

Analysis of Broadband GEVD-Based Blind Source Separation

Soydan Redif¹ Jen Pestana² Ian K. Proudler³

¹ Dept. of Electronic & Electrical Engineering, European University of Lefke, Cyprus

²Department of Mathematics, Univerity of Strathclyde

³Dept. of Electronic & Electrical Engineering, Univerity of Strathclyde

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GEVD-Based Blind Source Separation: Overview



1. Overview

- 2. Broadband Blind Signal Separation Problem
- 3. GEVD-based Solution
- 4. Analysis of GEVD approach
 - 4.1 Existence of pGEVD
 - 4.2 Relationship between pGEVD and BSS problem
 - 4.3 Signal Recovery
- 5. Computer Simulations
- 6. Conclusions



Broadband Blind Source Separation



Consider a broadband MIMO system:

$$x_{i}[n] = \sum_{j=1}^{M} \sum_{m=-\infty}^{\infty} H_{i,j}[n-m]s_{j}[m] \quad 1 \le i \le N$$

$$\boldsymbol{x}(z) = \boldsymbol{s}(z)\boldsymbol{H}(z)$$

- We are interested in estimating the source signals s(z) without knowledge of the channel transfer functions H(z)
- Can we use a narrowband solution as a guide?
 - Stationary problem requires higher-order statistics
 - Non-stationary problem can be solved using generalised eigenvalue decomposition (GEVD)



GEVD-based Blind Source Separation



Approach:

- 1. Assume sources have non-stationary statistics
- 2. Assume channel mixing matrix is stationary
- 3. Collect two datasets at different times
- 4. Form two space-time covariance matrices
- 5. Calculate GEVD: $AU = BU\Lambda$
- 6. Use matrix of generalised eigenvectors to unmix signals
- Broadband algorithms:
 - Corr, Pestana, Weiss, Redif, & Moonen
 - Redif
- No analysis showing validity of step 6 or conditions under which it works





Overview BB-BBS GEVD BBS Analysis Simulations Conclusions

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- 1. Existence of pGEVD
 - GEVD not well defined if both matrices are rank deficient (Bai)
 Without loss of generality, we assume that B(z) is invertible
 - Weiss et. al. show that a parahermitian pEVD exists but with caveats
 - GEVD can be cast as a parahermitian EVD

$$\boldsymbol{A}(z)\boldsymbol{U}(z) = \boldsymbol{B}(z)\boldsymbol{U}(z)\boldsymbol{\Lambda}(z)$$

becomes:

$$\boldsymbol{C}(z)\boldsymbol{V}(z)=\boldsymbol{V}(z)\boldsymbol{\Lambda}(z)$$

where

$$\boldsymbol{V}(z) = \boldsymbol{L}(z)\boldsymbol{U}(z)$$

– $\boldsymbol{L}(z)$ is derived from $\boldsymbol{B}(z)$ and is full rank



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- 1. Existence of pGEVD \dots
 - Weiss et. al. show that:
 - The generalised eigenvalues $\Lambda(z)$ exist as unique, convergent but likely infinite-length Laurent series provided they are Hölder continuous on the unit circle
 - If the eigenvalues are analytic functions on the unit circle, and V(z) is Hölder continuous with $\alpha > 1$ on the unit circle, then the generalised eigenvectors U(z) exist as a convergent Laurent series.
 - The generalised eigenvectors $\boldsymbol{U}(\boldsymbol{z})$ are unique up to an arbitrary phase response
 - Analytic eigenvalues do not exist if ${\bm C}(z)$ can be made block pseudo-circulant via a paraunitary similarity transformation
 - If the generalised eigenvalues or eigenvalues are not analytic, they can generally be approximated by Laurent polynomials.

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- 2. Relationship between pGEVD and BB-BBS
 - We have two space-time covariance matrices:

$$\boldsymbol{R}_i(z) = \boldsymbol{H}^P(z)\boldsymbol{S}_i(z)\boldsymbol{H}(z) \quad 1 \leq i \leq 2$$

where $\boldsymbol{S}_i(z)$ is the cross spectral density (CSD) matrix for the i-th dataset and is diagonal

▶ pGEVD requires that $R_2(z)$ must be full rank Hence H(z) and $S_2(z)$ need to be full rank i.e. $M \le N$ If M < N we have an under-determined BSS problem: assume M = N. Overview BB-BBS GEVD BBS Analysis Simulations Conclusions

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2. Relationship between pGEVD and BB-BBS

Consider two pGEVD Problems:

$$\begin{aligned} \boldsymbol{R}_1(z)\boldsymbol{U}(z) &= \boldsymbol{R}_2(z)\boldsymbol{U}(z)\Lambda_R(z)\\ \boldsymbol{S}_1(z)\boldsymbol{V}(z) &= \boldsymbol{S}_2(z)\boldsymbol{V}(z)\Lambda_S(z) \end{aligned}$$

After some algebra we find:

$$\Lambda_R(z) = \Lambda_S(z) (\equiv \Lambda(z))$$
$$\Lambda(z) = \mathbf{S}_1(z) / \mathbf{S}_2(z)$$
$$\mathbf{U}(z) = \mathbf{H}^{-1}(z) \mathbf{V}(z)$$

Hence U(z) is nearly the unmixing matrix
 Need to look at V(z)



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2. Relationship between pGEVD and BB-BBS

Consider V(z) in:

$$\boldsymbol{S}_1(z)\boldsymbol{V}(z) = \boldsymbol{S}_2(z)\boldsymbol{V}(z)\Lambda(z)$$

Note S₁(z), S₂(z) and Λ(z) are diagonal
 After some maths we find:

$$\boldsymbol{V}(z) = \boldsymbol{\Delta}(z) \boldsymbol{\Pi}$$

where ∆(z) is a block-diagonal matrix and Π is a permutation
 The size of the blocks in ∆(z) is determined by the algebraic multiplicity of the eigenvalues



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- 1. Signal Recovery
 - Recall that

$$\boldsymbol{x}(z) = \boldsymbol{s}(z) \boldsymbol{H}(z)$$

and

$$\boldsymbol{U}(z) = \boldsymbol{H}^{-1}(z)\boldsymbol{\Delta}(z)\boldsymbol{\Pi}$$

Hence

$$\hat{\boldsymbol{s}}(z) = \boldsymbol{x}(z)\boldsymbol{U}(z) = \boldsymbol{s}(z)\boldsymbol{\Delta}(z)\boldsymbol{\Pi}$$

- Thus source signals with distinct PSD ratios can be recovered up to a scaling and permutation
- Source signals with identical PSD ratios could be subject to parunitary mixing as well



Computer Simulations



- ► The analysis assumes the existence of an analytic pGEVD
- Existing algorithms are based on the use of pEVD algorithms which produce majorised solutions



Top: Majorised Eigenvalues $\Lambda(z)$ – Redif algorithm (not analytic)

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Bottom: True Eigenvalues \mathbf{\Lambda}_0(z)
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- In the absence of an analytic pGEVD, the simulations were based on a pseudo-algorithm which requires human intervention
- The permutation that makes the eigenvalues a smooth function of frequency is determined manually

Computer Simulations







Top: Analytic Eigenvalues $\Lambda(z)$ – Pseudo-analytic algorithm

Bottom: PSD Ratios $\boldsymbol{S}_1(z)/\boldsymbol{S}_2(z)$

Signal Separation Matrix $\boldsymbol{H}(z)\boldsymbol{U}(z)$

- Good separation



Computer Simulations



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Top: Analytic Eigenvalues $\Lambda(z)$ – Pseudo-analytic algorithm

Bottom: PSD Ratios $\boldsymbol{S}_1(z)/\boldsymbol{S}_2(z)$

Signal Separation Matrix $\boldsymbol{H}(z)\boldsymbol{U}(z)$

- Poor separation



Conclusions



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- Broadband blind signal separation problem with non-stationary signals
- Potentially solution using a polynomial GEVD (generalisation of narrowband case)
- pGEVD can be shown to exist with similar caveats to the pEVD (Weiss et. al.)
- Need PSD ratios (eigenvalues) to be distinct
- Signals are recovered up to scaling and permutation
- Need an analytic pGEVD algorithm