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Denoising Method for Wireless Communication Signals Based on Convolutional AutoEncoder

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Abstract: In this paper, we propose a method to effectively remove noise from signals by utilizing convolutional autoencoder. In particular, the proposed method focuses on converting sequence signals into images and removing noise through image-based signal processing methods to improve signal quality while preserving key signal characteristics. Experiments were conducted using 5G demodulation reference signal data simulating real-world wireless communication environments, and a test bed was built based on two rdio universal software peripherals to obtain reliable results. Experimental results show that the proposed method achieves an average classification accuracy improvement of 32.6% and a maximum of 47.9%, and also performs well in low signal-to-noise ratio environments, especially in the -2.81dB signal-to-noise ratio environment, where it achieves a significant accuracy improvement over the model without denoising. This work demonstrates the potential to effectively improve the quality of wireless signals in various noisy environments and suggests its applicability to real-world communication systems.

1 INTRODUCTION

In wireless networks, accurate signal transmission and reception is critical to maintain communication performance. Signal classification might be one of the key challenges for efficient communication. However, unpredictable noise in the transmission channel due to various factors such as inter-channel interference, propagation paths, and environmental conditions can significantly degrade communication quality. To address these issues, effective techniques are needed to mitigate the impact of noise. Traditionally, frequency domain-based signal processing techniques, such as filtering techniques, have been used to remove noise. While these methods can be effective in static environments, they also have clear limitations in complex wireless environments.

With the recent advancement of deep learning technology, data denoising has been actively studied in various fields, especially in the field of image processing, where convolutional AutoEncoder(CAE)-based methods have demonstrated excellent performance [1, 2, 3]. In addition, research on denoising using CAE for various signal data is gradually expanding [4, 5, 6]. However, since wireless communication data is composed of complex numbers, there are limitations in applying existing denoising models. Therefore, a customized approach that reflects the characteristics of wireless communication data is required.

With recent advances in deep learning technology, data denoising has been actively studied in various fields, and CAE-based methods have demonstrated excellent performance, especially in image processing However, since wireless communication data is composed of complex numbers, there are limitations in applying existing denoising models to wireless communication data. Therefore, a customized approach that reflects the characteristics of wireless communication data is required.

In this study, we propose a method to effectively denoise complex signals using CAE after converting the data into a form that considers the relationship between the real and imaginary parts of wireless communication data. In addition, we systematically analyzed the effect of adding various levels of noise on denoising performance, and evaluated the performance of the proposed method using real 5G DeModulation Reference Signal(DMRS) data to verify its applicability in real-world environments. This study aims to provide a basic technology that can maintain reliable communication quality even in complex wireless environments. The main contributions of this re-

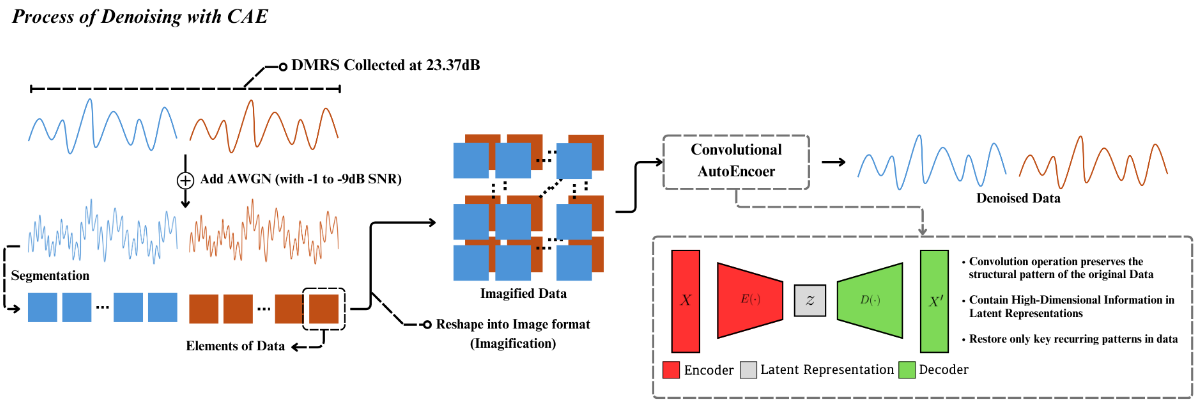

Figure 1: Overall Structure of CAE based Denoising

search can be summarized as follows:

- Propose a method to remove noise from noisy radio signals based on CAE after converting radio signal data into image form.
- Quantitatively analyze the denoising effect of different noise levels by adding different levels of noise.
- Demonstrate the effectiveness of the proposed method through a real-world testbed implementation utilizing 5G DMRS data.

2 DENOISING METHOD BASED ON CAE

2.1 Light-weight Imagification

Reference signals in communication systems are typically represented as continuous sequences in the time domain. To effectively visualize the complex patterns of these continuous signals and extract their spatial features, this study utilizes a lightweight technique based on the RGB color model proposed in our previous work [7, 8, 9]. In a wireless communication environment, a signal is composed of in-phase and quadrature components. In this study, we map the in-phase and quadrature components to the R and G channels of the RGB color model, respectively. This process is defined as Equation 1:

$$DMRS\_RG_i = \begin{cases} R_i[n] = I_i[n] \\ G_i[n] = Q_i[n] \end{cases}, n \in [0, 143] \quad (1)$$

Here, $I_i[n]$ and $Q_i[n]$ represent the In-phase and Quadrature-Phase of the input signal, respectively, and the spatial features are visually represented by converting the principal components of the signal into two independent color channels. In addition, the process of converting the one-dimensional signal into a two-dimensional matrix was performed to visualize the signal. The transformation process is defined as Equation 2, 3:

$$N = ceil[\sqrt{max(n)}] \quad (2)$$

$$DMSR_{1D}Seq[n] \rightarrow DMRS_{2D}Seq[n/N][n \quad (3)$$

Where N determines the size of the row and column of the two-dimensional matrix, which is determined by the total number of samples, n, in the input signal. By reorganizing a one-dimensional sequence signal into a two-dimensional matrix, this transformation facilitates visual interpretation of the signal and allows for more effective spatial pattern extraction. Based on the generated visual signal data, the denoising model removes noise and contributes to learning the main features of the signal.

2.2 Denoising Method

CAE is a model that adds a convolutional layer to an auto-encoder structure consisting of an encoder and a decoder, which can effectively remove noise from the input signal while preserving the main signal characteristics.

The general learning process of this study is presented in Figure 1. First, the sequence signal is converted to a two-dimensional image using an imaging technique, and then additive white Gaussian noise(AWGN) is added to the converted image. The noisy image is then compressed into a latent representation by an encoder. This latent space retains the main patterns of the original signal and contains information that has been effectively filtered out by the noise. The decoder restores the latent vector to a signal of the same size as the input signal, and finally, the classifier classifies the indices in the signal. The classifier consists of a convolutional layer and a dense layer.

The Rectified Linear Unit(ReLU) activation function is applied to each layer of the CAE, and the Softmax activation function is used for the output layer of the classifier. During the training process of the model, the loss function is defined as Equation 4:

$$\mathfrak{L} = \lambda \cdot MSE(x, \hat{x}) + (1 - \lambda) \cdot CCE(y, \hat{y}) \quad (4)$$

Where $MSE(x, \hat{x})$ denotes the Mean Squared Error between the original signal x and the reconstructed signal $\hat{x}$, and $CCE(y, \hat{y})$ denotes the Categorical Cross Entropy loss between the actual class y of the signal and the predicted class $\hat{y}$. λ is a hyperparameter that adjusts the weight between the reconstruction loss and classification loss, which is experimentally set to λ=0.3 in this study. The encoder in CAE consists of two convolutional layers, which use 16 and 8 3×3 kernels, respectively. The decoder consists of two Transposed Convolution layers that use the same size kernels. This structure enables learning-based denoising, which can effectively remove noise while preserving the main characteristics of the signal during denoising.

3 EXPERIMENTS & RESULTS

The experiments in this study were set to a batch size of 256 and an epoch count of 100, and the Adam optimizer was used as the optimization algorithm. The experimental data was collected using 5G DMRS acquired from a Universal Software Radio Peripheral(USRP) B210 and a PC-based user equipment(UE) in a general purpose environment [10, 11]. The data includes real and imaginary components of the signal, with each component consisting of 144 samples. The overall shape of the collected data is $N, 144 \times 2$, where N represents the total number of data samples. Figure 2 schematizes the data collection process and the experimental scenario. In this study, we collected data under 12 different Signal-to-Noise Ratio(SNR) environments, ranging from 23.37dB to -4.6dB, each of which is designed to reproduce realistic wireless channel conditions. In addition, the collected data contains a total of 8 classes (Index), ranging from 0 to 7. Each class represents a unique characteristic of the signal, and was used to evaluate the classification model.

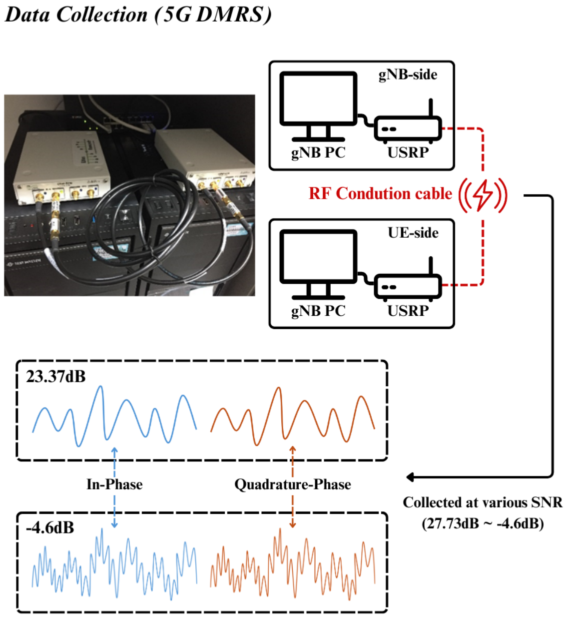

Figure 2: Testbeds and data collection process

SNR	23.37dB, 9.56dB, -2.51dB, -2.74dB, -2.81dB, -2.99dB, -3.13dB, -3.42dB, -3.7dB, -4.11dB, -4.5dB, -4.6dB
Index	0, 1, 2, 3, 4, 5, 6, 7
Data Shape	$1 \times 144 \times 2$
Total Data	12(SNR) × 8(Index) × 5,000 → 480,000

To evaluate the performance of the proposed model in this study, experiments were conducted under different SNR environments. Figure 3 schematizes the results of the denoising experiments as a function of noise level, showing the change in classification accuracy under each SNR condition. The experimental results show that when noise of -1dB SNR was added, the classification accuracy improved by 32.6% on average, and at -2.81dB, the accuracy increased to 47.9%, where -1 dB SNR means that the SNR reached -1dB due to the added noise, which is defined as noise of -1dB SNR in this study.

On the other hand, when the amount of noise was increased excessively, a sharp degradation in signal identification performance was observed. In particular, when noise of -7dB and -9dB SNR was added, the model did not learn, which is interpreted as the original characteristics of the signal were completely lost. These results suggest that a moderate level of noise can contribute to the improvement of the classification performance of the signal. The results presented in Figure 3 show that the proposed denoising model can effectively restore the main patterns of the signal under different noise levels. Furthermore, by utilizing AWGN for training, we demonstrate that the model

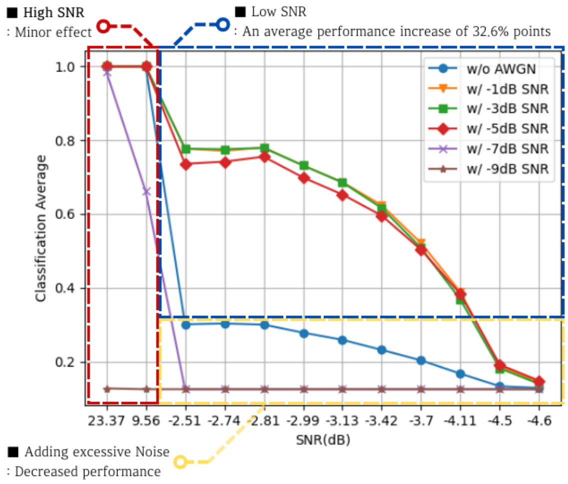

Figure 3: Accuracy Comparison by Normal Classifier and CAE(※ Noise at -1 to -9 dB SNR level)

can effectively remove the random noise that may occur in the real world.

4 CONCLUSIONS

In this study, we propose a wireless signal denoising framework based on imagification and CAE. The proposed denoising framework has been shown to improve signal classification performance at various SNR levels. We also evaluated the model using signals collected in real-world environments and confirmed that the model is robust to random noise. As various types of noise exist in real-world communication environments, further research is needed to consider them. In future work, experiments that reflect realistic problems such as non-Gaussian noise and channel distortion can be conducted to further validate the generality and performance of the proposed method.

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