3D Path Planning Based on Probabilistic Foam for UAV Indoor Applications ⋆

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Abstract: The recent growth of the Unmanned Aerial Vehicle (UAV) industry stimulated research development to solve different problems, such as inspection in hard-to-reach places, mapping, and search and rescue. Frequently, these applications require navigation in indoor environments, so searching for safe paths for the UAVs to fly is essential for mission accomplishment. In this context, we propose in this paper the employment of the Goal-Biased Probabilistic Foam (GBPF) method to perform the path planning for a UAV in indoor missions. The GBPF method ensures a fast search of a path with a safe region provided by a structure called bubble that will be modeled for the UAV. The bubble represents a free-space region that allows safe UAV maneuvers, decreasing the probability of obstacles collision. To validate the proposed methodology, we used the Virtual Robot Experimentation Platform (V-REP) to simulate an UAV flight in an indoor environment using the path generated by the GBPF.

Keywords: UAV; Probabilistic Foam; Path Planning; Bubble of Free Space; V-REP.

1. INTRODUCTION

In recent years, many researches related to Unmanned Aerial Vehicle (UAV), also known as drones, were developed, showing the potential that this aeronautical technology can offer in different applications (Zhao et al., 2018). Among them, it is possible to highlight the usage of UAVs on tasks of inspection in hard-to-reach places, such as wind turbines, power transmission towers, bridges, and solar panels (Shakeri et al., 2019), surveillance system (Jung et al., 2018), assistance in monitoring plantations (Ju and Son, 2018) and ocean (Ma et al., 2020).

On the other hand, indoor applications with UAVs are more complex than the outdoor ones, mainly because of the restrictions imposed by the autonomous navigation system of the aircraft, such as communications limitations and proximity to obstacles, where, in case of collision, it may endanger the aircraft integrity, completeness of the mission and even human lives (Grzonka et al., 2009).

An example of these indoor applications was discussed by La Scalea et al. (2019), where they mention the possibility of using drones for cave exploration. In Zhang et al. (2017), the authors present a solution called SmartCaveDrone, a system capable of mapping caves in 3D models. Furthermore, in McCabe et al. (2017), the authors detail the benefits that UAVs can bring to monitoring construction works in civil construction.

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The usage of UAVs in diverse applications is growing up fast, and for the development of this technology, it is necessary to look for solutions that integrate these aircraft with environments that are becoming increasingly complex, making UAV systems more resilient, reliable, and improving their capabilities.

Path planning is one of the main issues in autonomous navigation, and it has been debated in the scientific community since the 1980s (Chien et al., 1984; Canny, 1988; Takahashi and Schilling, 1989). The planning is particularly relevant since it is practically a requirement for an autonomous mobile robot to move from an initial to a goal configuration, avoiding collisions in an environment with obstacles and narrow passages (LaValle, 2006).

Most path planning techniques have the purpose of creating optimal paths or finding feasible paths with low running time (Volna and Kotyrba, 2018). However, it is also important to guarantee safety for a robot when moving in unstructured environments (Plaku et al., 2018). Thus, planning paths sufficiently far from the obstacles is crucial for most applications (Berglund et al., 2009). Besides, when considering an indoor mission for a UAV, it is essential to incorporate techniques in which it can avoid collisions so that there is no physical damage to the robot. Aggarwal and Kumar (2020).

Proposed in (Nascimento et al., 2018b), Goal-Biased Probabilistic Foam (GBPF) is an interesting global path planning method capable of providing short paths with safe regions for maneuverability. Therefore, in this paper, we

present the application of GBPF method for a UAV to accomplish indoor missions safely.

This paper is organized as follows: Section 2 introduces the UAV modeling that was used in the path planning method. Section 3 describes the Goal-biased Probabilistic Foam, a variant method of the original PFM. Section 4 presents simulation results and discussions. Finally, Section 5 discusses conclusions and future works.

2. BUBBLE MODELING FOR UAV

The concept of *bubbles of free-space*, proposed by Quinlan (1995), makes possible the computation of a volumetric collision-free region in C-space C around a robot configuration q based on distance information in workspace W. This region, called bubble, will be used by our path planner to provide safe paths.

Let us consider for the experiments a quadrotor UAV denoted by A. Disregarding the rotational degrees of freedom (DoF), the robot A will present three translational DoF, denoted by X, Y, and Z, as can be seen in Figure 1.

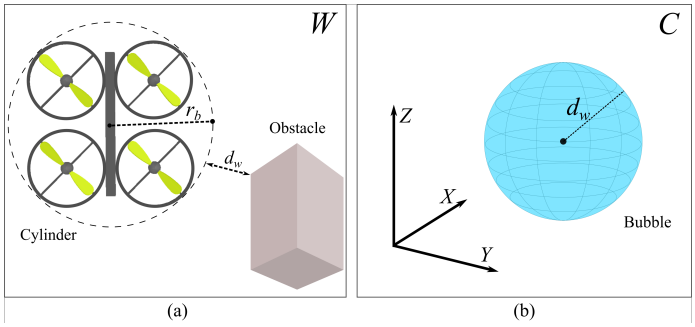


Figure 1. Bubble modeling. (a) Measuring the minimum distance between the obstacle and the cylinder which encloses the UAV in workspace W. (b) The bubble computed in C-space C.

Figure 1a illustrates an environment with the UAV and an obstacle, representing the workspace W. Also, let us consider that the robot is inscribed in a cylinder that contains the entire robot. The measure d_W is the minimum distance between the cylinder and the obstacles.

Now, let us consider moving the UAV from configurations q to p along a straight line, where the distance traveled by the UAV will be $||q - p||$. If the UAV moves a distance no greater than d_W, it will not collide with any obstacles or walls in the environment. The bubble, as can be seen in Figure 1b, is a volumetric region in free C-space, which represents the set of all these configurations p.

More formally, the bubble is defined as a $n-$ball with radius d_W, centered in configuration q.

$$B(q) = \{p : ||q - p|| \leqslant d_W\} \quad (1)$$

In Quinlan (1995), this region B was proposed for general non-rotating free-flying robots in planar environments. In this work, we apply this concept to a UAV robot, which will navigate using a path planning method based on Probabilistic Foam.

3. GOAL-BIASED PROBABILISTIC FOAM

The method Goal-Biased Probabilistic Foam (Nascimento et al., 2018b) is a global sampling-based path planner ideal for robots that need to perform safe motion. The GBPF is a variant of the Probabilistic Foam Method (Nascimento et al., 2018a, 2020) where bubbles are expanded in the free configuration space and propagate with a strategy inspired on the expanding method of the search tree from the RRT-GoalBias algorithm Lavalle et al. (2000), a variant of the classic Rapidly-Exploring Random Tree (RRT) LaValle (1998). The method GBPF converges to the goal configuration faster than the original PFM and provides paths with high clearance, differently from RRT. The propagation process of GBPF is shown in Figure 2

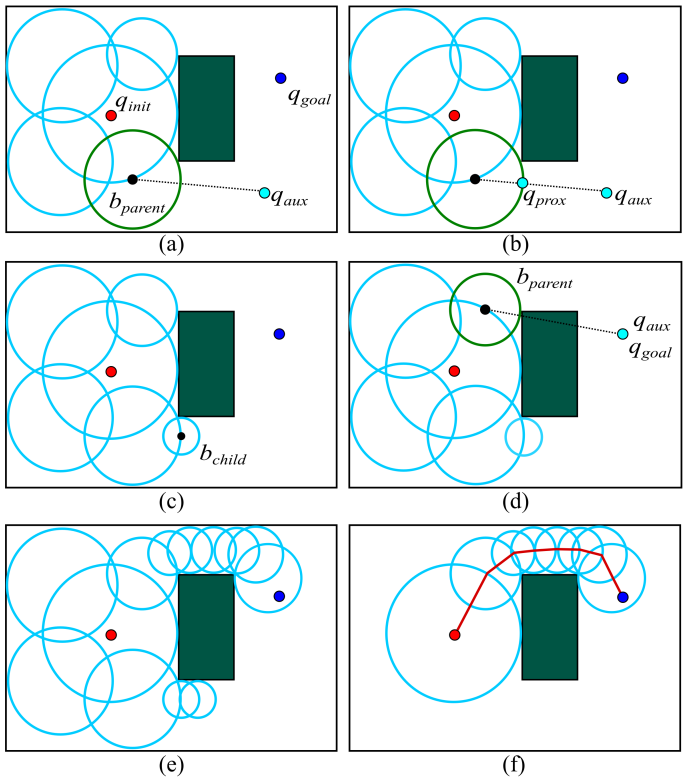


Figure 2. GBPF propagation. (a) Selection of a parent bubble (green circle). (b) Find the new child bubble center q_{prox}. (c) Child bubble expanded. (d) Biased selection of b_{parent}. (e) Probabilistic foam. (f) Rosary found and path extracted (red line).

During the foam propagation process, a configuration q_{aux} is sampled in the configuration space and the bubble with the center closest to configuration q_{aux} is selected as parent bubble b_{parent} (Figure 2a). Next, the configuration q_{near} is found on the surface of the bubble b_{parent} (Figure 2b), and then, a new child bubble b_{child} centered in q_{near} is expanded (Figure 2c), finishing a generation.

The method tends to propagate the foam towards to q_{goal} due to the bias, defined as a small probability (such as 0.05, as suggested by Lavalle et al. (2000)) for the auxiliary configuration q_{aux} to be sampled on the goal configuration. Figure 2d illustrates this bias configuration in the propagation process. In this way, the next parent bubble will be the bubble with the center closest to q_{goal}.

This process repeats until a bubble encloses the goal configuration, ending the propagation of the probabilistic foam, as seen in Figure 2e. Finally, the Rosary $\mathcal{R}$, shown in Figure 2f, is the sequence of overlapped bubbles from q_{goal} to q_{init}, following the parentship relation between bubbles. The resulted path can be easily extracted from the rosary.

3.1 GBPF pseudocode

The pseudocode of the Goal-biased Probabilistic Foam method is described in Algorithm 1.

Algorithm 1 Goal-biased Probabilistic Foam

Input: q_{init}, q_{goal}, r_{min}, *bias*
Output: $\mathcal{R}$
1: $F = \varnothing$
2: $r \leftarrow$ expand_bubble(q_{init})
3: F.add($\{q_{init}, r\}$)
4: **while** $\mathcal{R} = \varnothing$ **do**
5: **if** rand() > bias **then**
6: $q_{aux} \leftarrow$ random_config()
7: **else**
8: $q_{aux} \leftarrow q_{goal}$;
9: **end if**
10: $\{q_p, r_p\} \leftarrow$ nearest_bubble(q_{aux}, F)
11: $q_{near} \leftarrow$ nearest_config(q_p, r_p, q_{aux})
12: **if** interior(q_{near}, F) = false **then**
13: $r_{near} \leftarrow$ expand_bubble(q_{near})
14: **if** $r_{near} \geq r_{min}$ **then**
15: F.add($\{q_{near}, r_i\}$)
16: **if** $||q_{near} - q_{goal}|| \leq r_{near}$ **then**
17: $\mathcal{R} \leftarrow F$.get_rosary()
18: **return** success
19: **end if**
20: **end if**
21: **end if**
22: **end while**

The method described in Algorithm 1 receives as input q_{init}, q_{goal}, r_{min}, the value of *bias*, and returns the rosary $\mathcal{R}$. In *line 2* the first bubble is expanded using the function expand_bubble(), and it is added in the foam F. At *lines 5-9* occurs the sampling of q_{aux}. The function rand() returns a uniform random value between [0,1].

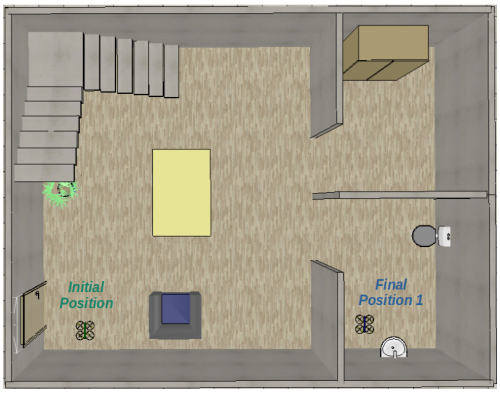
The function nearest_bubble(q_{aux}, F) obtains the bubble (center and radius) inside F with the nearest center to q_{aux}. The function nearest_config(q_p, r_p, q_{aux}) returns the nearest point q_{near} between the surface of this bubble and the configuration q_{aux} (*lines 10 and 11*). If q_{near} was not sampled in the interior of another bubble in F (verification using the function interior() at *line 11*), a new bubble is expanded (*line 12*). If the radius of the new bubble is greater or equal to r_{min}, this bubble is stored in F. The method GBPF runs while the rosary $\mathcal{R}$ is not found. Other stopping criteria that can be considered are the execution time and the total number of computed bubbles.

3.2 Path smoothing

The path obtained by GBPF is bounded by a sequence of overlapped bubbles (rosary) that provide safety constraints. An interesting advantage of this region is that the path remains safe while it crosses all bubbles from the rosary through the intersection region between two consecutive bubbles. Therefore, this feature can be used to perform path adjustments and, consequently, smooth the resulted path. Nascimento et al. (2020) present an optimization approach to smooth the path obtained by path planners based on the probabilistic foam. We use the same approach in this work to make the path smoother.

4. RESULTS

To test the methodology presented in this paper, we created a simulation environment in the Virtual Robot Experimentation Platform software, also known as V-REP [1]. This scenario represents a two-floored house, as shown in Figure 3. Furthermore, we used the quadricopter mobile robot available in V-REP as UAV to follow the planned path by the Probabilistic Foam Method, which was generated using MATLAB.



(a)

(b)

Figure 3. Scenario created in V-REP: (a) First floor with initial (green) and final (blue) UAV position for Simulation 1. (b) Second floor with the final UAV position for Simulation 2.

In this paper, we created two experiments that represent an indoor mission. In Experiment 1, the UAV will navigate only in the first floor, from configuration $q_{init} = [5.5, 1, 0.5]$ m to $q_{goal} = [5.4, 6.4, 0.5]$ m. These configurations q_{init} and q_{goal} are represented by Initial Position and Final Position 1 in Figure 3a, respectively.

In Experiment 2, the UAV will navigate from the first to the second floor, i.e., from $q_{init} = [5.5, 1, 0.5]$ m,

[1] https://www.coppeliarobotics.com/

represented by Initial Position in Figure 3a, to $q_{goal} = [1.5, 7, 4.3]$, represented by Final Position 2 in Figure 3b.

The experiments were performed on a 1.8 GHz Intel Core i7 with 8 GB RAM. The GBPF parameters were $r_{min} = 0.08$ m and $bias = 0.05$. These values were defined empirically by testing different configurations and choosing the best results. The radius of the cylinder (Figure 1) used for computing bubbles is $r_b = 0.2$ m, which was chosen based on the UAV geometry available in V-REP. The path planning with GBPF for Experiment 1 is presented in Figure 4.

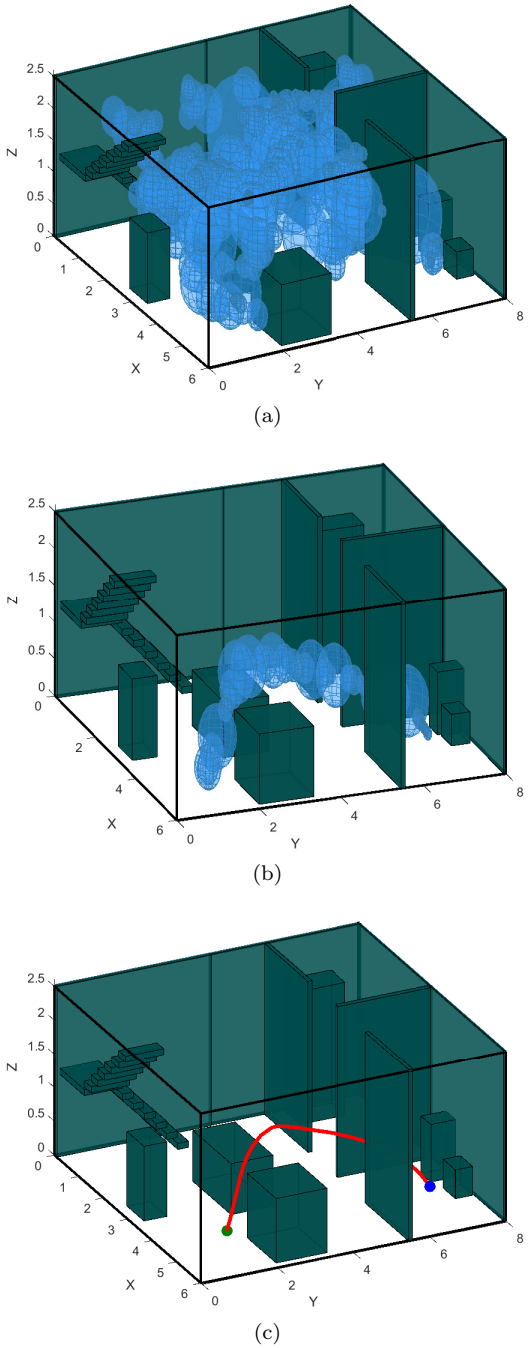


Figure 4. Path Planning in 1st Floor (a) Probabilistic Foam. (b) Rosary. (c) Planned Path from initial (green dot) to goal (blue dot) configurations.

In this first experiment where only the first floor was considered, GBPF found a feasible path in 0.8321 seconds with a total of 185 computed bubbles.

The GBPF path planning for Experiment 2 is presented in Figure 5.

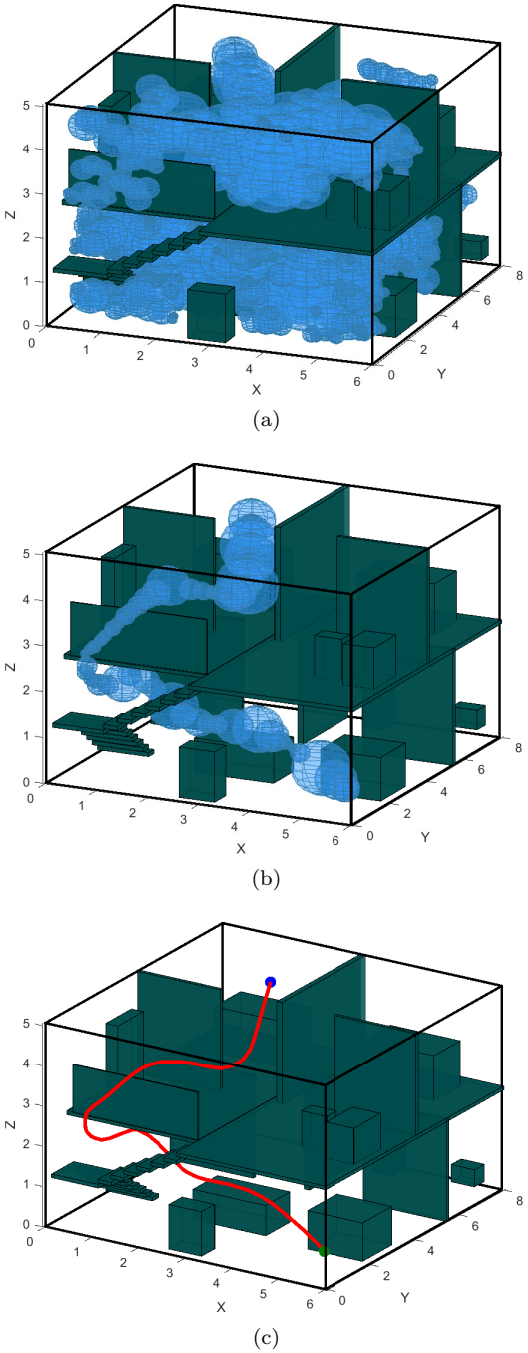


Figure 5. Path Planning from 1st to 2nd Floor (a) probabilistic Foam. (b) Rosary formed. (c) Planned Path from initial (green dot) to goal (blue dot) configurations.

For the second experiment where the first and second floors were considered, GBPF found a feasible path in 1.3661 seconds with a total of 873 computed bubbles. The number of computed bubbles and the search time were higher than the values from experiment 1, which is expected, since the environment is more complex.

An approximated representation of the realistic environment in V-REP was created in MATLAB considering only simple cuboids in order to facilitate the computation of the path planning. However, it is important to observe that it was not necessary to compute the region of the obstacles in the configuration space (C-obstacle) for the calculation of the bubble, which is an important advantage of the presented bubble modeling.

Finally, the application of the paths obtained for experiments 1 and 2 with the UAVs in V-REP is presented in Figures 6 and 7, respectively. Additionally, a demonstrative video with the experiments' results is available and can be seen on https://youtu.be/f68tPGB0HTk.

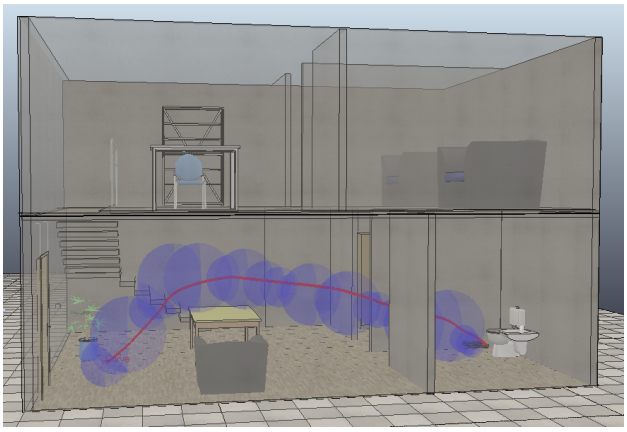


Figure 6. Simulation with the UAV for the path obtained by Experiment 1 considering one floor. The purple spheres represent the rosary and the red line is the trajectory performed by the UAV.

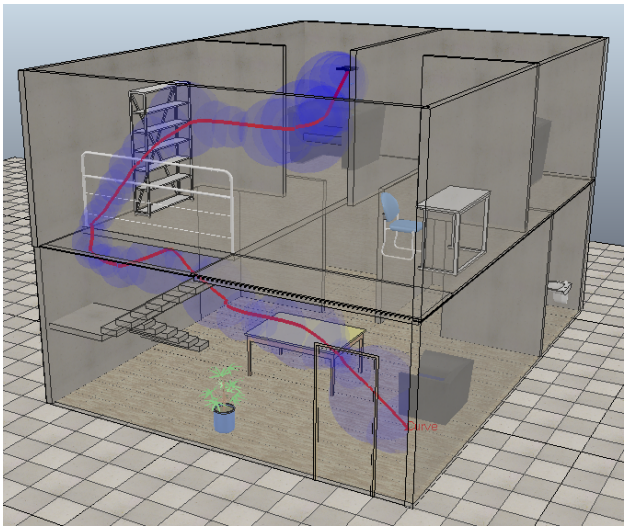


Figure 7. Simulation with the UAV for the path obtained by Experiment 2 considering two floors. The purple spheres represent the rosary and the red line is the trajectory performed by the UAV.

In these simulations, it was possible to observe the mentioned advantage of the rosary structure. During the entire UAV trajectory (red line), there was no part of the robot outside the bubbles, even when the UAV performs some maneuvers to follow the path. Thus, the UAV was capable of performing the entire indoor mission without colliding with any obstacles. Besides, it also kept distance from the obstacles, proving the practicability of the method for this application.

Considering that GBPF is a stochastic algorithm, the method was performed 100 times (for both presented scenarios) in order to analyze the processing time (Time), the number of generated bubbles (Bubbles), and the length (Path) of the obtained path. Table 1 presents the average results for these simulations.

Table 1. Numerical results of processing time, number of bubbles, and path length for many simulations with the GBPF.

Apartment floors	Time (s)		Bubbles		Path (m)	
	avg	std	avg	std	avg	std
1st floor	0.554	0.544	252.280	149.998	11.136	1.276
1st and 2nd	2.091	0.786	923.600	183.110	21.898	2.024

The information shown in Table 1 is similar to the simulation results previously presented, which shows that the method is in accord with the simulations performed. Besides, it is possible to note that the method was capable of finding paths in a relatively short time and that no errors were found in any of the experiments.

5. CONCLUSION

This work presented an application of the Goal-biased Probabilistic Foam for generating paths for an Unmanned Aerial Vehicle to navigate in indoor missions. By using a structure called bubble, the method created a path considering only the free-space region, ensuring a safe motion for the UAV.

The approach used for computing the bubble made feasible paths, with high clearance from the obstacles. Besides, this bubble enabled GBPF to plan paths without the need for the obstacles explicit representation in the configuration space (C-obstacle), which would make this application computationally impracticable for complex scenarios.

Considering that the path planning strategy was executed in Matlab and the UAV motion simulation was performed in V-REP, it was necessary an approximated representation of the scene. In this sense, as future works, we suggest the implementation of a mapping system using consolidated techniques, which can expand the studies for local planning in real-time.

Finally, this work brought some early results for the application of Probabilistic foam-based path planning methods for UAV motion. For future research, we intend to compare these results with some state-of-the-art path planning algorithms for this application. Furthermore, we also seek to investigate strategies that allow safe navigation for autonomous multi-UAV systems.

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