Boston University Department of Electrical and Computer Engineering

EC505 STOCHASTIC PROCESSES

Exam 1 Summary

1. Probability and Random Variables:

- Axiomatic definition of probability: Triple (Ω, F, P) , Ω = Set of outcomes, F = Set of events, and $P(\cdot)$ = Probability measure which satisfies axioms:
 - (a) $P(\Omega) = 1$
 - (b) $P(A) \ge 0, \forall A \in F$.
 - (c) $P(\cup A_i) = \sum P(A_i)$ if $A_i \cap A_j = \emptyset$, $i \neq j$.
- One Random Variable
 - Probability Distribution Function (PDF): $P_X(x) \equiv P(X \le x)$

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$$P[x_1 < X \le x_2] = P_X(x_2) - P_X(x_1)$$

– Probability Density Function (pdf): $p_X(x) = \frac{dP_X(x)}{dx}$

$$* P(A) = \int_A p_X(x) \, dx$$

$$- E[g(X)] \equiv \int_{-\infty}^{\infty} g(x) p_X(x) dx$$

- Mean: $m_X = E[X]$
- *n*-th moment: $E[X^n] = \int_{-\infty}^{\infty} x^n p_X(x) dx$
- Variance: $\sigma_X^2 = E[(X m_X)^2] = E[X^2] (E[x])^2$
- Two Random Variables *X*, *Y*
 - Joint Distribution Function: $P_{X,Y}(x,y) \equiv P[(X \le x) \cap (Y \le y)]$
 - Joint Density Function: $p_{X,Y}(x,y) = \frac{\partial^2 P_{X,Y}(x,y)}{\partial x \partial y}$
 - Marginal pdf: $p_X(x) = \int_{-\infty}^{\infty} p_{X,Y}(x,y) dy$
 - Conditional Density: $p_{X|Y}(x \mid y) = \frac{p_{X,Y}(x,y)}{p_Y(y)} = \frac{p_{Y|X}(y|x)p_X(x)}{p_Y(y)}$
 - Bayes' Rule: $p_{X|Y}(x | y) = \frac{p_{Y|X}(y | x)p_{X}(x)}{p_{Y}(y)}$
 - X, Y statistically independent $\Leftrightarrow p_{X,Y}(x,y) = p_X(x)p_Y(y)$
 - Expected value: $E[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) p_{X,Y}(x,y) dx dy$
 - Correlation: E[XY]
 - Covariance: $\sigma_{XY} = E[(X m_X)(Y m_Y)] = E[XY] m_X m_Y = Cov(X, Y)$
 - $-X, Y \text{ uncorrelated} \Leftrightarrow \sigma_{XY} = 0 \Leftrightarrow E[XY] = E[X]E[Y]$
 - $-X, Y \text{ orthogonal } \Leftrightarrow E[XY] = 0$
 - $-(X,Y \text{ Independent}) \Longrightarrow_{\neq =} (X,Y \text{ Uncorrelated}),$
 - Conditional Expectation (mean) of *X* given *Y*: $E[X \mid Y] = \int_{-\infty}^{\infty} x p_{X|Y}(x|y) dx$

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• Random Vectors

$$-\underline{X} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix}, \underline{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{bmatrix}$$

- Joint distribution function:

$$P_{\underline{X}}(\underline{x}) = P[(X_1 \le x_1), \dots, (X_N \le x_N)] \text{ or } P_{\underline{X},\underline{Y}}(\underline{x},\underline{y}) = P[(X_1 \le x_1), \dots, (X_N \le x_N), (Y_1 \le y_1), \dots, (Y_N \le y_N)]$$

- Joint density:
$$p_{\underline{X}}(\underline{x}) = \frac{\partial^N P_{\underline{X}}(\underline{x})}{\partial x_1 \dots \partial x_N}$$
 or $p_{\underline{X},\underline{Y}}(\underline{x},\underline{y}) = \frac{\partial^{2N} P_{\underline{X},\underline{Y}}(\underline{x},\underline{y})}{\partial x_1 \dots \partial x_N, \partial y_1 \dots \partial y_N}$

 $-\underline{X}, \underline{Y}$ independent if $p_{\underline{X},\underline{Y}}(\underline{x},y) = p_{\underline{X}}(\underline{x})p_{\underline{Y}}(y)$

$$- \ \ \text{Conditional Density:} \ p_{\underline{X}|\underline{Y}}(\underline{x}|\underline{y}) = \frac{p_{\underline{X},\underline{Y}}(\underline{x},\underline{y})}{p_{\underline{Y}}(y)} = \frac{p_{\underline{Y}|\underline{X}}(\underline{y}|\underline{x})p_{\underline{X}}(\underline{x})}{p_{\underline{Y}}(y)}$$

$$-E[\underline{g}(\underline{x})] = \begin{pmatrix} E[g_1(\underline{x})] \\ \vdots \\ E[g_N(\underline{x})] \end{pmatrix} = \int_{-\infty}^{\infty} \underline{g}(\underline{x}) f(\underline{x}) d\underline{x}$$

- Mean Vector:
$$E[\underline{X}] = m_{\underline{X}} = \begin{pmatrix} E[X_1] \\ \vdots \\ E[X_N] \end{pmatrix}$$

- Covariance Matrix:

$$Cov(\underline{X},\underline{X}) = \Lambda_{\underline{X}\underline{X}} = \Sigma_{\underline{X}\underline{X}} = E[(\underline{X} - m_X)(\underline{X} - m_X)^T] = E[\underline{X}\underline{X}^T] - m_{\underline{X}}m_{\underline{X}}^T$$

– Convariance matrix constraints: Σ_{XX} must be a symmetric, PSD matrix

- Cross-Covariance Matrix:

$$Cov(\underline{X},\underline{Y}) = \Lambda_{\underline{XY}} = \Sigma_{\underline{XY}} = E[(\underline{X} - m_{\underline{X}})(\underline{Y} - m_{\underline{Y}})^T] = E[\underline{XY}^T] - m_{\underline{X}}m_{\underline{Y}}^T$$

- Conditional Mean:
$$E[\underline{X}|\underline{Y}] = \int_{-\infty}^{\infty} \underline{x} f(\underline{x}|\underline{y}) d\underline{x}$$

- Conditional Covariance:
$$\Sigma_{X|Y} = \int_{-\infty}^{\infty} (\underline{x} - E[\underline{x}|\underline{y}]) (\underline{x} - E[\underline{x}|\underline{y}])^T f(\underline{x}|\underline{y}) d\underline{x}$$

– Uncorrelated:
$$\Sigma_{\underline{XY}} = 0$$
, $\Rightarrow E[\underline{XY}^T] = E[\underline{X}]E[\underline{Y}]^T$.

- Orthogonal: $E[\underline{XY}^T] = 0$.

- Gaussian Random Vectors: $\underline{a}^T \underline{X}$ is a Gaussian random variable for all \underline{a} .

2. Characterization and Manipulation of Random Processes

- Complete Characterization of Random Processes: In terms of N-th order probability distribution or density functions $p_{X(t_1),X(t_2),\cdots,X(t_N)}(x_1,x_2,\cdots,x_N)$ for all t_i,N .
- Joint pdfs
- · Marginal pdfs
- · Conditional pdfs
- Mean: $m_x(t) = E[X(t)]$
- Autocorrelation: $R_{XX}(t_1, t_2) = E[X(t_1)X(t_2)]$
- Autocovariance: $K_{XX}(t_1, t_2) = C_{XX}(t_1, t_2) = E[X(t_1)X(t_2)] E[X(t_1)]E[X(t_2)]$
- Constraints on $R_{XX}(t_1, t_2)$, $K_{XX}(t_1, t_2)$: Var $\left[\int a(t)X(t) dt \right] \ge 0$
- General Expectation E[g(x)]
- Conditional Expectation E[g(x)|y]
- Second order characterization: <u>Partial</u> characterization in terms of $m_x(t)$ and $K_{XX}(t_1,t_2)$.
- Special Types of Stochastic Processes

- Gaussian: X(t) is Gaussian process $\iff \sum_{i=1}^{N} a_i X(t_i)$ a Gaussian random variable for all a_i, t_i, N .
- Markov: $p_{X(t_N)|X(t_{N-1}),X(t_{N-2}),\cdots,X(t_1)}(X_N|X_{N-1},\cdots,X_1) = p_{X(t_N)|X(t_{N-1})}(X_N|X_{N-1})$, for all t_i with $t_i \ge t_{i-1}$
- IIP: $X(t_i) X(t_{i-1})$ independent of $X(t_{i-1})$ for all $t_i \ge t_{i-1}$. IIP \longrightarrow Markov. IIP $\longrightarrow K_{XX}(t,s) = \text{Var}[\min(t,s)]$
- Strict Sense Stationary: $p_{X(t_1),X(t_2),\cdots,X(t_N)}(x_1,x_2,\cdots,x_N) = p_{X(t_1+\tau),X(t_2+\tau),\cdots,X(t_N+\tau)}(x_1,x_2,\cdots,x_N)$ for all τ , N.
- Wide Sense or weakly Stationary: $m_x(t) = m_x$, $K_{XX}(t_1, t_2) = K_{XX}(t_2 t_1)$
- Special random processes and their means and variances: e.g.
 - Poisson Counting Process: $\Pr[N(t) = n] = \frac{(\lambda t)^n}{n!} e^{-\lambda t}$, $m_N(t) = \lambda t$, $K_{nn}(t,s) = \lambda \min(t,s)$. N(t) is IIP.
 - Random Telegraph Wave
 - Random Walk
 - Wiener Process: $m_x(t) = 0$, $K_{XX}(t,s) = \alpha \min(t,s)$, IIP

3. Convergence, Mean Square Calculus

- Mean Square Convergence: $\lim_{n\to\infty} E\left[(X_n-X)^2\right]=0$
- Cauchy Criterion for MSS Convergence: $\lim_{n\to\infty} E\left[(x_n-x_m)^2\right]\to 0$
- Mean Square Continuity: $\lim_{\epsilon \to 0} X(t+\epsilon) \stackrel{\text{mss}}{=} X(t)$. Mean Square Continuous if $R_{XX}(t_1, t_2)$ continuous.
- Mean Square Derivative: $\lim_{\epsilon \to 0} \left(\frac{X(t+\epsilon) X(t)}{\epsilon} \right) \stackrel{\text{mss}}{=} \dot{X}(t)$. Mean Square differentiable if $\frac{\partial^2}{\partial t_1 \partial t_2} R_{XX}(t_1, t_2)$ exists.
- Mean Square Integral: $\lim_{N\to\infty} \left(\sum_{i=1}^N X(s+i\Delta)\Delta\right) \stackrel{\text{mss}}{=} Y$. Mean square integrable if $\int_s^t \int_s^t R_{XX}(\sigma,\tau) d\sigma d\tau$ exists.

4. Ergodicity

- Idea: Time average = Ensemble average in MSS sense.
- Ergodic in the Mean: $\lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} X(t) dt = \lim_{T \to \infty} \langle m_x \rangle_T \stackrel{\text{mss}}{=} m_x$
- Ergodic in Autocorrelation: $\lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} X(t+\tau)X(t) dt = \lim_{T \to \infty} \langle R_{XX}(\tau) \rangle_{T} \stackrel{\text{mss}}{=} R_{XX}(\tau)$
- Completely Ergodic: $\lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} g\{X(t)\} dt \stackrel{\text{mss}}{=} E[g\{X(t)\}]$

5. Power Spectral Density

- For X(t) WSS
- Beware WSS Notation: $R_{XY}(t,t+\tau) \equiv R_{XY}(t+\tau-t) = R_{XY}(\tau)$ verses $R_{XY}(t,t+\tau) \equiv R_{XY}(t-t-\tau) = R_{XY}(-\tau)$.
- Power Spectral Density: $S_{XX}(\omega) = F[R_{XX}(\tau)] = \int_{-\infty}^{\infty} R_{XX}(\tau)e^{-j\omega\tau}d\tau$, $S_{XX}(f) = F[R_{XX}(\tau)] = \int_{-\infty}^{\infty} R_{XX}(\tau)e^{-j2\pi f\tau}d\tau$
- Inverse Power Spectral Density: $R_{XX}(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{XX}(\omega) e^{j\omega\tau} d\omega = \int_{-\infty}^{\infty} S_{XX}(f) e^{j2\pi f\tau} df$
- Cross-Spectral Density: $S_{XY}(\omega) = F[R_{XY}(\tau)] = \int_{-\infty}^{\infty} R_{XY}(\tau) e^{-j\omega\tau} d\tau$, $S_{XY}(f) = F[R_{XY}(\tau)] = \int_{-\infty}^{\infty} R_{XY}(\tau) e^{-j2\pi f\tau} d\tau$

- Inverse Cross-Power Spectral Density: $R_{XY}(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{XY}(\omega) e^{j\omega\tau} d\omega = \int_{-\infty}^{\infty} S_{XY}(f) e^{j2\pi f\tau} df$
- For sequences: $S_{XX}(f) = \sum_{n=-\infty}^{\infty} R_{XX}(n)e^{-j2\pi fn}$, -1/2 < f < 1/2. $S_{XX}(\omega) = \sum_{n=-\infty}^{\infty} R_{XX}(n)e^{-j\omega n}$, $-\pi < \omega < \pi$.
- $S_{XX}(f)$ average power at frequency f.
- Properties of $S_{XX}(f)$ and $S_{XY}(f)$:
 - $S_{XX}(\omega)$ real, non-negative.

- Total average power in
$$X(t)$$
: $R_{XX}(0) = \int_{-\infty}^{\infty} S_{XX}(\omega) d\omega$

$$-X(t)$$
 Real $\longrightarrow S_{XX}(\omega) = S_{XX}(-\omega)$

$$-\alpha X(t) \longrightarrow \alpha^2 S_{XX}(\omega)$$

$$-\frac{d}{dt}X(t)\longrightarrow \omega^2 S_{XX}(\omega)$$

$$-X(t)e^{j\omega_0t}\longrightarrow S_{XX}(\omega-\omega_0)$$

$$-X(t)+b\longrightarrow S_{XX}(\omega)+2\pi|b|^2\delta(\omega).$$

6. Advice:

- Have basic results at your fingertips
- Know the assumptions/conditions behind formulas that you use!
- Perform sanity checks on answers go back to basics if totally stuck (i.e. defining equation of expectation, variance etc)
- Don't forget to deal with the mean! (e.g. $R_{XX}(t)$ vs $K_{XX}(t)$, etc.)