

Problem 1. (a) From Problem 1 of HW8 we have:

$$q_0 = 1 + aa^* \quad (1)$$

$$b = q_0 \left(1 + \frac{1}{SNR_{MFB}}\right) \quad (2)$$

$$r_2 = \frac{-b + \sqrt{b^2 - 4aa^*}}{2a} \quad (3)$$

$$W_{MMSE-LE}(D) = \frac{1}{a^*D^{-1} + b + aD} = \frac{1}{a} \frac{D}{(D - r_1)(D - r_2)} \quad (4)$$

$$Q(D) + \frac{q_0}{SNR_{MFB}} = a^*D^{-1} + aD + q_0 + \frac{q_0}{SNR_{MFB}} \quad (5)$$

$$= a^*D^{-1} + b + aD = \frac{1}{W_{MMSE-LE}(D)} \quad (6)$$

$$= a \frac{(D - r_1)(D - r_2)}{D} \quad (7)$$

$$= a(D - r_1)(1 - r_2D^{-1}) \quad (8)$$

$$= ar_1(Dr_2^* - 1)(1 - r_2D^{-1}) \quad (9)$$

$$= -ar_1(1 - r_2D^{-1})(1 - r_2^*D) \quad (\text{since } r_1r_2^* = 1) \quad (10)$$

$$\implies \gamma_0 = -ar_1 \quad (11)$$

$$= a \frac{b + \sqrt{b^2 - 4aa^*}}{2a} \quad (12)$$

$$= \frac{b + \sqrt{b^2 - 4aa^*}}{2} \quad (13)$$

(b)

$$A(D) = G(D) = 1 - r_2^*D \quad (14)$$

$$= 1 - \frac{-b + \sqrt{b^2 - 4aa^*}}{2a^*} D \quad (15)$$

$$W(D) = A(D)W_{MMSE-LE}(D) \quad (16)$$

$$= \frac{A(D)}{\left(Q(D) + \frac{q_0}{SNR_{MFB}}\right)} \quad (17)$$

$$= -\frac{1}{ar_1(1 - r_2D^{-1})} \quad (18)$$

(c)

$$SNR_{MMSE-DFE} = \gamma_0 SNR_{MFB}/q_0 \quad (19)$$

$$\implies \gamma_{MMSE-DFE} = 10 \log_{10} \frac{q_0}{\gamma_0} \quad (20)$$

$$= 10 \log_{10} \left(\frac{2(1+aa^*)}{b + \sqrt{b^2 - 4aa^*}} \right) \quad (21)$$

$$\text{where, } b = (1+aa^*) \left(1 + \frac{1}{SNR_{MFB}} \right) \quad (22)$$

$$= (1+aa^*) \left(1 + \frac{N_0}{E_x(1+aa^*)} \right) \quad (23)$$

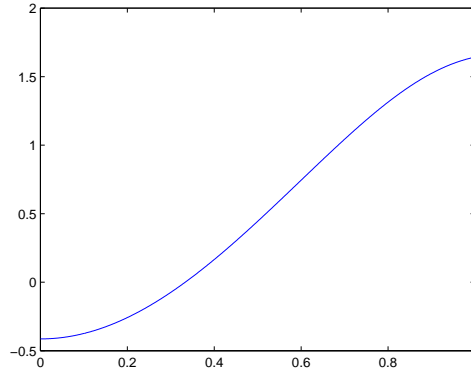
$$= (1+aa^*) + 0.1 = 1.1 + aa^* \quad (24)$$

For $a = 0$, $\gamma = 10 \log_{10} \left(\frac{1}{1.1} \right) = -10 \log_{10}(1.1) = -0.41$

For $a = 0.5$, $\gamma = 10 \log_{10}(1.11) = 0.44$

For $a = 1$, $\gamma = 10 \log_{10}(1.46) = 1.64$

The plot for γ_{DFE} :



Problem 2.

- (a) Since everything is symmetric we estimate 1 if $y_k > 0$ and 0 if $y_k \leq 0$. The error probability of such estimator is:

$$P_e = \Pr\{x_k = x_{k-1}\} \cdot \Pr\{z_k > 2A\} + \Pr\{x_k \neq x_{k-1}\} \cdot \Pr\{z_k > 0\} = \frac{1}{2}Q\left(\frac{2A}{\sigma}\right) + \frac{1}{4}$$

- (b) The best decision rule is to estimate A if $y_k - \hat{x}_{k-1} > 0$ and $-A$ if $y_k - \hat{x}_{k-1} \leq 0$. The error probability of the estimator is now:

(i)

$$\Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} = x_{k-1}) = Q\left(\frac{A}{\sigma}\right)$$

(ii)

$$\begin{aligned}
\Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} \neq x_{k-1}) &= \Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} \neq x_{k-1}, x_k \neq x_{k-1}) \Pr(x_k \neq x_{k-1}) + \\
&\quad \Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} \neq x_{k-1}, x_k = x_{k-1}) \Pr(x_k = x_{k-1}) \\
&= \frac{1}{2} Q\left(\frac{-A}{\sigma}\right) + \frac{1}{2} \cdot Q\left(\frac{3A}{\sigma}\right)
\end{aligned}$$

(iii)

$$\begin{aligned}
\Pr(\hat{x}_k \neq x_k) &= \Pr(\hat{x}_{k-1} \neq x_{k-1}) \cdot \Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} \neq x_{k-1}) + \\
&\quad \Pr(\hat{x}_{k-1} = x_{k-1}) \cdot \Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} = x_{k-1}) \\
&= \Pr(\hat{x}_k \neq x_k) \cdot \Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} \neq x_{k-1}) + \\
&\quad (1 - \Pr(\hat{x}_k \neq x_k)) \cdot \Pr(\hat{x}_k \neq x_k | \hat{x}_{k-1} = x_{k-1})
\end{aligned}$$

By solving the equation we obtain:

$$\Pr(\hat{x}_k \neq x_k) = \frac{2Q\left(\frac{A}{\sigma}\right)}{1 + 3Q\left(\frac{A}{\sigma}\right) - Q\left(\frac{3A}{\sigma}\right)}$$

We can observe that as A increases the probability of error goes to 0 while without feedback the error probability is lower bounded by $\frac{1}{4}$.

Problem 3.

(a)

$$\begin{aligned}
\mathbf{y} &= \mathbf{H}\mathbf{x} + \mathbf{z} \\
\mathbf{V}\mathbf{y} &= \mathbf{V}\mathbf{S}\mathbf{P}\mathbf{x} + \mathbf{V}\mathbf{z} \\
\Rightarrow \mathbf{Y} &= \mathbf{V}\mathbf{S}\mathbf{V}^*\mathbf{D}\mathbf{V}\mathbf{x} + \mathbf{V}\mathbf{z} \\
\Rightarrow \mathbf{Y} &= \underbrace{\mathbf{V}\mathbf{S}\mathbf{V}^*\mathbf{D}}_{\mathbf{G}}\mathbf{X} + \mathbf{Z} \\
\Rightarrow \mathbf{Y} &= \mathbf{G}\mathbf{X} + \mathbf{Z}
\end{aligned}$$

(b)

$$\mathbf{Y}_l = \mathbf{G}_{l,l}\mathbf{X}_l + \underbrace{\sum_{q \neq l} \mathbf{G}(l,q)\mathbf{X}_q}_{\text{ICI + noise}} + \mathbf{Z}_l, \quad l = 0, \dots, N-1,$$

Hence,

$$\text{SINR} = \frac{\mathbb{E}(|\mathbf{G}_{l,l}\mathbf{X}_l|^2)}{\mathbb{E}\left(|\sum_{q \neq l} \mathbf{G}_{l,q}\mathbf{X}_q|^2\right) + \mathbb{E}|Z_l|^2} = \frac{\mathcal{E}_x |\mathbf{G}_{l,l}|^2}{\mathcal{E}_x \sum_{q \neq l} |\mathbf{G}_{l,q}|^2 + \sigma_z^2}$$

(c)

$$\begin{aligned}
\mathbb{E}(\mathbf{Y}\mathbf{Y}^*) &= \mathbb{E}((\mathbf{G}\mathbf{X} + \mathbf{Z})(\mathbf{X}^*\mathbf{G}^* + \mathbf{Z}^*)) \\
&= \mathcal{E}_x \mathbf{G}\mathbf{G}^* + \mathbf{I}\sigma_z^2.
\end{aligned} \tag{25}$$

$$\begin{aligned}
\mathbb{E}(\mathbf{X}_l\mathbf{Y}^*) &= \mathbb{E}(\mathbf{X}_l(\mathbf{X}^*\mathbf{G}^* + \mathbf{Z}^*)) \\
&= \mathbb{1}_l^T \mathcal{E}_x \mathbf{G}^*,
\end{aligned} \tag{26}$$

where $\mathbb{1}_l^T = \begin{bmatrix} 0 & \dots & \underbrace{1}_{l^{\text{th}} \text{ position}} & 0 & \dots & 0 \end{bmatrix}$. Orthogonality principle implies,

$$\begin{aligned} \mathbb{E}((\mathbf{W}_l^* \mathbf{Y} - \mathbf{X}_l) \mathbf{Y}^*) &= 0 \\ \Rightarrow \mathbb{E}(\mathbf{W}_l^* \mathbf{Y} \mathbf{Y}^*) &= \mathbb{E}(\mathbf{X}_l \mathbf{Y}^*) \\ \Rightarrow \mathbf{W}_l^* &= \mathbb{E}(\mathbf{X}_l \mathbf{Y}^*) (\mathbb{E}(\mathbf{Y} \mathbf{Y}^*))^{-1} \end{aligned}$$

Using equations 25,26 we get that,

$$\Rightarrow \mathbf{W}_l^* = \mathcal{E}_x \mathbb{1}_l^T \mathbf{G}^* (\mathcal{E}_x \mathbf{G} \mathbf{G}^* + \mathbf{I} \sigma_z^2)^{-1}$$

(d)

$$\mathbf{G}_{l,q} = (\mathbf{V} \mathbf{S})_l (\mathbf{V}^* \mathbf{D})_q$$

where $(\mathbf{V} \mathbf{S})_l$ denotes the l^{th} row of $\mathbf{V} \mathbf{S}$ and $(\mathbf{V}^* \mathbf{D})_q$ denotes the q^{th} column of $\mathbf{V}^* \mathbf{D}$.

$$\begin{aligned} \mathbf{G}_{l,q} &= \frac{1}{N} \begin{bmatrix} e^{j2\pi f_0(N-1)} & e^{j2\pi f_0(N-2)} e^{-j\frac{2\pi}{N}(l-1)} & \dots & e^{j2\pi f_0(N-N)} e^{-j\frac{2\pi}{N}(l-1)(N-1)} \end{bmatrix} \begin{bmatrix} d_q \\ d_q e^{j\frac{2\pi}{N}(q-1)} \\ \vdots \\ d_q e^{j\frac{2\pi}{N}(q-1)(N-1)} \end{bmatrix} \\ \Rightarrow \mathbf{G}_{l,q} &= \frac{d_q}{N} e^{j2\pi f_0(N-1)} \sum_{p=1}^N e^{(j\frac{2\pi}{N}(q-l) - j2\pi f_0)(p-1)} \end{aligned}$$

By using the summation formula for the geometric series we get,

$$\mathbf{G}_{l,q} = \frac{d_q}{N} e^{j2\pi f_0(N-1)} \left[\frac{1 - e^{-j2\pi f_0 N}}{1 - e^{j\frac{2\pi}{N}(q-l-f_0 N)}} \right] \quad \text{for } f_0 \neq 0.$$

The ICI is significant when $\mathbf{G}_{l,q}$ is comparable to $\mathbf{G}_{l,l}$. When $f_0 N$ is large then this could occur, i.e., there is significant time variation over the block.