

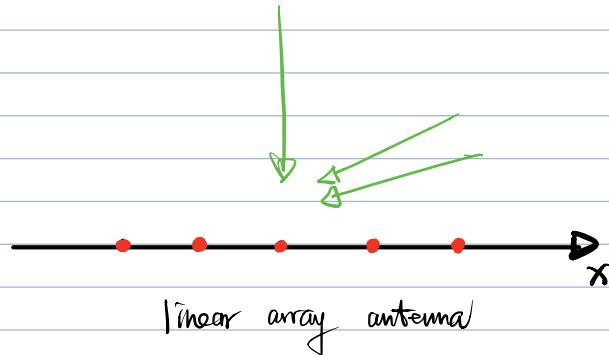
# Experiment A M

## Array Communications & Processing

Main MATLAB codes are at  
the end of this logbook

5 sensors along x-axis

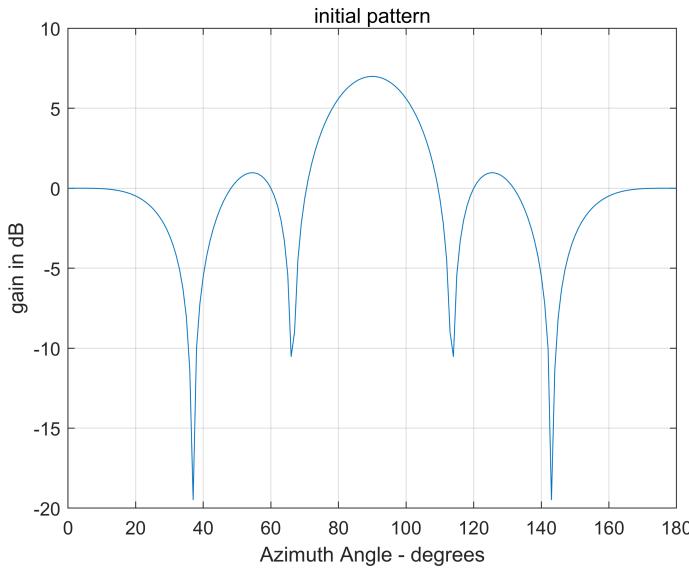
$$\text{array} = \begin{bmatrix} -2 & 0 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 2 & 0 & 0 \end{bmatrix}$$



direction of sources

$$\text{direction} = \begin{bmatrix} 30 & 0 \\ 35 & 0 \\ 90 & 0 \end{bmatrix}$$

## 1. Pattern of the array



If there is no beamforming, the pattern of the array is shown on the left, where the maximum gain is obtained at the degree of 90°.

## 2. Theoretical Covariance Matrix

Array manifold vector

$$S(\theta, \phi) = e^{-j \cdot r^T E(\theta, \phi)} \quad S = [S_1, S_2, \dots, S_L]$$

Received signal

$$\underline{x}(t) = S \cdot \underline{m}(t) + \underline{n}(t)$$

$$\underline{m} = \begin{bmatrix} m_1 \\ m_2 \\ m_3 \end{bmatrix} \quad R_{mm} = \mathbb{E} [\underline{m} \cdot \underline{m}^H]$$
$$= \begin{bmatrix} \mathbb{E}[m_1 m_1^H] & \mathbb{E}[m_1 m_2^H] & \mathbb{E}[m_1 m_3^H] \\ \mathbb{E}[m_2 m_1^H] & \mathbb{E}[m_2 m_2^H] & \mathbb{E}[m_2 m_3^H] \\ \mathbb{E}[m_3 m_1^H] & \mathbb{E}[m_3 m_2^H] & \mathbb{E}[m_3 m_3^H] \end{bmatrix}$$

As different sources are uncorrelated and the power is 1

$$\Rightarrow R_{mm} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_{xx} = \mathbb{E} [\underline{x}(t) \underline{x}(t)^H]$$

$$= \mathbb{E} [(S \underline{m}(t) + \underline{n}(t)) \cdot (S \underline{m}(t) + \underline{n}(t))^H]$$

$$= \mathbb{E} [S \underline{m}(t) \cdot \underline{m}(t)^H S^H] + \mathbb{E} [\underline{n}(t) \cdot \underline{n}(t)^H] + \mathbb{E} [S \underline{m}(t) \cdot \underline{n}(t)^H] + \mathbb{E} [\underline{n}(t) \cdot \underline{m}(t)^H S^H]$$

If  $\underline{n}(t)$  is isotropic AWGN,  $\mathbb{E}[\underline{n}(t) \cdot \underline{n}(t)^H] = \sigma_n^2 I_N$

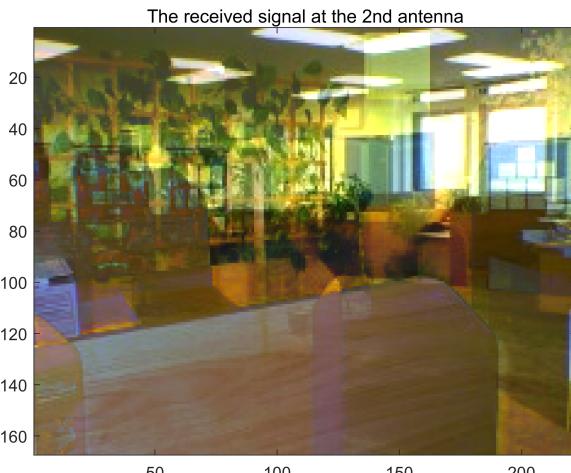
If  $\underline{n}(t)$  and  $\underline{m}(t)$  are uncorrelated,  $\mathbb{E}[S \underline{m}(t) \cdot \underline{n}(t)^H] = \mathbb{E}[\underline{n}(t) \underline{m}(t)^H S^H] = 0$

$$\Rightarrow R_{xx} = \mathbb{E} [S \underline{m}(t) \cdot \underline{m}(t)^H S^H] + \sigma_n^2 I_N$$

$$= S \cdot R_{mm} \cdot S^H + \sigma_n^2 I_N$$

### 3. Practical Covariance Matrix

The image received at the second antenna.



For the received signal with finite snapshots

$$\underline{X} = [\underline{x}_1(t_1), \underline{x}_2(t_2), \underline{x}_3(t_3), \dots, \underline{x}_L(t_L)]$$

The covariance matrix can be calculated by

$$R_{xx} = \frac{1}{L} \underline{X} \cdot \underline{X}^H$$

## 5. Detection Problem

For  $R_{xx}$

Observing the theoretical  $R_{xx}$  matrix

$$R_{xx} = S \cdot R_{mm} \cdot S^H + \sigma_n^2 I_N$$

$$= R_{\text{signal}} + \sigma_n^2 I_N$$

$$R_{xx} = R_{\text{signal}} + \sigma_n^2 I_N$$

$$= E[\Lambda] E^H + \sigma_n^2 E E^H$$

$$= E[\Lambda + \sigma_n^2 I_N] E^H$$

As there are  $M$  sources

$$\text{rank}\{R_{\text{signal}}\} = M$$

i.e.  $R_{\text{signal}}$  has  $N-M$  duplicate eigenvalue  $\lambda=0$

Therefore, the eigen-decomposition of  $R_{\text{signal}}$  is

$$R_{\text{signal}} = E \Lambda E^H$$

$$\Lambda = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ 0 & & & \lambda_M & 0 \\ & & & & \ddots & 0 \end{bmatrix}_{N \times N}$$

The  $D = \Lambda + \sigma_n^2 I_N$  is the eigenvalue matrix of  $R_{xx}$

$$D = \begin{bmatrix} \lambda_1 + \sigma_n^2 & & & & \\ & \lambda_2 + \sigma_n^2 & & & \\ & & \ddots & & \\ 0 & & & \lambda_M + \sigma_n^2 & \\ & & & & \sigma_n^2 \end{bmatrix}$$

The power of noise can be estimated by the average of  $N-M$  smallest values of eigenvalues of the estimated covariance matrix of received signals

The number of sources can be estimated by

The eigenvalues of  $R_{xx}$ -theoretical are

$$[9.9369, 4.9681, 0.0943, 0.0001, 0.0001]$$

$$M = N - \text{multiplicity of minimum eigenvalues of } R_{xx}$$

The eigenvalues of  $R_{xx}-\text{our}$  is

$$[4.382 \times 10^5, 1.072 \times 10^4, 1.733 \times 10^2, \underbrace{0.0101, 0.0103}_{\text{noise}}] \quad M=3, \quad \sigma_n^2 = \frac{0.0101 + 0.0103}{2} \approx 0.01$$

The eigenvalues of  $R_{xx}-\text{im}$  is

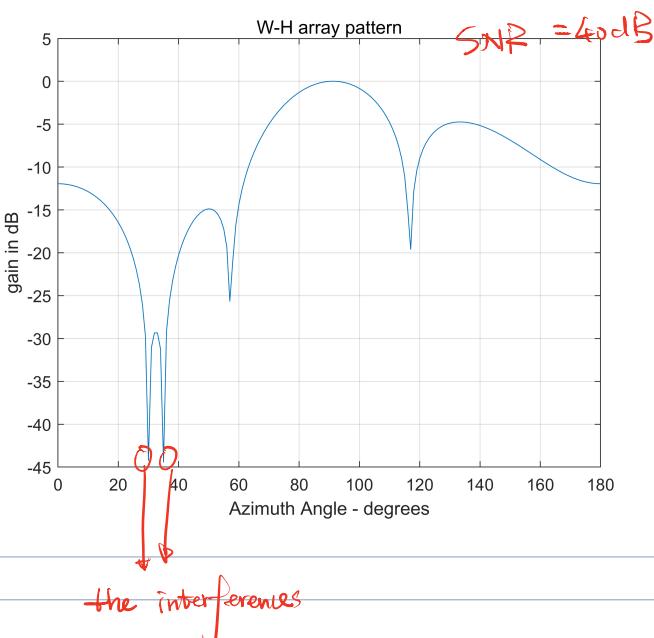
$$[2.178 \times 10^5, 2.039 \times 10^4, 1.909 \times 10^3, \underbrace{7.061 \times 10^{-11}, -9.492 \times 10^{-11}}_{\text{noise}}] \quad M=3, \quad \sigma_n^2 = \frac{7.061 \times 10^{-11} + -9.492 \times 10^{-11}}{2} = -1.216 \times 10^{-11}$$

## 6. Estimation

The WIENER-HOPF Beamformer is used

the weights

$$\underline{w} = C \cdot R_{ntj}^{-1} \underline{s}_d$$

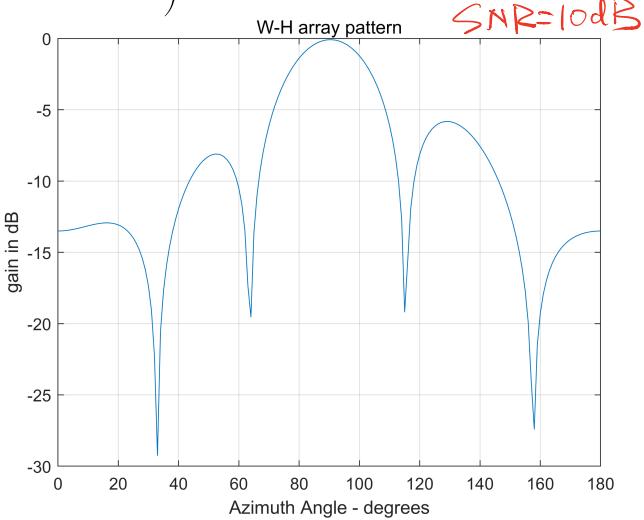


The pattern of WIENER-HOPF is shown on the left. We can notice that the gains at  $30^\circ$  and  $35^\circ$  degrees are smallest, therefore the directions of the interferences are  $30^\circ$  and  $35^\circ$ .

For the noise level 10dB below the level of the sources

$$\text{i.e. } \sigma_n^2 = \frac{1}{10} P_S = 0.1$$

The result of WIENER-HOPF is



Compared with the situation where  $\sigma_n^2 = 0.001$ , the results is bad, as the pattern is not changed too much from the initial pattern.

This result shows that WIENER-HOPF beamformer performs badly with 10dB SNR.

## 9. MUSIC Algorithm.

$$\mathcal{Z}(p) = \underline{\Sigma}(p)^H \cdot P_n \cdot \underline{\Sigma}(p)$$

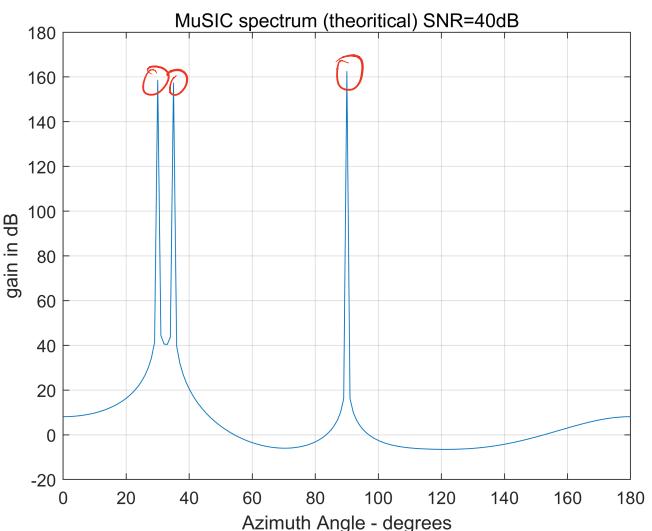
$P_n$  is the projection matrix of  $L^H L$ ?

This equation can be simplified to

$$\mathcal{Z}(p) = \underline{\Sigma}(p)^H \cdot E_n \cdot E_n^H \cdot \underline{\Sigma}(p)$$

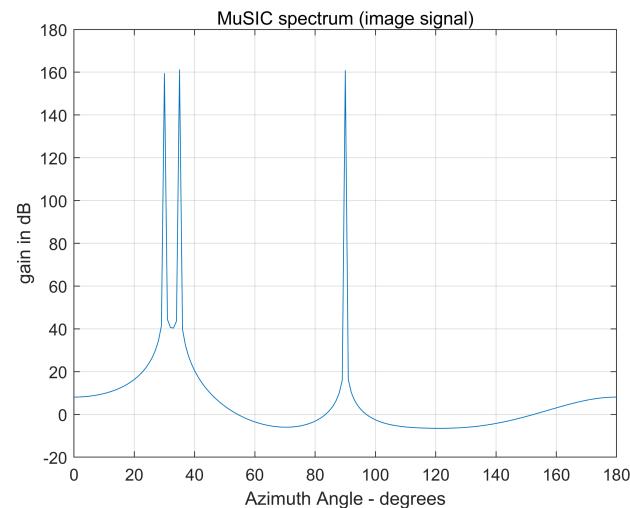
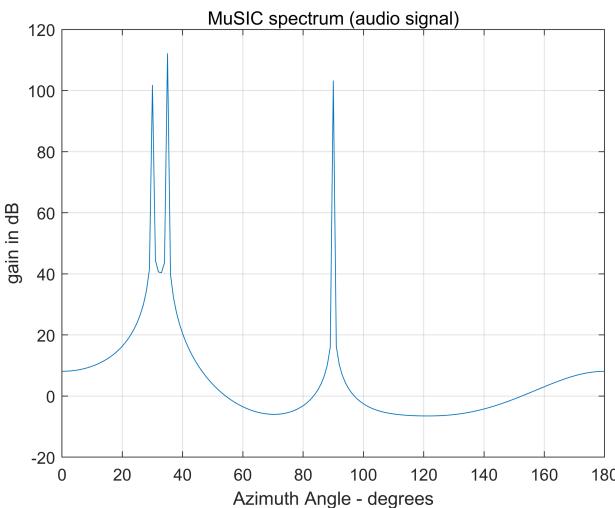
Matrix  $E_n$  is the eigenvector matrix of the

$N-M$  smallest eigenvalues of  $P_{xx}$



In result figure, we can notice that there are three DOAs, which are  $(30^\circ, 0^\circ)$   $(35^\circ, 0^\circ)$   $(90^\circ, 0^\circ)$

# Apply the MuSIC Algorithm on audio and image signals



Both of the signals have the same DOAs, which are  $(35^\circ, 0^\circ)$   $(95^\circ, 0^\circ)$

But the gains of each DOA are different for the two signals

## N. Coherent Sources

$$R_{mm} = \mathbb{E}[m \cdot m^*]$$

$$= \begin{bmatrix} \mathbb{E}[m_1 m_1^*] & \mathbb{E}[m_1 m_2^*] & \mathbb{E}[m_1 m_3^*] \\ \mathbb{E}[m_2 m_1^*] & \mathbb{E}[m_2 m_2^*] & \mathbb{E}[m_2 m_3^*] \\ \mathbb{E}[m_3 m_1^*] & \mathbb{E}[m_3 m_2^*] & \mathbb{E}[m_3 m_3^*] \end{bmatrix}$$

$m_1$  is the signal arriving at  $35^\circ$   
 $m_2$  is the signal arriving at  $95^\circ$ .

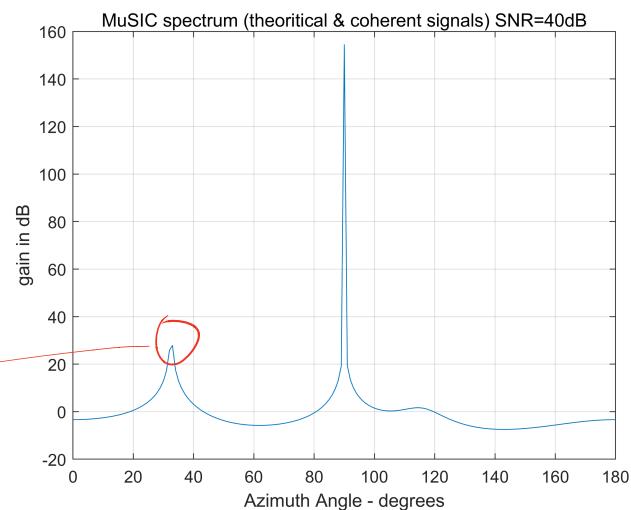
Assuming  $m_1$  and  $m_2$  are fully correlated

we have  $\mathbb{E}[m_1 m_2^*] = \mathbb{E}[m_2 m_1^*] = 1$

$$\Rightarrow R_{mm} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

If the two sources from  $35^\circ$  and  $95^\circ$  are fully correlated,

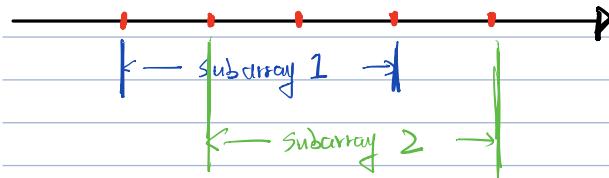
MUSIC cannot separate these two sources



# MUSIC with Spatial Smoothing

K=4

Define the subarrays with the length K



There are L elements in the ULA

$$\Rightarrow \# \text{ subarrays} = L - k + 1$$
$$N = L - k + 1$$

Using the smoothed covariance  $R_{xx\text{-smooth}}$  instead of the original  $R_{xx}$

$$R_{xx\text{-smooth}} = \frac{1}{N} \sum_{s=1}^N R_s$$

where  $R_s$  is the covariance of each subarray

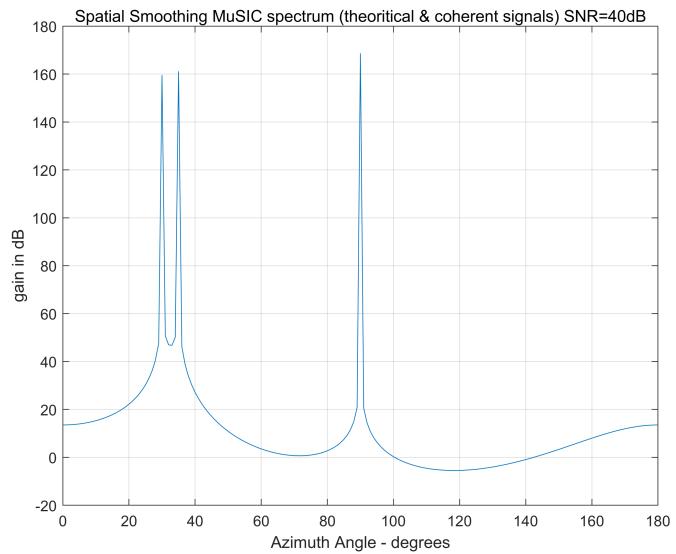
$$R_s = R_{xx}(s:s+k-1, s:s+k-1)$$

The result of smoothing MUSIC is shown on the right.

We can notice that the sources from  $30^\circ$  and  $35^\circ$  can be separated.

However, the size of smoothed covariance is  $K \times K$ , which means that the aperture of array is reduced.

Therefore, the spatial smoothing technique is capable of addressing the coherent problem, with the penalty of reducing the aperture of array.

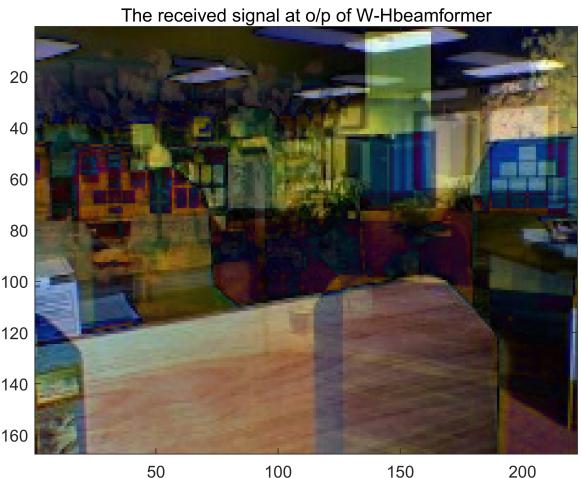


## 12. Superresolution Techniques

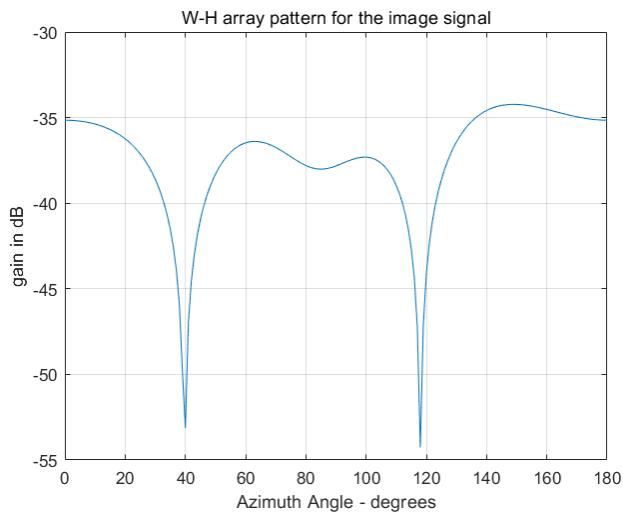
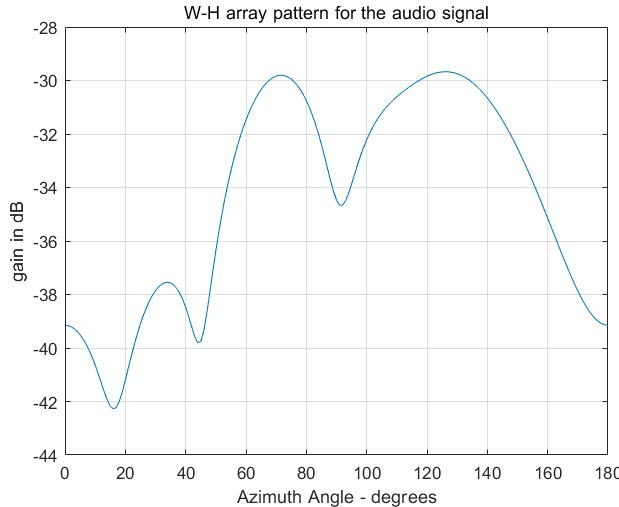
Applying the W-H beamformer to the audio signals with the desired direction or  $(90^\circ, 0)$ .

The received audio signal by W-H beamformer is not clear, and there is the same problem for the image signal.

The result of image signal received by W-H beamformer is shown on the right. There are lots of interference in this image and the image is not clear.



Check the W-H array pattern for both audio and image signal



These results indicate that the W-H array pattern is not good enough for these audio and image signals with desired direction of  $(90^\circ, 0^\circ)$

## Superresolution Beamformer

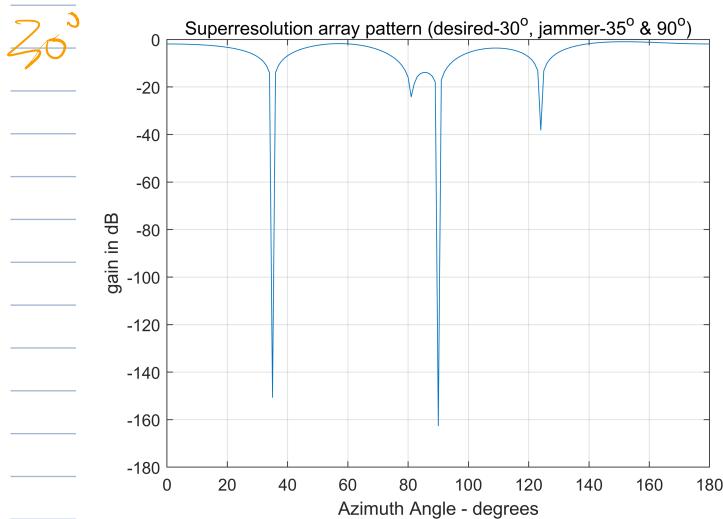
### 10. Superresolution Beamformer based on DOA estimation

$$W = P_{Sj}^{\perp} \cdot S_{\text{desired signal}}$$

According to the MUSIC Algorithm question 9, the DOAs of audio and image signals are  $(30^\circ, 0^\circ)$ ,  $(35^\circ, 0^\circ)$ ,  $(90^\circ, 0^\circ)$

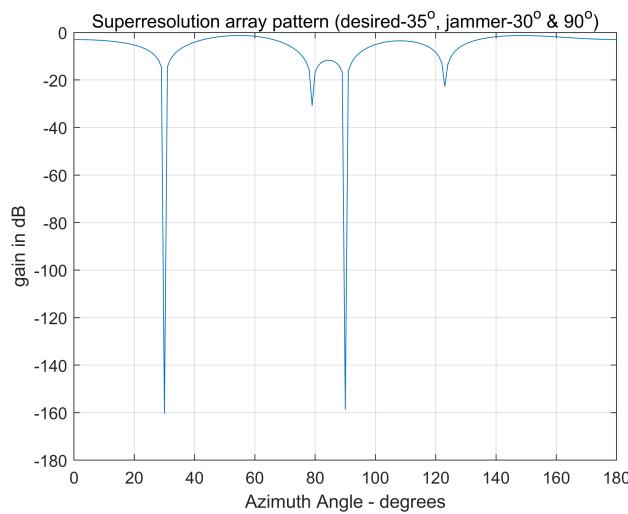
$P_{Sj}^{\perp} = I_N - S_j \cdot (S_j^H \cdot S_j)^{-1} \cdot S_j^H$

The pattern of the arrays with this superresolution beamformer and the result image is shown below

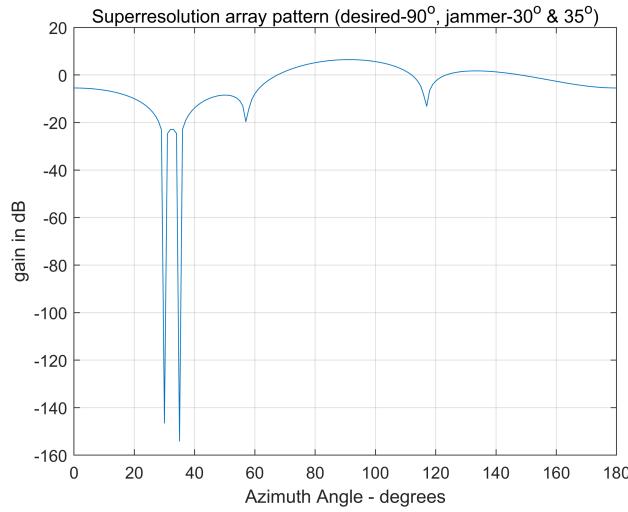


Do the same operations by setting the DoA of  $(35^\circ, 0)$  and  $(90^\circ, 0)$  as the DoA of desired signals. The result is shown below

$35^\circ$



$90^\circ$



20 Superresolution Beamformer not based on DoA estimation of interference

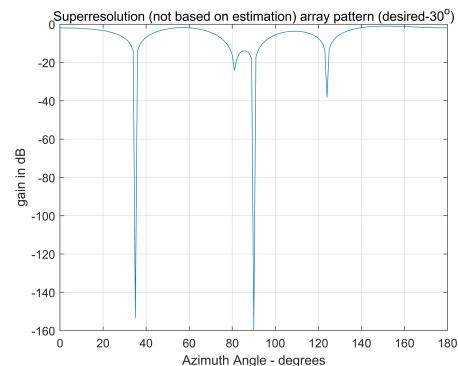
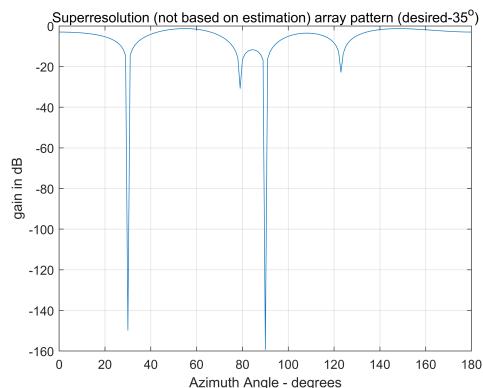
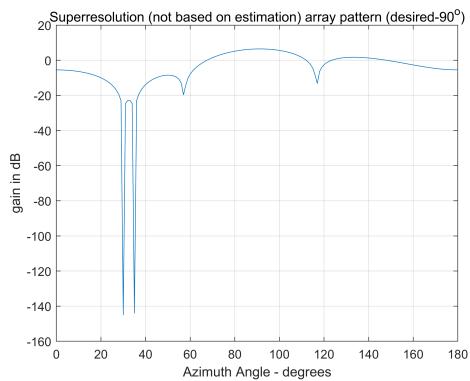
$$\underline{W} = \underline{P}_{E_{nj}}^+ - \text{[Desired Signal]}$$

where  $E_{nj}$  is the interference subspace of  $R_{nj}$

and  $R_{nj}$  is the covariance matrix generated by removing the effect of desired signal from  $R_{xx}$

i.e.  $R_{nj} = R_{xx} - \underbrace{\underline{P}_d \cdot S_d \cdot S_d^H}_{\text{power of desired signal}}$

① Apply this beamformer on the  $R_{xx}$ -theoretical



We can notice that, although we don't know the DOAs of interference signals, the superresolution beamformer for interference cancellation can also be obtained.

② For Image & Audio signal

For the  $R_{xx}$ -theoretical, we know the power of desired signal  $P_d = 1$ . However, for  $R_{xx\text{-im}}$  or  $R_{xx\text{-au}}$ , we don't know the  $P_d$ . Therefore, it requires the estimation of  $P_d$ .

## 13. Practical Selection Criteria

generate the 250 snapshots

```

1- array=[-2 0 0; -1 0 0; 0 0 0; 1 0 0; 2 0 0];
2- directions = [30, 0; 35, 0 ; 90, 0];
3-
4- % random source signal from 3 directions
5- L = 250;
6- N = size(array, 1);
7- M = size(directions, 1);
8- m = (randn(M, L) + 1i*randn(M, L)) / sqrt(2);
9-
10- % random noise
11- sigma2 = 0.1; → change  $\sigma^2$  to evaluate the performance under
12- noise = sqrt(sigma2) * (randn(N, L) + 1i*randn(N, L)) / sqrt(2); different SNR
13- S = spv(array, directions);
14-
15- % received signal
16- X = S * m + noise;
17-
18- % covariance matrix
19- Rxx = X*X' / length(X(1,:));
20-
```

$\Rightarrow$  when  $\sigma^2 = 0.0001$ , i.e. SNR = 40 dB

the eigenvalues of  $R_{xx}$  are

10.7398, 4.8704, 0.1092, 0.0001, 0.0001

It is easy to identify there are  $M=3$  sources

$\geq$  However, when  $\sigma^2 = 0.1$ , i.e. SNR = 10 dB,

the eigenvalues of  $R_{xx}$  are

10.737, 4.824, 0.1395, 0.1034, 0.0890

It is no easy to identify there are  $M=3$  sources, because the last 3 eigenvalues are similar

Using AIC and MDL methods to estimate the number of sources  $M$

$$AIC(k) = -2 \ln \left( \frac{\prod_{l=k+1}^N d_l^{1/(N-k)}}{\frac{1}{N-k} \cdot \sum_{l=k+1}^N d_l} \right)^{(N-k)L} + 2k(2N-k)$$
$$M = \arg \min_k \{ AIC(k) \}$$

$$MDL(k) = -\ln \left( \frac{\prod_{l=k+1}^N d_l^{1/(N-k)}}{\frac{1}{N-k} \cdot \sum_{l=k+1}^N d_l} \right)^{(N-k)L} + \frac{1}{2} k(2N-k) \ln L$$
$$\text{or } \arg \min_k \{ MDL(k) \}$$

For both high SNR (e.g. 40dB) or low SNR (e.g. 10dB)

Both AIC and MDL methods estimate the correct result  $M=3$

# MATLAB Codes (Main Parts)

1 & 2

```
4 - array=[-2 0 0; -1 0 0; 0 0 0; 1 0 0; 2 0 0]; % locations of array sensors
5 - directions = [30, 0; 35, 0 ; 90, 0]; % DOAs of sources
6 - Z = my_pattern(array); % array pattern
7 - figure(1);
8 - plot2d3d(Z, [0:180], 0, 'gain in dB', 'initial pattern');
9 -
10 - S = spv(array,directions); % array manifold vectors
11 -
12 - sigma2 = 0.0001; % noise power
13 - Rmm = eye(3);
14 - Rxx_theoretical = S*Rmm*S' + sigma2*eye(5,5); % covariance matirx of received signals
```

3

```
19 - load Xaudio/Xaudio.mat
20 - load Ximage/Ximage.mat
21 - soundsc(real(X_au(2,:)), 11025);
22 - displayimage(X_im(2,:), image_size, 201, 'The received signal at the 2nd antenna');
23 -
24 - % covariance matrix in practice
25 - Rxx_au = X_au*X_au' / length(X_au(1,:));
26 - Rxx_im = X_im*X_im' / length(X_im(1,:));
27 -
```

4

```
28 - %estimated parameters
29 - directions = [];
30 - Rmm = [];
31 - S = [];
32 - sigma2 = [];
```

6

```

41 %% Estimation Problem
42 Sd = spv(array, [90, 0]);
43 wopt = iny(Rxx_theoretical) * Sd;
44 Z = my_pattern(array, wopt);
45 plot2d3d(Z, [0:180], 0, 'gain in dB', 'W-H array pattern');

```

9.

```

1 function nc = music(array, Rxx, M, K)
2 % MUSCI algorithm
3 N = size(Rxx, 1);
4 if nargin<=3
5     K = N; % for spatial smoothing techniques
6 end
7
8 [E, D] = eig(Rxx); %eigenvalues and eigenvectors
9 D = diag(D);
10 [~, I] = sort(D);
11
12 E = E(:, I);
13 En = [];% eigenvectors of nosie subspace
14 for i=1:N-M
15     En = [En E(:, N-M-i+1)];
16 end
17
18 nc = [];% gain of different directions
19 for azimuth = 0:180
20     S = spv(array, [azimuth, 0]);
21     S = S(1:K);
22     nc = [nc S' * (En*En') * S];
23 end
24
25 nc = -10*log10(nc);
26 end

```

M

```
1 function nc = smooth_music(array, Rxx, M, K)
2 % MUSCI algprithm with spatial smoothing technique
3
4 L = size(Rxx, 1);
5 N = L-K+1;
6 Rxxs = zeros(K, K);
7 for i=1:N
8     Rxxs=Rxxs+Rxx(i:i+K-1, i:i+K-1);
9 end
10 Rxxs = Rxxs/N; % smoothed covariance matrix
11
12 nc = music(array, Rxxs, M, K);
13 end
```

## 12 Based on DoA estimation

```
4
5 array=[-2 0 0; -1 0 0; 0 0 0; 1 0 0; 2 0 0];
6 load Xaudio/Xaudio.mat
7 load Ximage/Ximage.mat
8
9 %% WH beamformer
10 Rxx_au = X_au*X_au' / length(X_au(1,:));
11 Sd = spv(array, [90, 0]);
12 wopt = inv(Rxx_au) * Sd;
13 Z = my_pattern(array, wopt);
14 plot2d3d(Z, [0:180], 0, 'gain in dB', 'W-H array pattern for the audio signal');
15
16 yt=wopt'*X_au;
17 % soundsc(real(yt), 11025);
18
19 Rxx_im = X_im*X_im' / length(X_im(1,:));
20 Sd = spv(array, [90, 0]);
21 wopt = inv(Rxx_im) * Sd;
22 yt=wopt'*X_im;
23 yt = abs(yt);
24 yt = (yt-min(yt)) * 255/(max(yt)-min(yt)); % normalize the image to [0, 255]
25 displayimage(yt, image_size, 202, 'The received signal at o/p of W-Hbeamformer');
26 Z = my_pattern(array, wopt);
27 plot2d3d(Z, [0:180], 0, 'gain in dB', 'W-H array pattern for the image signal');
```

```

29 %% superresolution techniques
30 array=[-2 0 0; -1 0 0; 0 0 0; 1 0 0; 2 0 0];
31 directions = [30, 0; 35, 0 ; 90, 0];
32 % DOAs - 30, 35 and 90;
33 S = spv(array,directions);
34 Sd = S(:,2); % desired signal is 35
35
36 S_J = [S(:,1) S(:,3)]; % DOA of jammer signal
37
38 P_J = S_J*inv(S_J'*S_J)*S_J';
39 P_J_orth = eye(size(P_J))-P_J;
40
41 wsuper = P_J_orth*Sd;
42 Z = my_pattern(array, wsuper);
43 plot2d3d(Z,[0:180],0,'gain in dB','Superresolution array pattern (desired-35^o, jammer-30^o & 90^o)');
44
45 yt=wsuper'*X_im;
46 yt = abs(yt);
47 yt = (yt-min(yt)) * 255/(max(yt)-min(yt)); % normalize the image to [0,255]
48 displayimage(yt, image_size, 202,'The received signal at o/p of Superresolution Beamformer (35^o)');
49

```

*Not Based on DOA estimation of interference*

```

52 %% not based on DOA estimation (Theoretical Signal)
53 array=[-2 0 0; -1 0 0; 0 0 0; 1 0 0; 2 0 0];
54 directions = [30, 0; 35, 0 ; 90, 0];
55 S = spv(array,directions);
56 sigma2 = 0.1; % noise power SNR=10dB
57
58 Rmm = eye(3);
59 Rxx_theoretical = S*Rmm*S' + sigma2*eye(5, 5);
60 Sd = S(:,3); % desired signal - 90
61
62 R_nJ = Rxx_theoretical - Sd*Sd';
63
64 [E, D] = eig(R_nJ);
65 D = diag(D);
66 [D, I] = sort(D, 'descend');
67 E = E(:, I);
68 Ej = []; % eigenvectors of interference subspace
69 Ej = E(:, 1:2);
70
71 P_nJ = Ej*inv(Ej'*Ej)*Ej';
72 P_nJ_orth = eye(size(P_nJ))-P_nJ;
73 wsuper = P_nJ_orth*Sd;
74 Z = my_pattern(array, wsuper);
75 plot2d3d(Z,[0:180],0,'gain in dB','Superresolution not based on estimation array pattern (desired-90^o)');

```

13

```
1 -     array=[-2 0 0; -1 0 0; 0 0 0; 1 0 0; 2 0 0];
2 -     directions = [30, 0; 35, 0 ; 90, 0];
3 -
4 -     % random source signal from 3 directions
5 -     L = 250;
6 -     N = size(array, 1);
7 -     M = size(directions, 1);
8 -     m = (randn(M, L) + 1i*randn(M, L)) / sqrt(2);
9 -
10 -    % random noise
11 -    sigma2 = 0.1;
12 -    noise = sqrt(sigma2) * (randn(N, L) + 1i*randn(N, L)) / sqrt(2);
13 -    S = spv(array, directions);
14 -
15 -    % received signal
16 -    X = S * m + noise;
17 -
18 -    % covariance matrix
19 -    Rxx = X*X' / length(X(1, :));
20 -
21 -    eigenv = sort(real(eig(Rxx)), 'descend')
22 -
23 -    %% AIC and MDL criterion
24 -    AIC = zeros(1, N);
25 -    MDL = zeros(1, N);
26 -    for k = 0:N-1
27 -        a = vpa(prod(eigenv(k+1:N) .^(1/(N-k))), 6);
28 -        b = (1/(N-k)) * sum(eigenv(k+1:N));
29 -        AIC(k+1) = -2 * log((a / b).^( (N-k)*L)) + 2*k*(2*N-k);
30 -        MDL(k+1) = -1 * log((a / b).^( (N-k)*L)) + 1/2 * k*(2*N-k) * log(L);
31 -    end
32 -
33 -    [~, M_AIC] = min(AIC);
34 -    [~, M_MDL] = min(MDL);
35 -
36 -    M_AIC = M_AIC - 1;
37 -    M_MDL = M_MDL - 1;
38 -
```