

ESPRIT(LS)

Hello

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1 Problem Formulation

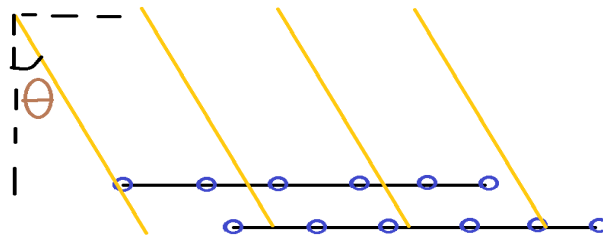
There are D signal sources, 2 subarrays with elements.

Note: $D < m$.

The signal is far away from the arrays.

Meanwhile, the 2 subarrays are same totally except their location.

Then, we can go!



2 Deducing

$$\mathbf{X} = \mathbf{A}\mathbf{S} + \mathbf{N}_x \quad (1)$$

\mathbf{X} is the data on each element of the first subarray. It is a $m \cdot n$ matrix. m is the number of the elements in each subarray, while n is the number of snapshots.

\mathbf{A} is the array manifold of the first subarray.

N_x is the noise on the first subarray.

Similarly.

$$\mathbf{Y} = \mathbf{A}\phi\mathbf{S} + \mathbf{N}_y \quad (2)$$

\mathbf{Y} is the data on each element of the second subarray.

$\mathbf{A}\phi$ is the array manifold of the second subarray. Note: the second array manifold is just a rotation of the first array manifold. So, ϕ is the rotation operator.

N_y is the noise on the second subarray manifold.

Looking at the ϕ in more details:

$$\phi = \text{diag}\{e^{j\gamma_1} \ e^{j\gamma_2} \ e^{j\gamma_3} \ \dots \ e^{j\gamma_D}\} \quad (3)$$

In this equation, $\gamma_k = \omega_i \Delta \sin \theta_k / c$, and ω_i is the central frequency of the i -th signal source. θ_k is the angle of incidence of the i -th source.

Let's simplify it. Assuming

$$\bar{\mathbf{A}} = \begin{bmatrix} \mathbf{A} \\ \mathbf{A}\phi \end{bmatrix}, \mathbf{N}_z = \begin{bmatrix} \mathbf{N}_x \\ \mathbf{N}_y \end{bmatrix}, \mathbf{Z} = \begin{bmatrix} \mathbf{X} \\ \mathbf{Y} \end{bmatrix} \quad (4)$$

Thus, we can denote this:

$$\mathbf{Z} = \bar{\mathbf{A}}\mathbf{S} + \mathbf{N}_z \quad (5)$$

Then, to find the correlation matrix.

$$\mathbf{R}_{zz} = \bar{\mathbf{A}}\mathbf{R}_{ss}\bar{\mathbf{A}}^H + \sigma^2\mathbf{I} \quad (6)$$

\mathbf{R}_{zz} is the correlation matrix of \mathbf{Z} .

\mathbf{R}_{ss} is the correlation matrix of \mathbf{S} .

σ^2 is the square error of the noise. (Here we assume that all the noise are gaussian)

\mathbf{I} is the identity matrix.

With all the given information, next step is to find the feature vectors of

\mathbf{R}_{zz} . And the linear subspace of the signal is available. Find the D biggest feature numbers and their feature vectors accordingly.

$\mathbf{U}_s = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_D]$

Since \mathbf{U}_s is equivalent to the linear subspace expanded by $\bar{\mathbf{A}}$, There must be full-order matrix \mathbf{T} satisfying: $\mathbf{U}_s = \bar{\mathbf{A}}\mathbf{T}$

which means:

$$\mathbf{U}_s = \begin{bmatrix} \mathbf{U}_x \\ \mathbf{U}_y \end{bmatrix} = \begin{bmatrix} \mathbf{A}\mathbf{T} \\ \mathbf{A}\phi\mathbf{T} \end{bmatrix} \quad (7)$$

Note: \mathbf{A} is a $m \times D$ matrix. $\bar{\mathbf{A}}$ is a $2m \times D$ matrix. $\mathbf{R}\{E_x\}$, $\mathbf{R}\{E_y\}$ and $\mathbf{R}\{A\}$ are the same.

Then we can denote $\mathbf{U}_{xy} = [\mathbf{U}_x, \mathbf{U}_y]$

It's a $d \cdot 2d$ matrix with d order. Then, there must be a $2d \cdot d$ matrix $\mathbf{F} = [\mathbf{F}_x, \mathbf{F}_y]$ satisfying:

$$\mathbf{0} = \mathbf{U}_s^T \mathbf{F} = \mathbf{U}_x \cdot \mathbf{F}_x + \mathbf{U}_y \cdot \mathbf{F}_y = \mathbf{A}^T \mathbf{F}_x + \mathbf{A} \phi^T \mathbf{F}_y \quad (8)$$

Then we can denote $\boldsymbol{\psi} = -\mathbf{F}_x \mathbf{F}_y^{-1}$

The equation above is equal to the following:

$$\begin{aligned} \mathbf{A}^T \boldsymbol{\psi} &= \mathbf{A} \phi^T \\ \rightarrow \mathbf{A}^T \boldsymbol{\psi} \mathbf{T}^{-1} &= \mathbf{A} \phi \\ \rightarrow \mathbf{U}_s \boldsymbol{\psi} &= \mathbf{U}_y \end{aligned} \quad (9)$$

Then if \mathbf{A} is full-order, it will be like this:

$$\mathbf{T} \boldsymbol{\psi} \mathbf{T}^{-1} = \phi \quad (10)$$

All we have to do is to find a $\boldsymbol{\psi}$ that fits the above equation best.

3 Solving

3.1 What we know

Well, to solve the issue, first figure out what we know.

We have the data on every element. Use that, we can estimate the $\mathbf{R}\{E_s\}$

. Where E_s is the matrix made by feature vectors of received data.

Note: E_s is an estimation, not true E_s . As a consequence, we use \widehat{E}_s to denote it.

Thus, we got the \widehat{E}_x and \widehat{E}_y .

They are the matrixes made by feature vectors of the signal subspace and noise subspace respectively.

3.2 step1

We have data about \mathbf{X} , and we can use it to calculate $\widehat{\mathbf{U}}$

3.3 step2

With \mathbf{U} , we can select two subarrays. After that, we can have our \mathbf{U}_x and \mathbf{U}_y

3.4 step3

In practice, we have the estimates for $\mathbf{U}_x, \mathbf{U}_y$.

We can denote them as $\widehat{\mathbf{U}}_x$ and $\widehat{\mathbf{U}}_y$

The rule for the best estimate of $\boldsymbol{\psi}$ is that:!!!!It minimizes the difference between \mathbf{U}_y and $\mathbf{U}_s \boldsymbol{\psi}$

$$\begin{aligned}\hat{\boldsymbol{\psi}}_{\text{LS}} &= \arg \min \{ ||\mathbf{U}_y - \mathbf{U}_s \boldsymbol{\psi}|| \} \\ &= \arg \min \left\{ \text{tr} \left\{ [\mathbf{U}_y - \mathbf{U}_s \boldsymbol{\psi}]^{\text{H}} [\mathbf{U}_y - \mathbf{U}_s \boldsymbol{\psi}] \right\} \right\}\end{aligned}\quad (11)$$

Note Here: tr means the sum of the elements in the diagonal.

To be detailed, the result is that :

$$\hat{\boldsymbol{\psi}}_{\text{LS}} = \left[\widehat{\mathbf{U}}_x^{\text{H}} \widehat{\mathbf{U}}_x \right]^{-1} \widehat{\mathbf{U}}_x^{\text{H}} \widehat{\mathbf{U}}_y \quad (12)$$

3.5 step4

Find eigenvalues of $\hat{\boldsymbol{\psi}}_{\text{LS}}$, and we can denote them as $\hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3, \dots, \hat{\lambda}_D$

3.6 step5

Like MUSIC, we can estimate DOA.