# UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN Department of Electrical and Computer Engineering

# ECE 417 MULTIMEDIA SIGNAL PROCESSING Fall 2018

#### **EXAM 1 SOLUTIONS**

Thursday, October 18, 2018

# Problem 1 (16 points)

A particular random signal u[n] has the following DTFT:

$$U(e^{j\omega}) = ae^{j\theta}\delta(\omega - 0.2\pi) + ae^{-j\theta}\delta(\omega + 02.\pi)$$

where

- a is a real-valued Gaussian random variable with mean 0 and variance  $\sigma^2$
- $\theta$  is a real-valued random variable uniformly distributed between 0 and  $2\pi$ .

Find the random signal u[n], and its statistical autocorrelation  $R_{uu}[m]$ , in terms of  $a, \sigma^2, \theta, n$ , and/or m.

### Solution

$$u[n] = \frac{a}{2\pi} e^{j\theta} e^{j0.2\pi n} + \frac{a}{2\pi} e^{-j\theta} e^{-j0.2\pi n}$$
$$= \frac{a}{\pi} \cos(\theta + 0.2\pi n)$$

$$R_{uu}[m] = E [u[n]u[n - m]]$$
  
=  $E \left[ \left( \frac{a}{\pi} \right)^2 \cos \left( \theta + 0.2\pi n \right) \cos \left( \theta + 0.2\pi (n - m) \right) \right]$   
=  $E \left[ \frac{a^2}{2\pi^2} \cos(2\theta + 0.2\pi (2n - m)) \right] + E \left[ \frac{a^2}{2\pi^2} \cos(0.2\pi m) \right]$   
=  $0 + \frac{\sigma^2}{2\pi^2} \cos(0.2\pi m)$ 

#### Problem 2 (17 points)

A particular voiced speech signal has pitch period P, and vocal tract transfer function  $H(e^{j\omega})$ . The signal is windowed by a window function w[n] of length N, producing the windowed signal

$$s[n] = \begin{cases} w[n] \sum_{\ell=-\infty}^{\infty} h[n-\ell P] & 0 \le n \le N-1 \\ 0 & \text{otherwise} \end{cases}$$

Find S[k], the N-point DFT of s[n], in terms of  $k, P, N, H(e^{j\omega})$ , and  $W(e^{j\omega})$ .

## Solution

s[n] = w[n] (e[n] \* h[n]), where

$$e[n] = \sum_{\ell=-\infty}^{\infty} \delta[n-\ell P] \leftrightarrow E(e^{j\omega}) = \left(\frac{2\pi}{P}\right) \sum_{m=0}^{P-1} \delta\left(\omega - \frac{2\pi m}{P}\right)$$

$$\begin{split} S(e^{j\omega}) &= \frac{1}{2\pi} W(e^{j\omega}) \circledast \left( H(e^{j\omega}) E(e^{j\omega}) \right) \\ &= \frac{1}{2\pi} W(e^{j\omega}) \circledast \left( \frac{2\pi}{P} \sum_{m=0}^{P-1} H(e^{j\frac{2\pi m}{P}}) \delta \left( \omega - \frac{2\pi m}{P} \right) \right) \\ &= \frac{1}{P} \sum_{m=0}^{P-1} H(e^{j\frac{2\pi m}{P}}) W \left( e^{j\left( \omega - \frac{2\pi m}{P} \right)} \right) \\ S[k] &= \frac{1}{P} \sum_{m=0}^{P-1} H(e^{j\frac{2\pi m}{P}}) W \left( e^{j\left( \frac{2\pi k}{N} - \frac{2\pi m}{P} \right)} \right) \end{split}$$

#### Problem 3 (17 points)

Your goal is to find a positive real number, a, so that ax[n] is as similar as possible to y[n] in the sense that it minimizes the following error:

$$\epsilon = \int_{-\pi}^{\pi} \left( |Y(e^{j\omega})| - a |X(e^{j\omega})| \right)^2 d\omega$$

Find the value of a that minimizes  $\epsilon$ , in terms of  $|X(e^{j\omega})|$  and  $|Y(e^{j\omega})|$ .

## Solution:

$$\frac{\partial \epsilon}{\partial a} = 2 \int_{-\pi}^{\pi} \left( a |X(e^{j\omega})| - |Y(e^{j\omega})| \right) |X(e^{j\omega})| d\omega$$

which equals 0 at:

$$a = \frac{\int_{-\pi}^{\pi} |X(e^{j\omega})| |Y(e^{j\omega})| d\omega}{\int_{-\pi}^{\pi} |X(e^{j\omega})|^2 d\omega}$$

### Problem 4 (17 points)

A 2-dimensional Gaussian random vector has mean  $\vec{\mu}$  and covariance  $\Sigma$  given by

$$\vec{\mu} = \begin{bmatrix} 1\\1 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2}\\ \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \end{bmatrix} \begin{bmatrix} 8 & 0\\0 & 2 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2}\\ \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \end{bmatrix}$$

Draw a curve of some kind, on a two-dimensional Cartesian plane, showing the set of points  $\left\{\vec{x}: p_X(\vec{x}) = \frac{1}{8\pi}e^{-\frac{1}{2}}\right\}$ .

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#### Solution:

 $|\Sigma| = |\Lambda| = 16$ , so

$$p_X(\vec{x}) = \frac{1}{8\pi} e^{-\frac{1}{2}d_{\Sigma}^2(\vec{x},\vec{\mu})}$$

so the solution is the set  $\{\vec{x}: d_{\Sigma}^2(\vec{x}, \vec{\mu}) = 1\}.$ 

$$d_{\Sigma}^{2}(\vec{x},\vec{\mu}) = \vec{y}^{T}\Lambda^{-1}\vec{y} = \frac{y_{1}^{2}}{8} + \frac{y_{2}^{2}}{2}$$
$$\vec{y} = \frac{\sqrt{2}}{2} \begin{bmatrix} (x_{1}-1) + (x_{2}-1) \\ (x_{1}-1) - (x_{2}-1) \end{bmatrix}$$

So the solution is the set

$$\left\{ \vec{x} : \frac{(x_1 + x_2 - 2)^2}{16} + \frac{(x_1 - x_2)^2}{4} = 1 \right\}$$

... which is an ellipse, centered at (1,1), with a radius of  $2\sqrt{2}$  along the (1,1) direction, and a radius of  $\sqrt{2}$  along the (1,-1) direction.

#### Problem 5 (16 points)

In terms of  $\alpha_t(i)$ ,  $\beta_t(i)$ ,  $a_{ij}$ ,  $\pi_i$  and  $b_i(\vec{x}_t)$ , find

$$p(q_6 = i, q_7 = j | \vec{x}_1, \dots, \vec{x}_{20})$$

### Solution:

$$p(q_6 = i, q_7 = j, \vec{x}_1, \dots, \vec{x}_{20}) = p(\vec{x}_1, \dots, \vec{x}_6, q_6 = i)p(q_7 = j|q_6 = i)p(\vec{x}_7|q_7 = j)p(\vec{x}_8, \dots, \vec{x}_{20}|q_7 = j)$$
$$= \alpha_6(i)a_{ij}b_j(\vec{x}_7)\beta_7(j)$$
$$p(q_6 = i, q_7 = j|\vec{x}_1, \dots, \vec{x}_{20}) = \frac{\alpha_6(i)a_{ij}b_j(\vec{x}_7)\beta_7(j)}{\sum_{k=1}^N \sum_{\ell=1}^N \alpha_6(k)a_{k\ell}b_\ell(\vec{x}_7)\beta_7(\ell)}$$

#### Problem 6 (17 points)

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A particular HMM-based speech recognizer only knows two words: word  $w_0$ , and word  $w_1$ . Word  $w_0$  has a higher *a priori* probability:  $p_Y(w_0) = 0.7$ , while  $p_Y(w_1) = 0.3$ . Each of the two words is modeled by a four-state Gaussian HMM (N = 4) with three-dimensional observations (D = 3). All states, in both HMMs, have identity covariance ( $\Sigma_i = I$ ). Both HMMs have *exactly* the same transition probabilities and state-dependent means, given by:

**Both Words:** 
$$A = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \end{bmatrix}, \quad \vec{\mu}_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad \vec{\mu}_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \quad \vec{\mu}_3 = \begin{bmatrix} 1 \\ -1 \\ -1 \\ -1 \end{bmatrix}, \quad \vec{\mu}_4 = \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}$$

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But the initial residence probabilities are different:

Word 0: 
$$\pi_i = \begin{cases} 1 & i = 1 \\ 0 & \text{otherwise} \end{cases}$$
 Word 1:  $\pi_i = \begin{cases} 1 & i = 4 \\ 0 & \text{otherwise} \end{cases}$ 

Suppose that you have a two-frame observation,  $X = [\vec{x}_1, \vec{x}_2]$ , where  $\vec{x}_t = [x_{1t}, x_{2t}, x_{3t}^T]$ . The MAP decision rule, in this case, can be written as a linear classifier,

$$\hat{y} = \begin{cases} w_1 & \vec{w}_1^T \vec{x}_1 + \vec{w}_2^T \vec{x}_2 + b > 0\\ w_0 & \text{otherwise} \end{cases}$$

Find  $\vec{w}_1$ ,  $\vec{w}_2$ , and b.

# Solution:

The Bayesian classifier chooses  $w_1$  if

$$p(w_0)p(X|w_0) < p(w_1)p(X|w_1)$$

$$0.7\mathcal{N}(\vec{x}_1|\vec{\mu}_1) \sum_j a_{1j}\mathcal{N}(\vec{x}_2|\vec{\mu}_j) < 0.3\mathcal{N}(\vec{x}_4|\vec{\mu}_4) \sum_j a_{4j}\mathcal{N}(\vec{x}_2|\vec{\mu}_j)$$

$$0.7\mathcal{N}(\vec{x}_1|\vec{\mu}_1) < 0.3\mathcal{N}(\vec{x}_1|\vec{\mu}_4)$$

$$\ln(0.7) - \frac{1}{2}(\vec{x}_1 - \vec{\mu}_1)^T(\vec{x}_1 - \vec{\mu}_1) < \ln(0.3) - \frac{1}{2}(\vec{x}_1 - \vec{\mu}_4)^T(\vec{x}_1 - \vec{\mu}_4)$$

$$\ln(0.7) - \frac{1}{2}\|\vec{x}_1\|^2 < \ln(0.3) - \frac{1}{2}\|\vec{x}_1\|^2 + \vec{\mu}_4^T\vec{x}_1 - \frac{1}{2}\|\vec{\mu}_4\|^2$$

Which is satisfied if

$$\vec{\mu}_4^T \vec{x}_1 + \ln\left(\frac{3}{7}\right) - \frac{3}{2} > 0$$

 $\operatorname{So}$ 

$$\vec{w}_1 = \begin{bmatrix} -1\\ -1\\ 1 \end{bmatrix}, \quad \vec{w}_2 = \begin{bmatrix} 0\\ 0\\ 0 \end{bmatrix}, \quad b = \ln\left(\frac{3}{7}\right) - \frac{3}{2}$$