A Path Planning Method for Sweep Coverage With Multiple UAVs

Jing Li, Yonghua Xiong, Jinhua She, *Senior Member, IEEE*, and Min Wu, *Fellow, IEEE*

***Abstract*—Wireless sensor networks (WSNs) are usually deployed in the target area to carry out detecting or monitoring tasks. Sweep coverage is an important concern of WSNs that more targets in the area can be monitored with fewer mobile sensor nodes. With the rapid development of unmanned aerial vehicle (UAV) technology, UAV has been increasingly used in military and civil fields. UAVs can be regarded as sensor nodes to perform specific tasks. Due to the limited battery lifetime of UAV in flight mission, it is difficult to achieve full coverage of all targets in a large-scale monitoring scenario. In this article, we study how to plan the paths of multiple UAVs for sweep coverage. Based on the background of forest fire early warning and monitoring, we consider a min-time max-coverage (MTMC) issue in sweep coverage, where a set of UAVs is dispatched to efficiently patrol the targets in the given area to achieve maximum coverage in minimum time. We establish a mathematical model considering the different coverage quality requirements of the targets in the given area. Then, we analyze the characteristics of the model and propose a heuristic algorithm weighted targets sweep coverage (WTSC) to find the optimal path, which considers the weights of the targets and the performance constraints of UAVs. Finally, we provide various numerical experiments and comparisons with several previous works to validate the superiority of the proposed algorithm.**

***Index Terms*—Path planning, sweep coverage, unmanned aerial vehicles (UAVs), weighted targets sweep coverage (WTSC) algorithm.**

I. Introduction

NOWADAYS, wireless sensor networks (WSNs) have turned out to be a dominant subject of research due to the various applications, such as environment monitoring, traffic surveillance, and security protection [1]. In such applications, coverage is a critical and fundamental issue [2], [3]. By deploying mobile sensor nodes to patrol a group of targets in a surveillance region, each target can be visited within a period of time so that more targets in the region can be covered by fewer sensors, which is referred to as sweep coverage [4]–[6]. Usually, the sensor nodes in WSNs are dispersed over remote areas or hazardous environments (such as battlefields, mines, forests, etc.) while these regions are hardly accessed by human beings [7]. In this regard, it is necessary to deploy sensor nodes with a more reliable mobile carrier in the surveillance region.

In recent years, with the rapid development of unmanned aerial vehicle (UAV) technology, UAV has been highly applied into military and civil fields [8]–[10], which can not only provide comprehensive environmental information by using airborne sensors but also work in environments that are dangerous to human beings [11]. Compared with traditional mobile sensors, UAVs are more suitable for conducting various surveillance missions due to their faster moving speed, wider deployment range, and longer working time [12]–[14]. Hence, if UAVs are used in the monitoring scenarios, it will lead to an increased monitoring area and to better the overall performance. For example, in a forest fire early warning scenario, there are some important places in the forest that are critical or of high potential in taking fire. UAVs can be used to visit these places periodically to monitor forest resources which is of great significance for early detection of any possible trouble and protection of the forest from fire [15]. In other words, how to discover and control the source of forest fire in time before it happens is very critical.

Note that UAVs can only work in the endurance time as the battery life is limited. In order to improve their efficiency, the highly effective path during their execution should be planned before the mission begins. Thus, [16]–[18] sought to answer the question of how to plan the optimal path for multi-UAV to cover the given area in minimum time. In [16], the trajectory is designed to pass near all the predefined waypoints and minimize the total path length with guaranteed communication time. Nevertheless, if the targets are distributed in a large-scale monitoring scenario, the coverage time will increase to achieve this goal, and the number of UAVs will inevitably increase greatly, which will lead to high hardware costs. In our real-life scenarios, suppose that a fixed number of UAVs are used to perform the sweep coverage mission for a large number of targets, there may be some targets that cannot be visited by any UAV in a sweep cycle due to the limited battery power.

Manuscript received December 26, 2019; revised March 25, 2020 and May 15, 2020; accepted May 26, 2020. Date of publication June 1, 2020; date of current version September 15, 2020. This work was supported in part by the National Natural Science Foundation of China under Grant 61873249 and Grant 61976197, in part by the Hubei Provincial Natural Science Foundation of China under Grant 2015CFA010, and in part by the 111 Project under Grant B17040. *(Corresponding author: Yonghua Xiong.)*

Jing Li, Yonghua Xiong, and Min Wu are with the School of Automation and Hubei Key Laboratory of Advanced Control and Intelligent Automation for Complex Systems, China University of Geosciences, Wuhan 430074, China (e-mail: lijing0966@163.com; xiongyh@cug.edu.cn; wumin@cug.edu.cn).

Jinhua She is with the School of Automation and Hubei Key Laboratory of Advanced Control and Intelligent Automation for Complex Systems, China University of Geosciences, Wuhan 430074, China, and also with the School of Engineering, Tokyo University of Technology, Tokyo 192-0982, Japan (e-mail: she@stf.teu.ac.jp).

Digital Object Identifier 10.1109/JIOT.2020.2999083

In this article, we consider the sweep coverage problem in the large-scale target area as a min-time max-coverage (MTMC) issue, where a set of UAVs are dispatched to efficiently patrol the targets in a large-scale monitoring area to achieve maximum coverage rate in minimum task time. The MTMC issue is NP-hard since it is the extension of the well-known traveling salesman problem. It is very challenging to construct effective flight paths for UAVs to ensure that the goal of minimizing the task time and maximizing the coverage rate is met under the performance constraints of UAVs. Moreover, it will be fussy to establish the mathematical model since the performance restriction of UAVs must be considered, such as battery life, setup time, etc., which is different from the traditional mobile sensors. In order to ensure the monitoring quality of the given area, the targets are assigned weights indicating their importance where more important targets should receive higher priority. Accordingly, we define the coverage rate as the ratio of the sum of the weights of the covered targets to the sum of the weights of all targets in a sweep cycle. As there is a conflict between minimizing task time and maximizing coverage rate, we establish a new objective function by assigning weights to the two index functions and propose a weighted targets sweep coverage (WTSC) algorithm to construct the effective flight paths for UAVs to solve the MTMC issue. The main contributions can be summarized as follows.

1) We consider an MTMC issue in sweep coverage that UAVs should patrol the targets in the given area to obtain maximum coverage in minimum time.
2) We establish a mathematical model considering the maneuverability of UAVs, which will affect the task time, and the importance of the targets that more important targets should be given higher priority.
3) We propose a WTSC algorithm to construct the optimal paths for UAVs to solve the MTMC issue.

The remainder of this article is organized as follows. Approaches related to the proposed work are discussed in Section II. Section III illustrates the network environment and the problem formulation of the proposed approach. Section IV presents the details of the proposed algorithm. The experimental results in simulated are shown in Section V. The conclusions and some perspectives for future works are presented in Section VI.

II. Related Works

The concept of sweep coverage initially comes from the context of robotics, which usually aims to find a complete solution for robot path planning from the start location to the destination location [19]–[21]. As a typical aerial robot, UAV is widely used in the aerial monitoring mission. Many works have been carried out on path planning for UAVs [22]–[25]. In this section, we review the related literature on the coverage path planning with multiple UAVs, as well as the sweep coverage with traditional mobile sensors.

A. UAV Coverage Path Planning

The existing studies on UAV coverage path planning have made great efforts to find the optimal path with the minimum cost on the premise of completing the task. They usually solve the coverage path planning issue according to one or several optimization criteria, such as minimum energy consumption [16], [24], minimum flight time [25], [27], maximum coverage rate [22], [28], and so on. In order to find the optimal path with minimum energy consumption, Schacht-Rodrígue *et al.* [26] introduced two degradation models and proposed a path planning generation algorithm considering the relationship between flight path and battery lifetime. Avellar *et al.* [25] designed two strategies, a heuristic algorithm and an iterative method, to solve the multi-UAV coverage task in minimum time considering the impact of setup time for launching and retrieving on the total task time. In a search and rescue mission, the goal is to detect the target by coverage of a certain area and to communicate this information to ground personnel for further response. The proposed approach in [27] tried to allocate tasks and plan paths for a team of UAVs to minimize the task completion time, including the time to find the target and the time to set up a communication path. In [22], a new genetic path planning algorithm with adaptive operator selection was proposed to maximize the coverage on a designated area, considering the time limit of the UAV and the feasibility of the path. Mansouri *et al.* [28] established a novel mathematical framework by segmentation of the target area and calculating the shortest path, which provided a path for maximizing the coverage of the area.

The above works mainly focus on providing coverage for the full area and the goal is usually to explore the target area exhaustively for one time with multiple UAVs. However, the sweep coverage task in this article only aims to cover the dispersedly distributed targets in the area, rather than the whole area. Therefore, the existing UAV coverage path planning methods could not be directly applied to this article.

B. Sweep Coverage With Traditional Mobile Sensors

Researchers have made many contributions to the path planning of the mobile sensors to guarantee the sweep coverage of the targets. They usually focus on these two issues: 1) determining the minimum number of mobile sensors under a time constraint [29]–[31] or 2) finding the minimum sweep period given the number of sensors [32]–[34].

In [29], a heuristic algorithm PDBA was proposed to minimize the number of mobile sensors and the total energy consumed. They chose a target to join the route of a mobile sensor according to its perpendicular distance to the bottom of the graph. However, it would deploy more mobile sensors when the paths of the existing mobile sensors exceeded the length constraint. Liu *et al.* [30] studied the sweep coverage issue with return time constraints, which required that the targets should be covered and the collected data should be delivered to the base station within a preset time window. They designed two heuristic algorithms G-MSCR and MinD-Expand to calculate the minimum number of mobile sensors to solve the issue. In addition, experiments proved that the algorithm G-MSCR could also shorten the return time. The work in [31] aimed to find the minimum number of mobile sensors and their trajectories for the minimum distance constraint sweep coverage, so that each target could be visited at least once by some mobile sensor every required time interval and every mobile sensor would visit the base before running out of its energy.

From other perspectives, in order to find the shortest route for mobile sensors with large sensing ranges, Chen *et al.* [32] considered two different scenarios that the single sensing-point case and the general case, and proposed two route scheduling algorithms, ROSE and G-ROSE, respectively, for different sweep coverage issues. Gao *et al.* [33] tried to deal with the sweep coverage issue with multiple mobile sensors to periodically cover n targets in the surveillance region, in which the number of mobile sensors is given, and the goal is to minimize the maximum sweep period. Based on it, the work in [34] further proposed an approximation algorithm CycleSplit for the min-period sweep coverage problem in which each mobile sensor worked independently along a predetermined trajectory cycle. Then they extended the study to the heterogeneous velocity min-period sweep coverage problem, where each mobile sensor has a different velocity.

However, these existing schemes mainly focus on how to control the trajectory of mobile nodes to patrol a set of given targets with identical quality of coverage requirements. As an aside, a time-constrained weighted target patrolling algorithm is proposed in [35] but with different network architectures and different goals. They point out that the targets are assigned weights indicating their importance, where more important targets should be visited more frequently to ensure the stability and fairness for all targets.

In sweep coverage, UAVs equipped with various sensors can be treated as mobile sensor nodes to accomplish the surveillance mission. To the best of our knowledge, there is a little literature study on coverage quality for sweep coverage with multiple UAVs.

III. Problem Formulation

This section presents the network environment and model assumptions. Subsequently, the problem formulation of the proposed approach is presented.

A. Network Environment

Assume that several targets are set in a large forest monitoring scenario and multiple UAVs in the base are used to patrol these targets. The sweep coverage mission is performed under the following constraints.

1) Each target is covered at most once by a UAV in a sweep cycle.
2) Each UAV must start and end its route at the base.
3) The mission begins with the first UAV taking off and ends with the last UAV returning.

As shown in Fig. 1, there are N targets randomly deployed in the given area. Each target is assigned a weight to indicate its importance. For example, the location of frequent fires in the forest is more important, and the weight of the corresponding target is also greater. It is assumed that M UAVs in the base are dispatched to patrol these targets. When the last UAV returns to the base, the task is completed. The task time is defined as the time interval between the first UAV taking off and the last UAV returning. Due to the limited energy of UAVs, they may not be able to cover all targets, thus, the UAVs should visit the more important targets in their endurance. Therefore, the MTMC issue is essential to maximize the total weight of the covered targets in the minimum time by planning the flight path of each UAV. For ease of the following presentation, the main parameters in this article are listed in Table I.

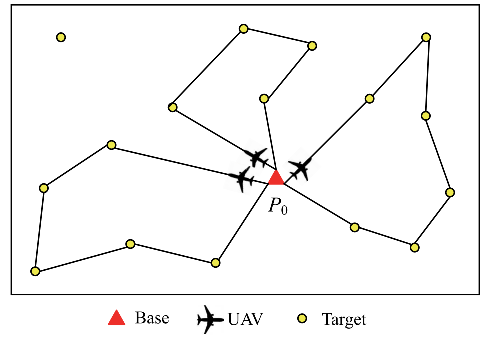


Fig. 1. Example of sweep coverage for multi-UAV.

TABLE I
Main Parameters

Symbol	Definition
N	The number of targets
W_i	The weight of the i-th target P_i
(x_i, y_i)	The coordinate of the i-th target P_i
(x_0, y_0)	The coordinate of the base P_0
M	The number of UAVs
O	The number of operators
d_{ij}	The flight distance from P_i to P_j
θ_{ijp}	The turning angle at P_j
V	The linear velocity of the UAV
ω	The angular velocity of the UAV
X_{jp}^k	A binary variable
$T_{\mathrm{f}p}$	The flight time from P_j to P_p
$T_{\mathrm{f}}(k)$	The total flight time of the k-th UAV U_k
$T_{\mathrm{fmax}}(k)$	The maximum flight time of the k-th UAV U_k
T_{s}	The setup time of a UAV
$T_{\mathrm{w}}(k)$	The waiting time of the k-th UAV U_k
$T_{\mathrm{c}}(k)$	The cumulative time of the k-th UAV U_k
T	The total time of completing the task
W_{t}	The sum of the weights of the covered targets
W_{all}	The sum of the weights of all targets
η	The coverage rate
α	A tuning parameter
F	A utility function
$Cost_i$	A cost function of the i-th target P_i

In order to simplify the issue, the following assumptions are made on the modeling object before presenting the mathematical formulation.

1) A set of target points $P = \{P_1, P_2, \ldots, P_N\}$ is randomly deployed in the monitoring area, and the position of them is fixed.
2) Each target P_i is assigned a weight W_i representing its importance, where $i \in \{1, 2, \ldots, N\}$, as the greater the weight is, the more important the target is.
3) In the area, the base is denoted as P_0, and the position is fixed. A set of UAVs $U = \{U_1, U_2, \ldots, U_M\}$ controlled by O operators in the base is sent to patrol these targets.

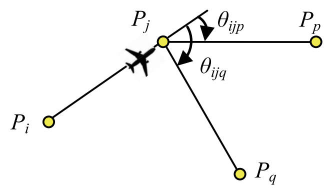


Fig. 2. Diagram of UAV at the turning.

4) The maximum flight time of the kth UAV is defined as $T_{\mathrm{fmax}}(k)$, where $k \in \{1, 2, \ldots, M\}$, which is related to the battery life of the UAV U_k.
5) In sweep coverage, it is considered that the linear velocity of each UAV is a constant V in the straight flight, and the angular velocity is a constant ω at the turning.
6) Before the flight of each UAV, we assume the setup time is a constant T_{s}, which includes the connection of the batteries, the GPS fixing, and the launching itself, among other tasks.

B. Model Formulation

Definition 1 (Flight Distance, d_{ij}): When a UAV flies from P_i to P_j, the straight line is an optimal flight path, the length of which is described as the Euclidean distance between two points, that is d_{ij}

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

In most previous studies [22]–[28], assuming that the UAV flies at a fixed altitude and velocity, minimizing the time of the task is equal to minimizing the length of the path. However, in a real scenario, the UAV needs to adjust its direction at the turning that the time consumed cannot be ignored. For example, when a UAV arrives at P_j from P_i, it could choose to continue to fly to P_p or P_q. As shown in Fig. 2, it is assumed that the distance from P_j to P_p is equal to that from P_j to P_q, that is, $d_{jp} = d_{jq}$, but the turning angle is different, that is, $\theta_{ijp} < \theta_{ijq}$. Although the length of the flight path is equal under the two choices, the turning time will be different under the condition of constant angular velocity due to the different turning angles. Obviously, the time flying to P_p is shorter. Therefore, it is necessary to consider the turning time in the flight.

Definition 2 (Turning Angle, θ_{ijp}): The flight path from P_i to P_j is expressed by vector $\vec{d}_{ij}$, and the vector $\vec{d}_{jp}$ indicates the flight path from P_j to P_p. Thus, the turning angle at the point P_j is defined as the angle between the two vectors, denoted by θ_{ijp}, which is calculated by the cosine law

$$\theta_{ijp} = \arccos \frac{\vec{d}_{ij} \cdot \vec{d}_{jp}}{\left|\vec{d}_{ij}\right| \cdot \left|\vec{d}_{jp}\right|} \quad \forall i, j, p \in \{0, 1, 2, \ldots, N\}. \tag{2}$$

It should be pointed out that the turning angle is ranging from 0 to π, especially, if the coordinates of P_i and P_j are the same or the coordinates of P_j and P_p are the same, the turning angle would be zero.

Definition 3 (Flight Time, T_{fp}): The flight time refers to the time interval from the current location P_j to the next location P_p, which is defined as T_{fp}. Suppose the last location is at point P_i. When the velocity is a given constant, it is calculated by

$$T_{fp} = \frac{d_{ij}}{V} + \frac{\theta_{ijp}}{\omega} \quad \forall i, j, p \in \{0, 1, 2, \ldots, N\} \tag{3}$$

where V and ω denote the linear velocity in the straight flight and the angular velocity in the turning flight, respectively. In addition, the total flight time $T_f(k)$ of the kth UAV is

$$T_f(k) = \sum_{j=1}^{N} \sum_{p=0}^{N} T_{fp} X_{jp}^k \quad \forall k \in \{1, 2, \ldots, M\} \tag{4}$$

where X_{jp}^k indicates whether or not the kth UAV is going to fly from P_j to P_p. If the kth UAV is about to fly from P_j to P_p, $X_{jp}^k = 1$, otherwise, $X_{jp}^k = 0$.

Definition 4 [Waiting Time, $T_w(k)$]: In a practical scenario, each UAV needs a setup time T_{s} before flight, including battery connection, GPS fixing, launch, and recovery of the UAV [25]. As one operator cannot prepare more than one UAV at the same time, the waiting time of each UAV before flight is different when the number of operators responsible for launching and retrieving the UAVs is less than the number of UAVs. The waiting time of the kth UAV is generated as

$$T_{\mathrm{w}}(k) = T_{\mathrm{s}} \left\lceil \frac{k}{O} \right\rceil \quad \forall k \in \{1, 2, \ldots, M\} \tag{5}$$

where O denotes the number of operators and T_{s} denotes the setup time of a UAV.

For instance, assume that there are a set of $M = 3$ UAVs with individual setup time $T_{\mathrm{s}} = 10$ min. If the number of operators is the same as the number of UAVs ($O = 3$), they can launch their own UAV at the same time. According to (5), we can get that $\lceil (k/O) \rceil = 1$ for each UAV. In this case, the waiting time of each UAV will be equal to the setup time 10 min.

However, if a single operator is launching the UAVs ($O < M$), the waiting time of each UAV is computed by (5) as follows.

$$T_{\mathrm{w}}(1) = 10 \times \lceil 1/1 \rceil = 10$$
$$T_{\mathrm{w}}(2) = 10 \times \lceil 2/1 \rceil = 20$$
$$T_{\mathrm{w}}(3) = 10 \times \lceil 3/1 \rceil = 30.$$

Note that the first launched UAV U_1 has the shortest waiting time and the last launched UAV U_3 has the longest waiting time. This is because the operator will prepare U_1 for takeoff in the first 10 min, and then U_2 will be prepared after the takeoff of U_1 which requires another 10 min, and finally prepare U_3. In short, the number of operators will directly affect the waiting time before takeoff, which will be counted into the task time.

Definition 5 [Cumulative Time, $T_c(k)$]: The cumulative time of the kth UAV in sweep coverage is defined as the sum of the total flight time and the waiting time, denoted by $T_c(k)$

$$T_c(k) = T_f(k) + T_{\mathrm{w}}(k) \quad \forall k \in \{1, 2, \ldots, M\} \tag{6}$$

where $T_f(k)$ is the total flight time of the kth UAV calculated by (4), and $T_w(k)$ is the waiting time of the kth UAV calculated by (5).

Definition 6 (Task Time, T): As stated above, when the last UAV returns to the base, it indicates that the sweep coverage task is completed. Therefore, the total time of completing the task is defined as the time spent by the last UAV returning to the base, denoted by T

$$T = \max\{T_c(1), T_c(2), \ldots, T_c(M)\}. \tag{7}$$

Definition 7 (Total Weight, W_t): Total weight is the sum of the weights of the targets visited in the sweep paths of all UAVs, denoted by W_t

$$W_t = \sum_{i=1}^{N} W_i X_i \tag{8}$$

where $X_i \in \{0, 1\}$ indicates whether the paths contain the target P_i. If P_i is included in the paths, $X_i = 1$, otherwise, $X_i = 0$.

Definition 8 (Coverage Rate, η): Coverage rate is the ratio of the sum of the weights of the covered targets to the sum of the weights of all targets, denoted by η

$$\eta = W_t / W_{\text{all}} \tag{9}$$

where W_{all} indicates the sum of the weights of all targets, that is, $W_{\text{all}} = \sum_{i=1}^{N} W_i$. When the weight of each target is known, W_{all} is a constant.

Our main objective is to obtain the maximum coverage rate in the minimum task time. This can be accomplished by minimizing the task time T and maximizing the total weight W_t since W_{all} is a constant

$$\begin{cases} \min & (T) \\ \max & (W_t). \end{cases} \tag{10}$$

Definition 9 (Objective Function, F): In order to satisfy the two optimization objectives simultaneously, a utility function F is designed to transform the multiobjective optimization problem into a single-objective optimization problem

$$F = \alpha T + (1 - \alpha)/W_t \tag{11}$$

where $\alpha \in [0, 1]$ is a tuning parameter, which reflects the importance of task time in the sweep coverage task. The setting of the parameter will be given in the simulation experiment section. Therefore, the optimization problem is written as

$$\min \quad (F) \tag{12}$$

$$\text{subject to} \quad T_f(k) \le T_{\text{fmax}}(k) \quad \forall k \in \{1, 2, \ldots, M\} \tag{13}$$

$$\sum_{k=1}^{M} \sum_{i=0}^{N} X_{ij}^{k} = 1 \quad \forall j \in \{1, 2, \ldots, N\} \tag{14}$$

$$\sum_{i=0}^{N} X_{ij}^{k} - \sum_{p=0}^{N} X_{jp}^{k} = 0 \quad \forall j \in \{1, 2, \ldots, N\} \quad \forall k \in \{1, 2, \ldots, M\} \tag{15}$$

where $T_{\text{fmax}}(k)$ represents the maximum flight time of the kth UAV, since the battery duration is finite. We consider that the charge of battery energy is negligible while the UAV is waiting for launch at the base, in this mean, as long as the flight time of each UAV does not exceed its maximum flight time, the path is feasible, which is constrained in (13). In the flight process, to guarantee that each target can only be visited by a single UAV, the constraint is expressed by (14). Moreover, the constraint in (15) guarantees that the UAV that arrives at a target is the same one that leaves this target.

Algorithm 1 WTSC Algorithm

Input: Target set $P = \{P_1, P_2, \cdots, P_N\}$
Weight set: $W = \{W_1, W_2, \cdots, W_N\}$
UAV set: $U = \{U_1, U_2, \cdots, U_M\}$
Base: P_0
Output: Path set: $L = \{L_1, L_2, \cdots, L_M\}$
Task time: T
Total weight: W_t

Set the sweep path $L_k = \varnothing, \forall k, 1 \le k \le M$
for $k = 1$ to M **do**
  while $P \ne \varnothing$ and $P_0 \notin L_k$ **do**
    for $i = 1$ to N **do**
      Calculate $Cost_i$ using equation (16)
    end for
    $p = \{i | Cost_i = \min(Cost_i, \forall i, 1 \le i \le N)\}$
    Calculate $T_f(k)$ according to equation (4)
    if $T_f(k) < T_{\text{fmax}}(k)$ **then**
      $L_k = L_k + \{P_p\}$
      $P = P - \{P_p\}$
    else
      $L_k = L_k + \{P_0\}$
    end if
  end while
  Calculate $T_c(k)$ using equation (6)
end for
Calculate T and W_t using equation (7) and (8)

IV. Weighted Targets Sweep Coverage Algorithm

To solve the MTMC issue, we propose a path planning algorithm WTSC. Due to the limited battery life of UAVs, some targets may not be covered by any UAV during a sweep cycle when the number of UAVs is fixed. The goal of this algorithm is to obtain the maximum coverage rate in the duration of UAVs, that is, to maximize the sum of the weights of the covered targets. In addition, since the waiting time will be included in the task time, we should ensure the task time is also the shortest.

A. Detailed Description

In WTSC, the targets in the area are assigned to the path of each UAV according to the multiple rounds of target assignment decisions, and the path of each UAV starts from and returns to the base. The main idea of the WTSC algorithm is to add one target with the minimum flight time and the maximum weight to the current path in each assignment decision.

Definition 10 (Cost Function, $Cost_i$): In our research, we use a cost function Cost_i to choose the desired target P_i with the minimum flight time and the maximum weight. The formula of Cost_i is as follows:

$$\text{Cost}_i = \alpha T_{fi} + (1-\alpha)/W_i \quad \forall i \in \{1, 2, \ldots, N\}. \tag{16}$$

Based on this, the target P_i with the minimum Cost_i will be added to the current path. This procedure will be repeated until all UAVs have returned to the base or all targets have been covered, which means that the paths for multiple UAVs have been generated. The details of the WTSC algorithm are summarized in Algorithm 1.

In the beginning, we randomly deploy a set of targets P, assign a weight to each target, fix the location of the base P_0, and determine the UAV group U to perform the sweep coverage task. In step 1, the sweep path of each UAV is set to be an empty set. From steps 2 to 15, add the targets to the path of each UAV. We use a greedy target assignment strategy to determine which target should be assigned to the current path in steps 4–7, where the target P_p is the desired result. In steps 8–14, if the total flight time does not exceed the endurance of the UAV U_k, add the target to the current path L_k and remove it from the target set P, otherwise, let the UAV U_k return to the base. This ends a round of assignment decisions. Then, calculate the cumulative time $T_c(k)$ according to (6) in step 16. The algorithm will be conducted again to assign the remaining targets to the next UAV, and so on until all UAVs return to the base.

B. Theoretical Analysis

In this section, we present a theoretical analysis of the WTSC algorithm. Through the mathematical description of the algorithm, it can be seen that the algorithm is correct only when the proposition is correct that if the target P_p found from the set P can make Cost_i become the minimum value at every turn, Cost_p is the optimal solution from the current location to the next location. Thus, the feasibility of the algorithm is guaranteed by the correctness of the following propositions.

Proposition 1: Cost_{p1} is the optimal solution with the shortest time and the largest weight from the base to the next location if the first target found by the algorithm is P_{p1}.

Proof: Obviously, Cost_{p1} must be the minimum value, if the first target found by the algorithm is P_{p1}. Assume that Cost_{p1} is not the optimal solution. Then, we could find another target P_{px} from the set P, which makes $T_{fpx} < T_{fp1}$ or $W_{px} > W_{p1}$. From (16), it can be concluded that $\text{Cost}_{px} < \text{Cost}_{p1}$, which contradicts that Cost_{p1} is the minimum value. Thus, the hypothesis is not tenable and the subproposition is proved. ■

Proposition 2: There exists the nth target to make Cost_{pn} is the optimal solution, if n-1 targets have been found from the set P through the algorithm and each Cost_i is the optimal solution.

Proof: If the UAV has arrived at the target P_{p1}, we can make the starting point at P_{p1}. According to the algorithm, n-1 targets can be found to make $\text{Cost}_{p2}, \ldots, \text{Cost}_{pn}$ are all optimal solutions. Then, we can obtain an optimal solution that the flight time from P_{p1} to P_{pn} is the shortest and the total weight is the largest. Then, the sum from Cost_{p2} to Cost_{pn}, $I_1 = \text{Cost}_{p2} + \cdots + \text{Cost}_{p(n-1)} + \text{Cost}_{pn}$, is the minimum value.

Since the UAV starts from the base P_0, $I_0 = \text{Cost}_{p1} + \text{Cost}_{p2} + \cdots + \text{Cost}_{p(n-1)} + \text{Cost}_{pn}$ is considered as the minimum value from P_{p0} to P_{pn}. Assume that Cost_{pn} is not the optimal solution for the UAV starting from the base P_0. Then, we could find another target P_{px} from the set P, which makes $\text{Cost}_{px} < \text{Cost}_{pn}$. In this case,

$$I_0^* = \text{Cost}_{p1} + \text{Cost}_{p2} + \cdots + \text{Cost}_{p(n-1)} + \text{Cost}_{px} < I_0.$$

Then,

$$I_0^* - \text{Cost}_{p1} < I_0 - \text{Cost}_{p1} = I_1.$$

This contradicts that I_1 is the minimum value. Therefore, the hypothesis is not tenable and the subproposition is proved. ■

Proposition 3: The time complexity of Algorithm 1 is $O(MN^2)$.

Proof: In the for-loop of the WTSC algorithm from steps 4 to 7, finding the target P_p with minimal Cost_i takes time complexity $O(N)$. Since there are at most N targets in the set P, the time complexity of the while-loop from steps 3 to 15 is $O(N)$. Then, we perform this process for M times as M UAVs are dispatched to patrol these targets. Therefore, the time complexity of Algorithm 1 is $O(MN^2)$. ■

V. Simulation Results

In this section, we carry out experiments to evaluate the performance of the proposed algorithm for sweep coverage. Specifically, we compare our algorithm with the CycleSplit algorithm in [34] and the G-MSCR algorithm in [30]. The CycleSplit algorithm is designed to solve the min-period sweep coverage problem. The main idea is to first construct a traveling salesman problem (TSP) cycle for the given targets, split the TSP cycle into several segments, and finally form distinct cycles. The G-MSCR algorithm is aimed to find the minimum number of mobile sensors to achieve sweep coverage with a return time constraint. The basic idea is to add one target with the maximum remaining time to the current route at a time until all targets are covered. All the simulations in this section are performed in MATLAB and the detailed experimental results are presented as follows.

A. Simulation Model

The parameters considered in the simulation environment are illustrated as follows. We consider a scenario with an area of 50 km ×50 km and randomly deploy a number of targets. The number of the targets N is varied from 50 to 400 with a step of 50 while the number of UAVs M is fixed to 5. The weight of each target is randomly set between 1 and 10, which indicates the importance of the location. In the area, there are five UAVs dispatched to perform the sweep coverage task, and their taking off and landing positions are fixed at the base. The UAVs are flying at a constant linear velocity of 72 km/h during the task and each UAV has a duration of 90 min. The setup time of one UAV is 8 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. Each UAV is equipped with a Sony NEX-5N camera with a field of view of 73.5° × 53.1°, and a coverage range of 1.5 km at an altitude of 1 km [7].

TABLE II
SWEEP COVERAGE DATA BY VARYING α

	α	0.1	0.3	0.5	0.7	0.9
N=50	Task time	109.82	109.28	**106.54**	108.25	107.66
	Coverage rate	1	1	**1**	1	0.90
N=100	Task time	113.20	111.25	**108.97**	**108.97**	110.43
	Coverage rate	0.94	0.85	**0.88**	**0.88**	0.86
N=150	Task time	111.23	111.38	**112.82**	111.17	113.73
	Coverage rate	0.79	0.79	**0.84**	0.81	0.74
N=200	Task time	113.49	**112.70**	113.09	113.16	113.47
	Coverage rate	0.72	**0.76**	0.76	0.69	0.67
N=250	Task time	113.99	113.70	113.45	**112.08**	113.70
	Coverage rate	0.69	0.73	0.74	**0.74**	0.68

Furthermore, we also consider that if two targets are within the coverage range of the sensor on the UAV, they can be covered at the same time.

B. Performance Evaluation of the WTSC Algorithm

Here, we provide simulation results to investigate the impact of system parameters on the performance of the WTSC algorithm. In order to achieve the goal of minimum task time and maximum coverage rate, the weights of the targets should be taken into account in the path planning. In (11), we use a tuning parameter α to balance the relationship between task time and total weight. We set α to change from 0.1 to 0.9 and conduct simulation experiments. Table II shows the comparison of task time and coverage rate varying with the parameter α in different scenarios.

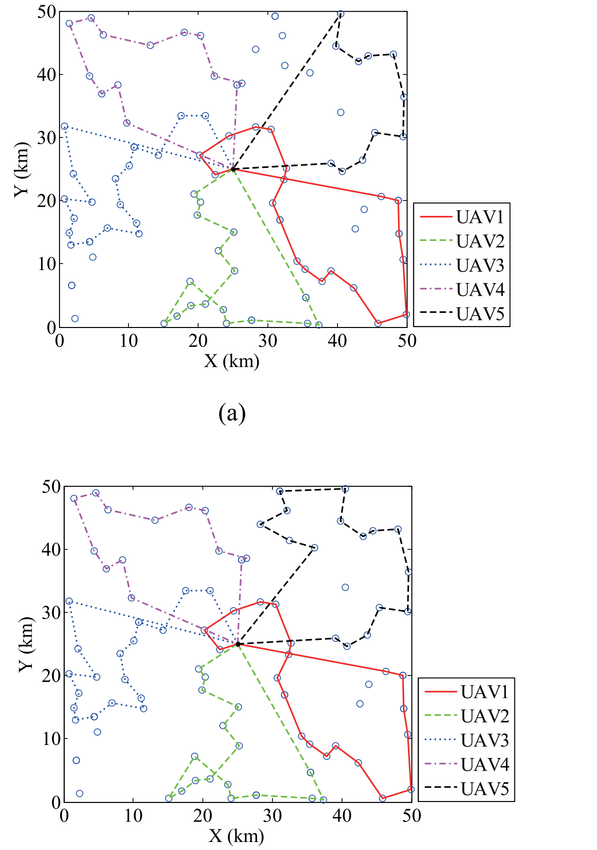
The experiment proves that the effect is better when α is between 0.3 and 0.7, and we can get the maximum coverage rate in minimum time as shown in Table II.

In our first set of path planning simulations, the number of targets N is set to 100 and the parameter α is fixed to 0.5. The simulations are carried out under the condition of changing the number of operators O by the WTSC algorithm. As stated before, one operator cannot set up more than one UAV at the same time. That is to say, each UAV has different waiting time before the flight in the case of $O < M$, while each UAV has the same waiting time in the case of $O = M$. The sweep paths of UAVs are shown in Fig. 3(a) and (b) with $O = 1$ and $O = 5$, respectively. The experimental data are exhibited in Tables III and IV.

Fig. 3(a) presents the sweep paths for UAVs in the case of one operator preparing for five UAVs ($O < M$). As shown in Table III, the waiting time of U_1 is 8 min while that of U_5 is 40 min. The total weight of the covered targets in the paths is 526 accounting for 89% of the weight of all targets, and the task time is 113.15 min including the waiting time of 40 min.

Fig. 3(b) shows the sweep paths for UAVs when there are five operators ($O = M$). In this case, the waiting time of each UAV is equal to 8 min since each operator can prepare their own UAV at the same time. As shown in Table IV, the coverage rate is 94% when the total weight is 553, and the task time is 97.83 min including 8 min to wait before the flight.

From the experimental results, the task time is shortened by 15.32 min and the coverage rate is increased by 5% when the number of operators increases from $O = 1$ to $O = 5$, that is, the number of operators has a certain impact on the path planning when the number of targets is constant. Thus, the waiting time before the flight should be considered in the path planning.



(a)

(b)

Fig. 3. Path planning for UAVs by the WTSC algorithm with different number of operators under constant parameters α. (a) Path planning with $O = 1$. (b) Path planning with $O = 5$.

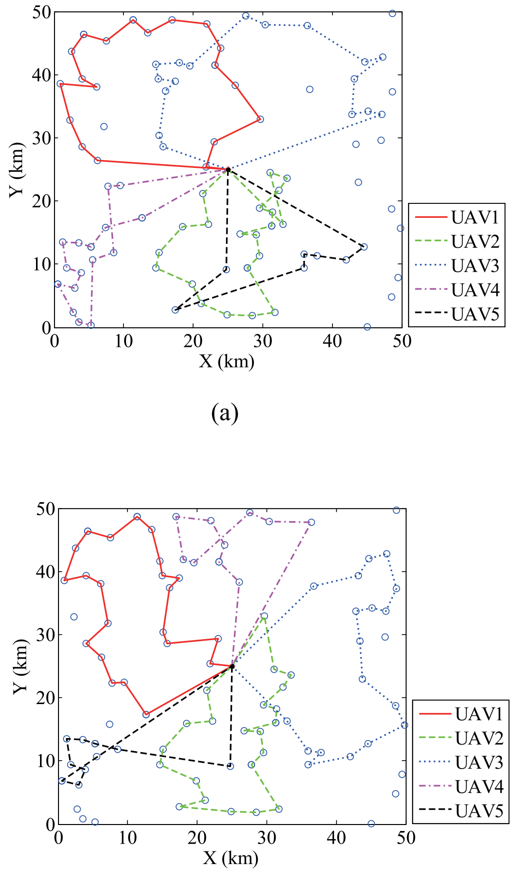
TABLE III
SWEEP COVERAGE DATA WITH $O = 1$

UAV	1	2	3	4	5
Waiting time	8	16	24	32	**40**
Cumulative time	97.83	98.32	110.43	104.71	**113.15**
Total weight			526		
Task time			113.15		
Coverage rate			0.89		

TABLE IV
SWEEP COVERAGE DATA WITH $O = 5$

UAV	1	2	3	4	5
Waiting time	**8**	8	8	8	8
Cumulative time	**97.83**	90.32	94.43	80.71	95.27
Total weight			553		
Task time			97.83		
Coverage rate			0.94		

If a single operator is launching the UAVs in sequence ($O < M$), the system has to wait for all of the UAVs to finish their tasks and return to the base. Considering this, we set the parameter α to different values for each UAV according to its position in the queue. The first UAV to be launched should



(a)

(b)

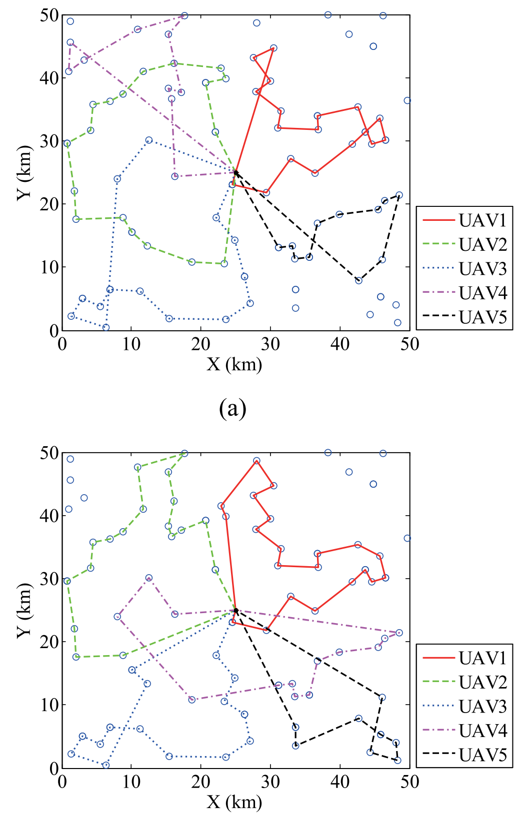
Fig. 4. Path planning for UAVs by the WTSC algorithm with constant parameter α and variable parameter α. (a) Path planning with $\alpha = 0.5$. (b) Path planning with $\alpha = 0.3-0.7$.

TABLE V
SWEEP COVERAGE DATA WITH $\alpha = 0.5$

UAV	1	2	3	4	5
Waiting time	8	16	24	**32**	40
Cumulative time	95.81	100.65	113.24	**109.41**	108.18
Total weight			530		
Task time			113.24		
Coverage rate			0.90		

TABLE VI
SWEEP COVERAGE DATA WITH $\alpha = 0.3$–0.7

UAV	1	2	3	4	5
Waiting time	8	16	**24**	32	40
Cumulative time	97.45	105.00	**111.33**	104.29	109.81
Total weight			544		
Task time			111.33		
Coverage rate			0.92		



(a)

(b)

Fig. 5. Path planning for UAVs by the WTSC algorithm with different numbers of operators under variable parameter α. (a) Path planning with $O = 1$ and $\alpha = 0.3$–0.7. (b) Path planning with $O = 5$ and $\alpha = 0.5$.

prioritize the *total weight* as the system will still be waiting on the later UAVs after it returns back, while the last launched UAV should prioritize the *task time* as the system is waiting on it to finish. Then, our second set of simulations compare the sweep paths of UAVs with constant parameter α and variable parameter α. When the number of targets is $N = 100$ and the number of operators is $O = 1$, the sweep paths of UAVs are shown in Fig. 4(a) and (b) with $\alpha = 0.5$ and $\alpha = 0.3$–0.7, respectively. The experimental data are exhibited in Tables V and VI.

In Fig. 4(a), we let α be fixed to 0.5. The task time is 113.24 min and the total weight of the covered targets in the paths is 530, corresponding to the coverage rate of 90%.

In Fig. 4(b), the parameter α changes from 0.3 to 0.7, in other words, according to the launch sequence of UAVs, the parameter α is 0.3, 0.4, 0.5, 0.6, and 0.7, respectively. The task time is 111.33 min and the total weight of the covered targets in the paths is 544, corresponding to the coverage rate of 92%. The experimental results demonstrate that the UAVs take the reduced task time of 1.91 min and an increased coverage rate of 2% when the parameter α changes according to the launch sequence of UAVs.

If the number of operators is equal to the number of UAVs ($O = M$), the waiting time of each UAV is the same, that is, they will be launched at the same time. For the next set of simulations, we explore the effect of one operator ($O < M$) with variable parameter α and five operators ($O = M$) with constant parameter α, using the same number of targets ($N = 100$) of the previous simulations. The results are shown in Fig. 5(a) and (b). The experimental data are exhibited in Tables VII and VIII.

Fig. 5(a) shows that the UAVs are launched in sequence and the parameter α varies from 0.3 to 0.7 when $O = 1$, that is, according to the launch sequence of UAVs, the parameter

TABLE VII
SWEEP COVERAGE DATA WITH $O = 1$ AND $\alpha = 0.3$–0.7

UAV	1	2	3	4	5
Waiting time	8	16	**24**	32	40
Cumulative time	91.02	101.21	**113.35**	111.78	107.24
Total weight			490		
Task time			113.35		
Coverage rate			0.86		

TABLE VIII
SWEEP COVERAGE DATA WITH $O = 5$ AND $\alpha = 0.5$

UAV	1	2	3	4	5
Waiting time	**8**	8	8	8	8
Cumulative time	**96.59**	96.22	91.22	95.15	77.16
Total weight			522		
Task time			96.59		
Coverage rate			0.92		

α is 0.3, 0.4, 0.5, 0.6, and 0.7, respectively. The task time is 113.35 min and the total weight of the covered targets in the paths is 490, corresponding to the coverage rate of 86%.

Fig. 5(b) shows that the UAVs are launched at the same time and the parameter α is fixed to 0.5 when $O = 5$. The task time is 96.59 min and the total weight of the covered targets in the paths is 522, corresponding to the coverage rate of 92%. In this case, the task time is shortened by 16.76 min and the coverage rate is improved by 6% when the number of operators increases from $O = 1$ to $O = 5$.

C. Performance Comparison of the Three Algorithms

We also compare the effects on task time and coverage rate by different algorithms when the number of targets and operators changes.

The comparison of task time by these three algorithms varying with the number of targets N is shown in Fig. 6. The x-axis denotes the number of targets N in the area varying from 50 to 400, while the y-axis shows the task time calculated by each algorithm. As the number of operators O has an impact on path planning, which has been proved in Fig. 3, we also perform simulations to show the impact of the number of operators in Fig. 6(a)–(d). To this end, we let the number of operators O be fixed to 1–4, respectively.

In Fig. 6(a), the results show that when there is only one operator, the task time by the WTSC algorithm is shorter than the other two algorithms under the same experimental conditions. Moreover, the task time by the WTSC algorithm basically remains the same when the number of targets N increases. The reason why this phenomenon occurs is that the waiting time of the UAV is not taken into account in the path planning of the other two algorithms. Clearly, the waiting time of U_5 is 40 min when there is only one operator, as shown in Table III. In the WTSC algorithm, we consider the influence of this factor on path planning, while they ignore it in the other two algorithms. In practice, the waiting time needs to be included in the task time.

From Fig. 6(a)–(d), we can see that when the number of operators O increases, the task time decreases by these three algorithms. Note that the difference of the task time among three algorithms becomes smaller when the number of operators O becomes larger, as shown in Fig. 6(a)–(d). This is probably because the waiting time of some UAVs is shortened

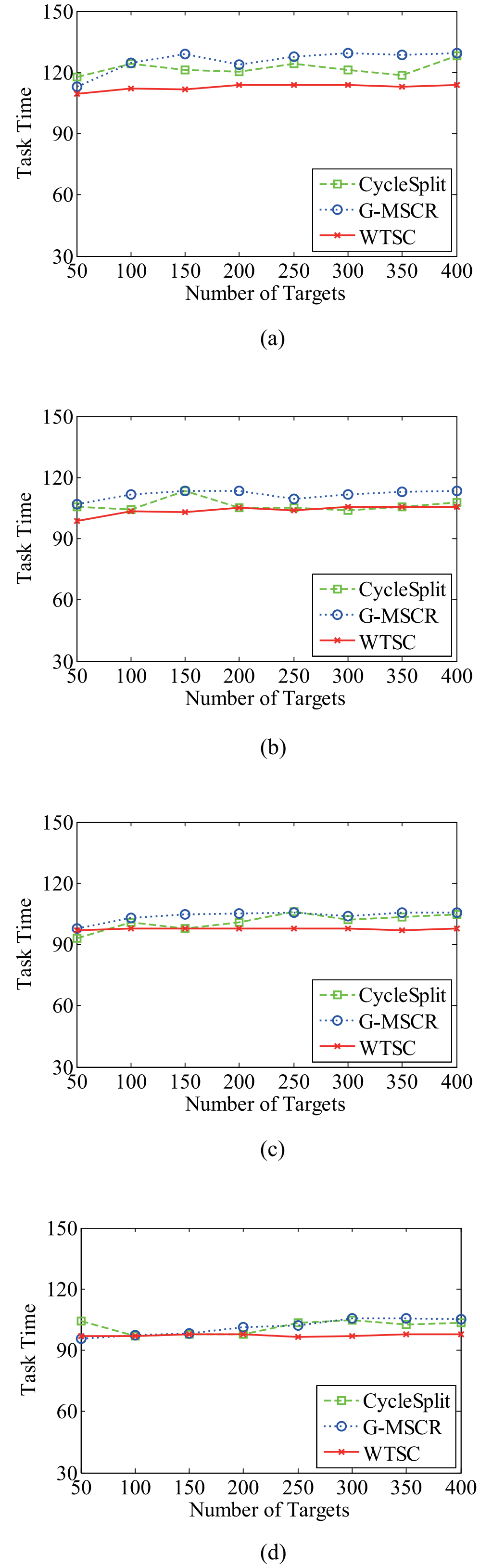
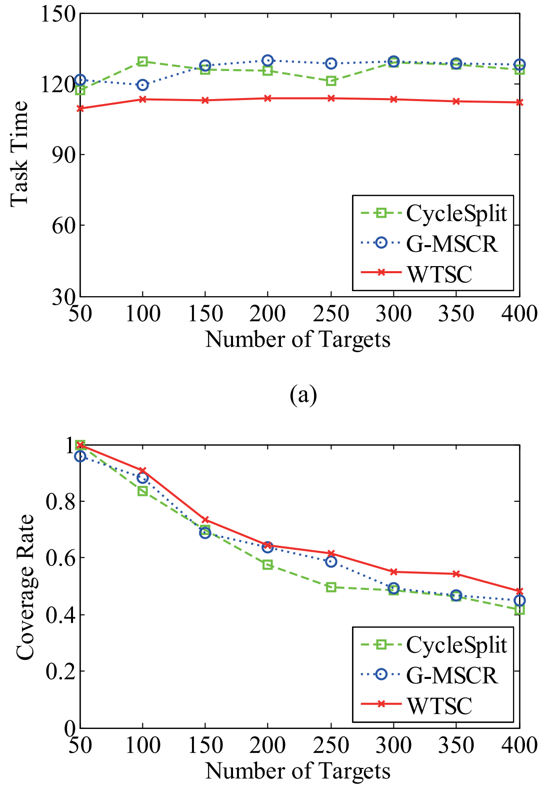


Fig. 6. Comparison of task time varying with the number of targets when the number of operators is fixed to 1–4, respectively. (a) $O = 1$. (b) $O = 2$. (c) $O = 3$. (d) $O = 4$.



(b)

Fig. 7. Comparison of task time and coverage rate varying with the number of targets when the number of operators is fixed to 1. (a) Task time. (b) Coverage rate.

TABLE IX
COMPARISON OF TASK TIME VARYING WITH THE NUMBER OF TARGETS WHEN THE NUMBER OF OPERATORS IS FIXED TO 1

Number of targets	Task time WTSC	CycleSplit	G-MSCR	Reduction ratio CycleSplit	G-MSCR
50	110	118	122	0.07	0.10
100	114	130	120	0.12	0.05
150	113	126	128	0.10	0.11
200	114	126	130	0.09	0.12
250	114	121	129	0.06	0.11
300	114	129	129	0.12	0.12
350	113	129	129	**0.12**	**0.12**
400	112	126	128	0.11	0.12

with the increase in the number of operators, and the difference in the task time will also decrease. This way, the task time is shortened correspondingly. Especially, the task time by the three algorithms is almost the same since the waiting time of each UAV is equal to 8 min when the number of operators O is 5, as shown in Table IV.

Then, we perform simulations to show the impact on task time and coverage rate by these three algorithms. The number of targets N ranges from 50 to 400, while the number of operators O is fixed to 1.

Table IX shows the comparison of task time to achieve sweep coverage varying with the number of targets. A graphical representation of Table IX is illustrated in Fig. 7(a). Table IX and Fig. 7(a) show that when the number of targets N is 50, the task time by the WTSC algorithm, CycleSplit

TABLE X
COMPARISON OF COVERAGE RATE VARYING WITH THE NUMBER OF TARGETS WHEN THE NUMBER OF OPERATORS IS FIXED TO 1

Number of targets	Coverage rate WTSC	CycleSplit	G-MSCR	Improvement ratio CycleSplit	G-MSCR
50	1.00	1.00	0.96	0.00	0.04
100	0.91	0.84	0.88	0.09	0.03
150	0.74	0.70	0.69	0.05	0.07
200	0.65	0.58	0.64	0.12	0.01
250	0.62	0.50	0.59	**0.24**	0.05
300	0.55	0.49	0.49	0.13	0.12
350	0.54	0.47	0.47	0.17	**0.16**
400	0.48	0.42	0.45	0.16	0.07

algorithm, and G-MSCR algorithm is 110, 118, and 122 min, respectively. With an increasing number of targets, the task time by the WTSC algorithm basically remains the same while it increases by the other two algorithms. As we can see, compared with the CycleSplit algorithm and G-MSCR algorithm, the task time by the WTSC algorithm is reduced by 12% at most. That is, our algorithm performs better than the other algorithms, CycleSplit and G-MSCR, with respect to the task time.

Table X shows the comparison of coverage rate to achieve sweep coverage varying with the number of targets. A graphical representation of Table X is illustrated in Fig. 7(b). Table X and Fig. 7(b) show that when the number of targets N is 50, the coverage rate is 100% by the WTSC algorithm and CycleSplit algorithm, while that is 96% by the G-MSCR algorithm. However, the task time by the WTSC algorithm is 110 min, which is the shortest one. With an increasing number of targets, the coverage rate decreases by all three algorithms. This is due to the fact that the flight time/total distance of each UAV has reached its upper limit after the number of targets exceeds a certain value. In this case, more targets will not be covered when the number of targets N continues to increase. Yet in spite of this, the coverage rate is still the largest by the WTSC algorithm, no matter how the number of targets changes. Note that compared with the CycleSplit algorithm and G-MSCR algorithm, our algorithm achieves a maximum of 24% and 16% improvement in coverage rate, respectively.

It is clear that the WTSC algorithm outperforms the other two algorithms, as for each scenario, the WTSC algorithm can always obtain the minimum task time and the maximum coverage rate. This proves that the performance of the WTSC algorithm is better than that of the previous algorithms.

D. Discussion

From the above simulation results, the following conclusions can be drawn.

1) In sweep coverage, our proposed algorithm has higher coverage quality than the previous methods because we consider not only the task time but also the coverage rate in combination with the actual situation to achieve the maximum coverage in the minimum time.
2) For the case of a small number of targets in the area, the task time is not the shortest when using the WTSC algorithm. However, when the number of targets is large, the WTSC algorithm can complete the sweep coverage

task in the minimum time. This is mainly because the performance constraints of UAV have been considered in the process of modeling, such as battery life and setup time.

3) For a large-scale monitoring scenario, the optimal coverage path generated by the WTSC algorithm has a smaller task time and higher coverage rate than the other two algorithms because it takes the influence of the weights of the targets into account in the path planning. In this case, the UAV prefers to cover the target with higher value when facing the targets with the same time consuming.

VI. Conclusion

In this article, we consider an MTMC issue for multi-UAV in sweep coverage and establish a mathematical model to achieve maximum coverage rate in minimum task time so as to achieve high-quality coverage. In path planning, the weights of the targets and the performance constraints of UAVs are considered, which will not only affect the task time but also affect the coverage rate. In addition, a greedy target assignment strategy is presented for multi-UAV sweep coverage. With heuristic, a WTSC algorithm is developed to address the MTMC issue, where the UAV tends to patrol the target with higher weight in each round of assignment decisions. The performance results show that the proposed WTSC algorithm outperforms the other two algorithms, i.e., CycleSplit and G-MSCR, regarding the task time and the coverage ratio.

As it is based on the offline path planning method, the proposed algorithm could not find a solution for the sweep coverage in some situations, including when the region environment changes during the execution of tasks by UAVs. In such a situation, the UAV needs to update the area information in real time during the flight and update the flight path in real time under the new conditions. This strategy is considered as future work to achieve online path planning.

References

[1] M. Iqbal, M. Naeem, A. Anpalagan, N. N. Qadri, and M. Imran, "Multi-objective optimization in sensor networks," *Comput. Netw.*, vol. 99, pp. 134–161, Apr. 2016.

[2] A. Pananjady, V. K. Bagaria, and R. Vaze, "Optimally approximating the coverage lifetime of wireless sensor networks," *IEEE/ACM Trans. Netw.*, vol. 25, no. 1, pp. 98–111, Feb. 2017.

[3] C.-H. Kuo, T.-S. Chen, and S.-C. Syu, "Robust mechanism of trap coverage and target tracking in mobile sensor networks," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 3019–3030, Apr. 2018.

[4] X. Gao, Z. Chen, F. Wu, and G. Chen, "Energy efficient algorithms for *k*-sink minimum movement target coverage problem in mobile sensor network," *IEEE/ACM Trans. Netw.*, vol. 25, no. 6, pp. 3616–3627, Dec. 2017.

[5] X. Gao, Z. Chen, J. Pan, F. Wu, and G. Chen, "Energy efficient scheduling algorithms for sweep coverage problem in mobile sensor networks," *IEEE Trans. Mobile Comput.*, vol. 19, no. 6, pp. 1332–1345, Jun. 2020, doi: 10.1109/TMC.2019.2910074.

[6] B. Gorain and P. S. Mandal, "Solving energy issues for sweep coverage in wireless sensor networks," *Discr. Appl. Math.*, vol. 228, pp. 130–139, Sep. 2017.

[7] P. Sun and A. Boukerche, "Performance modeling and analysis of a UAV path planning and target detection in a UAV-based wireless sensor network," *Comput. Netw.*, vol. 146, pp. 217–231, Dec. 2018.

[8] V. Roberge, M. Tarbouchi, and G. Labonte, "Fast genetic algorithm path planner for fixed-wing military UAV using GPU," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 54, no. 5, pp. 2105–2117, Oct. 2018.

[9] M. Erdelj, M. Krol, and E. Natalizio, "Wireless sensor networks and multi-UAV systems for natural disaster management," *Comput. Netw.*, vol. 124, pp. 72–86, Sep. 2017.

[10] G. Lindner, K. Schraml, and R. Mansberger, "UAV monitoring and documentation of a large landslide," *Appl. Geomatics*, vol. 8, no. 1, pp. 1–11, 2016.

[11] X. Liu *et al.*, "Transceiver design and multi-hop D2D for UAV IoT coverage in disasters," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1803–1815, Apr. 2019.

[12] P. Sun, A. Boukerche, and Y. Tao, "Theoretical analysis of the area coverage in a UAV-based wireless sensor network," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst.*, New York, NY, USA, 2018, pp. 117–120.

[13] Y. Zhao, Z. Zheng, and Y. Liu, "Survey on computational-intelligence-based UAV path planning," *Knowl. Based Syst.*, vol. 158, pp. 54–64, Oct. 2018.

[14] C. Yin, Z. Xiao, X. Cao, X. Xi, P. Yang, and D. Wu, "Offline and online search: UAV multi-objective path planning under dynamic urban environment," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 546–558, Apr. 2018.

[15] K. Harikumar, J. Senthilnath, and S. Sundaram, "Multi-UAV oxyrrhis marina-inspired search and dynamic formation control for forest firefighting," *IEEE Trans. Autom. Sci. Eng.*, vol. 16, no. 2, pp. 863–873, Apr. 2019.

[16] D. Popescu, C. Dragana, F. Stoican, L. Ichim, and G. Stamatescu, "A collaborative UAV-WSN network for monitoring large areas," *Sensors*, vol. 18, no. 12, pp. 4202–4226, 2018.

[17] E. D'Amato, M. Mattei, and I. Notaro, "Bi-level flight path planning of UAV formations with collision avoidance," *J. Intell. Robot. Syst.*, vol. 93, no. 1, pp. 193–211, 2019.

[18] Y. Qu, Y. Zhang, and Y. Zhang, "A global path planning algorithm for fixed-wing UAVs," *J. Intell. Robot. Syst.*, vol. 91, nos. 3–4, pp. 691–707, 2018.

[19] J. Lee, "Heterogeneous-ants-based path planner for global path planning of mobile robot applications," *Int. J. Control Autom. Syst.*, vol. 15, no. 4, pp. 1754–1769, 2017.

[20] Y. Wang, T. Kirubarajan, R. Tharmarasa, R. Jassemi-Zargani, and N. Kashyap, "Multiperiod coverage path planning and scheduling for airborne surveillance," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 54, no. 5, pp. 2257–2273, Oct. 2018.

[21] E. T. S. Alotaibi and H. Al-Rawi, "A complete multi-robot path-planning algorithm," *Auton. Agents Multiagent Syst.*, vol. 32, no. 5, pp. 693–740, 2018.

[22] S. M. Ahmadi, H. Kebriaei, and H. Moradi, "Constrained coverage path planning: Evolutionary and classical approaches," *Robotica*, vol. 36, no. 6, pp. 904–924, 2018.

[23] Y. Lin and S. Saripalli, "Sampling-based path planning for UAV collision avoidance," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 11, pp. 3179–3192, Nov. 2017.

[24] K. Sundar, S. Venkatachalam, and S. Rathinam, "Formulations and algorithms for the multiple depot, fuel-constrained, multiple vehicle routing problem," in *Proc. IEEE Amer. Control Conf.*, Boston, MA, USA, 2016, pp. 6489–6494.

[25] G. S. C. Avellar, G. A. S. Pereira, L. C. A. Pimenta, and P. Iscold, "Multi-UAV routing for area coverage and remote sensing with minimum time," *Sensors*, vol. 15, no. 11, pp. 27783–27803, 2015.

[26] R. Schacht-Rodríguez, J. C. Ponsart, C.-D. García-Beltrán, C.-M. Astorga-Zaragoza, D. Theilliol, and Y. Zhang, "Path planning generation algorithm for a class of UAV multirotor based on state of health of lithium polymer battery," *J. Intell. Robot. Syst.*, vol. 91, no. 1, pp. 115–131, 2018.

[27] S. Hayat, E. Yanmaz, T. X. Brown, and C. Bettstetter, "Multi-objective UAV path planning for search and rescue," in *Proc. IEEE Int. Conf. Robot. Autom.*, Singapore, 2017, pp. 5569–5574.

[28] S. S. Mansouri, C. Kanellakis, G. Georgoulas, D. Kominiak, T. Gustafsson, and G. Nikolakopoulos, "2D visual area coverage and path planning coupled with camera footprints," *Control Eng. Pract.*, vol. 75, pp. 1–16, Jun. 2018.

[29] B. H. Liu, N. T. Nguyen, and V. T. Pham, "An efficient method for sweep coverage with minimum mobile sensor," in *Proc. IEEE Int. Conf. Intell. Inf. Hiding Multimedia Signal Process.*, Kitakyushu, Japan, 2014, pp. 289–292.

[30] C. Liu, H. Du, and Q. Ye, "Sweep coverage with return time constraint," in *Proc. IEEE Global Commun. Conf.*, Washington, DC, USA, 2016, pp. 1–6.

[31] J. Liang, X. Huang, and Z. Zhang, "Approximation algorithms for distance constraint sweep coverage with base stations," *J. Comb. Optim.*, vol. 37, no. 4, pp. 1111–1125, 2019.

[32] Z. Chen, X. Zhu, X. Gao, F. Wu, J. Gu, and G. Chen, "Efficient scheduling strategies for mobile sensors in sweep coverage problem," in *Proc. IEEE Int. Conf. Sens. Commun. Netw.*, London, U.K., 2016, pp. 1–4.

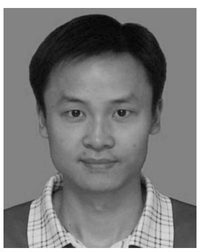
[33] X. Gao, X. Zhu, Y. Feng, F. Wu, and G. Chen, "Data ferry trajectory planning for sweep coverage problem with multiple mobile sensors," in *Proc. IEEE Int. Conf. Sens. Commun. Netw.*, London, U.K., 2016, pp. 1–9.

[34] X. Gao, J. Fan, F. Wu, and G. Chen, "Approximation algorithms for sweep coverage problem with multiple mobile sensors," *IEEE/ACM Trans. Netw.*, vol. 26, no. 2, pp. 990–1003, Apr. 2018.

[35] C.-Y. Chang, G. Chen, G.-J. Yu, T.-L. Wang, and T.-C. Wang, "TCWTP: Time-constrained weighted targets patrolling mechanism in wireless mobile sensor networks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 45, no. 6, pp. 901–914, Jun. 2015.

Jing Li received the M.S. degree in engineering from China University of Geosciences, Wuhan, China, in 2013, where she is currently pursuing the Ph.D. degree with the School of Automation.

Her research interests include wireless sensor network and UAV technology.



Yonghua Xiong received the M.S. and Ph.D. degrees in engineering from Central South University, Changsha, China, in 2004 and 2009, respectively.

He was a Lecturer and then an Associate Professor with the School of Information Science and Engineering, Central South University from January 2005 to August 2014. He joined the staff of the China University of Geosciences in September 2014, where he is currently a Professor with the School of Automation. He was a Visiting Scholar with the Department of Computer Science, City University of Hong Kong, Hong Kong, from 2006 to 2008. He was a Postdoctoral Fellow with the Department of Computer Information Technology and Graphics, Purdue University Northwest, Hammond, IN, USA, from 2015 to 2017. His research interests include computational intelligence, scheduling algorithms, and cloud computing.

Jinhua She (Senior Member, IEEE) received the B.S. degree in engineering from Central South University, Changsha, China, in 1983, and the M.S. and Ph.D. degrees in engineering from Tokyo Institute of Technology, Tokyo, Japan, in 1990 and 1993, respectively.

In 1993, he joined the School of Engineering, Tokyo University of Technology, Tokyo, where he is currently a Professor. His research interests include the applications of advanced control theory, repetitive control, process control, mobile learning, and assistive robotics.

Prof. She was a recipient of the International Federation of Automatic Control Engineering Practice Paper Prize in 1999 (jointly with M. Wu and M. Nakano). He is a member of the Society of Instrument and Control Engineers, the Institute of Electrical Engineers of Japan, the Japan Society of Mechanical Engineers, the Architectural Institute of Japan, and the Asian Control Association.

Min Wu (Fellow, IEEE) received the B.S. and M.S. degrees in engineering from Central South University, Changsha, China, in 1983 and 1986, respectively, and the Ph.D. degree in engineering from the Tokyo Institute of Technology, Tokyo, Japan, in 1999.

He was a Faculty Member with the School of Information Science and Engineering, Central South University from 1986 to 2014, and was promoted to a Professor in 1994. In 2014, he moved to the China University of Geosciences, Wuhan, China, where he is a Professor with the School of Automation. He was a Visiting Scholar with the Department of Electrical Engineering, Tohoku University, Sendai, Japan, from 1989 to 1990, and a Visiting Research Scholar with the Department of Control and Systems Engineering, Tokyo Institute of Technology from 1996 to 1999. He was a Visiting Professor with the School of Mechanical, Materials, Manufacturing Engineering and Management, University of Nottingham, Nottingham, U.K., from 2001 to 2002. His current research interests include process control, robust control, and intelligent systems.

Prof. Wu received the IFAC Control Engineering Practice Prize Paper Award in 1999 (together with M. Nakano and J. She). He is a Fellow of the Chinese Association of Automation.