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Faster Training for Robotic Manipulation in GPU Parallelized Robotics Simulation

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ABSTRACT

Robotic manipulation is a challenging research area, particularly in developing policies that generalize across diverse real-world scenarios. While real-world data can be slow and unsafe, simulations offer a safer and faster alternative. However, training in simulations can still be time-consuming, hindering rapid model iteration. This paper explores using graphics processing unit (GPU) acceleration to speed up training for robotic manipulation tasks in simulations. By comparing GPU and CPU performance, we demonstrate a significant reduction in training time. The findings show that GPU hardware enhances policy development efficiency, accelerating research and applications, including sim-to-real transfer. Additionally, it broadens exploration of state and action spaces, providing agents with a diverse range of training experiences. A simulation benchmark was also created to test GPU acceleration, detailing task selection, environment setup, and performance measurement. This benchmark forms the basis for evaluating the speedup achieved by GPUs in training robotic manipulation models.

KEYWORDS

Robotic Manipulation, Deep Reinforcement Learning, Simulation, GPU acceleration, Benchmarking, Sim-to-Real Transfer

INTRODUCTION

Training a robotic arm to solve complex problems in the real world is a highly challenging task, demanding large quantities of data and advanced, often highly specialized models. The process of acquiring real-world data can be slow, expensive, and potentially unsafe. For this reason simulators are widely used in robotics to create synthetic data and prototype models and to debug systems and train reinforcement learning (RL) algorithms. These simulators enable faster and more controlled testing environments, allowing researchers to experiment with robotic models and systems without the constraints and risks associated with physical environments (Juliani et al., 2020, Todorov et al., 2012). However, these applications, while effective, still require vast computational resources, especially as the complexity of the models and simulations increases.

Recent advancements in physics engines, particularly those incorporating graphics processing unit (GPU)-based simulation capabilities, have dramatically improved the performance and scalability of these simulators. GPU-based physics simulations allow for the parallelization of computations, facilitating the simultaneous training of thousands of RL agents on a single GPU, as shown in Figure 1 (Mittal et al., 2023; Tao et al., 2024; Zakka et al., 2025). This acceleration enables more efficient training processes and allows researchers to iterate faster when developing policies for robotic

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manipulation. By using GPU-based simulations, we can handle more extensive datasets, perform more complex calculations, and achieve higher levels of fidelity in simulations, ultimately speeding up the development of robotic systems.

Figure 1. Multiple environments for graphics processing unit (GPU)-based pipeline

I conceptualize the simulation environment as the final step in the progression of dataset evolution—from basic raw data types like sound, text, and images to more advanced forms, including video and full-scale simulations. While the availability of various data sources has increased over the years, there is still a significant gap in the availability of high-quality simulation environments equipped with GPU-accelerated physics simulations. In comparison to real-world data, synthetic data generated within these simulation environments offers distinct advantages such as speed, cost-effectiveness, and safety (Tobin et al., 2017). However, there remains a notable need for simulation platforms that can reliably replicate the complexity of real-world physics while harnessing the computational power of GPUs. My research addresses this gap, providing a foundation for more efficient and scalable training of robotic manipulation models.

The key contributions of this paper include the integration of GPU-based physics simulation to enhance the development of better simulation environments. My work directly supports the acceleration of RL for robotic manipulation, which is crucial for creating systems that can adapt to real-world variability (Zhou, G., et al., 2023). I believe that enabling faster simulation-based training will help researchers and developers make significant strides in robotic control, task optimization, and deployment in various applications.

Further, I explore the diverse applications of simulation environments in robotics. One of the most common applications is training deep learning models, which typically requires massive amounts of data. In many cases, synthetic data generated in simulations can serve as an effective replacement for real-world data. Collecting data in the real world can be a time-consuming and costly process, with the added challenge of managing safety concerns when dealing with complex robots. In contrast, generating data in a simulator is faster, safer, and more controllable, though it introduces the problem of the sim-to-real gap, the discrepancy between a robot's performance in a simulation and its performance in a real-world environment. This gap must be minimized for simulated training to effectively transfer to real-world tasks (Mulero et al., 2023).