A Review of Cloud-Edge-Vehicle Collaborative Computing for Intelligent Transportation Systems

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Abstract: As both intelligent connected vehicles and intelligent transportation systems are undergoing rapid development, the massive volume of in-vehicle computing tasks requiring ultra-low latency and high reliability poses significant challenges to traditional cloud computing architectures. Cloud-edge-vehicle collaborative computing is widely recognized as the most promising and worthy core enabling technology to address this bottleneck, as it organically integrates the abundant computing resources of the cloud, the low-latency response capabilities of edge nodes, and the real-time perception data from vehicles.Therefore, this paper reviews the research progress on cloud-edge-vehicle collaborative computing for intelligent transportation systems: first clarifying the basic concepts and hierarchical architecture of collaborative computing systems; then summarizing key technologies, typical applications, and existing achievements; followed by an objective and thorough analysis of the primary challenges in current technology implementation; and finally, based on this, offering a reasonable discussion of future research directions. This provides a systematic reference for subsequent research.

Keywords: Cloud Computing; Edge Computing; Vehicle-to-Everything (V2X); Cloud-Edge-Vehicle Collaborative Computing; Intelligent Transportation Systems

1. Introduction

As the global transportation industry undergoes a transformation toward intelligence and connectivity, Intelligent Transportation Systems (ITS) have gradually become the core infrastructure for the construction of new smart cities.In recent years, various applications such as high-level autonomous driving, in-vehicle smart cockpits, and city-level real-time traffic control have developed rapidly, and the number of intelligent connected vehicles has grown explosively. Accompanying this growth are the massive, heterogeneous, ultra-low-latency, highly reliable, and highly dynamic characteristics of in-vehicle perception data and computing tasks.

Traditional centralized computing architectures centered on a central cloud cannot meet the fundamental requirements of intelligent transportation scenarios, nor can they satisfy the strict latency requirements of autonomous driving (within 10 ms). Edge computing nodes suffer from limitations such as limited computing power, discontinuous coverage, and the inability to perform global optimization. Meanwhile, in-vehicle computing power is characterized by strong heterogeneity and uneven distribution of idle resources. Consequently, a single vehicle or edge node alone cannot yet support the full-scenario demands of high-level intelligent transportation services.

However, if cloud-edge-vehicle collaborative computing is implemented-integrating computing power, storage, networking, and data resources from the cloud, edge, and vehicle layers to form a three-tier collaborative computing system characterized by “global coordination, local response, and edge execution”-it can meet the diverse requirements of intelligent transportation services, including low latency, high reliability, large scale, and global optimization.

This review takes cloud-edge-vehicle collaborative computing for intelligent transportation systems as its central research focus, summarizing the research progress and technical framework in this field. The structure of the paper is as follows:Chapter 2 reviews existing literature in related fields, identifies current challenges, and establishes the research value of this paper. Chapter 3 presents the basic concepts and hierarchical architecture of cloud-edge-vehicle collaborative computing. Chapter 4 provides a systematic summary of the four core key technologies. Chapter 5 discusses typical application scenarios for intelligent transportation,Chapter 6 analyzes the major challenges encountered in technology implementation and outlines future directions and trends, and finally, Chapter 7 provides a summary of the entire paper.

2. Literature Review

In recent years, both in-vehicle edge computing and V2X (Vehicle-to-Everything) technologies have made significant strides. The academic community, both domestically and internationally, has produced a substantial body of review studies in these fields. Therefore, this section aims to systematically organize existing reviews from three dimensions to clarify current challenges.

In-vehicle edge computing serves as the foundation for cloud-edge-vehicle collaboration. The review of in-vehicle edge computing systems published by Zhao et al.[1] in *IEEE Internet of Things Magazine* in 2025 effectively summarizes the latest architectures, key technologies, and typical applications of in-vehicle edge computing; however, it lacks a comprehensive framework for establishing and integrating multi-faceted in-vehicle edge computing technologies.

Liu et al.[2] established a technical framework for in-vehicle edge computing and networking in 2021 in *Mobile Networks and Applications*, covering four aspects: network architecture, communication protocols, resource management, and security protection. The review by Raza et al.[3] , published in 2019, refined the research framework for in-vehicle edge computing across four dimensions: architecture, applications, technical challenges, and future directions.

A limitation of this literature is its narrow research perspective. Currently, most reviews on in-vehicle edge computing focus on a single dimension, failing to provide a systematic, hierarchical analysis of the three-tier cloud-edge-vehicle collaboration system or to clarify the boundaries and collaboration models among the three components.

A 2023 review on fog computing applications in vehicle-to-everything (V2X) networks published in *Vehicular Communications*[4] highlighted the role of vehicles as distributed computing nodes but lacked discussion on collaboration with edge computing; a 2022 review in *IEEE Access* on the integration of multi-access edge computing (MEC) and in-vehicle networks discussed collaborative technical solutions under different communication standards[5]; Campolo et al.[6] pointed out the inevitable trend of V2X evolving from single-communication systems toward the convergence of “communication + computing”; the in-vehicle fog computing architecture proposed by Hou et al.[7] incorporates vehicles as part of the transportation infrastructure into a distributed computing resource pool, establishing a solid theoretical foundation for the collaborative utilization of vehicle-side computing power.

However, algorithms are currently evolving at a rapid pace, and such literature has not addressed the shortcomings of algorithms under existing resource constraints and various changing scenarios; consequently, global coordination and full resource utilization have not yet been achieved.

Edge intelligence technology is the most direct and powerful support for cloud-edge-vehicle collaborative AI applications. The review on edge intelligence published by Zhou et al.[8] in *Proceedings of the IEEE* in 2019 clarified the core technical architecture of “cloud training and edge inference.”In 2020, Deng et al.[9] supplemented the technical framework of edge intelligence by coordinating processes such as model training, model inference, and model updates, thereby identifying six major application scenarios for edge intelligence. In 2021, Li et al.[10] conducted research on AI-enabled edge computing for vehicle-to-everything (V2X) networks, clarifying the adaptation strategies and application value of AI technology in in-vehicle scenarios.

However, most current research on general in-vehicle scenarios has not been integrated with the implementation of Intelligent Transportation Systems (ITS), let alone combined with the rapidly evolving field of AI. Consequently, existing literature lacks direct discussion of city-level ITS operations such as traffic control and emergency response, as well as imagination regarding integration with AI.

Having identified some shortcomings in existing literature, this paper presents a systematic improvement, summarized as follows:

Theoretically, a cloud-edge-vehicle collaborative computing framework for intelligent transportation systems (ITS) was established, deriving a three-tier architecture and four major collaboration modes. The research findings were organized and reviewed from the perspectives of task offloading, resource management, edge intelligence, and security protection. Based on the practical implementation scenarios of ITS, this paper analyzes various pain points, challenges, and future directions in technology application, and offers several recommendations.

3. System Architecture

3.1 Core Concepts and Technological Evolution

Cloud-Edge-Vehicle collaborative computing takes the business requirements of intelligent transportation as its starting point and ultimate goal. It integrates the computing power, storage, network, and data resources possessed by three main entities: central cloud platforms, roadside/base station edge computing nodes, and in-vehicle terminals. Based on current discussions, the development of this technology can be divided into three distinct phases:

Centralized Cloud Computing Phase: This approach treats the central cloud as the sole computing hub, providing global coordination capabilities. However, this model suffers from issues such as high latency, significant bandwidth pressure, and a high risk of single points of failure.

In-Vehicle Edge Computing Phase: Computational resources are decentralized to roadside units (RSUs) and 5G base station MEC nodes located near the vehicle, enabling localized processing of in-vehicle tasks and controlling end-to-end latency. However, this model suffers from limited computing power at edge nodes, discontinuous coverage, and a lack of coordination among edge nodes, which can lead to uneven load distribution.

Cloud-Edge-Vehicle Three-Tier Collaboration Phase: This approach breaks down the resource barriers between the cloud, edge, and vehicle, integrating the cloud's global coordination capabilities, the edge's low-latency response capabilities, and the vehicle's real-time perception and distributed computing capabilities. Consequently, tasks are dynamically and optimally assigned to the appropriate nodes based on their latency requirements, computing power needs, and security levels.

3.2 Hierarchical Architecture of Cloud-Edge-Vehicle Collaborative Computing for Intelligent Transportation Applications

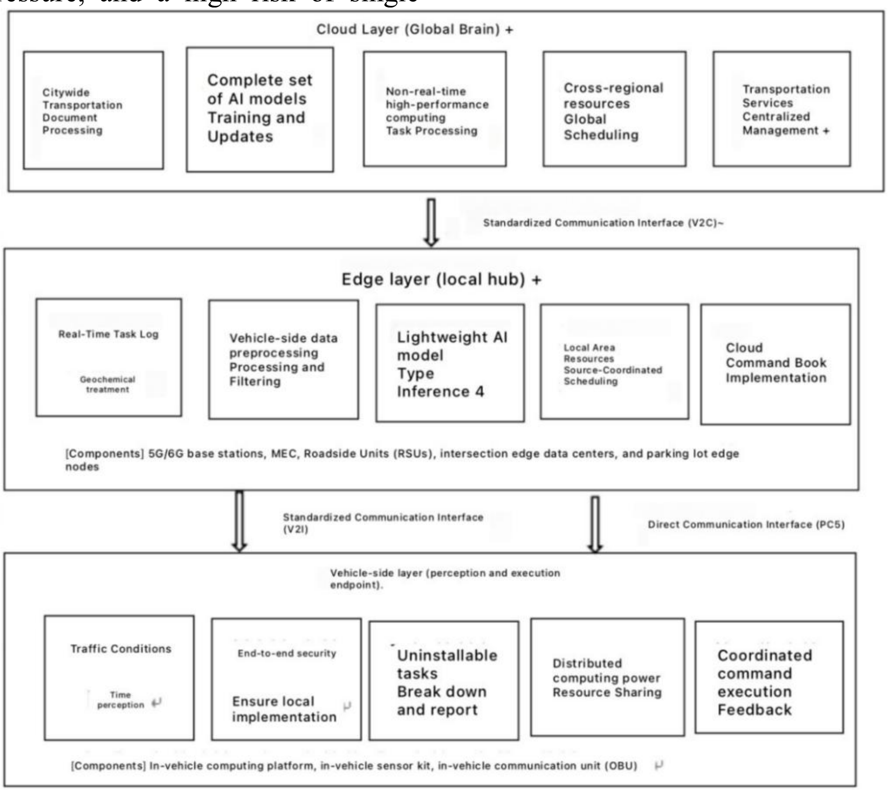

Figure1. Three-Tiered Cloud-Edge-Vehicle Collaborative Computing Architecture for Intelligent Transportation Systems

As shown in Figure 1,it depicts the functional and component breakdown of the three-tier cloud-edge-vehicle collaborative architecture. The Cloud Layer handles global non-real-time tasks. The Edge Layer runs latency-sensitive real-time operations, supported by 5G/6G, MEC and RSUs. The Vehicle-side Layer acts as the perception-execution endpoint. Standardized V2C, V2I and PC5 interfaces enable seamless inter-layer communication.Each layer has a clearly defined functional role, a well-defined composition, and distinct service boundaries, and standardized interfaces must be used to enable collaborative interaction between layers.

3.2.1 Cloud Layer

The cloud layer serves as the “global brain” of the collaborative system. It is typically deployed by transportation authorities and cloud service providers as regional or national central cloud platforms, possessing massive computing power, storage resources, and global network scheduling capabilities, thereby functioning as the central control hub for the entire system.

3.2.2 Edge Layer

The edge layer serves as the “local hub” within the collaborative system and acts as the most natural bridge connecting the cloud and vehicle layers. Deployed in physical locations very close to the vehicles, it is the most ideal and reliable processing node for low-latency in-vehicle services.

3.2.3 Vehicle Layer

The vehicle-side layer serves as the explicit “perception terminal and execution endpoint” within the collaborative system. Comprising the in-vehicle computing platform of intelligent connected vehicles, in-vehicle sensor suites, and on-board units (OBUs), it is both the source of traffic data and the final execution point for collaborative computing instructions.

3.3 Various Coordination Modes

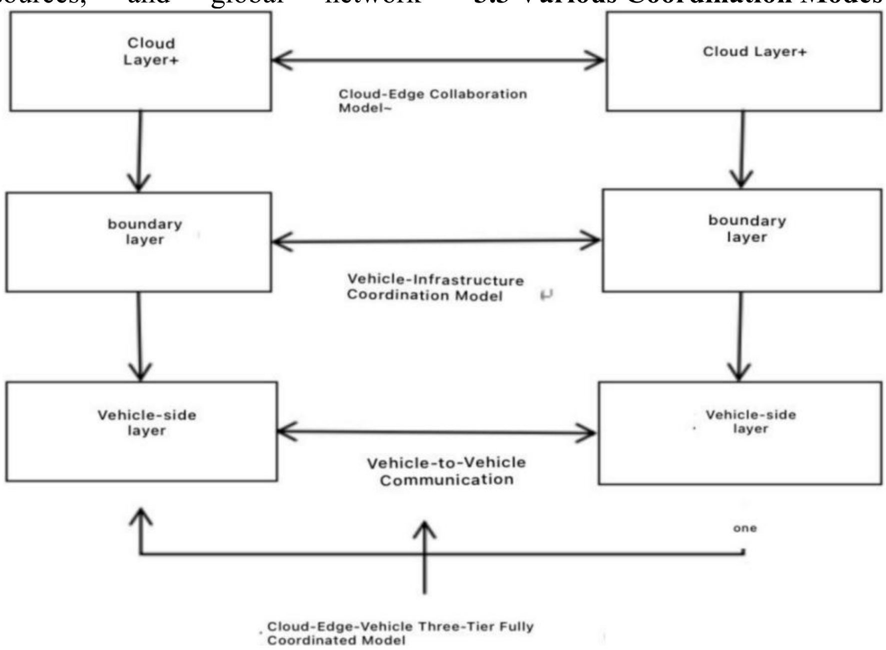

Figure 2. Interaction Architecture of Cloud-Edge-Vehicle Collaborative Modes

As shown in Figure 2,.it illustrates the three-tier fully coordinated interaction model. It defines three core pairwise collaborative modes: cloud-edge collaboration, vehicle-infrastructure coordination and vehicle-to-vehicle communication. These modes form an integrated system that dynamically allocates resources, balancing global optimization and low-latency local response.

3.3.1 Cloud-Edge Collaboration Model

Cloud-edge collaboration is a typical model of bidirectional coordination between the cloud and edge nodes, and it serves as an ideal foundational model for combining global optimization with local responsiveness: the cloud handles global model training, resource coordination, and non-real-time task processing, while edge nodes perform local real-time inference, data preprocessing, and low-latency task execution. This gives rise to AI collaboration characterized by “cloud training and edge inference”, global-local resource coordination, and hierarchical data processing collaboration.Therefore, this model is well-suited for various scenarios such as city-level traffic control, large-scale model updates, and global traffic flow optimization.

3.3.2 Edge-Vehicle Collaboration Model

Edge-to-vehicle collaboration is a typical form of real-time coordination between edge nodes and vehicles, and it is also the most core and commonly used collaboration model in cloud-edge-vehicle systems: edge nodes provide vehicles with low-latency computation offloading, data fusion, and collaborative perception services, while vehicles promptly provide edge nodes with perception data and local status information, naturally forming a real-time closed-loop for local operations.Furthermore, this model strictly limits end-to-end latency to within 10 ms, making it highly suitable for various highly time-sensitive business scenarios such as autonomous driving collaborative perception, intersection collision warning, and real-time path planning.

3.3.3 Vehicle-to-Vehicle (V2V) Collaboration

Vehicle-to-Vehicle (V2V) collaboration involves direct coordination between adjacent vehicles without relaying through edge nodes or the cloud. It serves as the fundamental model for ultra-low-latency applications: adjacent vehicles utilize PC5 direct communication links to share perception data, share computing resources, and distribute task offloading. This supports various applications such as beyond-line-of-sight perception, platooning, and collaborative obstacle avoidance, with end-to-end latency strictly controlled within 5 ms.Therefore, this mode is highly suitable for scenarios such as high-level autonomous driving platooning, emergency obstacle avoidance, and vehicle coordination in areas without roadside coverage.

3.3.4 Full Coordination of the Cloud-Edge-Vehicle Three-Tier System

The full-coordination model integrates resources from the cloud, edge, and vehicle. It represents the most typical and comprehensive coordination model for future intelligent transportation systems and is best suited to address the challenges involved: specifically, by actively and intelligently partitioning and assigning tasks to cloud, edge, and vehicle nodes based on the latency requirements, computing power demands, and security levels dictated by the application, thereby achieving global resource scheduling, hierarchical data processing,and full-process AI collaboration. This effectively balances the requirements for low latency, high reliability, and global optimization.

4. Key Technologies

Cloud-Edge-Vehicle collaborative computing is the product of the high-level integration of technologies across multiple fields. Its core key technologies can be categorized into four major types: computing task offloading and scheduling technology, network communication and resource optimization management technology, edge intelligence and vehicle-side AI lightweighting technology, and collaborative system security and privacy protection technology.

4.1 Task Offloading and Scheduling

Table1 : Summary of Comparative Analysis of Representative Studies

Decision-Making Methods	Core Advantages	Core Limitations	Suitable Scenarios
Convex Optimization Methods	Can find the theoretical optimal solution with high accuracy	Applicable only to static scenarios	Low-dynamic vehicle task offloading
Heuristic Algorithms	Fast solution speed and low computational overhead; suitable for medium-to-low dynamic scenarios	Can only obtain near-optimal solutions; global optimality cannot be guaranteed	Routine driving scenarios on urban roads, routine multi-node task scheduling
Deep Learning Algorithms	Highly adaptive, suitable for highly dynamic and highly uncertain scenarios	High training costs for deterministic scenario models; requires a large number of samples	High-dynamic highway scenarios, real-time task offloading in complex urban road networks

As shown in Table 1, the three major optimization methods each have their own strengths and weaknesses. In different scenarios, the most suitable decision-making method must be selected. Deep learning algorithms offer the greatest advantages but also come with the highest costs.

Task offloading and scheduling are the most fundamental technologies in cloud-edge-vehicle collaborative computing, with the objectives of minimizing system latency, minimizing energy consumption, and maximizing resource utilization.

Mobility-adaptive task partitioning and migration schemes can address the processing of long-running in-vehicle tasks: Surayya et al.[11] provided further refinements to reduce the probability of task interruptions caused by node switching.

With the development of cloud-native technologies, microservice architecture has become the mainstream architecture for cloud-edge-vehicle collaborative computing. Al-Allawee et al.[12] proposed a highly logical, cluster-service-based collaborative edge computing scheme for in-vehicle networks, which significantly improved both the efficiency of collaborative computing and resource utilization.

4.2 Resource Optimization Management

Since reliable network communication is the foundation of cloud-edge-vehicle collaboration, and effective resource management is critical to the system's normal operation, such technologies are naturally employed to address communication assurance and the coordination of heterogeneous resources within collaborative systems.

4.2.1 In-Vehicle Collaborative Network Communication Technologies

Table 1. Summary of Technological Evolution

Communication Technology	**Core Performance**	**Suitable Business Scenarios**	**Deployment Maturity**
5G C-V2X	End-to-end latency ≤ 10 ms, reliability 99.99%	Level 3 and below autonomous driving, urban traffic management	Large-scale deployment
6G In-Vehicle Communications	End-to-end latency ≤ 1 ms, reliability 99.999%, full coverage	Level 4/5 Advanced Autonomous Driving, Comprehensive Emergency Traffic Management	Technology Validation and Pilot Phase

As shown in Table 2, there are currently two main types of in-vehicle cooperative network communication technologies. While 5G C-V2X communication technology has reached a relatively mature stage, it remains insufficient for the rapidly evolving higher-level autonomous driving systems and broader-scale traffic control. Consequently, 6G in-vehicle communication technology will gradually emerge as a more suitable solution, and promoting its rapid development and large-scale deployment has become a key research focus.

Tang et al.[13] provide an overview of future intelligent in-vehicle networks for 6G, clarifying how core technologies such as 6G terahertz communication, air-space-ground integration, and intrinsic security provide a communication foundation with comprehensive coverage and deterministic latency for cloud-edge-vehicle collaboration. This is complemented by the analyses of Saad et al.[14] and Dang et al.[15] on the technical characteristics of 6G wireless systems and their application trends in vehicle-to-everything (V2X) networks.

4.2.2 Heterogeneous Resource Coordination Management Technologies

The resources involved in cloud-edge-vehicle collaboration systems exhibit significant heterogeneity, with vast differences in computing power, storage, and network capabilities across nodes. Furthermore, the high-speed movement of vehicles causes resource states to change constantly, making resource management extremely challenging.

The in-vehicle fog computing architecture proposed by Hou et al.[7] was the first to incorporate idle vehicle computing power into a global resource pool, resolving the issue of unified abstraction of vehicle-side resources. Meanwhile, Al-Allawee et al.[12] effectively aggregated resources from adjacent vehicles and edge nodes using clustering algorithms, thereby improving the utilization efficiency of heterogeneous resources.

Meanwhile, in-vehicle networks must not be overlooked. In 2024, Zheng et al.[16] discussed an optimization model for in-vehicle network data queries in edge environments, deriving optimization methods for query routing strategies and execution logic, and designing a collaborative query mechanism for edge nodes based on these methods, thereby reducing data query latency and bandwidth consumption.

4.3 Edge Intelligence and Vehicle-Side AI Lightweighting

Artificial intelligence is the fundamental driving force behind intelligent transportation systems, while edge intelligence technology enables the distributed deployment of AI capabilities across cloud-edge-vehicle systems, addressing the latency bottlenecks and privacy issues associated with traditional centralized AI.

The edge intelligence technology framework proposed by Zhou et al.[8] establishes a "cloud training, edge deployment" infrastructure, wherein the cloud performs full-scale training of large-scale AI models, while edge nodes perform real-time inference using lightweight models. Deng et al.[9] further expanded upon this edge intelligence technology framework.

Wei et al.[17] successfully experimentally validated the inference of a collaborative perception model for autonomous driving on edge nodes using model lightweighting techniques, demonstrating the application value of lightweighting technology in in-vehicle scenarios.

4.4 Security of Collaborative Systems

Cloud-edge-vehicle collaborative systems handle various sensitive information, including vehicle driving control, global traffic management, and user privacy data; security is the bottom line for the implementation of these technologies. The communication links in cloud-edge-vehicle collaboration consist of V2V, V2I, and V2C components; therefore, the communication process inevitably faces various security threats such as spoofing attacks, replay attacks, man-in-the-middle attacks, and denial-of-service attacks. A breach of the communication links could lead to severe consequences.

Table 2. Comparison of Cybersecurity Protection Technologies for Collaborative Computing Networks

Security Technologies	Core Function	Protection Objectives	Technology Maturity
Identity-Based Access Control	Performs identity authentication and access control for vehicles, edge nodes, and terminal devices	Prevents unauthorized nodes from accessing the system	Large-scale Deployment
Cryptographic Communication Encryption	End-to-end encryption of all communication data using national cryptographic algorithms and AES	Prevent data eavesdropping and tampering	Large-scale Deployment
Attack Detection Based on Intrusion Detection	Real-time detection of abnormal network traffic and attack behavior using deep learning methods	Enables real-time detection and response to attacks	Pilot Implementation and Optimization Phase

As shown in Table 3, there are currently three main protection technologies. This table summarizes three V2X security protection technologies, clarifying their core functions and protection objectives. The first two have been deployed at scale, while the third remains in the pilot and optimization phase.

In their research on 6G in-vehicle networks, Tang et al. [13] proposed an in-vehicle network security protection scheme based on a zero-trust architecture, charting a new direction for end-to-end security protection in cooperative systems.

5. Typical Application Scenarios of Intelligent Transportation Systems

Cloud-edge-vehicle collaborative computing technology has already been successfully implemented in various intelligent transportation scenarios. This section analyzes four typical application scenarios from the perspectives of technical characteristics and business requirements.

5.1 Collaborative Perception and Decision-Making in High-Level Autonomous Driving

High-level autonomous driving (Level 4 and above) is the most typical application scenario for cloud-edge-vehicle collaborative computing. The technical bottlenecks of single-vehicle perception are well-defined: single vehicles have blind spots caused by obstructions, perception accuracy drops sharply under adverse weather conditions (rain, snow, fog), and long-range perception capabilities are limited, making it difficult to detect intersection risks in a timely and reliable manner. Wei et al.[17] proposed a collaborative perception architecture for autonomous driving based on in-vehicle edge computing.

5.2 City-Level Intelligent Traffic Control and Optimization

Cloud-edge-vehicle collaborative computing establishes a closed-loop control system comprising “real-time perception-edge optimization-global coordination.” The edge environmental data query optimization technique proposed by Zheng et al.[16] enables millisecond-level real-time queries of traffic data across the entire road network, improving urban road network traffic efficiency by 20%–30%, and is a key component of new smart city development.

5.3 V2X Value-Added Services

Cloud-edge-vehicle collaborative computing facilitates the provision of various V2X value-added services to vehicle owners, including intelligent in-vehicle cockpits, remote vehicle diagnostics, and OTA updates.

Vehicle-wide OTA updates are a typical application in cloud-edge-vehicle collaboration scenarios: In traditional centralized OTA updates, all vehicles download update packages directly from the cloud, leading to core network bandwidth congestion and slow update speeds.Solution: The cloud pre-distributes update packages to edge nodes in various cities, allowing vehicles to download them from the nearest edge node. This enables the smooth parallel OTA update of tens of thousands of vehicles. This solution has been implemented on a nationwide scale in the 5G edge computing OTA update system jointly developed by Xpeng Motors and China Mobile, and was selected as a benchmark case for the MIIT’s 2023 5G Application Sailing Initiative;Official data shows that the system increases the average OTA update package download speed by 420%, reduces average download time by 76%, lowers core network bandwidth consumption by 82%, and boosts the update success rate from 92.1% in the traditional cloud-based model to 99.83%, supporting concurrent updates for millions of vehicles[18] .

5.4 Traffic Emergency Response and Safety Assurance

Cloud-edge-vehicle collaborative computing facilitates the detection, early warning, and handling of traffic emergencies within seconds, thereby enhancing the safety assurance capabilities and emergency response efficiency of transportation systems.

When a vehicle experiences a traffic accident, malfunction, or emergency braking, the vehicle immediately reports the event information, vehicle location, and driving status to the nearest edge node. Within 100 ms, the edge node broadcasts collision warnings and deceleration alerts to all vehicles within a radius of several hundred meters. Simultaneously, the edge node synchronizes the event information to the cloud, which then performs globally optimal emergency traffic dispatch based on the event location and surrounding traffic conditions.

6. Challenges and Future Directions

Although cloud-edge-vehicle collaborative computing technology currently has a solid research foundation and has seen initial applications in intelligent transportation scenarios, its large-scale engineering implementation must address five key challenges.

6.1 The Challenge of Coordinated Resource Scheduling

The resources utilized in cloud-edge-vehicle collaborative systems exhibit significant heterogeneity. Achieving globally optimal resource scheduling in highly dynamic and heterogeneous environments remains the most pressing challenge. 6G technology can effectively enable integrated coverage across air, land, sea, and space, while offering end-to-end latency of less than 1 ms, Tbps-level transmission rates, 99.9999% ultra-high reliability, and the capacity for millions of concurrent connections per square kilometer.

Future Core Research Directions: Based on 6G technology, construct a cloud-edge-vehicle collaborative communication network featuring comprehensive coverage, deterministic latency, and ultra-high reliability to achieve seamless V2X coverage and collaborative computing capabilities, thereby effectively supporting Level 5 fully autonomous driving applications.

6.2 Challenges in High-Reliability, Low-Latency Deterministic Communications

Safety-critical scenarios such as autonomous driving and emergency traffic management impose explicit deterministic requirements on communication latency and reliability. In particular, autonomous driving cooperative control scenarios require end-to-end latency of less than 5 ms and reliability of 99.999%.Current limitations of 5G C-V2X technology: During peak urban hours, when hundreds of vehicles access the network concurrently, issues such as latency jitter and packet loss are prone to occur. High-speed vehicle movement inevitably causes communication interruptions and latency jitter, both of which interfere with the continuous execution of collaborative computing tasks.

Future core research directions: Enable collaborative interaction between high-precision real-time digital twins at local edge nodes and city-level global digital twins in the cloud through cloud-edge-vehicle coordination.

6.3 Accuracy Issues in Edge Intelligence

Current edge intelligence technologies inevitably sacrifice some model accuracy during model lightweighting. The in-vehicle environment is highly dynamic, and pre-trained AI models often experience accuracy degradation when transferred to new scenarios. Achieving dynamic adaptation and incremental updates for AI models to ensure good accuracy and generalization capabilities across all scenarios remains a significant technical challenge.
Future core research directions: Enabling AI models to autonomously perform incremental learning and optimization updates based on local environmental changes without centralized cloud intervention, adapting to diverse traffic scenarios, and integrating with in-vehicle vertical large models to support autonomous driving and intelligent traffic management.

6.4 Implementation Challenges in System Security and Privacy Protection

The attack surface of cloud-edge-vehicle collaborative systems is vast; a breach in any single link could lead to severe security incidents. However, current security technologies primarily defend against specific attacks from a single point of view, and there is still a lack of a collaborative security framework that truly covers the entire cloud-edge-vehicle chain and all scenarios. Achieving data sharing and value extraction while safeguarding user privacy and strictly adhering to compliance requirements is the most prominent and fundamental challenge facing technological implementation.
Future Core Research Directions: We can establish intrinsic security protection mechanisms by leveraging both zero-trust architecture and blockchain technology.

6.5 Standards and Compliance Issues in Cross-Entity Collaboration

The development and implementation of cloud-edge-vehicle collaborative systems involve multiple stakeholders, each using different devices, systems, data formats, communication protocols, and interface specifications. Consequently, there are currently no unified end-to-end technical standards within the industry, making efficient collaboration between different systems difficult and naturally leading to the formation of numerous “data silos” and “system silos.”The development of intelligent transportation infrastructure varies across regions, and achieving cross-regional and cross-city interoperability for cloud-edge-vehicle collaboration remains a major challenge for large-scale technical implementation.
Future Core Development Direction: Establish unified standards for cloud-edge-vehicle collaboration, break down industry barriers, eliminate data silos, and enable the large-scale application of cloud-edge-vehicle collaboration technology across the entire industry and all regions.

7. Conclusion

First, this paper reviews the research progress on cloud-edge-vehicle collaborative computing for intelligent transportation systems. It presents a novel three-tier collaborative architecture comprising the "cloud layer, edge layer, and vehicle layer," and summarizes four typical collaborative modes for full three-tier coordination.
Building on this foundation, the paper systematically reviews key technologies and the latest research findings in this field across four dimensions, with data updated through 2026. By integrating the practical needs of intelligent transportation, the paper provides a clear analysis of the application models and practical value of cloud-edge-vehicle collaborative computing across four typical scenarios.
Finally, this paper logically addresses five major challenges encountered in technology implementation, such as the scheduling of dynamic heterogeneous resources, and identifies five future research directions, including 6G-enabled integrated air-ground-space collaborative networks.
Cloud-edge-vehicle collaborative computing is an ideal solution for addressing the latency bottlenecks and resource constraints inherent in traditional cloud computing architectures within intelligent transportation systems. Furthermore, it meets the diverse requirements of intelligent transportation services, including low latency, high reliability, and global optimization, thereby offering excellent research prospects and practical value. The purpose of this paper is to provide a systematic and clear reference for

future related research and to effectively promote the large-scale application of cloud-edge-vehicle collaborative computing technology in intelligent transportation systems.

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