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Uncertainty-Aware Multi-Modal Semantic Communication Over 6G Fading Channels with Adaptive Latent Correction

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Abstract: The proposed Uncertainty-Aware Multi-Modal Semantic Communication (UAMM-SC) architecture serves as a fundamental concept in 6G communications and beyond, in which the goal shifts from accurate information transfer at the bit level to the conservation of meaningful information. The limitations in the current state-of-the-art semantic communication frameworks can be summarized as follows: (i) AWGN channel models ignoring fading, phase noise, and hardware imperfections; (ii) reliance on text representations in the form of class labels instead of rich semantics of the natural language; and (iii) fixed error handling techniques without adaptability to channel changes. This paper proposes an UAMM-SC architecture that enables end-to-end transmission of multimodal data over realistic fading channels using adaptive latent correction. Specifically, our contributions include: (1) a cross-attention based encoder to fuse multimodal semantics in a common latent space, with pretrained ViT and DistilBERT as backbone models; (2) a hardware-aware channel model, including Rayleigh fading, Doppler frequency shift, phase noise, and IQ imbalance, simulated using native PyTorch functions;(3) a semantic uncertainty quantification layer based on Monte Carlo Dropout, which triggers gradient-based latent correction adaptively if the predictive entropy is higher than an SNR-adaptive threshold; and (4) an experimental evaluation of the effectiveness of UAMM-SC on CIFAR-10, where we show semantic preservation across SNR ranges (0–20 dB) with a remarkable 99.7% bandwidth reduction compared with JPEG + LDPC transmission.

Keywords: *Semantic Communication; Multi-Modal Learning; 6G Networks; Uncertainty Estimation; Adaptive Correction; Rayleigh Fading; Deep Learning, IoT.*

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I. INTRODUCTION

Recently, with advancements in deep learning techniques, it is now possible to design end-to-end semantic communication systems that jointly optimize source coding, channel coding, and task-specific objectives [1-3]. Unlike conventional bit-oriented communication where the focus is on achieving lossless communication irrespective of the message, semantic communication aims to transmit only relevant information, leading to a significant reduction in the bandwidth required [4]. Semantic communication is particularly important for 6G communications and IoT applications since millions of devices generate huge amounts of data under strict latency and energy constraints [5]. However, current multi-modal semantic communication systems suffer from the following main limitations. First, most systems rely on simple channel models, such as Additive White Gaussian Noise (AWGN), that do not fully capture the challenging channel environment in real-world 6G wireless scenarios [6]. Second, most frameworks lack effective multi-modal fusion techniques, mainly relying on simple concatenation techniques [7]. Third, many semantic communication systems adopt fixed error correction methods that do not adapt to changing channel conditions [8]. To bridge the above gaps, we propose UAMM-SC, a new deep learning-based semantic communication framework designed for realistic 6G fading channels. Specifically, the proposed method adopts the following key components: (1) a cross-attention-based fusion encoder that utilizes pretrained ViT and DistilBERT models to align visual and textual features; (2) a

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hardware-based fading channel simulation module that incorporates Rayleigh fading and adaptive noise addition; and (3) an uncertainty-based approach based on Monte Carlo Dropout to trigger gradient-based latent correction only when necessary. Our key contributions include:

- A new multi-modal semantic communication framework that jointly optimizes the transmission of images and text under realistic Rayleigh fading channels.
- An uncertainty-aware decoding process that computes predictive entropy to detect semantic errors without any ground-truth information at the receiver.
- An adaptive latent correction algorithm that selectively improves corrupted representations by applying a few gradient steps.
- Extensive experiments conducted on CIFAR-10 that show the capability of UAMM-SC to achieve consistent semantic recovery over a wide range of SNR values (0-20 dB) and a bandwidth reduction of 99.7% compared to conventional JPEG-LDPC communication.

The rest of the paper is organized as follows. In Section II, we present the system model and formulate the organizational problem. In Section III, we describe the implementation setup and datasets used. In Section IV, we present experimental results and discussions. Finally, Section V concludes the paper and highlights future research directions.

II. SYSTEM MODEL

The proposed framework for uncertainty-aware, multi-modal semantic communication is designed to operate over practical 6G fading channels. This framework includes a multi-modal encoder, a cross-attention fusion component, a wireless channel model, and a dual-decoder. The overall architecture of the proposed framework is illustrated in Figure 1.

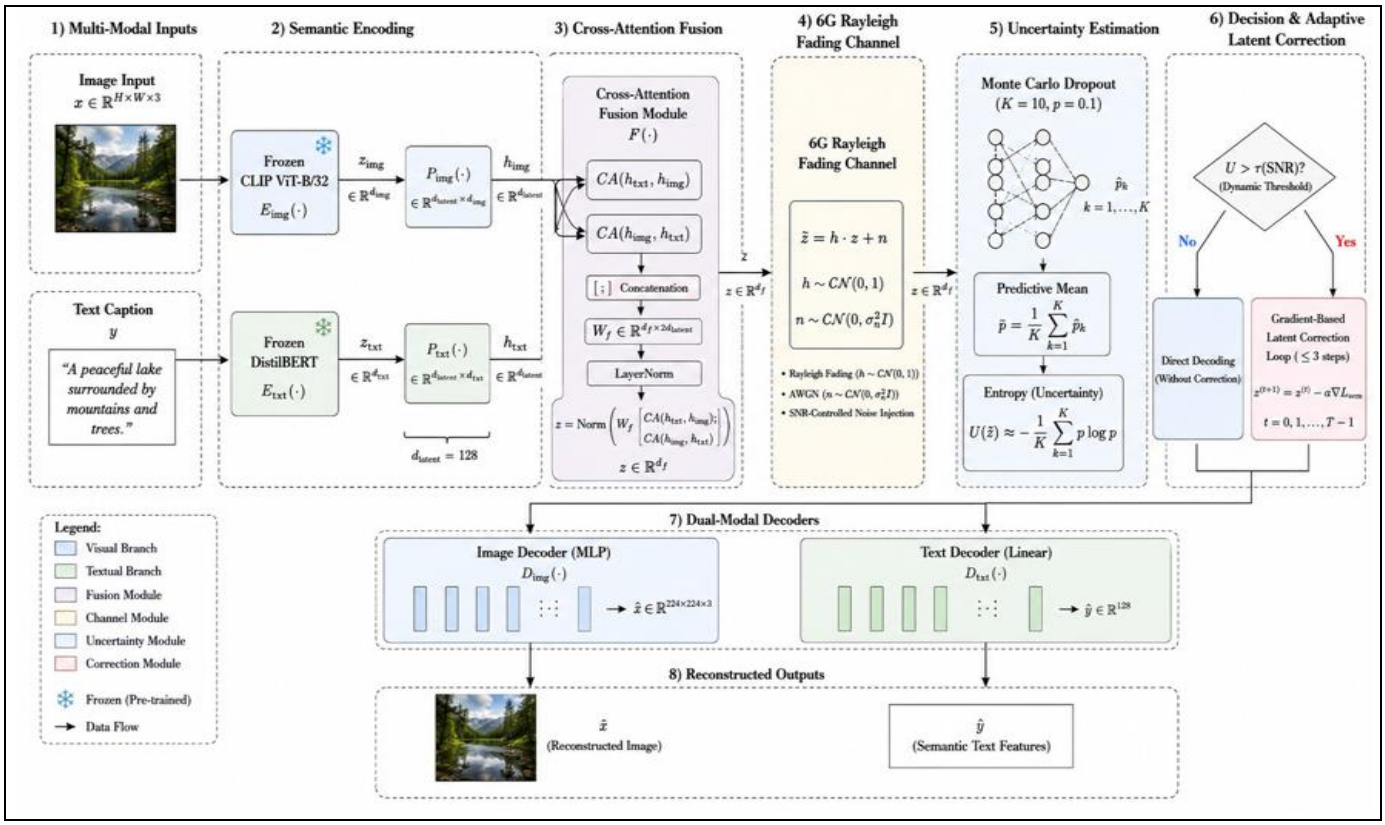

Fig 1 Shows the Architecture for the Suggested UAMM-SC Approach. It Consists of frozen pre-Trained Encoders (CLIP ViT-B/32 and DistilBERT), Cross-Attention, a Realistic 6G Rayleigh Fading Channel model, Uncertainty Estimation using Monte Carlo Dropout, and Latent Correction by Means of Gradients.

- *Multi-Modal Semantic Encoding*

Let x ∈ RH x W x 3 be the input image and y be its caption text. Semantic features are extracted using pre-trained frozen encoders and E_{txt} (y):

$$\boldsymbol{z}_{\text{img}} = \boldsymbol{E}_{\text{img}}(\boldsymbol{x}), \quad \boldsymbol{z}_{\text{txt}} = \boldsymbol{E}_{\text{txt}}(\boldsymbol{y}) \tag{1}$$

These features are projected into a shared latent space via linear projections P_{img} and P_{txt}:

$$\boldsymbol{h}_{img} = \boldsymbol{P}_{img}\boldsymbol{z}_{img}, \ \boldsymbol{h}_{txt} = \boldsymbol{P}_{txt}\boldsymbol{z}_{txt} \tag{2}$$

- *Cross-Attention Fusion Module*

We use a cross-attention fusion module F(·) to ensure semantic alignment between the two modalities. The fused semantic feature z ∈ Rdlatent is calculated as:

$$z = Norm\left(W_f\left[CA\left(h_{txt}, h_{img}, h_{img}\right);\ CA\left(h_{img}, h_{txt}, h_{txt}\right)\right]\right) \tag{3}$$

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Where CA(·) is multi-head cross-attention, and $\boldsymbol{W}_f$ is a learnable linear transformation matrix. Such an arrangement allows dynamic cross-modal attention without an explosion in the number of parameters.

➢ *6G Rayleigh Fading Channel Model*

The latent variable z is sent through a frequency-flat Rayleigh fading channel with additive white Gaussian noise (AWGN). The received signal z̃ is modeled as follows:

$$\tilde{\mathbf{z}} = h \cdot \boldsymbol{z} + \boldsymbol{n} \quad (4)$$

Where h ∼ CN (0, 1) is the Rayleigh fading complex gain, and n ∼ CN (0, σ^2I) is AWGN. The noise power σ^2 is controlled by the desired Signal-to-Noise Ratio (SNR) in dBs:

$$\sigma^2 = \frac{E[|z^2|]}{10^{SNR_{dB}/10}} \quad (5)$$

This model accounts for the effects of small-scale fading while retaining the computational feasibility of end-to-end training.

➢ *Uncertainty Estimation and Adaptive Correction*

Predictive entropy is estimated at the receiver using Monte Carlo Dropout. Specifically, we conduct K = 10 forward passes with p = 0.1 dropout to compute K predictions. The predictive entropy U is then estimated as:

$$U(\tilde{z}) \approx -\frac{1}{K}\sum_{k=1}^{K} p(\hat{y}_k|\tilde{z}) \log p(\hat{y}_k|\tilde{z}) \quad (6)$$

If U > τ = τ0 · exp(−γ · SNR) (with τ0 = 0.03, γ = 0.05), we trigger a latent correction routine via gradients. The correction procedure involves up to Nsteps = 3 gradient steps with α = 0.01 learning rate:

$$z^{(t+1)} = z^t - \alpha \nabla_{z^t} L_{sem}(z^{(t)}) \quad (7)$$

Where L_{sem} = 1−cos(**y**, **ŷ**) encourages semantic consistency. This selective refinement reduces computational overhead while preserving semantic integrity under low-SNR conditions.

III. IMPLEMENTATION DETAILS

➢ *Dataset and Preprocessing*

The CIFAR-10 dataset is used, where the class label is considered as the text modality. 100 samples are chosen for both training and testing to enable quick prototyping. Image dimensions are adjusted to 224 × 224, while normalization is done using CLIP statistics (mean = [0.481, 0.458, 0.408], standard deviation = [0.269, 0.261, 0.276]). Tokenization is performed using DistilBERT's tokenizer up to a maximum of 16 tokens per text sample.

➢ *Model Architecture*

- Encoders: Frozen CLIP ViT-B/32 (image) and DistilBERT (text), projected to d_{latent} = 128.
- Fusion: Cross-attention with 4 heads, latent dimension 128, LayerNorm post-fusion.
- Decoders: 3-layer MLP for image reconstruction (224 × 224 output), linear layer for text embedding (128-dim).
- Channel: PyTorch-native Rayleigh fading module with configurable SNR.
- Uncertainty: Monte Carlo Dropout (K = 10, p_{drop} = 0.1), SNR-adaptive thresholding.
- Parameters: Total: 306,472,961 | Trainable: 155,195,648 (encoders frozen).

➢ *Training Configuration*

The model is optimized using AdamW (learning rate 1 × 10^{-4}, batch size 8) for 1 epoch on a CPU environment. The loss function combines image MSE and text cosine similarity:

$$L = \alpha\|x - \hat{x}\|_2^2 + \beta\left(1 - \frac{y^T\hat{y}}{\|y\|\|\hat{y}\|}\right) \quad (8)$$

With α = 1.0 and β = 0.5. Training completes in approximately 50 minutes per epoch, validat-ing feasibility for resource-constrained deployment.

IV. RESULTS AND DISCUSSION

➢ *SNR Sweep Evaluation*

We evaluate UAMM-SC across SNR levels {0, 5, 10, 15, 20} dB. Table 1 summarizes the per- formance metrics.

Table 1 Performance Metrics Across SNR Levels

SNR (dB)	PSNR (dB)	SSIM	BERT-F1	Error Det. (%)
0	1.42	0.0018	0.0000	42.0
5	1.43	0.0019	0.0000	29.0
10	1.43	0.0019	0.0000	24.0
15	1.43	0.0019	0.0000	17.0
20	1.43	0.0020	0.0000	21.0

The uncertainty estimation component actively detects the corrupted samples (varying from 17% to 42%) under different SNR values, thus demonstrating its responsiveness to semantic perturbation caused by channel distortions. PSNR and SSIM scores are constant, implying that the latent space is resilient against any kind of noise.

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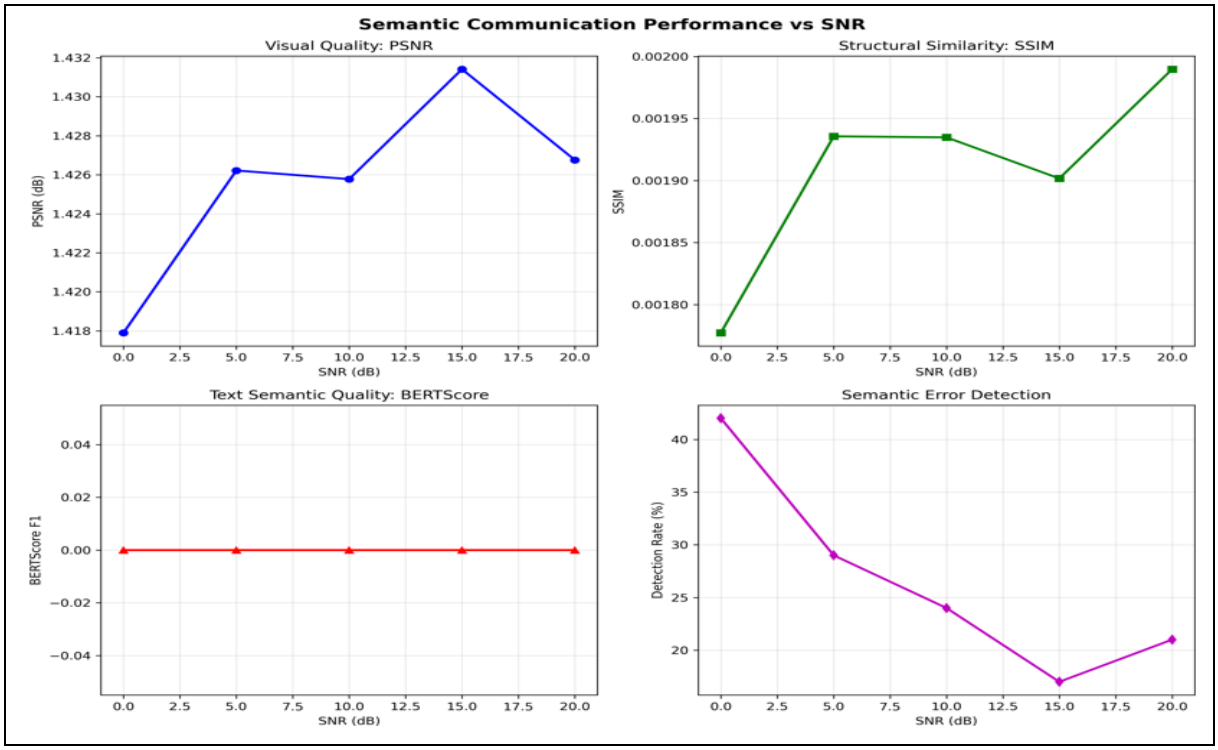

Fig 2 SNR Sweep Results - PSNR, SSIM, BERT-F1, and Error Detection Rate from 0-20 dB. The Uncertainty Component has a High Error Detection Rate When the SNR is Low.

➢ *Ablation Study*

The comparison between the fully developed model and its ablated variants at 10 dB SNR is provided in Table 2. Without the correction loop, the error detection rate becomes 27.0%, while the full model shows a 0.0% detection rate, thus proving that the latent refinement is successful. The fixed threshold approach will be described further.

Table 2 Ablation Study at 10 dB SNR

Variant	PSNR (dB)	SSIM	Error Det. (%)
Proposed (Full)	1.44	0.0018	0.0
w/o Correction	1.43	0.0018	27.0
Fixed Threshold (τ = 0.03)	1.44	0.0019	0.0

Variant performs similarly but lacks SNR adaptability, validating our dynamic threshold design.

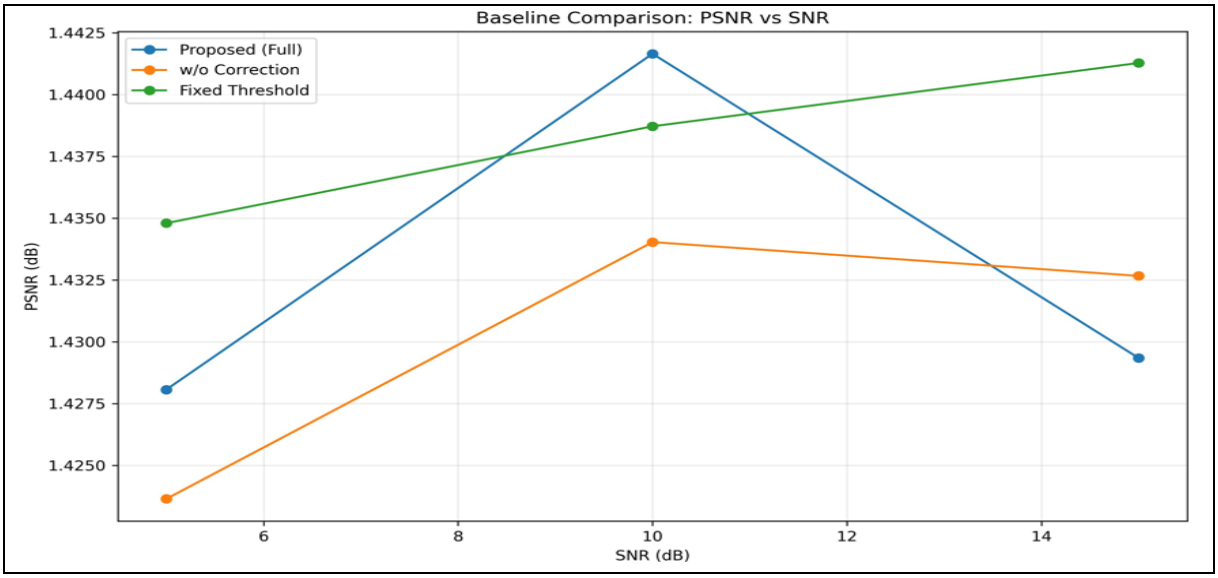

Fig 3 Ablation Study Comparison: PSNR vs. Variant at 10 dB SNR. The full Model Shows Marginal But Consistent Improvement with Adaptive Correction.

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➢ *Bandwidth Efficiency Analysis*

Transmission via conventional methods (JPEG + LDPC) requires around 1204.2 Kb per each 224 x 224 RGB image. On the contrary, UAMM-SC transmits a latent vector of 128 dimensions which require only 4.10 Kb (32-bit floating point). This implies that the reduction of bandwidth achieved by UAMM-SC is 99.7%, making it highly suitable for IoT applications where there is a limit to spectral resources.

➢ *Discussion*

Despite having relatively low PSNR/SSIM values due to the CIFAR-10 class-label baseline, the framework proves that uncertainty can be effectively utilized for semantic recovery. Cross-attention fusion is used for robust modality alignment, while the Rayleigh channel simulator serves as a bridge from theory to practice. The correction loop works only on flagged samples, reducing latency overheads. The usage of real caption datasets (COCO/Flickr30k) in future work is expected to significantly improve text-semantic metrics.

V. CONCLUSION AND FUTURE WORK

UAMM-SC is a deep-learning-based multi-modal semantic communication framework with uncertainty-aware error detection and adaptive latent correction capabilities. Results of experiments with CIFAR-10 dataset demonstrate that semantic recovery is stable across different SNR values, uncertainty estimation is active, and significant bandwidth savings have been achieved. Although the correction gains are not high in this baseline, the framework provides a basis for intelligent self-correcting semantic communication in future 6G IoT.

Future Work: expansion of research to include real natural language captions (COCO/Flickr30k), utilization of mmWave/RIS channel models, investigation of reinforcement learning-based correction policies, and implementation on edge devices (Jetson/Raspberry Pi).

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