Impact of Fast-Converging PEVD Algorithms on Broadband AoA Estimation

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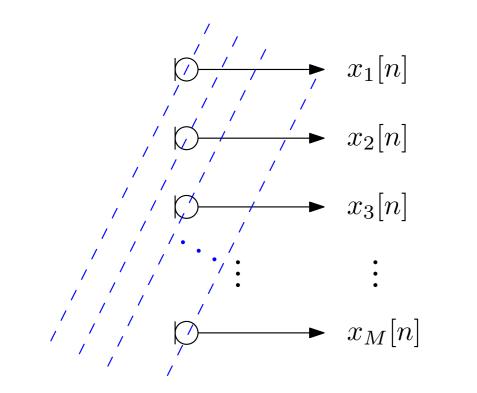
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Background

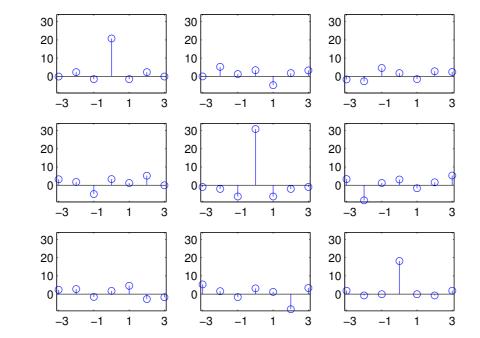
Motivation: Polynomial matrix eigenvalue decomposition (PEVD) algorithms have been shown to enable a solution to the broadband angle of arrival (AoA) estimation problem.

Aim: Employ low complexity divide-and-conquer approach to the PEVD for AoA estimation and investigate performance relative to traditional PEVD methods. Simultaneously, quantify the performance trade-offs for divide-and-conquer algorithm parameters.



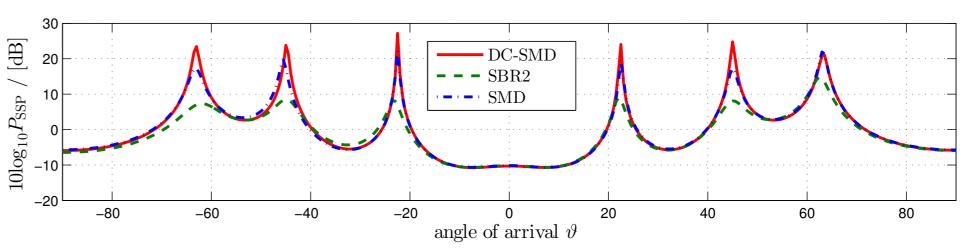
- Cross spectral density ${m R}(z) = \sum_{\tau} {m R}[\tau] z^{-\tau}$ is a polynomial matrix.
- \blacktriangleright Parahermitian: $\boldsymbol{\tilde{R}}(z) = \boldsymbol{R}^{\mathrm{H}}(1/z^{*}) = \boldsymbol{R}(z)$

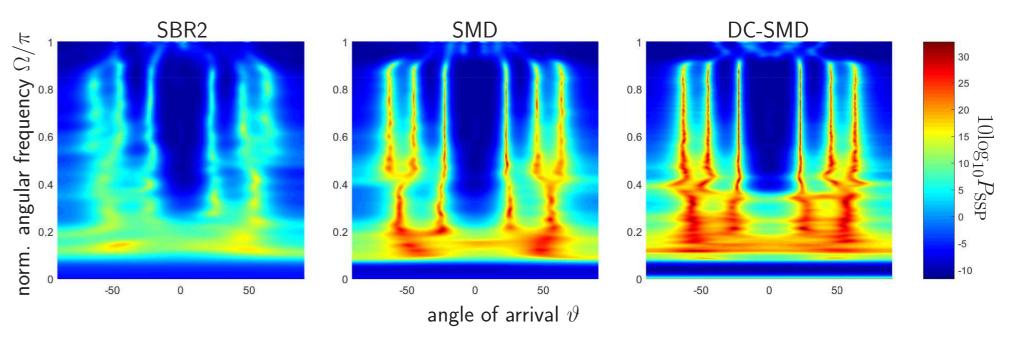
- Space-time covariance matrix: $\mathbf{R}[\tau] = \mathcal{E} \{ \mathbf{x}[n] \mathbf{x}^{\mathrm{H}}[n-\tau] \}, \ \mathbf{R}[\tau] \in \mathbb{C}^{M \times M}$
- Matrix of auto- & cross- correlation sequences
- Symmetry: $\mathbf{R}[\tau] = \mathbf{R}^{\mathrm{H}}[-\tau]$



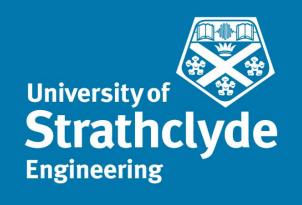
Results

Impact example: broadband angle of arrival estimation with fixed execution time.





Algorithm	Diagonalisation $/ dB$	Paraunitary filter length	Decomposition error	Paraunitarity error
DC-SMD	-17.17	297	1.27×10^{-5}	1.83×10^{-3}
SBR2	-8.035	221	7.19×10^{-9}	4.91×10^{-5}



Spatio-Spectral Polynomial MUSIC

- ► Approximate Polynomial EVD [1]: $D(z) \approx \tilde{Q}(z)R(z)Q(z)$
- Thresholding the polynomial eigenvalues reveals the number of independent broadband sources R contributing to $\mathbf{R}(z)$, and permits a distinction between signal-plus-noise and noise only subspaces $\mathbf{Q}_s(z) \in \mathbb{C}^{M \times R}$ and $\mathbf{Q}_n(z) \in \mathbb{C}^{M \times (M-R)}$,

$$oldsymbol{R}(z) = egin{bmatrix} oldsymbol{Q}_s(z) & oldsymbol{Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{D}_s(z) & oldsymbol{0} \ oldsymbol{O} & oldsymbol{D}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_s(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \end{bmatrix} egin{bmatrix} oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde Q}_n(z) \ oldsymbol{ ilde$$

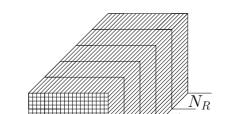
- $\blacktriangleright \ R < M, \ \boldsymbol{D}_{s}(z) \in \mathbb{C}^{R \times R} \text{ and } \boldsymbol{D}_{n}(z) \in \mathbb{C}^{(M-R) \times (M-R)}.$
- The spatio-spectral polynomial MUSIC (SSP-MUSIC) algorithm [2] is an extension of narrowband MUSIC [3] to the broadband case.
- ▶ SSP-MUSIC algorithm scans the noise-only subspace $Q_n(z) = [Q_{R+1}(z) \dots Q_M(z)].$
- The steering vectors of sources that contribute to $\mathbf{R}(z)$ will define the signal-plus-noise subspace $\mathbf{Q}_s(z)$ and therefore lie in the nullspace of its complement $\mathbf{Q}_n(z)$.
- Vector $\tilde{\boldsymbol{Q}}_n(e^{j\Omega})\boldsymbol{A}_{\vartheta,\varphi}(e^{j\Omega})$ is close to the origin if $\boldsymbol{A}_{\vartheta,\varphi}(e^{j\Omega})$ is a steering vector of a contributing source at frequency Ω , azimuth φ , and elevation θ .
- ► The SSP-MUSIC algorithm evaluates the reciprocal of the norm of this vector,

$$P_{\rm SSP}(\vartheta,\varphi,e^{j\Omega}) = \frac{1}{\tilde{\boldsymbol{A}}_{\vartheta,\varphi}(z)\boldsymbol{Q}_n(z)\tilde{\boldsymbol{Q}}_n(z)\boldsymbol{A}_{\vartheta,\varphi}(z)}|_{z=e^{j\Omega}}$$

• $P_{\text{SSP}}(\vartheta, \varphi, e^{j\Omega})$ can determine over which frequency range sources in the direction defined by the steering vector $A_{\vartheta,\varphi}(z)$ are active.

Divide-and-Conquer Sequential Matrix Diagonalisation

- Work in [4] describes a divide-and-conquer approach for the PEVD. This algorithm titled divide-and-conquer sequential matrix diagonalisation (DC-SMD) — can be utilised to reduce algorithm complexity and has a framework based on the SMD [5] algorithm.
- While traditional PEVD algorithms attempt to diagonalise an entire M × M parahermitian matrix at once, the DC-SMD algorithm first divides the matrix into a number of smaller, independent parahermitian matrices, before diagonalising — or conquering — each matrix separately.



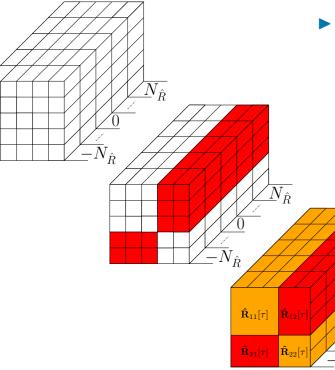
SMD	-12.87	170	1.15×10^{-7}	1.94×10^{-4}

 $\delta = 5 \times 10^{-4}$ $\delta = 10^{-4}$ $\delta = 10^{-3}$ Ω/π angular frequency S $10\log_{10}P_{\rm SSP}$ norm. angle of arrival ϑ $P = \hat{M} = 2$ $P = \hat{M} = 4$ $P = \hat{M} = 6$ Ω/π angular frequency $10\log_{10}P_{\mathrm{SSP}}$ 0.2 norm. -50 50 0 -50 0 angle of arrival ϑ o 0.6 ISE Lime / MSE 0.2 0.4 0.6 0.8 Threshold. δ Division factor, Division factor, P 9° 200 **⊱** 1.5 0.4 0.6 0.8 x 10 Threshold. Division factor, I Division factor, 1

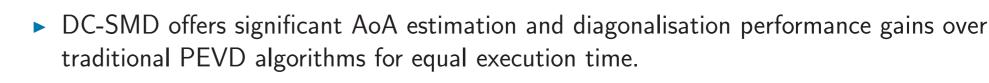
Performance trade-offs of DC-SMD for fixed diagonalisation level.

Conclusions

An algorithm named sequential matrix segmentation (SMS) [4] is used to recursively divide R(z) into multiple independent parahermitian matrices. Each parahermitian matrix is then diagonalised in sequence through the use of the SMD algorithm.



- SMS is a novel variant of SMD designed to segment an input matrix $\hat{R}(z) \in \mathbb{C}^{M' \times M'}$ into two independent parahermitian matrices $\hat{R}_{11}(z) \in \mathbb{C}^{(M'-P) \times (M'-P)}$ and $\hat{R}_{22}(z) \in \mathbb{C}^{P \times P}$, and two matrices $\hat{R}_{12}(z) \in \mathbb{C}^{(M'-P) \times P}$ and $\hat{R}_{21}(z) \in \mathbb{C}^{P \times (M'-P)}$, where $\hat{R}_{12}(z) = \tilde{R}_{21}(z)$ are approximately zero.
 - SMS iteratively minimises the energy in select regions of a parahermitian matrix in an attempt to segment the matrix. SMS operates until a specified number of iterations have been executed, or when the energy in the targeted regions falls below a threshold.



- These benefits come with the disadvantage of increasing the mean squared reconstruction error, paraunitary filter length, and paraunitarity error.
- Through careful choice of DC-SMD input parameters δ, P, and M, a balance can be obtained between decomposition MSE, algorithm execution time, filter paraunitarity, paraunitary filter length, and AoA estimation performance.
- A further advantage of the DC-SMD algorithm is its ability to produce multiple independent parahermitian matrices, which may be processed in parallel.

References

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[5] S. Redif et al. Sequential Matrix Diagonalisation Algorithms for Polynomial EVD of Parahermitian Matrices. *IEEE Trans. on Signal Processing*, Jan. 2015.