

MASTER THESIS

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

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July 15, 2025

Abstract

In autonomous vehicles (AVs), making the right decision in unknown traffic situations remains a critical challenge. Traditional AVs, which are based on pre-programmed rules or pre-trained models, often struggle in scenarios where human-like reasoning is required. This research examines how Large Language Models (LLMs) can act as a main decision agent for AVs, responding to text-based real-world traffic situations simulation.

We propose a multi-agent framework consisting of two key components, a Decision Agent powered by LLMs, and a Communication Agent that enables Vehicle-to-Vehicle (V2V) information exchange. The Communication Agent shares structured, real-time data such as obstacle presence, speed, and intended actions, which is then incorporated into the Decision Agent’s reasoning process.

To evaluate the proposed system, we conducted a series of text-based simulations that simulate real-world traffic conditions. These scenarios are used to test whether LLMs, when provided with scenario-specific prompts and contextual V2V data, can generate consistent and human-like decisions. Our results indicate that while LLMs show strong reasoning abilities, their precision and reliability of decision improve significantly when augmented with contextual information through V2V communication. This research presents a preliminary approach to bridge the gap between current AV capabilities and the demands of real-world accidental conditions.

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List of Abbreviations

| | |
|------------|------------------------------------|
| AI | Artificial Intelligence |
| AV | Autonomous Vehicle |
| ADS | Autonomous Driving System |
| LLM | Large Language Model |
| MAS | Multi-Agent System |
| NLP | Natural Language Processing |
| RL | Reinforcement Learning |
| V2V | Vehicle-to-Vehicle |

Chapter 1

Introduction

The advancement of autonomous vehicle technology brings us closer to the long-held vision of fully automated transportation, where vehicles operate without human intervention. However, achieving this goal of complete automation remains a significant challenge, particularly in ensuring safe and reliable decision-making in complex and uncertain environments.

1.1 Research Background

Our research investigates the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework [2] to improve decision-making in autonomous vehicles (AVs), particularly in unknown-unsafe domains. Our main concern is to explore the use of an LLM as the primary decision-making agent within an autonomous driving system (ADS) [3], evaluating its ability to reason [4] and handle uncertain traffic situations. We aim to contribute to the development of safer and more reliable Level 5 (complete automation) autonomous vehicles, as defined by the Society of Automotive Engineers (SAE International) [5], [6]. Although traditional AVs can handle predictable ‘known-safe’ and ‘known-unsafe’ situations, they struggle with highly unpredictable events, such as a pedestrian unexpectedly crossing the road while the light is red for oncoming traffic representing an unknown unsafe condition. These scenarios, which are difficult to cover in training datasets, represent the primary barrier to achieving complete automation. Human drivers use common sense [7] and past experiences to navigate these unexpected events. However, current AV systems, even those use advanced reinforcement learning (RL) [8], struggle in these scenarios. This limitation is especially evident where the correct action is not immediately clear [9]. Addressing these unknown-unsafe scenarios is critical for improving an AV’s ability to handle real-world driving environments and ensuring the development of truly reliable autonomous systems.

1.2 Research Objectives

Determining how autonomous vehicles (AVs) should make decisions in complex or fully unknown traffic situations remains a major challenge in the development of fully autonomous systems. This problem has been widely explored in the fields of artificial intelligence, robotics, and autonomous system design. The ability to make safe and contextually appropriate decisions in real-time becomes especially critical when AVs encounter unknown-unsafe scenarios traffic conditions not represented in training data or handled poorly by traditional algorithms. Traditional autonomous vehicle systems used these approaches to take driving decisions,

- Rule-based system, which operates on predefined logic and hard-coded behaviors such as "if-then" conditions. These systems cannot take decisions in unfamiliar or edge-case situations that fall outside of their rule sets.
- Supervised learning or machine learning-based models, which are heavily dependent on training data. They often fail in new contexts because they cannot reason beyond the patterns they have learned.

A fundamental challenge is to prepare for truly unknown situations. Any scenario researchers create is technically 'known,' even if unfamiliar to AVs, making it difficult to test how vehicles handle genuinely unknown-unsafe situations. In addition, recreating complex real-world scenarios in simulation environments is challenging, and accurately simulating unpredictable human actions or complicated environmental conditions remains nearly impossible. In real life, it is nearly impossible to include all the uncertain situations in training datasets for traditional autonomous driving systems. Human drivers rely on common sense to navigate these situations effectively. To address this limitation, we are going to investigate whether LLMs can provide human-like reasoning [10] that traditional systems lack, such as how human drivers handle unexpected situations. The main objective of this research is to evaluate how effectively LLMs can act as decision agents in unfamiliar traffic conditions, and potentially bridging the gap between programmed responses and adaptive decision making in autonomous vehicle systems.

1.3 Research Motivation

1.3.1 Motivating Example 1 : What a current AV might do in Unknown situation

Imagine a traffic situation where a road is partially blocked by construction cones, with a 'STOP' sign placed near the cones (Figure 1.1). A traditional AV,

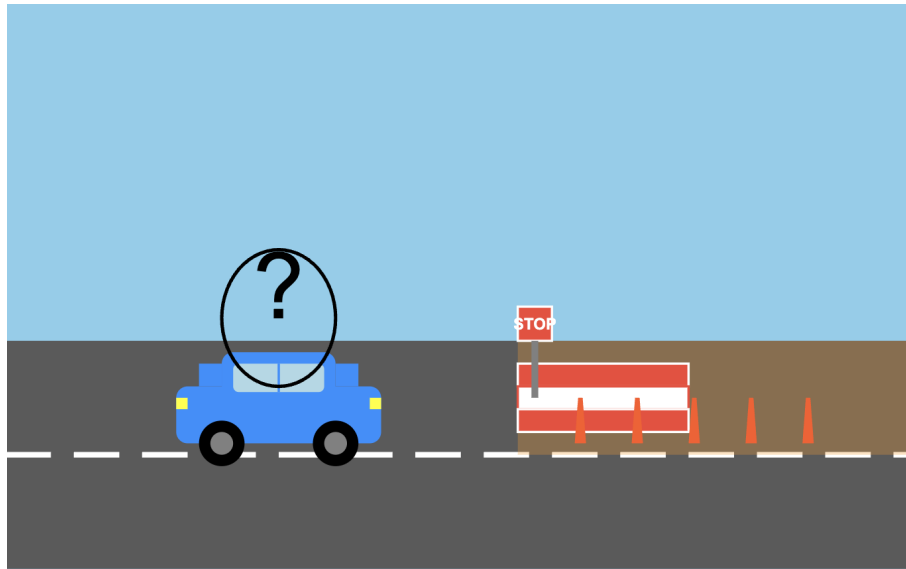


FIGURE 1.1: What a current AV might do in this situation

programmed with rigid rules, would likely interpret the 'STOP' sign literally and come to a complete halt, potentially causing a traffic obstruction. It lacks the context to understand that the sign applies only to the blocked portion of the lane. However, a human driver would use common sense to recognize that the road is only partially closed, slow down, and safely navigate through the open section. This scenario highlights the need for a reasoning system that can interpret context beyond literal rules.

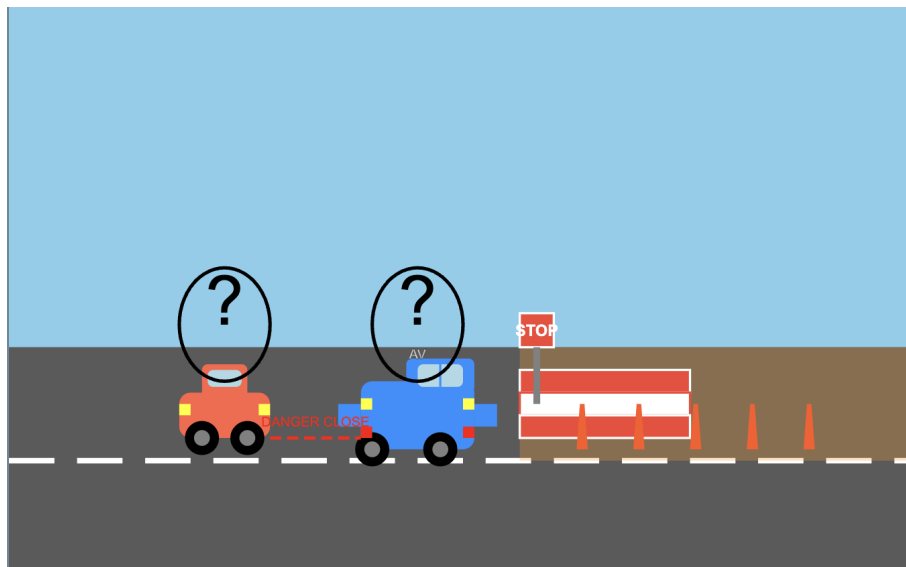


FIGURE 1.2: Lack of communication between vehicles may lead to an accident

1.3.2 Motivating Example 2 : Lack of communication between vehicles

Now, consider a more complex and realistic scenario (Figure 1.2). An autonomous truck (AV1) suddenly brakes upon detecting a partially visible ‘STOP’ sign, an action based on its own perception. Behind it, another vehicle (AV2), which could be human-driven or autonomous, is following closely. Due to AV1’s size, AV2 has no line of sight to the sign and no prior indication that AV1 is about to stop. Without any communication between the vehicles, AV2 is unaware of the hazard ahead, greatly increasing the risk of a rear-end collision. This scenario illustrates a critical limitation of single agent perception in autonomous systems. The issue is not only whether each vehicle can make the right decision for itself but also whether it can contribute to a collectively safe environment. As autonomous vehicles begin to share the road with human drivers, this limitation becomes even more pronounced, human drivers cannot anticipate AV decisions, and AVs cannot rely on human predictability. In our research, we will investigate how Large Language Models (LLMs) utilize this shared V2V information to make driving decisions. Specifically, our goal is to assess whether the inclusion of contextual data, such as obstacle positions, speed, and vehicle intentions, enables the LLM to produce safer and more accurate decisions in complex traffic scenarios.

1.4 Research Questions

One of the primary objectives of this investigation is to answer two main research questions.

- **Research Question 1:** Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation?
- **Research Question 2:** Is a single centralized decision-making agent sufficient to process all incoming Vehicle-to-Vehicle (V2V) data, or is a multi-agent system required for improved efficiency and scalability?
- **Sub-Research Question:** Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?

1.5 Research Contribution

This research introduces a novel multi-agent architecture that integrates Large Language Models (LLMs) with Vehicle-to-Vehicle (V2V) communication [11] to enhance autonomous vehicle decision-making in unknown-unsafe driving scenarios. This work demonstrates how their combined use enables emergent

reasoning capabilities, allowing autonomous vehicles to make more accurate and context-aware decisions in safety-critical scenarios. This research presents a standardized text-based simulation framework that replicates real traffic situations, used to test the LLM's capabilities in logical reasoning, rule compliance, and dynamic decision-making domain for autonomous vehicle. Additionally, a multi-agent communication system is implemented, enabling the vehicle to share structured information such as obstacle locations, speed, and future intentions in a certain radius. This data serves as a contextual input for the LLM-based Decision Agent. The work demonstrates how contextual information sharing can transform potentially hazardous scenarios into safe outcomes. Through empirical experimentation, this research provides definitive evidence that structured V2V communication data significantly improves the accuracy of LLM-based decision making. The research develops novel approaches for quantifying the consistency and reliability of decisions in LLM-based systems, addressing one of the most critical concerns for the deployment of AI in safety-critical applications. By addressing these research areas, this work contributes to the advancement of both theoretical understanding and practical implementation of AI-enhanced autonomous driving systems, with particular emphasis on navigation through safety-critical scenarios.

1.6 Thesis Outline

This thesis is organized into six different chapters as follows:

Chapter 1 *Introduction*: This chapter describes a brief introduction to the thesis, including the research background, objectives, questions, contributions, and key motivations.

Chapter 2 *Background and Related Work*: This chapter introduces the research topics of autonomous vehicle decision-making, unknown-unsafe scenarios, Large Language Models (LLMs), and Multi-Agent Systems, defining the basic concepts and discussing related work in the field.

Chapter 3 *Approach and Example-based Analysis*: This chapter describes the problems and solving approach of this research and introduces the detailed multi-agent framework and example scenarios used for evaluation.

Chapter 4 *Simulation and results*: This chapter explains the simulation setup, implementation, approach on the codes and the analysis with limitations.

Chapter 5 Conclusion: This chapter describes the summary of the work, discusses the key findings, and outlines directions for future research as the conclusion.

Chapter 2

Background and Related Work

This chapter introduces the fundamental concepts and technologies that form the basis for this research. We examine the current state of autonomous vehicle decision-making systems, identify the critical challenges they face, and explore emerging technologies that can potentially address these limitations.

2.1 Autonomous Vehicle Decision-Making

The existing definitions of autonomous driving specified by the SAE for Levels 1 to 5 can be interpreted as, At level 1 vehicles, driving assistance systems that can sometimes help the driver complete some lateral or longitudinal driving tasks. At Level 2 vehicles can automatically provide multidimensional assistance. At level 3, vehicles can perform automatic acceleration and deceleration steering in a specific environment without the driver's intervention. At level 4, if a vehicle is currently in an autonomous driving state under limited conditions, the driver is not required to continuously control the steering wheel. At Level 5, vehicles can run automatically under any conditions and scenarios. At this level, the automatic system of a vehicle completely replaces the human driver and achieves complete automation. A complete autonomous vehicle (AV) is capable of sensing its environment and operating without human involvement. The decision-making process in autonomous vehicles follows a fundamental three-stage pipeline: perception, planning, and control.

- **Perception (See):** The vehicle uses a variety of sensors and cameras, such as LiDAR (Light Detection and Ranging), and radar systems to construct a comprehensive three-dimensional representation of its environment. This stage involves detecting and classifying objects such as other vehicles, pedestrians, traffic signs, and lane markings.
- **Planning and Decision-Making (Think):** This represents the core focus of our research. Based on the perceived environmental information, the vehicle's computational system must determine the appropriate course of action. This involves planning and taking decisions such as lane changes,

speed adjustments, and navigation through complex traffic scenarios. Traditional rule-based approaches perform well in structured and predictable traffic environments. They can only execute actions that have been explicitly predefined and encoded. When unexpected or novel situations arise that fall outside the scope of their programmed rules, these systems often do not respond appropriately [12]. Our research focuses on improving the intelligence of this decision-making component through advanced reasoning capabilities.

- **Control (Act):** Once a decision is made, the system translates the planned actions into control signals that activate the vehicle's physical components, including steering, acceleration, and braking systems. The decision-making module is particularly critical, as it is responsible for planning and performing safely.

2.2 The Challenge of Unknown-Unsafe Scenarios

The driving domain can be divided into three primary categories: known-safe, known-unsafe, and unknown-unsafe. While traditional Autonomous Vehicle (AV) systems can take proper decisions in the first two categories, which can be addressed with pre-programmed rules, their primary limitation lies in handling the complex and unpredictable nature of unknown-unsafe scenarios.

- **Known Safe Scenarios:** These are routine traffic conditions where the environment is predictable and the appropriate response is well-established. For example, driving straight on an empty highway or stopping at a red light. AVs can reliably navigate these situations using pre-defined logic.
- **Known Unsafe Scenarios:** These are situations where a clear and present danger is identifiable based on established rules. Examples include an object stationary on the road, a speeding in a school zone, or another vehicle running a red light. AVs can be trained to recognize and react to these predictable hazards.
- **Unknown-Unsafe Scenarios:** These are unexpected and unplanned situations that are not explicitly covered by pre-programmed rules and can occur without warning or precedent. Examples include a ball rolling onto the road, a pedestrian unexpectedly crossing a red light, or ambiguous hand signals from another driver. These situations require quick context-aware judgment and are difficult to cover exhaustively in training datasets.

Traditional AVs are generally capable of handling known-safe and known-unsafe scenarios effectively using pre-programmed rules, supervised learning, or reinforcement learning models. For example, they can detect and respond to traffic lights, lane markings, and other common characteristics of the driving

environment. However, they struggle when faced with new or unusual situations that are not directly covered by their programming. Human drivers, on the other hand, use common sense and past experiences to handle unexpected events, such as recognizing that traffic cones on a moving truck are not a stationary obstacle. Current AV systems, even those that use advanced reinforcement learning (RL), will struggle to make such a nuanced distinction. This limitation poses a serious safety risk in real-world driving and can lead in several critical failure modes, such as AV can incorrectly identify a safe situation as dangerous, leading to unnecessary and potentially disruptive actions like sudden braking. For example, an AV might stop for a tree shadow across the road, treating it as a solid obstacle. The AV can fail to recognize an actual danger because it does not fit a pre-programmed pattern. This is the most critical failure mode, as it can lead directly to collisions. Addressing this gap is essential for the development of fully autonomous systems that can be trusted to operate safely and reliably in the complexity of real-world environments.

2.3 Large Language Models (LLMs) for Reasoning

An important development in artificial intelligence is represented by Large Language Models (LLMs). LLMs are a type of Machine Learning (ML) model trained in vast amounts of text and code from the Internet, allowing them to comprehend and produce language similar to that of a human. LLMs represent a significant leap in natural language processing and artificial intelligence. Unlike traditional rule-based systems, these machine learning models, driven by deep learning techniques, excel at comprehending and generating extensive human-like text. 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 emerging abilities [13], such as in-context learning [14], role play [15], and analogical reasoning [16]. These abilities allow LLMs to go beyond natural language processing problems to facilitate a wider range of tasks, such as code generation [17], robotic control [18], and autonomous agents [19]. 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 [20], which can obtain step-by-step human-like reasoning processes at the test time without additional training.

This research investigates the potential of LLMs to serve as the main decision makers within AV systems, assessing whether they can reason and react more like humans in complex scenarios.

2.4 Multi-Agent Systems and V2V Communication

A Multi-Agent System (MAS) is a computerized system composed of multiple interacting intelligent agents. Within an MAS, each agent has an incomplete perspective and is capable of autonomous action, but the overall goal of the system is achieved through coordination and communication between agents [21]. In the context of autonomous driving, this paradigm is highly relevant. **Vehicle-to-Vehicle (V2V) communication** is a key enabling technology for a multi-agent approach to driving. V2V allows vehicles to wirelessly exchange information about their position, speed, direction, and intended actions. This creates a collective awareness that extends far beyond the perception range of any single vehicle's onboard sensors (e.g., LiDAR, cameras). By structuring a V2V system within a multi-agent framework, we can address some of the fundamental limitations of single-agent AVs: This research proposes to integrate LLM-based decision-making within a multi-agent framework, where V2V communication provides the crucial context needed for robust reasoning in accidental conditions.

2.5 Related Work

Research in autonomous vehicle decision making has evolved through several paradigms. Traditional autonomous vehicles are based on data-driven approaches, which are categorized into modular and end-to-end frameworks [22]. Modular-based systems break the entire autonomous driving process into separate components, such as the perception module, the prediction module, and the planning module. Including tasks such as object detection [23] and object occupancy prediction. Early systems relied heavily on rule-based and finite-state machines, which are effective for predictable structured environments, but lack the flexibility to handle novel situations. The work of Fu et al. [24] established the concept of 'Drive like a human', demonstrating that LLMs can generate plausible driving behaviors in response to textual descriptions of traffic scenes. Their work primarily focused on a single agent perspective and highlighted the promise of LLMs for high-level reasoning. Our research builds directly on this foundation by investigating LLM performance in a multi-agent context. The use of Multi-Agent Systems (MAS) for traffic management and coordination is well-established. Research in this area has often focused on optimizing traffic flow, coordinating intersections, and cooperative path planning [25]. However, these works typically used simpler, more formally defined agent behaviors. This research [26] presents experiments on learning decision-making policies in multi-agent environments for autonomous systems like connected autonomous vehicles. The agents were able to learn to navigate their environment and avoid collisions even in a partially observable environment with obstacles and other moving agents. However, learning decision-making policies

is challenging due to the non-stationary nature of the environment. This research [27] explores a multi-agent system (MAS) architecture designed to facilitate cooperative control of CAVs. This hierarchical architecture enables vehicles to collaborate effectively in complex traffic environments, sharing information and making collective decisions that enhance safety and efficiency. The study emphasizes the importance of cooperation among autonomous vehicles, particularly in scenarios where rapid decision-making and coordination are critical to preventing accidents and ensuring smooth traffic flow. In this research [28], they explored how the combination of large language models (LLMs) with visual models, called Vision Foundation Models (VFMs), can make autonomous driving systems smarter and more capable [17]. Their work explains how technology evolved from basic sensors in early systems to more advanced deep learning methods that improve how self-driving cars see, plan, and make decisions. In this research [29], they introduced a method for training systems to better understand driving situations. They connected numerical driving data with GPT-3.5, a powerful LLM, which helped the system answer questions and make better driving decisions. The 'DriveMLM' research [30] created a new self-driving system that connects LLMs with vehicle planning tasks. This allowed the car to make decisions in a simulator and control the vehicle more effectively by using a standard planning module. The 'Drive As You Speak' [31] research took things a step further by allowing drivers to talk to the car using natural language. This made it possible for LLMs to understand and follow voice commands, improving the user experience and making driving more intuitive. In this research, AccidentGPT [32] introduced a model that can analyze traffic accidents. It uses different types of data (such as text and images) to recreate accident scenes and generate detailed reports. This research [33] reviews the integration of large language models (LLMs) into autonomous driving systems, highlighting their potential to improve decision-making, perception, and interaction through advanced reasoning and contextual understanding. The survey categorizes current research into planning, perception, question answering, and generation, addressing the challenges of transparency, scalability, and real world application. It underscores the need for robust datasets and interpretable models to build trust and improve system reliability in autonomous driving. This study [34] looks to explore the ability of integrating LLMs into autonomous driving (AD) structures to emulate human-like behavior. LLMs can use their memory to apply past experiences to future decision-making, improving adaptability and decision-making in AD systems. It can improve reliability and safety by enabling human-like reasoning and adaptability. Human drivers instinctively reason with common sense knowledge to predict hazards in unfamiliar scenarios and to understand the intentions of other road users. However, this essential capability is completely missing from traditional decision-making systems in autonomous driving. In response, this paper presents DriveLLM [35], a decision-making framework that integrates large language models (LLMs) with

existing autonomous driving stacks. This integration allows for the use of common sense in decision-making. DriveLLM also features a unique cyber-physical feedback system, allowing it to learn and improve from its mistakes. In real-world case studies, the proposed framework outperforms traditional decision-making methods in complex scenarios, including difficult edge cases. However, using massive amounts of human-generated data to train these models introduces potential bias issues, as the models can unintentionally reinforce the social biases found in the data [36]. Mitigating these biases is an essential and ongoing area of research [37]. This study [38] shows a potential approach of using large language models (LLMs) to evaluate fairness.

The intersection of LLMs and multi-agent communication presents a promising new direction for autonomous driving research. Existing work has shown that LLMs can replicate human-like reasoning and that MAS frameworks improve coordination and safety. However, our research uniquely combines these strengths, and using LLMs as decision agents within a cooperative V2V-enabled architecture represents a novel integration.

Chapter 3

Our Approach

This chapter begins by introducing the overall approach and then provides a detailed explanation of our methodology, including how the experiments were set up, what assumptions were made, and the key factors considered when selecting models for evaluation. This is followed by illustrative example scenarios that demonstrate the system's behavior in representative traffic situations.

3.1 Conceptual Framework: A Multi Agent Approach

To contribute to the advancement of full automation in autonomous vehicles (AVs), this research proposes a conceptual framework based on a multi-agent architecture. The framework is designed to emulate human-like reasoning while enabling cooperative behavior among vehicles through structured communication. The framework focused on two primary agents: the Decision Agent and the Communication Agent, which work collaboratively to enhance decision-making capabilities in dynamic and uncertain traffic scenarios. The interaction between the Decision Agent and the Communication Agent is the core of this framework. The Decision Agent uses both its internal scenario understanding and externally shared V2V data to make informed decisions. This hybrid reasoning system provides the AV with both self-perception and extended perception capabilities with shared information.

- We investigated whether Large Language Models (LLMs) as a decision agent can replicate human-like decision-making processes in autonomous vehicle contexts.
- We also investigated how the information sharing facilitated by the communication agent impacts and potentially improves the accuracy decision in the autonomous driving system.

During this investigation with various LLMs as main decision agent, we proceed under two assumptions.

- 1) Certain AI systems can transform real-world situations into text-based explanations, which are later used as input for the LLMs

- 2) the outputs generated by the LLMs can be translated into actual decisions made by the decision agent by interpreting the responses from the LLMs.

We have investigated the effectiveness of various LLMs for use as decision-making agents in autonomous driving systems. Our initial objective was to answer the research question (Research Question 1): Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation? We have also assumed that vehicle-to-vehicle (V2V) communication has already 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, it can exchange data regarding their current status, such as obstacle detection, traffic conditions, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we have investigated how LLMs process and utilize this information. Specifically, we have examined 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 (Research Question 2): 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? In this research, we have investigated the answers to these two research questions. Through this multi-agent approach, the research aims to bridge the gap between current autonomous vehicle capabilities and the complex decision-making requirements of fully automated transportation systems.

To test large language models as decision agent, we have prepared a set of simple, text-based simulation scenarios of different traffic situations using Python. These scenarios are designed to cover situations that require logical reasoning or the application of common sense knowledge, such as recognizing a traffic red 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.

3.2 The Decision Agent

The Decision Agent is responsible for making context-aware driving decisions. It leverages the reasoning capabilities of pre-trained Large Language Models (LLMs), such as GPT-4, Claude, and open-source alternatives. These models are capable of processing natural language prompts that describe traffic scenarios and generate corresponding driving actions (e.g. STOP or FORWARD).

Hugging Face¹ is a platform where various open LLM models are available. LM Studio² is a platform to test and integrate LLM available on Hugging Face into 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 [39] 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.** More 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, interpretability, and real-time inference.

The selected models are shown in Figure 3.1. However, all the Hugging Face models are not 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 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 limited open source availability.

¹<https://huggingface.co/>

²<https://lmstudio.ai/>

| 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) |

FIGURE 3.1: Selected Models for the Experimentation

3.3 The Communication Agent

The **Communication Agent** facilitates structured Vehicle-to-Vehicle (V2V) information exchange, allowing autonomous vehicles (AVs) within a defined communication radius to share and receive critical environmental data. This includes information such as obstacle presence, road conditions, current speed, and the intended action of the vehicle. To ensure compatibility with Large Language Models (LLMs), the data is formatted in a simple, human-readable structure that can be seamlessly incorporated into text-based prompts. Table 3.1 defines the standardized message schema used by the Communication Agent.

The Communication Agent ensures that all AVs within the information-sharing radius can access and benefit from collective situational awareness. For example, if a vehicle cannot directly see a stop sign due to traffic or any reason to sight block, it can still receive a warning from another vehicle that has a clear line of sight. This enables more accurate and safer decisions, particularly in complex or uncertain scenarios.

The structured data format allows for seamless integration into the LLM-based Decision Agent, allowing it to reason with both local observations and external context. Figure 3.2 illustrates the information exchange process facilitated by the Communication Agent. This multi-agent communication approach significantly improves the accuracy of the AV's decision by expanding its environmental perception beyond the local perception limit.

| Field | Type | Description |
|--------------------|-------------|--|
| Vehicle_ID | String | A unique identifier for the broadcasting vehicle. |
| Current_Speed | Float | The vehicle's current speed in meters per second (m/s). |
| Obstacle_Presence | Boolean | Indicates whether the vehicle detects a critical obstacle in its immediate path. |
| Obstacle_Type | Enum / Null | Type of detected obstacle (e.g., 'stop_sign', 'pedestrian', 'road_block'). This is null if Obstacle_Presence is False. |
| Obstacle_Proximity | Float | Distance to the detected obstacle in meters. |
| Intended_Action | Enum | Planned action from the broadcasting vehicle Decision Agent (e.g., 'stop', 'forward') |

TABLE 3.1: Structured Information for V2V Communication

3.4 Text-Based Simulation and Scenario Design

The core concept is to investigate the reasoning capabilities of LLMs for AVs. In this research, we initially used a series of traffic situations and developed text-based simulation scenarios using Python to evaluate the effectiveness of LLMs as the decision agent in autonomous vehicle (AV). These scenarios were designed to test the capabilities of LLMs in these three domains, logical reasoning, rule compliance, and dynamic decision-making, as shown in Figure 3.3. We did extend our experiment however, capability checking domain was the same.

- **Scenario 1: Rule compliance** This scenario tested whether the LLM could correctly interpret a green traffic light and determine that the AV should proceed. It would assess the basic understanding of large language models of common traffic rules. This simulation is shown on fig 3.1(A)
- **Scenario 2: Common sense** In this case, a stop sign appears on a partially blocked road. The goal was to evaluate how the LLM interprets such ambiguous situations and whether it can determine an appropriate action based on partial cues. This simulation is shown on fig 3.1(B)
- **Scenario 3: Dynamic Decision Making** A more complex test involving a pedestrian suddenly crossing in front of the AV. This scenario assessed whether the LLM could dynamically adapt its decision to an unexpected and potentially hazardous situation. This simulation is shown on fig 3.1(C)

```

1  import json
2  from dataclasses import dataclass, asdict
3  from typing import Dict, List, Any
4  import random
5  import time

```

PROBLEMS

OUTPUT

PORTS

TERMINAL

Pyt

```

--- Vehicle 2 Communication Agent: Sending Own Status ---
Nearby Vehicles: ['001', '003']
Vehicle 2 Status Details:
  Vehicle ID: 002
  Obstacle Presence: True
  Obstacle Type: stop_sign
  Obstacle Proximity: 13.123529423503923 meters
  Traffic Density: heavy
  Intended Action: stop

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 001 ---
Received Status Details:
  Vehicle ID: 001
  Obstacle Presence: True
  Obstacle Type: pedestrian
  Obstacle Proximity: 14.77517543510873 meters
  Traffic Density: heavy
  Intended Action: turn_right

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 003 ---
Received Status Details:
  Vehicle ID: 003
  Obstacle Presence: False
  Obstacle Type: traffic_light
  Obstacle Proximity: 2.6441289855223764 meters
  Traffic Density: light
  Intended Action: forward

```

FIGURE 3.2: An illustration of Communication Agent

3.5 Prompt Engineering

The Natural Language Processing capabilities of Large Language Models and the growing interest in their potential applications have made prompt engineering increasingly important, as the primary method of interaction with LLMs is through prompts [40]. The design of the prompt determines LLM behavior, making prompt engineering critical, since the prompt acts as a guide and directly impacts the results. To carry out our experiment, we tested different LLM models with text-based traffic simulation scenarios using a simple prompt. Each scenario was presented to various LLM models using this simple prompt asking the models to simply respond with a single word without further explanation,

“What would the AV do? Please, just answer STOP or FORWARD.”


```

AV = Autonomous Vechiels,
S = Stop Sign of a partial road,
Other lane is open.

AV      S
- - - - -

-----

Initial Position:
AV      S
- - - - -

-----

Position Right Before STOP sign:
      AV S
- - - - -

-----

Simulation ended.

```

((A)) Traffic Light

```

H = Human Car,
AV = Autonomous Vechiels,
TL = traffic light.

Initial Position:
AV      TL:green
- - - - -

H
-----

Position Right Before TL:
      AV TL:green
- - - - -

      H
-----

Simulation ended.

```

((B)) Stop Sign on Partial Road

```

H = Human,
AV = Autonomous Vechiels,

Initial Position:

AV
- - - - -

-----

Position Right Before H:

      AV      H
- - - - -

-----

Simulation ended.

```

((C)) Human Suddenly Crossing Road

FIGURE 3.3: Illustration of real-life traffic scenarios tested in the LLM-based decision system.

We are assuming that the output from the LLMs would be used as a real decision in the autonomous driving system.

Chapter 4

Conclusion and Future Work

4.1 Conclusion

We presented an approach for leveraging Large Language Models (LLMs) to enhance reasoning capabilities in uncertain traffic situations within a multi-agent framework for autonomous vehicles. We have investigated LLMs from Hugging Face, LM Studio, as well as major commercial services such as Claude, GPT-4, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. Our results show that for RQ1, Large Language Models (LLMs) were able to make intelligent and safe decisions even in unfamiliar or novel traffic situations. They did not require specific training for each scenario and showed strong general reasoning skills, similar to how a human driver would respond to unexpected conditions. For RQ2, the use of multiple agents, such as a Decision Agent and a Communication Agent, improved the system performance compared to the single agent setup. When vehicles shared data such as speed, obstacles, and intentions through V2V communication, decisions became more accurate, consistent, and safer. This design also made the system more scalable and flexible for handling complex real-world traffic situations. These results reveal both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed approach aims at the realization of adaptive autonomous systems capable of human-like reasoning in unpredictable situations. 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.

4.2 Limitations and Future Work

- **Simulation Expansion:** Extend the simulation environment to include multi-lane roads and multiple vehicles, simulating more realistic traffic conditions with varying visibility and road complexity.

- **Increased the number of trails for Consistency Testing:** Run the same prompt more than 100 times per scenario per LLM to obtain a stronger statistical basis to evaluate the consistency of the decision.
- **Offline Evaluation of Local LLMs:** Test the effectiveness of local LLMs in disconnected environments to assess their viability in real-world AV applications.
- **Emergency Broadcasting via Communication Agent:**
 - Implement dynamic emergency messaging (e.g., broadcast STOP or CAUTION to nearby vehicles).
 - Evaluate radius-based alerts: Determine what warnings should be sent to the following vehicles based on proximity and shared intent.
- **Limited Scenario Diversity:** The simulation environment includes a limited range of traffic scenarios, which may restrict the system's ability to generalize to real-world driving conditions.
- **Lack of Fail-Safe Mechanisms:** The current system lacks built-in redundancy or error handling mechanisms to recover from incorrect LLM output or detect unsafe decisions in real time.
- **Unaddressed V2V Communication Constraints:** This study assumes ideal communication conditions, without evaluating real-world issues such as network congestion, signal interference, or latency, especially in dense traffic scenarios.

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Publications

International Conference

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

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Abstract—In autonomous vehicles (AVs), making the right decision in unknown traffic situations remains a challenge. Traditional AVs rely on pre-trained models, which often struggle in such cases where human-like reasoning is required. In this paper, we examine how Large Language Models (LLMs) act as a decision agent responding to scenario-specific text prompts derived from real-world traffic situations. In addition, we propose a Communication Agent that enables vehicle-to-vehicle (V2V) information sharing, such as speed, obstacles, and future intentions, in a structured format to provide contextual support for the decision agent. This paper proposes a preliminary approach to assess whether LLMs within a multi-agent framework, when provided with structured prompts and contextual data, can support consistent and human-like decision making.

Index Terms—autonomous vehicles, large language models (LLMs), multi-agent, vehicle-to-vehicle (V2V) communication, decision making agent, communication agent.

I. INTRODUCTION

This paper explores the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework [2] to improve decision making in autonomous vehicles (AVs), particularly in unknown and unsafe traffic situations. Our main concern would be to explore the use of LLMs for autonomous driving systems (ADS) as the main decision-making agent within a multi-agent framework to evaluate its reasoning ability [3] to handle uncertain traffic situations. Our goal is to contribute to the development of safer and more reliable Level 5 [4] autonomous vehicles. We aim to contribute to Level 5 (complete automation [5]). 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 [6]), will struggle in these scenarios. This limitation is especially evident in what we call unknown-unsafe domain situations

where the correct action is not immediately clear [7]. During this investigation with various LLMs, we proceed under two assumptions: 1) certain AI systems can transform real-world situations into text-based explanations, which are later used as input for the LLMs, and 2) the outputs generated by the LLMs can be translated into actual decisions made by the AV's decision agent by interpreting the responses from the LLMs. We are investigating the effectiveness of various LLMs for use as decision-making agents in autonomous driving systems. Our initial objective is to answer the research question (Research Question 1): 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, it can exchange data regarding their current status, such as obstacle detection, traffic conditions, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we will investigate how 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, (Research Question 2): 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? In this paper, we investigate the answers to these two research questions.

II. MOTIVATION AND BACKGROUND

Imagine a traffic situation, where a road is partially blocked due to construction, with traffic cones and a 'STOP' sign indicating a partial road block. A typical autonomous vehicle (AV) might see the 'STOP' sign and interpret it as a complete

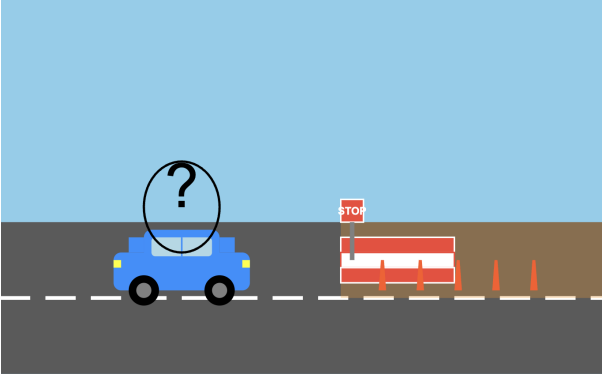


Fig. 1: What a current AV might do in this situation?

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.

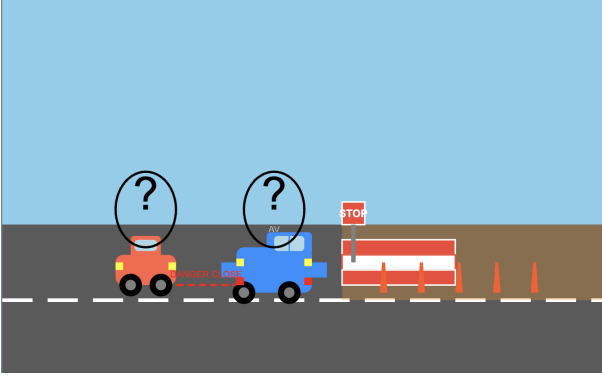


Fig. 2: Lack of communication between vehicles may lead to a potential accident.

Now imagine a more complicated situation where 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 would shift into the adjacent open lane, relying on instinct, experience, and situational awareness. Anticipating the possibility of an oncoming vehicle from the opposite direction or from behind, the driver would proactively slow down, assessing the risk, and would take 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, it could alert the other

driver about its intended actions, particularly if the lane were to close suddenly, helping to prevent a potential accident. A fundamental challenge in traditional autonomous vehicles (AVs) is to prepare for all truly unknown situations [8]. Any scenario we create is technically ‘known’ to us, even if it feels unfamiliar to the AVs, 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 paper 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 for integrating 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 will allow vehicles to exchange information with other vehicles. This capability is also essential for creating realistic and complex driving scenarios.

III. PRELIMINARY

| 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

To investigate the use of LLMs as a decision agent in AVs, we have utilized open-source and local deployment platforms. Hugging Face¹ offers a wide range of open-source pre-trained models, while LM Studio² integrates LLM models from Hugging Face into a local system, even without powerful GPUs. Now, the question is what factors were considered in the selection of LLMs for this study? One key factor in

¹<https://huggingface.co/>

²<https://lmstudio.ai/>

```

AV = Autonomous Vechiels,
S = Stop Sign of a partial road,
Other lane is open.

AV      S
-----

Initial Position:
AV      S
-----

Position Right Before STOP sign:
      AV S
-----

Simulation ended.

```

(a) Stop sign on Partial road

```

H = Human Car,
AV = Autonomous Vechiels,
TL = traffic light.

Initial Position:
AV      TL:green
-----
H
-----

Position Right Before TL:
      AV TL:green
-----
      H
-----

Simulation ended.

```

(b) Traffic Light

```

H = Human,
AV = Autonomous Vechiels,

Initial Position:
AV
-----

Position Right Before H:
      AV      H
-----

Simulation ended.

```

(c) Human suddenly crossing road

Fig. 4: Illustration of real life traffic scenarios

our model selection was quantization, which optimizes model performance while reducing computational requirements. This research [9] 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 uphold 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, interpretability, 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 cover situations that require logical reasoning or the application of common rules 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.

IV. OUR APPROACH

The main phase of this research focuses on using the shared data of the 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. 5. 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. For initial testing, we selected a basic traffic scenario involving an autonomous vehicle (AV) approaching a green traffic light, as illustrated in Fig. 4(b), 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 Claude³ 3.7 Sonnet, GPT⁴-4 Turbo, Falcon⁵ 3 7B and open-source alternatives such as OpenHermes-2.5-Mistral-7B and google/flan-t5-large. The responses of these models, sourced from Hugging Face, LM

³<https://claude.ai/chats>

⁴<https://chat.openai.com/>

⁵<https://chat.falconllm.tii.ae/>

```

1 import json
2 from dataclasses import dataclass, asdict
3 from typing import Dict, List, Any
4 import random
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99
100

```

```

--- Vehicle 2 Communication Agent: Sending Own Status ---
Nearby Vehicles: ['001', '003']
Vehicle 2 Status Details:
Vehicle ID: 002
Obstacle Presence: True
Obstacle Type: stop_sign
Obstacle Proximity: 13.123529423503923 meters
Traffic Density: heavy
Intended Action: stop

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 001 ---
Received Status Details:
Vehicle ID: 001
Obstacle Presence: True
Obstacle Type: pedestrian
Obstacle Proximity: 14.77517543510873 meters
Traffic Density: heavy
Intended Action: turn_right

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 003 ---
Received Status Details:
Vehicle ID: 003
Obstacle Presence: False
Obstacle Type: traffic_light
Obstacle Proximity: 2.6441289855223764 meters
Traffic Density: light
Intended Action: forward

```

Fig. 5: An illustration of Communication Agent

Studio, and commercial providers, are shown in Fig. 11. GPT-4 Turbo 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. The subresearch question, ‘Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?’ will be one of such investigations of consistency. To test this, each scenario was submitted to the models multiple times for regenerating the outputs. This approach allowed us to observe whether the models produced stable and repeatable responses

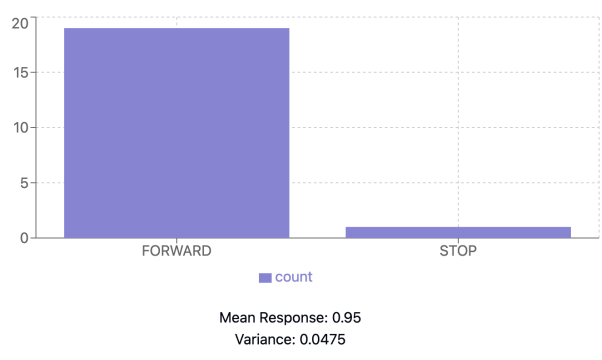


Fig. 6: LLM Model Consistency on the Tested Scenario

or if their decisions varied unpredictably. Consistency is especially critical in autonomous vehicle (AV) applications, where uncertain output can cause serious safety concerns.

For giving an example of this analysis, we ran the prompt at least 20 times on OpenHermes-2.5-Mistral-7B, and the consistency results are presented in Fig. 6. Consistency was calculated by mapping ‘FORWARD’ = 1 and ‘STOP’ = 0. ‘FORWARD’ mean is closer to 1, it indicates that the output is having greater consistency with the expected response.



Fig. 7: Extended Traffic Scenario with V2V Communication

To investigate the impact of V2V communication on autonomous decision-making, we extended our simulation to a more complex traffic scenario. In this extended scenario, AV2 (an autonomous car) follows AV1 (an autonomous truck), with a stop sign ahead that AV2 cannot see because its line of sight is blocked by AV1, as shown in Fig. 7. To investigate how LLMs process and utilize this information, this scenario was presented to the LLM with the same prompt: ‘What would the AV on the above do? Please, just answer STOP or FORWARD’. The model responded with ‘FORWARD’, as shown in Fig. 8, for the case of using GPT-4 Turbo. This decision could potentially lead to an accident. We then examine whether the incorporation of V2V exchanged data improves the accuracy of the decisions and enables AVs to make more precise and context-aware decisions. By enabling

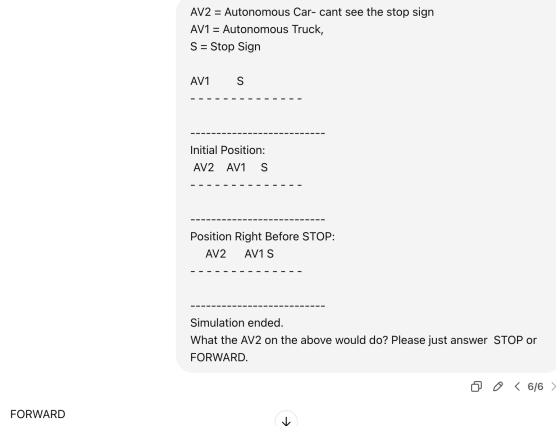


Fig. 8: LLM Model response without Communication agent's information (GPT-4 Turbo)

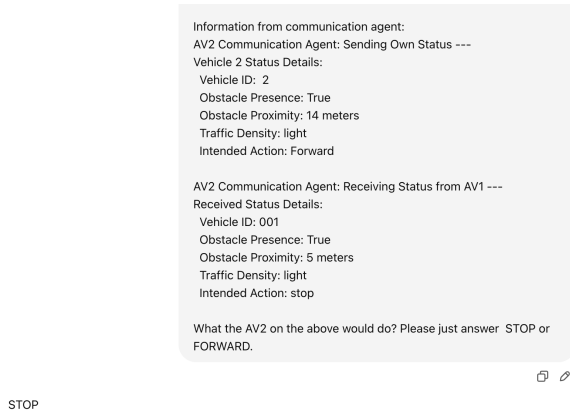


Fig. 9: LLM Model response with Communication agent's information (GPT-4 Turbo)

the Communication Agent, AV1 shares its intended action and information about the obstacle ahead with AV2. These data are structured and passed as additional input presented to the model, as shown in Fig. 9, for the case of using GPT-4 Turbo. With access to this contextual information, the model responds with 'STOP', even without direct visual confirmation of the traffic sign in the case where GPT-4 Turbo was used.

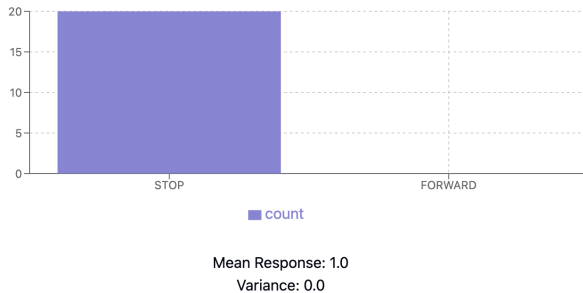


Fig. 10: LLM Model Consistency with V2V Communication support (GPT-4 Turbo)

To evaluate the consistency of the model decision, we ran the same prompt 20 times. The consistency was calculated by mapping 'FORWARD' = 1 and 'STOP' = 0. The resulting mean value of 1 for 'STOP' indicates that the output is having greater consistency with the expected response. The consistency of GPT-4 Turbo's responses with V2V support is shown in Fig. 10, which confirms that communication agent inputs help LLMs generate more accurate decisions in critical traffic environments.

V. CONCLUSION

We presented an approach for utilizing Large Language Models (LLMs) to enhance reasoning capabilities in uncertain traffic situations within a multi-agent framework for autonomous vehicles. We have investigated LLMs from Hugging Face, LM Studio, as well as major commercial services such as Claude, GPT-4 Turbo, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. These results revealed both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed approach aims at the realization of adaptive autonomous systems capable of human-like reasoning in unpredictable situations. By integrating contextual data derived from V2V communication with LLM reasoning, we can have further investigations to bridge the critical gap in decision-making accuracy for autonomous vehicles.

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H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do?

Please just answer STOP or FORWARD.

< 3 / 3 >

FORWARD

(a) Output from DeepSeek-V3

H = Human Car,

AV = Autonomous vehicle

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

what the AV car on the above would do? please just answer

STOP or FORWARD

FORWARD

(b) Output from GPT-4 turbo

R'

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do? Please just answer STOP or FORWARD.

Edit

Based on the scenario you've presented:

FORWARD

The autonomous vehicle (AV) is approaching a traffic light that is green, and there is a human-driven car (H) in a separate lane that appears to be parallel to the AV's path. Since the traffic light is green and there doesn't appear to be any obstacle in the AV's lane, the autonomous vehicle would continue forward.

(c) Output from Claude 3.7 Sonnet

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do? Please just answer STOP or FORWARD.

Compute

*+Enter

STOP

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

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do? Please just answer STOP or FORWARD.

FORWARD

(d) Output from Falcon3 7B

USER

H = Human Car,

AV = Autonomous vehicle

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

what the AV car on the above would do? please just answer STOP or FORWARD

ASSISTANT

FORWARD

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

Fig. 11: Responses from different LLMs

Acknowledgements

Alhamdulillah. In the name of Allah, the Most Gracious and the Most Merciful.

First of all, I would like to express my gratitude to Almighty God ALLAH SWT for the blessing, kindness and inspiration that guided me to complete the course.

I would like to express my sincere gratitude to my supervisor **Professor FUKUTA Naoki** for his motivation and enormous contribution of knowledge. His guidance and support were invaluable to the success of this work. This study is the result of guidance from my Supervisor. I want to acknowledge and give my sincerest gratitude and heartfelt appreciation for being my Supervisor and allowing me to be a part of Fukuta lab. Our professor consistently supervised me with excellent guidance on my research, which also aided me in conducting extensive studies and learning about bunches of new topics. The encouragement, advice, support, and most importantly, the belief in us, from the initial to the final phase, helped us a lot to understand the subject. Besides my supervisors, I would like to thank my parents for their blessing, my lab members, and my friend for their support. I am incredibly grateful to all the lab members of Fukuta Laboratory and my friends at Shizuoka University for always being supportive and friendly. They are very hardworking, and I believe their academic achievement will continue to increase. Thank you for comforting me with every difficulty and suggesting the proper way to deal with it. They helped me to adopt a new culture and daily life. I am also eternally grateful to all S-port staff who lovingly and carefully advised us.

Furthermore, I want to thank my respected advisory committee and ... for giving me very helpful comments and questions at the time of the plan presentation, the mid-term presentation, and the final presentation.

I am incredibly grateful to the faculty and administrators of the **Shizuoka University's Asia Bridge Program (ABP-SU)** for the golden opportunity to be a part of it.

Finally, words are insufficient to express gratitude to my cherished family members for supporting me and encouraging me.

*Hamamatsu, Japan
July 15, 2025
Rafi Md Ashifujjman*