Deep Semantic-Aware SCMA Codebook Learning for Semantic Communication Systems

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***Abstract*—Sparse code multiple access (SCMA) has emerged as a promising non-orthogonal multiple access (NOMA) technique for future wireless communications. However, conventional SCMA is inherently designed for bit-level transmission, which ignores semantic-level information and lacks semantic-aware codebook construction capabilities. To address this limitation, this paper proposes a semantic-aware SCMA codebook learning framework, named SCMA-SC, which jointly optimizes semantic representation and sparse codeword generation through an end-to-end trainable architecture. By integrating semantic communications with SCMA, the proposed framework enables semantic-aware overloaded transmission over limited wireless resources. Simulation results demonstrate that SCMA-SC outperforms both conventional SCMA and power-domain NOMA semantic communication systems in terms of semantic reconstruction quality and image transmission performance.**

***Index Terms*—Sparse code multiple access, codebook learning framework, semantic communication.**

I. Introduction

With the evolution of wireless communication technologies, high data rates, low latency, and massive connectivity have emerged as core requirements for future networks [1]. However, limited spectrum resources and the inherent constraints of traditional orthogonal multiple access (OMA) techniques make it challenging to meet these demands. As a promising non-orthogonal multiple access (NOMA) scheme, sparse code multiple access (SCMA) [2] improves connectivity and spectral efficiency by allowing multiple users to share the same time-frequency resources through sparse codeword multiplexing, while achieving favorable bit error rate (BER) performance.

Extensive research has recently focused on SCMA codebook design. For instance, in [3], a non-linear SCMA framework has been proposed to improve BER performance through non-linear codeword mapping. The work in [4] has introduced a separable structure-based codebook design to enhance BER performance in high-overload scenarios by optimizing the minimum Euclidean distance. In [5], the authors have integrated Polarization Phase Shift Keying with SCMA to improve spectral efficiency by leveraging polarization-domain degrees of freedom. Additionally, the work in [6] has presented an uplink SCMA codebook optimization method using evolutionary strategies to reduce BER through single-stage construction. Meanwhile, other studies have addressed resource allocation and multi-user access mechanisms. Finally, in [7], a support vector machine(SVM) based subcarrier allocation and inter-group power assignment algorithm has been proposed to enhance access capacity in high-density scenarios.

Despite the significant advancements of SCMA in enhancing connection capacity and spectral efficiency, existing deep learning-based SCMA schemes mainly focus on bit-level constellation optimization [8], without considering semantic-aware feature representation. Meanwhile, current semantic NOMA systems primarily rely on power-domain multiplexing [9], which limits the number of simultaneously accessed users and constrains spectral efficiency in massive access scenarios. Furthermore, the work in [10] has introduced a scalable semantic coding framework to reduce semantic ambiguity in image transmission, but it has not considered efficient multi-user access scenarios. Consequently, breaking through the constraints of traditional bit-level transmission to construct semantic-oriented communication mechanisms has emerged as a formidable challenge for efficient intelligent systems [11].

To address these issues, this paper introduces a novel semantic-aware codebook learning framework for SCMA-based semantic communication (SCMA-SC), which establishes a paradigm for semantic-level multiple access among multiple users. The contributions are as follows:

- We propose an end-to-end semantic communication architecture that integrates semantic coding with sparse code multiple access, enabling semantic-aware codebook generation through a learnable SCMA mapping framework.
- We develop a semantic-aware SCMA codebook learning framework that jointly optimizes semantic representation and sparse codeword generation, enabling semantic-aware dynamic codebook construction.
- We utilize a deep learning-based joint decoder to replace the traditional iterative belief propagation algorithm, which significantly reduces computational complexity while achieving superior decoding performance.

The rest of the paper is organized as follows. In Section II, we introduce the system model of the semantic communication framework based on the proposed semantic-aware SCMA codebook learning framework. Section III elaborates on the design and implementation of semantic mapping and SCMA codebook mapping. The simulation results and performance

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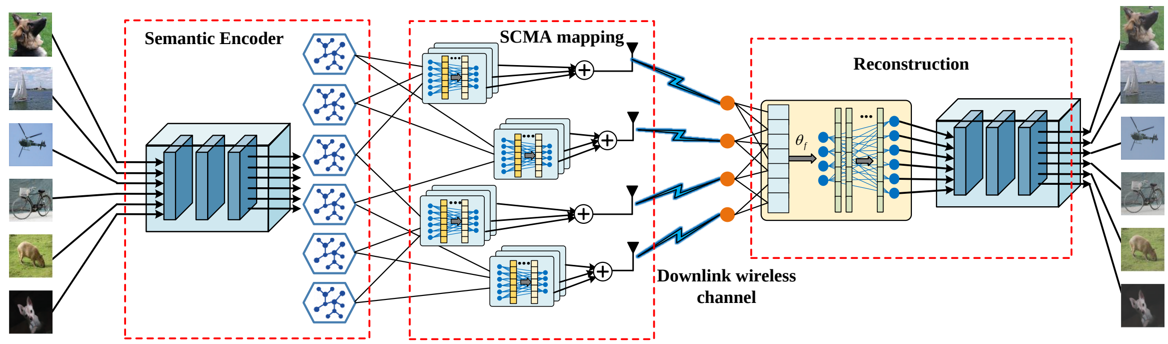


Fig. 1. A Deep-SCMA semantic communication system model

analysis are given in Section IV. Finally, Section V concludes the research findings and discusses future research directions.

II. System Model

A. Overall Framework

As illustrated in Fig. 1, the proposed SCMA-SC framework consists of semantic feature extraction, DNN-based sparse SCMA mapping, and joint semantic decoding. Consider a SCMA system with J resources and N semantic users. Unlike orthogonal transmission requiring $N \leq J$, SCMA supports overloaded access ($N > J$) through sparse multiplexing. During downlink transmission, the n-th signal x_n is encoded into a semantic feature vector $v_n = f_{\text{enc}}(x_n)$, which is subsequently quantized and mapped onto a finite constellation. The quantization and modulation process can be expressed as:

$$s_n = \theta_{\text{mod}}(\Phi(v_n)). \tag{1}$$

where $\Phi(\cdot)$ denotes the quantization operation and $\theta_{\text{mod}}(\cdot)$ represents the modulation.

The superposition of different signals on the j-th resource block can be represented as $\mathbf{x}_j = [s_1^j, s_2^j, \dots, s_{d_f}^j]^\top$, and the received signal can be expressed as

$$\mathbf{y} = \sum_{j=1}^{J} \text{diag}(\mathbf{h}^j)\mathbf{x}_j + \mathbf{n}, \tag{2}$$

where $\mathbf{h}^j = [h_1^j, h_2^j, \dots, h_{d_f}^j]^\top$ denotes the channel coefficient vector associated with the j-th resource block, $\text{diag}(\cdot)$ denotes the diagonalization operation, and $\mathbf{n}$ is additive white Gaussian noise (AWGN) with mean zero and variance σ^2.

B. Semantic Codec and Quantization

We employ a multi-scale hierarchical semantic image codec [12] based on generative adversarial networks (GANs) to process image-type data. Its core consists of a foundation model and a semantic enhancement slice model.

For an m-bit quantizer, the representable integer range is $[0, 2^m - 1]$. The quantization size and zero point are calculated based on the range $[v_{\text{min}}, v_{\text{max}}]$ of the feature values:

$$q_s = \frac{2^m - 1}{v_{\text{max}} - v_{\text{min}}}, \quad p_z = \text{round}(v_{\text{min}} \cdot q_s). \tag{3}$$

According to equation (1), the quantization process for each element s_n in the feature vector can be expressed as:

$$s_n = \text{clamp}\left(\text{round}(v_n \cdot q_s - p_z), 0, 2^m - 1\right), \tag{4}$$

where $\text{clamp}(\cdot)$ constrains the output to the target integer range. The quantization process partitions the semantic feature space into 2^m discrete levels, forming a semantic constellation.

During training, the straight-through estimator (STE) is adopted to approximate the rounding operation and preserve gradient propagation.

C. SCMA Codebook Mapping

In SCMA-SC, a DNN is employed to learn the mapping from semantic symbols to sparse SCMA codewords. The mapping from semantic symbol s_n to resource j is denoted as $f_{nj}(s_n)$, which is implemented by a neural network with L hidden layers:

$$f_{nj}(s_n) = \Phi_L(W_L\Phi_{L-1}(\cdots\Phi_1(W_1 s_n + b_1)) + b_L), \tag{5}$$

where the weight W_l, bias b_l, and activation function Φ constitute the DNN unit. For example, when $J = 4$ and $N = 6$, the SCMA codebook mapping matrix is given by:

$$\mathbf{F}_{4\times 6} = \begin{bmatrix} 0 & f_{21}(s_2) & f_{31}(s_3) & 0 & f_{51}(s_5) & 0 \\ f_{12}(s_1) & 0 & f_{32}(s_3) & 0 & 0 & f_{62}(s_6) \\ 0 & f_{23}(s_2) & 0 & f_{43}(s_4) & 0 & f_{63}(s_6) \\ f_{14}(s_1) & 0 & 0 & f_{44}(s_4) & f_{54}(s_5) & 0 \end{bmatrix}. \tag{6}$$

D. Spectral Efficiency and Overloading Analysis

In the proposed SCMA-SC framework, the overload capability is determined by the overload factor

$$\lambda = \frac{N}{J}, \tag{7}$$

where N and J denote the numbers of semantic users and resource blocks, respectively. Since $\lambda > 1$, multiple semantic users can simultaneously share limited wireless resources through sparse non-orthogonal transmission.

Accordingly, the spectral efficiency of the proposed SCMA-SC system can be expressed as

$$\eta = \lambda \cdot \log_2(M), \tag{8}$$

where M denotes the modulation order of semantic symbols. Compared with orthogonal multiple access schemes, the proposed framework achieves higher spectrum utilization under overloaded transmission conditions.

III. Proposed Algorithm

A. Semantic Mapping Method Based on WGAN-GP

To ensure high-quality image transmission in wireless communication systems, the image source must be encoded. The basic model of the semantic encoder can be represented as $\varepsilon(\theta_{\text{sem}})$, where θ_{sem} denotes the set of trainable parameters in the model, consisting of three components: an encoder ε_{enc}, a generator ε_{dec}, and a discriminator ε_{dis}. Adversarial loss is based on WGAN-GP, with the generator's objective being the negative mean of discriminator scores on generated samples:

$$L_G = -\mathbb{E}_{\boldsymbol{x}_{\text{gen}}}\left[D(\varepsilon_{\text{dis}}(x_n^*))\right], \tag{9}$$

where x_n^* represents the generated image. The discriminator loss consists of the difference between the mean outputs for real samples and generated samples, with an additional gradient penalty term to enforce the Lipschitz constraint:

$$L_D = \mathbb{E}_{\boldsymbol{x}_{\text{real}}}\left[D(\varepsilon_{\text{dis}}(x_n))\right] - \mathbb{E}_{\boldsymbol{x}_{\text{gen}}}\left[D(\varepsilon_{\text{dis}}(x_n^*))\right] + \lambda_{\text{GP}} \cdot R_{\text{GP}}, \tag{10}$$

R_{GP} denotes the gradient norm penalty on discriminator. For reconstruction, we adopt the structural similarity (SSIM) loss:

$$L_{\text{SSIM}} = \frac{1}{N}\sum_{n=1}^{N}\big(1 - \text{SSIM}(x_n, x_n^*)\big), \tag{11}$$

where N is the number of semantic signal streams.

The end-to-end reconstruction loss for semantic coding and image reconstruction is defined as:

$$L_{\text{rec}} = \left\|\mathbf{s}_n - (\varepsilon_{\text{dec}}(\mathbf{s}_n) \circ \mathbf{h} + \mathbf{n})\right\|_2^2, \tag{12}$$

where $\boldsymbol{h}$ denotes the wireless channel coefficient, $\boldsymbol{n}$ is the additive noise, and $\circ$ represents element-wise multiplication. The composite training loss is formed as follows:

$$\begin{aligned} L_{\text{sem}} = &\underbrace{-\mathbb{E}_{\boldsymbol{x}_{\text{gen}}}\left[D(\varepsilon_{\text{dis}}(x_n^*))\right]}_{L_G} + \alpha L_{\text{SSIM}} \\ &+ \beta \underbrace{\left\|\mathbf{s}_n - (\varepsilon_{\text{dec}}(\mathbf{s}_n) \circ \mathbf{h} + \mathbf{n})\right\|_2^2}_{L_{\text{rec}}}, \end{aligned} \tag{13}$$

where α and β are the weights for the training losses.

B. DNN-based SCMA Codebook Mapping

Specifically, within the SCMA-SC framework, the mapping from data stream to resource units is realized by a set of parameterized nonlinear functions. The mapping from the M-ary symbol s_n of the n-th user to the complex constellation point on the j-th resource unit is defined as $f_{nj}(s_n;\theta_f)$, where θ_f represents the trainable parameters of the neural network.

As shown in Algorithm 1, the proposed SCMA-SC framework is jointly trained in an end-to-end manner using the Adam optimizer and batch size of 32. The training process terminates after E epochs or when the loss converges.

Algorithm 1 Joint Training of SCMA-SC

Require: Training dataset $\{x_n\}$, learning rates $\eta_{\text{sem}}, \eta_f, \eta_g$, hyperparameters $\alpha, \beta, \lambda_{\text{GP}}$, quantization bits m, epoch number E.

Initialize all network parameters randomly.
while $e = 1$ to E **do**
  Sample a mini-batch of images $\{x_n\}$.
  Semantic encoding: $v_n \leftarrow \varepsilon_{\text{enc}}(x_n;\theta_{\text{enc}})$ for each n.
  Asymmetric quantization: $s_n = \mathcal{Q}(v_n;m)$, where $\mathcal{Q}$ follows Eq. (3)–(4).
  SCMA mapping and channel superposition:
  for each resource $j = 1,\ldots,J$ **do**
    $y_j \leftarrow \sum_{n:\gamma_{j,n}=1} h_{nj} f_{nj}(s_n;\theta_f) + n_j$
  end for
  $\mathbf{y} \leftarrow [y_1,\ldots,y_J]^\top$.
  Decoding:
  for each user $n = 1,\ldots,N$ **do**
    $\hat{x}_n \leftarrow g\big(\{y_j : \gamma_{j,n} = 1\};\theta_g\big)$
  end for
  Discriminator loss computation:
  $L_D \leftarrow D_{\text{real}} - D_{\text{fake}} + \lambda_{\text{GP}} R_{\text{GP}}$
  Generator-related losses:
  $L_{\text{sem}} \leftarrow L_G + \alpha L_{\text{SSIM}} + \beta L_{\text{rec}}$
  Update discriminator: $\theta_{\text{dis}} \leftarrow \theta_{\text{dis}} - \eta_{\text{sem}} \nabla_{\theta_{\text{dis}}} L_D$
  Update network parameters: $(\theta_{\text{enc}}, \theta_{\text{dec}}, \theta_f, \theta_g)$
end while
Output: semantic mapping network $\{\varepsilon_{\text{enc}}, \varepsilon_{\text{dec}}, \varepsilon_{\text{dis}}\}$, SCMA mapping functions $\{f_{nj}\}$, and decoder g.

The superimposed signal received at the j-th resource unit can be expressed as:

$$y_j = \sum_{n\in\gamma_j} h_{nj} f_{nj}(s_n;\theta_f) + n_j, \tag{14}$$

where γ_j denotes the set of users occupying the j-th resource block, and n_j is the additive white Gaussian noise on resource j. Meanwhile, the DNN parameters and decoder parameters are determined by solving the following optimization problem:

$$\min_{\theta_f,\theta_g} \left\| s - g\left(\sum_{n\in\gamma_j} h_{nj} f_{nj}(s_n;\theta_f) + n;\theta_g\right)\right\|_2, \tag{15}$$

where $g(\cdot;\theta_g)$ denotes the decoder and its parameters, the original signal is s, h_{nj} is the corresponding channel coefficient, and n is additive white Gaussian noise. The optimization objective in Eq. (15) focuses on sparse semantic symbol recovery for SCMA transmission. Based on the loss function in Eq. (13), the network parameters are jointly optimized using the Adam optimizer:

$$(\theta_f,\theta_g) \leftarrow (\theta_f,\theta_g) - \alpha\nabla_{\theta_f,\theta_g} L(s,\hat{s};\theta_f,\theta_g). \tag{16}$$

The SCMA codebook mapping matrix is given by:

$$\mathbf{F}_{J\times N} = \begin{bmatrix} \gamma_{1,1}f_{11}(s_1) & \cdots & \gamma_{1,n}f_{n1}(s_n) & \cdots & \gamma_{1,N}f_{N1}(s_N) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \gamma_{j,1}f_{1j}(s_1) & \cdots & \gamma_{j,n}f_{nj}(s_n) & \cdots & \gamma_{j,N}f_{Nj}(s_N) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \gamma_{J,1}f_{1J}(s_1) & \cdots & \gamma_{J,n}f_{nJ}(s_n) & \cdots & \gamma_{J,N}f_{NJ}(s_N) \end{bmatrix}$$

$$n \in N,\ j \in J, \quad \gamma_{j,n} = \begin{cases} 1, & \text{if semantic symbol } n \\ & \quad \text{occupies resource } j, \\ 0, & \text{otherwise.} \end{cases} \tag{17}$$

It should be noted that the binary indicator factor $\gamma_{j,n}$ is predefined and fixed during training to preserve the sparse mapping structure of SCMA, while the corresponding codewords in the codebook remain trainable and adaptive.

C. Joint Semantic Decoding

The proposed DNN-based joint decoder replaces the conventional belief propagation (BP) detector by directly recovering semantic features from the received sparse superposition signal. The decoded semantic representation is given by

$$\hat{\mathbf{s}}_n = g\big(\{y_j : \gamma_{j,n} = 1\}; \theta_g\big), \tag{18}$$

where $g(\cdot)$ denotes the neural decoder parameterized by θ_g. The reconstructed image is then obtained as

$$\hat{x}_n = \varepsilon_{\text{dec}}(\hat{\mathbf{s}}_n; \theta_{\text{dec}}), \tag{19}$$

where $\varepsilon_{\text{dec}}(\cdot)$ denotes the semantic decoder.

D. Computational Complexity

The computational complexity of the proposed SCMA-SC framework consists of semantic feature extraction, sparse SCMA mapping, and joint semantic decoding.

For semantic feature extraction, multiple convolution layers are employed to encode images. The complexity is given by

$$\mathcal{O}_{\text{sem}} = \sum_{l=1}^{L} \mathcal{O}(H_l W_l K_l^2 C_{l-1} C_l), \tag{20}$$

where H_l, W_l, K_l, and C_l denote the feature-map size, kernel size, and channel dimensions of the l-th layer, respectively. For the SCMA mapping, the complexity is given by

$$\mathcal{O}_{\text{map}} = \mathcal{O}\left(\sum_{j=1}^{J}\sum_{n=1}^{N} \|\gamma_{j,n}\|_0 d_h^2\right), \tag{21}$$

where d_h denotes the hidden dimension, and $\|\cdot\|_0$ denotes the L_0 norm, which characterizes the sparsity of the mapping structure. At the receiver, the DNN-based joint decoder recovers semantic features from the received signal with complexity

$$\mathcal{O}_{\text{dec}} = \mathcal{O}(d_{\text{in}} d_h + d_h^2 + d_h d_{\text{out}}), \tag{22}$$

where d_{in} and d_{out} denote the input and output dimensions. Therefore, the overall complexity is

$$\mathcal{O}_{\text{total}} = \mathcal{O}_{\text{sem}} + \mathcal{O}_{\text{map}} + \mathcal{O}_{\text{dec}}. \tag{23}$$

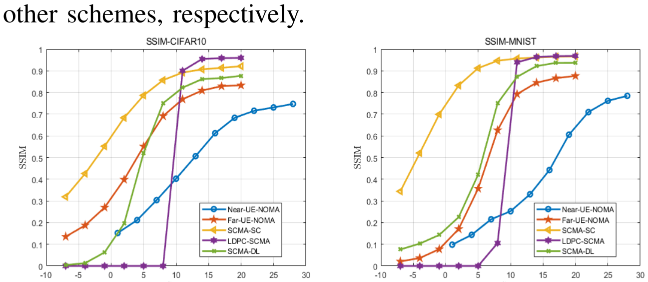
IV. Simulation Results

Experiments are conducted on the MNIST [13] and CIFAR-10 [14] datasets with $N = 6$ users and $J = 4$ resources under AWGN channels. The benchmark algorithms include a power allocation-based NOMA semantic communication (NOMASC) system [9], a conventional SCMA system, and a deep learning-based SCMA (SCMA-DL) scheme [15]. For both SCMA benchmarks, JPEG source coding and LDPC channel coding are employed. The conventional SCMA scheme uses a fixed codebook, whereas SCMA-DL adopts a deep learning-based codebook design and detection framework.

TABLE I
Parameters Settings

Notation	Value	Description
N	6	Number of semantic users
J	4	Number of orthogonal resources
η_f, η_g	0.0001	Learning rate
m	3	Quantization bits
E	200	Training epochs
η_{sem}	0.0001	Semantic encoder learning rate
SNR_{Train}	15 dB	Training SNR
SNR_{Test}	[-8,20] dB	Test SNR
α, β	0.03, 0.01	Weight of loss
λ_{GP}	0.1	Gradient penalty coefficient

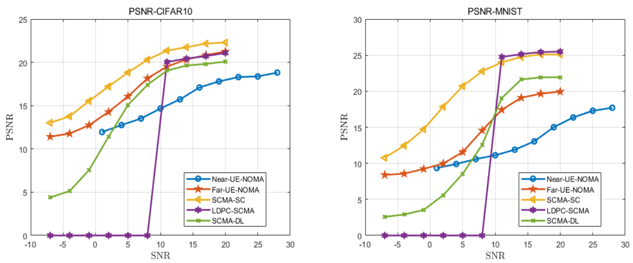
The performance of SCMA-SC and the benchmark is evaluated under AWGN. In Fig. 2(a) on CIFAR-10, SCMA-SC achieves higher SSIM across all SNRs. NOMASC shows a power-induced disparity between far and near users. SCMA-SC maintains stable, high SSIM even at low SNRs, demonstrating superior robustness. Fig. 2(b) on MNIST shows similar gains, as end-to-end joint training enables efficient extraction and protection of key semantic features from images. For example, with SNR = 11 dB, the SCMA-SC increases the SSIM by 1.87%, 8.47%, 18.49%, 58.09% compared to all the other schemes, respectively.



(a) SSIM in CIFAR-10 (b) SSIM in MNIST

Fig. 2. Evaluation of SSIM on the dataset under different SNRs

In Fig. 3(a) on CIFAR-10, SCMA-SC consistently outperforms NOMASC in PSNR across all SNR levels by leveraging sparse codebook mapping and superimposed coding, which effectively mitigate inter-user interference and enhance reconstruction accuracy. Fig. 3(b) on MNIST demonstrates similar gains, SCMA-SC jointly optimizes codebook mapping within an end-to-end semantic communication framework, enabling high-fidelity reconstruction of images. For example, with SNR = 11 dB, the SCMA-SC increases the PSNR by 6.55%, 12.15%, 19.51%, 45.56% compared to all the other schemes, respectively.



(a) PSNR in CIFAR-10 (b) PSNR in MNIST

Fig. 3. Evaluation of PSNR on the dataset under different SNRs

Furthermore, as illustrated in the Fig. 4 and Fig. 5, a comparison of transmitted data samples using the baseline and proposed algorithms under different SNR levels is presented. At low SNRs, the proposed algorithm successfully achieves reconstruction and attains optimal performance.

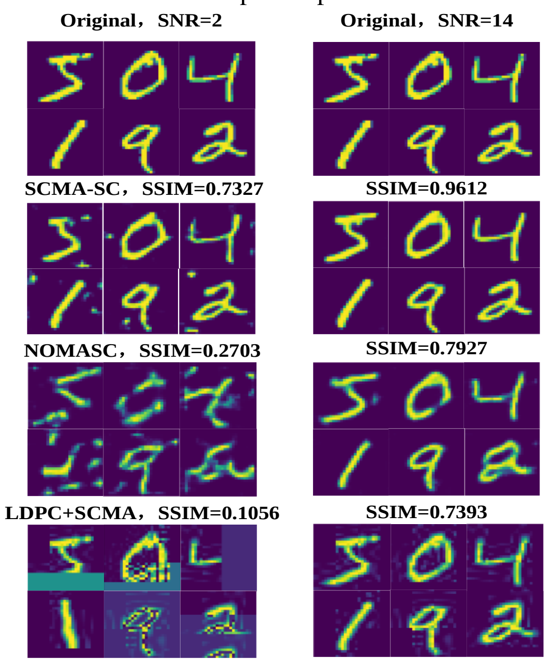


Fig. 4. Examples of image transmission by 6 users in MNIST

Fig. 5. Examples of image transmission by 6 users in CIFAR-10

V. Conclusion

In this paper, we proposed SCMA-SC, an end-to-end semantic communication framework based on semantic-aware SCMA codebook learning. By jointly optimizing semantic representation and sparse codeword generation, SCMA-SC enables efficient semantic transmission under overloaded access scenarios. Simulation results on CIFAR-10 and MNIST demonstrate that the proposed scheme achieves superior SSIM and PSNR performance compared with conventional SCMA and NOMASC systems across various SNR conditions.

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