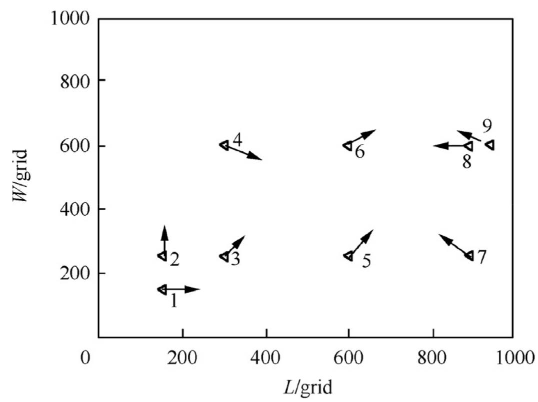


Fig. 6 Target movement diagram.

Table 2 Description and value of system parameters.

Parameter	Value	Description
$\Delta\tau_{l0}$	2	Local pheromone attenuation coefficient
$\Delta\tau_{g0}$	10	Global pheromone update coefficient
α	2	Importance factors of pheromone concentration
β	5	Importance factors of heuristic visibility
F	0.022	Uncertainty coefficient
I_t	50	Iteration threshold

Step 1. Initialize the multi-UAV system and the mission area.

Step 2. Based on the exchange information among the multi-UAV system and the dynamic environment, the UAV moves along the optimal path obtained by the ACO algorithm, computes the surveillance coverage rate and detects the mission area.

Step 3. If there is a target detected, the UAV tracks the target based on the PA guidance method, strikes the target and computes the attack benefit, and then the algorithm goes to Step 5.

Step 4. If there is a threat detected and it is necessary to avoid the threat after judgment, the UAV avoids the threat based on the DC scheme, and then the algorithm goes to Step 5.

Step 5. Judge whether the mission is finished. If it is not finished, go back to Step 2, otherwise the mission is finished.

(5) Complexity analysis. According to the DISOMP algorithm, each UAV has a separate processor to solve its own local optimization problem. The information of other UAVs can be obtained through communication. Therefore, each local optimization problem is mainly related to the state and decision input of the local UAV, which greatly reduces the complexity of the problem. Based on the distribution strategy, the local pheromone update mechanism combined with global pheromone update mechanism is proposed, which avoids the problem of reducing the algorithm efficiency due to excessive communication and pheromone update. Therefore, the DISOMP algorithm takes less time consumption than traditional ACO.

4.2. Mission completeness analysis of DISOMP

In order to analyze the mission completeness of DISOMP for the dynamic targets search-attack problem, the mission is divided into the following six sub-missions. The simulation results are shown in Fig. 7(a)–(f), where the dotted (solid) triangle represents the starting (ending) position of the target, and the hexagonal star represents the target that has been destroyed.

Sub-mission 1. the goal is to search and attack the first target. Fig. 7(a) shows that UAV2 discovers target 3 after flying 21 steps, attacks and successfully destroys the moving target after flying 25 steps.

Sub-mission 2. the goal is to search and attack the second target. Fig. 7(b) shows that UAV1 discovers target 5 after flying 93 steps, attacks and successfully destroys the moving target after flying 97 steps.

Sub-mission 3. the goal is to search and attack the third target. Fig. 7(c) shows that UAV1 discovers target 6 after flying 161 steps, attacks and successfully destroys the moving target after flying 165 steps.

Sub-mission 4. the goal is to search and attack the fourth target. Fig. 7(d) shows that UAV2 discovers target 7 after flying 172 steps, attacks and successfully destroys the moving target after flying 175 steps.

Sub-mission 5. the goal is to search and attack the fifth target. Fig. 7(e) shows that UAV2 discovers target 8 after flying 491 steps, attacks and successfully destroys the moving target after flying 495 steps.

Sub-mission 6. the goal is to search and attack all the targets until the UAV reaches its flying range. Fig. 7(f) shows that the two UAVs discover 6 targets until they reach their flying range (1000 steps limited).

Above all, the DISOMP algorithm can search and attack most of the dynamic targets. The mission completeness is mainly determined by the number of the UAVs, the performance (including the flight, detection and attack performance) of the UAV and the motion performance of the dynamic targets.

4.3. Mission execution efficiency analysis of DISOMP

In order to analyze the efficiency of the DISOMP algorithm for the dynamic targets search-attack problem, the Scan-Search (SS) algorithm[25] as a traditional searching method is compared with the DISOMP algorithm. Two algorithms' iteration numbers are 500.

(1) Algorithm 1 (SS algorithm). The cooperative search-attack mission response results based on the SS algorithm are shown in Fig. 8(a). UAV1 discovers and attacks the moving targets 4, while UAV2 discovers and attacks the moving targets 4.

(2) Algorithm 2 (DISOMP algorithm). The cooperative search-attack mission response results based on DISOMP algorithm are shown in Fig. 8(b). UAV1 discovers and attacks the moving target 6 and target 8, while UAV2 discovers and attacks the moving target 3, target 5 and target 7.

(3) Comparison results. The simulation of DISOMP algorithm is carried out 20 times, the comparison results of which are given in Fig. 9. It is found that the UAVs with SS algorithm can search and attack 2 targets, while the UAVs with DISOMP algorithm can search and attack 2.5 targets on average. Therefore, the average efficiency of the DISOMP algorithm is much greater than that of the SS algorithm. Furthermore, the SS algorithm is an ergodic algorithm, and

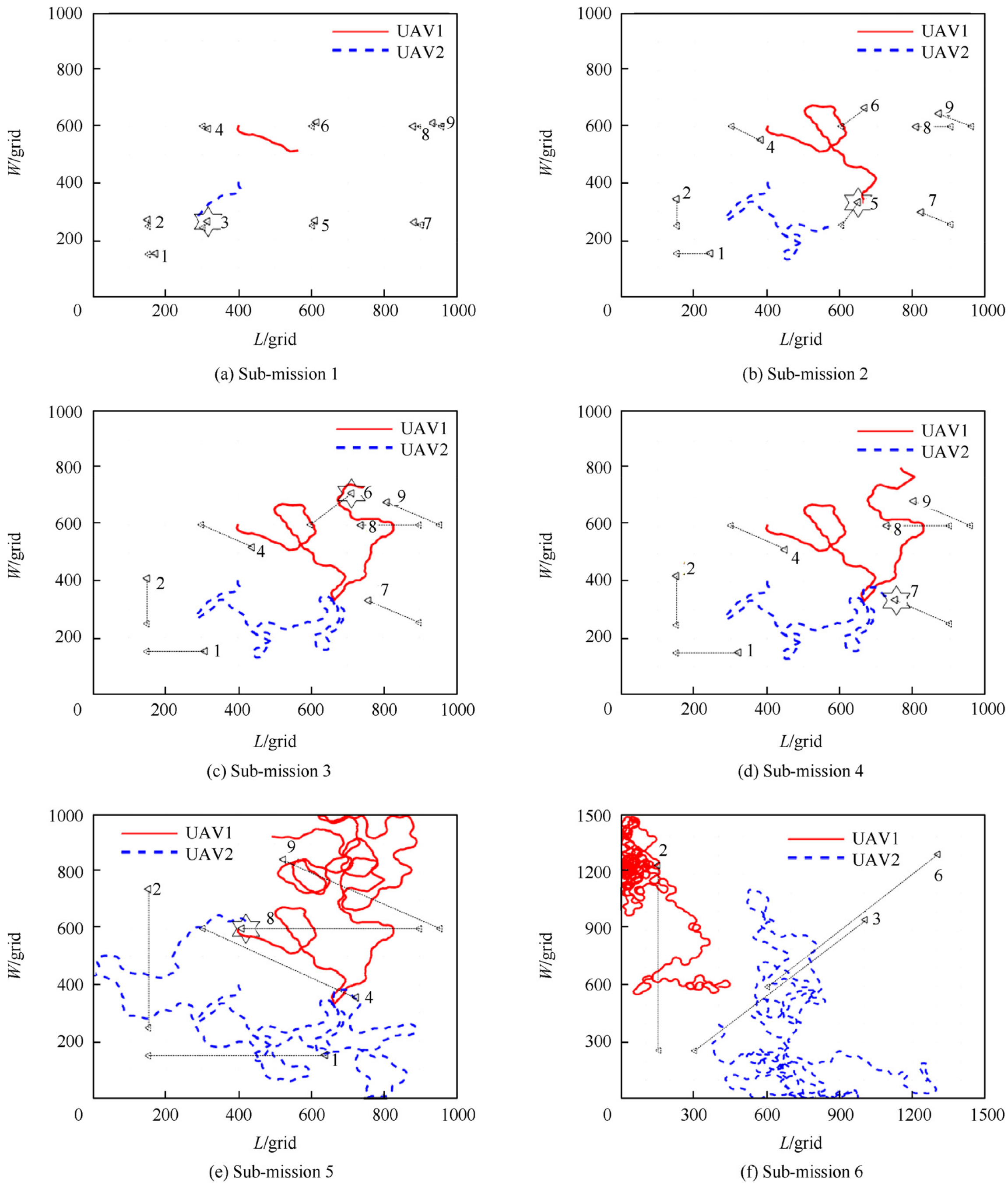
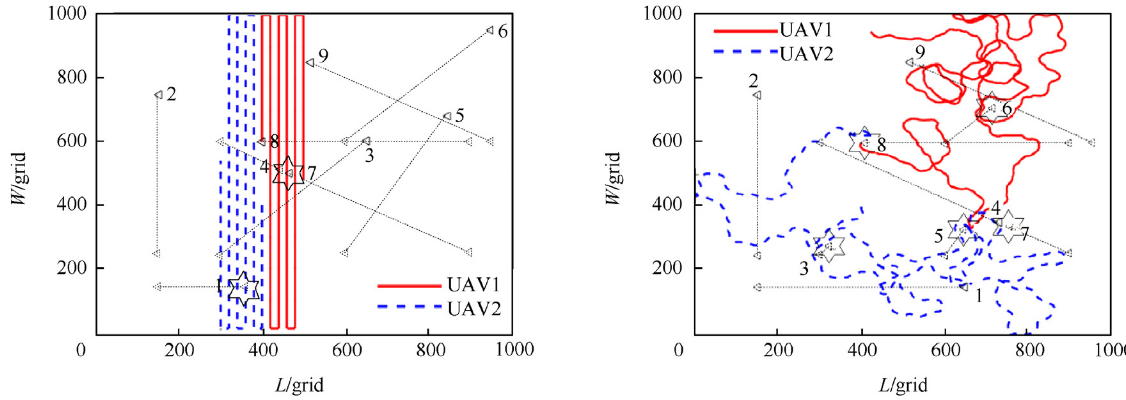


Fig. 7 Cooperative search-attack mission response results of DISOMP.

thus the efficiency will be degraded when the targets are far from the UAVs. However, as an optimization algorithm, the DISOMP algorithm is operated by minimizing a performance index Eq. (9), which guides the UAVs directly to the area with higher surveillance coverage rate and attack benefit. Therefore, the efficiency of the DISOMP algorithm will not be influenced by the positions of the targets.

(4) Real-time performance. The DISOMP algorithm is an online decision-making algorithm, and therefore the real-time performance is very important. However, there is little uniform quantitative criterion to evaluate the time consumption performance of the mission planning algorithm. The time consumptions under different iterations of the DISOMP algorithm are calculated as given in Table 3. It is found that one iteration of the DISOMP algorithm for an UAV takes 90 ms on average. The mission planning belongs to the decision making (upper level) so that its cycle is definitely greater than the navigation and control (lower level). Theoretically, if the interval time between two decisions is greater than the time consumption of each decision, the real-time requirement can be satisfied. Therefore, the time consumption 90 ms for each iteration is reasonable for online applications.



(a) SS algorithm (b) DISOMP algorithm

Fig. 8 Cooperative search-attack mission response results.

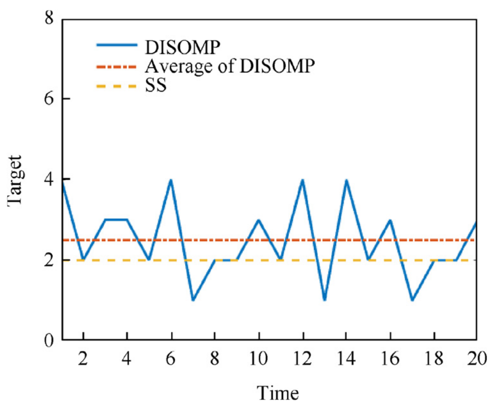


Fig. 9 Mission execution efficiency comparison between DISOMP and SS.

Table 3 Time consumption analysis.

Number of iteration	1	50	100	200	500	1000
Time consumption (s)	0.07	4.33	8.78	19.00	45.39	92.19

4.4. Multi-UAV system suitability analysis of DISOMP

In order to further verify the multi-UAV system suitability of the DISOMP algorithm, four cases are considered, including adding a new UAV at the beginning, adding a new UAV during the process of mission execution, considering the randomly moving targets and considering the threats.

Case 1. New UAV enters at the beginning. A new UAV (UAV3) entering to the multi-UAV system needs to establish a new communication topology. Assume that the UAV3 is initially located at the coordinate (14, 12) km, and the mission execution results are given in Table 4 and Fig. 10, where it is found that six targets sorted by the order are detected and attacked by UAV3 and UAV2. However, UAV1 does not detect any target and there are still three targets which have not been detected, mainly because the targets are moving and the mission area is large. Fig. 11 shows the simulation results of performing 20 times. It shows that two UAVs can search and attack 2.5 targets on average, while three UAVs can search and attack 3.3 targets on average. Therefore, the new UAV can fast adapt to the multi-UAV system and will improve the mission execution speed.

Case 2. New UAV enters during mission process. Assume that a new UAV (UAV3) is initially located at the position (14, 12) km and joins into the multi-UAV system at the 172th iteration. The search-attack mission response results are shown in Fig. 12. The black dashed line indicates the flight path of new UAV during the mission. The fifth target (target 8) is quickly detected after 253 iterations, which is faster than the

Table 4 Mission response results of Case 1.

Target label	UAV label	Number of search iterations	Number of attack iterations
4	3	72	75
8	3	137	141
2	2	139	143
9	3	169	172
6	3	174	178
5	3	279	281

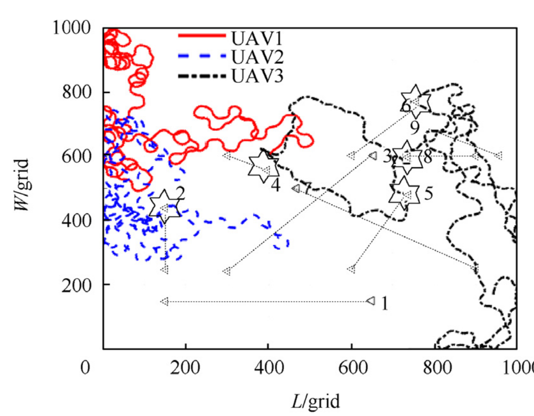


Fig. 10 Mission response results of Case 1.

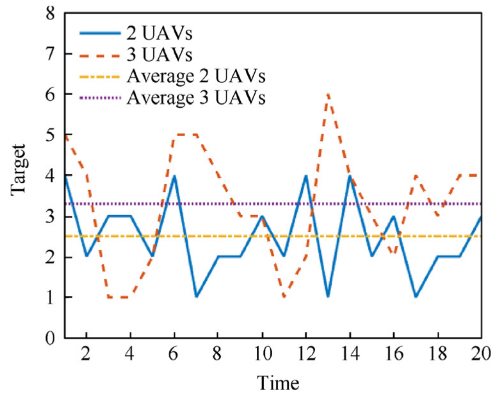


Fig. 11 Comparison results of Case 1.

case of two UAVs (493 iterations). It can be seen that the DISOMP algorithm based multi-UAV system is flexible and scalable.

Case 3. Targets move randomly. Assume that target 1, target 4, target 6 and target 8 are moving randomly, while the other targets are moving straightly. The cooperative search-attack mission response results are shown in Fig. 13, where target 2 is attacked by UAV1 at the 391th iteration and target 1 is attacked by UAV2 at the 458th iteration. These results exhibit the good mission adaptability of the DISOMP algorithm for the cooperative search-attack mission in the presence of randomness.

Case 4. Threats appear in mission area. Assume that there are three threats in the mission area, which should be avoided by the UAVs for safety. The threats can be considered as the circular areas. The center coordinates of threat 1, threat 2 and threat 3 are (12, 6) km, (4, 14) km and (16, 16) km, respectively. The radii of threat 1, threat 2 and threat 3 are 3.6 km, 3 km and 1 km, respectively. The cooperative search-attack mission response results are shown in Fig. 14. Target 1 and target 3 are searched and attacked by UAV2 at the 37th iteration and 158th iteration, respectively. It can be seen that the UAVs can effectively avoid the threats and continue to execute the search and attack mission, which shows the good environmental adaptability of the DISOMP algorithm for the cooperative search-attack mission in the presence of threats.

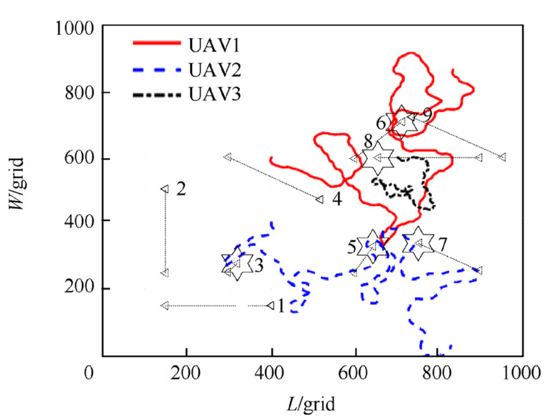


Fig. 12 Mission response results of Case 2.

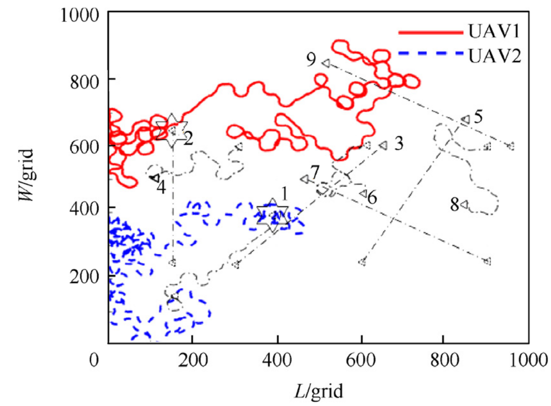


Fig. 13 Mission response results of Case 3.

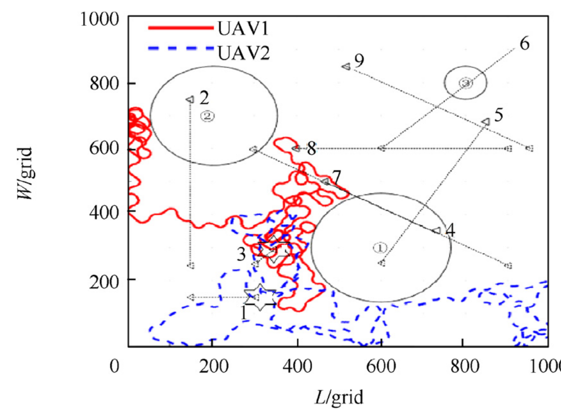


Fig. 14 Mission response results of Case 4.

5. Conclusions

A novel distributed down-top scheme for the cooperative search-attack integration mission problem with dynamic targets and threats is developed for the multi-UAV system. The DISOMP algorithm is composed of search, attack, avoidance and communication modules. The thorough simulation results show that the DISOMP algorithm has high mission completeness, execution efficiency and system suitability. It contributes to making the multi-UAV system flexible, scalable and adaptive to the environment and mission changes. In a word, it is an online mission planning algorithm which is suitable for the practical applications.

Moreover, the DISOMP algorithm can be extended to the cooperative search-attack mission problem of the UAV swarm or the heterogeneous multi-UAV system. For the UAV swarm, a reliable and flexible communication topology needs to be designed. For the heterogeneous multi-UAV system, a cooperative task allocation strategy is very important.

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