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A Novel Hybrid Auction Algorithm for Multi-UAVs Dynamic Task Assignment

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ABSTRACT The auction algorithm is a widely used method for task assignments. However, most existing auction algorithms yield poor performance when applied to multi-UAVs dynamic task assignment. To end this, we propose a novel hybrid ''Two-Stage'' auction algorithm based on the hierarchical decision mechanism and an improved objective function, which simultaneously realizes heterogeneous multi-UAVs dynamic task assignment with limited resources of each UAV and avoidance obstacle path planning. In the first stage, according to the novel proposed hierarchical decision mechanism, we select a task that is urgently needed to be performed in the task group by using the decision function and three attribute values of tasks. After the first stage, it will result in a reasonable auction sequence, instead of random auction sequence as in previous algorithms. In the second stage, by considering the coverage factor and adaptive-limitation penalty term, a novel objective function is proposed and directs related UAVs for auction. In addition, we combine the structural advantages of the centralized and distributed auction algorithm, which greatly promotes its performance in dynamic task assignment. The experimental results demonstrate that the proposed method outperforms many state-of-the-art models in efficiency and robustness.

INDEX TERMS Hierarchical decision mechanism, unmanned air vehicle, dynamic task assignment, auction algorithm, decision function.

I. INTRODUCTION

For highly autonomous multi-UAVs systems, dynamic task assignment is a crucial problem that needs to be addressed efficiently. The multi-UAVs dynamic task assignment can be stated as follows: *Given a set of UAVs and tasks, where each UAV has upper bound on the number of tasks that it can perform, and each UAV has a payoff for each task, find an assignment of UAVs to tasks such that the sum of the payoff of all UAVs is maximized. And when environment changes, such as when the UAV finds new targets or is destroyed in dynamic environment, the original assignment scheme can be constantly adjusted to maximize the overall payoff.* However, basic task assignment problem, which usually formulated as the integer programming problem [1] or a set of optimization problems [2], is difficult to be addressed. In the past few decades, there are many optimization algorithms to solve this problem, e.g., the Hungarian algorithms [2], the integer programming methods [3], and some heuristic algorithms such as genetic algorithm [4], particle swarm optimization [5]. However, these methods may fail in dealing with dynamic task assignment problem in complex environment. In recent years, more and more researchers begin to focus on auction algorithm which has made excellent performances in dynamic task assignment. Existing auction algorithm can be roughly categorized into centralized auction algorithm [1], [6]–[8], distributed auction algorithm [10]–[40], and hybrid auction algorithm [41]–[44].

The centralized auction algorithm requires a central station, which distributes global information about current prices and assignment results among bidders [9], [10]. The representative model proposed by Bertsekas *et al.* [1], addresses the problem of assigning a set of tasks to a few agents on well-connected network. This kind of model

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performs well in task assignment when there are few agents, due to its simple network topology. However, when agent increases or agent systems run on less reliable networks, the communication cost of maintaining a central station could become prohibitive [9]. Besides, the network topology may affect the scalability of centralized algorithm [22]. To address these shortcomings, distributed auction algorithm is proposed, which uses local information and limited communication ability to accomplish task assignment instead of using a central station [10]. For example, Kim *et al.* [12] propose a resource-oriented, distributed auction algorithm, which considers multiple resources of the agents and limited communication range. In [25], it uses a distributed auction algorithm to handle the task assignment problem while taking path planning into account. Because of using a well constructive distributed auction algorithm, the method in literature [26] can provide desirable assignment results in the constraint of limited resources and deadlines. In [27]–[29], the UAV can obtain its available task period and resources according to task sequence mechanism in dynamic environment. This mechanism can effectively handle the scenario which has real-time and resources limited requirements of task assignment. A series of distributed auction algorithms based on hierarchical mechanism are presented to solve multi-UAVs task assignment problem [30]–[34]. Similarly, the distributed algorithms are proposed to solve dynamic task assignment problems in robotic swarm [35]–[40]. Nevertheless, the distributed auction algorithm cannot handle dynamic task assignment very well due to its complex structure and organization [22].

To solve the above problems, the hybrid auction algorithm has been proposed where other advanced algorithms are incorporated into the distributed auction algorithm. For example, Choi *et al.* [42] put forward the consensus-based bundle algorithm (CBBA) that utilizes both distributed auction algorithm and decision strategy, to deal with dynamic multi-assignment problems. When the environment changes, Cao *et al.* [41] propose a hybrid dynamic task assignment method. Firstly, they use a centralized particle swarm optimizer-fish swarm algorithm (PSO-FSA) between groups and then use auction algorithm in group to realize dynamic task assignment in multi-UAVs system. Kim *et al.* [43] propose a distributed task allocation method for heterogeneous UAV team based on the concept of social welfare in economics. Another dynamic task assignment algorithm based on sequential single item auctions (DTAP) is presented by Farinelli *et al.* [44], where agents announce their desired tasks and then collect bids from other agents to decide whether it can perform its desired tasks or leave them for another agents. However, the auction sequence in the above algorithms is randomly generated, which may affect the performance of dynamic assignment [41]–[44].

In this paper, we propose a novel hybrid "Two-Stage" auction algorithm based on the hierarchical decision mechanism and centralized-distributed auction structure. Specifically, UAV obtains initial information of the mission area from the central station before starting from the base to perform tasks. In the first stage, the algorithm finds a task from the task group that is urgently needed to be performed based on the hierarchical decision mechanism. Therefore, it generates a reasonable auction sequence according to the change of the environment, which is the key to the method. Furthermore, related UAVs bid for this task under the guidance of the novel objective function and repeat above procedures until all tasks are assigned. Since the objective function contains the new coverage factor and penalty term, our method can better deal with dynamic task assignment problem. Besides, UAV must consider its current resource surplus and existing tasks queue before bidding for other new tasks. The above task assignment is usually called offline allocation because the information of tasks is known in advance. The dynamic assignment mechanism will be activated when UAVs leave the base. Correspondingly, each UAV can act as an auctioneer when it finds new tasks in the mission area. Moreover, when UAV is destroyed by threatening targets, the central station can use the challenge mechanism to confiscate its unexecuted tasks and reauction these tasks.

In summary, the contributions of this paper include the following:

- A novel hierarchical decision mechanism is proposed based on the three attribute values of tasks and decision function, which not only realizes the dynamic task selection according to changes of the environment, but also improves the speed of the multi-UAVs system to remove high threat targets in dynamic environment.
- By incorporating novel coverage factor into objective function, we construct an improved auction mechanism to consider the association cost between tasks that further improves the performance of dynamic assignment. Meanwhile, the coverage factor with reasonable L_{cov} can make UAV swarms more fully distribute in the mission area.
- Instead of limiting the number of tasks that each agent can perform with a fixed constant, we propose a novel adaptive-limitation penalty term based on the potential function, which balances the use of individuals in UAV swarm and makes full use of the resources carried by each UAV.

The rest of the paper is organized as follows: Section II reviews three related auction algorithms. In Section III we propose our novel hybrid auction algorithm. In section IV, the performance of "Two-Stage" auction algorithm is analyzed in detail. Finally, Section V concludes the paper.

II. BACKGORUND AND RELATED WORK

A. CONVENTIONAL AUCTION ALGORITHM (CAA)

In [1], it was the first time that the auction algorithm was proposed as a polynomial-time algorithm for the single-assignment problems, then many extensions and improvements have been made to solve multi-assignment problems. In CAA [1], [6], [7], the central station acts as an auctioneer and issues auction call for tasks. All agents are bidder and submit their bid values to the auctioneer for bidding their interested tasks. Since the central station contains the system's global variables, all agents have permission to read and write. After comparing bid values, the auctioneer assigns the task to the bidder who gives the highest bid price. To be specific, the value of a task is defined by $c_{ij} = a_{ij} - p_j$, where a_{ij} denotes the reward of assigning task j to agent i, and p_j is the global price of task j. Note that the value of p_j is continuously updated to manifest the current bid for the task. Auctions shall be done in rounds and continue until all agents are assigned to the task that gives it the maximum value ($\max_j c_{ij}$). Every round selects some agent i that has not been assigned a task and finds out $j^* \triangleq \arg\max_j(a_{ij}-p_j)$. Once task j^* has already been assigned to another agent, the two agents swap tasks. At the end of each round, the price of the task j^* is increased such that the value c_{ij^*} is the same as the second highest valued task in agent i's list. However, the centralized topology seriously affects the performance of dynamic task assignment [22].

B. CONSENSUS-BASED BUNDLE ALGORITHM (CBBA)

In [42], Choi*et al.* propose the CBBA model based on a decentralized market-based decision strategy, which addresses dynamic task assignment to coordinate a fleet of autonomous vehicles. The CBBA is a multi-assignment strategy that utilizes both auction and consensus. The algorithm consists of iterations between two phases: bundle construction and conflict resolution. In the first phase, each agent generates only one bundle and updates it as the allocation progresses and adds tasks to its bundle until it is incapable of adding any other task. Moreover, tasks in the bundle are ordered based on the added time, that is, the earlier a task is added, the higher its position in the bundle.

$$c_{ij}[b_i] = \begin{cases} 0, & \text{if } j \in b_i \\ \max_{n \le |p_i|} S_i^{p_i \oplus_n \{j\}} - S_i^{p_i}, & \text{otherwise} \end{cases} \tag{1}$$

where $|\cdot|$ represents the cardinality of the list, and operation $\oplus_n$ inserts the second list right after the $n-$ th element of the first list. $S_i^{p_i}$ denotes the total reward value for agent i performing the tasks along the path p_i. In CBBA, the marginal score will be used if a task j is added to the bundle b_i. The score function is initialized as $S_i^{\{\emptyset\}} = 0$, while the path and bundle are updated as:

$$b_i = b_i \oplus_{end} \{J_i\}, \quad p_i = p_i \oplus_{n_i, J_i} \{J_i\} \tag{2}$$

In the second phase, three vectors are used for consensus. The winning bids list $y_i \in R_+^{N_t}$ and the winning agents list $z_i \in I^{N_t}$. The third vector $s_i \in R^{N_u}$ denotes the time node of the last information update of all agents. The update of the time vector follows the following formula:

$$s_{ik} = \begin{cases} \tau_r, & \text{if } g_{ik} = 1 \\ \max_{m:g_{im}=1} s_{mk}, & \text{otherwise} \end{cases} \tag{3}$$

where τ_r represents the message reception time.

Due to the combination of distributed structure and consensus mechanism, the flexible topology of CBBA performs well in multi-assignment problems. But in complex dynamic environments, such as multi-obstacles and high-risk military environment, its assignment results are unsatisfactory because of the random auction sequence. Besides, if an agent disappears during mission execution, the tasks it carried will never be performed.

C. DTA BASED ON SEQUENTIAL SINGLE ITEM AUCTIONS (DTAP)

The DTAP [44] takes inspiration from sequential single item auctions, where agents assign one task at the time, and when they calculate their bid values, they need to consider previous assigned tasks. The basic idea of DTAP is that agents broadcast their interested tasks to everyone, and then collect quotations from their team-mates. These quotations weigh how well each agent fits to a given task. To be specific, each agent selects the task that maximizes the utility function. Then, the agent announces its selected tasks and corresponding bid values to all team-mates. After comparing the bid values, the agent checks whether it is the best bidder for the selected task. If this is the case, the agent performs the selected task, otherwise it selects next task and iterates the selection process.

In specific patrolling problem, tasks are nodes to be visited, i.e., there are a set of patrol nodes $P = \{p_1, \ldots p_m\}$, and the agent decides to visit or not to visit such node depending on the average idleness of the node and its travel cost. The utility function, that is $v_{ij} = U(r_i, p_j, t)$, which weighs how fit it is for the system assignment robot r_i to node p_j at current time t.

$$U(r_i, p_j, t) = \theta_1 I^{p_j}(t) + \theta_2 Tc(r_i, p_j, t) \tag{4}$$

$$p = \arg\max_{p' \in CurrentTasks} U(r_k, p', t) \tag{5}$$

where $I^{p_j}(t)$ denotes the idleness of p_j at time t, $Tc(r_i, p_j, t)$ denotes the distance cost for robot r_i to arrive at p_j considering its position at time t, and θ_1, θ_2 are positive parameters that balance the above two terms. In addition, only one robot should be assigned to a specific node (i.e., $\forall t, j \sum_i a_{ij} \le 1$) to keep a similar frequency across the nodes.

In general, DTAP model produces significant improvements in multi-obstacles environment due to its on-line strategy. Moreover, the problem that agents disappear during mission execution is addressed by the *forceBid*$(dst, value, sender)$ function (5), which forces the current bid as the best one. However, similar with the CBBA model, the auction sequence of DATP model is still generated randomly, which limits its performance in complex and changeable environment. Besides, both DTAP and CBBA limit the number of tasks that each agent can perform with a fixed constant, the flexibility of dynamic assignment results will be seriously affected.

III. PROPOSED "TWO-STAGE" AUCTION ALGORITHM

In this section, we will present and discuss the details of the proposed "Two-Stage" auction algorithm. According to the above analysis, we know that CAA, CBBA and DATP all use random auction sequence, which may produce poor performances in complex dynamic environment. To solve this problem in these models, we divide the multi-UAVs dynamic task assignment problem into two stages, where the first stage judges which tasks are prioritized, and the second stage executes auction process to find the suitable agent and plans the path with the consideration of avoiding obstacles. To be specific, the first stage produces a reasonable auction sequence according to the novel hierarchical decision mechanism. Then, related UAVs bid for the task based on the novel objective function and build their own local task queue and path.

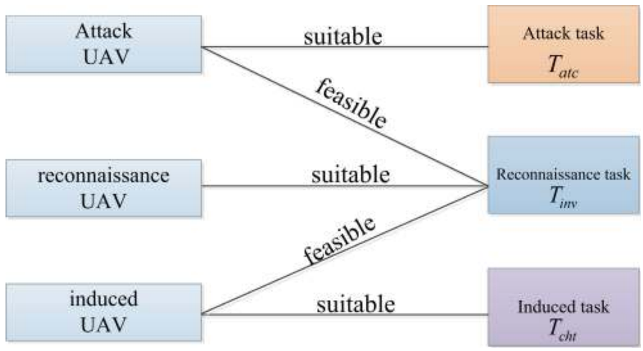

FIGURE 1. Heterogeneous type constraint diagram.

A. DYNAMIC TASK ASSIGNMENT MODEL

Definition 1 (Task Space): There is a task set $\{T_1, T_2, T_3, \ldots, T_M\}$ existing in a two-dimensional plane, and $T_j (j = 1, 2, \ldots, M)$ has four attributes: location coordinates (X_j, Y_j), gain value $V(T_j)$, threat value $Th(T_j)$ and blind value $B(T_j)$. The above four attributes come from the initialization of the mission area. Note that there are multiple types of tasks in this environment, which can be categorized into attack, reconnaissance and induced task subsets.

Definition 2 (Executive Unit): There are N agents (UAVs) with integrated wireless communication capabilities. $\{U_1, U_2, U_3, \ldots, U_N\}$ denotes the set of UAVs. Considering the multi-UAVs operational scenario, there are three basic configurations: attack UAV, reconnaissance UAV, and induced UAV. The reconnaissance UAV U_{inv} is equipped with an advanced sensing system and high airspeed configuration. In addition, it has a fast flight speed and a large field of view. Therefore, it is suitable to execute reconnaissance missions. Attack UAV U_{atc} is suitable for attack missions due to its high maneuverability and the capabilities to carry weapons and ammunition. The induced UAV U_{cht} can imitate the radar reflection cross-section RCS characteristics of important aircraft through airborne equipment. Thus, it will mislead the enemy air defense radar to protect our important aircrafts. Heterogeneous type constraint is shown in Fig. 1.

Due to the limited task resources of each UAV, we establish the resource vector of each UAV based on the resource constraints principles.

$$res^i = (r_1^i, r_2^i, r_3^i, r_4^i) \tag{6}$$

$$req_i^j = (rq_1^{i,j}, rq_2^{i,j}, rq_3^{i,j}, rq_4^{i,j}) \tag{7}$$

where res^i indicates the fuel, ammunition, reconnaissance, and induced resources of $i - th$ UAV, and req_i^j indicates the resources required to assign task j to U_i.

After getting a task, each UAV updates its own resource vector:

$$res^i = res^i - \sum req_i^j \tag{8}$$

Before bidding process, each UAV will check its own resource vector res^i, if $r_s^i < rq_s^{i,j}$, $s = 1, 2, 3, 4$, it indicates that there are no enough resources to bid any new tasks.

The allocation model can be a balanced assignment or an unbalanced assignment. For the undifferentiated hybrid model with variable number of tasks and execution units, we define the target allocation matrix $X^{N \times M}$:

$$x_{ij} = \begin{cases} 1, & \text{if } \mathrm{U}_i \text{ perform task } T_j \\ 0, & \text{else} \end{cases} \tag{9}$$

If the target allocation matrix is $U_{i-} = [11\ 1\ 0]$, it means that the UAV U_i acquires the task queue $U_i^{Tseq} = \{T_1, T_2, T_3\}$. Then, we define an objective function of the UAV U_i in this assignment:

$$G(U_i^{Tseq}) = Rwd(U_i(T_1)) + Rwd(U_i(T_2)) + Rwd(U_i(T_3)) \tag{10}$$

$$Rwd(U_I(T_j)) = Benefit(U_i(T_j)) - Cost(U_i(T_j)) \tag{11}$$

Formula (10) and (11) denote the revenue that UAV U_i accomplishes the local task queue U_i^{Tseq}. $Rwd\left(U_i\left(T_j\right)\right)$ is the net profit of UAV U_i to accomplish the task T_j. $Benefit(U_i(T_j))$ denotes the revenue that UAV U_i completes task T_j in the task queue U_i^{Tseq}. $Cost(U_i(T_j))$ is the cost of UAV U_i to complete the task T_j in the task sequence U_i^{Tseq}. The $Benefit(U_i(T_j))$ term comes from two aspects. On the one hand, it is the value attribute of the target. For example, the value $V(T_j)$ gains from destroying high-value targets such as base stations or airports. On the other hand, it comes from the threat value $Th(T_j)$ of a target. For example, high-threat targets such as air-defense radar or anti-aircraft artillery could destroy UAVs on missions. In the scenario of multi-UAVs cooperative protect piloted airplanes, sweeping battlefield threats target usually takes precedence over attack targets. We define task benefit that UAV U_i accomplish the task T_j:

$$Benefit\left(U_i\left(T_j\right)\right) = k_a V\left(T_j\right) + k_b Th\left(T_j\right) \tag{12}$$

$$\begin{cases} k_a + k_b = k_c \\ 0 \le k_a, \quad k_b \le 1 \end{cases} \tag{13}$$

where $V(T_j)$ indicates the gain value of the task T_j. $Th(T_j)$ denotes the threat value of the task T_j. The above two attribute values reflect the current attributes of the mission area. When the environment changes, the value of these attributes will change accordingly, which is one of the conditions for starting dynamic assignment. k_a and k_b are the normalization coefficients of these factors for the benefit function, which indicates the preference of the benefit function for gain or threat. k_c denotes the weight coefficient of the benefit function among the objective function.

The $Cost\left(U_i\left(T_j\right)\right)$ term is usually the fuel cost, time cost, etc. There are some literatures consider the risk factor for UAVs to perform tasks as part of the cost. The fuel consumption during the actual flight is related to many factors such as altitude, speed, distance, wind speed, etc., thereby the actual fuel consumption is difficult to be calculated accurately in the simulation. Since the UAV flight distance and fuel consumption are close to linear in the constant speed cruise phase, this paper replaces the fuel consumption cost with the route cost. We define the cost of UAV U_i to complete task T_j as follows:

$$Cost(U_i(T_j)) = k_{mt}^{U_iT_j}(k_d D(U_iT_j) + k_p p_i^j) \tag{14}$$

where $D(U_iT_i)$ is the distance cost of U_i to complete task T_j. p_i^j denotes the probability that U_i destroyed by the counterattack on missions. k_d and k_p are the normalization coefficients of the distance cost and the destroyed cost. $k_{mt}^{U_iT_j}$ represents the cost coefficients when task crossover occurs. When $k_{mt}^{U_iT_j} \leq 1$, it indicates U_i is suitable for task T_j, and the execution cost is lower. Otherwise, it denotes that U_i is not suitable for the task T_j.

Besides the benefits and costs of the UAV executes missions that usually used in dynamic task assignment scheme. In this paper, we also propose two new terms to optimize the dynamic task assignment scheme $X^{N\times M}$, the coverage factor and penalty term. For example, some targets may not be in the UAV local task queue U_i^{Tseq}, but within the coverage of the UAV mission area. Therefore, it has a lower execution cost for these targets in the following dynamic task assignment. The novel coverage factor allows the UAV individuals to be more evenly distributed in the mission area instead of gathering at high-value and low-cost areas, which is conducive to the following dynamic task assignment and further optimization of the objective function. We define the target coverage factor as:

$$Cover\left(X^{N\times M}\right) = \frac{\sum U_i^{Tcov}}{sum\,(T)} \tag{15}$$

$$T_{cov} = \{T \,|\, D(TU_i^{Tseq}) \leq L_{cov}\} \tag{16}$$

$$D(TU_i^{Tseq}) = \min\left(\sqrt{(X_j - X_i)^2 + (Y_j - Y_i)^2}\right) \tag{17}$$

where U_i^{Tcov} is the coverage tasks set of U_i. $sum\,(T)$ is the number of tasks in the mission. $D(TU_i^{Tseq})$ denotes the minimum distance between task T_j and the tasks in U_i's local task queue. (X_j, Y_j) and (X_i, Y_i) are corresponding point coordinates. When $D(TU_i^{Tseq}) \leq L_{cov}$, task T_j is considered to be under the coverage of U_i and belongs to T_{cov}. If the size of mission area is relatively small, the value of L_{cov} should be smaller. Conversely, larger L_{cov} can be chosen if the size of mission area is larger. We found that the performance of our algorithm is optimal when the threshold L_{cov} equals 2500 in the 10km*10km square area.

In order to balance the use of individuals in the UAV swarm and make full use of the resources carried by each UAV, we propose a novel penalty term using a potential function.

$$P = \mu(L_i - n)^2 \tag{18}$$

where μ is negative constant. n is positive constant. L_i represents the number of tasks carried by the UAV.

Obviously, when $L_i = n$, the penalty term is 0. The larger the deviation of L_i from n, the larger penalty will be imposed on the profit of a task in the auction process, which adaptively limits the number of tasks that the UAV can perform. After a great number of trials, we find that the penalty term works well as $n = 3$.

In summary, we define the objective function as follow:

$$G(X^{N\times M}) = \sum_{i=1}^{N} Benefit(U_i(U_i^{Tseq})) - \sum_{i=1}^{N} Cost(U_i(U_i^{Tseq})) + Cover(X^{N\times M}) + \mu(L_i - n)^2 \tag{19}$$

$G(X^{N\times M})$ denotes the objective function of the mission planning scheme $X^{N\times M}$, which includes four terms: mission benefit, mission cost, coverage factor and penalty term. The first two terms determine the net profit of the assignment results, their specific contents have been described above. The third term mainly considers the association cost between tasks. Specifically, new tasks found by the UAVs are associated with the tasks in their local task queue. If the new task is within combat path of the UAV, the subsequent dynamic assignment has a lower cost for this UAV. The last penalty term balances the use of individuals in the UAV swarm and make full use of the resources carried by each UAV using a potential function. Therefore, the last two terms in novel objective function can make the assignment results get higher payoff when all other conditions are equal. The allocation algorithm is looking for the maximum value of the objective function. We define the mathematical form of the optimization objective function is:

$$\max\left(G\left(X_{fin}^{N\times M}\right)\right) \tag{20}$$

The purpose of assignment algorithm is to optimize the objective function for finding the optimal or sub-optimal scheme $X_{fin}^{N\times M}$ of the objective function. Dynamic task assignment algorithm often abandons the global perspective to reduce the computational cost and optimize the global allocation efficiency from local optimization through the greedy principle, so it usually has better response speed.

B. FIRST STAGE: UPPER DECISION

Upper decision function:

$$Class_{\{T\}} = \max[k_v \cdot V_{score}, k_{th} \cdot Th_{score}, k_{hr} \cdot Hr_{score}] \tag{21}$$

$$V_{score} = a_1 \sum_{j=1}^{m} V(T_j)$$
$$Th_{score} = a_2 \sum_{j=1}^{m} Th(T_j)$$
$$Hr_{score} = a_3 \sum_{j=1}^{m} B(T_j) \tag{22}$$

where $a_1, a_2, a_3 > 0$ are weighting parameters. m is the sum of the three types UAVs in the mission area. $V(T_j)$, $Th(T_j)$ and $B(T_j)$ represent the gain value, threat value, and blind value of $j-th$ task. V_{score}, Th_{score} and Hr_{score} denote the gain value, threat value, and blind value of the mission area, respectively. k_v, k_{th} and k_{hr} are normalization coefficients.

In order to optimize the auction sequence, we propose a novel hierarchical decision mechanism based on the three attribute values of tasks and decision function. First, the hierarchical decision mechanism is used, depending on the novel decision function, to select the subset of task types $\{T_{classi}\}$ as current auction task set. Obviously, the decision function used here is essentially an extremal function. Second, it will choose a specific task in above auction task set according to the attribute values of tasks. To be specific, the output of the decision function (21) determines the current environment attribute. When $k_v \cdot V_{score}$ is the largest in (21), the environment of the mission area is determined to be the high-profit situation. As a result, the attack tasks will be executed first and their sequence in local task queues will be ordered based on their gain values. Similarly, if $k_{th} \cdot Th_{score}$ is the largest of the three, the environment is judged as the high-risk situation, then induced tasks are prioritized. When there are many blind zones in the mission area, the corresponding term $k_{hr} \cdot Hr_{score}$ reaches the maximum. Therefore, reconnaissance-type UAVs are given priority to execute reconnaissance tasks. In general, task sequence in local task queues is ordered based on the three attribute values. The purpose of imposing the hierarchical decision mechanism is not only to arrange the auction sequence dynamically depending on the change of the environment attributes, but also to improve the speed of the multi-UAVs system to remove high threat targets in dynamic environment. By incorporating the novel hierarchical decision mechanism into auction algorithm, our method can handle dynamic task assignment problem better in complex and changeable environment.

C. SECOND STAGE: AUCTION MECHANISM

In the second stage, each UAV bids for their interested tasks based on the novel objective function (19) and puts corresponding tasks in its local task queue. Different from the CBBA model, the local task queue is ordered based on the attribute values of tasks in our method. All UAVs calculate the profit of tasks independently and continuously updates its local task queue. Besides, each UAV plans its path according to the obstacle avoidance algorithm. It should be noted that the path-planning is not as optimal as in [26], due to the

Algorithm 1 The Algorithm of "Two-Stage"

Input:

Read in the tasks set $\{T_{atc}, T_{inv}, T_{cht}\}$, UAVs set $\{U_{atc}$,U_{inv},$\text{U}_{cht}\}$ and Constraint set $\{R\}$.

Initialization:

Initialize the attribute values of tasks $V(T_j)$, $Th(T_j)$, $B(T_j)$, and resource vector of UAVs res^i, req_j^i; Set cross-cost coefficient $k_{mt}^{U_iT_j}$, distance threshold L_{cov}, coefficientsμ, n, a_1, a_2, a_3, the value of normalization coefficients$k_a, k_b, k_d, k_p, k_v, k_{th}, k_{hr}$, the number of UAVs N and tasks M, and the number of iteration termination m.

Repeat:

1. Compute the decision function according to Eq.21;
2. Based on the attribute values of tasks, find a specific task $T_{typical}$ form the subset that is determined by above step.
3. Start the auction process according to Eq.19;
4. If new tasks suddenly appear or the UAV disappears in the mission area, adjusts the original assignment plan according to the relevant mechanism immediately.
5. Path planning and obstacle avoidance.

Until:

The number of iterations is equal to m.

Output:

The final dynamic task assignment results.

priority of the environment attributes in the mission area. In dynamic assignment situation, new found tasks have associated cost with tasks which has existed in the local task queue. The execution efficiency of the allocation scheme will be reduced if new found tasks are directly assigned at the end of the local task queue without considering the previous tasks. In addition, due to resource constraints, each UAV can only perform limited tasks and must return to base to replenish resources when the resources are about to run out. The last term in objective function (19) can ingeniously accomplish the full use of resources carried by each UAV. Specifically, the three algorithms introduced in section II set the number of tasks that each agent can perform using a fixed constant. For example, although the agent has enough resources to bid for another tasks, it must exit the bidding process when it reaches the fixed constant. However, our method can completely avoid this problem. In order to illustrate the advantages of our method, we set $n = 3$. Although there is a penalty cost for getting the fourth task, it is less than the cost of using a new agent. Moreover, profits will sharp decrease when L_i seriously deviates from n, which balances the use of individuals in UAV swarm.

The "Two-Stage" auction algorithm proposed in this paper not only quickly finds the most suitable UAV for the selected task, but also realizes dynamic task assignment in complex and changeable environment. The novel objective function is more conducive to maximize the overall payoff by considering the coverage factor and penalty term, which can optimize the overall task execution efficiency. Moreover, the introduction of the penalty term can balance the UAV mission load

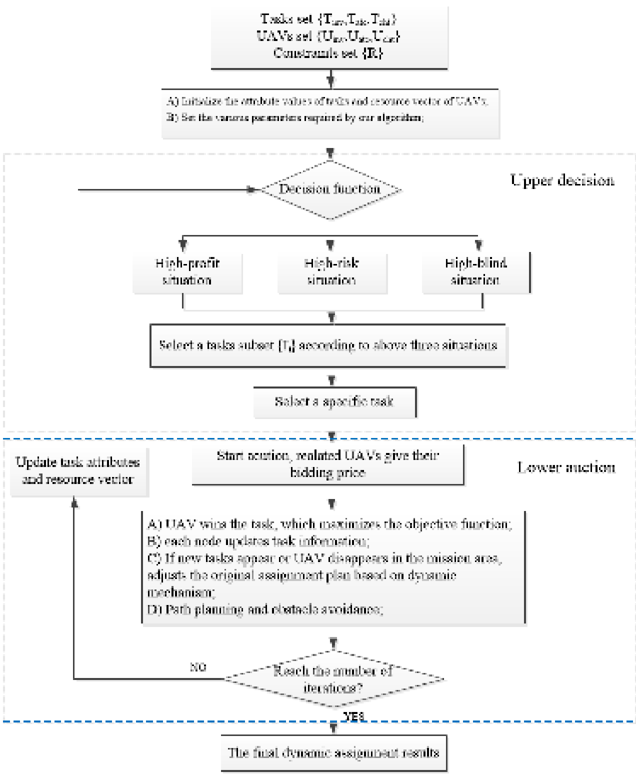

FIGURE 2. The algorithm flowchart.

and use UAVs in the swarm as reasonably as possible. The algorithm flowchart, which shows in Fig. 2, clearly explains the specific process of the algorithm.

In summary, our algorithm consists in following steps:

IV. EXPERIMENTS

The mission area is set to a square area of 10km*10km, and there are up to 20 known targets and 4 unknown targets in this area. UAV swarm consists of 8 UAVs, including 4 attack UAVs, 3 reconnaissance UAVs and 1 induced UAV. The flight speed of every UAV is 50m/s by default. In order to make the simulation closer to the actual situation, we set obstacles (no-fly-zones) in the mission area, which need to be avoided in the path planning process. Unless other specified, we use the following parameters in this paper: $N = 8$, $\mu = 0.5$, $n = 3$, $a_1 = a_2 = a_3 = 1$, $k_b = k_d = k_p = 0.8$, $k_a = 0.5$, $k_v = k_{th} = k_{hr} = 0.6$, $L_{cov} = 2500$, $m = 30$.

we mainly carry out our experiments from the following five aspects. 1) Dynamic task assignment for known targets. 2) Dynamic task assignment for new found targets. 3) Dynamic task assignment after UAV lost. 4) Dynamic task assignment under different scenarios. 5) Comparison experiments with CAA, CBAA, and DTAP in terms of the total allocation payoff and the completion speed of tasks.

A. DYNAMIC TASK ASSIGNMENT FOR KNOWN TARGETS

Among all 8 UAVs, U_1-U_4 are attack UAVs, U_5-U_7 are reconnaissance UAVs, and the last one U_8 is induced UAV.

TABLE 1. The initial information of UAVs.

U_i	Initial Position	Vector of Resources
U_1	(100, 100)	(100, 6, 2, 0)
U_2	(100, 100)	(100, 5, 2, 0)
U_3	(100, 100)	(100, 7, 1, 0)
U_4	(100, 100)	(100, 5, 2, 0)
U_5	(100, 100)	(120, 0, 4, 1)
U_6	(100, 100)	(120, 0, 3, 2)
U_7	(100, 100)	(120, 0, 5, 1)
U_8	(100, 100)	(120, 0, 3, 5)

TABLE 2. The initial information of attack tasks.

T_j	Initial Position	Requirement for Attack Resources
T_1	(2560, 4960)	1
T_2	(2100, 9100)	1
T_3	(2560, 8500)	2
T_4	(4800, 4200)	2
T_5	(6200, 9300),	1
T_6	(9800, 6000)	1
T_7	(6200, 3000)	1
T_8	(9600, 3200)	2

TABLE 3. The initial information of reconnaissance tasks.

T_j	Initial Position	Requirement for Reconnaissance Resource
T_9	(8000, 4100)	1
T_{10}	(9100, 9000)	1
T_{11}	(8000, 9600)	1
T_{12}	(9000, 1000)	2
T_{13}	(900, 9800)	1

TABLE 4. The initial information of induced tasks.

T_j	Initial Position	Requirement for Induced Resource
T_{14}	(3000, 2000)	2
T_{15}	(4000, 6000)	2

All UAVs take off from the same initial position (100, 100) in this paper. Each UAV has a corresponding vector, which indicates four kinds of resources carried by the UAV. Note that the initial position of tasks, the three attribute values of tasks, and the last three values in resource vector are generated in random way. The initial information of UAVs is shown in Table 1. The initial information of tasks is respectively shown in Table 2, Table 3 and Table 4. In the first scenario, there are 15 known targets and 2 unknown targets.

TABLE 5. The results of high-profit situation task assignment.

Attribute Values	U_i	Task Sequence	Remained Resource
$k_v \cdot V_{score} = 87.21$ $k_{th} \cdot Th_{score} = 76.15$ $k_{hr} \cdot Hr_{score} = 66.98$	U_1	$\lvert T_5, T_3, T_2 \rvert$	(69.33, 2, 2, 0)
	U_2	$\lvert T_7, T_4, T_1 \rvert$	(78.15, 1, 2, 0)
	U_3	$\lvert T_8, T_6 \rvert$	(74.40, 4, 1, 0)
	U_4	None	(100.00, 5, 2, 0)
	U_5	$\lvert T_{13} \rvert$	(100.53, 0, 3, 1)
	U_6	$\lvert T_{10}, T_{11} \rvert$	(92.18, 0, 1, 2)
	U_7	$\lvert T_{12}, T_9 \rvert$	(95.60, 0, 2, 1)
	U_8	$\lvert T_{14}, T_{15} \rvert$	(104.82, 0, 3, 1)

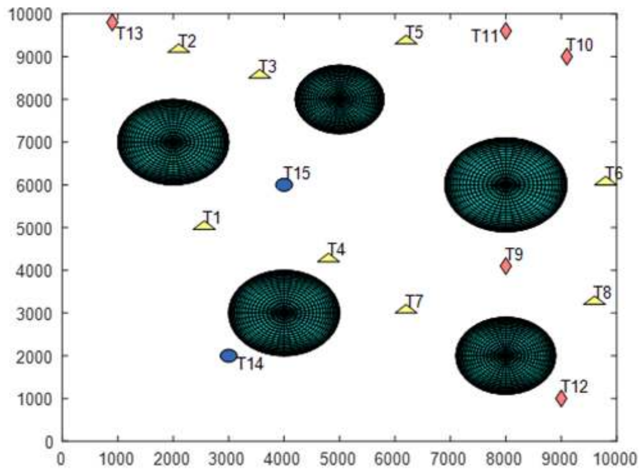

FIGURE 3. The initial environment of the task assignment.

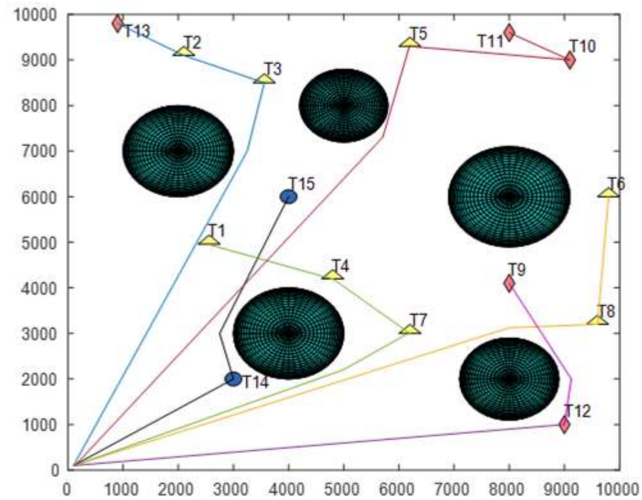

FIGURE 4. High-profit situation dynamic task assignment results.

Specifically, Fig. 3 shows the initial environment of the first scenario. Different types of tasks are represented by different colors and shapes, where yellow triangle, red diamond, and blue circle represent attack, reconnaissance, and induced tasks, respectively. The dark green circle indicates the obstacles that UAVs cannot fly over. The unknow tasks are not shown in Fig. 3, which will be discussed in IV-B and IV-D.

Assume that each task has three attribute values, namely gain value, threat value, and blind value. The hierarchical decision mechanism determines the current environment attributes of the mission area based on these values, and then generates a reasonable auction sequence. Due to the dynamic changes of the environment in mission area, the output of the hierarchical decision function will change accordingly. When the environment is high-profit, high-risk, or high-blind situation, the dynamic assignment results of our method will be different. We verify the efficiency and robustness of the proposed algorithm according to these three situations.

As shown in Fig. 4, there are five obstacles in the mission area. When $k_v \cdot V_{score}$ is the largest, the environment is determined to be the high-profit situation, then the attack-type tasks are preferentially executed. Tasks in the local task queues of attack UAVs are ordered based on the gain value, which is shown in Table 5. Since the attack tasks are prioritized for auction, the attack UAVs are first to fly out of the base, which is conducive to their competition for nearby reconnaissance-type tasks. Considering the cross-execution of tasks, U_1 bids T_3, T_2 and T_{13} with higher prices. Besides, U_2 puts T_5, T_{10} and T_{11} in its local task queue, which causes two reconnaissance UAVs have no tasks to perform. It needs to be emphasized that because of incorporating the adaptive-limitation penalty term into objective function, all UAVs except U_6 and U_7 get about three tasks in the auction process. Due to the use of obstacle avoidance path planning algorithm, our method achieves desirable dynamic assignment results in the environment with some obstacles.

As can be seen from Fig. 5, when $k_{hr} \cdot Hr_{score}$ reaches the maximum, it means that there are many blind regions in the mission area. Then, reconnaissance-type UAVs are given priority to perform reconnaissance tasks. In this case, all three

TABLE 6. **The results of high-blind situation task assignment.**

Attribute Values	U_i	Task Sequence	Remained Resource
$k_v \cdot V_{score}=61.24$ $k_{hr} \cdot Hr_{score}=90.13$ $k_{th} \cdot Th_{score}=47.15$	U_1	$\lvert T_3, T_2, T_{13}\rvert$	(75.89, 3, 1, 0)
	U_2	$\lvert T_5, T_{10}, T_{11}\rvert$	(69.58, 4, 0, 0)
	U_3	$\lvert T_7, T_4, T_1\rvert$	(78.07, 3, 1, 0)
	U_4	$\lvert T_8, T_6\rvert$	(74.40, 2, 2, 0)
	U_5	$\lvert T_{12}, T_9\rvert$	(75.60, 0, 1, 1)
	U_6	None	(120.00, 0, 3, 2)
	U_7	None	(120.00, 0, 5, 1)
	U_8	$\lvert T_{14}, T_{15}\rvert$	(104.82, 0, 3, 1)

TABLE 7. **The results of high-risk situation task assignment.**

Attribute Values	U_i	Task Sequence	Remained Resources
$k_v \cdot V_{score}=59.13$ $k_{hr} \cdot Hr_{score}=75.64$ $k_{th} \cdot Th_{score}=84.36$	U_1	$\lvert T_5, T_3, T_2\rvert$	(69.33, 2, 2, 0)
	U_2	$\lvert T_7, T_4, T_1\rvert$	(78.15, 1, 2, 0)
	U_3	$\lvert T_8, T_6\rvert$	(74.40, 4, 1, 0)
	U_4	None	(100.00, 5, 2, 0)
	U_5	$\lvert T_{13}\rvert$	(100.53, 0, 3, 1)
	U_6	$\lvert T_{10}, T_{11}\rvert$	(92.18, 0, 1, 2)
	U_7	$\lvert T_{12}\rvert$	(102.11, 0, 3, 1)
	U_8	$\lvert T_{14}, T_{15}, T_9\rvert$	(95.96, 0, 2, 1)

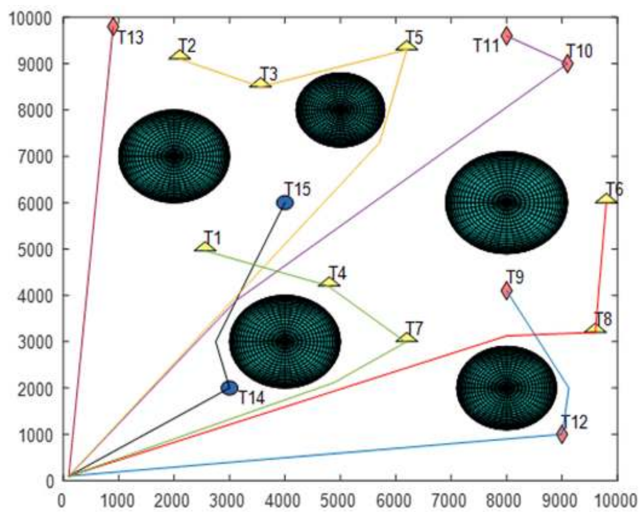

FIGURE 5. **High-blind situation dynamic task assignment results.**

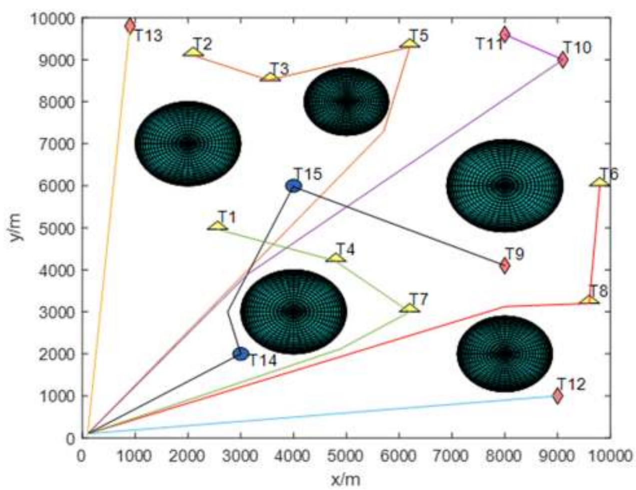

FIGURE 6. **High-risk situation dynamic task assignment results.**

reconnaissance-type UAVs fly out of the base to perform mission. Since the reconnaissance UAVs cannot execute attack tasks and induced tasks, there are no cross-execution in this situation. The specific tasks queues and resources surpluses are shown in Table 6.

When $k_{th} \cdot Th_{score}$ is the largest among three attributes, the environment is judged as the high-risk situation. Therefore, the induced tasks are prioritized. Considering the coverage factor of the tasks, as is shown in Fig. 6, U_8 also puts the reconnaissance task T_9 into its task queue after accomplishing T_{14} and T_{15}. The specific dynamic tasks assignment results of this situation are shown in Table 7. Moreover, we observed that the priority of the reconnaissance tasks is higher than attack tasks because of $k_{hr} \cdot Hr_{score} > k_v \cdot V_{score}$. In addition, except for induced tasks, the assignment results and trajectory

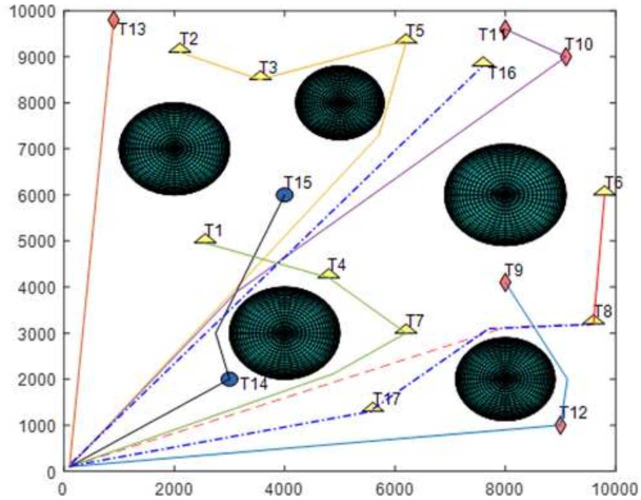

FIGURE 7. High-profit situation dynamic task assignment results after finding new targets.

of other tasks are similar to Fig. 4, which strongly illustrates the stability and reliability of our algorithm.

B. DYNAMIC TASK ASSIGNMENT FOR NEW FOUND TARGETS

Due to the complex and changeable environment in mission area, some targets may not be detected during initialization, and they can be discovered when UAVs execute assigned tasks according to their radar detector. When new tasks are detected in the mission area, the UAV who finds these tasks will transform their information to its neighbors by broadcast. The neighbors immediately check its own local task queue and resources surpluses. If conditions permit, they will bid the tasks based on the received information, otherwise, they will not. Then, the winner inserts these tasks into the appropriate position of its local task queue according to the attribute values or rearranges the local task queue based on the remained resources. Above process does not need the participation of the central station for cooperative control. The assignment of tasks and the calculation of remaining resources are completed by highly autonomous UAVs.

For example, as shown in Fig. 7, in high-profit situation, U_2 finds task T_{16} on the way to its first task T_5, and U_3 finds task T_{17} on the way to T_7, respectively. The new found tasks T_{16} and T_{17} are attack tasks, and their positions and required resources are shown in Table 8. For further analysis, when U_2 and U_3 respectively find tasks T_{16} and T_{17}, they immediately establish an auction network with its neighbors. Then, each UAV gives its bidding price by comprehensively considering some factors, such as resources and distance. The bidding information of neighbors shows in Table 9. Here, we take T_{16} as an example to illustrate the detail process. Since U_4 is not within the communication range of U_2, it cannot participate in the auction process. In the bidding of U_1, U_2 and U_3, U_2 finally gets T_{16} with the highest bid price, and it changes

TABLE 8. The information of two new tasks.

T_j	Initial Position	Requirement for Induced Resource
T_{16}	(7600, 8800)	3
T_{17}	(5600, 1300)	2

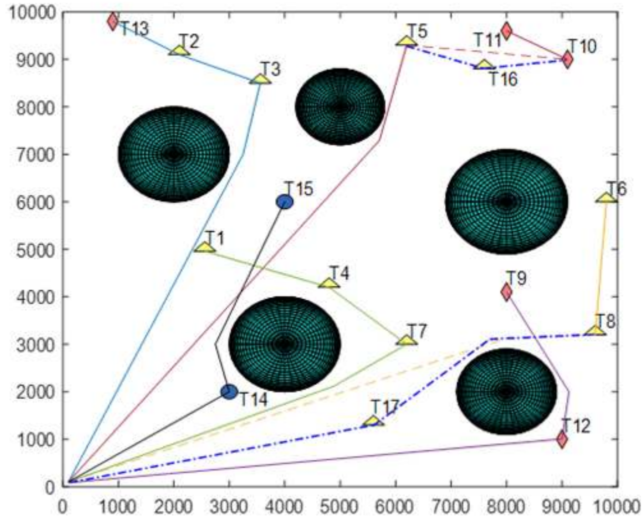

FIGURE 8. High-blind situation dynamic task assignment results after finding new targets.

the original flight trajectory. Note that dashed line indicates the original trajectory, and dash-dot line indicates the current trajectory after finding new tasks.

When environment becomes high-blind situation, the results of dynamic assignments will change dramatically. As shown in Fig. 8, U_6 and U_7 find new tasks T_{16} and T_{17} during the way to perform original plan, respectively. To be specific, U_6 sends the detailed information of T_{17} to U_1, U_2 and U_3 as soon as it finds this task. New task T_{17} will be directly assigned to U_3 because U_1 and U_2 have insufficient resources to execute it. Besides, none of UAVs near task T_{16} have enough resources to execute this task. Therefore, the central station will assign T_{16} to U_4, which is on standby at the base. The specific remained resources of U_1, U_2 and U_3 are shown in Table 6. Table 8 shows the requirement for attack resources of T_{16} and T_{17}. Since the dynamic task assignment results of the high-blind situation are similar to the high-risk situation, which is shown in Fig. 9. We do not describe this situation in detail here.

C. DYNAMIC ASSIGNMENT AFTER UAV LOST

In the military environment, there is a risk that the UAV may be destroyed. Once the UAV disappears in the mission area, the tasks it carried will never be performed.

This paper adopts a centralized-distributed hybrid auction structure, where central station sends challenge messages to each UAV at regular intervals. If the UAV does not respond to the challenge within specified time, central station will

TABLE 9. The bidding information of neighbors.

Attribute Value	T_i	Bid Price of U_1	Bid Price of U_2	Bid Price of U_3	Bid Price of U_4
$k_v \cdot V_{score} = 96.75$	T_{16}	125.18	**171.55**	71.33	None
$k_{th} \cdot Th_{score} = 79.36$ $k_{hr} \cdot Hr_{score} = 71.34$	T_{17}	60.23	69.14	168.96	**170.38**

TABLE 10. The bidding information of neighbors after U_2 lost.

Attribute Value	T_i	Bid Price of U_1	Bid Price of U_3	Bid Price of U_4	Bid Price of U_5
$k_v \cdot V_{score} = 95.13$	T_5	**99.26**	73.51	85.17	None
$k_{th} \cdot Th_{score} = 74.61$	T_{10}	56.19	40.36	**78.60**	59.36
$k_{hr} \cdot Hr_{score} = 69.22$	T_{11}	52.35	36.74	**73.26**	65.15

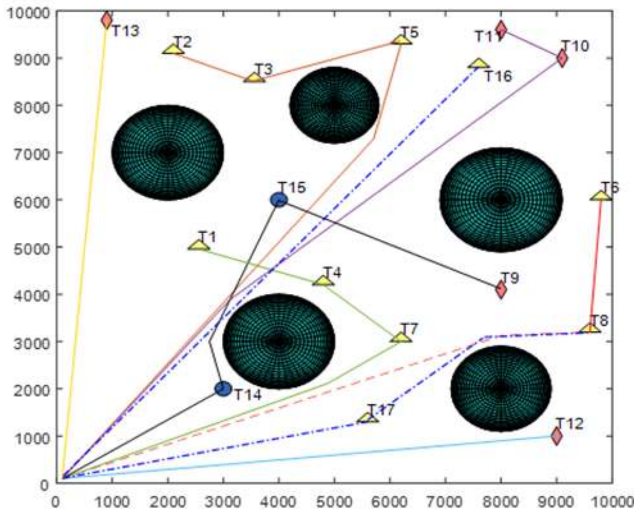

FIGURE 9. High-risk situation dynamic task assignment results after finding new targets.

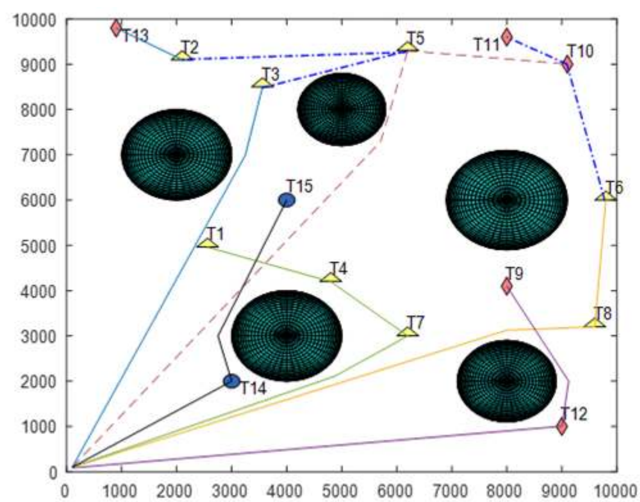

FIGURE 10. High-risk situation dynamic task assignment results after U_2 lost.

TABLE 11. Dynamic allocation after U_2 Lost.

U_i	Original Task Queue	Current Task Queue	Remained Resources
U_1	$\lvert T_3, T_2, T_{13} \rvert$	$\lvert T_3, T_5, T_2, T_{13} \rvert$	(65.32, 0, 1, 0)
U_2	$\lvert T_5, T_{10}, T_{11} \rvert$	None	(0, 0, 0, 0)
U_4	$\lvert T_8, T_6 \rvert$	$\lvert T_8, T_6, T_{10}, T_{11} \rvert$	(65.73, 2, 0, 0)

confiscate its unexecuted tasks and reauction them. Hence, this mechanism solves the problem of losing both UAV and its carried tasks. As previous experiment shown in Fig. 6, U_2 is destroyed when it passes by T_{15}. Thus, three tasks T_5, T_{10} and T_{15} it carried are reauctioned by the central station.

We show the dynamic assignment results when U_2 disappears from the mission area in Fig. 10 and Table 10, respectively. Table 11 shows the comparison of the results between the original assignment and dynamic assignment after losing U_2. We observed that U_1 gets T_5 with the highest bid price, and then it inserts T_5 in the second position of its local task queue. U_4 gets T_{10} and T_{11} with the similar way. Note that, dashed line indicates the original trajectory, and the dash-dot line shows the trajectory after dynamic assignments.

D. DYNAMIC ASSIGNMENT UNDER DIFFERENT SCENARIOS

To further evaluate the efficiency and robustness of our method, we conduct the above experiments in different scenarios. We increase the number of tasks and obstacles (no-fly-zones) in the mission area. Specifically, the mission area is still a square area of 10km*10km, and there are 20 known targets, 4 unknown targets and 7 obstacles. UAV swarm consists of 8 UAVs, including 4 attack UAVs, 3 reconnaissance UAV and 1 induced UAV. Besides, the position of tasks and obstacles has changed. The choice of other parameters is

TABLE 12. Local task queue dynamic statistics.

U_i	Original Task Queue	Task Queue after New Tasks Appears	Task Queue after U_2 Lost
U_1	$\lvert T_3, T_1, T_{17} \rvert$	$\lvert T_3, T_{21}, T_1, T_{17} \rvert$	$\lvert T_3, T_1, T_4, T_{17} \rvert$
U_2	$\lvert T_4, T_2 \rvert$	$\lvert T_{20}, T_4, T_2, T_8 \rvert$	None
U_3	$\lvert T_{10}, T_7, T_8 \rvert$	$\lvert T_{10}, T_{22}, T_7 \rvert$	$\lvert T_{10}, T_7, T_8, T_2 \rvert$

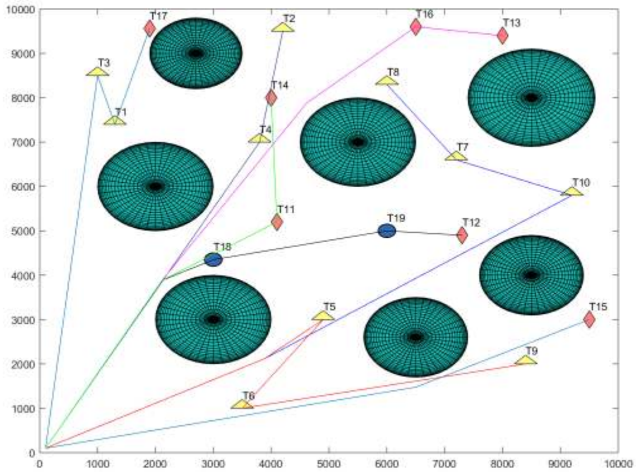

FIGURE 11. Dynamic task assignment results under high-profit situation.

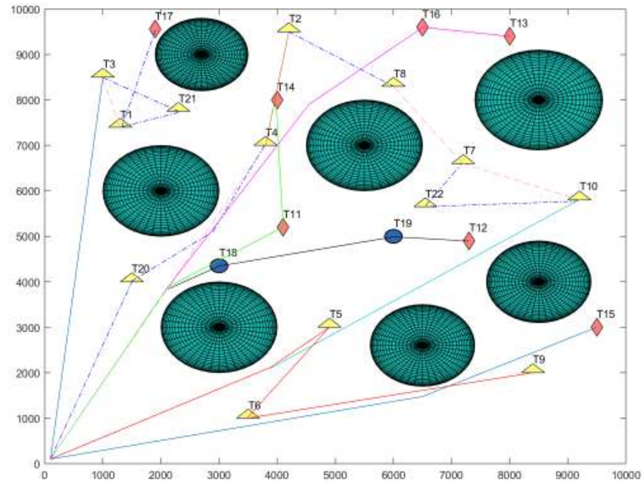

FIGURE 12. Dynamic task assignment results under high-profit situation after U_2 lost.

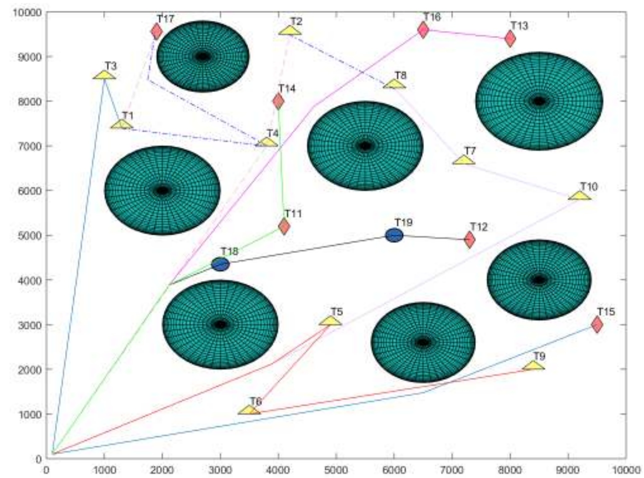

FIGURE 13. Dynamic task assignment results under high-profit situation after finding new targets.

the same as the above experiments. Due to space limitation, the following experiments only focus on the high-profit situation which is the most complex case. First, we show the dynamic assignment results under high-profit situation for known tasks in Fig. 11. Since the increased number of tasks, all UAVs participated in auction process. We observed that most of the UAVs obtain three tasks. As shown in Fig. 12, when U_1 finds task T_{20} and T_{21} on the way to its first task T_3, it transforms the information about these two tasks to its neighbors U_2, U_5 and U_6.

After the bidding process, U_1 gets the task T_{21} and rearranges its local task queue. Because U_3 adds the new task T_{22} into its local task queue, it has insufficient resources to execute T_8. Therefore, U_3 removes T_8 from the local task queue and sends its information to U_2 and U_4. Then, U_2 gets task T_8 and puts it at the end of the local task queue. Finally, we show the dynamic assignment results when U_2 disappears from the mission area in Fig. 13. With the intervention of central station, T_4 and T_2 are obtained by U_1 and U_3, respectively. It is clearly seen that our method produces desirable assignment results in more complex scenarios.

The detailed statistical analysis of UAVs finding new tasks and U_2 disappearing from the mission area shows in Table 12. Note that, dashed line indicates the original trajectory, and dash-dot line indicates the latest trajectory after finding new tasks or losing UAV.

For further validation of the performances of our method, we implement our algorithm in other scenarios. As is shown in Fig. 14, the dynamic assignment results for known tasks are still satisfactory in this case. Fig. 15 shows the assignment results of our method for new found tasks in high-profit situation. We observed that U_1 finds T_{12} during the execution of its tasks, and then sends its information to neighbors U_2 and U_5. Due to the limitation of task type and resources, U_2 finally adds T_{12} in its local task queue and adjusts the sequence of tasks. U_3 and U_4 deal with this problem in a similar way to the above process, which are no longer discussed here.

When U_3 is shot down during the continuous flight over two high risk regions, the subsequent dynamic assignment results are shown in Fig. 16. Specifically, U_4 removes the last three tasks from its local task queue in order to execute T_6 and T_9. Meanwhile, U_2 takes over the three tasks removed by U_4 after abandoning the reconnaissance task T_{13}. Besides, U_5 adds T_{13} into its local task queue. The specific changes to the local task queue are shown in Table 13.

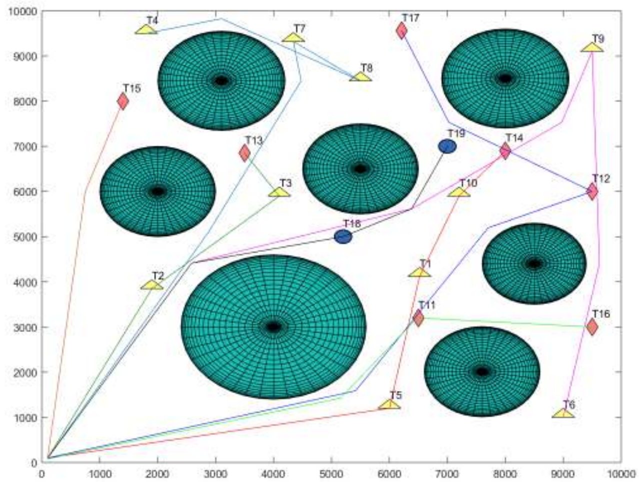

FIGURE 14. Dynamic task assignment results under high-profit situation.

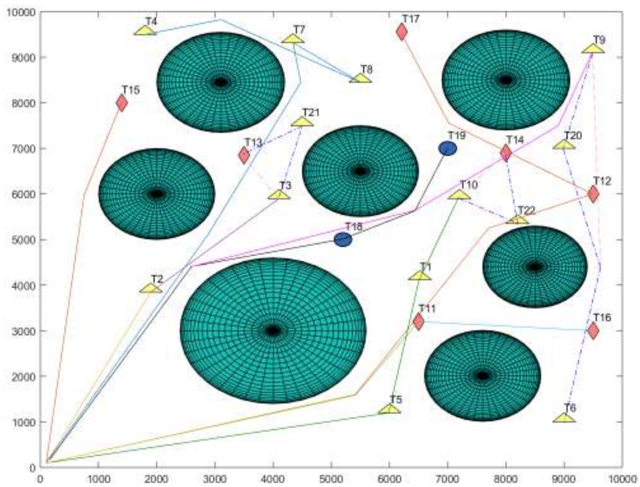

FIGURE 15. Dynamic task assignment results under high-profit situation after finding new targets.

TABLE 13. Local task queue dynamic statistics.

U_i	Original Task Queue	Task Queue after New Tasks Appears	Task Queue after U_3 Lost
U_2	$\lvert T_2, T_3, T_{13}\rvert$	$\lvert T_2, T_3, T_{21}, T_{13}\rvert$	$\lvert T_2, T_3, T_1, T_{10}, T_{14}\rvert$
U_3	$\lvert T_9, T_6\rvert$	$\lvert T_9, T_{20}, T_6\rvert$	None
U_4	$\lvert T_5, T_1, T_{10}, T_{14}\rvert$	$\lvert T_5, T_1, T_{10}, T_{22}, T_{14}\rvert$	$\lvert T_5, T_6, T_9\rvert$
U_5	$\lvert T_{15}\rvert$	$\lvert T_{15}\rvert$	$\lvert T_{15}, T_{13}\rvert$

E. COMPARISON EXPERIMENTS

To verify the efficiency of the proposed algorithm, we compare our method with conventional auction algorithm (CAA) [7], Consensus-based Bundle Algorithm (CBBA) [42], and market-based dynamic task assignment algorithm (DTAP) [44] in terms of the total allocation payoff and the completion speed of tasks. Fig. 17 shows the total assignment payoff of four algorithms. As we can see

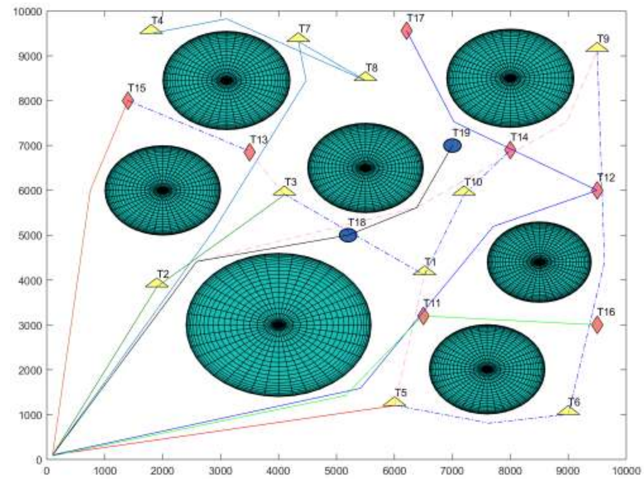

FIGURE 16. Dynamic task assignment results under high-profit situation after U_3 lost.

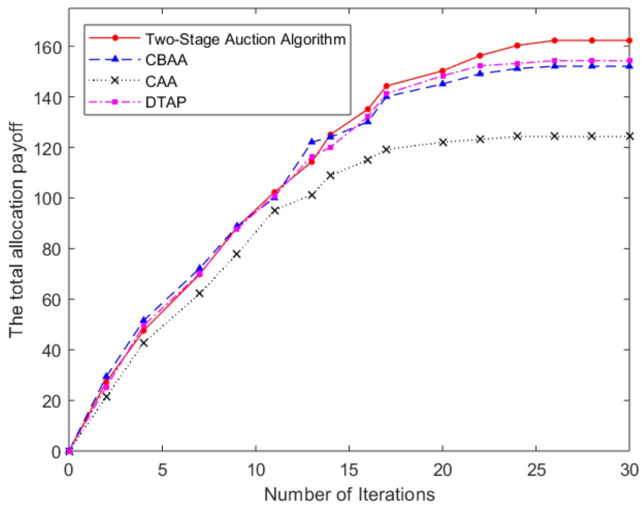

FIGURE 17. The total assignment payoff of four algorithms.

from that, the final convergence values of DTAP and CBBA are almost the same, while their values are higher than CAA. However, our method makes the total assignment payoff converge to the highest value. This is because CBBA can outbid earlier assigned tasks in the consensus stage to provide better dynamic assignments and DTAP employs an informed coordination protocols approach, while CAA locks the task into that assignment once it has a winner. Nevertheless, the novel objective function adopts the adaptive-limitation penalty term and considers the association costs between tasks. Therefore, it eventually gets the highest payoff than other three algorithms. In Fig. 18, when the environment is high-profit situation, we observed that the attack tasks in the mission area were completed very quickly. The reason is due to that the hierarchical decision mechanism adaptively adjusts the auction sequence based on the attribute values and places the attack tasks in front of the local task queue of related UAVs. The task completion speed of CBBA, DTAP,

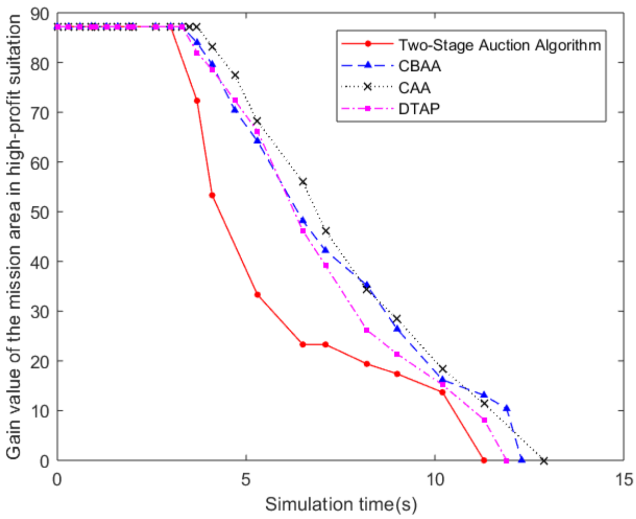

FIGURE 18. The gain values of the mission area in high-profit situation.

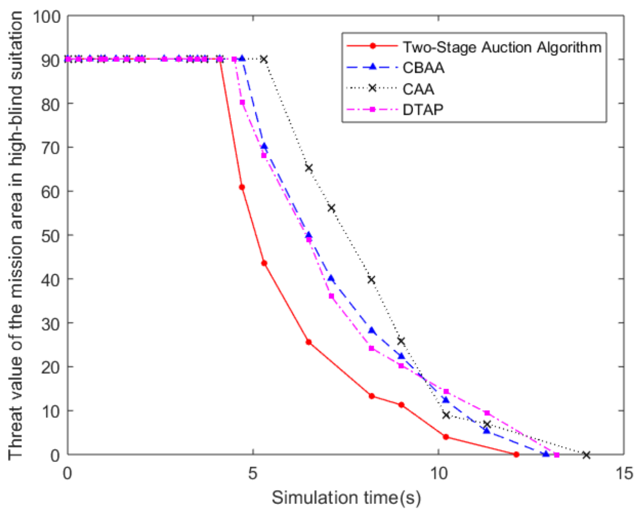

FIGURE 19. The threat values of the mission area in high-blind situation.

and CAA are relatively uniform due to their auction sequence are random. In Fig. 19, related UAVs execute reconnaissance tasks first under high-blind situation, that is, the value of $k_{hr} \cdot Hr_{score}$ decreases faster than others. In summary, the hierarchical decision mechanism combining with the novel objective function proposed in this paper significantly improves the performance of dynamic task assignments in complex environment. These three comparison experiments have demonstrated that our method is efficient and robust for handling dynamic task assignment.

V. CONCLUSION

In this paper, we propose a novel hybrid "Two-Stage" auction algorithm, which solves the problem of dynamic task assignment of heterogeneous multi-UAVs in complex and changeable environment. The hierarchical decision mechanism can adaptively adjust the auction sequence based on the attribute values. Therefore, it improves the threat removal rate of the mission area. Moreover, the proposed novel objective function considers the association cost between tasks, which further improves the performance of dynamic task assignment. Besides, the novel adaptive-limitation penalty term not only balances the use of individuals in the UAV swarm, but also makes full use of the resources carried by each UAV. The simulation experiments results show that the proposed algorithm outperforms state-of-the-art algorithms.

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