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Implementation of Self Driving Car using DRL & Carla

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Abstract: Research on self-driving automobiles is one of the many areas in which artificial intelligence (AI) is expanding rapidly in technology. Deep learning and reinforcement learning have attracted a lot of attention in recent years, which has fueled rapid progress in this field, particularly in subsystems that rely on vision. Our primary output is a PPO-based agent capable of reliably learning how to drive within our CARLA-based environment. To assist our agent learn more quickly, we also constructed a Variational Autoencoder (VAE), which compresses high-dimensional data into a low-dimensional latent space that may be simpler to understand. the goal of this effort is to create an end-to-end autonomous driving system that can communicate with the car and give directions to assist steer it in the proper direction and minimize collisions we will be free to apply cutting-edge techniques.

Keywords: Carla Simulator, Self-Driving Car, Deep Reinforcement Learning (DRL), Machine Learning, Autonomous Driving

1. Introduction

The development of self-driving automobiles, which hold the potential to improve mobility, lessen environmental impact, and provide safer roadways, is a major turning point in the history of transportation technology. Researchers and engineers are leading efforts to build autonomous driving systems that can navigate complicated urban landscapes with human-like skill, by utilizing advances in deep learning and simulation platforms such as CARLA.

Combining deep learning algorithms with the CARLA simulator offers a compelling way to test and develop self-driving technologies more quickly in a scalable and controlled environment. The project intends to solve issues with safety, scalability, and practical implementation while breaking new ground in autonomous driving research by utilizing neural networks' capacity for perception, reasoning, and action.We demonstrate the system's capacity to handle challenging settings, follow traffic laws, and guarantee passenger safety in a variety of environmental conditions by combining perception, decision-making, and control modules in a synergistic way. Through the detailed explanation of our methodology and the performance of the system as demonstrated by extensive testing and assessment, we want to add to the body of knowledge that is propelling the development of autonomous vehicle technology.

2. Motivation

The developments in automobile technology, especially in driverless cars, are exciting and motivating for me as a computer science student. There is a great deal of promise for these technical advancements to improve mobility and road safety. Working on a project involving autonomous cars provides a special chance to gain extensive knowledge and expertise in important fields including robotics, deep learning, and reinforcement learning.Getting involved in autonomous vehicle projects is a great way to improve your deep learning, reinforcement learning, and robotics abilities while also gaining invaluable experience that can help you further your career. Rapid changes in the automotive sector are driving up need for qualified workers with experience in robotics, machine learning, and artificial intelligence. Participating in such initiatives establishes you as a qualified and attractive applicant who can help develop cutting-edge solutions that influence mobility and transportation in the future.

3. Literature Review

Ahmad El Sallab, Mohammed Abdou, Etienne Perot and Senthil Yogamani (2017) "Deep Reinforcement Learning framework for Autonomous Driving" provides a comprehensive overview of recent advancements in Deep Reinforcement Learning (DRL) applied to autonomous driving . The proposed DRL framework integrates RNNs for handling Partially Observable MDP scenarios and attention models to optimize computational complexity. [1]

I Sonata , Y Heryadi, L Lukas and A Wibowo (2021) "Autonomous car using CNN deep learning algorithm" It focuses on using CNN for recognizing the surrounding environment to enable automatic navigation in autonomous vehicles. The study highlights the shift towards artificial intelligence and machine learning in autonomous vehicle technology, emphasizing image recognition for navigation. The CNN model processes images from cameras to predict steering commands, demonstrating successful autonomous driving in simulations. [2]

R. S. Sutton and A. G. Barto (2018) "Book Reviews Reinforcement Learning". It highlights the fusion of psychological traditions, optimal control theory, and learning concepts that underpin reinforcement learning algorithms. The review emphasizes the book's focus on machine learning and artificial intelligence, detailing how it explores the concepts of reward functions, state-action pairs, value functions, and policies in reinforcement learning. Additionally, it discusses the mathematical background assumed for readers, the importance of the reward function in defining an agent's objectives, and the continuous updating of the value function based on experienced consequences. [3]

Koustava Goswami (2019) "Decision Making for Autonomous Car Driving using Deep Reinforcement Learning (DRL)" discusses the use of LSTM in machine translation, attention models in deep learning, and the application of deep reinforcement learning in autonomous car driving. It highlights the challenges of autonomous driving, the importance of simulation, and the role of simulators like CARLA in training autonomous agents effectively. [4]

Ekim Yurtsever, Linda Capito, Keith Redmill and Umit Ozguner (2020) "Integrating Deep Reinforcement Learning with Model-based Path Planners for Automated Driving" it proposes a hybrid approach that integrates path planning into a vision-based DRL framework to address the shortcomings of both traditional and pure learning-based methods. This hybrid method involves training a DRL agent to follow waypoints generated by a path planner while interacting with the environment, with a reward function emphasizing collision avoidance and adherence to the planned path. The study presents a general framework for integrating path planners into DRL agents, implemented with an A* planner and a DQN RL agent. [5]

This provides a discussion about the related surveys of scholarly sources that have been made on this topic. It provides an overview of current knowledge, and identifies relevant theories, methods, in the existing researches that had been carried out so far.

4. Proposed System

The suggested architecture for the self-driving automobile system integrates semantically segmented (SS) pictures and external characteristics obtained from the CARLA simulator as its primary inputs. Pixel-by-pixel identification of roads, pedestrians, automobiles, and backdrops may be found in these SS pictures. In addition, external factors like the time of day or the weather improve contextual awareness of the driving environment. These inputs are subsequently processed by a pretrained auto-encoder, a neural network designed for unsupervised learning.The auto-encoder reduces dimensionality by compressing the SS images into a bottleneck encoding representation, which is lower-dimensional and maintains significant environmental features. The next policy network uses this bottleneck encoding together with the external characteristics as input. The policy network uses the decoded picture and contextual data to build the control actions for the self-driving automobile.For safe and efficient navigation, it generates projected steering angles ($\hat{s}$) and anticipated throttle angles ($\hat{t}$), which are utilized to calculate the appropriate steering and acceleration/deceleration commands. By using sophisticated image processing methods and machine learning algorithms, this design aims to make it easier for autonomous vehicles to navigate complex environments.

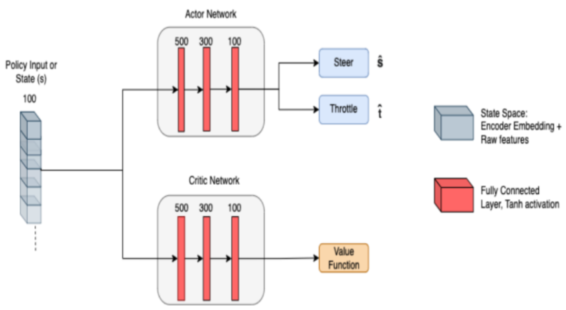

Figure 1: Proposed System

5. Methodology

- Front Camera (SS) Image: The system receives as input an image that was taken by the front camera of the vehicle. The system uses this picture as its raw observation.
- Encoder: The encoder of the VAE processes the picture input to produce a latent space representation. This compressed form of the image, known as the latent space representation, captures the key elements of the scene.
- Reward: In response to the agent's behavior, the CARLA environment sends it a reward signal. The agent may learn which behaviors are bad (like running into things) and which are desirable (like staying on the road) with the aid of this reward signal.
- PPO: The reward signal from the environment and the latent space representation from the VAE's encoder are inputs to the Proximal Policy Optimization (PPO) agent. It learns a policy for driving the automobile using this data. The policy connects actions (like as steering and throttle control) with latent spatial representations, or what the vehicle perceives.
- (Steer, Throttle): The latent space vector, which represents the current state, is used by the PPO agent to output steering and throttle commands. The CARLA simulator receives these commands and uses them to control the car's movement.
- New State: The vehicle responds to steering and throttle orders from the agent in the CARLA environment. As a result, the automobile takes on a new condition, or appearance.

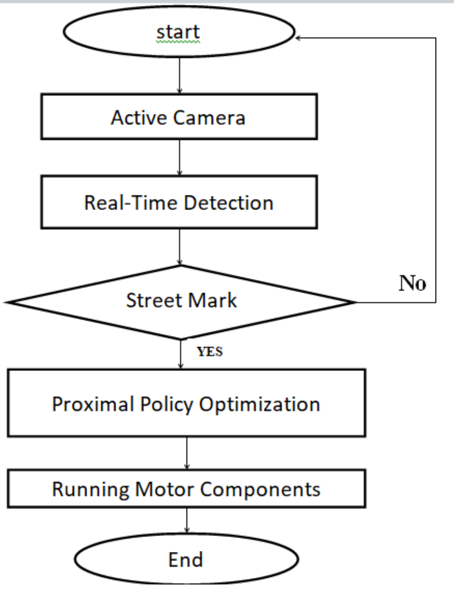

Figure 2: Workflow

Step 1: Start
- The procedure gets started.

Step 2: Active Camera
- The camera is turned on by the system to begin recording live footage of the surroundings.

Step 3: Real-Time Detection
- The technology analyzes the video stream to instantly identify pertinent elements and objects. This probably involves spotting obstructions, traffic signals, street markings, etc.

Step 4: The Decision Point, or Street Mark
- The system looks for the presence of roadway markings.
- No: Should the system fail to identify any street markings, it may proceed with an alternate course of action, which may entail stopping the vehicle.
- In the event that street markings are found, the procedure proceeds.

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Step 5: Proximal Policy Optimization

- The PPO algorithm is used to process the information that has been found. Models are trained using PPO, a reinforcement learning method, to make decisions depending on input data. It probably determines how the automobile behaves in this situation (steering, acceleration, braking).

Step 6: Running Motor Components

- The PPO algorithm's decisions are converted into actions. Using information from the recognized street markings and other environmental elements, the car's motor components are regulated to follow the intended course.

Step 7: End

- After completing one iteration, the process either terminates or loops back to carry out the original job.

6. Results

Figure 3: Initial State of the Car

Figure 4: The Car starts controlling the Steering

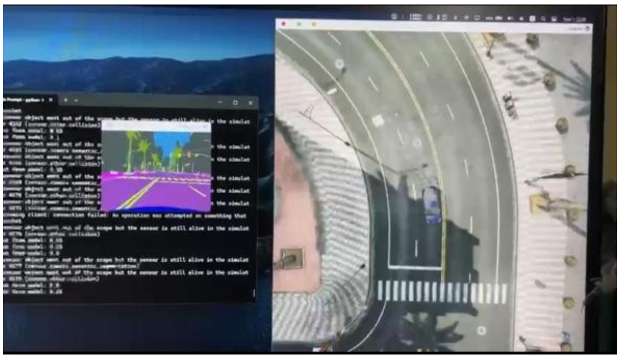

Figure 5: The Car start taking decisions to take left or right

7. Conclusion

In this experiment, we have examined many approaches to the construction of autonomous driving bots using deep reinforcement learning. Our results validate the idea that variational autoencoders help expedite DRL agents' learning process. Furthermore, we have offered a comprehensive examination of the ways in which various state representations affect the agents' performance. We have successfully created a standalone DRL system that can be used in combination with CARLA, despite some challenges in setting up the final environment in CARLA. We offer a method that combines front camera views and control values with waypoints as external input features. Additionally, we created an architecture that uses an on-policy DRL algorithm (Proximal Policy Optimization) to learn planning and control directly from semantically segmented pictures and external data. Remember that it was done in the absence of any dynamic actors, and the agent picked up effective navigation techniques. To further evaluate and disentangle the representation issue in policy learning, we suggest focusing on policy learning using low-dimensional features. Numerous techniques, such as value-based and policy-based algorithms, are produced by this self-learning algorithm, and each of these approaches is claimed to address a distinct issue. To reference our work, we developed an autonomous driving agent by applying a variety of approaches to the CARLA environment.

8. Future Scope

There are several ways in which this work might be extended in the future. Try alternative state-of-the-art off-policy algorithms that operate in continuous domains and are more resilient to perturbations in the hyperparameters, including TD3, SAC, and DDPG. It is also possible to discretize and define the continuous action domain for Dueling Deep Q networks, Double Deep Q networks, and so on. It is also necessary to tackle some open challenges, such as defining the optimization problem with imitation learning or reinforcement learning goals, in order to achieve the best potential outcomes. When these two learning paradigms are combined, this can be improved even further.

9. Social Relevance

When paired with Deep Reinforcement Learning (DRL), the advanced simulation platform CARLA becomes a crucial component in determining the course of autonomous vehicles, which has the potential to greatly enhance society. The social norms might be drastically altered by this combination of technology. By significantly enhancing safety protocols, expanding accessibility to mobility options, and minimizing environmental consequences through optimal driving algorithms, it lays the groundwork for a more productive and sustainable society.

Furthermore, the integration of DRL and CARLA fosters innovation and creates new business and job opportunities in the IT and automotive industries, all of which support economic growth. Examining these systems' complexities from an educational perspective offers invaluable learning opportunities that prepare the future generation to function in a technologically advanced world and traverse it. Therefore, it is essential that this field's research and development continue in order to both pave the way for new discoveries and allow individuals and society to fully benefit from the promise of cutting-edge technology.

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