EE381 | Robotics – I

Project Proposal

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Towards Collaborative and Fuel-Efficient Maneuvers for Autonomous Vehicles

1 Abstract

The growing prevalence of autonomous vehicles necessitates robust decision-making algorithms that optimize not only safety but also fuel efficiency. This paper proposes a novel approach that leverages multi-agent coordination and deep reinforcement learning to achieve these goals. Building upon existing game-theoretic frameworks for lane-changing scenarios, we extend the model to include interactions with multiple surrounding vehicles. This allows autonomous vehicles to anticipate and react strategically to the actions of others, promoting smoother traffic flow and reducing the likelihood of unnecessary braking or acceleration. Furthermore, the model integrates a fuel optimization variable, enabling autonomous vehicles to dynamically adjust their speed and trajectory to minimize fuel consumption while maintaining safety and adhering to traffic regulations.

2 Introduction

The widespread adoption of autonomous vehicles (AVs) holds immense promise for revolutionizing transportation. However, for this technology to reach its full potential, robust decision-making algorithms are paramount. Beyond ensuring safety, these algorithms must optimize fuel efficiency to address environmental concerns and operational costs. This paper presents a novel approach that leverages multi-agent coordination and deep reinforcement learning to achieve these objectives.

2.1 Challenges in Single-Agent Decision Making

Current research on AV decision-making often focuses on single-agent scenarios, where the vehicle primarily considers its own state and the immediate surrounding environment. Although this approach can achieve basic functionality, it overlooks the crucial element of interaction with other vehicles on the road.

2.2 Our Contributions

This paper builds upon existing advancements by proposing a novel approach with the following key contributions:

- **Multi-Agent Coordination:** We extend the existing multi-agent framework to consider interactions with a larger number of surrounding vehicles. This allows for more nuanced decision making, enabling AVs to anticipate and react strategically to the maneuvers of others, fostering smoother traffic flow and reducing unnecessary braking or acceleration events.
- **Fuel Efficiency Optimization:** We introduce a fuel optimization variable into the model. This allows AVs to dynamically adjust their speed and trajectory to minimize fuel consumption while maintaining safety and adhering to traffic regulations. Through DRL, the vehicles can learn optimal behaviors that balance these competing objectives.

3 Methodology

This paper proposes a novel approach for collaborative and fuel-efficient maneuvers in autonomous vehicles through the combination of multi-agent coordination and deep reinforcement learning (DRL).

3.1 Multi-Agent Environment Design

- Define the traffic scenario and road network with varying levels of complexity.
- Specify the number and types of surrounding vehicles as agents within the environment.

3.2 State and Action Space Definition

- Define the state space that describes the environment from the AV's perspective. This could include information like its own speed, position, surrounding vehicles' positions and speeds, traffic signals, and road infrastructure.
- Define the available actions for the AV, such as maintaining speed, changing lanes, or adjusting acceleration/deceleration.

3.3 Fuel Efficiency Modeling

- Develop a fuel consumption model that considers factors like vehicle speed, acceleration, and road grade item & integrate this model into the reward function for the DRL agent.

3.4 Deep Reinforcement Learning

- We extend the existing multi-agent framework to consider interactions with a larger number of surrounding vehicles. This allows for more nuanced decision making, enabling AVs to anticipate and react strategically to the maneuvers of others, fostering smoother traffic flow and reducing unnecessary braking or acceleration events.
- We introduce a fuel optimization variable into the model. This allows AVs to dynamically adjust their speed and trajectory to minimize fuel consumption while maintaining safety and adhering to traffic regulations. Through DRL, the vehicles can learn optimal behaviors that balance these competing objectives.

3.5 Evaluation and Analysis

- Evaluate the performance of the trained model in various traffic scenarios. Metrics could include average fuel consumption, traffic flow efficiency, and safety measures.
- Analyze the learned behaviors of the AVs to understand how they achieve fuel efficiency while coordinating with other agents.
- Compare the results with existing single-agent or non-fuel-optimized multi-agent approaches to highlight the benefits of the proposed method.

4 Block Diagram

Fig. 1 illustrates the proposed approach for collaborative and fuel-efficient maneuvers in autonomous vehicles. The system operates within a simulated environment (World) where the AV perceives its surroundings using sensors. A Deep Reinforcement Learning (DRL) algorithm analyzes this sensor data in conjunction with a fuel consumption model to make optimal control decisions. These decisions are then translated into control signals for the AV's steering, influencing its movement within the simulated environment.

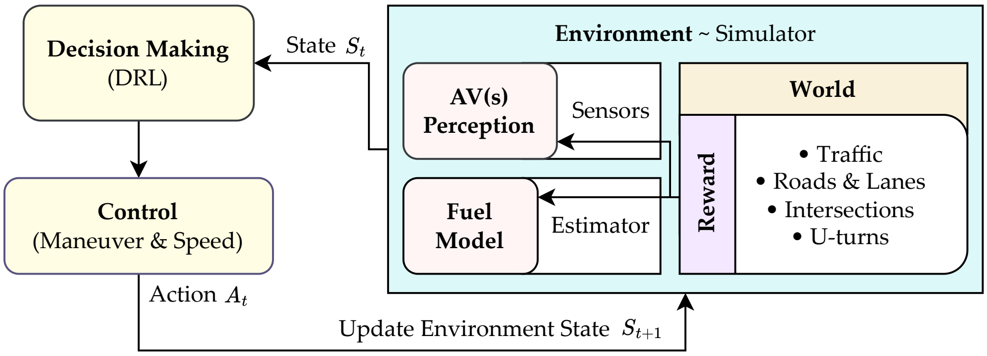

Figure 1: Block Diagram of Collaborative and Fuel-Efficient AV Maneuvers

5 Conclusion

This paper introduces a novel approach for autonomous vehicles, leveraging multi-agent coordination and deep reinforcement learning. By enabling AVs to anticipate surrounding vehicles' actions and prioritize fuel efficiency, this approach has the potential to significantly improve traffic flow and reduce emissions. Further research can explore communication protocols, real-world data integration, and adaptation to different vehicle types to enhance practical applications.