# Benchmarking OMPL Planning Algorithms for Robot Arms in Cluttered Settings

Shibao Yang
*Dept. Computer Science*
*University of York*
York, United Kingdom
shibao.yang@york.ac.uk

Pengcheng Liu
*Dept. Computer Science*
*University of York*
York, United Kingdom
pengcheng.liu@york.ac.uk

Nick Pears
*Dept. Computer Science*
*University of York*
York, United Kingdom
nick.pears@york.ac.uk

## I. Introduction

Motion planning is essential for industrial robots to ensure precise movements and avoid obstacles. However, challenges persist, including limited generalizability across robotic arm systems and insufficient examination of cluttered environments. Several benchmarking studies have been conducted to evaluate and compare the performance of motion planning algorithms and robotic arm systems. For instance, a study [1] focused on the optimization and evaluation of motion planning algorithms in various scenarios, proposing a motion planning pipeline connecting the OMPL with optimized CHOMP or STOMP algorithms. Also [2] 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. [3] introduced the Motionbenchmaker tool to generate and benchmark motion planning datasets. Another study by [4] presented an extensible infrastructure for the analysis and visualization of motion planning algorithms. While these studies provide valuable insights into motion planning algorithm performance, the 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.

In this paper, we conduct benchmarking studies that compare the performance of the Open Motion Planning Library (OMPL) [5] motion planners with robotic arms (TABLE I) Franka [6], UR5 [7], and Kuka [8] in cluttered environments. The Motionbenchmaker tool will be utilized to facilitate the benchmarking process, providing a unified platform for performing the evaluation of different motion planners and robotic arms. The experiment will investigate the performance of three robotic arms to determine their suitability for motion planning tasks in cluttered environments. The motion planners will be tested in three distinct cluttered environments with varying levels of complexity: simple, moderate, and difficulty, based on the benchmarks proposed by [9]. 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 [10]: time efficiency, success rate, sensitivity to *range* parameter.

TABLE I: Feature 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 |

The main contributions of this paper are: (1) an 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) the development of a recommendation for selecting an appropriate motion planner based on 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 for motion planning researchers. The results will 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.

## II. Method

### A. Variation definitions

Motionbenchmaker tool 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.

### *B. Metrics for selection*

In this research, 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.

## III. 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 RRTConnect and BKPIECE consistently exhibit the best time efficiency and robustness across all robotic arms. SBL and LBKPIECE are potential candidates with reasonable performance, particularly for Franka and UR5 in challenging scenarios. The Franka, paired with 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 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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