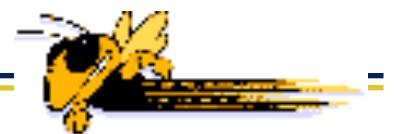

Subspace Methods: Eigenvalue Method and MUSIC

**ECE 6279: Spatial Array Processing
Spring 2013
Lecture 16**

Prof. Aaron D. Lanterman

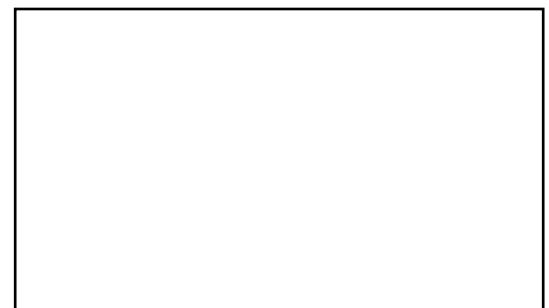
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Where We Are in J&D

- Section 7.3

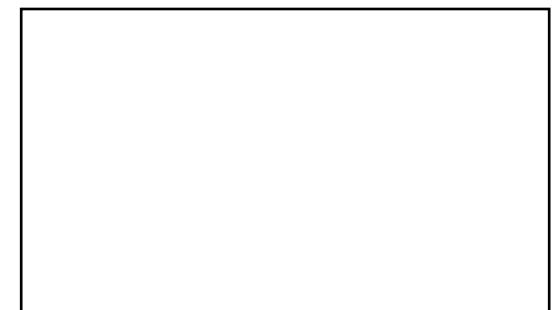


Eigenexpansions

- Write correlation matrix in terms of its eigensystem:

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

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



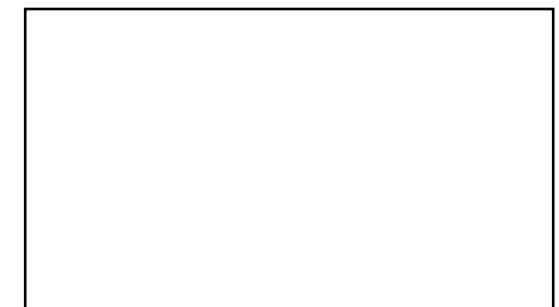
Eigensystem for a One-Signal Case (1)

- 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

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



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



Eigensystem for a One-Signal Case (2)

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

$$= MA_s^2 \mathbf{v}_1 \mathbf{v}_1^H + \sum_{m=1}^M \sigma_n^2 \mathbf{v}_i \mathbf{v}_i^H$$

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

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

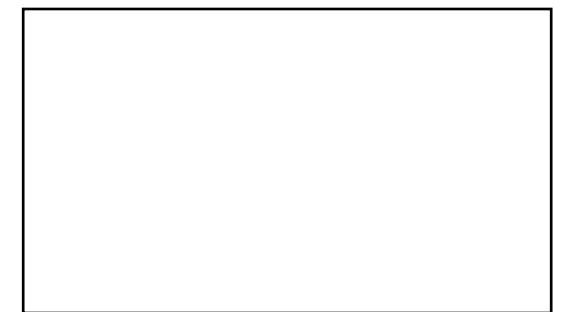


Eigensystem for a Two-Signal Case

- **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 $\mathbf{v}_1, \mathbf{v}_2$**

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

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



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
T, so focus on **noise** subspace



Decomposing MVDR

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



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

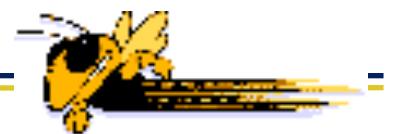


Considering the Noise Terms

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

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

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



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



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

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

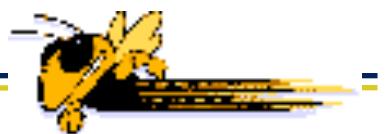


MUSIC (2)

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

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



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



Special Cases (2)

- The Pisarenko method says:

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 $N_s = M - 1$

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


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



Drawbacks of EV and MUSIC

- Neither EV or MUSIC are very robust to mismatches w.r.t. 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
- Coherent sources badly mess up subspace methods (see p. 389)

