

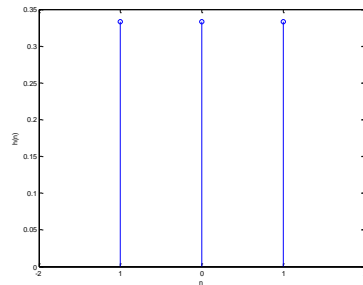
Autumn Semester 2011-12 (2.0 hours)

EEE6440 Advanced Signal Processing

Solutions for Part A:

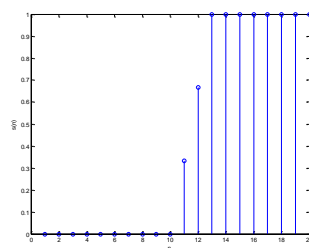
1.

- a. $y(n) = 1/3(x[n+1] + x[n] + x[n-1])$
 $h(n) = \{ 1/3, 1/3, 1/3 \}$ the second element represents $n=0$.
 Or a graphical solution.



(1)

b.



Convolve the $h(n)$ with step function $u(n)$. In other words taking the discrete integral of $h(n)$. Results in $\{ \dots 0, 1/3, 2/3, 1, \dots \}$

Time-domain performance:

- Fast response, No overshoot, linear phase
- Filter kernel is short. Therefore,
 - o Average performance on smoothing a signal corrupted
 - o can retain the edge information in the signal

(2)

- c. $y(n) = 1/3(x[n+1] + x[n] + x[n-1])$

$$h(n) = 1/3 \ 1/3 \ 1/3$$

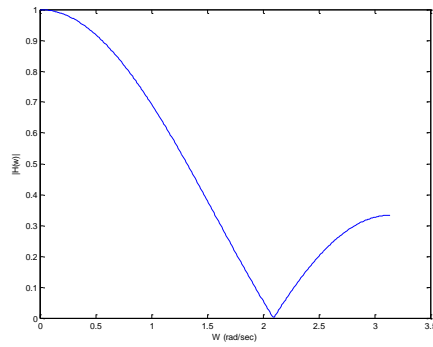
$$h(z) = 1/3 (z + 1 + z^{-1})$$

$$z = e^{j\omega},$$

$$H(j\omega) = 1/3 (e^{j\omega} + 1 + e^{-j\omega}) = (1 + 2 \cos \omega)/3$$

$$|H(j\omega)| = |(1 + 2 \cos \omega)/3|$$

(3)



d.

$$y(i) = \frac{1}{M} \sum_{k=\frac{1-M}{2}}^{\frac{M-1}{2}} x(i+k)$$

$$y(i+1) = \frac{1}{M} \sum_{k=\frac{1-M}{2}}^{\frac{M-1}{2}} x(i+1+k)$$

$$y(i+1) = \frac{1}{M} \left(\sum_{k=\frac{1-M}{2}}^{\frac{M-1}{2}} x(i+1+k) \right) + x(i+1 + \frac{M-1}{2})$$

$$y(i+1) = \frac{1}{M} \left(-x(i + \frac{1-M}{2}) + \sum_{k=\frac{1-M}{2}}^{\frac{M-1}{2}} x(i+k) \right) + x(i+1 + \frac{M-1}{2})$$

$$y(i+1) = \frac{1}{M} \left(-x(i + \frac{1-M}{2}) + My(i) + x(i+1 + \frac{M-1}{2}) \right)$$

That means, for any M, y[i] is computed as

$$y[i] = y[i-1] + (x[i+p] - x[i-q]) \quad (\text{division by } M \text{ can be done at the end})$$

$$\text{where } p=(M-1)/2 \text{ and } q=p+1$$

Number of multiplications: M (to compute y[0]) -----(A)

Number of additions: (M-1) + 2L (L is the signal length) -----(B)

For non-recursive implementation

Number of multiplications: ML -----(C)

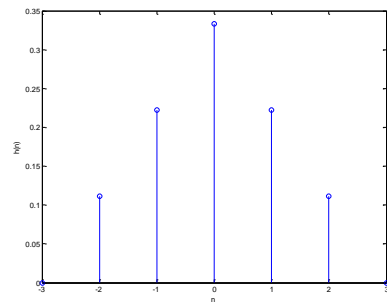
Number of additions: (M-1)L -----(D)

(A) and (B) are much smaller than (C) and (D).

(4)

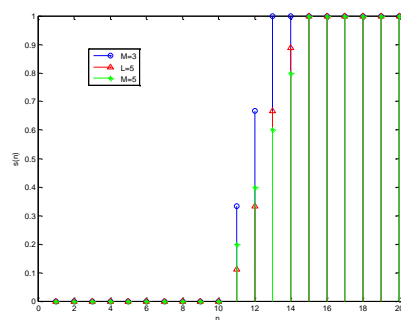
e. Convolve $h(n) = \{1/3, 1/3, 1/3\}$ with itself.

$$\{1/3, 1/3, 1/3\} * \{1/3, 1/3, 1/3\} = \{1/9, 2/9, 1/3, 2/9, 1/9\}$$



$L=5$

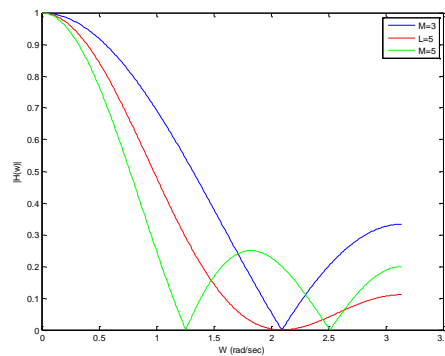
Now compare $M=3$, $M=5$ and $L=5$



For $M=3$, $|H(j\omega)| = |(1 + 2 \cos \omega)/3|$

For $M=5$, $|H(j\omega)| = |(1 + 2 \cos(\omega) + 2 \cos(2\omega))/5|$

For $L=5$, $|H(j\omega)| = |(3 + 4 \cos(\omega) + 2 \cos(2\omega))/9|$



(Only an estimated sketch is required to explain the performance difference.)

$L=5$ provides a faster time-domain response compared to $M=5$ with better stop-band attenuation and compared to both $M=3$ and $M=5$. It has better smoothing performance (compared to $M=3$ and $M=5$) and ability to retain edges compared to $M=5$.

2.

- a. In T each row corresponds to a basis vector f_v .

$$f_0 = \begin{bmatrix} h & h & 0 & 0 \end{bmatrix} \quad f_1 = \begin{bmatrix} 0 & 0 & h & h \end{bmatrix}$$

$$f_2 = \begin{bmatrix} h & -h & 0 & 0 \end{bmatrix} \quad f_3 = \begin{bmatrix} 0 & 0 & h & h \end{bmatrix}$$

(2)

- b. For the orthogonality condition

$$\text{If the inner product } \langle f_n, f_m \rangle = 1 \text{ when } n = m \text{ and} \\ = 0 \text{ when } n \neq m.$$

$$\text{In other words } \sum_{i=0}^3 f_{ni} f_{im} = \delta_{nm}$$

$$\langle f_0, f_0 \rangle = \langle f_1, f_1 \rangle = \langle f_2, f_2 \rangle = \langle f_3, f_3 \rangle = ((h \cdot h) + (h \cdot h) + (0) + (0)) = 2h^2 = 1 \\ h = \pm 1/\sqrt{2}$$

$$\langle f_1, f_2 \rangle = 0$$

$$\langle f_1, f_3 \rangle = ((h \cdot h) + (-h \cdot h) + (0) + (0)) = 0$$

$$\langle f_1, f_4 \rangle = 0$$

$$\text{Similarly, } \langle f_2, f_2 \rangle = \langle f_3, f_3 \rangle = \langle f_4, f_4 \rangle = 1 \text{ and}$$

$$\langle f_2, f_3 \rangle = \langle f_2, f_4 \rangle = \langle f_4, f_3 \rangle = 0$$

(3)

- c. low pass $\begin{bmatrix} 1 & 1 \end{bmatrix}/\sqrt{2}$

$$\text{high pass } \begin{bmatrix} 1 & -1 \end{bmatrix}/\sqrt{2}$$

(1)

- d. F is orthogonal. Therefore, the inverse matrix is the transpose.

$$T^{-1} = \begin{bmatrix} h & 0 & h & 0 \\ h & 0 & -h & 0 \\ 0 & h & 0 & h \\ 0 & h & 0 & -h \end{bmatrix}$$

Compute the $T^{-1}T$ and show it is the Identity matrix (I)

$$TT^{-1} = \begin{bmatrix} h & h & 0 & 0 \\ 0 & 0 & h & h \\ h & -h & 0 & 0 \\ 0 & 0 & h & -h \end{bmatrix} \begin{bmatrix} h & 0 & h & 0 \\ h & 0 & -h & 0 \\ 0 & h & 0 & h \\ 0 & h & 0 & -h \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

(3)

e.
$$T = \begin{bmatrix} h & h & 0 & 0 \\ h & -h & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

(2)

- f. $y_0 = (x_0 + x_1) \cdot h$

$$y_1 = (x_2 + x_3) \cdot h$$

$$(x_0 + x_1 + x_2 + x_3) = (y_0 + y_1)/h$$

$$\text{mean}(x_0 + x_1 + x_2 + x_3) = (y_0 + y_1)/(4h)$$

OR

Perform the second level transform on y to get $z = (z_0, z_1, z_2, z_3)$. Then $\text{mean} = z_0/2$.

(2)

- g.** Transform matrix for 2 data points

$$T = \begin{bmatrix} h & h \\ h & -h \end{bmatrix}$$

Create low pass transform matrix L (64x128) and H (64x128)

$$L = \begin{bmatrix} h & h & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & h & h & & 0 & 0 \\ \vdots & \vdots & & & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & h & h \end{bmatrix}$$

$$H = \begin{bmatrix} h & -h & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & h & -h & & 0 & 0 \\ \vdots & \vdots & & & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & h & -h \end{bmatrix}$$

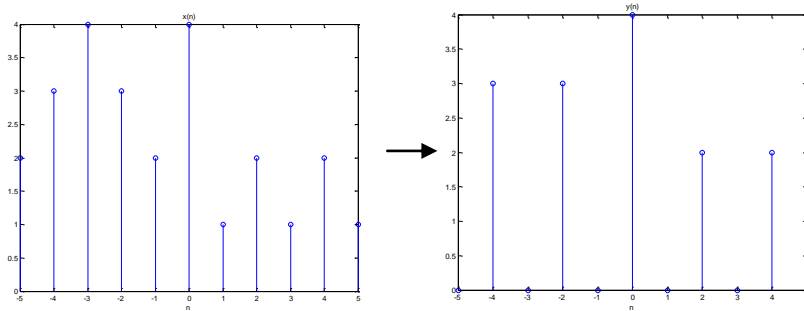
$$T = \begin{bmatrix} L \\ H \end{bmatrix}$$

Apply T on the data vector [X] as a matrix multiplication TX.

(2)

- 3. a.** (i)

$$y(n) = \{0, 3, 0, 3, 0, 4, 0, 2, 0, 2, 0\}$$



- (ii) This represents a situation where $x(n)$ is decimated by a factor of 2 followed by interpolation by a factor of 2.

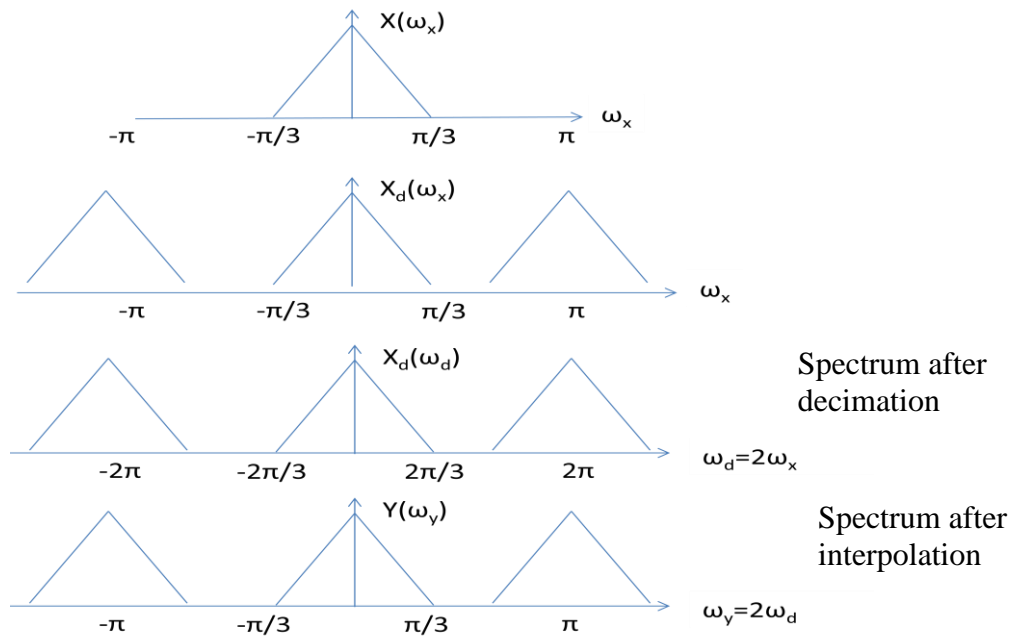
Starting from:

$$Y(j\omega_x) = \frac{1}{M} \sum_{k=0}^{M-1} X(j(\omega_x - 2\pi k / M))$$

For $M=2$,

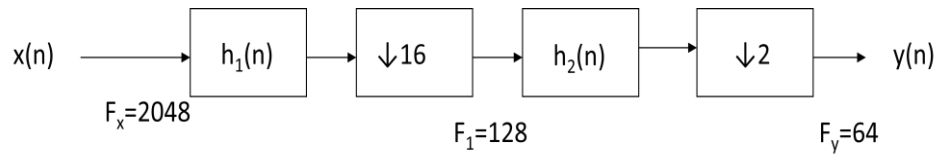
$$Y(j\omega_x) = \frac{1}{2} \sum_{k=0}^1 X(j(\omega_x - \pi k))$$

(5)



(iii) an anti-imaging filter required with transition band from $\pi/3$ to $2\pi/3$.

b.



Passband deviation: $0.01\text{dB} \rightarrow 0.00115$

Stopband attenuation: $80\text{dB} \rightarrow 0.0001$

For both filters we choose

$$\delta_p = 0.00115/2 = 0.00058$$

$$\delta_s = 0.0001$$

Filter length given by $N \approx \frac{-10 \log(\delta_p \delta_s) - 13}{14.6(\Delta f)} + 1$

$$N \approx \frac{-10 \log(0.00058 \times 0.0001) - 13}{14.6(\Delta f)} + 1$$

$$N \approx \frac{4.066}{14.6(\Delta f)} + 1$$

For h_2 :

Passband 0 - 30 Hz

Stopband 32-64 Hz

Transition band 30Hz – 32Hz

Normalised transition bandwidth $(32-30)/128 = 2/128$

$$\text{Therefore } N_2 \approx \frac{4.066}{14.6\left(\frac{2}{128}\right)} + 1 = 261$$

For h_1 :

Passband 0 - 30 Hz

Stopband $(128-64/2) - 1024 \text{ Hz} = 96-1024$

Transition band 30Hz – 96Hz

Normalised transition bandwidth $(96-30)/2048 = 66/2048$

$$\text{Therefore } N_1 \approx \frac{4.066}{14.6\left(\frac{66}{2048}\right)} + 1 = 127$$

$$\text{(ii) MPS} = \sum_{i=1}^2 F_i N_i = 128 \times 127 + 261 \times 64 = 32\,960$$

(iii) N is inversely proportion to Δf . If a single-stage was used Δf would have been $(32-30)/2048$. To make this value larger, we need to make the numerator bigger and the denominator smaller. This can be achieved by factoring F into a product of several smaller sampling rates. Each of the early stage filters the transition bandwidth is large because the corresponding sampling rates are closer to F .

c. Sampling rate 8kHz means 8000 samples/sec.

- Subband 5 represents $\frac{1}{2}$ of the total bandwidth, while each of the other subbands represent $\frac{1}{8^{\text{th}}}$ of the total bandwidth.
- Therefore the data rate
 $((5+4+4+2)/8 + \frac{1}{2}) \times 8000$
 $= 19 \text{ kHz}$

(2)

Part B

Q4 a.

The variance $\sigma_x^2(n)$ of a random variable $x(n)$ is the mean-square variation about the mean $m_x(n)$.

$$\begin{aligned}\sigma_x^2(n) &= E[(x(n) - m_x(n))^2] \\ &= E[x^2(n) - x(n)m_x(n) - x(n)m_x(n) + m_x^2(n)] \\ &= E[x^2(n)] - 2E[x(n)]m_x(n) + m_x^2(n) \\ &= E[x^2(n)] - 2m_x^2(n) + m_x^2(n) = E[x^2(n)] - m_x^2(n)\end{aligned}$$

Q4 b.

i) $H_1(z) = 1 - 3z^{-1}$

z-transform of the autocorrelation at the output

$$\begin{aligned}S_{y_1 y_1}(z) &= H_1(z) H_1^*(z^{-1}) \sigma_x^2 \\ &= (1 - 3z^{-1})(1 - 3z) = 1 - 3z^{-1} - 3z + 9 = -3z + 10 - 3z^{-1}\end{aligned}$$

Inverse z-transform by inspection to give autocorrelation sequence:

$$\phi_{y_1 y_1}(m) = Z^{-1}[S_{y_1 y_1}(z)]$$

Autocorrelation sequence: -3 for $m=-1$, 10 for $m=0$, -3 for $m=1$ and zero for other values of m

ii)

$$H_1(z) = 1 - 3z^{-1}$$

$$H_2(z) = 1 - 2z^{-2}$$

Cross-correlation sequence $\phi_{y_1 y_2}(m) = E[y_1(n) y_2(n+m)]$.

z-transform of the cross-correlation at the outputs

$$\begin{aligned}S_{y_1 y_2}(z) &= H_1(z^{-1}) H_2(z) \sigma_x^2 \\ &= (1 - 3z)(1 - 2z^{-2}) = 1 - 2z^{-2} - 3z + 6z^{-1} \\ &= -3z + 1 + 6z^{-1} - 2z^{-2}\end{aligned}$$

Inverse z-transform yields: $\phi_{y_1 y_2}$

-3 for $m=-1$, 1 for $m=0$, 6 for $m=1$, -2 for $m=2$ and zero for other values of m

The second cross-correlation is most easily obtained by using the property that $\phi_{xy}(m) = \phi_{yx}(-m)$ i.e.

$$\phi_{y_2 y_1}(m) = \phi_{y_1 y_2}(-m)$$

-2 for $m=-2$, 6 for $m=-1$, 1 for $m=0$, -3 for $m=1$, zeros for other values of m

Q4 c.

i)

For cosine wave input, the dynamic range R_D of the quantiser can be calculated from the equation in Section 7.5.2 since sine wave and cosine wave have the same power given the same amplitude.

Then, for a 20-bit A/D converter ($M=20$):

$$R_D = 1.76 + 6M \text{ dB} = 1.76 + 20 \times 6 = 121.76 \text{ dB},$$

ii)

For uniformly distributed input signal, its power is given by $P_i = (2A)^2/12$, where A is its amplitude.

The stepsize δx is given by $\delta x = 2A/2^M$

The quantisation noise also has a uniform distribution, then its power is $P_n = (\delta x)^2/12$.

Then its dynamic range is given by

$$R_D = 10 \log_{10}(P_i/P_n) = 6M = 120 \text{ dB}$$

Q5 a.

There are four zeros for $S_{yy}(z)$: $1/2$, 3 , 2 , $1/3$. So $S_{yy}(z)$ can be formed by passing a zero-mean white signal through four possible filters:

$$H_0(z) = (z - 1/2)(z - 3)$$

$$H_1(z) = (z - 1/2)(z - 1/3)$$

$$H_2(z) = (z - 2)(z - 3)$$

$$H_3(z) = (z - 2)(z - 1/3)$$

The inverse of any of the above four filters will whiten the signal $y(n)$. The inverse of $H_1(z)$ will be the one with minimum phase since all of its zeros are inside the unit circle.

Q5 b.

$$e(n) = x(n) - \hat{x}(n)$$

The mean-square error (MSE) cost function

$$\xi(n) = E[e^2(n)]$$

$$\hat{x}(n) = \sum_{i=0}^{N-1} h_i y(n-i)$$

$$= [h_0 \ h_1 \ \cdots \ h_{N-1}] \begin{bmatrix} y(n) \\ y(n-1) \\ \vdots \\ y(n-N+1) \end{bmatrix}$$

$$= \mathbf{h}^T \mathbf{y}(n) = \mathbf{y}^T(n) \mathbf{h}$$

Differentiate

$$\frac{\partial \xi}{\partial h_j} = \frac{\partial}{\partial h_j} E[\{ e^2(n) \}]$$

$$= E[\frac{\partial}{\partial h_j} \{ e^2(n) \}]$$

$$= E[2 e(n) \frac{\partial e(n)}{\partial h_j}]$$

$$= E[2 e(n) \frac{\partial}{\partial h_j} \{ x(n) - \mathbf{h}^T \mathbf{y}(n) \}]$$

$$= E[2 e(n) \frac{\partial}{\partial h_j} \{ -h_j y(n-j) \}]$$

$$= E[2 e(n) y(n-j) \}]$$

$$= 0$$

for $j=0, 1, \dots, N-1$.

In vector form, the gradient is given by

$$\begin{aligned}
\underline{\nabla} &= -2 E[\mathbf{y}(n) e(n)] \\
&= -2 E[\mathbf{y}(n) (x(n) - \mathbf{y}^T(n) \mathbf{h})] \\
&= -2 E[\mathbf{y}(n) x(n)] + 2 E[\mathbf{y}(n) \mathbf{y}^T(n)] \mathbf{h} \\
&= -2 \Phi_{yx} + 2 \Phi_{yy} \mathbf{h} \\
&= \underline{0}
\end{aligned}$$

where

Autocorrelation matrix

$$\Phi_{yy} = E[\mathbf{y}(n) \mathbf{y}^T(n)]$$

Cross-correlation vector

$$\Phi_{yx} = E[\mathbf{y}(n) x(n)]$$

Optimal Solution

$$\Phi_{yy} \mathbf{h}_{opt} = \Phi_{yx}$$

Alternative formulation

$$\mathbf{h}_{opt} = \Phi_{yy}^{-1} \Phi_{yx}$$

Q6 a.

i)

Suppose the z-transform of the filter is given by $H(z)$, then the relationship is given by

$$S_{xy}(z) = H(z) S_{xx}(z)$$

ii)

For a white input, we have

$$S_{xy}(z) = H(z) \sigma_x^2$$

where σ_x^2 is variance of the input.

Taking inverse transforms gives:

$$\phi_{xy}(m) = h_m \sigma_x^2$$

where h_m is the impulse response of the filter. It can be measured by estimating the cross-correlation directly from the data with the following three steps:

$$\hat{\phi}_{xy}(m) = \frac{1}{M} \sum_{n=0}^{M-1} x(n) y(n+m)$$

$$\hat{\sigma}_x^2 = \frac{1}{M} \sum_{n=0}^{M-1} x^2(n)$$

$$\hat{h}_m = \frac{\hat{\phi}_{xy}(m)}{\hat{\sigma}_x^2}$$

Q6 b.

i)

A Time Recursion

$$\mathbf{h}(n) = \mathbf{h}(n-1) - \mu \hat{\mathbf{v}}(n-1) .$$

The Exact Gradient

$$\begin{aligned} \underline{\mathbf{v}}(n) &= -2 \text{E} [\mathbf{y}(k) (x(k) - \mathbf{h}^T(n) \mathbf{y}(k))] \\ &= -2 \text{E} [\mathbf{y}(k) e(k)] \end{aligned}$$

A Simple Estimate of the Gradient

$$\hat{\underline{\mathbf{v}}}(n) = -2 \mathbf{y}(n+1) e(n+1)$$

The Error

$$e(n+1) = x(n+1) - \mathbf{h}^T(n) \mathbf{y}(n+1)$$

Then the updated equation of the LMS algorithm is given by

$$\mathbf{h}(n) = \mathbf{h}(n-1) + 2\mu \mathbf{y}(n)e(n)$$

ii)

$$\begin{aligned} e(4) &= x(4) - \mathbf{h}^T(3) \mathbf{y}(4) = -0.27 - [1 \ 3][0.5 \ 0.25]^T \\ &= -1.52 \end{aligned}$$

The impulse response is then updated by

$$\begin{aligned} \mathbf{h}(4) &= \mathbf{h}(3) + 2\mu \mathbf{y}(4)e(4) \\ &= [1 \ 3]^T + 0.2 * (-1.52) * [0.5 \ 0.25]^T \\ &= [0.848 \ 2.924]^T \end{aligned}$$