RADemics

SIMULATION ENVIRONMENTS FOR TRAINING REINFORCEMENT LEARNING DRIVEN ROBOTIC SYSTEMS

Balraj Hooda, P Daniel Jeyakumar, K. Bharathi

GANGA INSTITUTE OF TECHNOLOGY AND MANAGEMENT, SRI RAMAKRISHNA COLLEGE OF ARTS & SCIENCE, AMET UNIVERSITY

SIMULATION ENVIRONMENTS FOR TRAINING REINFORCEMENT LEARNING DRIVEN ROBOTIC SYSTEMS

[1]Balraj Hooda, Assistant Professor, Department of Mechanical Engineering, Ganga Institute of Technology and Management, Kablana, Jhajjar, Haryana – 124104. balraj.me@gangainstitute.com

[2]P Daniel Jeyakumar, Assistant Professor, PG & Research Department of Electronics, Sri Ramakrishna College of Arts & Science, Coimbatore – 641006. jkdanny5655@gmail.com

[3]K. Bharathi, Associate Professor, Department of Marine Engineering, AMET University, 135 East Coast Road, Kanathur, Chennai – 603112. bharathihve@gmail.com

Abstract

The rapid advancement of autonomous robotic systems has increased the demand for intelligent learning frameworks capable of adapting to complex and dynamic environments. Reinforcement Learning (RL) has emerged as a promising approach for enabling robots to acquire optimal behaviors through continuous interaction and experience-based decision-making., Real-world RL training faces significant challenges related to safety risks, hardware limitations, high data requirements, and experimental costs. Simulation environments provide an effective solution by offering controlled, scalable, and realistic platforms for training, testing, and optimizing RL-driven robotic systems. This chapter explores the role of advanced simulation frameworks in robotic reinforcement learning, focusing on physics-based modeling, simulation parameter configuration, digital twin integration, domain randomization, and simulation-to-reality transfer mechanisms. Various robotic simulation platforms, including Gazebo, MuJoCo, NVIDIA Isaac Sim, CoppeliaSim, and Webots, are examined based on their capabilities for robot modeling, sensor integration, computational efficiency, and learning performance. The chapter highlights the importance of accurate environmental representation, dynamic system modeling, and optimized simulation conditions for improving policy convergence and generalization capability. Emerging approaches such as parallel simulation, synthetic data generation, and adaptive virtual environments are discussed to address current limitations in RL-based robotic development. The chapter provides insights into future research directions toward intelligent, scalable, and reliable simulation ecosystems for next-generation autonomous robotic applications.

Keywords: Reinforcement Learning, Robotic Simulation, Simulation-to-Reality Transfer, Digital Twin, Autonomous Robots, Physics-Based Modeling.

Introduction

The emergence of intelligent robotic systems has significantly transformed modern automation by enabling machines to perform complex tasks with improved autonomy, adaptability, and decision-making capability [1]. Recent developments in artificial intelligence, machine learning, and advanced control techniques have accelerated the transition from conventional programmed robots toward learning-based robotic platforms [2]. Reinforcement Learning (RL) has gained considerable attention as an effective computational approach for developing autonomous robotic behaviors through continuous interaction with surrounding environments [3]. Unlike traditional control strategies that require explicit mathematical models and predefined operating rules, reinforcement learning allows robotic agents to discover optimal actions by maximizing cumulative rewards obtained through experience [4]. This learning mechanism supports the development of adaptive robots capable of handling uncertain conditions, dynamic environments, and complex operational requirements. Applications such as industrial automation, autonomous vehicles, robotic manipulation, healthcare robotics, and human–robot collaboration increasingly depend on RL techniques to achieve higher levels of intelligence and flexibility [5].

The successful implementation of reinforcement learning-based robotic systems requires extensive training experiences, which creates significant challenges when performed directly on physical platforms [6]. Real-world robotic training involves limitations related to hardware durability, operational safety, financial cost, and time-consuming data collection processes [7]. During the learning phase, robotic agents often require numerous explorations attempts to identify effective control strategies, and unsuccessful actions can result in equipment damage or unsafe conditions [8]. Simulation environments provide an efficient solution by creating virtual spaces where robotic systems can safely explore different actions, evaluate performance, and optimize learned policies. These environments enable repeated experiments under controlled conditions while reducing dependency on physical prototypes [9]. The capability to generate large-scale training data, modify environmental parameters, and reproduce experimental scenarios makes simulation platforms an essential component in the development of reinforcement learning-driven robotic applications [10].

Advanced simulation environments have evolved from basic visualization platforms into comprehensive robotic development ecosystems that integrate physics engines, sensor models, environmental dynamics, and artificial intelligence-based learning frameworks [11]. Modern simulation platforms such as Gazebo, MuJoCo, NVIDIA Isaac Sim, CoppeliaSim, and Webots provide realistic representations of robotic systems and their interactions with surrounding environments [12]. Accurate modeling of mechanical structures, actuator behavior, collision responses, and sensor characteristics allows reinforcement learning algorithms to acquire more reliable and transferable policies [13]. Physics-based simulation frameworks support the analysis of robot movement, object interaction, navigation behavior, and collaborative operations under diverse conditions. The selection of appropriate simulation platforms and configuration of their parameters significantly influence learning efficiency, computational performance, and the quality of final robotic behaviors [14]. Consequently, simulation environment design has become a critical research area for improving the effectiveness of autonomous robotic learning systems [15].