



Robust Underdetermined Blind Audio Source Separation of Sparse Signals in the Time-Frequency Domain

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Main Problem

- Underdetermined system of linear equations

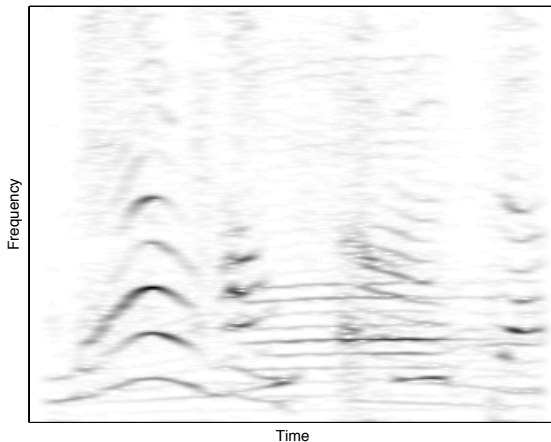
$$\begin{array}{c} m \\ \updownarrow \\ \boxed{x(t)} \end{array} = \begin{array}{c} \xleftarrow{n} \quad \xrightarrow{\quad} \\ \boxed{A} \end{array} \begin{array}{c} \boxed{s(t)} \end{array} + \begin{array}{c} \boxed{b(t)} \end{array}$$

- Instantaneous mixing case with independent AWGN
- The n components of $s(t)$ are sparse in the time frequency domain (in cont. of [Aïssa-El-Bey, IEEE-IT, 2007], [Bofill, Zibulevsky, Elsevier SP, 2001], [Linh-Trung et al, JASP, 2005])
- See survey [Pedersen et al, Springer Press, 2007]



Weak sparseness

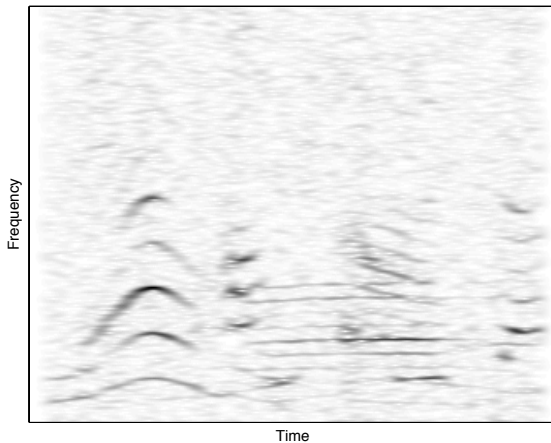
Noiseless mixture spectrogram: dark points indicate large-amplitude coefficients





Weak sparseness

Noisy mixture spectrogram (5dB): dark points indicate large-amplitude coefficients





Weak sparseness

Hypotheses [P., IEEE-IT 2002]

1. Signal components are either present or absent in the transformed domain (Fourier, wavelet, ...) with a probability of presence $\leq 1/2$,
2. When present, signal components are *relatively big* in that their amplitude is above some *minimum amplitude* $\rho > 0$.

Comments

- weak sparseness = constraints that bound our lack of prior knowledge on the signal distributions
- weak sparseness slightly differs from sparsity in compressed sensing



Outline

- 1 Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)
- 2 Experimental results
- 3 Conclusions and perspectives



Hypotheses

Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)

- Any $m \times m$ submatrix of the mixing matrix has full rank, that is, for all $J \subset \{1, 2, \dots, n\}$ of cardinality less than or equal to m , the column vectors $(A_j)_{j \in J}$ are linearly independent.

$$\begin{array}{c} \begin{array}{c} \updownarrow \\ m \end{array} \left(\begin{array}{cccc} & & & \\ A_1 & A_2 & \cdots & A_n \\ & & & \end{array} \right) \begin{array}{c} \leftarrow \overbrace{\hspace{1.5cm}}^n \rightarrow \end{array} \end{array}$$



Hypotheses

Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)

- Any $m \times m$ submatrix of the mixing matrix has full rank, that is, for all $J \subset \{1, 2, \dots, n\}$ of cardinality less than or equal to m , the column vectors $(A_j)_{j \in J}$ are linearly independent.
- The number of active sources at any time-frequency point is strictly less than the number m of sensors.

Time-Frequency model :

$$X(t, f) = A_J S_J(t, f) + B(t, f)$$

J : indexes of the active sources at (t, f)

Procedure (extends [Aïssa-El-Bey et al., IT-SP, 2007])

Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)

1. Compute STFT of the mixtures ;

Procedure (extends [Aïssa-El-Bey et al., IT-SP, 2007])

Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)

1. Compute STFT of the mixtures ;
2. Estimate the noise standard deviation via the Modified Complex Essential Supremum Estimate (MC-ESE);

[Socheleau, P. and Aïssa-El-Bey, IEEE-AES, 2011] :

[P., CSDA, 2008] (weak sparseness) \rightarrow for coord. # k :

$$\frac{\sum_{t,f} |X_k(t,f)| \mathbf{1}(|X_k(t,f)| \leq \sigma_0 \tau)}{\sum_{t,f} \mathbf{1}(|X_k(t,f)| \leq \sigma_0 \tau)} - \sigma_0 \frac{\int_0^\tau t^2 e^{-t^2/2} dt}{1 - e^{-\tau^2/2}} \approx 0$$

Procedure (extends [Aïssa-El-Bey et al., IT-SP, 2007])

Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)

1. Compute STFT of the mixtures ;
2. Estimate the noise standard deviation via the Modified Complex Essential Supremum Estimate (MC-ESE);
3. Reject the time frequency points that correspond to observations of noise alone ;

Thresholding test:

$$\mathcal{T}(X(t, f)) = \begin{cases} 1 & \text{if } \|X(t, f)\|_{\infty} \geq \hat{\sigma}_0 \sqrt{-2 \ln \mathcal{P}_{FA}} \\ 0 & \text{if } \|X(t, f)\|_{\infty} < \hat{\sigma}_0 \sqrt{-2 \ln \mathcal{P}_{FA}} \end{cases}$$
$$u = (u_1, \dots, u_m)^T \quad \|u\|_{\infty} = \max_i \{|u_i|\}$$

Procedure (extends [Aïssa-El-Bey et al., IT-SP, 2007])

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1. Compute STFT of the mixtures ;
2. Estimate the noise standard deviation via the Modified Complex Essential Supremum Estimate (MC-ESE);
3. Reject the time frequency points that correspond to observations of noise alone ;
4. Estimate STFT of the sources at the accepted points ;
 - Identification of active sources

Identification:

- Compute $P_{\mathcal{J}} = I_m - A_{\mathcal{J}}(A_{\mathcal{J}}^H A_{\mathcal{J}})^{-1} A_{\mathcal{J}}^H$ where $\#(\mathcal{J}) < m$.
- Compute $\mathcal{K} = \arg \min_{\mathcal{J}} \{\|P_{\mathcal{J}} X(t, f)\|\}$.

Procedure (extends [Aïssa-El-Bey et al., IT-SP, 2007])

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Linear estimation (Wiener filtering):

$$\hat{S}_{\mathcal{J}}(t, f) \approx \hat{\mathbf{R}}_{\mathcal{J}} \mathbf{A}_{\mathcal{J}}^H (\mathbf{A}_{\mathcal{J}} \hat{\mathbf{R}}_{\mathcal{J}} \mathbf{A}_{\mathcal{J}}^H + \hat{\sigma}_0^2 \mathbf{I}_m)^{-1} X(t, f)$$

$\hat{\mathbf{R}}_{\mathcal{J}}$: empirical correlation matrix of $S_{\mathcal{J}}$

Procedure (extends [Aïssa-El-Bey et al., IT-SP, 2007])

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 - Linear estimation
5. Inverse STFT to recover the sources in the time domain.



Procedure

Proposed Algorithm: Robust Underdetermined Blind Source Separation (RUBSS)

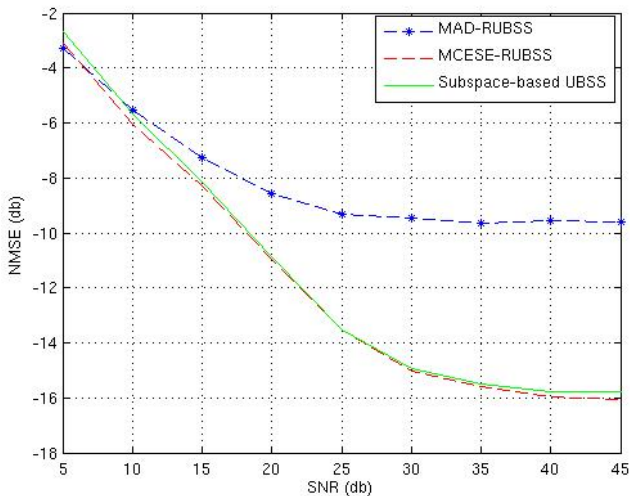
1. Compute STFT of the mixtures ;
2. Estimate the noise standard deviation with MC-ESE ;
3. Reject the time frequency points that correspond to observations of noise alone ;
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[Our contribution]

[Aïssa-El-Bey et al., IT-SP, 2007]

Source separation performance: NMSE vs SNR ($P_{FA} = 10^{-3}$)

Experimental results



Source separation performance: Audio Results

Experimental results

Mixtures

- Mixture 1
- Mixture 2
- Mixture 3

Original signals

- Sound 1
- Sound 2
- Sound 3
- Sound 4

Estimated signals

- Estimated sound 1
- Estimated sound 2
- Estimated sound 3
- Estimated sound 4



Conclusions and perspectives

Conclusions and perspectives

Conclusions

- The role of sparseness
- Only one parameter
- No prior knowledge on the exact nature of the sources

Perspectives

- Computational cost of MC-ESE \implies DATE algorithm ;
- False alarm rate dependence \implies Alternative approaches in robust and non parametric detection;
- The convolutive mixing case