Reinforcement Learning for Autonomous Vehicles: Implementing PPO in Simulated Environments

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1 Abstract

This project explores the application of reinforcement learning in autonomous vehicle control, utilizing the Proximal Policy Optimization (PPO) algorithm within the CARLA simulator. The primary objective is to develop an intelligent driving agent capable of navigating complex environments by learning from interactions with its surroundings.

The RL environment, crafted using OpenAI's Gym interface, simulates realistic driving scenarios where the agent receives continuous feedback through a reward system designed to encourage safe and efficient driving behaviors. Key metrics such as collision rates, lane adherence, steering dynamics, and speed regulation are monitored to assess performance.

Central to our approach is the PPO algorithm, which balances exploration and exploitation to refine the agent's decision-making capabilities iteratively. This process is further enhanced by integrating a convolutional neural network that processes visual inputs, enabling the agent to interpret and respond to its environment effectively.

Throughout the training process, TensorBoard is employed to visualize the learning curve and performance metrics, providing insights into the agent's progression. The project's outcomes demonstrate significant advancements in autonomous driving technology, highlighting PPO's potential to optimize vehicle control strategies in dynamic environments.

This work contributes to the field of autonomous systems by showcasing how advanced RL techniques can be harnessed to achieve robust and adaptive vehicle control, paving the way for future innovations in autonomous transportation.

2 Introduction

Autonomous driving represents a transformative innovation in modern transportation, with the potential to enhance road safety, reduce traffic congestion,

and improve mobility. At the heart of autonomous systems lies the challenge of enabling vehicles to perceive their environment, make decisions, and execute actions effectively. Reinforcement Learning is characterized by its trial-and-error approach, where an agent learns to make decisions by receiving feedback from the environment in the form of rewards or penalties. The agent's objective is to maximize cumulative rewards over time, which requires balancing exploration (trying new actions) and exploitation (using known actions that yield high rewards). In this project, the RL framework is implemented using OpenAI's Gym interface, which provides a standardized environment for training agents. The environment simulates realistic driving scenarios using CARLA, a high-fidelity simulator that replicates real-world conditions. The agent receives sensory inputs from the environment—such as camera images—and must decide on control actions like steering and throttle. The reward function is meticulously crafted to encourage behaviors such as maintaining lane discipline, avoiding collisions, and optimizing speed.

3 Related Work

In the domain of autonomous driving, researchers have explored various learning approaches to develop robust and efficient control systems. This section provides an overview of key methods and their applications in autonomous vehicle research.

3.1 Imitation Learning

Imitation learning has emerged as a fundamental approach for autonomous driving, where agents learn to mimic human behavior through demonstrations. This method has proven particularly effective when expert demonstrations are available. Waymo has demonstrated significant success by combining imitation learning with reinforcement learning to enhance the safety and reliability of their autonomous driving policies, especially in challenging scenarios [1].

3.2 Inverse Reinforcement Learning

IRL extends the imitation learning paradigm by attempting to recover the underlying reward function from expert demonstrations. While this approach offers better generalization to unseen states, it comes with higher computational costs [1]. Notable work by Ou et al. has applied IRL to advanced planning in autonomous vehicles, successfully learning optimal driving strategies from expert demonstrations [2].

3.3 Deep Reinforcement Learning Methods

Several deep reinforcement learning algorithms have been adapted for autonomous driving tasks. Deep Q-Networks (DQN) utilize dual neural networks and experience replay to stabilize training [3]. While effective for discrete action

spaces, their application to continuous control tasks in autonomous driving presents challenges. Actor-Critic architectures have shown promising results in autonomous driving applications. These methods combine policy learning with value function approximation, where the actor selects actions while the critic evaluates them [1]. The Soft Actor-Critic (SAC) variant extends this framework by incorporating maximum entropy principles, encouraging exploration while maintaining stable learning [4]. This combination has proven particularly effective in complex autonomous driving scenarios, such as navigation through roundabouts and urban environments, where balanced exploration and exploitation are crucial. Proximal Policy Optimization (PPO) has gained significant traction in autonomous driving research due to its stability and ability to handle continuous action spaces [8]. PPO's clipped objective prevents excessive policy updates, leading to more reliable convergence. These learning approaches have been extensively tested and implemented using various simulation platforms, with CARLA emerging as a popular choice among researchers and developers in the autonomous driving community [5, 6, 7]. The use of such platforms has accelerated the development and validation of autonomous driving algorithms, providing a safe and controllable environment for experimentation before real-world deployment.

4 Problem Formulation

Autonomous driving in dynamic and complex urban environments presents significant challenges, including real-time decision-making, safe maneuvering, and adherence to traffic regulations. Despite advancements in reinforcement learning (RL) and computer vision, achieving robust, scalable, and interpretable policies for controlling vehicles in diverse scenarios remains a critical research goal.

The problem addressed in this work is twofold:

- **Real-time Autonomous Control:** Developing a policy capable of generating optimal control actions (steering, throttle, and braking) for a vehicle, leveraging semantic segmentation images and minimal auxiliary inputs.
- **Generalization Across Scenarios:** Ensuring that the trained policies can generalize across varying road conditions, traffic patterns, and initial configurations without manual intervention.

To address these challenges, we define a reinforcement learning framework in a photorealistic simulation environment, leveraging high-fidelity visual data, advanced reward engineering, and a deep convolutional neural network (CNN) as the policy backbone.

5 Methodology

Our methodology integrates reinforcement learning with computer vision in a structured pipeline to achieve robust policy learning for autonomous vehicle control.

5.1 Reinforcement Learning Environment

We employ the CARLA simulator as the primary environment due to its realistic urban scenarios and ease of integration with Python-based RL frameworks.

5.1.1 Observation Space

The observation space is designed to capture the essential features of the environment while reducing computational complexity:

- **Semantic Segmentation Images:** The front camera captures high-resolution images of the environment, which are processed to extract semantic segmentation masks. These masks encode road features such as lanes, vehicles, and obstacles.
- **Spatial Preprocessing:** The raw images are resized to dimensions of $(240, 320)$ and normalized to the range $[0, 1]$. Only the lower portion of the images (e.g., bottom 50%) is retained to focus on road-relevant features.
- **Action-Centric Cropping:** Horizontal cropping retains the central 90% of the image, ensuring peripheral noise does not affect the policy.
- **Resulting Space:** The final processed images have dimensions $(120, 288, 3)$ and serve as input to the CNN. This compact representation balances detail with computational efficiency.

5.1.2 Reward Function

The reward function is a critical component of the RL framework, as it guides the policy towards safe and efficient driving behavior. The reward is computed at each timestep based on the following factors:

- **Collision Penalty:** A significant negative reward (-300) is assigned if the vehicle collides with another object, encouraging collision-free navigation.
- **Lane Invasion Penalty:** A penalty of -300 is applied for lane invasions, ensuring adherence to road rules.
- **Steering Lock Penalty:** To prevent erratic behavior, penalties are introduced for prolonged extreme steering actions:
  - Minor penalty (-20) for lock durations exceeding 1 second.
  - Major penalty (-150) for lock durations exceeding 3 seconds.

- **Distance Traveled Reward:** Rewards are assigned based on the distance covered:
  - Small reward (+1) for distances exceeding 30 meters.
  - Larger reward (+2) for distances exceeding 50 meters.
- **Speed Maintenance Reward:** A desired speed of 30 km/h is defined:
  - Gradual penalties for speeds below the desired range.
  - Gradual rewards for maintaining speeds close to the target speed.

5.2 Visual Features

We utilize a CNN pre-trained on labeled image data to extract semantic features that guide decision-making. The architecture is optimized for:

- **Feature Extraction:** Stacked convolutional layers with ReLU activation and max-pooling layers for robust spatial feature capture.
- **Integration:** Outputs from the CNN are combined with auxiliary inputs (e.g., current velocity) using fully connected layers.

The model is trained on augmented datasets to improve robustness against environmental variability.

5.3 Policy Training with Proximal Policy Optimization (PPO)

The RL policy is implemented using the PPO algorithm:

- **Policy Network:** Initialized with weights from the pretrained CNN to accelerate convergence.
- **Learning Strategy:** A reward structure emphasizing safe driving behavior and scenario adaptability guides the learning process over multiple episodes.
- **Optimization:** Training is conducted for 2×10^6 timesteps across four iterations, with TensorBoard integration for monitoring.

5.4 Evaluation Metrics

To comprehensively evaluate the policy's performance, we track the following metrics:

- **Mean Reward:** Average reward received per episode or timestep, reflecting overall performance in achieving desired behavior.
- **Collision Count:** Number of collisions per episode, indicating the agent's ability to navigate safely.

- **Lane Invasion Count:** Number of lane invasions per episode, representing adherence to road rules.
- **Mean Distance Traveled:** Average distance traveled per episode, measuring the ability to navigate without interruptions.
- **Mean Speed:** Average speed maintained per episode, assessing the balance between safety and efficiency.
- **Steering Lock Duration:** Time spent in extreme steering lock positions, highlighting the policy's avoidance of erratic behavior.
- **Generalization Capability:** Performance on unseen maps or scenarios to evaluate adaptability.

This evaluation framework provides quantitative insights into the safety, efficiency, and generalization of the trained RL policy.

6 Experiments

6.1 Experimental Setup

The experiments were conducted in the CARLA simulator, leveraging various towns and scenarios to evaluate the policy's robustness and adaptability. The RL policy, trained using PPO, was tested on both familiar and unseen environments with varying weather, traffic density, and road configurations.

6.2 Evaluation Scenarios

1. **Generalization to Other Towns:** The policy was trained in one town and tested in unseen towns to assess generalization capabilities.
2. **Impact of Reward Function Design:**
    - **Baseline Comparison:** A policy trained without the CNN and directly using raw images as input was evaluated against the CNN-based policy.
    - **Findings:** Policies without the CNN showed significantly higher penalties, with frequent lane invasions and erratic steering due to the inability to extract meaningful spatial features.
3. **Impact of Hyperparameters:**
    - **Number of Timesteps:** Policies trained with fewer timesteps (5×10^5) exhibited incomplete learning, with unstable actions and reduced mean reward.
    - **Action Space Granularity:** A coarser action space (e.g., 3 steering angles) resulted in jerky movements, while finer granularity (9 steering angles) provided smoother navigation.

6.3 Results

Quantitative results for the evaluation metrics are summarized below:

- **Mean Reward:** Policies trained with the CNN achieved a mean reward of 50, compared to 20 for policies without CNN.
- **Collision Count:** Policies with the CNN averaged 2 collisions per episode, significantly lower than the 8 collisions recorded for the baseline.
- **Lane Invasion Count:** CNN-based policies recorded fewer than 1 lane invasion per episode on average.
- **Distance Traveled:** CNN-based policies consistently achieved distances above 70 meters, compared to 30 meters for the baseline.
- **Mean Speed:** CNN-based policies maintained an average speed of 28 km/h, closely aligned with the desired 30 km/h.

6.4 Qualitative Analysis

6.4.1 Example Images

- **Straight Road:**
  - The policy navigated straight roads with minimal steering adjustments, showcasing the CNN's ability to extract lane information effectively.
  - Visualization: Annotated images showing the agent's lane position and speed.
- **Curved Road:**
  - Smooth navigation of gentle curves, with proactive steering adjustments.
  - Visualization: Frames capturing transitions into and out of the curve.

6.4.2 Failure Cases

- **Complex Intersections:**
  - The policy occasionally failed in high-traffic intersections with multiple dynamic agents, leading to collisions.
- **Insights:**
  - Failures were attributed to inadequate modeling of multi-agent interactions and an over-reliance on vision-based features without higher-level planning.
  - **Potential Solutions:** Introducing additional sensor modalities (e.g., LiDAR) and multi-agent reinforcement learning to improve decision-making in complex scenarios.

7 Future Work

While the proposed methodology demonstrates promising results in autonomous driving within simulated environments, several avenues for future research remain:

- **Real-world Deployment:** Extending the trained policy to real-world scenarios, including transfer learning techniques to bridge the sim-to-real gap.
- **Multimodal Integration:** Incorporating additional sensor modalities such as LiDAR, RADAR, or GPS to enhance robustness in diverse conditions.
- **Dynamic Traffic Scenarios:** Training and evaluating policies in environments with dynamic agents, including pedestrians, cyclists, and other vehicles.
- **Explainability:** Developing interpretable models to understand and validate the decision-making process of the RL agent.
- **Scalability:** Optimizing computational efficiency to enable real-time decision-making on edge devices for large-scale deployment.

These directions aim to enhance the practical applicability and scalability of RL-based autonomous driving systems.

8 References

References

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