Benchmarking of robot arm motion planning in cluttered environments

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***Abstract*—Motion planning is essential for robotic automation across various industries. However, generalizing research outcomes has been challenging due to the narrow focus of previous work on a specific robot arm system. Here, we take a broader approach by exploring the combinations of three popular robot arm systems, three levels of clutterness in the environment, and twelve popular motion planners. To conduct the necessary performance analysis, we employ Motionbenchmaker tool and introduce a sensitivity metric. Our approach is structured and accessible, enabling the identification of the best-performing planner-robotic arm combinations. We find that the LBKPIECE, RRTConnect, and BKPIECE planners with Franka and UR5 offers the best balance of effectiveness and robustness. More generally, our results help researchers and practitioners make informed decisions when selecting robotic arms and motion planners, for use in environments with different degrees of clutterness.**

***Index Terms*—Motion planning, Benchmarking, Motionbenchmaker, Robotic arms**

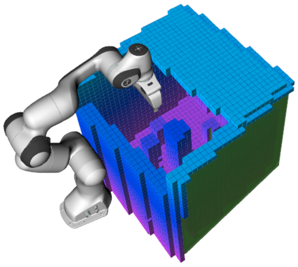


Fig. 1: An illustration of motion planning for Scenario 2. The end-effector of the Franka robot arm is inside the box, moving from one of the objects to the top of the other object without obstacle collisions in the process.

I. Introduction

Motion planning is essential for industrial robots to ensure precise movements and avoid obstacles [1]. However, challenges persist, including limited generalizability across robotic arm systems and insufficient examination of cluttered environments [2]–[4]. Several benchmarking studies have been conducted to evaluate and compare the performance of motion planning algorithms and robotic arm systems. For instance, a study [5] focused on the optimization and evaluation of motion planning algorithms in various scenarios, proposing a motion planning pipeline connecting the Open Motion Planning Library (OMPL) with optimized CHOMP or STOMP algorithms. Also [6] performed benchmarking tests on a 7-DOF robotic arm with various controllers to evaluate their accuracy, control efficiency, jitter, and robustness. While these studies provide valuable insights into motion planning algorithm performance, there are still gaps that need to be addressed. [7] introduced the Motionbenchmaker tool to generate and benchmark motion planning datasets. Another study [8] presented an extensible infrastructure for the analysis and visualization of motion planning algorithms. While these studies provide valuable insights into motion planning algorithm performance, various gaps still need to be addressed.

One of the major gaps in existing studies is the limited generalizability of the results to other robotic arm systems, as many studies focused on one robotic arm. Moreover, there is a lack of comprehensive investigation into the impacts of the working environment on motion planning, especially in the context of cluttered environments. The influence of the environment's properties, such as the size of the working space and the dimensions of obstacles, on motion planning performance, remains unexplored. Furthermore, there is a need for a standardized framework that enables the systematic comparison and evaluation of motion planners and robotic arm systems in various environments.

To address this gap, we conduct benchmarking studies that compare the performance of twelve OMPL [9] motion planners used with three different robotic arms: Franka [10], UR5 [11], and Kuka [12], see (TABLE I), in three environments of different levels of clutter. The Motionbenchmaker tool [7] is utilized to facilitate the benchmarking process, providing a unified platform for performing the evaluation of different motion planners and robotic arms. Our experiments investigate the performance of three robotic arms to determine their suitability for motion planning tasks in cluttered environments. The motion planners are tested in three distinct cluttered environments with varying levels of complexity: simple, moderate, and difficult, based on the benchmarks proposed by [13]. These environments will present unique features and require different planning strategies. The performance of the motion planners and robotic arms will be evaluated using the following metrics, as suggested by [14]: time efficiency, success rate, and sensitivity to the *range* parameter.

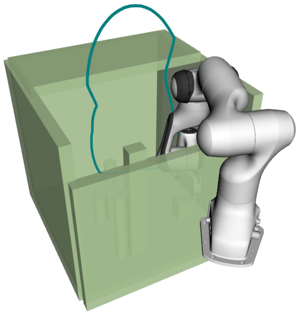


Fig. 2: In Scenario 2, the Franka robot arm's motion planning resulted in a trajectory depicted by a blue line.

TABLE I: Features of the robotic arm

Robotic arm	**Feature**	**Application**
Franka	7 DOFs, real-time motion planning, compliance control, advanced sensing capabilities, scalability	Assembly complex mechanical parts in manufacturing, inspections and measurements in research, surgical procedures in healthcare
UR5	6 DOFs, user-friendly interface, safe operation, repeatability, flexibility integration	Picking and placing goods, testing and evaluating new robotic algorithms, assisting to patients
Kuka	6 DOFs, precision and accuracy, high speed and performance, safe operation, customization, integration	It can be used in industrial production to automate the process of placing goods or products onto pallets

Contributions are: (1) exploration and analysis of the influence of the working environment properties on motion planning for robotic arms, with a focus on the size of the working space and the height of obstacles, (2) the evaluation of motion planning methods using three key metrics: time efficiency, success rate, and parameter sensitivity, (3) developing a cost function that can score motion planners across different scenarios, and recommend the appropriate planner based on the specific task requirements, and (4) a comparison of the performance of three robotic arms (Franka, UR5, and Kuka) in various cluttered environments, providing insights into the most efficient and robust planner-arm combinations. Our results enable researchers and practitioners to make informed decisions when selecting robotic arms and motion planners for their specific applications, ultimately improving the efficiency and robustness of robotic systems in complex environments.

In the following section, we review related work on motion planning in benchmarking. Section 3 presents the variations in scenarios and queries, as well as the metrics used for benchmarking. In Section 4, we describe the experimental setup and methodology for the benchmarking. A final section draws conclusions and discusses the implications of the findings.

II. Related works

Chamzas et al. [7] introduced MotionBenchMaker, a tool for generating diverse datasets with various robotic arms for benchmarking. They assessed planners using planning time and best cost but only tested three planners, limiting the analysis. In this paper, we address this limitation by analyzing twelve motion planners across three robotic arm systems and different levels of environmental clutter.

The RRT [15] motion planner uses randomized search and a tree-like structure in the configuration space to find a path between an initial and a goal configuration. RRTConnect [15] is a variant of RRT that generates two trees, one starting from the initial configuration and the other from the goal configuration, and connects them to find a path. RRTstar [15] is another RRT variant that employs cost-based rewiring to dynamically adjust the tree structure and find a lower-cost path. TRRT [16] is a version of RRT that uses adaptive sampling to adjust the distribution of random samples based on the current state of the tree and the progress toward the goal. EST [17] employs randomized search and space expansion principles, where the tree size is dynamically adjusted to focus the search in areas of the configuration space more likely to contain a path to the goal. SBL [18], KPIECE [19], BKPIECE [19], and LBKPIECE [19] are variants of single-query motion planning algorithms that use a graph-based structure in the configuration space to find a path. STRIDE [20] is designed for use in dynamic environments, where the environment changes over time, and FMT (Fast Marching Tree) [21] is a fast marching algorithm that uses a hierarchical tree structure to find a path.

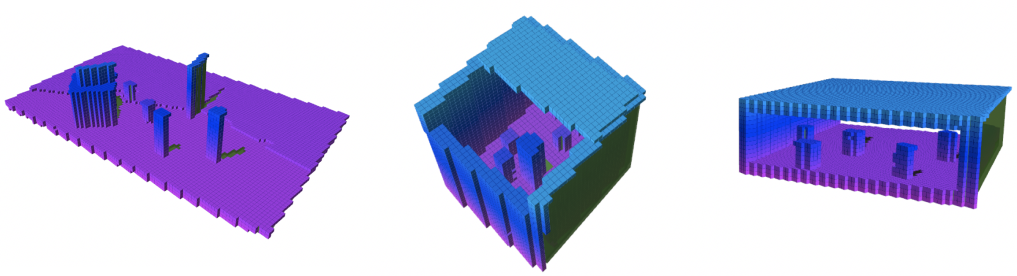
III. Software

We employ the Robot Operating System (ROS) [22] framework, the MoveIt [23] library for planning and executing robotic arm movements, and the Motionbenchmaker [7] repository for benchmarking motion planning algorithms. ROS is an open-source platform for building robot applications, while MoveIt provides a unified interface for performing complex tasks, such as grasping objects and navigating in three-dimensional space. The Motionbenchmaker repository offers a standardized and modular interface for benchmarking motion planning algorithms, supporting a wide range of robotic platforms and planning algorithms for performance evaluation and comparison.

IV. Problem formulation

A. *Variation definitions*

Motionbenchmaker can generate diverse scenes by introducing random variations to a nominal scene's object poses, both globally and locally. These perturbations are controlled by parameters specified in a configuration file and follow a Gaussian distribution for the probability of the random variable that perturbs the nominal positions of the objects. It can also define start and goal manipulation queries as pose offsets, creating a variety of motion planning problems. By combining scene sampling with problems, motion planning algorithms can be evaluated across a wide range of environments and scenarios under varying conditions influenced by Gaussian-based variations.



(a) Scenario 1

(b) Scenario 2

(c) Scenario 3

Fig. 3: Three scenarios setting: (a) represents a flat surface on which obstacles of different shapes are placed, the simplest scene without space constraints; (b) is a semi-closed box, which compresses a lot of space compared to (a); (c) is similar to a drawer, where the working space is significantly limited compared to (a) and (b).

B. Scenarios

In the first scenario (Fig.3.a), cluttered environments without spatial constraints feature obstacles on a single plane. A scene generation module is utilized to add random noise to the pose of collision objects relative to the global frame in a standard scene, as described in [24]. This study focuses on motion planning, not object grasping, with the robotic arm reaching an object.

The second scenario (Fig.3.b) reduces workspace with a semi-closed box, adding spatial constraints. The robotic arm must plan movements within the restricted space and reach an object, simulating motion planning in a more confined space compared to the previous scenario.

The third scenario (Fig.3.c) resembles a living room drawer with a more restricted workspace and obstacles that cannot be bypassed directly from above. The robotic arm must enter the drawer and reach an object, simulating motion planning in an even more confined space than before.

C. Metrics for selection

Various metrics are used based on time efficiency and success rate. Time efficiency is defined by the mean time taken by motion planners to compute feasible paths, while success rate assesses the percentage of successful path planning attempts. The robustness of the motion planner is evaluated by analyzing the impact of varying the parameter *range* on computation time. This study serves as a foundation for further investigations into refining parameters. In motion planning, the *range* parameter represents a finite interval or a set of discrete values, such as the maximum length of motion segments in tree-based algorithms. Larger *range* values can decrease the number of samples required but increase the complexity of collision checking, while smaller values may simplify these processes, albeit at the expense of slower planning.

D. Planners' score

To evaluate the planners' performance in each scenario and across all scenario-arm combinations, we calculate the average time efficiency (T_{avg}) for each planner in every scenario. Then we normalize the time efficiency scores using the subsequent formula:

$$N_t = 1 - \frac{T_{avg} - \min(T_{avg})}{\max(T_{avg}) - \min(T_{avg})} \tag{1}$$

Here, N_t represents the normalized time efficiency scores, which are inverted and scaled to a range of 0 to 1, with 1 signifying optimal performance.

Apply a weighted average function to aggregate the normalized time efficiency scores (N_t) from each scenario, accounting for the varying difficulty levels of the scenarios with weights w_1, w_2, and w_3. The essential function for computing the weighted average scores (W_{avg}) is presented as follows:

$$W_{avg} = w_1 * N_{t_1} + w_2 * N_{t_2} + w_3 * N_{t_3} \tag{2}$$

In this equation, N_{t_1}, N_{t_2}, and N_{t_3} denote the normalized time efficiency scores for each planner within their respective scenarios. The planners are subsequently ranked according to their weighted average scores.

V. Experiments

We conducted experiments using Motionbenchmaker tool to create scenarios for benchmarking motion planners in conjunction with robotic arms. These scenarios and queries were generated through C++ and Python scripts. For environmental configuration benchmarking, we used single-query planners from OMPL, selecting the most popular motion planners for comparison during parameter sensitivity benchmarking. Each test in Section 1 consisted of 100 runs with a planned timeout of 30 seconds. Planners' scores depend on assigned weights (1/6, 1/3, 1/2) for Scenarios 1, 2, and 3. For Section 2, each parameter *range* trial included 100 runs with a 30-second scheduled timeout, where a 0 mean time indicated all experiments failed. The mean time units in the experiments were seconds, and the success rate was expressed as a percentage. We conducted the experiment on a computer equipped with an Intel i9-11900 processor and an NVIDIA 3050.

A. Environment configuration benchmarking

As shown in TABLE II,III, and IV, the RRTConnect, SBL, BKPIECE, and LBKPIECE planners demonstrate impressive success rates in all three scenarios. Our evaluation considered

TABLE II: Scenario 1

Planner name	Franka		UR5		Kuka	
	Mean time (s)	Success rate (%)	Mean time (s)	Success rate (%)	Mean time (s)	Success rate (%)
RRT	1.504	89	4.793	59	1.622	65
RRTConnect	0.014	100	0.069	100	0.070	100
RRTstar	30.003	75	30.040	47	30.030	60
TRRT	1.288	66	5.150	37	1.216	70
EST	0.073	100	1.670	100	0.696	100
SBL	0.042	100	0.354	100	0.397	100
KPIECE	0.060	100	1.771	100	0.617	100
BKPIECE	0.063	100	0.793	100	1.542	100
LBKPIECE	0.066	100	1.507	100	1.579	100
PDST	0.059	99	3.351	97	0.685	100
STRIDE	0.095	100	1.762	100	0.794	100
FMT	0.615	100	5.643	100	22.058	99

TABLE III: Scenario 2

Planner name	Franka		UR5		Kuka	
	Mean time (s)	Success rate (%)	Mean time (s)	Success rate (%)	Mean time (s)	Success rate (%)
RRT	2.196	9	7.935	43	0.048	47
RRTConnect	0.408	100	1.047	100	3.616	99
RRTstar	30.001	4	30.058	31	30.057	52
TRRT	0.592	30	2.343	26	0.069	48
EST	2.239	98	5.228	97	2.086	53
SBL	0.529	100	1.505	99	5.762	100
KPIECE	2.521	94	6.349	92	4.157	57
BKPIECE	0.975	100	3.883	98	9.398	85
LBKPIECE	0.235	100	2.351	99	4.916	100
PDST	1.154	100	6.587	76	2.119	53
STRIDE	1.967	97	6.256	87	2.727	60
FMT	1.989	98	6.240	100	8.476	66

TABLE IV: Scenario 3

Planner name	Franka		UR5		Kuka	
	Mean time (s)	Success rate (%)	Mean time (s)	Success rate (%)	Mean time (s)	Success rate (%)
RRT	2.219	63	2.063	65	5.462	2
RRTConnect	0.092	100	0.330	100	7.351	79
RRTstar	30.002	50	30.023	55	30.005	1
TRRT	3.987	23	5.089	40		0
EST	2.419	95	4.255	88	15.719	5
SBL	0.156	100	0.488	100	6.100	91
KPIECE	1.084	84	4.039	85	15.166	6
BKPIECE	0.571	100	1.543	100	10.484	62
LBKPIECE	0.086	100	1.486	100	4.650	100
PDST	1.648	85	5.822	61	8.602	3
STRIDE	2.183	93	4.414	81	10.424	6
FMT	1.789	90	5.791	100	22.036	17

normalized time efficiency scores and employed a weighted average for each scenario. Based on these calculations, the planners score according to their success rates as follows: RRTConnect (0.88), SBL (0.82), LBKPIECE (0.75), and BKPIECE (0.04). Although BKPIECE falls under the high success rates category, it is important to note that its planning time of approximately 10 seconds is considerably longer than that of the other planners, particularly in high clutter environments like scenarios 2 and 3. This analysis indicates that RRTConnect stands out as the most time-efficient planner across the three scenarios, with SBL coming in a close second. LBKPIECE takes third place, while BKPIECE significantly lags behind the other planners in terms of time efficiency.

As per TABLE II,III, and IV, the PDST, STRIDE, EST, KPIECE, and FMT planners exhibit moderate success rates across all three scenarios. The scores for these moderate success rate planners are as follows: PDST (0.98), STRIDE (0.90), EST (0.77), KPIECE (0.68), and FMT (0.00). PDST stands out as the leading planner in this group, achieving the highest overall score. STRIDE takes the second spot, displaying strong performance in these environments, though not as efficient as PDST. Interestingly, despite being classified as moderate success rate planners, PDST and STRIDE's time efficiency is close to that of the top-performing RRTConnect, SBL, BKPIECE, and LBKPIECE planners. In fact, they are even slightly faster by 2 seconds in scenario 2, indicating promising motion planning capabilities in moderately cluttered environments. EST and KPIECE show respectable performance in these scenarios, securing the third and fourth positions, respectively. In contrast, FMT underperforms in this group, obtaining the lowest score, which suggests that it may not be well-adapted for moderate success rate scenarios.

In TABLE II,III and IV, RRT, TRRT, and RRTstar reveal low success rates across all three scenarios. The resulting ranking for low success rate planners is as follows: RRT (1.00), TRRT (0.73), RRTstar (0.00). RRT emerges as the top-performing planner in this category, attaining the highest overall score, emphasizing RRT's efficiency in handling low success rate scenarios. TRRT, ranking second, displays considerable performance in low success rate scenarios, albeit not reaching the same level of efficiency as RRT. RRTstar, on the other hand, ranks last with the lowest score, suggesting it may not be well-suited for low success rate scenarios.

RRTConnect, SBL, and LBKPIECE consistently demonstrate superior efficiency and robustness, and are the most scalable planners, maintaining high success rates and relatively low mean times across different clutter levels making them ideal candidates for diverse situations. While BKPIECE, PDST, and STRIDE display potential for further research, RRT, RRTstar, and TRRT exhibit the least favorable performance among all planners.

B. Parameter sensitivity benchmarking

In this benchmarking (Fig. 4), for Franka, LBKPIECE, RRTConnect, and BKPIECE consistently showed the best time efficiency across all scenarios, with SBL performing well in

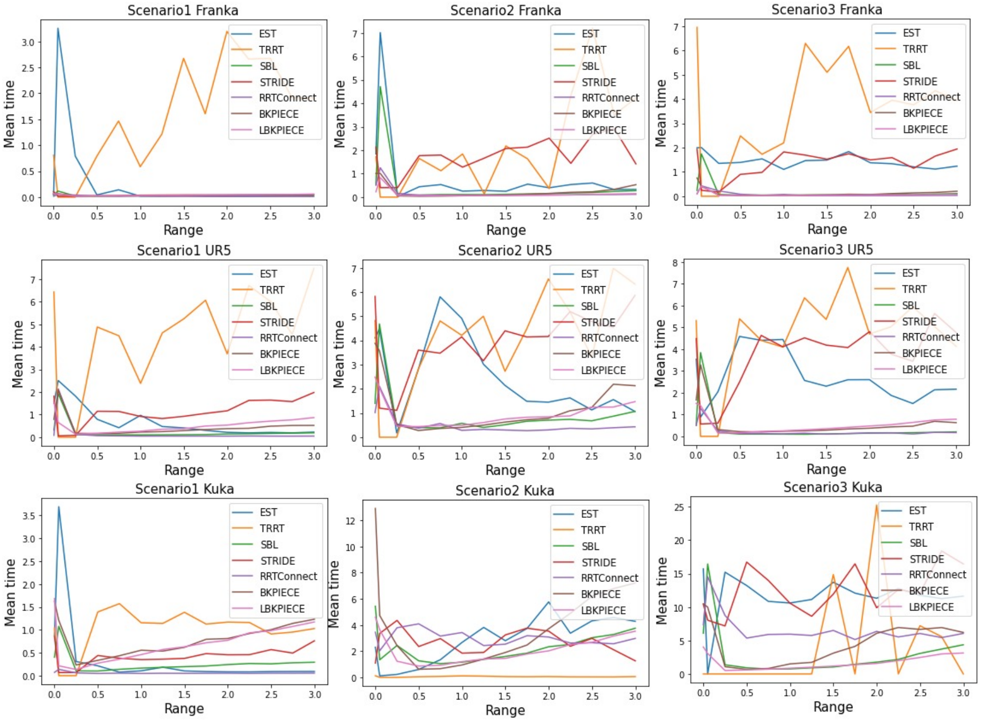


Fig. 4: The present study employed six motion planners, namely EST, TRRT, SBL, STRIDE, RRTConnect, BKPIECE, and LBKPIECE to analyze the difference in mean time, measured in seconds, among robotic arms and planners by varying the parameter *range*. Specifically, the parameter is systematically varied from 0 to 3 with an incremental interval of 0.25. The trials for each parameter range consist of 100 runs with a planned timeout of 30 seconds, where a mean time of 0 seconds indicates that all failed.

less complex environments. EST, TRRT, and STRIDE had higher mean times. For UR5, LBKPIECE, RRTConnect, and BKPIECE displayed the best performance across all scenarios, while SBL showed promising results for lower *range* values. EST, TRRT, and STRIDE had higher mean times and lower success rates. For Kuka, LBKPIECE, RRTConnect, and BKPIECE outperformed other planners consistently. SBL, with proper *range* adjustment, could perform better in complex scenarios. EST, TRRT, and STRIDE showed higher mean times and significantly lower success rates. Additionally, it is demonstrated that the majority of planners exhibit low mean times and high success rates within the parameter *range* interval of 0.25 to 0.5. It can also be observed that most of the curves begin to stabilize regionally after the parameter value reaches 1.5, including the notably unstable TRRT, whose amplitude frequency displays a decreasing trend beyond this point.

Overall, LBKPIECE, RRTConnect, and BKPIECE demonstrated robust performance across all scenarios and robotic arms, making them suitable for various tasks. SBL also performed well with appropriate *range* adjustment. EST, TRRT, and STRIDE were generally less efficient. Franka had the most comprehensive performance, while UR5 and Kuka's performance varied depending on the planner and *range* parameters.

C. *Discussion*

In conclusion, LBKPIECE, RRTConnect, and BKPIECE consistently demonstrate time-efficient performance for all three robot arms in the tested scenarios, featuring low mean times, high success rates, and robust performance across various *range* parameter values. EST, and SBL could also be viable options, depending on the desired performance, but their effectiveness may vary depending on specific *range* values and environmental complexity. The influence of the *range* parameter on LBKPIECE, RRTConnect, and BKPIECE's performance is less pronounced in simpler cluttered environments, where these planners can often find feasible paths quickly, regardless of the *range* value. Conversely, for EST and SBL, a smaller *range* value may slow the planning process due to increased samples and connections, while a larger value could accelerate the convergence of trees.

In Scenario 1's open space, planners benefit from multiple path options, resulting in high timeliness and success rates, although obstacle configurations can still impact performance. Scenarios 2 and 3 illustrate that workspace size significantly affects robot arm motion planning. Restricted spaces constrain arm joint mobility, reducing both arm and planner performance in cluttered environments, where obstacles also impede computational efficiency. Nevertheless, fine-tuning the *range* parameter in complex environments can enhance planning performance and enable planners to thrive in otherwise challenging settings. Empirical studies suggest adjusting the *range* parameter to optimize performance across different environments, with a *range* of 0.25 to 0.5 typically yielding good performance. However, in constrained and cluttered environments like Scenario 3, increasing the parameter to 1.5 or higher has shown improved robustness and success rates. This adjustment should account for the specific characteristics and constraints of the environment. Further research is needed to investigate the impact of *range* parameter adjustments on performance in diverse environments.

Concerning the robot arms in Table 1, the Franka, with its 7 DOFs, is well-suited for researchers working on complex tasks requiring precise positioning when paired with LBKPIECE, RRTConnect, and BKPIECE. For those focusing on slightly simpler experiments, the UR5 offers a user-friendly interface and safety features, making it an excellent choice for beginners and algorithm testing. In contrast, the Kuka is more appropriate for applications with higher technical requirements, targeting industrial production and automation.

VI. CONCLUSIONS

In conclusion, this paper presents a comprehensive study on the performance of various motion planners in cluttered environments using three robotic arms: Franka, UR5, and Kuka. The primary focus is to investigate time efficiency, robustness, and parameter sensitivity.

Experimental results show that LBKPIECE, RRTConnect, and BKPIECE consistently exhibit the best time efficiency and robustness across all robotic arms. SBL is potential candidates with reasonable performance, particularly for Franka and UR5 in challenging scenarios. The Franka, paired with LBKPIECE, RRTConnect, and BKPIECE, is ideal for complex tasks and precision. The UR5 suits simpler experiments, beginners, and algorithm testing. Meanwhile, the Kuka targets industrial production and automation.

In summary, our research contributes to the field of motion planning by providing a thorough analysis of the performance of various motion planners and robotic arms in cluttered environments. The insights gained from this study can serve as a valuable recommendation for researchers and practitioners in selecting the most appropriate motion planners and robotic arms for their specific tasks and applications. Future work may explore various environment configurations, such as different obstacle types, sizes and distributions, as well as the interaction between static and dynamic obstacles.

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