

#### **LECTURE11**

· 随机参量,已知PDF: BAYES估计

• 均匀代价函数: MAP 
$$\frac{\partial}{\partial \theta} \Big[ \ln f(Y \setminus \theta) + \ln f(\theta) \Big] \bigg|_{\theta = \hat{\theta}_{\text{MAP}}} = 0$$

• 平方代价函数: MMSE 
$$\hat{\theta}_{MS}(Y) = \int \theta f(\theta \mid Y) d\theta$$

• 绝对值代价函数: MED 
$$\int_{-\infty}^{\hat{ heta}} fig( heta ig) d heta = \int_{\hat{ heta}}^{\infty} fig( heta ig) d heta$$

• 非随机参量: ML估计 
$$\left. \frac{\partial}{\partial \theta} [lnf(Y | \theta)] \right|_{\theta = \hat{\theta}_{MI}} = \theta$$

·估计性能评价: 一阶矩、二阶矩



# 估计背景

- ・平稳过程
- ・线性估计方程
- ・待估参数与观测噪声无关
- PDF?







- 1 估计方程
- 2 线性观测方程下的LMS
- 3 白噪声下的LMS标量估计
- 4 序贯LMS算法





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#### 一般形式

- Linear Mean Square
- ・线性估计方程

$$\hat{\theta}_{LMS} = A + BY$$

・均方误差最小

$$E\left\{e^{2}\left(\theta,\hat{\theta}\right)\right\} = E\left\{\left[\theta - A - BY\right]^{T}\left[\theta - A - BY\right]\right\}$$

$$\Rightarrow \begin{cases} \frac{\partial}{\partial A}E\left\{e^{2}\left(\theta,\hat{\theta}\right)\right\} = E\left\{-2\left(\theta - A - BY\right)\right\} = \theta \\ \frac{\partial}{\partial B}E\left\{e^{2}\left(\theta,\hat{\theta}\right)\right\} = E\left\{-2\left(\theta - A - BY\right)Y^{T}\right\} = \theta \end{cases}$$



### 一般形式

$$\begin{cases} A_{L} = E\{\theta\} - B_{L}E\{Y\} \\ E\{\theta Y^{T}\} = A_{L}E\{Y^{T}\} + B_{L}E\{Y \cdot Y^{T}\} \end{cases}$$

$$\Rightarrow E\{\theta Y^{T}\} = E\{\theta\}E\{Y^{T}\} - B_{L}E\{Y\}E\{Y^{T}\} + B_{L}E\{Y \cdot Y^{T}\} \}$$

$$\Rightarrow B_{L}E\{Y \cdot Y^{T}\} - B_{L}E\{Y\}E\{Y^{T}\} = E\{\theta\}E\{Y^{T}\} - E\{\theta\}E\{Y^{T}\} \}$$

$$\Rightarrow B_{L}\{E\{Y \cdot E(Y)\} \cdot [Y \cdot E(Y)]^{T}\} = E\{[\theta \cdot E(\theta)] \cdot [Y \cdot E(Y)]^{T}\} \}$$

$$\Rightarrow \begin{cases} B_{L} = cov(\theta, Y) cov(Y, Y)^{-1} \\ A_{L} = E\{\theta\} - cov(\theta, Y) cov(Y, Y)^{-1} E\{Y\} \end{cases}$$

$$\hat{\theta}_{LMS} = A_L + B_L Y = E\{\theta\} + \operatorname{cov}(\theta, Y) \operatorname{cov}(Y, Y)^{-1} \left[ Y - E\{Y\} \right]$$

$$\text{vol Chinese Academy of Sciences}$$

#### 特殊形式

$$\hat{\theta}_{LMS} = BY$$

$$E\left\{e^{2}\left(\theta, \hat{\theta}\right)\right\} = E\left\{\left[\theta - BY\right]^{T}\left[\theta - BY\right]\right\}$$

$$\Rightarrow \frac{\partial}{\partial B}E\left\{e^{2}\left(\theta, \hat{\theta}\right)\right\} = E\left\{-2(\theta - BY)Y^{T}\right\} = 0$$

$$B_{L} = R_{\theta Y}R_{Y}^{-1}$$

$$LMS: \hat{\theta}_{LMS} = B_{L}Y = R_{\theta Y}R_{Y}^{-1}Y$$



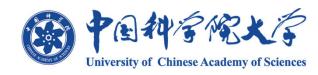
### 正交性

#### 由系数 $B_L$ 的求取过程:

$$\begin{split} \hat{\theta}_{LMS} &= A_L + B_L Y : \\ E\left\{\left(\theta - \hat{\theta}_{LMS}\right)Y^T\right\} = E\left\{e\left(\theta, \hat{\theta}_{LMS}\right)Y^T\right\} = E\left\{\left(\theta - A - BY\right)Y^T\right\} = \theta \\ \hat{\theta}_{LMS} &= B_L Y : \\ E\left\{\left(\theta - \hat{\theta}_{LMS}\right)Y^T\right\} = E\left\{e\left(\theta, \hat{\theta}_{LMS}\right)Y^T\right\} = E\left\{\left(\theta - BY\right)Y^T\right\} = \theta \end{split}$$

#### 估计误差与观测值之间正交

Q: 矢量空间?



### 均方误差阵最小

$$\hat{\theta} = A + BY$$

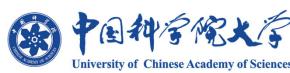
$$\hat{\varphi}C = A - E\{\theta\} + BE\{Y\}$$

$$E\{\left[\theta - \hat{\theta}\right]\left[\theta - \hat{\theta}\right]^T\} = E\{\left[\theta - A - BY\right]\left[\theta - A - BY\right]^T\}$$

$$= E\{\left[\theta - E\{\theta\} - C - B(Y - E\{Y\})\right]\left[\theta - E\{\theta\} - C - B(Y - E\{Y\})\right]^T\}$$

$$= cov(\theta, \theta) + CC^T + B\left[cov(Y, Y)\right]B^T - \left[cov(\theta, Y)\right]B^T - B\left[cov(Y, \theta)\right]$$

补项
$$\operatorname{cov}(\theta, Y) [\operatorname{cov}(Y, Y)]^{-1} \operatorname{cov}(Y, \theta) +$$
 后三项
$$\rightarrow [B\operatorname{cov}(Y, Y) - \operatorname{cov}(\theta, Y)] \Big\{ B - \operatorname{cov}(\theta, Y) [\operatorname{cov}(Y, Y)]^{-1} \Big\}^{T}$$



#### 均方误差阵最小

$$= CC^{T} + \operatorname{cov}(\theta, \theta) - \operatorname{cov}(\theta, Y) \left[\operatorname{cov}(Y, Y)\right]^{-1} \operatorname{cov}(Y, \theta)$$

$$+ \left[B \operatorname{cov}(Y, Y) - \operatorname{cov}(\theta, Y)\right] \left\{B - \operatorname{cov}(\theta, Y) \left[\operatorname{cov}(Y, Y)\right]^{-1}\right\}^{T}$$

$$= CC^{T}$$

$$+ \left[B - \operatorname{cov}(\theta, Y) \operatorname{cov}^{-1}(Y, Y)\right] \operatorname{cov}(Y, Y) \cdot \left[B - \operatorname{cov}(\theta, Y) \operatorname{cov}^{-1}(Y, Y)\right]^{T}$$

$$+ \operatorname{cov}(\theta, \theta) - \operatorname{cov}(\theta, Y) \left[\operatorname{cov}(Y, Y)\right]^{-1} \operatorname{cov}(Y, \theta)$$

$$\geq \operatorname{cov}(\theta, \theta) - \operatorname{cov}(\theta, Y) \left[\operatorname{cov}(Y, Y)\right]^{-1} \operatorname{cov}(Y, \theta)$$



#### 均方误差阵最小

$$E\left\{\left[\theta-\hat{\theta}_{LMS}\right]\cdot\left[\theta-\hat{\theta}_{LMS}\right]^{T}\right\}$$

$$=E\left\{\left[\theta-E\left\{\theta\right\}-cov\left(\theta,Y\right)cov\left(Y,Y\right)^{-1}\left[Y-E\left\{Y\right\}\right]\right]\right\}$$

$$\cdot\left[\theta-E\left\{\theta\right\}-cov\left(\theta,Y\right)cov\left(Y,Y\right)^{-1}\left[Y-E\left\{Y\right\}\right]\right]^{T}\right\}$$

$$=cov\left(\theta,\theta\right)-cov\left(\theta,Y\right)\left[cov\left(Y,Y\right)\right]^{-1}cov\left(Y,\theta\right)$$

$$\Rightarrow E\left\{\left[\theta-\hat{\theta}\right]\cdot\left[\theta-\hat{\theta}\right]^{T}\right\} \geq E\left\{\left[\theta-\hat{\theta}_{LMS}\right]\cdot\left[\theta-\hat{\theta}_{LMS}\right]^{T}\right\}$$



# 无偏性

$$E\left\{\hat{\theta}_{LMS}\right\} = E\left\{\theta\right\} + \operatorname{cov}\left(\theta, Y\right) \operatorname{cov}\left(Y, Y\right)^{-1} \left[E\left\{Y\right\} - E\left\{Y\right\}\right]$$
$$= E\left\{\theta\right\}$$
$$= \theta_0$$

BLUE: 最佳线性无偏估计







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#### 线性场景

#### 线性观测方程: Y=H0+N

$$E\{\theta\} = \theta_{\theta}$$

$$cov(\theta,\theta) = E\left\{ \left[\theta - \theta_0 \right] \theta - \theta_0^T\right\} = C_\theta$$

$$E\{N\}=0$$

$$cov{N,N} = E{N \cdot N^T} = R_N$$

$$E\left\{\theta\cdot N^T\right\}=0$$

$$E\{Y\} = HE\{\theta\} = H\theta_{\theta}$$



#### 系数计算

$$cov(Y,Y) = E\left\{ \left[ Y - E\left\{ Y \right\} \right] \left[ Y - E\left\{ Y \right\} \right]^{T} \right\}$$

$$= E\left\{ \left[ H\left(\theta - \theta_{\theta}\right) + N \right] \left[ H\left(\theta - \theta_{\theta}\right) + N \right]^{T} \right\} = HC_{\theta}H^{T} + R_{N}$$

$$cov(\theta,Y) = E\left\{ \left[ \theta - \theta_{\theta} \right] \left[ Y - E\left\{ Y \right\} \right]^{T} \right\}$$

$$= E\left\{ \left[ \theta - \theta_{\theta} \right] \left[ H\left(\theta - \theta_{\theta}\right) + N \right]^{T} \right\} = C_{\theta}H^{T}$$

$$\Rightarrow \begin{cases} A_{L} = E\left\{ \theta \right\} - cov(\theta,Y) cov(Y,Y)^{-1} E\left\{ Y \right\} \right\}$$

$$= \theta_{\theta} - C_{\theta}H^{T} \left[ HC_{\theta}H^{T} + R_{N} \right]^{-1} H\theta_{\theta}$$

$$B_{L} = cov(\theta,Y) cov(Y,Y)^{-1} = C_{\theta}H^{T} \left[ HC_{\theta}H^{T} + R_{N} \right]^{-1}$$

# 估计方程

$$\begin{split} \hat{\theta}_{LMS} \\ &= A_L + B_L Y \\ &= E\{\theta\} + cov(\theta, Y)cov(Y, Y)^{-1}[Y - E\{Y\}] \\ &= \theta_0 - C_\theta H^T [HC_\theta H^T + R_N]^{-1} H\theta_0 \\ &\quad + C_\theta H^T [HC_\theta H^T + R_N]^{-1} Y \\ &= \theta_0 + C_\theta H^T [HC_\theta H^T + R_N]^{-1} [Y - H\theta_0] \end{split}$$



#### 误差矩阵

$$cov(Y,\theta) = E\left\{ \left[ Y - E\left\{ Y \right\} \right] \left[ \theta - \theta_{0} \right]^{T} \right\}$$

$$= E\left\{ \left[ H(\theta - \theta_{0}) + N \right] (\theta - \theta_{0})^{T} \right\}$$

$$= HC_{\theta}$$

$$E\left\{ \left[ \theta - \hat{\theta}_{LMS} \right] \left[ \theta - \hat{\theta}_{LMS} \right]^{T} \right\}$$

$$= cov(\theta,\theta) - cov(\theta,Y) \left[ cov(Y,Y) \right]^{-1} cov(Y,\theta)$$

$$= C_{\theta} - C_{\theta}H^{T} \left[ HC_{\theta}H^{T} + R_{N} \right]^{-1} HC_{\theta}$$





**傅里叶分析**。数据模型表示为 $y_k$ = $acosk\omega_0$ + $bsink\omega_0$ + $n_k$ , k=1,2...N,  $f_0$ 为(1/N)的倍数。a和b为待估参量,均值为零,方差  $\sigma_\theta^2$ ,高斯分布; $\{n_k\}$ 为独立于信号的均值零、方差 的高斯噪声。N次独立观测。MMSE估计。

$$Y = H\theta + N$$

$$H = \begin{bmatrix} \cos \omega_0 & \sin \omega_0 \\ \cos 2\omega_0 & \sin 2\omega_0 \\ \vdots & \vdots \\ \cos N\omega_0 & \sin N\omega_0 \end{bmatrix}$$

$$\theta = \begin{bmatrix} a & b \end{bmatrix}^{T}$$

$$E \{\theta\} = 0$$

$$C_{\theta} = \sigma_{\theta}^{2} I$$

$$C_{n} = \sigma_{n}^{2} I$$





$$\hat{\theta} = E\left\{\theta \setminus Y\right\} = E\left\{\theta\right\} + C_{\theta Y}C_{YY}^{-1}\left(Y - E\left\{Y\right\}\right)$$

$$C_{YY} = E\left\{\left[Y - E\left\{Y\right\}\right]\left[Y - E\left\{Y\right\}\right]^{T}\right\}$$

$$= E\left\{\left[H\theta + N\right]\left[H\theta + N\right]^{T}\right\} = HC_{\theta}H^{T} + C_{n} = \sigma_{\theta}^{2}HH^{T} + C_{n}$$

$$= \left(\frac{N\sigma_{\theta}^{2}}{2} + \sigma_{n}^{2}\right)I$$

$$C_{\theta Y} = E\left\{\left[\theta\right]\left[Y - E\left\{Y\right\}\right]^{T}\right\}$$

$$= E\left\{\left[\theta\right]\left[H\theta + N\right]^{T}\right\} = C_{\theta}H^{T} = \sigma_{\theta}^{2}H^{T}$$

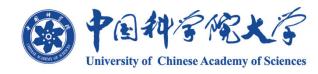


$$\begin{split} \hat{\theta} &= C_{\theta Y} C_{YY}^{-1} Y \\ &= \begin{bmatrix} \cos \omega_0 & \cos 2\omega_0 & \cdots & \cos N\omega_0 \\ \sin \omega_0 & \sin 2\omega_0 & \cdots & \sin N\omega_0 \end{bmatrix}. \end{split}$$

$$\begin{bmatrix} \frac{\sigma_{\theta}^{2}}{N\sigma_{\theta}^{2}} & \cdots & \mathbf{0} \\ \vdots & \frac{\sigma_{\theta}^{2}}{2} + \sigma_{n}^{2} \\ \vdots & \frac{N\sigma_{\theta}^{2}}{2} + \sigma_{n}^{2} \\ \vdots & \frac{\sigma_{\theta}^{2}}{2} + \sigma_{n}^{2} \end{bmatrix} = \frac{\frac{2}{N}}{1 + \frac{2\sigma_{n}^{2}/N}{\sigma_{\theta}^{2}}} \begin{bmatrix} \sum_{k=1}^{N} y_{k} \cos k\omega_{0} \\ \vdots \\ y_{N} \end{bmatrix} = \frac{1}{1 + \frac{2\sigma_{n}^{2}/N}{\sigma_{\theta}^{2}}} \begin{bmatrix} \sum_{k=1}^{N} y_{k} \cos k\omega_{0} \\ \sum_{k=1}^{N} y_{k} \sin k\omega_{0} \end{bmatrix}$$

$$\frac{\sigma_{\theta}^2}{\frac{N\sigma_{\theta}^2}{2} + \sigma_n^2}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \frac{\frac{2}{N}}{1 + \frac{2\sigma_n^2/N}{\sigma_\theta^2}} \begin{bmatrix} \sum_{k=1}^N y_k \cos k\omega_0 \\ \sum_{k=1}^N y_k \sin k\omega_0 \end{bmatrix}$$







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#### 理想观测

观测样本 $Y=[y_1,y_2,...y_m]^T$ 

观测方程  $y_i = \theta + n_i, i = 1, 2, ...$  m

观测噪声 $n_i$ :  $E\left\{n_i\right\} = 0$ ;  $E\left\{n_i n_j\right\} = \sigma_n^2 \delta_{ij}$ 

待估参量(随机标量) $\theta$ :  $E\{\theta\}=\theta_{\theta}$ ;  $Var\{\theta\}=\sigma_{\theta}^{2}$ 

$$cov(\theta, Y)$$

$$= E\{(\theta - \theta_0)[y_1 - E\{y_1\}, y_2 - E\{y_2\}, \dots, y_m - E\{y_m\}]\}$$

$$= E\{(\theta - \theta_0)[(\theta - \theta_0) + n_1, (\theta - \theta_0) + n_2, \dots, (\theta - \theta_0) + n_m]\}$$

$$= [\sigma_{\theta}^2, \sigma_{\theta}^2, \dots, \sigma_{\theta}^2] = P_{\theta}$$



#### 系数计算

$$cov(Y,Y) = E\{[Y-E\{Y\}][Y-E\{Y\}]^T\}$$

$$= E\left\{\begin{bmatrix} y_1 - \theta_0 \\ \vdots \\ y_m - \theta_0 \end{bmatrix} \left[ y_1 - \theta_0, \cdots y_m - \theta_0 \right] \right\} = \begin{bmatrix} \sigma_\theta^2 + \sigma_n^2 & \sigma_\theta^2 & \cdots & \sigma_\theta^2 \\ \sigma_\theta^2 & \sigma_\theta^2 + \sigma_n^2 & \cdots & \sigma_\theta^2 \\ \vdots & \cdots & \cdots & \vdots \\ \sigma_\theta^2 & \sigma_\theta^2 & \cdots & \sigma_\theta^2 + \sigma_n^2 \end{bmatrix}$$

$$=G$$

$$\Rightarrow cov(\theta, Y)[cov(Y, Y)]^{-1} = P_{\theta}G^{-1} = K = \begin{bmatrix} k_{1}, k_{2}, \cdots, k_{m} \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} \sigma_{\theta}^{2} + \sigma_{n}^{2} & \sigma_{\theta}^{2} & \cdots & \sigma_{\theta}^{2} \\ \sigma_{\theta}^{2} & \sigma_{\theta}^{2} + \sigma_{n}^{2} & \cdots & \sigma_{\theta}^{2} \\ \vdots & \cdots & \vdots \\ \sigma_{\theta}^{2} & \sigma_{\theta}^{2} & \cdots & \sigma_{\theta}^{2} + \sigma_{n}^{2} \end{bmatrix} \begin{bmatrix} k_{1} \\ k_{2} \\ \vdots \\ k_{m} \end{bmatrix} = \begin{bmatrix} \sigma_{\theta}^{2} \\ \sigma_{\theta}^{2} \\ \vdots \\ \sigma_{\theta}^{2} \end{bmatrix}$$



# 估计方程

$$\Rightarrow k_i = \frac{\sigma_\theta^2}{m\sigma_\theta^2 + \sigma_n^2} = \frac{1}{m+b}$$

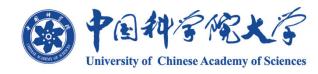
其中
$$b = \frac{\sigma_n^2}{\sigma_\theta^2}$$

$$\hat{\theta}_{LMS} = E\{\theta\} + \operatorname{cov}(\theta, Y)\operatorname{cov}(Y, Y)^{-1}[Y - E\{Y\}]$$

$$= \theta_0 + K \begin{bmatrix} y_1 - \theta_0 \\ \vdots \\ y_m - \theta_0 \end{bmatrix} = \theta_0 + \frac{1}{m+b} \sum_{i=1}^m (y_i - \theta_0)$$

$$E\left\{e^{2}\left(\theta,\hat{\theta}_{LMS}\right)\right\} = \operatorname{cov}\left(\theta,\theta\right) - \operatorname{cov}\left(\theta,Y\right)\left[\operatorname{cov}\left(Y,Y\right)\right]^{-1}\operatorname{cov}\left(Y,\theta\right)$$

$$=\frac{b}{m+b}\sigma_{\theta}^{2}$$



$$y_{i} = h_{i}\theta + n_{i}$$

$$\Leftrightarrow K = [k_{1}, k_{2}, \dots, k_{m}] = cov(\theta, Y)[cov(Y, Y)]^{-1}$$

$$cov(\theta, Y)$$

$$= E\{(\theta - \theta_{\theta})[Y - E\{Y\}]^{T}\}$$

$$= E\{(\theta - \theta_{\theta})[h_{1}(\theta - \theta_{\theta}) + n_{1}, h_{2}(\theta - \theta_{\theta}) + n_{2}, \dots, h_{m}(\theta - \theta_{\theta}) + n_{m}]\}$$

$$= [h_{1}\sigma_{\theta}^{2}, h_{2}\sigma_{\theta}^{2}, \dots, h_{m}\sigma_{\theta}^{2}]$$

$$= P_{\theta}$$



$$cov(Y,Y) = E\{[Y - E\{Y\}][Y - E\{Y\}]^T\}$$

$$= E\{\begin{bmatrix} h_1(\theta - \theta_0) + n_1 \\ \vdots \\ h_m(\theta - \theta_0) + n_m \end{bmatrix} [h_1(\theta - \theta_0) + n_1, \dots, h_m(\theta - \theta_0) + n_m] \}$$

$$= \begin{bmatrix} h_1^2 \sigma_\theta^2 + \sigma_n^2 & h_1 h_2 \sigma_\theta^2 & \cdots & h_1 h_m \sigma_\theta^2 \\ h_1 h_2 \sigma_\theta^2 & h_2^2 \sigma_\theta^2 + \sigma_n^2 & \cdots & h_2 h_2 \sigma_\theta^2 \\ \vdots & \cdots & \cdots & \vdots \\ h_1 h_m \sigma_\theta^2 & h_2 h_m \sigma_\theta^2 & \cdots & h_m^2 \sigma_\theta^2 + \sigma_n^2 \end{bmatrix} = G$$



$$G^{T}K^{T} = P_{\theta}^{T} \Rightarrow \begin{cases} \left(h_{1}^{2}\sigma_{\theta}^{2} + \sigma_{n}^{2}\right)k_{1} + h_{1}h_{2}\sigma_{\theta}^{2}k_{2} + \cdots + h_{1}h_{m}\sigma_{\theta}^{2}k_{m} = h_{1}\sigma_{\theta}^{2} \\ h_{1}h_{2}\sigma_{\theta}^{2}k_{1} + \left(h_{2}^{2}\sigma_{\theta}^{2} + \sigma_{n}^{2}\right)k_{2} + \cdots + h_{2}h_{2}\sigma_{\theta}^{2}k_{m} = h_{2}\sigma_{\theta}^{2} \\ \vdots \\ h_{1}h_{m}\sigma_{\theta}^{2}k_{1} + h_{2}h_{m}\sigma_{\theta}^{2}k_{2} + \cdots + \left(h_{m}^{2}\sigma_{\theta}^{2} + \sigma_{n}^{2}\right)k_{m} = h_{m}\sigma_{\theta}^{2} \end{cases}$$

$$\Rightarrow \left[\sum_{i=1}^{m}h_{i}^{2} + b\right]h_{1}k_{1} + \left[\sum_{i=1}^{m}h_{i}^{2} + b\right]h_{2}k_{2} + \cdots + \left[\sum_{i=1}^{m}h_{i}^{2} + b\right]h_{m}k_{m} = \sum_{i=1}^{m}h_{i}^{2} \end{cases}$$

$$\Rightarrow k_{i} = kh_{i}, \qquad k = 1$$

$$\sum_{i=1}^{m}h_{i}^{2} + b$$

$$k_{i} = kh_{i}, \qquad k = 1$$



$$\hat{\theta}_{LMS} = E\{\theta\} + \operatorname{cov}(\theta, Y)\operatorname{cov}(Y, Y)^{-1} \left[Y - E\{Y\}\right]$$

$$= \theta_0 + \left[kh_1, \dots kh_m\right] \begin{bmatrix} y_1 - h_1\theta_0 \\ \vdots \\ y_m - h_m\theta_0 \end{bmatrix} = \theta_0 + k\sum_{i=1}^m h_i \left(y_i - h_i\theta_0\right)$$

$$E\left\{e^{2}\left(\theta,\hat{\theta}_{LMS}\right)\right\} = \operatorname{cov}\left(\theta,\theta\right) - \operatorname{cov}\left(\theta,Y\right) \left[\operatorname{cov}\left(Y,Y\right)\right]^{-1} \operatorname{cov}\left(Y,\theta\right)$$

$$= \sigma_{\theta}^{2} - \left[kh_{1}, \dots kh_{m}\right] \begin{bmatrix} h_{1}\sigma_{\theta}^{2} \\ \vdots \\ h_{m}\sigma_{\theta}^{2} \end{bmatrix} = \sigma_{\theta}^{2} - k\sum_{i=1}^{m} h_{i}^{2}\sigma_{\theta}^{2} = \frac{\sigma_{n}^{2}}{\sum_{i=1}^{m} h_{i}^{2} + b}$$





观测某个点的匀速直线运动。已知观测时间间隔 $\triangle$ t=1min, var(v)=0.3(km/min) $^2$ ,E(v)=10km/min;观测噪声 $n_k$ ,E( $n_k$ )=0,E( $n_j n_k$ )=0.6 $\delta_{jk}$ (km/min) $^2$ ,且E( $v n_k$ )=0。观测方程 $z_k$ = $k v + n_k$ ,k=1,2...5。在获得观测值 $z_1$ =9.8km, $z_2$ =20.4km, $z_3$ =30.6km, $z_4$ =40.2km, $z_5$ =49.7km的情况下,求速度v的LMS估计。



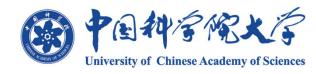


解:
$$\hat{v}_{LMS}(z) = E(v) + \frac{1}{\sum_{k=1}^{N} h_k^2 + b} \sum_{k=1}^{N} h_k \left[ z_k - h_k E(v) \right]$$

其中
$$E(v) = 10km / min; b = \frac{\sigma_n^2}{\sigma_v^2} = \frac{0.6}{0.3} = 2; h_k = k, k = 1, 2, ....5$$

$$\hat{v}_{LMS}(z) = 10 + \frac{1}{55 + 2} \sum_{k=1}^{N} k [z_k - 10k]$$

$$=10\frac{17}{570}km/min\approx10.03km/min$$







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#### time step: $m=0 \rightarrow m=1$

$$\hat{\theta}_{\theta} = E\{\theta\} = \theta_{\theta}$$

$$\xi_{\theta} = E\{(\theta - \theta_{\theta})^{2}\} = \sigma_{\theta}^{2}$$

$$\begin{aligned} \hat{\theta}_{1} &= \hat{\theta}_{0} + k_{1}h_{1}(y_{1} - h_{1}\hat{\theta}_{0}) = \theta_{0} + k_{1}h_{1}(y_{1} - h_{1}\theta_{0}) \\ &E\{(\theta - \hat{\theta}_{1})y_{1}\} \\ &= E\{[\theta - \theta_{0} - k_{1}h_{1}(y_{1} - h_{1}\theta_{0})](h_{1}\theta + n_{1})\} \\ &= E\{[\theta - \theta_{0} - k_{1}h_{1}(h_{1}\overline{\theta - \theta_{0}} + n_{1})](h_{1}\overline{\theta - \theta_{0}} + h_{1}\theta_{0} + n_{1})\} \\ &= h_{1}\sigma_{\theta}^{2} - k_{1}h_{1}(h_{1}^{2}\sigma_{\theta}^{2} + \sigma_{n}^{2}) = \theta \end{aligned}$$

$$\Rightarrow k_1 = \frac{\sigma_\theta^2}{h_1^2 \sigma_\theta^2 + \sigma_n^2}$$



#### time step: m=1

$$\hat{\theta}_1 = \theta_0 + \frac{1}{h_1^2 + \frac{\sigma_n^2}{\sigma_\theta^2}} h_1 \left( y_1 - h_1 \theta_0 \right)$$

$$\begin{aligned} \xi_{1} &= E\left\{\left(\theta - \hat{\theta}_{1}\right)^{2}\right\} \\ &= E\left\{\left(\theta - \hat{\theta}_{1}\right)\left[\theta - \theta_{0} - k_{1}h_{1}\left(y_{1} - h_{1}\theta_{0}\right)\right]\right\} \\ &= E\left\{\left(\theta - \hat{\theta}_{1}\right)\left[\theta - \theta_{0} - k_{1}h_{1}^{2}\theta_{0}\right]\right\} \\ &= E\left\{\left(\theta - \hat{\theta}_{1}\right)\left(\theta - \theta_{0}\right)\right\} = E\left\{\left[\theta - \theta_{0} - k_{1}h_{1}\left(y_{1} - h_{1}\theta_{0}\right)\right]\left(\theta - \theta_{0}\right)\right\} \\ &= \sigma_{\theta}^{2} - k_{1}h_{1}^{2}\sigma_{\theta}^{2} = k_{1}\sigma_{n}^{2} = \sigma_{n}^{2} \frac{1}{h_{1}^{2} + \frac{\sigma_{n}^{2}}{\sigma_{\theta}^{2}}} \end{aligned}$$



#### time step: m=2

$$\begin{split} \widehat{\theta}_{2} &= \widehat{\theta}_{1} + k_{2}h_{2}\left(y_{2} - h_{2}\widehat{\theta}_{1}\right) \\ &= E\left\{\left[\theta - \widehat{\theta}_{2}\right]y_{2}\right\} \\ &= E\left\{\left[\theta - \widehat{\theta}_{1} - k_{2}h_{2}\left(y_{2} - h_{2}\widehat{\theta}_{1}\right)\right]\left(h_{2}\theta + n_{2}\right)\right\} \\ &= E\left\{\left[\overline{\theta - \theta_{0}} - k_{1}h_{1}\left(h_{1}\overline{\theta - \theta_{0}} + n_{1}\right) - k_{2}h_{2}\left[h_{2}\theta + n_{2}\right]\right. \\ &- h_{2}\left(\theta_{0} + k_{1}h_{1}\overline{h_{1}}\overline{\theta - h_{1}\theta_{0}} + k_{1}h_{1}n_{1}\right)\right] \cdot \left(h_{2}\theta + n_{2}\right)\right\} \\ &= E\left\{\left[\overline{\theta - \theta_{0}} - k_{1}h_{1}\left(h_{1}\overline{\theta - \theta_{0}} + n_{1}\right) - k_{2}h_{2}\left(h_{2}\overline{\theta - \theta_{0}} + n_{2}\right)\right. \\ &+ k_{1}k_{2}h_{1}^{2}h_{2}^{2}\overline{\theta - \theta_{0}} - k_{1}k_{2}h_{1}h_{2}^{2}n_{1}\right] \cdot \left(h_{2}\overline{\theta - \theta_{0}} + h_{2}\theta_{0} + n_{2}\right)\right\} \end{split}$$



#### time step: m=2

$$= E\{ [\overline{\theta - \theta_0} - k_1 h_1^2 \overline{\theta - \theta_0} - k_1 h_1 n_1 - k_2 h_2^2 \overline{\theta - \theta_0} - k_2 h_2 n_2 + k_1 k_2 h_1^2 h_2^2 \overline{\theta - \theta_0} - k_1 k_2 h_1 h_2^2 n_1 ] \cdot (h_2 \overline{\theta - \theta_0} + h_2 \theta_0 + n_2) \}$$

$$= h_2 \Big[ \sigma_{\theta}^2 - k_1 h_1^2 \sigma_{\theta}^2 - k_2 h_2^2 \sigma_{\theta}^2 + k_1 k_2 h_1^2 h_2^2 \sigma_{\theta}^2 - k_2 \sigma_n^2 \Big] = 0$$

$$\Rightarrow \sigma_{\theta}^2 - k_1 h_1^2 \sigma_{\theta}^2 - k_2 h_2^2 \sigma_{\theta}^2 + k_1 k_2 h_1^2 h_2^2 \sigma_{\theta}^2 - k_2 \sigma_n^2 = 0$$

$$\Rightarrow k_2 = \frac{\sigma_{\theta}^2 - k_1 h_1^2 \sigma_{\theta}^2}{h_2^2 \sigma_{\theta}^2 - k_1 h_1^2 h_2^2 \sigma_{\theta}^2 + \sigma_n^2} = \frac{k_1}{1 + k_1 h_2^2}$$

$$\xi_2 = \frac{\sigma_n^2}{h_1^2 + h_2^2 + \sigma_n^2} = k_2 \sigma_n^2 = \frac{k_1}{1 + k_1 h_2^2} \sigma_n^2 = \frac{\xi_1}{1 + k_1 h_2^2}$$



#### time step: m=i+1

标量形式 
$$\hat{\theta}_{i+1} = \hat{\theta}_i + k_{i+1}h_{i+1}(y_{i+1} - h_{i+1}\hat{\theta}_i)$$

$$k_{i+1} = \frac{k_i}{1 + h_{i+1}^2 k_i}$$

$$\xi_{i+1} = k_{i+1}\sigma_n^2 = \frac{\xi_i}{1 + h_{i+1}^2 k_i} < \xi_i$$

$$\widehat{\theta_{i+1}} = \widehat{\theta_i} + K_{i+1} \left( Y_{i+1} - H_{i+1} \widehat{\theta_i} \right)$$
矢量形式
$$K_{i+1} = P_i H_{i+1}^T \left[ H_{i+1} P_i H_{i+1}^T + R_N \right]^{-1}$$

$$P_{i+1} = E \left\{ e \left( \theta, \widehat{\theta_{i+1}} \right) e \left( \theta, \widehat{\theta_{i+1}} \right)^T \right\} = \left[ P_i^{-1} + H_{i+1}^T R_N H_{i+1} \right]^{-1}$$





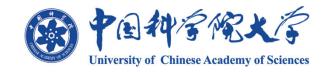
观测某个点的匀速直线运动。已知观测时间间隔 $\triangle$ t=1min, var(v)=0.3(km/min) $^2$ ,E(v)=10km/min;观测噪声 $n_k$ ,E( $n_k$ )=0,E( $n_j n_k$ )=0.6 $\delta_{jk}$ (km/min) $^2$ ,且E( $v n_k$ )=0。观测方程 $z_k$ = $k v + n_k$ ,k=1,2...5。在获得观测值 $z_1$ =9.8km, $z_2$ =20.4km, $z_3$ =30.6km, $z_4$ =40.2km, $z_5$ =49.7km的情况下,求速度v的序贯LMS估计。





起始估计值
$$v_0 = E(v) = 10km / min; k_0 = \frac{\sigma_v^2}{\sigma_n^2} = \frac{0.3}{0.6} = 0.5$$

第一次:
$$\begin{cases} \hat{v}_1(z) = v_0 + k_1 h_1(y_1 - h_1 v_0) \\ k_1 = \frac{k_0}{h_1^2 k_0 + 1} = \frac{0.5}{1 + 0.5} = \frac{1}{3} \\ \hat{v}_1(z) = 10 + \frac{1}{3}(9.8 - 10) = 9\frac{14}{15} km / min \end{cases}$$





第二次:
$$\begin{cases} \hat{v}_{2}(z) = \hat{v}_{1} + k_{2}h_{2}(y_{2} - h_{2}\hat{v}_{1}) \\ k_{2} = \frac{k_{1}}{h_{2}^{2}k_{1} + 1} = \frac{\frac{1}{3}}{1 + 4 \cdot \frac{1}{3}} = \frac{1}{7} \\ \hat{v}_{2}(z) = 9\frac{14}{15} + \frac{1}{7} \times 2 \times \left(20.4 - 2 \times 9\frac{14}{15}\right) = 10.087 \text{ km / min}$$





第三次:
$$\begin{cases} k_3 = \frac{k_2}{h_3^2 k_2 + 1} = \frac{1}{1 + 9 \cdot \frac{1}{7}} = \frac{1}{16} \\ \hat{v}_3(z) = \hat{v}_2 + k_3 h_3 \left( y_3 - h_3 \hat{v}_2 \right) \\ = 10.087 + \frac{1}{16} \times 3 \times \left( 30.6 - 3 \times 10.087 \right) = 10.151 \text{km/min} \end{cases}$$





第四次:
$$\begin{cases} k_4 = \frac{k_3}{h_4^2 k_3 + 1} = \frac{1/16}{1 + 16 \cdot 1/16} = \frac{1}{32} \\ \hat{v}_4(z) = \hat{v}_3 + k_4 h_4 \left( y_4 - h_4 \hat{v}_3 \right) \\ = 10.151 + \frac{1}{32} \times 4 \times \left( 40.2 - 4 \times 10.151 \right) = 10.101 km / min \end{cases}$$





第五次:
$$\begin{cases} k_5 = \frac{k_4}{h_5^2 k_4 + 1} = \frac{\frac{1}{32}}{1 + 25 \cdot \frac{1}{32}} = \frac{1}{57} \\ \hat{v}_5(z) = \hat{v}_4 + k_5 h_5 \left( y_5 - h_5 \hat{v}_4 \right) \\ = 10.101 + \frac{1}{57} \times 5 \times \left( 49.7 - 5 \times 10.101 \right) = 10.08 km / min \end{cases}$$



#### **summary**

- ・线性估计则只需一阶矩、二阶矩
- ・均方误差最小→估计误差与观测值正交
- ・均方误差矩阵最小
- 线性观测下可基于均值、方差和线性系数实现序贯估计

Ref: §5.8(赵版)、第12章 (KAY版)



