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A U-NET ARCHITECTURE FOR TIME-FREQUENCY INTERFERENCE SIGNAL SEPARATION OF RF WAVEFORMS

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ABSTRACT

This paper presents a data-driven approach to solve the challenge of separating co-channel mixture signals in the radio spectrum. The main aim is to extract the signal-of-interest with high fidelity from the mixture signal, allowing improved performance in demodulation and decoding tasks. We have developed a U-Net architecture specifically designed for the separation of interference signals within the time-frequency domain. This architecture integrates elements of OFDM signal resource grid configurations, like the cyclic prefix, ensuring a tailored and effective approach to signal processing. This approach has demonstrated a significant improvement, with an average 63% enhancement in MSE performance over the baseline model on four different interference types.

Index Terms— Source separation, machine learning, interference rejection, Short-Time Fourier Transform (STFT), wireless communication.

1. INTRODUCTION

In the evolving landscape of communication systems, a critical challenge emerges from the shared use of the same segments of the radio frequency spectrum by various communication technologies. This leads to co-channel interference, a phenomenon where multiple signals overlap in the same frequency band, resulting in significant degradation of signal quality and reliability. This issue is particularly pronounced in scenarios where spectrum resources are limited [1]. Historically, the challenge of source separation in the radio frequency domain has been a topic of considerable research interest. Traditional methods such as linear minimum mean squared error (LMMSE) often rely on signal processing techniques that require knowledge of the signal characteristics or the environment. However, these methods face limitations in adaptability and scalability, especially in dynamic or complex interference scenarios.

As the demand for spectrum resources continues to grow, the need for more efficient and intelligent source separation techniques becomes increasingly important [2]. In recent years, deep learning has emerged as a powerful tool for addressing complex signal processing challenges, including the separation of overlapping signals in the RF spectrum. The ICASSP 2024 conference hosted a competition on RF separation, focusing on QPSK and OFDM QPSK, hereafter referred to as OFDM [3]. This paper delves into the intricacies of a U-Net[1] based architecture, exploring how it leverages the known configurations of OFDM signal grids and time-frequency representations to effectively mitigate co-channel interference.

2. METHODOLOGY

This research introduces a U-Net model tailored for the task of RF signal separation [4], with a focus on OFDM signals. The architecture of our model is a U-Net, comprising six encoder layers and five decoder layers.

2.1. Model Architecture

In the OFDM signal structure, each symbol is comprised of 80 samples, of which the first 16 are the Cyclic Prefix (CP), and the remaining 64 correspond to the subcarriers. Out of these 64 subcarriers, 56 carry nonzero symbols [3]. Our model applies a short-time Fourier transform (STFT) with an FFT size of 64 and a hop length of 80, ensuring each FFT computation captures only the 64 subcarrier samples and skips the 16-sample CP, aligning precisely with each OFDM symbol. Conversely, at the output of the model, the inverse STFT (iSTFT) is applied to reconstruct the time-domain signal. The kernel size for each layer is consistently set to 3, and group normalization is implemented across all layers with a size of 8 to enhance the model's ability to generalize. Our U-Net model, Fig. 1, employs a configuration of varying encoder strides [1, 2, 2, 2, 2, 2] and encoder filters [192, 256, 384, 512, 512, 512]. Additionally, we utilize residual connection-based convolution blocks in our network architecture, which effectively prevent the vanishing gradient problem while adding depth and complexity.

2.2. Data Handling and Preprocessing

The dataset utilized follows the guidelines set by the challenge organizers [3]. To augment the dataset, we apply transformations to both the phase and amplitude of the interference

[1] https://github.com/MostafaUgent/UNet_time_freq_CP

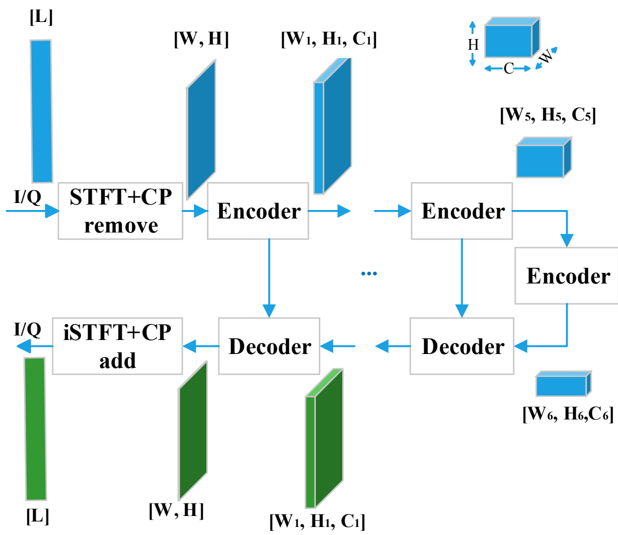

Fig. 1. Schematic of the interference cancellation model, detailing the input tensor's progression. Starting with an in-phase and quadrature (I/Q) baseband RF signal, the model applies STFT and CP removal to obtain the time-frequency domain representation [W, H]. The signal is then processed through a sequence of encoders and decoders, culminating in an iSTFT with CP addition for interference mitigation.

signal. During training, we process the complex-valued input samples into real values, training them with a batch size of 2. The data is formatted into two separate channels representing the real and imaginary parts, conforming to a structure of $[batch, channel, length]$, where $batch = 2$, $channel = 2$, and $length = 40960$. We employ 5-fold cross-validation to ensure distinct separation of training and validation sets.

2.3. Model Parameters and Configuration

The model is trained using a truncated mean squared error loss, aligning with the challenge's scoring criteria [3]. The optimization is carried out using the Adam optimizer, with an initial learning rate of 0.0002 and a cosine annealing scheduler. This setup is selected to achieve a balance between rapid convergence and avoiding local minima. For testing, we utilize separate frames that were not included in the training and validation datasets. This approach ensures the robustness and generalizability of the model's performance.

3. RESULTS

Table 1 demonstrates the performance of the proposed U-Net model as compared to no mitigation, LMMSE, as well as U-Net and WaveNet baselines. Utilizing a 2D U-Net architecture for OFDM signal processing, our model achieved average MSE values: -19.31 dB for EMI, -13.32 dB for Comm2, -4.84 dB for Comm3, and -14.39 dB for Comm5G scenarios. These figures notably surpass those of challenge baseline methods, such as Baseline WaveNet and Baseline U-Net, across all interference types. While our 2D U-Net model excelled in the OFDM signal-of-interest (SOI), a different approach was adopted for the QPSK SOI, where a 1D U-Net model was utilized. This distinction is crucial, as it highlights the model's adaptability to different signal characteristics. The superior performance of the 2D model in OFDM scenarios can be attributed to its design. This tailored approach to handling the unique aspects of OFDM signal structures, such as dealing efficiently with the CP, likely contributes to its outstanding performance in these contexts.

Method	EMI	Com2	Com3	Com5G
No Mitigation	15/0	15/0	15/0	15/0
LMMSE	-3.3/0	-2.0/0	-1.9/0	-5.4/0
Base U-Net	-9.2/1.6	-5.4/0.8	-1.8/0	-8.4/0
Base WaveNet	-12.9/1.6	-6.6/0.8	-2.3/0	-10.8/1.6
Proposed Model	**-19.3/2.7**	**-13.3**/0.8	**-4.8**/0	**-14.4**/1.6

Table 1. Performance comparison in terms of average MSE (in dB)/BER score for SINRs ranging from -30 to 0 dB across various interference types. Our proposed method improves MSE (linear) by 76.93%, 78.67%, 43.77%, 55.84% for EMI, Comm2, Comm3, and Comm5G, respectively.

4. REFERENCES

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