

**ECE4110: Random Signals in Communications and
Signal Processing**

Random Processes

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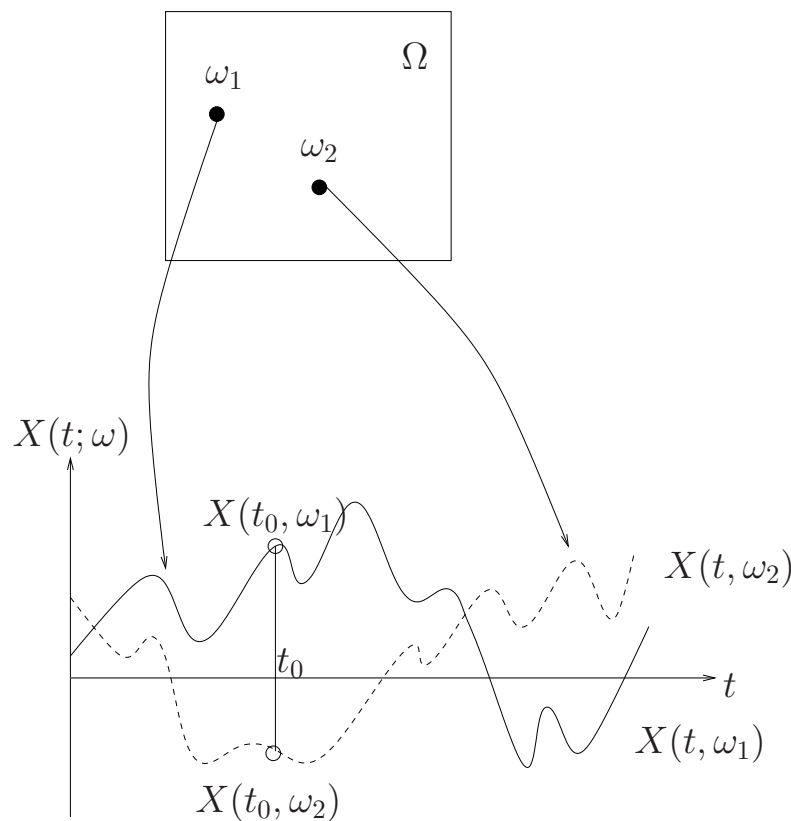
Outline

- Definition of random processes
- Description of a random process:
 - Complete characterization
 - Partial characterization: moments of a random process
- Important properties of a random process:
 - Stationarity and wide-sense stationarity
 - Independent increments
- Examples of widely used random processes:
 - Discrete-time processes:
i.i.d. sequence, the sum process, random walk, and Binomial counting process
 - Continuous-time processes:
Poisson process, Gaussian process, Wiener process and Brownian motion

Random Processes

Random Process:

Each sample $\omega \in \Omega$ in the sample space is mapped to a time function $X(t, \omega)$.



- For a fixed time $t = t_0$, $X(t_0; \omega)$ is a random variable.
- For a fixed ω , $X(t; \omega)$ is a time function referred to as a **realization** or a **sample path** of the random process.
- $X(t)$ denotes a random process (without explicitly including ω); it is an indexed (by t) family of random variables.
- $x(t)$ denote a sample path of $X(t)$.

Examples of Random Processes

Examples of Discrete-Time Random Processes:

- An i.i.d. Sequence of Discrete Random Variables:

$$X_1, X_2, X_3, \dots$$

where $X_i \sim B(p)$ are i.i.d. Bernoulli random variables.

- An i.i.d. Sequence of Continuous Random Variables:

$$X_1, X_2, X_3, \dots$$

where $X_i \sim \mathcal{N}(\mu, \sigma^2)$ are i.i.d. Gaussian.

- Binomial Counting Process (counting the number of “heads” in a sequence of coin flips):

$$S_n = \sum_{i=1}^n X_i$$

where $X_i \sim B(p)$ are i.i.d. Bernoulli random variables.

- Random Walk:

$$S_n = \sum_{i=1}^n Y_i$$

where $\{Y_i\}_{i \geq 1}$ are i.i.d. with PMF given by

$$\Pr(Y_i = 1) = \Pr(Y_i = -1) = \frac{1}{2}.$$

⁰We use subscript n or i rather than (t) for discrete-time random processes.

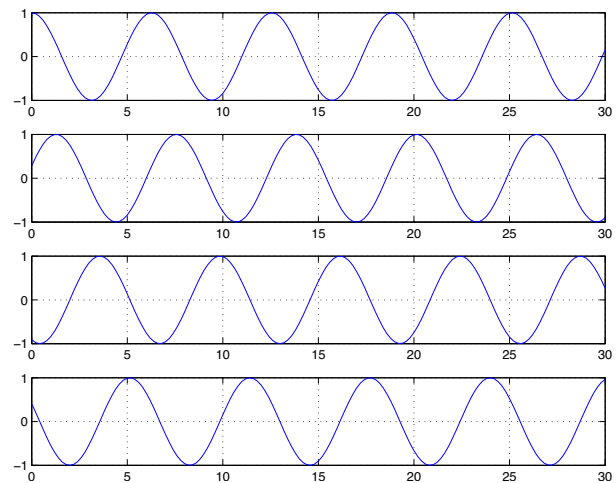
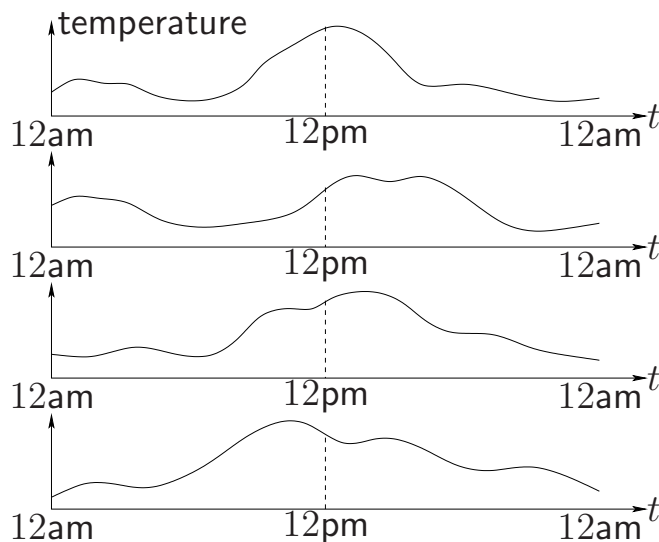
Examples of Random Processes

Examples of Continuous-Time Random Processes:

- Temperature in Ithaca on Jan 1.
- Sinusoid with Random Phase:

$$X(t) = \cos(2\pi t + \Theta)$$

where $\Theta \sim \mathcal{U}(0, 2\pi)$ is uniformly distributed in $(0, 2\pi)$.



- Random Parabolas:

$$X_t = A + Bt + t^2$$

where $A \sim \mathcal{N}(0, 1)$ and $B \sim \mathcal{N}(0, 1)$ are independent.

Descriptions of Random Processes

Description of a Random Process:

A random process is fully specified by the joint CDF

$$F_{X(t_1), \dots, X(t_k)}(x_1, \dots, x_k)$$

for all k and all sets of t_1, \dots, t_k .

Moments of a Random Process

- The **mean function**:

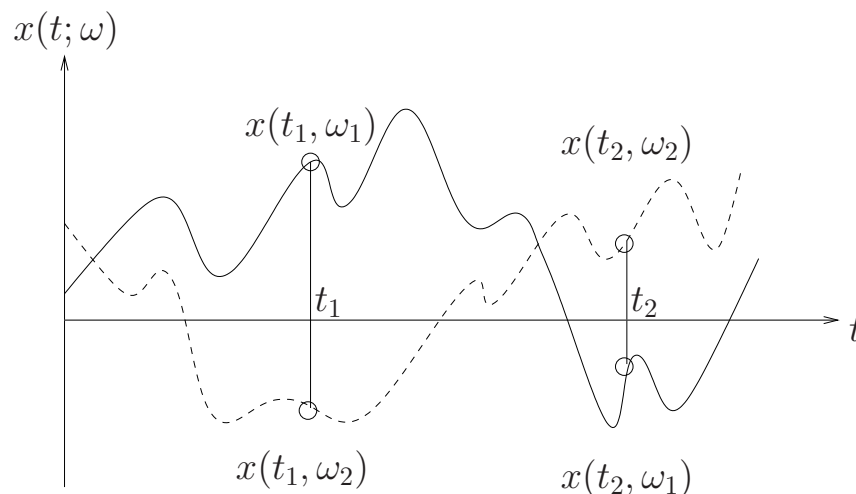
$$\mu_X(t) = \mathbb{E}[X(t)]$$

- The **autocorrelation function**:

$$R_X(t_1, t_2) \triangleq \mathbb{E}[X(t_1)X(t_2)]$$

- The **autocovariance function**:

$$\begin{aligned} C_X(t_1, t_2) &\triangleq \mathbb{E}[(X(t_1) - \mu_X(t_1))(X(t_2) - \mu_X(t_2))] \\ &= R_X(t_1, t_2) - \mu_X(t_1)\mu_X(t_2) \end{aligned}$$



Examples

- The example of i.i.d. sequence of Bernoulli random variables:

$$\mu_X(n) = p, \quad R_X(m, n) = \begin{cases} p & \text{if } m = n \\ p^2 & \text{if } m \neq n \end{cases}$$

- The example of sinusoid with random phase:

$$\begin{aligned} \mu_X(t) &= \mathbb{E}[\cos(2\pi t + \Theta)] \\ &= \int_0^{2\pi} \cos(2\pi t + \theta) f_\Theta(\theta) d\theta \\ &= \frac{1}{2\pi} \int_0^{2\pi} \cos(2\pi t + \theta) d\theta \\ &= 0 \end{aligned}$$

$$\begin{aligned} R_X(t_1, t_2) &\triangleq \mathbb{E}[X(t_1)X(t_2)] = \mathbb{E}[\cos(2\pi t_1 + \Theta) \cos(2\pi t_2 + \Theta)] \\ &= \frac{1}{2} \mathbb{E}[\cos(2\pi(t_2 - t_1)) + \cos(2\pi(t_2 + t_1) + 2\Theta)] \\ &= \frac{1}{2} \left\{ \cos(2\pi(t_2 - t_1)) + \frac{1}{2\pi} \int_0^{2\pi} \cos(2\pi(t_2 + t_1) + 2\theta) d\theta \right\} \\ &= \frac{1}{2} \cos(2\pi(t_2 - t_1)) \end{aligned}$$

- The example of random parabolas:

$$\begin{aligned} \mu_X(t) &= t^2 \\ R_X(t_1, t_2) &= 1 + t_1 t_2 + t_1^2 t_2^2 \\ C_X(t_1, t_2) &= R_X(t_1, t_2) - \mu_X(t_1) \mu_X(t_2) = 1 + t_1 t_2 \end{aligned}$$

Stationarity of Random Processes

Stationarity:

A random process is **strictly stationary** if its statistical characteristics do not change with time, or in another word, a shift of time origin is impossible to detect.

Mathematically,

$$F_{X(t_1), \dots, X(t_n)}(x_1, \dots, x_n) = F_{X(t_1+\Delta), \dots, X(t_n+\Delta)}(x_1, \dots, x_n)$$

for all n , t_i , and Δ .

Wide Sense Stationarity (WSS):

A random process is **wide sense stationary (WSS)** if

- (i) $\mathbb{E}[X(t)] = \mu$ (a constant not changing with t)
- (ii) $R_X(t_1, t_2) \triangleq \mathbb{E}[X(t_1)X(t_2)] = R(\tau)$, where $\tau = t_2 - t_1$

Examples:

- i.i.d. sequences: strictly stationary.
- Binomial counting process: not WSS.
- Random walk: not WSS.
- Temperature in Ithaca on Jan 1: not WSS.
- Sinusoid with random phase: strictly stationary thus also WSS.
- Random parabolas: not WSS.

Independent Increments

Increment:

The **increment** of a random process $\{X(t)\}$ over an interval $[a, b]$ is the random variable $X(b) - X(a)$.

Independent Increments:

A random process has **independent increments** if for all n and for all $t_0 < t_1 < \dots < t_n$, the increments $X(t_1) - X(t_0)$, $X(t_2) - X(t_1)$, \dots , $X(t_n) - X(t_{n-1})$ over these n non-overlapping intervals are mutually independent.

Stationary Increments:

A random process has **stationary increments** if the distribution of the increment $X(t + \tau) - X(t)$ depends only on τ , not t . In other words, the increments in intervals of the same length have the same distribution regardless of when the interval begins.

Examples:

- i.i.d. sequence of Bernoulli random variables: stationary but not independent increments.
- Binomial counting process: independent and stationary increments:
 $S_n - S_m \sim \text{Binomial}(n - m, p)$ for all $n \geq m$.
- Random walk: independent and stationary increments.

Processes with Independent Increments

Characterizing Processes with Independent Increment:

Key idea: express the random variables of the process in terms of increments over non-overlapping intervals.

Example: Binomial Counting Process:

□ Joint PMF of $S_{n_1}, S_{n_2}, S_{n_3}$ ($n_1 < n_2 < n_3$):

$$\begin{aligned}
 & \Pr[S_{n_1} = s_1, S_{n_2} = s_2, S_{n_3} = s_3] \\
 &= \Pr[S_{n_1} = s_1, S_{n_2} - S_{n_1} = s_2 - s_1, S_{n_3} - S_{n_2} = s_3 - s_2] \\
 &= \Pr[S_{n_1} = s_1] \Pr[S_{n_2} - S_{n_1} = s_2 - s_1] \Pr[S_{n_3} - S_{n_2} = s_3 - s_2] \\
 &= \Pr[S_{n_1} = s_1] \Pr[S_{n_2 - n_1} = s_2 - s_1] \Pr[S_{n_3 - n_2} = s_3 - s_2] \\
 &= \binom{n_1}{s_1} p^{s_1} (1-p)^{n_1 - s_1} \binom{n_2 - n_1}{s_2 - s_1} p^{s_2 - s_1} (1-p)^{n_2 - n_1 - (s_2 - s_1)} \\
 &\quad \binom{n_3 - n_2}{s_3 - s_2} p^{s_3 - s_2} (1-p)^{n_3 - n_2 - (s_3 - s_2)} \\
 &= \binom{n_1}{s_1} \binom{n_2 - n_1}{s_2 - s_1} \binom{n_3 - n_2}{s_3 - s_2} p^{s_3} (1-p)^{n_3 - s_3}
 \end{aligned}$$

□ Moments:

$$\begin{aligned}
 \mu_S(n) &= np \\
 R_S(m, n) &= \mathbb{E}[S_m S_n] \quad (\text{assume } m < n) \\
 &= \mathbb{E}[S_m (S_n - S_m + S_m)] \\
 &= \mathbb{E}[S_m^2] + \mathbb{E}[S_m (S_n - S_m)] \\
 &= \mathbb{E}[S_m^2] + \mathbb{E}[S_m] \mathbb{E}[S_n - S_m] \\
 &= ((mp)^2 + mp(1-p)) + mp(n-m)p \\
 &= mp(np + 1 - p)
 \end{aligned}$$

Summary of Binomial Counting

Binomial Counting: A Discrete-Time Counting Process:

Counting the number of “heads” in a sequence of coin flips:

$$S_n = \sum_{i=1}^n X_i$$

where $X_i \sim B(p)$ are i.i.d. Bernoulli random variables.

- $\{S_n\}_{n \geq 1}$ is not stationary or wide-sense stationary.
- $\{S_n\}_{n \geq 1}$ has independent and stationary increments with $S_n - S_m \sim \text{Binomial}(n - m, p)$ for all $n \geq m$.
- The inter-arrival times are i.i.d. with a geometric distribution with parameter p .
- The joint PMF of $S_{n_1}, S_{n_2}, \dots, S_{n_k}$ ($n_1 < n_2 < \dots < n_k$):

$$\begin{aligned} & \Pr [S_{n_1} = s_1, S_{n_2} = s_2, \dots, S_{n_k} = s_k] \\ &= \binom{n_1}{s_1} \binom{n_2 - n_1}{s_2 - s_1} \dots \binom{n_k - n_{k-1}}{s_k - s_{k-1}} p^{s_k} (1 - p)^{n_k - s_k} \end{aligned}$$

- Moment Functions:

$$\mu_S(n) = np$$

$$\text{Var}(S_n) = np(1 - p)$$

$$R_S(m, n) = mp(np + 1 - p)$$

Poisson Process

Three Equivalent Definitions of Poisson Process:

1. $\{N(t)\}_{t \geq 0}$ is a Poisson process with rate λ if $\{N(t)\}_{t \geq 0}$ is a counting process with independent increments and $N(t) - N(s) \sim \text{Poisson}(\lambda(t - s))$ for all $t \geq s$.
2. $\{N(t)\}_{t \geq 0}$ is a Poisson process with rate λ if $\{N(t)\}_{t \geq 0}$ is a counting process with i.i.d. inter-arrival times that have an exponential distribution with parameter λ .
3. $\{N(t)\}_{t \geq 0}$ is a Poisson process with rate λ if $\{N(t)\}_{t \geq 0}$ is a counting process such that for all $\tau > 0$, $N(\tau) \sim \text{Poisson}(\lambda\tau)$ and given $N(\tau) = n$, these n arrival times are i.i.d. with distribution $\mathcal{U}[0, \tau]$.

Poisson Process as a Limit of Discrete-Time Binomial Counting:

- Consider a continuous-time arrival process with rate λ .
- Partition $[0, t]$ into equal-length intervals with length δ .
- For δ sufficiently small, assume that the probability of having more than one arrival in the same interval is negligible and the number of arrivals is independent across intervals.
- Let p denote the probability of having an arrival in an interval. Since the expected number of arrivals in $[0, t]$ is λt , we have

$$\frac{t}{\delta} p = \lambda t \implies p = \lambda \delta$$

- The resulting discrete-time counting process $S_\delta(t)$ has independent increments with

$$S_\delta(t_2) - S_\delta(t_1) \sim \text{Binomial}\left(\frac{t_2 - t_1}{\delta}, \lambda \delta\right) \xrightarrow{\delta \rightarrow 0} \text{Poisson}(\lambda(t_2 - t_1))$$

- Geometric inter-arrival time approaches to exponential inter-arrival time:

$$\Pr[T_1 > t] = (1 - p)^{\frac{t}{\delta}} = (1 - \lambda \delta)^{\frac{t}{\delta}} \xrightarrow{\delta \rightarrow 0} e^{-\lambda t}$$

Poisson Process

Properties of Poisson Processes:

- Moments of a Poisson process $\{N(t)\}_{t \geq 0}$ with rate λ :

$$\mu_N(t) = \lambda t$$

$$\text{Var}(N(t)) = \lambda t$$

$$C_N(t_1, t_2) = \lambda \min(t_1, t_2)$$

- **Merging independent Poisson processes:** Let $N_1(t), \dots, N_k(t)$ be independent Poisson processes with rates $\lambda_1, \dots, \lambda_k$, respectively. Then the sum (i.e., by counting arrivals in all k processes together)

$$N(t) = \sum_{i=1}^k N_i(t)$$

is a Poisson process with rate $\lambda = \sum_{i=1}^k \lambda_i$.

- **Thinning a Poisson process:** Let $N(t)$ be a Poisson process with rate λ . For each arrival in this process, label it to be of type i ($i = 1, \dots, k$) with probability p_i where $\sum_{i=1}^k p_i = 1$. This labeling is independent across arrivals and independent of the arrival times. Then the type i arrivals form a Poisson process with rate $p_i \lambda$ for all $i = 1, \dots, k$, and these k Poisson processes are independent.

Gaussian Processes

Gaussian Processes:

A random process $X(t)$ is Gaussian if for all n and t_1, \dots, t_n , random variables $X(t_1), \dots, X(t_n)$ are jointly Gaussian.

Properties of Gaussian Random Process:

- It is completely specified by its mean function and autocorrelation function:
 - For all n and t_1, \dots, t_n , $[X(t_1), \dots, X(t_n)]^T$ is a Gaussian random vector with mean

$$[\mu_X(t_1), \dots, \mu_X(t_n)]^T$$

and covariance matrix

$$\mathbf{K} = \left\{ R_X(t_i, t_j) - \mu_X(t_i)\mu_X(t_j) \right\}_{n \times n} = \left\{ C_X(t_i, t_j) \right\}_{n \times n}$$

- Wide sense stationarity implies strict stationarity.

The random parabolas process is a Gaussian process.

Brownian Motion

Brownian Motion:

A **Brownian motion** (also called a **Wiener process**) with parameter $\sigma^2 > 0$ is a random process $\{X(t)\}_{t \geq 0}$ such that

1. $X(0) = 0$.
2. $\{X(t)\}_{t \geq 0}$ has independent increments.
3. $X(t_2) - X(t_1) \sim \mathcal{N}(0, \sigma^2(t_2 - t_1))$ for all $t_2 \geq t_1$.
4. Every sample path is continuous.

Properties of Brownian Motion:

- $\mu_X(t) = 0$.
- $R_X(t_1, t_2) = \sigma^2 \min(t_1, t_2)$.
- $\{X(t)\}_{t \geq 0}$ is a Gaussian process.