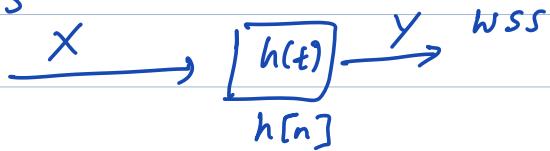


- Lab report due on Dec 29.

Recap:

WSS



$$m_y = m_x \sum h[k]$$

$$C_{y,y}(k,j) = \sum_n \sum_m h[n] h[m] C_x((k-j)-(n-m))$$

$$\mathcal{H}(f) = \sum_n h[n] e^{-j2\pi f n}$$

$$m_y = H(0) m_x$$

$$\tau = k - j$$

$$C_{y,y}(\tau) = \sum_n \sum_m h[n] h[m] C_x(\tau - (n-m))$$

$$\mathcal{F}(C_{y,y}(\tau)) = \sum_{\tau} C_{y,y}(\tau) e^{-j2\pi f \tau}$$

$$= \sum_{\tau} \sum_n \sum_m h[n] h[m] C_x(\tau - (n-m)) e^{-j2\pi f \tau}$$

$$= \sum_n \sum_m e^{-j2\pi f(n-m)} \sum_{\tau} C_x(\tau - (n-m)) e^{-j2\pi f \tau}$$

$$= \sum_n \sum_m e^{-j2\pi f(n-m)} \sum_{\tau} C_x(\tau - (n-m)) e^{-j2\pi f(\tau - (n-m))}$$

$$\underbrace{\sum_{\tau} C_x(\tau - (n-m)) e^{-j2\pi f(\tau - (n-m))}}_{\mathcal{F}(C_x)}$$

$$= \sum_n h[n] e^{-j2\pi f n}$$

$\mathcal{H}(f)$

$$\sum_m h[m] e^{j2\pi fm}$$

$\mathcal{F}(C_x)$

[ LTI system has  
real coefficients ]

$$= \mathcal{H}(f) \mathcal{H}^*(f) \mathcal{F}(C_x)$$

$$= |\mathcal{H}(f)|^2 \mathcal{F}(C_x)$$

$$F(C_y) = |\mathcal{H}(f)|^2 \mathcal{F}(C_x) - (x)$$

Express Eqn (\*) in terms of auto-correlation

$$R_x \text{ & } R_y$$

$$F(R_y) = |\mathcal{H}(f)|^2 F(R_x)$$

[ Exercise: Show this! ]

Power Spectral Density (PSD)

$S(f) = F(\text{Auto-correlation function})$   
- WSS process

$$S_X(f) = F(R_X(\tau))$$

$$\left\{ \begin{array}{l} \int R_X(\tau) e^{-j2\pi f\tau} d\tau \\ \sum_k R_X(k) e^{-j2\pi kf} \end{array} \right.$$

$$R_X(\tau) = \int_{-\infty}^{\infty} S_X(f) e^{j2\pi f\tau} df$$

$$= \int_{-\gamma_2}^{\frac{1}{2}} S_x(f) e^{j2\pi kf} df$$

0 to  $2\pi$  : radians  
 $(-\pi$  to  $\pi)$   
 0 to 1 : f  
 $(-\frac{1}{2}$  to  $\frac{1}{2})$

w: notation ( $w = 2\pi f$ )

$$S_x(w) = \int R_x(\tau) e^{-jw\tau} d\tau$$

$$R_x(\tau) = \frac{1}{2\pi} \int S_x(w) e^{jw\tau} dw$$

$$R_x(\tau) = \int_{\tau=0}^{\infty} S_x(f) e^{j2\pi f \tau} df$$

$$R_x(0) = \mathbb{E}[x(t)^2] = \text{Power of the process}$$

$$R_x(0) = \int_{-\infty}^{\infty} S_x(f) df$$

Obtain power by integrating  $S_x(f)$  over entire freq range.

[Power per unit freq / bandwidth]

Power of the process from  $f_1$  to  $f_2$

$$R_x(f_1, f_2) = \int_{f_1}^{f_2} S_x(f) df$$

Properties:  $S_x(f) \geq 0$  [real, symmetric]  
positive

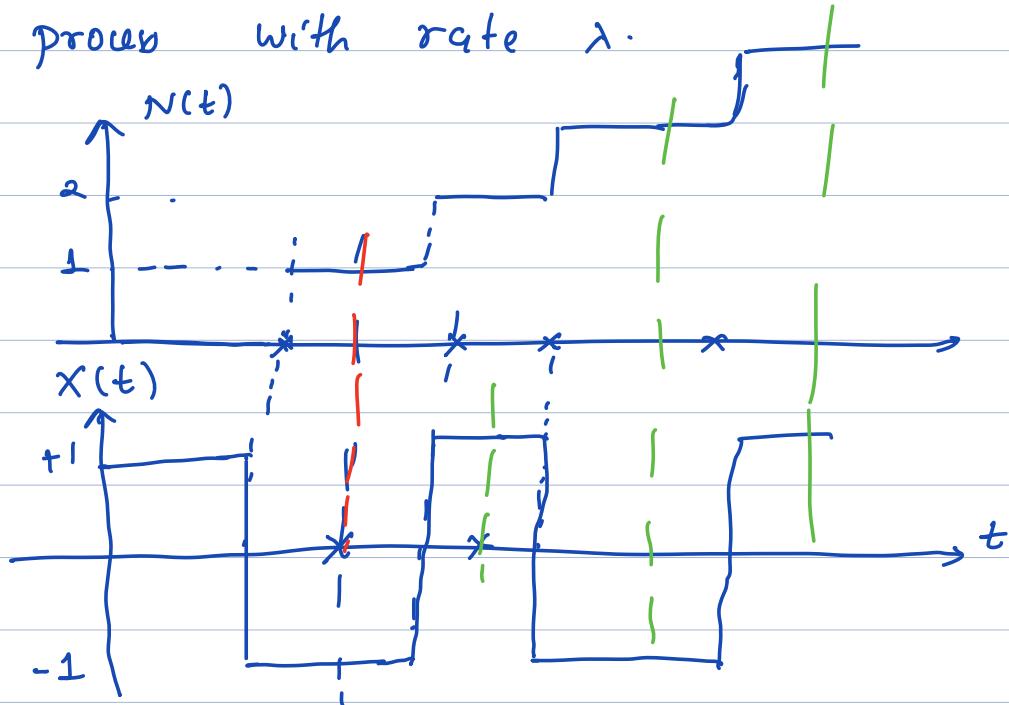
Proof:  $[R_x(\tau) \text{ is even function}]$

Example: Random Telegraph Signal

Random process  $X(t)$  takes  $\pm 1$

$$X(0) = \begin{cases} +1 & \text{w.p. } \frac{1}{2} \\ -1 & \text{w.p. } \frac{1}{2} \end{cases}$$

$X(t)$  changes according to a Poisson process with rate  $\lambda$ .



Mean, Covariance, PSD ?

Distr of  $X(t)$

$$P[X(t) = 1 \mid X(0) = 1] = P[N_t^{\uparrow} = 0, 2, 4, \dots \text{ even}]$$

$$P[X(t) = -1 \mid X(0) = -1] =$$

$$P[N_t = 0, 2, 4, \dots]$$

↓

Poisson( $\lambda t$ )

$$= \sum_{i=0, 2, 4, \dots} (\lambda t)^i \frac{e^{-\lambda t}}{i!}$$

$$= e^{-\lambda t} \left[ 1 + \frac{(\lambda t)^2}{2!} + \frac{(\lambda t)^4}{4!} + \dots \right]$$

$$e^{\lambda t} = 1 + (\lambda t) + \frac{(\lambda t)^2}{2!} + \frac{(\lambda t)^3}{3!} + \dots$$

$$e^{-\lambda t} = 1 + (-\lambda t) + \frac{(-\lambda t)^2}{2!} + \frac{(-\lambda t)^3}{3!} + \dots$$

$$e^{\lambda t} + e^{-\lambda t} = 2 \left[ 1 + \frac{(\lambda t)^2}{2!} + \dots \right]$$

$$= e^{-\lambda t} \left[ e^{\lambda t} + e^{-\lambda t} \right]$$

$$= \frac{1}{2} \left[ 1 + e^{-2\lambda t} \right] // \begin{array}{l} P[X(t)=1 | X(0)=+1] \\ P[X(t)=-1 | X(0)=-1] \end{array}$$

$$P[X(t) = -1 | X(0) = +1]$$

$$= P[N_t = \text{odd}]$$

↓

Poisson( $\lambda t$ )

$$= \sum_{i=1, 3, 5, \dots} e^{-\lambda t} \frac{(\lambda t)^i}{i!}$$

$$= e^{-\lambda t} \frac{1}{2} [e^{\lambda t} - e^{-\lambda t}]$$

$$= \frac{1}{2} [1 - e^{-2\lambda t}]$$

$$P[X(t) = i \mid X(0) = j] ; \quad i = \pm 1 \\ j = \pm 1$$

$$P[X(t) = 1]$$

$$\stackrel{\text{Law of Total Prob}}{=} \sum_{i \in \{-1, +1\}} P[X(t) = 1, X(0) = i]$$

$$= \sum_{i \in \{-1, +1\}} P[X(0) = i] P[X(t) = 1 \mid X(0) = i]$$

$$= P(X(0) = 1) P[X(t) = 1 \mid X(0) = 1] + \\ P[X(0) = -1] P[X(t) = 1 \mid X(0) = -1]$$

$$= \frac{1}{2} \cdot \frac{1}{2} (1 + e^{-2\lambda t}) + \\ \frac{1}{2} \cdot \frac{1}{2} (1 - e^{-2\lambda t}) = \frac{1}{2} //$$

$$P(X(t) = -1) = 1 - P(X(t) = 1) = \frac{1}{2}$$

$$M_X(t) = 1 \cdot \frac{1}{2} + (-1) \cdot \frac{1}{2} = 0//$$

$$C_X(t_1, t_2) = R_X(t_1, t_2)$$

$$= E[X(t_1) X(t_2)]$$

$$X(t_1) X(t_2) = \begin{cases} +1 & \text{w.p. } \frac{1}{2} (1 + e^{-2\lambda |t_1 - t_2|}) \\ -1 & \text{w.p. } \frac{1}{2} (1 - e^{-2\lambda |t_1 - t_2|}) \end{cases}$$

$$t_1 \geq t_2$$

$$\begin{aligned} & X(t_2) = +1, \quad X(t_1) = +1 \quad \frac{1}{2}(1 + e^{\frac{-2\lambda(t_1-t_2)}{}}) \\ & X(t_2) = -1, \quad X(t_1) = -1 \\ & P[X(t_1) = +1 \mid X(t_2) = +1] \\ & = \underbrace{N(t_1) - N(t_2)}_{\text{Poisson } (\lambda(t_1 - t_2))} = (\text{even}) \end{aligned}$$

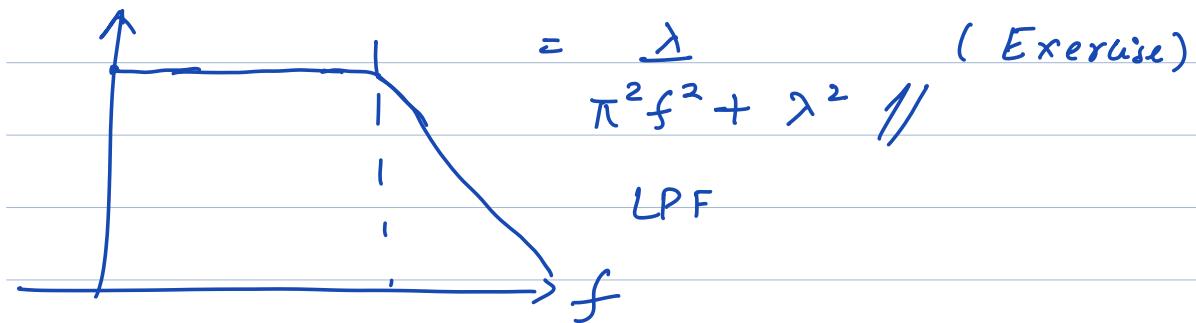
$$\begin{aligned} & P[X(t_2) = +1, X(t_1) = +1] \\ & = P[X(t_2) = +1] \cdot P[X(t_1) = +1 \mid X(t_2) = +1] \\ & = \frac{1}{2} \cdot \frac{1}{2} (1 + e^{-2\lambda(t_1-t_2)}) \end{aligned}$$

$$\begin{aligned} & P[X(t_2) = -1, X(t_1) = -1] \\ & = \frac{1}{2} \cdot \frac{1}{2} (1 + e^{-2\lambda(t_1-t_2)}) \end{aligned}$$

$$C_X(t_1, t_2) = R_X(t_1, t_2) = +1 \cdot \frac{1}{2}(1 + e^{-2\lambda|t_1-t_2|}) - 1 \cdot \frac{1}{2} \cdot (1 - e^{-2\lambda|t_1-t_2|})$$

$$= e^{-2\lambda|t_1-t_2|}$$

$$\begin{aligned} \text{PSD } S_X(f) &= \int R_X(z) e^{-j2\pi f z} dz \\ &= \int e^{-2\lambda|z|} e^{-j2\pi f z} dz \end{aligned}$$



White noise (Discrete case)

Theorem: If  $\{X_n\}$  is a WSS process, uncorrelated with mean  $m$  and variance  $\sigma^2$ .

$$C_x[k] = \sigma^2 \delta[k]$$

$$R_x[k] = \sigma^2 \delta[k] + m^2$$

Delta function.

Proof:  $E[X_n] = m$

$$C_x[k] = E[(X_n - m)$$

$$\begin{aligned} k \neq 0 &= E[(X_{n-k} - m)] \\ &\stackrel{\text{uncorrelated}}{=} E[(X_n - m)^T] \\ &\quad E[(X_{n-k} - m)^T] \\ &= 0 \end{aligned}$$

$$\begin{aligned} k = 0 &= E[(X_n - m) \\ &\quad (X_n - m)] \end{aligned}$$

$$= \sigma^2$$

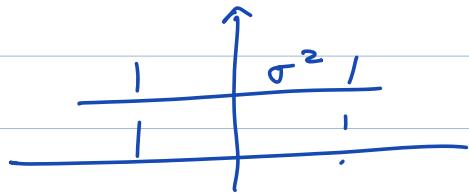
$$C_x[k] = \sigma^2 \delta[k]$$

$$R_x[k] = \sigma^2 \delta[k] + m^2$$

Zero-mean, uncorrelated, WSS

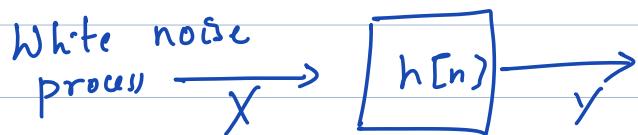
$$R_x[k] = \sigma^2 \delta[k]$$

$$S_x(f) = \sigma^2 \quad \forall k$$



$\Rightarrow$  White noise process

Theorem: A discrete time white noise process (flat p.s.d) iff it is zero mean, WSS and uncorrelated.



$$\begin{aligned} S_y(f) &= |H(f)|^2 \underbrace{S_x(f)}_{\sigma^2} \\ &= \sigma^2 |H(f)|^2 \end{aligned}$$

$$R_y(k) = \text{IFT}(S_y(f))$$

$$\begin{aligned} &= \sigma^2 \sum_{n=0}^{\infty} x[n] h[n-k] \\ &\stackrel{\text{(Causal filter)}}{=} \sigma^2 \sum_{n=k}^{\infty} h[n] h[n-k] \end{aligned}$$