

4.7.13 例3.19, 2013/10/09

$$C_{x'} = C_x = C$$

4.1) $x[n] = \sum_{i=1}^p A_i r_i^n + w[n]$

$$x = H\theta + w$$

$$\theta = [A_1, A_2, \dots, A_p]^T$$

$$H = \begin{bmatrix} 1 & \dots & 1 \\ r_1 & \dots & r_p \\ \vdots & \dots & \vdots \\ r_1^{N-1} & \dots & r_p^{N-1} \end{bmatrix}$$

$$\hat{\theta} = (H^T H)^{-1} H^T x, \quad C_{\hat{\theta}} = \sigma^2 (H^T H)^{-1}$$

$p=2, r_1=1, r_2=-1, N$ 偶数

$$H = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ \vdots & \vdots \\ 1 & -1 \end{bmatrix} \rightarrow H^T H = \begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix}$$

$$\hat{\theta} = \frac{1}{N} H^T x = \begin{bmatrix} \frac{1}{N} \sum_{n=0}^{N-1} x[n] \\ \frac{1}{N} \sum_{n=0}^{N-1} (-1)^n x[n] \end{bmatrix}$$

$$C_{\hat{\theta}} = \frac{\sigma^2}{N} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \frac{\sigma^2}{N} & 0 \\ 0 & \frac{\sigma^2}{N} \end{bmatrix}$$

4.14 $x = H\theta + w$

$$H = \begin{cases} [1, \dots, 1]^T, & p = 1-\epsilon \\ [\underbrace{1, \dots, 1}_M, \underbrace{0, \dots, 0}_{N-M}]^T, & p = \epsilon \end{cases}$$

$$\hat{\theta} = \hat{A} = (H^T H)^{-1} H^T x = \begin{cases} \frac{1}{N} \sum_{n=0}^{N-1} x[n] & \text{不衰落} \\ \frac{1}{M} \sum_{n=0}^{M-1} x[n] & \text{衰落} \end{cases}$$

$$C_A = \sigma^2 E_H [(H^T H)^{-1}]$$

$$= \sigma^2 \left((1-\epsilon) \frac{1}{N} + \epsilon \frac{1}{M} \right)$$

$$= \frac{\sigma^2}{N} (1 + (M-1)\epsilon) \geq \frac{\sigma^2}{N} \quad \text{当且仅当 } M=N \text{ 或 } \epsilon=0 \text{ 时取“=”}$$

即在衰落情况下方差会变大

6.6. $E x[n] = \theta S[n] + \beta$

$$\hat{\theta} = \sum_{n=0}^{N-1} a_n x[n] + b$$

$$E \hat{\theta} = E \left[\sum_{n=0}^{N-1} a_n x[n] + b \right] = \sum_{n=0}^{N-1} a_n (E x[n]) + b = \theta$$

即 $\sum_{n=0}^{N-1} a_n S[n] = 1, \beta \sum_{n=0}^{N-1} a_n = -b$

$$\text{所以 } \hat{\theta} = \sum_{n=0}^{N-1} a_n x[n] - \beta \sum_{n=0}^{N-1} a_n = \sum_{n=0}^{N-1} a_n (x[n] - \beta)$$

令 $x'[n] = x[n] - \beta$ 则回到 BLUE 问题

$$\hat{\theta} = \frac{S^T C^{-1} x'}{S^T C^{-1} S} = \frac{S^T C^{-1} (x - \beta 1)}{S^T C^{-1} S}$$

$$\text{var} \hat{\theta} = \frac{1}{S^T C^{-1} S}$$

6.9.

$$x[n] = A \cos 2\pi f_1 n + w[n]$$

$$E x[n] = \theta S[n] = A \cos 2\pi f_1 n$$

$$S = [1, \cos 2\pi f_1, \dots, \cos 2\pi f_1 (N-1)]^T$$

$$\hat{A} = \frac{S^T C^{-1} x}{S^T C^{-1} S} = \frac{S^T x}{S^T S} = \frac{\sum_n x[n] \cos 2\pi f_1 n}{\sum_n \cos^2 2\pi f_1 n}$$

$$= \frac{N/2}{\sum_n \cos^2 2\pi f_1 n} \cdot \underbrace{\frac{2}{N} \sum_n x[n] \cos \frac{2\pi (N f_1) n}{N}}_{\text{DFT 系数}}$$

$$\text{var} \hat{A} = \frac{1}{S^T C^{-1} S} = \frac{\sigma^2}{S^T S} = \frac{\sigma^2}{\sum_n \cos^2 2\pi f_1 n} \geq \frac{\sigma^2}{N}$$

当 $f_1=0$ 时, \hat{A} 方差最小为 $\frac{\sigma^2}{N}$, 此时 $x[n] = A + w[n]$

注: $w_b[n], w_l[n]$ 被简化成 w_b, w_l .

$$6.14 \quad p(w[n]) = (1-\varepsilon) \mathcal{N}(0, \sigma_b^2) + \varepsilon \mathcal{N}(0, \sigma_l^2) = (1-\varepsilon) p(w_b) + \varepsilon p(w_l) \quad \text{其中 } w_b \sim \mathcal{N}(0, \sigma_b^2)$$

$$E w[n] = (1-\varepsilon) \cdot 0 + \varepsilon \cdot 0 = 0$$

$$\text{则 } w[n] = (1-\varepsilon) w_b + \varepsilon w_l \quad w_l \sim \mathcal{N}(0, \sigma_l^2), \text{ 两者独立}$$

$$\begin{aligned} \text{var } w[n] &= E w^2[n] = E[(1-\varepsilon)w_b + \varepsilon w_l]^2 \\ &= E[(1-\varepsilon)^2 w_b^2 + \varepsilon^2 w_l^2 + 2\varepsilon(1-\varepsilon)w_b w_l] \end{aligned}$$

$$p(w[n]) = (1-\varepsilon) \mathcal{N}(0, \sigma_b^2) + \varepsilon \mathcal{N}(0, \sigma_l^2)$$

$$E w[n] = 0$$

$$\begin{aligned} \text{var } w[n] &= E w^2[n] = \int_{-\infty}^{+\infty} w^2 (1-\varepsilon) \frac{1}{\sqrt{2\pi}\sigma_b} e^{-\frac{w^2}{2\sigma_b^2}} dw + \int_{-\infty}^{+\infty} w^2 \varepsilon \frac{1}{\sqrt{2\pi}\sigma_l} e^{-\frac{w^2}{2\sigma_l^2}} dw \\ &= (1-\varepsilon)\sigma_b^2 + \varepsilon\sigma_l^2 \end{aligned}$$

$$\text{即 } \sigma^2 = (1-\varepsilon)\sigma_b^2 + \varepsilon\sigma_l^2$$

利用数据变量 $y[n] = w^2[n]$

$$\hat{\sigma}^2 = \sum_{n=0}^{N-1} a_n w^2[n], \quad E \hat{\sigma}^2 = \sum_n a_n \sigma^2 = \sigma^2$$

$$E w^2[n] = 1 \cdot \sigma^2 \quad \text{即 } \mathbf{s} = [1, \dots, 1]^T,$$

$$\hat{\sigma}^2 = \frac{\mathbf{s}^T \mathbf{C}^{-1} \mathbf{w}^2[n]}{\mathbf{s}^T \mathbf{C}^{-1} \mathbf{s}} = \frac{\mathbf{s}^T \mathbf{w}^2[n]}{\mathbf{s}^T \mathbf{s}} = \frac{1}{N} \sum_{n=0}^{N-1} w^2[n]$$

$$\text{由 6.12 知, } \sigma_l^2 = \frac{\sigma^2 - (1-\varepsilon)\sigma_b^2}{\varepsilon}$$

$$\text{即 } \hat{\sigma}_l^2 = \frac{\frac{1}{N} \sum_n w^2[n] - (1-\varepsilon)\sigma_b^2}{\varepsilon}$$