International Journal of Management Science Research, Vol.8, Issue 5, (May) **2025**
ISSN 2536-605X
DOI: 10.53469/ijomsr.2025.08(05).06

Improving Real-Time Performance of Autonomous Driving Systems with Edge Computing

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Abstract: ***High-latency bottlenecks in traditional cloud-based architectures pose significant challenges for real-time autonomous driving applications. To address this issue, this study introduces an edge computing-based optimization framework tailored for autonomous driving systems. A hierarchical collaborative computing architecture is designed to distribute perception and decision-making tasks across edge nodes, thereby improving response efficiency. The framework incorporates Docker container technology to enable lightweight modularization of system components, while the Kubernetes orchestration platform ensures dynamic resource scheduling and flexible deployment. Empirical evaluation on the Baidu Apollo autonomous driving open platform demonstrates that the proposed solution reduces end-to-end system latency by 23.6%, with only a marginal decrease in target detection performance (mAP drop ≤ 2.8%). The results also confirm the framework's scalability and adaptability, offering practical guidance for engineering deployment in autonomous driving scenarios.***

Keywords: Edge computing; Autonomous driving system; Real-time performance optimization; Modular deployment; Container orchestration; Apollo platform.

1. INTRODUCTION

With the accelerated transformation of intelligent transportation systems, autonomous driving technology is undergoing a critical transition from theoretical exploration to industrial implementation [1]. The Society of Automotive Engineers (SAE International) divides autonomous driving into six levels, from L0 to L5. Currently, Level 2 driving assistance systems have been widely adopted in the passenger vehicle market [2,3]. Representative intelligent driving solutions, such as Tesla's Autopilot and NIO's NOP, achieve partial automation in specific scenarios by integrating multi-sensor data and path planning algorithms [4,5]. However, breakthroughs required for Level 3 and above — covering high-level and full automation — still face core technical challenges such as complex environment perception and real-time decision-making [6]. According to a forecast by Markets and Markets, the global autonomous vehicle market size is expected to exceed USD 1.5 trillion by 2030 [7]. The realization of this industrial goal urgently depends on overcoming the technical barrier of real-time performance, which not only determines the system's ability to respond to sudden road conditions but also directly impacts traffic safety and user experience [8].

The traditional cloud computing architecture increasingly reveals inherent contradictions between system architecture and business demands when applied to autonomous driving systems [9]. This architecture uploads massive heterogeneous data collected by onboard sensors (LiDAR, cameras, millimeter-wave radar, etc.) to the cloud for processing [10]. Although cloud computing centers possess strong computational capabilities to support complex algorithm operations, they encounter unavoidable latency gaps during data transmission [11]. According to the "2024 Global Autonomous Driving Network Latency White Paper," under 4G network conditions, the end-to-end latency from data collection to processing result return can reach 680 milliseconds, and even under 5G networks, the average latency remains about 220 milliseconds [12]. Such latency can lead to catastrophic consequences for vehicles traveling at high speed. A vehicle moving at 60 km/h will travel an additional 16.7 meters during a one-second delay, which can cause it to miss the optimal decision window in highway emergency braking or urban obstacle avoidance scenarios [13]. A recent simulation analysis based on 500 autonomous driving accidents shows that 37% of accidents are related to latency issues under cloud computing architectures [14]. Moreover, problems such as bandwidth consumption and network stability dependency during data transmission further increase operational risks, highlighting the structural limitations of traditional architectures in supporting real-time tasks.

Edge computing, as a new generation of distributed computing paradigm, provides a revolutionary approach to solving real-time performance problems in autonomous driving [15]. Its core lies in migrating computing, storage, and networking resources to the edge side. Through onboard edge units (OBUs) and roadside units (RSUs), localized processing capabilities are established, enabling nearby data processing and rapid response [16]. Recent research by IEEE indicates that edge computing can reduce data processing latency by 60% to 80%, significantly improving the system's efficiency in perceiving dynamic environments [17]. In practical applications, RSUs can aggregate information such as surrounding vehicle statuses and obstacle data, process it locally to form regional traffic situation awareness results, and deliver decision recommendations to vehicles within milliseconds, greatly enhancing system responsiveness [18,19]. In addition, edge computing reduces long-distance data transmission, thereby lowering the risk of data breaches [20]. According to the "2023 Internet of Vehicles Security Report" by Qi An Xin, adopting edge computing can reduce data breach risks by about 45% [21]. It also enables systems to maintain autonomous operations during network failures, effectively improving system robustness [22]. Despite the significant potential of edge computing, its deep application in autonomous driving still faces multiple technical challenges [23]. The computing power and storage capacity of edge nodes are relatively limited, making it difficult to support the continuous and efficient operation of complex deep learning models [24]. For example, when deploying advanced object detection models such as YOLOv5 on edge devices, insufficient computational resources often cause a sharp decline in processing frame rates [25]. In multi-edge node collaborative computing, dynamic resource scheduling mechanisms are still immature. There is a lack of adaptive strategies for prioritizing different types of tasks (perception, decision-making, and control) and allocating computing resources, which easily results in load imbalance among nodes [26]. Moreover, challenges exist in optimizing the deployment of lightweight algorithm models on edge devices, particularly in maintaining detection accuracy while compressing model parameters. Therefore, in-depth research on real-time performance optimization of autonomous driving systems based on edge computing architectures is essential. It not only addresses technical bottlenecks but also acts as a core driver for advancing the commercialization of autonomous driving technologies and reshaping the future transportation ecosystem.

2. METHODOLOGY

2.1 Design of Heterogeneous Collaborative Architecture Based on Edge Computing

A three-layer heterogeneous collaborative computing architecture of "cloud–edge–end" is constructed [27]. On the terminal side, an OBU (equipped with an NVIDIA Jetson Xavier NX providing 14 TOPS of computing power) is configured. The OBU connects to one 20 Hz scanning LiDAR (160,000 points per frame), six cameras with a resolution of 1920×1080 (30 frames per second), and three millimeter-wave radars capable of detecting objects up to 200 meters (10 Hz). On the edge side, an RSU with 50 TOPS of computing power is deployed, and 5G-V2X technology is used to achieve vehicle-road-cloud communication. A hierarchical offloading strategy is employed. After preprocessing sensor data, the OBU locally handles urgent, low-latency tasks, while complex tasks are transmitted to the RSU. The RSU aggregates data from multiple vehicles to improve perception accuracy. Ultra-large-scale tasks are further uploaded to the cloud through edge-cloud collaboration, and the processing results are transmitted back to the vehicles, forming an efficient processing chain [28].

2.2 Modular Deployment Scheme Based on Container Technology

Docker is used to package modules such as perception, decision-making, and control into lightweight container images. The resource usage of each module is presented in Table 1.

Table 1: Resource Usage of Containerized Modules in the Autonomous Driving System

Functional Module	Average Container Memory Usage (MB)	CPU Usage Rate Under Normal Load
Perception Module	512	18%–25%
Decision-Making Module	480	15%–22%
Control Module	450	12%–20%

Container orchestration and scheduling are performed based on Kubernetes [29]. A management framework is established by defining resource objects such as Pods and Services. The system is capable of completing container scaling operations within 2.3 seconds according to load conditions. It utilizes service discovery and load balancing to achieve task collaboration and resource sharing among nodes, thereby enhancing system scalability and fault tolerance.

2.3 Edge-Side Algorithm Model Optimization Strategy

The perception algorithms adopt lightweight networks, namely MobileNetV3-Large and ShuffleNetV2-1.5x, combined with knowledge distillation techniques. The key indicators of the models before and after optimization are compared in Table 2.

Table 2: Comparison of Key Indicators of Perception Algorithms Before and After Optimization

Model	Number of Parameters	Reduction Ratio of Parameters on COCO Dataset	mAP on Cityscapes Test Dataset	mAP Difference Compared to Teacher Model
YOLOv5s (Teacher Model)	7.3M	–	–	–
MobileNetV3-Large	5.4M	26%	72.3%	3.5%
ShuffleNetV2-1.5x	2.2M	69%	68.7%	5.1%

The decision-making algorithm improves the RRT algorithm by introducing heuristic search and vehicle dynamics constraints. In the simulated urban road tests, the performance comparison of the path planning algorithm before and after optimization is presented in Table 3.

Table 3: Performance Comparison of Path Planning Algorithm Before and After Optimization

Algorithm	Path Planning Time (ms)	Speed Improvement Percentage
A* Algorithm	820	–
Improved RRT Algorithm	150	81.7%

3. RESULTS AND DISCUSSION

3.1 Experimental Environment and Testing Scheme

The testing environment was built based on the Baidu Apollo platform. The experimental vehicle was configured according to the system architecture design, and the RSU communicated with the vehicle through 5G with a bandwidth of 800 Mbps and a latency of 15 ms. Typical scenarios, including urban roads and highways were set up. Each scenario was tested with 50 repeated groups. A comparison was conducted between the traditional cloud computing architecture and the proposed scheme of this study, monitoring indicators such as end-to-end latency, mean average precision (mAP), and decision-making accuracy.

3.2 Analysis of Experimental Results

The experimental results are presented in the following table, which directly shows the performance differences between different architectures under various scenarios:

Table 4: Performance Comparison of Different Architectures in Typical Scenarios

Test Scenario	Architecture Type	End-to-End Latency (ms)	Data Transmission Latency (ms)	Computation Processing Latency (ms)	Target Detection mAP
Urban Road	Traditional Cloud Computing Architecture	450	280	170	98.5%
Urban Road	Proposed Edge Computing Architecture	344	80	264	95.7%
Highway	Traditional Cloud Computing Architecture	380	250	130	97.8%
Highway	Proposed Edge Computing Architecture	290	70	220	95.0%

In terms of latency performance, the edge computing architecture proposed in this study exhibits significant optimization effects. In the urban road scenario, the average end-to-end latency of the traditional cloud computing architecture reaches 450 ms, whereas the proposed scheme reduces it to 344 ms, achieving a 23.6% reduction. In the highway scenario, latency is optimized from 380 ms to 290 ms, also realizing a substantial decrease. A detailed analysis of the latency composition shows that data transmission latency is sharply reduced from 280 ms to 80 ms, with a reduction rate of 71.4%. This fully demonstrates the advantage of edge computing in pushing data processing to the network edge and reducing the latency caused by long-distance transmission [30]. Although the computation processing latency increases from 170 ms to 264 ms, with an increase of 55.3%, the significant reduction in transmission latency still effectively controls the overall latency. This indicates that through reasonable task offloading and resource scheduling strategies, it is possible to improve the overall system response speed even under limited computing power at edge nodes [31]. Compared with recent studies published in *IEEE Transactions on Intelligent Transportation Systems*, the proposed scheme shows an advantage in latency optimization, as most related research achieves only a 15%–20% reduction, further highlighting the effectiveness of this approach. Regarding target detection accuracy, the performance of lightweight models under the edge computing architecture deserves attention [32]. Taking pedestrian detection as an example, the recognition accuracy of the traditional YOLOv5s model is 96.5%, while the lightweight MobileNetV3-Large model achieves 95.2% under the proposed architecture. In the overall testing, the mAP of the optimized model decreases by 2.8% compared to the traditional model [33]. Although there is a slight loss of accuracy, knowledge distillation techniques effectively control the magnitude of the decline, enabling the lightweight model to meet the practical requirements of autonomous driving systems when deployed on edge devices. This result verifies the feasibility of combining lightweight models with knowledge distillation techniques in edge computing scenarios, providing practical evidence for deploying efficient perception models on resource-constrained edge nodes. Compared with current mainstream edge-side perception model optimization studies, where some methods achieve higher compression rates but often incur accuracy losses exceeding 5%, the proposed scheme achieves a better balance between accuracy and efficiency. In terms of decision-making accuracy, the improved RRT algorithm demonstrates significant performance improvements. In 100 simulated intersection decision-making tests, the traditional path planning algorithm results in 18 decision errors, while the improved RRT algorithm records only 6 errors, achieving a 12% improvement in decision-making accuracy. In various test scenarios, the optimized decision-making algorithm can quickly generate feasible paths, benefiting from the introduction of heuristic search strategies and the consideration of vehicle dynamics constraints [34,35]. These enhancements allow the algorithm to more accurately evaluate path feasibility in complex traffic environments, significantly improving the system's decision-making reliability [36]. Compared with the traditional A* algorithm and other improved path planning methods, the proposed scheme not only ensures high path planning quality but also significantly reduces computation time, providing strong support for real-time decision-making in dynamic environments for autonomous vehicles [37].

3.3 Discussion of Results

The experimental results of this study fully validate the effectiveness of the edge computing-based optimization scheme for autonomous driving systems in enhancing real-time performance. Through distributed computing and collaborative processing at edge nodes, the system's dependence on remote cloud computing was successfully reduced, significantly improving response speed while achieving a good balance between model accuracy and decision-making precision. However, some issues observed during the experiments also point to directions for future research. In high-concurrency scenarios, the problem of insufficient computing power at edge nodes becomes particularly evident. When node load exceeds 80%, the average task processing latency increases from 50 ms to 120 ms, indicating that the current computational resources at edge nodes face bottlenecks when handling large-scale data processing tasks. Future research should further explore dynamic computing resource scheduling mechanisms for edge nodes, such as dynamic resource allocation strategies based on reinforcement learning, which can adjust computing resources in real time according to task priorities and node load conditions, thereby improving system stability under high-load situations [38]. In addition, optimizing collaborative computing among multiple edge nodes is also crucial. By constructing edge node clusters, resource sharing and task collaboration among nodes can be achieved, enhancing the overall processing capability of the system. The lack of a comprehensive data security protection mechanism is another important challenge for applying edge computing to autonomous driving systems. Although edge computing reduces long-distance data transmission and mitigates some security risks, edge nodes in the vehicle-to-everything (V2X) environment still face threats such as data breaches and malicious attacks. Future research should focus on strengthening the security protection system across terminal–edge–cloud architectures. Blockchain technology can be introduced to achieve secure data storage and transmission, while encryption algorithms and access control mechanisms can be used to protect sensitive data, ensuring the security and reliability of autonomous driving systems under edge computing frameworks.

Moreover, the generalizability of the proposed scheme across different traffic scenarios requires further validation. Although good results were obtained in urban road and highway scenarios, system performance may still be affected under extreme weather conditions (such as heavy rain or snow) and complex traffic events (such as road construction or traffic accident scenes). Future studies should collect more data under such special scenarios to optimize algorithm models and enhance the system's adaptability to complex environments. From a broader perspective, the outcomes of this study provide important references for promoting the transition of autonomous driving systems from theoretical research to practical application, accelerating the deep integration of edge computing technology and autonomous driving, and are expected to have a profound impact on the future development of intelligent transportation systems.

4. CONCLUSION

This study addresses the latency bottleneck of traditional cloud computing architectures by proposing an optimization scheme for autonomous driving systems based on edge computing, and conducts empirical validation on the Baidu Apollo platform. Experimental results show that, in the urban road scenario, the proposed scheme reduces the system's end-to-end latency from 450 ms to 344 ms, achieving a 23.6% reduction. In the highway scenario, latency is optimized from 380 ms to 290 ms. Regarding the maintenance of target detection accuracy, the mAP of the lightweight model decreases by only 2.8% compared with the traditional model, with pedestrian detection accuracy slightly declining from 96.5% to 95.2%, and the accuracy loss is effectively controlled through knowledge distillation techniques. For decision-making accuracy, the improved RRT algorithm reduces the number of decision errors from 18 to 6 in 100 simulated intersection decision-making tests, achieving a 12% improvement. Meanwhile, the proposed scheme realizes modular deployment and dynamic resource scheduling through the use of Docker containers and Kubernetes, demonstrating excellent architectural scalability and deployment flexibility. In practical engineering applications, it is necessary to flexibly adjust task offloading strategies and resource scheduling schemes based on the characteristics of different traffic scenarios and the resource configurations of edge nodes, in order to achieve optimal system performance. Future research will focus on the deep integration of edge computing and artificial intelligence technologies, exploring intelligent collaborative computing mechanisms among edge nodes. Efforts will be directed towards addressing critical issues such as the computing resource bottleneck at edge nodes and data security protection, further enhancing system real-time performance, security, and reliability under complex scenarios. These advancements are expected to provide strong technical support for the commercialization and large-scale deployment of autonomous driving technologies, promoting the advancement of autonomous driving systems to higher stages.

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