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Lecture 14

从参量估计到波形估计

lecture13

- 最小二乘法无需统计先验知识:线性观测方程$Y=H\theta+N$

$$\hat{\theta}_{LS}=\left[H^T H\right]^{-1} H^T Y$$

- 以噪声二阶矩作为权重因子的LSW误差矩阵最小

$$\hat{\theta}_{LSW}=\left[H^T R_N^{-1} H\right]^{-1} H^T R_N^{-1} Y$$

- 性能评价：无偏、有效、一致、充分
- CRLB: $var\left\{\hat{\theta}\right\} \geq \dfrac{1}{J(\theta)}$

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估计背景

- 波形中含有未知参量
- Bayes估计序贯实现
- 波形估计

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波形中参量估计

- 接收信号波形

$$y(t)=s(t;\vec{\theta})+n(t),0\le t\le T$$

- 似然函数

$$f(y\backslash\vec{\theta})=F\,exp\left\{-\frac{1}{N_0}\int_0^T\left[y(t)-s(t;\vec{\theta})\right]^2dt\right\}$$

$$F=\lim_{N\to\infty}\left(\frac{1}{\pi N_0}\right)^{N/2}$$

ML估计

$$\frac{\partial \ln f\left(y \backslash \vec{\theta}\right)}{\partial \theta_j} = \frac{2}{N_0}\int_0^T \left[y(t) - s\left(t;\vec{\theta}\right)\right]\frac{\partial s\left(t;\vec{\theta}\right)}{\partial \theta_j}dt$$

$$\Rightarrow \int_0^T \left[y(t) - s\left(t;\vec{\theta}\right)\right]\frac{\partial s\left(t;\vec{\theta}\right)}{\partial \theta_j}dt\Bigg|_{\theta=\hat{\theta}_{ML}} = 0, j = 1, 2, \cdots, M$$

信号振幅的估计

$$s(t;\theta) = As(t), 0 \le t \le T$$

$$\int_0^T \left[y(t) - As(t) \right] \frac{\partial As(t)}{\partial A} dt \Big|_{A=\hat{A}_{ML}} = 0$$

$$\int_0^T \left[y(t) - \hat{A}s(t) \right] s(t) dt = 0$$

$$\Leftrightarrow \hat{A}_{ML} = \frac{\int_0^T y(t)s(t)dt}{\int_0^T s^2(t)dt} \overset{\text{归一化信号}}{=} \int_0^T y(t)s(t)dt$$

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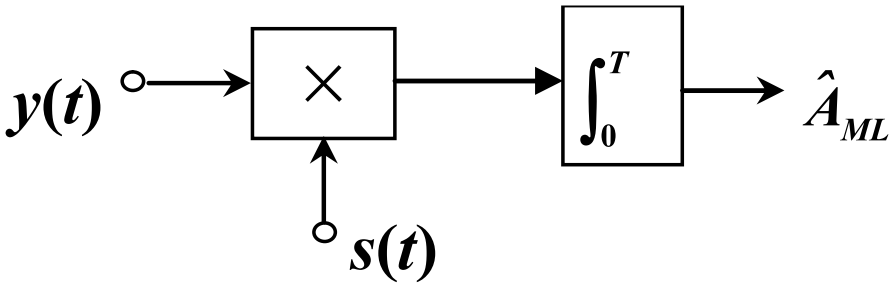
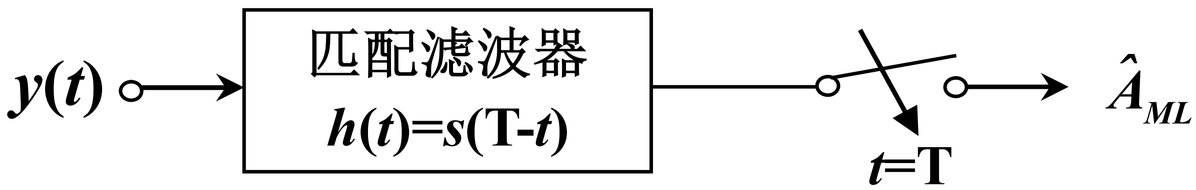
信号振幅的估计





信号相位的估计

$$s(t;\theta) = A\sin(\omega_0 t + \theta), 0 \le t \le T$$

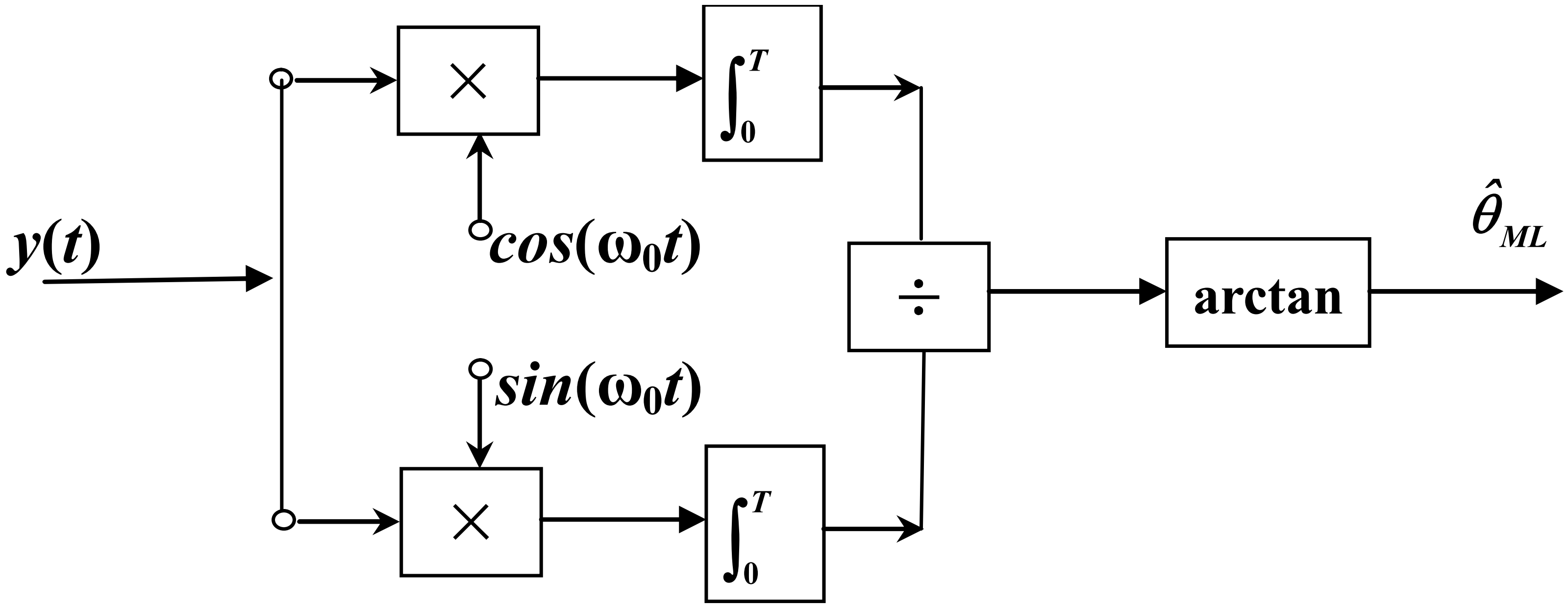
$$\int_0^T \left[y(t) - A\sin(\omega_0 t + \theta)\right] A\cos(\omega_0 t + \theta)\,dt\Big|_{\theta=\hat{\theta}_{ML}} = 0$$

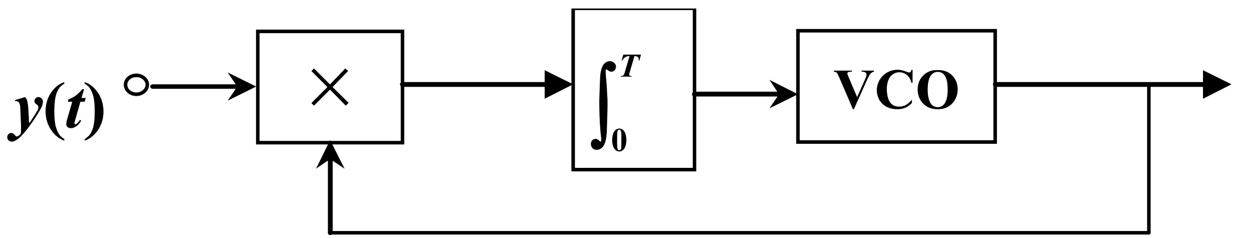
$$\int_0^T y(t)\cos(\omega_0 t + \theta)\,dt - \frac{A}{2}\int_0^T \sin\left[2(\omega_0 t + \theta)\right]dt\Big|_{\theta=\hat{\theta}_{ML}} = 0$$

$$\Leftrightarrow \int_0^T y(t)\cos\left(\omega_0 t + \hat{\theta}_{ML}\right)dt = 0$$

$$\hat{\theta}_{ML} = \arctan\left[\frac{\int_0^T y(t)\cos\omega_0 t}{\int_0^T y(t)\sin\omega_0 t}\right]$$

信号相位的估计





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ML估计

线性观测方程：Y=Hθ+N

$$f(Y\backslash\theta)=\frac{1}{\sqrt{(2\pi)^k|R_n|}}exp\left(-\frac{1}{2}[Y-H\theta]^T R_n^{-1}[Y-H\theta]\right)$$

$$\frac{\partial}{\partial\theta}ln\,f(Y\backslash\theta)=\frac{\partial}{\partial\theta}\left[-\frac{1}{2}[Y-H\theta]^T R_n^{-1}[Y-H\theta]\right]$$

$$=-\frac{1}{2}\frac{\partial}{\partial\theta}\left[-Y^T R_n^{-1}H\theta-\theta^T H^T R_n^{-1}Y+\theta^T H^T R_n^{-1}H\theta\right]$$

$$=-\frac{1}{2}\left[-\left(R_n^{-1}H\right)^T Y-H^T R_n^{-1}Y+\left[H^T R_n^{-1}H+\left(H^T R_n^{-1}H\right)^T\right]\theta\right]$$

$$=H^T R_n^{-1}Y-H^T R_n^{-1}H\theta$$

$$\hat{\theta}=\left(H^T R_n^{-1}H\right)^{-1}H^T R_n^{-1}Y$$

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ML估计性能

- 无偏估计（噪声零均值）

$$E\left\{\hat{\theta}_{LSW}\right\}=\left[H^T R_n^{-1} H\right]^{-1} H^T R_n^{-1} E\left\{Y\right\} = E\left\{\theta\right\}$$

- 有效估计

$$E\left\{\left[\theta-\hat{\theta}_{LSW}\right]\left[\theta-\hat{\theta}_{LSW}\right]^T\right\}=\left[H^T R_n^{-1} H\right]^{-1}$$

$$F = -E\left\{\frac{\partial}{\partial\theta}\left(H^T R_n^{-1} Y - H^T R_n^{-1} H\theta\right)\right\} = H^T R_n^{-1} H$$

MAP估计

$$f(\theta)=\frac{1}{\sqrt{(2\pi)^k|A_\theta|}}exp\left(-\frac{1}{2}[\theta-\mu_\theta]^T A_\theta^{-1}[\theta-\mu_\theta]\right)$$

$$\frac{\partial}{\partial\theta}ln\,f(Y\backslash\theta)+\frac{\partial}{\partial\theta}ln\,f(\theta)=0$$

$$\frac{\partial}{\partial\theta}ln\,f(\theta)=\frac{\partial}{\partial\theta}\left[-\frac{1}{2}[\theta-\mu_\theta]^T A_\theta^{-1}[\theta-\mu_\theta]\right]=-A_\theta^{-1}[\theta-\mu_\theta]$$

$$\Rightarrow H^T R_n^{-1}Y-H^T R_n^{-1}H\theta-A_\theta^{-1}[\theta-\mu_\theta]=0$$

$$\hat{\theta}_{MAP}=\left(H^T R_n^{-1}H+A_\theta^{-1}\right)^{-1}\left(H^T R_n^{-1}Y+A_\theta^{-1}\mu_\theta\right)$$

Q：LMS?

MAP估计性能

- 无偏估计

$$
\begin{aligned}
& E\left\{\hat{\theta}_{MAP}\right\} \\
& =\left(H^T R_n^{-1} H+A_\theta^{-1}\right)^{-1}\left(H^T R_n^{-1} E\{Y\}+A_\theta^{-1} \mu_\theta\right) \\
& =\left(H^T R_n^{-1} H+A_\theta^{-1}\right)^{-1}\left(H^T R_n^{-1} H \mu_\theta+A_\theta^{-1} \mu_\theta\right) \\
& =\mu_\theta
\end{aligned}
$$

MAP估计性能

- 有效性

$$令\Delta = H^T R_n^{-1} H + A_\theta^{-1}$$

$$\theta_\varepsilon = \theta - \hat{\theta}_{MAP} = \theta - \Delta^{-1} H^T R_n^{-1} H\theta - \Delta^{-1} A_\theta^{-1}\mu_\theta - \Delta^{-1} H^T R_n^{-1} N$$

$$= \Delta^{-1}\left[\left(H^T R_n^{-1} H + A_\theta^{-1}\right)\theta - H^T R_n^{-1} H\theta - A_\theta^{-1}\mu_\theta - H^T R_n^{-1} N\right]$$

$$= \Delta^{-1}\left[A_\theta^{-1}\left(\theta - \mu_\theta\right) - H^T R_n^{-1} N\right]$$

$$R_\varepsilon = E\left\{\Delta^{-1}\left[A_\theta^{-1}\left(\theta - \mu_\theta\right) - H^T R_n^{-1} N\right]\left[\left(\theta - \mu_\theta\right)^T A_\theta^{-1} - N^T R_n^{-1} H\right]\Delta^{-1}\right\}$$

$$= \Delta^{-1}\left[A_\theta^{-1} E\left\{\left(\theta - \mu_\theta\right)\left(\theta - \mu_\theta\right)^T\right\} A_\theta^{-1} + H^T R_n^{-1} E\left\{NN^T\right\} R_n^{-1} H\right]\Delta^{-1}$$

$$= \Delta^{-1}\left[A_\theta^{-1} + H^T R_n^{-1} H\right]\Delta^{-1} = \left[A_\theta^{-1} + H^T R_n^{-1} H\right]^{-1}$$

MAP估计性能

- **Cramer-Rao下限**

$$\frac{\partial}{\partial\theta} ln\, f(Y,\theta) = \frac{\partial}{\partial\theta} ln\, f(Y \backslash \theta) + \frac{\partial}{\partial\theta} ln\, f(\theta)$$

$$= H^T R_n^{-1} Y - H^T R_n^{-1} H\theta - A_\theta^{-1}\left[\theta - \mu_\theta\right]$$

$$\frac{\partial^2}{\partial^2\theta} ln\, f(Y,\theta) = -H^T R_n^{-1} H - A_\theta^{-1}$$

$$-\left[\frac{\partial^2}{\partial^2\theta} ln\, f(Y,\theta)\right]^{-1} = \left[H^T R_n^{-1} H + A_\theta^{-1}\right]^{-1}$$

MAP序贯估计

$$\hat{\theta}_{MAP} = \left(H^T R_n^{-1} H + A_\theta^{-1}\right)^{-1} \left(H^T R_n^{-1} Y + A_\theta^{-1} \mu_\theta\right)$$

$$= \left(H^T R_n^{-1} H + A_\theta^{-1}\right)^{-1} \left[H^T R_n^{-1} Y + A_\theta^{-1} \mu_\theta + H^T R_n^{-1} H \mu_\theta - H^T R_n^{-1} H \mu_\theta\right]$$

$$= \left(H^T R_n^{-1} H + A_\theta^{-1}\right)^{-1} \left[H^T R_n^{-1} \left(Y - H \mu_\theta\right) + \left(H^T R_n^{-1} H + A_\theta^{-1}\right) \mu_\theta\right]$$

$$= \mu_\theta + \left(H^T R_n^{-1} H + A_\theta^{-1}\right)^{-1} H^T R_n^{-1} \left(Y - H \mu_\theta\right)$$

$$= \mu_\theta + K \left(Y - H \mu_\theta\right)$$

其中$K = R_\varepsilon H^T R_n^{-1}$

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白噪声下MAP序贯估计

$$\hat{\theta}_{MAP_l} = \hat{\theta}_{MAP_{l-1}} + K_l\left(Y_l - H_l\hat{\theta}_{MAP_{l-1}}\right)$$

$$K_l = R_{\varepsilon_l} H_l^T R_{n_l}^{-1}$$

$$R_{\varepsilon_l} = \left(H_l^T R_{n_l}^{-1} H_l + R_{\varepsilon_{l-1}}^{-1}\right)^{-1}$$

$$H_l = \left[h_{l1} \ldots h_{lL}\right]$$

$$R_{n_l} = \sigma_l^2 I$$

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波形估计(连续信号)

- $y(t)=s(t)+n(t) \qquad 0\leq t \leq T$
- 由$y(t)$得到$s(t)$的估计—滤波
- 由$y(t)$得到$s(t+\alpha)(\alpha>0)$的估计—预测（外推）
- 由$y(t)$得到$s(t+\alpha)(\alpha<0)$的估计—平滑（内插）

- $y_k=H_k s_k+n_k \qquad k=1,2,\ldots$
- 由y_k得到s_k的估计—滤波
- 由y_k得到$s_{k+l|k}$的估计—预测（外推）
- 由y_k得到$s_{k-l|k}$的估计—平滑（内插）

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预测

零均值的平稳随机过程$s(t)$，由当前值预测$s(t+\alpha)(\alpha>0)$的信号估计值。

解：

$$LMS\left(\text{理想观测}\right):\hat{s}\left(t+\alpha\right)=as\left(t\right)$$

$$\text{正交：}\ E\left\{\left[s\left(t+\alpha\right)-as\left(t\right)\right]s\left(t\right)\right\}=0$$

$$\rightarrow a=\frac{R_s\left(\alpha\right)}{R_s\left(0\right)},\hat{s}\left(t+\alpha\right)=\frac{R_s\left(\alpha\right)}{R_s\left(0\right)}s\left(t\right)$$

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平滑

零均值的平稳随机过程$s(t)$，由两端点值估计任意时刻$s(t)(0\le t\le T)$的信号估计值。

解：

$$LMS\left(\text{理想观测}\right):\hat{s}\left(t\right)=as\left(0\right)+bs\left(T\right)$$

$$\text{正交}:\begin{cases}E\left\{\left[s\left(t\right)-as\left(0\right)-bs\left(T\right)\right]s\left(0\right)\right\}=0\\E\left\{\left[s\left(t\right)-as\left(0\right)-bs\left(T\right)\right]s\left(T\right)\right\}=0\end{cases}$$

平滑

$$\Rightarrow \begin{cases} R_s(t) - aR_s(0) - bR_s(T) = 0 \\ R_s(T-t) - aR_s(T) - bR_s(0) = 0 \end{cases}$$

$$\Rightarrow \begin{cases} a = \dfrac{R_s(0)R_s(t) - R_s(T)R_s(T-t)}{R_s^2(0) - R_s^2(T)} \\ b = \dfrac{R_s(0)R_s(T-t) - R_s(T)R_s(t)}{R_s^2(0) - R_s^2(T)} \end{cases}$$

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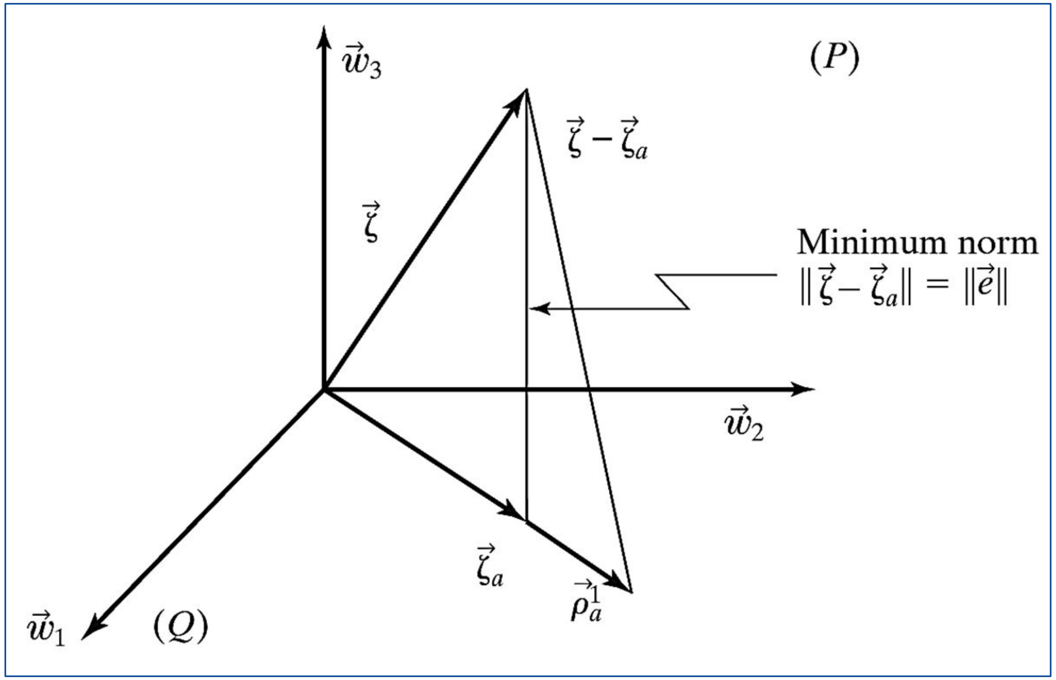
正交原理

$\vec{e} = \vec{\varsigma} - \vec{\varsigma}_a$

误差最小 ⇔ 正交原理

$$(\vec{e}, \vec{\varsigma}_a) = (\vec{\varsigma} - \vec{\varsigma}_a, \vec{\varsigma}_a) = 0$$

$$\Rightarrow (\vec{\varsigma} - \vec{\varsigma}_a, \vec{w}_l) = 0, l = 1, 2$$



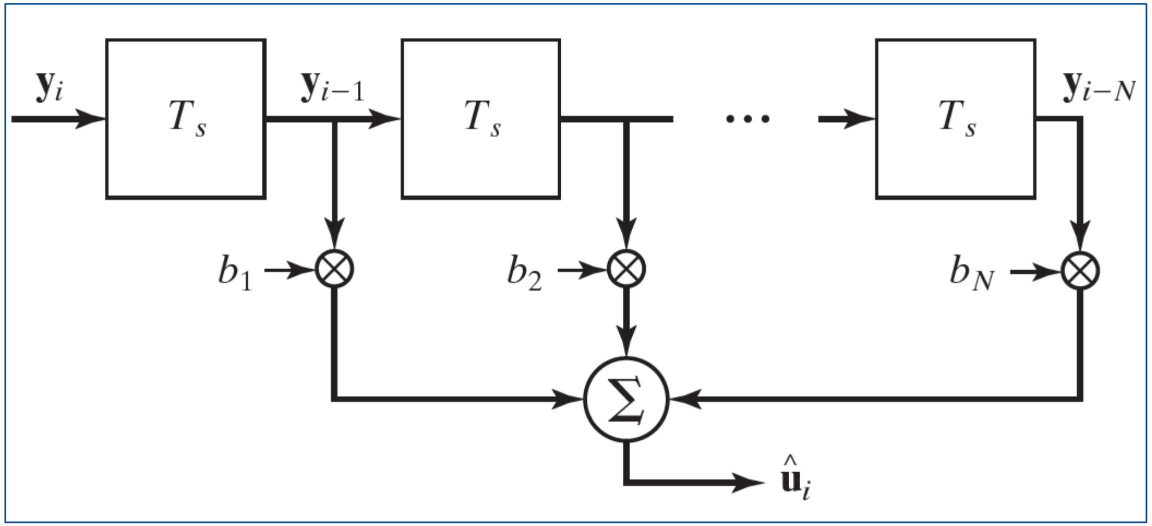
推广到k维：

$$\left(\vec{\varsigma} - \sum_{i=1}^{k} \beta_i \vec{w}_i, \vec{w}_j\right) = 0 \Rightarrow (\vec{\varsigma}, \vec{w}_j) = \sum_{i=1}^{k} \beta_i (\vec{w}_i, \vec{w}_j), j = 1, \ldots k$$

离散维纳滤波

$$y_i = u_i + z_i, i = 1,\dots L$$

$$\hat{u}_i = \sum_{m=1}^{N} b_m y_{i-m}$$



$$e_i = u_i - \hat{u}_i, i = 1,\dots, L$$

$$\varepsilon_N = E\left\{\left|e_i\right|^2\right\} \xrightarrow{MSE} E\left\{y_{i-l} e_i^*\right\} = 0$$

$$E\left\{y_{i-l} u_i^*\right\} = \sum_{m=1}^{N} b_m^* E\left\{y_{i-l} y_{i-m}^*\right\}, l = 1,\dots N$$

$$g_l^* = \sum_{m=1}^{N} b_m^* r_{m-l}$$

离散$Wienner-Hopf$方程：$g_l = \sum_{m=1}^{N} b_m r_{l-m}$

注：$r_{m-l} = r_{l-m}^*$

连续维纳滤波

$$y(t)=s(t)+n(t)\quad 0\le t\le T$$

$$\hat{s}(t)=\lim_{\substack{\Delta u\to 0\\ N\Delta u=T}}\sum_{k=1}^{N}h(t,u_k)\,y(u_k)\,\Delta u\Rightarrow\hat{s}(t)=\int_0^T h(t,u)\,y(u)\,du$$

$$E\left\{\left[s(t)-\int_0^T h(t,u)\,y(u)\,du\right]y(\tau)\right\}=0$$

$$\Rightarrow R_{sy}(t,\tau)=\int_0^T h(t,u)\,R_y(u,\tau)\,du,\ 0\le\tau\le T$$

连续维纳滤波

- 平稳随机过程$y(t)$和$s(t)$，均值为零，且二者联合平稳
- 因果系统

$$\hat{s}(t)=\int_{-\infty}^{t} h(t-u)\,y(u)\,du$$

$$\Rightarrow R_{sy}(t-\tau)=\int_{-\infty}^{t} h(t-u)\,R_{y}(u-\tau)\,du$$

$$Wienner-Hopf\text{积分方程}R_{sy}(\eta)=\int_{0}^{\infty} h(\lambda)\,R_{y}(\eta-\lambda)\,d\lambda,\ 0<\eta<\infty$$

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模型

系统动态模型	$\vec{u}_k = A(k,k-1)\vec{u}_{k-1} + B_{k-1}\vec{\xi}_{k-1}$
系统噪声协方差	$\varXi_k = E\{\vec{\xi}_k \vec{\xi}_k^{T*}\}$
当前估计误差	$\vec{e}_k = \vec{u}_k - \hat{\vec{u}}_k$
测量模型	$\vec{y}_k = H_k \vec{u}_k + \vec{z}_k$
测量噪声协方差	$V_k = E\{\vec{z}_k \vec{z}_k^{T*}\}$
新息矢量	$\vec{\varepsilon}_{k,k-1} = \vec{y}_k - \hat{\vec{y}}_k = \vec{y}_k - H_k \hat{\vec{u}}_{k,k-1}$
当前信号估计	$\hat{\vec{u}}_k = \hat{\vec{u}}_{k,k-1} + G_k \vec{\varepsilon}_{k,k-1}$
当前信号预测	$\hat{\vec{u}}_{k,k-1} = A(k,k-1)\hat{\vec{u}}_{k-1}$

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矢量空间的正交

新息

$$\vec{\varepsilon}_{k,k-1}=\vec{y}_k-\hat{\vec{y}}_k=\vec{y}_k-H_k\hat{\vec{u}}_{k,k-1}=H_k\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)+\vec{z}_k$$

正交原理

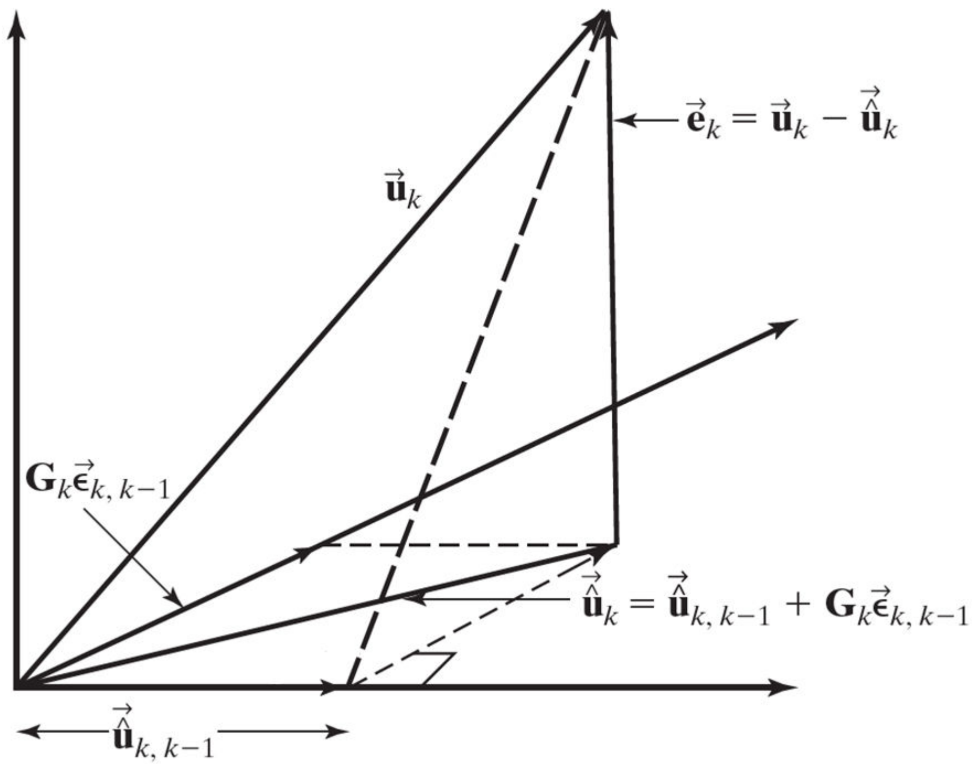
$$E\left\{\hat{\vec{y}}_k\vec{\varepsilon}_{k,\ k-1}^{\,T*}\right\}=0\Leftrightarrow E\left\{\hat{\vec{u}}_{k,k-1}\vec{\varepsilon}_{k,\ k-1}^{\,T*}\right\}=0$$

且$E\left\{\hat{\vec{u}}_k\vec{e}_k^{\,T*}\right\}=0$

而$\hat{\vec{u}}_k=\hat{\vec{u}}_{k,k-1}+G_k\vec{\varepsilon}_{k,k-1}$

$$\Rightarrow E\left\{\left(\hat{\vec{u}}_{k,k-1}+G_k\vec{\varepsilon}_{k,k-1}\right)\vec{e}_k^{\,T*}\right\}=0$$

$$E\left\{\hat{\vec{u}}_{k,k-1}\vec{e}_k^{\,T*}\right\}=0;\ E\left\{\vec{\varepsilon}_{k,k-1}\vec{e}_k^{\,T*}\right\}=0$$



卡尔曼增益

$$E\left\{\vec{\varepsilon}_{k,k-1}\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}-G_k\vec{\varepsilon}_{k,k-1}\right)^{T*}\right\}=0\Rightarrow E\left\{\vec{\varepsilon}_{k,k-1}\vec{u}_k^{T*}\right\}=E\left\{\vec{\varepsilon}_{k,k-1}\vec{\varepsilon}_{k,k-1}^{T*}\right\}G_k^{T*}$$

$$\Rightarrow \text{卡尔曼增益}G_k=E\left\{\vec{u}_k\vec{\varepsilon}_{k,k-1}^{T*}\right\}\left[E\left\{\vec{\varepsilon}_{k,k-1}\vec{\varepsilon}_{k,k-1}^{T*}\right\}\right]^{-1}$$

$$E\left\{\vec{u}_k\vec{\varepsilon}_{k,k-1}^{T*}\right\}=E\left\{\vec{u}_k\vec{\varepsilon}_{k,k-1}^{T*}\right\}-E\left\{\hat{\vec{u}}_{k,k-1}\vec{\varepsilon}_{k,k-1}^{T*}\right\}=E\left\{\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)\left[H_k\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)+z_k\right]^{T*}\right\}=C_{k,k-1}H_k^{T*}$$

$$\text{预测误差协方差}C_{k,k-1}=E\left\{\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)^{T*}\right\}$$

$$E\left\{\vec{\varepsilon}_{k,k-1}\vec{\varepsilon}_{k,k-1}^{T*}\right\}=E\left\{\left[H_k\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)+z_k\right]\left[H_k\left(\vec{u}_k-\hat{\vec{u}}_{k,k-1}\right)+z_k\right]^{*}\right\}=H_kC_{k,k-1}H_k^{T*}+V_k$$

$$\Rightarrow G_k=C_{k,k-1}H_k^{T*}\left[H_kC_{k,k-1}H_k^{T*}+V_k\right]^{-1}$$

误差协方差矩阵

当前信号误差协方差矩阵$C_k = E\left\{\vec{e}_k \vec{e}_k^{T*}\right\}$

$$
\begin{aligned}
C_k &= \left\|\vec{e}_k\right\|^2 = \left\|\vec{u}_k - \hat{\vec{u}}_k\right\|^2 = \left\|\vec{u}_k - \hat{\vec{u}}_{k,k-1}\right\|^2 - \left\|G_k \vec{\varepsilon}_{k,k-1}\right\|^2 \\
&= E\left\{\left(\vec{u}_k - \hat{\vec{u}}_{k,k-1}\right)\left(\vec{u}_k - \hat{\vec{u}}_{k,k-1}\right)^{T*}\right\} - E\left\{G_k \vec{\varepsilon}_{k,k-1}\left(G_k \vec{\varepsilon}_{k,k-1}\right)^{T*}\right\} \\
&= C_{k,k-1} - G_k E\left\{\vec{\varepsilon}_{k,k-1} \vec{\varepsilon}_{k,k-1}^{T*}\right\} G_k^{T*} \\
&= C_{k,k-1} - G_k H_k C_{k,k-1}
\end{aligned}
$$

$$
\begin{aligned}
C_{k,\ k-1} &= E\left\{\left[A(k,k-1)\left(\vec{u}_{k-1} - \hat{\vec{u}}_{k-1}\right) + B_{k-1}\vec{\xi}_{k-1}\right] \cdot \left[A(k,k-1)\left(\vec{u}_{k-1} - \hat{\vec{u}}_{k-1}\right) + B_{k-1}\vec{\xi}_{k-1}\right]^{T*}\right\} \\
&= A(k,k-1) C_{k-1} A(k,k-1)^{T*} + B_{k-1} \Xi_k B_k^{T*}
\end{aligned}
$$

序贯实现

预测方程

$$\hat{\vec{u}}_{k,k-1} = A(k,k-1)\hat{\vec{u}}_{k-1}$$

$$C_{k,\ k-1} = A(k,k-1)C_{k-1}A(k,k-1)^{T*} + B_{k-1}\Xi_k B_k^{T*}$$

更新方程

$$\hat{\vec{u}}_k = \hat{\vec{u}}_{k,k-1} + G_k\vec{\varepsilon}_{k,k-1}$$

$$C_k = C_{k,k-1} - G_k H_k C_{k,k-1}$$

$Kalman$增益

$$G_k = C_{k,k-1}H_k^{T*}\left[H_k C_{k,k-1}H_k^{T*} + V_k\right]^{-1}$$

summary

- 基于检测部分中获得的波形形式PDF，实现波形中参量估计
- 某些松弛条件下，Bayes估计也可序贯实现
- 波形估计基于LMS的正交原理

Ref： §5.7、 §5.10&第六章(赵版)、第13章 (KAY版)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