Research on Cooperative Consensus of Multi-Vehicle Systems Based on Point Cloud and Dynamic Leader

Chongqing Liu

School of Electronic Engineering, Beijing University of Posts and Telecommunications, Beijing, China

Abstract. This paper explores the integration of point cloud perception and dynamic leader mechanisms to enhance cooperative consensus among multi-vehicle systems in autonomous driving environments. As autonomous driving technologies evolve, the necessity for multi-vehicle intelligence becomes apparent due to the complexities and variability of traffic environments which single vehicles alone cannot efficiently navigate. This study introduces a method that utilizes point cloud data for creating a unified environmental model that facilitates data sharing among vehicles, thus enabling a dynamic leader election system that optimizes traffic flow and energy consumption. By leveraging the capabilities of point cloud technology to provide a comprehensive view and high-precision spatial semantic information, and integrating it with a dynamic leader mechanism, this approach aims to improve decision-making accuracy and reduce system latency. The fusion of these technologies not only enhances the operational efficiency of individual vehicles but also ensures a cooperative interaction between multiple vehicles, leading to more effective management of complex traffic scenarios. This research potentially paves the way for significant advancements in smart transportation and unmanned logistics, promoting broader implementation of vehicle-road-cloud integration technologies.

1 Introduction

The burgeoning development of intelligent connected vehicles (ICVs) heralds a transformative era in transportation, marked by the rapid progression toward autonomous driving. As of April 2024, China's aggressive expansion of ICV test roads to over 29,000 kilometers and the issuance of more than 6,800 test demonstration licenses signify a significant leap forward, with road testing exceeding 88 million kilometers [1]. This burgeoning technological landscape presents profound implications not only for vehicle automation but also for the broader dynamics of urban and interurban mobility.

The evolution from human-operated to autonomous vehicles introduces new complexities in traffic environments that single vehicles alone cannot address efficiently. The intricate and dynamic nature of modern traffic systems demands a paradigm shift from

lcqn@bupt.edu.cn

single-vehicle intelligence to a multi-vehicle cooperative framework. The crux of this shift lies in the vehicle's ability to process and respond to vast and varied data streams, a task that stretches the limits of individual vehicle capabilities [2]. Thus, the integration of multi-vehicle cooperative systems emerges as a crucial step toward realizing the full potential of autonomous driving technologies.

Current autonomous technologies, while proficient in handling isolated vehicle operations, falter when required to manage the inter-vehicle dynamics essential for smooth traffic flow and enhanced road safety. Traditional approaches, such as fixed formation driving where only designated vehicles lead, result in suboptimal traffic efficiency due to rigid and unadaptive formations [3]. This highlights the necessity for advanced methodologies that not only enhance vehicle autonomy but also foster a collaborative operational framework among multiple vehicles.

This paper proposes a novel integration of point cloud perception with dynamic leader mechanisms to facilitate cooperative consensus among multi-vehicle systems. Point cloud data, obtained from sophisticated LIDAR and other sensory technologies, offers a three-dimensional environmental model crucial for comprehensive spatial understanding and decision-making. The dynamic leader mechanism, on the other hand, introduces a flexible leadership model that adapts to varying traffic conditions, optimizing traffic flow and reducing energy consumption through strategic vehicle coordination.

The theoretical foundation of this research rests on a collaborative framework termed "perception sharing-role evolution-control emergence." This model systematically integrates point cloud data sharing, dynamic leader election, and consensus-based control strategies to achieve an efficient multi-vehicle cooperative system. The dual integration of point cloud technology and dynamic leadership aims to synchronize the operational states of multiple vehicles, thereby ensuring a cohesive and intelligent vehicle network capable of complex decision-making and environmental interaction.

Such advancements in multi-vehicle coordination hold significant promise for various applications, notably in logistics and urban traffic management. In logistics, truck platooning can substantially reduce aerodynamic drag and fuel consumption, while in urban settings, collaborative vehicle operations can enhance traffic capacity, minimize congestion, and elevate overall traffic management efficiency [3]. By constructing a global view of the environment and facilitating high-precision decision-making, this approach enables vehicles to operate seamlessly in complex, ever-changing traffic scenarios, thus significantly enhancing the safety and reliability of autonomous driving systems.

the transition from isolated autonomous vehicles to an integrated multi-vehicle system represents a pivotal development in the pursuit of fully autonomous driving. By harnessing the power of advanced point cloud data analytics and dynamic leadership strategies, this research not only addresses the immediate challenges of vehicle automation but also lays the groundwork for future innovations in smart transportation and unmanned logistics. This integration marks a critical step towards the realization of sophisticated vehicle-road-cloud technologies, setting the stage for the next generation of autonomous vehicle systems.

2 Collaborative Point Cloud Perception Fusion

2.1 Data-Level Fusion

In autonomous driving technology, point cloud data acquired by vehicles through LIDAR and other sensing modalities plays a crucial role. However, these data may not be comprehensive due to a variety of reasons (such as the occlusion of vehicles or obstacles in front of them, the blind areas of point cloud perception, etc.), which may make the single-vehicle appears inadequate in dealing with emergencies. To overcome this problem, consider adopting an innovative approach, namely, generating a global dense point cloud model by merging the original data of each vehicle and merging the point cloud data of multiple vehicles. This method can not only obtain the situation of its surrounding environment from the bicycle, but also depict the environment situation of the whole team, thus providing a comprehensive view of the environment for the team. The generation of this global dense point cloud model will greatly benefit the global judgment and decision making, enabling the team to better deal with various complex road conditions, so as to get better results.

But there are also challenges when merging raw data from multiple vehicles: the amount of raw point cloud data is simply too large. In the case of single-vehicle, the 64-frame LIDAR point cloud generates about 2.2 million points (about 367,000 points per frame) per frame, with hundreds of thousands of data in a single frame. In the scenario of multi-vehicle collaboration, the point cloud data scale generated by the airborne / on-board laser scanning system can reach tens to hundreds of GB, and the multi-vehicle raw data transmission requires hundred-megabit-class Megabytes of bandwidth [4]. Therefore, if directly try to merge and share the point cloud data from multiple vehicles, then the demand for communication bandwidth will grow exponentially. This growth can not only easily lead to excessive load of network resources, but also may cause network congestion and data transmission delay problems.

To effectively reduce the data transmission amount and improve transmission efficiency, a strategy of dynamic region compression and selective transmission is proposed. This strategy encompasses three main aspects:
Transmission of point cloud data is limited to the blind areas of other vehicles. For instance, at an intersection, the vehicle in front may transmit information about blind spots to vehicles behind it. This targeted transmission mode significantly reduces the redundancy of data transmission, thereby optimizing overall communication efficiency.

Dynamic adjustment of the point cloud resolution based on the distance to the target object is implemented. For objects in close proximity, high-resolution point cloud data is used to ensure accuracy; for more distant objects, lower resolution data suffices, conserving bandwidth resources. This approach effectively balances accuracy with bandwidth needs, maintaining the necessary precision for effective vehicle operation.

Lightweight coding:adopt the compression method based on Octree.To enhance the efficiency of data transmission, lightweight encoding technology, specifically the highly efficient compression method of Octree, is utilized. Octree coding significantly reduces the data volume by encoding only the regions containing point cloud data. Studies indicate that the compression rate of this method can reach 20% -30%, substantially lowering the bandwidth requirements for data transmission, while still maintaining the integrity and availability of the data [4].

2.2 Feature-Level Fusion

In order to extract point cloud features from a single vehicle, preprocessing of point cloud data must first be completed. Subsequently, the point cloud features of the single vehicle are combined with those of other vehicles through cross-vehicle feature fusion technology. This approach involves the transmission of voxelized features or BEV semantic features, significantly reducing the volume and bandwidth consumption of the original point cloud data. Moreover, by utilizing edge computing technology for feature fusion, the end-to-end processing delay is maintained within the strict real-time performance requirements of the autonomous driving system.

In terms of specific methods and technical implementation, voxel-based feature coding techniques are adopted. The core of this technique involves converting point cloud data into 3D voxel grids, followed by the use of sparse convolution techniques to extract multi-scale geometric features. Dynamic indexing with hash tables is utilized to efficiently map and handle these features, thus achieving effective feature encoding and fusion. The related research literature provides more in-depth technical details [5, 6].

Cross-vehicle feature interaction techniques, driven by the attention mechanism, are also introduced. This method generates attention weight maps based on the density information of the single point cloud and the sensor's confidence level. This allows for the dynamic fusion of BEV features from different vehicles, thereby enhancing the intelligence and adaptability of feature fusion [7].

To further optimize transmission efficiency and computational resource usage, a strategy of lightweight transmission coordinated with edge computing is employed. Octree compression technology is utilized to reduce data transfer and is combined with edge computing offloading strategies to minimize the load on communication bandwidth and on-board computing resources. This strategy not only improves the efficiency of data processing but also alleviates the computational pressure on the on-board system [8].

3 Collaborative Decision Making and Dynamic Leader Mechanisms

3.1 Dynamic Leader Election Strategy

Under the premise of realizing multi-vehicle information sharing through point-cloud collaborative perception, the Leader of the fleet can be dynamically elected in the complex and changeable environment to realize the dynamic allocation of roles, and thus achieve the purpose of optimizing the global traffic.

In order to avoid frequent election of the Leader, which may lead to election disorder and instability, the election is triggered under certain conditions. The conditions for triggering the election can be categorized as follows: (1) When the fleet enters a complex roadway, intersection, ramp and other areas that require cooperative sensing. (2) When encountering unexpected situations or sudden changes in the environment, such as rainy and foggy weather leading to a decline in the performance of the sensor, or the emergence of sudden obstacles.

In the process of electing Leader, the first thing that needs to be understood is the weighted voting mechanism based on performance metrics. According to the literature, a priority-based leader dynamic election algorithm can be used to set dynamic priorities for each node [9]. This mechanism involves several key performance metrics, including the sensing ability, communication quality, and arithmetic margin of candidate nodes. These metrics are not set in stone, but are involved in scoring through a dynamic weight distribution method that Tensures the fairness and adaptability of the election process.

The problem of dynamic weight adjustment. The weights are adjusted according to different scenarios, e.g., in the urban road scenario and the rainy and foggy weather scenarios, the weights will be assigned differently. Taking rainy and foggy weather as an example, the importance of communication quality will be significantly increased at this time, so its weight may be adjusted to 50% to ensure that the communication quality can still be fully emphasized under adverse weather conditions.

Then it goes to the evaluation election where each adjacent car scores the candidates based on the evaluation metrics mentioned above during the neighboring car evaluation process. The scoring range is from 0 to 1 and each candidate is given a composite score.

Eventually, after all the scores are aggregated, the candidate with the highest total score will be elected as Leader.

3.2 A hierarchical collaborative control architecture

Leader roles can be divided into Global Leader and Local Leader, functioning collaboratively to enhance multi-vehicle cooperative control. The Global Leader takes charge of the overall planning and scheduling of the entire fleet, ensuring that all vehicles adhere to a predetermined route and speed. Conversely, the Local Leader manages the fine coordination and control of surrounding vehicles within its jurisdiction to respond adeptly to unexpected road conditions or traffic events. This layered architectural approach not only boosts system flexibility and response time but also maintains a high degree of consistency and stability for the entire fleet amidst complex and evolving traffic scenarios.

At the global level, the roadside unit (RSU) or cloud server is the global leader. The main responsibilities of the leader include the prediction of traffic flow across regions, such as global path planning during peak hours, responsible for the allocation of resources, such as the scheduling of charging pile and parking space, and coordinating emergencies, such as the global detour strategy in the event of traffic accidents.

At the local level, sub-leaders are elected for each road segment, which can be edge nodes with high computational power or lead vehicles in a convoy. Their task is to perform real-time signal timing optimization, which improves traffic efficiency by intelligently adjusting the timing of signals. At the same time, sub-leaders are also responsible for lane-level traffic regulation, e.g., implementing variable lane control strategies to dynamically adjust lane usage based on real-time traffic conditions to adapt to traffic variations at different times of the day. In emergency situations, the sub-leader is also required to implement emergency obstacle avoidance measures to ensure that vehicles can safely and quickly avoid obstacles and maintain traffic order.

3.3 Decision fusion outputs optimal solutions

To enhance the robustness of the system, increase fault tolerance, and improve resource efficiency, independent decision results from multiple sensors across different sources can be integrated to generate a globally optimal output for more efficient and accurate decision-making processes. The specific steps include:

First independent sensing: each sensor completes the detection and tracking of the target separately to provide basic data for subsequent decision making

Next is decision generation: each sensor outputs its detected target location, category, and other relevant information.

Finally, fusion policy: using methods such as weighted voting, Bayesian inference, or deep learning models, the decision results from different sensors are integrated to generate a globally optimal decision output [10].

4 Multi-vehicle consistency control in a dynamic environment

4.1 State Synchronization and Error Compensation driven by Point Cloud Perception

State synchronization and error compensation are crucial aspects in achieving coherent control of multiple vehicles. In order to achieve this goal, point cloud sensing technology can be utilized to obtain the relative position and velocity information between vehicles through accurate sensing and modeling of the surrounding environment, and then achieve accurate state synchronization.

To achieve time synchronization, GPS/Beidou timing signals, specifically PPS pulses and GPRMC time telegrams, are used to synchronize the clocks of multiple sensors. This ensures that the timestamp error of key devices such as LIDAR and cameras is kept within 1 ms. For asynchronous point cloud data, the nearest neighbor frame matching method is adopted to ensure data consistency and accuracy [11,12].

In terms of spatial synchronization, a global virtual world coordinate system is established, and lidar point cloud data from both the vehicle end and the road end are uniformly transformed into this coordinate system through an accurate calibration matrix. This method effectively eliminates the point cloud data offset caused by differences in installation and location, thus ensuring the accuracy and consistency of the spatial data.

For error compensation, a detailed approach is taken where the vehicle point cloud is divided into a number of sub-regions, and then the point density within each sub-region is statistically analyzed. This allows for the identification of missing parts in the point cloud data. When a significant difference in point cloud density is detected, a compensation algorithm is automatically triggered to fill in the missing data, ensuring the completeness and accuracy of the point cloud data. This process references techniques described in related literature.

5 Discussion

The simulation test can be conducted through the simulation platform to verify the performance of multi-vehicle after the integration of these technologies. Based on the OpenCDA platform, the multi-vehicle collaborative simulation under urban roads, expressways and extreme scenes (rain and fog point cloud density <40%, dynamic obstacles interference) is built to test the performance of dynamic Leader mechanism and point cloud fusion algorithm. Key indicators include target detection mAP, lateral tracking error, queue response delay, and verifying the system robustness through simulated communication delay (50~200ms) and packet loss rate (1%~10%). Through theoretical analysis, dynamic Leader hybrid voting mechanism and eight tree coding, the point cloud compression rate, delay and target detection mAP can be greatly improved. The high efficiency and reliability of multi-vehicle collaboration in a dynamic environment are verified.

6 Conclusions

This research has demonstrated that the integration of point cloud perception and dynamic leader mechanisms significantly enhances the cooperative consensus and operational efficiency of multi-vehicle systems in autonomous driving environments. By leveraging point cloud data for comprehensive environmental modeling and utilizing dynamic leadership for adaptive control, vehicles are able to effectively share information and make precise decisions. This not only optimizes traffic flow and reduces energy consumption but also addresses the complexities of modern traffic scenarios more effectively than traditional autonomous systems..

The future may have the following development directions:

(1) Algorithm intelligent optimization: dynamically adjust the weight allocation in combination with the federated learning framework to improve the data privacy protection ability of cross-car companies.

(2) Enhancement of fault-tolerance mechanism: research on multi-leader fault-tolerance strategy to solve the decision-making conflict in the scenarios of brain splitting and network partitioning.

References

1. Tan, Y.: 'Autonomous driving is accelerating', Road Traffic Management, 2024, 6, pp. 28-29
2. Li, C., Zhang, Y., Zhang, Y., et al.: 'Multi-vehicle formation task allocation strategy for automated cooperative driving', Journal of Electronics & Information Technology, 2020, 42, (1), pp. 65-73
3. Wu, Y., & Wang, Q.: 'Hybrid intersection passing strategy based on formation and dynamic priority', Complex Systems and Complexity Science, 2024, 21, (1), pp. 126-131,144
4. Zhu, X., Liu, Z., Cambria, E., Yu, X., Fan, X., Chen, H., Wang, R.: 'A client–server based recognition system: Non-contact single/multiple emotional and behavioral state assessment methods', Comput. Methods Programs Biomed., 2025, 260, pp. 108564.
5. Wang, R., Zhu, J., Wang, S., Wang, T., Huang, J., Zhu, X.: 'Multi-modal emotion recognition using tensor decomposition fusion and self-supervised multi-tasking', Int. J. Multimed. Inf. Retr., 2024, 13, (4), pp. 39.
6. Wang, F., Ju, M., Zhu, X., Zhu, Q., Wang, H., Qian, C., Wang, R.: 'A Geometric algebra-enhanced network for skin lesion detection with diagnostic prior', J. Supercomput., 2025, 81, (1), pp. 1-24.
7. Zhao, Z., Zhu, X., Wei, X., Wang, X., Zuo, J.: 'Application of Workflow Technology in the Integrated Management Platform of Smart Park', IEEE Adv. Inf. Manag., Communicates, Electron. Automat. Control Conf., 2021, 4, pp. 1433-1437.
8. Zhang, Y., Zhao, H., Zhu, X., Zhao, Z., Zuo, J.: 'Strain Measurement Quantization Technology based on DAS System', IEEE Adv. Inf. Manag., Communicates, Electron. Automat. Control Conf., 2019, pp. 214-218.
9. Wu, Y., & Cao, X.: 'Adjacent cell computation algorithm for Hilbert octree'. Proc. Int. Conf. Geomatics and Information Science of Wuhan University, 2022, 47, (4), pp. 613-622
10. Gao, P.: 'Priority-based Raft leader dynamic election algorithm and log replication research'. Proc. Int. Conf. Master's thesis, Tianjin University of Technology, China, 2023
11. Wen, L.: 'Research on efficient Bayesian inference algorithms in deep learning'. Proc. Int. Conf. Ph.D. dissertation, University of Electronic Science and Technology of China, Sichuan, China, 2021
12. Shi, X., Zhao, D., Kong, Z., et al.: 'High-precision vehicle positioning technology based on multi-sensor information fusion', China Mechanical Engineering, 2022, 33, (19), pp. 2381-2387