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Multi-Region Coverage Path Planning for Heterogeneous Unmanned Aerial Vehicles Systems

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***Abstract*— Recently unmanned aerial vehicles (UAVs) have been widely adopted by military and civilian applications due to their strong autonomies and adaptabilities. Although UAVs can achieve effective cost reduction and flexibility enhancement in the development of systems with search or surveillance missions, they result in a complex path planning problem. Especially in region coverage systems, coverage path planning problem, which seeks a path that covers all regions of interest, has a NP-Hard computational complexity and is difficult to solve. In this paper, we study the coverage path planning problem for heterogeneous UAVs in multiple region systems. First, with the models of UAVs and regions, an exact formulation based on mixed integer linear programming is presented to produce an optimal coverage path. Then taking into account both the scanning time on regions and the flight time between regions, an efficient heuristic is proposed to assign regions and to obtain coverage orders for UAVs. Finally, experiments are conducted to show the reliability and efficiency of the proposed heuristic from several aspects.**

Keywords—unmanned aerial vehicle, coverage path planning, region coverage, coverage order

I. INTRODUCTION

With the rapid development of electrical and computer engineering, unmanned aerial vehicle (UAV) has been widely adopted by military and civilian application domains, such as surveillance, searching, rescuing and agriculture [1]. Compared with the manned vehicles, UAV does not place human life at risk [2], and has significant advantages in executing the dull and dangerous tasks [3]. Due to UAVs' limited energy, communication bandwidth and sensing range, many practical applications have outgrown a single UAV's capability [4]. Multiple UAV systems with high parallelism and robustness, have gradually become a discrete research field to take advantage of the cooperation of UAVs and to obtain higher operation efficiency [5].

Although UAVs can achieve effective cost reduction and flexibility enhancement in the development of practical applications, they make the systems more complex to carry out path planning, systemic decision-making and collaborative control [6]. Especially in region coverage systems where the position of a reconnaissance target is uncertain or the point of interest concerns all information of certain regions [7], coverage path planning problem has a NP-Hard computational complexity [8] and is difficult to solve.

Coverage path planning of UAVs is a complicated global optimum problem, which is mainly about seeking out an optimal flight path able to fully cover a given region of interest under specific constraint conditions. Coverage path planning is one of the key research points of UAV systems [9], and many factors, such as terrain, data, threat information, fuel consumption [10] and system schedulability [11], should be taken into consideration. The optimal coverage path for UAVs should be obtained such that the time cost can be reduced as much as possible.

Faced with the significantly increasing number of UAVs and regions, system designers gradually tend to rely on decision-making tools to produce valid coverage path for each UAV. Series of algorithms have been proposed to solve this problem from a geometrical point of view. However, most researches mainly focus on coverage path planning for UAVs on a single region, the problem of multiple UAVs covering multiple separated regions is not often taken into account due to its extraordinary complexity.

Multiple heterogeneous UAVs are usually adopted to fully cover multiple separated regions in practical applications. For example, in military fields, multiple UAVs are required to participate in the search task at the same time to completely find out enemy targets in a limited time. In agriculture fields, multiple UAVs are used to detect the state of vegetation and the growth of weeds on terraces separated from the mountains [12]. In all of the above applications, multiple UAVs have to cooperatively search various regions to detect objects of interest. Regions should be allocated to the best UAV and the coverage path should be optimized. Coverage path planning for UAVs is necessary and significant to guarantee that the searching or detecting tasks are finished correctly and efficiently.

In this paper, we study the coverage path planning problem for heterogeneous UAVs on multiple separated regions. We aim to find an efficient method to assign the regions and to produce coverage order for each UAV such that the coverage task would be finished as early as possible. The main contributions of the paper can be summarized as follows:

1. Models of heterogeneous UAVs and separated regions are built, and an exact formulation based on mixed integer linear programming is presented to obtain an optimal coverage path for UAVs.

2. Taking into account both the scanning time on regions and the flight time between regions, a heuristic is proposed to assign regions to UAVs and to optimize the coverage order. This heuristic does not completely search the solution space, and can solve the coverage path planning problem of heterogeneous UAVs effectively.

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The rest of this paper is organized as follows. Section II introduces the related work. Section III gives the models used in this paper and presents an exact formulation. Section IV proposes an efficient heuristic to obtain the coverage order for each UAV. Section V conducts the experiments and analyses the performance of our approach. Finally, Section VI gives a summary of this paper and the directions for future work.

II. Related Work

As part of mission planning, coverage path planning (CPP) plays an important role to improve viability and mission ability [7] by finding a path that covers the regions of interest. CPP has been addressed extensively in literature, and mainly studies the influence of factors, such as the shape of regions, internal obstacles, and UAV performances. Based on the relevance of UAV's speed and energy, the authors in [1] established a speed-energy model for a single UAV, and proposed a coverage path generation algorithm by taking resolution constraints into account. In [13], the CPP problem was formulated as a Travelling Salesman Problem (TSP), and a multi-population parallel genetic algorithm was used to simulate the coverage path generation in the region with obstacles. With the energy and operability constraints of UAVs, the authors in [14] presented a coverage path planning strategy satisfying the requirements of high autonomy and real-time capacity. However, in all of those works, the number of UAVs is only one, and the results proposed cannot be adapted to the applications where systems are complex and multiple UAVs are used.

At present, researches on coverage path planning problem mainly focus on multiple UAVs covering a single region. Generally, coverage path planning for multiple heterogeneous UAVs on a single region requires three important steps: performance evaluation of heterogeneous UAVs, region segmentation and allocation, and coverage path generation. Path planning, as well as task scheduling [15], is an important requirement for collision-free operation for UAVs. In [16], the authors first presented algorithms to divide the whole region into different parts, by taking into account UAVs relative capabilities and initial locations. Then they used a back-and-forth path generation method to provide the coverage path for each UAV. In [17], a cooperative search methodology was proposed to integrate the multiple agents into an advantageous formation, without been affected by the midway failure of some drones. Although the above studies analysed the CPP problem of multiple UAVs, they only work in situations where only one region is considered. This constraints sharply restricts the use of algorithms proposed. These results could not be directly extended to applications where multiple UAVs cooperatively cover multiple regions.

CPP problem for multiple UAVs on multiple regions are generally modelled as combinatorial optimization models and solved with various optimization algorithms. In [18], the CPP problem was modelled as a commercial supply and demand network logistics optimization model, and the path planning for multiple UAVs was achieved by minimizing the total cost of network traffic. In [19], the authors proposed an integer programming model for multiple UAV task assignment, and simulated the typical enemy fire suppression. In [20], the authors modelled the UAVs as Dubins vehicles flying at a constant altitude with bounded turning radius, and provided convoy protection to a group of ground vehicles. The CPP problem for multiple UAVs on multiple regions usually has a high complexity with a large number of optimization objectives and constraints. In order to find an exact coverage path for UAVs, the existing optimization algorithms should consider all possible allocations of regions and require a significant amount of time. Especially in the applications with hard real-time requirements, it is not acceptable to solve the CPP problem by using the existing optimization algorithms.

III. System Model and Exact Formulation

A. Notations and System Model

In this paper, we consider a team of n heterogeneous UAVs $U = \{U_1, U_2, .., U_n\}$ with different speeds and sensor performances. The UAVs has a mission of completely searching m regions $R = \{R_1, R_2, ..., R_m\}$, and does this most efficiently. A UAV is characterized by a tuple $U_i = \langle V_i, W_i \rangle$ where V_i is its speed and W_i is the scan width of its sensor on the speed V_i. We use A_j to denote the scanning area of the region R_j. Since the regions are distributed in different locations, the distances between each two regions are different. We use an $m \times m$ matrix $D = \{D_{i,j}\}$ to represent the distances. Each value of $D_{i,j}$ denotes the distance between regions R_i and R_j. If R_i and R_j are the same region, we assume the distance is 0, i.e., $D_{j,j} = 0$.

We use $TC_{i,j}$ to denote the time cost for UAV U_i in covering a region R_j. According to the above definition, $TC_{i,j}$ can be obtained by

$$TC_{i,j} = \frac{A_j}{V_i W_i} \tag{1}$$

Similarly, we use $TF_{i,j,k}$ to represent the time cost for UAV U_i in flying from region R_j to region R_k, then

$$TF_{i,j,k} = \frac{D_{j,k}}{V_i} \tag{2}$$

In this paper, we assume that all UAVs should fly from and back to the same base. A virtual region R_0 is adopted to denote this base. Since the base need not be scanned, the scanning area of R_0 is 0, i.e., $A_0 = 0$. We use $D_{0,j}$ and $D_{j,0}$ $(1 \leq j \leq m)$ to represent the flight distances from the base to R_j and from R_j to the base, respectively. Table I summarizes the basic notations used in this paper.

TABLE I. Basic notations used in this paper

Symbol	Description
U	the set composed of all UAVs
n	the number of UAVs in U
R	the set composed of all regions
m	the number of regions in R
U_i	the ith UAV in U
V_i	the speed of U_i
W_i	the scan width of the sensor of U_i
R_j	the jth region in R
A_j	the scanning area of R_j
$D_{i,j}$	the distance between regions R_i and R_j
$TC_{i,j}$	the time cost for U_i in covering a region R_j
$TF_{i,j,k}$	the time cost for U_i in flying from R_j to R_k

B. Exact Formulation

In this subsection, based on mixed integer linear programming (MILP) [21], we present an exact formulation of the path planning problem for multiple UAVs on multiple regions. MILP is a powerful method for coverage path planning problem because it can handle dynamic systems with discrete decision variables and there are many efficient solvers available. The path planning problem is defined as minimizing a linear objective function (the maximum time cost of all UAVs) subject to linear constraints (coverage constraints of regions).

We use a three dimensional array $X = \{x_{i,j,k} \mid i \in [1,n], j \in [0,m], k \in [1,m]\}$ to describe the flight paths of UAVs. Each element $x_{i,j,k}$ is a Boolean variable, representing whether the UAV U_i flies from R_j to R_k. If U_i flies from R_j to R_k, $x_{i,j,k} = 1$; otherwise $x_{i,j,k} = 0$, i.e.,

$$x_{i,j,k} = \begin{cases} 1 & \text{if } U_i \text{ flies from } R_j \text{ to } R_k \\ 0 & \text{otherwise} \end{cases}$$

With the flight path array X, the MILP formulation for the coverage path planning problem can be written as,

$$\text{minimize } T = \max_{1 \le i \le n} \Big\{ \min \Big\{ \sum_{j=0}^{m} \sum_{k=0}^{m} (TC_{i,j} + TF_{i,j,k}) x_{i,j,k} \Big\} \Big\}$$

subject to

$$\sum_{i=1}^{n} \sum_{k=1}^{m} x_{i,0,k} \le n \tag{3}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{m} x_{i,0,k} = \sum_{i=1}^{n} \sum_{j=1}^{m} x_{i,j,0} \tag{4}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} x_{i,j,k} = 1, \forall k \in [1,m] \tag{5}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{m} x_{i,j,k} = 1, \forall j \in [1,m] \tag{6}$$

This formulation guarantees that all regions are fully covered, and seeks optimal values for the elements in the flight path array to minimize the maximum time cost of all UAVs. Constraint (3) shows that the number of UAVs taking off from the base is not more than the total number of UAVs. Constraint (4) guarantees that the number of UAVs taking off from the base is equal to the number of UAVs flying back to the base. Constraints (5) and (6) represent the non-overlapping restrictions of the regions: each region should be covered by one and only one UAV.

IV. Highest Effective Time Ratio First Algorithm

Even though the MILP formulation proposed can find an exact coverage path planning solution, it considers all possible flight paths and coverage orders of UAVs, which is exceedingly laborious and time-consuming. This is due to the fact that the coverage path planning problem for multiple UAVs is NP-Hard. The complexity of the problem rapidly grows as the number of variables increases and therefore it is often not suitable for real-time practical applications. A relatively efficient heuristic is proposed in this section.

Based on models of UAVs and regions built in Sect. III, we propose a highest effective time ratio first (HETRF) algorithm to plan the coverage path for each UAV. This algorithm takes into account the flight time between each two regions and the scanning time on each region. In this algorithm, the regions with large areas or near the current scanned regions are most likely chosen to be covered in the next step. Meanwhile, an optimization strategy is adopted to reduce the time cost, by adjusting the covering order of each UAV.

HETRF is a path planning algorithm for a bounded number of heterogeneous UAVs, and has two major phases: a region allocation phase and a sequence adjustment phase. The region allocation phase computes the efficient time ratio of all unallocated regions when a UAV finishes its coverage tasks, selects the region with the highest efficient time ratio, and assigns the selected region to this free UAV. The sequence adjustment phase adjusts the coverage order of the regions allocated to the same UAV, and minimizes the time cost required by each UAV.

A. Region Allocation Phase

In the region allocation phase of the HETRF algorithm, once one of the UAVs finishes its coverage task, effective time ratios of all unallocated regions should be calculated, and the region with the highest time ratio is assigned to the free UAV. We first introduce the concept of the effective time ratio.

Assume that a UAV U_i plans to cover a region R_k after it finishes the coverage task of region R_j. The time cost for U_i in flying from R_j to R_k is $TF_{i,j,k} = \frac{D_{j,k}}{V_i}$, and the time cost for U_i in covering R_k is $TC_{i,k} = \frac{A_k}{V_i W_i}$. Since the aim of the flight of U_i is only fully scanning the region R_k, $TC_{i,k}$ is valuable and could not be discarded. We refer to the time spent in scanning the target region as the effective time, and refer to the time speeding in flying to and scanning the target region as the total time. Then the effective time ratio (ETR) of the target region is defined as the percentage of the effective time in the total time, i.e.,

$$ETR_{i,j,k} = \frac{TC_{i,k}}{TC_{i,k} + TF_{i,j,k}} = \frac{A_k}{A_k + D_{j,k} W_i} \tag{7}$$

From Eq. (7) we can find that, the effective time ratio will increase with the areas of target regions increasing and with the distances between regions decreasing. When any UAV U_i finishes its current coverage task, the effective time ratios of all unallocated regions should be calculated. The region with the highest effective time ratio is assigned to the UAV U_i.

Based on the effective time ratio, the region, which has a lager searching area and is nearer to the current covered region, would be selected and scanned first. The highest effective time ratio algorithm takes into account both the area priority and the distance priority of the regions, can achieve a better performance in reducing the time cost of the coverage tasks. The pseudo-code of the highest effective time ratio algorithm is shown in Algorithm 1.

Algorithm 1: Highest effective time ratio first algorithm proposed in this paper

Input: a UAV set U and a region set R

Output: coverage orders for UAVs

1 $LeftRegion \leftarrow R$;

2 $\forall i \in [1, n]$, $FinishTime[i] \leftarrow 0$, $Region[i] \leftarrow \emptyset$;

3 **repeat**

4 $\quad i \leftarrow$ the index of UAV whose finish time is the earliest;

5 $\quad j \leftarrow$ the index of region that is last covered by UAV U_i ;

6 $\quad$ Compute the effective time ratio of each region in $LeftRegion$ according to Eq. (7);

7 $\quad k \leftarrow$ the index of region whose ETR is the highest;

8 $\quad$ Remove R_k out from $LeftRegion$;

9 $\quad$ Put R_k into $Region[i]$;

10 $\quad FinishTime[i] += TC_{i,k} + TF_{i,j,k}$;

11 **until** $LeftRegion \neq \emptyset$;

12 **for** $i = 1$ *to* n **do**

13 $\quad p \leftarrow$ the number of regions in $Region[i]$;

14 $\quad$ **for** $j = 0$ *to* $p - 1$ **do**

15 $\quad\quad k \leftarrow$ the index of region that is closest to R_j in the left regions;

16 $\quad\quad$ Place R_k behind R_j in the coverage order of U_i;

17 $\quad$ **end**

18 **end**

B. Sequence Adjustment Phase

In the region allocation phase, regions are allocated to UAVs based on their effective time ratios. Each UAV obtains a region sequence in which all regions should be covered by this UAV in order. However, in the region allocation phase, regions are selected based solely on their effective time ratios, the coverage order is not optimal in most cases. A sequence adjustment phase is required to adopt an optimized policy to change the coverage order of each UAV such that the time cost would be reduced as much as possible.

Shortest distance first strategy is one of the most frequently used optimized policies in path planning problems. We also adopt this strategy to adjust the coverage order of the UAVs. In this strategy, once a UAV finishes the coverage task on a given region, the distances between left regions and the current region should be calculated. The UAV would choose the closest region to do the coverage task. The adjustment is moved round after round until all regions are considered. Finally a new region sequence is obtained for each UAV. The UAVs will take off from the base, cover the regions in the new sequence one by one, and fly back to the base.

C. Running Time Analysis

We analyze the computational complexity of the HETRF algorithm in this subsection. From Algorithm 1 we know, the main computation part of the algorithm is from line 3 to 28, which has two phrases: the region allocation phase and the sequence adjustment phase.

We consider the region allocation phase (from line 3 to 11) first. The region allocation phase is a loop that repeats m times at most. In each iteration, the most time consuming operations are calculating the effective time ratio of each unallocated region in line 6, and finding the highest values in line 7. In the worst case, all regions should be considered to obtain the highest effective time ratio according to Eq. (7). The largest running time cost of each iteration is $O(m)$. Therefore, the region allocation phase runs in $O(m^2)$.

Now we analyze the running time cost of the sequence adjustment phase (from line 12 to 18), which has a structure of double closed loops. The inner loop (from line 14 to 17) tries to optimize the coverage order of a given UAV. Since the number of regions allocated to a given UAV is not more than m, the inner loop runs m times at most. In each iteration, the region which has the shortest distance to the current covered region should be found. The largest running time cost of the inner loop is $O(m^2)$. Given the outer loop repeats n times, the total running time of the sequence adjustment phase is $O(m^2 n)$.

Putting the region allocation phase and the sequence adjustment phase together, we can find that the overall time cost of Algorithm 1 is $O(m^2)$+$O(m^2 n)$, which is equal to $O(m^2 n)$. Since the running time cost of Algorithm 1 depends on the number of regions m and the number of all UAVs n, this algorithm runs in pseudo-polynomial time. The complexity explodes as soon as m becomes larger. However, the number of calculation steps of this algorithm is considered in a very pessimistic situation, we find in our experiments that the average performances of our approach typically perform better to solve the coverage path planning problem.

V. Experiments and Results

In this section we conduct experiments to analyse the performance of our approach. We compare the experimental results of our approach with those of three existing solutions including the large area first scheduling (LAF) algorithm, the short distance first scheduling (SDF) algorithm and genetic algorithm (GA) [10]. The machine used has an Intel(R) Core(TM) i5-3320M CPU 2.60GHz and 4.00GB of system memory and there is only one processor in use for all of the experiments.

A. Region Generation

The region data used in experiments is from the land use map of Fuzhou City in China. This map shows the locations and areas of different land-use types including water, forest, grassland, road, artificial land-use and unused land. Since most of land-use regions in the original map are irregular polygons and hard to be calculated in experiments, we preprocess the map at first and represent the original land-use regions by approximately convex polygons. The preprocessed map is shown in Fig. 1. We assume that the forest lands identified in red and the unused lands identified in yellow are the regions of interest and would be covered by UAVs.

In this paper, we take the lower left corner of the map as the origin of the coordinate system, and the coordinates of vertices of the regions can be obtained according to their locations. The searching area of each region can be calculated via Eq. (8).

$$S = \frac{1}{2}(\sum_{i=1}^{n-1})(x_i y_{i+1} - x_{i+1} y_i) + (x_n y_1 - x_1 y_n)) \quad (8)$$

where n is the number of vertices of the regions, and $(x_1, y_1), (x_2, y_2), ..., (x_i, y_i), ..., (x_n, y_n)$ are the coordinates of vertices arranged in the opposite clock direction.

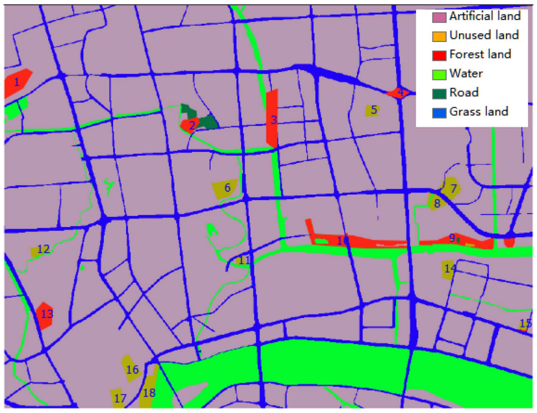

Fig. 1. Land-use regions of Fuzhou City after preprocess

Similarly, the centroid coordinates of regions and the distance of each two regions can be calculated by Eq. (9) and Eq. (10) respectively.

$$(\bar{x}, \bar{y}) = (\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i) \tag{9}$$

$$D_{j,k} = \sqrt{(\bar{x_j} - \bar{x_k})^2 + (\bar{y_j} - \bar{y_k})^2} \tag{10}$$

Table II shows the searching areas calculated by the above equations. From Table II, it can be seen that the searching areas of regions vary dramatically. Region 3 has the largest searing area, which is 20 times more than that of Region 11.

TABLE II. SEARCHING AREAS OF REGIONS IN FIG. 1

Region No.	1	2	3	4	5	6	7	8	9
Area (m^2)	53113	17925	106212	12349	20224	22934	35723	10900	77511
Region No.	10	11	12	13	14	15	16	17	18
Area (m^2)	82662	5127	9655	24107	23572	7576	41764	24595	45646

In this paper, there are six heterogeneous UAVs that can be adopted to finish the coverage tasks. The speeds and scan widths are shown in Table III.

TABLE III. UAVS ADOPTED IN EXPERIMENTS

UAV No.	1	2	3	4	5	6
Speed (m/s)	5.0	5.0	5.0	4.5	5.5	8.0
Scan width(m)	4.0	5.0	6.0	5.0	4.0	2.0

B. Performance Evaluation

The first experiment we carry out is to evaluate the performances of algorithms on a fixed number of UAVs. First three UAVs listed in Table III are used to cover the forest lands and the unused lands in Fig. 1. With the HETRF algorithm proposed in Sect. IV, the coverage order of each UAV is shown in Table IV, and the Gantt chart on UAV scheduling is shown in Fig. 2.

In Fig. 2, the green rectangles represent the flights of UAVs between regions, whereas the red ones represent the scanning processes on regions. We can find that the coverage tasks of all UAVs are finished almost at the same time. The time cost obtained by our approach is 163.61 minutes. However, the results calculated by LAF algorithm, SDF algorithm and GA method are 197.25 minutes, 184.11 minutes and 174.12 minutes, respectively. This demonstrates that our approach has a better performance in solving the path planning problem when the number of UAVs is fixed.

TABLE IV. COVERAGE ORDERS AND TIME COSTS OF UAVS

UAV No.	Coverage order	Time cost (min)
1	$0 \rightarrow 16 \rightarrow 10 \rightarrow 7 \rightarrow 4$	163.61
2	$0 \rightarrow 17 \rightarrow 18 \rightarrow 13 \rightarrow 12 \rightarrow 1 \rightarrow 2 \rightarrow 6 \rightarrow 11$	161.90
3	$0 \rightarrow 3 \rightarrow 5 \rightarrow 8 \rightarrow 9 \rightarrow 14 \rightarrow 15$	161.95

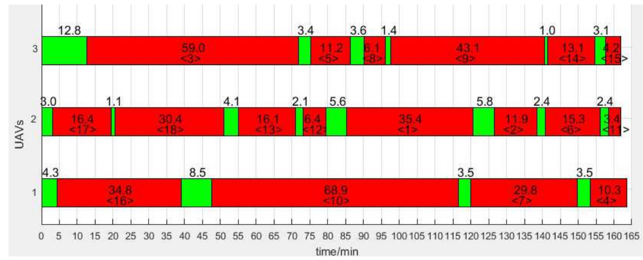

Fig. 2. Gantt chart on UAV scheduling

Through varying the number of UAVs, Fig. 3 shows the time costs obtained by different methods. As can be seen in Fig . 3, along with the increase of the number of UAVs, the time costs obtained by all methods have the same changing tendency that they reduce gradually from more than 260 minutes to less than 140 minutes. However, when the number of UAVs is fixed, our approach obtains a lower time cost than the other methods. When the number of UAVs is 5, the time required by UAVs calculated by our approach is 116 minutes, which is 9.3%, 15.2%, 3.1% less than those obtained by LAF, SDF and GA method, respectively.

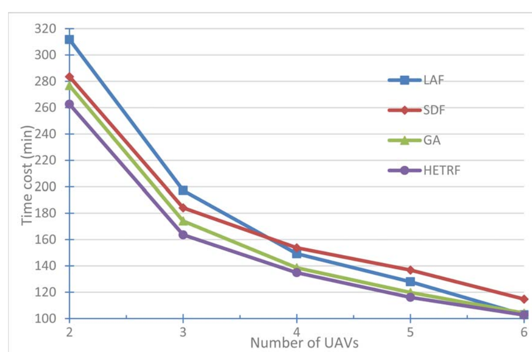

Fig. 3. Time costs obtained by our approach and other methods along with the increase of the number of UAVs

In the experiment of Fig. 4, the first three UAVs are chosen to cover the regions of interest, and the number of regions is increasing from 6 to 18. Each point in Fig. 4 represents the average execution time of the results of 1000 instances. Fig. 4 demonstrates that the average execution time required by different methods grows along with the increase of the number of regions. It can be found that the time consumption of our approach is larger than those of LAF algorithm and SDF algorithm. This is because that our approach takes into account both the scanning time on regions and the flight time between regions. However, the differences of average execution time among our approach, LAF algorithm and SDF algorithm are very slight. When the number of regions is 18, the average execution time of our approach is 1620 milliseconds, which is 24% larger than that of LAF algorithm but 2 times less than that of GA method.

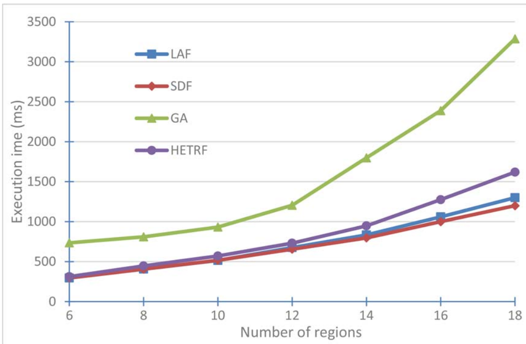

Fig. 4. Average execution time required by the four methods to solve the path planning problem

VI. Conclusions and Further Work

In this paper, we aimed at solving the coverage path planning problem for heterogeneous UAVs on multiple regions. We built the models of UAVs and regions, and presented an exact formulation based on mixed integer linear programming to completely search the solution space and obtain an exact coverage path. Meanwhile, we proposed a heuristic to assign regions and to obtain coverage order for each UAV. The heuristic takes into account both the scanning time on regions and the flight time between regions, and can solve the coverage path planning problem effectively.

Although our approach can achieve a reasonable solution in a relatively short amount of time, we would like to find a more efficient way to improve its performance. Meanwhile, we are interested in studying the coverage path planning problem in regions with obstacles, and would like to see whether some of the results in this paper can be adapted to more complex situations.

VII. Acknowledgment

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