THE DATA-DRIVEN RADIO FREQUENCY SIGNAL SEPARATION CHALLENGE

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ABSTRACT

The radio-frequency (RF) signal separation challenge involves isolating a signal-of-interest (SOI) from a superimposed 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 [2–5]. 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.

Supported, in part, by AFRL and the MIT-DAF AI Accelerator under Cooperative Agreement No. FA8750-19-2-1000, and MIT SuperCloud.

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 one of the frames from our *dataset* (detailed in Section 3). In this challenge, we focus on two types of SOI, single-carrier QPSK and multi-carrier orthogonal frequency division multiplexing (OFDM), whose 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 both the SOI waveform and its bit-sequence message from the given signal y. The performance metrics are: 1) the *mean-square error (MSE)* between the estimated signal $\hat{s}$ and the true SOI waveform s; and 2) the *bit error rate (BER)* between the estimated bits $\hat{m}$ and the true transmitted bits m. Participants' final scores are computed based on these metrics, with details provided in the challenge specifications.

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.

The examples in EMISignal1, CommSignal2, and CommSignal3 were recorded over-the-air, and CommSignal5G1 was generated and recorded in a controlled wired lab environment.

4. SUMMARY OF RESULTS

Figure 1 shows the performance of the 5 best submissions on the final evaluation set TestSet2Mixtures, benchmarked

[1] `https://rfchallenge.mit.edu/wp-content/uploads/2023/11/ICASSP24_RF_Challenge.pdf`

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

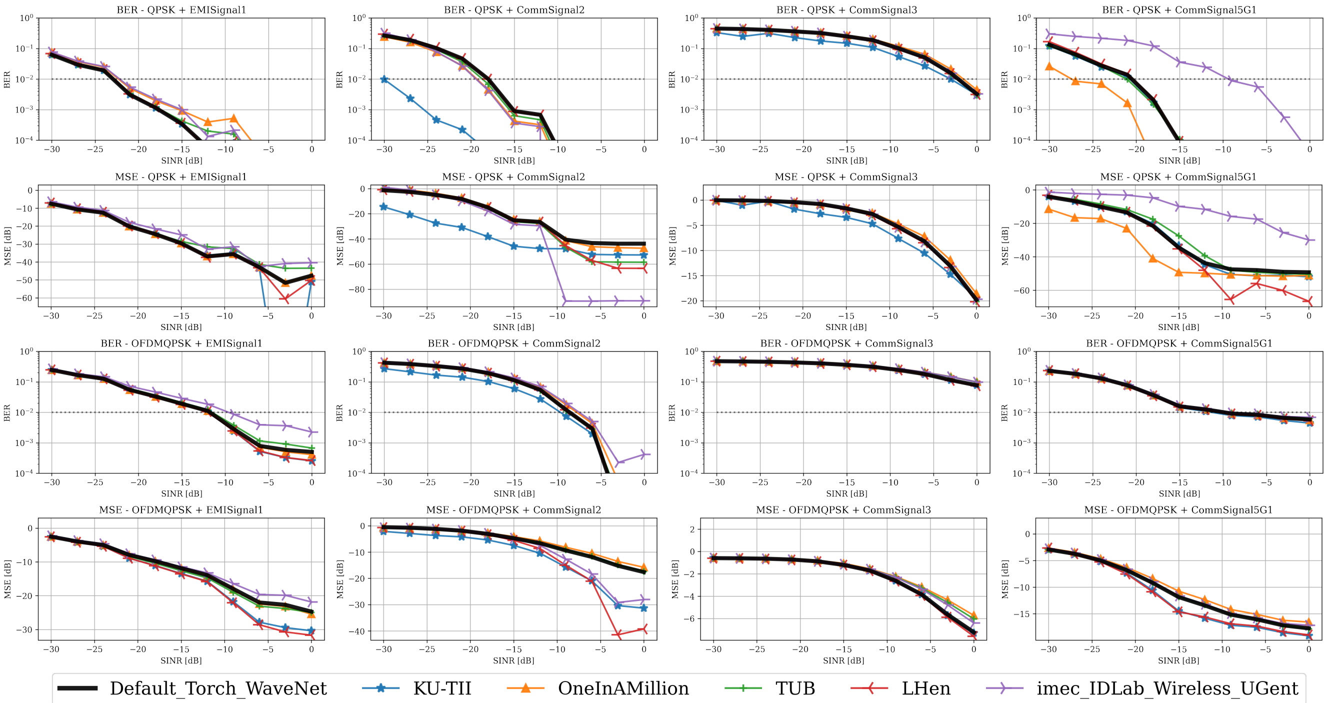

Fig. 1: BER and MSE as a function of the target SINR for all combinations of SOI and interferences in this challenge.[2]

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

against our strongest learning-based baseline. The plots depict BER and MSE versus target SINR for the respective SOI-interference combinations. We also show in Table 1 the ranking of the top 5 teams according to the MSE and BER scores defined for the challenge.[1] The baseline method was trained on INTERFERENCESET, using a modified WaveNet architecture [5, 6]. Relevant code and implementation details are included with the challenge's starter code.[3]

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 challenged 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. REFERENCES

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[3] https://github.com/RFChallenge/icassp2024rfchallenge