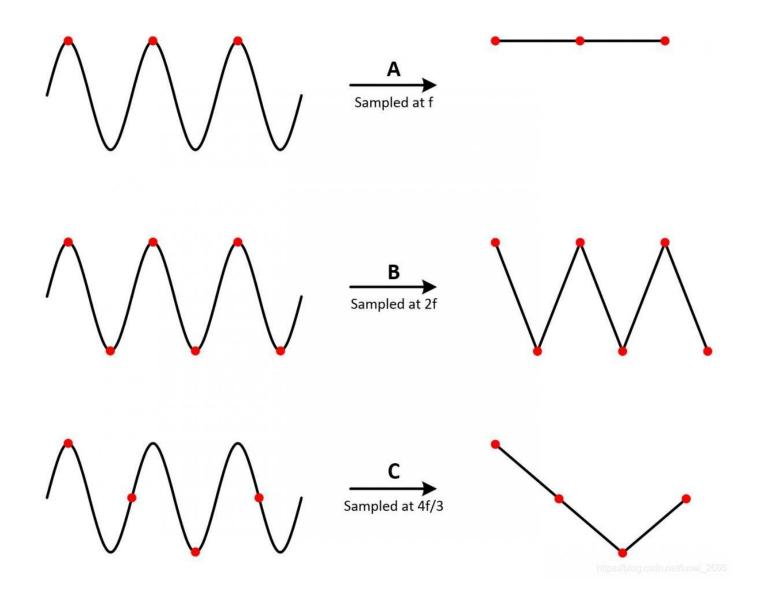
# Stochastic Signal Processing

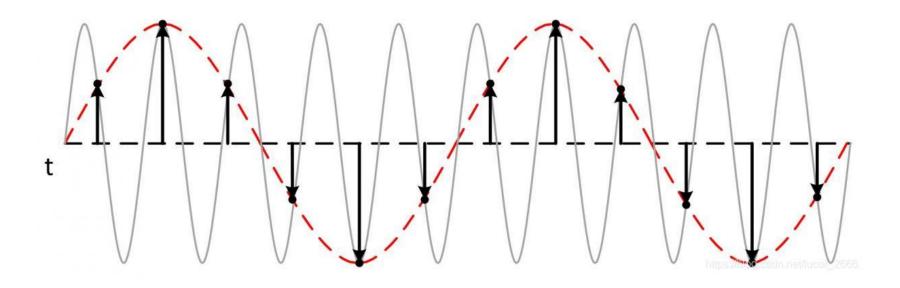
Lesson 13-2: Spectrum Estimation and Detection

Weize Sun

- A source send out signal.
- A sensor record the signal  $x(t) = Ae^{j(\omega t + \theta)}$ , where  $\omega = 2\pi \frac{f}{f_s}$ , where f is the frequency to be estimated.  $f_s$  is the sampling frequency.
- According to the Nyquist Sampling theory,  $f_s \ge 2f$ . The larger the  $f_s$ , the higher the cost of the sampling system, therefore, we usually set  $f_s = 2f$ , and have  $\omega \in [0, \pi]$  (positive frequency only)
- In some applications, we can assume that there are negative frequency, then  $\omega \in [-\pi, \pi]$ , or we can also write it as  $\omega \in [0, 2\pi]$  ( $[\pi, 2\pi]$  refers to  $[-\pi, 0]$ )
- In the remainder, we will tackle the  $\omega$  directly.



• if  $f_s < 2f$ 



$$x(t) = Ae^{j(\omega t + \theta)}$$

- Usually, it is a discrete time system. Therefore we set  $t = 0,1,2,...,\infty$
- And change *t* to *n*:

$$x(n) = Ae^{j(\omega n + \theta)}$$
  
 $n = 0,1,2,...,N-1$ 

Where *N* is the number of samples.

• And we might have noise:

$$y(n) = Ae^{j(\omega n + \theta)} + q(n)$$

Where q(n) is i.i.d Gaussian noise.

$$y(n) = Ae^{j(\omega n + \theta)} + q(n)$$

- There are three parameters unknown: A,  $\omega$  and  $\theta$ .
- The target is estimate A,  $\omega$  and  $\theta$  from the received signal y(n), n = 0,1,2,...,N-1

$$y(n) = Ae^{j(\omega n + \theta)} + q(n), n = 0,1,2,...,N-1$$

- Note that  $Ae^{j(\omega n + \theta)} = Ae^{j\theta} \times e^{j\omega n} = \alpha e^{j\omega n}$
- Assume that we already get  $\omega$ , then:

$$Y = \alpha S + Q, \text{ or } Y \approx \alpha S$$

$$Y = \begin{bmatrix} y(0) \\ y(1) \\ \vdots \\ y(N-1) \end{bmatrix}; S = \begin{bmatrix} e^{j\omega 0} \\ e^{j\omega 1} \\ \vdots \\ e^{j\omega(N-1)} \end{bmatrix}; Q = \begin{bmatrix} q(0) \\ q(1) \\ \vdots \\ q(N-1) \end{bmatrix}$$

• Then  $\alpha = (S^H S)^{-1} S^H Y$ ,  $\alpha$  can be calculated from a linear equation

$$y(n) = Ae^{j(\omega n + \theta)} + q(n)$$
,  $n = 0,1,2,...,N - 1$   
 $Ae^{j(\omega n + \theta)} = Ae^{j\theta} \times e^{j\omega n} = \alpha e^{j\omega n}$   
 $Y = \alpha S + Q$ , or  $Y \approx \alpha S$ 

• Then  $\alpha = (S^H S)^{-1} S^H Y$ ,  $\alpha$  can be calculated from a linear equation; and

$$A = |\alpha|, \theta = \angle \alpha$$

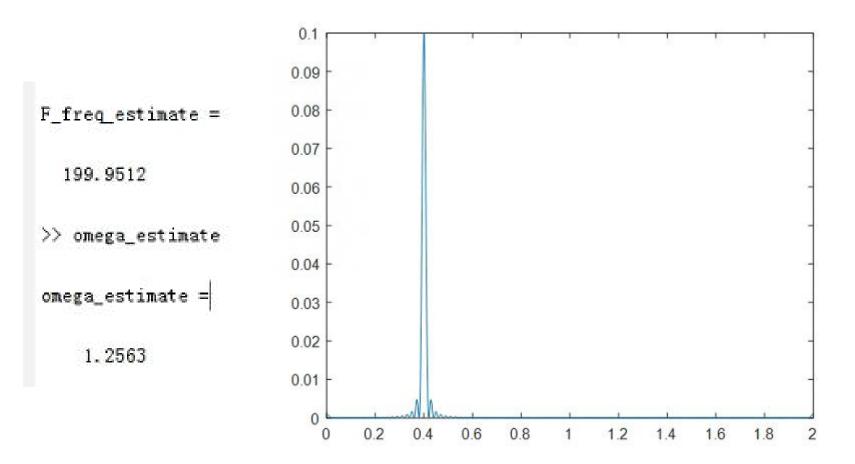
- A and  $\theta$  can be calculated from a linear equation, thus called linear parameter
- $\omega$ , instead, should be search from  $[-\pi, \pi]$  and thus called non-linear parameter

$$y(n) = Ae^{j(\omega n + \theta)} + q(n)$$
,  $n = 0,1,2,...,N - 1$   
 $Ae^{j(\omega n + \theta)} = Ae^{j\theta} \times e^{j\omega n} = \alpha e^{j\omega n}$   
 $Y = \alpha S + Q$ , or  $Y \approx \alpha S$   
 $\alpha = (S^H S)^{-1} S^H Y$   
 $A = |\alpha|$ ,  $\theta = \angle \alpha$ : linear parameter  
 $\omega$ : non-linear parameter

- Therefore, we usually first estimate  $\omega$  then  $A = |\alpha|$ ,  $\theta = \angle \alpha$
- We can use the periodogram

```
Theta = rand(1)*2*pi;
                  X_signal = Amplitude_A*exp(1j*(omega*n_array+Theta));
code1
                  Noise sigma2 = Amplitude A^2 / [10^(SNR/10)];
                  Noise = sqrt(Noise_sigma2) * randn(N, 1) .* exp(1j*rand(N, 1)*2*pi);
                  Y receive = X signal + Noise sigma2;
                  window = boxcar(N); %矩形窗
                  [Peri_Y, f_Y] = periodogram(Y_receive, window, FFT_length, F_sam_freq);
                  [Max value, Max index] = max(Peri Y);
clear
                  F freq estimate = (Max index-1)/FFT length*F sam freq;
clc
                  omega estimate = (Max index-1)/FFT length*2*pi;
N = 100:
F_sam freq=1000; %采样频率
F freq = 200;
                                              figure(1)
omega = F freq/F sam freq*2*pi;
SNR = 10:
                                              X plot = [0:FFT length-1]/FFT length*2;
Amplitude_A = 1;
                                              plot(X plot, Peri Y)
n_array=[0:N-1]';
FFT_length = 4096;
```

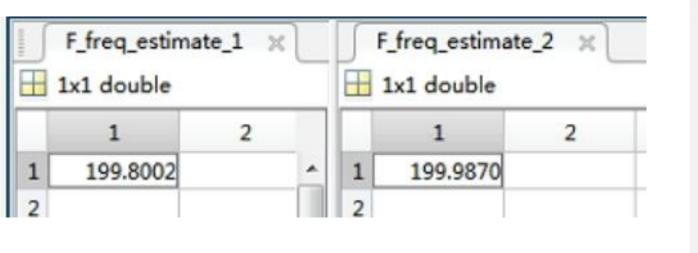
- The estimation is correct, but cannot reach 200Hz even in noise free case.
- The 'FFT\_length = 4096' is called 'grid No.', the larger the 'grid No.', the higher the accuracy, but the longer to compute the periodogram.

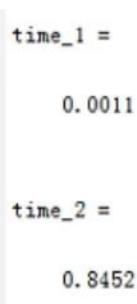


- The estimation is correct, but cannot reach 200Hz even in noise free case.
- The 'FFT\_length = 4096' is called 'grid No.', the larger the 'grid No.', the higher the accuracy, but the longer to compute the periodogram.
- We can test it by

```
%% test of computational time of 'periodogram'
length 1 = 1001;
length 2 = 10000001;
                                        code1
tic
[Peri_Y, f_Y] = periodogram(Y_receive, window, length_1, F_sam_freq);
time 1 = toc;
[Max_value, Max_index] = max(Peri_Y);
F_freq_estimate_1 = (Max_index-1)/length_1*F_sam_freq;
tic
[Peri_Y, f_Y] = periodogram(Y_receive, window, length_2, F_sam_freq);
time 2 = toc;
[Max_value, Max_index] = max(Peri_Y);
F_freq_estimate_2 = (Max_index-1)/length_2*F_sam_freq;
```

- The estimation is correct, but cannot reach 200Hz even in noise free case.
- The 'FFT\_length = 4096' is called 'grid No.', the larger the 'grid No.', the higher the accuracy, but the longer to compute the periodogram.
- We can test it by





- The estimation is correct, but cannot reach 200Hz even in noise free case.
- The 'FFT\_length = 4096' is called 'grid No.', the larger the 'grid No.', the higher the accuracy, but the longer to compute the periodogram.
- We can also set 'FFT\_length = 1024', then use 'bisection method'(二分法) to do the accurate estimation.
- However, such method requires a 'search', therefore referred to as 'grid search' method.
- Is there other methods?

$$y(n) = x(n) + q(n) = Ae^{j(\omega n + \theta)} + q(n)$$

• We have  $x(n) = x(n-1) \times e^{j\omega}$ , or says,  $y(n) \approx y(n-1) \times e^{j\omega}$ 

In matrix form: 
$$Y_1 \approx \beta Y_2$$
,  $\beta = e^{j\omega}$ 

$$\mathbf{Y}_{1} = \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(N-1) \end{bmatrix}; \mathbf{Y}_{2} = \begin{bmatrix} y(0) \\ y(1) \\ \vdots \\ y(N-2) \end{bmatrix}$$
$$\beta = (\mathbf{Y}_{2}^{H} \mathbf{Y}_{2})^{-1} \mathbf{Y}_{2}^{H} \mathbf{Y}_{1}$$
$$\omega = \angle \beta$$

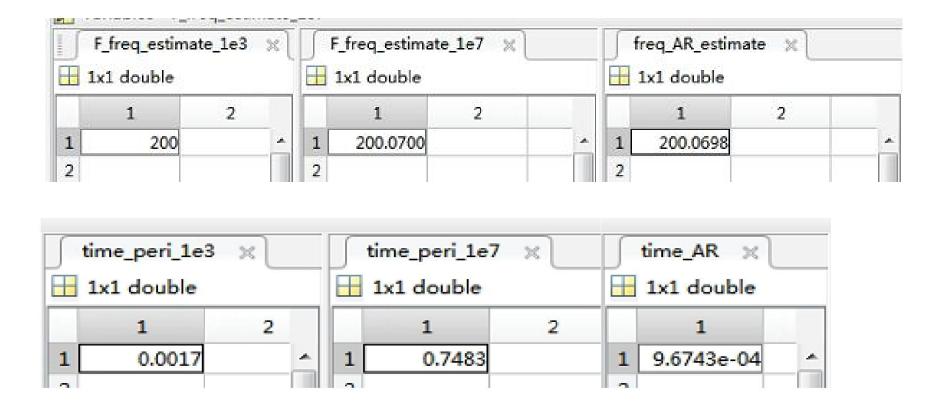
Let's test it!

code2

```
%% the Auto Regressive (AR) method
Y r1 = Y receive(2:end);
Y r2 = Y receive(1:end-1);
tic
beta_est = (Y_r2'*Y_r2)\Y_r2'*Y_r1;
time_AR = toc;
omega_AR_estimate = angle(beta_est);
freq_AR_estimate = omega_estimate/2/pi*F_sam_freq;
```

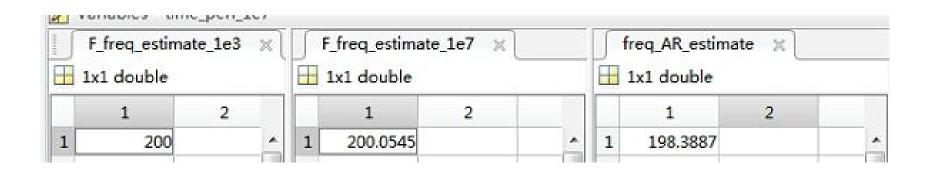
Frequency 200.07Hz, SNR = 40dB

When noise is small, AR method is fastest almost the same accuracy comparing to periodogram with 'grid No.' 10<sup>7</sup>



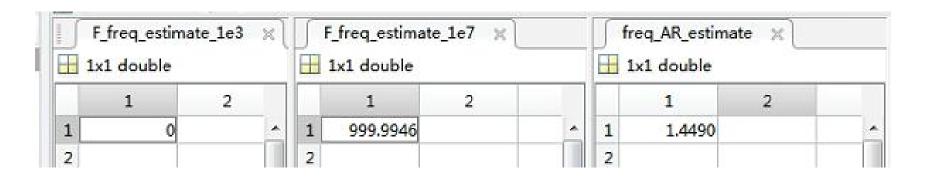
Frequency 200.07Hz, SNR = 10dB

When noise is large, the accuracy of AR method is poor comparing to periodogram even with 'grid No.' 10<sup>3</sup>



Frequency 200.07Hz, SNR = -10dB

When noise is very large, all methods fail



You can test the methods under different  $\omega$  and/or SNR, and do the statistics of 'MSE' or 'probability of success' by yourself

## Hilbert transforms (回顾)

• A system with system function

$$H(\omega) = -j\operatorname{sgn}\omega = \begin{cases} -j & \omega > 0 \\ j & \omega < 0 \end{cases} \text{ where } \operatorname{sgn}\omega = \begin{cases} 1 & \omega > 0 \\ -1 & \omega < 0 \end{cases}$$

is called a **quadrature filter** (正交滤波器). The corresponding impulse response equals  $1/\pi t$ .

- $H(\omega)$  is all-pass with  $-90^{\circ}$  phase shift; hence its response to  $\cos \omega t$  equals  $\cos(\omega t 90^{\circ}) = \sin \omega t$  and its response to  $\sin \omega t$  equals  $\sin(\omega t 90^{\circ}) = -\cos \omega t$ .
- The response of a quadrature filter to a real process  $\mathbf{x}(t)$  is denoted by  $\hat{\mathbf{x}}(t)$  and it is called the Hilbert transform of  $\mathbf{x}(t)$ . Thus

$$\hat{\mathbf{x}}(t) = \mathbf{x}(t) * \frac{1}{\pi t} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\mathbf{x}(\alpha)}{t - \alpha} d\alpha$$

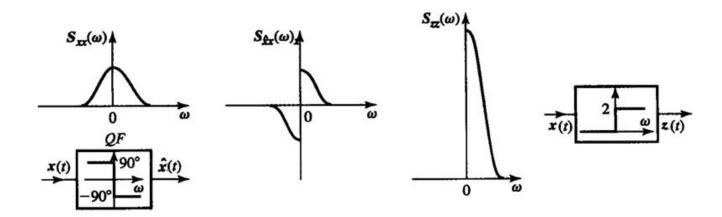
## Hilbert transforms (回顾)

• The response of a quadrature filter to a real process  $\mathbf{x}(t)$  is denoted by  $\hat{\mathbf{x}}(t)$  and it is called the Hilbert transform of  $\mathbf{x}(t)$ . Thus

$$\hat{\mathbf{x}}(t) = \mathbf{x}(t) * \frac{1}{\pi t} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\mathbf{x}(\alpha)}{t - \alpha} d\alpha$$

$$S_{X\widehat{X}}(\omega) = jS_X(\omega) \operatorname{sgn}\omega = -S_{\widehat{X}X}(\omega)$$

$$S_{\widehat{X}}(\omega) = S_X(\omega)$$



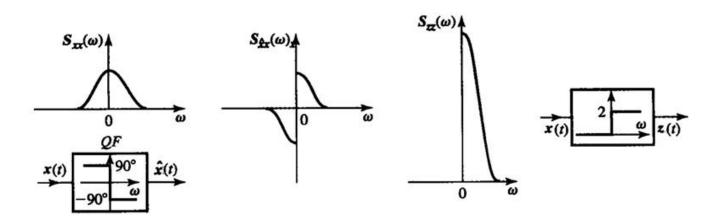
## Hilbert transforms (回顾)

• The complex process  $\mathbf{z}(t) = \mathbf{x}(t) + j\hat{\mathbf{x}}(t)$  is calked the analytic signal associated with  $\mathbf{x}(t)$ . Clearly,  $\mathbf{z}(t)$  is the response of the system

$$1 + j(-j\operatorname{sgn}\omega) = 2U(\omega)$$

• with input  $\mathbf{x}(t)$ . Hence:

$$S_Z(\omega) = 4S_X(\omega)U(\omega) = 2S_X(\omega) + 2jS_{\hat{X}\hat{X}}(\omega)$$
$$R_Z(\tau) = 2R_X(\tau) + 2jR_{\hat{X}X}(\tau)$$



$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
$$x(n) = A\cos(\omega n + \theta)$$
$$x(n) \neq \alpha x(n - 1) \text{ for any } \alpha$$

- Is there other methods?
- The Hilbert transform of  $cos(\omega n + \theta)$  is  $sin(\omega n + \theta)$ , and Hilbert transform of  $sin(\omega n + \theta)$  is  $-cos(\omega n + \theta)$ . (You can try to prove it yourself)

$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
  
 $x(n) = Acos(\omega n + \theta)$   
 $x(n) \neq \alpha x(n - 1) \text{ for any } \alpha$   
 $H\{y(n)\} = H\{x(n)\} + H\{q(n)\}$   
 $H\{x(n) = Acos(\omega n + \theta)\} = Asin(\omega n + \theta)$ 

Define

$$y'(n) = y(n) + j * H\{y(n)\} = x'(n) + q'(n)$$

then

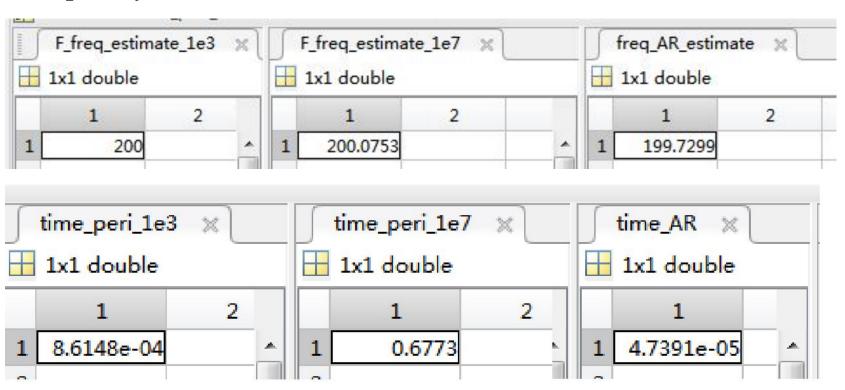
$$x'(n) = A \{ cos(\omega n + \theta) + j sin(\omega n + \theta) \}$$
$$= Ae^{j(\omega n + \theta)}$$

code3

```
Theta = rand(1)*2*pi;
X_signal = Amplitude_A * cos(omega*n_array+Theta);
Noise_sigma2 = mean(X_signal.^2) / [10^(SNR/10)];
Noise = sqrt(Noise_sigma2) * randn(N, 1);
Y receive real = X signal + Noise sigma2;
%%use Hilbert transform to get the iscrete-time analytic signal
Y_receive = hilbert(Y_receive_real);
window = boxcar(N); %矩形窗
%% the Auto Regressive (AR) method
Y r1 = Y receive(2:end);
Y r2 = Y receive(1:end-1);
```

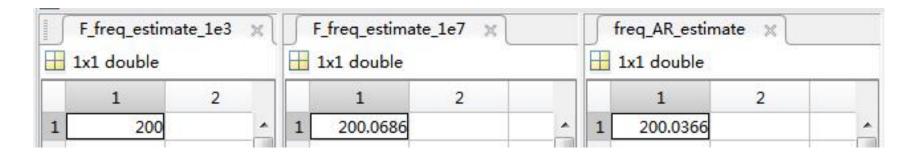
$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
$$x(n) = A\cos(\omega n + \theta)$$
$$x'(n) = A\left\{\cos(\omega n + \theta) + j\sin(\omega n + \theta)\right\} = Ae^{j(\omega n + \theta)}$$

Frequency 200.07Hz, SNR = 10dB

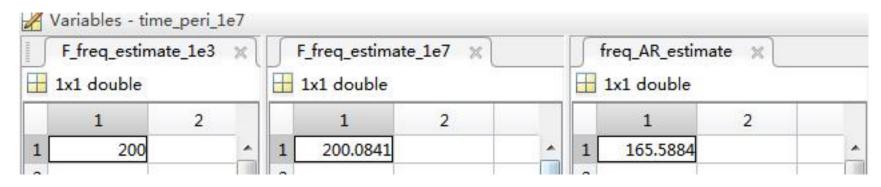


$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
$$x(n) = A\cos(\omega n + \theta)$$
$$x'(n) = A\left\{\cos(\omega n + \theta) + j\sin(\omega n + \theta)\right\} = Ae^{j(\omega n + \theta)}$$

Frequency 200.07Hz, SNR = 40dB



SNR = 0dB



$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
  
real: 
$$x(n) = A\cos(\omega n + \theta)$$
  
complex: 
$$x(n) = Ae^{j(\omega n + \theta)}$$

- Application
  - Microphone array
  - Radar target (DOA/point cloud) estimation

$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
  
real: 
$$x(n) = A\cos(\omega n + \theta)$$
  
complex: 
$$x(n) = Ae^{j(\omega n + \theta)}$$

• In array model, in each x(n), there exist much more than 1 sample. Then we have:

$$\mathbf{Y}^{k} = \begin{bmatrix} y^{k}(0) \\ y^{k}(1) \\ \vdots \\ y^{k}(N-1) \end{bmatrix}$$
 for  $k = 1, 2, ..., K$ 

How to make the estimation more accurate?

$$y(n) = x(n) + q(n), n = 0,1,2,...,N - 1$$
  
real: 
$$x(n) = A\cos(\omega n + \theta)$$
  
complex: 
$$x(n) = Ae^{j(\omega n + \theta)}$$

 Can we detect whether there is a signal? Or says, seperate

$$y(n) = x(n) + q(n)$$
$$y(n) = q(n)$$

#### The array

$$y(n,t) = x(n,t) + q(n,t)$$
  
 $n = 0,1,2,...,N-1$   
 $t = 1,2,...,T$ 

Where *N* is the number of sensors / microphones / antennas. *T* is the number of samples / snapshots.

real: 
$$x(n,t) = A(t)cos(\omega n + \theta(t))$$
  
complex:  $x(n,t) = A(t)e^{j(\omega n + \theta(t))}$ 

An array of size N receive signal for T times.

#### The array – detection problem

$$y(n,t) = x(n,t) + q(n,t)$$

complex:  $x(n, t) = A(t)e^{j\theta(t)}e^{j\omega n}$ 

- For each time t, the amplitude A(t) and the phase  $\theta(t)$  of the signal is different, but the frequency  $\omega$  does not change.
- The target: detect whether there is a signal?

$$y(n) = x(n) + q(n)$$
$$y(n) = q(n)$$

$$y(n,t) = x(n,t) + q(n,t)$$
 complex: 
$$x(n,t) = A(t)e^{j\theta(t)}e^{j\omega n} = \alpha(t) e^{j\omega n}$$

• In matrix form: Y = X + Q

$$\mathbf{X} = \begin{bmatrix} x(0,0) & \cdots & x(0,T-1) \\ \vdots & \ddots & \vdots \\ x(N-1,0) & \cdots & x(N-1,T-1) \end{bmatrix}$$

Note that

$$egin{aligned} oldsymbol{X} &= oldsymbol{u} * oldsymbol{v}^T \ oldsymbol{u} &= egin{bmatrix} e^{j\omega 0} & e^{j\omega 1} & \dots & e^{j\omega(N-1)} \end{bmatrix}^T \ oldsymbol{v} &= egin{bmatrix} lpha(0) & lpha(1) & \dots & lpha(T-1) \end{bmatrix}^T \end{aligned}$$

$$y(n,t) = x(n,t) + q(n,t)$$

complex:  $x(n, t) = A(t)e^{j\theta(t)}e^{j\omega n} = \alpha(t) e^{j\omega n}$ 

- In matrix form:  $Y = uv^T + Q$
- Then we can get the covariance matrix of Y:  $C = YY^H = XX^H + QX^H + XQ^H + QQ^H$
- $\boldsymbol{X}(x(n,t))$  and  $\boldsymbol{Q}(q(n,t))$  independent:

$$E(QX^H) = E(XQ^H) = 0 \text{ (when } T \to \infty)$$

•  $\boldsymbol{Q}^H \boldsymbol{Q}$  is full rank noise, and

$$XX^H = uv^Tv^*u^H$$

•  $m{v}^*$  is the conjugate,  $m{v}^T$  is transpose,  $m{u}^H$  is conjugate transpose

$$y(n,t) = x(n,t) + q(n,t)$$
 complex: 
$$x(n,t) = A(t)e^{j\theta(t)}e^{j\omega n} = \alpha(t) e^{j\omega n}$$

• ovariance matrix of **Y**:

$$egin{aligned} oldsymbol{C} &= oldsymbol{Y}oldsymbol{Y}^H &= oldsymbol{u}oldsymbol{v}^Toldsymbol{v}^*oldsymbol{u}^H + oldsymbol{Q}oldsymbol{Q}^H \ oldsymbol{u} &= egin{bmatrix} e^{j\omega 0} & e^{j\omega 1} & \dots & e^{j\omega(N-1)} \end{bmatrix}^T \ oldsymbol{v} &= egin{bmatrix} lpha(0) & lpha(1) & \dots & lpha(T-1) \end{bmatrix}^T \end{aligned}$$

 $v^Tv^* = a$  is a number, refers the signal 'strength'  $C = YY^H = a uu^H + QQ^H$ 

$$y(n,t) = x(n,t) + q(n,t)$$
complex: 
$$x(n,t) = A(t)e^{j\theta(t)}e^{j\omega n} = \alpha(t) e^{j\omega n}$$

$$C = YY^{H} = a uu^{H} + QQ^{H}$$

• Now we do the eigenvalue decomposition of *C*:

$$C = U\Sigma U^H$$

Then

$$egin{aligned} oldsymbol{U} &= [oldsymbol{u}_1, oldsymbol{u}_2, ..., oldsymbol{u}_N] \ oldsymbol{u}_1 &= oldsymbol{u} + noise \ ; \ oldsymbol{u}_n &= noise \ \text{for} \ n \neq 1 \ oldsymbol{\Sigma} &= \mathbf{diag}([\alpha_1, \alpha_2, ..., \alpha_N]) \ lpha_1 &= a + noise \ \text{is} \ \mathbf{large} \ lpha_n &= noise \ \text{is} \ \mathbf{small} \ \text{for} \ n \neq 1 \end{aligned}$$

• Noise only:

$$y(n,t) = q(n,t)$$
  
 $C = YY^H = QQ^H$ 

• Now we do the eigenvalue decomposition of *C*:

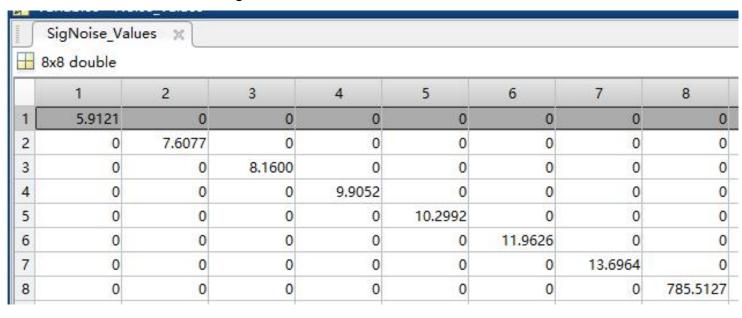
$$C = U\Sigma U^H$$

Then

$$egin{aligned} oldsymbol{U} &= [oldsymbol{u}_1, oldsymbol{u}_2, ..., oldsymbol{u}_N] \ oldsymbol{u}_n &= noise ext{ for all } n \ oldsymbol{\Sigma} &= \mathbf{diag}([lpha_1, lpha_2, ..., lpha_N]) \ lpha_n &= noise ext{ is } \mathbf{small} ext{ for all } n \end{aligned}$$

```
TILES
                     DOCUMENT TABS
   code4.m* ×
                +
        clear
        clc
3
        N = 8:
        T_{snapshot} = 100;
        F_sam_freq=1000; %采样频率
        F_{freq} = 200.07;
        omega = F_freq/F_sam_freq*2*pi
        SNR = 10:
10 -
        Amplitude_A_mean = 0;
        Amplitude_A_std = 1;
11 -
        n_{array} = [0:N-1]:
2 -
        t_array = [0: T_snapshot-1];
13 -
```

```
Theta = rand(1)*2*pi:
Amplitude At = Amplitude A std*randn(1, T snapshot)+Amplitude A mean;
Theta t = rand(1, T snapshot)*2*pi;
Frequnecy t = exp(1j*omega*n array);
X signal = Frequency t * (Amplitude At.*exp(1;*Theta t));
X reshape = reshape(X signal, N*T snapshot, 1);
X signal power = X reshape'*X reshape/(N*T snapshot);
Noise sigma2 = X signal power / [10 (SNR/10)];
Noise = sqrt(Noise sigma2) * randn(N, T snapshot) .* exp(1j*rand(N, T snapshot)*2*pi);
Y receive = X signal + Noise:
%% detection method
Y cov matrix = Y receive*Y receive':
[SigNoise Vectors, SigNoise Values] = eig(Y cov matrix);
Noise cov matrix = Noise*Noise';
[Noise Vectors, Noise Values] = eig(Noise cov matrix):
```



注意,Matlab的 eig函数的奇异 值是从小到大排 列的,和数学公 式的写法有些许 不一样

	8x8 double							
	1	2	3	4	5	6	7	8
1	5.8884	0	0	0	0	0	0	0
2	0	6.5446	0	0	0	0	0	0
3	0	0	7.9414	0	0	0	0	0
4	0	0	0	9.4648	0	0	0	0
5	0	0	0	0	10.0606	0	0	0
5	0	0	0	0	0	11.2955	0	0
7	0	0	0	0	0	0	12.6686	0
3	0	0	0	0	0	0	0	14.4646

$$y(n,t) = x(n,t) + q(n,t)$$
complex: 
$$x(n,t) = A(t)e^{j\theta(t)}e^{j\omega n} = \alpha(t) e^{j\omega n}$$

$$C = YY^{H} = a uu^{H} + QQ^{H}$$

• Now we do the eigenvalue decomposition of *C*:

$$C = U\Sigma U^H$$
 $\alpha_1 = a + noise \text{ is large}$ 
 $\alpha_n = noise \text{ is small for } n \neq 1$ 

• If  $\alpha_1/\alpha_2$  or  $\alpha_1/\alpha_N$  is large, for example, > 10, then we can judge that there is signal; otherwise, there exists noise only

#### More

• How about?:

$$y(n,t) = x_1(n,t) + x_2(n,t) + q(n,t)$$

That is, there are two signals?

Or

$$y(n,t) = \sum_{i=1}^{K} x_i(n,t) + q(n,t)$$

That is, there are *K* signals?

K known?

*K* unknown?

Try yourself