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DEBRE MARKOS INSTITUTE OF
TECHNOLOGY
SCHOOL OF ELECTRICAL AND COMPUTER
ENGINEERING

Probability and Random Process (ECEg2103)

For 2012 Second Year ECE Regular
Students;

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Chapter Four

Stationery and Ergodicity

Outlines

- Introduction
- Stationary Stochastic Processes
- Ergodic Processes
- Power Spectral Density

4.1 Introduction

- As we recall, A stochastic process (random process) $X(t)$ is a mapping that assigns a time function $X(t,w)$ to every outcome w of points in the sample space S .
- Since $X(t_1)$ and $X(t_2)$ are random variables, various types of **joint moments** can be defined; as we were try to see in chapter three. To revise these;
 1. **Mean:-** of $X(t)$ is a function of time called the **ensemble average** and is denoted by $\mu_X(t)=E[X(t)]$
 2. **Autocorrelation:-**this function provides a **measure of similarity between two observations** of the random process $X(t)$ at different points t_1 & t_2 .

Cont...

- ✓ The autocorrelation function (AC) $R_X(t_1, t_2)$ is defined as the expected value of the product $X(t_1)$ and $X(t_2)$:

$$R_X(t_1, t_2) = E[X(t_1)X(t_2)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 f_X(x_1, x_2; t_1, t_2) dx_1 dx_2$$

- ✓ By substituting $t_1=t_2=t$; in the above equation; we can obtain the second moment or the **average power** of the random process:

$$R_X(t) = E[X^2(t)] = \int_{-\infty}^{\infty} x^2 f_X(x; t) dx$$

Cont...

3. Autocovariance:- it is quantitative measure of the statistical **coupling** between $X(t_1)$ and $X(t_2)$.

✓ The autocovariance function (ACF) $C_X(t_1, t_2)$ is defined as the covariance between $X(t_1)$ and $X(t_2)$:

$$\begin{aligned}C_X(t_1, t_2) &= E[(X(t_1) - \mu_X(t_1))(X(t_2) - \mu_X(t_2))] \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x_1 - \mu_X(t_1))(x_2 - \mu_X(t_2)) f_X(x_1, x_2; t_1, t_2) dx_2 dx_1 \\ &= E[X(t_1)X(t_2)] - \mu_X(t_1)\mu_X(t_2)\end{aligned}$$

✓ Thus, the interrelationships between AC and ACF are

$$C_X(t_1, t_2) = R_X(t_1, t_2) - \mu_X(t_1)\mu_X(t_2)$$

$$R_X(t_1, t_2) = C_X(t_1, t_2) + \mu_X(t_1)\mu_X(t_2)$$

Cont...

4. **Normalized Autocovariance**:- The normalized autocovariance function (NACF) is the ACF normalized by the variance and is defined by

$$\rho_X(t_1, t_2) = \frac{C_X(t_1, t_2)}{\sqrt{\sigma_X^2(t_1)\sigma_X^2(t_2)}} = \frac{C_X(t_1, t_2)}{\sigma_X(t_1)\sigma_X(t_2)}$$

- The NACF finds wide applicability in many problems in random processes, particularly in time-series analysis.

Cont...

❖ The following definitions pertain to two different random processes $X(t)$ and $Y(t)$:

1. **Cross-Correlation**:- The cross-correlation function (CC) $R_{XY}(t_1, t_2)$ is defined as the expected value of the product $X(t_1)$ and $Y(t_2)$:

$$R_{XY}(t_1, t_2) = E[X(t_1)Y(t_2)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 y_2 f_{XY}(x_1, y_2; t_1, t_2) dy_2 dx_1$$

✓ By substituting $t_1=t_2=t$ in the above equation; we obtain the joint moment between the random processes $X(t)$ and $Y(t)$ as

$$R_{XY}(t) = E[X(t)Y(t)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{XY}(x, y; t) dy dx$$

Cont...

2. **Cross-Covariance**:-The cross-covariance function (CCF) $C_{XY}(t_1, t_2)$ is defined as the covariance between $X(t_1)$ and $Y(t_2)$:

$$\begin{aligned}C_{XY}(t_1, t_2) &= E[(X(t_1) - \mu_X(t_1))(Y(t_2) - \mu_Y(t_2))] \\&= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x_1 - \mu_X(t_1))(y_2 - \mu_Y(t_2)) f_{XY}(x_1, y_2; t_1, t_2) dy_2 dx_1 \\&= E[X(t_1)Y(t_2)] - \mu_X(t_1)\mu_Y(t_2)\end{aligned}$$

➤ Thus, the interrelationships between CC and CCF are

$$C_{XY}(t_1, t_2) = R_{XY}(t_1, t_2) - \mu_X(t_1)\mu_Y(t_2)$$

$$R_{XY}(t_1, t_2) = C_{XY}(t_1, t_2) + \mu_X(t_1)\mu_Y(t_2)$$

Cont...

3. **Normalized Cross-Covariance**:- The normalized cross-covariance function (NCCF) is the CCF normalized by the variances and is defined by

$$\rho_{XY}(t_1, t_2) = \frac{C_{XY}(t_1, t_2)}{\sqrt{\sigma_X^2(t_1)\sigma_Y^2(t_2)}} = \frac{C_{XY}(t_1, t_2)}{\sigma_X(t_1)\sigma_Y(t_2)}$$

Some Properties of X(t) and Y(t)

- Two random processes X(t) and Y(t) are **independent** if for all t1 and t2

$$F_{XY}(x, y; t_1, t_2) = F_X(x; t_1)F_Y(y; t_2)$$

Cont...

✓ They are **uncorrelated** if

$$C_{XY}(t_1, t_2) = R_{XY}(t_1, t_2) - \mu_X(t_1)\mu_Y(t_2) = 0$$

Or

$$R_{XY}(t_1, t_2) = \mu_X(t_1)\mu_Y(t_2) \quad \text{for all } t_1 \text{ and } t_2$$

✓ They are **orthogonal** if for all t_1 and t_2

$$R_{XY}(t_1, t_2) = 0$$

Example 4.1:- A random process $X(t)$ is given by $X(t)$

$X(t) = A \sin(\omega t + \phi)$ where A is a uniformly distributed random variable; then find the mean, variance, autocorrelation, autocovariance, and normalized autocovariance of $X(t)$.

Cont...

Solution

➤ Review of Some Trigonometric Identities

1. $\sin(A + B) = \sin A \cos B + \cos A \sin B$

$$\sin(A - B) = \sin A \cos B - \cos A \sin B$$

Adding (1); $\sin A \cos B = \frac{1}{2} \{ \sin(A + B) + \sin(A - B) \}$

2. $\cos(A - B) = \cos A \cos B + \sin A \sin B$

$$\cos(A + B) = \cos A \cos B - \sin A \sin B$$

Adding(2); $\cos A \cos B = \frac{1}{2} \{ \cos(A - B) + \cos(A + B) \}$

Subtracting(2); $\sin A \sin B = \frac{1}{2} \{ \cos(A - B) - \cos(A + B) \}$

Cont...

➤ More common trigonometric identities

$$2 \cos \theta \cos \varphi = \cos(\theta - \varphi) + \cos(\theta + \varphi)$$

$$2 \sin \theta \sin \varphi = \cos(\theta - \varphi) - \cos(\theta + \varphi)$$

$$2 \sin \theta \cos \varphi = \sin(\theta + \varphi) + \sin(\theta - \varphi)$$

$$2 \cos \theta \sin \varphi = \sin(\theta + \varphi) - \sin(\theta - \varphi)$$

$$\tan \theta \tan \varphi = \frac{\cos(\theta - \varphi) - \cos(\theta + \varphi)}{\cos(\theta - \varphi) + \cos(\theta + \varphi)}$$

$$\tan\left(\frac{\alpha + \beta}{2}\right) = \frac{\sin \alpha + \sin \beta}{\cos \alpha + \cos \beta} = -\frac{\cos \alpha - \cos \beta}{\sin \alpha - \sin \beta}$$

$$\sin \theta \pm \sin \varphi = 2 \sin\left(\frac{\theta \pm \varphi}{2}\right) \cos\left(\frac{\theta \mp \varphi}{2}\right)$$

$$\cos \theta + \cos \varphi = 2 \cos\left(\frac{\theta + \varphi}{2}\right) \cos\left(\frac{\theta - \varphi}{2}\right)$$

$$\cos \theta - \cos \varphi = -2 \sin\left(\frac{\theta + \varphi}{2}\right) \sin\left(\frac{\theta - \varphi}{2}\right)$$

Cont...

➤ Now come to Example#1 solution

Mean:

$$E[X(t)] = \mu_X(t) = E[A \sin(\omega t + \phi)] = \mu_A \sin(\omega t + \phi)$$

Variance:

$$\begin{aligned} \text{var}[X(t)] &= \sigma_X^2(t) = E[A^2 \sin^2(\omega t + \phi)] - \mu_A^2 \sin^2(\omega t + \phi) \\ &= \{E[A^2] - \mu_A^2\} \sin^2(\omega t + \phi) = \sigma_A^2 \sin^2(\omega t + \phi) \end{aligned}$$

Autocorrelation

$$\begin{aligned} R_X(t_1, t_2) &= E[X(t_1)X(t_2)] = E[A^2] \sin(\omega t_1 + \phi) \sin(\omega t_2 + \phi) \\ &= \frac{1}{2} E[A^2] \{\cos[\omega(t_1 - t_2)] - \cos[\omega(t_1 + t_2) + 2\phi]\} \end{aligned}$$

Cont...

Autocovariance

$$\begin{aligned}C_X(t_1, t_2) &= R_X(t_1, t_2) - \mu_X(t_1)\mu_X(t_2) \\&= E[A^2] \sin(\omega t_1 + \phi) \sin(\omega t_2 + \phi) - \mu_A^2 \sin(\omega t_1 + \phi) \sin(\omega t_2 + \phi) \\&= \sigma_A^2 \sin(\omega t_1 + \phi) \sin(\omega t_2 + \phi) \\&= \frac{1}{2} \sigma_A^2 \{ \cos[\omega(t_1 - t_2)] - \cos[\omega(t_1 + t_2) + 2\phi] \}\end{aligned}$$

Normalized Autocovariance

$$\rho_X(t_1, t_2) = \frac{C_X(t_1, t_2)}{\sigma_X(t_1)\sigma_X(t_2)} = \frac{\sigma_A^2 \sin(\omega t_1 + \phi) \sin(\omega t_2 + \phi)}{\sigma_A^2 \sin(\omega t_1 + \phi) \sin(\omega t_2 + \phi)} = 1$$

Cont...

Example 4.2:- Two random processes $X(t)$ and $Y(t)$ are given by $X(t) = A \sin(\omega t + \phi_1)$; $Y(t) = B \sin(\omega t + \phi_2)$

where A and B are two random variables; then find the means and variances of $X(t)$ and $Y(t)$ and their crosscorrelation, cross-covariance, and normalized cross-covariance.

Solution

- Means: $\mu_X(t) = E[A \sin(\omega t + \phi_1)] = \mu_A \sin(\omega t + \phi_1)$
 $\mu_Y(t) = E[B \cos(\omega t + \phi_2)] = \mu_B \cos(\omega t + \phi_2)$
- Variances: $\sigma_X^2(t) = \sigma_A^2 \sin^2(\omega t + \phi_1)$
 $\sigma_Y^2(t) = \sigma_B^2 \cos^2(\omega t + \phi_2)$

Cont...

- Cross-Correlation:

$$\begin{aligned}R_{XY}(t_1, t_2) &= E[X(t_1)Y(t_2)] = E[AB] \sin(\omega t_1 + \phi_1) \cos(\omega t_2 + \phi_2) \\ &= \frac{1}{2} E[AB] \{ \sin[\omega(t_1 + t_2) + \phi_1 + \phi_2] + \sin[\omega(t_1 - t_2) + \phi_1 - \phi_2] \}\end{aligned}$$

- Cross-Covariance:

$$\begin{aligned}C_{XY}(t_1, t_2) &= R_{XY}(t_1, t_2) - \mu_X(t_1)\mu_Y(t_2) \\ &= E[AB] \sin(\omega t_1 + \phi_1) \cos(\omega t_2 + \phi_2) - \mu_A \mu_B \sin(\omega t_1 + \phi_1) \cos(\omega t_2 + \phi_2) \\ &= \sigma_{AB} \sin(\omega t_1 + \phi_1) \cos(\omega t_2 + \phi_2) \\ &= \frac{1}{2} \sigma_{AB} \{ \sin[\omega(t_1 + t_2) + \phi_1 + \phi_2] + \sin[\omega(t_1 - t_2) + \phi_1 - \phi_2] \}\end{aligned}$$

- Normalized Cross-Covariance:

$$\rho_{XY}(t_1, t_2) = \frac{C_{XY}(t_1, t_2)}{\sigma_X(t_1)\sigma_Y(t_2)} = \frac{\sigma_{AB} \sin(\omega t_1 + \phi_1) \cos(\omega t_2 + \phi_2)}{\sigma_A \sigma_B \sin(\omega t_1 + \phi_1) \cos(\omega t_2 + \phi_2)} = \frac{\sigma_{AB}}{\sigma_A \sigma_B} = \rho_{AB}$$

4.2 Stationary Stochastic Processes

- Stationary processes exhibit **statistical** properties that are **invariant** to **shift** in the **time index**.
- ✓ **First-order stationarity** implies that the statistical properties of $X(t_i)$ and $X(t_i + \tau)$ are the same for any τ
- ❖ A random process is first-order stationary if

$$F_X(x; t) = F_X(x; t + \tau) = F_X(x)$$

$$f_X(x; t) = f_X(x; t + \tau) = f_X(x)$$

and the distribution and density functions are independent of time.

Cont...

✓ **Second-order stationarity** implies that the statistical properties of the pairs $\{X(t_1) , X(t_2) \}$ and $\{X(t_1+ \tau) , X(t_2+\tau)\}$ are the same for *any* τ .

❖ A random process is second-order stationary if

$$F_X(x_1, x_2; t_1, t_2) = F_X(x_1, x_2; t_1 + \tau, t_2 + \tau) = F_X(x_1, x_2; \tau)$$

$$f_X(x_1, x_2; t_1, t_2) = f_X(x_1, x_2; t_1 + \tau, t_2 + \tau) = f_X(x_1, x_2; \tau)$$

- The distribution and density functions are dependent not on two time instants t_1 and t_2 but on the time difference $\tau = t_1 - t_2$ only.
- **Second-order stationary** processes are also called **wide-sense stationary** or **weakly stationary**.

Cont...

- Random processes in which the **mean** and **autocorrelation** function **do not depend on absolute time** are called **wide-sense stationary (WSS) processes**.
- If a random process is wide-sense stationary, then it is **necessary** and **sufficient** that the following two conditions be satisfied:
 1. The expected value is a constant, $E[X(t)] = \mu_X$.
 2. The autocorrelation function R_X is a function of the time difference $t_2 - t_1 = \tau$ and not individual times, $R_X(t_1, t_2) = R_X(t_2 - t_1) = R_X(\tau)$.

Cont...

- ✓ **nth-order stationary** processes- the probabilities of the samples of a random process $X(t)$ at times t_1, \dots, t_n will not differ from those at times $t_1 + \tau, \dots, t_n + \tau$.

i.e
$$F_X(x_1, \dots, x_n; t_1, \dots, t_n) = F_X(x_1, \dots, x_n; t_1 + \tau, \dots, t_n + \tau)$$

$$f_X(x_1, \dots, x_n; t_1, \dots, t_n) = f_X(x_1, \dots, x_n; t_1 + \tau, \dots, t_n + \tau)$$

- **Astrict-sense or strongly stationary** process is a random process that satisfies the above equations for all n , and any τ .
- ❖ **nth-order stationarity implies lower-order stationarities.**
- **Strict-sense stationarity implies wide-sense stationarity;** but the converse is not necessarily true; except Gaussian.

Cont...

Some Properties of Correlation Functions of WSS

1. $R_X(0) = E[X^2(t)] = \text{average power} \geq 0$
2. $R_X(\tau) = R_X(-\tau)$. Or, $R_X(\tau)$ is an even function.

$$R_X(\tau) = E[X(t)X(t + \tau)] = E[X(t + \tau)X(t)] = R_X(-\tau)$$

3. $|R_X(\tau)| \leq R_X(0)$.
4. If a constant $T > 0$ exists such that $R_X(T) = R_X(0)$, then the $R_X(\tau)$ is periodic
5. $E[X(t + \phi)X(t + \tau + \phi)] = R_X(\tau) = E[X(t)X(t + \tau)]$
6. If $E[X(t)] = \mu_X$ and $Y(t) = a + X(t)$, where a is constant, then $E[Y(t)] = a + \mu_X$

$$E[X(t + \phi)Y(t + \tau + \phi)] = R_{XY}(\tau) = E[X(t)Y(t + \tau)]$$

$$R_Y(\tau) = E\{[a + X(t)][a + X(t + \tau)]\}$$

and

$$= a^2 + aE[X(t + \tau)] + aE[X(t)] + E[X(t)X(t + \tau)]$$

$$= a^2 + 2a\mu_X + R_X(\tau) = a^2 + 2a\mu_X + \mu_X^2 + C_X(\tau)$$

$$= (a + \mu_X)^2 + C_X(\tau)$$

Cont...

□ In a similar manner, two processes $X(t)$ and $Y(t)$ are **jointly stationary** if for all n

$$\begin{aligned} F_{XY}(x_1, \dots, x_n; y_1, \dots, y_n; t_1, \dots, t_n) \\ = F_{XY}(x_1, \dots, x_n; y_1, \dots, y_n; t_1 + \tau, \dots, t_n + \tau) \end{aligned}$$

or

$$\begin{aligned} f_{XY}(x_1, \dots, x_n; y_1, \dots, y_n; t_1, \dots, t_n) \\ = f_{XY}(x_1, \dots, x_n; y_1, \dots, y_n; t_1 + \tau, \dots, t_n + \tau) \end{aligned}$$

and they are **jointly wide-sense stationary** if

$$\begin{aligned} F_{XY}(x_1, y_2; t_1, t_2) \\ = F_{XY}(x_1, y_2; t_1 + \tau, t_2 + \tau) = F_{XY}(x_1, y_2; \tau) \end{aligned}$$

and

$$f_{XY}(x_1, y_2; t_1, t_2) = f_{XY}(x_1, y_2; t_1 + \tau, t_2 + \tau) = f_{XY}(x_1, y_2; \tau)$$

Cont...

- The cross-moments of two jointly stationary processes $X(t)$ and $Y(t)$ are defined below:

1. Cross-Correlation:

$$R_{XY}(\tau) = E[X(t)Y(t + \tau)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 y_2 f(x_1, y_2; \tau) dy_2 dx_1$$

2. Cross-Covariance

$$\begin{aligned} C_{XY}(\tau) &= E\{[X(t) - \mu_X][Y(t + \tau) - \mu_Y]\} \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x_1 - \mu_X)(y_2 - \mu_Y) f(x_1, y_2; \tau) dy_2 dx_1 \\ &= R_{XY}(\tau) - \mu_X \mu_Y \end{aligned}$$

3. Normalized Cross-Covariance:

$$\rho_{XY}(\tau) = \frac{C_{XY}(\tau)}{\sigma_X \sigma_Y}$$

Cont...

- If a stationary random process $X(t)$ is passed through a **linear** system with impulse response $h(t)$; the input–output relationship will be given by the **convolution integral**:

$$Y(t) = \int_{-\infty}^{\infty} X(t - \alpha)h(\alpha)d\alpha = \int_{-\infty}^{\infty} X(t)h(t - \alpha)d\alpha$$

- The cross-correlation function $R_{XY}(t)$ between the input and the output can be found as follows:

$$E[X(t)Y(t + \tau)] = E \int_{-\infty}^{\infty} X(t)X(t + \tau - \alpha)h(\alpha)d\alpha$$

or

$$R_{XY}(\tau) = \int_{-\infty}^{\infty} R_X(\tau - \alpha)h(\alpha)d\alpha$$

- Since the cross-correlation function depends only on τ , the output $Y(t)$ will also be a stationary random process.

Cont...

Example 4.3:- A random process $X(t)$ is defined by
 $X(t) = A \cos t + B \sin t ; -\infty < t < \infty$

where A and B are independent random variables each of which has a value -2 with probability $1/3$ and a value 1 with probability $2/3$. Show that $X(t)$ is a wide-sense stationary process.

Solution

$$E[A] = E[B] = \frac{1}{3}(-2) + \frac{2}{3}(1) = 0$$

$$E[A^2] = E[B^2] = \frac{1}{3}(-2)^2 + \frac{2}{3}(1)^2 = 2$$

➤ $E[X(t)] = 0$

- Since A and B are independent, $E[AB] = E[A]E[B] = 0$.

Cont...

- Thus; let; $t_1=t$ & $t_1-\tau=t_2=s$

$$\begin{aligned}R_{XX}(t, s) &= E[X(t)X(s)] = E[\{A \cos(t) + B \sin(t)\}\{A \cos(s) + B \sin(s)\}] \\ &= [A^2 \cos(t) \cos(s) + AB \cos(t) \sin(s) + AB \sin(t) \cos(s) \\ &\quad + B^2 \sin(t) \sin(s)] \\ &= E[A^2] \cos(t) \cos(s) + E[AB]\{\cos(t) \sin(s) + \sin(t) \cos(s)\} \\ &\quad + E[B^2] \sin(t) \sin(s) \\ &= 2\{\cos(t) \cos(s) + \sin(t) \sin(s)\} \\ &= 2 \cos(t - s)\end{aligned}$$

- Since the mean is constant and the autocorrelation function is a function of the difference between the two times, we conclude that the random process $X(t)$ is wide-sense stationary.

Cont...

Example 4.4:-Find the conditions necessary for the random process $X(t) = A \sin(\omega t + \Phi)$ to be WSS where;
a, A & ω are constants and ϕ is a random variable,
b, ω is constants and ϕ & A are random variables.

Solution

a; 1. Mean: $E[X(t)] = AE[\sin(\omega t + \Phi)] = A \int_{-a}^b \sin(\omega t + \phi) f_{\Phi}(\phi) d\phi$

One of the ways the integral will be independent of t is for ϕ to be uniformly distributed in $(0, 2\pi)$, in which case we have

$$E[X(t)] = \frac{1}{2\pi} \int_0^{2\pi} \sin(\omega t + \phi) d\phi = \frac{-1}{2\pi} \cos(\omega t + \phi) \Big|_0^{2\pi} = 0$$

Cont...

2. Autocorrelation:

$$\begin{aligned} E[X(t_1)X(t_2)] &= A^2 E[\sin(\omega t_1 + \Phi) \sin(\omega t_2 + \Phi)] \\ &= A^2 E\{\cos[\omega(t_2 - t_1)] - \cos[\omega(t_2 + t_1) + 2\Phi]\} \\ &= A^2 \cos[\omega(t_2 - t_1)] - A^2 E\{\cos[\omega(t_2 + t_1) + 2\Phi]\} \\ E\{\cos[\omega(t_2 + t_1) + 2\Phi]\} &= \frac{1}{2\pi} \int_0^{2\pi} \cos[\omega(t_2 + t_1) + 2\phi] d\phi \\ &= \frac{1}{2\pi} \frac{1}{2} \sin[\omega(t_2 + t_1) + 2\phi] \Big|_0^{2\pi} = 0 \end{aligned}$$

$$\text{Hence, } R_X(t_1, t_2) = A^2 \cos[\omega(t_2 - t_1)] = A^2 \cos[\omega\tau]$$

- $X(t)$ is stationary if ϕ is uniformly distributed in $(0, 2\pi)$. Since $R_X(\tau)$ is periodic, $X(t)$ is a periodic WSS process.

Cont...

b; 1. Mean: $E[X(t)] = E[A \sin(\omega t + \Phi)] = \iint a \sin(\omega t + \phi) f_{A\Phi}(a, \phi) d\phi da$

- The first condition for the double integral to be independent of t is for A and ϕ to be statistically independent, in which case we have

$$E[A \sin(\omega t + \Phi)] = \iint a \sin(\omega t + \phi) f_A(a) f_\Phi d\phi da$$

- and the second condition is for ϕ to be uniformly distributed in $(0, 2\pi)$, in which case we have

$$(1/2\pi) \int_0^{2\pi} \sin(\omega t + \phi) d\phi = 0 \text{ and } E[X(t)] = 0.$$

2. Autocorrelation:

$$E[X(t_1)X(t_2)] = E[A^2 \sin(\omega t_1 + \Phi) \sin(\omega t_2 + \Phi)]$$

- Since A and ϕ are independent, we have

Cont...

$$\begin{aligned} E[X(t_1)X(t_2)] &= E[A^2]E\{\cos[\omega(t_2 - t_1)] - \cos[\omega(t_2 + t_1) + 2\Phi]\} \\ &= E[A^2]\cos[\omega(t_2 - t_1)] - E[A^2]E\{\cos[\omega(t_2 + t_1) + 2\Phi]\} \end{aligned}$$

$$E\{\cos[\omega(t_2 + t_1) + 2\Phi]\} = 0.$$

- Hence,

$$R_X(t_1, t_2) = E[A^2]\cos[\omega(t_2 - t_1)] = E[A^2]\cos[\omega\tau]$$

- $X(t)$ is stationary if A and ϕ are independent and if ϕ is uniformly distributed in $(0, 2\pi)$.
- Since $R_X(\tau)$ is periodic, $X(t)$ a periodic WSS process.

Cont...

Example 4.5:- If $X(t) = A \cos(\omega t) + B \sin(\omega t)$, where A and B are random variables with density functions $f_A(a)$ and $f_B(b)$; and ω is constant. Then find the conditions under which $X(t)$ will be WSS.

Solution

1. Mean: $E[X(t)] = E[A \cos(\omega t) + B \sin(\omega t)] = \cos(\omega t)E[A] + \sin(\omega t)E[B]$

➤ If $E[X(t)]$ is to be independent of t , then $E[A] = E[B] = 0$, in which case $E[X(t)] = 0$.

2. Autocorrelation: $R_X(t_1, t_2) = E[X(t_1)X(t_2)] = E\{[A \cos(\omega t_1) + B \sin(\omega t_1)][A \cos(\omega t_2) + B \sin(\omega t_2)]\}$

$$= E\{A^2 \cos(\omega t_1) \cos(\omega t_2) + B^2 \sin(\omega t_1) \sin(\omega t_2) + AB[\sin(\omega t_1) \cos(\omega t_2) + \cos(\omega t_1) \sin(\omega t_2)]\}$$

Cont...

$$\begin{aligned} &= \frac{1}{2}E[A^2][\cos(\omega(t_2 - t_1)) + \cos(\omega(t_2 + t_1))] \\ &\quad + \frac{1}{2}E[B^2][\cos(\omega(t_2 - t_1)) - \cos(\omega(t_2 + t_1))] \\ &\quad + E[AB]\sin(\omega(t_2 + t_1)) \end{aligned}$$

- The conditions under which this equation will be dependent only on $(t_2 - t_1)$ are $E[A^2] = E[B^2]$ and $E[AB] = 0$. In this case $R_X(t_1, t_2) = E[A^2][\cos(\omega(t_2 - t_1))] = E[A^2][\cos(\omega\tau)]$
- We can now summarize the conditions for WSS:
 - (a) $E[A] = E[B] = 0$
 - (b) $E[A^2] = E[B^2]$
 - (c) $E[AB] = 0$

4.3. Ergodic Processes

- **Ergodicity** refers to **certain time averages** of random processes **converging** to their respective **statistical averages**.
- An ergodic random process is a stationary process in which **every member** of the **ensemble** exhibits the **same statistical behavior** as the ensemble.
- This implies that it is possible to determine the statistical behavior of the ensemble by examining only one typical sample function.
- Thus, for an ergodic random process, the **mean values and moments** can be determined by time averages as well as by ensemble averages (or expected values), which are equal. i.e;

$$E[X^n] = \overline{X^n} = \int_{-\infty}^{\infty} x^n f_X(x) dx = \lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T X^n(t) dt$$

Cont...

❖ Mean-Ergodic

- A stationary random process $X(t)$ is called mean-ergodic if the **ensemble average** is equal to the **time average of the sample function** $x(t)$.

$X(t)$ is stationary, implying that it has a constant mean μ_X , and the autocorrelation function $R_X(t, t + \tau)$ is a function of τ only, or $R_X(t, t + \tau) = R_X(\tau)$.

$R_X(0) = E[X^2(t)]$ is bounded, or $R_X(0) < \infty$. Hence $C_X(0) = R_X(0) - \mu_X^2 < \infty$.

- A necessary and sufficient condition for a random process to be mean-ergodic is
$$\int_{-\infty}^{\infty} |C_X(\tau)| d\tau < \infty$$

Cont...

- Even though we have derived necessary and sufficient condition for a mean-ergodic process, we cannot use it to test the ergodicity of any process since it **involves prior knowledge** of the autocovariance function $CX(\tau)$.
- However, if a partial knowledge of the ACF such as $|CX(\tau)|$ goes to 0 as τ goes to infinity, then we can conclude that the process is ergodic.
- Although **ergodic processes must be stationary**, stationary processes need not be ergodic.

Cont...

❖ Correlation-Ergodic

- A stationary random process $X(t)$ is correlation-ergodic if time autocorrelation is equal to ensemble autocorrelation.

i.e
$$\lim_{T \rightarrow \infty} \left[\frac{1}{2T} \int_{-T}^T X(t)X(t+\lambda)dt \right] = R_X(\lambda) \quad \text{for all } \lambda.$$

Where; λ is time shift,

$$\lim_{T \rightarrow \infty} \left[\frac{1}{2T} \int_{-T}^T X(t)X(t+\lambda)dt \right] \text{ is time autocorrelation,}$$
$$R_X(\lambda) \text{ is ensemble autocorrelation,}$$

Cont...

Example 4.6:- A random process has sample functions of the form $X(t)=A\cos(\omega t+\Theta)$

where ω is constant, A is a random variable that has a magnitude of $+1$ and -1 with equal probability, and Θ is a random variable that is uniformly distributed between 0 and 2π . Assume that the random variables A and Θ are independent.

- (a) Is $X(t)$ a wide-sense stationary process?
- (b) Is $X(t)$ a mean-ergodic process?

Cont...

Solution

$$E[A] = 0$$

$$\sigma_A^2 = \frac{1}{2}(1)^2 + \frac{1}{2}(-1)^2 = 1 = E[A^2]$$

$$E[\Theta] = \pi$$

$$\sigma_\Theta^2 = \frac{(2\pi)^2}{12} = \frac{\pi^2}{3}$$

(a) Since A and Θ are independent, $E[X(t)] = E[A]E[\cos(\omega t + \Theta)] = 0$, which is a constant. Also, the autocorrelation function of $X(t)$ is given by

$$\begin{aligned} R_{XX}(t, t + \tau) &= E[A \cos(\omega t + \Theta) A \cos(\omega t + \omega\tau + \Theta)] \\ &= E[A^2] E[\cos(\omega t + \Theta) \cos(\omega t + \omega\tau + \Theta)] \\ &= \frac{1}{2} E[\cos(-\omega\tau) + \cos(2\omega t + \omega\tau + 2\Theta)] \end{aligned}$$

Cont...

$$\begin{aligned} &= \frac{1}{2}E[\cos(-w\tau)] + \frac{1}{2}E[\cos(2wt + w\tau + 2\Theta)] \\ &= \frac{1}{2}\cos(w\tau) + \frac{1}{2}E[\cos(2wt + w\tau + 2\Theta)] \\ &= \frac{1}{2}\cos(w\tau) + \frac{1}{2}\int_0^{2\pi} \frac{\cos(2wt + w\tau + 2\theta)}{2\pi} d\theta \\ &= \frac{1}{2}\cos(w\tau) + \frac{1}{8\pi}[\sin(2wt + w\tau + 2\theta)]_0^{2\pi} \\ &= \frac{1}{2}\cos(w\tau) + \frac{1}{8\pi}\{\sin(2wt + w\tau + 4\pi) - \sin(2wt + w\tau)\} \\ &= \frac{1}{2}\cos(w\tau) \end{aligned}$$

- Since the mean is constant and the autocorrelation function depends only on the difference between the two times and not on t , we conclude that the process is wide-sense stationary.

Cont...

(b)

Time average is;

$$\begin{aligned}\lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T X(t) dt &= \lim_{T \rightarrow \infty} \frac{1}{2T} \int_0^{2\pi} A \cos(\omega t + \Theta) dt = \lim_{T \rightarrow \infty} \frac{A}{2T\omega} [\sin(\omega t + \Theta)]_0^{2\pi} \\ &= \lim_{T \rightarrow \infty} \frac{A}{2T\omega} [\sin(2\pi\omega + \Theta) - \sin \Theta] = 0\end{aligned}$$

- time average = $E[X(t)] = 0$.
- Thus, $X(t)$ is mean-ergodic.

4.4 Power Spectral Density

- The power spectral density (psd) function of a real **stationary** random process $X(t)$ is defined as the **Fourier transform** of the **autocorrelation** function:

➤ For Continuous Time:

$$S_X(\omega) = \text{FT}[R_X(\tau)] = \int_{-\infty}^{\infty} R_X(\tau) e^{-j\omega\tau} d\tau$$

- It represents the average power per hertz, and hence the term power spectral density.
- From the Fourier inversion theorem we can obtain the autocorrelation function from the power spectral density:

$$R_X(\tau) = \text{IFT}[S_X(\omega)] = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_X(\omega) e^{j\omega\tau} d\omega$$

Cont...

- The mean-square value of the random process , which is also called the average power, is given by

$$E[X^2(t)] = R_{XX}(0) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{XX}(w)dw$$

- Other properties of the power spectral density;
 1. $S_{XX}(w) \geq 0$, which means that $S_{XX}(w)$ is a nonnegative function
 2. $S_{XX}(-w) = S_{XX}(w)$, which means that $S_{XX}(w)$ is an even function
 3. The power spectral density is a real function if $X(t)$ is real because we have that

$$\begin{aligned} S_{XX}(w) &= \int_{-\infty}^{\infty} R_{XX}(\tau) e^{-jw\tau} d\tau = \int_{-\infty}^{\infty} R_{XX}(\tau) \{\cos(w\tau) - j\sin(w\tau)\} d\tau \\ &= \int_{-\infty}^{\infty} R_{XX}(\tau) \cos(w\tau) d\tau - j \int_{-\infty}^{\infty} R_{XX}(\tau) \sin(w\tau) d\tau \\ &= \int_{-\infty}^{\infty} R_{XX}(\tau) \cos(w\tau) d\tau = 2 \int_0^{\infty} R_{XX}(\tau) \cos(w\tau) d\tau \end{aligned}$$

Cont...

- The **cross-spectral density** (csd) $S_{XY}(\omega)$ of two real stationary random processes $X(\tau)$ and $Y(\tau)$ is defined as the Fourier transform of the cross-correlation function, $R_{XY}(\tau)$

$$S_{XY}(\omega) = \text{FT}[R_{XY}(\tau)] = \int_{-\infty}^{\infty} R_{XY}(\tau) e^{-j\omega\tau} d\tau$$

and the inverse Fourier transform of $S_{XY}(\omega)$ gives the cross-correlation function

$$R_{XY}(\tau) = \text{IFT}[S_{XY}(\omega)] = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{XY}(\omega) e^{j\omega\tau} d\omega$$

- The **cross-spectral density** $S_{XY}(\omega)$ **will be complex**, in general, even when the random processes $X(t)$ and $Y(t)$ are real.

Cont...

Some Common Fourier Transform Pairs

$x(\tau)$	$X(\omega)$
$e^{-a \tau }, a > 0$	$\frac{2a}{a^2 + \omega^2}$
$e^{-a\tau}, a > 0, \tau \geq 0$	$\frac{1}{a + j\omega}$
$e^{b\tau}, b > 0, \tau < 0$	$\frac{1}{b - j\omega}$
$\tau e^{-a\tau}, a > 0, \tau \geq 0$	$\frac{1}{(a + j\omega)^2}$
1	$2\pi\delta(\omega)$
$\delta(\tau)$	1
$e^{j\omega_0\tau}$	$2\pi\delta(\omega - \omega_0)$
$\begin{cases} 1 & -T/2 < \tau < T/2 \\ 0 & \text{otherwise} \end{cases}$	$T \frac{\sin(\omega T/2)}{(\omega T/2)}$
$\begin{cases} 1 - \tau /T & \tau < T \\ 0 & \text{otherwise} \end{cases}$	$T \left[\frac{\sin(\omega T/2)}{(\omega T/2)} \right]^2$
$\cos(\omega_0\tau)$	$\pi\delta(\omega - \omega_0) + \pi\delta(\omega + \omega_0)$
$\sin(\omega_0\tau)$	$-j\pi[\delta(\omega - \omega_0) - \delta(\omega + \omega_0)]$
$e^{-a \tau } \cos(\omega_0\tau)$	$\frac{a}{a^2 + (\omega - \omega_0)^2} + \frac{a}{a^2 + (\omega + \omega_0)^2}$

Cont...

➤ For discrete-time:

- The power spectral density of $X[n]$ is given by the following discrete-time Fourier transform of its autocorrelation function:

$$S_{XX}(\Omega) = \sum_{m=-\infty}^{\infty} R_{XX}[m]e^{-j\Omega m}$$

Note that $e^{-j\Omega n}$ is periodic with period 2π . That is, $e^{-j(\Omega+2\pi)n} = e^{-j\Omega n}e^{-j2\pi n} = e^{-j\Omega n}$ because $e^{-j2\pi n} = 1$. Thus, $S_{XX}(\Omega)$ is periodic with period 2π , and it is sufficient to define $S_{XX}(\Omega)$ only in the range $(-\pi, \pi)$. This means that the autocorrelation function is given by

$$R_{XX}[m] = \frac{1}{2\pi} \int_{-\pi}^{\pi} S_{XX}(\Omega) e^{j\Omega m} d\Omega$$

Cont...

- The properties of $S_{XX}(\Omega)$ include the following:
 1. $S_{XX}(\Omega + 2\pi) = S_{XX}(\Omega)$, which means that $S_{XX}(\Omega)$ is periodic with period 2π as stated earlier.
 2. $S_{XX}(-\Omega) = S_{XX}(\Omega)$, which means that $S_{XX}(\Omega)$ is an even function.
 3. $S_{XX}(\Omega)$ is real, which means that $S_{XX}(\Omega) \geq 0$.
 4. $E[X^2[n]] = R_{XX}[0] = \frac{1}{2\pi} \int_{-\pi}^{\pi} S_{XX}(\Omega) d\Omega$, which is the average power of the process.

Cont...

- **White-Noise Process:-** is a **zero mean** stationary random process $X(t)$ whose **autocovariance** or **autocorrelation** is given by $C_X(\tau) = R_X(\tau) = \sigma_X^2 \delta(\tau)$
- The energy of a white-noise process is infinite.
 - White noise is the term used to define a random function whose **power spectral density is constant** for all frequencies.
 - Thus, if $N(t)$ denotes white noise, $S_{NN}(w) = N_0/2$ where N_0 is a real positive constant.
 - The **inverse Fourier transform** of $S_{NN}(w)$ gives the **autocorrelation** function of $N(t)$, $R_{NN}(\tau) = (N_0/2)\delta(\tau)$ where $\delta(\tau)$ is the impulse function.

Cont...

Example 4.7:- Determine the autocorrelation function of the random process with the power spectral density given by

$$S_{XX}(w) = \begin{cases} S_0 & |w| < w_0 \\ 0 & \text{otherwise} \end{cases}$$

Solution

- Just find the inverse Fourier transform

$$\begin{aligned} R_{XX}(\tau) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{XX}(w) e^{jw\tau} dw \\ &= \frac{1}{2\pi} \int_{-w_0}^{w_0} S_0 e^{jw\tau} dw = \frac{S_0}{2j\pi\tau} [e^{jw\tau}]_{-w_0}^{w_0} \\ &= \frac{S_0}{2j\pi\tau} [e^{jw_0\tau} - e^{-jw_0\tau}] = \frac{S_0}{\pi\tau} \left(\frac{e^{jw_0\tau} - e^{-jw_0\tau}}{2j} \right) \\ &= \frac{S_0}{\pi\tau} \sin(w_0\tau) \end{aligned}$$

Cont...

Example 4.8:- Let $Y(t)=X(t)+N(t)$ be a wide-sense stationary process where $X(t)$ is the actual signal and $N(t)$ is a zero-mean noise process with variance σ_N^2 and independent of $X(t)$. Find the power spectral density of $Y(t)$.

Solution

- Since $X(t)$ and $N(t)$ are independent random processes, the autocorrelation function of $Y(t)$ is given by
$$\begin{aligned}R_{YY}(\tau) &= E[Y(t)Y(t+\tau)] = E[\{X(t) + N(t)\}\{X(t+\tau) + N(t+\tau)\}] \\ &= E[X(t)X(t+\tau) + X(t)N(t+\tau) + N(t)X(t+\tau) + N(t)N(t+\tau)] \\ &= E[X(t)X(t+\tau)] + E[X(t)]E[N(t+\tau)] + E[N(t)]E[X(t+\tau)] \\ &\quad + E[N(t)N(t+\tau)]\end{aligned}$$

Cont...

$$= R_{XX}(\tau) + R_{NN}(\tau) = R_{XX}(\tau) + \sigma_N^2 \delta(\tau)$$

- The power spectral density of $Y(t)$ is the inverse Fourier transform its autocorrelation function.

➤ Thus, the power spectral density of $Y(t)$ is given by

$$S_{YY}(w) = S_{XX}(w) + \sigma_N^2$$

Example 4.9:- Assume that $X[n]$ is areal process, which means that $R_{XX}[-m] = R_{XX}[m]$. Find the power spectral density $S_{XX}(\Omega)$.

$$\begin{aligned} S_{XX}(\Omega) &= \sum_{m=-\infty}^{\infty} R_{XX}[m] e^{-j\Omega m} = \sum_{m=-\infty}^{-1} R_{XX}[m] e^{-j\Omega m} + \sum_{m=0}^{\infty} R_{XX}[m] e^{-j\Omega m} \\ &= \sum_{k=1}^{\infty} R_{XX}[-k] e^{j\Omega k} + \sum_{m=0}^{\infty} R_{XX}[m] e^{-j\Omega m} \end{aligned}$$

Cont...

$$\begin{aligned} &= R_{XX}[0] + 2 \sum_{m=1}^{\infty} R_{XX}[m] \frac{\{e^{j\Omega m} + e^{-j\Omega m}\}}{2} \\ &= R_{XX}[0] + 2 \sum_{m=1}^{\infty} R_{XX}[m] \cos(m\Omega) \end{aligned}$$

Example 4.10:- Find the power spectral density of a random sequence $X[n]$ whose autocorrelation function is given by $R_{XX}[m] = a^{|m|}$.

Solution

The power spectral density is given by

$$\begin{aligned} S_{XX}(\Omega) &= \sum_{m=-\infty}^{\infty} R_{XX}[m] e^{-j\Omega m} = \sum_{m=-\infty}^{\infty} a^{|m|} e^{-j\Omega m} \\ &= \sum_{m=-\infty}^{-1} a^{-m} e^{-j\Omega m} + \sum_{m=0}^{\infty} a^m e^{-j\Omega m} \end{aligned}$$

Cont...

$$\begin{aligned} &= \sum_{k=1}^{\infty} a^k e^{j\Omega k} + \sum_{m=0}^{\infty} a^m e^{-j\Omega m} = \sum_{k=1}^{\infty} \{ae^{j\Omega}\}^k + \sum_{m=0}^{\infty} \{ae^{-j\Omega}\}^m \\ &= \frac{1}{1 - ae^{j\Omega}} - 1 + \frac{1}{1 - ae^{-j\Omega}} \\ &= \frac{1 - a^2}{1 + a^2 - 2\cos(\Omega)} \end{aligned}$$

THANK YOU!!!!!!

After we will do these and some other Examples on a board; Chapter Four be Ended!!!

If You have Any question???
Welcome!!!!!!