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## Array Processing

Julien Lesouple

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# Array Processing

## IENAC22 SAT - ASNAT23

Julien Lesouple (TELECOM/SIGNAV)

[julien.lesouple@enac.fr](mailto:julien.lesouple@enac.fr)



## Class organization

- 10 classes: lectures mixed with Python coding
- Matlab codes will be available on e-campus to replicate figures (and play with it)
- one hour exam, A4 Sheets both sides handwritten, not photocopied

I would very appreciate any feedback on the class

# Plan

- ① Introduction
- ② Model
- ③ Beamforming
- ④ Direction of arrival estimation
- ⑤ Conclusion

# Plan

## ① Introduction

Multichannel processing  
Array processing

## ② Model

## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Plan

## ① Introduction

Multichannel processing

Array processing

## ② Model

## ③ Beamforming

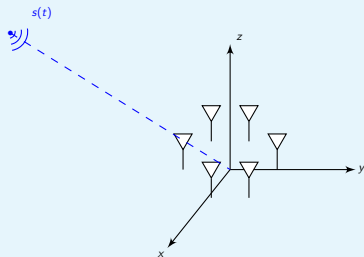
## ④ Direction of arrival estimation

## ⑤ Conclusion

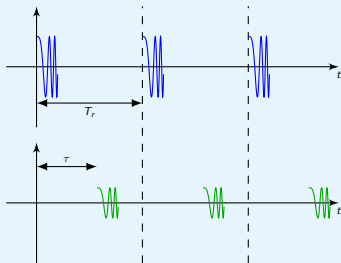
# Multichannel processing

Observations are now stored in a measurement vector:  $\mathbf{y}(\cdot) = \begin{bmatrix} y_1(\cdot) \\ y_2(\cdot) \\ \vdots \\ y_N(\cdot) \end{bmatrix}$

## 1 sample on $N$ sensors



## $N$ samples on 1 sensor



# Analysis/processing of multichannel measurements

- Analysis: what is the relation between  $y_n(\cdot)$  and  $y_m(\cdot)$ ?
  - how correlated are  $y_n(\cdot)$  and  $y_m(\cdot)$ ?
  - can  $\mathbf{y}(\cdot)$  be explained by a small number of variables?
- Processing: combination of the signals, e.g., linear filtering

$$y_F(\cdot) = \sum_{n=1}^N w_n^* y_n(\cdot)$$

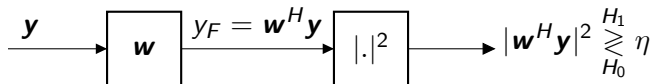


## Example: linear filtering for detection

We want to detect if a known signal  $\mathbf{a}$  is in a received signal  $\mathbf{y}$  with addition of noise  $\mathbf{n}$ , i.e., we have the hypothesis testing

$$\begin{cases} H_0 : \mathbf{y} = \mathbf{n} \\ H_1 : \mathbf{y} = \alpha \mathbf{a} + \mathbf{n} \end{cases}$$

Linear filter:  $\mathbf{w}$  such as  $y_F = \mathbf{w}^H \mathbf{y} \rightarrow \text{energy } |\mathbf{w}^H \mathbf{y}|^2$



For instance, for pure tone  $a_n = e^{j2\pi f_0 n}$ , we can take  $w_n = e^{j2\pi f_0 n}$  leading to the Fourier transform of  $\mathbf{y}$  at  $f_0$

# Plan

## ① Introduction

Multichannel processing  
Array processing

## ② Model

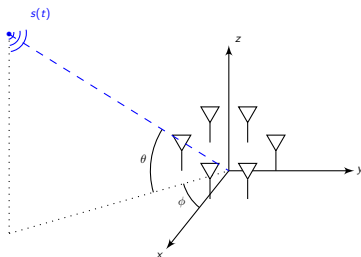
## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion

## Context of the course

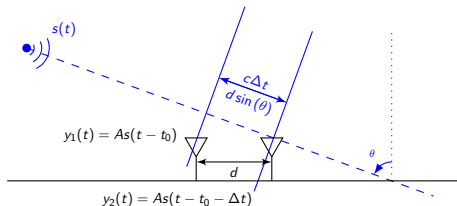
- Signals are received on an array of  $N$  antennas



- $y_n(k)$  represents the signal received on **antenna  $n$**  at **time  $k$**
- $n = 1, \dots, N$  is a spatial index (related to a **position** in space)  $\rightarrow$  spatial processing (e.g.,  $\sum_{n=1}^N w_n^* y_n(\cdot)$ )

# Principle of array processing

Considering two antennas and a source in the far field



## Principle

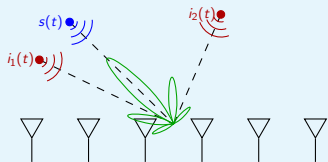
Additional delay  $\Delta t$  only depends on the geometry and the angle of arrival

- if  $\theta$  is known: spatial filtering (beamforming)
- if  $\theta$  is unknown: estimation of  $\Delta t$  (source localization)

# Beamforming vs. DoA estimation

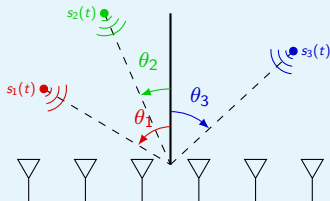
## Beamforming

Retrieve signal from direction of interest, possibly eliminate interference



## DoA estimation

Estimate directions of arrival of incoming signals



# Array of sensors: conclusion

## Possibilities

Sensor array offer an additional dimension (**space**) to perform filtering of signals (possibly coupled with temporal or frequency filtering)

- 1 source separation
- 2 direction finding

## Applications

- 1 Radar, sonar (detection, localization, anti-jamming)
- 2 Communications (capacity improvements, better reception, spatial focusing, interference mitigation)

# Plan

## ① Introduction

## ② Model

- Principle

- Multichannel receiver

- Received signals

- The steering vector

- Covariance matrix

- Limitations

## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Plan

## ① Introduction

## ② Model

### Principle

Multichannel receiver

Received signals

The steering vector

Covariance matrix

Limitations

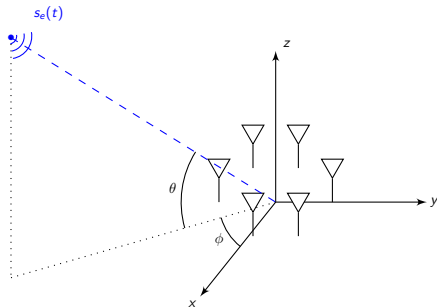
## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion



# Arrays and waveforms



- Wavefront impinging from direction  $(\theta, \phi)$
- Assumptions: homogeneous propagation medium, source in the far field of the array  $\rightarrow$  plane wavefront

# Plan

## ① Introduction

## ② Model

Principle

**Multichannel receiver**

Received signals

The steering vector

Covariance matrix

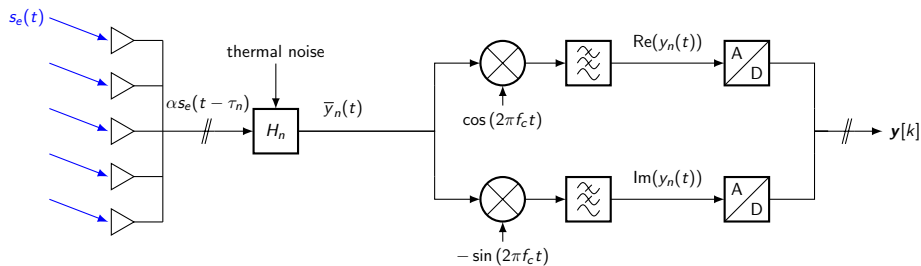
Limitations

## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Multichannel receiver



# Plan

## ① Introduction

## ② Model

Principle

Multichannel receiver

**Received signals**

The steering vector

Covariance matrix

Limitations

## ③ Beamforming

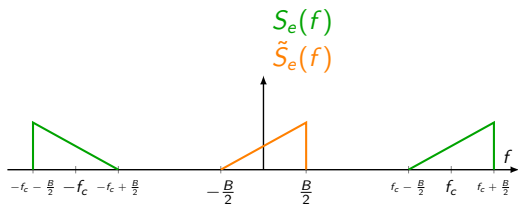
## ④ Direction of arrival estimation

## ⑤ Conclusion

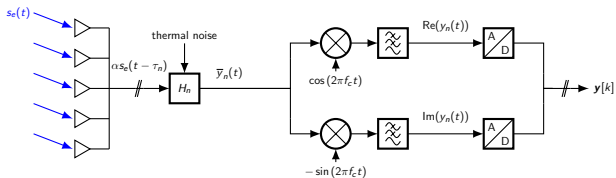
# Emitted signal

Narrowband signal :  $B \ll f_c$

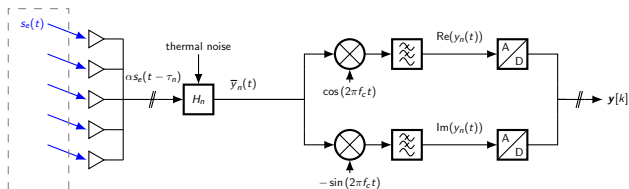
$$s_e(t) = 2\text{Re} \left\{ \tilde{s}_e(t) e^{j2\pi f_c t} \right\}$$



# Received signals

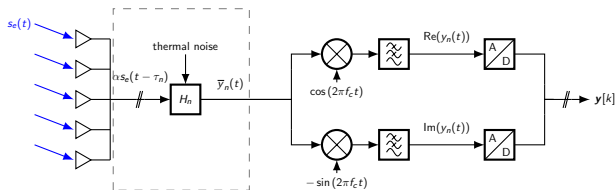


# Received signals



- Narrow band:  $B \ll f_c \rightarrow s_e(t) = 2\text{Re} \{ \tilde{s}_e(t) e^{j2\pi f_c t} \}$

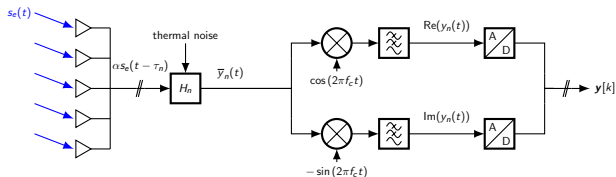
# Received signals



- Narrow band:  $B \ll f_c \rightarrow s_e(t) = 2\text{Re} \{ \tilde{s}_e(t) e^{j2\pi f_c t} \}$
- Impulse response  $h_n$ :  $\bar{y}_n(t) = h_n * (\alpha s_e(t - \tau_n)) + \check{n}(t)$

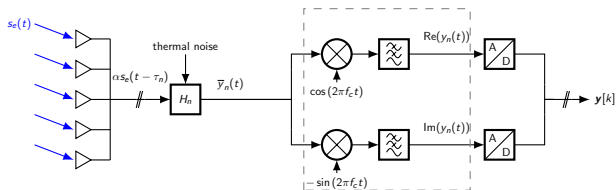


# Received signals



- Narrow band:  $B \ll f_c \rightarrow s_e(t) = 2\text{Re} \{ \tilde{s}_e(t) e^{j2\pi f_c t} \}$
- Impulse response  $h_n$ :  $\bar{y}_n(t) = h_n * (\alpha s_e(t - \tau_n)) + \check{\epsilon}_n(t)$
- Fourier:  $\bar{Y}_n(f) = \alpha H_n(f) S_e(f) e^{-j2\pi f \tau_n} + \check{E}_n(f)$

# Received signals



- Narrow band:  $B \ll f_c \rightarrow s_e(t) = 2\text{Re} \{ \tilde{s}_e(t) e^{j2\pi f_c t} \}$
- Impulse response  $h_n$ :  $\bar{y}_n(t) = h_n * (\alpha s_e(t - \tau_n)) + \check{e}_n(t)$
- Fourier:  $\bar{Y}_n(f) = \alpha H_n(f) S_e(f) e^{-j2\pi f \tau_n} + \check{E}_n(f)$
- Baseband:  $Y_n(f) = \alpha H_n(f + f_c) \tilde{S}_e(f) e^{-j2\pi(f+f_c)\tau_n} + \check{E}_n(f + f_c)$

## Received signals

Relatively to a given reference ( $\tau_n = \tau_0 + \Delta\tau_n$ )

$$\begin{aligned} Y_n(f) &= \alpha H_n(f + f_c) \tilde{S}_e(f) e^{-j2\pi(f+f_c)\tau_n} + \check{E}_n(f + f_c) \\ &= \alpha H_n(f + f_c) \tilde{S}_e(f) e^{-j2\pi(f+f_c)(\tau_0 + \Delta\tau_n)} + \check{E}_n(f + f_c) \\ &= \alpha H_n(f + f_c) \tilde{S}_e(f) e^{-j2\pi f \tau_0} e^{-j2\pi f_c \tau_0} e^{-j2\pi(f+f_c)\Delta\tau_n} + \check{E}_n(f + f_c) \end{aligned}$$

Short delays and narrowband ( $e^{-j2\pi(f+f_c)\Delta\tau_n} \approx e^{-j2\pi f_c \Delta\tau_n}$ )

$$Y_n(f) = \alpha H_n(f + f_c) \tilde{S}_e(f) e^{-j2\pi f \tau_0} e^{-j2\pi f_c \tau_0} e^{-j2\pi f_c \Delta\tau_n} + \check{E}_n(f + f_c)$$

Narrowband ( $H_n(f + f_c) \tilde{S}_e(f) \approx H_n(f_c) \tilde{S}_e(f)$ )

$$Y_n(f) \approx \alpha e^{-j2\pi f_c \tau_0} H_n(f_c) \tilde{S}_e(f) e^{-j2\pi f \tau_0} e^{-j2\pi f_c \Delta\tau_n} + \check{E}_n(f + f_c)$$

Back to temporal (inverse Fourier)

$$y_n(t) \approx \alpha e^{-j2\pi f_c \tau_0} H_n(f_c) \tilde{s}_e(t - \tau_0) e^{-j2\pi f_c \Delta\tau_n} + e_n(t)$$

## Received signals

Calibrated sensors  $H_n(f_c) = \dots = H_N(f_c)$  and gathering constants in  $\alpha$

$$y_n(t) = \alpha \tilde{s}_e(t - \tau_0) e^{-j2\pi f_c \Delta \tau_n} + e_n(t)$$

### Narrowband signal

A short time shift is equivalent to a phase shift

$$s(t - \Delta \tau_n) \Leftrightarrow s(t) e^{-j2\pi f_c \Delta \tau_n}$$

Main signal on reference point ( $s(t) = \alpha \tilde{s}_e(t - \tau_0)$ )

$$y_n(t) = s(t) e^{-j2\pi f_c \Delta \tau_n} + e_n(t)$$

In the following:  $\Delta \tau_n \leftrightarrow \tau_n$

## Snapshots

Individual signals

$$y_n(t) = s(t)e^{-j2\pi f_c \tau_n} + e_n(t)$$

Output of multichannel receiver

$$\mathbf{y}(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_N(t) \end{bmatrix} = \begin{bmatrix} e^{-j2\pi f_c \tau_1} \\ e^{-j2\pi f_c \tau_2} \\ \vdots \\ e^{-j2\pi f_c \tau_N} \end{bmatrix} s(t) + \begin{bmatrix} e_1(t) \\ e_2(t) \\ \vdots \\ e_N(t) \end{bmatrix}$$

Far field (planar waves):  $\tau_n$  depends only on source location  $(\theta, \phi)$

Snapshot before ADC

$$\mathbf{y}(t) = \mathbf{a}(\theta, \phi)s(t) + \mathbf{e}(t)$$

# Snapshots

Temporal sampling at rate  $T_s$  leads a matrix

$$\mathbf{Y} = [\mathbf{y}[1] \quad \mathbf{y}[2] \quad \cdots \quad \mathbf{y}[K]] \in \mathbb{C}^{N \times K}$$

where

$$\mathbf{y}[k] = \mathbf{y}(kT_s) = \mathbf{a}(\theta, \phi)s[k] + \mathbf{e}[k]$$

## Vector of phase shifts

$\mathbf{a}(\theta, \phi)$  is referred to as the **steering vector** and depends only on the DOA of the source

## In presence of several sources

Snapshot received in the presence of  $P$  sources

$$\begin{aligned}
 \mathbf{y}[k] &= \sum_{p=1}^P \mathbf{y}_p[k] + \mathbf{e}[k] \\
 &= \sum_{p=1}^P \mathbf{a}(\theta_p, \phi_p) s_p[k] + \mathbf{e}[k] \\
 &= [\mathbf{a}(\theta_1, \phi_1) \quad \cdots \quad \mathbf{a}(\theta_P, \phi_P)] \begin{bmatrix} s_1[k] \\ \vdots \\ s_P[k] \end{bmatrix} + \mathbf{e}[k] \\
 &= \mathbf{A}(\boldsymbol{\theta}, \boldsymbol{\phi}) \mathbf{s}[k] + \mathbf{e}[k] \text{ where } \mathbf{A}(\boldsymbol{\theta}, \boldsymbol{\phi}) \in \mathbb{C}^{N \times P} \text{ and } \mathbf{s}[k] \in \mathbb{C}^P
 \end{aligned}$$

In the following:  $\mathbf{a}(\theta_p)$ ,  $\mathbf{A}(\boldsymbol{\theta})$  for clarity

# Plan

## ① Introduction

## ② Model

Principle

Multichannel receiver

Received signals

**The steering vector**

Covariance matrix

Limitations

## ③ Beamforming

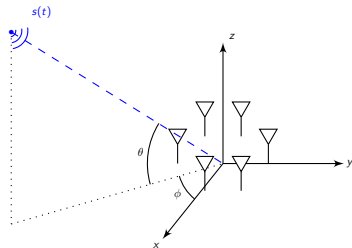
## ④ Direction of arrival estimation

## ⑤ Conclusion



# Steering vector in 3D

Reference at frame origin



Delay

$$\tau_n = \frac{1}{c} (x_n \cos \theta \cos \phi + y_n \cos \theta \sin \phi + z_n \sin \theta)$$

Steering vector

$$\mathbf{a}_n(\theta, \phi) = e^{-j\frac{2\pi}{\lambda} (x_n \cos \theta \cos \phi + y_n \cos \theta \sin \phi + z_n \sin \theta)}$$

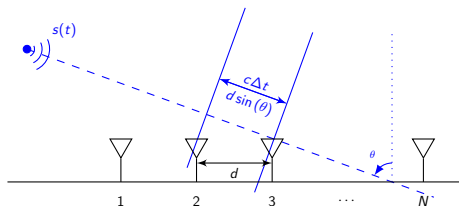
Received signal

$$s_n(t) = s(t) e^{-j\mathbf{r}_n^T \mathbf{k}} = s(t) e^{-j2\pi f_c \tau_n}$$

where

$$\mathbf{r}_n = \begin{bmatrix} x_n \\ y_n \\ z_n \end{bmatrix} \quad \mathbf{k} = \frac{2\pi}{\lambda} \begin{bmatrix} \cos \theta \cos \phi \\ \cos \theta \sin \phi \\ \sin \theta \end{bmatrix}$$

## Simpler 2D case: Uniform Linear Array (ULA)



$$\theta \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right]$$

$$\tau_n = (n-1) \frac{d \sin \theta}{c} \Rightarrow \mathbf{a}(\theta) = \left[ 1 \quad e^{-j2\pi f_c \frac{d \sin \theta}{c}} \quad \dots \quad e^{-j2\pi f_c (N-1) \frac{d \sin \theta}{c}} \right]$$

### Spatial sampling frequency

$$f_s = f_c \frac{d \sin \theta}{c} = \frac{d}{\lambda} \sin \theta \Rightarrow \mathbf{a}(\theta) = \left[ 1 \quad e^{-j2\pi f_s} \quad \dots \quad e^{-j2\pi (N-1) f_s} \right]$$

## Simpler 2D case: Uniform Linear Array (ULA)

The phase shift is

$$\Delta\phi = 2\pi f_c \frac{d \sin \theta}{c}$$

Unambiguous if  $\Delta\phi \in [-\pi, \pi]$  for all  $\theta \in [-\frac{\pi}{2}, \frac{\pi}{2}]$

$$-\pi \leq -2\pi f_c \frac{d}{c} \leq \Delta\phi \leq 2\pi f_c \frac{d}{c} \leq \pi$$

Spatial sampling requirement

$$d \leq \frac{\lambda}{2}$$

# Plan

## ① Introduction

## ② Model

Principle

Multichannel receiver

Received signals

The steering vector

**Covariance matrix**

Limitations

## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion

## Autocorrelation matrix of WSS signals

The autocorrelation matrix of a snapshot is defined as

$$\begin{aligned} \mathbf{R} &= \mathbb{E} \left[ \mathbf{y}[k] \mathbf{y}[k]^H \right] \\ &= \mathbb{E} \left[ \begin{bmatrix} y_1[k] \\ y_2[k] \\ \vdots \\ y_N[k] \end{bmatrix} \begin{bmatrix} y_1^*[k] & y_2^*[k] & \dots & y_N^*[k] \end{bmatrix} \right] \end{aligned}$$

The  $(n, l)$  entry of matrix  $\mathbf{R}$  measures the correlation between signals received at sensors  $n$  and  $l$  at the same time index

## Covariance matrix of WSS signals

The covariance matrix of a snapshot is defined as

$$\begin{aligned}\Sigma &= \mathbb{E} \left[ (\mathbf{y}[k] - \mathbb{E}[\mathbf{y}[k]])(\mathbf{y}[k] - \mathbb{E}[\mathbf{y}[k]])^H \right] \\ &= \mathbb{E} \left[ \mathbf{y}[k]\mathbf{y}[k]^H \right] - \mathbb{E}[\mathbf{y}[k]] \mathbb{E}[\mathbf{y}[k]]^H\end{aligned}$$

### Covariance matrix

When signals are zero-mean, the autocorrelation matrix is the same as the covariance matrix

In the following, if not specified, signals are assumed zero-mean

## Structure of the signal covariance matrix

For a mixture of signals

$$\begin{aligned}\mathbb{E} \left[ \mathbf{A}(\boldsymbol{\theta}) \mathbf{s}[k] \mathbf{s}[k]^H \mathbf{A}(\boldsymbol{\theta})^H \right] &= \mathbf{A}(\boldsymbol{\theta}) \mathbb{E} \left[ \mathbf{s}[k] \mathbf{s}[k]^H \right] \mathbf{A}(\boldsymbol{\theta})^H \\ &= \mathbf{A}(\boldsymbol{\theta}) \mathbf{R}_s \mathbf{A}(\boldsymbol{\theta})^H\end{aligned}$$

with  $\mathbf{R}_s \in \mathbb{C}^{P \times P}$  the covariance matrix of incoming signals

Uncorrelated signals:  $\mathbf{R}_s = \text{diag} (P_1, \dots, P_P)$

$$\mathbb{E} \left[ \mathbf{A}(\boldsymbol{\theta}) \mathbf{s}[k] \mathbf{s}[k]^H \mathbf{A}(\boldsymbol{\theta})^H \right] = \sum_{p=1}^P P_p \mathbf{a}(\theta_p) \mathbf{a}^H(\theta_p)$$

## Signal covariance matrix range

The range of a matrix  $\mathbf{A} = [\mathbf{a}_1 \ \cdots \ \mathbf{a}_n] \in \mathbb{C}^{m \times n}$  is the space spanned by its columns

$$\mathcal{R}(\mathbf{A}) = \left\{ \mathbf{y} = \mathbf{A}\mathbf{x} = \sum_{i=1}^n x_i \mathbf{a}_i, \forall \mathbf{x} \in \mathbb{R}^n \right\}$$

### Rank of a matrix

The rank of a matrix is the dimension of its range. A matrix  $\mathbf{A} \in \mathbb{C}^{m \times n}$  is said to be *full rank* if its rank is  $\min(m, n)$

If  $\mathbf{A}(\theta)$  and  $\mathbf{R}_s$  are full rank, the signal covariance matrix has rank  $P$ , and its range is spanned by the steering vectors  $\mathbf{a}(\theta_p), p = 1, \dots, P$



## Structure of the signal covariance matrix

WSS noise

$$\mathbb{E}[\mathbf{e}[k]] = \mathbf{0}, \quad \mathbb{E}[\mathbf{e}[k]\mathbf{e}[k]^H] \text{ indep. of } k$$

Spatially white noise with same power on each channel

$$\mathbb{E}[\mathbf{e}[k]\mathbf{e}[k]^H] = \sigma^2 \mathbf{I}_N$$

Leading for uncorrelated sources (noise and sources independant)

$$\mathbf{R} = \sum_{p=1}^P P_p \mathbf{a}(\theta_p) \mathbf{a}^H(\theta_p) + \sigma^2 \mathbf{I}_N$$

# Plan

## ① Introduction

## ② Model

Principle

Multichannel receiver

Received signals

The steering vector

Covariance matrix

**Limitations**

## ③ Beamforming

## ④ Direction of arrival estimation

## ⑤ Conclusion

## Model limitations

The model  $\mathbf{y}[k] = \mathbf{a}(\theta)s[k] + \mathbf{e}[k]$  is an idealized model which doesn't take into account

- non homogeneous propagation medium

$$y_n[k] = \rho_n[k] e^{j\varphi_n[k]} a_n(\theta) s[k] + e_n[k]$$

- uncalibrated arrays

$$y_n[k] = \alpha H_n(f_c) a_n(\theta) s[k] + e_n[k]$$

- wideband signals (time delay  $\neq$  phase shift)

$$Y_n(f) = \underbrace{\tilde{S}(f) e^{-j2\pi(f+f_c)\tau_n}}_{A_n(f,\theta)} + \check{E}(f + f_c)$$

- colored noise

$$\mathbb{E} \left[ \mathbf{n}[k] \mathbf{n}[k]^H \right] \neq \sigma^2 \mathbf{I}_N$$

# Plan

## ① Introduction

## ② Model

## ③ Beamforming

- Principle

- Array beampattern

- Spatial filtering

- Adaptive beamforming

- Robust adaptive beamforming

- Partially adaptive beamforming

- Summary

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Plan

## ① Introduction

## ② Model

## ③ Beamforming

### Principle

Array beampattern

Spatial filtering

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Partially adaptive beamforming

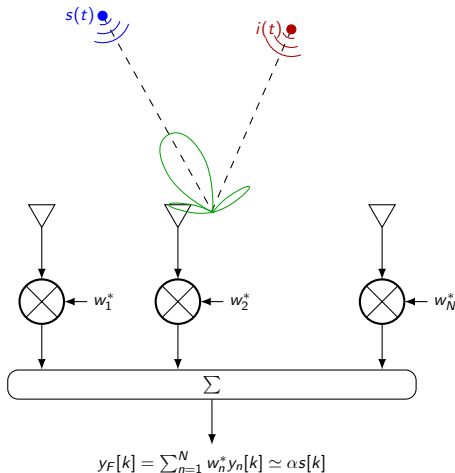
Summary

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Spatial filtering

Principle: linear combination of each sensor to point in a direction



# Plan

## ① Introduction

## ② Model

## ③ Beamforming

Principle

**Array beampattern**

Spatial filtering

Adaptive beamforming

Robust adaptive beamforming

Partially adaptive beamforming

Summary

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Array beampattern

For a given  $\mathbf{w}$

$$y_F[k] = \sum_{n=1}^N w_n^* y_n[k] = \mathbf{w}^H \mathbf{y}[k] = \mathbf{w}^H \mathbf{a}(\theta) s[k] + \mathbf{w}^H \mathbf{e}[k]$$

Corresponding array beampattern (gain at direction  $\theta$ )

$$G_{\mathbf{w}}(\theta) = |g_{\mathbf{w}}(\theta)|^2 = |\mathbf{w}^H \mathbf{a}(\theta)|^2$$

For ULA, the natural beampattern ( $w_n = 1$ ) is

$$g(\theta) = \sum_{n=0}^{N-1} e^{-j2\pi n \frac{d \sin \theta}{\lambda}} = \frac{1 - e^{-j2\pi N \frac{d \sin \theta}{\lambda}}}{1 - e^{-j2\pi \frac{d \sin \theta}{\lambda}}}$$



## ULA natural beampattern

$$\begin{aligned}
 g(\theta) &= \frac{e^{-j\pi N \frac{d \sin \theta}{\lambda}}}{e^{-j\pi \frac{d \sin \theta}{\lambda}}} \frac{e^{j\pi N \frac{d \sin \theta}{\lambda}} - e^{-j\pi N \frac{d \sin \theta}{\lambda}}}{e^{j\pi \frac{d \sin \theta}{\lambda}} - e^{-j\pi \frac{d \sin \theta}{\lambda}}} \\
 &= e^{-j\pi(N-1) \frac{d \sin \theta}{\lambda}} \frac{\sin\left(\pi N \frac{d \sin \theta}{\lambda}\right)}{\sin\left(\pi \frac{d \sin \theta}{\lambda}\right)}
 \end{aligned}$$

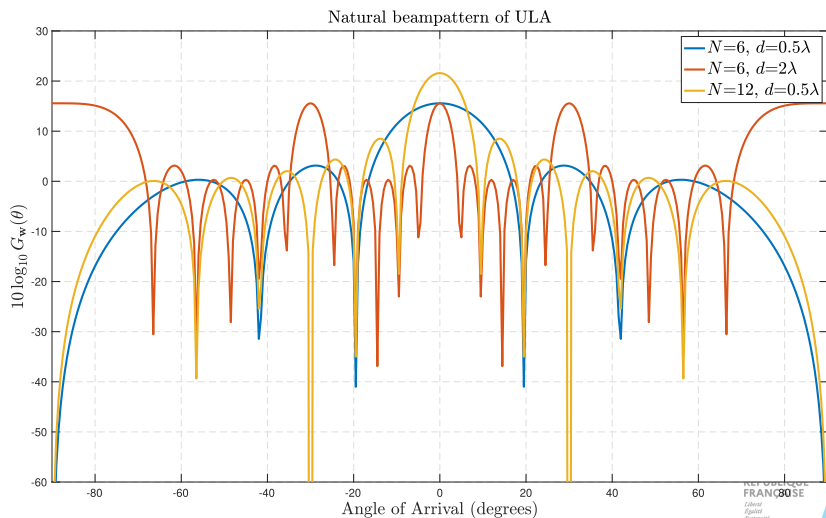
leading

$$G(\theta) = |g(\theta)|^2 = \left| \frac{\sin\left(\pi N \frac{d \sin \theta}{\lambda}\right)}{\sin\left(\pi \frac{d \sin \theta}{\lambda}\right)} \right|^2$$

Property (main lobe width)

$$\theta_{3\text{dB}} \approx \frac{0.9\lambda}{Nd}$$

# ULA natural beampattern



# Plan

## ① Introduction

## ② Model

## ③ Beamforming

Principle

Array beampattern

**Spatial filtering**

Adaptive beamforming

Robust adaptive beamforming

Partially adaptive beamforming

Summary

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Beamforming

Objective: focus on a given direction to enhance reception of some signals, and possibly mitigate signals from fixed directions

## Principle

Each sensor output is weighted by  $w_n^*$  before summation

$$y_F[k] = \sum_{n=1}^N w_n^* y_n[k] = \mathbf{w}^H \mathbf{y}[k]$$

Problem: how to choose  $\mathbf{w}$  when  $\mathbf{y}[k] = \mathbf{a}(\theta_s)s[k] + \dots$  so that  $y_F[k] \approx \alpha s[k]$ ?

# Conventional beamformer

Notation:  $\mathbf{a}_s = \mathbf{a}(\theta_s)$  with  $\theta_s$  the DOA of signal of interest

## Principle

Compensate for the phase shift induced by propagation from  $\theta_s$  and sum coherently

For ULA, considering only the signal of interest

$$\begin{aligned} y_F[k] &= \mathbf{a}_s^H \mathbf{a}_s s[k] \\ &= \sum_{n=0}^{N-1} e^{+j2\pi n \frac{d \sin \theta_s}{\lambda}} e^{-j2\pi n \frac{d \sin \theta_s}{\lambda}} s[k] \\ &= Ns[k] \end{aligned}$$

# Conventional beamformer

## Beampattern

$$g(\theta) = \mathbf{a}_s^H \mathbf{a}(\theta) = \sum_{n=0}^{N-1} e^{j2\pi n \frac{d(\sin \theta_s - \sin \theta)}{\lambda}}$$

## leading

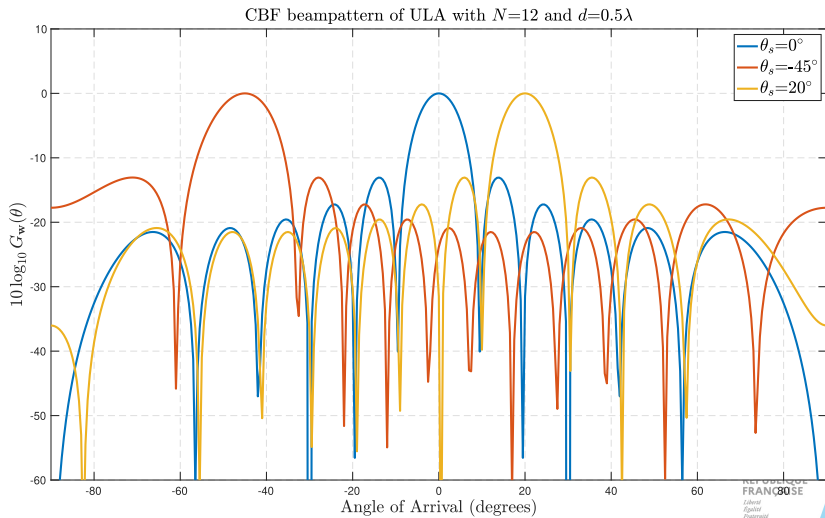
$$G(\theta) = |g(\theta)|^2 = \left| \frac{\sin \left( \pi N \frac{d(\sin \theta_s - \sin \theta)}{\lambda} \right)}{\sin \left( \pi \frac{d(\sin \theta_s - \sin \theta)}{\lambda} \right)} \right|^2$$

Property: max for  $\theta = \theta_s$

## Conventional beamformer

$$\mathbf{w}_{\text{CBF}} = \frac{\mathbf{a}_s}{\mathbf{a}_s^H \mathbf{a}_s}$$

# ULA CBF beampattern



## Impact on SNR

Considering a single source in white uncorrelated noise at input

$$\mathbf{y}[k] = \mathbf{a}_s s[k] + \mathbf{e}[k] \quad \text{SNR}_{\text{in}} = \frac{\mathbb{E}[|s[k]|^2]}{\mathbb{E}[|\mathbf{e}[k]|^2]} = \frac{P}{\sigma^2}$$

After beamforming

$$y_F[k] = \mathbf{w}^H \mathbf{y}[k] = \mathbf{w}^H \mathbf{a}_s s[k] + \mathbf{w}^H \mathbf{e}[k]$$

leading

$$\text{SNR}_{\text{out}} = \frac{\mathbb{E}[|\mathbf{w}^H \mathbf{a}_s s[k]|^2]}{\mathbb{E}[|\mathbf{w}^H \mathbf{e}[k]|^2]} = \frac{|\mathbf{w}^H \mathbf{a}_s|^2}{\|\mathbf{w}\|^2} \text{SNR}_{\text{in}} \leq \|\mathbf{a}_s\|^2 \text{SNR}_{\text{in}}$$



## Impact on SNR

Leading  $\text{SNR}_{\text{out}} \leq N \times \text{SNR}_{\text{in}}$  with equality if and only if  $\mathbf{w} \propto \mathbf{a}_s$

### Property

The CBF is the beamformer that maximizes the SNR at the output with unitary maximum gain

$$\mathbf{w}_{\text{CBF}} = \arg \max_{\mathbf{w}} \text{SNR}_{\text{out}} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1$$

### White noise array gain

For any  $\mathbf{w}$  such that  $\mathbf{w}^H \mathbf{a}_s = 1$ , the white noise array gain is

$$A_{\text{WN}} = \frac{\text{SNR}_{\text{out}}}{\text{SNR}_{\text{in}}} = \|\mathbf{w}\|^{-2} \leq N$$

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# Adaptive beamforming

## Conventional beamformer

$$\mathbf{w}_{\text{CBF}} = \arg \max_{\mathbf{w}} \text{SNR}_{\text{out}} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1$$

$$\Leftrightarrow \mathbf{w}_{\text{CBF}} = \arg \min_{\mathbf{w}} \|\mathbf{w}\|^2 \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1$$

The CBF is optimal in white noise: minimize  $\mathbf{w}^H \mathbf{w}$  (i.e., output power when input is  $\mathbf{e}$ ) under  $\mathbf{w}^H \mathbf{a}_s = 1$  (i.e., maintain unit gain in desired direction). Other directions are treated the same

## Adaptive beamforming

Takes into account potentiel interfering signals in some directions

# Adaptive beamforming

In presence of an interfering signal

$$\mathbf{y}[k] = \mathbf{a}_s s[k] + \mathbf{y}_i[k] + \mathbf{e}[k]$$

Filtered signal

$$y_F[k] = \underbrace{\mathbf{w}^H \mathbf{a}_s s[k]}_{\text{signal}} + \underbrace{\mathbf{w}^H (\mathbf{y}_i[k] + \mathbf{e}[k])}_{\text{interference + noise}}$$

## Signal to Interference plus Noise Ratio (SINR)

For a beamformer  $\mathbf{w}$ , the figure of merit is the Signal to Interference plus Noise Ratio (SINR)

$$\begin{aligned} \text{SINR}(\mathbf{w}) &= \frac{\mathbb{E}[|\mathbf{w}^H \mathbf{a}_s s[k]|^2]}{\mathbb{E}[|\mathbf{w}^H (\mathbf{y}_i[k] + \mathbf{e}[k])|^2]} \\ &= \frac{P_s |\mathbf{w}^H \mathbf{a}_s|^2}{\mathbf{w}^H \mathbf{C} \mathbf{w}} \end{aligned}$$

where  $\mathbf{C} = \mathbb{E}[(\mathbf{y}_i[k] + \mathbf{e}[k])(\mathbf{y}_i[k] + \mathbf{e}[k])^H]$  is the interference plus noise covariance matrix

## Interference plus Noise covariance matrix

Under zero mean, independence and narrow band assumptions

$$\begin{aligned}
 \mathbf{R} &= \sum_{p=1}^P P_p \mathbf{a}_p(\theta_p) \mathbf{a}_p^H(\theta_p) + \sigma^2 \mathbf{I}_N \\
 &= P_s \mathbf{a}_s(\theta_s) \mathbf{a}_s^H(\theta_s) + \underbrace{\sum_{j=1}^J P_j \mathbf{a}_j(\theta_j) \mathbf{a}_j^H(\theta_j)}_C + \sigma^2 \mathbf{I}_N
 \end{aligned}$$

where  $J$  is the number of interfering signals, and terms indexed by  $j$  are the corresponding parameters

# Optimal beamformer

CBF: maximises SNR while keeping unit gain in desired direction

## Optimal beamformer

Maximizes the SINR while ensuring unit gain towards  $\theta_s$

$$\begin{aligned} \max_{\mathbf{w}} \frac{P_s |\mathbf{w}^H \mathbf{a}_s|^2}{\mathbf{w}^H \mathbf{C} \mathbf{w}} \quad & \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1 \\ \Leftrightarrow \min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w} \quad & \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1 \end{aligned}$$

For CBF: consequence of its definition. How to solve this for Optimal beamformer?

## Reminder: constrained optimization (1/3)

One wants to solve

$$\min_{\mathbf{w} \in \mathbb{R}^N} f(\mathbf{w}) \quad \text{s.t. } g(\mathbf{w}) = 0 \quad \text{where } f : \mathbb{R}^N \rightarrow \mathbb{R} \text{ and } g : \mathbb{R}^N \rightarrow \mathbb{R}$$

### Lagrangian

We introduce the vector of Lagrange multiplier  $\lambda \in \mathbb{R}$  and define the Lagrangian as

$$\mathcal{L}(\mathbf{w}, \lambda) = f(\mathbf{w}) + \lambda g(\mathbf{w})$$

KKT conditions

$$\frac{\partial \mathcal{L}(\mathbf{w}, \lambda)}{\partial \mathbf{w}} = \mathbf{0} \quad \text{and} \quad \frac{\partial \mathcal{L}(\mathbf{w}, \lambda)}{\partial \lambda} = 0$$

Here, variables are complex



## Reminder: constrained optimization (2/3)

One wants to solve

$$\min_{\mathbf{w} \in \mathbb{C}^N} f(\mathbf{w}) \quad \text{s.t. } g(\mathbf{w}) = 0 \quad \text{where } f : \mathbb{C}^N \rightarrow \mathbb{R} \text{ and } g : \mathbb{C}^N \rightarrow \mathbb{C}$$

### Lagrangian

We introduce the vector of Lagrange multiplier  $\lambda \in \mathbb{C}$  and define the Lagrangian as

$$\mathcal{L}(\mathbf{w}, \lambda) = f(\mathbf{w}) + \text{Re}(\lambda^* g(\mathbf{w})) = f(\mathbf{w}) + \frac{1}{2} (\lambda^* g(\mathbf{w}) + \lambda g^*(\mathbf{w}))$$

KKT conditions

$$\frac{\partial \mathcal{L}(\mathbf{w}, \lambda)}{\partial \mathbf{w}^*} = \mathbf{0} \quad \text{and} \quad \frac{\partial \mathcal{L}(\mathbf{w}, \lambda)}{\partial \lambda^*} = 0$$

In complex derivatives,  $z$  and  $z^*$  are considered independent variables

## Reminder: constrained optimization (3/3)

For convex problems, KKT lead optimal solution

### Optimal beamformer

The problem

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1$$

is convex

Lagrangian

$$\mathcal{L}(\mathbf{w}, \lambda) = \mathbf{w}^H \mathbf{C} \mathbf{w} + \frac{1}{2} \left( \lambda^* (\mathbf{w}^H \mathbf{a}_s - 1) + \lambda (\mathbf{w}^H \mathbf{a}_s - 1)^* \right)$$

N.B.

$$\frac{\partial \mathbf{a}^T \mathbf{x}}{\partial \mathbf{x}} = \frac{\partial \mathbf{x}^T \mathbf{a}}{\partial \mathbf{x}} = \mathbf{a}$$

# Optimal beamformer

## Optimal beamformer

Maximizes the SINR while ensuring unit gain towards  $\theta_s$

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{a}_s = 1$$

leading

$$\mathbf{w}_{\text{opt}} = \frac{\mathbf{C}^{-1} \mathbf{a}_s}{\mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s}$$

For such  $\mathbf{w}$

$$\text{SINR}(\mathbf{w}_{\text{opt}}) = P_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s$$

# Principles

CBF: minimize the output power when input is  $\mathbf{e}$  under the constraint that the actual steering vector  $\mathbf{a}_s$  goes non distorted

Optimal: minimize the output power when input is  $\mathbf{y}_i + \mathbf{e}$  under the constraint that the actual steering vector  $\mathbf{a}_s$  goes non distorted

## Issues

In practice: neither  $\mathbf{a}_s$  nor  $\mathbf{C}$  is known. Actual steering vector might differ from its expected value and  $\mathbf{C}$  needs to be estimated from the data

# Minimum Variance Distortionless Response (MVDR)

## MVDR beamformer

Minimize output power (when input is  $\mathbf{y}_i + \mathbf{e}$ ) under the constraint that the steering vector in the **assumed** direction  $\theta_0$  goes non distorted

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w} \text{ subject to } \mathbf{w}^H \mathbf{a}_0 = 1$$

with  $\mathbf{a}_0 = \mathbf{a}(\theta_0)$  the assumed steering vector of the signal of interest (Sol)

$$\mathbf{w}_{\text{MVDR}} = \frac{\mathbf{C}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0}$$

$$\text{SINR}(\mathbf{w}_{\text{MVDR}}) = P_s \frac{|\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0}$$

# Minimum Power Distortionless Response (MPDR)

## MPDR beamformer

Minimize output power (when input is  $\mathbf{a}_s s + \mathbf{y}_i + \mathbf{e}$ ) under the constraint that the steering vector in the **assumed** direction  $\theta_0$  goes non distorted

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{R} \mathbf{w} \text{ subject to } \mathbf{w}^H \mathbf{a}_0 = 1$$

with  $\mathbf{R} = P_s \mathbf{a}_s \mathbf{a}_s^H + \mathbf{C}$  the signal plus noise plus interference covariance matrix

$$\mathbf{w}_{\text{MPDR}} = \frac{\mathbf{R}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_0}$$

$$\text{SINR}(\mathbf{w}_{\text{MPDR}}) = P_s \frac{|\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{C} \mathbf{R}^{-1} \mathbf{a}_0}$$

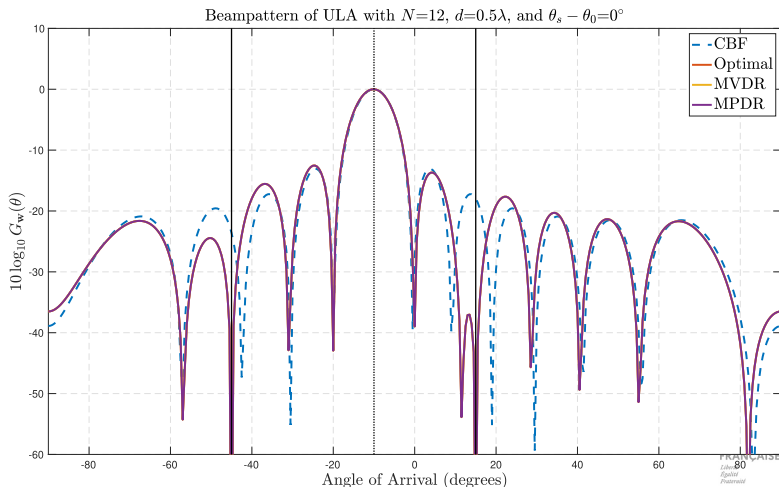
## Summary of adaptive beamformers (known covariances)

Beamformer	Principle	Weight vector
Optimal	$\min_{\mathbf{w}} \underbrace{\mathbf{w}^H \mathbf{C} \mathbf{w}}_{\text{output power}} \text{ s.t. } \underbrace{\mathbf{w}^H \mathbf{a}_s = 1}_{\text{gain constraint}}$	$\mathbf{w}_{\text{opt}} = \frac{\mathbf{C}^{-1} \mathbf{a}_s}{\mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s}$
MVDR	$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w} \text{ s.t. } \mathbf{w}^H \mathbf{a}_0 = 1$	$\mathbf{w}_{\text{MVDR}} = \frac{\mathbf{C}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0}$
MPDR	$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{R} \mathbf{w} \text{ s.t. } \mathbf{w}^H \mathbf{a}_0 = 1$	$\mathbf{w}_{\text{MPDR}} = \frac{\mathbf{R}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_0}$

- $\mathbf{a}_s$ : true steering vector
- $\mathbf{a}_0$ : assumed steering vector
- $\mathbf{C}$ :  $\text{cov}(\mathbf{y}_i + \mathbf{e})$
- $\mathbf{R}$ :  $\text{cov}(\mathbf{a}_s + s\mathbf{y}_i + \mathbf{e})$

# ULA adaptive beamformer beampatterns

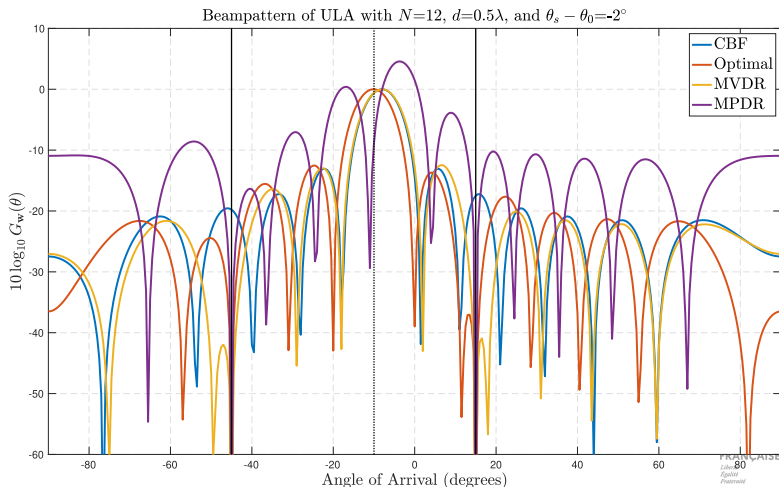
Misalignment:  $0^\circ$





# ULA adaptive beamformer beampatterns

Misalignment:  $2^\circ$



## CBF vs MVDR: single interference

If  $\mathbf{y}[k] = \mathbf{a}_s s[k] + \mathbf{a}_I s_I[k] + \mathbf{e}[k]$  then  $\mathbf{C} = P_I \mathbf{a}_I \mathbf{a}_I^H + \sigma^2 \mathbf{I}_N$

For  $\text{INR} = \frac{P_I}{\sigma^2} \gg 1$  it can be shown

$$\text{SINR}_{\text{CBF}} \approx \frac{P_s}{\sigma^2} \times \frac{1}{g \times \text{INR}} \quad \text{SINR}_{\text{opt}} \approx \frac{P_s}{\sigma^2} \times N(1 - g)$$

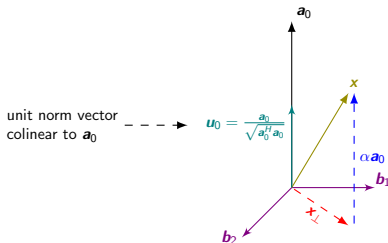
where  $g = \cos^2(\mathbf{a}_s, \mathbf{a}_j) = \frac{|\mathbf{a}_s^H \mathbf{a}_j|^2}{(\mathbf{a}_s^H \mathbf{a}_s)(\mathbf{a}_j^H \mathbf{a}_j)} \in [0, 1]$

### Remarks

- $P_I \nearrow$  leads  $\text{SINR}_{\text{CBF}} \searrow$  while  $\text{SINR}_{\text{opt}}$  is constant
- $\text{SINR} \searrow$  when  $\mathbf{a}_j \rightarrow \mathbf{a}_s$  ( $g \rightarrow 1$ )

## Reminder: linear algebra in Hilbert spaces (1/4)

Given a vector  $\mathbf{a}_0 \in \mathbb{C}^N$  and  $\mathbf{u}_0 = \frac{\mathbf{a}_0}{\sqrt{\mathbf{a}_0^H \mathbf{a}_0}}$ .  $\mathbf{u}_0$  can be completed with vectors  $\{\mathbf{b}_1, \dots, \mathbf{b}_{N-1}\}$  to form an orthonormal basis



Any vector  $\mathbf{x} \in \mathbb{C}^N$  can then be decomposed as

$$\mathbf{x} = \underbrace{\mathbf{u}_0^H \mathbf{x}}_{\alpha \sqrt{\mathbf{a}_0^H \mathbf{a}_0}} \mathbf{u}_0 + \underbrace{\mathbf{x} - \mathbf{u}_0^H \mathbf{x} \mathbf{u}_0}_{\mathbf{x}_\perp}$$

## Reminder: linear algebra in Hilbert spaces (2/4)

The vector space spanned by  $\mathbf{a}_0$  (or its range) is defined as

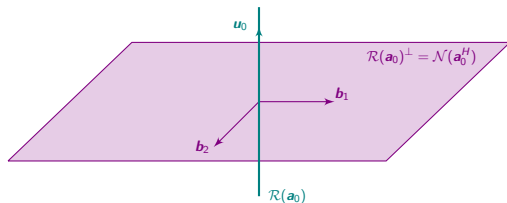
$$\mathcal{R}(\mathbf{a}_0) = \{\alpha \mathbf{a}_0, \forall \alpha \in \mathbb{C}\} \subset \mathbb{C}^N \text{ and } \dim(\mathcal{R}(\mathbf{a}_0)) = 1$$

Its orthogonal subspace is the null-space (or kernel) of  $\mathbf{a}_0^H$

$$\mathcal{R}(\mathbf{a}_0)^\perp = \{\mathbf{x} \in \mathbb{C}^N, \mathbf{a}_0^H \mathbf{x} = 0\} = \mathcal{N}(\mathbf{a}_0^H) \text{ and } \dim(\mathcal{N}(\mathbf{a}_0^H)) = N - 1$$

and

$$\mathcal{R}(\mathbf{a}_0) \oplus \mathcal{R}(\mathbf{a}_0)^\perp = \mathbb{C}^N$$



## Reminder: linear algebra in Hilbert spaces (3/4)

Expanding  $\mathbf{u}_0$  leads

$$\begin{aligned}\mathbf{x} &= \frac{\mathbf{a}_0^H \mathbf{x} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{a}_0} + \mathbf{x} - \frac{\mathbf{a}_0^H \mathbf{x} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{a}_0} \\ &= \Pi_{\mathbf{a}_0} \mathbf{x} + \Pi_{\mathbf{a}_0}^\perp \mathbf{x}\end{aligned}$$

where

$$\Pi_{\mathbf{a}_0} = \frac{\mathbf{a}_0 \mathbf{a}_0^H}{\mathbf{a}_0^H \mathbf{a}_0}$$

is the orthogonal projector<sup>1</sup> on  $\mathcal{R}(\mathbf{a}_0)$  and

$$\Pi_{\mathbf{a}_0}^\perp = I_N - \Pi_{\mathbf{a}_0}$$

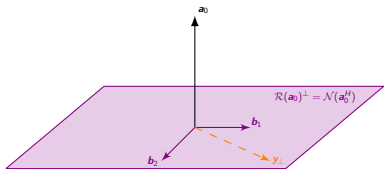
is the orthogonal projector on  $\mathcal{R}(\mathbf{a}_0)^\perp$

---

<sup>1</sup> $\Pi_{\mathbf{a}_0} \times \Pi_{\mathbf{a}_0} = \Pi_{\mathbf{a}_0}$  and  $\Pi_{\mathbf{a}_0}^H = \Pi_{\mathbf{a}_0} \Rightarrow$  orthogonal projector and  $\forall \mathbf{x} \in \mathbb{C}^N, \Pi_{\mathbf{a}_0} \mathbf{x} \in \mathcal{R}(\mathbf{a}_0)$

## Reminder: linear algebra in Hilbert spaces (4/4)

We have  $\mathbf{b}_i^H \mathbf{a}_0 = 0, i = 1, \dots, N - 1$  and the family  $\{\mathbf{b}_1, \dots, \mathbf{b}_{N-1}\}$  is an orthonormal basis of  $\mathcal{R}(\mathbf{a}_0)^\perp$



$$\mathbf{y}_\perp = \sum_{i=1}^{N-1} y_{a,i} \mathbf{b}_i \quad \text{where } y_{a,i} = \mathbf{b}_i^H \mathbf{y}_\perp$$

We consider

$$\mathbf{B} = [\mathbf{b}_1 \quad \dots \quad \mathbf{b}_{N-1}] \in \mathbb{C}^{N \times N-1} \quad \text{and} \quad \mathbf{y}_a = [y_{a,1} \quad \dots \quad y_{a,N-1}]^T \in \mathbb{C}^{N-1}$$

### Properties

$\mathbf{B}$  is rank  $N - 1$ ,  $\mathbf{B}^H \mathbf{a}_0 = \mathbf{0} \in \mathbb{C}^{N-1}$  and  $\mathbf{y}_\perp = \mathbf{B} \mathbf{y}_a$

## Generalized sidelobe canceler

Any beamformer can be decomposed as

$$\mathbf{w} = \alpha \mathbf{a}_0 + \mathbf{w}_\perp \quad \text{where } \mathbf{w}_\perp^H \mathbf{a}_0 = 0$$

- the component along  $\mathbf{a}_0$  ensures the unit gain constraint

$$\mathbf{w}^H \mathbf{a}_0 = \alpha \mathbf{a}_0^H \mathbf{a}_0 + \mathbf{w}_\perp^H \mathbf{a}_0 = \alpha \mathbf{a}_0^H \mathbf{a}_0 \Rightarrow \alpha = (\mathbf{a}_0^H \mathbf{a}_0)^{-1}$$

- orthogonal component is arbitrary, in a space of dimension  $N - 1$

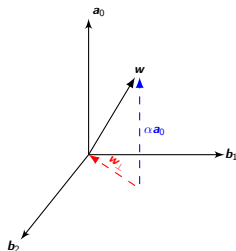
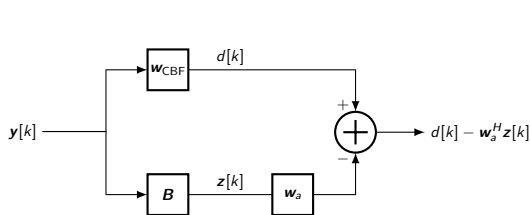
$$\mathbf{w}_\perp = \mathbf{B} \mathbf{w}_a \quad \text{with } \mathbf{B} \in \mathbb{C}^{N \times N-1}, \mathbf{B}^H \mathbf{a}_0 = 0, \mathbf{w}_a \in \mathbb{C}^{N-1}$$

## Generalized sidelobe canceler

We have

$$\mathbf{w} = (\mathbf{a}_0^H \mathbf{a}_0)^{-1} \mathbf{a}_0 - \mathbf{w}_\perp = \mathbf{w}_{\text{CBF}} - \mathbf{B} \mathbf{w}_a$$

$$\Rightarrow \mathbf{w}^H \mathbf{y} = \mathbf{w}_{\text{CBF}}^H \mathbf{y} - \mathbf{w}_a^H \mathbf{B}^H \mathbf{y} = d - \mathbf{w}_a^H \mathbf{z}$$



The  $N - 1$  auxiliary channels in  $\mathbf{z}[k]$  are free of signal and can be used to remove the contribution of interferences



## Generalized sidelobe canceler

MVDR is obtained equivalently by solving<sup>2</sup>

$$\underbrace{\min_{\mathbf{w}, \mathbf{w}^H \mathbf{a}_0 = 1} \mathbf{w}^H \mathbf{C} \mathbf{w}}_{\text{direct form, constrained}} \qquad \underbrace{\min_{\mathbf{w}_a} (\mathbf{w}_{\text{CBF}} - \mathbf{B} \mathbf{w}_a)^H \mathbf{C} (\mathbf{w}_{\text{CBF}} - \mathbf{B} \mathbf{w}_a)}_{\text{GSC form, unconstrained}}$$

The GSC form of the MVDR beamformer is

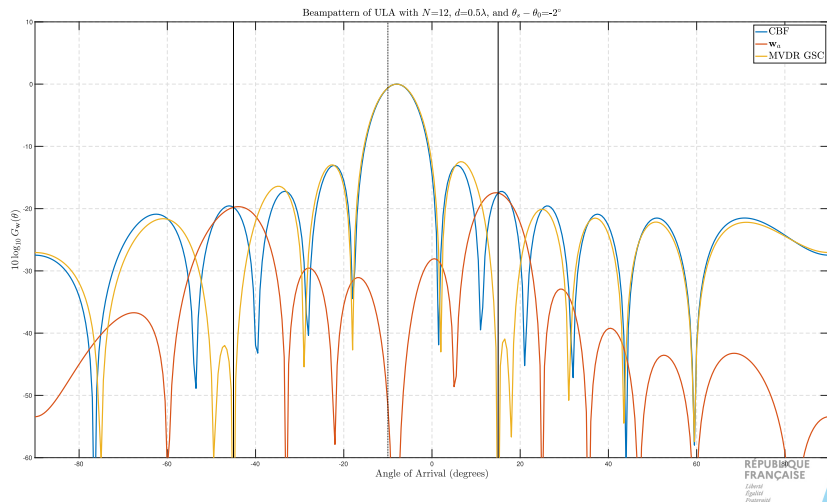
$$\mathbf{w}_{\text{GSC}} = \mathbf{w}_{\text{CBF}} - \mathbf{B} \mathbf{w}_{a, \text{MVDR}}$$

where  $\mathbf{w}_{a, \text{MVDR}}$  solves the above estimation problem

$$\mathbf{w}_{a, \text{MVDR}} = (\mathbf{B}^H \mathbf{C} \mathbf{B})^{-1} \mathbf{B}^H \mathbf{C} \mathbf{w}_{\text{CBF}}$$

<sup>2</sup>MPDR:  $\mathbf{C} \leftrightarrow \mathbf{R}$

# ULA adaptive beamformer beampatterns



## Adaptive beamformer comparison

Three beamformers

- ① Opt:  $\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w}$  subject to  $\mathbf{w}^H \mathbf{a}_s = 1$
- ② MVDR:  $\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w}$  subject to  $\mathbf{w}^H \mathbf{a}_0 = 1$
- ③ MPDR:  $\min_{\mathbf{w}} \mathbf{w}^H (\mathbf{C} + P_s \mathbf{a}_s \mathbf{a}_s^H) \mathbf{w}$  subject to  $\mathbf{w}^H \mathbf{a}_0 = 1$

The optimal, MVDR, and MPDR beamformers are equivalent when

- the assumed steering vector  $\mathbf{a}_0$  coincides the true steering vector  $\mathbf{a}_s$
- the covariance matrix of the incoming signal  $\mathbf{R}$  is known

In practice

- uncalibrated arrays and pointing errors lead  $\mathbf{a}_0 \neq \mathbf{a}_s$
- the covariance matrix is estimated leading estimation errors  $\hat{\mathbf{R}} - \mathbf{R}$

⇒ Degradation of optimal SINR ( $P_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s$ )

## Influence of the steering vector (MVDR)

We have

$$\begin{aligned}
 \text{SINR}(\mathbf{w}_{\text{MVDR}}) &= P_s \frac{|\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0} \\
 &= P_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s \frac{|\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s|^2}{(\mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s)(\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0)} \\
 &= \text{SINR}_{\text{opt}} \frac{|\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s|^2}{(\mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s)(\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0)} \\
 &= \text{SINR}_{\text{opt}} \cos^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1}) \\
 &\leq \text{SINR}_{\text{opt}}
 \end{aligned}$$

## Influence of the steering vector (MPDR)

We have

$$\text{SINR}(\mathbf{w}_{\text{MPDR}}) = P_s \frac{|\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{C} \mathbf{R}^{-1} \mathbf{a}_0}, \quad \mathbf{R} = P_s \mathbf{a}_s \mathbf{a}_s^H + \mathbf{C}$$

Using matrix inversion lemma<sup>3</sup>

$$\mathbf{R}^{-1} = \mathbf{C}^{-1} - \frac{P_s \mathbf{C}^{-1} \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1}}{1 + P_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s} = \mathbf{C}^{-1} - \frac{P_s \mathbf{C}^{-1} \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1}}{1 + \text{SINR}_{\text{opt}}}$$

hence

$$\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_s = \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s \left( 1 - \frac{\text{SINR}_{\text{opt}}}{1 + \text{SINR}_{\text{opt}}} \right)$$

leading

$$P_s |\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_s|^2 = \frac{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 \text{SINR}(\mathbf{w}_{\text{MVDR}})}{(1 + \text{SINR}_{\text{opt}})^2}$$

<sup>3</sup> $(\mathbf{A} + \mathbf{CBC}^H)^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1} \mathbf{C} (\mathbf{B}^{-1} + \mathbf{C}^H \mathbf{A}^{-1} \mathbf{C})^{-1} \mathbf{C}^H \mathbf{A}^{-1}$

# Influence of the steering vector (MPDR)

Denominator

$$\begin{aligned}
 & \mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{C} \mathbf{R}^{-1} \mathbf{a}_0 \\
 &= \mathbf{a}_0^H \mathbf{C}^{-1} \left( \mathbf{I}_N - \frac{P_s \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1}}{1 + \text{SINR}_{\text{opt}}} \right) \left( \mathbf{I}_N - \frac{P_s \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1}}{1 + \text{SINR}_{\text{opt}}} \right) \mathbf{a}_0 \\
 &= \mathbf{a}_0^H \mathbf{C}^{-1} \left( \mathbf{a}_0 - 2 \frac{P_s \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_0}{1 + \text{SINR}_{\text{opt}}} + \frac{P_s^2 \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s}{(1 + \text{SINR}_{\text{opt}})^2} \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_0 \right) \\
 &= \left( \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 - 2 \frac{P_s \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_0}{1 + \text{SINR}_{\text{opt}}} + \frac{P_s^2 \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s}{(1 + \text{SINR}_{\text{opt}})^2} \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_0 \right) \\
 &= \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 \left( 1 - 2 \frac{P_s |\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 (1 + \text{SINR}_{\text{opt}})} + \frac{P_s^2 |\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_s|^2 \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s}{\mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 (1 + \text{SINR}_{\text{opt}})^2} \right)
 \end{aligned}$$

# Influence of the steering vector (MPDR)

Denominator

$$\begin{aligned} & \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 \left( 1 - 2 \frac{P_s \cos(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s}{(1 + \text{SINR}_{\text{opt}})} + \frac{P_s^2 \cos(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 (\mathbf{a}_s^H \mathbf{C}^{-1} \mathbf{a}_s)^2}{(1 + \text{SINR}_{\text{opt}})^2} \right) \\ &= \mathbf{a}_0^H \mathbf{C}^{-1} \mathbf{a}_0 \left( 1 - 2 \frac{\cos(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \text{SINR}_{\text{opt}}}{(1 + \text{SINR}_{\text{opt}})} + \frac{\cos(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \text{SINR}_{\text{opt}}^2}{(1 + \text{SINR}_{\text{opt}})^2} \right) \end{aligned}$$

Hence

$$\text{SINR}(\mathbf{w}_{\text{MPDR}}) = \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}})}{\left(1 + \text{SINR}_{\text{opt}}\right)^2 \left(1 - 2 \frac{\cos(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \text{SINR}_{\text{opt}}}{(1 + \text{SINR}_{\text{opt}})} + \frac{\cos(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \text{SINR}_{\text{opt}}^2}{(1 + \text{SINR}_{\text{opt}})^2}\right)}$$

# Influence of the steering vector (MPDR)

## Leading

$$\begin{aligned}
 & \text{SINR}(\mathbf{w}_{\text{MPDR}}) \\
 &= \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}})}{\left(1 + \text{SINR}_{\text{opt}}\right)^2 - 2 \cos^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \text{SINR}_{\text{opt}}(1 + \text{SINR}_{\text{opt}}) + \cos^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})^2 \text{SINR}_{\text{opt}}^2} \\
 &= \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}})}{1 + 2\text{SINR}_{\text{opt}} + \text{SINR}_{\text{opt}}^2 - 2 \cos^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})\text{SINR}_{\text{opt}} - \cos^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})\text{SINR}_{\text{opt}}^2} \\
 &= \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}})}{1 + \left(2\text{SINR}_{\text{opt}} + \text{SINR}_{\text{opt}}^2\right) \left(1 - \cos^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})\right)} \\
 &= \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}})}{1 + \left(2\text{SINR}_{\text{opt}} + \text{SINR}_{\text{opt}}^2\right) \sin^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})}
 \end{aligned}$$



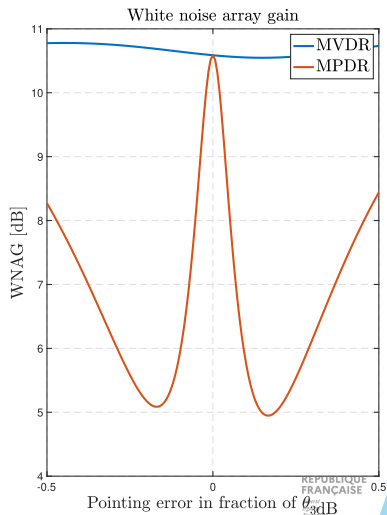
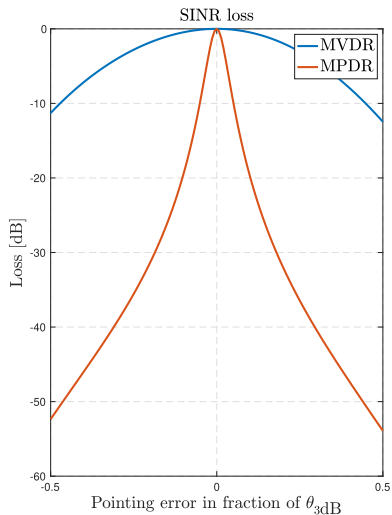
## Influence of the steering vector (MPDR)

Finally

$$\begin{aligned} \text{SINR}(\mathbf{w}_{\text{MPDR}}) &= \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}})}{1 + (2\text{SINR}_{\text{opt}} + \text{SINR}_{\text{opt}}^2) \sin^2(\mathbf{a}_s, \mathbf{a}_0; \mathbf{C}^{-1})} \\ &\leq \text{SINR}(\mathbf{w}_{\text{MVDR}}) \end{aligned}$$

The degradation is more important as  $\text{SINR}_{\text{opt}}$  (hence  $P_s$ ) increases

# Influence of a steering vector error on SINR and WNAG



## Case of an uncalibrated array

Uncalibrated arrays lead different gains and phases

$$y_n[k] = \underbrace{(1 + g_n)e^{j\phi_n} a_n(\theta)}_{\tilde{a}_n(\theta)} s[k] + e_n[k]$$

with  $g_n$  and  $\phi_n$  independent random gains and phases such as

$$\mathbb{E}[g_n] = 0, \quad \mathbb{E}[g_n^2] = \sigma_g^2, \quad \mathbb{E}[e^{j\phi_n}] = \gamma$$

For any beamformer  $\mathbf{w}$

$$\mathbb{E}[\tilde{G}_{\mathbf{w}}(\theta)] = |\gamma|^2 G_{\mathbf{w}}(\theta) + \underbrace{(1 + \sigma_g^2 - |\gamma|^2) \|\mathbf{w}\|^2}_{\text{sidelobe level increase}}$$

## Influence of the number of snapshots

In practice, limited number of snapshots  $K$

$$\mathbf{y}[k] = \mathbf{a}_s s[k] + \underbrace{\mathbf{y}_i[k] + \mathbf{e}[k]}_{\mathbf{y}_{i+e}[k]}, \quad k = 1, \dots, K$$

Covariance matrices are estimated from these snapshots

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_{k=1}^K \mathbf{y}[k] \mathbf{y}^H[k] \quad \Rightarrow \quad \mathbf{w}_{\text{MPDR}}^{\text{smi}} = \frac{\hat{\mathbf{R}}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \hat{\mathbf{R}}^{-1} \mathbf{a}_0}$$

$$\hat{\mathbf{C}} = \frac{1}{K} \sum_{k=1}^K \mathbf{y}_{i+e}[k] \mathbf{y}_{i+e}^H[k] \quad \Rightarrow \quad \mathbf{w}_{\text{MVDR}}^{\text{smi}} = \frac{\hat{\mathbf{C}}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \hat{\mathbf{C}}^{-1} \mathbf{a}_0}$$

smi: "sample matrix inversion"

## Influence of the number of snapshots

Beamformers  $\mathbf{w}_{M \times DR}^{\text{smi}}$  will differ from  $\mathbf{w}_{M \times DR}$  since

$$\hat{\mathbf{R}} = \mathbf{R} + \Delta \mathbf{R} \quad \hat{\mathbf{C}} = \mathbf{C} + \Delta \mathbf{C}$$

$\mathbf{w}_{M \times DR}^{\text{smi}}$  are random vectors, and so are their SINR

$$\text{SINR}(\mathbf{w}_{\text{MPDR}}^{\text{smi}}) = P_s \frac{|\mathbf{a}_0^H \hat{\mathbf{R}}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \hat{\mathbf{R}}^{-1} \mathbf{C} \hat{\mathbf{R}}^{-1} \mathbf{a}_0}$$

$$\text{SINR}(\mathbf{w}_{\text{MVDR}}^{\text{smi}}) = P_s \frac{|\mathbf{a}_0^H \hat{\mathbf{C}}^{-1} \mathbf{a}_s|^2}{\mathbf{a}_0^H \hat{\mathbf{C}}^{-1} \mathbf{C} \hat{\mathbf{C}}^{-1} \mathbf{a}_0}$$

Importance of the convergence speed of the estimators

## SINR loss with finite number of snapshots (MVDR)

Defining

$$\rho_{\text{MVDR}} = \frac{\text{SINR}(\mathbf{w}_{\text{MVDR}}^{\text{smi}})}{\text{SINR}_{\text{opt}}}$$

one can show

$$\rho_{\text{MVDR}} \sim \text{Beta}(K - N + 2, N - 1)$$

which is independent of  $\mathbf{C}$ , and

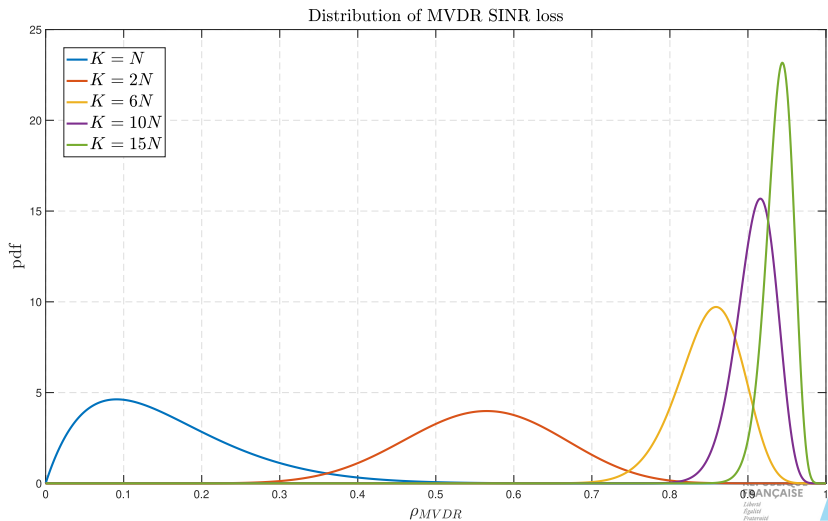
$$\mathbb{E}[\rho_{\text{MVDR}}] = \frac{K - N + 2}{K + 1}$$

For  $K_{\text{MVDR}} = 2N - 3$

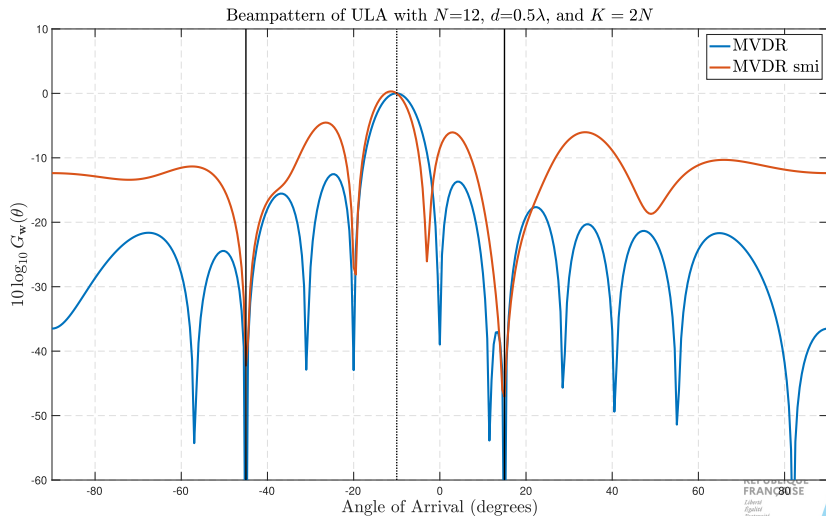
$$\mathbb{E}[\text{SINR}(\mathbf{w}_{\text{MVDR}}^{\text{smi}})] = \frac{\text{SINR}_{\text{opt}}}{2} \quad (3 \text{ dB loss on average})$$

Rule of thumb:  $K = 2N$

# SINR loss with finite number of snapshots (MVDR)



# MVDR versus smi version





## SINR loss with finite number of snapshots (MPDR)

Defining

$$\rho_{\text{MPDR}} = \frac{\text{SINR}(\mathbf{w}_{\text{MPDR}}^{\text{smi}})}{\text{SINR}_{\text{opt}}}$$

one can show that

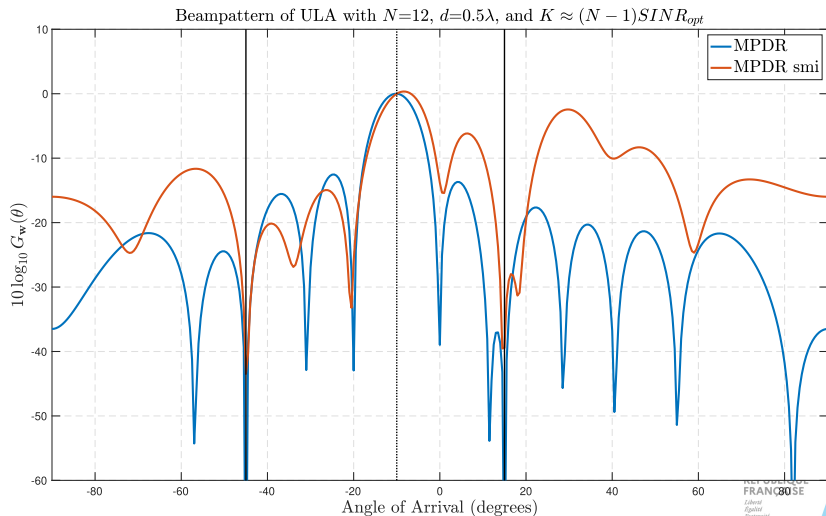
$$\mathbb{E}[\rho_{\text{MPDR}}] \approx \frac{K}{K + \text{SINR}_{\text{opt}}(N - 1)}$$

and to be within 3 dB of the optimal value

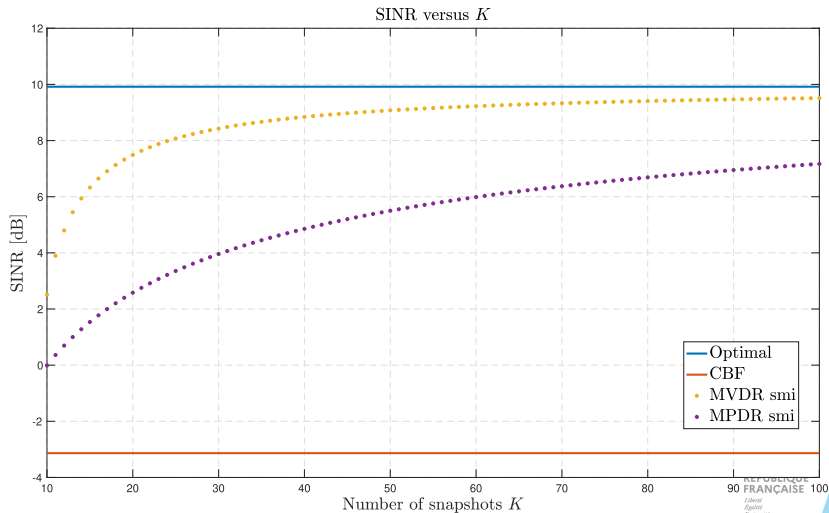
$$K_{\text{MPDR}} \approx (N - 1)\text{SINR}_{\text{opt}}$$

and in general,  $K_{\text{MPDR}} \gg K_{\text{MVDR}}$

# MPDR versus smi version



# Influence of $K$



# Conclusion

## In practice

- Estimation of covariance matrices  $\Rightarrow$  SINR loss (especially MPDR)
  - interference is less eliminated
  - sidelobe level increase ( $\Rightarrow$  lower white noise gain)
- Uncalibrated arrays: white noise gain  $\searrow$  (or  $\|\mathbf{w}\|^2 \nearrow$ )  $\Rightarrow$  steering vector errors  $\nearrow$

How to make these beamformers more robust?

# Plan

## ① Introduction

## ② Model

## ③ Beamforming

- Principle

- Array beampattern

- Spatial filtering

- Adaptive beamforming

- Robust adaptive beamforming**

- Partially adaptive beamforming

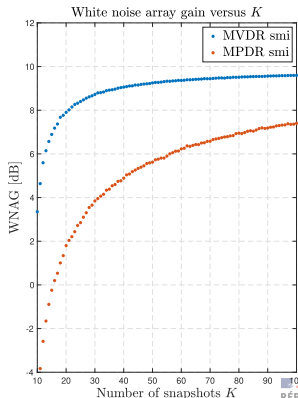
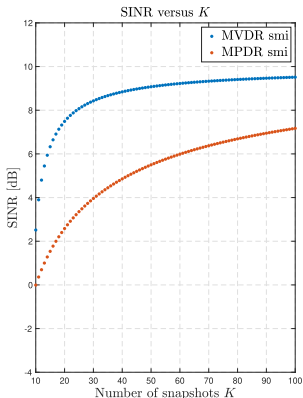
- Summary

## ④ Direction of arrival estimation

## ⑤ Conclusion

# Motivation

- For calibration error, error grows with  $\|\mathbf{w}\|^2$
- For limited snapshot numbers



Idea: minimize  $\|\mathbf{w}\|^2$  (i.e., maximize WNAG)

# Diagonal loading

## Principle

Solve

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \text{ subject to } \mathbf{w}^H \mathbf{a}_0 = 1 \text{ and } \|\mathbf{w}\|^2 \leq A_{\text{WN}}^{-1}$$

where  $\|\mathbf{w}\|^{-2} \leq N$  imposes  $A_{\text{WN}} \leq N$

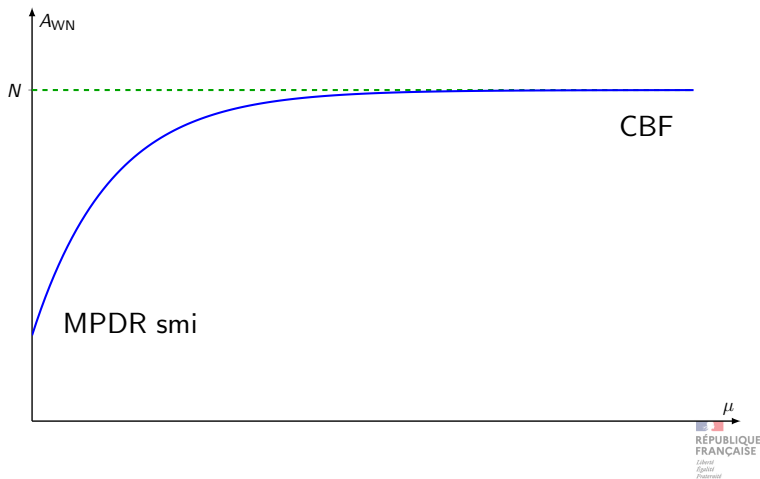
## Solution

We have

$$\mathbf{w}_{\text{MPDR-DL}}(\mu) = \frac{\left(\hat{\mathbf{R}} + \mu \mathbf{I}_N\right)^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \left(\hat{\mathbf{R}} + \mu \mathbf{I}_N\right)^{-1} \mathbf{a}_0}$$

with  $\mu$  such as  $\|\mathbf{w}_{\text{MPDR-DL}}(\mu)\|^{-2} = A_{\text{WN}}$

# Diagonal loading: adaptivity versus robustness





## Setting the value of $\mu$

Several methods in the literature to set  $\mu$

- set  $A_{WN}$  and compute  $\mu$  from  $\|\mathbf{w}_{MPDR-DL}(\mu)\|^{-2} = A_{WN}$
- directly, a few dB above noise level (see next part)
- from the theory of ridge regression (and compute  $\mu$  from the data)
- it can be shown DL is equivalent to

$$\max_{P, \mathbf{a}} \left\| \hat{\mathbf{R}} - P\mathbf{a}\mathbf{a}^H \right\|^2 \quad \text{subject to } \|\mathbf{a} - \mathbf{a}_0\|^2 \leq \varepsilon^2$$

deduce  $\mu$  from  $\varepsilon$

- set  $A_{WN}$  and compute DL from GSC form
- ...

## Linear algebra reminder: eigenvalue decomposition

If  $\mathbf{A} \in \mathbb{C}^{N \times N}$  is Hermitian ( $\mathbf{A}^H = \mathbf{A}$ ), there exists a unitary matrix  $\mathbf{U} \in \mathbb{C}^{N \times N}$  ( $\mathbf{U}^H \mathbf{U} = \mathbf{U} \mathbf{U}^H = \mathbf{I}_N$ ) such as

$$\mathbf{A} = \mathbf{U} \mathbf{\Lambda} \mathbf{U}^H$$

where  $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_N) = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_N \end{bmatrix}$  is a diagonal matrix

containing the eigenvalues of  $\mathbf{A}$  (Hermitian  $\Rightarrow \lambda_n \in \mathbb{R}$ )

### Convention

If not stated otherwise, we assume  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_N$

## Application to signal covariance matrix

We have the (Hermitian) covariance matrix

$$\mathbf{R} = \mathbf{A}(\theta)\mathbf{R}_s\mathbf{A}(\theta)^H + \sigma^2\mathbf{I}_N$$

$\mathbf{A}(\theta)\mathbf{R}_s\mathbf{A}(\theta)^H$  is Hermitian, positive and with rank  $P$

eigenvalues are  $\underbrace{\lambda_1, \dots, \lambda_P}_{>0}, \underbrace{0, \dots, 0}_{N-P}$

$\sigma^2\mathbf{I}_N$  directly diagonal

$\exists \mathbf{U} \in \mathbb{C}^{N \times N}, \mathbf{R} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H$  with  $\mathbf{\Lambda} = \text{diag}(\lambda_1 + \sigma^2, \dots, \lambda_P + \sigma^2, \sigma^2, \dots, \sigma^2)$

and  $\mathbf{R}^{-1} = \mathbf{U}\mathbf{\Lambda}^{-1}\mathbf{U}^H$

## Application to signal covariance matrix

With 1 signal of interest and  $J$  interferences:  $P = J + 1$ . Denoting

$$\mathbf{U} = [\mathbf{u}_1 \quad \cdots \quad \mathbf{u}_N]$$

we have

$$\begin{aligned} \mathbf{R}^{-1} &= \sum_{n=1}^{J+1} \frac{1}{\lambda_n + \sigma^2} \mathbf{u}_n \mathbf{u}_n^H + \sum_{n=J+2}^N \frac{1}{\sigma^2} \mathbf{u}_n \mathbf{u}_n^H \\ &= \sum_{n=1}^{J+1} \frac{1}{\lambda_n + \sigma^2} \mathbf{u}_n \mathbf{u}_n^H + \sum_{n=1}^N \frac{1}{\sigma^2} \mathbf{u}_n \mathbf{u}_n^H - \sum_{n=1}^{J+1} \frac{1}{\sigma^2} \mathbf{u}_n \mathbf{u}_n^H \\ &= \frac{1}{\sigma^2} \mathbf{I}_N - \frac{1}{\sigma^2} \sum_{n=1}^{J+1} \frac{\lambda_n}{\lambda_n + \sigma^2} \mathbf{u}_n \mathbf{u}_n^H \end{aligned}$$

## Consequence on MPDR (or MVDR)

The beamformer is expressed as

$$\mathbf{w}_{\text{MPDR}} = \frac{\mathbf{R}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_0}$$

leading

$$\begin{aligned} g_{\text{MPDR}}(\theta) &= \left( \frac{\mathbf{R}^{-1} \mathbf{a}_0}{\mathbf{a}_0^H \mathbf{R}^{-1} \mathbf{a}_0} \right)^H \mathbf{a}(\theta) \\ &= \alpha \mathbf{a}_0^H (\mathbf{R}^{-1})^H \mathbf{a}(\theta) \\ &= \alpha \mathbf{a}_0^H \left( \frac{1}{\sigma^2} \mathbf{I}_N - \frac{1}{\sigma^2} \sum_{n=1}^{J+1} \frac{\lambda_n}{\lambda_n + \sigma^2} \mathbf{u}_n \mathbf{u}_n^H \right)^H \mathbf{a}(\theta) \end{aligned}$$

## Interpretation of DL and the choice of $\mu$

Beampattern with true covariance matrix

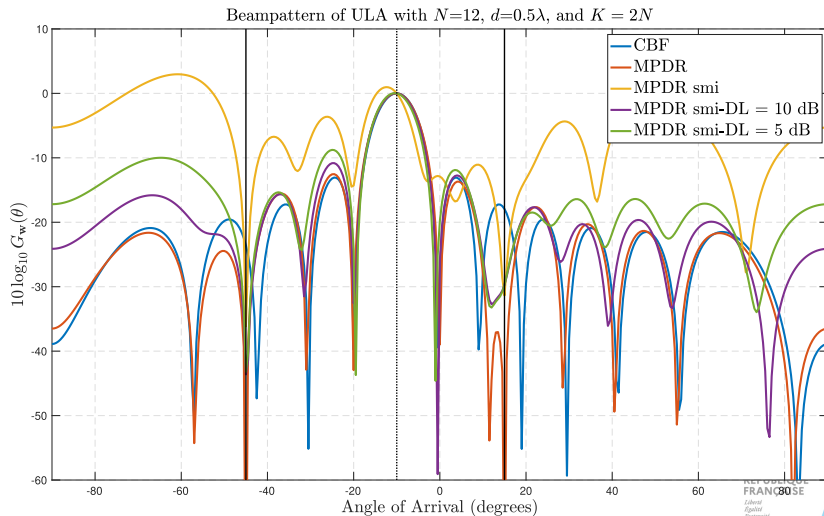
$$g_{\text{MPDR}}(\theta) = \frac{\alpha}{\sigma^2} \left( \mathbf{a}_0^H \mathbf{a}(\theta) - \sum_{n=1}^J \frac{\lambda_n}{\lambda_n + \sigma^2} (\mathbf{a}_0^H \mathbf{u}_n)(\mathbf{u}_n^H \mathbf{a}(\theta)) \right)$$

With estimated covariance matrix

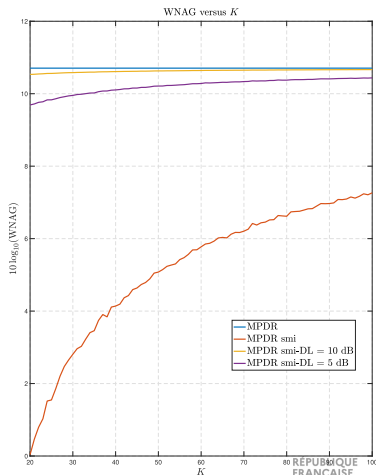
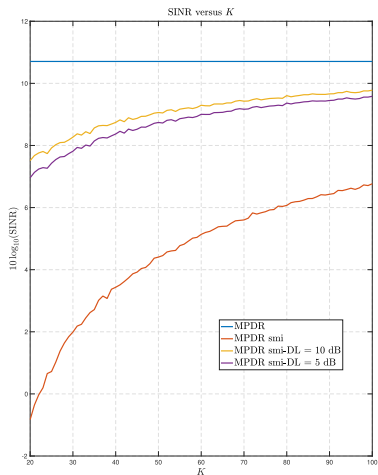
$$g_{\text{MPDR}}^{\text{smi}}(\theta) = \frac{\alpha}{\hat{\lambda}_{\min}} \left( \mathbf{a}_0^H \mathbf{a}(\theta) - \sum_{n=1}^N \frac{\hat{\lambda}_n}{\hat{\lambda}_n + \hat{\lambda}_{\min}} (\mathbf{a}_0^H \hat{\mathbf{u}}_n)(\hat{\mathbf{u}}_n^H \mathbf{a}(\theta)) \right)$$

- degradation is due to  $\hat{\lambda}_{J+2} \neq \hat{\lambda}_{J+3} \neq \dots \neq \hat{\lambda}_N = \hat{\lambda}_{\min}$
- replacing  $\hat{\mathbf{R}}$  with  $\hat{\mathbf{R}} + \mu \mathbf{I}_N$  replaces  $\hat{\lambda}_n$  with  $\hat{\lambda}_n + \mu$
- if  $\mu \gg \sigma^2$  and  $\mu < \lambda_{J+1}$ : equalization of last eigenvalues

# Diagonal loading: beampatterns

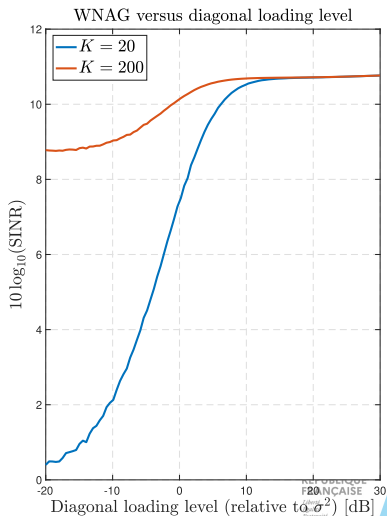
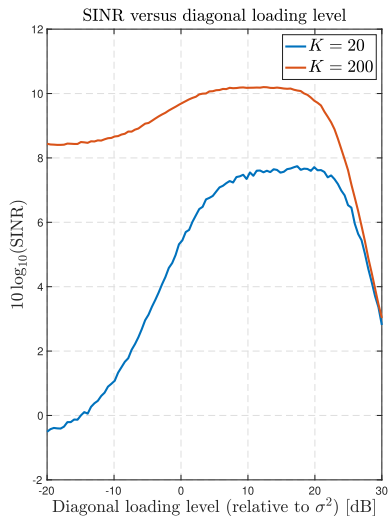


# Diagonal loading: influence of $K$ on SINR and WNAG





# Diagonal loading: influence of $\mu$ on SINR and WNAG



# Linearly constrained beamforming

To mitigate pointing errors: multiple constraints

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{C} \mathbf{w} \text{ subject to } \mathbf{Z}^H \mathbf{w} = \mathbf{d}$$

Solution:  $\mathbf{w} = \mathbf{C}^{-1} \mathbf{Z} (\mathbf{Z}^H \mathbf{C}^{-1} \mathbf{Z})^{-1} \mathbf{d}$

Constraint exemples

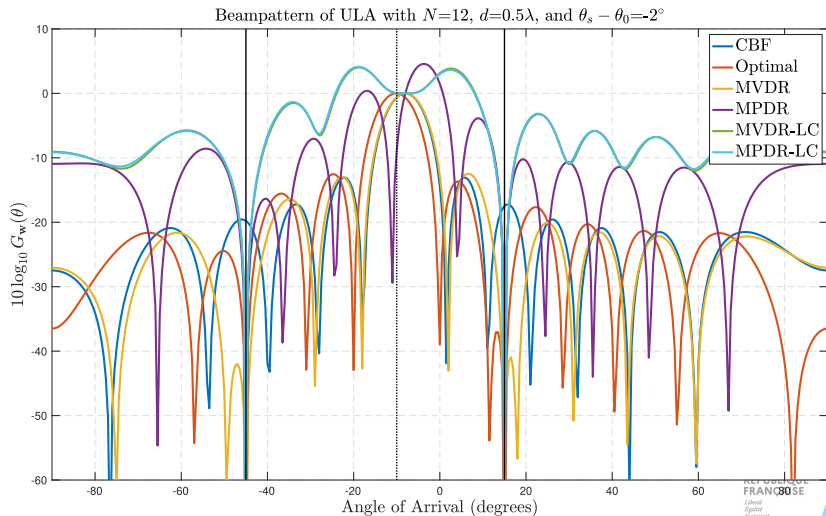
- unit gain around presumed DOA

$$\mathbf{Z} = [\mathbf{a}(\theta_0) \quad \mathbf{a}(\theta_0 + \delta_1) \quad \cdots \quad \mathbf{a}(\theta_0 + \delta_L)], \quad \mathbf{d} = [1 \quad 1 \quad \cdots \quad 1]^T$$

- smoothness around presumed DOA

$$\mathbf{Z} = \left[ \mathbf{a}(\theta_0) \quad \frac{\partial \mathbf{a}(\theta)}{\partial \theta} \quad \cdots \quad \frac{\partial^L \mathbf{a}(\theta)}{\partial \theta^L} \right], \quad \mathbf{d} = [1 \quad 0 \quad \cdots \quad 0]^T$$

# Linearly constrained beamforming: beampatterns



# Plan

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## ② Model

## ③ Beamforming

Principle

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Adaptive beamforming

Robust adaptive beamforming

**Partially adaptive beamforming**

Summary

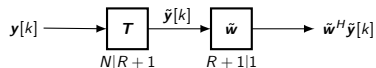
## ④ Direction of arrival estimation

## ⑤ Conclusion

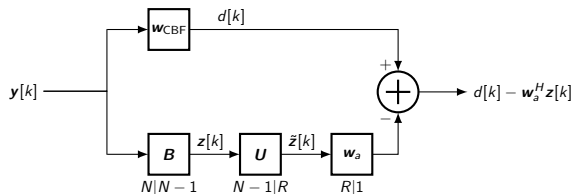
# Partially adaptive beamforming

Principle: work in a lower dimensional subspace

- Direct form



- GSC form ( $\mathbf{T} = [\mathbf{w}_{\text{CBF}} \quad \mathbf{B}\mathbf{U}]$ )

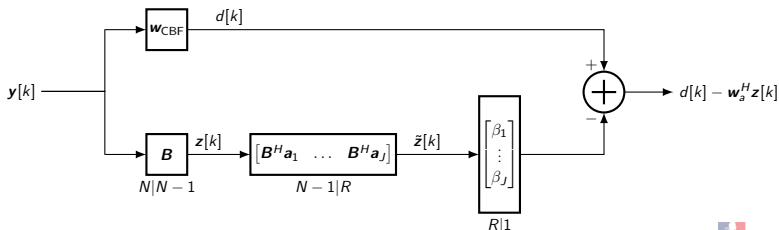


## Motivation for partially adaptive beamforming

When  $\mathbf{C} = \sum_{j=1}^J P_j \mathbf{a}_j \mathbf{a}_j^H + \sigma^2 \mathbf{I}_N$ , one can show

$$\mathbf{w}_{\text{opt}} = \mathbf{w}_{\text{CBF}} - \mathbf{B} \sum_{j=1}^J \beta_j \mathbf{B}^H \mathbf{a}_j$$

The optimal beamformer subtracts a linear combinations  $J$  beams steered towards interference



The optimal beamformer is a partially adaptive beamformer!

# Optimality of partially adaptive beamformer

Is it possible to obtain  $\mathbf{w}_{\text{opt}}$ ?

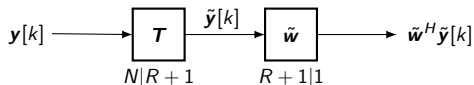
## Direct form

- $\mathbf{w}_{\text{PA-DF}} = \mathbf{w}_{\text{opt}} \Leftrightarrow \mathbf{C}^{-1} \mathbf{a}_s \in \mathcal{R}(\mathbf{T})$
- Not useful: if  $\mathbf{C}^{-1} \mathbf{a}_s$  is known, optimal beamformer can be implemented
- if  $\mathbf{C} = \sum_{j=1}^J P_j \mathbf{a}_j \mathbf{a}_j^H + \sigma^2 \mathbf{I}_N \Rightarrow \mathbf{C}^{-1} \mathbf{a}_s = \eta_s \mathbf{a}_s + \sum_{j=1}^J \eta_j \mathbf{a}_j$
- so if  $[\mathbf{a}_s \quad \mathbf{a}_1 \quad \dots \quad \mathbf{a}_J] \in \mathcal{R}(\mathbf{T})$  then  $\mathbf{w}_{\text{PA-DF}} = \mathbf{w}_{\text{opt}}$

## GSC form

- $\mathbf{w}_{\text{PA-GSC}} = \mathbf{w}_{\text{opt}} \Leftrightarrow \mathbf{B}^H \mathbf{C}^{-1} \mathbf{a}_s \in \mathcal{R}(\mathbf{U})$
- if  $[\mathbf{B}^H \mathbf{a}_1 \quad \dots \quad \mathbf{B}^H \mathbf{a}_J] \in \mathcal{R}(\mathbf{U})$  then  $\mathbf{w}_{\text{PA-GSC}} = \mathbf{w}_{\text{opt}}$

## Expression of partially adaptive beamformer



### Direct form

- Minimize output power

$$\min_{\tilde{w}} \tilde{w}^H R_{\tilde{y}} \tilde{w} \quad \text{subject to} \quad \tilde{w}^H \tilde{a}_0 = 1$$

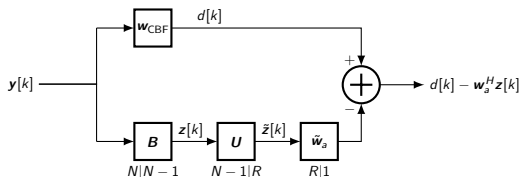
where  $R_{\tilde{y}} = T^H R_y T$  and  $\tilde{a}_0 = T^H a_0$

- Solution

$$\tilde{w} = \alpha R_{\tilde{y}}^{-1} \tilde{a}_0 \Rightarrow w_{\text{PA-DF}} = \alpha T R_y^{-1} a_0$$



## Expression of partially adaptive beamformer



### GSC form

- Minimize output power

$$\min_{\tilde{\mathbf{w}}_a} \mathbb{E} \left\{ |d[k] - \tilde{\mathbf{w}}_a^H \tilde{\mathbf{z}}[k]|^2 \right\}$$

- Solution ( $\mathbf{r}_{dz} = \mathbb{E} \{ \mathbf{z}[k] d^*[k] \}$ )

$$\tilde{\mathbf{w}}_a = \mathbf{R}_{\tilde{\mathbf{z}}}^{-1} \mathbf{r}_{d\tilde{\mathbf{z}}} = \left( \mathbf{U}^H \mathbf{R}_z \mathbf{U} \right)^{-1} \mathbf{U}^H \mathbf{r}_{dz} \Rightarrow \mathbf{w}_{\text{PA-GSC}} = \mathbf{w}_{\text{CBF}} - \mathbf{B} \mathbf{U} \mathbf{R}_{\tilde{\mathbf{z}}}^{-1} \mathbf{r}_{d\tilde{\mathbf{z}}}$$

## Selection of $\mathbf{T}$ and $\mathbf{U}$

Fixed transformations: pre-steered beams

$$\mathbf{T} = \left[ \mathbf{a}(\theta_s) \quad \mathbf{a}(\tilde{\theta}_1) \quad \mathbf{a}(\tilde{\theta}_2) \quad \dots \quad \mathbf{a}(\tilde{\theta}_R) \right]$$
$$\mathbf{U} = \mathbf{B}^H \left[ \mathbf{a}(\tilde{\theta}_1) \quad \mathbf{a}(\tilde{\theta}_2) \quad \dots \quad \mathbf{a}(\tilde{\theta}_R) \right]$$

Requires prior knowledge about interferences DOA

## Selection of $\mathbf{T}$ and $\mathbf{U}$

### Adaptive transformations

- optimal beamformer:  $\mathbf{w}_{\text{opt}} = \mathbf{w}_{\text{CBF}} - \mathbf{B} \sum_{j=1}^J \beta_j \mathbf{B}^H \mathbf{a}_j$
- only need a basis for  $\mathcal{R} \{ [\mathbf{B}^H \mathbf{a}_1 \ \dots \ \mathbf{B}^H \mathbf{a}_J] \}$
- for  $\mathbf{R}_z = \mathbf{B}^H \mathbf{C} \mathbf{B}$

$$\begin{aligned} \mathbf{R}_z &= \sum_{j=1}^J P_j (\mathbf{B}^H \mathbf{a}_j) (\mathbf{B}^H \mathbf{a}_j)^H + \sigma^2 \mathbf{I}_{N-1} \\ &= \sum_{n=1}^{N-1} \lambda_n \mathbf{q}_n \mathbf{q}_n^H \quad \lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_{N-1} \end{aligned}$$

- Property:  $\mathcal{R} \{ [\mathbf{B}^H \mathbf{a}_1 \ \dots \ \mathbf{B}^H \mathbf{a}_J] \} = \mathcal{R} \{ [\mathbf{q}_1 \ \dots \ \mathbf{q}_J] \}$

## Selection of $\mathbf{T}$ and $\mathbf{U}$

### Principal Component

Choose the  $R$  principal eigenvectors of  $\mathbf{R}_z$ ,  $\mathbf{U} = [\mathbf{q}_1 \ \dots \ \mathbf{q}_R]$  leading

$$\mathbf{R}_z = \mathbf{U}^H \mathbf{R}_z \mathbf{U} = \mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_R)$$

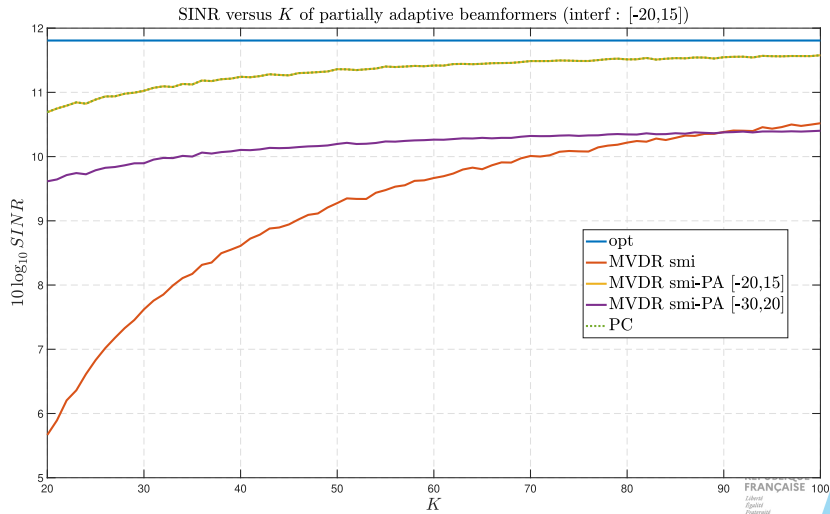
and

$$\mathbf{w}_{\text{PA-GSC}} = \mathbf{w}_{\text{CBF}} - \mathbf{B} \mathbf{U} \mathbf{\Lambda}^{-1} \mathbf{r}_{dz}$$

### Cross Spectral Metric

Choose the  $R$  eigenvectors which contribute most to increase the SINR

# Partially adaptive beamforming: influence of $K$



# Plan

## ① Introduction

## ② Model

## ③ Beamforming

- Principle

- Array beampattern

- Spatial filtering

- Adaptive beamforming

- Robust adaptive beamforming

- Partially adaptive beamforming

- Summary**

## ④ Direction of arrival estimation

## ⑤ Conclusion

## Beamforming: synthesis

- Conventional beamforming:  $\mathbf{w}_{\text{CBF}} = (\mathbf{a}_0^H \mathbf{a}_0)^{-1} \mathbf{a}_0$ , optimal in white noise,  $\theta_{3\text{dB}} \approx 0.9 (N \frac{d}{\lambda})^{-1}$
- Adaptive beamforming:
  - $\mathbf{w}_{\text{opt}} \propto \mathbf{C}^{-1} \mathbf{a}_s$ ,  $\mathbf{w}_{\text{MVDR}} \propto \mathbf{C}^{-1} \mathbf{a}_0$ ,  $\mathbf{w}_{\text{MPDR}} \propto \mathbf{R}^{-1} \mathbf{a}_0$ ,
  - all equivalent if  $\mathbf{R}$ ,  $\mathbf{C}$  known and  $\mathbf{a}_0 = \mathbf{a}_s$
  - $\text{SINR}_{\text{opt}} \geq \text{SINR}_{\text{MVDR}} \gg \text{SINR}_{\text{MPDR}}$  when  $\mathbf{a}_s \neq \mathbf{a}_0$
  - $\text{SINR}_{\text{MVDR-SMI}} \gg \text{SINR}_{\text{MPDR-SMI}}$  and convergence for about  $2N$  snapshots for MVDR and  $N \times \text{SINR}_{\text{opt}}$  for MPDR
- Diagonal loading: helps to mitigate finite sample errors and steering vector errors. Especially useful in MPDR context with low power signal of interest
- Partially adaptive beamforming: enables to achieve faster convergence by operating in low-dimensional subspace. Especially effective with strong, low-rank interference

# Plan

① Introduction

② Model

③ Beamforming

④ Direction of arrival estimation

- Problem formulation

- Non parametric methods

- Parametric methods

- Sparse estimation

⑤ Conclusion



# Plan

① Introduction

② Model

③ Beamforming

④ Direction of arrival estimation

Problem formulation

Non parametric methods

Parametric methods

Sparse estimation

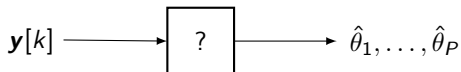
⑤ Conclusion

## DOA estimation problem

Collection of  $K$  snapshots of  $P$  signals impinging the array

$$\mathbf{y}[k] = \sum_{p=1}^P \mathbf{a}(\theta_p) s_p[k] + \mathbf{e}[k] = \mathbf{A}(\boldsymbol{\theta}) \mathbf{s}[k] + \mathbf{e}[k]$$

How to retrieve  $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_P\}$ ?



### Approaches

- Non parametric approaches: don't rely on a model for  $\mathbf{y}[k]$  (similar to Fourier in time domain)
- Parametric approaches: a model is assumed and its properties are exploited (algebraic structure, distribution)

# Plan

① Introduction

② Model

③ Beamforming

④ Direction of arrival estimation

Problem formulation

**Non parametric methods**

Parametric methods

Sparse estimation

⑤ Conclusion

# Beamforming for direction finding purposes

Idea: form a beam  $\mathbf{w}(\theta)$  for each angle  $\theta$  and evaluate the power at the output

$$\mathbf{y}[k] \longrightarrow \boxed{\mathbf{w}(\theta)} \longrightarrow P_{\mathbf{w}}(\theta) = \mathbb{E} \left\{ |\mathbf{w}^H(\theta)\mathbf{y}[k]|^2 \right\} = \mathbf{w}^H(\theta)\mathbf{R}_y\mathbf{w}(\theta)$$

Large peaks should correspond to the DOA

## CBF for direction finding purposes

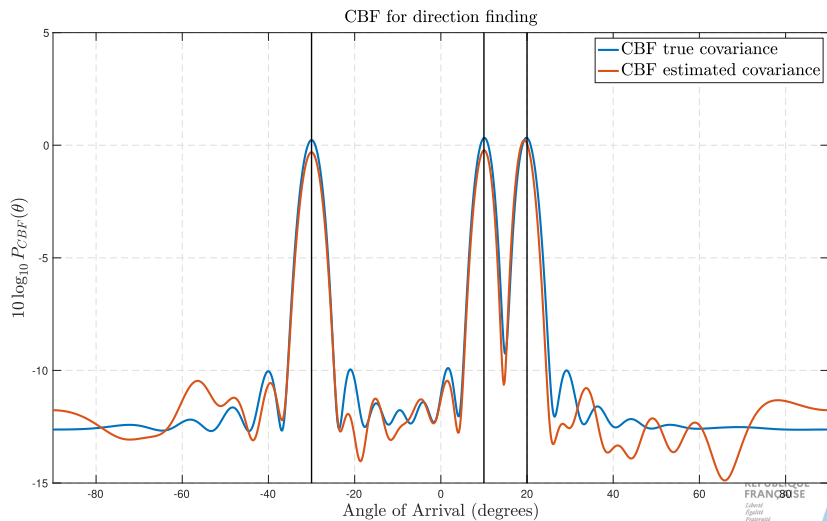
Conventional beamformer

$$\mathbf{w}_{\text{CBF}}(\theta) = \frac{\mathbf{a}(\theta)}{N} \Rightarrow \mathbf{w}_{\text{CBF}}^H(\theta) \mathbf{R} \mathbf{w}_{\text{CBF}}(\theta) = \frac{\mathbf{a}^H(\theta) \mathbf{R} \mathbf{a}(\theta)}{N^2}$$

In practice,  $\mathbf{R}$  is unknown

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_{k=1}^K \mathbf{y}[k] \mathbf{y}^H[k] \Rightarrow P_{\text{CBF}}(\theta) = \frac{\mathbf{a}^H(\theta) \hat{\mathbf{R}} \mathbf{a}(\theta)}{N^2}$$

# CBF for direction finding purposes



## Interpretation of CBF for direction finding

The estimated power at the output of the CBF is

$$\begin{aligned} P_{\text{CBF}}(\theta) &= \frac{1}{N^2} \mathbf{a}^H(\theta) \hat{\mathbf{R}} \mathbf{a}(\theta) \\ &= \frac{1}{KN^2} \sum_{k=1}^K \left| \mathbf{a}^H(\theta) \mathbf{y}[k] \right|^2 \\ &= \frac{1}{KN^2} \sum_{k=1}^K \left| \sum_{n=1}^N y_n[k] e^{-j2\pi(n-1)f_s} \right|^2 \end{aligned}$$

with  $f_s = \frac{d}{\lambda} \sin \theta$

## Interpretation of CBF for direction finding

The estimated power at the output of the CBF is

$$\begin{aligned}
 P_{\text{CBF}}(\theta) &= \frac{1}{N^2} \mathbf{a}^H(\theta) \hat{\mathbf{R}} \mathbf{a}(\theta) \\
 &= \frac{1}{KN^2} \sum_{k=1}^K \left| \mathbf{a}^H(\theta) \mathbf{y}[k] \right|^2 \\
 &= \frac{1}{KN^2} \sum_{k=1}^K \left| \sum_{n=1}^N y_n[k] e^{-j2\pi(n-1)f_s} \right|^2
 \end{aligned}$$

with  $f_s = \frac{d}{\lambda} \sin \theta$

⇒ Spatial Fourier transform of each snapshot



# MPDR for direction finding purposes: Capon's method

MPDR beamformer

$$\mathbf{w}_{\text{MPDR}}(\theta) = \frac{\mathbf{R}^{-1} \mathbf{a}(\theta)}{\mathbf{a}^H(\theta) \mathbf{R}^{-1} \mathbf{a}(\theta)}$$

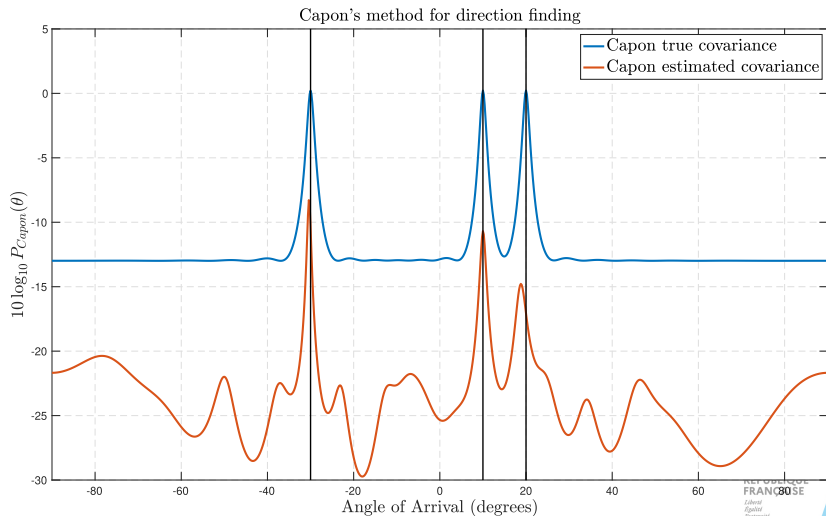
leads

$$\mathbf{w}_{\text{MPDR}}^H(\theta) \mathbf{R} \mathbf{w}_{\text{MPDR}}(\theta) = \frac{\mathbf{a}^H(\theta) \mathbf{R}^{-1} \mathbf{R} \mathbf{R}^{-1} \mathbf{a}(\theta)}{(\mathbf{a}^H(\theta) \mathbf{R}^{-1} \mathbf{a}(\theta))^2} = \frac{1}{\mathbf{a}^H(\theta) \mathbf{R}^{-1} \mathbf{a}(\theta)}$$

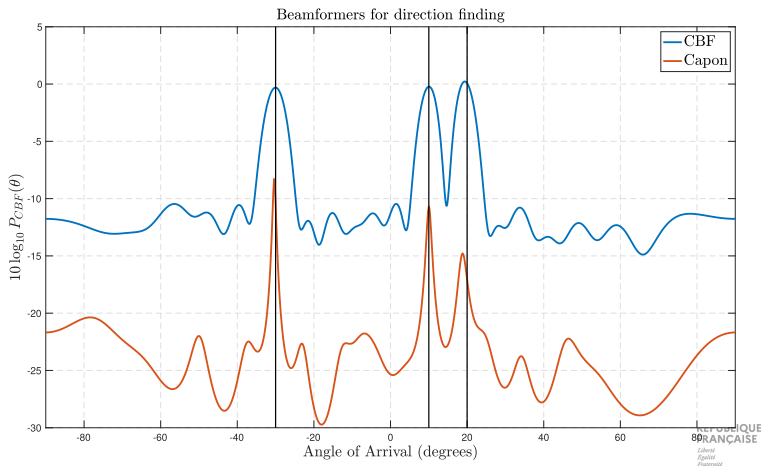
In practice,

$$P_{\text{Capon}}(\theta) = \frac{1}{\mathbf{a}^H(\theta) \hat{\mathbf{R}}^{-1} \mathbf{a}(\theta)}$$

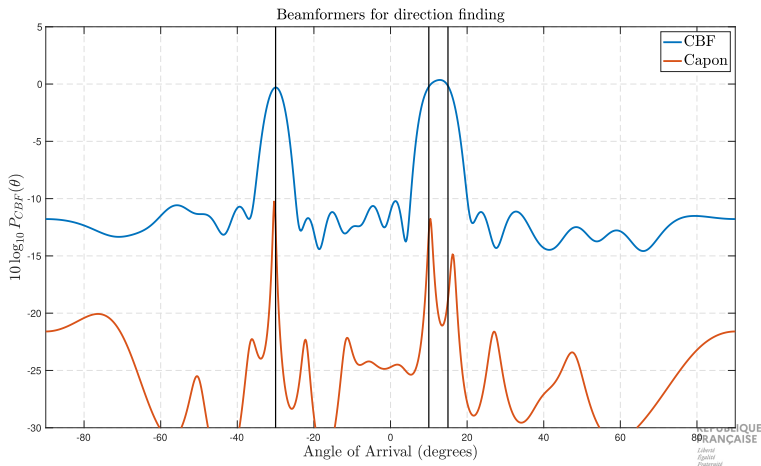
# Capon for direction finding purposes



# Comparison of beamformers for direction finding purposes (low resolution)



# Comparison of beamformers for direction finding purposes (high resolution)



# Plan

## ① Introduction

## ② Model

## ③ Beamforming

## ④ Direction of arrival estimation

Problem formulation

Non parametric methods

**Parametric methods**

Maximum likelihood estimation

Subspace-based methods

Covariance fitting

Sparse estimation

## ⑤ Conclusion

# Model-based methods

Principle: based on the model

$$\mathbf{y}[k] = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k] + \mathbf{e}[k]$$

with

$$\begin{aligned}\boldsymbol{\theta} &= [\theta_1 \quad \dots \quad \theta_P]^T \\ \mathbf{A}(\boldsymbol{\theta}) &= [\mathbf{a}(\theta_1) \quad \dots \quad \mathbf{a}(\theta_P)] \\ \mathbf{s}[k] &= [s_1[k] \quad \dots \quad s_P[k]]^T\end{aligned}$$

# Classes of methods

- **Maximum likelihood methods:** maximize the likelihood function  $\rightarrow$  find the parameters that best explain the data
- **Subspace-based methods:** signal subspace coincides with the subspace spanned by the principal eigenvectors of  $\mathbf{R}$ , which is orthogonal to the one spanned by the minor eigenvectors
- **Covariance matching:** relies on a model  $\mathbf{R}(\eta)$  of the covariance matrix, finds the parameter that makes it the closest to  $\hat{\mathbf{R}}$

## Reminder: MLE

We have  $K$  independent observations from the same distribution parametrized by  $\boldsymbol{\eta}$

$$\mathbf{y}_k \sim p(\mathbf{y}_k; \boldsymbol{\eta}), \quad k = 1, \dots, K$$

The likelihood is defined as

$$\begin{aligned} \mathcal{L}(\boldsymbol{\eta}; \mathbf{y}_1, \dots, \mathbf{y}_K) &= p(\mathbf{y}_1, \dots, \mathbf{y}_K; \boldsymbol{\eta}) \\ &= \prod_{k=1}^K p(\mathbf{y}_k; \boldsymbol{\eta}) \end{aligned}$$

MLE: find  $\boldsymbol{\eta}$  that best explains the observations

$$\begin{aligned} \hat{\boldsymbol{\eta}}_{\text{ML}} &= \arg \max_{\boldsymbol{\eta}} \mathcal{L}(\boldsymbol{\eta}; \mathbf{y}_1, \dots, \mathbf{y}_K) \\ &= \arg \min_{\boldsymbol{\eta}} (-\log \mathcal{L}(\boldsymbol{\eta}; \mathbf{y}_1, \dots, \mathbf{y}_K)) \end{aligned}$$



# Reminder: MLE

## Advantages

- asymptotically unbiased

$$\lim_{K \rightarrow +\infty} \mathbb{E} \{ \hat{\boldsymbol{\eta}}_{\text{ML}} \} = \boldsymbol{\eta}$$

- asymptotically efficient

$$\lim_{K \rightarrow +\infty} \text{Var} ( \hat{\boldsymbol{\eta}}_{\text{ML}} ) = \text{CRB} ( \boldsymbol{\eta} )$$

## Drawback

Usually multi-dimensional optimization problem: computationally intensive, possible to reach local maxima

## MLE for direction finding

There are two expressions, based on the signal model

- **Deterministic MLE:** the received signal is assumed deterministic (Conditional signal model)
- **Stochastic MLE:** the received signal is assumed random (Unconditional signal model)

For each model, it is assumed

$$\mathbf{e}[k] \sim \mathcal{CN}(\mathbf{e}[k]; \mathbf{0}, \sigma^2 \mathbf{I}_N)$$

where

$$p(\mathbf{e}; \boldsymbol{\mu}, \mathbf{R}) = \frac{1}{\pi^N |\mathbf{R}|} \exp\left(-(\mathbf{e} - \boldsymbol{\mu})^H \mathbf{R}^{-1} (\mathbf{e} - \boldsymbol{\mu})\right)$$

## Deterministic MLE

We have

$$\mathbf{y}[k] = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k] + \mathbf{e}[k]$$

hence

$$\mathbf{y}[k] \sim \mathcal{CN}(\mathbf{y}[k]; \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k], \sigma^2 \mathbf{I}_N)$$

with unknown parameters  $\boldsymbol{\eta} = \{\sigma^2, \mathbf{s}[1], \dots, \mathbf{s}[K], \boldsymbol{\theta}\}$

### Likelihood

$$\mathcal{L}(\boldsymbol{\eta}; \mathbf{y}_1, \dots, \mathbf{y}_K) = \prod_{k=1}^K \frac{1}{(\sigma^2 \pi)^N} \exp\left(-\frac{1}{\sigma^2} \|\mathbf{y}[k] - \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k]\|^2\right)$$

# Deterministic MLE

Maximum likelihood estimator

$$\hat{\boldsymbol{\eta}}_{\text{ML}} = \arg \min_{\boldsymbol{\eta}} NK \log(\sigma^2) + \frac{1}{\sigma^2} \sum_{k=1}^K \|\mathbf{y}[k] - \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k]\|^2$$

leading <sup>4</sup>

$$\hat{\boldsymbol{\theta}}_{\text{ML}}^{\text{det}} = \arg \min_{\boldsymbol{\theta}} \text{Tr} \left( \boldsymbol{\Pi}_{\mathbf{A}(\boldsymbol{\theta})}^{\perp} \hat{\mathbf{R}} \right) = \arg \max_{\boldsymbol{\theta}} \text{Tr} \left( \boldsymbol{\Pi}_{\mathbf{A}(\boldsymbol{\theta})} \hat{\mathbf{R}} \right)$$

For a single source

$$\hat{\theta}_{\text{ML}}^{\text{det}} = \arg \max_{\theta} \mathbf{a}^H(\theta) \hat{\mathbf{R}} \mathbf{a}(\theta) \Rightarrow \text{CBF}$$

<sup>4</sup> $\boldsymbol{\Pi}_{\mathbf{A}} = \mathbf{A} (\mathbf{A}\mathbf{A}^H)^{-1} \mathbf{A}^H$  and  $\boldsymbol{\Pi}_{\mathbf{A}}^{\perp} = \mathbf{I} - \boldsymbol{\Pi}_{\mathbf{A}}$

## Gaussian vectors: reminder

### Property: independence

Let  $\mathbf{x}$  and  $\mathbf{y}$  two Gaussian vectors. Then

$$\mathbf{x} \text{ and } \mathbf{y} \text{ are independent} \Leftrightarrow \text{cov}(\mathbf{x}, \mathbf{y}) = \mathbf{0}$$

### Property: affine transformation

Let  $\mathbf{x} \sim \mathcal{N}(\mathbf{m}, \Sigma) \in \mathbb{R}^n$ ,  $\mathbf{A} \in \mathbb{R}^{p \times n}$  ( $p \leq n$ ) with full rank and  $\mathbf{b} \in \mathbb{R}^p$ , and let  $\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{b}$ . Then

$$\mathbf{y} \sim \mathcal{N}(\mathbf{A}\mathbf{m} + \mathbf{b}, \mathbf{A}\Sigma\mathbf{A}^T)$$

These results can be extended to complex Gaussian vectors (with Hermitian instead of transpose)

# Stochastic MLE

We have

$$\mathbf{y}[k] = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k] + \mathbf{e}[k]$$

and we assume

$$\mathbf{s}[k] \sim \mathcal{CN}(\mathbf{s}[k]; \mathbf{0}, \mathbf{R}_s)$$

and independent with  $\mathbf{e}[k]$ . Then

$$\mathbf{y}[k] \sim \mathcal{CN}(\mathbf{y}[k]; \mathbf{0}, \mathbf{R} = \mathbf{A}(\boldsymbol{\theta})\mathbf{R}_s\mathbf{A}^H(\boldsymbol{\theta}) + \sigma^2\mathbf{I}_N)$$

with unknown parameters  $\boldsymbol{\eta} = \{\sigma^2, \mathbf{R}_s, \boldsymbol{\theta}\}$

## Likelihood

$$\mathcal{L}(\boldsymbol{\eta}; \mathbf{y}_1, \dots, \mathbf{y}_K) = \prod_{k=1}^K \frac{1}{\pi^N |\mathbf{R}|} \exp\left(-\mathbf{y}[k]^H \mathbf{R}^{-1} \mathbf{y}[k]\right)$$

# Stochastic MLE

## Maximum likelihood estimator

$$\begin{aligned}\hat{\boldsymbol{\eta}}_{\text{ML}} &= \arg \min_{\boldsymbol{\eta}} K \log(|\mathbf{R}|) + \sum_{k=1}^K \mathbf{y}^H[k] \mathbf{R}^{-1} \mathbf{y}[k] \\ &= \arg \min_{\boldsymbol{\eta}} \log(|\mathbf{R}|) + \text{Tr} \left( \mathbf{R}^{-1} \hat{\mathbf{R}} \right)\end{aligned}$$

closed-form expressions for  $\hat{\sigma}^2(\boldsymbol{\theta})$  and  $\hat{\mathbf{R}}_s(\boldsymbol{\theta})$  can be found (book<sup>5</sup>, Eqs. (14.64) and (14.65)) yielding

$$\hat{\boldsymbol{\theta}}_{\text{ML}}^{\text{sto}} = \arg \min_{\boldsymbol{\theta}} \log \left| \mathbf{A}(\boldsymbol{\theta}) \hat{\mathbf{R}}_s(\boldsymbol{\theta}) \mathbf{A}^H(\boldsymbol{\theta}) + \hat{\sigma}^2(\boldsymbol{\theta}) \mathbf{I}_N \right|$$

<sup>5</sup>Rama Chellappa Abdelhak M. Zoubir Mats Viberg and Sergios Theodoridis. *Array and Statistical Signal Processing*. Academic Press, 2014.

# Solving MLE

Several methods can be employed to solve these problems, as

- extensive grid search: try all possible values of  $\theta \rightarrow$  complexity increases exponentially as  $P$  increases
- EM algorithm: find unobserved variables that simplifies the problem, iterate between estimation of these variables and the parameters of interest
- SAGE algorithm: same approach, instead the unobserved variables change  $\rightarrow$  speeds up the previous one

All can be used for conditional or stochastic MLE, here only conditional



# EM<sup>6</sup> approach

## Expectation maximization

Principle: augment the observations  $\mathbf{Y}$  with imputed values  $\mathbf{X}$  to simplify the maximization, and apply the augmented data to estimate the unknown parameters

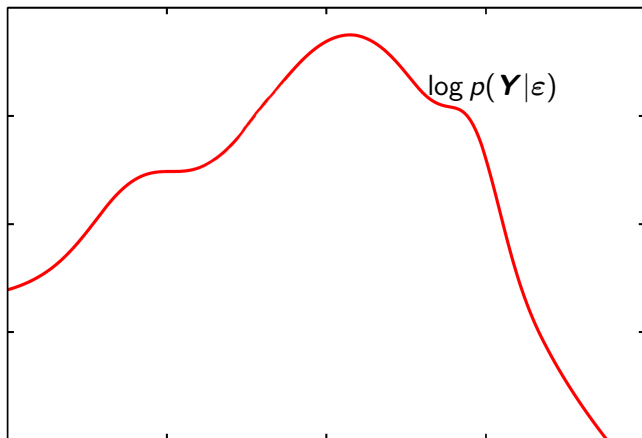
Find a many-to-one mapping  $\mathcal{M} : \mathbf{X} \mapsto \mathcal{M}(\mathbf{X}) = \mathbf{Y}$

- EM algorithm for estimating  $\varepsilon$  when observing  $\mathbf{y}$ 
  - E-step: compute  $Q(\varepsilon|\varepsilon^{(t)}) = \mathbb{E}_{\mathbf{X}|\mathbf{Y},\varepsilon^{(t)}}[\log p(\mathbf{X}|\varepsilon)]$
  - M-step: solve  $\varepsilon^{(t+1)} = \arg \max_{\varepsilon} Q(\varepsilon|\varepsilon^{(t)})$

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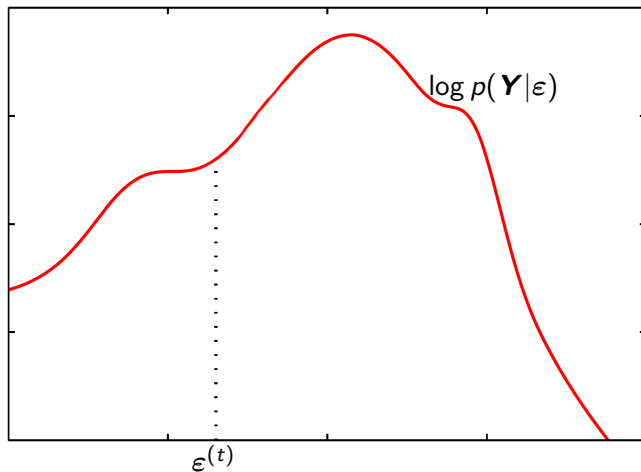
<sup>6</sup>A.P. Dempster, N.M. Laird, and Do. Rubin. "Maximum Likelihood from Incomplete Data via the EM Algorithm". In *Stat. Soc. Series B* 39.1 (1977), pp. 1–38.

# EM principle



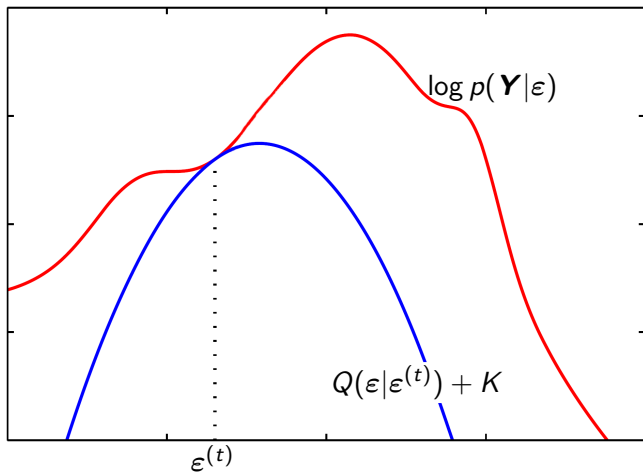
Adapted from Christopher M. Bishop, "Pattern Recognition and Machine Learning," Chap. 9

# EM principle



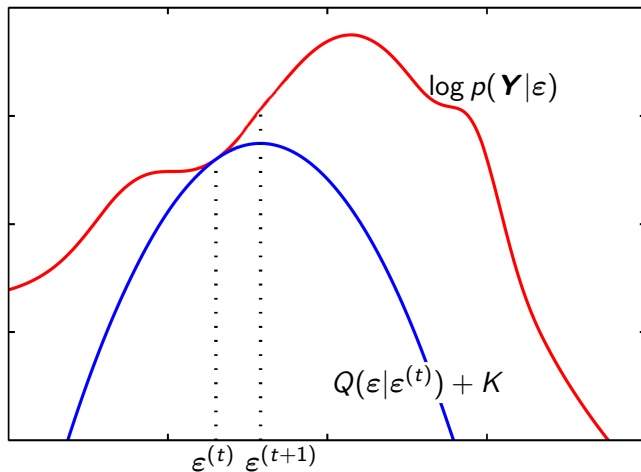
Adapted from Christopher M. Bishop, "Pattern Recognition and Machine Learning," Chap. 9

# EM principle



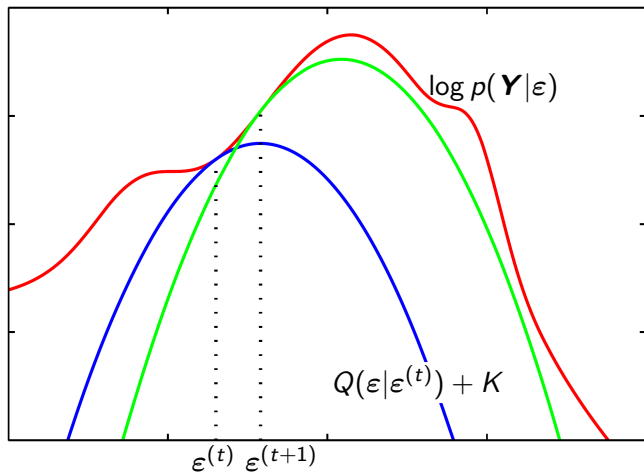
Adapted from Christopher M. Bishop, "Pattern Recognition and Machine Learning," Chap. 9

# EM principle



Adapted from Christopher M. Bishop, "Pattern Recognition and Machine Learning," Chap. 9

# EM principle



Adapted from Christopher M. Bishop, "Pattern Recognition and Machine Learning," Chap. 9

## Application of EM to MLE (conditional)

We define

$$\mathbf{x}[k] = \begin{bmatrix} \mathbf{x}_1[k] \\ \vdots \\ \mathbf{x}_P[k] \end{bmatrix} = \begin{bmatrix} \mathbf{a}(\theta_1)s_1[k] + \mathbf{e}_1[k] \\ \vdots \\ \mathbf{a}(\theta_P)s_P[k] + \mathbf{e}_P[k] \end{bmatrix}$$

such as

$$\mathbf{y}[k] = \sum_{p=1}^P \mathbf{x}_p[k] = [\mathbf{I}_N \quad \dots \quad \mathbf{I}_N] \mathbf{x}[k]$$

and

$$\mathbf{X} = \{\mathbf{x}[1], \dots, \mathbf{x}[K]\}, \quad \mathbf{Y} = \{\mathbf{y}[1], \dots, \mathbf{y}[K]\}$$

## Application of EM to MLE (conditional)

We define the unknown parameters

$$\boldsymbol{\varepsilon} = \{\boldsymbol{\varepsilon}_1, \dots, \boldsymbol{\varepsilon}_P\}, \quad \boldsymbol{\varepsilon}_p = \{\theta_p, s_p[1], \dots, s_p[K], \sigma_p^2\}$$

and we have

$$\mathbf{x}_p[k] | \boldsymbol{\varepsilon}_p \sim \mathcal{CN}(\mathbf{x}_p[k]; \mathbf{a}(\theta_p) s_p[k], \sigma_p^2 \mathbf{I}_N)$$

where  $\sum_{p=1}^P \sigma_p^2 = \sigma^2$  (e.g.,  $\sigma_p^2 = \frac{\sigma^2}{P}$ ), leading

$$\log p(\mathbf{X} | \boldsymbol{\varepsilon}) = C - \sum_{k=1}^K \sum_{p=1}^P \frac{1}{\sigma_p^2} \|\mathbf{x}_p[k] - \mathbf{a}(\theta_p) s_p[k]\|^2$$



## Application of EM to MLE (conditional)

One can show<sup>7</sup>

$$\mathbb{E}_{\mathbf{X}|\mathbf{Y},\boldsymbol{\varepsilon}^{(t)}}[\mathbf{x}_p[k]] = \hat{\mathbf{x}}_p[k] = \mathbf{a}(\theta_p^{(t)})s_p^{(t)}[k] + \frac{1}{P} \left( \mathbf{y}[k] - \mathbf{A}(\boldsymbol{\theta}^{(t)})\mathbf{s}^{(t)}[k] \right)$$

leading (when not interested in  $\sigma_p^2$ )

$$Q(\boldsymbol{\varepsilon}|\boldsymbol{\varepsilon}^{(t)}) = D - \sum_{k=1}^K \sum_{p=1}^P \frac{1}{\sigma_p^2} \|\hat{\mathbf{x}}_p[k] - \mathbf{a}(\theta_p)s_p[k]\|^2$$

The M step is equivalent to

$$\boldsymbol{\varepsilon}^{(t+1)} = \arg \min_{\boldsymbol{\varepsilon}} \sum_{p=1}^P \sum_{k=1}^K \|\hat{\mathbf{x}}_p[k] - \mathbf{a}(\theta_p)s_p[k]\|^2$$

<sup>7</sup>Rama Chellappa Abdelhak M. Zoubir Mats Viberg and Sergios Theodoridis. *Array and Statistical Signal Processing*. Academic Press, 2014.

# Application of EM to MLE (conditional): wrap up

## EM approach to solve conditional MLE

- 1 initialize  $\epsilon^{(0)}$
- 2 iterate until convergence
  - $\hat{\mathbf{x}}_p[k] \leftarrow \mathbf{a}(\theta_p^{(t)})s_p^{(t)}[k] + \frac{1}{P} (\mathbf{y}[k] - \mathbf{A}(\theta^{(t)})\mathbf{s}^{(t)}[k])$
  - $\hat{\mathbf{R}}_{x_p} \leftarrow \frac{1}{K} \sum_{k=1}^K \hat{\mathbf{x}}_p[k]\hat{\mathbf{x}}_p^H[k]$
  - $\hat{\theta}_p^{(t+1)} = \arg \max_{\theta_p} \mathbf{a}^H(\theta_p)\hat{\mathbf{R}}_{x_p}\mathbf{a}(\theta_p)$
  - $s_p^{(t+1)}[k] = \frac{\mathbf{a}^H(\hat{\theta}_p^{(t+1)})\hat{\mathbf{x}}_p[k]}{N}$

# SAGE<sup>8</sup> approach

## Space Alternating Generalized EM

Principle: break the problem into several smaller problems by conditioning sequentially on a subset of the parameters, then applies EM to each reduced problem.

Each iteration has  $C$  cycles: at cycle  $c$ ,

- E-step: compute  $Q^{(c)}(\boldsymbol{\varepsilon}_c | \boldsymbol{\varepsilon}^{(t,c-1)}) = \mathbb{E}_{\mathbf{Z} | \mathbf{Y}, \boldsymbol{\varepsilon}^{(t,c-1)}} [\log p(\mathbf{Z}_c | \boldsymbol{\varepsilon}_c)]$
- M-step: solve  $\boldsymbol{\varepsilon}^{(t,c)} = \arg \max_{\boldsymbol{\varepsilon}_c} Q^{(c)}(\boldsymbol{\varepsilon}_c | \boldsymbol{\varepsilon}^{(t,c-1)})$

at the end of the last cycle:  $\boldsymbol{\varepsilon}^{(t+1,0)} = \boldsymbol{\varepsilon}^{(t,C)}$

<sup>8</sup>J.A. Fessler and A.O. Hero. "Space-Alternating Generalized Expectation-Maximization algorithm". In: *IEEE Transactions on Signal Processing* 42.10 (1994), pp. 2664–2677.

## Application of SAGE to MLE (conditional)

We use  $P$  cycles and define

$$\mathbf{z}_p[k] = \mathbf{a}(\theta_p)s_p[k] + \mathbf{e}[k]$$

Using same reasoning as for EM

$$\hat{\mathbf{z}}_p[k] = \mathbf{a}(\theta_p^{(t,p-1)})s_p^{(t,p-1)}[k] + \mathbf{y}[k] - \mathbf{A}(\theta^{(t,p-1)})\mathbf{s}^{(t,p-1)}[k]$$

Leading the update

$$\theta_p^{(t,c)} = \arg \max_{\theta_p} \mathbf{a}(\theta_p^H) \hat{\mathbf{R}}_{\mathbf{z}_p} \mathbf{a}(\theta_p)$$

where

$$\hat{\mathbf{R}}_{\mathbf{z}_p} = \frac{1}{K} \hat{\mathbf{z}}_p[k] \hat{\mathbf{z}}_p^H[k]$$

# Application of SAGE to MLE (conditional): wrap up

## SAGE approach to solve conditional MLE

- 1 initialize  $\boldsymbol{\varepsilon}^{(0,0)}$
- 2 iterate until convergence
  - For  $p = 1, \dots, P$ 
    - $\hat{\mathbf{z}}_p[k] \leftarrow \mathbf{a}(\theta_p^{(t,p-1)})s_p^{(t,p-1)}[k] + \mathbf{y}[k] - \mathbf{A}(\theta^{(t,p-1)})\mathbf{s}^{(t,p-1)}[k]$
    - $\hat{\mathbf{R}}_{z_p} \leftarrow \frac{1}{K} \hat{\mathbf{z}}_p[k] \hat{\mathbf{z}}_p^H[k]$
    - $\hat{\theta}_p^{(t,p)} = \arg \max_{\theta_p} \mathbf{a}(\theta_p^H) \hat{\mathbf{R}}_{z_p} \mathbf{a}(\theta_p)$
    - $s_p^{(t,p)}[k] = \frac{\mathbf{a}^H(\hat{\theta}_p^{(t,p)}) \hat{\mathbf{z}}_p[k]}{N}$
  - $\boldsymbol{\varepsilon}^{(t+1,0)} \leftarrow \boldsymbol{\varepsilon}^{(t,P)}$

# Initialization of EM or SAGE

## Several possibilities

- easy one
  - 1 assume a single source:

$$\hat{\theta}_1^{(0)} = \arg \max_{\theta} \text{Tr} \left( \mathbf{\Pi}_{\mathbf{a}(\theta)} \hat{\mathbf{R}} \right)$$

- 2 augment the steering matrix with a new source:

$$\mathbf{A}(\theta) = \begin{bmatrix} \mathbf{a}(\hat{\theta}_1^{(0)}) & \mathbf{a}(\theta) \end{bmatrix} \text{ and } \hat{\theta}_2^{(0)} = \arg \max_{\theta} \text{Tr} \left( \mathbf{\Pi}_{\mathbf{A}(\theta)} \hat{\mathbf{R}} \right)$$

- 3 continue until the total number of sources is reached
- any other method

## Subspace-based methods: principle

- Theorem (reminder): if  $\mathbf{A} \in \mathbb{C}^N$  is an Hermitian matrix, then its eigenvalues are real and there is an orthonormal basis formed by eigenvectors of  $\mathbf{A}$

Eigenvalue decomposition of the covariance matrix ( $P < N$  signals)

$$\begin{aligned}
 \mathbf{R} &= \mathbf{A}(\boldsymbol{\theta})\mathbf{R}_s\mathbf{A}^H(\boldsymbol{\theta}) + \sigma^2\mathbf{I}_N \quad (\mathbf{R}_s \text{ full rank}) \\
 &= \sum_{p=1}^P \lambda_p \mathbf{u}_p \mathbf{u}_p^H + \sigma^2 \sum_{p=1}^N \mathbf{u}_p \mathbf{u}_p^H \quad (\lambda_1 \geq \dots \geq \lambda_P) \\
 &= \sum_{p=1}^P (\lambda_p + \sigma^2) \mathbf{u}_p \mathbf{u}_p^H + \sigma^2 \sum_{p=P+1}^N \mathbf{u}_p \mathbf{u}_p^H \quad (\lambda_1 \geq \dots \geq \lambda_P) \\
 &= \mathbf{U}_s \boldsymbol{\Lambda}_s \mathbf{U}_s^H + \sigma^2 \mathbf{U}_e \mathbf{U}_e^H
 \end{aligned}$$

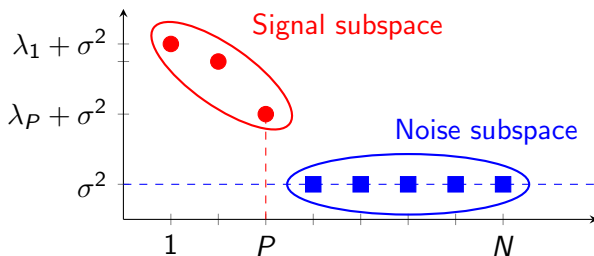
where  $\mathbf{U}_s = [\mathbf{u}_1 \ \dots \ \mathbf{u}_P] \perp \mathbf{U}_e = [\mathbf{u}_{P+1} \ \dots \ \mathbf{u}_N]$

## Signal and noise subspaces

Subspace-based methods rely on either

- $\mathcal{R}\{\mathbf{U}_s\} = \mathcal{R}\{\mathbf{A}(\boldsymbol{\theta})\}$ : the signal subspace is spanned by  $\mathbf{U}_s$  so there is a non-singular matrix  $\mathbf{T}$  such that  $\mathbf{U}_s = \mathbf{A}(\boldsymbol{\theta})\mathbf{T}$
- $\mathcal{R}\{\mathbf{U}_e\}$  is orthogonal to  $\mathcal{R}\{\mathbf{U}_s\} = \mathcal{R}\{\mathbf{A}(\boldsymbol{\theta})\}$  so  $\mathbf{A}^H(\boldsymbol{\theta})\mathbf{U}_e = \mathbf{0}$

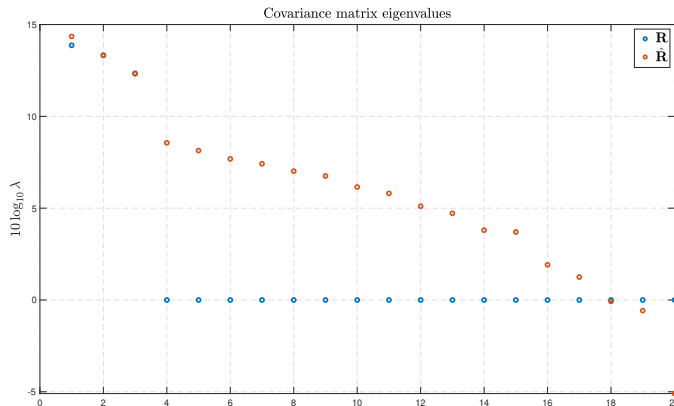
Eigenvalues of the covariance matrix





# Principle

In practice: estimated covariance matrix



# MUSIC (MULTiple Signal Classification)

The steering vectors are orthogonal to  $\mathcal{R}\{\mathbf{U}_e\}$

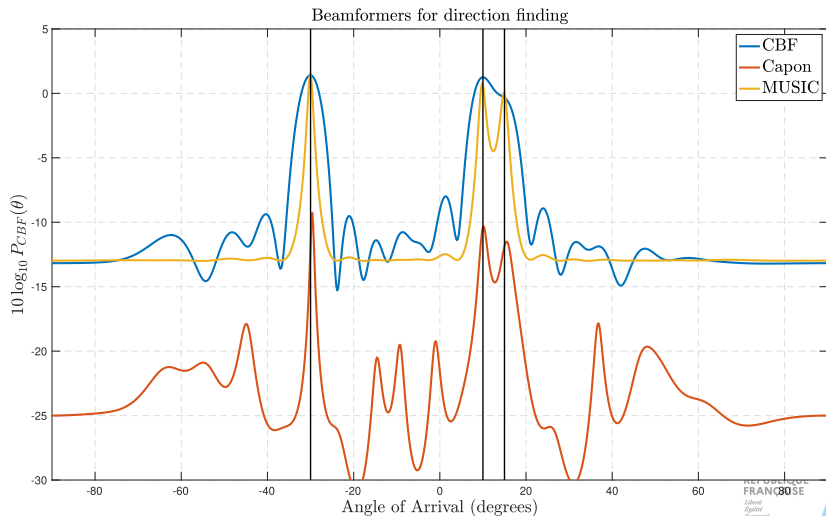
$$\mathbf{U}_e^H \mathbf{a}(\theta_p) = \mathbf{0} \Rightarrow \mathbf{u}_n^H \mathbf{a}(\theta_p) = 0 \text{ for } n = P + 1, \dots, N$$

Principle: look for the  $P$  largest maxima of

$$P_{\text{MUSIC}}(\theta) = \frac{1}{\mathbf{a}^H(\theta) \hat{\mathbf{U}}_e \hat{\mathbf{U}}_e^H \mathbf{a}(\theta)} = \frac{1}{\sum_{n=P+1}^N |\hat{\mathbf{u}}_n^H \mathbf{a}(\theta)|^2}$$

When  $\sigma^2 \rightarrow 0$  or  $K \rightarrow +\infty$  one has  $P_{\text{MUSIC}}(\theta) \rightarrow +\infty$

# MUSIC



# Root-MUSIC

Let  $\mathbf{a}_z(z) = [1 \quad z \quad \dots \quad z^{N-1}]^T$ . For ULA

$$\mathbf{a}(\theta) = \left[ 1 \quad e^{-j2\pi f_c \frac{d \sin \theta}{c}} \quad \dots \quad e^{-j2\pi f_c (N-1) \frac{d \sin \theta}{c}} \right]^T = \mathbf{a}_z \left( e^{-j2\pi f_c \frac{d \sin \theta}{c}} \right)$$

leading for a DOA

$$\mathbf{a}^H(\theta) \hat{\mathbf{U}}_e \hat{\mathbf{U}}_e^H \mathbf{a}(\theta) = \mathbf{a}_z^T \left( e^{j2\pi f_c \frac{d \sin \theta}{c}} \right) \hat{\mathbf{U}}_e \hat{\mathbf{U}}_e^H \mathbf{a}_z \left( e^{-j2\pi f_c \frac{d \sin \theta}{c}} \right) = 0$$

One can look for the roots of

$$P_{\text{MUSIC}}(z) = \mathbf{a}_z^T(z^{-1}) \hat{\mathbf{U}}_e \hat{\mathbf{U}}_e^H \mathbf{a}_z(z)$$

closest to the unit circle

## Root-MUSIC

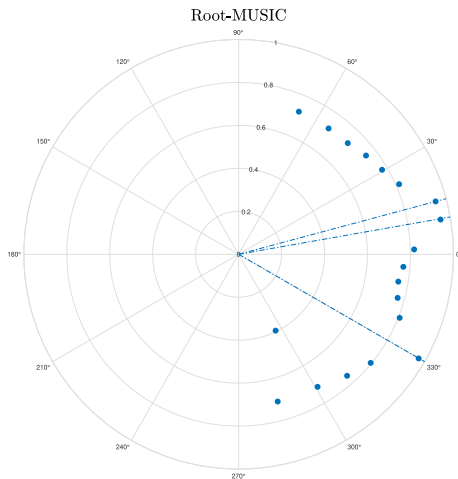
Moreover,  $P_{\text{MUSIC}}(z) = \sum_{n=-(N-1)}^{N-1} p_n z^n$  has  $2(N-1)$  roots, but  $\mathbf{a}_z(z^*) = \mathbf{a}_z^*(z)$  leads

$$\begin{aligned}
 P_{\text{MUSIC}}^* \left( \frac{1}{z^*} \right) &= \left( \mathbf{a}_z^T(z^*) \hat{\mathbf{U}}_e \hat{\mathbf{U}}_e^H \mathbf{a}_z \left( \frac{1}{z^*} \right) \right)^* \\
 &= \mathbf{a}_z^T(z) \hat{\mathbf{U}}_e^* \hat{\mathbf{U}}_e^T \mathbf{a}_z(z^{-1}) \\
 &= \mathbf{a}_z^T(z^{-1}) \hat{\mathbf{U}}_e \hat{\mathbf{U}}_e^H \mathbf{a}_z(z) \\
 &= P_{\text{MUSIC}}(z)
 \end{aligned}$$

so only  $(N-1)$  are inside the unit circle

No need to try several values of  $\theta$ , directly given by the roots

# Root-MUSIC



# ESPRIT (Estimation of Signal Parameters via Rotational Invariance Techniques)

Partition of  $\mathbf{A} = \mathbf{A}(\theta)$

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 \\ - \end{bmatrix} = \begin{bmatrix} - \\ \mathbf{A}_2 \end{bmatrix}$$

where  $\mathbf{A}_1$  (resp.  $\mathbf{A}_2$ ) contains all but last (resp. first) row of  $\mathbf{A}$ .

For ULA

$$\mathbf{A}_2 = \mathbf{A}_1 \Phi \text{ with } \Phi = \text{diag} \left( \left\{ e^{-j2\pi \frac{d}{\lambda} \sin \theta_p} \right\}_{p=1}^P \right)$$

The DOAs are in  $\Phi$ , which can be deduced from  $\mathbf{A}_1$  and  $\mathbf{A}_2$  which are unknown

# ESPRIT

We know  $\mathbf{U}_s = \mathbf{A}\mathbf{T}$ . We can decompose  $\mathbf{U}_s = \begin{bmatrix} \mathbf{U}_{s,1} \\ - \end{bmatrix} = \begin{bmatrix} - \\ \mathbf{U}_{s,2} \end{bmatrix}$  leading

$$\begin{cases} \mathbf{U}_{s,1} = \mathbf{A}_1 \mathbf{T} \\ \mathbf{U}_{s,2} = \mathbf{A}_2 \mathbf{T} = \mathbf{A}_1 \Phi \mathbf{T} \end{cases}$$

$$\Rightarrow \mathbf{U}_{s,2} = \mathbf{U}_{s,1} \mathbf{T}^{-1} \Phi \mathbf{T}$$

$$\Rightarrow \mathbf{U}_{s,2} = \mathbf{U}_{s,1} \Psi$$

Moreover, if  $\mathbf{u}$  is an eigenvector of  $\Phi$ , then  $\Psi \mathbf{T}^{-1} \mathbf{u} = \mathbf{T}^{-1} \Phi \mathbf{u} = \lambda \mathbf{T}^{-1} \mathbf{u}$

$\rightarrow \Phi$  and  $\Psi$  share the same eigenvalues  $e^{-j2\pi \frac{d}{\lambda} \sin \theta_p}$ ,  $p = 1, \dots, P$



# ESPRIT

In practice, one solves  $\hat{\mathbf{U}}_{s,2} = \hat{\mathbf{U}}_{s,1}\Psi$  with a least squares approach

$$\hat{\Psi} = (\hat{\mathbf{U}}_{s,1}^H \hat{\mathbf{U}}_{s,1})^{-1} \hat{\mathbf{U}}_{s,1}^H \hat{\mathbf{U}}_{s,2}$$

and compute the eigenvalues of  $\hat{\Psi}$

As root-MUSIC, no need for a grid

## Subspace fitting

Principle: minimize error between subspaces spanned by  $\hat{\mathbf{U}}_s$  and  $\mathbf{A}(\theta)$  using a weighted least square criterion

$$\begin{aligned}\hat{\theta}, \hat{\mathbf{T}} &= \arg \min_{\theta, \mathbf{T}} \|\hat{\mathbf{U}}_s - \mathbf{A}(\theta)\mathbf{T}\|_W^2 \\ &= \arg \min_{\theta, \mathbf{T}} \text{Tr} \left( (\hat{\mathbf{U}}_s - \mathbf{A}(\theta)\mathbf{T})\mathbf{W}(\hat{\mathbf{U}}_s - \mathbf{A}(\theta)\mathbf{T})^H \right)\end{aligned}$$

As for ML, we replace with the estimator of  $\mathbf{T}$ , leading

$$\hat{\theta} = \arg \min_{\theta} \text{Tr} \left( \mathbf{\Pi}_{\mathbf{A}(\theta)}^{\perp} \hat{\mathbf{U}}_s \mathbf{W} \hat{\mathbf{U}}_s^H \right)$$

# Subspace fitting

Possible weights<sup>9</sup>

$$\mathbf{W} = \hat{\hat{\Lambda}}^2 \hat{\Lambda}_S^{-1}, \quad \hat{\hat{\Lambda}} = \hat{\Lambda}_S - \hat{\sigma}^2 \mathbf{I}_P, \quad \hat{\sigma}^2 = \frac{1}{N-P} \sum_{n=P+1}^N \hat{\lambda}_n$$

Alternative: use the fact that  $\mathbf{A}^H(\boldsymbol{\theta})\mathbf{U}_n = \mathbf{0}$  and solve

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \|\hat{\mathbf{U}}_e^H \mathbf{A}(\boldsymbol{\theta})\|_{\mathbf{W}}^2$$

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<sup>9</sup>Rama Chellappa Abdelhak M. Zoubir Mats Viberg and Sergios Theodoridis. *Array and Statistical Signal Processing*. Academic Press, 2014.

## Some matrix operations

Kronecker product:  $\mathbf{A} \in \mathbb{C}^{m \times n}$ ,  $\mathbf{B} \in \mathbb{C}^{r \times q}$

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} A_{1,1}\mathbf{B} & A_{1,2}\mathbf{B} & \dots & A_{1,n}\mathbf{B} \\ A_{2,1}\mathbf{B} & A_{2,2}\mathbf{B} & \dots & A_{2,n}\mathbf{B} \\ \vdots & \vdots & \vdots & \vdots \\ A_{m,1}\mathbf{B} & A_{m,2}\mathbf{B} & \dots & A_{m,n}\mathbf{B} \end{bmatrix} \in \mathbb{C}^{mr \times nq}$$

Vec (vectorize) operator (linear)

$$\mathbf{A} = \begin{bmatrix} A_{1,1} & A_{1,2} & \dots & A_{1,n} \\ A_{2,1} & A_{2,2} & \dots & A_{1,n} \\ \vdots & \vdots & \vdots & \vdots \\ A_{m,1} & A_{m,2} & \dots & A_{m,n} \end{bmatrix} = [\mathbf{a}_1 \quad \mathbf{a}_2 \quad \dots \quad \mathbf{a}_n] \Rightarrow \text{vec}(\mathbf{A}) = \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_n \end{bmatrix}$$

Property

$$\text{vec}(\mathbf{AXB}) = (\mathbf{B}^T \otimes \mathbf{A})\text{vec}(\mathbf{X})$$

# Covariance fitting

Covariance matrix

$$\mathbf{R} = \mathbf{A}(\boldsymbol{\theta})\mathbf{R}_s\mathbf{A}^H(\boldsymbol{\theta}) + \sigma^2\mathbf{I}_N$$

leads

$$\begin{aligned} \mathbf{r} = \text{vec}(\mathbf{R}) &= \text{vec}(\mathbf{A}(\boldsymbol{\theta})\mathbf{R}_s\mathbf{A}^H(\boldsymbol{\theta})) + \text{vec}(\sigma^2\mathbf{I}_N) \\ &= (\mathbf{A}^*(\boldsymbol{\theta}) \otimes \mathbf{A}(\boldsymbol{\theta}))\text{vec}(\mathbf{R}_s) + \sigma^2\text{vec}(\mathbf{I}_N) \\ &= \boldsymbol{\Psi}(\boldsymbol{\theta})\mathbf{P} + \sigma^2\boldsymbol{\Sigma} \\ &= \begin{bmatrix} \boldsymbol{\Psi}(\boldsymbol{\theta}) & \boldsymbol{\Sigma} \end{bmatrix} \begin{bmatrix} \mathbf{P} \\ \sigma^2 \end{bmatrix} \\ &= \boldsymbol{\Phi}(\boldsymbol{\theta})\boldsymbol{\alpha} \end{aligned}$$

# Covariance fitting

Principle: minimize the error between  $\mathbf{R}$  and its estimate  $\hat{\mathbf{R}}$

$$\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\alpha}} = \arg \min_{\boldsymbol{\theta}, \boldsymbol{\alpha}} \|\hat{\mathbf{r}} - \Phi(\boldsymbol{\theta})\boldsymbol{\alpha}\|_{\mathbf{W}}^2 = (\hat{\mathbf{r}} - \Phi(\boldsymbol{\theta})\boldsymbol{\alpha})^H \mathbf{W} (\hat{\mathbf{r}} - \Phi(\boldsymbol{\theta})\boldsymbol{\alpha})$$

Solving for  $\boldsymbol{\alpha}$  then  $\boldsymbol{\theta}$  leads

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \|\mathbf{\Pi}^{\perp} \mathbf{W}^{\frac{1}{2}} \Phi(\boldsymbol{\theta}) \mathbf{W}^{\frac{1}{2}} \hat{\mathbf{r}}\|^2$$

Proposed weights

$$\hat{\mathbf{W}} = \left( \hat{\mathbf{R}}^T \otimes \hat{\mathbf{R}} \right)^{-1}$$

# Covariance fitting

## Avantages

- asymptotically equivalent to ML estimates
- no need for assumptions on the pdf (only  $\mathbf{R}$ )
- criterion usually simpler to minimize
- can be used with full-rank covariance  $\mathbf{R}_s$  (subspace methods require it to be rank deficient)

## Drawback

- requires an important number of samples

# Plan

① Introduction

② Model

③ Beamforming

④ Direction of arrival estimation

Problem formulation

Non parametric methods

Parametric methods

**Sparse estimation**

⑤ Conclusion



## Overcomplete representation

Signal model,  $\boldsymbol{\theta}$  and  $\mathbf{s}[k]$  unknown

$$\boldsymbol{\theta} = \{\theta_1, \theta_2, \dots, \theta_P\}, \quad \mathbf{y}[k] = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}[k] + \mathbf{e}[k]$$

Overcomplete representation, only  $\tilde{\mathbf{s}}[k]$  unknown

$$\tilde{\boldsymbol{\theta}} = \{\tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_{N_\theta}\}, \quad \mathbf{y}[k] = \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{s}}[k] + \mathbf{e}[k], \quad N_\theta \gg P$$

where

$$\tilde{s}_j[k] = 0 \text{ if } \tilde{\theta}_j \notin \boldsymbol{\theta}, \quad j = 1, \dots, N_\theta$$

Only few non-zero elements in  $\tilde{\mathbf{s}}[k]$  (sparse vector)

# Regularization

Overcomplete representation

$$\mathbf{y}[k] = \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{s}}[k] + \mathbf{e}[k] \text{ with } \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}}) \in \mathbb{C}^{N \times N_{\theta}} \text{ and } N_{\theta} \gg N$$

Problem:  $\tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})$  not full-rank (doesn't admit pseudoinverse)

Solution: regularization (add constraints to the vector to estimate)

$$\arg \min_{\tilde{\mathbf{s}}[k]} \underbrace{\|\mathbf{y}[k] - \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{s}}[k]\|_2^2}_{\text{data-fidelity term}} + \lambda \underbrace{f(\tilde{\mathbf{s}}[k])}_{\text{regularization term}}$$

Hyperparameter  $\lambda$  controls the balance between fidelity and regularization

# Regularization

For instance: minimize signal energy (ridge regression)

$$\arg \min_{\tilde{\mathbf{s}}[k]} \|\mathbf{y}[k] - \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{s}}[k]\|_2^2 + \lambda \|\tilde{\mathbf{s}}[k]\|_2^2$$

Solution

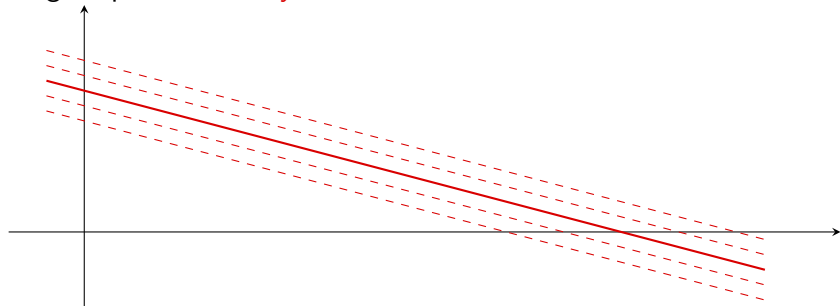
$$\hat{\tilde{\mathbf{s}}}_{\ell_2}[k] = \left( \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})^H \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}}) + \lambda \mathbf{I}_{N_\theta} \right)^{-1} \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})^H \mathbf{y}[k]$$

We want sparsity, are there regularizations providing sparsity?

$$\ell_1 \text{ norm: } \|\mathbf{x}\|_1 = \sum_{i=1}^N |x_i| \text{ provides sparsity}$$

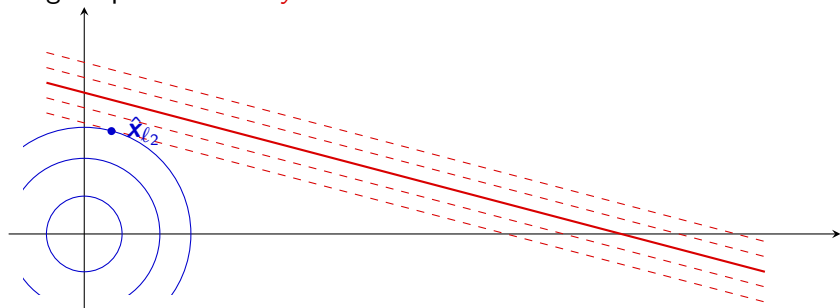
# Sparse regularization: illustration

Single equation in 2D  $y = \mathbf{h}^T \mathbf{x}$



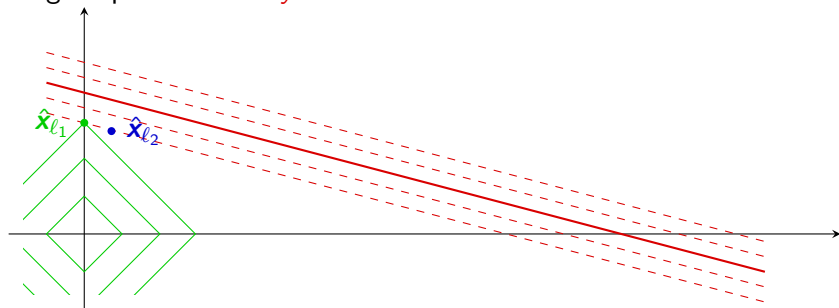
# Sparse regularization: illustration

Single equation in 2D  $y = \mathbf{h}^T \mathbf{x}$



# Sparse regularization: illustration

Single equation in 2D  $y = \mathbf{h}^T \mathbf{x}$



# Sparse DOA with a single snapshot

Solve

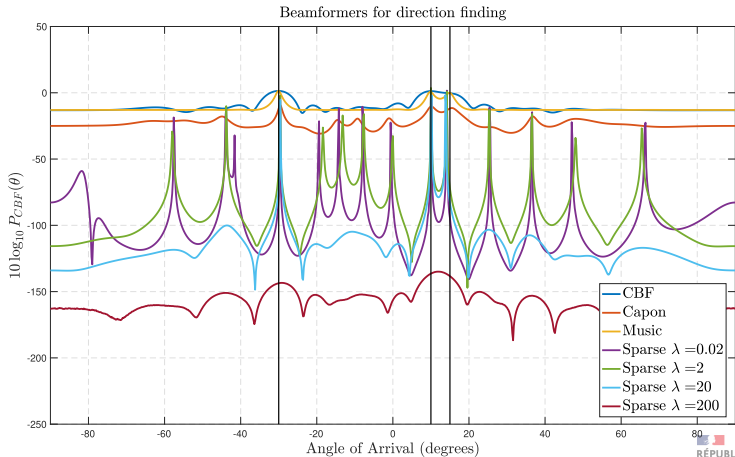
$$\arg \min_{\tilde{\mathbf{s}}[k]} \|\mathbf{y}[k] - \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{s}}[k]\|_2^2 + \lambda \|\tilde{\mathbf{s}}[k]\|_1$$

We can plot a pseudospectrum for all values of  $\tilde{\theta}_j$  as  $|\tilde{s}_j[k]|^2$

## Influence of $\lambda$

$\lambda$  controls the level of sparsity of the solution

# Sparse DOA with a single snapshot





## Sparse DOA with all snapshots

Define

$$\mathbf{Y} = [\mathbf{y}[1] \ \dots \ \mathbf{y}[K]], \quad \tilde{\mathbf{S}} = [\tilde{\mathbf{s}}[1] \ \dots \ \tilde{\mathbf{s}}[K]] \quad \text{and} \quad \mathbf{E} = [\mathbf{e}[1] \ \dots \ \mathbf{e}[K]]$$

then

$$\mathbf{Y} = \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{S}} + \mathbf{E}$$

We want to induce sparsity on the rows of matrix  $\tilde{\mathbf{S}}$ . Define

$$\tilde{\mathbf{s}}_j^{(\ell_2)} = \left\| [\tilde{\mathbf{s}}_j[1] \ \dots \ \tilde{\mathbf{s}}_j[K]]^T \right\|_2, \quad j = 1, \dots, N_\theta$$

and

$$\tilde{\mathbf{s}}^{(\ell_2)} = \begin{bmatrix} \tilde{\mathbf{s}}_1^{(\ell_2)} & \dots & \tilde{\mathbf{s}}_{N_\theta}^{(\ell_2)} \end{bmatrix}$$

## Reminder: Singular Value Decomposition (SVD)

Let  $\mathbf{M} \in \mathbb{C}^{N \times K}$  a rectangular matrix. Then, there exists  $\mathbf{U} \in \mathbb{C}^{N \times N}$ ,  $\mathbf{\Sigma} \in (\mathbb{R}^+)^{N \times K}$  and  $\mathbf{V} \in \mathbb{C}^{K \times K}$  such as

- $\mathbf{M} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H$
- $\mathbf{U}^H\mathbf{U} = \mathbf{I}_N$
- $\mathbf{V}^H\mathbf{V} = \mathbf{I}_K$
- $\mathbf{\Sigma}$  is a rectangular diagonal matrix

## Sparse DOA with all snapshots

Solve

$$\arg \min_{\tilde{\mathbf{S}}} \|\mathbf{Y} - \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}})\tilde{\mathbf{S}}\|_2^2 + \lambda \|\tilde{\mathbf{s}}^{(\ell_2)}\|_1$$

SVD

$$\mathbf{Y} = \mathbf{U}\mathbf{L}\mathbf{V}^H, \quad \mathbf{U} \in \mathbb{C}^{N \times N}, \quad \mathbf{L} \in (\mathbb{R}^+)^{N \times K}, \quad \mathbf{V} \in \mathbb{C}^{K \times K}$$

can help to reduce the dimension of  $\mathbf{Y}$

$$\mathbf{Y}_s = \mathbf{U}\mathbf{L}\mathbf{D}_P = \mathbf{Y}\mathbf{V}\mathbf{D}_P, \quad \mathbf{D}_P = [\mathbf{I}_P \quad \mathbf{0}_{(K-P) \times K}]^T$$

Related to eigenvalue decomposition of  $\hat{\mathbf{R}}$

$$\hat{\mathbf{R}} = \frac{1}{K} \mathbf{Y}\mathbf{Y}^H = \frac{1}{K} \mathbf{U}\mathbf{L}\mathbf{V}^H \mathbf{V}\mathbf{L}\mathbf{U}^H = \frac{1}{K} \mathbf{U}\mathbf{L}^2 \mathbf{U}^H$$

# Sparse DOA with all snapshots

Defining

$$\tilde{\mathbf{S}}_s = \tilde{\mathbf{S}} \mathbf{V} \mathbf{D}_P, \quad \mathbf{E}_s = \mathbf{E} \mathbf{V} \mathbf{D}_P,$$

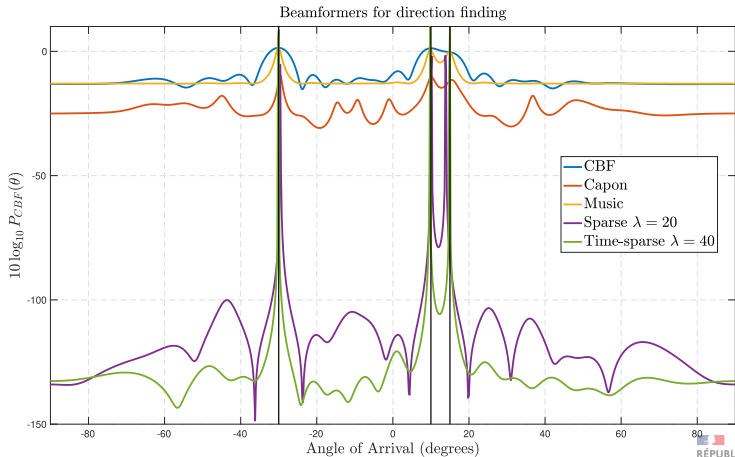
we have

$$\mathbf{Y}_s = \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}}) \tilde{\mathbf{S}}_s + \mathbf{E}_s$$

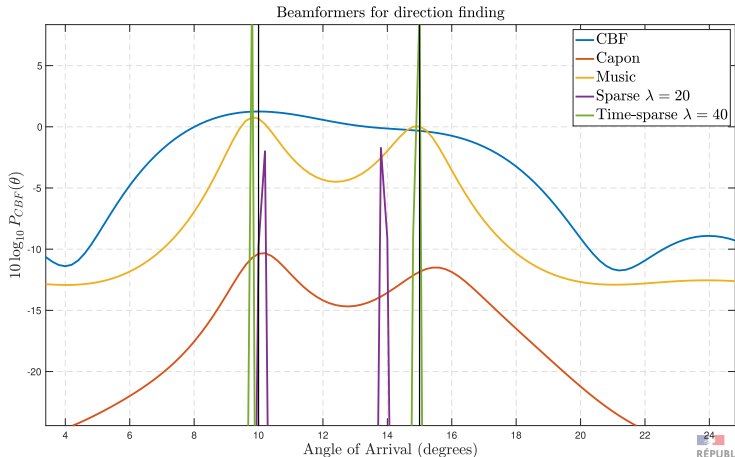
Solve

$$\arg \min_{\tilde{\mathbf{S}}_s} \|\mathbf{Y}_s - \tilde{\mathbf{A}}(\tilde{\boldsymbol{\theta}}) \tilde{\mathbf{S}}_s\|_2^2 + \lambda \|\tilde{\mathbf{S}}_s^{(\ell_2)}\|_1$$

# Sparse DOA with all snapshots



# Sparse DOA with all snapshots



# Conclusion on sparse DOA

## Advantages

- sharp peaks
- lower side lobes

## Drawbacks

- $\lambda$  selection
- depends on a grid
- numerical optimisation

# Plan

- ① Introduction
- ② Model
- ③ Beamforming
- ④ Direction of arrival estimation
- ⑤ Conclusion



# Conclusions

- Array processing, thanks to additional degrees of freedom, enables one to perform spatial filtering of signals
- Adaptive beamforming, possibly with reduced-rank transformations, enables one to achieve high SINR with a fast rate of convergence in adverse conditions (interference, noise)
- Robustness issues are of utmost importance in practical systems, and should be given a careful attention
- Non-parametric direction finding methods are simple and robust but may suffer from a lack of resolution
- Parametric methods offer high resolution, often at the price of degraded robustness

Please provide any useful comment on SIDE!