Non - Prehensile Manipulation With Model Predictive Path Integral Control Using Physics Simulator

Rohith Poola

***Abstract*—This project addresses the challenge of performing non-prehensile manipulation tasks using complex, high-degree-of-freedom robotic manipulators through Model Predictive Path Integral (MPPI) control. Traditional approaches to MPPI require explicit robot dynamics models, which are difficult to derive accurately for complicated robotic systems. To overcome this limitation, I utilize the PyBullet physics simulator directly as the robot's implicit dynamic model within the MPPI framework. At each iteration, I generate multiple trajectory rollouts by perturbing control inputs, simulating their effects through PyBullet, and employing importance sampling to identify an optimal control sequence. This simulator-in-the-loop approach simplifies the integration of MPPI for highly articulated robots, eliminating the need for explicit dynamics modeling and making it widely applicable to various robotic platforms. Experimental validation with a 7-DOF manipulator demonstrates effective trajectory tracking and successful non-prehensile manipulation tasks, showcasing the flexibility and practical utility of the proposed method.**

I. Introduction

As robotic systems evolve toward performing increasingly complex tasks in unstructured environments, their ability to interact with objects through physical contact becomes crucial. Many real-world tasks—such as pushing, sliding, or guiding objects without grasping—fall under the category of non-prehensile manipulation, where robots manipulate objects using external forces instead of firm grasps. This form of manipulation is particularly useful in scenarios where gripping is infeasible or unnecessary, enabling agile and efficient behaviors.

However, executing such contact-rich tasks with high-degree-of freedom (DOF) manipulators presents a major challenge: the difficulty of modeling their complex, often discontinuous, dynamics. Conventional model-based controllers, like Model Predictive Control (MPC), struggle under these conditions as they rely on explicit dynamic models and often require simplifications, manual tuning, or extensive engineering effort to remain tractable in real-time applications.

Inspired by recent work [1] leveraging physics simulators as black-box dynamic models in MPPI frameworks, this project implements a sampling-based Model Predictive Path Integral (MPPI) controller for non-prehensile manipulation with a 7-DOF robotic arm. Unlike the referenced approach which uses GPU-parallelized simulation in IsaacGym, our implementation employs the PyBullet simulator for forward dynamics. At each control step, multiple control sequences are sampled and simulated through PyBullet to generate rollouts, which are then evaluated based on a cost function. Using importance sampling, the optimal control input is selected without needing an explicit dynamics model or offline training.

This simulator-in-the-loop approach allows MPPI to scale to robots with complex dynamics and high DOF, enabling real-time control for tasks such as pushing objects to target locations. The success of this method in simulation demonstrates its flexibility and potential for broader application in contact-rich robotic tasks without the need for data-driven policy learning or handcrafted dynamic models.

II. Related Work

Motion planning strategies in robotics are typically classified into global and local planners. Local motion planning methods include operational space control using receding-horizon control approaches such as Model Predictive Control (MPC) [2]. MPC has been extensively used in robotics due to its ability to incorporate system dynamics and constraints in real-time. In some cases, it has also been combined with learned components to improve adaptability.

However, standard MPC methods often assume smooth and continuous dynamics, making them difficult to apply directly to contact-rich scenarios involving discontinuities such as collisions, stick-slip transitions, and impacts. These non-smooth behaviors introduce challenges in gradient-based optimization, often requiring extensive hand-tuned modeling and ad hoc solutions [3].

To address these limitations, Model Predictive Path Integral (MPPI) control has been proposed as a sampling-based alternative to traditional MPC [4]. MPPI reformulates the control problem as a stochastic optimal control task and solves it via importance sampling over perturbations to nominal control sequences. It is inherently gradient-free and well-suited for systems with non-convex dynamics and cost functions, enabling real-time control even for high-DOF manipulators. Some works extend MPPI with additional strategies like ensemble sampling [5] or learning-based collision avoidance, although many such approaches still assume limited or no physical interaction with the environment.

To further reduce the reliance on analytic models, some recent approaches propose using physics simulators as dynamic models within sampling-based MPC frameworks. For example, Howell et al. [6] demonstrated a method that integrates MuJoCo into the MPPI loop to roll out input sequences directly using the simulator. These techniques shift the burden of modeling to the simulator, which simplifies controller design and broadens applicability.

Tasks like non-prehensile manipulation—where robots manipulate objects by pushing rather than grasping—require especially large sample sizes due to their hybrid dynamics and sensitivity to contact conditions. Prior works often rely on learned forward models for predicting push effects [7], which then inform trajectory planning at the end-effector level. These methods often require a separate tracking controller and are difficult to generalize across robotic platforms or task setups.

III. Contributions

In this project, I implement a sampling-based Model Predictive Path Integral (MPPI) controller for non-prehensile manipulation using a high-degree-of-freedom (DOF) robotic manipulator, with PyBullet serving as the simulator-based motion model. My key contributions are as follows:

- **MPPI Control with PyBullet Simulator:** I develop an MPPI controller that utilizes PyBullet for forward dynamics rollouts. This eliminates the need for an explicit dynamic model, enabling control over complex manipulators without relying on differentiable or learned dynamics.
- **Contact-Rich Manipulation without Parallelization:** Unlike existing works that require GPU-parallelized simulation [1], my implementation achieves real-time control using CPU-only rollouts. This demonstrates the feasibility of simulation-in-the-loop MPPI for high-DOF robots in practical settings.
- **Simplified and Generalizable Framework:** My approach requires only a cost function definition and no task-specific modeling or training. It provides a transferable foundation for solving contact-rich tasks across diverse robotic platforms.

Through this project, I successfully performed real-time non-prehensile manipulation using a 7-DOF manipulator, and could able to demonstrate the power of simulation-based MPPI as a general-purpose control strategy.

IV. Methodology

V. Experiments

VI. Results and Discussion

VII. Conclusion

References

[1] C. Pezzato, C. Salmi, E. Trevisan, M. Spahn, J. Alonso-Mora, and C. H. Corbato, "Sampling-based model predictive control leveraging parallelizable physics simulations," *IEEE Robotics and Automation Letters*, vol. 10, no. 3, Mar. 2025.

[2] G. B. Avanzini, A. M. Zanchettin, and P. Rocco, "Constrained model predictive control for mobile robotic manipulators," *Robotica*, vol. 36, no. 1, pp. 19–38, Jan. 2018.

[3] J. Moura, T. Stouraitis, and S. Vijayakumar, "Non-prehensile planar manipulation via trajectory optimization with complementarity constraints," in *Proceedings of the 2022 IEEE International Conference on Robotics and Automation (ICRA)*, Philadelphia, PA, USA, May 2022, pp. 970–976.

[4] G. Williams, A. Aldrich, and E. A. Theodorou, "Model predictive path integral control: From theory to parallel computation," *Journal of Guidance, Control, and Dynamics*, vol. 40, no. 2, pp. 344–357, Feb. 2017.

[5] I. Abraham, A. Handa, N. Ratliff, K. Lowrey, T. D. Murphey, and D. Fox, "Model-based generalization under parameter uncertainty using path integral control," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2864–2871, Apr. 2020.

[6] T. Howell, N. Gileadi, S. Tunyasuvunakool, K. Zakka, T. Erez, and Y. Tassa, "Predictive sampling: Real-time behaviour synthesis with mujoco," 2022. [Online]. Available: https://arxiv.org/abs/2212.00541

[7] L. Cong, M. Grüner, P. Ruppel, H. Liang, N. Hendrich, and J. Zhang, "Self-adapting recurrent models for object pushing from learning in simulation," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Las Vegas, NV, USA, 2020, pp. 5304–5310.