

Subspace Methods: Eigenvalue Method and MUSIC

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Prof. Aaron D. Lanterman

School of Electrical & Computer Engineering
Georgia Institute of Technology
AL: 404-385-2548
<lanterma@ece.gatech.edu>

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Where We Are in J&D

- Section 7.3



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Eigenexpansions

- Write correlation matrix in terms of its eigensystem:

$$\mathbf{R}_y = \sum_{m=1}^M \lambda_m \mathbf{v}_m \mathbf{v}_m^H$$

$$\mathbf{R}_y^{-1} = \sum_{m=1}^M \lambda_m^{-1} \mathbf{v}_m \mathbf{v}_m^H$$



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Eigensystem for a One-Signal Case (1)

- Think about one signal in white noise:

$$\mathbf{R}_y = A_s^2 \mathbf{e}(\vec{k}^0) \mathbf{e}^H(\vec{k}^0) + \sigma_n^2 \mathbf{I}$$

- Let $\mathbf{v}_1 = \mathbf{e}(\vec{k}^0) / \sqrt{M}$
- Let $\mathbf{v}_2, \dots, \mathbf{v}_M$ be any set of orthogonal vectors orthogonal to \mathbf{v}_1

$$\mathbf{R}_y = M A_s^2 \mathbf{v}_1 \mathbf{v}_1^H + \sum_{m=1}^M \sigma_n^2 \mathbf{v}_m \mathbf{v}_m^H$$

$$\lambda_1 = M A_s^2 + \sigma_n^2, \lambda_2, \dots, \lambda_M = \sigma_n^2$$



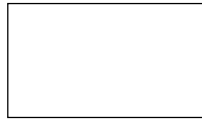
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Eigensystem for a One-Signal Case (2)

$$\begin{aligned} \mathbf{R}_y &= A_s^2 \mathbf{e}(\vec{k}^0) \mathbf{e}^H(\vec{k}^0) + \sigma_n^2 \mathbf{I} \\ &= MA_s^2 \mathbf{v}_1 \mathbf{v}_1^H + \sum_{m=1}^M \sigma_n^2 \mathbf{v}_m \mathbf{v}_m^H \\ \lambda_1 &= MA_s^2 + \sigma_n^2, \lambda_2, \dots, \lambda_M = \sigma_n^2 \end{aligned}$$

- If we had \mathbf{R}_y exactly, we could find $\mathbf{e}(\vec{k}^0)$ without knowing anything about the array!



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Eigensystem for a Two-Signal Case

- Two signals in white noise: $\mathbf{R}_y = A_1^2 \mathbf{e}(\vec{k}_1^0) \mathbf{e}^H(\vec{k}_1^0) + A_2^2 \mathbf{e}(\vec{k}_2^0) \mathbf{e}^H(\vec{k}_2^0) + \sigma_n^2 \mathbf{I}$

- Can express steering vectors as linear combinations of the two largest eigenvalues $\mathbf{v}_1, \mathbf{v}_2$

$$\mathbf{e}(\vec{k}_1^0) = t_{11} \mathbf{v}_1 + t_{21} \mathbf{v}_2$$

$$\mathbf{e}(\vec{k}_2^0) = t_{12} \mathbf{v}_1 + t_{22} \mathbf{v}_2$$



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Subspace Decompositions

$$\begin{bmatrix} \mathbf{e}(\vec{k}_1^0) & \mathbf{e}(\vec{k}_2^0) \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 \end{bmatrix}}_{\mathbf{V}_{s+n}} \underbrace{\begin{bmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{bmatrix}}_{\mathbf{T}}$$

For $N_s < M$ signals, we have

$\mathbf{v}_1, \dots, \mathbf{v}_{N_s}$ signal+noise subspace

$\mathbf{v}_{N_s+1}, \dots, \mathbf{v}_M$ noise subspace

Can never really know

\mathbf{T} , so focus on noise subspace



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Decomposing MVDR

$$\begin{aligned} P^{MV}(\vec{k}) &\equiv \left[\mathbf{e}^H(\vec{k}) \mathbf{R}_y^{-1} \mathbf{e}(\vec{k}) \right]^{-1} \\ &= \left[\sum_{i=1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 \right]^{-1} \end{aligned}$$

$$\underbrace{\sum_{i=1}^{N_s} \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2}_{\text{signal+noise terms}} + \underbrace{\sum_{i=N_s+1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2}_{\text{noise terms}}$$

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Considering the Signal+Noise Terms

- How can we get more “dramatic” peaks from the MVDR spectrum?

$$\sum_{i=1}^{N_s} \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 + \sum_{i=N_s+1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2$$

- When $\mathbf{e}(\vec{k})$ corresponds to an actual signal, inner products of it with signal+subspace eigenvectors are large
- This makes the term above not as small as it could be, so MVDR power (reciprocal above term) is not as big as it could be

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Considering the Noise Terms

- How can we get more “dramatic” peaks from the MVDR spectrum?

$$\sum_{i=1}^{N_s} \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 + \sum_{i=N_s+1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2$$

- When $\mathbf{e}(\vec{k})$ corresponds to an actual signal, inner products of it with noise eigenvectors are small (ideally zero)
- Reciprocals of small numbers are big!

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Eigenvalue Method

~~$$\sum_{i=1}^{N_s} \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 + \sum_{i=N_s+1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2$$~~

$$P^{EV}(\vec{k}) \equiv \left[\sum_{i=N_s+1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 \right]^{-1} = \left[\mathbf{e}^H(\vec{k}) \mathbf{R}_{EV}^{-1} \mathbf{e}(\vec{k}) \right]^{-1}$$

where $\mathbf{R}_{EV}^{-1} = \sum_{i=N_s+1}^M \lambda_i^{-1} \mathbf{v}_i \mathbf{v}_i^H$

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MUSIC (1)

$$P^{EV}(\vec{k}) \equiv \left[\sum_{i=N_s+1}^M \lambda_i^{-1} \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 \right]^{-1}$$

- If $\mathbf{K}_n = \sigma_n^2 \mathbf{I}$, noise subspace eigenvalues are theoretically σ_n^2

$$P^{MUSIC}(\vec{k}) \equiv \left[\sum_{i=N_s+1}^M \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 \right]^{-1}$$

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MUSIC (2)

$$P^{MUSIC}(\vec{k}) = \left[\mathbf{e}^H(\vec{k}) \mathbf{R}_{MUSIC}^{-1} \mathbf{e}(\vec{k}) \right]^{-1}$$

where $\mathbf{R}_{MUSIC}^{-1} = \sum_{i=N_s+1}^M \mathbf{v}_i \mathbf{v}_i^H$

- “Whitens” noise subspace
- “Flattens” background
- “Pulls” signals out of noisy background



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Modified Correlation Matrices

$$\mathbf{R}_{EV}^{-1} = \sum_{i=N_s+1}^M \lambda_i^{-1} \mathbf{v}_i \mathbf{v}_i^H \quad \mathbf{R}_{EV} = \sum_{i=N_s+1}^M \lambda_i \mathbf{v}_i \mathbf{v}_i^H$$

$$\mathbf{R}_{MUSIC}^{-1} = \sum_{i=N_s+1}^M \mathbf{v}_i \mathbf{v}_i^H \quad \mathbf{R}_{MUSIC} = \sum_{i=N_s+1}^M \mathbf{v}_i \mathbf{v}_i^H$$

- Can use these modified correlations in other algorithms (linear prediction, etc.)
- But... almost always used in MVDR



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Special Cases (1)

- EV doesn't change the eigenvalues it keeps
- Hence, it reduces to MVDR if we take the number of sources to be zero



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Special Cases (2)

- Remember Pisarenko method:

Look for valleys in: $\left| \mathbf{e}^H(\vec{k}) \mathbf{v}_{\min} \right|$

Look for peaks in: $\left| \mathbf{e}^H(\vec{k}) \mathbf{v}_{\min} \right|^{-1}$

- Like MUSIC method with $N_s = M - 1$

$$P^{MUSIC}(\vec{k}) \equiv \left[\sum_{i=N_s+1}^M \left| \mathbf{e}^H(\vec{k}) \mathbf{v}_i \right|^2 \right]^{-1}$$



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Good Properties of EV and Music

- **Good resolution properties overall**
- **In white Gaussian noise:**
 - Resolution increases without limit with increasing SNR
 - Peak locations “asymptotically unbiased”
- **In non-white noise:
Resolution still good, but has limits**
 - Peak locations usually biased



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Drawbacks of EV and MUSIC

- **Neither EV or MUSIC are very robust to modeling assumptions**
 - Why conventional BF is still popular
- **MUSIC very sensitive to assumption of number of sources due to flattening the eigenvalues**
 - EV also sensitive, but not as sensitive
- **Correlated sources badly mess up subspace methods (see p. 389)**



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