Semantic Multiplexing for Multi-User Image Transmission

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다중 사용자 이미지 전송을 위한 의미적 다중화

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Abstract

We propose a novel semantic multiplexing framework for multi-user downlink image transmission that leverages semantic correlations among users. Each input image is encoded using an autoencoder into private and shared semantic features. The shared features are broadcast to all users once, while the private features are transmitted individually. At the receiver side, a decoder reconstructs each image by combining both feature types while accounting for wireless channel effects. Simulation results demonstrate that the proposed approach improves reconstruction quality and communication efficiency.

Ⅰ. Introduction

Semantic communication enables the extraction and transmission of high-level features or embeddings that capture essential information, reducing data overhead while maintaining task performance [1]. Conventional studies have long addressed spatial multiplexing in multi-input-multi-output (MIMO) systems [2, 3] and resource allocation in the frequency domain [4], and recent research on semantic communication has also integrated these techniques to improve throughput and reliability [5, 6]. Nonetheless, these approaches treat each user's data independently and rely on conventional domain separation without leveraging semantic similarities among users. In this paper, we propose a semantic multiplexing framework tailored for multi-user downlink image transmission. Unlike existing methods, our approach exploits semantic correlations between users by decomposing each input image into shared and private semantic components. The shared features, which capture common semantic information across users, are transmitted once and reused by all receivers. In contrast, private features unique to each user are transmitted separately. This novel strategy introduces a new dimension of multiplexing in the semantic domain, offering improved communication efficiency and scalability compared to traditional methods.

Ⅱ. Method

We adopt an autoencoder architecture to semantically encode distinct input images into compact codeword vectors. A fully-connected layer follows the encoder to prepare these representations for wireless transmission. This layer performs channel encoding and splits the semantic features into private features and shared features. To select the most relevant shared semantics, we apply a Gumbel-Softmax mechanism [7], which enables differentiable sampling from a categorical distribution. This allows the model to stochastically select a subset of representative shared semantic prototypes from a learned dictionary in a trainable way. At the receiver, the private and shared features are transmitted through separate wireless channels, then concatenated into a unified latent representation. This combined vector is passed through a decoder that models both spatial dependencies and channel distortions, enabling high-quality image reconstruction under varying wireless conditions. Both the encoder and decoder are trained in an end-to-end manner to minimize a distortion-based objective. Specifically, the training goal is to find the encoder and decoder parameter sets that reduce the expected discrepancy between the true image and its estimate.

Ⅲ. Simulation Results

In this section, we evaluate the proposed semantic multiplexing encoder-decoder under both additive white Gaussian noise (AWGN) and Rayleigh fading channels using the CIFAR-10 dataset. For comparison, we consider two baselines: (i) a CNN-based single-user encoder and (ii) a ViT-based single-user encoder. The proposed method is tested under two operating points, corresponding to different ratios of shared and private features. Performance is measured in terms of peak signal-to-noise ratio (PSNR) and perceptual loss at SNR levels {3, 6, 9, 15, 18} dB. The encoder-decoder structure and training procedures follow those described in Section II.

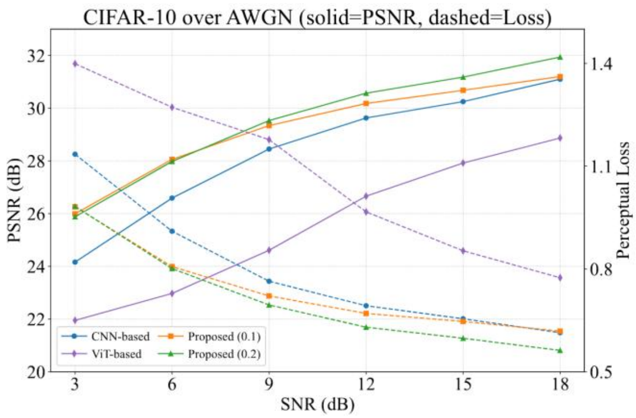

Figure 1. Performance comparison over an AWGN channel in terms of PSNR and perceptual loss. The proposed semantic multiplexing scheme consistently outperforms CNN- and ViT-based baselines across all SNR values.

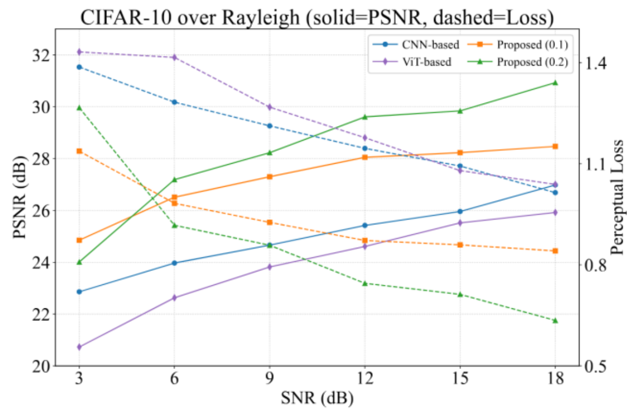

Figure 2. Performance comparison over a Rayleigh fading channel. The proposed method achieves higher PSNR and lower perceptual loss than the baselines, with notable gains in the medium-to-high SNR regime.

We first evaluate PSNR values of the proposed and conventional methods under AWGN Channel in Fig. 1. As the SNR increases, all schemes show improved PSNR and reduced perceptual loss. However, the proposed method consistently outperforms both baselines across the entire SNR range. The performance gap is most pronounced in the medium-to-high SNR region (≥ 9 dB), with gains of approximately 1 dB in PSNR. Among the two operating points, the configuration with a larger shared ratio (0.2) achieves the highest PSNR at high SNR, while both settings yield lower perceptual loss than the baselines. This indicates that reusing shared semantic features enhances noise suppression and stabilizes reconstruction. Under Rayleigh fading conditions in Fig. 2, the proposed method again outperforms the baselines across all SNR levels. The performance gains are particularly significant in the medium SNR range (6– 15 dB), where both PSNR improvement and perceptual loss reduction are clearly observed. Even at high SNR (18 dB), the proposed scheme maintains the best reconstruction quality. These results suggest that combining private and shared semantic features is especially effective in mitigating fading-induced distortions.

IV. Conclusion

We presented a semantic multiplexing framework for multi-user image transmission that separates shared and private semantic features. Simulation results over AWGN and Rayleigh channels showed clear gains in PSNR and perceptual loss compared to baseline methods. By adjusting the shared/private feature ratio, the framework offers a flexible trade-off between fidelity and efficiency, highlighting its potential for scalable semantic communication systems.

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