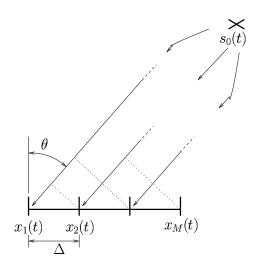
5. DIRECTION ESTIMATION USING ESPRIT

Problem

From the output of a uniform linear antenna array, estimate the angles of arrival



$$X = ABS = a(\theta_1)\beta_1s_1 + a(\theta_2)\beta_2s_2 + \cdots$$

General parametric procedure for DOA estimation:

$$rg \min_{\{\theta_i\}} \|\mathbf{X} - \mathbf{ABS}\|_F^2, \qquad \text{where} \quad \mathbf{A} = [\mathbf{a}(\theta_1) \ \mathbf{a}(\theta_2) \cdots]$$

■ We have to know the array manifold $\mathbf{a}(\theta)$.

For a uniform linear array, $\phi = e^{j\Delta 2\pi\sin(\theta)}$, and thus

$$\mathbf{a}(heta) = egin{bmatrix} 1 \ \phi \ \phi^2 \ dots \ \phi^{M-1} \end{bmatrix} egin{bmatrix} \mathbf{a}_x(heta) \ \mathbf{a}_y(heta) \ \end{pmatrix}$$

Shift-invariance property:

$$\mathbf{a}_x(heta) := egin{bmatrix} 1 \ \phi \ dots \ \phi \end{bmatrix}, \qquad \mathbf{a}_y(heta) := egin{bmatrix} \phi \ \phi^2 \ dots \ \phi^{M-1} \end{bmatrix}, \qquad ext{so that} \quad \mathbf{a}_y(heta) = \mathbf{a}_x(heta)\phi$$

Let us group the first and last M-1 antennas

$$\mathbf{x}(t) = \begin{bmatrix} x_1(t) \\ \vdots \\ x_{M-1}(t) \end{bmatrix}, \qquad \mathbf{y}(t) = \begin{bmatrix} x_2(t) \\ \vdots \\ x_M(t) \end{bmatrix}, \qquad \mathbf{X} = \begin{bmatrix} \mathbf{x}(0) & \cdots & \mathbf{x}(N-1) \end{bmatrix}$$

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}(0) & \cdots & \mathbf{y}(N-1) \end{bmatrix}$$

From the shift-invariance property:

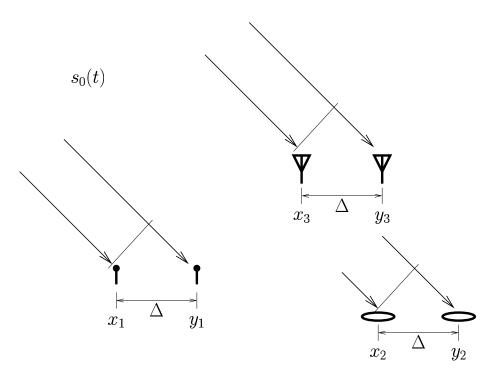
$$\mathbf{x}(t) = \sum_{k=1}^{d} \mathbf{a}_{x}(\theta_{k})\beta_{k}s_{k}(t) \qquad \Rightarrow \mathbf{X} = \mathbf{ABS}$$

$$\mathbf{y}(t) = \sum_{k=1}^{d} \mathbf{a}_{y}(\theta_{k})\beta_{k}s_{k}(t) = \sum_{k=1}^{d} \mathbf{a}_{x}(\theta_{k})\phi_{k}\beta_{k}s_{k}(t) \qquad \Rightarrow \mathbf{Y} = \mathbf{AOBS}$$

where

$$\mathbf{A} = \left[\mathbf{a}_x(heta_1) \quad \cdots \quad \mathbf{a}_x(heta_d)
ight], \qquad \mathbf{\Theta} = \left[egin{array}{ccc} \phi_1 & & & & \\ & \ddots & & & \\ & & \phi_d \end{array}
ight], \qquad \phi_k = e^{j2\pi\Delta\sin(heta_k)}$$

More general "doublet" antenna structure



$$x_i(t) = \sum_{k=1}^d a_{i,k} \beta_k s_k(t), \qquad y_i(t) = \sum_{k=1}^d a_{i,k} e^{j2\pi\Delta\sin(\theta_k)} \beta_k s_k(t)$$

$$\mathbf{z}(t) = \left[egin{array}{c} \mathbf{x}(t) \\ \mathbf{y}(t) \end{array}
ight] \qquad \Rightarrow \qquad \mathbf{Z} = \left[egin{array}{c} \mathbf{X} \\ \mathbf{Y} \end{array}
ight] = \left[egin{array}{c} \mathbf{A} \\ \mathbf{A}\mathbf{\Theta} \end{array}
ight] \mathbf{BS}$$

Given the data matrix **Z** from all antennas

$$\mathbf{Z} = \left[egin{array}{c} \mathbf{X} \\ \mathbf{Y} \end{array}
ight] = \mathbf{A}_z \mathbf{BS}, \qquad \mathbf{A}_z = \left[egin{array}{c} \mathbf{A} \\ \mathbf{A} \mathbf{\Theta} \end{array}
ight]$$

■ Note that **Z** has rank *d*. Compute an SVD of **Z**:

$$\mathbf{Z} = \mathbf{\hat{U}}_z \mathbf{\hat{\Sigma}}_z \mathbf{\hat{V}}_z^{\scriptscriptstyle \mathrm{H}}$$

 $\hat{\mathbf{U}}_z:2M\times d$ has d columns which together span the column space of \mathbf{Z}

Note that $\hat{\mathbf{U}}_z$ spans the same space as \mathbf{A}_z , hence there exists a $d \times d$ matrix \mathbf{T} :

$$\mathbf{\hat{U}}_z = \mathbf{A}_z \mathbf{T} = \left[egin{array}{c} \mathbf{AT} \ \mathbf{A} \mathbf{\Theta} \mathbf{T} \end{array}
ight]$$

lacksquare Split **Z** into **X** and **Y**, and $\hat{\mathbf{U}}_z$ accordingly into $\hat{\mathbf{U}}_x$ and $\hat{\mathbf{U}}_y$, then

$$\left\{ egin{array}{lll} \hat{\mathbf{U}}_x &=& \mathbf{AT} \ \hat{\mathbf{U}}_y &=& \mathbf{A}\mathbf{\Theta}\mathbf{T} \end{array}
ight.$$

$$\left\{ egin{array}{lll} \hat{f U}_x &=& {\sf AT} \ \hat{f U}_y &=& {\sf A}\Theta{\sf T} \end{array}
ight.$$

Note that $\hat{\mathbf{U}}_x^\dagger = (\mathbf{T}^{\scriptscriptstyle \mathrm{H}} \mathbf{A}^{\scriptscriptstyle \mathrm{H}} \mathbf{A} \mathbf{T})^{-1} \mathbf{T}^{\scriptscriptstyle \mathrm{H}} \mathbf{A}^{\scriptscriptstyle \mathrm{H}} = \mathbf{T}^{-1} \mathbf{A}^\dagger$ so that

$$\hat{\mathbf{U}}_{x}^{\dagger}\hat{\mathbf{U}}_{y}=\mathbf{T}^{-1}\mathbf{\Theta}\mathbf{T}$$
 .

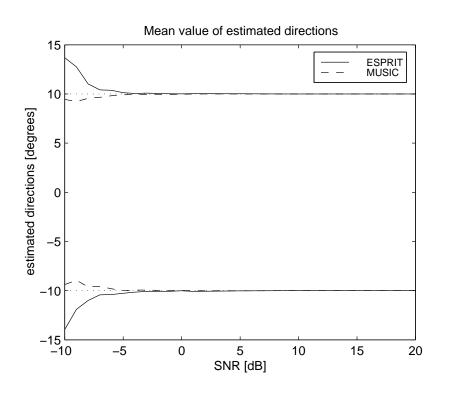
- Thus, \mathbf{T}^{-1} and $\mathbf{\Theta}$ are given by the eigenvectors and eigenvalues of $\hat{\mathbf{U}}_x^{\dagger}\hat{\mathbf{U}}_y$.
- From Θ we can derive $\{\phi_k\}$ and hence $\{\theta_k\}$
- From **T** we can derive a zero-forcing beamformer on **Z** as

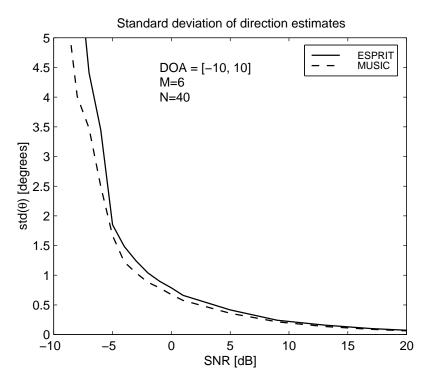
$$\mathbf{W} = \mathbf{\hat{U}}_z \mathbf{T}^{\scriptscriptstyle \mathrm{H}}$$

Proof:

$$egin{array}{lll} \mathbf{Z} &=& \hat{\mathbf{U}}_z \cdot \hat{\mathbf{\Sigma}}_z \hat{\mathbf{V}}_z^{\mathrm{H}} = \mathbf{A}_z \mathbf{S} = \mathbf{A}_z \mathbf{T} \cdot \mathbf{T}^{-1} \mathbf{S} \ &\Rightarrow & \mathbf{T}^{-1} \mathbf{S} &=& \hat{\mathbf{\Sigma}}_z \hat{\mathbf{V}}_z^{\mathrm{H}} = \hat{\mathbf{U}}_z^{\mathrm{H}} \mathbf{Z} \ &\Rightarrow & \mathbf{S} &=& \mathbf{T} \hat{\mathbf{U}}_z^{\mathrm{H}} \mathbf{Z} \end{array}$$

Performance (varying SNR)

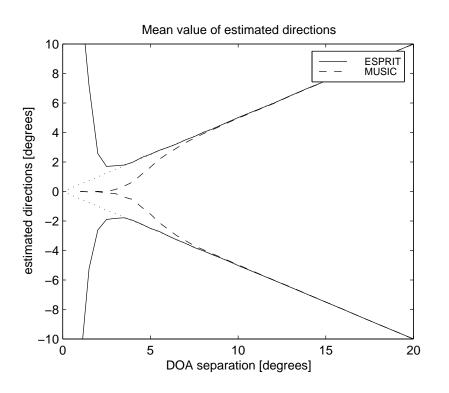


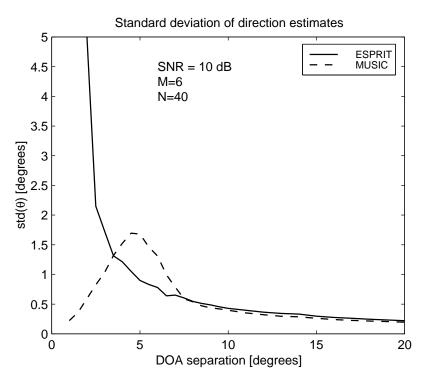


d=2 sources, M=6 antennas, N=40 samples, 20° separation.

Mean and standard deviations of ESPRIT and MUSIC as function of SNR

Performance (varying separation)





Mean and standard deviations of ESPRIT and MUSIC as function of DOA separation.

Principle

 \blacksquare Consider an FIR pulse shape function g(t) that is oversampled by a factor P:

$$g(t) \quad \leftrightarrow \quad \mathbf{g}(0) = \begin{bmatrix} g(0) \\ g(\frac{1}{P}) \\ \vdots \\ g(L - \frac{1}{P}) \end{bmatrix}$$

$$g(t-\tau) \quad \leftrightarrow \quad \mathbf{g}(\tau) = \begin{bmatrix} g(0-\tau) \\ g(\frac{1}{P}-\tau) \\ \vdots \\ g(L-\frac{1}{P}-\tau) \end{bmatrix}$$

 \blacksquare Q: Given $\mathbf{g}(\tau)$ and knowing $\mathbf{g}(0)$, how do we estimate τ ?

A: By using the fact that a Fourier transform maps a delay to a phase shift.

 \blacksquare Apply the DFT to $\mathbf{g}(0)$:

$$\tilde{\mathbf{g}}(0) \ := \ \mathcal{F} \, \mathbf{g}(0) \,, \qquad \mathcal{F} := \left[\begin{array}{ccccc} 1 & 1 & \cdots & 1 \\ 1 & W & \cdots & W^{LP-1} \\ \vdots & \vdots & & \vdots \\ 1 & W^{LP-1} & \cdots & W^{(LP-1)^2} \end{array} \right] \,, \quad W = e^{-j\frac{2\pi}{LP}}$$

■ The DFT of $\mathbf{g}(\tau)$ can then be written as

$$\tilde{\mathbf{g}}(\tau) := \mathcal{F} \, \mathbf{g}(\tau) \, = \, \tilde{\mathbf{g}}(0) \, \odot \, \begin{bmatrix} 1 \\ W^{\tau P} \\ (W^{\tau P})^2 \\ \vdots \\ (W^{\tau P})^{LP-1} \end{bmatrix} \, = \, \mathrm{diag}(\tilde{\mathbf{g}}(0)) \cdot \, \begin{bmatrix} 1 \\ W^{\tau P} \\ (W^{\tau P})^2 \\ \vdots \\ (W^{\tau P})^{LP-1} \end{bmatrix}$$

(⊙ represents entrywise multiplication of the two vectors)

From the DFT of $\mathbf{g}(0)$ and $\mathbf{g}(\tau)$ we can compute

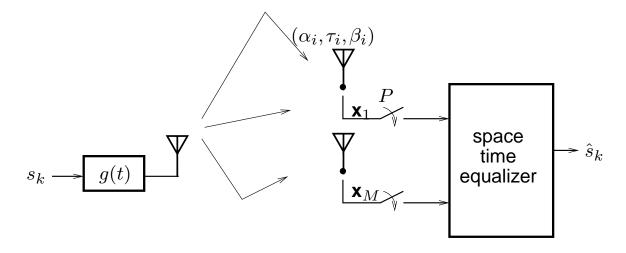
$$\mathbf{z} := \{ \operatorname{diag}(\tilde{\mathbf{g}}(0)) \}^{-1} \tilde{\mathbf{g}}(\tau)$$

The vector **z** has model

$$\mathbf{z} = \mathbf{f}(\phi)\,, \qquad \mathbf{f}(\phi) := \left[egin{array}{c} \phi \ \phi^2 \ \vdots \ \phi^{LP-1} \end{array}
ight]\,, \qquad \phi := e^{j2\pi au/L}$$

Now apply ESPRIT to compute ϕ and then τ .

Multiple paths



 $lue{}$ Consider a multipath channel which consists of r delayed copies of g(t)

$$h(t) = \sum_{i=1}^r \beta_i g(t - \tau_i) \qquad \Leftrightarrow \qquad \mathbf{h} = \sum_{i=1}^r \mathbf{g}(\tau_i) \beta_i = \left[\mathbf{g}(\tau_1) \,, \cdots \,, \mathbf{g}(\tau_r) \right] \left| \begin{array}{c} \beta_1 \\ \vdots \\ \beta_r \end{array} \right| =: \mathbf{G}\beta$$

lacktriangle Assume pulse shape g(t) is known and lacktriangle has been estimated using training.

As before:

$$\mathbf{z} := \{ \operatorname{diag}(\tilde{\mathbf{g}}(0)) \}^{-1} \mathcal{F} \mathbf{h}$$

The vector z has model

$$\mathbf{z} = \mathbf{F}eta, \qquad \mathbf{F} = [\mathbf{f}(\phi_1), \cdots, \mathbf{f}(\phi_r)], \qquad \mathbf{f}(\phi_i) := egin{bmatrix} 1 \ \phi_i \ \phi_i^2 \ dots \ \vdots \ \phi_i^{LP-1} \end{bmatrix}, \qquad \phi_i := e^{j2\pi au_i/L}$$

Conisder a shift of **z** and $f(\phi_i)$ of length LP - m + 1:

$$\mathbf{z}^{(l)} := \begin{bmatrix} z_l \\ z_{l+1} \\ \vdots \\ z_{l+LP-m} \end{bmatrix} \qquad \mathbf{f}(\phi_i)^{(l)} = \begin{bmatrix} \phi_i^l \\ \phi_i^{l+1} \\ \vdots \\ \phi_i^{l+LP-m} \end{bmatrix} = \begin{bmatrix} 1 \\ \phi_i \\ \vdots \\ \phi_i^{LP-m} \end{bmatrix} \phi_i^l =: \mathbf{f}'(\phi_i)\phi_i^l$$

Let us now stack the different shifts of **z**:

$$\mathbf{Z} = [\mathbf{z}^{(0)}, \, \mathbf{z}^{(1)}, \, \cdots, \, \mathbf{z}^{(m-1)}] = \mathbf{F}'\mathbf{B}', \qquad \mathbf{F}' = [\mathbf{f}'(\phi_1), \cdots, \mathbf{f}'(\phi_r)]$$

$$\mathbf{B}' = [eta \quad \mathbf{\Phi}eta \quad \mathbf{\Phi}^2eta \quad \cdots \quad \mathbf{\Phi}^{m-1}eta], \qquad \mathbf{\Phi} = \left[egin{array}{cccc} \phi_1 & & & & \\ & \ddots & & & \\ & & \phi_r \end{array}
ight]$$

- Model: $\mathbf{X} = \mathbf{F}''\mathbf{B}'$, $\mathbf{Y} = \mathbf{F}''\Phi\mathbf{B}'$.
- Now we can apply ESPRIT to estimate Φ and hence all $\{\tau_i\}$.
 - 1. Compute the SVD: $\mathbf{Z} = \hat{\mathbf{U}}_z \hat{\mathbf{\Sigma}}_z \hat{\mathbf{V}}_z^{\mathrm{H}}$
 - 2. Split $\hat{\mathbf{U}}_z$ into $\hat{\mathbf{U}}_x$ and $\hat{\mathbf{U}}_y$ (shift over 1 row): $\hat{\mathbf{U}}_z = \begin{bmatrix} \hat{\mathbf{U}}_x \\ \hline *** \end{bmatrix} = \begin{bmatrix} \frac{***}{\hat{\mathbf{U}}_y} \end{bmatrix}$

Model: $\hat{\mathbf{U}}_x = \mathbf{F}''\mathbf{T}$, $\hat{\mathbf{U}}_y = \mathbf{F}''\Phi\mathbf{T}$ for some $r \times r$ matrix \mathbf{T} .

3. Compute the eigenvalue decomposition: $\hat{\mathbf{U}}_x^{\dagger}\hat{\mathbf{U}}_y = \mathbf{T}^{-1}\mathbf{\Phi}\mathbf{T}$.

Multiple paths, multiple antennas

 \blacksquare The channel vector $\mathbf{h}(t)$ with M entries can then be written as

$$\mathbf{h}(t) = \sum_{i=1}^{r} \mathbf{a}(\theta_i) \beta_i g(t - \tau_i)$$

Oversampling at rate P we obtain

$$\mathbf{h} = \left[egin{array}{c} \mathbf{h}(0) \\ \mathbf{h}(rac{1}{P}) \\ dots \\ \mathbf{h}(L-rac{1}{P}) \end{array}
ight] = \sum_{i=1}^r [\mathbf{g}(au_i) \otimes \mathbf{a}(heta_i)] eta_i \ =: \ [\mathbf{G} \circ \mathbf{A}] eta$$

where

Kronecker product:
$$\mathbf{a} \otimes \mathbf{b} := \left[egin{array}{c} a_1 \mathbf{b} \\ \vdots \\ a_N \mathbf{b} \end{array} \right]$$

Khatri-Rao product: $\mathbf{A} \circ \mathbf{B} := [\mathbf{a}_1 \otimes \mathbf{b}_1 \quad \cdots \quad \mathbf{a}_r \otimes \mathbf{b}_r]$

■ Preprocess using DFT as before and construct **Z** from block-*M* shifts:

$$\mathbf{Z} = [\mathbf{z}^{(0)}, \, \mathbf{z}^{(1)}, \, \cdots, \, \mathbf{z}^{(m-1)}]$$
 $M(LP - m + 1) \times m$

Z has a model

$$\mathbf{Z} = [\mathbf{F}' \circ \mathbf{A}] \mathbf{B}', \qquad \mathbf{F}' = [\mathbf{f}'(\phi_1), \cdots, \mathbf{f}'(\phi_r)], \qquad \mathbf{f}'(\phi_i) = \begin{bmatrix} \phi_i \\ \vdots \\ \phi_i^{LP-m} \end{bmatrix}$$

Note

$$\mathbf{f}'(\phi_i) \otimes \mathbf{a}(heta_i) = egin{bmatrix} \mathbf{a}(heta_i) \ \phi_i \, \mathbf{a}(heta_i) \ dots \ \phi_i^{LP-m} \, \mathbf{a}(heta_i) \end{bmatrix}$$

We can now apply the ESPRIT algorithm to Z, where X and Y are submatrices of
 Z with last/first M rows omitted.

Frequency estimation

Use of ESPRIT to estimate frequencies

- Given that signal x(t) is the sum of d harmonic components, $x(t) = \sum_{i=1}^{d} \beta_i e^{j\omega_i t}$, estimate ω_i and β_i .
- Collect N samples in a data matrix Z with m rows:

$$\mathbf{Z} = \left[\begin{array}{cccc} x(0) & x(1) & \cdots & x(N-m-1) \\ x(1) & x(2) & \cdots & x(N-m) \\ \vdots & \vdots & \ddots & \vdots \\ x(m-1) & x(m) & \cdots & x(N-1) \end{array} \right]$$

Z has model

$$\mathbf{Z} = \mathbf{AS} := \begin{bmatrix} 1 & \cdots & 1 \\ \phi_1 & \cdots & \phi_d \\ \phi_1^2 & \cdots & \phi_d^2 \\ \vdots & \vdots & & \\ \beta_d & \beta_d \phi_d & \beta_d \phi_d^2 & \cdots \end{bmatrix}, \qquad \phi_i = e^{j\omega_i}$$