

## CHAPTER 10

10-1

- (a) If  $\underline{x}(t)$  is a Poisson process as in Fig. 9-3a, then for a fixed  $t$ ,  $\underline{x}(t)$  is a Poisson RV with parameter  $\lambda t$ . Hence [see (5-119)] its characteristic function equals  $\exp\{\lambda t(e^{j\omega} - 1)\}$ .
- (b) If  $\underline{x}(t)$  is a Wiener process then  $f(x,t)$  is  $N(0, \sqrt{at})$ . Hence [see (5-100)] its first order characteristic function equals  $\exp\{-at\omega^2/2\}$ .
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- 10-2 For large  $\underline{t}$ ,  $\underline{x}(t)$  and  $\underline{y}(t)$  can be approximated by two independent Wiener processes as in (10-52):

$$f_x(x,t) = \frac{1}{\sqrt{2\pi at}} e^{-x^2/2at} \quad f_y(y,t) = \frac{1}{\sqrt{2\pi at}} e^{-y^2/2at}$$

Hence,  $\underline{z}(t)$  has a Rayleigh density [see (6-70)]. [Note. Exactly,  $\underline{z}(t)$  is a discrete-type RV taking the values  $\sqrt{m^2+n^2}$  where  $m$  and  $n$  are integers]. The product  $f_z(z,t)dz$  equals approximately the probability that  $\underline{z}(t)$  is between  $z$  and  $z+dz$  provided that  $dz \gg T$ .

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10-3 The voltage  $v(t)$  is the output of a system with input  $n_e(t)$  and system function

$$H_1(s) = \frac{1}{LCs^2 + RCs + 1}$$

Hence,

$$S_v(\omega) = S_{n_e}(\omega) |H_1(j\omega)|^2 = \frac{2kTR}{(1 - \omega^2 LC)^2 + R^2 C^2 \omega^2}$$

Furthermore,

$$Z_{ab}(s) = \frac{R + Ls}{LCs^2 + RCs + 1} \quad \text{Re } Z_{ab}(j\omega) = \frac{R}{(1 - \omega^2 LC)^2 + R^2 C^2 \omega^2}$$

in agreement with (10-75).

The current  $i(t)$  is the output of a system with input  $n_e(t)$  and system function

$$H_2(s) = \frac{1}{R + Ls}$$

Hence,

$$S_i(\omega) = S_{n_e}(\omega) |H_2(j\omega)|^2 = \frac{2kTR}{R^2 + \omega^2 L^2}$$

Furthermore (short circuit admittance)

$$Y_{ab}(s) = \frac{1}{R + Ls} \quad \text{Re } Y_{ab}(j\omega) = \frac{2kTR}{R^2 + L^2 \omega^2}$$

in agreement with (10-78).

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10-4 The equation  $m\ddot{x}(t) + f\dot{x}(t) = F(t)$  specifies a system with

$$H(s) = \frac{1}{ms^2 + fs} \quad h(t) = \frac{1}{f}(1 - e^{-ft/m})U(t)$$

and (9-100) yields

$$E\{\underline{x}^2(t)\} = \frac{2kTf}{f^2} \int_0^t (1 - e^{-2\alpha\tau})^2 d\tau \quad \alpha = \frac{f}{2m}$$


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10-5 As in Example 12-2,  $a$  and  $b$  are such that

$$\underline{x}(\tau) = a \underline{x}(0) - b \underline{v}(0) \perp \underline{x}(0), \underline{v}(0)$$

This yields

$$R_{\underline{xx}}(\tau) = a R_{\underline{xx}}(0) + b R_{\underline{xv}}(0) \quad (i)$$

$$R_{\underline{xv}}(\tau) = a R_{\underline{xv}}(0) + b R_{\underline{vv}}(0)$$

where [see (10-163)]

$$R_{\underline{xx}}(\tau) = A e^{-\alpha\tau} \left( \cos \beta\tau + \frac{\alpha}{\beta} \sin \beta\tau \right) \quad \tau > 0$$

$$R_{\underline{xv}}(\tau) = -R'_{\underline{xx}}(\tau) = A e^{-\alpha\tau} (\sin \beta\tau) \frac{\alpha^2 + \beta^2}{\beta}$$

$$R_{\underline{vv}}(\tau) = R'_{\underline{xv}}(\tau) = A e^{-\alpha\tau} \left( \cos \beta\tau - \frac{\alpha}{\beta} \sin \beta\tau \right) \frac{\alpha^2 + \beta^2}{\beta}$$

Inserting into (i) and solving, we obtain

$$a = e^{-\alpha\tau} \left( \cos \beta\tau + \frac{\alpha}{\beta} \sin \beta\tau \right)$$

$$b = \frac{1}{\beta} e^{-\alpha\tau} \sin \beta\tau$$

Finally,

$$P = E\{[\underline{x}(t) - a \underline{x}(0) - b \underline{v}(0)] \underline{x}(t)\} = R_{\underline{xx}}(0) - a R_{\underline{xx}}(t) - b R_{\underline{xv}}(t)$$

$$= \frac{2kTf}{m^2} \left[ 1 - e^{-2\alpha t} \left( 1 + \frac{2\alpha^2}{\beta} \sin^2 \beta t + \frac{\alpha}{\beta} \sin 2\beta t \right) \right]$$

10-6 If  $\underline{x}(t) = \underline{w}(t^2)$  then [see (10-70)]

$$R_{\underline{x}}(t_1, t_2) = E\{\underline{w}(t_1^2) \underline{w}(t_2^2)\} = \alpha t_1^2$$

If  $\underline{y}(t) = \underline{w}^2(t)$  then [see (6-197)]

$$R_{\underline{y}}(t_1, t_2) = E\{\underline{w}^2(t_1) \underline{w}^2(t_2)\}$$

$$= E \underline{w}^2(t_1) E \underline{w}^2(t_2) + 2 E^2\{\underline{w}(t_1) \underline{w}(t_2)\} = \alpha^2 t_1 t_2 + 2\alpha^2 t_1^2$$

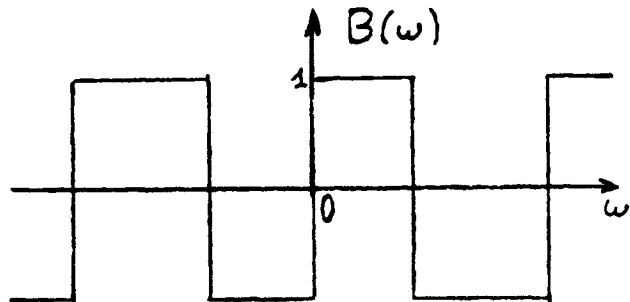
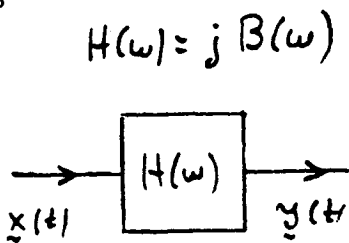
10-7 From (10-112) :

$$\eta_s = 3 \int_0^{10} 2 dt = 60 \quad \sigma_s^2 = 3 \int_0^{10} 4 dt = 120 \quad E\{\tilde{s}^2\} = 3720$$

$\tilde{s}(7) = 0$  if there are no points in the interval (7-10, 7). The number of points in this interval is a Poisson RV with parameter  $10\lambda = 30$ . Hence,  $P\{\tilde{s}(7) = 0\} = e^{-30}$ .

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10-8



From the assumption:  $S_{xx}(\omega) = S_{yy}(\omega) \quad S_{xy}(-\omega) = -S_{xy}(\omega)$

From (9-148):  $S_{yy}(\omega) = S_{xx}(\omega) |H(\omega)|^2 \quad S_{xy}(\omega) = S_{xx}(\omega) H^*(\omega)$

Combining, we obtain

$$|H(\omega)|^2 = 1 \quad H(-\omega) = -H(\omega)$$

Since  $h(t)$  is real, the second equation yields  $H(\omega) = jB(\omega)$  and from the first it follows that

$$|B(\omega)| = 1$$

as in the figure.

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10-9 With  $\underline{i}(t) = \underline{a}(t)$ ,  $\underline{q}(t) = \underline{b}(t)$ , (11-63) yields

$$S_i(\omega) = S_q(\omega) \quad S_{iq}(\omega) = -S_{qi}(\omega) = S_{qi}(-\omega)$$

Hence [see (11-75) and (11-82)],

$$S_w(\omega) = 2 S_i(\omega) + 2j S_{qi}(\omega)$$

$$S_w(-\omega) = 2 S_i(\omega) - 2j S_{qi}(\omega)$$

Adding and subtracting, we obtain

$$4 S_i(\omega) = S_w(\omega) + S_w(-\omega) \quad 4j S_{iq}(\omega) = S_w(-\omega) - S_w(\omega)$$


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10-10 From (10-133)

$$\underline{x}(t) = \text{Re} [\underline{w}(t) e^{j\omega_0 t}]$$

$$\underline{x}(t - \tau) = \text{Re} [\underline{w}_{-\tau}(t) e^{j\omega_0 t}] = \text{Re} [\underline{w}(t - \tau) e^{j\omega_0(t - \tau)}]$$

$$\underline{w}_{-\tau}(t) = \underline{w}(t - \tau) e^{-j\omega_0 \tau}$$


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10-11  $R_x''(\tau) \leftrightarrow -\omega^2 S_x(\omega)$

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} \omega^2 S_x(\omega) d\omega = -R_x''(0)$$

and with  $\omega_0$  the optimum carrier frequency, (10-150) yields

$$E\{|\underline{w}'(t)|^2\} = \frac{M}{2\pi} = -2R_x''(0) - 2\omega_0^2 R_x(0)$$


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10-12 From the stationarity of the process  $\underline{x}(t) \cos \omega t + \underline{y}(t) \sin \omega t$  it follows that [see (10-130)]

$$C_{xx}(\tau) = C_{yy}(\tau) \quad C_{xy} = -C_{yx}(\tau) \quad (i)$$

Using these identities, we shall express the joint density  $f(X, Y)$  of the  $2n$  RVs

$$\underline{X} = [\underline{x}(t_1), \dots, \underline{x}(t_n)] \quad \underline{Y} = [\underline{y}(t_1), \dots, \underline{y}(t_n)]$$

in terms of the covariance matrix  $C_{ZZ}$  of the complex vector  $\underline{Z} = \underline{X} + j\underline{Y}$ . From (i) it follows that

$$E\{\underline{x}(t_i)\underline{x}(t_j)\} = E\{\underline{y}(t_i)\underline{y}(t_j)\} \quad E\{\underline{x}(t_i)\underline{y}(t_j)\} = -E\{\underline{y}(t_i)\underline{x}(t_j)\}$$

This yields

$$C_{XX} = C_{YY}, \text{ and } C_{XY} = -C_{YX}; \text{ hence, } f(X, Y) \text{ is given by (8-62).}$$


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10-13 The signal  $\underline{c}(t) = f(t)$  is an extreme case of a cyclostationary process as in (10-178) with

$$h(t) = \begin{cases} f(t) & 0 \leq t < T \\ 0 & \text{otherwise} \end{cases} \quad \longleftrightarrow \quad H(\omega) = \int_0^T f(t) e^{-j\omega t} dt$$

and  $c_m = 1$ ,  $R[m] = 1$ . Hence [see (10A-2)]

$$\sum_{m=-\infty}^{\infty} R_m e^{-jm\omega T} = \sum_{m=-\infty}^{\infty} e^{-jm\omega T} = T \sum_{m=-\infty}^{\infty} \delta(\omega - \frac{2\pi}{T} m)$$

From the above and (10-180) it follows that the process  $\underline{x}(t) = f(t - \theta)$  is stationary with power spectrum

$$S(\omega) = \left| \int_0^T f(t) e^{-j\omega t} dt \right|^2 \sum_{m=-\infty}^{\infty} \delta(\omega - \frac{2\pi}{T} m)$$


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The process

$$y_{-N}(t) = x(t+\tau) - \sum_{n=-N}^N x(t+nT) \frac{\sin\sigma(\tau-nT)}{\sigma(\tau-nT)}$$

is the output of a system with input  $x(t)$  and system function

$$H_N(\omega) = e^{j\omega\tau} - \sum_{n=-N}^N \frac{\sin\sigma(\tau-nT)}{\sigma(\tau-nT)} e^{jnT\omega}$$

Furthermore,  $\varepsilon_{-N}(\tau) = y_{-N}(0)$ , hence [see (9-153)]

$$E\{\varepsilon_{-N}^2(\tau)\} = E\{y_{-N}^2(0)\} = \frac{1}{2\pi} \int_{-\infty}^{\infty} S(\omega) |H_N(\omega)|^2 d\omega \quad (i)$$

The function  $H_N(\omega)$  is the truncation error in the Fourier series expansion of  $e^{j\omega\tau}$  in the interval  $(-\sigma, \sigma)$ . Hence, for  $N > N_0$

$$|H_N(\omega)| < \varepsilon \quad |\omega| < \sigma$$

From this and (i) it follows that, if  $S(\omega) = 0$  for  $|\omega| < \sigma$ , then

$$E\{\varepsilon_{-N}^2(\tau)\} = \frac{1}{2\pi} \int_{-\sigma}^{\sigma} S(\omega) |H_N(\omega)|^2 d\omega < \varepsilon R(0) \quad N > N_0$$

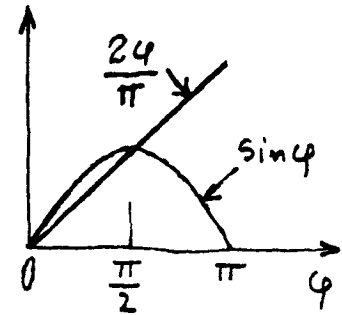
10-15 [see after (10-195)]

$$R(0) - R(\tau) = \frac{1}{2\pi} \int_{-\sigma}^{\sigma} S(\omega) (1 - \cos \omega \tau) d\omega$$

$$\leq \frac{\tau^2}{4\pi} \int_{-\sigma}^{\sigma} \omega^2 S(\omega) d\omega = \frac{-\tau^2}{2} R''(0)$$

Furthermore, since

$$\sin \phi \geq \frac{2\phi}{\pi} \quad 0 \leq \phi \leq \frac{\pi}{2}$$



we obtain

$$R(0) - R(\tau) = \frac{1}{2\pi} \int_{-\sigma}^{\sigma} S(\omega) 2 \sin^2 \frac{\omega \tau}{2} d\omega$$

$$\geq \frac{2\tau^2}{\pi} \frac{1}{2\pi} \int_{-\sigma}^{\sigma} \omega^2 S(\omega) d\omega = \frac{-2\tau^2}{\pi^2} R''(0)$$

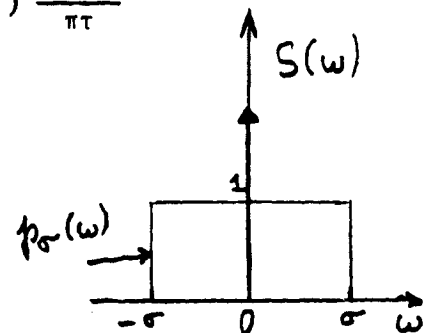
10-16 With  $T = \pi/\sigma$

$$R(mT) = E\{\underline{x}(nT + mT)\underline{x}(nT)\} = \begin{cases} I & m = 0 \\ \eta^2 & m \neq 0 \end{cases}$$

Hence [see (10-196)]

$$R(\tau) = \sum_{m=-\infty}^{\infty} R(mT) \frac{\sin \sigma(\tau - mT)}{\sigma(\tau - mT)} = \eta^2 + (I - \eta^2) \frac{\sin \sigma \tau}{\pi \tau}$$

$$S(\omega) = 2\pi \eta^2 \delta(\omega) + 2\pi(I - \eta^2) p_{\sigma}(\omega)$$





10-17 Given  $E\{\underline{x}(n+m)\underline{x}(n)\} = N\delta[m]$

This is a special case of Prob. 10-16 with  $\eta = 0, I = N$ .

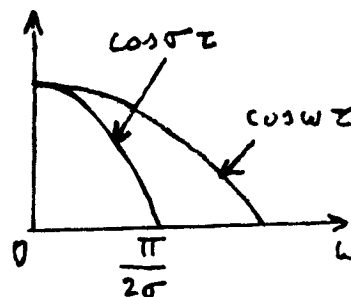
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10-18 If  $|\tau| < \pi/2\sigma$ , then

$$\cos \omega\tau \geq \cos \sigma\tau \quad |\omega| \leq \sigma$$

$$R(\tau) = \frac{1}{2\pi} \int_{-\sigma}^{\sigma} S(\omega) \cos \omega\tau d\omega$$

$$\geq \frac{\cos \sigma\tau}{2\pi} \int_{-\sigma}^{\sigma} S(\omega) d\omega = R(0) \cos \sigma\tau$$



10-19 From (10-133) with  $c = \sigma$

$$P_1(\omega, \tau) + j\omega P_2(\omega, \tau) = 1$$

$$P_1(\omega, \tau) + j(\omega + \tau)P_2(\omega, \tau) = e^{j\sigma\tau}$$

Hence,

$$P_1(\omega, \tau) = 1 - \frac{\omega}{\sigma} (e^{j\sigma\tau} - 1) \quad P_2(\omega, \tau) = \frac{1}{j\sigma} (e^{j\sigma\tau} - 1)$$

Inserting into (11-141), we obtain

$$P_1(\tau) = \frac{4 \sin^2(\sigma\tau/2)}{\sigma^2 \tau} \quad P_2(\tau) = \frac{4 \sin^2(\sigma\tau/2)}{\sigma^2 \tau}$$

and with  $t = 0$ , the desired result follows from (10-206) because  $\bar{T} = 2T$  and

$$\sin^2 \frac{\sigma(\tau - 2nT)}{2} = \sin^2 \left( \frac{\sigma\tau}{2} - n\pi \right) = \sin^2 \frac{\sigma\tau}{2}$$


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10-20 As in (10-213)

$$\underline{P}(\omega) = \frac{1}{\lambda} \int_{-a}^a \cos \omega t \underline{z}(t) \cos \omega_c t dt$$

$$E\{\underline{P}(\omega)\} = \int_{-a}^a \cos \omega t \cos \omega_c t dt$$

$$\sigma_{\underline{P}(\omega)}^2 = \frac{1}{\lambda} \int_{-a}^a \cos^2 \omega_c t_2 \cos^2 \omega t_2 dt_2$$

10-21 We shall show that if

$$\underline{X}_c(\omega) = \frac{1}{\lambda} \sum_{|t_i| < c} \underline{x}(t_i) e^{-j\omega t_i} = \frac{1}{\lambda} \int_{-a}^a \underline{x}(t) \underline{z}(t) e^{-j\omega t} dt$$

where  $\underline{z}(t) = \sum \delta(t-t_i)$  is a Poisson impulse train, then

$$E\{|\underline{X}_c(\omega)|^2\} \simeq 2cS_x(\omega) + \frac{2c}{\lambda} R_x(0)$$

Proof

Since  $R_x(r) = \lambda^2 + \lambda\delta(r)$ , it follows that

$$E\left\{|\underline{X}_c(\omega)|^2\right\} = \frac{1}{\lambda^2} \int_{-c}^c \int_{-c}^c R_x(t_1-t_2) e^{-j\omega(t_1-t_2)} dt_1 dt_2$$

$$= \int_{-c}^c e^{j\omega t_2} \int_{-c}^c R_x(t_1-t_2) e^{-j\omega t_1} dt_1 dt_2 + \frac{1}{\lambda} \int_{-c}^c R_x(0) dt_2$$

If  $\int_{-\infty}^{\infty} |R_x(r)| < \infty$  then for sufficient large  $c$ , the inner integral on the right is nearly equal to  $S_x(\omega) e^{-j\omega t_2}$  and (i) follows.

10-22  $E\{\underline{z}(t)\} = g(t)$        $E\{\underline{w}(t)\} = g(t) - g(T)t/T = g(t)$

$$\underline{w}(t) = \left(1 - \frac{t}{T}\right) \int_0^t \underline{x}(\alpha) d\alpha - \frac{t}{T} \int_t^T \underline{x}(\alpha) d\alpha$$

The above two integrals are uncorrelated because  $\underline{n}(t)$  is white noise. Hence, as in Example 9-5

$$\sigma_w^2 = \left(1 - \frac{t}{T}\right)^2 Nt + \frac{t^2}{T^2} N(T - t) = Nt\left(1 - \frac{t}{T}\right)$$

Note The above shows that the information that  $g(T) = 0$  can be used to improve the estimate of  $g(t)$ . Indeed, if we use  $\underline{w}(t)$  instead of  $\underline{z}(t)$  for the estimate of  $g(t)$  in terms of the data  $\underline{x}(t)$ , the variance is reduced from  $Nt$  to  $Nt(1 - t/T)$ .

10-23 (a) Since  $|\sum_i a_i b_i| \leq \sum_i |a_i| |b_i|$ , it suffices to assume that the numbers  $a_i$  and  $b_i$  are real. The quadratic

$$I(z) = \sum_i (a_i - z b_i)^2 = z^2 \sum_i b_i^2 - 2z \sum_i a_i b_i + \sum_i a_i^2$$

is nonnegative for every real  $z$ , hence, its discriminant cannot be positive. This yields (i).

(b) With  $f[n]$  and  $R_v[m] = S_0 \delta[m]$  as in Prob. 10-24a (white noise)

$$y_f[n_0] = \sum h[n] f[n_0 - n] \quad y_v[n] = \sum h[n] v[n]$$

$$E\{y_v^2[n]\} = S_0 \rho[0] = S_0 \sum |h[n]|^2$$

[see (9-213)] And (i) yields

$$\frac{y_f^2[n_0]}{E\{y_v^2[n]\}} = \frac{|\sum h[n] f[n_0 - n]|^2}{S_0 \sum |h[n]|^2} \leq \frac{1}{S_0} \sum |h[n]|^2$$

with equality iff  $h[n] = k f^*[n_0 - n]$ .

10-24 (a) Given  $F(z)$  and  $S_v(\omega) = S_0 \cong \text{constant}$ . The  $z$  transform of  $y_f[n]$  equals  $F(z)H(z)$ . Hence, [see (9-109)]

$$y_f[n] = \frac{1}{2\pi} \int_{-\pi}^{\pi} F(e^{j\omega T}) H(e^{j\omega T}) e^{jn\omega T} d\omega$$

$$\frac{y_f^2[n]}{E\{y_v^2[n]\}} = \frac{\left| \int_{-\pi}^{\pi} F(e^{j\omega T}) H(e^{j\omega T}) d\omega \right|^2}{S_0 \int_{-\pi}^{\pi} |H(e^{j\omega T})|^2 d\omega}$$

$$\leq \frac{1}{S_0} \int_{-\pi}^{\pi} |F(e^{j\omega T})|^2 d\omega$$

The last inequality follows from Schwarz's inequality with equality iff

$$H(e^{j\omega T}) = kF^*(e^{j\omega T}) = kF(e^{-j\omega T}), \text{ i.e., iff } H(z) = kF(z^{-1})$$

(b) Given arbitrary  $R_v[m]$ ,  $F(z)$ , and the form of  $H(z)$  (FIR); to find the coefficients  $a_m$  of  $H(z)$ . In this case

$$y_f[n] = a_0 f[n] + a_1 f[n-1] + \dots + a_N f[n-N]$$

$$y_v[n] = a_0 v[n] + a_1 v[n-1] + \dots + a_N v[n-N]$$

To maximize the signal-to-noise ratio it suffices to minimize

$$E\{y_v^2[n]\} = \sum_{k,r=0}^N a_k a_r R_v[k-r]$$

subject to the constraint that the sum

$$y_f[0] = a_0 f[0] + a_1 f[-1] + \dots + a_N f[-N]$$

is constant. With  $\lambda$  a constant (Lagrange multiplier), we minimize the sum

$$I = \sum_{k,r=0}^N a_k a_r R[k-r] - \lambda \left[ \sum_{k=0}^N a_k f[-k] - y_f[0] \right]$$

this yields the system

$$\frac{\partial I}{\partial a_k} = 0 = \sum_{r=0}^N \left[ a_r R_v[k-r] - \lambda f[-k] \right] \quad k = 0, \dots, N$$

whose solution yields  $a_k$ .

10-25

$$B = A |H(\omega_0)| = \frac{A}{\sqrt{\alpha^2 + \omega_0^2}}$$

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

$$R_{y_n}(\tau) = \frac{N}{2\alpha} e^{-\alpha|\tau|}$$

$$E\{y_n^2(t)\} = R_{y_n}(0) = \frac{N}{2\alpha}$$

$$\frac{B^2}{E\{y_n^2(t)\}} = \frac{2A^2}{N} \frac{\alpha}{\alpha^2 + \omega_0^2}$$

Max. if  $\alpha = \omega_0$

10-26 Since  $H(\omega)$  is determined within a constant factor, we can assume that the response  $y_f(t_0)$  of the optimum  $H(\omega)$  due to  $f(t)$  is constant:

$$y_f(t_0) = \sum_{i=0}^m a_i f(t_0 - iT) = c \quad (i)$$

Our problem is to minimize the variance

$$V = E(y_{\nu}^2(t)) = \sum_{n=0}^m a_n \sum_{i=0}^m a_i R(nT - iT) \quad (ii)$$

of  $y_{\nu}(t)$  subject to the constraint (i). This yields the system

$$\frac{\partial V}{\partial a_n} = \sum_{i=0}^m a_i R(nT - iT) - kf(t_0 - nT) = 0$$

where  $k$  is a constant (lagrange multiplier). With  $a_n$  so determined, we conclude from (ii) that

$$V = \sum_{n=0}^m ka_n f(t_0 - nT) = ky_f(t_0) \quad r^2 = \frac{y_f^2(t_0)}{ky_f(t_0)}$$


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10-27  $R_{yyy}(\mu, \nu) = E\{x(t+\mu)+c [x(t+\nu)+c] [x(t)+c]\} = R(\mu, \nu) + cR(\mu) + cR(\nu) + cR(\mu-\nu) + c^3$

because  $E\{x(t)\} = 0$ . Furthermore,

$$R(\mu) \leftrightarrow 2\pi S(u)\delta(v) \quad R(\nu) = 2\pi\delta(u)S(v) \quad c^3 \leftrightarrow 4\pi^2\delta(u)\delta(v)$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} R(\mu-\nu)e^{-j(u\mu+\nu\nu)}d\mu d\nu = \int_{-\infty}^{\infty} R(\tau)e^{-ju\tau}d\tau \int_{-\infty}^{\infty} e^{-j(u+\nu)\nu}d\nu = 2\pi S(u)\delta(u+\nu)$$


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10-28 We shall use the equations  $E\{\bar{x}(t)\} = 0$ ,  $E\{\bar{x}^2(t)\} = \lambda t$ . Suppose that  $t_1 < t_2 < t_3$ .

Clearly,

$$\bar{x}(t_2) = \bar{x}(t_1) + [\bar{x}(t_2) - \bar{x}(t_1)]$$

$$\bar{x}(t_3) = \bar{x}(t_1) + [\bar{x}(t_2) - \bar{x}(t_1)] + [\bar{x}(t_3) - \bar{x}(t_2)] \quad (i)$$

Inserting into the product  $\bar{x}(t_1)\bar{x}(t_2)\bar{x}(t_3)$  and using the identity  $E\{\bar{x}(t_i) - \bar{x}(t_j)\} = 0$  and the independence of the three terms on the right of (i), we obtain

$$E\{\bar{x}(t_1)\bar{x}(t_2)\bar{x}(t_3)\} = E\{\bar{x}^3(t_1)\} = \lambda t_1 = \lambda \min(t_1, t_2, t_3)$$

Since  $\bar{z}(t) = \bar{x}'(t)$ , we conclude from (9-120)-(9-122) that

$$R_{\bar{z}\bar{z}\bar{z}}(t_1, t_2, t_3) = \frac{\partial^3 R_{xxx}(t_1, t_2, t_3)}{\partial t_1 \partial t_2 \partial t_3} = \lambda \frac{\partial^3 \min(t_1, t_2, t_3)}{\partial t_1 \partial t_2 \partial t_3}$$

It suffices therefore to show that the right side equals  $\lambda \delta(t_1 - t_2) \delta(t_1 - t_3)$ . This is a consequence of the following:

$$\begin{aligned} \frac{\partial \min(t_1, t_2, t_3)}{\partial t_3} &= t_1 U(t_2 - t_1) \delta(t_3 - t_1) + t_2 U(t_1 - t_2) \delta(t_3 - t_2) \\ &\quad + U(t_1 - t_3) U(t_2 - t_3) - t_3 \delta(t_1 - t_3) U(t_2 - t_3) - t_3 U(t_1 - t_3) \delta(t_2 - t_3) \\ &= U(t_1 - t_3) U(t_2 - t_3) \end{aligned}$$

because  $t_i \delta(t_i - t_j) = t_j \delta(t_j - t_i)$ . Hence,

$$\frac{\partial^2 \min(t_1, t_2, t_3)}{\partial t_2 \partial t_3} = U(t_1 - t_3) \delta(t_2 - t_3) \quad \frac{\partial^2 \min(t_1, t_2, t_3)}{\partial t_1 \delta t_2 \partial t_3} = \delta(t_1 - t_2) \delta(t_1 - t_3)$$

10-29 See outline given in text.