

# TSKS04 Digital Communication Continuation Course

## Solutions for the exam 2014-08-22

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**1**

We are given impulse responses

$$g_{\text{RX}}(t) = g_{\text{TX}}(t) = \text{rect}\left(\frac{t}{T}\right), \quad g_{\text{C}}(t) = \text{rect}\left(\frac{t}{2T}\right),$$

of the receive filter, transmit filter and channel, respectively. Let  $p(t)$  be the total impulse response of the cascade of the sender filter and the channel i.e.

$$p(t) = (g_{\text{TX}} * g_{\text{C}})(t) = \begin{cases} T, & |t| < \frac{T}{2}, \\ \frac{3T}{2} - |t|, & \frac{T}{2} \leq t < \frac{3T}{2}, \\ 0, & t > T. \end{cases}$$

We notice that  $p(t)$  is real and even. Then we have the matched filter

$$p_{\text{MF}}(t) = p^*(-t) = p(t).$$

Furthermore, let  $y(t)$  denote the output from the channel.

- a. The optimal (ML) case is if we use  $p_{\text{MF}}(t)$  as our receiver filter. Let  $z_0[n]$  be the output from that filter, sampled in the time instances  $nT$ . Then we have

$$z_0[n] = (y * p_{\text{MF}})(nT) = \int_{-\infty}^{\infty} y(t)p_{\text{MF}}(nT - t) dt.$$

The actual output from the receiver filter, sampled in the time instances  $kT_s + \tau$  for all integers  $k$  is given by

$$z[k] = (y * g_{\text{RX}})(kT_s + \tau) = \int_{-\infty}^{\infty} y(t)g_{\text{RX}}(kT_s + \tau - t) dt.$$

The question is now: Can we write  $p_{\text{MF}}(nT - t)$  as a linear combination of  $g_{\text{RX}}(kT_s + \tau - t)$  for some constants  $\tau$  and  $T_s$  and some integer values of  $k$ ? No, we cannot, at least not with a finite number of values of  $k$  and a non-zero value of  $T_s$ . Thus, it is not possible to perform ML sequence detection for this situation.

- b. There are infinitely many choices of sender and receiver filter to make ML detection possible. The most immediate way is to keep the sender filter  $g_{\text{TX}}$  as it is, and let the receiver filter be given by

$$g_{\text{RX}} = p_{\text{MF}}(t)$$

as given above. Then ML detection is possible with  $T_s = T$  and  $\tau = 0$ . There will be a need for a trellis, but that was not part of the question here.

**Answer:**

- a. ML detection is impossible for the given situation.

b. Choose  $g_{\text{TX}}(t) = \begin{cases} T, & |t| < \frac{T}{2}, \\ \frac{3T}{2} - |t|, & \frac{T}{2} \leq t < \frac{3T}{2}, \\ 0, & t > T. \end{cases}$

**2**

Given situation: Our communication is disturbed additively by  $N$ , which is Laplacian with PDF

$$f_N(n) = \frac{1}{2}e^{-|n|}.$$

For a sent  $A$ , we receive  $Z = 4A + N$ , and  $A$  takes values 0 and 1.

- a. For the given situation, we have the conditional PDFs

$$f_{Z|A}(z|0) = f_N(z) = \frac{1}{2}e^{-|z|},$$
$$f_{Z|A}(z|1) = f_N(z - 4) = \frac{1}{2}e^{-|z-4|}.$$

The log-likelihood ratio is then given by

$$K(z) = \ln\left(\frac{f_{Z|A}(z|1)}{f_{Z|A}(z|0)}\right) = |z| - |z - 4|$$
$$= \begin{cases} -4, & z < 0, \\ 2z - 4, & 0 \leq z < 4, \\ 4, & z \geq 4. \end{cases}$$

- b. Given decision rule: Set the estimate to 1 if  $z > 1$ , otherwise set the estimate to 0. The probability  $P_{e|1}$ , i.e. the error probability given that we have sent 1 is then given by

$$\begin{aligned} P_{e|1} &= \int_{-\infty}^1 f_{Z|A}(z|1) dz = \int_{-\infty}^1 \frac{1}{2} e^{-|z-4|} dz \\ &= \int_{-\infty}^1 \frac{1}{2} e^{z-4} dz = \left[ \frac{1}{2} e^{z-4} \right]_{-\infty}^1 \\ &= \frac{1}{2} e^{-3} \approx 0.0249. \end{aligned}$$

- c. The MPE rule (minimum probability of error) as described on pages 91-92 in Madhow, states that  $K(z)$  should be compared to  $\ln(\Pr\{A=0\}/\Pr\{A=1\})$ . The region  $z < 1$  given by decision rule can be expressed as  $K(z) < -2$ . The given rule is therefore MPE if we have  $\ln(\Pr\{A=0\}/\Pr\{A=1\}) = -2$ , which gives us the prior probability

$$\Pr\{A=0\} = \frac{1}{e^2 + 1} \approx 0.119.$$

**Answer:**

$$\text{a. } K(z) = \begin{cases} -4, & z < 0, \\ 2z - 4, & 0 \leq z < 4, \\ 4, & z \geq 4. \end{cases}$$

$$\text{b. } P_{e|1} = \frac{1}{2} e^{-3} \approx 0.0249$$

$$\text{c. } \Pr\{A=0\} = \frac{1}{e^2+1} \approx 0.119$$

**3**

We have a channel with output  $y = hb + n$ , where

- $b$  is the transmitted symbol, taking values  $\pm 1$ .
- $h$  is a binary random variable taking values 1 and 2 with probabilities

$$\Pr\{h=1\} = 1/4 \quad \text{and} \quad \Pr\{h=2\} = 3/4$$

- $n$  is Gaussian with mean 0 and variance 1.

- a. Decision rule:  $\hat{b} = \text{sgn}(y)$ . The error probability is given by

$$\begin{aligned} P_e &= \Pr\{\hat{b} \neq b\} \\ &= \Pr\{h=1\} \Pr\{\hat{b} \neq b|h=1\} \\ &\quad + \Pr\{h=2\} \Pr\{\hat{b} \neq b|h=2\}. \end{aligned}$$

Let us analyze the two realizations of  $h$  separately. First  $h=1$ :

$$\begin{aligned} \Pr\{\hat{b} \neq b|h=1\} &= \\ &= \Pr\{b=-1\} \Pr\{y > 0|b=-1, h=1\} \\ &\quad + \Pr\{b=1\} \Pr\{y < 0|b=1, h=1\} \\ &= \Pr\{b=-1\} \Pr\{n > 1\} + \Pr\{b=1\} \Pr\{n < -1\}. \end{aligned}$$

The Gaussian variable  $n$  has an even PDF, since its expectation is 0. Therefore, we have

$$\Pr\{n > 1\} = \Pr\{n < -1\}$$

and thus

$$\Pr\{\hat{b} \neq b|h=1\} = \Pr\{n > 1\} = Q(1).$$

Similarly for the case  $h=2$ , we get

$$\Pr\{\hat{b} \neq b|h=2\} = \Pr\{n > 2\} = Q(2).$$

Putting this together, we have

$$P_e = \frac{1}{4} Q(1) + \frac{3}{4} Q(2).$$

We have

$$\begin{aligned} E_b &= E\{h^2\} = \Pr\{h=1\} \cdot 1^2 + \Pr\{h=2\} \cdot 2^2 \\ &= \frac{1}{4} \cdot 1 + \frac{3}{4} \cdot 4 = \frac{13}{4}, \end{aligned}$$

and

$$\sigma_n^2 = \frac{N_0}{2} = 1.$$

This gives us the SNR

$$\frac{E_b}{N_0} = \frac{13}{8}.$$

We know that the argument of the  $Q$  function is proportional to  $\sqrt{E_b/N_0}$  for Gaussian noise. Therefore, we finally have

$$\begin{aligned} P_e &= \frac{1}{4} Q\left(\sqrt{\frac{8}{13}} \sqrt{\frac{E_b}{N_0}}\right) + \frac{3}{4} \left(\sqrt{\frac{32}{13}} \sqrt{\frac{E_b}{N_0}}\right) \\ &\approx \frac{1}{4} Q(0.784 \sqrt{\frac{E_b}{N_0}}) + \frac{3}{4} (1.569 \sqrt{\frac{E_b}{N_0}}) \end{aligned}$$

- b. The likelihood ratio is in this case

$$L(y) = \frac{f_{Y|b}(y|1)}{f_{Y|b}(y|-1)}.$$

We have

$$\begin{aligned}
 f_{Y|b}(y|1) &= \\
 &= \Pr\{h=1\}f_{Y|b,h}(y|1,1) + \Pr\{h=2\}f_{Y|b,h}(y|1,2) \\
 &= \frac{1}{\sqrt{2\pi}} \left( \frac{1}{4}e^{-(y-1)^2/2} + \frac{3}{4}e^{-(y-2)^2/2} \right), \\
 &= \frac{e^{-y^2/2}}{4\sqrt{2\pi}} \left( e^{y-\frac{1}{2}} + 3e^{2y-2} \right), \\
 f_{Y|b}(y|-1) &= \\
 &= \Pr\{h=1\}f_{Y|b,h}(y|-1,1) + \Pr\{h=2\}f_{Y|-b,h}(y|1,2) \\
 &= \frac{1}{\sqrt{2\pi}} \left( \frac{1}{4}e^{-(y+1)^2/2} + \frac{3}{4}e^{-(y+2)^2/2} \right), \\
 &= \frac{e^{-y^2/2}}{4\sqrt{2\pi}} \left( e^{-y-\frac{1}{2}} + 3e^{-2y-2} \right),
 \end{aligned}$$

and thus the likelihood ratio

$$L(y) = \frac{e^{y-\frac{1}{2}} + 3e^{2y-2}}{e^{-y-\frac{1}{2}} + 3e^{-2y-2}}.$$

For a MPE detector, the likelihood ratio should be compared to 1. Obviously, we have  $L(0) = 1$ , and  $L(y)$  is monotonically increasing. The given decision rule coincides with the MPE rule in this case. Thus, the answer is Yes.

**Answer:**

a.

$$\begin{aligned}
 P_e &= \frac{1}{4}Q\left(\sqrt{\frac{8}{13}}\sqrt{\frac{E_b}{N_0}}\right) + \frac{3}{4}\left(\sqrt{\frac{32}{13}}\sqrt{\frac{E_b}{N_0}}\right) \\
 &\approx \frac{1}{4}Q(0.784\sqrt{\frac{E_b}{N_0}}) + \frac{3}{4}(1.569\sqrt{\frac{E_b}{N_0}})
 \end{aligned}$$

b. Yes, the given decision rule is the MPE rule.

4

Assumption according to the problem formulation:  $\pm 1$  BPSK symbols. We are given

$$\text{MMSE} = 1 - \bar{p}^T \bar{c}_{\text{MMSE}}$$

c. This demands that we solve part of problem b first: Given model (Eq. 5.25 in Madhow):

$$\bar{r}_n = b_n \bar{u}_0 + \sum_{i \neq 0} b_{n+1} \bar{u}_i + \bar{w}_n,$$

The MSE is given by

$$\text{MSE} = \text{E} \left\{ |\langle \bar{c}, \bar{r}_n \rangle - b_n|^2 \right\} = \text{E} \left\{ |b_n \langle \bar{c}, \bar{r}_n \rangle - 1|^2 \right\},$$

where we have used the given assumption  $b_n = \pm 1$ . Plugging in the model in this expression gives us

$$\begin{aligned}
 \text{MSE} &= \text{E} \left\{ \left| b_n \langle \bar{c}, b_n \bar{u}_0 + \sum_{i \neq 0} b_{n+1} \bar{u}_i + \bar{w}_n \rangle - 1 \right|^2 \right\} \\
 &= \text{E} \left\{ \left| \langle \bar{c}, \bar{u}_0 + b_n \sum_{i \neq 0} b_{n+1} \bar{u}_i + b_n \bar{w}_n \rangle - 1 \right|^2 \right\}
 \end{aligned}$$

Assuming that the sequence of BPSK symbols are IID and the two outcomes are equally probable, then the above simplifies to

$$\begin{aligned}
 \text{MSE} &= \text{E} \left\{ \left| \langle \bar{c}, \bar{u}_0 + b_n \sum_{i \neq 0} b_{n+1} \bar{u}_i + b_n \bar{w}_n \rangle - 1 \right|^2 \right\} \\
 &= |\langle \bar{c}, \bar{u}_0 \rangle - 1|^2 + \sum_{i \neq 0} |\langle \bar{c}, \bar{u}_i \rangle|^2 + \text{E} \left\{ |\langle \bar{c}, \bar{w}_n \rangle|^2 \right\}
 \end{aligned}$$

since the expectation of all mixed terms become zero. We notice that we have  $|\langle \bar{a}, \bar{b} \rangle|^2 = \bar{a}^T \bar{b} \bar{b}^T \bar{a}$  for vectors  $\bar{a}$  and  $\bar{b}$ , where  $\bar{b} \bar{b}^T$  is a square matrix. Using that observation, we rewrite our expression as

$$\text{MSE} = |\langle \bar{c}, \bar{u}_0 \rangle - 1|^2 + \bar{c}^T A \bar{c},$$

where we have  $A = \sum_{i \neq 0} \bar{u}_i \bar{u}_i^T + C_{\bar{w}_n}$ , and where  $C_{\bar{w}_n} = \text{E} \{ \bar{w}_n \bar{w}_n^T \}$  is the correlation matrix of the noise.

We want to minimize the MSE by choosing the correlator  $\bar{c}$ . Therefore, we take the derivative of the MSE with respect to  $\bar{c}$ . This gives us

$$\begin{aligned}
 \frac{d}{d\bar{c}} \text{MSE} &= \frac{d}{d\bar{c}} |\langle \bar{c}, \bar{u}_0 \rangle - 1|^2 + \bar{c}^T A \bar{c}, \\
 &= 2(\bar{c}^T \bar{u}_0 - 1) \bar{u}_0 + 2A \bar{c}.
 \end{aligned}$$

We set this equal to zero, which gives us

$$A \bar{c}_{\text{MMSE}} = (1 - \bar{c}_{\text{MMSE}}^T \bar{u}_0) \bar{u}_0.$$

Multiplying both sides by  $\bar{c}_{\text{MMSE}}^T$  gives us

$$\bar{c}_{\text{MMSE}}^T A \bar{c}_{\text{MMSE}} = \bar{c}_{\text{MMSE}}^T \bar{u}_0 (1 - \bar{c}_{\text{MMSE}}^T \bar{u}_0)$$

According to Equation 5.42 in Madhow, we have  $\bar{p} = \sigma_b^2 \bar{u}_0$ . Assuming uniform distribution of  $b$ , we have  $\sigma_b^2 = 1$  in this case. Then we have

$$\begin{aligned}
 \text{MMSE} &= 1 - \bar{p}^T \bar{c}_{\text{MMSE}} \\
 &= 1 - \bar{c}_{\text{MMSE}}^T \bar{p} = 1 - \bar{c}_{\text{MMSE}}^T \bar{u}_0.
 \end{aligned}$$

Since we have minimized the MSE, we have maximized the signal-to-interference ratio, which now is given by

$$\begin{aligned} \text{SIR} &= \frac{(\bar{c}_{\text{MMSE}}^T \bar{u}_0)^2}{\bar{c}_{\text{MMSE}}^T \bar{u}_0 (1 - \bar{c}_{\text{MMSE}}^T \bar{u}_0)} = \frac{\bar{c}_{\text{MMSE}}^T \bar{u}_0}{1 - \bar{c}_{\text{MMSE}}^T \bar{u}_0} \\ &= \frac{1 - \text{MMSE}}{\text{MMSE}} = \frac{1}{\text{MMSE}} - 1. \end{aligned}$$

- d. From Equation 5.31, we have that the MSE for zero-forcing is given by  $MSE(\bar{c}_{\text{ZF}}) = \sigma_w^2 \|\bar{c}_{\text{ZF}}\|^2$ . Obviously, as  $\sigma_w$  tends to zero, so does  $MSE(\bar{c}_{\text{ZF}})$ . But we also know that  $\bar{c}_{\text{MMSE}}$  minimizes the MSE. Thus, we have  $MSE(\bar{c}_{\text{MMSE}}) \leq MSE(\bar{c}_{\text{ZF}})$  and consequently, as  $\sigma_w$  tends to zero, so does  $MSE(\bar{c}_{\text{MMSE}})$ . We have, from above,

$$\begin{aligned} \text{MSE}(\bar{c}_{\text{MMSE}}) &= \\ &= |\langle \bar{c}_{\text{MMSE}}, \bar{u}_0 \rangle - 1|^2 + \sum_{i \neq 0} |\langle \bar{c}_{\text{MMSE}}, \bar{u}_i \rangle|^2 \\ &\quad + \sigma_w^2 \|\bar{c}_{\text{MMSE}}\|^2 \end{aligned}$$

The above is a sum of squares. Thus, since  $\text{MSE}(\bar{c}_{\text{MMSE}})$  tends to zero as  $\sigma_w$  tends to zero, so must each square. This means that  $\langle \bar{c}_{\text{MMSE}}, \bar{u}_0 \rangle \rightarrow 1$  and  $\langle \bar{c}_{\text{MMSE}}, \bar{u}_i \rangle \rightarrow 0$  as  $\sigma_w$  tends to zero. Thus, MMSE tends to ZF as  $\sigma_w \rightarrow 0$ .

**Answer:** Proven above.

## 5

We were given the two generator matrices

$$\begin{aligned} G_1(D) &= \begin{pmatrix} 1+D & D & 1 \\ D^2 & 1 & 1+D+D^2 \end{pmatrix}, \\ G_2(D) &= \begin{pmatrix} 1 & 1+D+D^2 & D^2 \\ 1+D & D & 1 \end{pmatrix}. \end{aligned}$$

- a. The two generator matrices generate the same code if we can go from one of them to the other using row operations. Let  $g_{i,j}(D)$  denote the  $j$ -th row of matrix  $G_i(D)$ . First, we note that  $g_{1,1}(D) = g_{2,2}(D)$  holds. What is left is then to show that  $g_{2,1}(D)$  can be written as a linear combination of  $g_{1,1}(D)$  and  $g_{1,2}(D)$ . By studying the last element in those rows, we see that if there is a solution, it has to be

$$g_{2,1}(D) = (1+D)g_{1,1}(D) + g_{1,2}(D).$$

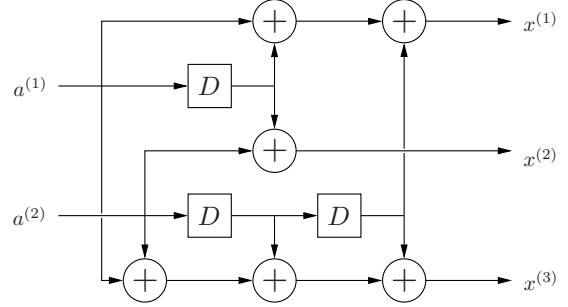
Evaluating that, we find

$$\begin{aligned} (1+D)g_{1,1}(D) + g_{1,2}(D) &= \\ &= (1+D)((1+D), D, 1) + (D^2, 1, 1+D+D^2) \\ &= (1+D^2, D+D^2, 1+D) + (D^2, 1, 1+D+D^2) \\ &= (1, 1+D+D^2, D^2), \end{aligned}$$

which indeed is  $g_{2,1}(D)$ . Done!

- b. No! A generator matrix is catastrophic if all entries in the matrix is divisible by the same polynomial. That is not the case for any of the two matrices, since both have 1 as at least one entry.

- c. An encoder, defined by  $G_1(D)$ :



**Answer:**

- a. Shown above.  
b. No. Both matrices are non-catastrophic.  
c. See encoder above.