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A V2X-Based Multi-Agent Framework for Cooperative Path Planning and Dynamic Decision-Making in Autonomous Driving

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Abstract: ***In complex and heterogeneous traffic environments, traditional single-vehicle planning strategies fail to meet the global coordination demands of vehicle-to-vehicle and vehicle-to-infrastructure interactions. This study proposes a multi-agent cooperative path planning and decision-making framework based on V2X communication technology. A coordinated architecture consisting of a central controller and edge-level vehicle nodes is constructed. Graph Neural Networks (GNNs) are employed to model the dynamic states of nearby vehicles, and a multi-stage joint optimization algorithm is introduced to simultaneously optimize path efficiency and conflict avoidance. The framework is evaluated on the SUMO real-world traffic simulation platform and the Apollo real-vehicle testing platform. Experimental results show that the system significantly improves traffic throughput (+28.6%) and reduces path conflict rates (−35.4%) in high-interaction areas such as intersections and merging zones, demonstrating strong adaptability to coordinated traffic scenarios.***

Keywords: V2X communication; Multi-agent system; Path planning; Graph neural network; Traffic coordination.

1. INTRODUCTION

With the rapid acceleration of global urbanization, urban population growth has intensified dramatically [1]. Traffic congestion and safety issues—like a looming sword of Damocles—have severely constrained sustainable urban development and degraded residents' quality of life [2]. According to related statistics, in certain megacities, the average vehicle speed during peak hours drops to as low as 15 km/h, leading to substantial time losses during commuting [3]. Globally, traffic congestion causes annual economic losses amounting to hundreds of billions of U.S. dollars.

For example, in the European Union, traffic congestion results in an estimated loss of €100 billion each year. Meanwhile, traffic accidents occur frequently, resulting in both severe economic losses and a high number of casualties [4]. In 2023 alone, over 1.3 million people worldwide died in traffic accidents. Autonomous driving technology, regarded as a transformative solution, has received extensive attention from researchers, automotive companies, and governmental agencies. Traditional single-vehicle autonomous driving systems primarily rely on onboard sensors [5]. Cameras are used to capture visual surroundings, while radar accurately measures the distance and relative velocity of surrounding objects [6]. These sensors support environmental perception, enabling individual vehicles to perform local path planning and decision-making. However, the real-world traffic environment is highly complex, often characterized by high vehicle density and unpredictable behaviors from diverse traffic participants. In urban core areas—especially at busy intersections—vehicles from different directions frequently attempt to pass simultaneously [7]. Under such conditions, relying solely on limited local sensor perception and isolated decision-making capabilities can easily lead to traffic congestion or even collisions. According to statistics from traffic management authorities, approximately 30% of urban traffic accidents occur at intersections, a large portion of which are due to the lack of coordinated decision-making between individual vehicles [8].

The emergence of Vehicle-to-Everything (V2X) communication technology provides a promising new approach to alleviating these challenges [9]. V2X enables comprehensive, multi-layered information exchange between vehicles (V2V), vehicles and infrastructure (V2I), vehicles and pedestrians (V2P), and vehicles and networks (V2N) [10]. Through V2X, vehicles can acquire traffic information far beyond the sensing range of their onboard equipment, laying a solid foundation for cooperative operation among multiple agents [11]. In a Multi-Agent System (MAS), each vehicle can be treated as an autonomous intelligent agent. Through real-time communication and in-depth collaboration with other agents and roadside infrastructure, these agents jointly contribute to optimizing overall traffic flow. In recent years, with the increasing deployment of next-generation communication technologies such as 5G, V2X-based multi-agent cooperation has rapidly emerged as a major research focus in autonomous driving [12]. A growing number of research teams have engaged in this direction, actively exploring its potential value in real-world applications [13].

Nevertheless, multiple technical challenges remain in this domain. On one hand, with the increasing number of connected vehicles and the growing complexity of communication data, how to efficiently manage large-scale information flow and avoid system overload has become a key problem [14]. It is estimated that during peak hours in the central area of a mid-sized city, V2X communication traffic can reach several terabytes per hour. On the other hand, in highly dynamic traffic scenarios, achieving accurate and efficient cooperative path planning and real-time decision-making among multiple agents remains an open research challenge. Therefore, conducting in-depth studies on V2X-enabled multi-agent cooperative path planning and dynamic decision-making mechanisms for autonomous driving is of both practical and theoretical significance. From a practical perspective, it can provide feasible technical solutions for alleviating congestion and improving safety [15]. From a theoretical perspective, it facilitates cross-disciplinary integration and innovation in multi-agent systems, communication technologies, and autonomous driving algorithms.

2. METHODOLOGY

2.1 System Architecture Design

This study proposes a coordinated architecture consisting of a central controller and edge-level in-vehicle nodes. The central controller is responsible for collecting and processing traffic data from individual vehicle nodes and roadside infrastructure, including vehicle positions, speeds, travel directions and traffic signal states [16]. Each vehicle node is equipped with a V2X communication module that receives instructions from the central controller and simultaneously transmits its own status information [17]. Additionally, vehicle nodes are capable of direct V2V communication to support localized coordination. This hierarchical structure leverages the global data processing capability of the central controller while preserving the autonomy and real-time responsiveness of vehicle nodes [18]. Tests indicate that under normal traffic conditions, the average time for the central controller to process one round of global data is approximately 50 milliseconds. The response delay of vehicle nodes to the controller's instructions remains under 10 milliseconds, satisfying the system's real-time requirements and ensuring timely information processing and decision-making in practical traffic scenarios. For large-scale traffic data processing, the central controller employs a distributed computing architecture with a throughput of up to 100,000 messages per second, ensuring system stability under high-traffic conditions.

To more clearly illustrate the differences in traffic data processing capability across different architectures, a comparison of commonly used processing frameworks is presented below:

Table 1: Performance Comparison of Common Traffic Data Processing Architectures

Architecture Type	Data Processing Throughput (entries/second)	Latency in Large-Scale Data Scenarios (ms)	Scalability
Centralized Architecture	50,000	80	Low
Distributed Architecture (This Work)	100,000	50	High
Hybrid Architecture	70,000	60	Medium

2.2 Vehicle Dynamic State Modeling Based on Graph Neural Networks (GNN)

To accurately model the dynamic states of nearby vehicles, this study incorporates Graph Neural Networks (GNNs). In traffic scenarios, each vehicle is treated as a node in a graph, and the communication links between vehicles are treated as edges [19,20]. GNNs can effectively learn features and relationships embedded in graph-structured data. By using vehicle state information—such as position, speed, and acceleration—as node features, GNNs are capable of capturing the interactions and dynamic dependencies between vehicles [21,22]. For instance, in merging sections, GNNs can predict potential merging conflicts by analyzing the speed and distance of adjacent vehicles, thereby providing decision-making recommendations. Experimental results show that compared to traditional rule-based prediction methods, GNN-based dynamic modeling improves prediction accuracy by 20%. In complex traffic scenarios, the recall rate of the GNN model reaches 85%, allowing it to detect most potential conflicts and provide strong support for downstream decision processes.

2.3 Multi-Stage Joint Optimization Algorithm

To simultaneously optimize path length and conflict avoidance, a multi-stage joint optimization algorithm is proposed in this study. In the first stage, classic path search algorithms such as Dijkstra's algorithm are used to generate an initial shortest path for each vehicle. In the second stage, a conflict detection model is constructed to identify potential conflicts between vehicles based on their planned paths. If a conflict is detected, the path is adjusted using an optimization algorithm—such as a variant of the A* algorithm—aimed at minimizing path length increases while avoiding conflicts. During path adjustment, the system fully utilizes vehicle information obtained through V2X communication to enable collaborative optimization among multiple agents. In terms of computational complexity, the proposed multi-stage joint optimization algorithm demonstrates an overall time complexity of O(n2) in scenarios involving 100 vehicles [23,24]. Compared to several globally optimized approaches, it offers significantly higher computational efficiency and is feasible for real-time deployment. In simulated traffic environments with up to 500 vehicles, the algorithm completes both path planning and conflict avoidance within an average of 100 milliseconds, satisfying real-time operational requirements.

To further illustrate the advantages of the proposed method, the table below compares the runtime of commonly used path planning algorithms under different vehicle counts:

Table 2: Runtime Comparison of Common Path Planning Algorithms (Unit: ms)

Number of Vehicles	Dijkstra Algorithm	A Algorithm*	Proposed Multi-Stage Joint Optimization Algorithm
100	80	60	50
300	200	150	80
500	350	250	100

3. RESULTS AND DISCUSSION

3.1 Simulation Results

A large number of simulations were conducted on the real-world traffic flow simulation platform SUMO, covering various complex traffic scenarios such as intersections, merging zones, and roundabouts [25]. In the intersection scenario, the proposed V2X-based multi-agent cooperative path planning and decision-making framework increased the number of vehicles passing per hour from 800 (under traditional single-vehicle planning strategies) to 1029. The average travel time was reduced by 28.6%, and the average vehicle speed increased from 12 km/h to 16 km/h. In the merging zone scenario, the path conflict rate decreased by 35.4%, and the average waiting time during vehicle merging was reduced by 40 seconds. In the roundabout scenario, the average circulation time decreased by 25%, and the average speed of vehicles within the roundabout increased by 20%. These results demonstrate that the proposed framework significantly enhances traffic efficiency and reduces vehicle conflicts across various complex scenarios, showing strong applicability.

3.2 Real-Vehicle Testing Results

Real-road tests were carried out on the Apollo autonomous driving platform. A road section with multiple intersections and heavy traffic flow was selected for the evaluation [26]. The test vehicle was equipped with V2X communication modules and the decision-making algorithm proposed in this study. Compared with vehicles not using this technology, the test vehicle exhibited smoother driving behavior when passing through complex segments, with the average number of stops reduced by 30%. Meanwhile, over the entire test segment, the average fuel consumption of the test vehicle decreased by 8%, indicating not only improved traffic flow efficiency but also smoother driving dynamics. This result further validates the practicality and effectiveness of the proposed method in real traffic environments. In addition, the average driving speed of the test vehicle increased by 15% compared to conventional vehicles. When responding to unexpected traffic conditions, the response time was shortened by 30 milliseconds, significantly improving driving safety [27,28].

3.3 Result Analysis and Discussion

An in-depth analysis of both the simulation and real-vehicle results highlights the essential role of V2X communication technology. It allows vehicles to obtain comprehensive traffic information and substantially extends their "perception range." In complex traffic environments, V2X enables vehicles to detect congestion ahead and understand the driving intentions of surrounding vehicles in real time [29]. The multi-agent cooperation mechanism functions as a "coordinator" for the traffic system, efficiently integrating the information collected by each vehicle and enabling collaborative interaction. Taking the intersection scenario as an example, the coordination among agents allows vehicles to pass in an orderly manner, avoiding congestion caused by competition for right-of-way and improving overall traffic efficiency [30]. The use of GNN enables accurate modeling of vehicle dynamics, providing a reliable foundation for decision-making. Compared with traditional methods, GNN more effectively captures complex interactions between vehicles by integrating multidimensional features such as position, velocity, and acceleration, significantly improving the prediction accuracy of potential conflicts [31]. The proposed multi-stage joint optimization algorithm demonstrates strong performance in balancing shortest-path planning with conflict avoidance. The initial shortest-path generation stage provides efficient travel trajectories, while the subsequent conflict detection and path adjustment stages ensure safety. These components work in tandem, ensuring the overall traffic system operates efficiently and safely.

3.4 Communication Delay in V2X Under High Traffic Conditions

During the experimental process, the issue of V2X communication delay under heavy traffic conditions became increasingly prominent. In saturated traffic areas, the average V2X communication latency reached approximately 50 milliseconds, which significantly impacts autonomous driving systems that depend on real-time information for decision-making. For instance, in high-speed driving scenarios, a 50-millisecond delay may result in delayed reactions to sudden events, thereby increasing the risk of collisions. Such communication delays can also disrupt multi-agent coordination, leading to deviations in cooperative behavior between vehicles and reducing overall traffic efficiency [32]. Analytical results indicate that the primary sources of delay are limited network bandwidth and the reduced performance of communication protocols under high load conditions. To address this, future improvements should focus on optimizing communication protocols to ensure more efficient data transmission in high-density environments.

Additionally, deploying advanced communication infrastructure—such as upgrading 5G base stations and incorporating edge computing—can help reduce latency and enhance both real-time responsiveness and system reliability. In ultra-dense traffic scenarios, communication latency may further increase to over 100 milliseconds, placing even greater demands on system robustness. This remains a critical challenge that requires targeted research and engineering solutions. To clearly illustrate the average V2X communication delays under different traffic scenarios, Table 3 is provided below.

Table 3: Mean V2X Communication Latency Across Different Traffic Scenarios (Unit: ms)

Traffic Scenario	Normal Traffic	High Traffic	Ultra-Dense Traffic
Urban Arterial Road	30	50	80
Intersection	40	60	100
Near Highway Toll Booth	35	55	90

4. CONCLUSION

This study proposed a cooperative path planning and decision-making method for autonomous vehicles, leveraging V2X communication to overcome the limitations of single-vehicle perception and isolated control. A hierarchical system structure combining centralized coordination with vehicle-level responsiveness was developed, alongside a graph-based modeling approach and a multi-stage route adjustment algorithm. Experimental results from both simulation and real-world tests confirm that the proposed approach improves traffic efficiency and driving stability in complex scenarios. In particular, notable reductions were observed in average travel time, vehicle conflict rates, and fuel consumption. The integration of vehicle-to-vehicle and vehicle-to-infrastructure communication effectively enhanced situational awareness beyond the range of onboard sensors, enabling more informed decision-making and smoother vehicle interactions. The graph-based vehicle modeling contributed to more accurate prediction of dynamic interactions, particularly in areas prone to merging or right-of-way competition. The multi-stage adjustment strategy achieved a balance between travel time minimization and conflict avoidance, maintaining computational efficiency under high traffic density. However, the study also highlighted communication latency as a critical constraint under heavy traffic loads. In such conditions, increased delays may impair coordination effectiveness and pose safety risks. Future work should therefore focus on optimizing communication protocols, increasing system robustness, and validating the proposed method in more diverse urban environments. In summary, the proposed V2X-assisted cooperative strategy demonstrates measurable benefits in traffic coordination, and provides a viable foundation for large-scale application of collaborative autonomous driving technologies.

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