

# Assignment Report of ADSP Part 2

Liu Xiangyu G1802061L

November 5, 2018

Q1.a) Given,

$$x[n] = s[n] + w[n] \quad (1)$$

$$s[n] = 0.8s[n-1] + v[n] \quad (2)$$

from eq.(2), the power spectral density of  $s[n]$ ,

$$\begin{aligned} \Gamma_{ss}(z) &= \sigma_v^2 H(z)H(z^{-1}) \\ &= \sigma_v^2 \frac{1}{1-0.8z^{-1}} \frac{1}{1-0.8z} \end{aligned} \quad (3)$$

By taking the inverse Z-transform, the autocorrelation functions

$$\gamma_{ss}[k] = 0.8^{|k|} \quad (4)$$

$$\gamma_{xx}[k] = \gamma_{ss}[k] + \gamma_{ww}[k] = 0.8^{|k|} + \delta[k] \quad (5)$$

b) Solve the following normal equations:

$$\begin{bmatrix} \gamma_{xx}[0] & \gamma_{xx}[-1] \\ \gamma_{xx}[1] & \gamma_{xx}[0] \end{bmatrix} \begin{bmatrix} h[0] \\ h[1] \end{bmatrix} = \begin{bmatrix} \gamma_{ss}[0] \\ \gamma_{ss}[1] \end{bmatrix} \quad (6)$$

$$\begin{bmatrix} 2 & 0.8 \\ 0.8 & 2 \end{bmatrix} \begin{bmatrix} h[0] \\ h[1] \end{bmatrix} = \begin{bmatrix} 1 \\ 0.8 \end{bmatrix} \quad (7)$$

Therefore,

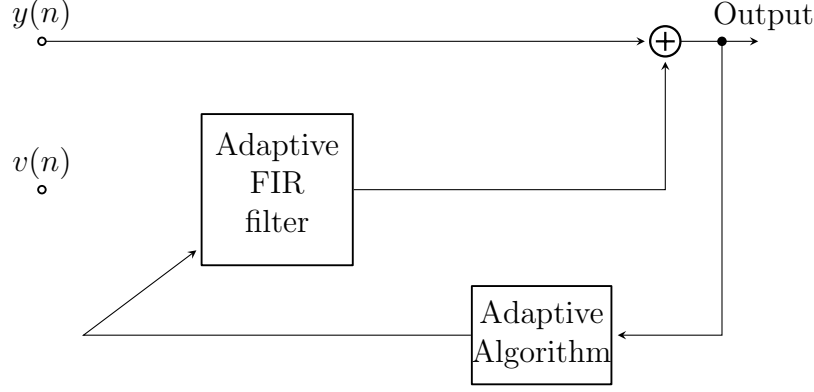
$$h_{opt}[0] = 0.405, h_{opt}[1] = 0.238 \quad (8)$$

c) Hence,

$$\varepsilon_2^h = \min \varepsilon_2^h = \gamma_{ss}[0] - \begin{bmatrix} \gamma_{ss}[0] & \gamma_{ss}[1] \end{bmatrix} \begin{bmatrix} h[0] \\ h[1] \end{bmatrix} = 0.405 \quad (9)$$

Q2.a) A linear adaptive filtering algorithm involves two basic processes: (1) a filtering process designed to produce an output in response to a sequence of input data, and (2) an adaptive process, the purpose of which is to provide a mechanism for the adaptive control of an adjustable set of parameters used in the filtering process

b)



The LMS algorithm is given by,

$$\mathbf{h}_M(n+1) = \mathbf{h}_M(n) + \mu e(n) \mathbf{X}_M^*(n), \quad n = 0, 1, 2, \dots \quad (10)$$

where,

1.  $\mathbf{h}_M(n)$  is the matrices of estimates of the true coefficients
2.  $\mu$  is a fixed step size
3.  $e(n) = d(n) - \hat{d}(n)$
4.  $\mathbf{X}_M(n)$  is the set of M signal samples in the filter at the  $n^{th}$  iteration.

Therefore, the adaptive FIR filter to estimate the noise  $\hat{w}_2(n)$  works as,

$$\hat{w}_2(n) = \sum_{m=0}^M h(m)v(n-m) \quad (11)$$

c) The convergence of the mean of the coefficient vector in the LMS algorithm depends on the range of  $\mu$ ,

$$0 < \mu < \frac{2}{\lambda_{max}} \quad (12)$$

where  $\lambda_{max}$  is the largest eigenvalue of  $\Gamma_M$ ,

$$\lambda_{max} < \sum_{k=0}^{M-1} \lambda_k = \text{trace} \Gamma_M = M\gamma_{xx}[0] \quad (13)$$

Given the input white noise signal has zero mean and variance  $w^2$ ,

$$\lambda_{max} < M\gamma_{xx}[0] = M\sigma^2\delta[0] = M\sigma^2 \quad (14)$$

Therefore, the condition for convergence is when the selected fixed step size  $\mu$  is less than the upper bound,

$$\mu < \frac{2}{M\sigma^2} \quad (15)$$

Q3. Given  $x(n) = s(n) + w(n)$ ,

$$\gamma_{xx}[m] = \gamma_{ss}[m] + \gamma_{ww}[m] = \gamma_{ss}[m] + \sigma_w^2 \delta[m] \quad (16)$$

$$\Gamma_{xx}(z) = \Gamma_{ss}(z) + \Gamma_{ww}(z) = \frac{\sigma_s^2}{|A(z)|^2} + \sigma_w^2 = \frac{\sigma_s^2 + \sigma_w^2 |A(z)|^2}{|A(z)|^2} \quad (17)$$

To model  $x(n)$  as ARMA(2,2) process, the power density spectrum of  $x(n)$  needs to have the formation:

$$\hat{\Gamma}_{xx}(z) = \hat{\sigma}_x \frac{\hat{B}(z)\hat{B}(z^{-1})}{\hat{A}(z)\hat{A}(z^{-1})} \quad (18)$$

where,

$$\begin{aligned} \hat{A}(z) &= a_0 + a_1 z^{-1} + a_2 z^{-2} \\ \hat{B}(z) &= b_0 + b_1 z^{-1} + b_2 z^{-2} \end{aligned} \quad (19)$$

In this case, since  $s(n)$  is given as an AR(2) process, we only need to find  $B(z)$  so that,

$$B(z)B(z^{-1}) = \sigma_s^2 + \sigma_w^2 |A(z)|^2 \quad (20)$$

Therefore, let

$$B(z) = c + \sigma_w A(z) \quad (21)$$

where  $c$  is a constant to determine. If there exists a value of  $c$  that makes  $\hat{B}(z)\hat{B}(z^{-1})$  equal to  $\sigma_s^2 + \sigma_w^2 |A(z)|^2$ ,  $x(n)$  can be modelled as an ARMA(2,2) process. Based on eq.(21),

$$\begin{aligned} B(z)B(z^{-1}) &= c^2 + c\sigma_w(A(z) + A(z^{-1})) + \sigma_w^2 |A(z)|^2 \\ &= c^2 + 2c\sigma_w \text{Re}\{A(z)\} + \sigma_w^2 |A(z)|^2 \end{aligned} \quad (22)$$

Considering eq.(20) equal to eq.(22), the proper  $c$  can be obtained,

$$\hat{c} = \sqrt{\sigma_s^2 + \sigma_w^2 \text{Re}^2\{A(z)\}} - \sigma_w \text{Re}\{A(z)\} \quad (23)$$

With  $c$  selected as above, the condition in eq.(20) is satisfied, and  $x(n)$  is an ARMA(2,2) process with  $A(z)$  given and  $B(z)$  as,

$$B(z) = \hat{c} + \sigma_w A(z) \quad (24)$$