THE DATA-DRIVEN RADIO FREQUENCY SIGNAL SEPARATION CHALLENGE

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ABSTRACT

The radio-frequency (RF) signal separation challenge involves recovering a signal-of-interest (SOI) from a super-imposed co-channel interference signal. The SOI is a digital communication waveform of known modulation, pulse-shape, timing, etc. The interferer is unknown and must be learned from data. Submissions featured a blend of signal processing strategies, leveraging RF-specific domain knowledge and novel neural network architectures with careful hyperparameter selection/optimization. The resulting solutions establish new benchmarks for data-driven RF modeling and interference cancellation.

Index Terms— Source separation, interference rejection, machine learning, wireless communication.

1. INTRODUCTION

Applications using bands of the RF spectrum increasingly experience substantial *co-channel* interference, i.e., degradation from other waveforms that are superimposed [1]. Such degradation is avoided by the use of *interference mitigation* techniques, often explicitly or implicitly via *signal separation*. The goal is to extract the signal-of-interest (SOI) with high fidelity, thereby enhancing downstream task's performance (e.g., demodulation and decoding). While machine learning techniques have shown promise in source separation within computer vision and audio domains, the RF setting presents unique challenges. The signal processing challenges of interest are: given nonGaussian, nonstationary co-channel interference, 1) separate a SOI from the interference; and 2) demodulate the SOI component in such a mixture. Because of lack of both othogonality between the constituent signals and prior knowledge of the interference structure, conventional separation via time- and frequency-selective filtering are ineffective. Hence, addressing these challenges calls for new learning methods and architectures [2, 3]. These methods must identify less obvious features not readily discernible through standard time and/or frequency domain analysis. Such data-driven RF signal separation and/or interference mitigation tools can significantly benefit various applications, even including several beyond the RF realm.

2. DEMODULATION CHALLENGE

We consider mixture signals, each 40960-samples long, of the form $y = s + b$ where s is the SOI, a digital communication signal whose generation process is known, and b is an interference signal, which is a time-series segment from our *dataset* (detailed in Section 3). We focus on two types of SOI, single-carrier QPSK and orthogonal frequency division multiplexing (OFDM)—specifications are provided.[1] We denote by m the bits comprising the message carried by the SOI.

The goal is to develop a data-driven solution to reject the co-existing interference, and ultimately estimate the SOI waveform and its bit-sequence message from y. The metrics are: 1) the *mean-square error (MSE)* between the estimate $\hat{s}$ and the true SOI s; and 2) the *bit error rate (BER)* between the estimated bits $\hat{m}$ and the true bits m. Participants' final scores are computed based on these metrics.

3. DATASET

The relevant mixture signals are created from a "global" dataset comprising examples of four types of interference:

1. EMISignal1: an electromagnetic interference due to unintentional radiation from a man-made source;
2. CommSignal2: a digital communication signal from a commercially available wireless device;
3. CommSignal3: a (different) digital communication signal from a commercially available wireless device; and
4. CommSignal5G1: a 5G-compliant waveform.

4. SUMMARY OF RESULTS

Figure 1 shows the performance of the 5 best submissions on the evaluation set TESTSET2MIXTURES, benchmarked against our best learning-based baseline. The plots depict BER and MSE versus target SINR for the respective SOI-interference combinations. Table 1 shows their team ranking based on challenge's MSE and BER scores.[1] The baseline method was trained on INTERFERENCESET, using a modified WaveNet architecture [3, 4]. Implementation details are included with the challenge's starter code.[3]

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[1]https://rfchallenge.mit.edu/wp-content/uploads/2023/11/ICASSP24_RF_Challenge.pdf
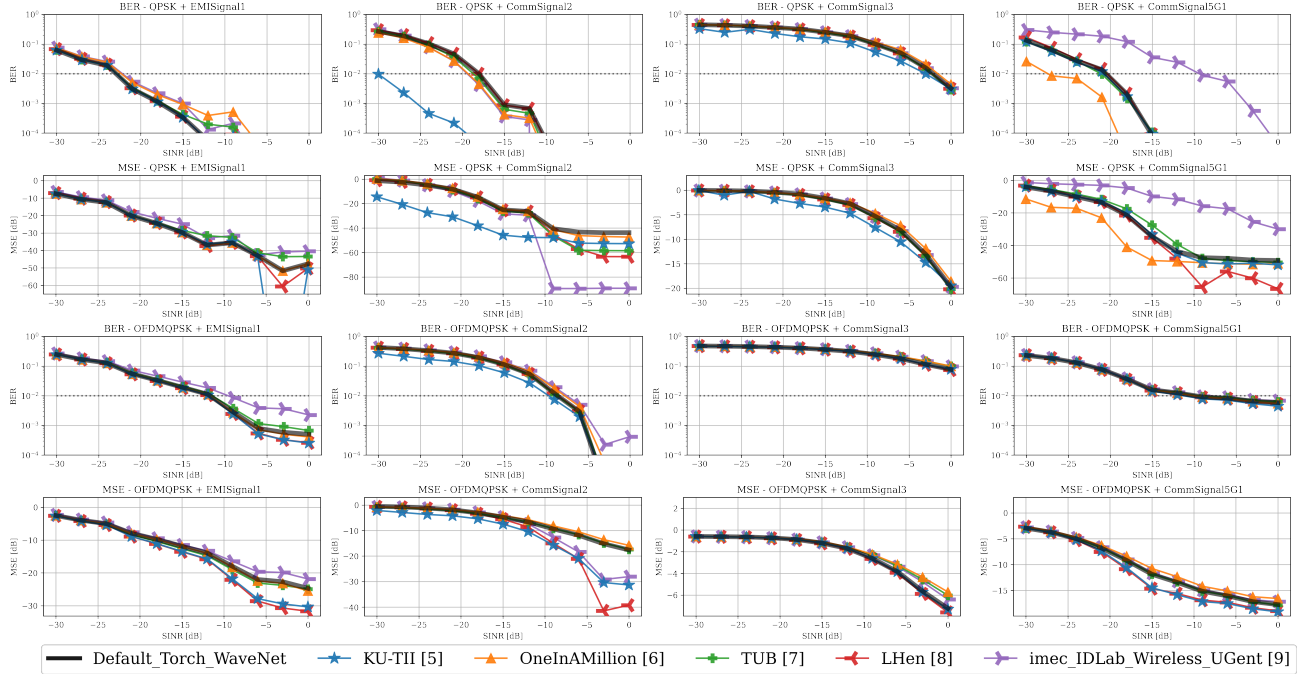[3]https://github.com/RFChallenge/icassp2024rfchallenge

Fig. 1: BER and MSE as a function of the target SINR for all combinations of SOI and interferences in this challenge.[2]

Table 1: MSE and BER Rankings

Team	MSE	Team	BER
1. KU-TII	-145.91	1. KU-TII	-96
2. LHen	-132.91	2. OneInAMillion	-87
3. OneInAMillion	-125.08	3. TUB	-81
4. TUB	-118.71	4. LHen	-75
5. imec-IDLab	-102.29	5. imec-IDLab	-69

All submissions outperformed basic benchmarks, such as linear estimation and naive treatments of interference as white noise (not shown in Fig. 1), and showed results comparable to our baseline neural network methods (see Default Torch Wavenet in Fig. 1). Notably, the top-performing teams improved significantly over these baselines in some cases, such as those involving EMISignal1 and CommSignal2. However, mixtures with CommSignal3 consistently cha llenged all entries. The specific reasons for CommSignal3's difficulty remain unclear, warranting further investigation. The top 5 teams were selected to provide detailed descriptions of their solutions, featured in the ICASSP 2024 proceedings [5–9].

5. REFERENCES

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[2]Full resolution of figures can be found on `https://rfchallenge.mit.edu/icassp24-single-channel/`