

# EE 514, Fall 2006

## Exam 4: Due ECE front desk, 1:45pm, December 6, 2006

**Solutions** (version: December 6, 2006, 20:30)

75 mins.; Total 50 pts.

**1.** (14 pts.) Let  $X_t = A \cos(\omega t + \Theta)$  ( $t \in \mathbb{R}$ ), where  $\omega > 0$  is constant,  $A$  is a random variable with exponential distribution,  $\Theta$  is a uniform random variable on  $(-\pi, \pi]$ , and  $A$  and  $\Theta$  are independent.

- Determine if the process is wide-sense stationary (and if so, find its correlation function). Provide a complete argument.
- Determine if the process is strictly stationary. Provide a complete argument.

**Ans.:** a. First, by independence, we calculate

$$E[X_t] = E[A]E[\cos(\omega t + \Theta)].$$

Using the argument in Example 10.8, we deduce that  $E[X_t] = 0$ . Next, again by independence, we calculate

$$R_X(t_1, t_2) = E[A^2]E[\cos(\omega t_1 + \Theta) \cos(\omega t_2 + \Theta)].$$

Again using the argument in Example 10.8, we find that

$$R_X(t_1, t_2) = \frac{E[A^2]}{2} \cos(\omega(t_1 - t_2)).$$

Hence, the process is WSS.

b. Yes, indeed the process is strictly stationary. The basic idea here is that time-shifting the process by  $\Delta$  (i.e., replacing  $t$  by  $t + \Delta$ ) is equivalent to using a different random phase shift:  $\Theta + \omega\Delta$ . But because  $\Theta$  is uniform on  $(-\pi, \pi]$ ,  $\Theta + \omega\Delta$  is uniform on  $(-\pi + \omega\Delta, \pi + \omega\Delta]$  (the width of this duration is  $2\pi$ , regardless of  $\Delta$ ). As a result, the law of  $X_{t+\Delta}$  is the same as that of  $X_t$ .

To show this rigorously, consider a finite set of times  $t_1 < t_2 < \dots < t_n$  and the associated finite-dimensional distribution function  $F_{X_{t_1}, \dots, X_{t_n}}(x_1, \dots, x_n)$ . Now,

$$\begin{aligned} F_{X_{t_1}, \dots, X_{t_n}}(x_1, \dots, x_n) &= P\{X_{t_1} \leq x_1, \dots, X_{t_n} \leq x_n\} \\ &= P\{A \cos(\omega t_1 + \Theta) \leq x_1, \dots, A \cos(\omega t_n + \Theta) \leq x_n\} \\ &= E[P\{A \cos(\omega t_1 + \Theta) \leq x_1, \dots, A \cos(\omega t_n + \Theta) \leq x_n | A\}] \\ &= E\left[\int_{-\pi}^{\pi} I_C(\theta) \frac{1}{2\pi} d\theta\right], \end{aligned}$$

where

$$C = \{\theta : A \cos(\omega t_1 + \theta) \leq x_1, \dots, A \cos(\omega t_n + \theta) \leq x_n\}$$

and  $I_C$  is the indicator function of  $C$ . Notice that  $I_C$  is a random function (because  $A$  appears in its definition), but its sample paths are periodic with period  $2\pi$ .

Next, consider the shift  $\Delta$ , and the associated distribution function

$$\begin{aligned}
F_{X_{t_1+\Delta}, \dots, X_{t_n+\Delta}}(x_1, \dots, x_n) &= \mathbb{P}\{X_{t_1+\Delta} \leq x_1, \dots, X_{t_n+\Delta} \leq x_n\} \\
&= \mathbb{P}\{A \cos(\omega(t_1 + \Delta) + \Theta) \leq x_1, \dots, A \cos(\omega(t_n + \Delta) + \Theta) \leq x_n\} \\
&= \mathbb{E}[\mathbb{P}\{A \cos(\omega(t_1 + \Delta) + \Theta) \leq x_1, \dots, A \cos(\omega(t_n + \Delta) + \Theta) \leq x_n | A\}] \\
&= \mathbb{E} \left[ \int_{-\pi}^{\pi} I_D(\theta) \frac{1}{2\pi} d\theta \right],
\end{aligned}$$

where

$$\begin{aligned}
D &= \{\theta : A \cos(\omega(t_1 + \Delta) + \theta) \leq x_1, \dots, A \cos(\omega(t_n + \Delta) + \theta) \leq x_n\} \\
&= \{\theta : A \cos(\omega t_1 + (\omega\Delta + \theta)) \leq x_1, \dots, A \cos(\omega t_n + (\omega\Delta + \theta)) \leq x_n\}.
\end{aligned}$$

Note that  $I_D(\theta) = I_C(\omega\Delta + \theta)$ . Hence, substituting the variable  $\tau = \omega\Delta + \theta$  in the integration, we get

$$F_{X_{t_1+\Delta}, \dots, X_{t_n+\Delta}}(x_1, \dots, x_n) = \mathbb{E} \left[ \int_{-\pi+\omega\Delta}^{\pi+\omega\Delta} I_C(\tau) \frac{1}{2\pi} d\tau \right] = F_{X_{t_1}, \dots, X_{t_n}}(x_1, \dots, x_n),$$

because the integrand above is periodic and the integral is over one period. This shows that the process is strictly stationary.

**2.** (20 pts.) Recall our discussion of the matched filter. We have the sum of a signal  $v(t)$  ( $t \in \mathbb{R}$ ) with a wide-sense stationary process  $X_t$ , and we pass this resulting process through an LTI filter with impulse response  $h$ . We then sample the output  $v_o(t) + Y_t$  of the filter at time 0. The SNR is then given by  $v_o(0)^2 / E[Y_0^2]$ .

Given  $S_X$ , find a signal  $v$  and an impulse response  $h$  such that the SNR is maximized, subject to the constraint that  $v$  satisfies  $\int_{-\infty}^{\infty} |V(f)|^4 df \leq 1$ . Note that, unlike in the standard matched filter problem, our problem here is to design *both*  $v$  and  $h$ . Whatever the design, it will depend on  $S_X$ . For technical reasons, assume that  $\int_{-\infty}^{\infty} 1/S_X(f)^p df < \infty$  for  $p = 1, 2, 3$  and identify when you rely on this assumption.

You may give your answer in terms of  $V(f)$  and  $H(f)$ , which are the Fourier transforms of  $v$  and  $h$ , respectively.

**Ans.:** We know that for any  $v$ , the  $h$  that maximizes the SNR is given by the formula

$$H(f) = \alpha \frac{V(f)^*}{S_X(f)}.$$

The SNR in this case is

$$SNR = \int_{-\infty}^{\infty} \frac{|V(f)|^2}{S_X(f)} df.$$

By the Cauchy-Schwarz inequality,

$$SNR^2 \leq \int_{-\infty}^{\infty} |V(f)|^4 df \int_{-\infty}^{\infty} 1/S_X(f)^2 df.$$

(Because of our assumptions on  $S_X$  and the constraint on  $V$ , the right-hand side is finite.) So, to maximize the SNR, we deduce that the optimal choice for  $V$  satisfies

$$|V(f)|^2 = \beta \frac{1}{S_X(f)}.$$

To find  $\beta$ , we note that the SNR is linear in  $\beta$ , so we need to maximize  $\beta$ . This is given by the value of  $\beta$  for which:  $\int_{-\infty}^{\infty} |V(f)|^4 df = 1$ . Hence,  $\beta$  is given by

$$\beta^2 = 1 / \int_{-\infty}^{\infty} 1/S_X(f)^2 df.$$

So a particular choice for  $V(f)$  is

$$V(f) = \frac{\sqrt{\beta}}{\sqrt{S_X(f)}}.$$

(Note that because of our assumption on  $S_X$ , this  $V(f)$  is square integrable, and is therefore legitimately the Fourier transform of some signal  $v$ .) The corresponding optimal  $H$  (ignoring scaling constants) is

$$H(f) = \frac{1}{S_X(f)^{3/2}}.$$

(Again, because of our assumption on  $S_X$ , this  $H(f)$  is square integrable, and is therefore legitimately the Fourier transform of some signal  $h$ .)

**3. (8 pts.)** Let  $b$  be a random variable uniform on  $\{-1, 1\}$ , representing a single bit. Next, let  $\{C_t\}$  represent a wide-sense stationary zero-mean random process with power spectral density  $S_C$ . Consider a communication system in which we communicate the bit  $b$  as follows: the transmitter transmits the signal  $bC_t$  over time and the receiver receives a noise-corrupted version:  $bC_t + N_t$  ( $t \in \mathbb{R}$ ), where  $N_t$  represents noise, and is wide-sense stationary with zero mean and power-spectral density  $S_N$ , and is independent of  $b$  and  $\{C_t\}$ . We filter this received signal using an LTI filter with transfer function  $H$ . Write down a formula for  $H$  (in terms of  $S_C$  and  $S_N$ ) such that if  $Y_t$  is the output of the filter, then the following is minimized for each fixed  $t$ :  $E[(Y_t - bC_t)^2]$ .

**Ans.:** Note that the process  $V_t = bC_t$  is WSS. Hence, the received signal  $U_t = bC_t + N_t$  is WSS also. Next, because  $bC_t$  and  $N_t$  are independent,  $U_t$  and  $V_t$  are J-WSS. Hence, the solution to this problem is the Wiener filter. To find this filter, we first write down (using problem 10.59)  $R_{VU} = R_V = R_C$  and  $R_U = R_V + R_N = R_C + R_N$ . Hence, the filter is given by

$$H = \frac{S_C}{S_C + S_N}.$$

**4. (8 pts.)** Give an example of a discrete-time random process  $\{X_n : n = 1, 2, \dots\}$  such that  $E[X_n]$  does not depend on  $n$  (i.e., the mean sequence is constant over  $n$ ),  $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i$  exists almost surely, but, with nonzero probability,

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i \neq E[X_1].$$

**Ans.:** Let  $Y$  be a random variable such that the mean  $E[Y]$  exists, and  $P\{Y \neq E[Y]\} > 0$  (e.g., Bernoulli(0.5)). Define the process  $\{X_n\}$  by  $X_n = Y$  for all  $n$ . Hence,  $E[X_n] = E[Y]$  does not depend on  $n$ . Moreover,  $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i = Y$ , and hence the limit exists a.s. However, by assumption on  $Y$ , with nonzero probability we have

$$E[X_n] = E[Y] \neq Y = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i.$$