3D Voxel-based Collaborative Path Planning for UAVs in Urban Emergency Response

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Abstract

In urban emergency response scenarios, the efficient deployment of Unmanned Aerial Vehicles (UAVs) is critical for timely and effective disaster management. In this paper, a 3D voxel-based collaborative path planning framework for UAVS is proposed, aimed at optimizing task completion time while ensuring obstacle avoidance and comprehensive area coverage. The study leverages voxel data for its simplicity and efficiency in handling large-scale urban environments, transforming traditional triangular mesh data into a voxel-based map for enhanced UAV navigation. The proposed methodology encompasses three key components: navigation map construction, local coverage path planning, and global coverage path planning. For local coverage, an improved Boustrophedon Cell Decomposition (BCD) algorithm is introduced, tailored for UAV operations, while global coverage is addressed through a multi-traveling salesman problem (MTSP) approach, optimized using the Jump Point Search (JPS) algorithm and Genetic Algorithm (GA). The experimental results verify the validity of this framework, compared to the conventional A* algorithm, the algorithm put forward in this study decreases the total route length by 23.80%, while also improving path smoothness. This study provides a robust foundation for multi-UAV collaborative operations in urban emergency response, offering improvements in efficiency and coverage.

1 Introduction

In modern society, transport accidents of dangerous goods have become an urgent challenge in the field of public safety and traffic management, and congestion on urban roads during peak hours has exacerbated the situation, causing serious consequences and making rescue operations difficult. Against this backdrop and under the national policy of vigorously promoting low-altitude economy, drone technology emerges prominently. Its flexibility and adaptability bring prospects for accident reconnaissance. However, a UAV often appears to be inadequate when faced with complex tasks. Consequently, the collaborative operation of multiple UAVs has become an inevitable trend (Sun, Tang, & Lao, 2017).

Since accidents occur frequently in cities, the study takes cities as the scenario, minimize task time as the goal, and comprehensively consider key elements such as obstacle avoidance and scanning area range (Zheng, Wang, & Li, 2018). This study focuses on the flight paths and search collaborative paths for drones to improve the efficiency of emergency resource utilization and provide innovative ideas and effective solutions to alleviate this severe situation. The subsequent sections of this paper are structured as follows: Section 2 presents the previous work related to this study. Section 3 introduces the main methods. Section 4 presents the experiments conducted and the final results. Section 5 summarizes the study and prospects the future work.

2 Related Work

2.1 Path planning for a single UAV

UAV path planning can be classified into point-to-point path planning and coverage path planning according to the type of mission. The objective of point-to-point path planning is to design a path from the source point to the destination point, considering crucial constraints like obstacle avoidance and safety, so as to minimize the cost. On the other hand, coverage path planning involves optimizing the UAV's flight path to cover a mission area where the target points are not predetermined. Since the focus of this paper is to construct a sub -region distance matrix by obtaining the shortest path length through point - to - point path planning, the emphasis is placed on point-to-point path planning.

Zhang et al. (2022) introduced an enhanced A* algorithm for the three-dimensional complex network environment, which improved the search efficiency of the algorithm. Mardani, Chiaberge, & Giaccone (2019) introduced two Quality of service (QoS) optimization methods based on the A* algorithm in UAV path planning. They carried out simulations using actual UAVs in real - world areas as well as test settings. The outcomes of these simulations indicated that the algorithm they proposed was capable of yielding the optimal path. Ma & Li (2023) proposed an enhanced artificial potential field method (APF) and adopted it to UAV path planning to address the problems of local optimal solutions, unreachable targets, non-smooth paths, and excessive gravity in the traditional APF. Lv, Chen, & Tian (2021) and Sonny, Yeduri, & Cenkeramaddi (2023) devised a three - dimensional path for UAVs operating within complicated environments. Moreover, an enhanced PSO algorithm was put forward for UAV path planning, with the aim of meeting the user rate requirements. On this basis, Gao & Bai (2023) investigated the problem that regarding the path planning of UAVs under complex - terrain conditions. They proposed a quantum squirrel search algorithm (QSSA) to address the premature convergence and search stagnation issues of the squirrel search algorithm in 3d path planning. Compared with the whale optimization algorithm (WOA), GWO, and squirrel search algorithm (SSA), the QSSA performed better. Wu et al. (2021) represented obstacles as small cubes, established environmental information, and proposed three algorithms for multi-path planning: the ACO clustering algorithm based on congestion classes, the improved ACO for multi-path planning, and the clustering improved ACO multi-path planning algorithm, to enhance the flight probability of UAVs. From the summary of the above work, it can be found that existing UAV path planning algorithms face significant limitations in complex urban environments. Many algorithms are designed only for specific simple scenes, and it is difficult to comprehensively consider the interaction of multiple complex factors in the urban environment. In this study, the efficiency of path planning and the accuracy of positioning and navigation of a single UAV in a complex urban environment were improved by reasonable selection of grid size, adoption of obstacle expansion processing mode and establishment of accurate coordinate transformation relationship.

2.2 Multi-UAV collaborative path planning

Cooperative path planning (CPP), which is composed of three aspects: mission type, frame structure and environment. It has its own internal division, in which the types of tasks can be divided into rendezvous tasks, assignment tasks, covering tasks. A rendezvous mission is defined as a scenario in which multiple UAVs depart from a common base and reach a shared target simultaneously. To fulfill the criteria of time synchronization and heading alignment, it is essential to generate a set of paths that are free from potential collisions among the UAVs. The assignment task refers to the assignment of different target points by multiple UAVs. It is necessary to allocate the target and UAVs reasonably and generate a collision-free path. The overlay task refers to multiple UAVs covering the entire mission space, which needs to consider the region division and sub-region allocation and generate a collision-free path. The frame structure can be classified as centralized, decentralized, and hybrid. Regarding the centralized framework, the central UAV gathers information from other UAVs and makes corresponding decisions. The path planning under this framework is often close to the global optimal solution, which is suitable for completing small-scale tasks. The distributed framework structure uses the information of adjacent UAVs to make decisions. The path planning under this framework is robust and scalable, but it may not be the optimal solution, which is suitable for completing large-scale tasks. The hybrid frame structure is mixed by the above two, and the UAV is grouped, and the centralized type is used within the group, and the decentralized type is used between the groups. The environment is divided into known environment and unknown environment. This paper focuses on CPP problems covering tasks, centralized, known environments.

Li, Li, & Yu (2018) developed the coordinated coverage path planning problem of multiple UAVs in a plateau environment and proposed a two-step strategy. First, parallel search tactic was adopted to optimize the path distance of each UAVs and resolve the global route planning problem. Secondly, the GA is employed to partition the region of search and optimize the quantity of UAVs needed. Shen et al. (2023) investigated the cooperative coverage path planning problem of multiple UAV under earthquake scenarios to find the target with the maximum target probability, and proposed an improved path search optimization algorithm based on depth-first search and spanning tree. Du et al. (2021) developed the coverage operations of multi-solar UAV and advanced a coverage path optimization model that is based on the search method of the undirected graph, which enabled UAS to visit nodes of undirected graphs in turn according to certain constraints, and used mixed integer linear programming to solve the optimal access order to minimize the total job completion time. Lin et al. (2018) proposed a coevolutionary algorithm based on ant colony algorithm to generate the raster access order of drones by raster processing of physical mountain maps, with the aim of shortest execution time and maximum coverage in a three-dimensional mountain environment. From the above work, it can be concluded that in the research of multi-UAV collaborative path planning, the shortcomings of the existing algorithm in the collaborative optimization of task assignment and path planning are that it does not consider the difference of the overall UAV group endurance and load capacity, which is easy to cause some UAVs to be overworked and some to be idle. In this study, the flight plan is determined by comprehensively considering the task completion time and endurance time, effectively reducing the path length, improving the path smoothness and UAV resource utilization efficiency, and better meeting the needs of urban emergency response.

3 Methodology

In this paper we study the subregion division, coverage path planning and task assignment algorithms, and proposes a multi-UAV collaborative coverage emergency search scenario algorithm to minimize the task completion time. In this section, the paper will elaborate the process of multi-UAV urban emergency rescue based on voxel map, which includes three parts: navigation map construction, path planning for local coverage and global overlay path planning.

3.1 Navigation map construction

3.1.1 Three-dimensional raster map construction:

Because the original vector-based map is inefficient for path planning, in this study we use the three-dimensional raster map for path planning by discretizing the environment. The three elements of its construction are grid size, obstacle handling method and mathematical representation method.

- Grid size selection: The resolution of the grid affects the accuracy of the map and the cost of path planning, and the appropriate grid size is related to the size of the UAV, the safe distance, and the actual working environment. Taking these factors into consideration, the grid size is finally selected as Formula (1)

$$l = \frac{a+1}{2\max(b,c)} \tag{1}$$

where a = the outer cuboid side length of the drone
b = the minimum safe distance between drone
c = the smallest safe distance that should be maintained between the drone and the building.

- Obstacle processing mode: When rasterizing the original map, there are two processing modes: reducing and expanding the partial occupied state grid. To guarantee the flight safety of the UAV, the obstacle expansion processing mode is chosen.
- Mathematical representation method: After processing obstacles, the rasterized map has only two states of unoccupied and occupied, which are represented by 0 and 1 codes respectively to guide drone flight and mission execution.

3.1.2 Coordinate conversion

Coordinate conversion is to match the grid map coordinate system with the actual application coordinate system to ensure accurate positioning and navigation of the UAV.

- Three-dimensional grid map coordinate establishment: We select the point with the smallest coordinates in the map model coordinate system as the origin, coordinates (x, y, z) represent the grid in the $x + 1$ column $y + 1$ row in the $z + 1$ layer, and select the center point of each grid as the representative point.

- Conversion of three-dimensional raster index coordinates to map model coordinates: This paper uses the following formulas for converting three-dimensional raster map coordinates to map model coordinates (UTM coordinates). Formula (2) is used for converting three - dimensional raster map coordinates from the original coordinate system to map model coordinates, Formula (3) is used for converting map model coordinates from the original coordinate system to three - dimensional raster map coordinates, where (x', y', z') is the smallest coordinate in the map model coordinate system, and l is the grid size.

$$\begin{cases} x' = x'_{min} + (x + 0.5) * l \\ y' = y'_{min} + (y + 0.5) * l \\ z' = z'_{min} + (z + 0.5) * l \end{cases} \tag{2}$$

$$\begin{cases} x = \frac{|x' - x_{min}|}{l} - 1 \\ y = \frac{|y' - y_{min}|}{l} - 1 \\ z = \frac{|z' - z_{min}|}{l} - 1 \end{cases} \tag{3}$$

3.2 Local coverage path planning

3.2.1 Visibility analysis based on building models

Visible field analysis is crucial for planning the flight path of UAVs, and building occlusion should be taken into account when calculating the coverage area. Visible field analysis theoretical basis: Visible field is affected by UAV height, visible field angle and building distribution, and the calculation methods include ray projection technology and digital elevation model (DEM). Because the study covers a small area and does not consider the relief of terrain, the ray projection technique is chosen.

- Visible field analysis based on 3D raster map: The following assumptions are made: the camera is mounted at the central position of the UAV with its orientation towards the ground, and the ground area exhibits symmetry with respect to the projection center. The visiable field based on the building model is shown in Figure 1. The radius of the circle formed by the intersection of the cone and the ground is given as formula 4. In a raster map, the potential range of visibility is represented by a raster within radius R.

$$R = \frac{H tan\theta}{2} \tag{4}$$

where H = drone observation point altitude
θ = field angle

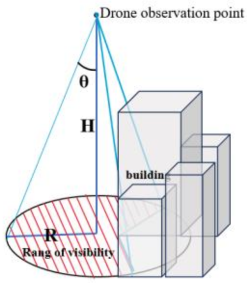

Figure 1. Visible field based on building models

- Visible field analysis algorithm: In this study, we employ ray - projection technology to devise a visible field analysis algorithm for fixed observation points. The ground grid within the cone is traversed, and a check is carried out to determine whether there is a line - of - sight obstruction between each grid cell and the drone's observation point. This process enables the identification of visible and invisible grids.

3.2.2 Sub-area division

Sub-area division is a key task of multi-UAV collaborative path planning, and the influencing factors include geographical characteristics and airspace restrictions.

- Modeling coverage area environment: Assume that N homogeneous UAVs perform coverage tasks in a rectangular region S with constant height H. According to the three-dimensional raster map, the raster map is sliced considering the fixed height, and the fixed height (W) index is calculated as Formula (5), where l represents the raster size.

$$W = \frac{H}{l} - 1 \tag{5}$$

- Improved cell decomposition method: The traditional BCD algorithm is oriented towards robot ground coverage, and does not consider the characteristics of UAV high altitude operation. This paper presents an enhanced algorithm, and the scanning width becomes $w=[W/l]$ (W is the visible field width of the UAV); The function of "scanning band" is changed, and the conflict and connectivity between the UAV column and obstacles are mainly considered when determining the subregion boundary. The scan start column (row) starts at the index $w/2$, and the scan step is w.

3.2.3 Subarea coverage path planning

The goal of this study is to plan the path with the least number of turns, the largest coverage area and the shortest path. To accomplish the aforementioned objectives, subarea coverage path planning is performed based on the following four aspects.

- Subarea coverage path planning strategy selection: This paper comprehensively considers the three key aspects of minimizing path length, minimizing the quantity of turns and maximizing the overlay area, and selects the "bow" coverage strategy, because it is suitable to quickly cover square areas and reducing the number of turns.

- The optimal scanning direction determined by the shape of the sub - area: For a rectangular area, the "bow" - shaped coverage has two scanning directions, namely parallel to the long side and parallel to the short side. By computing the horizontal and vertical spans of the target area and selecting the longer side as the direction for parallel scanning, the number of turns can be reduced.

- Optimal scanning spacing based on visible field model: The scanning spacing affects the coverage path length and coverage effect of the subregion, and its value must be evenly divided by the quantity of grid columns (rows) occupied by the observable field and the maximum scanning spacing is the number of grid columns (rows) occupied by the observable field of the UAV.

- Sub-area coverage path optimization: First, the optimal scanning direction is determined, and then the maximum scanning distance is optimized to calculate the number of invisible points on the ground under the corresponding coverage path. In the event that the quantity of invisible points exceeds the pre - determined threshold, the scanning distance is reduced until the number of invisible points is less than the threshold. In this case, the scanning distance is the best scanning distance.

3.3 Global coverage path planning

3.3.1 Multi-machine task assignment problem modeling

This paper transforms the global coverage problem into multi-traveling agent problem (MTSP), and describes and models it in detail.

- Problem description: MTSP is an extension of the traveling salesman problem. In this study, each subregion covers different path lengths and affects task assignment. The starting point of the subarea coverage path is considered as the city entrance, and the end point is regarded as the city exit. Drone swarm starts from the take-off point, flies in at the entrance of the subarea, flies out at the exit, and upon the completion of the coverage task, it makes its way back to the initial point. The task assignment problem can be converted into the solution of the MTSP.

- Problem formulation: Let P_i denote the flight path sequence of UAV u_i, and A_i represent the task set of UAV u_i, where A_i={a_{i1},a_{i2},…,a_{ij}}, and a_{ij} indicates the index of the sub-region that UAV u_i visits as the *j-th* sub-region. In this model:

$$\begin{cases} A_1 \cap A_2 \cap A_3 \cap \cdots \cap A_N \\ S = \{s_1, s_2, s_3 \cdots s_k\} = \{s_{A_1 \cup A_2 \cup A_3 \cdots \cup A_n}\} \end{cases} \tag{6}$$

where V^i_j represents UAV u_i visiting sub-region s_j, u_i departs from the take-off point s_0, executes the coverage task according to the task set A_i, and then returns to s_0. Thus, P_i={s_0,V^i_j,…,s_0}, where $j \in A_i$. Let d_j denote the internal coverage path length of sub-region s_j, the coverage path length between s_j^e and s_j^o, d_{0j} represent the shortest path length from s_0 to s_j^e, d_{j0} indicate the shortest path length from s_j^o to s_0, and d_{pq} signify the shortest path length from s_p^o to s_q^e.

$$D_i = d_{0a_{i1}} + d_{a_{i1}} + d_{a_{i1}a_{i2}} + d_{a_{i2}} + \cdots + d_{a_{im}0} \tag{7}$$

$$D = \sum_i D_i, \ i \in (1,2,3 \dots n) \tag{8}$$

where D_i represents the total flight path length of UAV u_i, let D represent the aggregate length of the flight paths of all UAVs. The objective is to minimize the total flight path length of the UAVs, and the objective function is established as: *min D*

3.3.2 Subregion distance calculation based on JPS algorithm

JPS algorithm is selected to calculate the distance between subregions, and the subregion distance matrix is constructed. JPS algorithm is an optimized path search algorithm, which reduces the number of nodes to be evaluated in the search process by identifying and utilizing "jump points", so as to improve the search efficiency. The jump point is a node of great significance in the path and is usually the key point where the path changes direction. The JPS algorithm initiates a search for jump points in the horizontal, vertical, and diagonal directions commencing from the starting point. The discovered jump points are then incorporated into the OpenList. This process is reiterated continuously until the target point is located. This method is especially suitable for the path planning of grid map, and can quickly find the minimum - length path between two points, which significantly improves the search efficiency and performance.

3.3.3 Task assignment based on Genetic Algorithm

The study uses genetic algorithm to solve MTSP problem. Genetic algorithm is a kind of optimization algorithm which simulates the process of biological evolution. Through the operation of selection, crossover and mutation, it gradually selects the individuals with high fitness from the initial population, and finally finds the optimal solution. Genetic algorithm is suitable for complex optimization problems and can effectively avoid local optimization and find global optimal solution.

3.3.4 Determination of the final flight plan of the UAVs

The final flight plan of the UAV is subject to the maximum acceptable task completion time and the endurance time of the UAV. After determining the number of UAVs, subarea coverage path and access sequence, the final flight path can be obtained. Make paths usable for real-world navigation by prioritizing drones to avoid flight conflicts and converting three-dimensional raster index coordinates to map model coordinates

4 Experimental process and results

In this study, we set the maximum altitude the drone could fly to 78m and the triangular mesh dataset of city of berlin was used. However, the processing of triangular mesh data is rather complex, especially when the data volume is large, as it requires extensive computation and optimization. On the other hand, voxel data has a regular and simple structure with fixed size and coordinate positions, much like "pixels" in three-dimensional space. It is easy to organize, store and manage. This regularity allows for rapid location and access to voxels during the search process, thereby reducing data lookup time. Therefore, in this study, the triangular mesh data map was transformed into a voxel data map for application in UAV navigation.

4.1 Navigation map generation

To convert a GLB map into a 3D raster map, the size of the raster must be determined first. According to the grid size selection method in Section 3.1.1, We used the calculation Formula (1) and selected a= 0.7m, b= 1.2m, and c=1m. In order to facilitate calculation, the mesh size was finally calculated to be 2m. The three-dimensional grid map is shown in Figure 2 and Figure 3. The three-dimensional grid map has a total of 1602*1703 * 67 grids. The grid index coordinates of the UAV take-off point are (0, 0, 16) and the accident point coordinates are (1300, 1000, 38).

Figure 2. 3D raster map of Berlin (Top view)

Figure 3. 3D raster partial enlarged map of Berlin

4.2 Local coverage path planning

4.2.1 Subregion division

The search area was partitioned by employing the improved BCD algorithm. The relevant parameters were field of view Angle 80 degrees, ground height 34, search area height 78 and grid size 2.

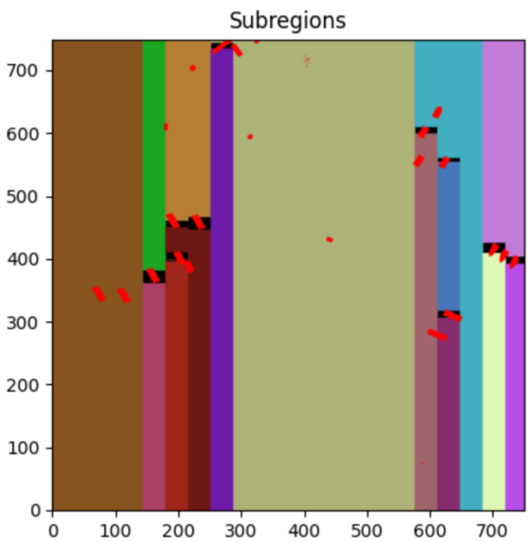

Figure 4. Operation result and schematic diagram of subregion division

As shown in the operation results of sub-region division and Figure. 4, the red grid indicates the buildings that still exist at the height of 78 meters, and other areas covered by different colors represent sub-areas. The visible field width of UAV is 73.84m, which is converted into 36 grids. The search area is divided into 16 sub-regions, the size of each sub-region is shown in Table 1, among which sub-region 9 is the largest and sub-region 5 the smallest.

Table 1 Grid number table of subregions

subdomain	Region1	Region2	Region3	Region4
Number of grids	108750	13357	13653	14652
subdomain	Region5	Region6	Region7	Region8
Number of grids	37	17946	20954	27158
subdomain	Region9	Region10	Region11	Region12
Number of grids	217002	22163	39666	11322
subdomain	Region13	Region15	Region16	Region17
Number of grids	8769	15133	22110	11760

4.2.2 Subarea coverage path planning

The parameters of the subarea coverage path optimization algorithm are set as the initial scan width of 36, the search area side length of 75, the field of view Angle of 80 degrees, and the threshold value of 0.1%. The optimal scanning spacing of each subregion is shown in Table 2. As can be observed from the table, when the acceptable proportion of invisible points is 0.1% of the sub - region area, the optimal scanning spacing of most molecular regions is 36. Finally, under this coverage path, the total quantity of invisible points in the search region is 304, and the total area of the search area is 562,500, so the coverage rate is 99.95%.

Table 2 Table of sub-area scanning spacing

subdomain	Region1	Region2	Region3	Region4
sweeps pacing	36	36	36	36
subdomain	Region5	Region6	Region7	Region8
sweeps pacing	1	36	18	18
subdomain	Region9	Region10	Region11	Region12
sweeps pacing	36	36	18	36
subdomain	Region13	Region15	Region16	Region17
sweeps pacing	36	18	36	36

4.3 Planning global coverage paths

4.3.1 Construction of distance matrix between subregions

Read the entry and exit of the coverage path of each subregion, and use the JPS algorithm for point-to-point path planning. As shown in Figure 5, the number of path points is the distance between subregions.

Figure 5. Point-to-point path planning based on JPS algorithm

In addition, the subregion distance matrix also needs to include the coverage distance within the subregion, and the number of path points covered by the subregion is the coverage distance within the subregion, as shown in Table 4.

Table 3. Subarea coverage distances

subdomain	Region1	Region2	Region3	Region4
Covering distance	3098	360	368	395
subdomain	Region5	Region6	Region7	Region8
Covering distance	37	501	1184	1482
subdomain	Region9	Region10	Region11	Region12
Covering distance	6270	598	2236	305
subdomain	Region13	Region15	Region16	Region17
Covering distance	236	832	704	391

The distance matrix of subregion is established by JPS algorithm. The first column is the entry to the subarea, and the first column is the exit to the subarea.

4.3.2 Task allocation

Based on the distance matrix between subregions, genetic algorithm will be used to optimize task allocation. Taking the number of drones as 5 for example, relevant parameters are as follows: the initial population is 500, tournament size is 5, and the variation rate is 0.1. The solution with the smallest total flight path length of UAVs in 10 operations was selected as the task assignment scheme, as shown in Table 4.

Table4. UAV task assignment based on genetic algorithm (JPS)

Drone number	Drone access sequence	Total grid length of UAV path
UAV1	start, region8, region17, Region9, region3, start	12144
UAV2	start, region4, region7, region5, start	4191
UAV3	start, region10, region11, region15, start	6636
UAV4	start, region1, region2, region6, start	6231
UAV5	start, region12, region13, region16, start	4367
Drone swarm		33569

4.4 Comparison of results

Distance matrix of each subregion obtained by A* algorithm. The solution with the smallest total flight path length in 10 operations was selected as the task assignment scheme, as shown in Table 5.

Table 5. UAV task assignment based on genetic algorithm (A*)

Drone number	Drone access sequence	Total grid length of UAV path
UAV1	start, region11, region17, region16, region13, start	8894
UAV2	start, region15, region12, region10, start	6838
UAV3	start, region7, region6, region2, start	6465
UAV4	start, region4, region5, region3, start	5403
UAV5	start, region1, region8, region9, start	16451
Drone swarm		44051

4.4.1 Comparison of total path length of UAVs

Under the scenario of assigning 5 UAV tasks by genetic algorithm, the minimum total distance using JPS algorithm is 33569, while the minimum total distance using A* algorithm is 44051. The total distance of JPS algorithm is reduced by nearly 23.80% compared with A* algorithm, and the reduction effect is particularly significant.

4.4.2 Path smoothness comparison

In the Berlin City voxel map, the starting point of a single drone is (0,0,16) and the ending point is (1300,1000,38). The point-to-point path planning under the JPS algorithm is shown in Figure 3, and the point-to-point path planning under the A* algorithm is shown in Figure 6. It can be clearly found that under the A* algorithm, the UAV path has more turns, while under the JPS algorithm, the number of turns is less. Therefore, JPS algorithm is superior to A* algorithm in path smoothness.

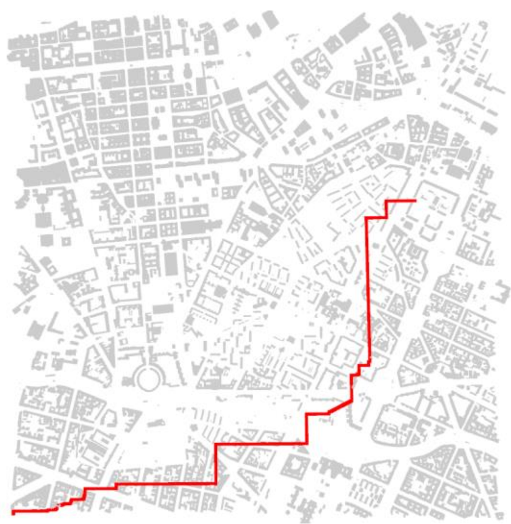

Figure 6. Point-to-point path planning based on A* algorithm

5 Summary and future work

In this paper, a 3D voxel-based UAV collaborative path planning framework is proposed for urban emergency response. Triangular grid data of urban environment is converted into voxel data, navigation map is constructed, and path planning is carried out locally and globally. Locally, the enhanced CTP algorithm is utilized for region division and path planning. Globally, the coverage problem is transformed into a MTSP, which is solved by the JPS algorithm and genetic algorithm. The experimental findings indicate that, when contrasted with the conventional A* algorithm, the framework is capable of reducing the total route length of the UAV by 23.80%. Moreover, the path generated by this framework is smoother. In the future, sparse voxel octree method can be used to reduce memory cost and improve path planning efficiency. Multi-UAV cooperative path planning should clarify relevant methods to avoid flight conflict; Local coverage path planning can optimize the scanning spacing with heuristic algorithm, so as to further improve the path planning framework and improve the application performance of UAVs in urban emergency response.

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