Paper:

Multi-task Planning of Heterogeneous UAVs Based on Indoor Topological Map

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Abstract. The high efficient task assignment and fast path planning for small unmanned aerial vehicles (UAVs) indoor task planning play a crucial role. Considering the complex indoor environment and multi-constraints on UAVs, the paper focuses on the problem of multi-task planning of heterogeneous UAVs with different abilities based on the indoor topological map. First, we model this problem as a multi-objective bi-level optimization problem. The objectives include the completion rate of the tasks and the consumption of UAVs performing the tasks. Then, the constraints on UAVs in an indoor environment are analyzed and the topological map is applied to the UAVs' path planning. The problem is solved by using four multi-objective optimization algorithms including NSGA-II, SPEA2, MOEA/D, and MOPSO. Finally, computational experiments are conducted with test instances of different scales. The experimental results show that NSGA-II and SPEA2 can find significantly better Pareto fronts.

Keywords: Multi-task Planning; Path Planning; Multi-objective Optimization Problem; Topological Map.

1. Introduction

Unmanned aerial vehicles (UAVs) are gaining more and more significance due to their adoption in a wide variety of engineering fields, such as surveying, monitoring, or precision agriculture [1]. Task assignment and path planning for multiple UAVs in the above scenarios are essential for successful mission execution. But, effectively balancing tasks to better excavate the potential of UAVs remains a challenge, as well as efficiently generating feasible solutions from the current one in constrained explosive solution spaces with the increase in the scale of optimization problems. [2] proposed an efficient approach for task assignment and path planning with the objective of balancing the tasks among UAVs and achieving satisfactory temporal resolutions.

For task assignment of multiple UAVs, many methods have been adopted to address this problem. For example, a hierarchical task assignment method was proposed in [3], which broke the original problem down to sub-problems and solved them with mixed-integer programming and ant colony algorithm. For UAVs with different sensor capabilities, a modified symbiotic organisms search algorithm was adopted to optimize UAVs-task sequence [4]. In article [5], an iterative strategy was proposed to enhance the performance of task assignment and path planning in applications of distributed multiple UAVs. For task allocation problems in a dynamic environment, article [6] proposed a quantum evolutionary inspired algorithm to minimize resource consumption and enhance the reliability of the coalitions of UAVs.

The article discussed above provides some useful methods for task assignment and path planning of UAVs. However, some important issues also urgently need to be addressed. Compared with the outdoor environment such as the urban environment and mountain environment, indoor environment has more restrictions on UAVs [7]. In outdoor environment, there may be no-fly areas and dangerous areas, such as bad meteorological areas and electromagnetic interference areas [8], which require the UAVs path to avoid those areas or pass through those areas in the shortest possible time. In contrast in indoor environment, these constraints may be different. Specifically, for mobility, the UAVs cannot move forward smoothly in an indoor environment because of the narrow indoor space, the limited size of doors and windows, and the safe distance of UAVs. Besides, there are many obstacles and occlusions in indoor environment, and the presence of some glass and mirrors on the windows and walls will directly interfere with visibility. Indoor environment is GPS-denied, so it directly weakens the positioning and communication ability of the UAVs. What's more, there are many metal materials and electromagnetic sources indoors, which will also affect the communication capabilities of the UAVs.

The main contributions of this paper are shown as follows:

•First, a framework for UAVs'task planning based on indoor topological maps is established.
•Second, the influences of the indoor environment on the mobility of UAVs are modeled.
•Finally, the paper solves the multi-objective bi-level optimization problem by using four different prevalent algorithms.

The remainder of this paper is organized as follows.

Section 2 gives the problem description and the mathematical model. The details of the algorithms used in this paper are described in Section 3. Numerical experiments are conducted in Section 4, followed by conclusions in Section 5.

2. Problem Formulation

The problem of multi-task planning of heterogeneous UAVs based on the indoor topological map can be decomposed into two levels. The first level is the multi-UAV multi-task assignment problem, and the second level is the multi-UAV path planning problem.

For the multi-UAV multi-task assignment problem, firstly, the overall task is divided into multiple task points. The task points are heterogeneous because they have different functional requirements for the UAVs. So the task points may be assigned to a single UAV or multiple UAVs. Suppose that when the UAVs perform the same task point, there is no requirement for the time sequence. UAVs are also heterogeneous because the sensors carried by them are different. So UAVs may be assigned to a single task or multiple tasks in an assignment plan. After task assignment, each UAV will plan the paths.

For multi-UAV path planning, it can be abstracted as a traveling salesman problem (TSP). The main purpose for each UAV is to visit all the task points and perform the corresponding reconnaissance task. In this process, the UAVs need to meet all the constraints of the system, and the time it takes to complete all tasks is expected as small as possible. Suppose that when two UAVs arrive at a task point at the same time or meet during execution of a task, the collision of UAVs is not considered.

Paper [9] proposed a generalized optimization framework of cooperative path planning problems from the viewpoint of three key elements, i.e., task, UAV group, and environment. Inspired by paper [9], the key elements in the problem of multi-task planning based on a topological map will be presented.

(1) UAVs

Heterogeneous UAVs with different abilities are used to perform the tasks.

(2) Reconnaissance tasks

Each UAV needs to find an optimal or feasible path from the initial location to the task points, and then reconnoiter the task points.

(3) Indoor environment

Fig.1 represents a floor plan view of the interior of a building. Each polygon represents a room. R1-R8 represents the number of rooms. They are connected by doors.

There are two objectives in multi-task planning problem. One is the path consumption of UAVs and the other is satisfaction rate of tasks demand in an assignment plan. Constraints are mainly manifested in the impact on UAVs' mobility. The overall framework of task planning is shown in Fig.2. In the figure, we first solve the problem of task assignment, and then solve the problem of path planning .

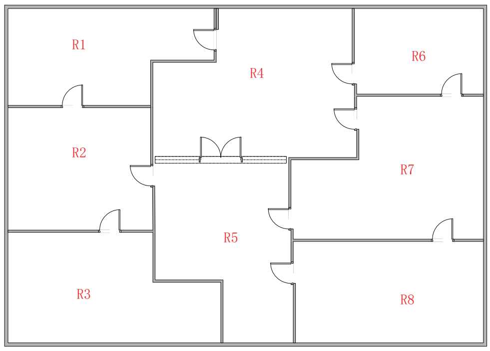

Fig. 1. The indoor environment.

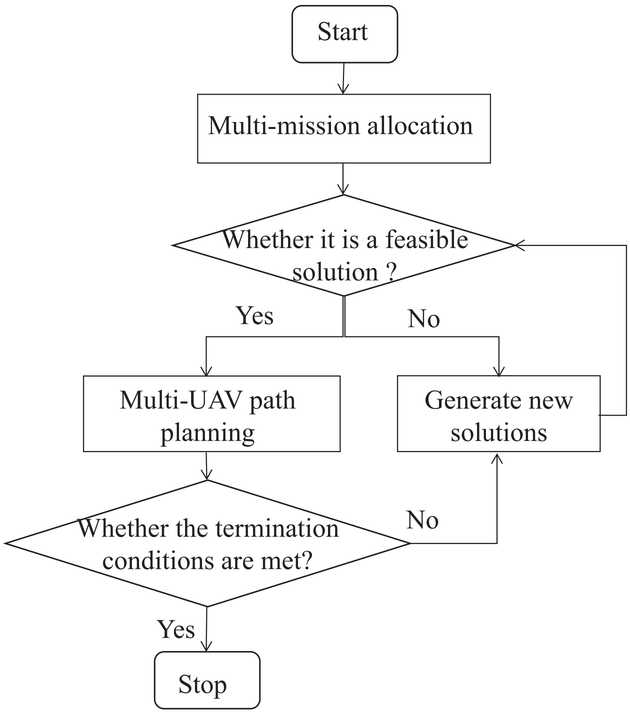

Fig. 2. The overall framework of task planning.

2.1. Objective Function

In this paper, we model the multi-task planning of heterogeneous UAVs as a multi-objective bi-level optimization problem and solve it using prevalent multi-objective optimization algorithms. The two objectives in our problem are as follows:

(1) The first objective is satisfaction rate of task demand. Satisfaction rate of task demand is as large as possible. The first objective is represented by f_1. The formula of f_1 is as follows:

$$f_1 = \sum_{j=1}^{J} w_{2j} \Big(\sum_{z=1}^{Z} w_{1z} \big(\big(\sum_{i=1}^{I} u_{iz} \big) / t_{jz} \big) \Big), \quad \ldots\ldots \quad (1)$$

where i means the ith UAV and the maximum value of i

is I. j means the jth task and the maximum value of j is J. z means the zth sensor of UAV and the maximum value of z is Z. w_{1z} represents the weight of the zth sensor in a task point. w_{2j} represents the weight of the jth task point in the total task. t_{jz} represents the zth sensor's demand in jth task point. u_{iz} represents the zth sensor's ability in ith UAV.

For convenience, the first objective will be normalized. The formula is as follows:

$$f_1' = (M - f_1)/M, \quad (2)$$

where M means the maximum value of satisfaction rate of task demand. f_1' is as small as possible.

(2) The second objective is the path consumption of the UAVs during performing the tasks represented by f_2. f_2 is as small as possible. The formula of f_2 is as follows:

$$f_2 = \sum_{i=1}^{I} c_i, \quad (3)$$

where c_i represents the ith UAV's path consumption when it completed all its tasks.

For convenience, the second objective will be normalized. The formula is as follows:

$$f_2' = (M_c - f_2)/M_c, \quad (4)$$

where M_c represents the maximum value of all UAVs' path consumptions. f_2' is as small as possible.

2.2. Constraints

The main influence on UAVs during task planning is the complex indoor structure. Topological maps are convenient for UAVs to plan the path in indoor environments. The paper uses the topological map to construct the connection relationship between the rooms. The topological map in Fig.3 is constructed depending on Fig.1. The straight line between R1 and R2 means that they are connected.

Constraints in multi-UAV task planning problem are shown as follows:

(1) The first constraint is that satisfaction rate of task demand must be greater than each task's threshold,

$$\sum_{i=1}^{I} u_{iz} \geq \theta_{jz} t_{jz}, \quad (5)$$

where θ_{jz} is the threshold of zth sensor's demand in jth task point. This constraint ensures that the selected UAVs have the abilities to perform the tasks.

(2) The second constraint is that the path consumption of each UAV must be less than its maximum endurance,

$$c_i \leq e_i, \quad (6)$$

where e_i means the ith UAV's maximum endurance. This constraint ensures that the solution is feasible. If the consumptions of UAVs are more than their maximum endurance, we will judge the solution as an infeasible one. Then, the infeasible solutions are used to generate new solutions by evolutionary operation in MOEAs.

(3) The third constraint is that the paths planned by the UAVs must meet the connection relationship of the indoor topology map. This constraint ensures that the paths planned for the UAVs are all passable.

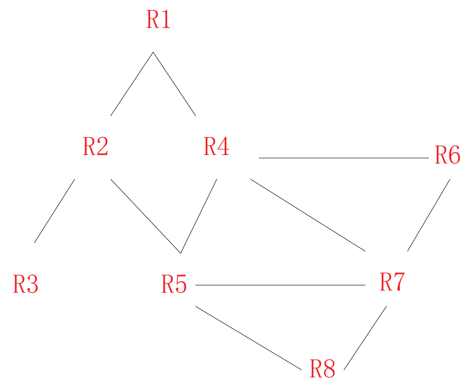

Fig. 3. The topological of Fig.1.

3. MOEAs on The Problem

Multi-objective evolutionary algorithms(MOEAs) are popular methods for approximating the whole Pareto front (PF) in a single run. According to the selection strategies, MOEAs can be grouped into three categories: Pareto domination based MOEAs (e.g., NSGA-II [10], SPEA2 [11]), indicator based MOEAs, and decomposition based MOEAs (e.g., MOEA/D [12]). There are four algorithms used in the paper that belong to the three categories mentioned above. In Pareto domination based MOEAs, we use NSGA-II and SPEA2. In decomposition based MOEAs, we use MOEA/D. In the swarm intelligence algorithm, we use MOPSO [13].

(1) NSGA-II [10] classifies a population into different non-dominated fronts and calculates the sharing function values of individuals located on the same front to obtain good diversity of a population. NSGA-II is good at searching the PF, can achieve good population diversity, and allow for the existence of multiple equivalent individuals. First, NSGA-II utilizes the fast non-dominated sorting procedure which has a low computation complexity, then NSGA-II maintains the parent population and the offspring population at the same time and adopts the elitism mechanism to select the best solutions.

(2) SPEA2 [11] maintains an archive to store non-dominated solutions during the evolutionary process and updates it iteratively. The fitness function value of each solution in SPEA2 is defined as the number of solutions that the current one dominates. Besides, the clustering method is used to maintain the diversity of a population. SPEA2 utilizes a fitness function and maintains the population diversity by estimating the density of neighboring solutions.

(3) MOEA/D [12] decomposes a complicated MOP in-

to a series of simple subproblems and solves them in a collaborative way to obtain a set of non-dominated solutions with good convergence and diversity. Decomposition-based MOEAs first attempt to combine classical optimization algorithms with EAs. MOEA/D converts an MOP into a series of scalar subproblems by using aggregation functions (e.g., weighted sum, Tchebycheff, PBI, and so on) and a set of uniformly distributed weight vectors. The concept of neighbor is defined based on Euclidean distance among weight vectors. These subproblems are optimized simultaneously by using information from neighboring subproblems, which leads to low computational complexity. Besides, the diversity of a population is guaranteed by a set of uniformly distributed weight vectors implicitly.

(4) MOPSO [13] utilizes directional information to promote faster approximation of the Pareto front, which makes it compatible with other optimization programs. First, the position of every particle is initialized, and velocity is set to zero. The initial position is considered as a personal best, and it is updated in succeeding steps. Global archive is used in MOPSO to store non-dominated optimum solutions of the population. Initially, the global archive is empty, but it can store the user-specified maximum number of Pareto solutions, and it is updated at every generation. If the number of non-dominated solutions exceeds, a few solutions are discarded. One of the unique features of MOPSO is that every individual particle also has a personal archive, and it is recognized as a personal best archive. During every iteration, global best and personal best are assigned from the personnel archive and global archive.

3.1. Encoding and Decoding

The solution of the first level of the optimization problem is a task assignment plan. The encoding of this problem is shown as the following formula:

$$s1 = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} & \cdots & a_{1J} \\ a_{21} & a_{22} & \cdots & a_{2j} & \cdots & a_{2J} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} & \cdots & a_{iJ} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ a_{I1} & a_{I2} & \cdots & a_{Ij} & \cdots & a_{IJ} \end{bmatrix}, \quad (7)$$

where $s1$ is a solution of the first level. i means the ith UAV and the maximum value of i is I. j means the jth task and the maximum value of j is J. $a_{ij} \in \{0, 1\}$, a_{ij} =1 means the ith UAV is assigned to perform the jth task, a_{ij} =0 means the ith UAV is not assigned to the jth task.

The solution of the second level of the optimization problem is a path sequences. The encoding of this problem is shown as the following formula:

$$s2 = \left[\; p_1 \quad p_2 \quad \cdots \quad p_m \quad \cdots \quad p_M \; \right], \quad (8)$$

where $s2$ is a UAV's solution of the second level. m means the mth task point and the maximum value of m is M. At this level, the encoding form of every UAV is the same as the formulation mentioned above. In every task assignment plans, the value of M may be different.

3.2. Crossover Operator and Mutation Operators

The crossover and mutation operators are designed according to the characteristics of the multi-task planning. An example of crossover operation is shown as follows:

$$\begin{aligned} a1 &= [a_{11} \quad a_{12} \quad \cdots \quad a_{1j} \quad \cdots \quad a_{1J}] \\ ai &= [a_{i1} \quad a_{i2} \quad \cdots \quad a_{ij} \quad \cdots \quad a_{iJ}] \\ &\qquad\qquad \downarrow \\ ai &= [a_{11} \quad a_{12} \quad \cdots \quad a_{1j} \quad \cdots \quad a_{1J}] \\ a1 &= [a_{i1} \quad a_{i2} \quad \cdots \quad a_{ij} \quad \cdots \quad a_{iJ}], \end{aligned} \quad (9)$$

where $a1$ is the task points assigned to the first UAV. ai is the task points assigned to the ith UAV. Crossover operation is that the first UAV and the ith UAV exchange their task points.

An example of mutation operation is shown as follows:

$$\begin{aligned} a1 &= [a_{11} \quad a_{12} \quad \cdots \quad a_{1j} \quad \cdots \quad a_{1J}] \\ &\qquad\qquad \downarrow \\ a1 &= [1-a_{11} \quad 1-a_{12} \quad \cdots \quad 1-a_{1j-1} \\ &\qquad\qquad a_{1j} \quad \cdots \quad a_{1J}], \end{aligned} \quad (10)$$

where j equals to $\lfloor rand{*}J \rfloor$, and $rand$ is a random real number between 0 and 1.

4. Computational Experiments

To provide a fair comparison, we use the same reproduction operators in each compared algorithm. Parameter settings adopted here are the same as those claimed in [10], [11], [12], and [13]. We set population size to 600 and set the number of iterations to 10000. All the compared algorithms are implemented in MATLAB R2018b and run 20 times independently on a workstation (Intel(R) Core (TM) i7-8700 CPU @ 3.20GHz 3.19 GHz, 16.00 GB of RAM).

4.1. Performance Metric

In the experimental study, we use the inverted generational distance (IGD) metric which is a comprehensive index of convergence and diversity [14] to evaluate the performance of all compared algorithms. Let P^* be a set of evenly distributed points over the PF (in the objective space). Suppose that P is an approximate set of the PF, the average distance from P^* to P is defined as:

$$IGD(P^*, P) = \frac{\sum_{v \in P^*} d(v, P)}{|P^*|}, \quad (11)$$

where $d(v, P)$ is the minimum Euclidean distance between v and the solutions in P. When P^* is large enough, $IGD(P^*, P)$ can measure both the uniformity and the convergence of P. A low value of $IGD(P^*, P)$ indicates that P is close to the PF and covers most of the whole PF. For all the benchmark algorithms, we use the evolutionary population as the population P to calculate the IGD metric. The experiments run 20 times for each algorithm independently, sort all the objectives in the Pareto fronts by non-dominated relations, and find the approximate Pareto front P^*. A smaller IGD value implies a better performance.

The HV metric measures the size of the objective space dominated by the solutions in P and bounded by the reference point r, r=(r_1, ..., r_m) is a reference point in the objective space dominated by any Pareto optimal point [15]. It is defined as:

$$HV(P,r) = VOL(\bigcup_{x\in P}[f_1(x),r_1]\times\ldots\times[f_m(x),r_m]), \quad (12)$$

where $VOL(\cdot)$ is the Lebesgue measure. A larger HV value implies a better performance.

4.2. Test Instances

(1)Test instance 1

In test instance 1, there are 5 UAVs to perform reconnaissance tasks. 10 task points with different demands need to be reconnoitered. The approximate Pareto fronts obtained by four algorithms in test instance 1 are shown in Fig.4.

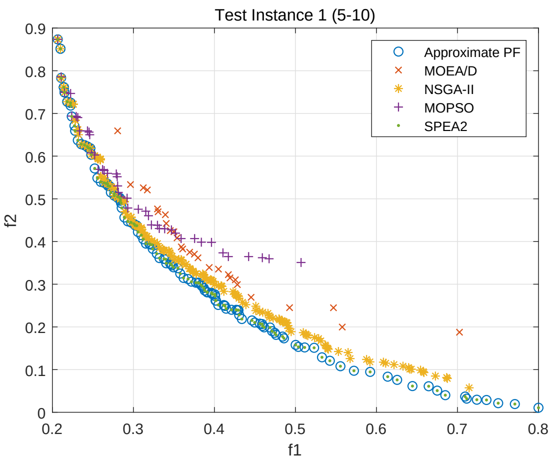

Fig. 4. PFs of four algorithms in test instance 1.

As shown in Fig.4, NSGA-II and SPEA2 perform well in convergence and coverage. We choose a solution in the Pareto front randomly which objectives are [0.2778;0.5685] and the routes of the UAVs in the solution are shown in Fig.5. In the figure, the lines in different color represent the paths of the different UAVs. $*$ represents the task points.

(2)Test instance 2

In test instance 2, there are 15 UAVs to perform reconnaissance task. 25 task points with different demands need to be reconnoitered. The approximate Pareto fronts obtained by four algorithms in test instance 2 are shown in Fig.6. The routes of the UAVs are shown in Fig.7.

As shown in Fig.6, NSGA-II performs well in convergence and coverage. We choose a solution in the Pareto front randomly which objectives are [0.1265;1.2464] and the routes of the UAVs in the solution are shown in Fig.7.

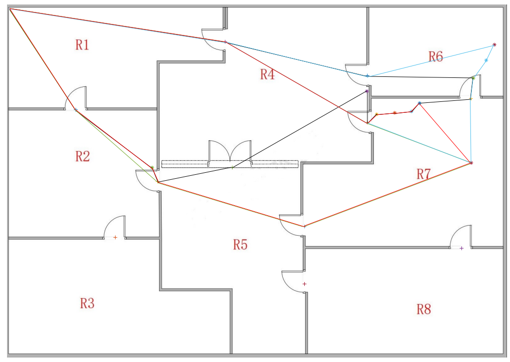

Fig. 5. The routes of test instance 1.

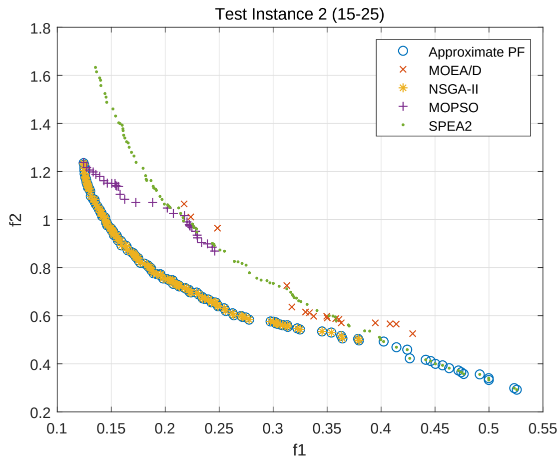

Fig. 6. PFs of four algorithms in test instance 2.

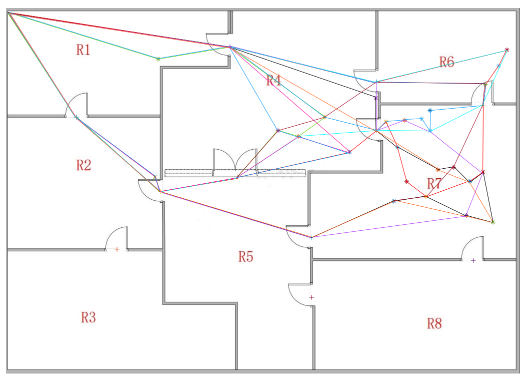

Fig. 7. The routes of test instance 2.

(3)Test instance 3

In test instance 3, there are 30 UAVs to perform reconnaissance task. 50 task points with different demands need to be reconnoitered. The approximate Pareto fronts obtained by four algorithms in test instance 3 are shown in Fig.8. The routes of the UAVs are shown in Fig.9.

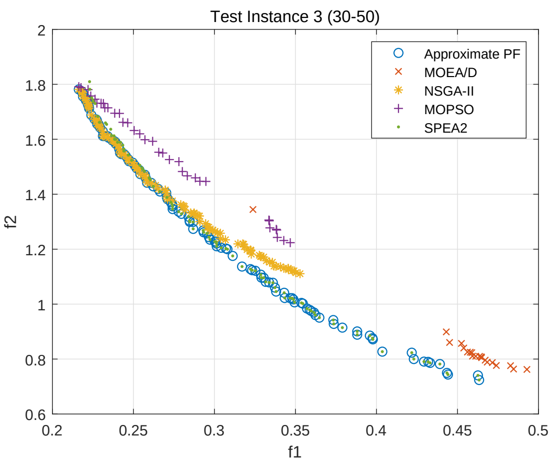

Fig. 8. PFs of four algorithms in test instance 3.

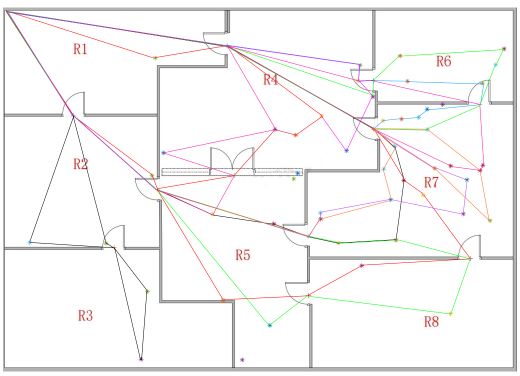

Fig. 9. The routes of test instance 3.

Table 1. Statistical results in test instance 1-3.

Methods	MOEA/D	NSGA-II	MOPSO	SPEA2
IGD-1	0.0168	8.9014e-04	0.0139	**7.7085e-04**
HV-1	0.5399	**0.8041**	0.7022	0.7595
IGD-2	0.0327	0.0065	0.0360	**0.0014**
HV-2	3.2447	3.7698	2.6515	**4.8509**
IGD-3	0.0467	0.0130	0.0157	**0.0011**
HV-3	2.8229	2.6269	2.2631	**3.8016**

As shown in Fig.8, SPEA2 performs well in convergence and coverage. We choose a solution in the Pareto front randomly which objectives are [0.3068;1.2341] and the routes of the UAVs in the solution are shown in Fig.9. In the figure, the lines in different color represent the paths of the different UAVs.

Table 1 shows the IGD and HV values of the four algorithms. NAGA-II and SPEA2 performs relatively well in coverage and convergence.

5. Conclusions

This paper focuses on the problem of multi-task planning of heterogeneous UAVs based on the indoor topological map, models this problem as a multi-objective optimization problem, and solves it by using four different multi-objective optimization algorithms. Different test instances are conducted and get the approximate Pareto fronts. The experimental results show that NSGA-II and SPEA-II perform well in convergence and coverage relatively.

In the future, we plan to analyze the constraints on UAVs' visibility and communication ability in indoor environments. We will also consider the opening and closing state of the doors and model the constraint on UAVs' path planning.

Acknowledgements

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