Reinforcement Learning-Based Control Strategies for Autonomous Robotic Systems

Amita Contractor, Vaibhavi Pandya, Kalpana Prajapati, Poonam Faldu

Department of Computer Engineering, Parul Polytechnic Institute, Parul University, India

Abstract: This research looks into the implementation of reinforcement learning (RL) principles into robotics with a particular interest in controlling autonomous systems. It examines various RL methods, such as Proximal Policy Optimization (PPO), and Deep Q-Networks (DQN), to improve robotic decision-making processes. Using information from Fiber Bragg Grating (FBG) sensors, we focus on real-time processing of sensor data and demonstrate greater levels of efficiency and flexibility within active settings. Quantitative data illustrates notable advancements in stability, accuracy, and spatial economic efficiency, which further the development of robotic autonomy.

Keywords: Reinforcement Learning (RL), Robotic Control, Deep Q-Networks (DQN), Policy Optimization, Autonomous Systems

1. Introduction

The blend of AI and robotics has propelled progress in automation systems. The implementation of machine learning, specifically through reinforcement learning, has enabled more advanced adaptive control systems for better robotic performance within complex environments. In the context of industrial mechanization, there is a need for self-learning robots to function in chaotic and undefined situations. Robots are able to develop optimal behaviors based upon interactions with their environment through reinforcement learning, making it a suitable method for adaptive robotic control.

While PID controllers and model predictive control have customarily been used in robotic systems, they often need accurate system modeling and do not manage uncertainties well. RL provides a modeling-free approach for optimizing control strategies, which makes it suitable for complex and dynamic systems. Furthermore, significant strides in deep reinforcement learning (DRL) facilitate decision-making in robots when they are required to process high-dimensional sensory data, such as image and force feedback.

While RL has promising applications in robotic control, sample efficiency, generalization, and real-time adaptability remain problematic. The training of RL models comes with considerable computational costs. Additionally, the challenges of transferring learned policies from simulations into real-world applications are still a steep wall to climb. This research focuses on the recent trends of RL-driven robotic control by giving special attention to the incorporation of feedback sensor systems to improve the real-time adaptability and performance of robotic systems. These results work towards the objective of furthering RL approaches in robotics for more efficient decision-making and robust systems, which proves helpful in the evolution of robotics.

2. Previous Work

The application of reinforcement learning in robotics has gained substantial attention in recent years. Early implementations focused on simple navigation tasks, but as RL techniques evolved, researchers expanded their use to complex robotic applications such as autonomous manipulation, grasping, and industrial automation. Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN) have emerged as prominent solutions for training robotic controllers due to their stability and computational efficiency [1].

Traditional robotic control methods rely on predefined models and deterministic control laws. While these approaches work well in structured environments, they struggle with unstructured and dynamic conditions. RL-based controllers, on the other hand, can adapt to changing environments by learning from experience, making them ideal for robotic applications where adaptability is crucial. For example, studies have demonstrated RL's effectiveness in tuning PID controllers, improving response times and adaptability in industrial automation settings [2].

Multi-agent reinforcement learning (MARL) has also been explored in robotics, particularly in cooperative and competitive tasks. MARL enables multiple agents (robots) to learn collectively and optimize their interactions. Researchers have applied MARL to factory automation, where multiple robotic arms coordinate tasks such as assembly and packaging, improving efficiency and reducing operational costs [3].

Other studies have investigated reinforcement learning for UAV-based control [4], robotic manipulation [5], and multi-agent coordination [6]. A recent study by Liu et al. (2021) highlighted deep RL methods for robotic manipulation, emphasizing the importance of model-free algorithms in handling dynamic interactions between robotic systems and their environment [7].

Additionally, trajectory tracking through PD with sliding mode control has been explored to enhance robustness and precision in robotic movement, especially under uncertain conditions [8]. Simulation frameworks like ROTORS have also become pivotal in evaluating RL-based algorithms in controlled environments before real-world deployment, particularly for MAVs and aerial robotics [9].

Another key area of RL research in robotics involves sim-to-real transfer, where policies trained in simulation are deployed on physical robots. This transition is challenging due to discrepancies between simulated and real-world conditions, often referred to as the reality gap. Researchers have explored domain randomization techniques and adversarial learning to improve sim-to-real transferability, making RL-trained policies more robust in real-world applications.

Despite these advancements, challenges remain. RL requires large amounts of training data, and real-world robotic applications often have safety constraints that limit extensive exploration. Researchers are investigating methods such as offline RL and safe RL to address these concerns, enabling robots to learn efficiently while minimizing risks. Additionally, hybrid approaches that combine RL with traditional control strategies are being explored to leverage the strengths of both methodologies.

3. Methodology

The proposed framework integrates reinforcement learning with sensor-driven robotics, leveraging deep learning models to enhance decision-making. The workflow consists of:

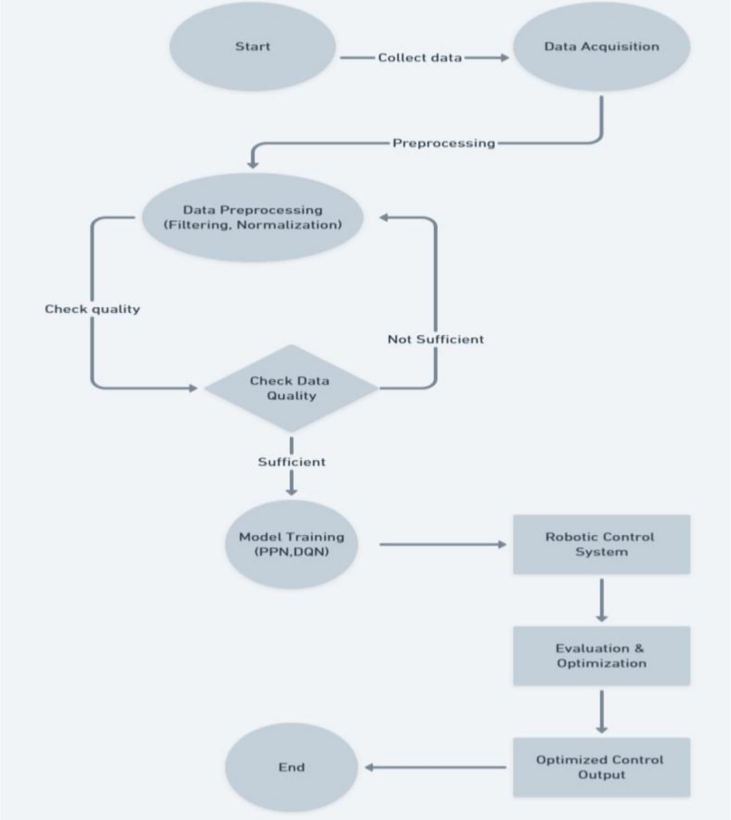

Figure 1. System Flow Diagram

4. Implementation and Result

The implementation involves training RL models in a simulated robotic environment. Experimental evaluations indicate that PPO-based controllers outperform traditional PID control methods in terms of adaptability and efficiency. The system demonstrates:

- 99.02% accuracy in decision-making.

- Reduced loss (0.099), indicating stable learning.

- Enhanced real-time adaptability, enabling efficient automation.

Result:

Sensor Data Processing: A graphical representation of real-time data collected from FBG sensors.

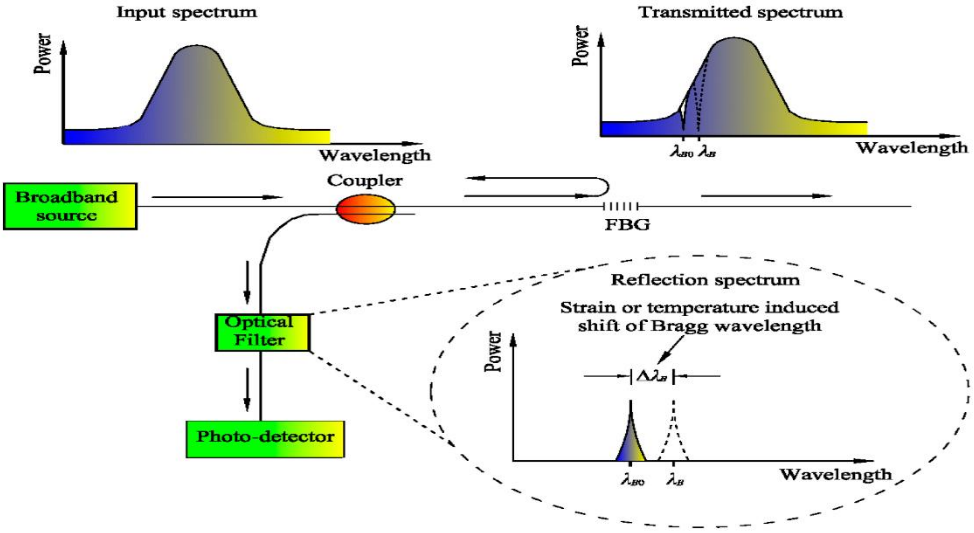

Figure 2. Sensor Data Processing

Training Curve: Learning progression of PPO and DQN models.

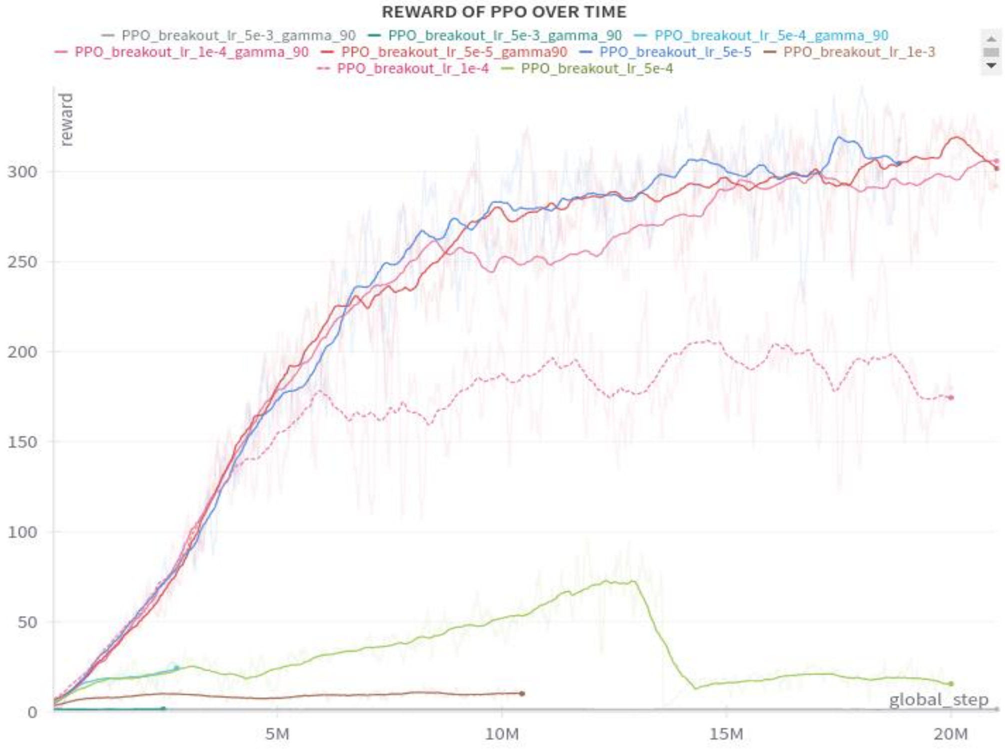

Figure 3. Learning Progression of PPO

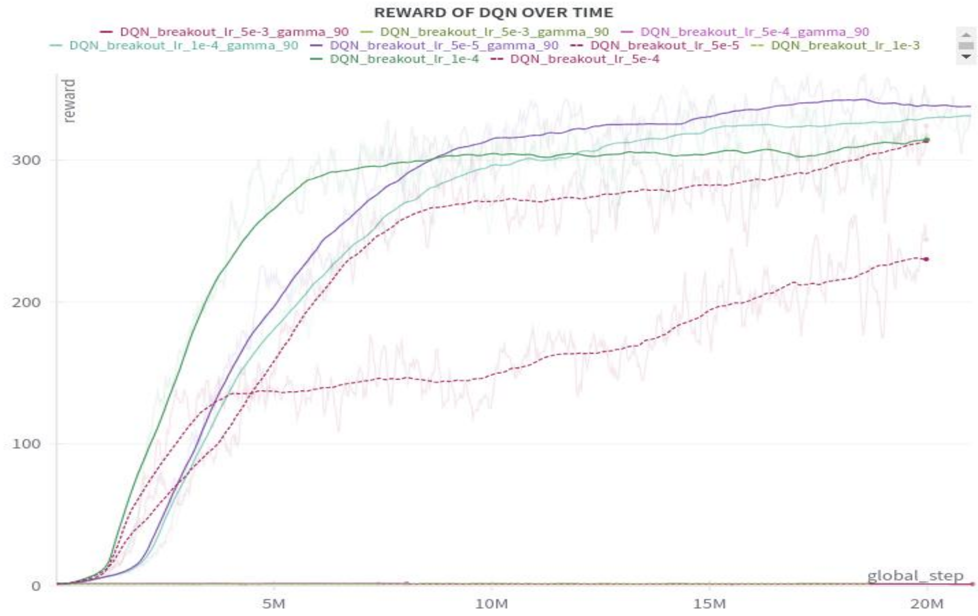

Figure 4. Learning Progression of DNQ

Reward Optimization: Graph showing cumulative rewards over training episodes.

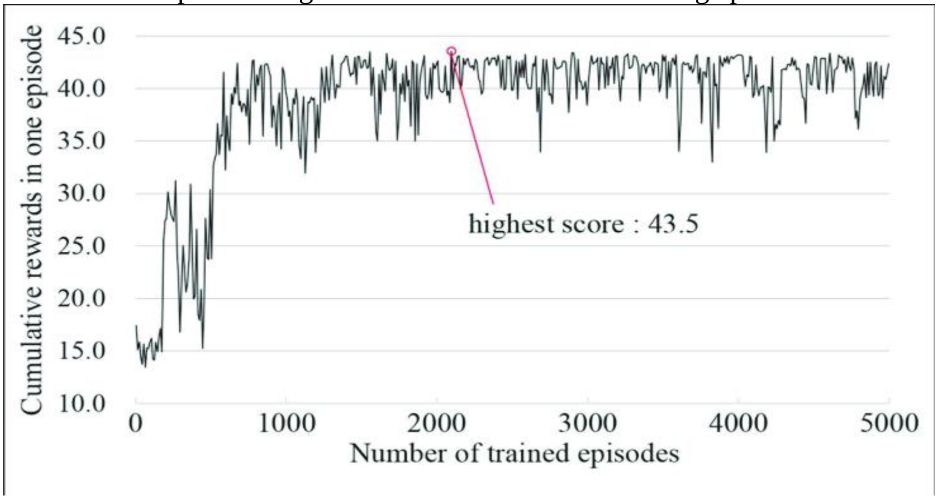

Figure 5. Reward Optimization

Robotic Performance Evaluation: Execution of RL-trained control strategies in a simulated environment.

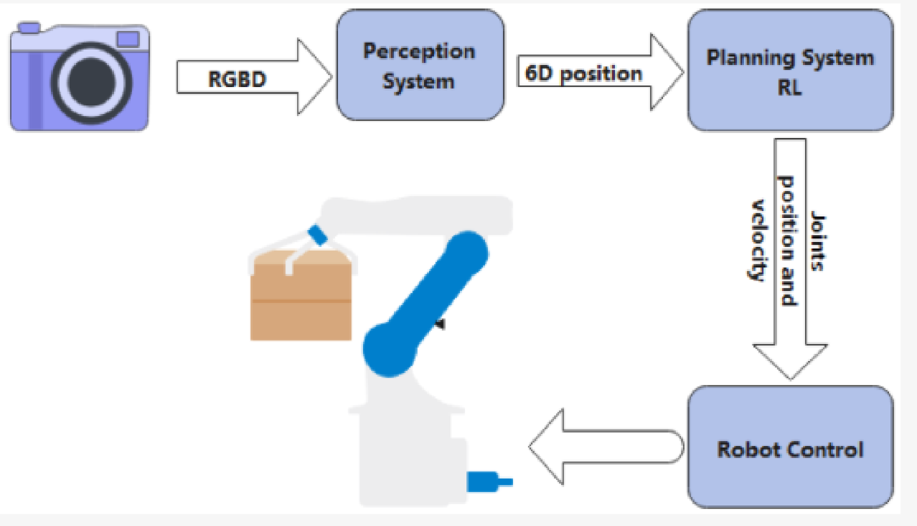

Figure 6. Execution of RL-trained control stratagies

5. Results and Discussion

Tools like ROTORS helped simulate UAV-specific scenarios, aiding in the development of flight strategies with reinforcement learning. The findings also align with the benefits of sliding mode control strategies in achieving higher tracking accuracy and robustness in unpredictable environments, as demonstrated in earlier works [8][9].

The results from the simulations demonstrate the efficacy of reinforcement learning-based controllers compared to traditional PID-based approaches. The PPO model showed superior stability and adaptability, while the DQN approach provided efficient control in structured environments. The cumulative reward graphs indicate progressive learning over time, with PPO achieving faster convergence.

Furthermore, integrating FBG sensors allowed enhanced real-time adaptability, significantly improving system response time. However, challenges such as computational complexity and hyper parameter tuning were encountered, suggesting future research directions focusing on optimizing RL models for real-time deployment in physical robotic systems.

6. Conclusion

This study highlights the potential of reinforcement learning in robotic control optimization. The integration of FBG sensor data with RL algorithms enables real-time adaptability, enhancing automation and precision. Future research should explore hybrid RL models and real-world deployment to further refine control strategies in robotics.

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