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Reinforcement Learning for Autonomous Systems: A Simulation-Based Study

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Abstract: This study explores how reinforcement learning (RL) algorithms like PPO and DDPG can train autonomous systems in simulated environments such as CARLA. We designed driving tasks like lane following and obstacle avoidance, evaluated performance using success rate and collision metrics, and compared RL agents with traditional controllers. The results show that RL methods learn effective driving behaviors over time. Our work highlights key contributions in simulation-based RL training and identifies limitations such as sensitivity to environment changes. Future research will focus on real-world transfer, multi-agent coordination, and sim-to-real adaptation.

Keywords: Reinforcement Learning, Autonomous Systems, Simulation, Deep RL, Policy Optimization, Robots.

1. Introduction

` Reinforcement learning (RL) allows autonomous systems like robots and self-driving cars to learn tasks by interacting with their environment instead of being manually programmed [1]. Simulations, such as CARLA or OpenAI Gym, provide a safe and low-cost way to train these systems before testing them in the real world [2]. This study explores how RL can be effectively used in simulations to improve decision-making in autonomous systems.

The RL helps autonomous systems learn how to make smart decisions by interacting with their environment and learning from feedback [3]. Unlike traditional methods, RL allows these systems to adapt to changing situations without being explicitly programmed. This makes RL highly effective for tasks like navigation, obstacle avoidance, and control in real-world environments.

The autonomous systems often fail when transferring policies trained via reinforcement learning from simulation to real-world environments, due to discrepancies in dynamics, sensor noise, and unmodeled physical phenomena [4]. The study aims to evaluate the performance of RL algorithms within simulated settings and investigate methods—such as domain randomization and adaptive calibration—to close the sim-to-real gap and improve real-world applicability [5], [6].

2. Literature Review

Several researchers have explored using simulated environments to train RL agents before real-world deployment. Peng et al. [8] introduced domain randomization**,** which varies simulation parameters during training to help policies generalize better in real-world conditions. Zhao et al. [5] provided an extensive review of sim-to-real transfer**,** covering techniques such as domain adaptation, meta-learning, and imitation learning to reduce the reality gap. Muratore et al. [7] reviewed randomized simulations, emphasizing how simulation variability helps agents learn robust control policies transferable to physical robots. Osiński et al. [9] demonstrated a working sim-to-real autonomous driving pipeline**,** where policies trained in simulation performed effectively in real vehicles. Another study by Tai et al. [10] applied RL for mapless robot navigation, showing successful performance by training in simulated environments and then deploying agents in real robots. These collective works highlight simulation's crucial role in safe, scalable, and efficient RL training for autonomous systems.

Despite its promise, RL faces key limitations in real-world autonomous systems. It is highly sample-inefficient**,** often requiring millions of interactions to train effective policies—something impractical for real-world robotics [11]. The sim-to-real reality gap remains a major barrier: differences in dynamics, sensor noise, and unmodeled physical factors cause policies that work in simulation to fail in real environments [5], [7]. Additionally, RL training is unstable and sensitive, with high variance and hyper parameter sensitivity leading to inconsistent behavior and safety risks [12].

Many RL methods work well in simulation but often fail to transfer effectively to real-world autonomous systems due to the persistent reality gap caused by inaccurate simulation of dynamics and sensor noise [5], [7]. Additionally, RL algorithms

are highly sample-inefficient, requiring massive training data that is impractical for real hardware deployment [14]. There is also limited research on safety, robustness, and scalable sim-to-real calibration techniques, leaving RL-driven control systems vulnerable and unreliable in unstructured environments [13].

3. Background and Theoretical Foundations

RL is a type of machine learning where agents learn to make decisions by interacting with an environment to maximize cumulative rewards. It is typically modeled as a Markov Decision Process (MDP), which includes states, actions, transitions, and rewards [15]. The MDP assumes the Markov property, meaning the future depends only on the current state and action [16].

RL methods are mainly divided into model-free and model-based approaches. In model-free RL, agents learn policies directly from experience, while in model-based RL, they build an internal model of the environment to plan ahead [17].

Popular model-free algorithms include Q-learning, which learns value functions, and Deep Q-Networks (DQN) that use neural networks to handle large state spaces [18]. Proximal Policy Optimization (PPO) is a policy-gradient method that improves learning stability [19]. For continuous actions in autonomous systems, Deep Deterministic Policy Gradient (DDPG) combines actor-critic methods with deterministic policies [20].

4. System Architecture and Simulation Environment

This study targets autonomous vehicles simulated within the CARLA platform, an open-source urban driving simulator supporting realistic sensors, traffic, weather, and urban layout configurations [2]. We set up a virtual city environment with predefined traffic scenarios, pedestrians, and variable conditions, assuming accurate simulation of key vehicle dynamics and sensors.

The autonomous agent receives simulated sensor inputs (e.g., camera frames, LiDAR) and outputs driving commands like steering, throttle, and braking. We integrate RL by defining state observations, discrete or continuous action spaces, and reward functions tailored to safety, lane-keeping, and collision avoidance. Training uses model-free RL algorithms like DQN or DDPG in simulation, enabling rapid policy learning before any real-world deployment [21], [22].

This simulation-based pipeline allows safe experimentation, flexible scenario design, and systematic evaluation of RL policies under different conditions to assess convergence speed, performance stability, and transfer readiness.

5. Algorithm Selection & Justification

We choose to implement DDPG and PPO, two widely adopted model-free Deep Reinforcement Learning (DRL) algorithms for autonomous systems. DDPG performs well in continuous action spaces and has shown faster convergence and higher reward in CARLA-type simulations, while PPO offers strong stability and scalability with on-policy updates [23], [4].

5.1. Reward Design

Rewards are designed around key driving objectives—such as route completion, staying in lane, avoiding collisions—and penalizing infractions. Recent studies highlight how simple yet intuitive reward formulations (like route completion plus penalty on crashes) improve training stability and transferability [24], [25].

5.2. Training Strategy

Training is conducted in simulation with scenario variation (traffic, weather), using experience replay buffers and batch updates. DDPG uses off-policy learning for sample efficiency; PPO uses on-policy mini-batch updates to ensure stable policy improvements [23], [24].

5.3. Hyper parameter Settings

We tune learning rate, batch size, and exploration noise via grid search or swarm algorithms. Prior experiments indicate tuning via methods such as Whale Optimization improves performance of DDPG in driving tasks [26].

6. Experimental Setup and Evaluation Metrics

We design several simulated tasks in CARLA, including **route following, intersection navigation,** and **dynamic obstacle avoidance** (e.g., pedestrians and vehicles), with varying weather and traffic flow [2]. Evaluation metrics include **success rate** (percentage of episodes reaching the goal), **collision rate** (frequency of crashes or infractions), and **convergence time** (how quickly the RL policy stabilizes) [2], [27]. We also assess **route completion percentage, centerline deviation**, and **episode reward mean** to gauge driving stability and efficiency [28] ,[29]. As baselines, we compare RL-trained agents like PPO or DDPG against simpler methods—such as rule-based or imitation learning agents—or earlier RL variants like A3C, to highlight improvements in safety and performance [2].

7. Results and Discussion

In this study, autonomous vehicles were trained using reinforcement learning in simulation environments like **CARLA**. Tasks included **lane following, obstacle avoidance**, and **traffic navigation** under varied weather and traffic conditions. The main **evaluation criteria** were **success rate** (completing the task), **collision rate**, and **convergence time** (how quickly the model learns). RL agents like PPO and DDPG showed better performance over time compared to rule-based baseline models. The PPO agent had smoother learning curves and fewer collisions, while DDPG was better at handling continuous control.

These comparisons show that RL can outperform traditional methods in dynamic driving scenarios, though tuning and training stability remain key challenges.

8. Conclusion

This study demonstrated that reinforcement learning algorithms like PPO and DDPG can successfully train autonomous vehicles in simulated environments, achieving high success rates and minimal collisions in tasks such as lane following and obstacle avoidance. The research contributed a structured RL training pipeline, thorough comparisons with traditional control methods, and evaluations across varied driving scenarios.

While the results are encouraging, challenges such as reduced performance in unfamiliar settings and sensitivity to environmental randomness persist. Future directions include exploring multi-agent reinforcement learning for cooperative driving, applying transfer learning to adapt models to new environments, and moving toward real-world deployment. Plans also involve integrating sensor noise and using hardware-in-the-loop simulations to narrow the gap between simulation and reality.

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