IMPROVING DATA-DRIVEN RF SIGNAL SEPARATION WITH SOI-MATCHED AUTOENCODERS

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ABSTRACT

While the use of deep learning-based methods in radio frequency (RF) signal processing has steadily increased in recent years, little attention was paid to RF signal separation, especially for scenarios with a single antenna receiver. In order to further investigate single-channel signal separation, the ICASSP 2024 SP Grand Challenge on "Data-Driven RF Signal Separation" was organized. This paper presents the challenge submission that was labeled *LHen*. We extend the WaveNet baseline model with an autoencoder that is matched to the signal of interest and significantly improves system performance in terms of mean squared error evaluation metric.

***Index Terms*—** RF challenge, single-channel signal separation, radio frequency machine learning, RFML

1. INTRODUCTION

The increasing use of wireless devices leads to radio frequency (RF) band congestion as different technologies share the same spectrum. Signal separation or interference mitigation capabilities are necessary to protect the own communication link from interference. For RF reception with multiple antennas, various smart antenna or beamforming approaches [1], including methods based on deep neural networks (DNNs) [2], exist. For single-channel scenarios, the rising capabilities of DNNs for audio source separation (ASS) promise potential for the RF domain as well. In [3] the authors applied neural architectures for ASS to OFDM signals and demonstrated improved separation performance with a modified architecture. To further investigate single-channel signal separation (SCSS) in the RF domain, the "Data-Driven RF Signal Separation Challenge" [4] was launched. In the challenge, submitted systems have to separate signals of interest (SOI) from interference, measured using the mean squared error (MSE) and bit error rate (BER), for different types of SOI and interfering signals.

In this paper, we present our submission to the challenge which ranks 2nd and 4th in terms of MSE and BER scores respectively. Our approach comprises SOI-matched autoencoders which extend the WaveNet baseline model and enable to learn the demodulation and re-synthetization of the SOI.

2. DATASETS

The SCSS challenge considers 2 types of SOI, QPSK and OFDM, and 4 types of interfering signals resulting in 8 different signal mixture scenarios [4]. The generation process of the SOI is known whereas the characteristics of the interfering signals have to be learned from recorded signal data. For QPSK signals, 16 samples per symbol and a pulse shaping filter of length 127 are used. For OFDM signals, an IFFT length of 64 is used to map QPSK symbols to their carriers, where only 56 of 64 carriers are active. A cyclic prefix of length 16 results in 80 samples per OFDM symbol. The SOI have constant signal energy and are assumed to be synchronized and equalized. The recorded interferences, on the other hand, are scaled and added to the SOI to obtain the desired range of signal-to-interference-plus-noise ratio (SINR). By subdividing the recordings, development and evaluation datasets are created for all scenarios.

3. METHODOLOGY

In the challenge, two DNNs were proposed as baseline methods to estimate the SOI: first, a modified UNet studied in [3] and second, a WaveNet variant [5], both trained with MSE loss functions. Since the WaveNet model has a better overall separation performance, it is utilized in our approach.

3.1. Proposed systems

We extend the WaveNet by an encoder-decoder structure which is matched to the modulation type of the SOI. The encoder is designed such that it is able to learn the demodulation of the waveform estimated by the WaveNet. The corresponding decoder learns the modulation process by re-synthesizing the SOI waveform from the extracted bit sequence, such that the estimated waveform results in a low MSE. The autoencoder architectures for both types of SOI are depicted in Figure 1. The output of the penultimate layer of the WaveNet is used as input for the encoder to provide a more informative input. The dimensions of the latent space correspond to the bit message length, i. e. 5120 for QPSK and 57344 for OFDM. For QPSK, the encoder downsamples the input using

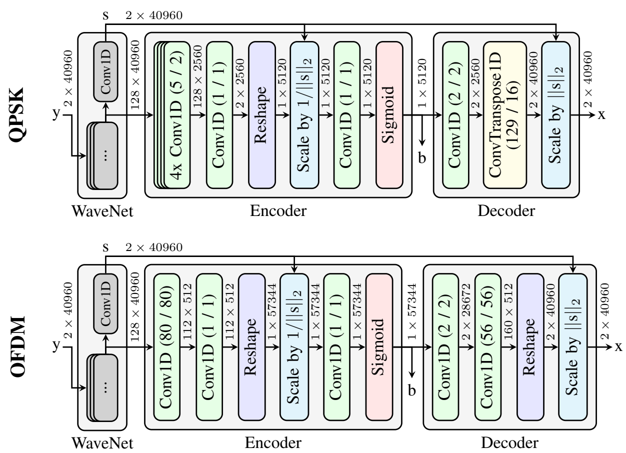

Fig. 1. Encoder-decoder architectures for both SOI.

4 convolutional layers with stride 2 and extracts QPSK symbols to estimate the transmitted bit sequence b. The decoder utilizes a convolutional layer to map the bit sequence back to QPSK symbols as well as a transposed convolutional layer with a kernel size of 129 and a stride of 16, such that an appropriate pulse shaping for generating the QPSK waveform x can be learned. For OFDM, the encoder's first convolutional layer learns the transformation of the input from time to frequency domain, using a kernel size and stride equal to the OFDM symbol length of 80. The number of output channels is related to the 56 active carriers, which allows to extract the QPSK symbols per carrier and finally the corresponding bits b. The decoder consists of a convolutional layer mapping b to QPSK symbols and another convolutional layer transforming sequences of 56 QPSK symbols to 80 I/Q samples such that the OFDM waveform x is retained after reshaping. A crucial final step is the scaling of the decoder output x, as it has an approximately constant signal power for binary input b of the decoder, independent of the SINR of the mixture signal y. To achieve a competitive MSE for all SINR values, we use the signal power of the WaveNet output s as a suitable estimate for the scaling factor with respect to the SINR of y.

3.2. Training details

By estimating bit sequence b with the encoder and waveform x with the decoder, we can introduce a modified loss function related to b and x, i. e. we use an equally weighted combination of binary cross entropy (BCE) and MSE as loss function. We train the systems using the Adam optimizer and a multistep learning rate schedule ranging from 10^{-3} to 10^{-7}. In a first step, the WaveNet parameters are fixed and only the encoder-decoder structure is trained for 100 epochs, where 1000 unique SOI realizations and corresponding signal mixtures are generated per epoch. In a second step, all parameters are fine-tuned for another 100 epochs, allowing improvements in the signal separation capabilities of the WaveNet.

Table 1. MSE and BER scores of the baseline models and our approach for all signal scenarios, with lower being better.

		QPSK				OFDM				
	Model	EMI	C2	C3	C5G	EMI	C2	C3	C5G	Total
MSE	UNet	-23.1	-17.4	-4.2	-4.8	-9.2	-5.4	-1.8	-8.4	-74.3
	WaveNet	-28.9	-23.2	-4.8	-29.8	-12.9	-6.6	-2.3	-10.8	-119.4
	Proposed	-29.0	-25.3	-5.0	-30.7	-15.9	-12.7	-2.4	-12.0	**-132.9**
BER	UNet	-21	-18	0	3	-9	-6	3	3	-45
	WaveNet	-21	-18	0	-18	-9	-6	3	-9	**-78**
	Proposed	-21	-15	0	-18	-9	-6	3	-9	-75

4. RESULTS

The performances of both baseline models and our approach on the final evaluation dataset are presented in Table 1. In terms of MSE, the autoencoder extension improves the system performance for all combinations of SOI and interferences, leading to a significantly lower final MSE score. Nevertheless, the performance with regard to BER remains the same and even deteriorates slightly in one scenario, with the latter only occuring after fine-tuning. While the initial autoencoder training already improves MSE, fine-tuning leads to even lower MSE scores in most signal scenarios.

5. CONCLUSIONS

Extending the baseline WaveNet by an SOI-matched autoencoder enables the model to learn the demodulation and resynthetization of the SOI. Our submission ranked 2nd and 4th out of 7 competitors in terms of MSE and BER scores respectively. The results show that our approach improves the separation performance in terms of MSE for all signal scenarios considered in this challenge. Since it is a modular approach, it can be applied to other signal separation systems including other submitted systems of the challenge.

6. REFERENCES

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