ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

School of Computer and Communication Sciences

Handout 19

Principles of Digital Communications Apr. 12, 2019

Midterm solutions

Problem 1. (a)

$$m_{i} = \mathbb{E}\left[\sum_{j} b_{j} Y_{j} \middle| H = i\right] = \sum_{j} b_{j} \mathbb{E}\left[Y_{j} \middle| H = i\right] = s_{i} \sum_{j} a_{j} b_{j} \mathbb{E}\left[Z_{j}\right] = s_{i} \sum_{j} a_{j} b_{j},$$
(1)
$$v_{i} = \operatorname{Var}\left[\sum_{j} b_{j} Y_{j} \middle| H = i\right] \stackrel{(*)}{=} \sum_{j} b_{j}^{2} \operatorname{Var}\left[Y_{j} \middle| H = i\right] = s_{i}^{2} \sum_{j} a_{j}^{2} b_{j}^{2} \operatorname{Var}\left[Z_{j}\right] = s_{i}^{2} \sum_{j} a_{j}^{2} b_{j}^{2},$$
(2)

where in (\star) we use the fact that the Y_j are uncorrelated. Combining eqs. (1) and (2) gives

$$q = \frac{(m_0 - m_1)^2}{v_0 + v_1} = \frac{(s_0 - s_1)^2}{s_0^2 + s_1^2} \frac{\left(\sum_j a_j b_j\right)^2}{\sum_j a_j^2 b_j^2}.$$
 (3)

(b) Let $\mathbf{c} = [a_1 b_1, \dots, a_n b_n] \in \mathbb{R}^n$.

$$\left(\sum_{j} a_{j} b_{j}\right)^{2} = \left(\sum_{j} c_{j}\right)^{2} = \left|\langle \mathbf{c}, \mathbf{1} \rangle\right|^{2} \overset{(\star)}{\leq} \|\mathbf{c}\|_{2}^{2} \|\mathbf{1}\|_{2}^{2} = n \sum_{j} a_{j}^{2} b_{j}^{2},$$

where (\star) is due to the Cauchy-Schwarz inequality. Plugging the above into eq. (3) gives

$$q \le n \frac{(s_0 - s_1)^2}{(s_0^2 + s_1^2)}. (4)$$

(c) Quality q is maximized when eq. (4) holds with equality, which is true if and only if \mathbf{c} and $\mathbf{1}$ are colinear, i.e.,

$$b_j = \frac{\lambda}{a_j},\tag{5}$$

for some constant $\lambda \in \mathbb{R}$.

(d)

$$f_{Y|H}(y|i) = \prod_{j=1}^{n} f_{Y_j|H}(y_j|i) = \prod_{j=1}^{n} f_{Z_j}\left(\frac{y_j}{s_i a_j}\right) = \exp\left(-\frac{1}{s_i} \sum_{j=1}^{n} \frac{y_j}{a_j}\right) \stackrel{eq. (5)}{=} \exp\left(-\frac{T}{\lambda s_i}\right).$$

As the joint distribution only depends on $Y = [Y_1, \ldots, Y_n]$ through T, the statistic is sufficient.

PROBLEM 2. (a) A simple orthonormal basis for $\mathcal{W} = \{w_0, w_1, w_2, w_3\}$ is

$$\mathcal{B} = \{ \psi_0(t) = \psi(t), \psi_1(t) = \psi(t-1) \}, \qquad \psi(t) = \mathbb{1}_{[0,1]}(t).$$

Using \mathcal{B} , the MAP optimal decision rule is given by

$$\hat{H} = \underset{i \in \{0.1,2,3\}}{\arg \max} \langle Y, c_i \rangle - \frac{1}{2} \|c_i\|_2^2,$$

where $Y = [\langle R, \psi_0 \rangle, \langle R, \psi_1 \rangle] \in \mathbb{R}^2$ and $c_i = [\langle w_i, \psi_0 \rangle, \langle w_i, \psi_1 \rangle] \in \mathbb{R}^2$. In practice we cannot obtain Y as above since we don't have a matched filter for ψ . Notice however that $\psi(t) = h_0(t) + h_1(t)$ such that

$$\langle R, \psi_0 \rangle = \int R(t)\psi_0(t) dt = \int R(t)h_0(t) dt + \int R(t)h_1(t) dt$$

$$= (R * h_1)(1) + (R * h_0)(1),$$

$$\langle R, \psi_1 \rangle = \int R(t)\psi_0(t-1) dt = \int R(t)h_0(t-1) dt + \int R(t)h_1(t-1) dt$$

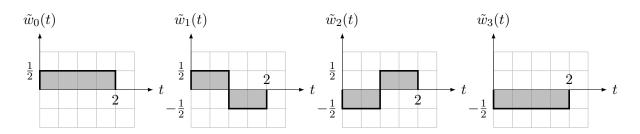
$$= (R * h_1)(2) + (R * h_0)(2).$$

Therefore the optimal MAP decoder is still achievable by choosing $Y = [Y_{10} + Y_{00}, Y_{11} + Y_{01}]$ with $t_{10} = t_{00} = 1$ and $t_{11} = t_{01} = 2$.

(b) The minimum energy signal set $\widetilde{W} = \{\widetilde{w}_0, \widetilde{w}_1, \widetilde{w}_2, \widetilde{w}_3\}$ is obtained by subtracting the mean signal m(t) from the w_i :

$$m = \frac{1}{4} \sum_{i} w_i = \frac{1}{2} \psi_0 + \frac{1}{2} \psi_1$$

$$\begin{split} \tilde{w}_0 &= w_0 - m = \frac{1}{2}\psi_0 + \frac{1}{2}\psi_1, \qquad \tilde{w}_1 = w_1 - m = \frac{1}{2}\psi_0 - \frac{1}{2}\psi_1, \\ \tilde{w}_2 &= w_2 - m = -\frac{1}{2}\psi_0 + \frac{1}{2}\psi_1, \qquad \tilde{w}_3 = w_3 - m = -\frac{1}{2}\psi_0 - \frac{1}{2}\psi_1. \end{split}$$



(c) Using basis \mathcal{B} given above, the codewords associated to $\widetilde{\mathcal{W}}$ are

$$\tilde{c}_0 = \begin{bmatrix} \frac{1}{2}, \frac{1}{2} \end{bmatrix}, \quad \tilde{c}_1 = \begin{bmatrix} \frac{1}{2}, -\frac{1}{2} \end{bmatrix}, \quad \tilde{c}_2 = \begin{bmatrix} -\frac{1}{2}, \frac{1}{2} \end{bmatrix}, \quad \tilde{c}_3 = \begin{bmatrix} -\frac{1}{2}, -\frac{1}{2} \end{bmatrix}.$$

Recognizing a QAM constellation with minimum codeword distance d = 1, the error probability is given by

$$P_e(\widetilde{\mathcal{W}}) = 2Q\left(\frac{1}{\sqrt{2N_0}}\right) - Q\left(\frac{1}{\sqrt{2N_0}}\right)^2.$$

(d) \mathcal{W} and $\widetilde{\mathcal{W}}$ are linked though an isometric transform, hence their error probabilities are identical:

$$P_e(\mathcal{W}) = P_e(\widetilde{\mathcal{W}}) = 2Q\left(\frac{1}{\sqrt{2N_0}}\right) - Q\left(\frac{1}{\sqrt{2N_0}}\right)^2.$$

PROBLEM 3. (a) By the Cauchy-Schwarz inequality:

$$\langle w_i, w_j \rangle^2 \le \|w_i\|_2^2 \|w_j\|_2^2.$$
 (6)

For $i \neq j$, eq. (6) simplifies to $\beta^2 \leq 1$, thus proving the claim.

(b) Based on the hint, we have

$$||w_0 + w_1 + w_2||_2^2 = ||w_0||_2^2 + ||w_1 + w_2||_2^2 + 2\langle w_0, w_1 + w_2 \rangle$$

$$= ||w_0||_2^2 + ||w_1||_2^2 + ||w_2||_2^2 + 2\langle w_0, w_1 \rangle + 2\langle w_0, w_2 \rangle + 2\langle w_1, w_2 \rangle$$

$$= 3 + 6\beta.$$
(7)

By the non-negativity property of $\|\cdot\|_2$, we must have $3+6\beta \ge 0$, which implies $\beta \ge -\frac{1}{2}$.

(c) The minimum energy signal set $\widetilde{\mathcal{W}} = \{\widetilde{w}_0, \widetilde{w}_1, \widetilde{w}_2\}$ is obtained by subtracting the mean signal m(t) from the w_i :

$$m = \frac{1}{3} \sum_{i} w_i.$$

$$\tilde{w}_0 = w_0 - m = +\frac{2}{3}w_0 - \frac{1}{3}w_1 - \frac{1}{3}w_2,$$

$$\tilde{w}_1 = w_1 - m = -\frac{1}{3}w_0 + \frac{2}{3}w_1 - \frac{1}{3}w_2,$$

$$\tilde{w}_2 = w_2 - m = -\frac{1}{3}w_0 - \frac{1}{3}w_1 + \frac{2}{3}w_2.$$

Let $\{w_i, w_j, w_k\}$ and $\{\tilde{w}_i, \tilde{w}_j, \tilde{w}_k\}$ be some arbitrary relabeling of $\{w_0, w_1, w_2\}$ and $\{\tilde{w}_0, \tilde{w}_1, \tilde{w}_2\}$ respectively:

$$\|\tilde{w}_{i}\|_{2}^{2} = \|w_{i} - m\|_{2}^{2} = \|w_{i}\|_{2}^{2} + \|m\|_{2}^{2} - 2\langle w_{i}, m \rangle$$

$$= \|w_{i}\|_{2}^{2} + \left\|\frac{1}{3}w_{i} + \frac{1}{3}w_{j} + \frac{1}{3}w_{k}\right\|_{2}^{2} - 2\langle w_{i}, \frac{1}{3}w_{i} + \frac{1}{3}w_{j} + \frac{1}{3}w_{k}\rangle$$

$$\stackrel{eq. (7)}{=} \|w_{i}\|_{2}^{2} + \frac{1}{9}(3 + 6\beta) - \frac{2}{3}(\|w_{i}\|_{2}^{2} + \langle w_{i}, w_{j} \rangle + \langle w_{i}, w_{k} \rangle)$$

$$= 1 + \frac{1}{9}(3 + 6\beta) - \frac{2}{3}(1 + 2\beta) = \frac{2}{3}(1 - \beta) = E,$$
(8)

$$\langle \tilde{w}_{i}, \tilde{w}_{j} \rangle = \langle \frac{2}{3} w_{i} - \frac{1}{3} w_{j} - \frac{1}{3} w_{k}, -\frac{1}{3} w_{i} + \frac{2}{3} w_{j} - \frac{1}{3} w_{k} \rangle$$

$$= -\frac{2}{9} \|w_{i}\|_{2}^{2} + \frac{5}{9} \langle w_{i}, w_{j} \rangle - \frac{1}{9} \langle w_{i}, w_{k} \rangle - \frac{2}{9} \|w_{j}\|_{2}^{2} - \frac{1}{9} \langle w_{j}, w_{k} \rangle + \frac{1}{9} \|w_{k}\|_{2}^{2}$$

$$= -\frac{1}{3} (1 - \beta)^{eq} \stackrel{(8)}{=} -\frac{E}{2}. \tag{9}$$

(d) $\widetilde{\mathcal{W}}$ is related to $\mathcal{W} = \{w_0, w_1, w_2\}$ through an isometric transform, hence they have the same error probability P_e . We will therefore consider $\widetilde{\mathcal{W}}$ below.

Notice from item c that $\|\tilde{w}_i\|_2^2 = E$ and $\frac{\langle \tilde{w}_i, \tilde{w}_j \rangle}{\|\tilde{w}_i\|_2 \|\tilde{w}_j\|_2} = -\frac{1}{2} = \cos(120^\circ)$, therefore $\widetilde{\mathcal{W}}$ is indeed a 3-PSK constellation and we can quantify its error rate P_e using $e_3(\cdot)$. To this end, let us define an orthonormal basis $\mathcal{B} = \{\psi_0, \psi_1\}$ for $\widetilde{\mathcal{W}}$:

$$\psi_0 = \frac{\tilde{w}_0}{\|\tilde{w}_0\|_2} = \frac{\tilde{w}_0}{\sqrt{E}}, \qquad \psi_1 = \frac{\tilde{w}_1 - \langle \tilde{w}_1, \psi_0 \rangle \psi_0}{\|\tilde{w}_1 - \langle \tilde{w}_1, \psi_0 \rangle \psi_0\|_2} = \frac{\sqrt{E}}{2} \tilde{w}_0 + \tilde{w}_1.$$

Using \mathcal{B} , the sufficient statistic $Y \in \mathbb{R}^2$ behaves as

$$Y|H=0 \sim \mathcal{N}\left(\left[\sqrt{E}, 0\right], \frac{N_0}{2}I_2\right).$$

Equivalently $\widetilde{Y} = \sqrt{\frac{2}{N_0}} Y$ behaves as

$$\widetilde{Y}|H=0 \sim \mathcal{N}\left(\left[A,0\right],I_{2}\right),$$

with $A = \sqrt{2E/N_0}$. Therefore communicating with \mathcal{W} over an AWGN channel of power spectral density $\frac{N_0}{2}$ gives rise to an error rate

$$P_e = e_3 \left(\sqrt{\frac{2E}{N_0}} \right) = e_3 \left(\sqrt{\frac{4(1-\beta)}{3N_0}} \right).$$

PROBLEM 4. (a) Conditioned on H and t_0 , Y follows the Gaussian distribution

$$Y|H, t_0 \sim \mathcal{N}\left(\left(w_H * h\right)(t_0), \frac{N_0}{2} \|h\|_2^2\right),$$
 (10)

$$(w_H * h) (t_0) = \int_{t_0 - \frac{1}{2}}^{t_0 + \frac{1}{2}} w_H(t) dt = \frac{(-1)^H}{2}.$$
 (11)

Given the above, we have

$$P_{e}|H, t_{0} = Q\left(\frac{|(w_{H} * h) (t_{0})|}{\sqrt{N_{0}/2} \|h\|_{2}}\right) = Q\left(\sqrt{\frac{1}{2N_{0}}}\right),$$

$$P_{e} = \mathbb{E}_{H,t_{0}} [P_{e}|H, t_{0}] = Q\left(\sqrt{\frac{1}{2N_{0}}}\right).$$

(b) eq. (10) still holds here, but now $||h||_2 = \sqrt{2}$ and $\mathbb{E}[Y|H, t_0]$ is given by

$$(w_H * h) (t_0) = \int_{t_0-1}^{t_0+1} w_H(t) dt = (-1)^H.$$

The error probability therefore becomes

$$P_{e}|H, t_{0} = Q\left(\frac{|(w_{H} * h) (t_{0})|}{\sqrt{N_{0}/2} \|h\|_{2}}\right) = Q\left(\sqrt{\frac{1}{N_{0}}}\right),$$

$$P_{e} = \mathbb{E}_{H,t_{0}} \left[P_{e}|H, t_{0}\right] = Q\left(\sqrt{\frac{1}{N_{0}}}\right).$$

(c) eq. (10) still holds here, but we will simplify terms differently:

$$||h||_{2}^{2} = \int_{-\infty}^{0} h^{2}(t) dt + \int_{0}^{\infty} h^{2}(t) dt = E_{-} + E_{+},$$

$$(w_{H} * h) (0.5) = \int w_{H}(t) h\left(\frac{1}{2} - t\right) dt = (-1)^{H} \int_{-\frac{1}{2}}^{\frac{1}{2}} h\left(\frac{1}{2} - t\right) dt$$

$$= (-1)^{H} \int_{0}^{1} h(\alpha) d\alpha = (-1)^{H} A_{+},$$

$$(w_{H} * h) (-0.5) = \int w_{H}(t) h\left(-\frac{1}{2} - t\right) dt = (-1)^{H} \int_{-\frac{1}{2}}^{\frac{1}{2}} h\left(-\frac{1}{2} - t\right) dt$$

$$= (-1)^{H} \int_{-1}^{0} h(\alpha) d\alpha = (-1)^{H} A_{-}.$$

The error probability therefore becomes

$$P_{e}|H, t_{0} = Q\left(\frac{\left|\left(w_{H} * h\right)\left(t_{0}\right)\right|}{\sqrt{N_{0}/2} \left\|h\right\|_{2}}\right) = \begin{cases} Q\left(\sqrt{\frac{2A_{+}^{2}}{N_{0}(E_{-}+E_{+})}}\right), & t_{0} = 0.5\\ Q\left(\sqrt{\frac{2A_{-}^{2}}{N_{0}(E_{-}+E_{+})}}\right), & t_{0} = -0.5 \end{cases},$$

$$P_{e} = \mathbb{E}_{H,t_{0}}\left[P_{e}|H, t_{0}\right] = \frac{1}{2}Q\left(\sqrt{\frac{2A_{+}^{2}}{N_{0}\left(E_{-}+E_{+}\right)}}\right) + \frac{1}{2}Q\left(\sqrt{\frac{2A_{-}^{2}}{N_{0}\left(E_{-}+E_{+}\right)}}\right).$$

(d)
$$A_{+}^{2} = \left(\int_{0}^{1} h(t) \cdot 1 \, dt\right)^{2} \le \int_{0}^{1} h^{2}(t) \, dt \int_{0}^{1} dt \le \int_{0}^{\infty} h^{2}(t) \, dt = E_{+},$$

where the first inequality is due to the Cauchy-Schwarz theorem. A similar argument applied to (A_-, E_-) also implies $A_-^2 \leq E_-$.

(e)
$$P_{e} \stackrel{(e)}{=} \frac{1}{2} Q\left(\sqrt{\frac{A_{+}^{2}}{\sigma^{2} (E_{-} + E_{+})}}\right) + \frac{1}{2} Q\left(\sqrt{\frac{A_{-}^{2}}{\sigma^{2} (E_{-} + E_{+})}}\right) \ge Q\left(\sqrt{\frac{A_{-}^{2} + A_{+}^{2}}{2\sigma^{2} (E_{-} + E_{+})}}\right) \stackrel{(d)}{\ge} Q\left(\sqrt{\frac{1}{2\sigma^{2}}}\right) = Q\left(\sqrt{\frac{1}{N_{0}}}\right).$$

As the lower bound is achieved by the filter used in (b), the former is optimal.