Toward a Multi Agent Approach for LLM-Based Dynamic Vehicle Control and Communication in Accidental Condition

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***Abstract*—**

I. Introduction

This paper explores the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework to improve 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 (LLM) for autonomous driving systems(ADS) as the main decision-making agent within a multi-agent framework to evaluate its reasoning ability to handle long-tail, False positive, and False negative scenarios.** Our goal is to contribute to the development of safer and more reliable Level 5 [2] autonomous vehicles. We aim to contribute for level 5 (complete automation [3]). There are numerous instances in which traditional autonomous vehicles are capable of making effective decisions in familiar scenarios using pre-trained models. However, they may have trouble facing new or unusual situations where their programmed knowledge is not directly covered in such situations. Human drivers can use common sense and past experiences to handle unexpected events, such as knowing that traffic cones on a moving truck are not dangerous. However, current AV systems, even those that use rule-based approaches or reinforcement learning (RL [4]), will struggle in these scenarios. This limitation is especially evident in what we call **unknown-unsafe** region situations where the correct action is not immediately clear [5]. During this investigation with various LLM, we proceed our investigation under two assumptions: 1) certain AIs can transform real-world situations into text-based explanations, which are subsequently used as input for the LLMs, and 2) the outputs generated by the LLMs can be translated into actual decisions made by the decision agent of AV by interpreting the responses from the LLMs. We are investigating the effectiveness of various Large Language Models (LLMs) for use as decision-making agents in autonomous driving systems. Our initial objective is to answer the research question, **Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation?** In our research, we will assume that vehicle-to-vehicle (V2V) communication has been achieved through a standardized networking protocol, such as LAN-based direct communication or a low-latency wireless system. Under this assumption, each vehicle can communicate with other vehicles within a defined radius (e.g., 10 meters). When a vehicle enters the information sharing radius of another vehicle, they exchange data regarding their current status, such as obstacle detection, traffic conditions, speed, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we will investigate how Large Language Models (LLMs) process and utilize this information. Specifically, we will examine whether the incorporation of V2V exchanged data improves decision accuracy and enables AVs to make more precise and context-aware decisions. However, V2V communication introduces a critical question, **Is a single centralized decision-making agent sufficient to process all incoming V2V data and make autonomous driving decisions, or is a multi-agent system required for improved efficiency and scalability?**

II. Motivation and Background

Imagine a situation where a road is partially blocked due to construction, with traffic cones and a "STOP" sign indicating obstruction. A typical autonomous vehicle (AV) might see the "STOP" sign and interpret it as a complete road closure, coming to a complete stop because that is what its pre-programmed data tell it to do. However, a human driver in the same situation might use common sense, realize that the road is only partially closed, and safely continue through the open section.

Now, let us make it more complicated that 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 cause a crash. Now imagine a human driver encountering a partially blocked road. To navigate safely, the driver shifts into the adjacent open lane,

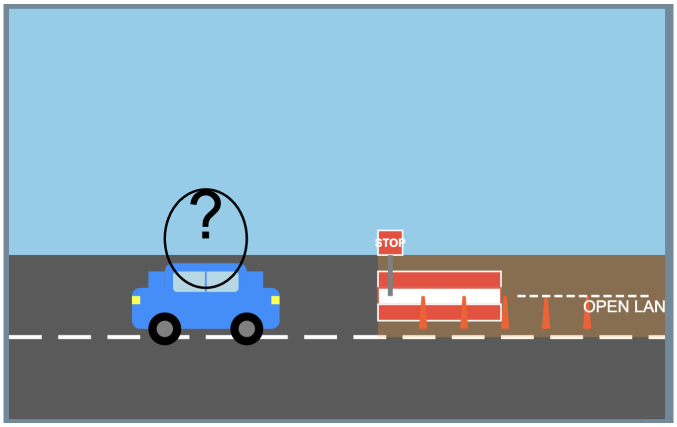


Fig. 1: What current AV might do in this situation?

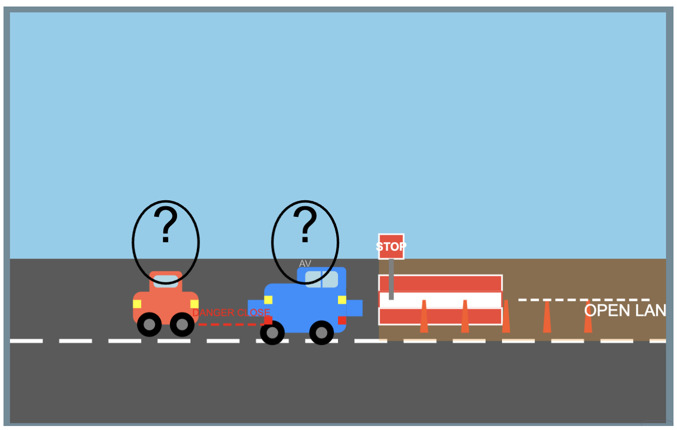


Fig. 2: Lack of communication between vehicles may lead to a potential accident.

relying on instinct and situational awareness. Anticipating the possibility of an oncoming vehicle from the opposite direction or from behind, the driver proactively slows down, assessing the risk and taking the necessary precautions to avoid a collision. In contrast, a traditional AV, which lacks human-like reasoning and predictive thinking, may not recognize the potential danger. Without contextual understanding, it can continue at its normal speed, assuming the lane is clear, increasing the risk of a head-on collision.

However, 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 or if the lane was suddenly closed, it could alert the other car about its actions, preventing a possible accident. A fundamental challenge in traditional autonomous vehicles (AVs) is to prepare for all truly unknown situations [6]. Any scenario we create is technically "known" to us, even if it feels unfamiliar to the AV, making it difficult to test how AVs handle truly unknown-unsafe situations. In addition, it is difficult to recreate complex real-world scenarios in simulation environments. For example, it is difficult to accurately simulate unpredictable human actions or complicated environmental conditions. In real life, there could be countless unexpected situations that are nearly impossible to include in training data sets for traditional autonomous driving systems (ADS) to avoid accidents. Human drivers use common sense to deal with these situations, so through this research we will explore whether LLMs can also show human-like reasoning to handle them effectively or not.

To address these challenges, we propose a possible approach on integrating Large Language Models (LLMs) into a multi-agent framework for autonomous driving control system. LLMs have the potential to provide common sense or reasoning ability that traditional systems lack, helping AVs better understand the context of complex real-world scenarios. Incorporating 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.

III. Preliminary

Reasoning is a fundamental aspect of human intelligence, essential for problem solving, decision-making, and critical thinking. In recent years, Large Language Models (LLMs) have demonstrated emergent abilities [7], such as in-context learning [8], role play [9] and analogical reasoning [10]. These abilities allow LLMs to go beyond natural language processing problems to facilitate a wider range of tasks, such as code generation [11], robotic control [12], and autonomous agents [13]. Among these abilities, human-like reasoning has garnered significant attention from both academia and industry, since it demonstrates great potential for LLMs to generalize to complex real-world problems through abstract and logical reasoning. A notable breakthrough in this area is the 'chain of thought' prompting technique [10], which can elicit step-by-step human-like reasoning processes at test time without any additional training.

Recommendation	Model Name	Benchmark Performance
LM Studio Recommended Models	Mistral 7B	74.6% (MMLU), 83.5% (GSM8K)
	OpenHermes 2.5	72.1% (MMLU), 79.2% (BIG-bench)
	DeepSeek 7B	76.3% (MMLU), 85.4% (GSM8K)
Hugging Face Open-Source Models	LLaMA 2 13B	75.8% (MMLU), 80.7% (BIG-bench)
	Mixtral 8x7B	78.2% (MMLU), 88.1% (GSM8K)
Top Commercial Services	Claude 3 Sonnet	82.3% (MMLU), 90.2% (BIG-bench)
	GPT-4 Turbo	85.6% (MMLU), 92.4% (GSM8K)
	Falcon 7B/40B	73.4% (MMLU), 78.9% (BIG-bench)

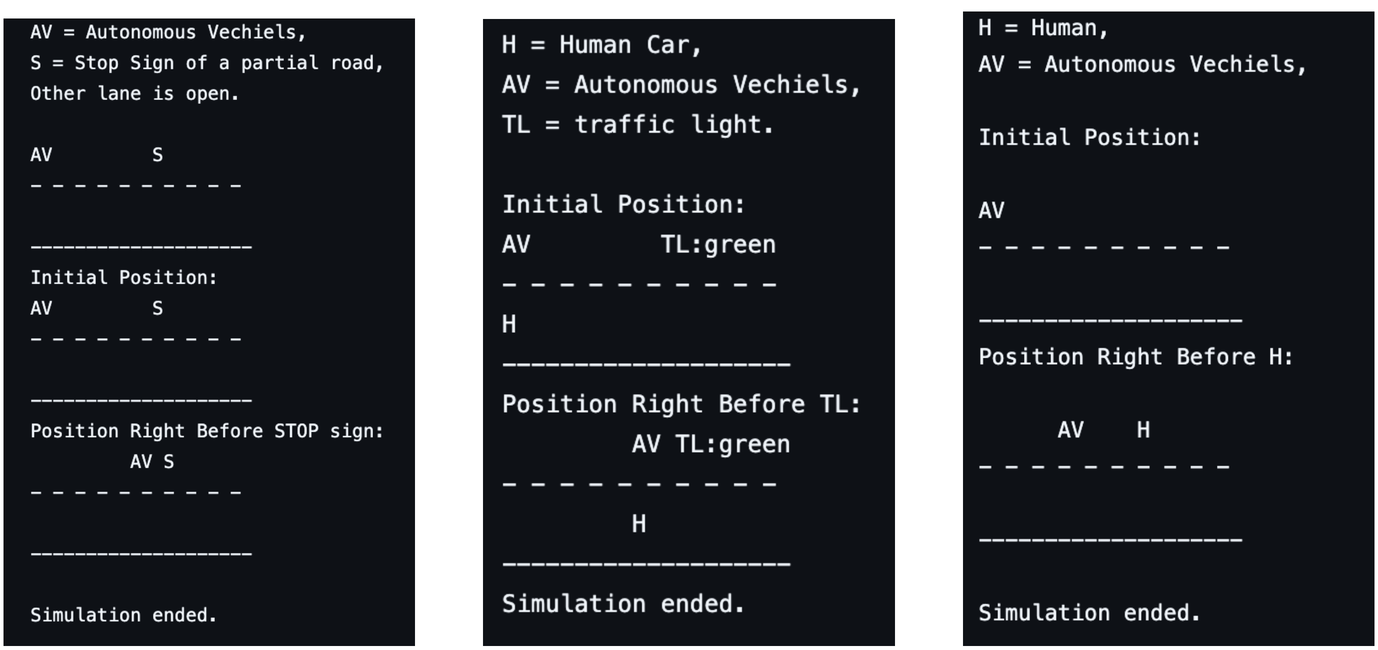
Fig. 3: Selected Models for the Experimentation

Hugging Face[1]is a platform where various open LLM models are available. LM Studio[2] is a platform to test and integrate LLM available on Hugging Face a locally available system on ordinary computing devices, even without powerful GPUs. Now, the question is what factors were considered in the selection of LLMs for this study? One key factor in our model selection was quantization, which optimizes model performance while reducing computational requirements. This research [14] indicates that 8-bit quantization enables the majority of LLMs to maintain a performance level comparable to their nonquantized equivalents, regardless of model size (e.g. 7B to 70B parameters). Moreover, LLMs that are quantized to 4 bits can also up hold similar performance to their non-quantized versions across most benchmarks. This approach achieves memory reduction of 50 to 75 % while preserving precision in complex tasks such as reasoning, decision making, and domain-specific applications. The models chosen for this investigation were selected using a structured approach based on three key factors: popularity and performance in text-to-text generation, LM Studio recommendations for optimized accuracy, and comparative evaluations of the top commercial services. Specifically, 1) Some models were chosen based on the highest number of downloads from Hugging Face, ensuring widespread adoption and benchmark effectiveness. 2) Models suggested by LM Studio were included due to their strong performance and compatibility with local inference environments. 3) The best commercial services were selected based on their comparative performance with open-source counterparts, prioritizing accuracy, interpret ability, and real-time inference. The selected models are shown in Fig. 3. However, not all Hugging Face models are fully compatible with the LM Studio runtime. As a result, some models were tested directly on the Hugging Face interface to avoid compatibility issues. Furthermore, while models such as OpenAI's o1, DeepSeek R1, and Llama 3.1 405B have demonstrated strong benchmark performance, they were not included in this study due to limited quantization support, lack of local deployment feasibility, and restricted open-source availability.

To test these selected models, we have prepared a set of simple, text-based simulation scenarios using Python, as illustrated in Fig. 4. These scenarios are designed to represent situations that cover situations that require logical reasoning or the application of common sense knowledge, such as recognizing a red traffic light and stopping accordingly. These scenarios will be used as input for various LLMs to assess how effectively they handle both types of challenges. The experiments will be conducted using the LLM selected in Fig.3.

For initial testing, we selected a basic traffic scenario involving an autonomous vehicle (AV) approaching a green traffic light, as illustrated in Fig. 4(a), and presented it to various language models to evaluate their decision-making behavior. The scenario was communicated through the prompt: 'What would the AV on the above do? Please just answer STOP or FORWARD.' The selected models included Claude[3] 3.7 Sonnet, GPT[4]-4 Turbo, Falcon[5]3 7B and open-source alternatives such as OpenHermes-2.5-Mistral-7B and google/flan-t5-

[1]https://huggingface.co/
[2]https://lmstudio.ai/
[3]https://claude.ai/chats
[4]https://chat.openai.com/
[5]https://chat.falconllm.tii.ae/



(a) Traffic Light (b) Stop sign of Partial road (c) Human suddenly crossing road

Fig. 4: Illustration of real life traffic scenarios

large. The responses of these models, sourced from Hugging Face, LM Studio, and commercial providers, are shown in Figure 6. GPT-4 and Falcon provided direct and expected responses ‘FORWARD’, which aligns with the logic of the situation. However, Claude deviated from the expected format by including an explanatory response, despite the prompt requesting a one-word answer. OpenHermes-2.5 responded with a clear ‘FORWARD’, demonstrating alignment with the input instructions. Surprisingly, the google/flan-t5-large output differed from all others by responding ‘STOP’, contradicting the intended logic of the scenario.

A major consideration was consistency. **Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?** To test this, each scenario was submitted to the models multiple times. This approach allowed us to observe whether the models produced stable and repeatable responses or if their decisions varied unpredictably. Consistency is especially critical in autonomous vehicle (AV) applications, where uncertain output can cause serious safety concerns. For this analysis, we ran the prompt at least 20 times on OpenHermes-2.5-Mistral-7B, and the consistency results are presented in Fig. 5.

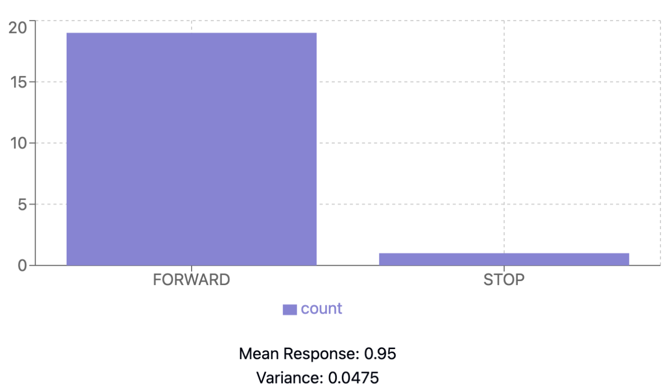


Fig. 5: LLM Model Consistency Analysis

IV. Our Approach

V. Conclusion

In terms of autonomous driving systems, handling unpredictable traffic situations remains one of the critical challenges that must be addressed. We presented a potential approach of using Large Language Models (LLMs) to enhance reasoning abilities in autonomous vehicles. We explored various LLMs from Hugging Face, LM Studio, and commercial services such as Claude, GPT-4, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. The preliminary evaluation reveals both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed multi-agent framework suggests a viable path toward more adaptive autonomous systems capable of human-like reasoning in unpredictable situations.

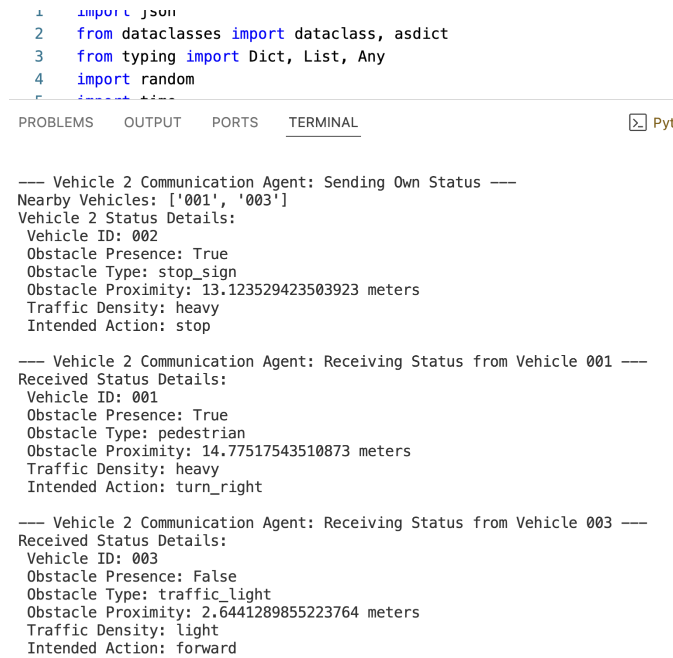


Fig. 6: An illustration of Communication Agent

The next phase of this research will focus on using the shared data from communication agent within our proposed multi-agent framework. The Communication Agent ensures that vehicles share critical information, including obstacle detection, traffic conditions, speed, and intended actions, in a standardized format within a defined radius, the expected format is demonstrated in Fig. 6. This structured data exchange is expected to significantly improve the accuracy of Decision Agent by providing a more comprehensive contextual understanding of the driving environment. This implementation will directly address our core research question. By integrating contextual data derived from V2V communication with LLM reasoning, our goal is to bridge the critical gap in decision-making accuracy for autonomous vehicles.

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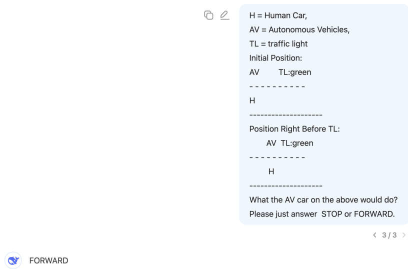
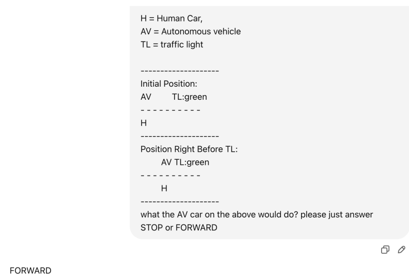
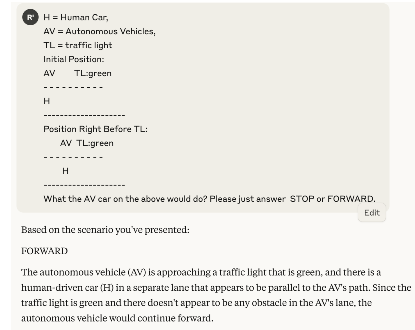


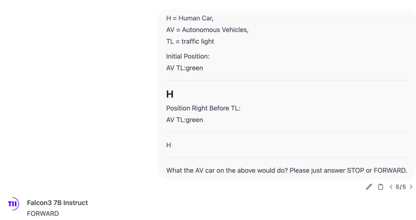
(a) Output from DeepSeek-V3



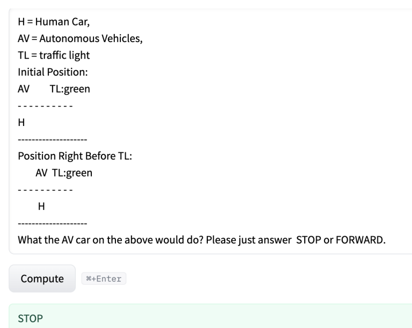
(b) Output from ChatGPT



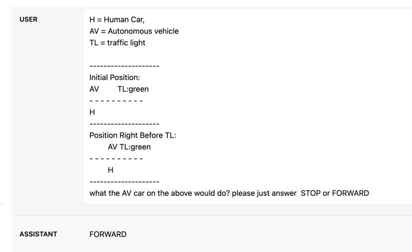
(c) Output from Claude 3.7 Sonnet



(d) Output from Falcon3 7B



(e) Output from google/flan-t5-large



(f) Output from OpenHermes-2.5-Mistral-7B

Fig. 7: Responses from different LLMs

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