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Research on multi-Unmanned aerial vehicle joint delivery mission assignment based on multiple Alliance

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Abstract: In order to improve the battlefield delivery ability, for the battlefield joint delivery process task is heavy, time, traditional iron, public, water and other vulnerable to terrain, transportation conditions lead to low delivery efficiency, large-scale delivery mission capacity, the paper considers to use drones joint delivery task, according to the problem, summarize inspired rules, design fast construction model algorithm, using dynamic comprehensive sorting method, improve the task allocation and delivery efficiency, provide a reference for enriching the military diversified delivery mode, and improve the air delivery ability.

Keywords: Multiple UAVs; Joint delivery; Task allocation.

1. Introduction

All along, the rapid delivery force has been one of the goals of the armed forces of all countries, which is the basis for concentrating strength, capturing fighters, getting rid of the passive and efficient implementation of equipment and material support. According to the different mobile space, the force delivery force can be divided into air delivery capability, water delivery capacity and ground delivery capacity. Among them, the air delivery capability refers to the air transport capacity of various aircraft to use the support forces, which is related to the transport capacity, mobility speed, endurance and meteorological adaptability of the air platform.

With the continuous progress of science and technology, uav has been applied in various fields due to its strong mobility, convenient deployment and low cost. Joint delivery is one of the basic combat operations of the army, is the army from the barracks before entering the combat area. Traditional land transportation is not the only way to deliver, the current drones as the main body of multiple agent air delivery way not only can overcome the terrain, climate, do maneuver, and can through the introduction of relevant algorithm, based on multiple alliance rules, intelligent delivery assignment, the battlefield delivery mission to make rapid response at the same time, realize the best cost ratio.

Uav joint delivery can be seen as a multi-agent joint delivery action, each agent has its own behavior rules, so it can be modeled using a multi-agent approach. The multi-agent system is a group system composed of multiple intelligent autonomous movements with the ability of perception, cognition, control and operation through information interaction. Through the interaction between individuals, complex and powerful intelligent behaviors emerge in the whole system at macro through interaction [1].

2. Description of the multi-UAV joint delivery mission allocation problem

Multi-UAV multi-task allocation refers to the allocation and processing of the delivery tasks assigned by the system before performing the mission, so that the multiple UAV can complete the material delivery tasks at the lowest possible cost. This paper studies the problem of multi-UAV joint delivery mission assignment, which is actually a multi-task allocation decision optimization problem. Whether the task allocation is reasonable directly affects the effectiveness and efficiency of multi-UAV delivery[2]。

Multi-UAV and multi-task allocation is a complex process [3]. When multi-UAV faces multi-delivery tasks, in order to perform and complete the tasks, we need to specify the UAV and tasks one by one, that is, to carry out multi-UAV and multi-task dynamic allocation work. When the number of unmanned aerial vehicles and tasks is relatively large, it is extremely difficult to task-assign and perform tasks directly through the UAV, which can easily lead to low distribution efficiency and unreasonable distribution results.

Under the control of the ground station, each drone according to the task allocation results, fly to different task target point material delivery tasks, for the number of drones, delivery tasks, prone to repeat tasks, mission omission, drones ineffective execution, in order to avoid more collaborative inefficiency, need to establish a strong coupling between delivery mission and drones, namely through the task allocation. In the task assignment, the tasks assigned by the system should be divided into multiple sub-tasks according to the optimization objectives or constraints, and respectively distributed to the corresponding UAV to achieve the optimization objectives of the task allocation [4].

3. Multi-UAV task assignment modeling based on multi-alliance technolog-y

Assuming that N existing UAVs can be used for delivery mission, the set is recorded as $C_{Agent} = [A_i]_{1\times n}$, and any UAV A_i has a $r = 2$ dimensional capability vector $B_i = [b_i^j]_{1\times r}$ (mobility capability, transportation capability, endurance capability), B_i a quantitative description of the mission capability of a UAV A_i, $b_i^j \geq 0$ indicating the capability j value of the UAV A_i; the cost of the UAV A_i to complete the task is $cost_i$, specifically, setting $cost_i = 1, i = 1, ..., N$. The set of the entire task area is recorded as $T = [t_k]_{1\times m}$, and the vector $P_k = [p_k^j]_{1\times r}$ represents the capability requirements to complete the task t_k. Figure 1 establishes a mapping model between UAV and delivery mission[5-6].

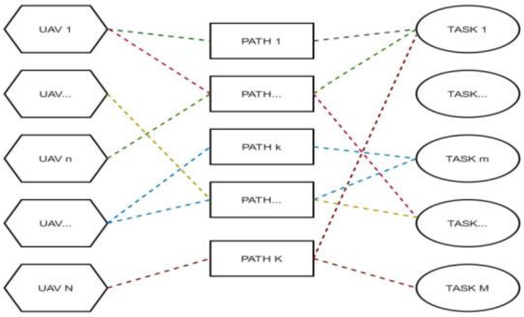

Figure 1. UAV-path-mission complex mapping relationship

According to the characteristics of multi-task and multi-alliance generation problems, the UAV is regarded as an agent [7] Summarize the following enlightening rules:

Rule R1: Maximum task total capability requirement ratio priority principle: among multiple tasks, the ability demand accounts for the largest proportion of the more priority to complete;

Rule R2: The sum ratio of maximum task single capability requirement and all task single capability requirement Priority principle: for the task to complete, the greater the proportion of the total capability requirement value of all tasks, the agent with a large capability value will be preferred to join the alliance;

Rule R3: Maximum task sum ratio of single capability requirement and agent individual capability priority principle: For the task to be completed, the greater the proportion of the total capability value of all agents, the agent with this capability value will be preferred to join the alliance;

Rule R4: The ratio of the maximum single task individual capability to the total capability of the task priority principle: for the task to be completed, the larger the capability requirement of the task accounts for the total capability and proportion of the task, the agent with this capability value will be preferred to join the alliance;

Rule R5: Maximum completion task expectation priority principle: For the task to be completed, the greater the total capability value of the agent, the more priority the agent is selected to join the alliance;

Rule R6: Minimum agent cost priority principle: For the pending task, the less expensive the agent is to complete this task, the more priority the agent is selected to join the alliance.

Combining the enlightening rules R1~R6 proposed above, the mathematical formula of the rules of selecting agents to join the alliance is described as follows:

$$ptt_k^j = \frac{p_k^j}{\sum_{k=1}^{m} p_k^j} \quad ptt_k^j = \frac{ptt_k^j}{\sum_{j=1}^{r} ptt_k^j} \tag{1}$$

$$pta_k^j = \frac{p_k^j}{\sum_{i=1}^{n} b_i^j} \quad pta_k^j = \frac{pta_k^j}{\sum_{j=1}^{r} pta_k^j} \tag{2}$$

$$pt_k^j = \frac{p_k^j}{\sum_{j=1}^{r} p_k^j} \quad pt_k^j = \frac{pt_k^j}{\sum_{j=1}^{r} pt_k^j} \tag{3}$$

$$pa_i = \sum_{j=1}^{r} (\sum_{k=1}^{m} ptt_k^j + pta_k^j + pt_k^j) \times b_i^j \tag{4}$$

$$ps_i = \frac{pa_i}{cost_i} \tag{5}$$

Where, $i \in [1, n]$, $j \in [1, r]$, $k \in [1, m]$, p_k^j represents the ability j requirement of the task k, b_i^j represents the ability j value size of the first agent i, and $cost_i$ represents the cost of the agent i in completing the task. In equation (1), the proportion of the task k capability requirement of the task j in the sum of all the task j capability requirement is expressed ptt_k^j, and the result is normalized, namely, the enlightening rule R2. In equation (2), the proportion of the capability j requirement of the task k to the total capability j value of all agents is expressed pta_k^j, and the result is normalized, namely, the enlightening rule R3. Equation (3) pt_k^j represents the proportion of the capability j requirement of the task k to the respective capability requirement of the task k, and normalizes the results, namely, the enlightening rule R4. In Equation (4), pa_i represents the sum of the agent capability value i calculated according to formula (1), formula (2) and equation (3), namely the enlightening rule R5. In equation (5), the priority of the agent i is selected is indicated ps_i. The greater the value ps_i, the more priority the intelligence i is to join the alliance, namely the enlightening rule R6.

According to the enlightening rule R1 proposed above, the order of task completion is calculated as follows:

$$st_k = \sum_{j=1}^{r} ptt_k^j \tag{6}$$

The fast configuration algorithm of multi-task and multi-alliance problems adopts the method of dynamic comprehensive ranking, which first judges the order of completing the task, and then comprehensively sorts the agent according to the inspiration rules, and only selects the current most suitable agent to join the alliance each time [8]. Task capabilities need to be dynamically updated by constraints, and we will continue to use inspired rules to select the next agent to join the alliance until all the capability requirements of the current task are met. Continue with the next task and repeat the above process with the following implementation steps:

Step 1: Calculate the order of task completion, such as equation (6), calculate the corresponding value of each task, and sorted from large to small, that is, as the order of task completion $Order$.

Step 2: $ind = 1$.Build the alliance from the first task;

Step 3: Calculate the priority of the agent being selected according to the capability requirements of the task, and Equation (1) ~ equation (5). Select the most preferred agent to join the alliance corresponding to the task;

Step 4: Update the remaining task capability requirement value, and the remaining agent capability value;

Step 5: Determine whether the generated alliance meets the capability requirements to complete the task $Order(ind)$. If satisfied $ind = ind + 1$, then go to Step 6; otherwise, go to Step 3;

Step 6: Determine whether the tasks have all been completed, or whether the agent has all been assigned to the corresponding alliance, and if so, then stop; otherwise, go to Step 3.

4. Application instances

4.1. Establishment of the test and simulation environment

This experiment is set as a two-dimensional experimental scene map, with M mission target points distributed in the task area, and N drones waiting for task assignment. The resource required for each mission target point are represented as D, and the mission resource owned by each UAV is represented as uav D. During the simulation experiments, the coordinates of the task target points and the required resources were randomly generated, assuming that the UAV has the same starting coordinates.

4.2. Establishment of the test and simulation environment

In X, X, XX Division XX regiment organized a batch of materials from ground A to ground B. If there are 55 delivery mission points in ground B, it plans to arrange 4 drones to carry out joint delivery tasks.

First, as shown in Figure 2, 55 task target points were randomly distributed on the map, and the tasks were divided into four sub-tasks through the inspired rules of multi-alliance technology, and the path planning within the subtasks was conducted to complete the allocation of the subtasks. The allocation results are shown in Figure 3.

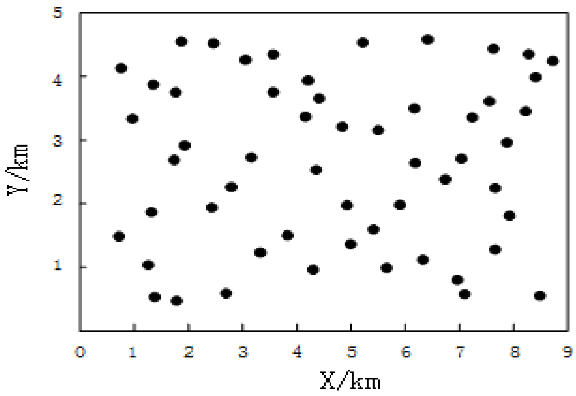

Figure 2. Distribution diagram of the delivery task points

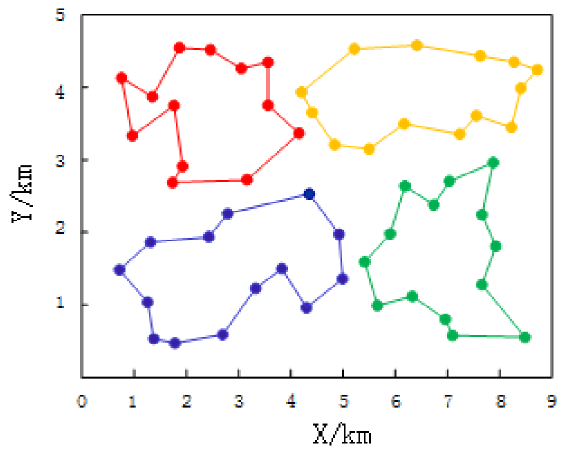

Figure 3. Projection task assignment map

As can be seen from the figure above, according to the UAV mobility, transportation capacity, endurance using rules for dynamic sorting, when delivery task more, also need to consider delivery mission importance, time node requirements, path length, eventually get more drone delivery mission set, the delivery mission assignment results can ensure that the task effectively, under the premise of optimal allocation of resources, can effectively save time cost, make efficient and flexible delivery on the battlefield [9].

5. Conclusion

With the extensive and in-depth application of artificial intelligence in military field, intelligent, unmanned combat forces and support forces have emerged in modern battlefield. Pushing forward unmanned equipment support and building unmanned delivery forces can overcome the limitations of human limits, restricted areas of life and harsh environments, and implement accurate, fast, efficient, direct delivery support [10].

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