

1. Papoulis 7-20: The event  $\{X \leq x\}$  occurs if at least one point falls in the interval  $(0, x]$ . The event  $\{Y \leq y\}$  occurs if all of the points fall in the interval  $(0, y]$ .

Let  $A_x \triangleq \{X \leq x\}$  and  $B_y = \{Y \leq y\} = \{\text{no points fall in } (y, 1)\}$ .

Hence for  $x \in [0, 1]$  and  $y \in [0, 1]$ , we have

$$F_x(x) = P(A_x) = 1 - P(\bar{A}_x) = 1 - (1-x)^n$$

$$F_y(y) = P(B_y) = y^n$$

$$F_{xy}(x, y) = P(A_x \cap B_y), \text{ and } \bar{B}_y = (A_x \cap B_y) \cup (\bar{A}_x \cap B_y)$$

Now if  $x \leq y$ , then  $\bar{A} \cap B = \{\text{all points in interval } (x, y]\}$

$$P(\bar{A} \cap B) = (y-x)^n$$

If  $x > y$ , then  $\bar{A} \cap B = \phi$  and  $P(\bar{A} \cap B) = 0$

Thus

$$F_{xy}(x, y) = P(A \cap B) = P(B) - P(\bar{A} \cap B) = \begin{cases} y^n - (y-x)^n, & x \leq y \\ y^n, & x > y. \end{cases}$$

2.

Papoulis 7-25 Note that

$$E\{(X_n - a)^2\} = E\{[(X_n - a_n) + (a_n - a)]^2\}$$

$$= E\{(X_n - a_n)^2\} + 2(a_n - a)E\{(X_n - a_n)\} + (a_n - a)^2$$

Now as  $n \rightarrow \infty$ , we are given 1)  $a_n \rightarrow a$

$$2) E\{(X_n - a_n)^2\} \rightarrow 0$$

$$\text{Thus we have } \lim_{n \rightarrow \infty} E\{(X_n - a)^2\} = \lim_{n \rightarrow \infty} \{E\{(X_n - a_n)^2\} + 2(a_n - a)E\{(X_n - a_n)\} + (a_n - a)^2\}$$

$$= 0 + 0 \cdot 0 + 0 = 0$$

$$\therefore E\{(X_n - a)^2\} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

3. Papoulis (7-27): We have  $E[X_k] = 0$  and  $E[X_k^2] = \sigma_k^2$ .

$\Leftarrow$ : Given  $\sum_{k=1}^{\infty} \sigma_k^2 < \infty$ , we wish to show that  $\sum_{k=1}^{\infty} X_k$  converges in mean square.

$\sum_{k=1}^{\infty} \sigma_k^2 < \infty \Rightarrow$  For any  $\varepsilon > 0$ , there exists an  $n_0 \in \mathbb{N}$  such that for any  $n > n_0$ ,

$$\sum_{k=n}^{\infty} \sigma_k^2 < \varepsilon.$$

For such an  $n_0$ , it follows that if  $Y_n = \sum_{k=1}^n X_k$ ,  
 $E[(Y_{n+m} - Y_n)^2] \stackrel{(*)}{=} \sum_{k=n+1}^{n+m} \sigma_k^2 \leq \sum_{k=n}^{\infty} \sigma_k^2 < \varepsilon, \forall n > n_0, \forall m \geq 1$

Aside (\*)

$$\begin{aligned} (*) \text{ Note: } E[(Y_{n+m} - Y_n)^2] &= E\left[\left(\sum_{k=n+1}^{n+m} X_k\right)^2\right] \\ &= E\left[\sum_{j=n+1}^{n+m} \sum_{k=n+1}^{n+m} X_j X_k\right] = \sum_{k=n+1}^{n+m} E[X_k^2] + \sum_{k=n+1}^{n+m} \sum_{\substack{j=n+1 \\ j \neq k}}^{n+m} E[X_j] \cdot E[X_k] \\ &= \sum_{k=n+1}^{n+m} \sigma_k^2 \end{aligned}$$

Thus  $E[(Y_{n+m} - Y_n)^2] \rightarrow 0, \forall m \geq 1$  as  $n \rightarrow \infty$

$\Rightarrow \sum_{k=1}^{\infty} X_k$  converges (m.s.)

$\Rightarrow$ : Show that given convergence (m.s.),  $\sum_{k=1}^{\infty} \sigma_k^2 < \infty$ .

If the sequence converges (m.s.), then the sequence of partial sums  $\{Y_n\}$  converges (m.s.).

This means that by the Cauchy criterion

$$E[(Y_{n+m} - Y_n)^2] \rightarrow 0 \text{ as } n \rightarrow \infty \text{ for all } m \geq 1.$$

$\Rightarrow$  For any  $\varepsilon > 0$ , there exists an  $n_0 \in \mathbb{N}$ , such that for  $n > n_0$  and  $m \geq 1$ ,  $E[(Y_{n+m} - Y_n)^2] = \sum_{k=n+1}^{n+m} \sigma_k^2 < \varepsilon$ ,  
 From which it follows that

$$\sum_{k=1}^{\infty} \sigma_k^2 = \lim_{n \rightarrow \infty} \sum_{k=1}^n \sigma_k^2 < \infty.$$

4. We have from the specification of the RVs  $X_k$  that

$$P(\{X_n = k\}) = \begin{cases} \frac{\alpha}{n^2}, & k = n \\ 1 - \frac{\alpha}{n^2}, & k = 0 \\ 0, & \text{elsewhere} \end{cases}$$

(recall that the RVs take on only non-negative integer values.)

In the limit, as  $n \rightarrow \infty$ , we have

$$\lim_{n \rightarrow \infty} X_n = \begin{cases} \lim_{n \rightarrow \infty} n \text{ (does not exist), with prob } 0 \\ 0, \text{ with probability one} \end{cases}$$

$\therefore X_n \rightarrow 0$  as  $n \rightarrow \infty$  almost everywhere  
or with probability one.

However

$$E[(X_n - 0)^2] = E[X_n^2] = n^2 \cdot \frac{\alpha}{n^2} + 0 \left(1 - \frac{\alpha}{n^2}\right) = \alpha.$$

Thus

$$\lim_{n \rightarrow \infty} E[(X_n - 0)^2] = \lim_{n \rightarrow \infty} \alpha = \alpha$$

$\therefore \{X_n\}$  does not converge in the mean-square sense.

5. Papoulis 7-13

$$\begin{aligned} \phi_Y(s) &= E\{e^{sY}\} = E\{e^{s(X_1 + \dots + X_N)}\} \\ &= E\{E\{e^{s(X_1 + \dots + X_N)} | N=k\}\} \end{aligned}$$

Now because  $N$  and the  $\{X_j\}$  are stat. indep., it follows that

$$\begin{aligned} E\{e^{sY} | N=k\} &= E\{e^{s(X_1 + \dots + X_k)}\} \\ &= E\{e^{sX_1}\} \dots E\{e^{sX_k}\} \\ &= \Phi_{X_1}(s) \dots \Phi_{X_k}(s) \end{aligned}$$

Because the  $\{X_j\}$  are i.i.d, this becomes

$$E\{e^{sY} | N=k\} = [\Phi_X(s)]^k$$

Hence we have

$$\begin{aligned} \phi_Y(s) &= E_N\{E\{e^{sY} | N\}\} = E_N\{[\Phi_X(s)]^N\} \\ &= \prod_N(\phi_X(s)), \text{ since } E\{z^N\} = \prod_N(z) \end{aligned}$$

Special case:

Now if  $N$  is Poisson with parameter  $a$ , this becomes

$$\begin{aligned} \phi_Y(s) &= \sum_{k=0}^{\infty} \frac{a^k e^{-a}}{k!} [\Phi_X(s)]^k = e^{-a} \sum_{k=0}^{\infty} \frac{[a \Phi_X(s)]^k}{k!} \\ &= e^{-a} e^{a \Phi_X(s)} = e^{a \Phi_X(s) - a} \\ &= e^a [\Phi_X(s) - 1] \end{aligned}$$

6. Papoulis 9-1

(a)  $E\{X(t)\} = \frac{1}{2} \cdot \sin \pi t + \frac{1}{2} \cdot 2t = \frac{1}{2} \sin(\pi t) + t$

(b)  $F_{X(t)}(x) = F(x, t) = P\{X(t) \leq x\}$

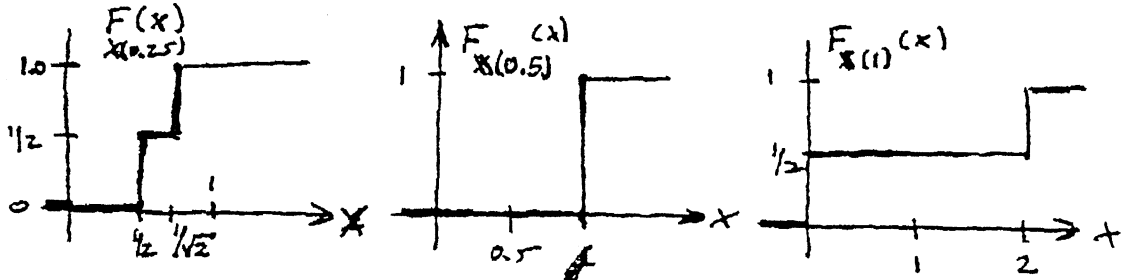
For any particular  $t$ ,  $X(t)$  is a RV:

$$X(0.25) = \begin{cases} \sin \pi/4 = \frac{1}{\sqrt{2}} & , \text{prob } 1/2 \\ 2 \cdot \frac{1}{4} = 1/2 & , \text{prob } 1/2 \end{cases}$$

$$X(0.5) = \begin{cases} \sin \frac{\pi}{2} = 1 & , \text{prob } \frac{1}{2} \\ 2 \cdot \frac{1}{2} = 1 & , \text{prob } \frac{1}{2} \end{cases} = 1 \text{ with prob } 1$$

$$X(1) = \begin{cases} \sin \pi = 0 & , \text{prob } 1/2 \\ 2 \cdot 1 = 2 & , \text{prob } 1/2 \end{cases}$$

Thus  $F_{X(t)}(x)$  for these 3 cases appear as follows:



7.

Papoulis 9-2:  $X(t) = e^{At} \Rightarrow A = \frac{1}{t} \ln X(t)$

$\bar{X}_x(t) = \int_{-\infty}^{\infty} e^{at} f_A(a) da = \phi_A(t)$  (generating f.t.u.)

$R_{XX}(t_1, t_2) = \int_{-\infty}^{\infty} e^{at_1} e^{at_2} f_A(a) da = \int_{-\infty}^{\infty} e^{a(t_1+t_2)} f_A(a) da = \phi_A(t_1+t_2)$

$f_{X(t)}(x) = f_A\left(\frac{1}{t} \ln x\right) \left| \frac{da}{dx} \right|$  ,  $\frac{da}{dx} = \frac{d}{dx} \left[ \frac{1}{t} \ln x \right] = \frac{1}{tx} = \frac{1}{t|x}$

$\therefore f_{X(t)}(x) = \frac{1}{x|t|} f_A\left(\frac{1}{t} \ln x\right) 1_{[0, \infty)}(x)$

8. Papoulis 9-3: From the discussion of Poisson processes on pages 290-291 of Papoulis, we know that  $E\{X(t)\} = \lambda t$ ,  $E\{X^2(t)\} = \lambda t + \lambda^2 t^2$ , and thus  $\text{var}\{X(t)\} = \lambda t$ .

(a) If  $E\{X(9)\} = 6 = \lambda \cdot 9 \Rightarrow \lambda = \frac{6}{9} = \frac{2}{3}$   
 Thus  $E\{X(8)\} = \lambda t|_{t=8} = \frac{2}{3} \cdot 8 = \frac{16}{3}$

$\text{var}\{X(8)\} = \lambda t|_{t=8} = \frac{2}{3} \cdot 8 = \frac{16}{3}$

(b)  $X(2)$  is a Poisson RV. with mean  $\lambda t|_{t=2} = \frac{2}{3} \cdot 2 = \frac{4}{3}$

$$P(\{X(2) \leq 3\}) = \sum_{k=0}^3 \frac{e^{-4/3} (4/3)^k}{k!} = \dots =$$

(c)  $X(2)$  is a Poisson RV with mean  $\lambda \cdot 2 = 4/3$ .  $U = X(4) - X(2)$  is also a Poisson RV with mean  $4/3$ .

Hence  $P(\{U = k\}) = \frac{e^{-4/3} (4/3)^k}{k!}$ ,  $P(\{V = m\}) = \frac{e^{-4/3} (4/3)^m}{m!}$

and by independent increments,  $U$  and  $V$  are stat. indep  $\Rightarrow P(\{U = k\} \cap \{V = m\}) = \frac{e^{-8/3} (4/3)^k (4/3)^m}{k! m!}$

Hence  $P(\{X(4) \leq 5\} | \{X(2) \leq 3\}) = \frac{P(\{U \leq 3\} \cap \{V \leq 5 - U\})}{P(\{U \leq 3\})}$

where  $P(\{U \leq 3\}) = \sum_{k=0}^3 \frac{e^{-4/3} (4/3)^k}{k!} =$

$$P(\{U \leq 3\} \cap \{V \leq 5 - U\}) = \sum_{k=0}^3 \sum_{m=0}^{5-k} \frac{e^{-8/3} (4/3)^k (4/3)^m}{k! m!}$$

$$= e^{-8/3} \sum_{k=0}^3 \sum_{m=0}^{5-k} \frac{(4/3)^{k+m}}{k! m!} = \frac{48373}{3645} e^{-8/3}$$

$$= 0.9221$$

9. Papoulis 9-81

(a)  $X(t)$  is Gaussian WSS with zero mean and variance  $\sigma^2 = E\{X^2(t)\}$   
 $X(t) = R_{XX}(0) = 4$

$$\Rightarrow f_{X(t)}(x) = \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{x^2}{\sigma^2}\right\} \sim N[0, 2] \Rightarrow P\{X(t) \leq 3\} = F_{X(t)}(3) = \Phi\left(\frac{3}{\sqrt{2}}\right) = 0.933$$

$$\begin{aligned} (b) E\{[X(t+1) - X(t-1)]^2\} &= E\{X^2(t+1)\} - 2E\{X(t+1)X(t-1)\} + E\{X^2(t-1)\} \\ &= R_{XX}(0) - 2R_{XX}(2) + R_{XX}(0) = 2[R_{XX}(0) - R_{XX}(2)] \\ &= 8[1 - e^{-2|2|}] = 8(1 - e^{-4}) = 8(0.98168) = 7.853 \end{aligned}$$

10. Papoulis 9-10

We wish to show that if  $X(t)$  is a zero-mean W.S.S. R.P. with autocovariance  $C_{XX}(\tau)$ , then  $Z(t) = X^2(t)$  has autocovariance  $C_{ZZ}(\tau) = 2C_{XX}^2(\tau)$ .

If  $X_1, X_2, X_3, X_4$  are jointly distributed zero-mean Gaussian RVs, then

$$\begin{aligned} E\{X_1 X_2 X_3 X_4\} &= E\{X_1 X_2\} E\{X_3 X_4\} + E\{X_1 X_3\} E\{X_2 X_4\} \\ &\quad + E\{X_1 X_4\} E\{X_2 X_3\} \end{aligned}$$

Let  $X_1 = X_2 = X(t+\tau)$ ,  $X_3 = X_4 = X(t)$ .

[See Example 8-9 of Papoulis, pp. 197-8 3rd. Edition]

Then it follows that

$$R_{ZZ}(\tau) = E\{Z(t+\tau)Z(t)\} = E\{X^2(t+\tau)X^2(t)\}$$

$$\begin{aligned} &= E\{X(t+\tau)X(t+\tau)\} E\{X(t)X(t)\} \\ &\quad + E\{X(t+\tau)X(t)\} E\{X(t+\tau)X(t)\} \\ &\quad + E\{X(t+\tau)X(t)\} E\{X(t+\tau)X(t)\} \end{aligned}$$

$$= R_{XX}(0) \cdot R_{XX}(0) + R_{XX}(\tau) \cdot R_{XX}(\tau) + R_{XX}(\tau) \cdot R_{XX}(\tau)$$

$$= [C_{XX}(0)]^2 + 2[C_{XX}(\tau)]^2, \quad R_{XX}(\tau) = C_{XX}(\tau) \text{ because } E\{X(t)\} = 0.$$

$$\begin{aligned} \text{But } C_{ZZ}(\tau) &= R_{ZZ}(\tau) - [E\{Z(t)\}]^2 = R_{ZZ}(\tau) - [R_{XX}(0)]^2 \\ &= R_{ZZ}(\tau) - [C_{XX}(0)]^2 = 2C_{XX}^2(\tau). \end{aligned}$$

11. Papoulis 9-37:

Just as in problem 9 of this assignment

$$\begin{aligned} E \{ x^2(t+T) x^2(t) \} &= E \{ x^2(t+T) \} E \{ x^2(t) \} + 2 E \{ x(t+T) x(t) \} E \{ x(t+T) x(t) \} \\ &= [R_{xx}(0)]^2 + 2 [R_{xx}(T)]^2 = I^2 + 2 I^2 e^{-2\alpha|T|} \cos^2 \beta T \\ &= I^2 [1 + e^{-2\alpha|T|} + e^{-2\alpha|T|} \cos 2\beta T] = R_{yy}(T) \end{aligned}$$

$$\begin{aligned} S_{yy}(\omega) &= \int_{-\infty}^{\infty} R_{xx}(T) e^{-i\omega T} dT = I^2 \int_{-\infty}^{\infty} [1 + e^{-2\alpha|T|} + e^{-2\alpha|T|} \cos 2\beta T] e^{-i\omega T} dT \\ &= I^2 \left[ 2\pi \delta(\omega) + \frac{4\alpha}{4\alpha^2 + \omega^2} + \frac{2\alpha}{4\alpha^2 + (\omega - 2\beta)^2} + \frac{2\alpha}{4\alpha^2 + (\omega + 2\beta)^2} \right] \end{aligned}$$

Furthermore

$$C_{yy}(T) = R_{yy}(T) - [E \{ y(t) \}]^2, \quad E \{ y(t) \} = E \{ x^2(t) \} = R_{xx}(0) = I$$

$$\therefore C_{yy}(T) = I^2 [1 + e^{-2\alpha|T|} (1 + \cos 2\beta T)] - I^2 = I^2 e^{-2\alpha|T|} (1 + \cos 2\beta T)$$

12. Papoulis 10-39

$$(a) S_{xx}(\omega) = \frac{1}{1 + \omega^4} \Rightarrow S_x(s) = \frac{1}{1 + s^4} = \frac{1}{(s^2 + \sqrt{2}s + 1)(s^2 - \sqrt{2}s + 1)}$$

This is a special case of example 10-27b with  $b = \sqrt{2}$  and  $c = 1$ .

Hence

$$R_{xx}(T) = \frac{1}{2\sqrt{2}} e^{-|T|/\sqrt{2}} \left[ \cos \frac{T}{\sqrt{2}} + \sin \frac{|T|}{\sqrt{2}} \right]$$

(b) We know that  $E \{ e^{-2|T|} \} = \frac{4}{4 + \omega^2}$ , Thus by the convolution

$$\text{therefore } E \{ e^{-2|T|} * e^{-2|T|} \} = \frac{16}{(4 + \omega^2)^2}$$

Now  $S_{xx}(\omega) = \frac{1}{(4 + \omega^2)^2}$ , thus

$$R_{xx}(T) = \frac{e^{-2|T|} * e^{-2|T|}}{16} = \dots = \frac{1 + 2|T|}{32} e^{-2|T|}$$



13. Papoulis 9-42.  $Y(t) = 2X(t) + 3X'(t)$

The system function corresponding to this diff. eq. is  
 $H(\omega) = 2 + i\omega 3$ .

The mean and covariance of  $X(t)$  are  $\mu_x = 5$  and  $C_{xx}(\tau) = 4e^{-2|\tau|}$

Hence  $\mu_y = \mu_x \int_{-\infty}^{\infty} h(t) dt = \mu_x H(0) = 5 \cdot 2 = 10$   
 and  $R_{xx}(\tau) = 25 + 4e^{-2|\tau|}$

$$S_{yy}(\omega) = S_{xx}(\omega) |H(\omega)|^2 = [25 \cdot 2\pi \delta(\omega) + \frac{16}{4+\omega^2}] [4+9\omega^2]$$

$$= \frac{16[4+9\omega^2]}{4+\omega^2} + 50\pi \delta(\omega) [4+9\omega^2]$$

$$= 144 - \frac{512}{4+\omega^2} + 200\pi \delta(\omega)$$

Thus  $R_{yy}(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{yy}(\omega) e^{i\omega\tau} d\omega = 144 \delta(\tau) - 128e^{-2|\tau|} + 100$   
 $= 144 \delta(\tau) + 100 - 128e^{-2|\tau|}$

14. If  $Z(t)$  is WSS, then  $E\{Z(t)\} = \text{constant}$  and  $R_{ZZ}(t_1, t_2) = R_{ZZ}(t_1 - t_2)$ .

Let's check this

$$E\{Z(t)\} = E\{X(t)Y(t)\} = E\{X(t)\}E\{Y(t)\} = \mu_x \cdot \mu_y = \text{constant}$$

$$E\{Z(t_1)Z(t_2)\} = E\{X(t_1)Y(t_1)X(t_2)Y(t_2)\} = E\{X(t_1)X(t_2)\}E\{Y(t_1)Y(t_2)\}$$

$$= R_{xx}(t_1 - t_2)R_{yy}(t_1 - t_2)$$

Thus  $Z(t)$  is always WSS in the above scenario.

15.  $X(t)$  is W.S.S. with  $R_{XX}(\tau) = \frac{1}{2} \cos \omega_0 \tau$

$Y(t)$  is W.S.S. with  $R_{YY}(\tau) = e^{-\alpha|\tau|}$

Given that  $\textcircled{H}$  is stat. indep of  $Y(t)$ , we have  $X(t) \perp\!\!\!\perp Y(t)$ . It follows that

$$\begin{aligned} R_{ZZ}(t_1, t_2) &= E\{X(t_1)Y(t_1)X(t_2)Y(t_2)\} \\ &= E\{X(t_1)X(t_2)\} E\{Y(t_1)Y(t_2)\} \\ &= R_{XX}(t_1, t_2) \cdot R_{YY}(t_1, t_2) \\ &= R_{ZZ}(t_1 - t_2), \end{aligned}$$

Just as in problem 13 above.

Now by the convolution theorem (and duality) of Fourier transforms, we have

$$S_{ZZ}(\omega) = \frac{1}{2\pi} [S_{XX}(\omega) * S_{YY}(\omega)].$$

Now  $S_{XX}(\omega) = \frac{\pi}{2} [\delta(\omega - \omega_0) + \delta(\omega + \omega_0)]$

$$S_{YY}(\omega) = \frac{2\alpha}{\alpha^2 + \omega^2}$$

$$\begin{aligned} \therefore S_{ZZ}(\omega) &= \frac{1}{2\pi} \left[ \frac{\pi\alpha}{\alpha^2 + (\omega - \omega_0)^2} + \frac{\pi\alpha}{\alpha^2 + (\omega + \omega_0)^2} \right] \\ &= \frac{\alpha/2}{\alpha^2 + (\omega - \omega_0)^2} + \frac{\alpha/2}{\alpha^2 + (\omega + \omega_0)^2} \end{aligned}$$