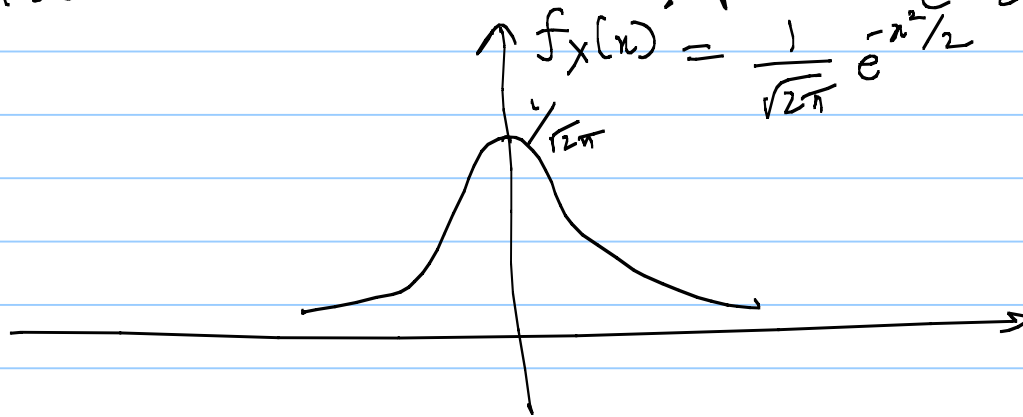


Lecture 5

Note Title

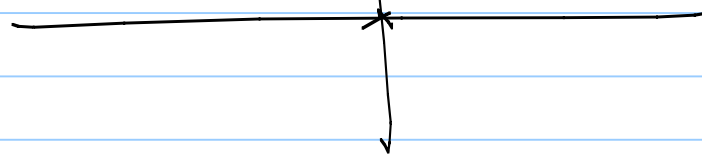
8/5/2008

Gaussian RV: $X \sim N(0, 1)$



$X, Y \sim$ Jointly Gaussian iid $N(0, 1)$

$f_{X,Y}(x, y)$



$$Y = X + N$$

\downarrow \downarrow $X \sim \text{Unif}[a, b]$
 Uniform $N(0, \sigma^2)$
 $[-1, 1]$
 Uniform $[-1, 1]$

Random Processes

$$\begin{array}{c} \text{DT} \\ \{X_k\} \end{array}$$

$$\begin{array}{c} \text{CT} \\ \{X(t)\} \end{array}$$

→ Finite distributions

$$X(t) = A \cos(\omega t + \phi)$$

Strict sense stationarity:

$$f_{X_{k_1}, X_{k_2}, \dots, X_{k_N}} = f_{X_{k_1+\delta}, X_{k_2+\delta}, \dots, X_{k_N+\delta}} \quad \begin{matrix} \text{CT} \\ \text{Similar} \end{matrix}$$

$\forall \delta, k_i, N$

Mean

$$m_x[k] = E[X_k]$$

↓
deterministic

$$m_x(t) = E[X(t)]$$

Auto correlation

$$R_{xx}(k_1, k_2) = E[X_{k_1} X_{k_2}]$$

$$R_{xx}(t_1, t_2) = E[X(t_1) X(t_2)]$$

Wide Sense Stationarity (WSS)

$$m_x[k] = m_x$$

$$R_{xx}(k_1, k_2) = R_{xx}(k_1+\delta, k_2+\delta)$$

WSS: $R_{xx}(m) = E[X_{k+m}X_k]$

↑
deterministic

$$R_{xx}(\tau) = E[X(t+\tau)X(t)]$$

Spectrum:

$$R_{xx}(m) \xleftrightarrow{\text{DTFT}} S_x(e^{j\omega})$$

$$\uparrow \text{ZT} \\ S_x(z)$$

PSD

$$R_{xx}(\tau) \xleftrightarrow{\text{FT}} S_x(f)$$

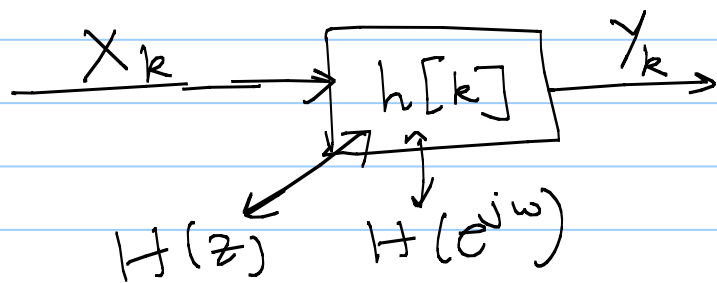
Cross-correlation: X, Y : two RPs

$$R_{xy}(k_1, k_2) = E[X(k_1)Y(k_2)]$$

Jointly WSS: $R_{xy}(k_1+s, k_2+s) = R_{xy}(k_1, k_2)$

$$R_{xy}(m) = E[X(k+m)Y(k)]$$

Filtering a WSS RP

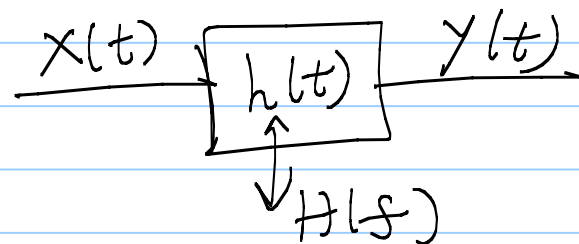


$$m_y = m_x H(e^{j0})$$

$$R_{yy}(m) = R_{xx}(m) * h[m] * h^*[-m]$$

$$S_y(e^{j\omega}) = S_x(e^{j\omega}) |H(e^{j\omega})|^2$$

$$S_y(z) = S_x(z) H(z) H^*(1/z^*)$$



$$m_y = m_x H(0)$$

$$R_{yy}(\tau) = R_{xx}(\tau) * h(\tau) * h^*(-\tau)$$

$$S_y(f) = S_x(f) |H(f)|^2$$

PSD: real & non-negative.

Gaussian RP:

→ finite distributions are jointly Normal

WSS: m_x , $R_{xx}(m)$

m_x , $R_{xx}(\tau)$

White: $m_x = 0$

$m_x = 0$

$$R_{xx}(m) = \frac{N_0}{2} \delta[m]$$

$$R_{xx}(\tau) = \frac{N_0}{2} \delta(\tau)$$

$$S_x(e^{j\omega}) = \frac{N_0}{2} \forall \omega$$

$$S_x(f) = \frac{N_0}{2} \forall f$$

→ Noise usually modeled as a white Gaussian process.

Sampling a CT RP

$$\underbrace{\{X(t)\}}_{\text{CT}} \xrightarrow{T \text{ secs}} \underbrace{\{Y_k\}}_{\text{DT}} \quad Y_k = X(kT)$$

$m_x, R_{xx}(\tau)$ \leftrightarrow $S_x(f)$

$m_y = m_x$

$R_{yy}(m) = R_{xx}(mT)$

$$S_y(e^{j\omega}) = \frac{1}{T} \sum_{m=-\infty}^{\infty} S_x\left(f - \frac{m}{T}\right)$$

$\omega = 2\pi fT$

PAM RP:

$$Y(t) = \sum_{k=-\infty}^{\infty} X_k h(t - kT)$$

$\{X_k\}$: DT RP $m_x, R_{xx}(m) \leftrightarrow S_x(e^{j\omega})$

T : symbol time, $h(t)$: deterministic

$$Z(t) = Y(t - \theta), \quad \theta \sim \text{Unif}[0, T]$$

$$Z(t) = \sum_{k=-\infty}^{\infty} X_k h(t - kT - \theta)$$

↓
WSS

$$S_Z(f) = \frac{1}{T} |H(f)|^2 \underbrace{S_X(e^{j2\pi fT})}_{\text{WSS}}$$

Summary: $y(t) = x(t) * h(t) + n(t)$

$$x(t) = T x(\underline{b}) \quad \hat{\underline{b}} = R_x(y(t))$$

$x(t)$: Power, BW $n(t)$: Power

Bit rate & Prob. of error

→ Signals/systems, DSP, PRP

Barry, Lee, Messers... : 1-3 ch.

Proakis (5th ed): 1-2 ch.