Collision-Free Local Path Planning: An Approach Using Skeletonization

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Abstract. *This study proposes an approach to find collision-free paths in dynamic environments, employing skeletonization. For this purpose, regions of interest are identified based on best driving criteria, prioritizing the smoothness of the route. We demonstrate that the free area skeleton generates trajectories equidistant from obstacles, avoiding collisions.*

1. Introduction

1.1. Collaborative Robotics

Industrial robots excel in repetitive tasks but lack dexterity for complex activities, as noted by [El Makrini et al. 2017]. Tasks requiring greater sensitivity necessitate human supervision, according to [Dobrokvashina et al. 2022]. Integrating human dexterity with robotic strength is essential, and collaborative robotics offers a solution to enhance human-robot cooperation, as stated by [Franklin et al. 2020].

1.2. Selective Compliance Assembly Robot Arm (SCARA)

The SCARA robot, an industrial robot with 4 degrees of freedom (DOF) [Ashok et al. 2024].Typical applications performed by SCARA robots include tasks such as picking up a part from one location and placing it in another, while avoiding obstacles and even people. In our experiments, we utilized only 2 degrees of freedom of the robot, as this approach simplifies the process and allows us to work with horizontal trajectories.

1.3. Skeletonization

Skeletonization, according to [Beom and Cho 1992], is a useful technique that simplifies the representation of the environment, highlighting areas of free passage and providing options for navigation. Thus, it is possible to find unobstructed trajectories for the navigation of robots or agent.

1.4. Previous Works

Trajectory planning algorithms typically require global information about the environment, as seen in classical approaches like artificial potential fields [Khatib 1986], generalized Voronoi diagrams [Takahashi and Schilling 1989], probabilistic roadmaps [Kavraki et al. 1996], and topological path planning [Batista et al. 2023]. However, in unfamiliar or dynamic environments, a complete view is not always available. Therefore, algorithms must be developed to generate trajectories based solely on the information at hand. Examples of such algorithms include Bug1 [Lumelsky and Stepanov 1986], Bug2 [Campbell et al. 2020] [Lumelsky and Stepanov 1986], and VFH [Borenstein and Koren 1991].

1.5. Contribution of the paper

This work aims to find local trajectories in obstacle-laden environments, effectively navigating around them and addressing these challenges. It suggests that the resulting skeleton will reveal essential patterns to guide the identification of the region to explore.

2. Proposed Method

Consider a grid C of size N x N, which represents a scenario; and an obstacle map $O \in C$. Given a starting point P and an ending point Q belonging to C, there is a need to navigate through this scenario efficiently while avoiding the obstacles (see Figure 1a).

Thus, within this scenario, a region of interest (ROI) of fixed size is defined with P as the center. The objective is to determine the center of the next ROI, denoted by P', to plan the next movement. To do this, a line is projected that extends from P to Q. Thus, P' will be the point of intersection of the line with the limit of the ROI (see Figure 1b). If this line, however, encounters any obstacle before reaching this limit, skeletonization of the ROI will occur (see Figure 1c and 1d).

After skeletonization, the center of the next ROI is determined by selecting one of the skeleton's endpoints. The selected endpoint, E, should be chosen in order to preserve the continuity of the movement's direction as much as possible, considering the relationship between points P, P', and E. As shown in Figure 1e, it can be observed that angle α is closer to $180°$ than β, which is why endpoint E is chosen. This ensures that P, P', and E maintain the best possible directionality. In this way, the choice of E is based on the direction that best aligns the movement towards Q, ensuring a smooth path. Furthermore, when selecting E, the possibility of collisions is also considered. Then, if the path between points P' and E results in a collision, E will be replaced by its nearest neighbor (see Figure 1f), thus ensuring safe movement around obstacles.

This process is repeated until the distance between the center of the ROI and Q is smaller than the distance between the center of the ROI and P', thus indicating that Q is within an area accessible from the center of the ROI.

2.1. Metrics and Scenarios

The metrics for evaluating the method are the same as those used by [Batista et al. 2023].

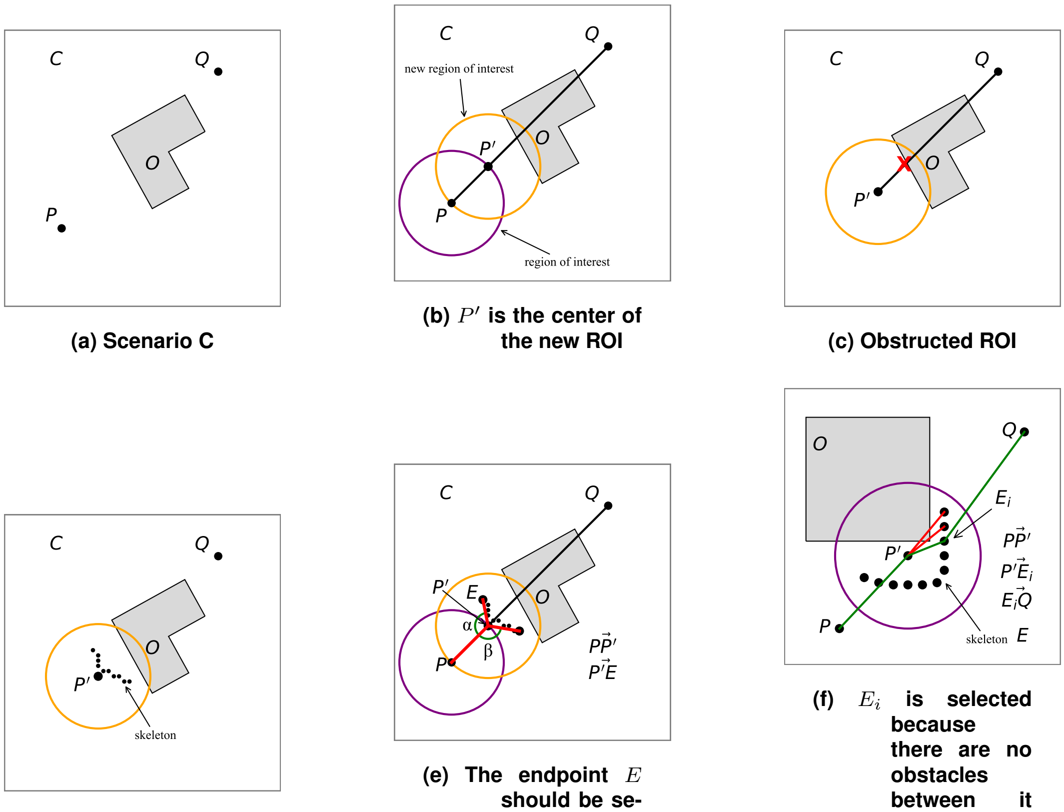
- Distance (cm): total length of the path, from the starting point to the ending point.
- Points: total number of discrete points that make up the path.
- Time (s): time required for the algorithm to calculate the path
- Standard Deviation of Joint Acceleration (std acc): measure of variation in acceleration along the path, indicating the intensity of changes in speed.
- Maximum Acceleration Rate (max jerk): maximum value of the rate of variation of acceleration along the path, reflecting sudden changes in acceleration.

We generate 100 scenarios using a 60×60 grid, and populated with 5 obstacles of different shape and size. The obstacles were positioned in random locations.

3. Results

3.1. Comparisons with global and local methods

Comparisons were made with the global Probabilistic Roadmap (PRM), Topological Path Planning (TPP), Generalized Voronoi Diagram (GVD) and Artificial Potential Field



(a) Scenario C **(b) P' is the center of the new ROI** **(c) Obstructed ROI**

(d) Skeletonized ROI **(e) The endpoint E should be selected** **(f) E_i is selected because there are no obstacles between it and P'**

Figure 1. Proposed Method

(APF) methods (see Figure 2). For each metric, a mean and standard deviation of all scenarios were calculated (see Table 1).

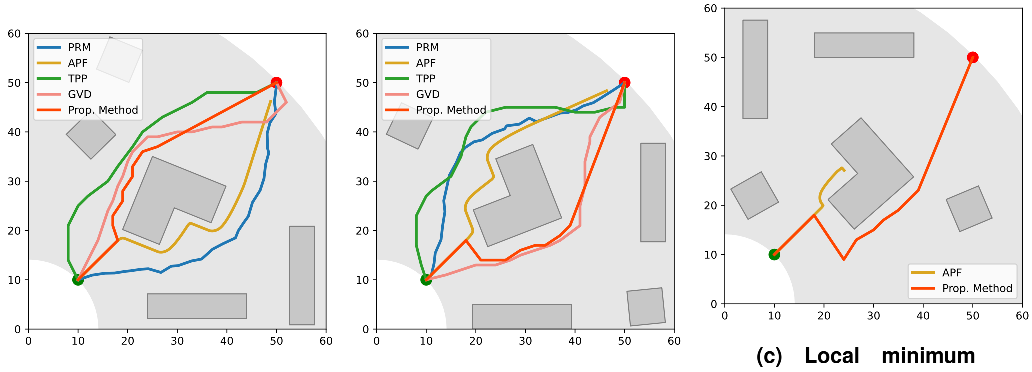
Table 1. Comparison with Global Methods

Method	Distance	Points	Max Jerk	Std Acc	Time
PRM	64.43 ± 1.54	30.46 ± 1.29	2.57 ± 0.55	10.15 ± 4.28	5.70 ± 1.59
APF	59.91 ± 1.80	717.12 ± 95.86	$\mathbf{0.07} \pm 0.10$	$\mathbf{0.20} \pm 0.30$	0.23 ± 0.14
TPP	68.96 ± 2.46	18.21 ± 1.06	4.79 ± 0.87	15.86 ± 7.25	1.99 ± 0.44
GVD	66.11 ± 3.80	18.33 ± 2.09	5.05 ± 1.34	16.25 ± 8.50	4.13 ± 0.94
Prop. Method	79.04 ± 11.88	19.79 ± 3.32	7.07 ± 1.39	24.18 ± 8.21	$\mathbf{0.02} \pm 0.01$

A comparison was also conducted with the local Bug 1, Bug 2 and Vector Field Histogram (VFH) methods (see Figure 3). Compared to other local methods, the proposed method obtained lower values for std acc and max jerk (see Table 2).

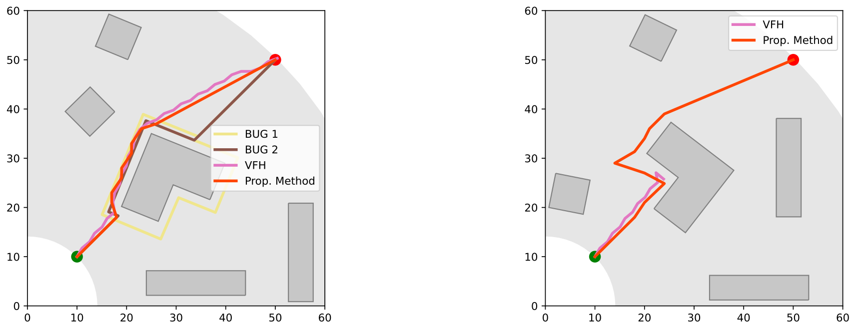
3.2. Discussion of Results

As mentioned in section 2, the next region of interest can be identified in two ways: first, by intersecting the boundary of the current region with the line connecting the starting and ending points; second, by using one of the endpoints of the skeleton of the region. In the second approach, a skeleton with at least two endpoints is generated when the region needs to be skeletonized. One endpoint is then selected as the center of the next



(a) Scenario 1 (b) Scenario 2 (c) Local minimum problem

Figure 2. Some results from PRM, GVD, TPP, APF and the proposed method



(a) Scenario 1 (b) Local minimum problem

Figure 3. Results of Bug 1, Bug 2, VFH and the proposed method

region of interest. While we aim to maintain the current trajectory direction, this selected endpoint may be sufficiently distant, leading to sharp curves or sudden direction changes in the path. As a result, some generated paths may be longer than those produced by global methods. Additionally, this approach can increase std acc and max jerk along the path. Qualitatively, the proposed method demonstrates performance in navigating around obstacles, producing smooth and continuous paths without sudden changes or deviations. It utilizes the available space, avoiding unnecessary detours. Moreover, it achieves a faster execution time compared to other global methods.

The APF method deserves special mention, as it produced excellent results for std acc and max jerk. However, in certain scenarios, the method may suffer from convergence to local minima. While it is capable of finding a path, the effectiveness of the method depends on the configuration of several parameters, which can make its applica-

Table 2. Comparison with Local Methods

Method	Distance	Points	Std Acc	Max Jerk	Time
Bug 1	122.54 ± 10.79	91.46 ± 10.00	7.64 ± 0.50	52.37 ± 12.82	0.04 ± 0.00
Bug 2	67.51 ± 5.22	40.17 ± 17.57	14.12 ± 5.88	55.69 ± 8.30	0.03 ± 0.00
VFH	**62.52** ± 0.88	32.26 ± 0.44	**5.27** ± 1.04	40.05 ± 11.73	**0.01** ± 0.00
Prop. Method	79.04 ± 11.88	**19.79** ± 3.32	7.07 ± 1.39	**24.18** ± 8.21	**0.01** ± 0.01

tion impractical in more complex situations (see Figure 2c).

VFH produces values similar to the proposed method (see Table 2), but shares a common limitation with APF: the tendency to converge to local minima (Fig. 3b). Compared to traditional local methods like Bug 1 and Bug 2, the proposed method shows significant improvements across key metrics, particularly in avoiding unnecessarily long paths. Furthermore, it tends to generate more optimized values for std acc and max jerk, which is crucial to guarantee smooth movements (see Table 2). Figure 4 shows the path found by the proposed method. The image below illustrates the operational environment for SCARA robots, which begin their journey from a designated starting point and navigate to a specific endpoint while avoiding obstacles in their path.

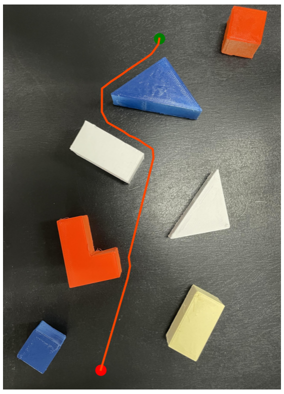


Figure 4. Planned SCARA robot trajectory avoiding obstacles with the proposed method

4. Conclusion

In our experiments, the proposed method successfully finds paths in all scenarios while ensuring that the generated trajectories are collision-free. We argue that using skeletonization offers several advantages. Since the location of the region of interest directly influences the path, adjusting its position to include the skeleton points enables a collision-free approach and helps overcome local minima issues. Furthermore, we demonstrate that the free area skeleton generates trajectories that are equidistant from obstacles, further ensuring collision avoidance. The proposed algorithm outperforms other local methods, especially in achieving smoother trajectories. The skeleton offers multiple trajectory options, making selection key for smoother direction. However, there is room for improvement, especially in choosing skeleton points to create smoother and shorter paths. The skeletonization uses only a small part of the scenario, sometimes pointing away from the destination. Future work could explore new criteria for positioning the region of interest, such as proximity to obstacles.

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