Importance-Aware Subcarrier Mapping for OFDM-Based Digital Semantic Communication

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***Abstract*—This paper proposes an importance-aware subcarrier mapping scheme for orthogonal frequency division multiplexing (OFDM)-based digital semantic communications. The proposed framework employs a pretrained vision transformer to estimate attention scores for individual image patches and selects the most informative patches for OFDM transmission. By exploiting the frequency-selective nature of OFDM channels, patches with higher attention scores are assigned to subcarriers with superior channel gains, thereby enhancing the reliability of critical semantic information delivery. Simulation results confirm that the proposed scheme consistently achieves higher classification accuracy than conventional mapping strategies, particularly under low signal-to-noise ratio conditions.**

I. Introduction

Artificial intelligence (AI) has advanced rapidly in recent years and achieved remarkable success across diverse application domains. This progress has fueled growing interest in semantic communications, representing a paradigm shift from traditional Shannon theory-based frameworks toward deep learning-enabled information extraction and transmission [1]. Unlike conventional communication systems, which are designed to minimize bit-level errors across the entire transmitted data, semantic communication systems focus on identifying and transmitting only essential information for accomplishing the target task.

Early studies have primarily focused on analog implementations. In recent years digital semantic communication approaches that preserve compatibility with standardized wireless systems have attracted growing research interest. For instance, in [2], a semantic-importance-aware scheme has been proposed in which an entropy model is trained to estimate the importance of each semantic symbol. Based on these importance measures, the scheme allocates bandwidth and reorders symbols such that those with higher importance are mapped to resources closer to pilot signals, thereby mitigating the impact of channel estimation errors. In [3], a masking strategy has been introduced within a vector-quantized variational autoencoder (VQ-VAE) framework, where an additional feature-importance estimation module is jointly trained. This module identifies noise-related image patches and suppresses their feature activations, ensuring that only important features are transmitted. Transmitting a smaller set of more relevant features enhances bandwidth efficiency and reduces communication overhead.

Building upon these prior studies, this work presents a method for importance-aware subcarrier mapping that eliminates the need to train an auxiliary model for importance estimation. The proposed scheme exploits the attention mechanism [4] inherently embedded within a pretrained Vision Transformer (ViT) to directly derive patch-level importance scores without incurring additional training cost. These scores are subsequently used to map high-importance patches to subcarriers with superior channel gains, thereby enhancing the reliability of semantic information delivery over orthogonal frequency division multiplexing (OFDM) channels, particularly under adverse channel conditions.

Our simulation results demonstrate that the proposed method consistently outperforms conventional mapping strategies in the single-view image classification task on the ImageNet100 [5] dataset with particularly notable gains in low signal-to-noise ratio (SNR) scenarios. These findings confirm the effectiveness of attention-based importance extraction for subcarrier mapping in enhancing the robustness of digital semantic communication systems.

II. System Model

In this work, we consider an OFDM-based digital semantic communication system for wireless image transmission. Let K denote the number of OFDM subcarriers. The received signal at subcarrier k is expressed as [6]

$$Y[k] = H[k]X[k] + N[k], \tag{1}$$

where $k \in \{1, \dots, K\}$, $X[k]$ is the symbol transmitted over subcarrier k obtained by M-ary quadrature amplitude modulation (M-QAM), where M denotes the modulation order, $H[k] \sim \mathcal{CN}(0, 1)$ represents the corresponding complex channel coefficient modeled as Rayleigh fading with unit variance, and $N[k] \sim \mathcal{CN}(0, \sigma_N^2)$ represents additive white Gaussian noise (AWGN) with variance σ_N^2. Assuming perfect channel state information (CSI) at the receiver, frequency-domain equalization is performed to recover the transmitted symbol as

$$\hat{X}[k] = \frac{H^*[k]}{|H[k]|^2} Y[k] = X[k] + \tilde{N}[k]. \tag{2}$$

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where $\tilde{N}[k] = H^*[k]N[k]/|H[k]|^2 \sim \mathcal{CN}\left(0, \sigma_N^2/|H[k]|^2\right)$. The effective SNR at the subcarrier k is then given by

$$\mathrm{SNR}_k = \frac{\mathbb{E}[|X[k]|^2]}{\mathbb{E}[|\tilde{N}[k]|^2]} = \frac{1}{\sigma_N^2/|H[k]|^2} = \frac{|H[k]|^2}{\sigma_N^2}. \tag{3}$$

Due to the frequency-selective nature of wireless channels, SNR_k varies across subcarriers, and the average SNR is computed as

$$\mathrm{SNR}_{\text{avg}} = \frac{1}{K}\sum_{k=1}^{K}\mathrm{SNR}_k. \tag{4}$$

III. Attention-Derived Importance-Aware Subcarrier Mapping

In this section, we present a novel subcarrier mapping scheme that leverages patch-wise importance levels and CSI to enhance semantic information delivery in OFDM systems.

A. Attention-Based Patch-Wise Importance Levels Estimation

We start by describing the process of computing patch-wise importance levels using the attention mechanism of a pretrained ViT. These scores quantify the relative contribution of each image patch to the overall task performance and serve as the basis for subsequent subcarrier mapping. Let L denote the number of transformer layers, H the number of attention heads, and N the total number of patches, consisting of one class (CLS) token and $N-1$ image patches. In the l-th layer and h-th head, the attention weight between the CLS token and the image patches is obtained as

$$\tilde{\mathbf{a}}_h^{(l)} = \mathrm{softmax}\left(\frac{\mathbf{q}_{\text{CLS},h}^{(l)}(\mathbf{k}_h^{(l)})^\mathsf{T}}{\sqrt{d}}\right) \in \mathbb{R}^{1\times(N-1)}, \tag{5}$$

where $\mathbf{q}_{\text{CLS},h}^{(l)} \in \mathbb{R}^{1\times d}$ denotes the query vector of the CLS token, $\mathbf{k}_h^{(l)} \in \mathbb{R}^{(N-1)\times d}$ denotes the key vectors of the image patches, and d denotes the dimension of the query and key vectors. The final importance score for $N-1$ patches is obtained by averaging $\tilde{\mathbf{a}}_h^{(l)}$ over all layers and heads, i.e.,

$$\mathbf{a} = \frac{1}{LH}\sum_{l=1}^{L}\sum_{h=1}^{H}\tilde{\mathbf{a}}_h^{(l)}. \tag{6}$$

The resulting vector $\mathbf{a} \in \mathbb{R}^{1\times(N-1)}$ represents the attention-based importance levels for all patches, which will be used for channel-adaptive subcarrier mapping in Sec. III-B.

B. Patch-Wise Importance-Guided Channel-Aware Mapping

The attention-based patch-wise importance levels obtained in Sec. III-A are exploited to guide the allocation of OFDM subcarriers according to their channel quality. Each patch consists of $P \times P$ pixels with $C = 3$ color channels (RGB), where each pixel is represented using B bits per channel. The total number of modulated symbols required to transmit all selected patches is expressed as

$$L_{\text{sym}} = \frac{N_{\text{tx}}BP^2C}{\log_2 M}, \tag{7}$$

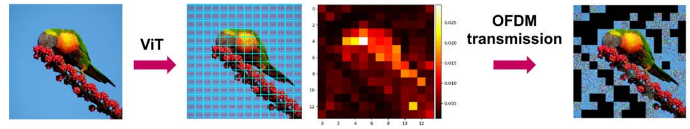

Fig. 1. Visualization of attention score map and selected patches for OFDM transmission in the single-view image classification task on the ImageNet100 dataset.

where N_{tx} denotes the number of patches selected for transmission. Selecting only the N_{tx} patches with the highest importance levels reduces transmission overhead and improves bandwidth efficiency by eliminating semantically insignificant content. In practical scenarios, L_{sym} typically exceeds the number of available OFDM subcarriers K. Therefore, the symbol sequence is first divided into multiple OFDM blocks for transmission. Once divided, the allocation procedure begins by sorting the set of K subcarriers in descending order of channel gain, i.e.,

$$\{H_{\text{sorted}}[m]\}_{m=0}^{K-1} = {}_{\text{mag}}\left(\{H[k]\}_{k=0}^{K-1}\right), \tag{8}$$

where ${}_{\text{mag}}(\cdot)$ denotes a sorting operation that arranges the elements of the input set in descending order of magnitude, (i.e., $|H_{\text{sorted}}[0]| \geq \cdots \geq |H_{\text{sorted}}[K-1]|$). Similarly, the symbol sequences of the selected patches are given by

$$\{\mathbf{X}_{\text{sorted}}^{(n)}\}_{n=0}^{N_{\text{tx}}-1} = {}_{\text{att}}\left(\{\mathbf{X}^{(p)}\}_{p\in\mathcal{P}_{\text{tx}}}\right), \tag{9}$$

where $\mathcal{P}_{\text{tx}} \subset \{0, 1, \ldots, N-1\}$ denotes the index set of the N_{tx} patches selected for transmission, and $\mathbf{X}^{(p)} \in \mathbb{C}^{L_{\text{sym}}/N_{\text{tx}}}$ represents the complex symbol sequence obtained from the p-th selected patch after quantization and M-QAM modulation. Here, $\mathbf{X}_{\text{sorted}}^{(n)} = [X_{\text{sorted}}^{(n)}[1], \ldots, X_{\text{sorted}}^{(n)}[L_{\text{sym}}/N_{\text{tx}}]]^\top$ denotes the symbol sequence corresponding to the n-th most important patch, and ${}_{\text{att}}(\cdot)$ arranges the set $\{\mathbf{X}^{(p)}\}_{p\in\mathcal{P}_{\text{tx}}}$ in descending order of the importance levels in (6).

Each selected patch requires $L_{\text{sym}}/N_{\text{tx}}$ symbols in total, but only K/N_{tx} symbols from each patch are transmitted in a given OFDM block. For the highest-importance patch (i.e., $n = 0$), K/N_{tx} symbols are randomly selected from $\mathbf{X}_{\text{sorted}}^{(0)}$ and mapped to the subcarriers $\{H_{\text{sorted}}[0], \ldots, H_{\text{sorted}}[K/N_{\text{tx}}-1]\}$, corresponding to the K/N_{tx} largest channel gains. Conversely, for the lowest-importance patch (i.e., $n = N_{\text{tx}} - 1$), the same number of symbols are mapped to the subcarriers $\{H_{\text{sorted}}[K - K/N_{\text{tx}}], \ldots, H_{\text{sorted}}[K-1]\}$, which correspond to the K/N_{tx} smallest channel gains. The remaining patches are mapped in the same manner, such that patches with higher importance levels are assigned to subcarriers with higher channel gains, thereby improving the reliability of semantically important content delivery. This mapping and transmission process is repeated L_{sym}/K times until all symbols of each patch are transmitted. At the receiver, each OFDM block is processed according to (2), followed by demodulation, dequantization, and patch reassembly to reconstruct the transmitted image. The reconstructed image is then used to perform the downstream task at the receiver.

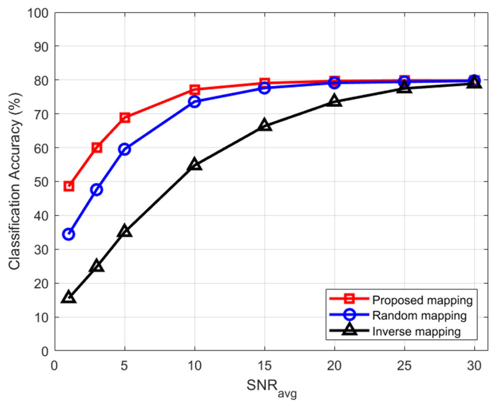

Fig. 2. Comparison of the classification accuracy of different subcarrier mapping strategies for the single-view image classification task on the ImageNet100 dataset.

Fig. 1 illustrates the image processing and transmission procedure of the proposed method in the single-view image classification task on the ImageNet100 dataset. From left to right, the figure shows the original image, the patch partitioning stage in the ViT, the attention scores visualized as a heatmap, and the received image after OFDM transmission. In this example, the image is divided into $N = 196$ patches. Based on the heatmap, the $N_{\rm tx} = 128$ patches with the highest importance levels are selected for transmission, while the remaining $N - N_{\rm tx}$ patches with importance levels below a predefined threshold are omitted, as their contribution to the target task is minimal. Consequently, the importance-aware subcarrier mapping enables the received image to preserve high-importance patch information robustly against channel distortion and noise, ensuring the retention of critical content for downstream task performance.

IV. Simulation Results

In this section, we evaluate the performance of the proposed importance-aware subcarrier mapping method through simulations for a single-view image classification task on the ImageNet100 dataset. The ViT encoder employed by both the transmitter and receiver is the DeiT-Tiny [7], pre-trained and fine-tuned on the ImageNet-1k dataset containing 1 million images from 1,000 classes. Each encoder processes an input image of size $(3, 224, 224)$, which is partitioned into $N = 196$ patches using a patch size of $P = 16$. The model consists of $L = 12$ encoder layers with $H = 3$ attention heads. Each patch is quantized with $B = 8$ bits per channel and the resulting bitstream is modulated using 4-QAM (i.e., $M = 4$) before transmission. The $N_{\rm tx} = 128$ most important patches are transmitted over an OFDM system with $K = 2048$ subcarriers. The classifier is realized as a single fully connected layer and jointly trained with the ViT encoder using the cross-entropy loss.

For performance comparison, we consider two baseline subcarrier mapping strategies: *random mapping* and *inverse mapping*. In the random mapping strategy, each patch is assigned to a subcarrier selected uniformly at random, irrespective of its importance level. In the inverse mapping strategy, patches with higher importance levels are intentionally assigned to subcarriers with lower channel gains, while less important patches are mapped to subcarriers with higher channel gains.

Fig. 2 compares the classification accuracies of various subcarrier mapping strategies for the single-view image classification task on the ImageNet100 dataset. Fig. 2 shows that the proposed mapping consistently outperforms both random and inverse mapping schemes across the entire $\mathrm{SNR}_{\rm avg}$ range. The performance gap is particularly pronounced in the low-SNR regime, where assigning high-importance patches to subcarriers with higher channel gains enables the proposed method to preserve critical semantic information more effectively. While the random mapping exhibits moderate performance by disregarding patch importance, the inverse mapping suffers from severe performance degradation due to intentionally allocating important patches to low-gain subcarriers.

V. Conclusion

In this paper, we have proposed a novel ViT-based importance-aware subcarrier mapping scheme for OFDM-based semantic communication systems. The key idea of the proposed framework is to leverage a pretrained ViT model to assess the importance of individual image patches and to map high-importance patches to OFDM subcarriers with higher channel gains. This design enables more reliable delivery of semantically critical information over frequency-selective fading channels. Simulation results demonstrate that the proposed method consistently achieves higher classification accuracy than conventional mapping schemes, with particularly significant gains in low-SNR scenarios, thereby ensuring more robust semantic communication performance.

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