Analysis Of Key Technology Research and Development Trends in Semantic Communication for V2X Scenarios

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Abstract. Semantic Communication (SemCom), as an advanced communication paradigm focused on transmitting "meaning" rather than mere "bits", is propelling the evolution of vehicle-to-everything (V2X) networks from perception-centric to cognition-centric systems. This paper systematically develops a network model for SemCom within V2X contexts, reviewing recent research achievements over the past three years across five critical domains: resource management, priority access protocols, data compression and coding, privacy safeguards, and interference mitigation strategies. It introduces task-oriented communication optimization frameworks, conducts layered analyses of typical applications and developmental trajectories, and assesses the technical challenges and future prospects for commercial deployment of SemCom in V2X environments. Findings indicate that semantic communication significantly improves transmission efficiency and robustness, laying the groundwork for applications such as cooperative perception, trajectory prediction, and swarm intelligence in intelligent connected vehicles. Despite obstacles like the lack of standardized protocols and inconsistent communication standards, the progression of SemCom in V2X faces hurdles but remains promising. This study aims to provide theoretical foundations and practical insights for designing smarter, more efficient, and safer V2X communication infrastructures.

Keywords: Semantic Communication; V2X; Resource Management; Joint Coding.

1. Introduction

V2X is transforming the transportation ecosystem at an unprecedented rate, shifting from mere data connectivity to intelligent decision-making. Traditional communication methods, constrained by limited bandwidth and resource scarcity, are inadequate for the real-time, high-density, low-latency demands of modern vehicular networks. In an era characterized by ubiquitous connectivity and data proliferation, conventional approaches struggle to cope with the volume of information generated. Vehicles no longer just "hear" data; they seek to "comprehend" it. Semantic communication emerges as a solution—transitioning from bit transmission to meaning conveyance. This paradigm shift enhances both efficiency and intelligence. Compared with traditional communication, semantic communication is a more direct and efficient way of communication[1]. Naturally compatible with V2X applications,semantic communication alleviates resource constraints by reducing redundant data transmission, ensuring data transfer aligns with specific tasks and decision-making processes. Low-latency obstacle alerts, intelligent route planning, and predictive collective behavior control are now attainable through semantic communication.

While promising, the deployment of semantic communication in V2X faces significant challenges. Resource management remains a primary concern: how to optimize resource utilization without degrading communication quality. Developing access control schemes that improve user connection success rates and network capacity, while optimizing data compression and encoding efficiency, is critical. Additionally, safeguarding data privacy, mitigating co-channel interference, and maintaining data integrity under malicious threats are pressing issues.

This paper consolidates and analyzes key technological trends in semantic communication tailored for V2X scenarios. Chapter 1 reviews recent global research developments over the past three years in resource scheduling, access control, data compression, transmission coding, privacy protection, and interference countermeasures. Chapter 2 presents a semantic communication-based V2X framework, detailing the roles and functions of each component. Chapter 3 examines the current technological landscape and identifies bottlenecks across five key areas: resource management, priority access, compression coding, privacy safeguards, and interference mitigation. Chapter 4 offers a hierarchical analysis of typical applications, summarizing technical challenges and future directions for commercializing semantic communication in V2X systems.

2. Related Researches at Home and Abroad

2.1. Resource Management and Access Protocols

Recent advances in semantic communication have provided valuable insights into resource management and access control within V2X networks. Chen et al.[2] proposed three system models and algorithms for resource allocation, highlighting their performance advantages across various intelligent task scenarios. However, these studies primarily focus on single-modal, single-task uplink semantic communication. Wang et al.[3] developed a resource allocation scheme based on semantic importance for multi-user downlink image semantic communication, integrating MIMO technology to establish a power allocation strategy and an attention-based semantic communication model. This approach enhances user performance while optimizing resource utilization. Meanwhile, Yan et al.[4] designed two resource allocation schemes for single-semantic-task and multi-modal multi-task scenarios. The former involves two optimization models balancing reliability and efficiency, demonstrating performance improvements, while the latter introduces a semantics-oriented Quality of Experience (QoE) model. By formulating an optimization problem aimed at maximizing QoE, they decompose it into semantic compression and channel/power allocation subproblems, solved via reinforcement learning and low-complexity matching algorithms, respectively. These methods also maintain compatibility with traditional communication systems. Recognizing the limitations of current access schemes, a generalized semantic information-based access control protocol is proposed, with simulation results confirming improvements in connection success rates and network capacity.

2.2. Data Compression and Coding Transmission

In the context of data compression and codec transmission within semantic communication systems, Zhang et al. [5] proposed a multi-user collaborative semantic communication framework. For uplink and downlink scenarios, they developed two collaborative semantic compression and joint recovery schemes. Correspondingly, they introduced two distinct deep neural network architectures trained to minimize transmission overhead and compress redundant information sources. To improve transmission efficiency in semantic communication, Han et al. [6] investigated a speech transmission semantic system, designing a speech-to-text encoder based on an attention mechanism, complemented by beam search and semantic correction modules to enhance decoding accuracy. Yao et al. [7] focused on optimizing semantic encoding and transmission, establishing semantic encoding criteria and system design principles, and proposing a loosely coupled semantic compression encoding method, a receiver-coupled joint source-channel semantic decoding approach, and a transmitter-receiver coupled joint semantic encoding and transmission method. These strategies effectively increased fault tolerance and decoding performance while enhancing semantic transmission efficiency.

2.3. Data Privacy Protection

Regarding data privacy, after semantic extraction of raw data, transmitted semantic information may be vulnerable to interception or malicious attacks. Han et al. [8] employed semantic segmentation techniques to differentiate critical from non-critical semantic regions, integrating entropy coding to address privacy protection and compression optimization, and designing a semantic decoder for high-fidelity image reconstruction. During collaborative training between edge servers and in-vehicle terminals, malicious entities may intercept or steal private data, risking privacy breaches. Luo et al. [9] proposed a U-shaped segmentation-based semantic encoding and decoding framework for edge-cooperative training, demonstrating vulnerabilities through feature analysis and simulation experiments, and providing insights for optimizing semantic communication encoding and decoding models to mitigate privacy leakage risks.

2.4. Multi-User Co-channel Interference and Malicious Interference Prevention

To counter multi-user co-channel interference and malicious disruptions, Zhang et al. proposed two semantic communication frameworks based on the modality of semantic information. For single-modal transmission, they designed interference suppression methods based on semantic and syntactic differences, satisfying both semantic and bit-level user requirements. For semi-orthogonal multimodal transmission, they developed an additive encoder aimed at minimizing Multi-modal Semantic Difference (MSeD) and a successive interference cancellation (SIC) module tailored for multimodal semantic streams, improving coding and decoding performance. Under malicious interference conditions, communication resources are degraded by interference signals. Huang et al. [10] introduced two anti-interference strategies: an adaptive semantic symbol dynamic adjustment method and an external information-assisted semantic symbol enhancement approach, to mitigate pulse and continuous interference effects.

3. Vehicle-to-Everything (V2X) Model Based on Semantic Communication

The V2X semantic communication model shifts the focus from bit-level restoration to task-oriented information flow. Its architecture comprises five core components: in-vehicle terminals, semantic communication modules, edge access devices with Multi-access Edge Computing (MEC) platforms, core network servers, and V2X application servers, forming a sequential "perception—abstraction—coordination—hub—closed-loop" transmission chain. The overall model framework is shown in Figure 1.

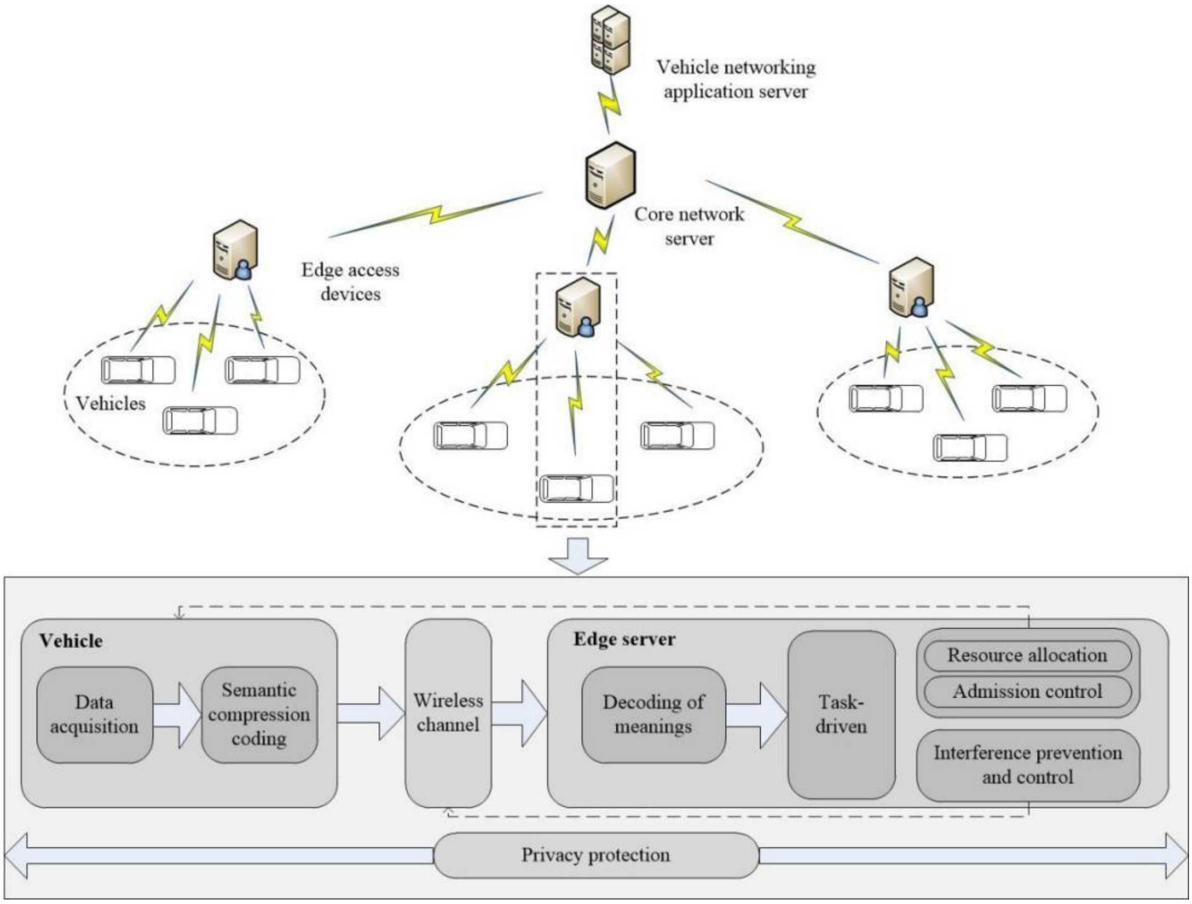

Figure 1: Semantic-driven vehicle networking system model

In vehicle devices, including cameras, millimeter-wave radars, lidars, and processing chips, serve as the initial nodes, collecting raw data and performing semantic extraction. Vehicles convert raw sensor data and location information into structured semantic units—such as "adjacent vehicle deviating from lane" or "collision risk within two seconds"—reducing data volume, improving transmission efficiency, and shortening response latency. The semantic communication module, deployed on vehicles or roadside units, manages semantic compression, encoding, and fault-tolerant reconstruction, utilizing neural networks or semantic embeddings to prioritize task-relevant information and maximize redundancy reduction. Under unstable channel conditions, inference-based restoration maintains semantic continuity, enhancing robustness. Edge access devices, positioned close to vehicles, facilitate local multi-vehicle semantic data fusion and real-time coordinated responses, such as traffic light control or emergency maneuvers, by aggregating and modeling semantic content from multiple sources into regional collaborative graphs. This local processing alleviates core network load and accelerates response times. Core network servers, located centrally, connect edge networks with cloud platforms, overseeing semantic communication policies, task scheduling, and model updates. V2X application servers in the cloud handle long-term tasks like path planning, environmental modeling, and traffic simulation, completing the closed-loop system.

Given constrained computational and communication resources, ensuring vehicular safety and prompt service response necessitates the deployment of five core semantic communication technologies: resource scheduling, priority access control, data compression coding, privacy preservation, and interference mitigation. The subsequent sections examine the application and advancement of semantic communication within V2X environments from these five technical perspectives.

4. Analysis of Key Technologies

The integration of semantic communication into V2X systems signifies a paradigm shift in vehicular communication and redefines system capability boundaries. To facilitate multi-layered semantic interactions among vehicles, edge devices, and cloud infrastructure, it is essential to develop task-oriented resource optimization frameworks, data compression mechanisms, access control protocols, and semantic security architectures. Current research, both domestically and internationally, emphasizes balancing "efficient data transmission" with "semantic comprehension". The following sections detail the current state and development challenges across these five critical technological domains.

4.1. Optimal Resource Allocation and Priority Access Control for Vehicular Devices

In the practical application of the Internet of Vehicles, the bandwidth conditions of the network, the available channel resources, and the computing power that the edge nodes can provide, these key elements will limit the overall available communication resources to a certain physical range. When there are multiple vehicles uploading a large amount of semantic information to the network at the same time, it will produce a very large communication pressure. The traditional scheduling method of allocating resources according to demand has been difficult to meet the differentiated service requirements between different tasks. Introducing the idea of ' task-oriented ' into the resource scheduling mechanism in semantic communication will become a key improvement direction. The research framework of resource allocation and access control is roughly shown in Figure 2.

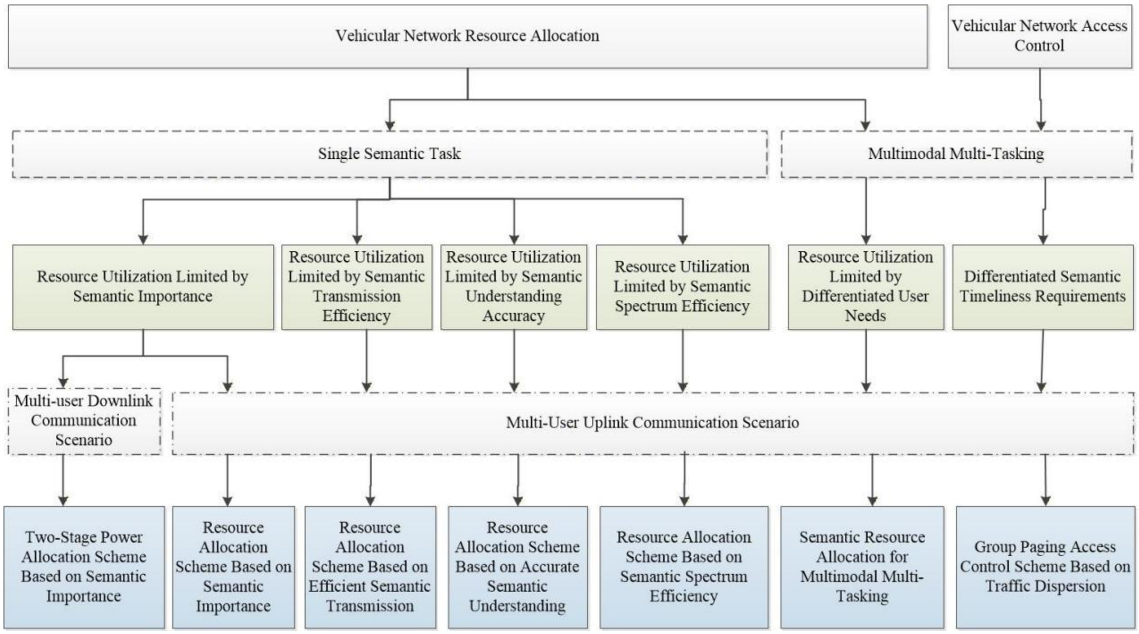

Figure 2: Research framework of resource allocation and access control

4.1.1 Resource Allocation Scheme Based on Semantic Importance

Three primary solutions address uplink communication scenarios for single semantic tasks. The first involves resource allocation based on semantic importance. We can design more targeted allocation strategies according to the characteristics of different tasks. For tasks that pay more attention to spatial semantic information, such as vehicle re-identification and target tracking, we can use siamese network to calculate the semantic similarity between image content and target object, and take this result as the weight of importance. After integrating these weights into the model of effective information amount, the bandwidth and power allocation scheme can be solved by convex optimization. For those tasks that rely more on temporal semantics, such as abnormal behavior detection in traffic scenes, it is also possible to calculate the degree of significant changes in timing through inter-frame difference and use it as a weight. With the help of multi-agent distributed Q-learning algorithm, the system can autonomously optimize the way of resource allocation to a better state in a changing operating environment. Through the results of simulation experiments, we can see that this set of resource allocation scheme can improve the mean Average Precision (mAP) performance in the vehicle re-identification task by nearly 10 %, and can also improve the related performance under the traffic detection task by nearly 5 %. At the same time, compared with the average allocation of resources, the use of this method can also increase the effective amount of information that can be transmitted per unit time by about 4Kbits, which also makes the overall transmission efficiency has been significantly improved.

4.1.2 Resource Allocation Scheme Based on Efficient Semantic Transmission

Subsequently, a semantic-efficient transmission resource allocation scheme is proposed. In order to better solve the problem of signal interference between users and insufficient communication resources, the non-orthogonal multiple access (NOMA) technology is introduced in the research to build a more reasonable communication system model, and then the ResNet network is used as the backbone network to extract image features. Through rounds of training cycles, the weight of the encoder is continuously updated to a better state, so as to realize the optimization of the semantic encoder, and then the distributed Q learning algorithm is used to solve the problems related to power allocation. The research also proposes a semantic communication system based on deep air computing. This system can directly fuse the feature information of multiple users with the help of a gated aggregation network, avoiding the steps of separating the various types of information generated by the vehicle separately through successive interference cancellation (SIC), and also reducing the complexity of the entire system. At the same time, in order to minimize the cross-entropy loss in the semantic understanding task, a network structure composed of three modules is designed to complete the supervised learning process. The correlation operation of the feature signal is completed through the fully connected layer, and the more targeted information aggregation operation is completed with the help of the deep air computing network. In this structure, the gating matrix will determine which user information to use when aggregating and how much proportion to use for each type of information according to the given supervision information in advance. The final result after semantic understanding can be obtained by inputting the aggregated features into the deep neural network at the end. Through the end-to-end training of the entire network structure, the parameters in the fully connected layer, the gating matrix, and the related configuration of the deep neural network can be optimized to a better state. Simulation results indicate that, for action recognition tasks, the deep aerial computing-based resource allocation algorithm achieves a 52% improvement in recognition accuracy at a signal-to-noise ratio of 0 dB, nearly doubling the transmission rate. For text reasoning tasks, NOMA outperforms alternative methods, increasing average F1 scores by 0.02 and matching accuracy by 0.05.

4.1.3 Resource Allocation Scheme Based on Accurate Semantic Understanding

The initial two resource management strategies focus solely on the allocation of communication bandwidth, whereas the semantic-aware resource allocation framework integrates computational resources into the optimization process. The optimization objectives for real-time and delay-tolerant applications prioritize low latency and high accuracy, respectively, while adhering to energy consumption constraints. Through extensive empirical data fitting, a mathematical model delineating the relationship between mean Average Precision (mAP), communication data rate, computational resources, and cache compression ratio is established. A distributed Deep Q-Network (DQN) algorithm models each vehicle as an agent, with the state space encompassing resource allocation and channel conditions, and the action space being multi-dimensional and discrete. The reward function combines the objective metrics with constraint considerations, utilizing experience replay and target network mechanisms to facilitate training. This approach enables dynamic optimization of communication, computational, and caching resources, thereby enhancing semantic understanding accuracy and satisfying diverse Quality of Service (QoS) requirements. Simulation results demonstrate that the proposed resource management algorithms improve mAP by approximately 0.15 under resource constraints and increase reward exploration efficiency by at least 5%.[2]

4.1.4 Two-Stage Power Allocation Scheme Based on Semantic Importance

In multi-user downlink image semantic communication scenarios, traditional resource allocation strategies within multi-user MIMO networks fail to differentiate the significance of semantic information, leading to inadequate protection of critical semantics and resource wastage. A two-stage power allocation scheme based on semantic importance is introduced. Semantic importance is quantified and ranked, with high-priority semantics mapped to high-quality channels and allocated more power to provide unequal protection, thereby enhancing overall system utility. Precoding via block diagonalization eliminates inter-user interference, and power distribution among users is optimized based on a fitted structural similarity–Signal-to-Noise Ratio (SNR) relationship. To improve individual user semantic communication performance, a hybrid attention mechanism quantifies the importance of each semantic element. Semantic compression employs the maximum correlation minimum redundancy algorithm, and semantic flows are mapped onto parallel subchannels derived from Singular Value Decomposition (SVD) according to importance scores. Subchannel power allocation is performed using a water-filling algorithm, culminating in the maximization of network utility. Experimental validation indicates at least a 5.9% enhancement in semantic communication performance[3].

4.1.5 Resource Allocation Scheme Based on Semantic Spectrum Efficiency

In single semantic task, another research proposes a set of resource allocation solutions aiming at maximizing semantic spectrum efficiency. By defining two new evaluation indicators of semantic transmission rate and semantic spectrum efficiency, the actual efficiency of information transmission is measured from the semantic level. Through the optimization of wireless resource allocation methods, the overall semantic spectrum efficiency of the system is maximized. For tasks such as text transmission, the basic unit of semantic information will be defined first, and then the mathematical model of semantic spectrum efficiency will be deduced. For the two types of semantic communication systems of separation design and joint design, the corresponding optimization problems will be built with the goal of maximizing semantic spectrum efficiency. The two sub-problems of symbol allocation and channel allocation are solved by exhaustive search method and Hungarian algorithm respectively, and finally the efficient resource allocation more in line with semantic perception requirements is realized. Through the verification of simulation experiments, it can be known that the performance of the resource allocation model based on separate design will be significantly better than the traditional model, and the model based on joint design can also achieve better results.

4.1.6 Semantic Resource Allocation for Multimodal Multi-Tasking

In multi-modal, multi-task environments, a cross-task fair resource allocation scheme based on semantic entropy and Quality of Experience (QoE) is proposed. Semantic entropy quantifies the semantic information across different modalities, and a QoE model integrating semantic transmission rate and fidelity is constructed as the optimization objective. Approximate semantic entropy measures are defined for tasks such as text and visual question answering, facilitating the development of a semantic QoE model expressed as a logical function. The original problem is decomposed into two sub-problems: semantic compression rate allocation and channel power distribution, solved respectively via task-specific deep Q-networks and a low-complexity matching algorithm. This framework enables equitable and efficient resource distribution across multiple tasks and users. Simulation results demonstrate that the proposed scheme achieves higher user satisfaction compared to resource allocation based solely on semantic spectrum efficiency, with performance surpassing traditional models.

4.1.7 Group Paging Access Control Scheme Based on Traffic Dispersion

Based on the issue of access congestion caused by excessive users within the same paging group in conventional group paging protocols and the inability to satisfy differentiated semantic latency requirements under multi-semantic tasks, a traffic dispersion-based group paging access control scheme is proposed. By defining generalized semantic information and considering semantic latency and transmission efficiency, users are prioritized according to their semantic latency demands and allocated to distinct random access slots for preferential access, thereby optimizing resource utilization and network capacity. A semantic latency-aware traffic dispersion strategy is designed to sequentially assign users based on task-specific semantic urgency. Subsequently, an access procedure and steady-state analytical model are established, deriving the successful access probability under preamble transmission and resource constraints. Through the optimization of the dispersion factor, the average system access capacity is maximized, effectively enhancing resource efficiency and user support capacity. Simulation results demonstrate that this scheme significantly elevates network access capacity[4]. Nonetheless, challenges such as enabling local semantic latency assessment without increasing device computational load and preventing disproportionate prioritization of high-weight tasks to ensure fairness must be addressed in future access control mechanism implementations.

4.2. Semantic Information Compression and Transmission via Coding

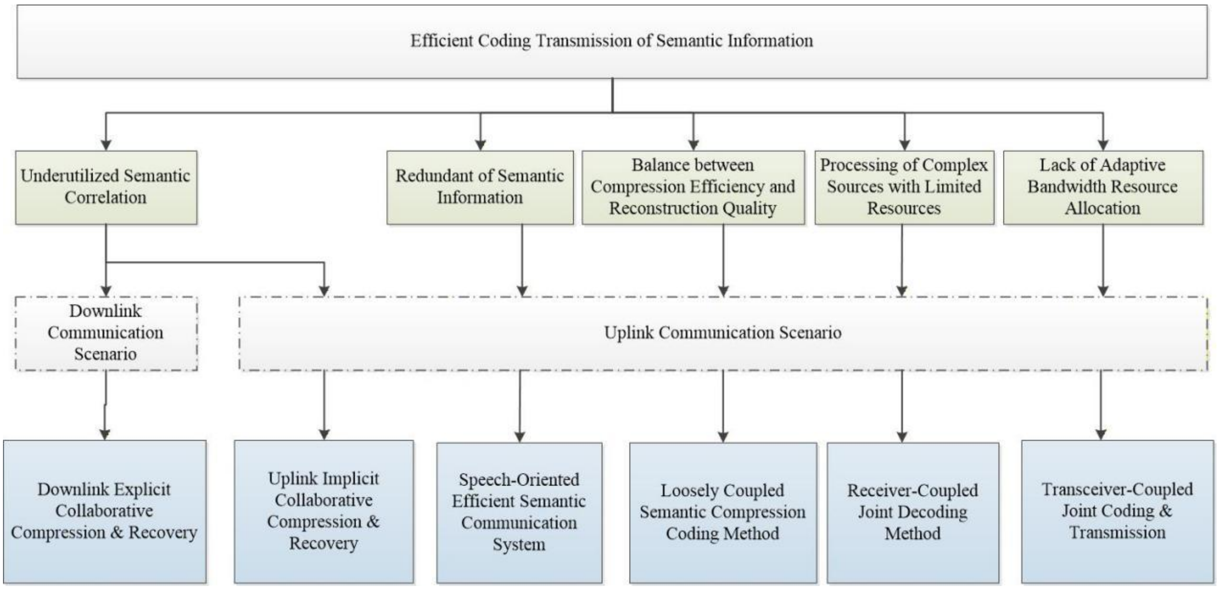

Figure 3: Research framework of compressed coding transmission of semantic information

4.2.1 Collaborative Semantic Compression and Joint Recovery Framework for Multi-User Communication

The homogenization of sensing data in Intelligent Vehicular Networks is prevalent, exemplified by similar-angle images from multiple vehicles, obstacle data from identical locations, and repetitive traffic signal recognition. Traditional compression methods primarily aim to minimize bit rate without addressing semantic redundancy. To this end, we propose some solutions, and the research direction is shown in Figure 3. Current multi-user semantic communication frameworks do not fully exploit semantic correlations among sources. Therefore, a collaborative semantic communication architecture is proposed to enhance compression and transmission efficiency by explicitly or implicitly mining multi-user semantic correlations. Deep learning models are employed to jointly learn semantic feature correlations, enabling collaborative compression and reconstruction through feature fusion and joint decoding. In downlink scenarios, the base station explicitly analyzes and fuses semantic features; in uplink scenarios, individual users implicitly embed correlations via pre-trained models, with the base station performing joint decoding. Both approaches utilize multi-stage training strategies to iteratively optimize semantic coding, joint source-channel coding (JSCC), and feature fusion modules. Simulation results indicate that this cooperative semantic transmission framework reduces transmission overhead and improves accuracy[5].

4.2.2 Speech-Oriented Efficient Semantic Communication System

When communication resources are constrained, redundant information can occupy significant bandwidth, reducing transmission efficiency. An efficient semantic communication system is thus proposed, featuring a speech-text semantic encoder based on attention mechanisms at the transmitter to extract key textual semantics from speech and significantly compress the transmitted sequence length. The receiver employs knowledge base-assisted semantic decoding and error correction to enhance text recovery accuracy. Additional speech features such as phoneme duration, tone, and power are incorporated, and a non-autoregressive speech reconstruction model is used to generate high-quality speech. After spectral features are extracted via VGG, they are mapped to semantic text representations through attention mechanisms. Following channel coding and transmission, the receiver reconstructs text via beam search and semantic correction, then utilizes additional speech information to synthesize high-fidelity speech through FastSpeech2 and HiFi-GAN models. Simulation results demonstrate that this system outperforms existing models in accuracy and semantic similarity. Although the current model size is substantial, future work will focus on compression techniques to reduce size and processing time. Furthermore, the underlying design principles can be adapted to other cross-modal tasks, highlighting its broad applicability and potential for further development[6].

4.2.3 Loosely Coupled Semantic Compression Coding Method

The current semantic coding standards lack consensus; therefore, a set of optimization criteria for semantic transmission and communication architecture design are proposed to provide theoretical guidance for future research. The traditional transform coding method will have the problem that the decorrelation ability is not strong enough in the face of the audio signal source with complex structure, and the high-dimensional vector quantization method will have a high operating complexity. It is difficult to achieve a better balance between higher compression efficiency and better signal reconstruction quality. In order to solve these problems, the research team proposed a speech semantic compression coding method based on variational probability modeling and super-prior information. This method will use nonlinear neural network to extract the semantic features in the audio, and will also introduce super-prior feature information. The corresponding probability modeling of these semantic features is done, and the idea of residual coding and perceptual loss is combined to further optimize the quality of the final signal reconstruction. In the specific implementation process, the speech frame will first be mapped to the corresponding semantic feature y through the encoder, and then the corresponding super-prior feature z will be derived from y. The z is used to complete the decorrelation processing and probability estimation of y, and the required bit rate is calculated. Finally, by minimizing the weighted objective function that integrates the bit rate, the distortion degree of the time-frequency domain and the perceptual loss, the joint optimization of the three aspects of rate, distortion degree and perceptual effect is realized. In order to further improve the robustness in the coding transmission process, the research team also proposed a fault-tolerant audio semantic compression coding method called SoundSpring. This method will learn from the mask learning mechanism used in the large language model. Through the residual vector quantization (RVQ) method, the original continuous audio features are converted into discrete tokens with a hierarchical structure, and then with the help of a mask language model (MLM) with two functions at the same time, while achieving more efficient entropy coding, while completing intelligent packet loss compensation processing. In practice, the audio signal will first go through the encoder and RVQ module, and be mapped into a token grid containing coarse-grained and fine-grained. The MLM model of the transmitter will model the distribution probability of these tokens according to the pre-set dependency relationship, so as to improve the overall compression efficiency. The receiver will dynamically call the same MLM model according to the actual packet loss situation of the current network, and use the adjacent tokens to predict and recover the lost content, so as to stabilize the final output audio quality at a good level.

4.2.4 Receiver-Coupled Joint Decoding Method

Given the limitations of traditional separate source-channel coding under resource constraints and the challenges of joint decoding for complex textual data, a receiver-coupled iterative semantic source-channel joint decoding approach is proposed. This method maintains the physical separation architecture while establishing an external iterative mechanism between the semantic decoder and channel decoder at the receiver. Soft information generated by semantic decoding provides prior knowledge to the channel decoder, aiding in correcting bit likelihood ratios affected by noise. The semantic encoder extracts and quantifies text, with the channel decoder producing soft bit information and the semantic decoder performing preliminary reconstruction. The semantic encoder remaps the reconstructed text into prior log-likelihood ratios within the probability domain, feeding this back to the channel decoder for subsequent iterations. Through multiple iterations, the accuracy and robustness of text reconstruction are significantly improved.

4.2.5 Transceiver-Coupled Joint Coding & Transmission

The conventional end-to-end joint source-channel coding approach exhibits limited adaptability, hindering dynamic bandwidth allocation and real-time streaming media processing. To address this, a semantic joint source-channel coding transmission framework with bidirectional transceiver coupling is proposed. Semantic features of speech are extracted via nonlinear transformations, enabling dynamic allocation of transmission symbols per frame based on information entropy and channel conditions. The encoder maps speech to semantic feature "y", with an entropy model estimating information content to inform bandwidth distribution. The joint encoder employs Transformer architecture to map y and channel signal-to-noise ratio into variable-length transmission symbols, which are transmitted to the receiver for mirror decoding. End-to-end optimization is achieved through a loss function balancing bandwidth cost, distortion, and perceptual quality, incorporating causal convolution and masked sliding window attention mechanisms for real-time scenarios, thereby facilitating low-latency streaming[7]. Future enhancements include multi-resolution semantic branches during model compression, an adaptive robustness adjustment mechanism at the receiver, and collaborative optimization of encoder and task classifier. Hardware co-implementation under lightweight vehicular deployment is also envisioned to enhance real-time responsiveness.

4.3. Semantic Privacy and Security in Data Transmission

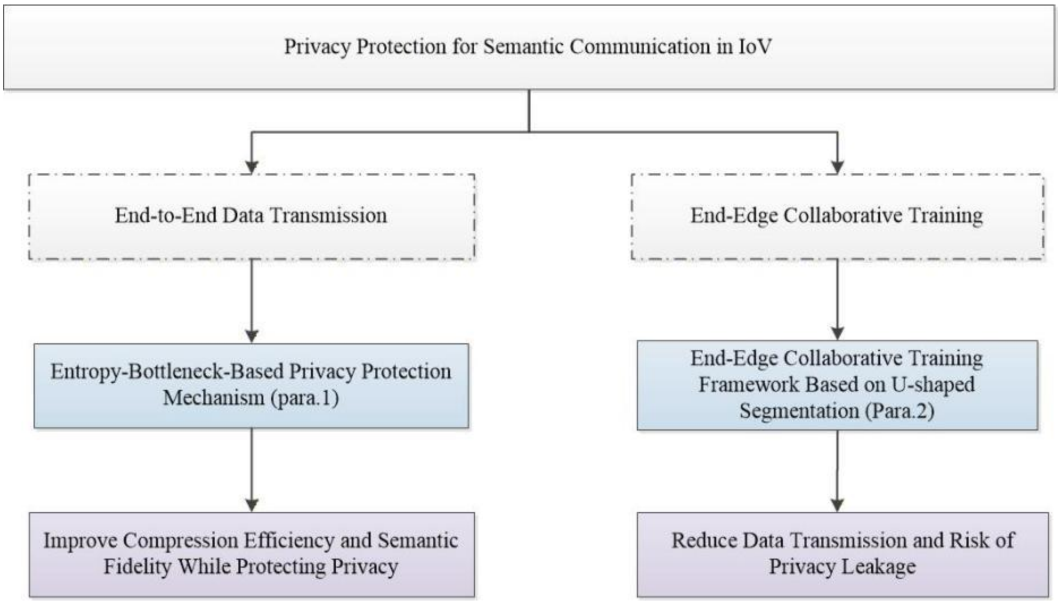

Figure 4: Research framework of privacy protection for data transmission

While semantic communication introduces novel data abstraction structures, its security vulnerabilities must be acknowledged. Semantic features may inadvertently reveal sensitive information, risking privacy breaches. In order to protect the security of private data, the research mentioned in this paper mainly focuses on two aspects, as shown in Figure 4. A privacy-preserving mechanism utilizing an entropy bottleneck is proposed. Semantic segmentation divides images into Regions of Interest (ROI) and Regions of Non-Interest (RONI), applying differentiated coding and compression strategies to enhance privacy and optimize bandwidth. U-Net performs pixel-level segmentation to distinguish ROI and RONI, followed by feature extraction via semantic encoder. The entropy bottleneck models feature probability distributions to generate compact bitstreams, reducing data correlation and privacy risks. The decoder reconstructs ROI and RONI, fusing them at the pixel level to restore the complete image. This mechanism demonstrates high compression efficiency, semantic fidelity, and privacy protection, with simulation results confirming optimal image reconstruction quality and noise robustness[8].

In collaborative end-to-end training between edge servers and vehicular terminals, data interception or theft poses privacy threats. A U-shaped segmentation-based training framework is proposed, dividing the model into head, middle, and tail segments. Only intermediate features and gradients are exchanged during forward and backward passes, preventing direct transmission of raw data. The middle model resides on the edge server, while the head and tail are maintained on the vehicle terminal. During forward propagation, local features are computed at the terminal and sent to the server for further processing, with reconstruction completed locally. Gradient exchange during backpropagation updates each segment's parameters, effectively reducing privacy leakage risks and data transmission volume. A feature leakage attack algorithm demonstrates residual security vulnerabilities, as intermediate features and gradients can be intercepted and reconstructed. Simulation results indicate strong privacy protection in deep networks, with weaker protection in shallow networks. Analysis underscores the importance of judicious segmentation point placement to mitigate privacy risks[9].

4.4. Multi-User Co-Channel Interference and Malicious Interference Prevention

Currently, in V2X communication, the proliferation of connected vehicle users is increasing, yet spectrum resources remain constrained. Consequently, industry adoption of non-orthogonal multiple access (NOMA) techniques aims to optimize spectral efficiency, though inter-user interference critically impacts semantic transmission performance. In addition, malicious interference from the outside world during semantic transmission is also one of the influencing factors. The main ways to solve the above problems are shown in Figure 5. In multi-user single-modal semantic communication, co-channel transmission of semantic-semantic and semantic-bit streams induces mutual interference. To address this, this paper proposes a NOMA framework for interference suppression based on semantic differences and grammatical differences. This approach actively induces feature mismatch or coordination at the semantic or grammatical level at the transmitter to mitigate interference during receiver decoding. Initially, the semantic and grammatical disparities among multi-user information are analyzed to optimize semantic symbol arrangement. Coupled with non-orthogonal power allocation and semantic successive interference cancellation (SIC) at the receiver, this facilitates efficient cooperative transmission and precise multi-user information recovery. Simulation results demonstrate an 8.09% and 4.8% enhancement in image reconstruction quality for semantic-semantic and semantic-bit users, respectively, along with at least 99.8% and 85.4% improvements in semantic transmission efficiency. In multi-modal semantic transmission, a semi-non-orthogonal multiple access (semi-NOMA) framework for interference mitigation is introduced to coordinate orthogonal and non-orthogonal transmission modes across multi-modal data streams. Leveraging semantic matching theory, the superposition order of information is adjusted to minimize distortion between the multi-modal superimposed signals and the target single-modal signals. Semantic codecs for images and texts are trained independently, and a multi-modal semantic symbol distance matrix is constructed. The Gale-Shapley algorithm is employed to determine stable matching and optimal transmission sequencing. At the receiver, SIC-based interference cancellation enables effective separation of semantic streams and suppression of multi-modal interference. Results indicate high fidelity in reconstructed text and images, with notable improvements in semantic transmission efficiency[5].

To counteract malicious interference in semantic communication, an anti-interference algorithm based on semantic symbol regulation and enhancement is proposed. This method perceives interference characteristics and utilizes statistical or external semantic information to dynamically adapt transmission strategies or compensate for semantic loss, thereby enhancing robustness against impulsive and continuous interference. For impulsive interference, a semantic-aware adaptive dynamic rearrangement strategy is implemented, repositioning low-importance semantic symbols into interference zones based on importance metrics, with subsequent mean replacement and inverse rearrangement at the receiver. For continuous interference, an external information-assisted semantic symbol enhancement strategy employs neural networks to extract external semantic data, which is used to residually enhance interference-suppressed semantic symbols, improving semantic recovery quality. Simulation experiments confirm that the adaptive dynamic rearrangement significantly stabilizes system performance, while the semantic symbol enhancement strategy boosts anti-jamming capability by approximately 3.07%[10].

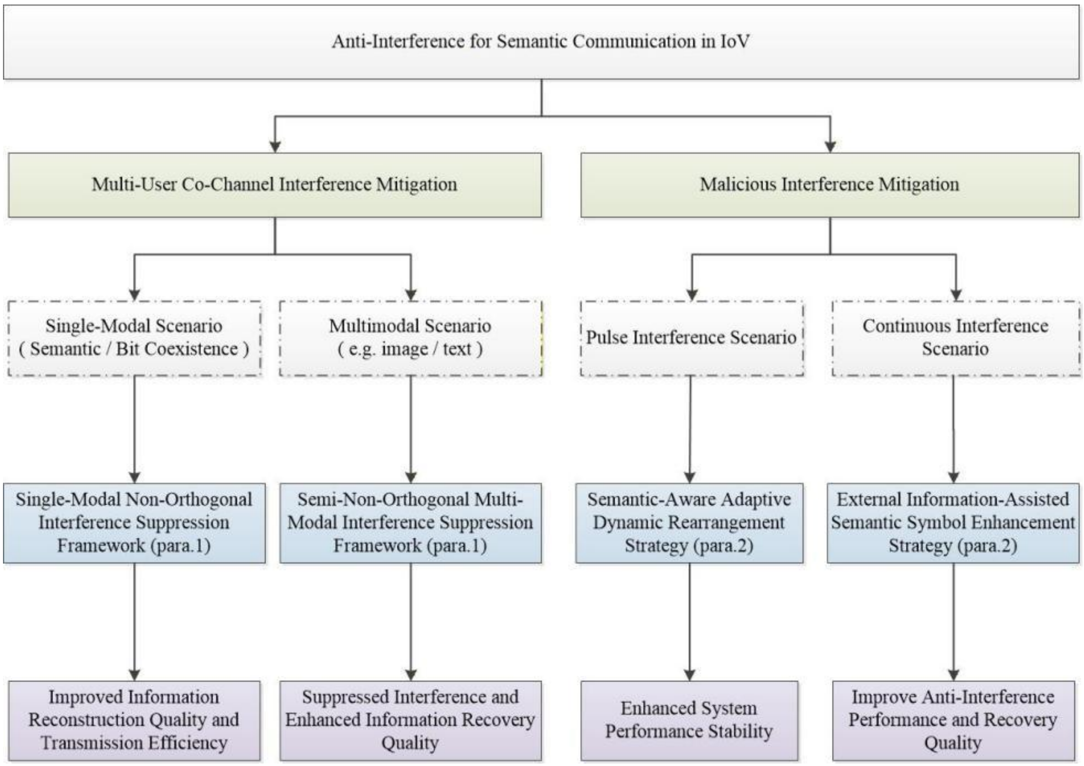

Figure 5:Research framework of interference prevention and control

5. Analysis of Future Development Trends

As the next-generation intelligent communication paradigm, semantic communication is progressively transitioning from theoretical research to practical deployment within V2X scenarios. Based on current research advancements and real-world implementation, future development trajectories can be comprehensively evaluated across dimensions such as application maturity, adaptation to typical tasks, and distribution of key challenges.

In low-speed scenarios, semantic communication has been initially applied to security early warning and state broadcasting tasks (maturity level 1), including semantic traffic light status recognition and static obstacle avoidance prompts. These tasks possess well-defined semantic structures and stable feedback channels, making them suitable for lightweight semantic model deployment[10]. Such scenarios represent a breakthrough in early semantic communication applications.

In complex collaborative tasks—such as dynamic path prediction, multi-vehicle obstacle avoidance, and multi-modal sensor fusion recognition—semantic communication remains in the prototype testing phase (maturity level 2). Major obstacles include the absence of standardized task labeling systems, difficulties in maintaining semantic consistency across terminals, and limited generalization of semantic scheduling strategies across diverse environments. Some theoretical frameworks and technical prototypes are still confined to laboratory validation (maturity level 3), exemplified by context-aware semantic scheduling mechanisms, task semantic quality QoS systems, and integrated end-edge-cloud semantic collaboration frameworks, which have yet to mature into commercial products[7].

Future development should prioritize: 1. advancing standardization of semantic compression and scheduling algorithms; 2. establishing task-driven semantic QoS mapping mechanisms; 3. enhancing the adaptive semantic modeling capabilities at the edge; 4. strengthening semantic security strategies to ensure transmission integrity. Only through multi-dimensional progress in standards, algorithms, platform architectures, and security protocols can semantic communication evolve from being merely feasible to fully deployable.

6. Conclusion

As an innovative paradigm for reconfiguring information transmission logic, semantic communication offers an effective solution to address the core challenges of high-density data, low latency, and task-oriented processing in V2X systems. This paper analyzes the current state of five key technological domains and forecasts future development trends based on task-specific applications. While semantic communication has been implemented in certain scenarios, overcoming bottlenecks related to algorithm standardization, semantic consistency modeling, and security assurance remains essential for widespread adoption. The future evolution of IoV communication will shift from a bit-centric to a semantic-centric approach, fostering the development of intelligent communication systems that genuinely "understand tasks".

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