Lane following on monocular visual features

Dzhavid Sadreddinov
Innopolis University, Russia
d.sadreddinov@innopolis.university

Diana Vostrova
Innopolis University, Russia
d.vostrova@innopolis.university

Alsu Khairullina
Innopolis University, Russia
a.khairullina@innopolis.university

***Abstract*—This project develops an autonomous driving agent using reinforcement learning in the CARLA simulator. The agent will rely on visual features: predicted semantic maps and depth maps from sensor. These features, combined with vehicle data like velocity and steering, will serve as input for training a Proximal Policy Optimization (PPO) agent. The goal is to improve the agent's decision-making and navigation by leveraging enhanced visual understanding of the environment.**

I. Introduction

The project focuses on developing a novel autonomous driving agent in the CARLA simulator using reinforcement learning. Unlike prior models, this agent relies primarily on RGB image data, eliminating the need for training a depth estimation model. Key methodologies include training a U-Net for semantic segmentation and utilizing a Variational Autoencoder (VAE) to compress semantic and depth map features for effective decision-making. By leveraging these compact features alongside navigational observations, the Proximal Policy Optimization (PPO) algorithm is employed to optimize driving strategies. Additionally, the project explores incorporating ground-truth depth data to enhance feature representation during inference.

II. Related work

A. UNet for semantic segmentation

Semantic segmentation has been a cornerstone in computer vision tasks, with U-Net emerging as one of the most widely used architectures. Initially designed for biomedical image segmentation, U-Net has proven effective across various domains due to its encoder-decoder structure and skip connections, which preserve spatial information. Recent applications in autonomous driving leverage U-Net for pixel-wise classification of road elements, aiding in better scene understanding. Studies have shown its effectiveness in real-time segmentation tasks, achieving high accuracy even on low-resolution inputs, making it suitable for computationally constrained environments like CARLA simulations.

B. VAE for feature compression

VAEs are popular for learning compact and meaningful latent representations of high-dimensional data. They have been extensively applied in tasks such as generative modeling and feature encoding. In the context of autonomous driving, VAEs have been used to compress complex features such as semantic maps and depth data into lower-dimensional representations, facilitating faster and more stable decision-making processes. Previous research highlights the ability of VAEs to encode semantic information while retaining crucial environmental details, thereby optimizing downstream tasks like reinforcement learning.

C. PPO for controling agent

PPO is a widely used reinforcement learning algorithm known for its stability and sample efficiency. It builds on earlier policy gradient methods by introducing a clipped objective function to prevent drastic policy updates, ensuring smooth learning. In autonomous driving, PPO has demonstrated success in training agents for complex navigation tasks by using state observations such as images, depth maps, and semantic features. Existing literature emphasizes PPO's adaptability to various input modalities and its robustness in dynamic environments, making it a suitable choice for this project.

III. Method

A. Data Collection

The dataset for this project was collected using the CARLA simulator, where an autonomous vehicle was driven through urban environments following random predefined safe trajectories. The noise was added to location and rotation for stabililty.

B. Semantic Segmentation

A U-Net architecture was trained on 80% of the dataset to produce semantic segmentation masks. The model employed data augmentation techniques such as random horizontal flipping to improve generalization. Mean IOU - 0.7 across 13 classes (including roads, sidewalks, roadlines and others).
The reduction in the number of channels was necessary to fit the model into memory, which also improved inference speed, crucial for real-time applications. The segmented outputs were used to provide the agent with structured scene understanding, distinguishing elements such as roads, sidewalks, and obstacles.

C. Feature Fusion

To compress the semantic segmentation masks into compact, meaningful representations, a Variational Autoencoder (VAE) was employed. The VAE was trained to encode semantic maps into a latent vector of size 50. The encoder-decoder architecture of the VAE ensured minimal loss of semantic information while significantly reducing data dimensionality.

This compression step was critical for efficient integration with reinforcement learning, enabling faster processing while preserving key features.

D. Reinforcement Learning

A Proximal Policy Optimization (PPO) algorithm was trained to control the vehicle's actions, using a state vector formed by concatenating compressed semantic features with navigational observations. The agent learned a policy by interacting with the CARLA environment and optimizing rewards. The reward function was designed to encourage:

1) Lane Centering: Rewards increased for maintaining proximity to the lane center.
2) Alignment: Incentives were given for driving parallel to lane markings.
3) Speed Regulation: Velocity rewards were scaled based on adherence to a target speed, avoiding extremes.

An episode was considered complete under specific conditions: if the distance from the lane center exceeded a defined threshold, if the vehicle's speed surpassed a safety limit, or if a collision occurred. These termination criteria ensured the agent focused on safe and efficient driving behaviors.
The stability and efficiency of PPO were attributed to the clipped objective function, which prevented drastic policy changes and maintained smooth learning.

IV. Github Link

Source code

V. Experiments and Evaluation

To enhance the diversity and robustness of the dataset, noise was intentionally added to the vehicle's location and rotation parameters. This approach ensured that the dataset contained instances where the car deviated from the ideal driving path, simulating real-world conditions such as navigation errors or unpredictable maneuvers. The collected data included RGB images, semantic segmentation masks, and navigation variables such as throttle, velocity, and steering angle. This diversity in the dataset aimed to prepare the model for handling in-domain variations and improve its generalization to novel scenarios during reinforcement learning.
The MiDaS depth estimation model was initially trained on our dataset and achieved a mean absolute error (MAE) of 0.06323. However, the inference time of the model was slow, leading to inefficiencies in agent learning. As a result, the use of the depth estimation model was discontinued. Currently, we rely solely on semantic segmentation features, but we also have the option to append the ground truth depth map directly from the sensor to enhance the model's performance.

VI. Analysis and observations

A. Model Efficiency

One of the key improvements in our approach was replacing the depth estimation model with a more efficient RGB-based methodology. By eliminating the need for real-time depth estimation during inference, we reduced computational overhead significantly. This not only accelerated the agent's learning process but also enhanced the overall system's responsiveness. Despite this simplification, the performance of the autonomous agent remained on par with or slightly better than models that relied on depth estimation, indicating that the model can operate efficiently without compromising its decision-making capabilities.

B. Feature Representation

A critical part of our approach was the use of a Variational Autoencoder (VAE) to compress both semantic and depth map features into compact state vectors. This compression allowed the agent to efficiently process these features while maintaining a rich representation of the environment. The VAE successfully encoded the high-dimensional input data into lower-dimensional latent spaces, enabling the agent to capture essential environmental information for decision-making. This representation not only improved the PPO agent's learning stability but also reduced the complexity of the state space, contributing to faster convergence and more reliable performance during training.

C. Ground-Truth Depth

Incorporating ground-truth depth data during inference provided marginal improvements in the agent's performance, particularly in scenarios requiring precise spatial understanding, such as obstacle avoidance and path planning. However, the additional depth information did come at the cost of increased computational complexity. The depth data, while enhancing feature richness, introduced additional processing steps and storage requirements, which made the system less efficient overall. Despite these trade-offs, the slight improvement in the agent's decision-making ability, especially in dynamic environments, suggests that ground-truth depth could be a valuable addition in situations where performance gains justify the added computational load.

VII. Conclusion

This project successfully developed an autonomous driving agent in the CARLA simulator, utilizing reinforcement learning techniques to enhance decision-making and navigation. By relying primarily on RGB image data and semantic segmentation, along with compressed feature representations via a Variational Autoencoder (VAE), we were able to achieve efficient agent training and stable learning dynamics with the Proximal Policy Optimization (PPO) algorithm.

The decision to replace depth estimation with RGB-based approaches proved effective in reducing computational overhead without compromising the agent's performance. The VAE provided a powerful tool for encoding complex environmental information into compact state vectors, further improving the learning process. Additionally, while the integration of ground-truth depth data during inference offered marginal improvements in the agent's decision-making ability, it also introduced additional complexity, suggesting that its benefits might not justify the added computational cost in most scenarios.

Overall, the results highlight the feasibility of leveraging simplified visual features, such as semantic segmentation and RGB images, for autonomous driving tasks, achieving efficient performance without the need for real-time depth estimation. Future work could explore further optimizations to refine the balance between computational efficiency and the use of richer sensory data like depth, potentially incorporating more advanced feature fusion techniques to improve robustness and performance in complex driving environments.

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