

Review

A Survey on Key Technologies and Applications of Semantic Communication for Vehicular Networks

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Abstract

To address the stringent demands of intelligent connected vehicles for high bandwidth, low latency, and highly reliable communication, this paper systematically summarizes the semantic communication technology of the Internet of Vehicles (IoV) based on information “meaning” transmission, covering basic theory, key technologies, application practice and challenge and trends. First, the paper expounds the knowledge driven and task oriented paradigm characteristics of semantic communication and its efficiency advantages in the IoV. Second, in terms of key technologies, semantic extraction achieves efficient feature compression through multimodal fusion and Generative Artificial Intelligence (GAI); semantic coding employs hierarchical codebooks and adaptive strategies to optimize transmission efficiency; semantic transmission leverages deep reinforcement learning for the joint scheduling of resources such as spectrum and power; and semantic decoding utilizes reconstruction networks and GAI to enhance resilience against impairments. Application practices demonstrate that semantic communication can significantly compress image data transmission volume for autonomous driving collaborative perception while maintaining high-fidelity reconstruction under adverse channel conditions. It significantly reduces the communication load and improves the system utility in vehicle-to-infrastructure coordination and in-vehicle service. Despite facing technical challenges such as semantic consistency, dynamic adaptability, and security trustworthiness, future semantic communication will evolve towards deep integration with distributed collaborative knowledge networks, lightweight real-time decision-making agents, and integrated “communication, sensing, and computing” architectures, positioning itself as a key enabling technology for empowering Sixth Generation mobile communication (6G) of intelligent vehicular networks.

Keywords: vehicular network; semantic communication; autonomous driving; collaborative perception; 6G



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1. Introduction

The evolution of intelligent connected vehicles and high-level autonomous driving relies on the real-time and reliable interaction of massive perception data and decision-making commands between vehicles and their environment. This imposes unprecedented stringent requirements on the bandwidth, latency, and reliability of vehicular network communication [1]. However, the traditional bit-level communication paradigm, centered on ensuring the accurate transmission of data bits, increasingly faces bottlenecks in transmission efficiency and resource constraints under scenarios characterized by high vehicle

mobility, rapidly changing network topology, and limited spectrum resources [2]. Particularly, achieving deep collaboration between vehicles, such as eliminating blind spots in single-vehicle perception and enabling intent-level interaction, leads to a surge in the amount of information that needs to be transmitted, further exacerbating the burden on the communication system [3]. In this context, semantic communication, as an emerging paradigm, provides innovative ideas for the implementation of efficient and intelligent Internet of Vehicles (IoV) communication by transmitting and processing the “meaning” of information rather than the original data stream, and is also a key candidate technology for the Sixth Generation mobile communication (6G) [4]. Its core advantage lies in the potential to significantly reduce transmission load, improve spectrum efficiency, and enhance robustness against channel impairments based on specific task requirements, thus being regarded as a key enabling technology to break through the performance bottlenecks of 6G vehicular networks [5].

Currently, research on semantic communication for vehicular networks is fully underway at the levels of fundamental theory, key technologies, and application exploration, showing a trend of deepening from theoretical frameworks to vertical scenarios. In terms of fundamental theory and frameworks, existing research aims to build semantic communication system models adapted to the dynamic characteristics of vehicular networks, covering knowledge base-aware communication [6], integrated perception, computing, and communication collaborative architecture [7] and a goal-oriented framework for specific driving tasks [8]. Regarding key technological pathways, research focuses on achieving the efficient and reliable generation and transmission of semantic information. On one hand, to meet the stringent deterministic latency requirements of vehicular network services, adaptive semantic coding designs for low latency have emerged. On the other hand, in highly dynamic vehicular wireless environments, semantic-aware resource allocation based on deep reinforcement learning has become a mainstream method for optimizing scarce resources like spectrum and power to ensure the transmission utility of semantic information [9]. In application exploration, existing research has demonstrated the potential of semantic communication in addressing core service bottlenecks in vehicular networks. In autonomous driving collaborative perception scenarios, by transmitting key semantic features such as surrounding objects and scenes rather than raw high-dimensional point clouds or image data, semantic communication can greatly reduce network load, thereby supporting broader and more efficient inter-vehicle information sharing [10]. Furthermore, its application has extended to service scenarios such as in-vehicle digital twin synchronization [11] and vehicular metaverse updates [12]. Notably, recent survey works, such as reference [13], have provided valuable overviews of semantic communication applications in the vehicular networks, focusing on aspects like traffic environment perception.

Despite the valuable contributions of the aforementioned works to the field of semantic communication, existing surveys still exhibit notable limitations in both scope and depth. As shown in Table 1, reference [13], as the IoV-specific survey, covers semantic extraction, coding, and transmission, but does not address the decoding stage. Moreover, it only discusses the autonomous driving perception scenario, without covering vehicle-to-infrastructure coordination or in-vehicle services. Although the general semantic communication references [14,15] offer relatively broad technical coverage, they are not anchored in vehicular networks and thus fail to systematically analyze the special requirements of vehicular networks, such as high mobility, low latency, and high reliability. Furthermore, none of the above surveys provide critical comparison or limitation analysis of existing methods.

Table 1. Comparison between this survey and existing survey papers on semantic communication.

Dimension	[13]	[14]	[15]	This Survey
Scope	IoV	General semantic communication	General semantic communication	IoV
Completeness of technology chain	Extraction Coding Transmission	Extraction Coding Transmission Decoding	Extraction Coding Transmission (limited coverage of decoding)	Extraction Coding Transmission Decoding
Three vertical scenarios	Only addresses autonomous driving perception	Does not address vehicular network scenarios	Only briefly mentions intelligent transportation in one subsection, without in-depth analysis	Autonomous driving scenarios, vehicle-to-infrastructure coordination scenarios, in-vehicle service scenarios
Forward-looking challenges	Does not discuss knowledge management, large models, etc.	Partially mentions knowledge bases, but not in the context of vehicular networks	Challenges are general, not specific to vehicular networks	Systematically discusses knowledge management, lightweight security, large model deployment, and integrated sensing-communication-computing
Critical comparison	Predominantly descriptive enumeration	Partially includes comparisons, but oriented toward tutorial exposition	Predominantly descriptive enumeration	Provides comparative discussion at the end of each subsection

Based on the above gaps, this survey aims to establish a clearer and more comprehensive technology roadmap for semantic communication in vehicular networks through the following core contributions:

- (1) **A Holistic Technology Framework:** This survey constructs a systematic analytical framework that comprehensively covers the full technological chain of vehicular semantic communication—from semantic extraction, coding, and transmission to intelligent decoding. Starting from the specific requirements of vehicular network scenarios, this framework unifies the analysis of various technologies under a coherent perspective, thereby addressing the deficiency of existing surveys in covering the decoding stage. Unlike the subsequent scenario-driven analysis and forward-looking challenges discussion, this framework focuses on the completeness of the technology chain itself and the logical connections among its constituent stages.
- (2) **Scenario-Driven Depth Analysis:** Going beyond the limitation of existing surveys that only address autonomous driving perception, this survey systematically and thoroughly analyzes the differentiated application logic, performance gains, and design requirements of semantic communication across three core vertical scenarios: autonomous driving, vehicle-to-infrastructure coordination, and in-vehicle services.
- (3) **Forward-Looking Challenges and Trends:** This survey identifies and elaborates on critical yet underexplored challenges, such as dynamic knowledge ecosystem management, lightweight security, and the tension between large model capabilities and deployment constraints. Furthermore, it prospectively discusses the deep integration trends with generative artificial intelligence (GAI) and integrated sensing, communication, and computing, outlining the evolutionary path toward cognitive vehicular networks.

The structure of this paper is as follows: Section 2 describes the review methodology, including the search databases, keywords, time range, inclusion and exclusion criteria, and the screening process. Section 3 analyzes the fundamental theory of semantic communication for vehicular networks, explaining its basic framework, the unique communication requirements of vehicular network scenarios, and summarizing its core advantages compared to traditional communication. Section 4 systematically reviews its key technology system, detailing research progress in semantic extraction, semantic coding, semantic transmission, and semantic decoding, respectively. Section 5 summarizes the application patterns and effectiveness of semantic communication in three typical scenarios: autonomous driving, vehicle-to-infrastructure coordination, and in-vehicle information services. Section 6 delves into the main technical challenges currently facing the field and looks forward to its future development trends. Finally, Section 7 concludes the paper and points out the key role of semantic communication in empowering the next-generation 6G intelligent vehicular networks.

2. Review Methodology

To ensure the breadth and objectivity of this survey, we adopted a systematic search and screening strategy during the literature collection process. The overall procedure is outlined as follows:

- (1) Search Sources: The search was primarily conducted through the electronic resource portal of Chongqing University Library, supplemented by direct searches in IEEE Xplore, Web of Science, Scopus, and China National Knowledge Infrastructure (CNKI).
- (2) Search Strategy: We constructed multiple keyword combinations around the two core themes of “semantic communication” and “vehicular networks”. The English search string was: (semantic communication OR semantic coding OR semantic transmission OR semantic extraction) AND (vehicular network OR Internet of Vehicles OR IoV OR intelligent transportation OR connected vehicle) AND (autonomous driving OR collaborative perception OR vehicle-to-infrastructure coordination OR 6G). For Chinese literature, corresponding terms such as “semantic communication”, “Internet of Vehicles”, “collaborative perception”, and “6G” were used in CNKI.
- (3) Time Frame: Considering that research on semantic communication for vehicular networks has grown significantly only since 2020, the search was limited to publications from January 2020 to June 2026.
- (4) Inclusion and Exclusion Criteria: Studies were included if they explicitly focused on vehicular network scenarios and investigated key semantic communication technologies (semantic extraction, coding, transmission, decoding) or typical applications (collaborative perception, vehicle-road coordination, in-vehicle services); and if they proposed novel methods, frameworks, or architectures accompanied by experimental validation or case studies. Exclusion criteria comprised studies discussing general semantic communication without addressing vehicular networks; studies limited to traditional bit-level communication without semantic processing; non-academic materials such as editorials, news articles, patents, and dissertations; and duplicate or highly overlapping content, where only the most recent or complete version was retained.
- (5) Screening Process: The initial search yielded approximately 500 papers (about 400 from English databases and 100 from Chinese databases). After removing duplicates, roughly 350 papers remained. Title and abstract screening eliminated about 250 papers that were clearly irrelevant, mainly due to a lack of focus on semantic communication or vehicular network contexts. The remaining approximately 100 papers underwent full-text review, from which those most relevant to the scope of this survey were

selected. Ultimately, 42 papers were included as core references for the main analysis, while another 17 were cited as background or supporting materials, resulting in a total of 59 references. The detailed screening process is illustrated in Figure 1.

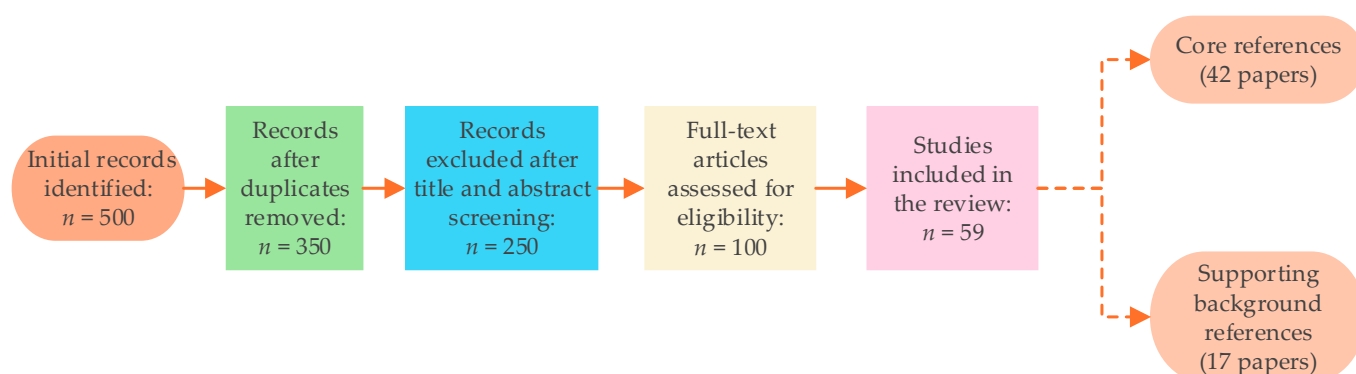


Figure 1. Literature screening flowchart.

3. Fundamental Theory of Semantic Communication for Vehicular Networks

3.1. Basic Framework of Semantic Communication

As a breakthrough new paradigm, the core of semantic communication lies in the ultimate purpose of communication being the successful delivery and understanding of information “meaning” to efficiently support specific tasks. A classic semantic communication system framework is shown in Figure 2. The complete process begins with the sender’s understanding of the scene, guided by a knowledge base, to extract core semantic information. This semantic information is then converted by a semantic encoder into a compact representation suitable for transmission. After being transmitted through the physical channel, the receiver’s semantic decoder, utilizing knowledge from a counterpart knowledge base, parses and reconstructs the received signal, ultimately recovering the semantics based on scene understanding. In this framework, the knowledge base is the foundation for efficient encoding/decoding and accurate semantic understanding, and is also the key distinction between semantic and traditional communication. With the deepening of research, this basic framework continues to evolve and expand to meet the specific needs of vehicular networks, which are dynamic, collaborative, and task-driven.

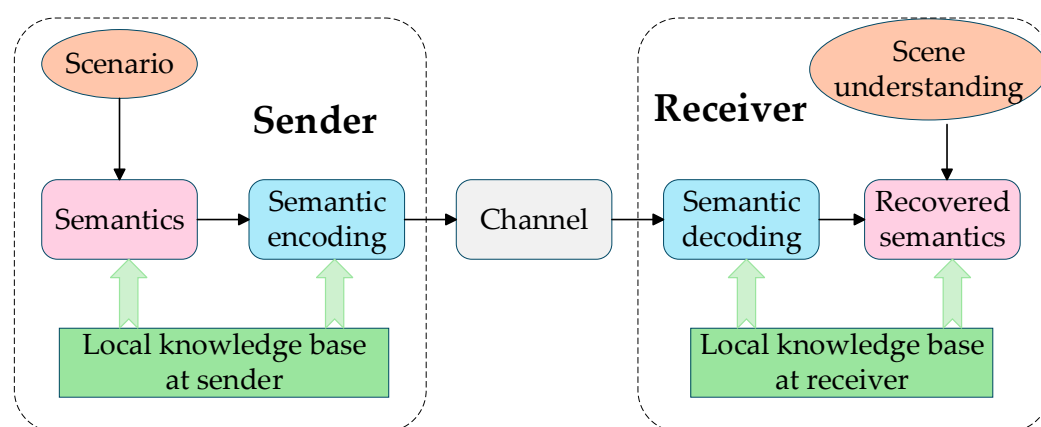


Figure 2. Classic semantic communication system framework.

To adapt to the stringent requirements of vehicular networks for high dynamics, low latency, high reliability, and task diversity, the basic framework of semantic communication is showing a trend of deep integration, evolving from “communication-semantics” to “sensing-communication-computing-semantics” integration. Integrated sensing and communication technology enables the system to simultaneously perform environmental sensing and semantic information transmission using the same wireless signal, sharing spectrum and hardware resources to improve overall efficiency. Meanwhile, the introduction of edge computing allows computationally intensive tasks such as semantic extraction and knowledge updating to be processed locally, effectively reducing end-to-end latency. This integrated architecture has given rise to unified frameworks capable of collaboratively optimizing sensing accuracy, communication secure rate, and computing overhead under resource constraints. Building upon this, addressing the multi-user, multi-service nature of vehicular networks, the dynamic construction, matching, and updating of knowledge bases have become key challenges, driving research in distributed knowledge management.

Furthermore, the semantic communication framework is further evolving towards being “goal-oriented” and integrating with technologies like blockchain and digital twins to form more intelligent and trustworthy system-level solutions. Goal-oriented communication emphasizes that transmitted information should fully serve the final task. For example, reference [16] designs a semantic reconstruction network at the receiver to combat transmission impairments, with the direct goal of ensuring the performance of downstream visual perception tasks. Going a step further, reference [8] explores a framework integrating goal-oriented semantic communication, blockchain, and smart contracts, using semantic information to drive the automatic execution of trustworthy contracts, thereby building a closed loop from semantic understanding to trustworthy automatic decision-making. These advancements collectively outline a clear path for the continuous evolution of the vehicular network semantic communication framework towards greater integration, intelligence, and reliability.

3.2. Communication Requirements in Vehicular Network Scenarios

As a key vertical application domain for semantic communication technology, vehicular networks possess distinct characteristics in their network and service environments compared to traditional wireless networks. As shown in Figure 3, vehicular networks include various communication connections such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Network (V2N), forming a complex and dynamic Vehicle-to-Everything (V2X) network. These characteristics fundamentally define the design constraints and core requirements for in-vehicle semantic communication systems.

At the network and channel level, vehicular networks exhibit high dynamics and uncertainty. High-speed vehicle movement causes rapid changes in network topology, exposing V2X communication links to severe risks of Doppler shift, frequent handovers, and interruptions [17]. Simultaneously, complex urban environments lead to significant time-varying and non-stationary channel characteristics. Vehicle trajectories and communication demands are not entirely random but are strongly constrained by road topology and traffic rules, which presents opportunities for predictive resource management but also increases modeling complexity. To address these challenges, the communication system must meet extremely high reliability and very low end-to-end latency.

At the service requirement level, vehicular network applications present extreme performance demands and high heterogeneity. To achieve high-level autonomous driving, services can be broadly categorized into two types: safety and cooperative control services, which have nearly stringent requirements for communication reliability and latency, with

latency budgets potentially as low as 3–20 ms and reliability requirements as high as 99.9% or more; and enhanced information services, which demand high throughput (up to Gbps level) but have relatively higher tolerance for latency (typically in the 100–500 ms range). This vast difference in performance demands requires the network to possess intelligent and fine-grained resource differentiation and service capabilities.

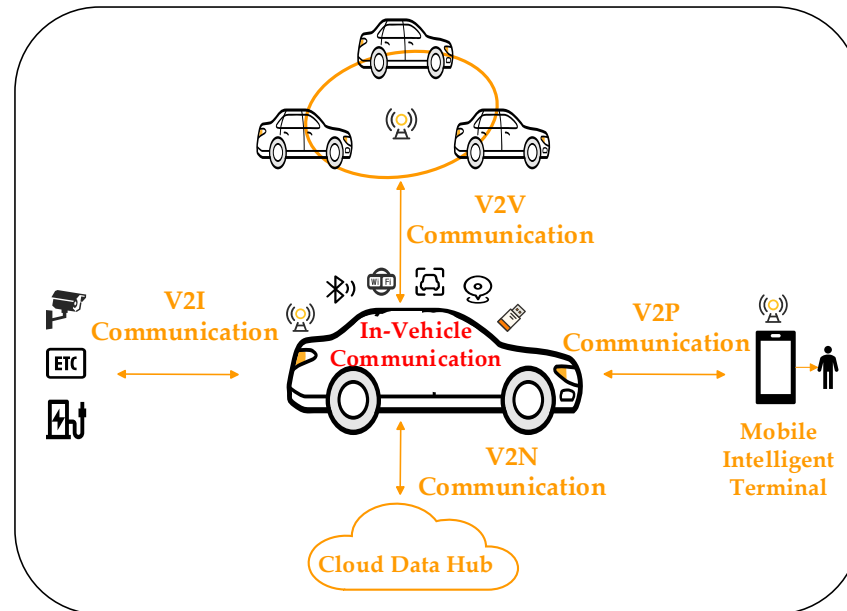


Figure 3. Communication scenarios for intelligent connected vehicles.

Vehicular networks also face severe resource constraints. Dedicated V2X spectrum resources in dense urban scenarios are a major bottleneck. Furthermore, the computing, storage, and energy resources of vehicles and edge nodes are also limited. Operations like semantic extraction and model inference in semantic communication are computationally intensive. Therefore, designing lightweight models and jointly optimizing communication and computing overhead is a key challenge for achieving high-performance systems [18].

Finally, considering communication modes and scenario complexity, vehicular networks involve various connection methods like V2V and V2I, and often exist in multi-hop, self-organizing forms. This makes traditional centralized scheduling inefficient, necessitating distributed intelligent decision-making mechanisms. Concurrently, as communication nodes, vehicle behavior is tightly coupled with driving tasks, meaning communication optimization cannot be independent of specific scenarios and application objectives [19]. Therefore, the design of semantic communication for vehicular networks must achieve an intelligent paradigm shift from “best-effort” generic transmission to “task-driven, utility-optimal” transmission.

The communication requirements discussed above impose clear constraints and guidance on the design of semantic communication systems for vehicular networks. Different requirements often necessitate different semantic communication mechanisms. To clearly illustrate this mapping relationship, Table 2 summarizes the corresponding semantic communication mechanisms, the involved technical stages, and the design rationale for each core requirement. This mapping provides a logical thread for the systematic discussion of key technologies in Section 4.

Table 2. Mapping between vehicular network requirements and semantic communication technologies.

Vehicular Network Requirement	Corresponding Semantic Communication Mechanism	Involved Technical Stage	Design Principle and Function
High mobility	Predictive channel estimation and adaptive coding switching	Semantic transmission	Leverages semantic context to predict channel variations and dynamically switch coding strategies to counteract Doppler effects
Ultra-low latency	Lightweight semantic models and edge-assisted inference	Semantic extraction, semantic coding	Reduces semantic processing and transmission latency through model compression and edge deployment
High reliability	Cooperative communication and knowledge base-assisted robust decoding	Semantic transmission, semantic decoding	Utilizes multi-vehicle cooperative diversity and prior knowledge to correct semantic errors caused by channel impairments
Limited spectrum	Task-oriented extreme semantic compression	Semantic coding, semantic transmission	Transmits only task-relevant semantic features, significantly reducing data volume to conserve spectrum
Heterogeneous V2X	Cross-network semantic service architecture and distributed knowledge base	Knowledge base management, system architecture	Constructs a unified semantic representation layer to shield underlying network heterogeneity and support seamless handover

3.3. Advantages of Semantic Communication for Vehicular Networks

Compared to the traditional bit-transmission paradigm, semantic communication provides a fundamental solution to address the stringent challenges of vehicular networks. Its core advantages are mainly reflected in the following aspects, summarized in Table 3.

- (1) **Knowledge Dependency and Context Awareness:** The premise for semantic communication to be effective is that the sender and receiver share a background knowledge base about the driving environment and rules. This allows communication content to be highly tailored based on task context. For example, in collaborative perception, only differential semantic information like “pedestrian ahead” is exchanged, thereby significantly compressing the load.
- (2) **Task-Oriented Extreme Compression Capability:** Semantic communication aims to efficiently support downstream driving tasks. Its encoding process actively filters out redundant details irrelevant to decision-making. Reference [10] shows that, on the Cityscapes dataset, an image encoding scheme based on semantic segmentation can compress data volume to about 1/79 of the PNG lossless size ($\approx 1/201$ of the uncompressed raw) under specific simulation conditions. This result is case-specific and may vary with different datasets or channel conditions.
- (3) **Potential for Improved Transmission Robustness:** Transmitting high-dimensional semantic features can, under certain conditions, offer improved tolerance to channel noise, as exemplified by the Signal-to-Noise Ratio (SNR)-adaptive coding scheme in [17]. It should be noted that this robustness advantage is task-dependent and does not equate to security: SNR-adaptive switching cannot defend against active threats such as eavesdropping or tampering. Furthermore, the dependency of decoding on a specific knowledge base does not by itself constitute physical layer security; encryption and authentication remain necessary.
- (4) **Deep Cross-Layer Fusion and System-Level Collaboration:** The semantic communication framework can be integrated with technologies like sensing and computing. The integrated sensing, computing, and semantic communication framework proposed in reference [7] can collaboratively optimize sensing accuracy, secure rate, and computing overhead under unified resource constraints. Further, reference [8] explores its

combination with blockchain smart contracts to achieve a closed loop from semantic understanding to trustworthy automatic execution.

- (5) **Paradigm Shift in Evaluation from Fidelity to Task Utility:** This is a fundamental change, where the optimization objective shifts to the completion quality of the downstream task. Reference [20] jointly optimizes the “granularity” of semantic coding with wireless resources to minimize semantic distortion under timeliness constraints, directly optimizing collaborative perception performance. Reference [16] designs a semantic reconstruction network at the receiver to repair transmission damage, with the ultimate goal also being to ensure visual task performance. This drives the vehicular network communication system to transform from a “data transmission pipeline” to a “task service provider”.

Table 3. Core advantages of semantic communication for vehicular networks.

Core Advantage	Key Characteristics	Key Technology Examples
Knowledge dependency & context awareness	Information is tailored based on a shared knowledge base, transmitting only task-relevant differential semantics, greatly reducing communication load.	Differential information exchange based on shared knowledge base; task-context-driven semantic filtering.
Task-oriented extreme compression	The encoding process filters redundant details, pursuing maximization of downstream task utility rather than bit-level fidelity.	Feature extraction based on semantic segmentation/detection; living semantic reconstruction assisted by GAI.
Potential for improved transmission robustness	High-dimensional semantic features can offer improved tolerance to noise under certain conditions, but this advantage is task-dependent and does not constitute security; decoding dependency on a knowledge base does not replace encryption or authentication.	SNR-based adaptive coding switching; controlled knowledge base distribution and endpoint authentication.
Deep cross-layer fusion & system collaboration	Easily deeply integrated with sensing and computing, enabling vertical integration optimization from lower-layer transmission to upper-layer applications.	Integrated sensing, computing, and semantic communication frameworks; fusion of semantic communication and blockchain smart contracts.
Fundamental shift in evaluation paradigm	Optimization target shifts from “bit fidelity” to “task completion quality”, driving the communication system to evolve into a task service provider.	Joint optimization of semantic granularity and wireless resources; task-performance-oriented receiver-side semantic reconstruction.

4. Key Technologies of Semantic Communication for Vehicular Networks

4.1. Semantic Extraction Technology

Semantic extraction is the starting point of vehicular semantic communication. Its core task is to distill high-level semantic representations that are most useful and comprehensible for downstream driving tasks from raw data collected by vehicle sensors. This is the foundation for achieving extreme communication load compression and intelligent interaction. In the harsh, high-dynamic, resource-constrained environment of vehicular networks, this technology must simultaneously meet requirements for high accuracy, low latency, and low computational overhead. The semantic extraction technologies discussed in this subsection are summarized in Table 4.

Current technological development mainly exhibits two characteristics: multimodal fusion and advanced semantic understanding driven by large models. Multimodal fusion improves the completeness and robustness of semantic understanding by integrating multi-source information such as images, point clouds, and text. For example, reference [21] proposes a multi-modal semantic communication framework that extracts 13 types of semantic features from camera-captured images, achieving a data compression rate exceeding 92% while maintaining competitive reconstruction quality on test images. (This compression rate is specific to the tested image type and task configuration, and may not be

achievable in all scenarios.) Simultaneously, large models represented by Vision-Language Models (VLMs) are bringing a paradigm shift to semantic extraction. Research in reference [22] shows that using large VLMs like LLaVA can automatically generate structured textual descriptions from vehicle images, accurately focusing on key objects and their spatial relationships, achieving efficient end-to-end conversion from pixels to semantics.

Table 4. Semantic extraction technologies for vehicular networks.

Ref.	Research Objective	Key Components	Core Contribution
[21]	Parallel semantic extraction and compression of multimodal data	Fusion of 13 feature types, attention mechanism	Achieves >92% compression ratio via multi-modal semantic extraction (13 feature types) while maintaining competitive reconstruction quality
[22]	Exploring VLM-based advanced semantic extraction in vehicular scenarios	LLaVA architecture, visual instruction fine-tuning	Enables end-to-end conversion from pixels to structured text descriptions
[23]	Lightweight semantic representation extraction for Vehicular digital twin network synchronization	Convolution Neural Network (CNN)-based task encoder, semantic representation rate α -u, multiagent soft actor-critic + resource-aware policy refinement algorithm task offloading	Proposes “semantic representation rate” optimization to reduce synchronization communication overhead
[24]	Optimizing semantic feature selection for edge nodes in federated learning	Semantic importance measurement, multi-scale selection, Block Coordinate Descent (BCD)-based joint optimization	Proposes Multi-scale Semantic Selection-based Federated Learning (MSSFL) scheme with semantic importance metric and BCD-based joint optimization; improves model accuracy and reduces communication latency
[25]	Adaptive optimization of semantic extraction strategies in dynamic vehicular networks	Federated learning-based semantic extraction, Dynamic Semantic-Aware TD3 (DSATD3) algorithm, semantic utility metric	Proposes FVSCom framework with DSATD3 for joint optimization of semantic selection and bandwidth allocation; achieves high convergence speed, extraction accuracy, and robustness to vehicle departures

To adapt to the dynamic environment and terminal computing constraints of vehicular networks, lightweight and adaptive extraction strategies have become key. On one hand, the extraction process needs to be deeply coupled with specific tasks, dynamically adjusting the extraction granularity based on “semantic importance”. For instance, in digital twin synchronization scenarios, reference [23] achieves a balance between task fidelity and communication cost by optimizing the “semantic representation rate”; in federated learning scenarios, reference [24] proposes an importance metric combining task relevance and semantic feature relevance to achieve intelligent multi-scale selection of semantically important model parameters for upload. On the other hand, the extraction framework itself needs to possess online learning and dynamic adjustment capabilities. The federated learning-empowered framework proposed in reference [25] dynamically optimizes semantic extraction strategies through deep reinforcement learning, enabling adaptation to the dynamic joining and leaving of vehicle nodes and fluctuations in network resources, thereby continuously ensuring optimal semantic utility.

The above methods exhibit a clear trade-off between resource overhead and semantic depth. Reference [21] achieves high compression through multimodal fusion but requires moderate Graphics Processing Unit (GPU) resources, making it suitable for edge deployment. Reference [22] attains the deepest semantic understanding via VLMs but incurs the highest computational cost, hindering real-time applicability. References [23–25] are designed with lower complexity for onboard deployment at the cost of limited semantic richness. Regarding channel adaptability, only reference [25] explicitly optimizes extraction strategies through Deep Reinforcement Learning (DRL), while others assume relatively

stable conditions. Current limitations include: difficulty in deploying large models onboard for real-time tasks [22], maintaining semantic consistency under high mobility, and the lack of formal reliability guarantees for safety-critical scenarios.

4.2. Semantic Coding Technology

Semantic coding is the core link in the semantic communication process. Its task is to efficiently and reliably map the extracted high-level semantic features into compact symbol sequences suitable for wireless channel transmission. This is a typical “task-oriented” coding paradigm aimed at meeting the stringent bandwidth and latency constraints of vehicular networks while maximizing the final utility of the coded information for downstream driving tasks. The semantic coding technologies discussed in this subsection are summarized in Table 5.

Table 5. Semantic coding technologies for vehicular networks.

Ref.	Research Objective	Key Components	Core Contribution
[20]	Coding granularity selection under information age constraints	Hierarchical codebooks, DRL, distortion-rate trade-off	Combines hierarchical codebooks with DRL to optimize coding granularity based on information age
[26]	Efficient semantic encoder training under high mobility	Split federated learning, transfer learning, Stackelberg game	Proposes MSFTL framework to reduce training cost and adapt to dynamic vehicular environments
[27]	Joint optimization of semantic compression and transmission power	Knowledge graph triples, Zipf prioritization, cooperative relay, Multi-Pass Deep Q-Network (MP-DQN)	Proposes SACC framework for cross-layer joint optimization of compression and power
[28]	Online semantic coding learning for time-varying channels	Online feature and channel attention network, real-time feedback	Proposes online learning strategy for rapid adaptation to channel variations

Currently, semantic coding technologies for vehicular networks are evolving mainly around three directions: adaptive coding strategies, hierarchical codebook design, and deep learning-driven coding. Adaptive coding aims to dynamically adjust coding parameters based on real-time channel state. For example, research in reference [20] combines hierarchical codebooks with deep reinforcement learning, providing multiple codebook layers with different distortion-rate trade-offs for semantic information. This allows the system to adaptively select the optimal coding granularity based on information age constraints, thereby minimizing semantic distortion while ensuring timeliness. To address the challenge of efficient semantic encoder training under high mobility, reference [26] proposes a Mobility-aware Split-Federated with Transfer Learning (MSFTL). By splitting the encoder into a pretrained model and fine-tuning layers, and integrating a Stackelberg game-based resource optimization mechanism, it reduces training costs and adapts to highly dynamic vehicular environments.

Deep learning provides powerful end-to-end joint optimization capabilities for semantic coding. Beyond optimizing compression and robustness, semantic coding is also evolving to represent information in forms that are more conducive to knowledge reasoning and task execution. For emergency communication, reference [27] employs a knowledge graph to structure information into semantic triples (entity-relation-attribute), prioritizing their transmission based on a Zipf-like importance distribution, thereby enhancing transmission efficiency for critical content. The online feature and channel attention network developed in reference [28] can incorporate Channel State Information (CSI) as auxiliary input to jointly optimize semantic compression and resilience against channel impairments, thereby improving reconstruction quality and transmission robustness. Beyond

channel-adaptive designs, the coding process is also increasingly coordinated with specific tasks and resource management. In the future, semantic coding technology will continue to develop towards intelligent collaboration with network resources, supporting online lifelong learning, and building more general open-scenario coding frameworks.

The above methods exhibit different trade-offs between coding flexibility and computational overhead. Reference [20] achieves finer granularity selection through hierarchical codebooks and DRL, offering higher flexibility at the cost of increased training complexity. Reference [26] focuses on encoder training efficiency under high mobility, suitable for dynamic vehicular scenarios but with limited applicability to stationary or low-mobility settings. Reference [27] jointly optimizes compression and power allocation through cross-layer design, achieving the best performance but requiring global channel information and incurring high deployment cost. Reference [28] enhances robustness by incorporating CSI but relies on real-time feedback links. Current limitations include: most methods assume known or predictable channel states, leading to insufficient generalization under highly dynamic environments; cross-layer optimization schemes struggle to balance system complexity and real-time performance.

4.3. Semantic Transmission Technology

Semantic transmission technology is responsible for delivering the encoded semantic information reliably and timely to the receiver through the dynamic wireless channel. This subsection focuses on channel adaptation, resource management, and transmission scheduling. Its core objective is to maximize the final task utility of semantic information under the stringent constraints of vehicular network services, rather than merely pursuing channel capacity. The semantic transmission technologies discussed in this subsection are summarized in Table 6.

First, semantic transmission must effectively adapt to the highly dynamic and uncertain channel environment of vehicular networks. Doppler shifts, deep fading, and frequent handovers caused by high-speed vehicle movement require transmission schemes to possess strong robustness and predictability. Research conducts prospective optimization through mobility-aware and environment-aware technologies. Accurate estimation of fast time-varying channels [29] and intelligent estimation schemes leveraging Graph Neural Networks (GNNs) to mine channel spatial correlation [30] provide new avenues for achieving low-complexity, high-accuracy channel estimation in vehicular networks, forming an important foundation for the robustness of semantic transmission systems. For example, the VREM-FL framework proposed in reference [31] integrates vehicle trajectory and radio environment maps to predict future channel conditions for intelligently scheduling model upload timing, optimizing the joint efficacy of learning and resources. Research in reference [32] integrates semantic communication with digital twins, utilizing the network state prior knowledge provided by digital twins to optimize transmission strategies to cope with high mobility challenges.

Second, semantic-aware intelligent resource management is key to improving transmission efficiency. The efficiency of multi-user semantic transmission fundamentally depends on the access strategy. The work in reference [33] proposes a context-aware hybrid access framework for collaborative sensing, which broadcasts critical semantic context orthogonally while aggregating detailed fusion features concurrently, significantly improving multi-user fusion efficiency. From a network-wide perspective, the framework in reference [34] demonstrates how semantic-aware edge computing resource optimization can drastically reduce latency and energy consumption for IoV applications. Reference [35] proposes a hierarchical semantic transmission framework for IoV that separates payload into a coarse metadata layer and fine-grained visual semantics, and formulates an Age

of Information (AoI)/CSI-aware online scheduling problem under per-frame budget constraints. A Lyapunov-based virtual queue stabilizes long-term bandwidth usage, while a greedy packing heuristic selects transmission modes adaptively across SNRs. Given the varying importance of semantic information, cross-layer joint allocation of resources like spectrum and power is required. Distributed decision-making based on deep reinforcement learning has become mainstream. Reference [36] proposes a long-term robust cross-layer resource allocation framework for Device-to-Device (D2D)-based vehicular semantic communication, jointly optimizing semantic access control in the application layer and power control in the physical layer under channel uncertainty via Lyapunov optimization and Bernstein approximation. Facing complex decision-making, reference [37] proposes a Tripartite Cooperative Semantic Communication (TCSC) framework that jointly optimizes the number of semantic symbols and task offloading ratios via V2I and V2V links, using a multi-agent reinforcement learning algorithm with parametric distribution noise combined with linear programming to minimize total system delay in highway scenarios.

Finally, transmission scheduling and coordination mechanisms for collaborative applications are crucial. Semantic transmission needs to be deeply coupled with upper-layer application performance. In collaborative perception, sharing of critical semantic information must be prioritized. The FullPerception framework in reference [38] coordinates semantic sharing and resource allocation at the network level, actively scheduling to eliminate vehicle blind spots to maximize overall perception accuracy. In computation offloading scenarios, research in reference [39] constructs a joint optimization model for task offloading and communication-computing resources, aiming to maximize comprehensive system utility. Furthermore, reference [40] proposes the Task-Centric Multi-User Semantic Communication (TCMSC) solution, which uses Stochastic Network Calculus to model V2I delay-bound violation probabilities and a Transformer-based reinforcement learning algorithm to jointly optimize relay selection, bandwidth allocation, and semantic symbol assignment for multi-user services.

The above methods exhibit different trade-offs between transmission efficiency and system complexity. Reference [40] achieves multi-user semantic scheduling via Transformer-based DRL with SNC delay modeling, suitable for dense bidirectional highway scenarios, but incurs higher training complexity. Reference [32] leverages digital twin prior knowledge to improve prediction accuracy but relies on real-time synchronization of the twin system. Reference [33] achieves excellent performance in multi-vehicle collaborative perception through the CoSC framework but requires strict semantic alignment among vehicles. Reference [34] optimizes resources from a system-level perspective but incurs high edge deployment costs. Reference [35] couples AoI-aware importance scoring with Lyapunov budget stabilization, enabling smooth multi-fidelity mode switching under tight bandwidth, but the Region of Interest (RoI)-based approach depends on object detection quality. Reference [36] handles channel uncertainty via Bernstein approximation, suitable for high-mobility D2D-vehicular scenarios but assumes statistical CSI and incurs computational overhead from Lyapunov iteration. Current limitations include: most methods assume ideal channel estimation, leading to significant performance degradation under highly dynamic environments; cross-layer optimization schemes struggle to balance real-time performance and complexity; and there exists an inherent tension between security mechanisms and transmission efficiency.

Table 6. Semantic Transmission Technologies for Vehicular Networks.

Ref.	Research Objective	Key Components	Core Contribution
[32]	Optimizing transmission strategies with digital twins	Digital twin prior knowledge, asynchronous DRL	Leverages digital twins to predict network states, optimizing transmission strategies under high mobility
[33]	Multi-user semantic fusion transmission	Context-aware hybrid multiple access, context-attentive cooperative channel encoding, Bayesian-guided diffusion receiver	Proposes the CoSC framework, achieving a 34.2% average precision gain on the OPV2V dataset under an SNR range of 0–20 dB, compared to conventional broadcast schemes
[34]	Semantic-empowered MEC resource optimization	Semantic-aware task offloading, dynamic semantic granularity adjustment	Significantly reduces task latency and system energy consumption
[35]	AoI/CSI-aware hierarchical semantic transmission and online scheduling for IoV	Two-layer payload, Lyapunov drift-plus-penalty virtual queue, AoI-weighted scoring, CSI-gated mode switch, greedy MCKP packing	Proposes hierarchical transmission + Lyapunov scheduler; SNR-adaptive switching between BBox-only and multi-scale ROI under per-frame budget
[36]	Long-term robust cross-layer resource allocation for D2D vehicular semantic communication under channel uncertainty	Lyapunov optimization, semantic access control, power control, Bernstein approximation for chance SINR constraints	Proposes a robust algorithm jointly optimizing access rate and transmit power, guaranteeing queue stability and delay constraints in high-mobility D2D-vehicular networks
[40]	Task-centric multi-user semantic scheduling and resource allocation for vehicular networks	SNC-based delay-bound violation modeling, joint relay selection/bandwidth/semantic symbol optimization	Proposes TCMSC solution; improves delay violation probability by 2.88% and reduces power consumption by 31.1% in bidirectional highway multi-service scenarios

4.4. Semantic Decoding Technology

Semantic decoding is the final step in the vehicular semantic communication process. Its core task is to accurately parse and reconstruct potentially impaired semantic representations at the receiver to restore complete semantic information capable of supporting driving decisions. Unlike traditional decoding that pursues bit-level restoration, semantic decoding aims to accurately recover “meaning” to efficiently complete downstream tasks, facing multiple challenges such as channel impairment, knowledge background differences, and edge scenario understanding. The semantic decoding technologies discussed in this subsection are summarized in Table 7.

To address these challenges, current technology primarily develops from three aspects: robust semantic reconstruction, GAI enhancement, and online adaptive decoding. In robust reconstruction, the goal-oriented communication framework proposed in reference [16] integrates a trainable semantic reconstruction network at the receiver. This network can predict and recover complete semantic representations from features impaired by compression and packet loss, thereby significantly improving downstream visual task performance without relying on retransmission. GAI brings leaps in decoding quality. Reference [41] proposes SD-Semantic, a Stable Diffusion-based image semantic decoding framework for low-SNR scenarios. It feeds SNR feedback into the diffusion denoising network and uses text prompts to guide reconstruction, outperforming JPEG, WebP, and Deep-JSCC in perceptual quality under Gaussian, Rayleigh, and Rician fading channels. This approach can be extended to vehicular visual perception tasks.

Table 7. Semantic decoding technologies for vehicular networks.

Ref.	Research Objective	Key Components	Core Contribution
[16]	Constructing a receiver-side semantic reconstruction network to recover impaired semantics	Semantic residual correction network, multi-level feature reconstruction decoder	Recovers complete semantic representations from compressed and packet-loss-impaired features without retransmission
[41]	Low-SNR image semantic decoding using pre-trained diffusion models	Stable Diffusion denoising network, SNR-adaptive denoising strength, prompt-guided cross-attention reconstruction	Proposes SD-Semantic; achieves superior LPIPS over JPEG/WebP/Deep-JSCC under low-SNR fading channels
[42]	Robust text-to-video retrieval in low-SNR vehicular networks	FIFO historical-query cache, CLIP ViT feature extraction, fine-grained matching, bidirectional matching	Leverages historical searches as a dynamic knowledge base to improve retrieval accuracy under low-SNR channels
[43]	Efficient model knowledge sharing across heterogeneous architectures	GAN-driven semantic decoder, generative dataset distillation	Distills model knowledge into semantic vectors and decodes them into tailored synthetic datasets via generative reconstruction
[44]	Deep scene understanding and corner case detection using MLLMs	Multimodal contextual reasoning, long-tail scenario recognition	Reasons for unseen extreme scenarios, improving generalization and safety of autonomous driving systems

Semantic understanding technology is deeply evolving from “information recovery” to “knowledge reasoning and decision-making”, with integration with Large Language Models (LLMs) becoming the frontier. This evolution is evident in advanced cross-modal tasks. For example, the SemTVR framework in reference [42] is designed for robust text-to-video retrieval in low-SNR IoV environments. It uses a first-in, first-out (FIFO) historical-query cache with cross-attention to enhance noisy query recovery at the receiver, followed by a cross-modal fine-grained matching module performing bidirectional interaction between video frames and query sentences as well as video and query words, with CLIP ViT features. Similarly, for knowledge sharing among vehicles with heterogeneous neural network architectures, the SCKS framework in reference [43] uses generative distillation to extract and transmit model semantics, and a GAN-based decoder for reconstruction, enabling efficient cross-model knowledge dissemination. Such models, with their vast knowledge bases and powerful contextual reasoning abilities, can perform deep-level interpretation of semantic information. For example, reference [44] utilizes a Multimodal Large Language Model (MLLM) to empower corner case detection in autonomous driving. The model can combine image and textual semantic inputs with its built-in knowledge to identify and explain rare abnormal traffic scenarios not present in training data, significantly enhancing perception robustness in open environments. This deep understanding capability enables vehicles to infer risks and predict intentions from semantic information, achieving a leap from “transmitting data” to “acquiring intelligence”. In the future, this technology will be more closely integrated with Embodied Artificial Intelligence (EAI) and world models, developing towards general semantic agents with continuous learning and causal reasoning capabilities.

The above methods exhibit different trade-offs between decoding depth and computational overhead. Reference [41] achieves high perceptual quality via diffusion-based decoding but incurs high computational cost due to iterative sampling, hindering real-time onboard deployment. Reference [16] offers higher efficiency with a lightweight reconstruction network suitable for onboard deployment, but its semantic recovery capability is limited by network capacity. Reference [42] improves robustness via historical-query cross-attention enhancement, suitable for low-SNR IoV retrieval, but the FIFO cache introduces semantic drift risk when cached context diverges from current query, and re-

trieval degrades to near-zero at $\text{SNR} \leq -15$ dB. Reference [43] enables cross-architecture knowledge sharing through generative decoding but suffers from GAN training instability. Reference [44] achieves the deepest semantic understanding through MLLMs but faces significant deployment challenges due to model size. Current limitations include: the unresolved tension between computational overhead and real-time performance in generative decoding; onboard deployment of large models constrained by computing power and energy consumption; and the robustness of most methods under extreme channel conditions remains to be validated.

5. Typical Application Scenarios of Semantic Communication for Vehicular Networks

5.1. Applications in Autonomous Driving Scenarios

In autonomous driving scenarios, semantic communication provides key technology for breaking through the limitations of single-vehicle perception and achieving efficient collaboration by transmitting task-related “meaning” rather than raw data. Its core value is reflected in three aspects: enhancing environmental perception, enabling cooperative driving, and improving system robustness in complex scenarios, directly supporting the perception, decision, and control loop.

First, semantic communication can significantly enhance environmental perception capability, especially achieving efficient visual information sharing under bandwidth constraints. For high-definition image transmission required by autonomous driving, research in reference [10] shows that, on the Cityscapes dataset, an encoding scheme based on semantic segmentation can compress data volume to about 1/79 of the PNG lossless size, thereby supporting higher frame rates under limited bandwidth, which is crucial for real-time environment cognition updates [45]. The multimodal framework proposed in reference [21] extracts and transmits thirteen types of features in parallel, including text descriptions, object bounding boxes, and depth maps, and uses GAI to reconstruct images at the receiver. Under a simulated Rayleigh fading channel with an SNR of 10 dB, the method in [21] can maintain high fidelity even under a 40% random packet loss rate. Reference [46] also systematically outlines its framework, indicating its effectiveness in serving tasks like traffic sign recognition and vehicle platooning.

Second, semantic communication is core to achieving network-level collaborative perception to eliminate single-vehicle blind spots. Collaborative perception requires efficient information exchange between vehicles to build a global view. Communication efficiency is a key bottleneck. By transmitting object-level semantic features, such as “vehicle 50 m ahead on the left”, rather than raw point clouds, semantic communication greatly reduces the load. The FullPerception framework proposed in reference [38] is a typical practice, as shown in Figure 4. This framework coordinates semantic feature sharing and resource scheduling among vehicles at the network layer, providing autonomous vehicles with global environmental cognition beyond line-of-sight, ensuring early warning and precise obstacle avoidance in potential danger zones.

Finally, the combination of semantic communication and Artificial Intelligence (AI) technology enhances system robustness in dealing with complex long-tail scenarios. The integrated sensing, computing, and semantic communication framework proposed in reference [7] deeply integrates environmental perception, secure communication, and edge computing. This enables roadside units to track vehicles while safely and efficiently sending warnings, enhancing systemic protection in dynamic environments. The introduction of LLMs brings deep semantic understanding capabilities. Research in reference [44] utilizes MLLMs to empower corner case detection. The model can understand images and textual information received via semantic communication to identify rare abnormal traffic scenarios

not in the training data, significantly improving the system's adaptability and safety in the open world.

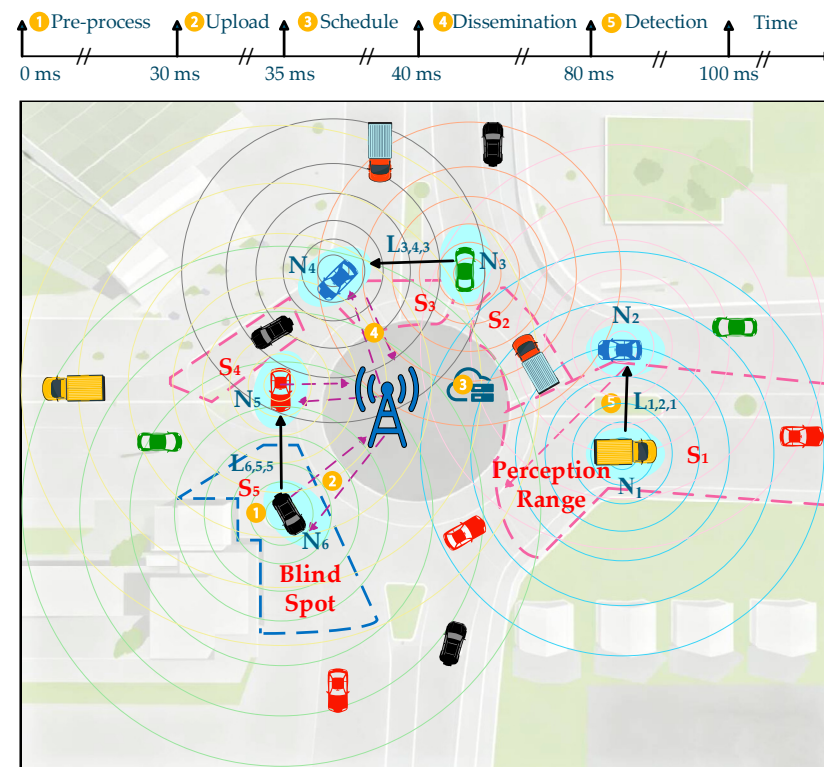


Figure 4. Application practice diagram of the FullPerception framework [38].

5.2. Applications in Vehicle-to-Infrastructure Coordination Scenarios

Vehicle-to-infrastructure coordination aims to achieve beyond-line-of-sight perception and global traffic optimization through deep interaction between vehicles and infrastructure like roadside units and traffic signals. As shown in Figure 5, its typical architecture achieves vehicle-road perception complementarity and information fusion through vehicle-to-infrastructure communication. Compared to vehicle-to-vehicle coordination that enhances single-vehicle perception, vehicle-to-infrastructure coordination focuses more on utilizing the wide-area coverage and strong computing power of infrastructure to provide regional vehicles with global services, such as intelligent signal timing and congestion mitigation [47]. However, the uplink transmission of massive roadside perception data can easily cause network congestion. By transmitting highly refined semantic information, such as “50 m queue on eastbound approach”, rather than raw data streams, semantic communication provides a new path to break this bottleneck. Its task-oriented nature allows communication content to be extremely concise, directly serving high-level decision-making, thereby greatly alleviating network load while ensuring utility.

The technological path of semantic communication in vehicle-to-infrastructure coordination is mainly reflected in three aspects: efficient semantic compression, semantic-enhanced decision-making, and semantic-aware resource scheduling. First, for uplink transmission of multi-sensor data from roadside units, semantic coding enables efficient compression. The SemanticTwin architecture proposed in reference [11] allows vehicles to upload lightweight social behavior semantic features for building digital twins and optimizes semantic caching through reinforcement learning, improving synchronization efficiency and experience quality. Second, semantic information from multiple sources can be fused and reasoned upon under a shared “traffic scene knowledge graph” to generate a more comprehensive global situation, supporting complex decisions like cooperative

intersection passing. Finally, the importance of semantic information can serve as a basis for dynamic resource scheduling. The semantic-aware computation offloading model constructed in reference [18] intelligently selects transmission content by evaluating semantic feature importance and uses hybrid-action deep reinforcement learning to jointly optimize communication resources and semantic compression ratio, thereby maximizing the system utility that comprehensively considers task delay, energy consumption, and semantic fidelity.

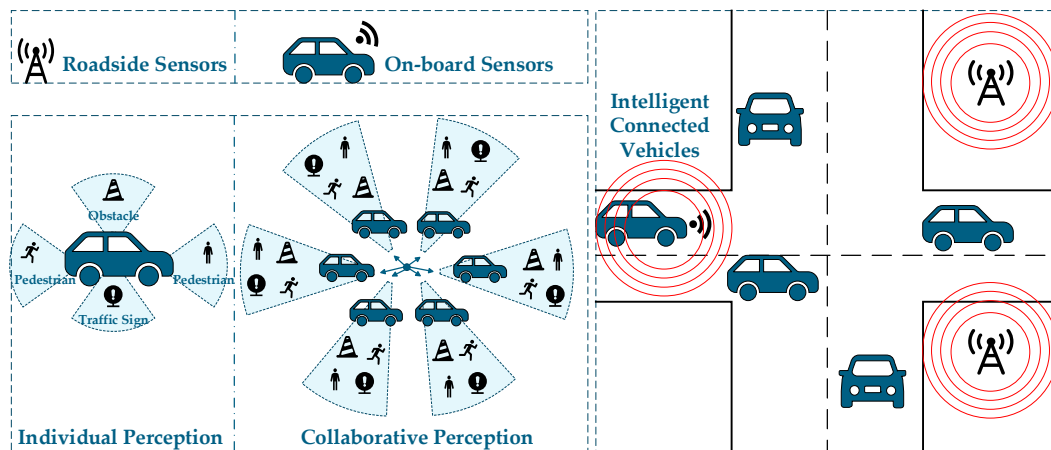


Figure 5. Schematic diagram of vehicle-to-infrastructure coordination.

Semantic communication is integrating with new technologies like blockchain and Intelligent reflecting surfaces, driving vehicle-to-infrastructure coordination systems towards greater intelligence, trustworthiness, and wide coverage. For example, reference [8] explores a framework integrating goal-oriented semantic communication and blockchain smart contracts, enabling roadside facilities to automatically trigger and execute trustworthy traffic control contracts based on semantic information. Reference [12] studies IRS-assisted vehicular metaverse scenarios, where its model simultaneously optimizes semantic utility, communication delay, and power consumption while providing metaverse updates via semantic communication. Looking ahead, with the development of 6G integrated sensing, communication, and computing, semantic communication will help build an integrated space-air-ground cooperative network. Reference [48] points out that, assisted by socially inspired semantic codec updating mechanisms, Non-Terrestrial Networks (NTN) can provide more robust and wider-coverage semantic information services for intelligent transportation systems.

5.3. Applications in In-Vehicle Service Scenarios

In-vehicle service scenarios focus on enhancing in-vehicle infotainment, personalized experience, and vehicle status management efficiency. Their core lies in efficiently transmitting rich media and personalized data. Leveraging its task-oriented compression and knowledge-driven interaction capabilities, semantic communication provides innovative solutions for high-bandwidth services like HD streaming, vehicular metaverse, and digital twin synchronization. As shown in Figure 6, the reliable delivery of these upper-layer applications relies on an underlying unified, transparent service communication architecture for support, to shield network heterogeneity and achieve transparent service invocation.

In terms of infotainment and immersive experiences, semantic communication can achieve extreme compression of original video streams by transmitting semantic features of video content and reconstructing them at the receiver using GAI. The SemanticTwin architecture proposed in reference [11] applies this concept, extracting and uploading

lightweight social behavior semantic features for cloud-assisted rendering and synchronization, significantly improving the quality of experience for services like streaming media. In the vehicular metaverse, research in reference [12] indicates that transmitting semantic information required for virtual world updates via semantic communication, rather than complete data, and jointly optimizing semantic utility and communication overhead, is a viable path to support immersive in-vehicle applications. Realizing such complex semantic interactions across vehicles, cloud, and edge first requires solving the fundamental engineering challenge of cross-network reachability for the services themselves. Traditional in-vehicle SOME/IP protocol cannot support cross-subnet communication. Addressing this, reference [49] proposes a “vsomeip + ETCD + Nginx” solution, establishing a stable cross-network communication pipeline for semantic-driven rich media services through global service registration and gateway proxy.

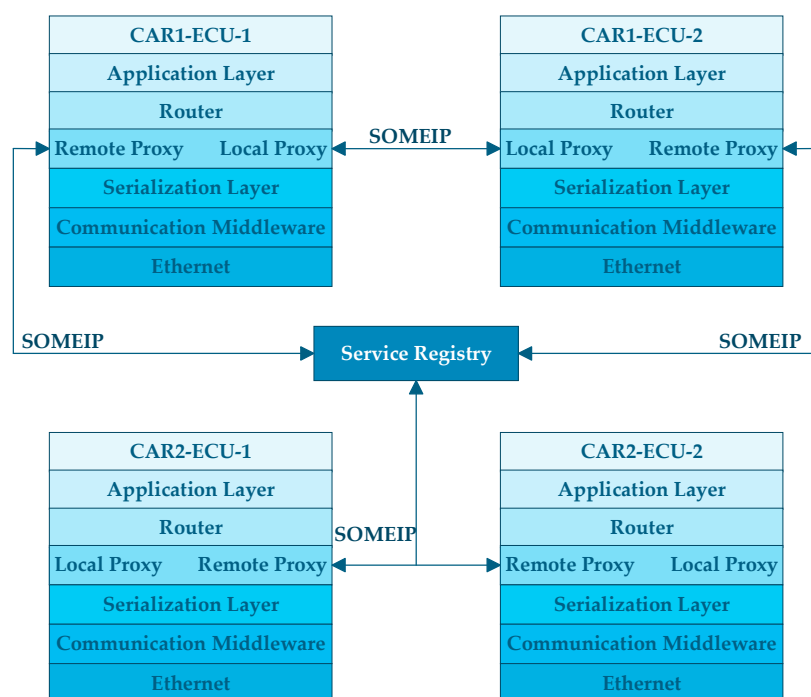


Figure 6. Overall architecture design diagram for in-vehicle services.

In vehicle status management and personalized services, semantic communication combined with federated learning and edge computing enables efficient collaboration while protecting data privacy. Vehicles can locally extract task-related semantic features (e.g., anomaly patterns, energy consumption trends) before uploading, avoiding raw data leakage and saving bandwidth. The federated learning-empowered framework in reference [25] efficiently supports model updates for personalized recommendation services by jointly optimizing semantic extraction and resource allocation. Research in reference [23] on vehicular digital twin networks also builds semantic-aware models to achieve efficient collaborative computing and status synchronization. The realization of these applications similarly relies on underlying service communication mechanisms to ensure the reliable and timely exchange of semantic information like model updates and control commands. Combined with robust service infrastructure, semantic communication technology is jointly driving in-vehicle services towards deep intelligence and personalization.

6. Technical Challenges and Development Trends of Semantic Communication for Vehicular Networks

6.1. Technical Challenges

Despite significant theoretical and application progress, the large-scale, highly reliable application of semantic communication for vehicular networks still faces multi-dimensional challenges arising from the intertwined nature of its technological paradigm and the stringent vehicular network environment.

The Challenge of Semantic Consistency and Dynamic Knowledge Management. The value of semantic information depends on the alignment of knowledge bases between sender and receiver. In open, heterogeneous vehicular networks, different entities may have ambiguous understandings of the same scene. Reference [50] points out that while its G-MSC framework enhances multimodal processing capability, unified representation and alignment of multi-source semantics remain core challenges. Simultaneously, the knowledge base supporting semantic interaction needs continuous evolution. How to efficiently and consistently update and synchronize semantic resources among massive distributed nodes and achieve low-latency matching constitutes unprecedented system complexity.

The high dynamics and resource constraints of vehicular networks impose nearly contradictory demands on the system's real-time adaptability, lightweight nature, and security. High-speed vehicle movement causes rapid channel and topology changes, requiring semantic processing and resource allocation strategies to possess millisecond-level online decision-making capability. Reference [51] uses hierarchical reinforcement learning to address time-varying channel optimization, but the training overhead and decision latency of such methods themselves face severe tests in dense scenarios. Meanwhile, the computationally intensive nature of semantic models directly conflicts with the limited computing power and energy of vehicle terminals. The MAHAS-DRL framework in reference [19] optimizes spectral efficiency, but its model complexity and collaborative training overhead face huge pressure for deployment in resource-constrained environments.

The openness and knowledge dependency of semantic communication introduce a new dimension of security and trust [52]. Malicious attacks can pollute knowledge bases, implant backdoored models, or inject false semantics, causing systematic damage to collaborative systems [53]. The three-layer trustworthy architecture constructed in reference [2] clarifies the need to simultaneously defend against transmission eavesdropping, model poisoning at the semantic coding layer, and untrustworthy behavior at the communication entity layer, highlighting the extreme complexity of building an endogenous secure semantic communication system.

The tension between large model capability and deployment is becoming increasingly prominent. LLMs and GAI bring powerful semantic understanding and generation capabilities, but their massive parameters and computational requirements make direct deployment on vehicle terminals difficult. Reference [54] utilizes large multimodal models to personalize communication, but how to effectively compress and adapt them to vehicle-side computing power while meeting personalized service demands is a core engineering challenge that urgently needs resolution.

6.2. Development Trends

To address the aforementioned challenges, semantic communication technology for vehicular networks is evolving towards distributed collaborative intelligence, lightweight adaptive decision-making, and deep integration with large models and integrated "communication, sensing, and computing". It exhibits distinct features of systematization, intelligence, and openness.

The primary trend is building a dynamic collaborative knowledge ecosystem to solve semantic consistency and knowledge update challenges. Future systems will rely on distributed collaborative training frameworks for efficient knowledge co-creation and continuous evolution. For example, the V-FedMM framework proposed in reference [55] can efficiently construct consensus semantic models by intelligently scheduling multimodal data and vehicle resources. Research in reference [56] shows that joint optimization of model partitioning and resource allocation enables low-cost, personalized model updates. This indicates that semantic communication will depend on a dynamically matching, continuously evolving knowledge network, rather than a static knowledge base.

Second, lightweight and adaptive real-time decision-making capabilities continue to strengthen to match the high dynamics of vehicular networks [57]. Model compression, edge AI, and other technologies facilitate the lightweight deployment of complex semantic processing models on vehicle terminals. Simultaneously, the deep integration of deep reinforcement learning and online learning drives systems to achieve millisecond-level autonomous optimization. The review in reference [58] points out that DRL-based resource management is developing towards multi-agent, hierarchical attention, and meta-learning directions to cope with environmental uncertainty and achieve global adaptive scheduling and joint optimization of communication, sensing, and computing resources.

Finally, large model-driven and integrated “communication, sensing, and computing” are shaping the next-generation system architecture. LLMs, as powerful semantic engines, combined with semantic communication frameworks, will support zero-shot reasoning and instruction-based service customization in open scenarios. The future trend is to build “communication, sensing, and computing” agents with semantics as the link and task utility as the goal. Deeply integrated with technologies like digital twins and blockchain, they will achieve a complete closed loop from environmental semantic perception and intent understanding to cooperative control and trustworthy execution, propelling vehicular networks to make a fundamental leap from “connection” to “cognition”. In this process, new waveforms with inherent anti-Doppler advantages like Orthogonal Time Frequency Space (OTFS) modulation may achieve deeper fusion with semantic communication systems at the physical layer, providing a more solid underlying foundation for integrated “communication, sensing, and computing” [59].

7. Conclusions

In response to the stringent demands of intelligent connected vehicles for communication bandwidth, latency, and reliability, semantic communication for vehicular networks has emerged as a new paradigm focusing on the transmission of information “meaning”. Through systematic review, this paper constructs a complete analytical framework covering fundamental theory, key technologies, typical applications, challenges, and trends.

The core contribution of this survey lies in its structured synthesis and forward-looking perspective, which distinguishes it from prior works. First, it establishes a holistic framework that maps the complete technological chain—from semantic extraction and encoding to transmission and intelligent decoding—providing a unified lens to analyze the ecosystem. Second, it delivers a scenario-driven, in-depth analysis, moving beyond generic summaries to detail the distinct application logic, performance gains, and design imperatives of semantic communication across three pivotal verticals: autonomous driving, vehicle-to-infrastructure coordination, and in-vehicle services. The study finds that semantic communication, through its knowledge-dependent and task-oriented characteristics, achieves a fundamental paradigm shift from traditional “bit fidelity” to “task utility optimal”, providing a new path to break through vehicular network resource bottlenecks. At the key technology level, research is evolving from single-modal processing

to multimodal fusion and generative large model-driven approaches, from static optimization to adaptive coding and cross-layer resource joint management based on deep reinforcement learning, and from pursuing signal reconstruction to enhancing robustness for downstream task performance. At the application level, semantic communication has demonstrated core value and potential in three major scenarios: autonomous driving collaborative perception, vehicle-to-infrastructure collaborative global optimization and personalized in-vehicle services.

From the review results, semantic coding and transmission are the most mature technical areas, and autonomous driving collaborative perception is the most studied application scenario, while semantic decoding and in-vehicle services remain in early stages. The most critical challenges for practical deployment are maintaining semantic consistency under high dynamics and real-time onboard deployment of lightweight models. This survey has three main limitations: first, some recent advances may not have been captured due to rapid developments; second, coverage of standardization and industrial deployment is limited; third, the literature search was primarily confined to English and Chinese publications. Future trends point towards building dynamic collaborative knowledge ecosystems, developing lightweight adaptive real-time decision-making agents, and deeply integrating generative large models with “communication, sensing, and computing” architectures. As the core link, semantic communication will empower the future intelligent transportation system, promoting vehicular networks from “connection” to “cognition”.

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