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Bubble Explorer: Fast UAV Exploration in Large-Scale and Cluttered 3D-Environments using Occlusion-Free Spheres

Benxu Tang*, Yunfan Ren*, Fangcheng Zhu, Rui F

***Abstract*— Autonomous exploration is a crucial aspect of robotics that has numerous applications. Most of the existing methods greedily choose goals that maximize immediate reward. This strategy is computationally efficient but insufficient for overall exploration efficiency. In recent years, some state-of-the-art methods are proposed, which generate a global coverage path and significantly improve overall exploration efficiency. However, global optimization produces high computational overhead, leading to low-frequency planner updates and inconsistent planning motion. In this work, we propose a novel method to support fast UAV exploration in large-scale and cluttered 3-D environments. We introduce a computationally low-cost viewpoints generation method using novel occlusion-free spheres. Additionally, we combine greedy strategy with global optimization, which considers both computational and exploration efficiency. We benchmark our method against state-of-the-art methods to showcase its superiority in terms of exploration efficiency and computational time. We conduct various real-world experiments to demonstrate the excellent performance of our method in large-scale and cluttered environments.**

I. Introduction

Autonomous exploration, where robots explore unknown environments and gather information independently, has become increasingly popular in applications such as mine exploration, industrial inspection, and search and rescue operations. Robots can access areas that are difficult for humans to reach, and reduce the risks humans expose to in hazardous environments.

The task of autonomous exploration is to plan a path to explore the entire unknown environment as quickly as possible. Various exploration methods have been proposed in recent years to tackle the task. Most of these methods adopt a greedy strategy. [1]–[3] span RRT in the environment and select the node with the highest information gain to visit. [4], [5] select the frontier that minimizes the traversal cost or the direction change of the UAV as the goal. The greedy-based methods are computationally efficient but insufficient in terms of overall exploration efficiency, as they ignore global optimality and generate back-and-forth movements. Other methods, such as [6], adopt a global optimization strategy that finds a global tour to visit unexplored regions. This strategy improves overall exploration efficiency but results in high computational time, leading to low planner update frequency and inconsistent planning motion. Moreover, existing methods generate viewpoints in a

*These two authors contributed equally to this work.

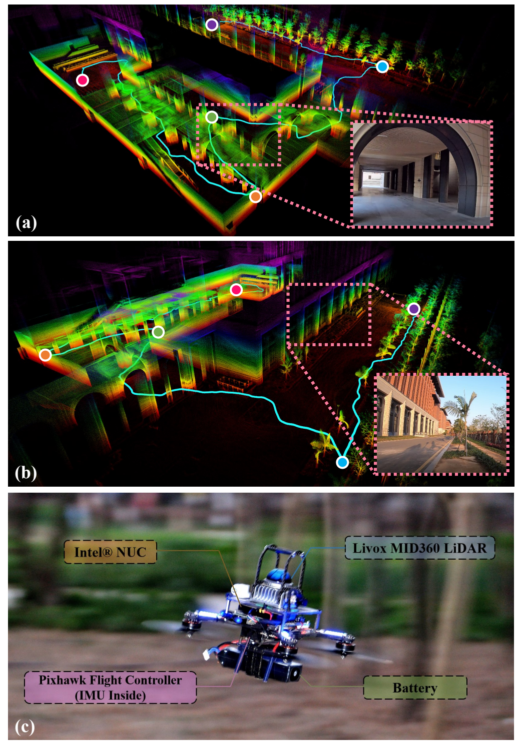

Fig. 1. Performing exploration task in a large-scale environment composed of both indoor and outdoor spaces. (a) and (b): Two different views of the online-built point cloud map, and trajectory executed by the UAV (light blue line), with images displaying the environment. The points with the same color indicate the same position. (c): The quadrotor platform used in the exploration. Video demonstration of all real-world experiments is avaiable at https://www.youtube.com/watch?v=4FqgNSbrx04

sampling way and evaluate the reward of the viewpoint using a computationally expensive ray-casting process, which further increases the computational cost.

Motivated by these facts, we propose a novel method that can support fast and efficient UAV exploration in large-scale and cluttered 3-D environments. We introduce two key contributions: 1) A novel concept of the occlusion-free sphere, which generates high-quality viewpoints at a low computational cost. 2) Based on the generated viewpoints, we introduce a novel strategy that combines greedy with global optimization, which finds an efficient global tour visiting high-gain viewpoints, balancing overall exploration efficiency and computational cost. Finally, we design a local planner that generates safe and kinodynamically feasible trajectories for the UAV to follow. We validate the proposed method through extensive simulation and real-world experiments, showing that it outperforms the state-of-the-art baselines in terms of both exploration efficiency and computational time.

To sum up, the contributions of this paper are listed below:

1) We propose a novel concept of the occlusion-free sphere to generate high-quality viewpoints, which significantly saves computational time and improves exploration efficiency.
2) Based on the generated viewpoints, we introduce a novel strategy that combines greedy and global optimization, which finds an efficient global tour to visit high-gain unexplored regions, balancing overall exploration efficiency and computational cost.
3) Extensive simulation experiments demonstrate the advantages of the proposed planner over the state-of-the-art baselines, in terms of exploration efficiency and computational time.
4) Implementation of the proposed planner on a fully autonomous quadrotor platform. Various real-world tests show the outstanding performance of the proposed planner in large-scale and cluttered real-world environments.

II. Related Works

Autonomous exploration has been an active area of research in recent years, and a variety of methods have been proposed to tackle the problem. Sampling-based exploration [1]–[3] is one of the classic approaches. The approach spans a Rapidly-exploring Random Tree (RRT) in free space. It evaluates the information gain of the nodes in RRT by the coverage of the unknown region, weighted with the traversal cost to reach it from the current position. The coverage is counted by the number of unknown voxels that fall in the sensor field of view (FoV) and are not occluded by occupied voxels (e.g., by ray-casting). The node with the highest gain is selected as the goal and a traversable path to the node is derived from the RRT. This scheme is first introduced by the Next-Best-View Planner (NBVP) [1], and further improved by GBP [2] and MBP [3]. In GBP [2], a topological global map is constructed during the local exploration process. When the local area is fully explored, or the vehicle encounters a dead end, the method finds a path on the global map and redirects the vehicle to unexplored areas. MBP [3] constructs RRT using motion-primitives and produces smooth trajectories for the vehicle to execute.

Another classic approach is frontier-based exploration [4]–[7]. In frontier-based exploration, the vehicle navigates close to the frontier, defined as the boundary between the free and unknown space, to continue exploring the unknown space. This method is first introduced by [4], in which the closest frontier is selected as the next goal. To achieve high-speed flight, [5] selects the frontier in sensor FoV and minimizes the velocity change of the vehicle. [8] analyzes the strengths and weaknesses of the sampling-based and frontier-based approaches. It combines them together by improving NBVP [1] for local exploration and using a frontier-based approach for global exploration.

The above methods are greedy-based, which select goals that maximize the immediate reward to visit at each planning iteration. This strategy is computationally efficient but insufficient in terms of overall exploration efficiency, as it produces back-and-forth planning motions. Fast UAV Exploration planner (FUEL) [6] considers the global optimality. It begins by generating viewpoints to cover frontier, followed by finding a global tour that minimizes the global traversal cost, starting from the current vehicle position and passing through all selected viewpoints. The problem of finding the global tour is formulated as a variant of the Traveling Salesman Problem (TSP). This method outperforms the greedy-based methods in terms of overall exploration efficiency, but performing global optimization in the entire environment incurs high computational overhead, especially in large-scale environments.

In the proposed method, we improve the scheme of FUEL [6] further by generating high-quality viewpoints using occlusion-free spheres, and combining greedy and global optimization strategies. We benchmark our method against the state-of-the-art baselines: FUEL [6], GBP [2] and NBVP [1]

III. Proposed Planner

A. Occlusion-Free Sphere

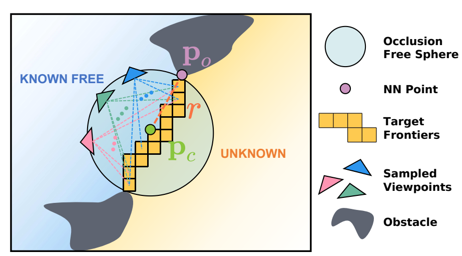

Fig. 2. The definition of the occlusion-free sphere.

An occlusion-free sphere is defined by its center $\mathbf{p}_c \in \mathbb{R}^3$, which lies on the target frontier, and the radius:

$$r = ||\mathbf{p}_c - \mathbf{p}_o||_2 \tag{1}$$

where $\mathbf{p}_o \in \mathbb{R}^3$ is the nearest neighbor obstacle point (NN point). In this way, the interior of the sphere is free from occupied grids. Since sphere is convex, any line segment that connects points within the sphere (including its surface) and the frontier is occlusion-free, as shown in Fig. 2. By employing a viewpoint sampling

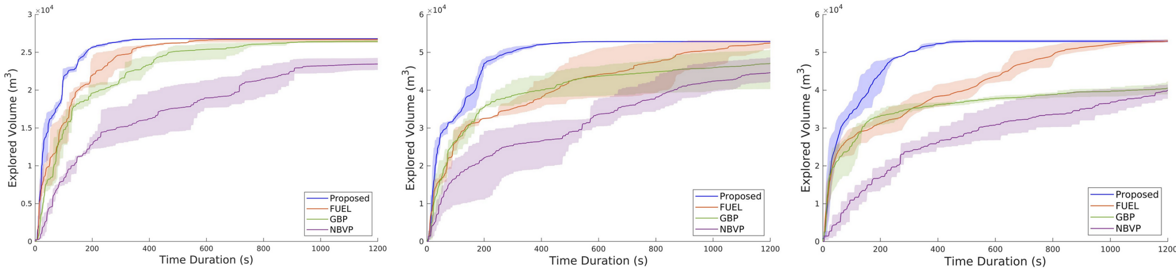

Fig. 3. The explored volume over time of experiments based on Livox AVIA in *Building* scenario (left) and *Forest* scenario (middle). The explored volume over time of experiments based on Livox MID360 in *Forest* scenario (right). The semi-transparent region in color is formed by the upper-bound and lower-bound of four algorithm runs, while the solid line represents the mean of these four runs.

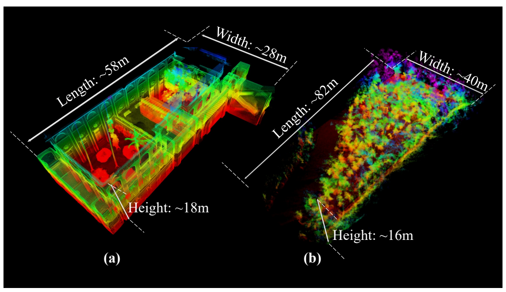

Fig. 4. The visualization of the two simulation scenarios. (a): The *Building* scenario. (b): The *Forest* scenario.

strategy on the sphere's surface, we can obtain high-quality viewpoints without resorting to computationally expensive ray casting techniques. We denote this process as $\texttt{GenerateNewSphere}(\mathbf{p}_c)$.

B. Viewpoints Generation

After generating an occlusion-free sphere s_l, the proposed method uniformly samples a set of viewpoints on the sphere surface using a spherical coordinate system. The yaw direction of the sampled viewpoints is optimized to have the maximum coverage of frontier cells, similar to [9]. We then remove the viewpoints in unknown space and perform a sensor FoV check to count the number of frontier cells covered by each remaining viewpoint. Finally, we select the viewpoint that has the highest coverage. This process is referred to as $\texttt{GenerateViewpoint}(s_l, \mathbf{F})$.

The workflow of the entire viewpoints generation process is presented in Alg. 1. Note that if the selected sphere s_l is smaller than a certain threshold, the proposed method generates the viewpoint v_b using a similar approach to FUEL [6].

C. Global Tour Planning

We define the gain of a viewpoint v as

$$g(v) = r(s)e^{-\lambda c(v,\xi)} \tag{2}$$

where $r(s)$ is the radius of the corresponding occlusion-free sphere. $c(v, \xi)$ is the cost going to the viewpoint v from the vehicle current configuration ξ. The cost is evaluated using Euclidean distance between v and ξ. λ is the tuning factor.

Algorithm 1: Generate Viewpoints

Notation: Input frontier cells $\mathbf{F}$; Viewpoints $\mathbf{V}$; Occlusion-free sphere priority queue sort by radius $\mathbf{S}$; Sphere center list $\mathbf{C}$; The generated viewpoint v_b; The frontier cells covered by v_b: $\mathbf{F}_v$; The sphere centers covered by v_b: $\mathbf{S}_v$
Input: $\mathbf{F}$
Output: $\mathbf{V}$

$\mathbf{C} = \texttt{DownsampleFrontier}(\mathbf{F})$;
for $\mathbf{p}_c \in \mathbf{C}$ **do**
    $s_i = \texttt{GenerateNewSphere}(\mathbf{p}_c)$;
    $\mathbf{S}.\texttt{PushBack}(s_i)$;
end
while ***not*** $\mathbf{S}.\texttt{empty}$ **do**
    $s_l = \mathbf{S}.\texttt{front}()$;
    $\mathbf{S}.\texttt{pop}()$;
    $v_b, \mathbf{F}_v, \mathbf{S}_v = \texttt{GenerateViewpoint}(s_l, \mathbf{F})$;
    $\mathbf{F}.\texttt{remove}(\mathbf{F}_v)$;
    $\mathbf{S}.\texttt{remove}(\mathbf{S}_v)$;
    $\mathbf{V}.\texttt{PushBack}(v_b)$;
end
return $\mathbf{V}$

The proposed method maintains a viewpoint priority queue $\mathbf{Q}$, with a fixed size of n_q. As described in section III.B, the proposed method generates a set of viewpoints $\mathbf{V}$ with a total number of n_v. For each viewpoint v_i in $\mathbf{V}$, we compute the gain of v_i defined by 2. Then we greedily select the viewpoint with the highest gain and push it into priority queue $\mathbf{Q}$ until the queue is full. The global planning problem is to find an open-loop tour starting from current vehicle position and passing through viewpoints in $\mathbf{Q}$. Similar to FUEL, we formulate the problem as the Asymmetric Travelling Salesman Problem (ATSP), a variant of TSP, and solve it using the available algorithm [10].

IV. EXPERIMENTS

A. Benchmark Comparison

In this section, we present a comparative analysis of the proposed method and three state-of-the-art exploration algorithms, namely FUEL [6], GBP [2],

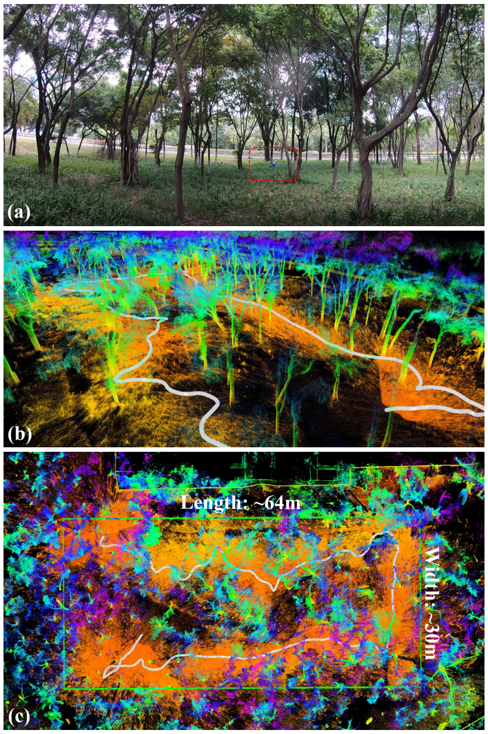

Fig. 5. (a): Real-world experiment conducted in a forest. (b) and (c): Two different views of the online-built point cloud map and executed trajectory of the UAV. The green box is the bounding box of the area to be explored.

and NBVP [1]. Fig. 4 displays the scenarios used in the benchmark experiments: a historical building and a cluttered forest. We conducted experiments in both scenarios based on Livox AVIA LiDAR, which has a $[70.4^\circ \times 77.2^\circ]$ cone-shape FoV. We also conducted experiments in *Forest* scenario based on Livox MID360, a 360-degree FoV LiDAR. Fig. 3 shows the explored volume of all methods over time of the above three sets of experiments. The proposed method showcases higher exploration rate than all benchmarked methods throughout the entire exploration process in both scenarios. Table. I presents the run time of all methods.

TABLE I

RUN TIME COMPARISON

Scene	Methods average run time (s)			
	Proposed	FUEL [6]	GBP [2]	NBVP [1]
Building	**0.155**	0.419	2.821	7.456
Forest	**0.288**	1.139	3.423	10.078
Forest (MID360)	**0.313**	1.467	5.438	19.622

B. Real-world Experiments

Various real-world experiments are conducted to further validate our method. We build a LiDAR-based quadrotor platform. The platform is equipped with an Intel NUC onboard computer with CPU i7-10710U, Pixhawk flight controller, and LiDAR (Livox AVIA or Livox MID360). First, we use the UAV to explore a large-scale environment containing both indoor and outdoor spaces. In this scene, we equip the UAV with Livox MID360 LiDAR. The online-built point cloud map and the executed trajectory are displayed in Fig. 1. Second, we use the UAV to explore a cluttered forest scene. In this test the UAV is equipped with Livox AVIA LiDAR. Results are displayed in Fig. 5.

V. CONCLUSION

In this paper, we proposed a novel method to support efficient autonomous exploration in large-scale and cluttered 3-D environments. We introduced the novel concept of an occlusion-free sphere to generate high-quality viewpoints at low computational cost, and adopts a novel strategy that combines greedy with global optimization. The proposed method demonstrated a significant improvement in exploration efficiency and computational time savings. Extensive simulation and real-world experiments showcased the outstanding performance of our method in large-scale and cluttered environments.

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