Toward a Multi-Agent Approach for Dynamic Traffic Control and Optimization

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***Abstract*—**

I. Introduction

LLMs are AI models that have been trained on extensive text datasets, allowing them to understand and process human language in a way that resembles human thinking. They can follow logical steps, explain their reasoning, and adapt to unfamiliar situations, making them particularly valuable for addressing long-tail edge cases in autonomous driving. [1]

A MAS consists of multiple autonomous agents that communicate and cooperate to achieve both individual and shared goals. For AVs, this means that vehicles can share information in real-time, coordinate their actions, and make better decisions during edge cases or complex situations.

II. Backgruound

Recent research explores integrating Large Language Models (LLMs) into autonomous vehicles to enhance decision-making and safety. Integrating LLMs can improve decision-making, personalization, and transparency [2]. This study investigated how LLMs can be utilized in self-driving scenarios to interpret, interact with, and reason about the driving environment. It also examined how LLMs can personalize the driving experience by adjusting driving behaviors based on verbal commands from passengers. The findings showed that using chain-of-thought prompting with LLMs resulted in better driving decisions, demonstrating the potential of LLMs to enhance the driving experience through continuous verbal feedback from passengers. This paper provides a comprehensive review of the application of multi-agent reinforcement learning (MARL) techniques in the field of connected and automated vehicles (CAVs) control, covering the advantages of MARL, its applications on various control dimensions, the simulation platforms used, and the challenges and potential solutions for deploying MARL in CAV control. [3]

III. Methodology

This section will tell how i gonna do this

IV. Conclusion

Autonomous vehicles (AVs), also known as self-driving cars, are designed to operate with minimal or no human input. These vehicles use a complex system of sensors, cameras, radar, and artificial intelligence (AI) to perceive their surroundings, make decisions, and control movement. AVs aim to make roads safer by reducing human errors, like distraction or fatigue, that are responsible for 94 percent of accidents. AVs are classified into six levels (0-5) of automation, [4]

- Level 0: No automation; the driver handles everything.
- Level 1: Basic automation, such as providing lane-change signals.
- Level 2: Partial automation; systems like Tesla's Autopilot assist with steering and acceleration.
- Level 4: High automation; systems like Waymo's driverless taxis operate without human input in specific areas.
- Level 5: Full automation; the vehicle can handle all driving conditions without any human input, but this level remains a challenge today.

Tesla was the first company to commercialize AVs with their Autopilot system in 2014 that offered level 2 autonomy. Waymo has launched their driverless taxi service with level 4 autonomy in 2018 in the metro Phoenix area in USA with 1000 – 2000 riders per week, among which 5 – 10 percent of the rides were fully autonomous. [5] Autonomous vehicles (AVs) have made significant progress, but they still struggle to make complex decisions, especially in unpredictable environments. This is evident in scenarios like partial road construction, where AVs might misinterpret signs or fail to anticipate other vehicles' actions. We aim to do some contribute for level 5. AVs can handle many known scenarios using pre-trained models, they struggle with unknown-unsafe situations, unpredictable conditions where their pre-programmed knowledge falls short. Human drivers can draw on common sense and past experiences to make sense of unusual situations, like recognizing that traffic cones on a truck are not a threat. But current AV systems, even those using rule-based approaches or reinforcement learning (RL), struggle in these scenarios. This limitation is especially evident in what we call ”unknown-unsafe” regions—situations where the correct action is not immediately clear. For AVs, this can lead to mistakes such as:

- False Positives: The system incorrectly identifies something as dangerous when it isn't, like mistaking a shadow for an obstacle.
- False Negatives: The system fails to identify something that is actually dangerous, like not recognizing a small animal on the road.

Unlike humans, AVs may fail in these cases. Additionally, In the near future, autonomous vehicles (AVs) and human drivers will likely share the road, creating mixed traffic scenarios. This coexistence presents significant challenges for traffic flow.

Fig. 1. What current AV might do in this situation?

Imagine a situation where a road is partially closed due to construction, with a ”STOP” sign and traffic cones marking off part of the road. A typical autonomous vehicle (AV) might see the ”STOP” sign and interpret it as a full road closure, coming to a complete stop because that's what its pre-programmed data tells it to do. However, a human driver in the same situation might use common sense, realize the road is only partially closed, and safely continue through the open section. Now, let's make it more complicated: an autonomous truck comes to a sudden stop when it sees the ”STOP” sign. There is another car, driven by a human or another AV, right behind it. This sudden stop could easily lead to a crash. But, if the AV had better reasoning abilities, it might recognize that the road is only partially closed and proceed safely through the open part. And if the AV could communicate with the vehicle behind it, it could warn the other car about its actions, preventing a possible accident.

To address these challenges, we propose integrating Large Language Models (LLMs) into a multi-agent framework for autonomous driving. LLMs have the potential to provide the commonsense reasoning that traditional systems lack, helping AVs better understand the context of complex, real-world scenarios. And incorporating the Vehicle-to-vehicle communication using multi-agent, which allows vehicles to exchange information with other vehicles. This capability is also essential for creating realistic and complex driving scenarios.

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Can LLMs effectively enhance decision-making for AVs in Unknown-Unsafe domains within a multi-agent framework compared to current mechanisms?

This paper explores the potential of integrating Large Language Models (LLMs) into a multi-agent framework for enhancing decision-making in Autonomous Vehicles (AVs), particularly in unknown and unsafe domains. Our main concern would be **To explore the use of Large Language Models(LLMs) for autonomous driving systems(ADS) as the main decision-making agent within a multi-agent framework for evaluating its reasoning abilities in handling long-tail. -False positive and False negative scenarios.** We will investigate whether LLMs can effectively improve upon current mechanisms in handling complex traffic scenarios, with a focus on replicating human-like reasoning and adaptability. We will create unknown-unsafe scenarios that self-driving cars don't handle well today. These will serve as tests for the LLM-powered decision-making system. We will see how well they perform compared to current systems. We'll look at whether they can reason like a human and adapt to unexpected situations. The proposed approach aims to address challenges in autonomous driving systems, especially in scenarios that require common sense reasoning and experience-based decision-making.

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