# Multiple Signal Classification (MUSIC) Algorithm for Angular Estimation

Multiple Signal Classification (MUSIC) is a classic algorithm for angular information estimation in wireless communications. In this article, I first model the far-field wireless channel in the view of angular-domain, and then describe the MUSIC algorithm for angular information extraction in the modeled angular-domain channel. The simulation codes will be attached for performance verification.

#### I. FAR-FIELD CHANNEL MODEL

We consider a single-input-multiple-output (SIMO) system where a single-antenna transmitter sends pilot signal x to the receiver with N antennas. As shown in Fig. 1(a), each of the N antennas receives a copy of the signal x. When the distance between the transmitter and receiver is large enough, the signal x can be assumed to arrive at each receiver antenna in a parallel way, as illustrated in Fig. 1(b). Due to the separation d between two neighboring receiver antennas, length of the parallel path from the transmitter to each receiver antenna is different. As shown in Fig. 1(b), the distance  $d_n$  between transmitter and nth receiver antenna is given by

$$d_n = d_1 + (n-1)d\sin(\theta), \quad n = 1, 2, \dots, N,$$
(1)

where  $d_1$  is the distance from the transmitter to the 1st antenna of the receiver. On this basis, the received signal at the nth antenna is computed as  $^1$ 

$$y_n = a(d_n)e^{j2\pi f_c \frac{d_n}{c}}x = a(d_n)e^{j\frac{2\pi}{\lambda}f_c d_1}e^{j\frac{2\pi}{\lambda}(n-1)d\sin(\theta)}x \stackrel{(a)}{\approx} a(d_1)e^{j\frac{2\pi}{\lambda}f_c d_1}e^{j\frac{2\pi}{\lambda}(n-1)d\sin(\theta)}x, \tag{2}$$

where  $a(d_n)$  is the large-scale attenuation (e.g., pathloss),  $e^{j2\pi f_c \frac{d_n}{c}}$  denotes the phase change of the signal due to propagation time delay  $\frac{d_n}{c}$ , (a) is because of the fact that  $a(d_1) \approx a(d_2) \approx \dots a(d_N)$  for large-scale attenuation. Based on (2), the received signal at all the N antennas are given by

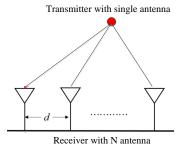
$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = a(d_1)e^{j\frac{2\pi}{\lambda}f_c d_1} x \underbrace{\begin{bmatrix} 1 \\ e^{j\frac{2\pi}{\lambda}d\sin(\theta)} \\ \vdots \\ e^{j\frac{2\pi}{\lambda}(N-1)d\sin(\theta)} \end{bmatrix}}_{\mathbf{e}(\theta)} = a(d_1)e^{j\frac{2\pi}{\lambda}f_c d_1} x \mathbf{e}(\theta)$$
(3)

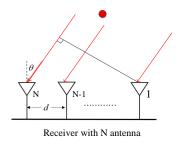
Note that (3) represents the received signals along with a certain path with length  $d_1$  and angle-of-arrival (AoA)  $\theta$ . In practise, the signal from transmitter can arrive at the receiver along with many different paths under different length distance and AoA. An extension of the (3) to the multi-path scenario is given by

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{e}(\theta_1) & \mathbf{e}(\theta_2) & \dots \mathbf{e}(\theta_L) \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{bmatrix}}_{\mathbf{x}} + \mathbf{n}, \tag{4}$$

where  $\theta_l$  is the AoA of the lth path, and  $x_l = a(d_{1,l})e^{j\frac{2\pi}{\lambda}f_cd_{1,l}}x$  is for the l the path, and  $\mathbf{n} \in \mathcal{C}^{Nr \times 1}$  is the noise with norm distribution  $\mathcal{CN}(\mathbf{0}, \mathbf{I})$ .

<sup>&</sup>lt;sup>1</sup>One can check my previous paper https://zhuanlan.zhihu.com/p/141475685 for the physical meaning in (2).





(a) True signal propagation model

(b) Far-field approximation, which holds when the distance between Tx and Rx is large enough.

Fig. 1: Far field channel model in free space with only line-of-site (LoS) path.

## II. MUSIC ALGORITHM THEORY

In this section, we theoretically describe the MUSIC algorithm. Note that the MUSIC can only work in the scenario with N > L, i.e., the number of receive antenna is larger than the number of paths in the channel  $\bf A$  in (4).

According to (4), the received signal can be expressed as

$$y = Ax + n. (5)$$

Due to the randomness of noise n, the y is a random vector with covariance matrix

$$\mathbf{R}_{\mathbf{y}} = \mathbb{E}[\mathbf{y}\mathbf{y}^*] = \mathbb{E}[(\mathbf{A}\mathbf{x} + \mathbf{n})(\mathbf{A}\mathbf{x} + \mathbf{n})^*]$$

$$\stackrel{(b)}{=} \mathbf{A}\mathbb{E}[\mathbf{x}\mathbf{x}^*]\mathbf{A}^* + \mathbb{E}[\mathbf{n}\mathbf{n}^*]$$

$$= \mathbf{A}\mathbf{R}_{\mathbf{x}}\mathbf{A}^* + \mathbf{R}_{\mathbf{n}},$$
(6)

where (b) is due to the fact that  $\mathbb{E}[\mathbf{x}\mathbf{n}^*] = 0$ . Since the  $\mathbf{R}_{\mathbf{y}} \in \mathcal{C}^{N \times N}$  in (6) is symmetric, we conduct the eigenvalue decomposition (EVD) for the  $\mathbf{R}_{\mathbf{y}}$  given by

$$\mathbf{R_y} = \begin{bmatrix} \mathbf{U_x} & \mathbf{U_n} \end{bmatrix} \begin{bmatrix} \mathbf{\Sigma_x} \\ \mathbf{\Sigma_n} \end{bmatrix} \begin{bmatrix} \mathbf{U_x^*} \\ \mathbf{U_n^*} \end{bmatrix} = \mathbf{U_x} \mathbf{\Sigma_x} \mathbf{U_x^*} + \mathbf{U_n} \mathbf{\Sigma_n} \mathbf{U_n^*}, \tag{7}$$

where  $\mathbf{U_x} \in \mathcal{C}^{N \times L}$ ,  $\mathbf{U_n} \in \mathcal{C}^{N \times (N-L)}$ ,  $\Sigma_{\mathbf{x}} \in \mathcal{C}^{L \times L}$ , and  $\Sigma_{\mathbf{n}} \in \mathcal{C}^{(N-L) \times (N-L)}$ . It is clear that  $\mathbf{U_x} \Sigma_{\mathbf{x}} \mathbf{U_x^*}$  is the EVD of the  $\mathbf{AR_x} \mathbf{A^*}$  and  $\mathbf{U_n} \Sigma_{\mathbf{n}} \mathbf{U_n^*}$  is the EVD of  $\mathbf{R_n}$  in (6). Based on the properties of EVD, we have

$$\mathbf{A}\mathbf{R_x}\mathbf{A^*}\mathbf{U_n} = \mathbf{U_x}\boldsymbol{\Sigma_x}\mathbf{U_x^*}\mathbf{U_n} = \mathbf{0},$$

which yields<sup>2</sup>

$$\left(\mathbf{R}_{\mathbf{x}}^{-1}(\mathbf{A}\mathbf{A}^*)^{-1}\mathbf{A}^*\right)\mathbf{A}\mathbf{R}_{\mathbf{x}}\mathbf{A}^*\mathbf{U}_{\mathbf{n}}=\mathbf{0}\Rightarrow\mathbf{A}^*\mathbf{U}_{\mathbf{n}}=\mathbf{0}.$$

This implies

$$\mathbf{e}(\theta_l)\mathbf{U_n} = \mathbf{0} \tag{8}$$

because of the expression of A in (4). It means a path angle  $\theta_l$  appears when

$$P(\theta) = \frac{1}{|\mathbf{e}(\theta_l)\mathbf{U_n}|^2} \to +\infty. \tag{9}$$

<sup>&</sup>lt;sup>2</sup>Since different paths will independently affect the transmit signal x, the  $\mathbf{R}_{\mathbf{x}}$  is full rank and its inverse exists.

### III. MUSIC ALGORITHM IMPLEMENTATION

In real system, one can sample the received signal y at different time  $t \in \{1, 2, ..., T\}$  yielding y(1), y(2), ..., y(T). Using these samples, the covariance matrix is computed as

$$\hat{\mathbf{R}}_{\mathbf{y}} = \frac{1}{T} \sum_{t=1}^{T} \mathbf{y}(t) \mathbf{y}(t)^*.$$
 (10)

Taking the EVD for the  $\hat{\mathbf{R}}_{\mathbf{y}}$  yields

$$\hat{\mathbf{R}}_{\mathbf{v}} = \hat{\mathbf{U}}\hat{\Sigma}\hat{\mathbf{U}}^*. \tag{11}$$

We sort the eigenvalues in  $\hat{\Sigma}$  at a descending order and accordingly adjust the corresponding eigenvectors in  $\hat{\mathbf{U}}$ . In this way, we obtain the  $\hat{\mathbf{U}}_{\mathbf{n}}$  as in (7) by taking the last N-L columns of the adjusted  $\hat{\mathbf{U}}$ . Under different  $\theta \in (0,\pi]$ , we can obtain different value for the function  $P(\theta)$  in (9). According to (9), the  $\theta$  yielding a locally maximum  $P(\theta)$  is a target AoA. Summaries of the MUSIC algorithm for AoA extraction is given in Algorithm 1.

# Algorithm 1 MUSIC algorithm for AoA Extraction

**Require:**  $y(1), y(2), \dots, y(T)$ , resolution for  $\theta \in (0, \pi]$ 

- 1. Compute the covariance matrix  $\mathbf{R}_{\mathbf{y}}$  in (10).
- 2. Find the noise space matrix  $\hat{\mathbf{U}}_{\mathbf{n}}$ .
- 3. Based on the resolution for  $\theta \in (0, \pi]$ , test each  $\theta$  and find the ones yielding the locally maximum  $P(\theta)$  in (9). These  $\theta$ s are the expected AoAs.