Data-Level Parameter Sampling for Channel-Adaptive Semantic Communications

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***Abstract*—Although semantic communication leverages deep learning–based joint source–channel coding to achieve robust transmission, transceiver models trained at a fixed signal-to-noise ratio (SNR) often fail to generalize under varying channel conditions. To address this limitation, we propose a data-level parameter sampling (DLPS)–based training framework. The proposed framework employs an equivalent parallel additive white Gaussian noise channel model to enable stochastic sampling of channel parameters during end-to-end training. In the proposed DLPS strategy, a single SNR value is assigned to each training data sample, providing structured exposure to diverse channel conditions and improving channel adaptability. The simulation results show that the proposed framework maintains strong reconstruction performance across a wide SNR range, thus outperforming alternative sampling strategies and achieving competitive performance with SNR-specific dedicated training using a single unified model.**

***Index Terms*—Generalization capability, parameter sampling, semantic communication, transceiver design.**

I. Introduction

Semantic communication has recently emerged as a promising paradigm that aims to transmit task-relevant information rather than exact symbol- or bit-level representations [1]–[5]. By exploiting deep learning-based joint source-channel coding, semantic transceivers have demonstrated remarkable robustness, particularly in low signal-to-noise ratio (SNR) regimes. However, reliable and efficient communication over diverse wireless channels remains a challenge in practice.

In semantic transceivers, the encoder network extracts a latent representation of the source data, which is transmitted through a wireless channel and then reconstructed by the decoder network [6]–[8]. This joint source–channel coding framework enables the neural network to learn task-oriented representations that are inherently robust to channel impairments. However, the performance of such transceivers critically depends on the channel conditions experienced during training, and models trained at a fixed SNR often fail to generalize when deployed in mismatched environments.

To alleviate this issue, parameter sampling techniques have been explored to expose semantic transceivers to multiple channel conditions during training [9], [10]. However, existing approaches lack a systematic analysis of sampling granularity and therefore provide no principled way to determine how SNR values should be sampled. This lack of granularity-aware design prevents achieving a proper balance between channel diversity and model adaptability, thereby motivating the need for a more structured parameter sampling strategy.

To address the absence of granularity-aware design in existing training approaches, we propose a data-level parameter sampling (DLPS) strategy for training of semantic communication systems. By assigning a single SNR value to each training data sample, the proposed method provides structured exposure to diverse channel conditions and improves channel adaptability. In the proposed training framework, an equivalent parallel additive white Gaussian noise (AWGN) channel model is employed to facilitate stochastic sampling of channel parameters and to guide semantic transceivers toward learning representations that generalize across a wide range of SNR values. A comprehensive comparison with batch-level and latent variable–level sampling schemes highlights the critical role of sampling granularity in balancing channel diversity and model adaptability. Furthermore, experimental results demonstrate that the proposed DLPS-based training framework achieves highly competitive performance across a wide range of SNR conditions compared to SNR-specific training.

The remainder of this paper is organized as follows. Section II describes the semantic communication system model. Section III presents the proposed DLPS-based training framework. Section IV justifies the effectiveness of the proposed approach through extensive simulations. Finally, Section V concludes the paper.

II. System Model

Fig. 1 illustrates the semantic communication system for image transmission [6]. At the transmitter, an N-dimensional input image $\mathbf{v}$ is mapped into a K-dimensional latent representation $\mathbf{x} = f_\theta(\mathbf{v})$ through the encoder network $f_\theta(\cdot)$ parameterized by weights θ. The latent variables $\{x_k\}_{k=1}^{K}$ are normalized to satisfy a unit-power constraint. The latent vector $\mathbf{x}$ is then transmitted over a complex baseband channel. The corresponding received vector is given by $\mathbf{y}$, whose k-th component is given by $y_k = hx_k + n_k$, where h denotes the complex channel gain and n_k represents the complex

This work was partly supported by the Institute of Information & Communications Technology Planning & Evaluation(IITP)-ITRC(Information Technology Research Center) grant funded by the Korea government(MSIT)(IITP-2026-RS-2023-00259991, 50%) , and by the Basic Science Research Program through the National Research Foundation of Korea (NRF), funded by the Ministry of Education (RS-2025-25432451, 50%).

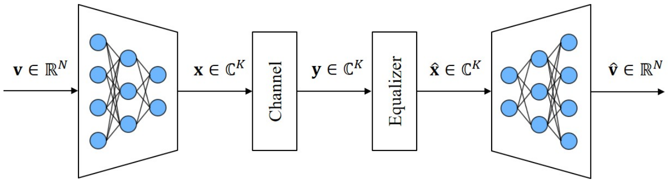

Fig. 1. Semantic communication system model.

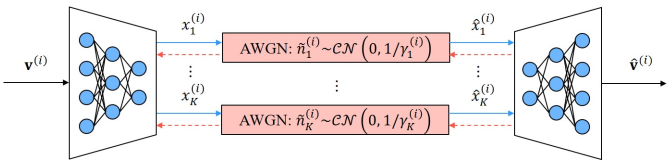

Fig. 2. Equivalent parallel AWGN channel model for training semantic communication transceivers.

AWGN with zero mean and variance σ^2. Under the unit-power normalization, the resulting SNR is given by $\gamma = |h|^2/\sigma^2$. At the receiver, single-tap equalization is applied to compensate for the channel gain. The equalized vector is defined as $\hat{\mathbf{x}}$, whose k-th component is given by $\hat{x}_k = x_k + \tilde{n}_k$, where $\tilde{n}_k = h^* n_k/|h|^2$ denotes the effective AWGN with zero mean and variance $1/\gamma$. The equalized vector $\hat{\mathbf{x}}$ is then fed into the decoder network $f_\phi(\cdot)$, parameterized by weights ϕ, which reconstructs the image as $\hat{\mathbf{v}} = f_\phi(\hat{\mathbf{x}})$.

III. Proposed Training Framework

Based on the equalized signal model, the latent variable transmission between the encoder output and decoder input can be represented as equivalent parallel AWGN channels, as illustrated in Fig. 2. We note that the characteristics of these equivalent channels are fully determined by their SNR values. Training the transceiver under a fixed SNR leads to a specialized model for that particular condition, limiting generalization ability to diverse channel conditions. To overcome this limitation, we propose a data-level parameter sampling (DLPS) strategy, in which the SNR (or noise variance) of each equivalent AWGN channel is randomly sampled during training. Based on these sampled parameters, a training framework is constructed to jointly optimize the encoder and decoder networks, enabling the transceiver to adaptively operate across various channel environments.

A mini-batch $\mathcal{B} = \{\mathbf{v}^{(i)}\}_{i=1}^{B}$ is drawn from the training dataset. During the forward pass, the i-th image sample $\mathbf{v}^{(i)}$ is transformed into a latent vector $\mathbf{x}^{(i)}$ by the encoder $f_\theta(\cdot)$. The latent variables $\{x_k^{(i)}\}_{k=1}^{K}$ are transmitted through the parallel equivalent AWGN channels in the complex baseband. For the k-th channel, the equalized signal is given by

$$\hat{x}_k^{(i)} = x_k^{(i)} + \tilde{n}_k^{(i)}. \tag{1}$$

Here, $\tilde{n}_k^{(i)}$ denotes the effective AWGN with zero mean and variance $1/\gamma_k^{(i)}$, where $\gamma_k^{(i)}$ represents the training SNR applied to the transmission of the k-th latent variable of the i-th image sample. The equalized signals $\{\hat{x}_k^{(i)}\}_{k=1}^{K}$ are then processed by the decoder $f_\phi(\cdot)$ to reconstruct the image $\hat{\mathbf{v}}^{(i)}$. For backpropagation, the loss function is defined as the mean-squared error between $\mathbf{v}^{(i)}$ and $\hat{\mathbf{v}}^{(i)}$, given by $L(\theta, \phi) = \frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{B}} \|\mathbf{v}^{(i)} - \hat{\mathbf{v}}^{(i)}\|^2$. To minimize the loss function, the forward pass and backpropagation are iteratively executed, thereby enabling joint optimization of the encoder and decoder parameters (θ, ϕ). To construct a transceiver that generalizes well across diverse wireless conditions, we adopt a parameter sampling strategy that varies the SNR applied to the equivalent parallel AWGN channels.

Let the operating SNR range be defined as $\Gamma = [\gamma_{\min}, \gamma_{\max}]$. In general parameter sampling, the SNR value $\gamma_k^{(i)}$ for the k-th latent variable of the i-th data sample can be randomly drawn from Γ, and applied to the corresponding AWGN channels. Such randomized assignment exposes the transceiver to a wide range of channel conditions, leading to robust reconstruction performance across the entire operating SNR. However, the effectiveness of SNR sampling is heavily influenced by the granularity at which the parameters $\{\gamma_k^{(i)}\}_{i,k}$ are sampled. To systematically control this granularity and enhance robustness to diverse channel conditions, we propose the DLPS strategy as follows.

The DLPS strategy assigns a single training SNR to each data sample when modeling the equivalent parallel AWGN channels. For the i-th data sample $\mathbf{v}^{(i)}$, one training SNR $\gamma^{(i)}$ is uniformly drawn from Γ, and applied identically to the transmission of latent variables through all K equivalent parallel AWGN channels, i.e.,

$$\gamma_k^{(i)} = \gamma^{(i)}, \quad \forall k \in \{1, \ldots, K\}. \tag{2}$$

Under this assignment, all latent variables within a data sample experience the same channel distribution during the forward pass, effectively mimicking a block-fading scenario. This per-sample consistency is advantageous when training semantic communication transceivers for practical fading environments, because exposure to a unified channel condition encourages the transceiver to learn representations that remain robust even when the channel changes abruptly across blocks.

IV. Simulation Results

To validate the performance of the proposed training framework, we consider a semantic communication system for image transmission [6] using the CIFAR-10 dataset. Image reconstruction quality is evaluated using the peak signal-to-noise ratio (PSNR). Training is performed with the Adam optimizer using a learning rate of 10^{-3}, a mini-batch size of 256, and 20 training epochs. To validate the effectiveness of the proposed granularity of parameter sampling, we consider the following two benchmark strategies.

- Batch-level parameter sampling (BLPS): BLPS assigns a single training SNR to the entire mini-batch $\mathcal{B}$. A value γ is randomly sampled from Γ, and identically applied to all K latent variables of all $|\mathcal{B}|$ data samples, as $\gamma_k^{(i)} = \gamma$, $\forall i, k$. This approach provides a consistent channel condition within each batch while still enabling the model to experience various SNR values across batches.

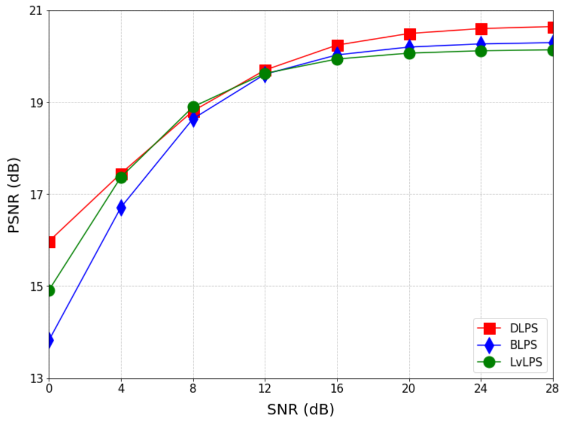

Fig. 3. Comparison of image reconstruction performance for different parameter sampling granularities, with latent space dimension $K = 88$.

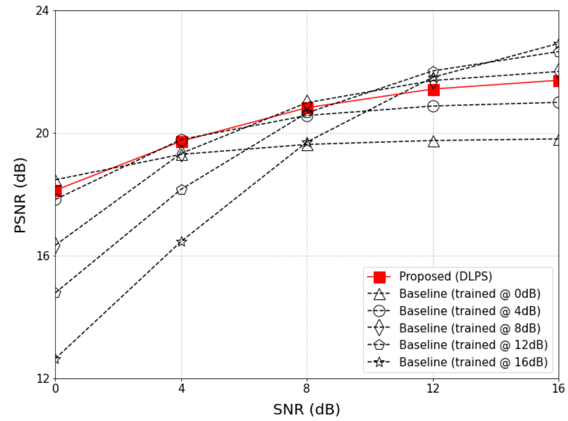

Fig. 4. Performance comparison between the proposed DLPS-based training and SNR-specific training (Baseline), with latent space dimension $K = 264$.

• Latent variable-level parameter sampling (LvLPS): LvLPS samples an independent training SNR for each latent-variable level. For all i and k, the SNR values $\gamma_k^{(i)}$ assigned to the k-th latent variable of the i-th sample is randomly drawn from Γ. Thus, each latent variable is transmitted through an equivalent AWGN channel with its own distribution, enabling the model to experience a wide variety of channel conditions simultaneously during training.

Fig. 3 presents the image reconstruction performance of the three sampling strategies. The proposed DLPS method consistently achieves the highest PSNR across the entire SNR range. In contrast, BLPS shows the poorest reconstruction quality under low-SNR conditions because the SNR discrepancies across batches slow down convergence during training. Although LvLPS increases channel diversity by independently sampling SNR values for each latent variable, the resulting high degree of randomness enlarges the loss variability and ultimately degrades PSNR performance. Overall, DLPS provides the most effective balance between controlled channel variability and adaptability, achieving the strongest generalization performance among the three approaches.

Fig. 4 demonstrates a performance comparison between the proposed DLPS-based training framework and a dedicated training framework, in which the transceiver is trained for a single operating SNR. Despite minor performance degradation in a limited SNR range, the DLPS approach maintains consistently competitive PSNR across the entire SNR range using only a single unified model. In contrast, the five dedicated models, each trained separately at $\{0, 4, 8, 12, 16\}$ dB, exhibit the highest performance only at their respective training SNRs, while exhibiting clear degradation under mismatched SNR conditions. These results confirm that the proposed DLPS-based training framework offers superior generalization capability and channel adaptability by exposing the model to diverse channel conditions within a single training process.

V. Conclusion

In this paper, we propose a DLPS-based training framework to enhance the generalization capability and channel adaptability of semantic communication transceivers across diverse wireless environments. By leveraging equivalent parallel AWGN channel modeling, the proposed framework stochastically samples channel parameters (i.e., SNRs) at the data-sample level, thereby enabling the encoder and decoder to experience a wide range of channel conditions within a single training process. Simulation results demonstrate that the proposed DLPS strategy outperforms other sampling-granularity methods and achieves highly competitive performance compared to dedicated SNR training. These findings confirm that the DLPS-based training framework effectively improves the robustness and adaptability of semantic communication systems under diverse channel conditions.

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