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V2X Communication and LLM-Based Driver Training System: Providing Scenario Semantic Explanations and Challenge Task Generation for Novice Drivers

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ABSTRACT

In today's era, autonomous driving technology, semantic communication, and large language models are advancing rapidly. Against this backdrop, driving training systems face both unprecedented opportunities and new challenges. Novice drivers, who are just beginning to learn, often encounter situations where they do not know how to respond or lack sufficient reaction time in complex and dynamic traffic environments. Traditional driving training methods are relatively rigid and struggle to meet the specific needs of novice drivers in these areas. This paper proposes an innovative dynamic driving task generation training system based on the integration of V2X communication and lightweight large language models. This system processes V2X communication data in real-time, converts it into natural language scenario explanations, and dynamically generates personalized driving tasks. It enhances novice drivers' comprehension of complex driving scenarios, thereby improving the timeliness and effectiveness of driving training. This paper details the system architecture, research methodology, and experimental results, validating its practicality and demonstrating its potential in novice driver training.

KEYWORDS

V2X communication; Lightweight large language model; Real-time scenario interpretation; Dynamic task generation; Novice driver training; Intelligent transportation system

1 Introduction

With the continuous advancement of intelligent transportation systems and autonomous driving technology, vehicle-to-vehicle communication has achieved remarkable technical progress, particularly V2X communication technology [1]. This technology establishes collaborative communication networks, enabling real-time data exchange and sharing between vehicles, surrounding traffic participants, and infrastructure. Consequently, it substantially enhances driving safety. V2X communication facilitates efficient transmission of real-time traffic flow information, road condition data, and potential hazard alerts among vehicles, providing drivers with immediate warnings and decision-making guidance [2]. However, novice drivers frequently encounter complex and dynamic traffic scenarios during actual driving. Such scenarios demand high levels of situational awareness and decision-making responsiveness from drivers. Novice drivers often make erroneous decisions due to stress responses, which has become a key risk factor contributing to traffic accidents.

Traditional driver training methods primarily rely on simulators and instructor guidance, featuring rigid, fixed routes and training programs. While research has confirmed that driving simulators significantly enhance novice drivers' real-road skills and safety performance [3], simulators create risk-free environments, offer flexible scenarios, and provide continuous feedback—all highly beneficial for skill development [4]. However, simulated driving ultimately differs from real-world driving. It cannot eliminate the nervousness learners feel during actual driving. Systems based on large language models can dynamically generate personalized tasks guided by real-time traffic data, thereby enhancing learners' ability to respond to risks.

To address these challenges, this paper proposes establishing an intelligent driving training system based on V2X communication and lightweight large language models. This system converts V2X data into natural language explanations and generates dynamic driving tasks based on these descriptions, thereby enhancing the effectiveness of driving instruction. Modern large language models offer novel insights into personalized human-machine interaction [5]. By integrating LLM with V2X, novice drivers can engage in real-world training to handle diverse driving scenarios. Through task completion, they progressively refine their driving skills while developing appropriate responses to unexpected situations.

2 Related Work

V2X communication technology has been extensively researched in intelligent transportation and autonomous driving. These studies highlight significant advancements in vehicle-to-vehicle communication, enabling efficient resource allocation [6]. The potential of V2X for driving assistance has also been demonstrated [7], allowing vehicles to exchange real-time data with surrounding vehicles and infrastructure. This enhances driving safety and improves the driver experience, with some cities already implementing this technology [8]. Additionally, numerous studies have focused on the safety and efficiency aspects of V2V communication [9]. These investigations aim to reduce traffic accidents, enhance speed control capabilities, and prevent collisions through real-time data exchange. To achieve these goals, researchers have developed various protocols, such as those based on DSRC [10] and C-V2X [11]. Research and practical applications have validated the effectiveness of these protocols in improving traffic safety and flow management. However, research on integrating V2X communication technology into driver training systems remains relatively scarce.

Traditional driving training systems largely rely on static training tasks and corresponding scenarios. A significant limitation of such systems is their inability to dynamically adjust training tasks. In recent years, relevant research has established a framework based on visual language models and V2X communication. This framework aims to effectively integrate and process multimodal data to achieve precise trajectory planning [12]. However, this framework also has certain limitations. It lacks the capability to dynamically generate driving tasks based on the actual surrounding environment, and its performance in the specific aspect of driving training remains somewhat inadequate.

In the field of large language models, recent advancements have opened new avenues for natural language processing. Lightweight large language models have demonstrated impressive performance in real-time systems and are widely applied in dialogue systems, text generation, sentiment analysis, and other domains, with ongoing developments in semantic understanding [13]. Nevertheless, their application in driving simulators remains limited. By integrating V2X communication data with LLMs, we can provide learners with real-time semantic feedback on driving scenarios and generate personalized driving tasks based on their performance.

3 System Design and Architecture

3.1 System Overview

The proposed driving training system integrates V2X communication with lightweight large language models to create a real-time, dynamic training platform for novice drivers. The system architecture is primarily divided into four modules: the V2X communication layer, the LLM interpretation layer, the dynamic task generation layer, and the simulation environment. Each module plays a critical role within the system, from processing V2X data in real time to generating tasks tailored to the learner's individual circumstances and providing timely feedback.

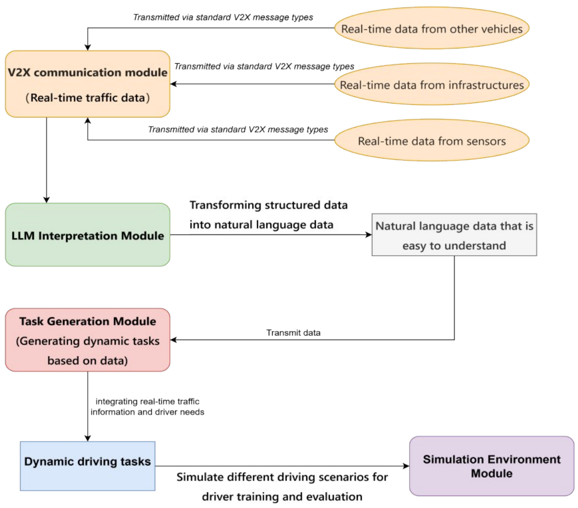

Figure 1 System Architecture Overview

3.2 V2X Communication Layer

The primary task of the V2X Communication Layer is to receive and process real-time data from other vehicles, infrastructure, and sensors. This layer primarily handles V2V, V2I, and V2X messages, including vehicle location information, driving speed, heading direction, and traffic signal data. This data is transmitted using standard V2X message types [14] and fed into the system in real time. This facilitates subsequent analysis of the data to generate corresponding tasks.

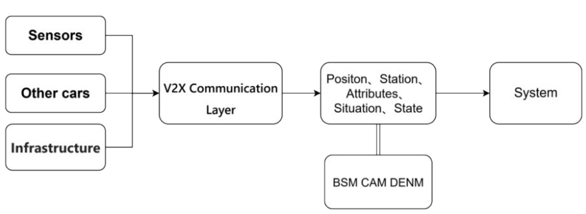

Figure 2 Schematic Diagram of the V2X Communication Layer

3.3 LLM Interpretation Layer

The LLM Interpretation Layer converts received structured V2X data into natural language descriptions, making the data more accessible and understandable. This system employs the lightweight Mistral-7B-Instruct-v0.2. Q4_K_M model, which demonstrates strong natural language processing capabilities while requiring minimal configuration and operating at high speed. After converting data into natural language, learners receive dynamically generated tasks [15]. For example, as a learner approaches an intersection, the system may generate prompts like: "The left-turn signal ahead has turned green. Prepare to proceed."

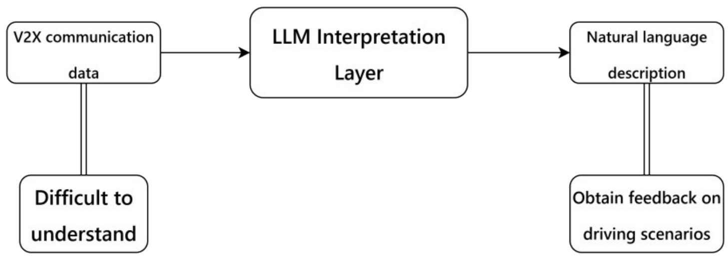

Figure 3 Schematic Diagram of the LLM Interpretation Layer

3.4 Dynamic Task Generation Layer

The Dynamic Task Generation Layer creates personalized training tasks based on real-time road conditions. Task generation dynamically adjusts according to live traffic data and the surrounding environment.

3.5 Simulation Environment

To realistically simulate actual driving scenarios, I specifically selected the CARLA simulation platform. CARLA is a powerful tool in autonomous driving research, capable of simulating real-world driving conditions while providing extensive sensor data for training and validating driving strategies [16]. This platform supplies signals for training driving strategies, including GPS coordinates, vehicle speed, acceleration, and detailed data on collisions and other violations [17]. In this experiment, I utilized the CARLA simulation platform to recreate dynamic road conditions, reconstructing the driving behavior of vehicles within the dataset. I then evaluated whether the generated dynamic tasks matched the generated environment. This approach allowed me to determine the accuracy of task generation.

4 Research Methodology

4.1 Data Collection and Preprocessing

The dataset employed in this study is NuScenes. Designed specifically for autonomous driving and intelligent transportation systems research, NuScenes is a large-scale, multimodal sensor data autonomous driving dataset. It has been widely applied in training, validating, and testing autonomous driving technologies and deep learning models. This dataset represents a significant advancement in both data volume and complexity. Using it, I collected extensive V2X communication data, including vehicle location, speed, heading, and surrounding traffic information. This structured data undergoes preprocessing to convert it into a standardized format compliant with system requirements, enabling its use by the LLM processing and task generation modules.

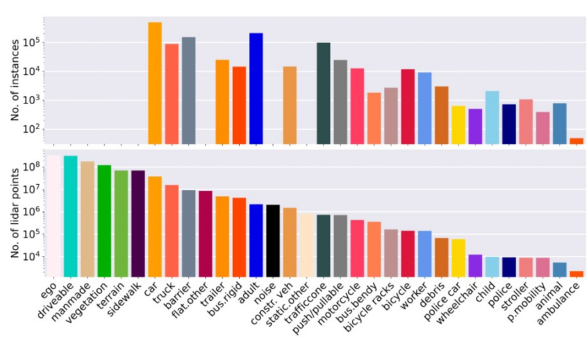

Figure 4 Comparison of instance counts versus lidar point counts for different object categories in this dataset

4.2 Model Design and Training

To achieve real-time scene semantic interpretation, this paper employs the Mistral-7B-Instruct-v0.2. Q4_K_M model. This quantized large language model, after extensive training, possesses the capability to convert structured V2X data into natural language descriptions. The model learns to generate accurate, contextually relevant linguistic feedback based on input V2X data, storing the generated natural language output in files. Leveraging its optimized instruction comprehension capabilities, this model delivers high-quality language outputs in low-latency environments—a critical feature for real-time feedback in driving training scenarios.

4.3 Dynamic Task Generation and Evaluation

We can utilize natural language data generated by large language models to describe the surrounding environment, thereby generating driving tasks. After generating driving tasks, we create the actual vehicle status on the simulation platform based on structured data. Through this process, we can verify whether the generated driving tasks are correct and whether they align with the actual conditions of the surrounding environment.

5 Experiments and Results

5.1 Experimental Setup

To validate the effectiveness of the V2X communication and LLM-based driving training system, I conducted experiments primarily evaluating the system's performance across diverse driving scenarios. Using the rich data from the Nuscenes dataset, my designed system generated corresponding tasks. My computer configuration included a Windows 11 operating system, an i9-13900HX processor, 16 GB of RAM, and a GeForce RTX 4060 GPU.

Figure 5 Generating scene conditions based on structured data within the CARLA simulation software

Furthermore, this system successfully generated driving tasks based on the surrounding environment.

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The following driving tasks are included in the scenario:
- Step 1: Turn to the right, check the right side of the road, ensure safety,
then start moving gradually to the right side of the road.
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Figure 6 Generated driving tasks

5.2 Results analysis

The experimental results demonstrate that a driving training system based on V2X communication and LLM offers significant advantages over traditional driving simulators and fixed task generation systems in multiple aspects.

During simulated task generation, the system enables real-time scenario interpretation based on the surrounding environment. The LLM interpretation module accurately converts V2X data into natural language descriptions while providing corresponding feedback. Real-time voice prompts and scenario explanations help trainees comprehend specific road conditions and react promptly. Testing within simulation software confirmed that task generation aligns with actual environmental conditions, and the generated tasks are operationally correct without any elementary errors.

5.3 Discussion

Experimental results fully validate the effectiveness of the V2X communication and LLM-based driving training system. This system processes V2X communication data in real-time and generates highly accurate natural language descriptions that effectively assist trainees in comprehending complex driving scenarios. Additionally, the system's dynamically generated training tasks enhance trainees' adaptability, thereby improving the specificity and effectiveness of training.

However, several challenges remain to be addressed. For instance, V2X communication faces stability and latency issues that may impact the real-time generation and accuracy of tasks. Furthermore, while large language models demonstrate strong performance in scenario interpretation, their accuracy and fluency in generating natural language descriptions still require optimization. Research is also needed on how to make tasks more diverse and refined.

6 Conclusion

This paper proposes a driving training system leveraging V2X communication and lightweight large language models. By semantically interpreting real-time scenarios and dynamically generating tasks, the system enhances novice drivers' skills. Experimental results demonstrate the system's ability to accurately generate dynamic tasks aligned with actual environmental conditions. Future work will focus on improving real-time performance and accuracy, expanding the scope of task generation, and validating the system in more complex scenarios.

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