

# Beamspace Adaptive Beamforming and the GSC

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- The MVDR beamformer: performance and behavior.
- Generalized Sidelobe Canceller reformulation.
- Implementation of the GSC.
- Beamspace interpretation of the GSC.
- Reduced complexity of beamspace MVDR.

**Model:** Signal, (spatially white) noise, and interference for  $M$ -element array

$$\vec{x} = A\vec{d} + \vec{n}, E \left\{ \vec{x}\vec{x}^H \right\} = \mathbf{R}_s + \mathbf{R}_n, \mathbf{R}_s = |A|^2 \vec{d}\vec{d}^H, \mathbf{R}_n = \mathbf{R}_i + \sigma_w^2 \mathbf{I} \quad (1)$$

For spatially white noise only, the DAS beamformer is optimal (in the sense of minimum noise power in output):

$$y_{DAS} = \vec{w}_{DAS}^H \vec{x} \text{ for } \vec{w}_{DAS} = \frac{1}{M} \vec{d} \quad (2)$$

For spatially non-white interference, the Minimum Variance beamformer minimizes interference-plus-noise power in the beamformer output:

$$\vec{w}_{mv} = \operatorname{argmin}_{\vec{w}} E \left\{ \left| \vec{w}^H \vec{x} \right|^2 \right\} = \operatorname{argmin}_{\vec{w}} \vec{w}^H \mathbf{R} \vec{w} \quad (3)$$

In other words:

$$E \left\{ \left| \vec{w}_{MV}^H \vec{n} \right|^2 \right\} \leq E \left\{ \left| \vec{w}^H \vec{n} \right|^2 \right\} \text{ for all weight vectors } \vec{w} \quad (4)$$

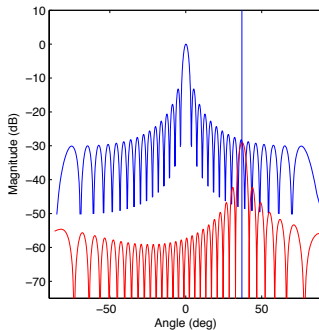
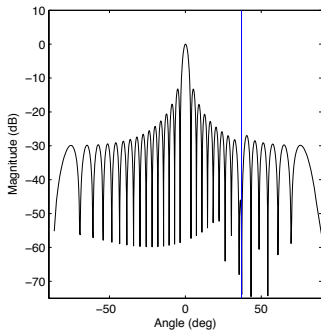
**Note:** This is actually *minimum power*, not *minimum variance*. Subtle difference, theoretical equivalence. Exchange  $\mathbf{R}$  for  $\mathbf{R}_n$ ...

## Repetition: MVDR Beamforming 2

MV weight vector for the case of one single interfering source with power  $\sigma_i^2$  and propagation vector  $\vec{d}_i$ :

$$\vec{w}_{MV} = \frac{\Lambda M}{\sigma_w^2} \left( \vec{w}_{das,s} - \rho_{si} \frac{M \sigma_i^2}{\sigma_w^2 + M \sigma_i^2} \vec{w}_{das,i} \right) \text{ for } \vec{w}_{das,s} = \frac{\vec{v}_s}{M}, \vec{w}_{das,i} = \frac{\vec{v}_i}{M} \quad (5)$$

- **Interpretation:** DAS beamformer steered towards signal minus (scaled) DAS beamformer steered towards interference.
- Scaling depends on INR, i.e.  $\frac{\sigma_i^2}{\sigma_w^2}$



- Constrained minimization is sometimes difficult to implement and analyze.
- *However:* MVDR can be reformulated as unconstrained minimization.
- First suggested by Griffiths and Jim (1982) as an alternative implementation of Frosts Linearly Constrained MV (LCMV) beamformer (1972).
- This implementation is usually referred to as the *Griffiths-Jim beamformer* or the *GSC*.

Given a matrix  $B \in \mathbb{C}^{M, M-1}$  such that  $\vec{d}^H \mathbf{B} = \vec{0}$ . Then the constrained optimization problem:

$$\min_{\vec{w}} \vec{w}^H \mathbf{R} \vec{w} \text{ s.t. } \vec{w}^H \vec{d} = 1 \quad (6)$$

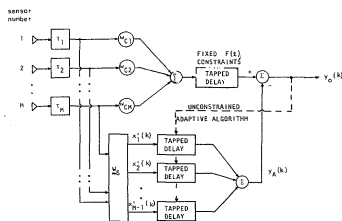
is identical to the unconstrained optimization problem:

$$\min_{\vec{\beta}} \left( \frac{1}{M} \vec{d} - \mathbf{B} \vec{\beta} \right)^H \mathbf{R} \left( \frac{1}{M} \vec{d} - \mathbf{B} \vec{\beta} \right) \quad (7)$$

with solution:

$$\vec{\beta} = \left( \mathbf{B}^H \mathbf{R} \mathbf{B} \right)^{-1} \mathbf{B}^H \mathbf{R} \frac{\vec{d}}{M} \quad (8)$$

- From now on: Assume  $\vec{d} = \vec{1}$ , i.e. signal arriving from broadside.
- Can be implemented as a transversal adaptive filter (using e.g. LMS or RLS algorithm).
- Looks like a *Wiener filter*, in that it subtracts adaptively filtered noise from desired signal...
- ...however, it does not produce MMSE output.
- **Note:** Sensitive to signal-interference correlation, just like MVDR.



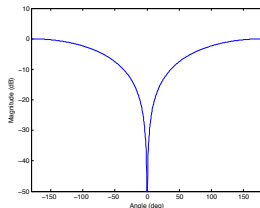
Blocking matrix  $\mathbf{B}$  suggested by Griffiths and Jim:

$$\mathbf{B} = \begin{bmatrix} 1 & -1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & -1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & -1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 & 0 & \\ 0 & 0 & 0 & 0 & \cdots & 1 & -1 \end{bmatrix} \quad (9)$$

What signals are processed by the lower branch of the GSC?

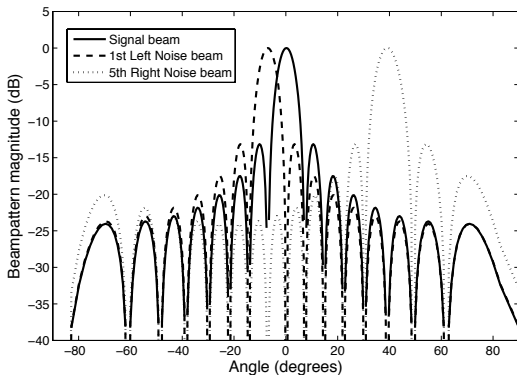
$$x'_m = x_m - x_{m+1} \text{ for } m = 0, 1, \dots, M-2 \quad (10)$$

Two-element endfire “beams”. Good for broadband; broadside nulling for all frequencies.



$$\mathbf{D} = \frac{1}{M} \left[ \vec{d}_0, \dots, \vec{d}_{M-1} \right], \left[ \vec{d}_m \right]_n = e^{j \frac{2\pi m}{M} n} \quad (11)$$

- Special case: ULA with DFT matrix  $\mathbf{B} = \mathbf{D}$  without first column ( $\vec{d}_0 = \vec{w}_{DAS}$  for broadside arrival).
- Invertible transformation:  $\mathbf{D}^H \mathbf{D} = \mathbf{D} \mathbf{D}^H = \frac{1}{M} \mathbf{I}$ .





The constrained optimization problem becomes:

$$\begin{aligned} \min_{\vec{w}} E \left\{ \left| (\vec{w}^H \mathbf{D}^H)(\mathbf{D}\vec{x}) \right|^2 \right\} \quad \text{s.t.} \quad \vec{w}^H \vec{1} = 1 \\ \Rightarrow \min_{\vec{w}_{BS}} E \left\{ \left| \vec{w}_{BS}^H \vec{x}_{BS} \right|^2 \right\} = \vec{w}_{BS}^H \mathbf{R}_{BS} \vec{w}_{BS} \quad \text{s.t.} \quad \vec{w}_{BS}^H \vec{e}_0 = 1 \end{aligned} \quad (12)$$

Beamspace solution:

$$\vec{w}_{BS} = \frac{\mathbf{R}_{BS}^{-1} \vec{e}_0}{\vec{e}_0^H \mathbf{R}_{BS}^{-1} \vec{e}_0} \quad (13)$$

Beamspace beamformer output:

$$y_{BS} = x_{BS,0} + \sum_{m=1}^{M-1} w_{BS,m}^* x_{BS,m} \quad (14)$$

- Interpretation is more obvious: DAS beamformer minus weighted set of other DAS beamformers.
- Note that there is only information about the signal in  $x_{BS,0}$ .
- Certain beams  $x_{BS,m}$  contain more information about interference than others.
- **Idea:** Remove those  $x_{BS,m}$  that are expected to contain little or no information about interference.
- **Result:**  $\vec{x}_{BS}$  becomes smaller, i.e.  $\mathbf{R}_{BS}$  becomes smaller and easier to invert.
- Inversion of  $\mathbf{R}$  is  $O(M^3)$ .
- Reduced-dimension beamspace presents a way of using a priori knowledge in the adaptive beamformer...
- ...but is this realistic knowledge?

Try  $\mathbf{B} = \vec{d}_m$ , base weights on *single-snapshot noise cov. matrix*  $\mathbf{R}_n = \vec{n}\vec{n}^H$ :

$$\beta = \left( \vec{d}_m^H \mathbf{R}_n \vec{d}_m \right) \vec{d}_m^H \mathbf{R}_n \vec{w}_{das} = \frac{y_{p,d} y_{p,das}^*}{|y_{p,d}|^2 + \frac{\sigma_w^2}{M}} \quad (15)$$

Yields beamspace MV weight vector:

$$\vec{w}_{bs} = \vec{w}_{das} - \beta \vec{d}_m \quad (16)$$

Yields interference in output:

$$y_{p,bs} = y_{p,das} \left( 1 - \frac{|y_{p,d}|^2}{|y_{p,d}|^2 + \frac{\sigma_w^2}{M}} \right) \quad (17)$$

- Is the choice of  $\vec{d}_m$  arbitrary?
- What is the impact on the white noise gain?
- What is the impact of spatially white noise?

- **Special case:** Adaptive Sidelobe Reduction (from Synthetic Aperture Radar).
- **Summary:** Only use  $x_{BS,m}$  for  $m = 0, 1, M - 1$  and set  $w_{BS,0} = 1, w_{BS,1} = w_{BS,M-1} = \alpha$ .
- Complexity reduced from determining  $M$  weights to 1 weight.
- Additionally, solution is on the form:

$$[\vec{w}_{ASR}]_m = 1 + \alpha \cos\left(\frac{2\pi m}{M}\right) \quad (18)$$

which corresponds to a known family of windows (including Hamming and Hann).

- GSC interpretation of MVDR beamformer yields *unconstrained optimization problem*.
- Unconstrained optimization problems are often easier to analyze and implement.
- Beamspace interpretation of GSC can give reduced complexity.
- **Example:** Ultrasound imaging. Reduction from 64-dimensional element space to 3-dimensional beamspace with similar performance. In general:  $O(M) \rightarrow O(3)$ .