

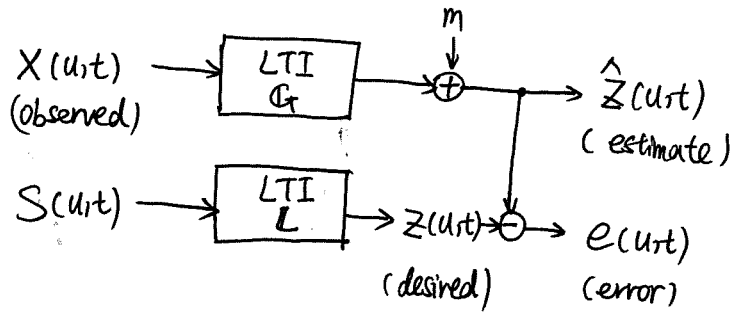
[Estimation]

(Chap 15-6)

MMSE estimator for w.s.s. ^{random} sequences ~~as~~ LTI operators

$X(u,t), S(u,t)$ are ^{jointly} w.s.s., with known 2nd moment description.

(1) Minimize $MSE \equiv E|e(u,t)|^2 = R_e(0) = R_e(0) + |m_e|^2$



We have

$$\begin{cases} \hat{z} = m + GX \\ z = LS \\ e = \hat{z} - z \end{cases}$$

$$1^\circ m_e = m_z - m_z = m + m_x G(0) - m_s L(0)$$

Let $m_e = 0$, we have $m = m_s L(0) - m_x G(0)$

$$2^\circ R_{e_0}(\tau) = E\left\{ \left(\hat{z}_0(u, t+\tau) - z_0(u, t+\tau) \right) \left(\hat{z}_0(u, t) - z_0(u, t) \right)^* \right\}$$

$$= R_{\hat{z}_0}(\tau) + R_{z_0}(\tau) - R_{\hat{z}_0 z_0^*}(\tau) - R_{z_0 \hat{z}_0^*}(\tau)$$

$$\therefore S_{e_0}(f) = S_{\hat{z}_0}(f) + S_{z_0}(f) - S_{\hat{z}_0 z_0^*}(f) - S_{z_0 \hat{z}_0^*}(f)$$

$$= S_{x_0}(f) |G(f)|^2 + S_{s_0}(f) |L(f)|^2 - G(f) S_{x_0 s_0^*}(f) L^*(f) - L(f) S_{s_0 x_0^*}(f) G^*(f)$$

$$\therefore R_{e_0}(0) = \int_{-\frac{1}{2}}^{\frac{1}{2}} S_{e_0}(f) df$$

$$= \int_{-\frac{1}{2}}^{\frac{1}{2}} S_{x_0}(f) \left| G(f) - \frac{S_{x_0 s_0^*}(f) L(f)}{S_{s_0}(f)} \right|^2 df +$$

$$\int_{-\frac{1}{2}}^{\frac{1}{2}} S_x(f) |L(f)|^2 - \frac{|S_{S_x X^*}(f) L(f)|^2}{S_{X_o}(f)} df$$

The 2nd term doesn't depend on $G(f)$, minimize $R_e(0)$ gives

$$G(f) = L(f) S_{S_x X^*}(f) (S_{X_o}(f))^{-1}$$

Hence

$$G_{opt}(f) = L(f) S_{S_x X^*}(f) (S_{X_o}(f))^{-1}$$

$$m_{opt} = \cancel{m_s L(0)} \cancel{G_{opt}(0)} m_s L(0) - m_x G_{opt}(0)$$

$$MMSE = \int_{-\frac{1}{2}}^{\frac{1}{2}} S_x(f) |L(f)|^2 - \frac{|S_{S_x X^*}(f) L(f)|^2}{S_{X_o}(f)} df$$

Note: 1° The optimal choices are called Wiener filters.

2° ~~MMSE~~ LMMSE estimator has a similar form, except it's noncentral.

(2) Minimize MSE with causal G .

1° Step is the same.

$$2° R_e(0) = MMSE + \int_{-\frac{1}{2}}^{\frac{1}{2}} S_{X_o}(f) \left| G(f) - \frac{L(f) S_{S_x X^*}(f)}{S_{X_o}(f)} \right|^2 df$$

Find causal system H that simulates X , s.t. $S_{X_o}(f) = |H(f)|^2$, then $R_e(0) - MMSE =$

$$\int_{-\frac{1}{2}}^{\frac{1}{2}} \left| H(f) G(f) - \frac{L(f) S_{S_x X^*}(f)}{H^*(f)} \right|^2 df$$

$$\begin{aligned} \text{(Parseval's thm)} &= \sum_{\tau=-\infty}^{+\infty} \left| \mathcal{F}^{-1}\{H(f)G(f)\} - \mathcal{F}^{-1}\left\{\frac{L(f) S_{S_x X^*}(f)}{H^*(f)}\right\} \right|^2 \\ &= \sum_{\tau=0}^{+\infty} \left| \mathcal{F}^{-1}\{H(f)G(f)\} - \mathcal{F}^{-1}\left\{\frac{L(f) S_{S_x X^*}(f)}{H^*(f)}\right\} \right|^2 \\ &\quad + \sum_{\tau=-\infty}^{-1} \left| \mathcal{F}^{-1}\left\{\frac{L(f) S_{S_x X^*}(f)}{H^*(f)}\right\} \right|^2 \end{aligned}$$

$$1^{st} \text{ term} = \sum_{\tau=-\infty}^{+\infty} \left| \mathcal{F}^{-1} \{ H(f) G(f) \} - U_r(\tau) \mathcal{F}^{-1} \left\{ \frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)} \right\} \right|^2$$

($U_r(\tau)$ is unit-step fn)

$$= \int_{-\frac{1}{2}}^{\frac{1}{2}} \left| H(f) G(f) - \mathcal{F} \left\{ U_r(\tau) \mathcal{F}^{-1} \left\{ \frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)} \right\} \right\} \right|^2 df$$

Minimize ~~MMSE~~ $\int_{-\frac{1}{2}}^{\frac{1}{2}} \dots df$ gives,

$$G(f) = H^{-1}(f) \mathcal{F} \left\{ U_r(\tau) \mathcal{F}^{-1} \left\{ \frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)} \right\} \right\}$$

Hence,

~~$M_{opt, causal}$~~

$$G_{opt, causal}(f) = (H^{-1}(f)) \mathcal{F} \left\{ U_r(\tau) \mathcal{F}^{-1} \left\{ \frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)} \right\} \right\}$$

$$M_{opt, causal} = m_s L(0) - m_x G_{opt, causal}(0)$$

$$MMSE_{causal} = \int_{-\frac{1}{2}}^{\frac{1}{2}} S_S(f) |L(f)|^2 df - \sum_{\tau=0}^{+\infty} \left| \mathcal{F}^{-1} \left\{ \frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)} \right\} \right|^2$$

$$= \int_{-\frac{1}{2}}^{\frac{1}{2}} S_S(f) |L(f)|^2 - \left| \mathcal{F} \left\{ \frac{S_{S_x S_x^*}(f) L(f)}{H^*(f)} \right\} \right|^2 df$$

Note: Eliminating $\mathcal{F} \{ U_r(\tau) \mathcal{F}^{-1} \{ \cdot \} \}$ gives the MMSE estimator.

(Causal operator \mathcal{C} for $\mathcal{T} = \mathcal{Z}$.)

We call $\mathcal{C} = \mathcal{F} U_r(\tau) \mathcal{F}^{-1}$ a causal part operator. It's a linear operator.

Suppose $\frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)}$ is rational fn of z , and has no repeated poles.

we can write

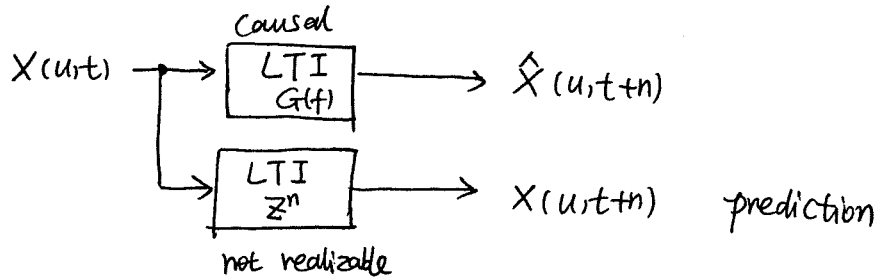
$$\frac{L(f) S_{S_x S_x^*}(f)}{H^*(f)} = \sum_{n=1}^D \frac{C_n z^{k_n}}{z - d_n}$$

If $\begin{cases} |d_n| > 1 \\ k_n \geq 1 \end{cases}$: $\frac{C_n z^{k_n}}{z - d_n} = \frac{(-d_n)^{-1} C_n z^{k_n}}{1 - d_n^{-1} z} = C_n (-d_n)^{-1} \sum_{j=0}^{\infty} d_n^{-j} z^{j+k_n}$

then $\mathcal{C} \frac{C_n z^{k_n}}{z - d_n} = 0$

If $\begin{cases} |d_n| < 1 \\ k_n \leq 1 \end{cases}$: $\frac{C_n z^{k_n}}{z - d_n} = \frac{C_n z^{k_n-1}}{1 - d_n z^{-1}} = C_n \sum_{j=0}^{\infty} d_n^j z^{k_n-j-1}$

E.g.: (pure prediction)



$$m_x = 0, S_x(f) = \frac{1}{|1 - az^{-1}|^2} \quad (|a| < 1)$$

The ~~best~~ causal MMSE estimator,

with $S_{x\hat{x}}(f) = S_x(f) = \frac{1}{|1 - az^{-1}|^2}$

$$H(f) = \frac{1}{1 - az^{-1}}, \quad L(f) = z^n$$

is $G_{opt, causal} = \frac{(H(f))^{-1} \circ L(f) S_{x\hat{x}}(f)}{H^*(f)}$

$$= (H(f))^{-1} \mathcal{F}^{-1} \{ \frac{z^n}{1 - az^{-1}} \}$$

$$= (H(f))^{-1} \mathcal{F}^{-1} \{ \sum_{m=0}^{\infty} a^m z^{-(m+n)} \}$$

$$= (H(f))^{-1} \mathcal{F}^{-1} \{ a^{\tau+n} U_r(\tau+n) \}$$

$$= (H(f))^{-1} \mathcal{F}^{-1} \{ a^{\tau+n} U_r(\tau) \}$$

$$= (H(f))^{-1} \frac{a^n}{1 - az^{-1}}$$

$$= a^n$$

$$\therefore g_{opt, causal}(t) = \mathcal{F}^{-1} G_{opt, causal} = a^n \delta(t)$$

$$\therefore \hat{X}(u,t+n) = (g * X)(u,t) = a^n X(u,t)$$

is the estimated prediction.

random wave form
~~in~~

AMMSE estimator for w.s.s. as LTI operators

Results are similar to AMMSE estimator for w.s.s. sequences.

(1) AMMSE estimator

$$G_{opt}(f) = \frac{L(f) S_{s_0 x_0}^*(f)}{S_{x_0}(f)}$$

$$m_{opt} = m_s L(0) - m_x G_{opt}(0)$$

$$\begin{aligned} \text{MMSE} &= \int_{-\infty}^{+\infty} |L(f)|^2 \left[S_{s_0}(f) - \frac{|S_{s_0 x_0}^*(f)|^2}{S_{x_0}(f)} \right] df \\ &= \int_{-\infty}^{+\infty} |L(f)|^2 S_{s_0}(f) - S_{z_0}(f) df \end{aligned}$$

(2) Causal AMMSE estimator

$$G_{opt, causal}(f) = \frac{1}{H(f)} \mathcal{F} U_r(t) \mathcal{F}^{-1} \left\{ \frac{L(f) S_{s_0 x_0}^*(f)}{H^*(f)} \right\}$$

where $S_{x_0}(f) = |H(f)|^2$, H is causal.

$$m_{opt, causal} = m_s L(0) - m_x G_{opt, causal}(0)$$

$$\begin{aligned} \text{MMSE}_{causal} &= \int_{-\infty}^{+\infty} |L(f)|^2 S_{s_0}(f) df \\ &\quad - \int_0^{+\infty} \left| \mathcal{F}^{-1} \left\{ \frac{L(f) S_{s_0 x_0}^*(f)}{H^*(f)} \right\} \right|^2 dt \\ &= \int_{-\infty}^{+\infty} |L(f)|^2 S_{s_0}(f) - \left| \mathcal{C} \left\{ \frac{L(f) S_{s_0 x_0}^*(f)}{H^*(f)} \right\} \right|^2 df \\ &= \int_{-\infty}^{+\infty} |L(f)|^2 S_{s_0}(f) - S_{z_0}(f) df \end{aligned}$$