

Homework #3 Solutions

1.

(1) (5%)

$$L_A = f(\mathbf{x}; A) = \frac{1}{(2\pi\sigma_\omega^2)^{M/2}} e^{-\frac{1}{2\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)]^2}$$

$$\frac{\partial \ln L_A}{\partial A} = \frac{\partial}{\partial A} \left[-\frac{M}{2} \ln(2\pi\sigma_\omega^2) - \frac{1}{2\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)]^2 \right] = \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)] s(n) = 0$$

$$A_{ML} = \frac{\sum_{n=0}^{M-1} x(n) s(n)}{\sum_{n=0}^{M-1} s^2(n)}$$

(2) (5%)

$$f(\mathbf{x} | A) = \frac{1}{(2\pi\sigma_\omega^2)^{M/2}} e^{-\frac{1}{2\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)]^2}$$

$$f(A) = \frac{1}{\sqrt{2\pi\sigma_A^2}} e^{-\frac{1}{2\sigma_A^2} (A - \bar{A})^2}$$

$$\frac{\partial}{\partial A} [\ln f(\mathbf{x} | A) + \ln f(A)] = \frac{\partial}{\partial A} \left[-\frac{M}{2} \ln(2\pi\sigma_\omega^2) - \frac{1}{2\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)]^2 - \frac{1}{2} \ln(2\pi\sigma_A^2) - \frac{1}{2\sigma_A^2} (A - \bar{A})^2 \right]$$

$$= \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)] s(n) - \frac{1}{\sigma_A^2} (A - \bar{A}) = 0$$

$$A_{MAP} \left[\frac{1}{\sigma_A^2} + \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} s^2(n) \right] = \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} x(n) s(n) + \frac{1}{\sigma_A^2} \bar{A}$$

$$A_{MAP} = \frac{\frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} x(n) s(n) + \frac{1}{\sigma_A^2} \bar{A}}{\frac{1}{\sigma_A^2} + \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} s^2(n)} = \frac{\sum_{n=0}^{M-1} x(n) s(n) + \frac{\sigma_\omega^2}{\sigma_A^2} \bar{A}}{\sum_{n=0}^{M-1} s^2(n) + \frac{\sigma_\omega^2}{\sigma_A^2}}$$

(3) (6%)

$$\frac{\partial}{\partial A} [\ln f(\mathbf{x} | A) + \ln f(A)] = \frac{\partial}{\partial A} \left[-\frac{M}{2} \ln(2\pi\sigma_\omega^2) - \frac{1}{2\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)]^2 + \ln A - \ln \sigma_A^2 - \frac{A^2}{2\sigma_A^2} \right]$$

$$= \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} [x(n) - As(n)] s(n) + \frac{1}{A} - \frac{A}{\sigma_A^2} = 0$$

$$A_{MAP}^2 \left[\frac{1}{\sigma_A^2} + \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} s^2(n) \right] - \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} x(n)s(n)A_{MAP} - 1 = 0$$

$$\because A \geq 0$$

$$\begin{aligned} A_{MAP} &= \frac{\frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} x(n)s(n) + \sqrt{\frac{1}{\sigma_\omega^4} \left[\sum_{n=0}^{M-1} x(n)s(n) \right]^2 + 4 \left[\frac{1}{\sigma_A^2} + \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} s^2(n) \right]}}{2 \left[\frac{1}{\sigma_A^2} + \frac{1}{\sigma_\omega^2} \sum_{n=0}^{M-1} s^2(n) \right]} \\ &= \frac{\sum_{n=0}^{M-1} x(n)s(n) + \sqrt{\left[\sum_{n=0}^{M-1} x(n)s(n) \right]^2 + 4 \left[\frac{\sigma_\omega^4}{\sigma_A^2} + \sigma_\omega^2 \sum_{n=0}^{M-1} s^2(n) \right]}}{2 \left[\frac{\sigma_\omega^2}{\sigma_A^2} + \sum_{n=0}^{M-1} s^2(n) \right]} \end{aligned}$$

2. (16%)

LMMSE estimator = Wiener filter

The normal equation: $\mathbf{R}\mathbf{f} = \mathbf{g} \Rightarrow E(\mathbf{xx}^T)\mathbf{f} = E(A\mathbf{x})$

$$\Rightarrow \begin{bmatrix} 1 + \frac{\sigma^2}{\sigma_A^2} & \mathbf{1} \\ \mathbf{1} & 1 + \frac{\sigma^2}{\sigma_A^2} \end{bmatrix} \begin{bmatrix} f_0 \\ \vdots \\ f_{M-1} \end{bmatrix} = \mathbf{1}_{M \times 1}$$

\Rightarrow Subtraction between any two equations from the above equation set:

$$\frac{\sigma^2}{\sigma_A^2} f_i - \frac{\sigma^2}{\sigma_A^2} f_j = 0, \quad \forall i \neq j$$

$$\therefore f_0 = f_1 = \dots = f_{M-1}$$

$$\therefore \left(1 + \frac{\sigma^2}{\sigma_A^2}\right) f_0 + (M-1) f_0 = 1 \Rightarrow f_0 = \frac{\sigma_A^2}{M\sigma_A^2 + \sigma^2}$$

$$\therefore f_n = \frac{\sigma_A^2}{M\sigma_A^2 + \sigma^2}, \quad n = 0, 1, \dots, M-1$$

$$\therefore \hat{\mathbf{A}}_{LMMSE} = \mathbf{f}^T \mathbf{x} = \frac{\sigma_A^2}{M\sigma_A^2 + \sigma^2} \sum_{n=0}^{M-1} x(n)$$

3.

$$\begin{aligned}
r(i-j) &= E\{x(n-n_0-i+1)x(n-n_0-j+1)\} = E\{x(n-i)x(n-j)\} \\
&= E\{[w(n-i) + aw(n-50-i)][w(n-j) + aw(n-50-j)]\} \\
&= (1+a^2)\delta(i-j) + a\delta(i-j+50) + a\delta(i-j-50) \\
\mathbf{g} &= [E\{aw(n-50)x(n-n_0)\} \quad \cdots \quad E\{aw(n-50)x(n-\hat{n}-L+1)\}]^T \\
E\{aw(n-50)x(n-n_0)\} &= E\{aw(n-50)[w(n-n_0) + aw(n-n_0-50)]\} \\
&= a\delta(n_0-50) + a^2\delta(\hat{n}) \\
E\{aw(n-50)x(n-n_0-L+1)\} &= E\{aw(n-50)[w(n-n_0-L+1) + aw(n-n_0-L+1-50)]\} \\
&= a\delta(n_0+L-1-50) + a^2\delta(n_0+L-1) \\
\mathbf{g} &= [a\delta(n_0-50) + a^2\delta(n_0) \quad \cdots \quad a\delta(n_0+L-1-50) + a^2\delta(n_0+L-1)]^T
\end{aligned}$$

(1) (8%)

i. prediction distance, $n_0 = 30$,

$$\begin{aligned}
\mathbf{g} &= [a\delta(n_0-50) + a^2\delta(n_0) \quad \cdots \quad a\delta(n_0+L-1-50) + a^2\delta(n_0+L-1)]^T \\
&= [a\delta(-20) + a^2\delta(30) \quad \cdots \quad a\delta(-6) + a^2\delta(44)]^T = \mathbf{0} \\
r(i-j) &= (1+a^2)\delta(i-j) + a\delta(i-j+50) + a\delta(i-j-50) \\
\mathbf{Rc} = \mathbf{g} = \mathbf{0} &\Rightarrow \mathbf{c} = \mathbf{0} \Rightarrow \hat{x}(n) = 0 \\
\text{Prediction error: } e(n) &= aw(n-50) - 0 = aw(n-50)
\end{aligned}$$

ii. prediction distance, $n_0 = 40$,

$$\begin{aligned}
\mathbf{g} &= [a\delta(n_0-50) + a^2\delta(n_0) \quad \cdots \quad a\delta(n_0+L-1-50) + a^2\delta(n_0+L-1)]^T \\
&= [a\delta(-10) + a^2\delta(40) \quad \cdots \quad a\delta(4) + a^2\delta(54)]^T \\
&= [0 \quad \cdots \quad 0 \quad a \quad 0 \quad 0 \quad 0 \quad 0]^T_{15 \times 1} \\
r(i-j) &= (1+a^2)\delta(i-j) + a\delta(i-j+50) + a\delta(i-j-50) \\
\mathbf{Rc} = \mathbf{g} &\Rightarrow (1+a^2)\mathbf{Ic} = [0 \quad \cdots \quad 0 \quad a \quad 0 \quad 0 \quad 0 \quad 0]^T_{15 \times 1} \\
c(n) &= \begin{cases} \frac{a}{1+a^2}, n=11 \\ 0, n \neq 11 \end{cases} \\
\hat{x}(n) &= \frac{a}{1+a^2}x(n-40-11+1) = \frac{a}{1+a^2}x(n-50) \\
\text{Prediction error:} &
\end{aligned}$$

$$\begin{aligned}
e(n) &= aw(n-50) - \hat{x}(n) \\
&= aw(n-50) - \frac{a}{1+a^2} w(n-50) - \frac{a^2}{1+a^2} w(n-100) \\
&= \frac{a^3}{1+a^2} w(n-50) - \frac{a^2}{1+a^2} w(n-100)
\end{aligned}$$

iii. prediction distance, $\hat{n} = 50$.

$$\begin{aligned}
\mathbf{g} &= \left[a\delta(n_0 - 50) + a^2\delta(n_0) \quad \cdots \quad a\delta(n_0 + L - 1 - 50) + a^2\delta(n_0 + L - 1) \right]^T \\
&= \left[a\delta(0) + a^2\delta(50) \quad \cdots \quad a\delta(14) + a^2\delta(64) \right]^T \\
&= \left[a \quad \cdots \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \right]_{15 \times 1}^T
\end{aligned}$$

$$r(i-j) = (1+a^2)\delta(i-j) + a\delta(i-j+50) + a\delta(i-j-50)$$

$$\mathbf{Rc} = \mathbf{g} \Rightarrow \mathbf{Rc} = \mathbf{g} \Rightarrow (1+a^2)\mathbf{Ic} = \left[a \quad \cdots \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \right]_{15 \times 1}^T$$

$$c(n) = \begin{cases} \frac{a}{1+a^2}, n=1 \\ 0, n \neq 1 \end{cases}$$

$$\hat{x}(n) = \frac{a}{1+a^2} x(n-50-1+1) = \frac{a}{1+a^2} x(n-50)$$

Prediction error:

$$\begin{aligned}
e(n) &= aw(n-50) - \hat{x}(n) \\
&= aw(n-50) - \frac{a}{1+a^2} w(n-50) - \frac{a^2}{1+a^2} w(n-100) \\
&= \frac{a^3}{1+a^2} w(n-50) - \frac{a^2}{1+a^2} w(n-100)
\end{aligned}$$

(2) (8%)

From the range of \mathbf{g} , $n_0 - 50 \leq 0$ and $n_0 + L - 1 - 50 \geq 0$,
 $50 - L + 1 \leq n_0 \leq 50 \Rightarrow 36 \leq n_0 \leq 50$

4. (16%)

$$\begin{aligned}
\sigma_d^2 &= E\{d^2(n)\} - E\{d(n)\}^2 \\
&= E\left\{\left(\sum_{i=0}^{\infty} h(i)w(n-i)\right)\left(\sum_{j=0}^{\infty} h(j)w(n-j)\right)\right\} \\
&= \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} h(i)h(j)E\{w(n-i)w(n-j)\} \\
&= \sigma_w^2 \sum_{i=0}^{\infty} h^2(i) \\
g(i) &= E\{x(n-i)d(n)\} = E\left\{x(n-i)\sum_{j=0}^{\infty} h(j)w(n-j)\right\} \\
&= \sum_{j=0}^{\infty} h(j)E\{w(n-i)w(n-j)\} \\
&= \sigma_w^2 h(i) \\
(\because E\{w(n-i)w(n-j)\}) &= \begin{cases} \sigma_w^2, i=j \\ 0, \text{otherwise} \end{cases} \\
\Rightarrow \mathbf{f}^* = \mathbf{R}^{-1} \mathbf{g} &= \frac{1}{\sigma_w^2} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \sigma_w^2 h(1) \\ \sigma_w^2 h(2) \\ \vdots \\ \sigma_w^2 h(L-1) \end{bmatrix} = \begin{bmatrix} h(1) \\ h(2) \\ \vdots \\ h(L-1) \end{bmatrix}
\end{aligned}$$

By the definition of J_{\min} , we can obtain

$$\begin{aligned}
J_{\min} &= \sigma_d^2 - (\mathbf{f}^*)^T \mathbf{g} = \sigma_w^2 \sum_{i=0}^{\infty} h^2(i) - \begin{bmatrix} h(1) \\ h(2) \\ \vdots \\ h(L-1) \end{bmatrix}^T \begin{bmatrix} \sigma_w^2 h(1) \\ \sigma_w^2 h(2) \\ \vdots \\ \sigma_w^2 h(L-1) \end{bmatrix} \\
&= \sigma_w^2 \sum_{i=0}^{\infty} h^2(i) - \sigma_w^2 \sum_{i=1}^{L-1} h^2(i) \\
&= \sigma_w^2 \sum_{i=L}^{\infty} h^2(i)
\end{aligned}$$

5.

(1) (5%)

$$r(i) = \sum_{n=-\infty}^{\infty} h(n)h(n+i), \quad g(i) = \sum_{n=-\infty}^{\infty} h(n-i)\delta(n) = h(-i)$$

$$\Rightarrow r(0) = \sum_{n=-\infty}^{\infty} h^2(n) = 1^2 + (-1)^2 + 0.25^2 = \frac{33}{16},$$

$$r(1) = \sum_{n=-\infty}^{\infty} h(n)h(n+1) = h(0)h(1) + h(1)h(2) = -\frac{5}{4},$$

$$g(0) = h(0) = 1, \quad g(1) = h(-1) = 0$$

$$\therefore \mathbf{R}\mathbf{f} = \mathbf{g} \Rightarrow \begin{bmatrix} r(0) & r(1) \\ r(1) & r(0) \end{bmatrix} \begin{bmatrix} f(0) \\ f(1) \end{bmatrix} = \begin{bmatrix} g(0) \\ g(1) \end{bmatrix} \Rightarrow \begin{bmatrix} 33/16 & -5/4 \\ -5/4 & 33/16 \end{bmatrix} \begin{bmatrix} f(0) \\ f(1) \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\Rightarrow \mathbf{f}^* = \mathbf{R}^{-1}\mathbf{g} = \frac{256}{689} \begin{bmatrix} 33/16 & 5/4 \\ 5/4 & 33/16 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 528/689 \\ 320/689 \end{bmatrix} = \begin{bmatrix} 0.7663 \\ 0.4644 \end{bmatrix}$$

(2) (5%)

$$J_{\min} = \delta^2(n) - \mathbf{f}^T \mathbf{g} = 1 - \frac{528}{689} = \frac{161}{689} = 0.2336$$

(3) (6%)

$$H(z) = 1 - z^{-1} + 0.25z^{-2}$$

$$\begin{aligned} & \frac{1 + z^{-1} + \dots}{1 - z^{-1} + 0.25z^{-2}} = \frac{1}{1 - z^{-1} + 0.25z^{-2}} \\ & \frac{z^{-1} + 0.25z^{-2}}{z^{-1} - z^{-2} + 0.25z^{-3}} \end{aligned}$$

Let $H'(z)$ be the truncated $1/H(z)$

$$\begin{aligned} H(z)H'(z) &= (1 - z^{-1} + 0.25z^{-2})(1 + z^{-1}) = 1 + z^{-1} - z^{-1} - z^{-2} + 0.25z^{-2} + 0.25z^{-3} \\ &= 1 - 0.75z^{-2} + 0.25z^{-3} \end{aligned}$$

$$\Rightarrow \delta'(0) = 1, \quad \delta'(1) = 0, \quad \delta'(2) = -0.75, \quad \delta'(3) = 0.25$$

$$J = [\delta(n) - \delta'(n)]^2 = (0.75)^2 + (0.25)^2 = \frac{9}{16} + \frac{1}{16} = \frac{10}{16} = 0.625$$

$$\therefore J_{\min} = \frac{161}{689} < J = \frac{10}{16}$$

6.

(1) (10%)

$$x(n) = s(n) - 2s(n-1) + v(n)$$

$$\mathbf{R}\mathbf{w} = \mathbf{g} \Rightarrow E(\mathbf{x}_n \mathbf{x}_n^T) \mathbf{w} = E(\mathbf{x}_n s(n)) \text{ where } \mathbf{x}_n = [x(n) \ x(n-1)]^T$$

$$\Rightarrow \begin{bmatrix} 5.1 & -2 \\ -2 & 5.1 \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \therefore \mathbf{w} = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix} = \begin{bmatrix} 0.2317 \\ 0.0909 \end{bmatrix}$$

$$\therefore W(z) = 0.2317 + 0.0909z^{-1}$$

(2) (10%)

$$H(z)W(z) = (a + bz^{-1} + az^{-2})(w_0 + w_1z^{-1} + w_2z^{-2} + w_1z^{-3} + w_0z^{-4})$$

Clearly, we need 6 delay units.