#### EGT3

### **ENGINEERING TRIPOS PART IIB**

Wednesday 24 April 2019 2 to 3.40

#### **Module 4F7**

#### STATISTICAL SIGNAL ANALYSIS

Answer not more than three questions.

All questions carry the same number of marks.

The **approximate** percentage of marks allocated to each part of a question is indicated in the right margin.

Write your candidate number not your name on the cover sheet.

# STATIONERY REQUIREMENTS

Single-sided script paper

## SPECIAL REQUIREMENTS TO BE SUPPLIED FOR THIS EXAM

CUED approved calculator allowed Engineering Data Book

10 minutes reading time is allowed for this paper at the start of the exam.

You may not start to read the questions printed on the subsequent pages of this question paper until instructed to do so. Let X be a zero mean random variable. Let  $Y_1, \ldots, Y_n$  be a further collection of n random variables and let  $\mathbb{E}\{Y_i\} = m_i$ . A linear estimate of X using  $Y_1, \ldots, Y_n$  is

$$\hat{X}_n = h_1 (Y_1 - m_1) + \ldots + h_n (Y_n - m_n).$$

(a) The constants  $h_1, \ldots, h_n$  that minimise the error  $\mathbf{E}\left\{(X - \hat{X}_n)^2\right\}$  can be expressed as

$$A\left[\begin{array}{c}h_1\\\vdots\\h_n\end{array}\right]=b.$$

Find the matrix A and vector b.

[30%]

(b) Let  $Y_n$  satisfy

$$\mathbf{E}\{Y_iY_n\} = \mathbf{E}\{Y_i\}\mathbf{E}\{Y_n\}, \quad \text{for } i = 1, \dots, n-1.$$

(i) Show that the minimising  $h_n$  satisfies

$$h_n = \left( \mathbf{E} \{ Y_n Y_n \} - \mathbf{E} \{ Y_n \}^2 \right)^{-1} \mathbf{E} \{ X Y_n \}.$$

[10%]

- (ii) Let  $\hat{X}_{n-1}$  be the best linear estimate of X using  $Y_1, \dots, Y_{n-1}$ . Find the equation that updates  $\hat{X}_{n-1}$  to  $\hat{X}_n$ . [20%]
- (c) Let X be a zero mean Gaussian random variable. A sensor provides noisy measurements of X,

$$Y_i = \operatorname{sign}(X) + W_i$$

for i = 1, ..., n-1 where  $W_i$  are independent zero mean random variables with variance  $\sigma^2$  and sign(X) = 1 if  $X \ge 0$  and sign(X) = -1 otherwise.

- (i) Find  $\hat{X}_{n-1}$ . [20%]
- (ii) Measurement  $Y_n$  is generated by a different sensor,  $Y_n = |X| + W_n$ . Find  $\hat{X}_n$ . [20%]

Consider the following hidden Markov model (HMM) where  $X_n$  is a two-state hidden Markov chain,  $X_n \in \{-1, 1\}$ , with transition probability matrix

$$P = \left[ \begin{array}{cc} 1 - \alpha & \alpha \\ \alpha & 1 - \alpha \end{array} \right].$$

Let  $Y_n$  be the observed process,  $Y_n \in \{-1, 1\}$ , where

$$p(y_n|x_n) = \begin{cases} 1 - \beta & \text{if } y_n = x_n, \\ \beta & \text{if } y_n \neq x_n. \end{cases}$$

Assume  $X_0 = x_0$ .

(a) Given 
$$p(x_n|y_1,...,y_{n-1})$$
, find  $p(x_{n+1}|y_1,...,y_n)$ . [20%]

(b) Given 
$$p(y_{n+1}, ..., y_T | x_{n+1})$$
, find  $p(y_n, ..., y_T | x_n)$ . [20%]

(c) Find 
$$p(x_n|y_1,...,y_T)$$
. [10%]

- (d) Given a sequence of values  $x_1, y_1, \dots, x_T, y_T$ , find the value of  $\beta$  that maximises  $p(x_1, y_1, \dots, x_T, y_T | x_0)$ . [20%]
- (e) Assume  $\alpha$  is known. Give the Expectation-Maximisation algorithm for finding the value of  $\beta$  that maximises  $p(y_1, \dots, y_T | x_0)$ . [20%]
- (f) Let  $S_n$  be the price of a financial asset (e.g. a share) and let

$$Y_n = \begin{cases} 1 & \text{if } S_n \ge S_{n-1}, \\ -1 & \text{otherwise.} \end{cases}$$

Describe what  $X_n$  signifies in this application and the impact, on de-noising the data, of choosing different values of  $\beta$  from the range  $0 \le \beta \le 1$ . [10%]

Consider the following state-space model with Gaussian noise: for  $k \ge 0$ ,

$$X_{k+1} = X_k + W_{k+1},$$
  
$$Y_k = X_k + V_k,$$

where  $\{W_k\}$  is an independent and identically distributed (i.i.d.) sequence of Gaussian random variables with mean zero and variance  $\sigma_w$ ,  $\{V_k\}$  is an i.i.d. sequence of Gaussian random variables with mean zero and variance  $\sigma_v$ .  $X_0$  is an independent Gaussian random variable with mean  $\mu_0$  and variance  $\sigma_0$ .

(a) Assume that the conditional probability density function (pdf)  $p(x_n|y_0,...,y_n)$  is a Gaussian pdf with mean  $\mu_n$  and variance  $\sigma_n$ .

(i) Find 
$$p(x_{n+1}|y_0,\ldots,y_n)$$
. [20%]

(ii) Find 
$$p(x_{n+1}|y_0,...,y_{n+1})$$
 and give its mean  $\mu_{n+1}$  and variance  $\sigma_{n+1}$ . [20%]

Hint: You may use the following facts about two independent random variables  $U_1$  and  $U_2$  with pdfs  $p_i(u_i)$ . If  $U_1 + U_2 = y$  then  $p(y) = \int p_2(y - u_1)p_1(u_1)\mathrm{d}u_1$ . If  $U_1$  is  $\mathcal{N}(\mu_1, \sigma_1)$  and  $U_2$  is  $\mathcal{N}(0, \sigma_2)$ , where  $\mathcal{N}(\mu_1, \sigma_1)$  denotes a Gaussian random variable with mean  $\mu_1$  and variance  $\sigma_1$ , then the conditional pdf  $p_2(y - u_1)p_1(u_1)/p(y)$  is Gaussian with mean  $(\sigma_1 y + \sigma_2 \mu_1)/(\sigma_1 + \sigma_2)$  and variance  $(\sigma_1 \sigma_2)/(\sigma_1 + \sigma_2)$ .

- (b) Show that if  $\sigma_{n+1} = \sigma_n$  then  $\sigma_{n+1}^2 \le \sigma_w \sigma_v$ . How might the bound  $\sigma_w \sigma_v$  be useful in practice? [30%]
- (c) Show that  $\mu_n$  is a linear combination of  $y_0, \ldots, y_n$  and  $\mu_0$ . [10%]
- (d) Show that  $\mu_n$  is the best linear estimate of  $X_n$  of the form

$$\hat{x}_n = h \; \mu_0 + h_0 \; y_0 + \ldots + h_n \; y_n$$

that minimises the error  $\int (\hat{x}_n - x_n)^2 p(x_n | y_0, \dots, y_n) dx_n$ . [20%]

4 Let  $X_0, X_1,...$  be a Markov chain with values in  $\{0, 1, 2,...\}$  with the following transition probabilities

$$\Pr(X_{n+1} = j | X_n = i) = \begin{cases} \alpha & \text{if } j = i+1, \\ 1-\alpha & \text{if } j = i-1, \end{cases}$$

when  $X_n = i > 0$ . For  $X_n = 0$ ,  $\Pr(X_{n+1} = 1 | X_n = 0) = \alpha$  and  $\Pr(X_{n+1} = 0 | X_n = 0) = 1 - \alpha$ . Assume  $\Pr(X_0 = k) = \exp(-\lambda)\lambda^k/k!$ , i.e.  $X_0$  has the probability mass function (pmf) of a Poisson random variable.

Let

$$Y_k = X_k + V_k$$

for  $k \ge 0$  where  $V_0, V_1, \ldots$  are independent zero mean Gaussian random variables with variance  $\sigma$ .

(a) Given the pmf 
$$p(x_n|y_0,...,y_n)$$
, find  $p(x_{n+1}|y_0,...,y_{n+1})$ . [20%]

- (b) Let  $X_{0:n}^1, \ldots, X_{0:n}^N$  be N independent samples from  $p(x_0, \ldots, x_n)$ .
  - (i) Find an unbiased estimate  $\hat{p}(y_0, \dots, y_n)$  of  $p(y_0, \dots, y_n)$ . [10%]
  - (ii) Give the importance sampling (IS) estimate of  $p(x_0, ..., x_n | y_0, ..., y_n)$ . [10%]
  - (iii) Give the IS estimate of the value  $\alpha$  such that

$$\sum_{x_0=0}^{\infty} \cdots \sum_{x_n=0}^{\infty} \frac{\mathrm{d}}{\mathrm{d}\alpha} \log p(x_1,\ldots,x_n|x_0) p(x_0,\ldots,x_n|y_0,\ldots,y_n) = 0.$$

[30%]

- (iv) Using sequential importance sampling with re-sampling, extend the IS estimate in part (b)(ii) to an IS estimate of  $p(x_0, ..., x_{n+1}|y_0, ..., y_n)$ . [10%]
- (v) Give the IS estimate  $\hat{p}(y_{n+1}|y_0,...,y_n)$  of the conditional probability density function  $p(y_{n+1}|y_0,...,y_n)$ . Show that the product of estimates

$$\hat{p}(v_{n+1}|v_0,\ldots,v_n)\hat{p}(v_0,\ldots,v_n)$$

is an unbiased estimate of  $p(y_0, \dots, y_{n+1})$ . [20%]

#### **END OF PAPER**

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