An improved ant colony optimization for path planning with multiple UAVs

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***Abstract*—As exploiting unmanned aerial vehicles (UAVs) as mobile elements is a new research trend recently, approximation algorithms to solve path planning problems for UAVs are promising approaches. This paper present a solution for the problem of minimum mission time to cover a set of target points in the surveillance area with multiple UAVs. In this methodology, we propose an improved ant colony optimization (ACO) combining ACO with greedy strategy. The main purpose is to find the optimal number of UAVs and to plan the paths of the minimum mission time. Simulation results demonstrate the validity and the superiority of the proposed algorithm.**

***Index Terms*—UAVs, path planning, ant colony optimization, greedy strategy**

I. Introduction

With the development of unmanned aerial vehicles (UAV) technology, UAV with onboard sensor has been widely used to acquire various information of ground regions in all walks of life [1], [2]. In a forest fire early warning scenario, for example, UAV can be used to perform the coverage mission to monitor forest resources, in which UAV needs to inspect the area with high risk for fires on a regular basis [3]. This is of great significant for early detection of any possible trouble and protection of the forest from fire.

The path planning for UAV plays a crucial role to successfully complete the coverage mission. As is known, there are time limits and restrictions in the flight of the UAV due to the limited battery life [4]. Some researchers have focused on solutions that take into account multiple UAVs. However, in most scenarios, the coverage mission requires UAVs to traverse the whole area along a fixed flight path [5], [6], which lacks flexibility, leads to a long coverage path and results in a great deal of time and energy consumption.

In order to reduce the time and improve the efficiency, we can mark a set of target points in the monitoring area. In this case, the coverage mission can be defined as the sweep coverage of the target points, in which the UAVs only need to fly over each target once. So the flight path planning will directly affect the efficiency of patrol and surveillance. That is, the optimal or near-optimal paths should be planned for UAVs in the base to fly over all target points and return to the base. This can be considered as a kind of multiple traveling salesman problem (MTSP) and many approximate algorithms or heuristic algorithms have been presented to deal with it [7], [8]. Nowadays, a variety of swarm intelligence algorithms are emerging to solve the path planning problem, such as genetic algorithm, ant colony algorithm, particle swarm optimization algorithm, etc. Yu et al. [9] propose an ant colony optimization plus A^* algorithm to find the optimal flight path for autonomous underwater vehicles (AUVs) in a complex environment with dense obstacles. Jamshidi et al. [10] integrate parallel genetic algorithm with parallel particle swarm optimization algorithm to improve the performance of the UAV path planning.

In general, these studies assume that all UAVs start at the same time, and take the path length, the flight time, the energy consumption and the other costs as the the optimal objective. Under this assumption, we can draw a conclusion that the more UAVs, the shorter the time, but the corresponding increase in costs of UAVs. In fact, it is impossible for the UAVs to start at the same time absolutely [11], and the time taken by the final UAV to depart is often longer, which will lead to the the previous conclusion not necessarily tenable. Therefore, it is necessary to select the optimal number of UAVs to be used in order to ensure the less time and less costs.

This paper presents a methodology for optimal mission time to cover a set of target points in the surveillance area with optimal number of UAVs. Firstly, for better analysis of the optimized methods, the monitoring area is usually abstracted to a two-dimensional space. Next, we establish a mathematical model considering the operability and maneuverability of UAVs which will affect the mission time. Then, we develop a two-layer algorithm by combining the ACO algorithm with greedy strategy, in which greedy strategy is used to allocate target points to find the optimal number of UAVs. Once the assignment of a given set of target points is completed, ACO is responsible for determining the order of target points in each path to minimize mission time. Finally, we provide various simulations and comparisons with the previous works to validate the superiority of the proposed algorithm.

II. Problem Formulation

In this section, we provide some assumptions and definitions for the path planning of UAVs.

A. Environment Representation

In our model, N target points $P = \{P_1, P_2, \cdots, P_N\}$ are distributed in a surveillance area. According to the urgency of

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each target point, each target P_i has a weight W_i to indicate its importance, where $i \in \{1, 2, \cdots, N\}$. That is, the greater the weight is, the more important the target is. The coordinates of the target P_i are represented as (x_i, y_i), then the path length between any two points can be expressed by Euclidean distance, denoted by d_{ij}.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2},\\ \forall i, j \in \{0, 1, 2, \cdots, N\} \tag{1}$$

Assume that a group of M UAVs $U = \{U_1, U_2, \cdots, U_M\}$ controlled by O operators has the mission to cover these target points in the area. Each UAV starts and ends its route at the base $P_0(x_0, y_0)$, and each target is only covered by one UAV in the mission. As for the operation of the UAVs, we assume the necessity of a setup time T_{s} for each UAV before flight, which includes the connection of the batteries, the GPS fixing, the launch and recovery, and other preparations [11].

Based on these assumptions, the specific problems discussed in this paper are as follows: i) to determine the optimal number of UAVs to complete the coverage mission, and ii) to determine the optimal path for each UAV to minimize the mission time, while taking into account the importance of each target.

B. Model Formulation

Our goal in this paper is to minimize the mission time, which is defined as the time interval between the first UAV taking off and the last UAV returning. Therefore, it can be equivalent to minimizing the maximum cumulative time, which is actually a minimum-maximum optimization. Since each UAV needs a setup time before flight, the cumulative time of UAV U_k should include not only the flight time but also the waiting time before flight, denoted by $T_{\mathrm{c}}(k)$.

$$T_{\mathrm{c}}(k) = T_{\mathrm{w}}(k) + T_{\mathrm{f}}(k), \forall k \in \{1, 2, \cdots, M\} \tag{2}$$

where $T_{\mathrm{w}}(k)$ and $T_{\mathrm{f}}(k)$ represent the waiting time and the flight time of the UAV U_k respectively, which can be calculated by Equations (3) and (4).

The waiting time corresponds to the time spent by the operator to launch and retrieve the UAVs for the mission. As one operator cannot prepare more than one UAV at the same time, the waiting time of each UAV is different when the number of operators is less than the number of UAVs. For example, there are two UAVs in the area controlled by only one operator. When the operator prepares the UAV U_1, the UAV U_2 is still on standby at the base. Only after the UAV U_1 has been launched does the operator start to prepare the UAV U_2. Then the waiting time of UAV U_k can be defined by

$$T_{\mathrm{w}}(k) = T_{\mathrm{s}} \lceil \frac{k}{O} \rceil, \forall k \in \{1, 2, \cdots, M\} \tag{3}$$

where T_{s} is the setup time of a UAV, O is the number of operators.

For instance, assume that a set of $M = 5$ UAVs with individual setup time $T_{\mathrm{s}} = 10$ min controlled by $O = 2$ operators to carry out the mission. The waiting time of each UAV is computed by (3) as follows:

$$\begin{aligned} T_{\mathrm{w}}(1) &= 10 \times \lceil 1/2 \rceil = 10 \\ T_{\mathrm{w}}(2) &= 10 \times \lceil 2/2 \rceil = 10 \\ T_{\mathrm{w}}(3) &= 10 \times \lceil 3/2 \rceil = 20 \\ T_{\mathrm{w}}(4) &= 10 \times \lceil 4/2 \rceil = 20 \\ T_{\mathrm{w}}(5) &= 10 \times \lceil 5/2 \rceil = 30. \end{aligned}$$

In this case, the two operators can prepare two UAVs at the same time. That is, U_1 and U_2 will take off in the first 10 minutes, and then U_3 and U_4 will be prepared after that which requires another 10 minutes, and finally U_5 takes off.

The flight time is refers to the time interval from the base P_0 to each target point belonging to the path, and finally returns to the base P_0. To indicate whether or not the UAV U_k is going to fly from P_i to P_j, the binary variable $X_{ij}^k \in \{0, 1\}$ is used. If the UAV U_k is about to fly from P_i to P_j, $X_{ij}^k = 1$, otherwise, $X_{ij}^k = 0$. Suppose the velocity of each UAV is the same and constant, it is calculated by

$$T_{\mathrm{f}}(k) = \sum_{i=0}^{N} \sum_{j=0}^{N} \frac{d_{ij}}{V} X_{ij}^k + \sum_{j=1}^{N} \sum_{i=0}^{N} \sum_{n=0}^{N} \frac{\theta_{ijn}}{\omega} X_{ij}^k X_{jn}^k,\\ \forall k \in \{1, 2, \cdots, M\} \tag{4}$$

where V and ω are the linear velocity and the angular velocity of the UAV respectively, θ_{ijn} represents the turning angle at the point P_j which can be calculated by the cosine law in Equation (5).

$$\theta_{ijn} = \arccos \frac{\vec{d_{ij}} \cdot \vec{d_{jn}}}{|\vec{d_{ij}}| \cdot |\vec{d_{jn}}|}, \forall i, j, n \in \{0, 1, 2, \cdots, N\} \tag{5}$$

where $\vec{d_{ij}}$ indicates the flight path from P_i to P_j, and $\vec{d_{jn}}$ indicates the flight path from P_j to P_n.

In order to transform the minimum-maximum problem into a linear problem, we define the mission time as T, which represents the maximum cumulative time among the time of all UAVs. Then the basic optimization problem is written as follows:

$$\min(T) \tag{6}$$

subject to

$$T_{\mathrm{c}}(k) \leq T, \forall k \in \{1, 2, \cdots, M\}, \tag{7}$$
$$T_{\mathrm{f}}(k) \leq T_{\mathrm{fmax}}(k), \forall k \in \{1, 2, \cdots, M\}, \tag{8}$$

$$\sum_{k=1}^{M}\sum_{i=0}^{N} X_{ij}^{k} = 1, \forall j \in \{1, 2, \cdots, N\}, \tag{9}$$

$$\sum_{i=0}^{N} X_{ij}^{k} - \sum_{p=0}^{N} X_{jp}^{k} = 0, \forall j \in \{1, 2, \cdots, N\},$$
$$\forall k \in \{1, 2, \cdots, M\} \tag{10}$$

$$\sum_{k=1}^{M}\sum_{i=1}^{N} X_{0i}^{k} = m \tag{11}$$

$$m \leq M \tag{12}$$

The constraint in (7) accounts for the time cost of each UAV, corresponding to $T_{\mathrm{c}}(k)$, which can be calculated by (2). By defining this constraint and the objective function in (6), we emphasize that the maximum cumulative time among the time of all UAVs must be minimum. Through doing so, we are actually minimizing the time required to complete the coverage mission. In (8), $T_{\mathrm{fmax}}(k)$ represents the maximum flight time of the UAV U_k, since the battery duration is finite. We consider that the charge of battery energy can be ignored when the UAV is waiting for launch at the base. Thus, it is only necessary to restrict the flight time of each UAV to not exceed its maximum flight time. In the flight process, to guarantee that each target can only be visited by a single UAV, the constraint is expressed by (9). In addition, constraint in (10) guarantees that the UAV that arrives at a target is the same one that leaves this target. Notice that, the optimal number of UAVs cannot be trivially chosen to be M as the UAVs don't have to be launched at the same time. To ensure that the number of UAVs performing the mission is less than the maximum number of UAVs available, the constraints are expressed in (11) and (12).

III. Algorithm Design

To better solve the path planning problem for UAVs, we will divide it into two stages, including the allocation of target points and the path planning for UAVs. In the first stage, the target points are assigned to determine the optimal number of UAVs suitable for carrying out coverage missions, which is mainly based on the battery duration and the setup time of the UAV. However, the path of each UAV is not necessarily optimal in this stage, as it may not achieve the minimum mission time. So, we re-plan the path of each UAV to ensure that the cumulative time of each UAV is the minimum in the second stage. The details are as follows.

Firstly, we have to distribute the initial target points to find the optimal number of UAVs m, which can guarantee both the lower cost in UAV resources and higher efficiency in accomplishing missions. Based on this, we present a greedy target assignment strategy for UAVs, and design a cost function $C = T + \lambda m$ to consider the optimal number of UAVs.

Algorithm 1 Target assignment strategy

Require: Point set: $P = \{P_1, P_2, \cdots, P_N\}$
UAV set: $U = \{U_1, U_2, \cdots, U_M\}$
The base: P_0
Ensure: The number of UAVs: m

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Initialize the distance between any two points, the
 waiting time of each UAV, and the current location
 of each UAV;
Let m = 1;
while P ≠ ∅ and m ≤ M do
    for i = 1 to N do
        Choose the point P_n which is closest to the
         current location of U_m;
        Calculate the flight time T_f(m) and the cost C;
        if T_f(m) ≤ T_fmax(m) and C ≤ C_max then
            Assign the point P_n to the path of U_m;
            Update the current location of U_m to P_n;
            Remove the point P_n from P;
        else
            m = m + 1;
        end if
end while
```

The maximum value is recorded as $C_{\max}$, when $m = M$. A correct choice of constant λ will make the optimizer find the best m. The pseudo code is given in Algorithm 1.

Then, we present a variant of ant colony optimization (ACO) algorithm to re-plan the paths for the m UAVs by introducing the weighting value into the heuristic function. That is, the weight of each target is considered to ensure that the target with larger weight can be covered as soon as possible, while minimizing the mission time. In this algorithm, we improve the heuristic function and the formula is shown in (13). The pseudo code is given in Algorithm 2.

$$\eta_{ij}(t) = \frac{1}{d_{ij}} + \frac{W_j}{W_{all}} \tag{13}$$

where W_{all} indicates the sum of the weights of all targets, that is, $W_{all} = \sum_{i=1}^{N} W_i$.

Algorithm 2 Improved ACO algorithm

1: Initialization the parameters such as: the population size, the maximum iteration times, etc.;
2: Route construction: determine the optimal number of UAVs m according to Algorithm 1, and generate multiple initial paths for m UAVs;
3: Local search: use the local search algorithm to obtain the best path for each UAV based on Equation (13);
4: Update pheromone;
5: If the algorithm reaches the maximum iteration times or the optimization results almost remain unchanged in recent iterations, go to Step 6, otherwise, return to Step 2 to continue the iteration;
6: Output the optimal path and end the algorithm.

IV. Simulation results

In order to show the effectiveness of the method proposed in this paper, simulation experiments are carried out in MATLAB on an Intel Core i3 2.0 GHz computer with 4 GB of RAM. The parameters considered in the simulation environment are illustrated as follows.

We consider a scenario with an area of 30 km $\times$ 30 km and randomly deploy a set of target points varying from 20 to 100 with a step of 20. The weight of each target is randomly set between 1 and 3, which indicates the importance of the target. As shown in Fig. 1, " $\bullet$ " represents the target with the highest weight, " $\circ$ " represents the target with the lower weight, and " $\diamond$ " represents the target with the lowest weight. In the area, at most 5 UAVs controlled by only one operator can be dispatched to perform the coverage mission from the base of which the coordinates are (15, 15), represented by "$\blacktriangle$". The UAVs are flying at a constant linear velocity of 72 km/h and each UAV has a duration of 90 min. The setup time of one UAV is 5 min. Under the constraint of the minimum turning radius of the UAV is 200 m, the angular velocity is set at 0.1 rad/s. In Algorithm 2, the population size is 50, and the maximum iteration times is 200.

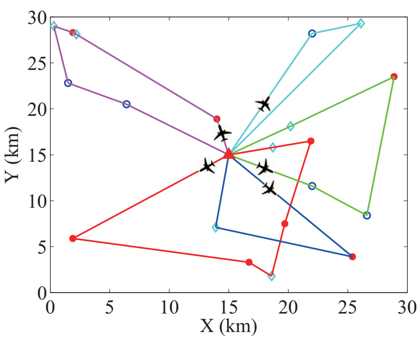
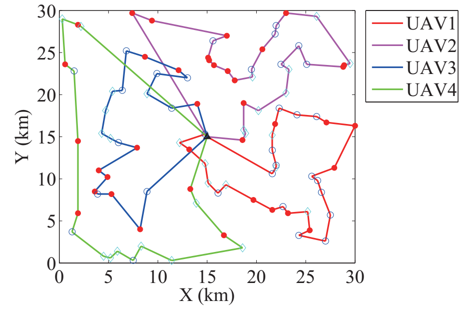


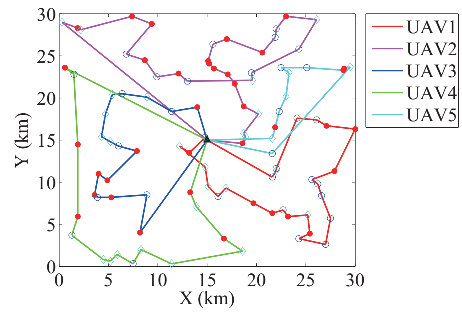
Fig. 1. Example of deploying 20 target points in the area and planning the paths for 5 UAVs

In our first simulation, the number of targets N is set to 100. According to Algorithm 1, the optimal number of UAVs is $m = 4$. As stated before, one operator cannot setup more than one UAV at the same time, that is, each UAV has different waiting time in the case of a single operator launching the UAVs in sequence. Fig. 2(a) shows the coverage paths of 4 UAVs, and the mission time is 91.34 min including the waiting time of 20 min. Simultaneously, we also have used all UAVs to perform the coverage missions to show the effect of this method. The path planning results are shown in Fig. 2(b), and the mission time is 91.05 min including the waiting time of 10 min. Notice that, when all UAVs are sent to complete their missions, the gain in time is only 0.29 min (or 17.4 sec), but an additional UAV is used. However, in most scenarios, this reduction is not worth the cost of an extra UAV. The experimental data are exhibited in Table I.

As shown in Table I, when all UAVs are used to perform the coverage mission, the cumulative time of the fifth UAV



(a) Path planning for 4 UAVs



(b) Path planning for 5 UAVs

Fig. 2. Path planning for 4 UAVs and 5 UAVs

TABLE I
Cumulative time of 4 UAVs and 5 UAVs for coverage missions

UAV number	1	2	3	4	5
Waiting time	5	10	15	20	×
Cumulative time	66.73	82.75	74.17	**91.34**	×
Waiting time	5	10	15	20	25
Cumulative time	65.66	**91.05**	62.68	83.75	62.31

is 62.31 min, including the waiting time of 25 min. That is, the flight time of UAV 5 is actually 37.31 min, accounting for only 60%, which is typically not cost effective. In addition, we have also carried out the simulation with different number of target points, and the results are shown in Table II.

TABLE II
Mission time with different number of target points

Targets	UAVs	Mission time	UAVs	Mission time
20	5	58.13	3	67.81
40	5	67.88	4	73.49
60	5	81.02	4	78.20
80	5	80.50	4	82.25
100	5	91.05	4	91.34

From Table II, we can find that, in the same scenario, it is not always the more the number of UAVs, the smaller the mission time. For example, in such a scene with 60 target points in the area, we only need four UAVs to complete their missions in 78.20 min by our method. Obviously, this result is better than that of five UAVs with the mission time of 81.02 min.

The next simulation shows the comparison of the mission time by different algorithms with the number of target points *N* varying from 20 to 100 with a step of 20, including the greedy algorithm, the original ACO algorithm, and the improved ACO algorithm proposed in this paper. The results are shown in Fig. 3. The *x*-axis denotes the number of target points *N*, while the *y*-axis shows the mission time calculated by each algorithm.

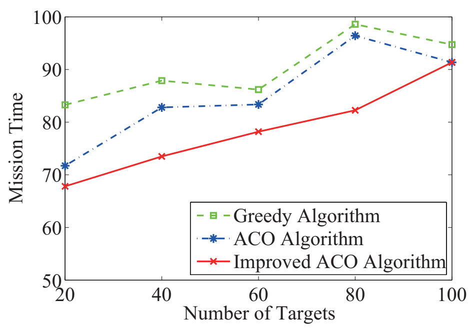


Fig. 3. Comparison of the mission time varying with the number of target points

In this simulation, we set the number of target points to 20, 40, 60, 80, and 100. The minimum number of UAVs to complete their missions is 2, 3, 3, 3, and 4, respectively. As shown in Table II, the number of UAVs by our method is one more compared with the other two methods, when the number of target points is 20 to 80. However, the minimum number of UAVs will lead to a significant increase in mission time as shown in Fig. 3. The simulation data of are exhibited in Table III.

TABLE III
COMPARISON OF THE MISSION TIME BY DIFFERENT ALGORITHMS WITH DIFFERENT NUMBER OF TARGET POINTS

Number of targets	Mission time			Reduced time	
	Improved ACO	Greedy	ACO	Greedy	ACO
20	67.81	83.28	71.73	15.47	3.92
40	73.49	87.88	82.79	14.39	**9.30**
60	78.20	86.18	83.37	7.98	5.17
80	82.25	98.58	96.42	**16.34**	4.17
100	91.34	94.72	91.34	3.38	0

From Table III, the mission time by our algorithm is reduced by at most 16.34 min and 9.30 min respectively, compared with the greedy algorithm and the original ACO algorithm. We can draw the conclusion that the improved ACO algorithm is better than the other two algorithms in the same scenario, as the improved ACO algorithm can always obtain the minimum mission time for each scenario.

V. Conclusion and Future Work

In this paper, we consider a path planning issue of obtaining minimum mission time to cover a set of target points in the surveillance area with optimal number of UAVs. In the process of modeling, the operability and maneuverability of UAVs are considered, which will also affect the mission time. In addition, an improved ACO algorithm combined with greedy strategy for path planning is presented to optimize mission time and number of UAVs. The performance results show that the proposed algorithm outperforms these two algorithms, i.e., the greedy algorithm and the original ACO algorithm.

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