

## Introduction

Extracting signals of interest and suppression of interference from corrupted sensor measurements remain fundamental challenges in many networked battlespace applications. Mathematically,

$$x(t) = A(t) \star s(t) + n(t),$$

where  $\star$  denotes the convolution operator,  $s$  denotes the **signal of interest**,  $x$  denotes the recorded **mixture measurements**,  $A$  denotes the **mixing matrix**, and  $n$  denotes the **noise vector**.

## Objectives

The objective of this work package is to develop **robust and low-complexity** algorithms for source separation (SS) and broadband distributed beamforming. We aim to achieve the above by developing --

- algorithms based on **Polynomial Matrix Eigenvalue Decomposition (PEVD)** techniques – this has the advantage of only requiring second-order statistics thereby reducing the computational load associated with higher order statistics
- **Sparse representations and T-F masking** techniques robust to noise/incomplete measurements for underdetermined SS.

## Current Focus

Let  $N_m$  denote the number of mixtures, and,  $N_s$  denote the number of sources. The case  $N_s > N_m$  characterizes the **underdetermined SS** problem.

Since the mixing matrix is an  $N_m \times N_s$  matrix, traditional matrix inversion demixing techniques are not applicable in the underdetermined case.

Techniques for underdetermined CBSS are based on the fact that speech signals satisfy the **W-disjoint orthogonality (WDO)** condition i.e., given speech signals  $s_1(t)$  and  $s_2(t)$

$$s_1(\omega, \tau) s_2(\omega, \tau) = 0 \text{ for all } (\omega, \tau),$$

i.e. signals have a **disjoint** support in the **time-frequency** domain.

Techniques relying on the sparsity of speech signals in the time-frequency domain proceed by assigning either a binary or probabilistic **weight** to the **dominant source** at each time-frequency point. The matrix of such weights at each T-F point is known as the **T-F mask**.

**Our Aim:** To **improve** the performance of model based expectation-maximization SS methods utilizing interaural and mixing vector cues, e.g. [Mandel et. al. 2010], [Sawada et. al. 2007], and the combined method [Atiyeh et. al. 2011] for **highly reverberant mixtures**

## Proposed Method

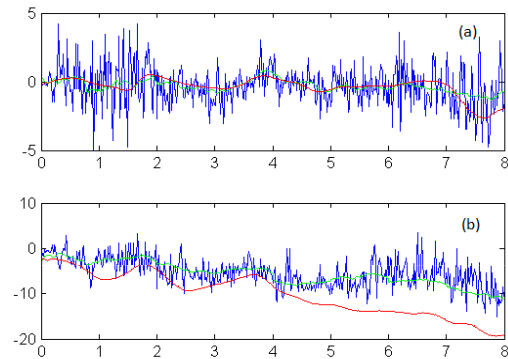
- Given  $\underline{x}(t) = [x_1(t), x_2(t)]$ , the ratio  $X_1(\omega, \tau)/X_2(\omega, \tau)$  is the **Interaural Spectrogram** denoted by  $IS(\omega, \tau)$ .
- $IS(\omega, \tau)$  is expressible in terms of the ILD and IPD.
- A **probabilistic T-F mask** is obtained as a by product of the EM algorithm that is used to obtain max likelihood estimates of unknown parameters of the assumed **ILD and IPD models**.
- We propose the idea of bootstrap averaging to improve parameter estimates which in turn determine the T-F mask –
  - Generate  $\underline{x}_1(t), \dots, \underline{x}_B(t)$  using an appropriate simulation methodology.
  - Obtain the ILD parameter estimates  $\alpha_i(\omega, \tau)$  and IPD parameter estimates  $\phi_j(\omega, \tau)$  for each of the  $\underline{x}_j(t)$  using Mandel's algorithm.
  - Use the **averaged parameter estimates**, i.e.

$$\alpha_{avg}(\omega, \tau) = \langle \alpha_i(\omega, \tau) \rangle / B \text{ and } \phi_{avg}(\omega, \tau) = \langle \phi_j(\omega, \tau) \rangle / B$$

to reconstruct the target source.

## Results

A comparison of the averaged ILD mean estimates (**green**) with the ground-truth direct response estimates (**red**) as well as the original estimates (**blue**) from Mandel's algorithm is shown below:



Clearly, the above plots suggest that the averaged parameter estimates may lead to better separation performance.

Our aim is to incorporate the smoothed parameter estimates of the ILD, IPD and/or mixing vector cue models appropriately in the model based SS algorithms.

**Signal-distortion-ratio (SDR)** and **Perceptual Evaluation of Speech Quality (PESQ)** will be used as measures to compare the performance of our proposed method with the hybrid method of [Atiyeh et. al.11] which combines interaural cues of [Mandel et al.] with the mixing vector cue of [Sawada et al.].

## Conclusion

- The idea of bootstrap averaging (bagging) is used to improve T-F mask estimates obtained from model based EM SS methods.
- The performance of bootstrap averaging heavily relies on:
  - The simulation technique used to obtain copies of the mixture vector, and
  - Variance of the parameter estimates with respect to different input mixture vectors  $\underline{x}(t)$ .
- Since  $\underline{x}(t)$  is a bivariate time series vector, with components  $x_1(t)$  and  $x_2(t)$  possibly correlated, it is important to recreate samples of  $\underline{x}(t)$  with the correct second-order statistical structure. This is achieved using the estimated power spectral density of  $\underline{x}(t)$ .

## References

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- H. Sawada et. al., "A two-stage frequency-domain blind source separation method for underdetermined convolutive mixtures," in *IEEE Workshop on Applications of Signal Processing to Audio and Acoustics, 2007*, pp. 139–142.
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- S. Chandna and A. Walden, "Simulation methodology for inference on physical parameters of complex vector-valued signals," *IEEE Transactions on Signal Processing*, vol. 61, pp. 5260–5269, 2013.

