semantic

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SNR-based Adaptive Semantic Communication in Vehicular Networks

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Abstract — Semantic communication aims to improve the efficiency of data transmission by focusing on meaning rather than exact signal reconstruction. This paper proposes an adaptive semantic communication system that dynamically adjusts the encoding strategy based on signal-to-noise ratio (SNR). Specifically, we employ a deep neural encoder-decoder pipeline for the MNIST dataset, selectively applying compression and denoising based on SNR levels. Our experiments show that, for MNIST the reconstructed image has 94% classification accuracy even under compression rate of 0.1, for CIFAR-10 the reconstructed images are acceptable at 0.7 compression which saves 30% of data usage in image transferring. The proposed method is designed with vehicular networks in mind, where wireless channels are highly dynamic due to rapid mobility and frequent topology changes. Our system is salient when bandwidth is limited and unstable which is constantly occurring between vehicles and infrastructure.

Index Terms—Semantic communication, adaptive encoding, SNR, deep learning, MNIST, CIFAR-10, PSNR, neural codec

I. Introduction

Conventional communication systems prioritize exact bit reconstruction. Semantic communication, in contrast, aims to preserve the transmitted meaning, allowing for lossy yet meaningful reconstructions [1][2]. Vehicular networks require real-time communication, but traditional systems struggle under fluctuating channel conditions. However, in scenarios such as autonomous driving [3], the semantic meaning of transmitted data (e.g., images, objects) is often more important than bit-level fidelity. Semantic communication has emerged as a promising solution by enabling systems to transmit only the most relevant information for a given task, such as classification or decision-making.

However, existing semantic communication methods often lack flexibility under dynamically changing wireless conditions. Most prior works either assume fixed SNR environments or rely on static encoding strategies, leading to suboptimal performance in real-world applications such as vehicular networks. These limitations motivate the need for adaptive semantic communication systems that respond to real-time channel variations with minimal latency and computation overhead.

With the growing relevance of intelligent edge devices and noisy wireless environments, there is a pressing need for communication systems that can adapt to varying channel conditions, particularly the signal-to-noise ratio (SNR) (1).

$$\text{SNR (dB)} = 10 \times \log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right) \tag{1}$$

In this paper, we explore an adaptive semantic communication strategy tailored for vehicular networks [4], where an autoencoder dynamically adjusts its behavior based on the prevailing SNR conditions. For high-SNR scenarios, direct transmission with minimal processing is sufficient to preserve semantic integrity. In contrast, under low-SNR conditions, more sophisticated processing is necessary—deep learning-based encoding, compression, and denoising become essential to maintain semantic fidelity.

We first implement this framework using the MNIST dataset, leveraging a lightweight neural encoder-decoder pipeline to assess classification accuracy and peak signal-to-noise ratio (PSNR) under varying SNR levels. To further evaluate the scalability and robustness of the proposed method, we extend our experiments to the more complex CIFAR-10 dataset. In this setting, we integrate a RED-CNN-based autoencoder with a GoogLeNet classifier [1] and analyze the system's performance under different compression ratios and SNR conditions.

II. Related Work

Semantic communication has recently gained traction as a promising alternative to traditional Shannon-based paradigms [2], particularly in the context of intelligent systems and bandwidth-constrained environments. Inspired by the original vision of Shannon and Weaver [5], recent efforts aim to model and optimize communication systems based on semantic effectiveness rather than exact bit fidelity [6]. Han et al. introduced DeepSC for semantic text communication [7], demonstrating the potential of neural models to achieve efficient and meaningful transmission. For images, convolutional autoencoders have been employed to reduce bandwidth by compressing data while preserving semantic content [8]. Vehicular networks—especially vehicular ad hoc networks (VANETs)—present unique challenges due to rapid mobility, high-speed dynamics, and frequent SNR fluctuations caused by fading, shadowing, and varying inter-vehicle distances. Traditional communication systems in VANETs struggle to maintain high performance under such variable conditions, motivating the need for robust, adaptive communication strategies [9]. Unlike our method, which dynamically adjusts compression and denoising strategies based on real-time SNR feedback, [1] applies a fixed semantic encoding policy regardless of channel condition.

Several studies have proposed adapting transmission strategies to varying channel conditions. For example, Wang et al. [10] introduced a semantic-aware dynamic coding approach that adjusts transmission according to semantic importance and channel quality. Other works have explored reinforcement learning or attention-based strategies to selectively allocate resources for semantic tasks under constraints [8]. In summary, while prior work has explored semantic-aware coding or channel modeling separately, our contribution lies in tightly integrating these into a unified, adaptive framework tailored for vehicular networks.

While previous approaches such as DeepSC [7] or attention-based schemes [8] have achieved semantic preservation, they either require high computational cost or operate under fixed SNR assumptions. Moreover, few works consider the integration of adaptive encoding strategies into vehicular networks, where SNR fluctuates rapidly due to mobility. This paper fills this gap by proposing a real-time, SNR-based adaptive encoding pipeline that selectively activates neural processing only when necessary, achieving efficiency and robustness under dynamic conditions.

III. System Model

A. Semantic Encoder-Decoder

We design a two-layer fully connected encoder that compresses the 784-dimensional MNIST input into a lower-dimensional latent space, followed by a decoder that mirrors this structure to reconstruct the original image. To simulate channel noise, Gaussian noise is injected into the latent representation, with the variance determined by the specified signal-to-noise ratio (SNR). This setup enables us to study the effect of compression and noise on semantic preservation under varying channel conditions.

To further evaluate the scalability of our approach, we extend the framework to the CIFAR-10 dataset, which consists of 32×32 RGB images with more complex semantic content. For this experiment, we employ a convolutional autoencoder based on RED-CNN to perform compression and denoising, and use a pretrained GoogLeNet classifier to assess semantic fidelity through classification accuracy. Similar to the MNIST pipeline, Gaussian noise is introduced in the latent space to simulate channel degradation. This setup allows us to test the efficacy of our SNR-based adaptive strategy under more challenging and realistic visual conditions.

B. Adaptive Strategy

1) Strategy Details

The encoder applies different strategies based on SNR which is illustrated in Figure 1.

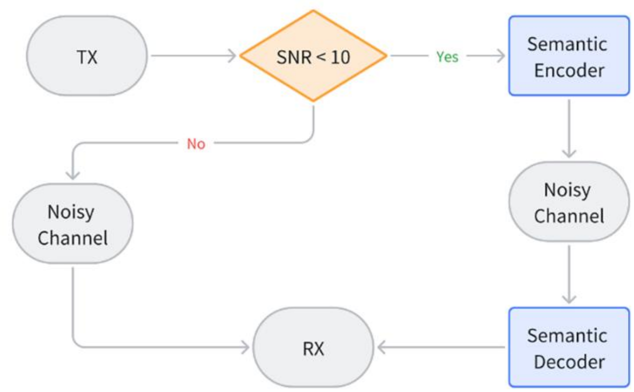

Figure 1: System Structure

a) Low-SNR Regime (SNR < 10 dB)

In this case, the channel is highly noisy, and directly transmitting raw images would result in significant degradation. Therefore, we employ a deep neural encoder-decoder pipeline that performs both compression and denoising. The encoder reduces the input dimensionality to a compact latent representation, which is more robust to noise, and the decoder reconstructs the image with enhanced perceptual quality. This neural processing helps preserve semantic meaning (e.g., class label) even when fine-grained pixel details are lost.

b) High-SNR Regime (SNR ≥ 10 dB)

When the channel is relatively clean, transmitting the raw image directly, without neural compression, is more efficient. In this regime, applying neural processing adds computational overhead without significant gains in semantic fidelity or image quality. Instead, we inject channel noise directly into the image and bypass the encoder-decoder network.

2) Strategy advantages

This adaptive strategy offers several advantages. First, it optimizes computational resources by only invoking the neural network, when necessary, which is particularly important for energy-constrained devices. Second, it maintains semantic robustness across a wide range of channel conditions, ensuring that classification or downstream tasks can still be performed reliably even in degraded environments. Lastly, the strategy demonstrates the flexibility of semantic communication systems in adapting to environmental dynamics, paving the way for more intelligent and context-aware communication protocols.

C. Classifier

A pre-trained 4-layer MLP classifier is used to evaluate semantic consistency. This network remains fixed and is used only to evaluate classification accuracy on decoded outputs. For the MNIST dataset, the classifier takes 28×28 grayscale images as input and outputs class predictions across the 10 digit classes.

GoogLeNet is a deep convolutional neural network architecture known for its inception modules, which allow it to extract multi-scale features efficiently with a relatively low parameter count. This architecture is particularly well-suited for complex datasets like CIFAR-10 due to its ability to capture hierarchical visual semantics. In our setup, GoogLeNet is first fine-tuned on the clean CIFAR-10 training set to achieve high classification accuracy. Once trained, the model is fixed and used solely for evaluation, serving as a semantic judge of the reconstructed images.

IV. Experimental Setup

A. Dataset

We use the MNIST dataset and the CIFAR-10 dataset to conduct our experiment. MNIST dataset [13] consist of handwritten digits, which contains 60,000 training and 10,000 test samples. CIFAR-10 dataset [14] consists of 60,000 32×32 color images across 10 classes, including airplanes, cars, birds, and animals. The dataset is split into 50,000 training and 10,000 test images.

The simplicity and low dimensionality of MNIST make it a widely used benchmark for evaluating semantic communication in low-complexity image scenarios. It also allows us to study the effectiveness of compression and denoising techniques in a controlled setting. Compared to MNIST, CIFAR-10 poses greater challenges due to its color channels, visual diversity, and the need for more expressive models to preserve semantic content. We preprocess the CIFAR-10 images by normalizing the pixel values and resizing them if needed to match the input requirements of our convolutional encoder-decoder architecture and the GoogLeNet classifier.

B. SNR Settings

To evaluate the robustness and adaptability of the proposed semantic communication system, we simulate a wide range of channel conditions by selecting ten random Signal-to-Noise Ratio (SNR) values uniformly distributed between 0 and 20 dB. This range reflects both harsh low-SNR environments, where noise dominates the signal, and high-SNR settings, where channel distortion is minimal. These values are representative of typical wireless communication scenarios and enable a comprehensive assessment of the encoder-decoder system's performance under varying noise conditions.

This SNR-based evaluation also helps justify the dynamic switching behavior in our system, which adjusts encoding strategy based on the current channel condition, balancing between performance and computational cost.

C. Compression Rates

To evaluate the effectiveness of the semantic communication framework under different bandwidth constraints, we experiment with a range of compression rates (2) from 0.1 to 1.0, where the compression rate is defined as the ratio of the size of the latent representation to the original input size.

$$\text{Compression Rate} = \frac{D_{\text{latent}}}{D_{\text{input}}} \quad (2)$$

Where D_{latent} is the dimensionality of the encoded (compressed) representation. D_{input} is the dimensionality of the original input image (e.g., 784 for MNIST).

The encoder network is trained to map the input images into a compact latent space based on the desired compression rate, and the decoder attempts to reconstruct meaningful outputs from this compressed and noise-corrupted representation. Lower compression rates are more susceptible to noise and semantic distortion but are critical in bandwidth-constrained settings such as IoT or edge devices.

D. Evaluation Metrics

To assess the performance of our SNR-based adaptive semantic communication system, we employ two complementary evaluation metrics that capture both semantic and perceptual aspects of the reconstructed data.

1) Accuracy

Classification accuracy is used as the primary semantic metric, reflecting how well the meaning or class label of the transmitted image is preserved after compression and channel transmission. For MNIST, a pre-trained 4-layer MLP classifier is used to evaluate the decoded images; for CIFAR-10, we utilize a pre-trained GoogLeNet classifier. These classifiers remain fixed during all evaluations and are not involved in the transmission process itself. A high accuracy score indicates that the essential semantic content of the original image is retained despite channel noise and compression.

2) Peak Signal-to-Noise Ratio (PSNR)

PSNR (3) quantifies the perceptual quality of the reconstructed images by measuring the difference between the original and decoded image pixels. It is calculated in decibels (dB), with higher PSNR values indicating better visual fidelity and lower distortion. While semantic communication systems tolerate some degree of distortion in pixel space, maintaining reasonable PSNR ensures that reconstructions are not only semantically accurate but also visually meaningful to human observers.

$$\text{PSNR (dB)} = 10 \times \log_{10}\left(\frac{MAX_I^2}{\text{MSE}}\right) \quad (3)$$

MAX_I: The maximum possible value of the signal (for 8-bit images, this is 255; for normalized images in [0,1], this is 1).

Together, accuracy and PSNR provide a balanced evaluation of the system’s ability to preserve both the meaning and visual quality of transmitted data. By analyzing these metrics across different SNR levels and compression rates, we demonstrate how our adaptive strategy maintains robust communication under varying conditions. In particular, we observe that neural encoding significantly improves classification accuracy in low-SNR regimes, while PSNR remains competitive with traditional transmission methods at higher SNR values.

V. Results and Analysis

A. Effect of SNR and Compression Rate

Table 1 and Table 2 summarize the classification accuracy achieved by our adaptive semantic communication system under two representative SNR levels: 4.46 dB and 8.44 dB, with compression rates set to 0.1 and 0.4, respectively. These conditions were selected to highlight the model's performance in low- and mid-SNR regimes, which are particularly relevant for real-world wireless communication scenarios.

Table 1: Accuracy over Epochs (SNR = 4.46dB)

Epoch	CR=0.1	CR=0.4
1	0.645	0.754
5	0.936	0.962
10	0.949	0.973
15	0.951	0.976
20	0.955	0.978
30	0.949	0.977

Table 2: Accuracy over Epochs (SNR = 8.44dB)

Epoch	CR=0.1	CR=0.4
1	0.685	0.769
5	0.953	0.968
10	0.971	0.978
15	0.973	0.98
20	0.975	0.981
30	0.974	0.981

B. Discussion

Our experimental results across both MNIST and CIFAR-10 datasets demonstrate the effectiveness of the proposed SNR-based adaptive semantic communication framework. Several key observations can be drawn.

Through comprehensive experiments on the MNIST dataset, we demonstrated that in low-SNR regimes (e.g., SNR $\approx$ 4.46 dB), deep neural encoding significantly improves both classification accuracy and perceptual quality, as measured by PSNR. Conversely, in high-SNR scenarios (e.g., SNR $\geqslant$ 10 dB), the system conserves computation by directly transmitting images, maintaining comparable accuracy while bypassing the encoder-decoder pipeline.

To evaluate generalizability, we extended our method to the more complex CIFAR-10 dataset, which contains 32×32 color images across diverse object categories. Despite high compression (e.g., a rate of 0.7) and significant channel noise, the adaptive semantic framework successfully preserved essential class information and maintained strong classification accuracy when evaluated with a pre-trained GoogLeNet model. These results affirm the system's adaptability across both simple (MNIST) and complex (CIFAR-10) visual domains.

The proposed approach is particularly well-suited for vehicular networks, where wireless channels are frequently disrupted due to rapid mobility, Doppler effects, and dynamic topology changes. In such environments, adaptive semantic encoding can ensure stable task-level performance under fluctuating SNR conditions, making it ideal for real-time vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) applications such as cooperative perception or object detection [11][12].

1) Adaptive Encoding Significantly Improves Low-SNR Performance

At an SNR of 4.46 dB, the channel is severely degraded, making raw transmission of images ineffective due to substantial corruption. This semantic-aware processing leads to a substantial increase in classification accuracy. For instance, in the MNIST case (Figure 2), we observe the accuracy rate still maintains high even under high compression ratios. Similar trends are evident for CIFAR-10 (Figure 3), where semantic preservation through neural encoding mitigates the impact of channel noise and improves the reliability of downstream inference.

Figure 2: MNIST Reconstructed Picture (Compression = 0.1)

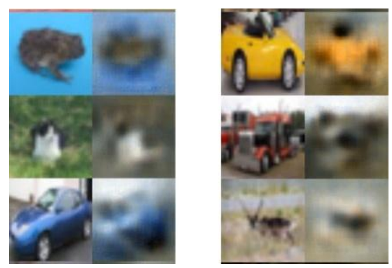

Figure 3: CIFAR-10 Reconstructed Picture (Compression = 0.7)

2) Higher Compression Rates Still Preserve Semantic Meaning

One of the main goals of semantic communication is to transmit "meaning" rather than raw data. Our experiments validate this principle: even at a compression rate of 0.1 (as shown in Figure 4), where 90% of the input information is discarded, the system is able to reconstruct semantically valid representations.

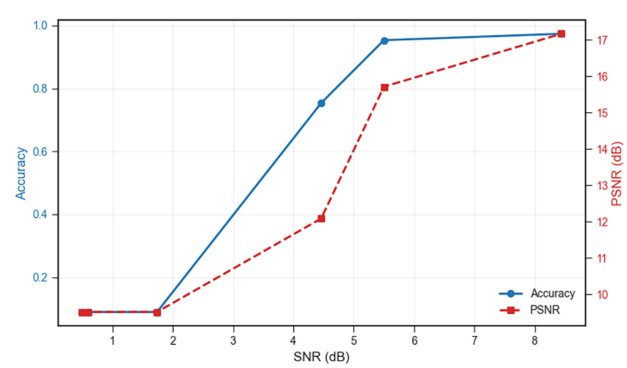

Figure 4: Accuracy and PSNR (Compression = 0.1)

For MNIST, this corresponds to achieving over 94%

classification accuracy at low SNRs. In CIFAR-10, while the dataset is more complex, semantic reconstruction under 0.7 compression still yields usable class information. This efficiency makes the system well-suited to bandwidth-constrained applications such as IoT and wireless edge devices.

2) At High SNRs, Direct Transmission Is Computationally Efficient with Negligible Performance Loss

When the channel is clean (e.g., SNR $\geq$ 10 dB), the adaptive system bypasses the neural encoder and sends the raw image with additive Gaussian noise. This strategy offers computational savings by avoiding the encoder-decoder pipeline when it is not needed. Our results confirm that at higher SNR levels, the performance difference between neural and direct transmission becomes minimal, particularly in terms of classification accuracy and PSNR. This dynamic adaptation ensures efficient utilization of computation and energy, enabling real-time operation in practical deployments.

The comparison of adaptive system to others is depicted in Figure 5.

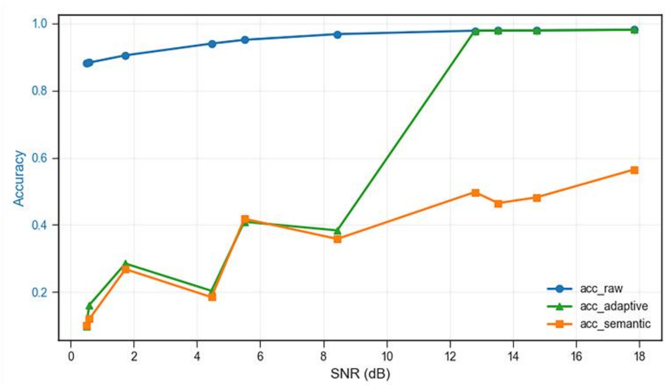

Figure 5: Comparison of Accuracy for CIFAR-10 (Compression = 0.7)

In summary, the adaptive semantic communication strategy enables the system to respond intelligently to channel conditions, improving both semantic fidelity and system efficiency. This represents a promising direction for the design of future communication systems that integrate machine learning with signal processing.

VI. Conclusion

In this work, we proposed an SNR-based adaptive semantic communication system that dynamically selects between neural encoding and direct transmission depending on the channel condition. This design enables the system to intelligently balance semantic fidelity, reconstruction quality, and computational efficiency. For MNIST dataset, higher compression rate still preserves accuracy. For example, at epoch 20, accuracy under CR = 0.4 is 0.978 (4.46 dB) and 0.981 (8.44 dB), and the corresponding CR = 0.1 has results (0.955 and 0.975). In addition, higher SNR enhances performance. At the same CR and epoch, accuracy under SNR = 8.44 dB (better channel quality) is higher than under SNR = 4.46 dB. For instance, at CR = 0.1 and epoch 10, accuracy increases from 0.949 (4.46 dB) to 0.971 (8.44 dB).

Overall, our findings suggest that adaptive semantic communication is a promising paradigm for future intelligent communication systems, particularly in scenarios involving bandwidth limitations, energy constraints, or dynamic wireless environments. Future work may extend this approach to video data, multimodal inputs, or reinforcement learning-based adaptation policies.

Acknowledgment

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Dear Editor and Reviewers,

We sincerely thank you for your valuable comments and suggestions, which have significantly improved the quality of our manuscript titled "SNR-based Adaptive Semantic Communication in Vehicular Networks." Below, we provide point-by-point responses to each of the reviewers' comments. All modifications have been highlighted in the revised manuscript.

This is for paper revision comments letter 1.

Comment 1:

"The end of the abstract should be summary of 2-3 sentences including the research results (with some data) and conclusion of the significance of this work."

Response:

We appreciate this suggestion. We have revised the end of the abstract to include a concise summary of the key experimental results and the significance of the proposed work. The updated abstract now includes:

> "Our experiments show that, for MNIST the reconstructed image has 94% classification accuracy even under compression rate of 0.1, for CIFAR-10 the reconstructed images are acceptable at 0.7 compression which saves 30% of data usage in image transferring. The proposed method is designed with vehicular networks in mind, where wireless channels are highly dynamic due to rapid mobility and frequent topology changes. Our system is salient when bandwidth is limited and unstable which is constantly occurring between vehicles and infrastructure."

Comment 2:

"The resolution of Figures needs to be improved. It should be at least 300dpi."

Response:

We have replaced all figures in the manuscript with higher-resolution versions (at least 300 dpi). These figures are now suitable for high-quality print and electronic display. All updated figures include:

> Figure 1: System Structure
>
> Figure 2: MNIST Reconstructed Picture
>
> Figure 3: CIFAR-10 Reconstructed Picture
>
> Figure 4: Accuracy and PSNR (Compression = 0.1)
>
> Figure 5: Comparison of Accuracy for CIFAR-10

Comment 3:

"The Conclusions section needs to summarize the main findings of the research, highlighting the most important results with data."

Response:

We have revised the Conclusion section to better highlight the core findings of our research with supporting data. Specific experimental results from different SNR levels and compression ratios have been added, including:

> "For MNIST dataset, higher compression rate still preserves accuracy. For example, at epoch 20, accuracy under CR = 0.4 is 0.978 (4.46 dB) and 0.981 (8.44 dB), and the corresponding CR = 0.1 has results (0.955 and 0.975). In addition, higher SNR enhances performance. At the same CR and epoch, accuracy under SNR = 8.44 dB (better channel quality) is higher than under SNR = 4.46 dB."

These changes provide a clearer summary of the effectiveness of our adaptive semantic communication system.

Comment 4:

“References should be numbered according to the citation appearance order. Please correct the numbers of references and citations.”

Response:

Thank you for pointing this out. We have carefully revised the reference list and in-text citations to ensure that all references are numbered according to their first appearance in the manuscript, following the required formatting guidelines. The citation order has been checked throughout the paper to ensure consistency.

This is for paper revision comments letter 2.

Comment 1:

“The summary of the research on semantic communication is relatively simple, and fails to highlight the limitations of existing methods and the pertinence of this study. It is recommended to conduct an in-depth analysis of the shortcomings of existing semantic communication methods.”

Response:

Thank you for this important suggestion. We have expanded the **Introduction** and **Related Work** sections to better contextualize our contribution. Changes including:

> “However, existing semantic communication methods often lack flexibility under dynamically changing wireless conditions. Most prior works either assume fixed SNR environments or rely on static encoding strategies, leading to suboptimal performance in real-world applications such as vehicular networks. These limitations motivate the need for adaptive semantic communication systems that respond to real-time channel variations with minimal latency and computation overhead.”

> “While previous approaches such as DeepSC [7] or attention-based schemes [8] have achieved semantic preservation, they either require high computational cost or operate under fixed SNR assumptions. Moreover, few works consider the integration of adaptive encoding strategies into vehicular networks, where SNR fluctuates rapidly due to mobility. This paper fills this gap by proposing a real-time, SNR-based adaptive encoding pipeline that selectively activates neural processing only when necessary, achieving efficiency and robustness under dynamic conditions.”

Comment 2:

“The current related research section does not clearly explain the intrinsic connection between these studies and this paper's work, making it difficult to highlight the innovation of this paper.”

Response:

We appreciate this feedback. In response, we revised the Related Work section by explicitly contrasting our method with prior efforts (e.g., DeepSC, reinforcement learning-based schemes) to clarify the gap in dynamic, SNR-aware systems. Adding summary remarks to each paragraph that link previous research to our proposed approach. Highlighting that few existing studies address vehicular networks with fine-grained, SNR-based adaptation. Changes including:

> “Unlike our method, which dynamically adjusts compression and denoising strategies based on real-time SNR feedback, [1] applies a fixed semantic encoding policy regardless of channel condition.”

> “In summary, while prior work has explored semantic-aware coding or channel modeling separately, our contribution lies in tightly integrating these into a unified, adaptive framework tailored for vehicular networks.”

Comment 3:

“The figure in the article is not clear, it is recommended to replace it with a clear figure.”

Response:

We have replaced all figures with high-resolution versions (at least 300 dpi) to ensure print quality and clear visual presentation.

Comment 4:

“It is recommended to add core formulas and explain them so that readers can understand.”

Response:

We have now included three core formulas to clarify key components of our framework, Compression rate. This quantifies the degree of dimensionality reduction in the encoder. Explanations for all formulas have been added in context within the manuscript

(Sections I and IV), providing readers with a clearer understanding of the system design and evaluation.

Comment 5:

"The reference format in the article is not unified. It is recommended to unify the reference format."

Response:

We have thoroughly revised the reference list and in-text citations to conform to the required format. All references now appear in numerical order based on first appearance in the text, and citation formats have been made consistent throughout the manuscript.

Comment 6:

"The English expression of the paper is generally clear, but some sentences are somewhat lengthy. It is suggested to polish the language to improve the readability and professionalism of the article."

Response:

We have performed a comprehensive language polish across the manuscript. Improvements include: Breaking up long or dense sentences for improved readability. Replacing informal or repetitive phrasing with precise academic language. Enhancing flow and coherence between technical sections. For example:

> Original: "Even under aggressive compression and noisy channels, the adaptive semantic framework preserved key class information and delivered robust classification performance."
>
> Revised: "Despite high compression and significant channel noise, the adaptive framework successfully preserved essential class information and maintained strong classification accuracy."
>
> Original: "The increasing demand for real-time communication in vehicular networks has exposed the limitations of traditional data transmission systems under varying channel conditions."
>
> Revised: "Vehicular networks require real-time communication, but traditional systems struggle under fluctuating channel conditions."

Once again, we would like to express our gratitude to the reviewers for their constructive feedback. We believe that the manuscript has been significantly improved as a result. Please do not hesitate to contact us for any further clarification.

Sincerely,

Zhentong Feng

On behalf of all co-authors

Email: fzt06011996@163.com