

Stochastic Signal Processing

Lesson 5: Basic of Stochastic Processes

Weize Sun

Basic of Stochastic Processes – outline

- **Definitions**
- Distributions of Stochastic Processes
 - One-dimensional distribution
 - Two-dimensional and multidimensional distributions
- Statistics of Stochastic Processes
 - Mean, variance, correlation function, covariance function
 - For Discrete time Processes
- Stationary stochastic processes

Definitions

- There are mainly two kinds of processes: deterministic processes and stochastic processes

deterministic
processes

The result obtained from each observation is the same: not related to time t .

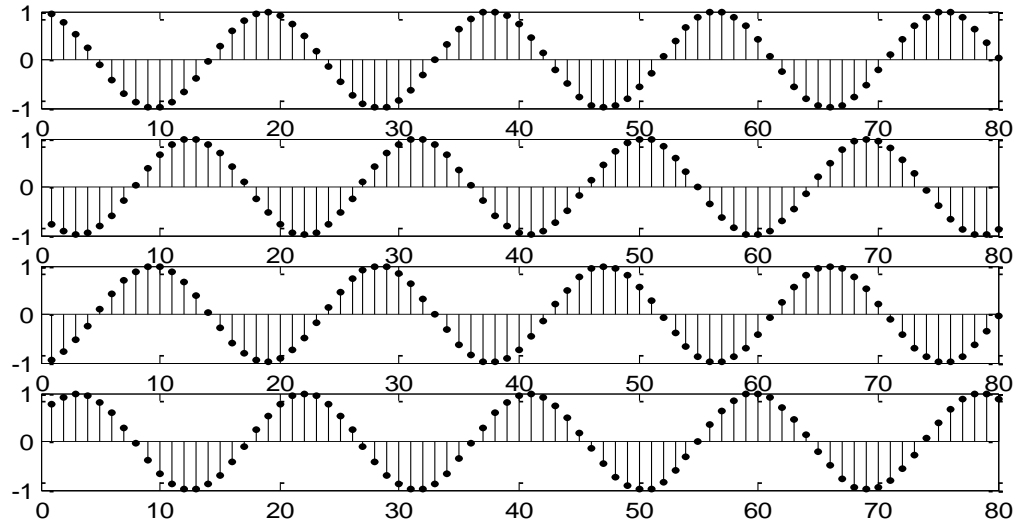
stochastic
processes

The result obtained from each observation might not be the same: related to time t .

Concepts and Definitions of Stochastic Processes

- Examples

$$X(n) = A \cos(\omega_0 n + \phi)$$

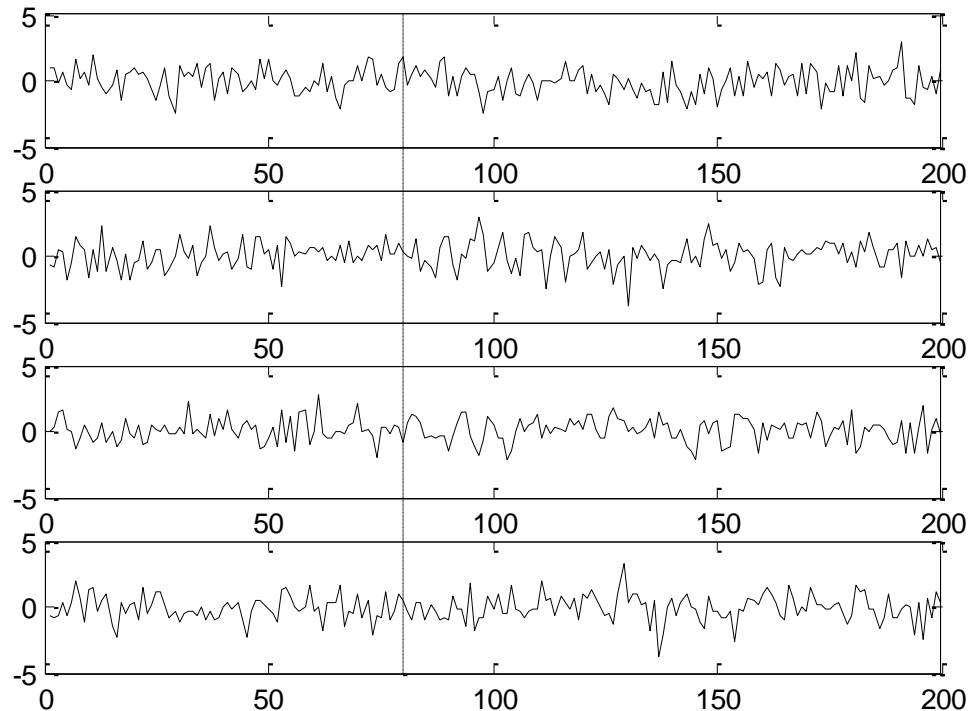


- Sinusoidal signal
- Sample (样本) : Each time a sample is taken $X_t(n, \phi_t) = A \cos(\omega_0 n + \phi_t)$, the phase ϕ_t is not necessarily the same and changes randomly according to time
- This is one typical **Stochastic Phase Signal**

Concepts and Definitions of Stochastic Processes

- Examples

- receiver noise

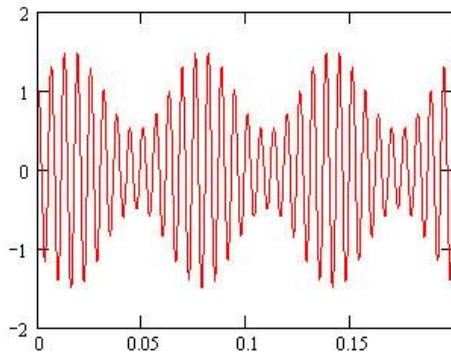


- In each time, when sampling this Stochastic Process, we get a random variable that changes according to time
- In this case, the Stochastic Process can be regarded as a collection of random variables

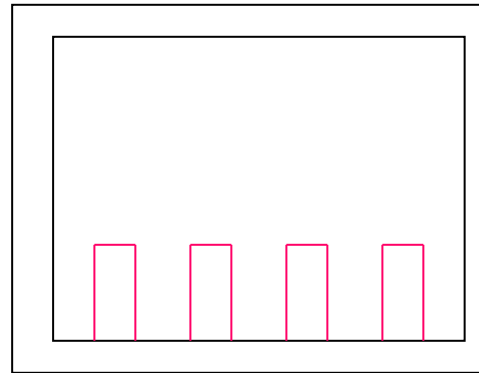
Concepts and Definitions of Stochastic Processes

- Other Stochastic processes

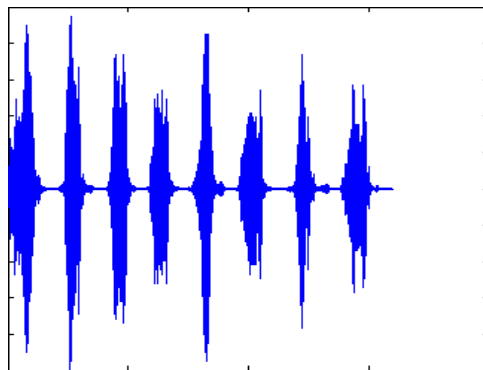
**Modulated
signal**
(调制信号)



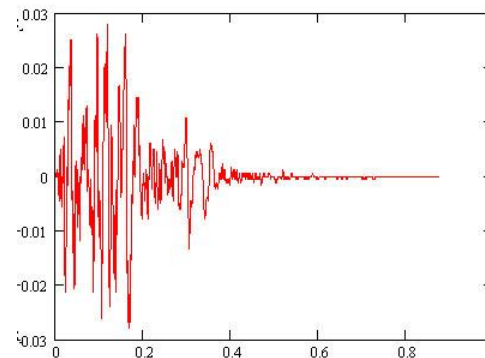
**Periodic pulse
signal**



bird call



blasting signal
(爆破信号)



Concepts and Definitions of Stochastic Processes

- Definition of Stochastic Process:
 - Definition 1: Let E be a random test (随机试验) with $S = \{e\}$, where S is a set. For each $e_i (i = 1, 2, \dots)$, we can use some methods to record a sample (样本) $x(t, e_i)$ then the ensemble (总体) $X(t, e)$ is a **Stochastic Processes, abbreviated as $X(t)$** .

Concepts and Definitions of Stochastic Processes

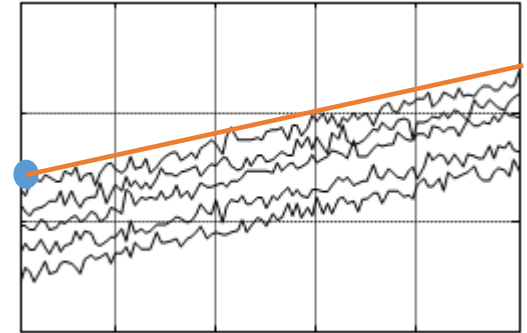
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 - From this: a stochastic process is a collection of a lot of samples

Assuming there are 5 values for $\{e\}$, for each value, determine a function, as shown on the right.

At a certain time t , start sampling, for example, the first line is picked.

Continue with time and we will get the first line



- When sampling, one of these five lines will be sampled randomly. The values from two samples might be completely different.
- The results are related to the 'initial state value' e .

Concepts and Definitions of Stochastic Processes

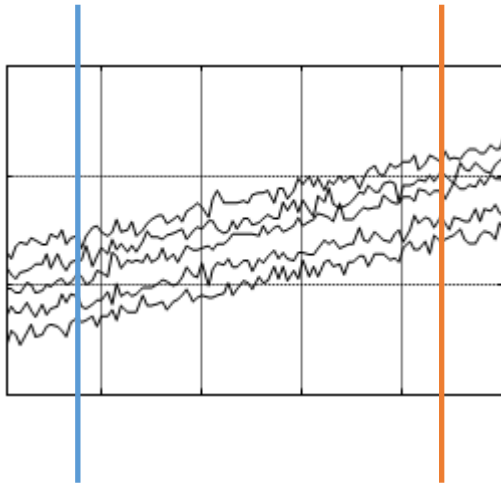
- Definition of Stochastic Process:
 - Definition 2 (from another perspective): Given a process $X(t)$, for any fixed time $t_j (j = 1, 2, \dots)$, $X(t_j)$ is a random variable, then the $X(t)$ is called a stochastic process.

Concepts and Definitions of Stochastic Processes

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 - From this : A stochastic process is a collection of random variables

At time t_1 , perform extensive experiments at the same time, and get all possible values to form a set of "random variables"

At time t_2 , do extensive experiments again at the same time and get all possible values to form a set of "random variables"



- When sampling at different times, the set of "random variables" that will be obtained might be completely different.
- Therefore, the stochastic process we finally get is related to the "time" t at the time of sampling.

Concepts and Definitions of Stochastic Processes

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- Definition 2 (from another perspective): Given a process $X(t)$, for any fixed time $t_j (j = 1, 2, \dots)$, $X(t_j)$ is a random variable, then the $X(t)$ is called a stochastic process.
 - From this : A stochastic process is a collection of random variables
- The above two definitions are in fact consistent and complement to each other.
 - In real world observation, definition 1 is usually used (we start observe, and keep observing for a long long time)
 - In theoretical analysis, definition 2 is usually used (we cannot observe a system many times at one moment, but we can analyze it)
- Later we will talk about 'ergodicity', it can be simply understood as: the equivalence of the above two definitions.

Concepts and Definitions of Stochastic Processes

- Definition of Stochastic Process:
 - Therefore, we generally use $X(t, e)$ to represent a stochastic process:
 - The meaning of random processes $X(t, e)$ in four different situations:

when t and e fixed

X is a number;

when t is fixed, e is variable

$X(e)$ is a random variable equal to the state of the given process at time t

when t is variable, e is fixed

$X(t)$ is a single time function, or a sample of the given process

when t is variable, e is variable

$X(t, e)$ is a stochastic process; in most cases, we write it as $X(t)$

Classification of stochastic processes

- Classified by state and time:

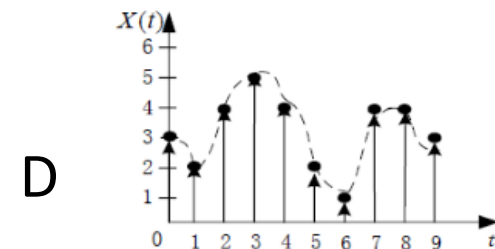
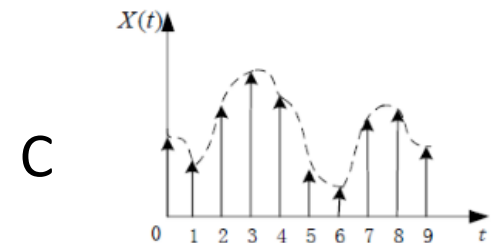
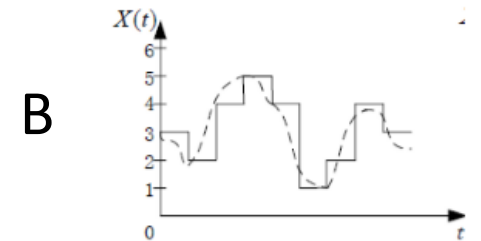
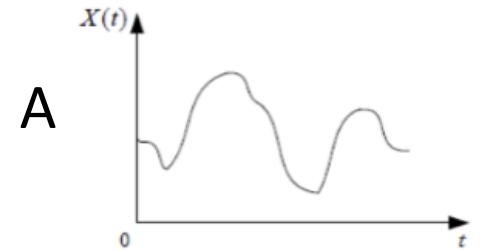
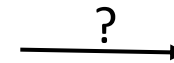
	state/ value	time/ time
continuous stochastic process	continuous	continuous
continuous stochastic sequence	continuous	discrete
discrete stochastic process	discrete	continuous
discrete stochastic sequence	discrete	discrete

- Indoor temperature in one day
- The daily closing price of the stock for a month
- Result of a football game
- Number of students taking one course in different years

Classification of stochastic processes

- Example 1: classified by state and time:

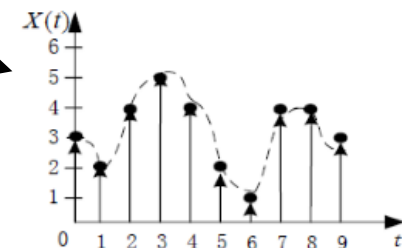
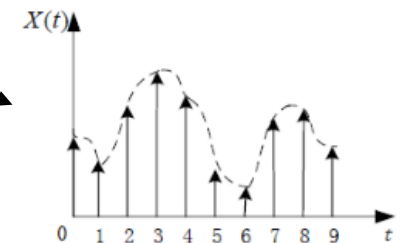
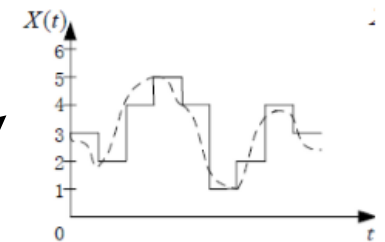
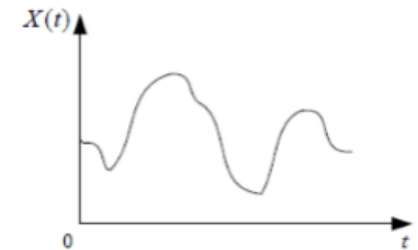
	state/ value	time/ time	
continuous stochastic process	continuous	continuous	?
continuous stochastic sequence	continuous	discrete	?
discrete stochastic process	discrete	continuous	?
discrete stochastic sequence	discrete	discrete	?



Classification of stochastic processes

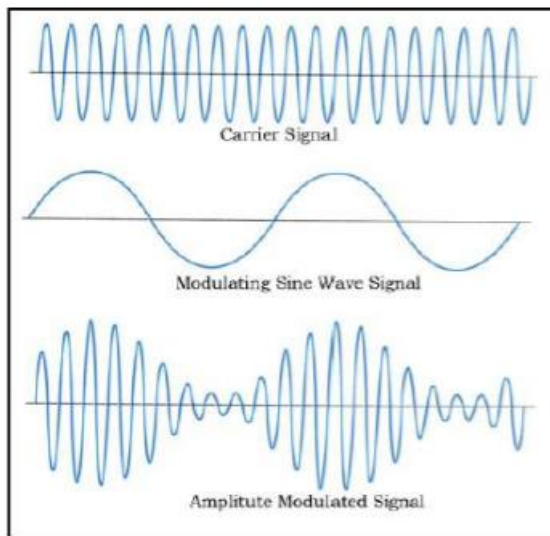
- Example 1: classified by state and time:

	state/ value	time/ time
continuous stochastic process	continuous	continuous
continuous stochastic sequence	continuous	discrete
discrete stochastic process	discrete	continuous
discrete stochastic sequence	discrete	discrete

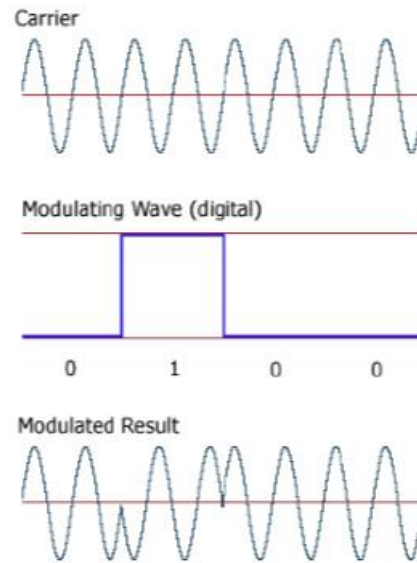


Example

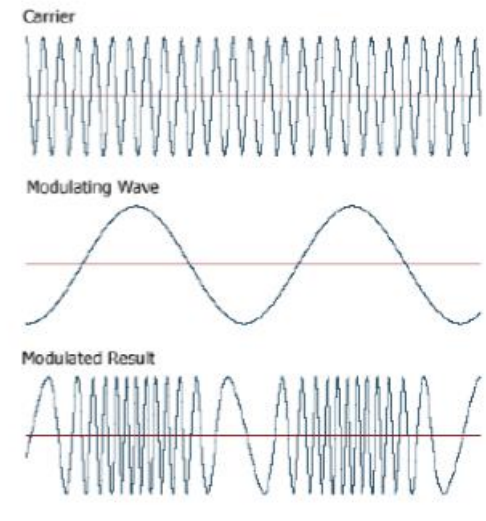
- The sinusoidal signal: $X(t) = A\cos(\omega t + \varphi)$
 - A is a random variable $A(t) : X(t) = A(t)\cos(\omega t + \varphi)$;
Amplitude modulation signal (AM)
 - $\varphi(t)$ is a random variable $\varphi(t) : X(t) = A\cos(\omega t + \varphi(t))$;
phase modulation signal (PM)
 - ω is a random variable $\omega(t) : X(t) = A\cos(\omega(t)t + \varphi)$;
frequency modulation signal (FM)



AM



PM



FM

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Distributions of Stochastic Processes

- By definition, a stochastic process can be regarded as a set of random variables that change according to time, therefore its statistics as the same as those from random variables:

	state/ value	time/ time
continuous stochastic process	continuous	continuous
continuous stochastic sequence	continuous	discrete
discrete stochastic process	discrete	continuous
discrete stochastic sequence	discrete	discrete

- One-dimensional (1D) CDF (left) and pdf (right)

- For continuous processes:

$$F_X(x, t) = P\{X(t) \leq x\} \quad f_X(x, t) = \frac{\partial F_X(x, t)}{\partial x}$$

- For discrete sequences:

$$F_X(x, n) = P\{X(n) \leq x\} \quad f_X(x, n) = \frac{\partial F_X(x, n)}{\partial x}$$

- 1D distribution can only describe of a certain time moment of the stochastic process $X(t)$, and **the relationship between different time moments cannot be seen.**

Distributions of Stochastic Processes

- Example 2: Given $X(t) = Y \cos \omega_0 t$, where ω_0 is a constant, Y is a normal variable with zero mean and variance 1, find the pdf when $t = 0, \frac{2\pi}{3\omega_0}, \frac{\pi}{2\omega_0}$.

Distributions of Stochastic Processes

- Example 2: Given $X(t) = Y \cos \omega_0 t$, where ω_0 is a constant, Y is a normal variable with zero mean and variance 1, find the pdf when $t = 0, \frac{2\pi}{3\omega_0}, \frac{\pi}{2\omega_0}$.

Solution:

1. $X(0) = Y$ therefore:

$$f_X(x, 0) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$$2. X\left(\frac{2\pi}{3\omega_0}\right) = -\frac{1}{2}Y, \quad f_X\left(x, \frac{2\pi}{3\omega_0}\right) = f_Y(y)|J|_{Y=-2X}, \quad |J| = 2$$

$$\rightarrow f_X\left(x, \frac{2\pi}{3\omega_0}\right) = \sqrt{\frac{2}{\pi}} e^{-2x^2}$$

$$3. X\left(\frac{\pi}{2\omega_0}\right) = 0 \quad \rightarrow \quad f_X\left(x, \frac{\pi}{2\omega_0}\right) = \delta(x)$$

Distributions of Stochastic Processes

- Two-dimensional(2D) distributions:
 - The distributions of a two-dimensional random variable $[X(t_1), X(t_2)]$ corresponding to any two moments t_1 & t_2 :

$$F_X(x_1, x_2, t_1, t_2) = P\{X(t_1) \leq x_1, X(t_2) \leq x_2\}$$

$$f_X(x_1, x_2, t_1, t_2) = \frac{\partial^2 F_X(x_1, x_2, t_1, t_2)}{\partial x_1 \partial x_2}$$

- Note: $X(t_1)$ and $X(t_2)$ are random variables, refer to two different moments t_1 & t_2 of the same stochastic process

Distributions of Stochastic Processes

- n-dimensional(n-D) distributions:

- For $X(t_1), X(t_2), \dots, X(t_n)$:

$$F_n(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n) = P\{X(t_1) \leq x_1, X(t_2) \leq x_2, \dots, X(t_n) \leq x_n\}$$

(n-D CDF)

$$f_n(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n) = \frac{\partial F_n(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)}{\partial x_1 \partial x_2 \dots \partial x_n}$$

(n-D pdf)

- When n is large, it can describe the stochastic processes in more detail, but will increase the complexity of the analysis.
- In theory, $n = \infty$ can fully describe the statistical properties of a stochastic process.
- In practice, only 2-D distributions are used, **it is a trade-off between accuracy and efficiency**
- If $X(t_1), X(t_2), \dots, X(t_n)$ **are statistically independent**, then

$$f_n(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n) = f_1(x_1, t_1) f_1(x_2, t_2) \dots f_1(x_n, t_n)$$

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Statistics of Stochastic Processes

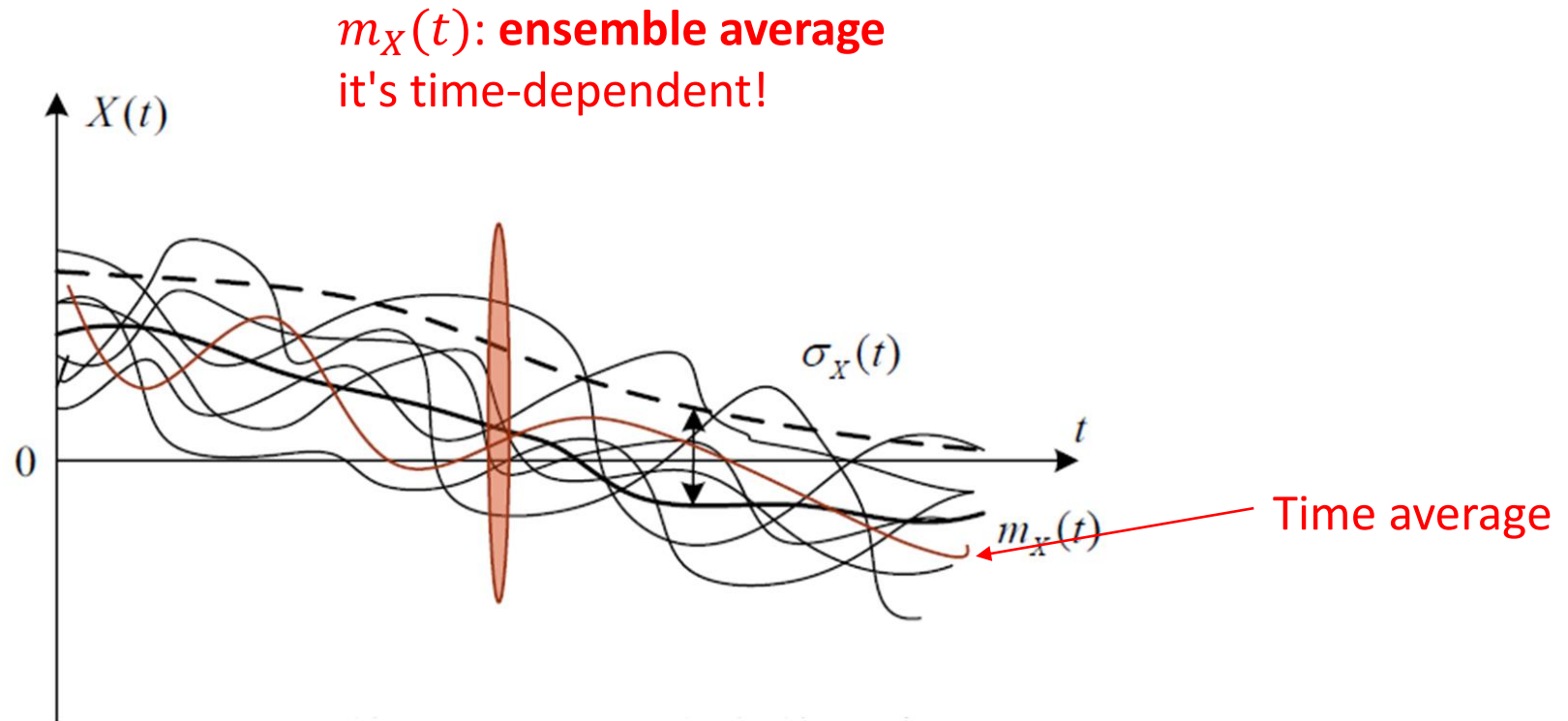
- Mean of a stochastic process:

$$m_X(t) = E\{X(t)\} = \int_{-\infty}^{+\infty} x f_X(x, t) dx$$

- The mean is a **function of time t** , also known as the **mean function**, this is the probability-weighted average of all the values of all samples of the stochastic process at time t , so it is also called the **ensemble average**(总体平均, 也有称为集合平均的).
- The mean value of a stochastic process can be intuitively understood as **the center of all sample at time t** (see definition 2 in page 8 of this ppt), the change of mean reflects the statistical average value of the stochastic process along time.
- Another important concept or definition of mean is **time average** (时间平均, see page 487 of text book), which is the average of a specific sample for a long time (see definition 1 in page 7 of this ppt), will explain later.

Statistics of Stochastic Processes

- Mean of a stochastic process:



- It is shown that the time average and the ensemble average are different.
- In most real world applications, we can only record the time average, then, is the time average = ensemble average?
- This is the problem of Ergodicity(各态历经性).

Statistics of Stochastic Processes

- Variance

$$\sigma_X^2(t) = E\{[X(t) - m_X(t)]^2\} = E\{X^2(t)\} - m_X^2(t)$$

- An example of the physical meaning of mean and variance:

$X(t)$ -----Voltage on unit resistance

$X^2(t)/1$ -----Instantaneous power consumed on unit resistance

$[X(t) - m_X(t)]^2/1$ -----Instantaneous AC power consumed on unit resistance

$E\{[X(t) - m_X(t)]^2/1\}$ -----Statistical average value of instantaneous AC power consumed on unit resistance

$$E\{X^2(t)\} = \sigma_X^2(t) + m_X^2(t)$$

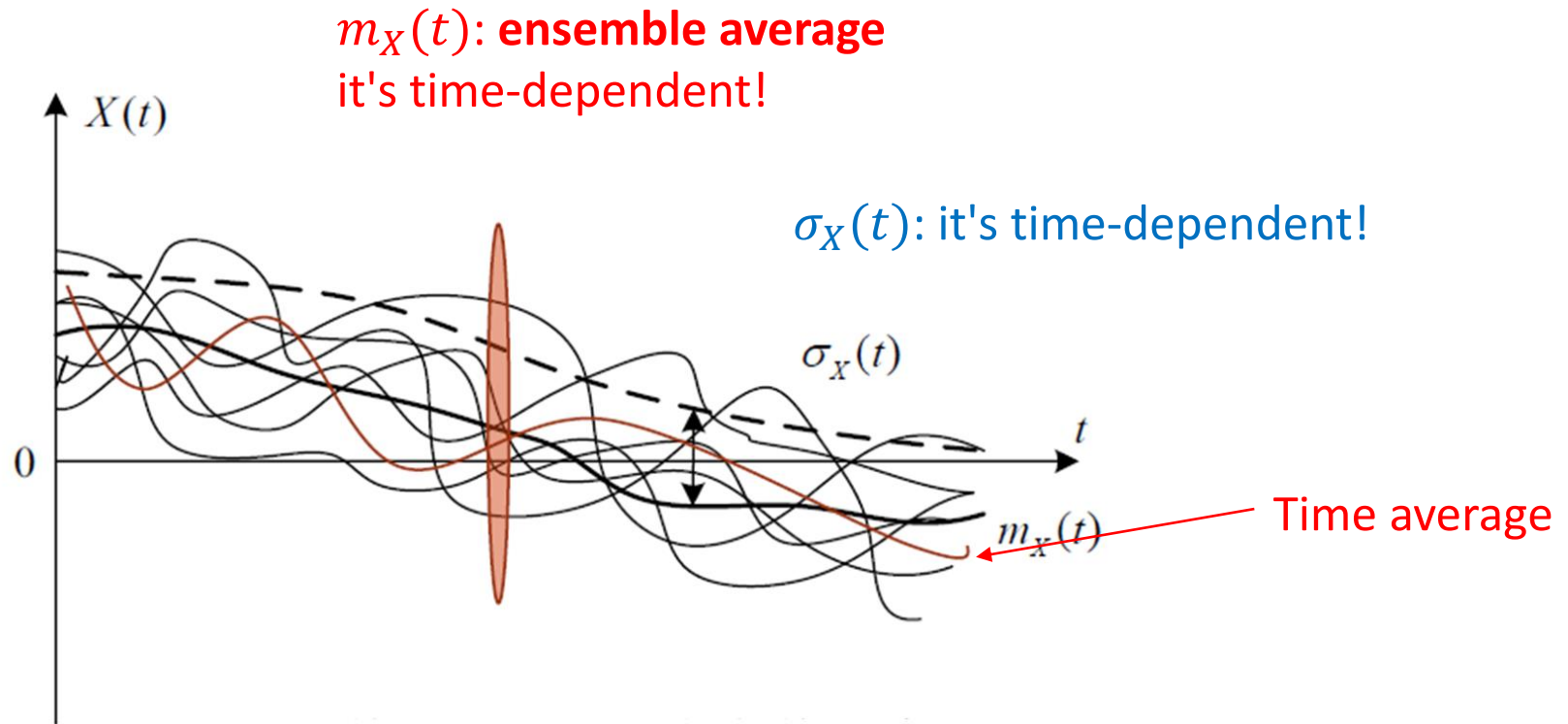
The total average power consumed on unit resistance.

Average AC power

Average DC power

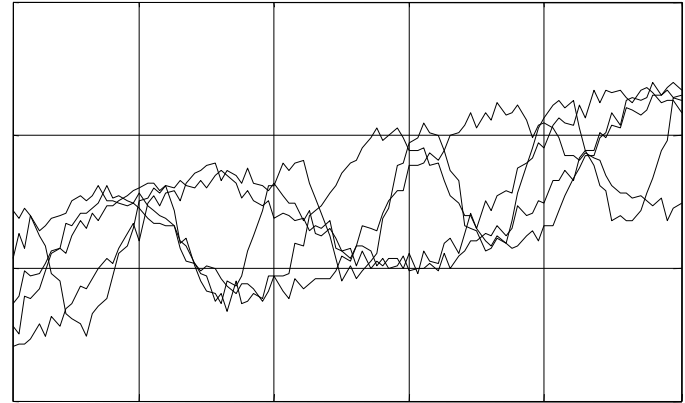
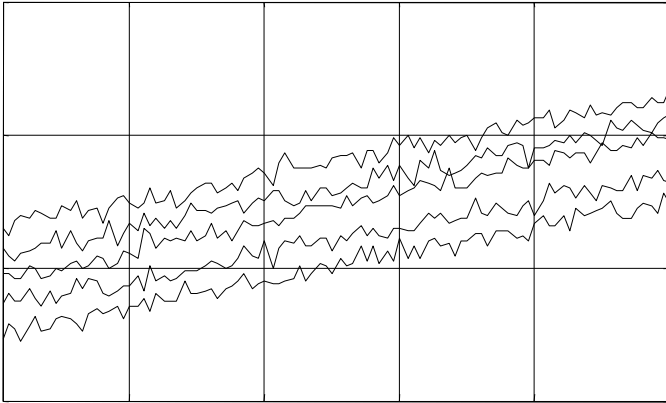
Statistics of Stochastic Processes

- Mean and variance



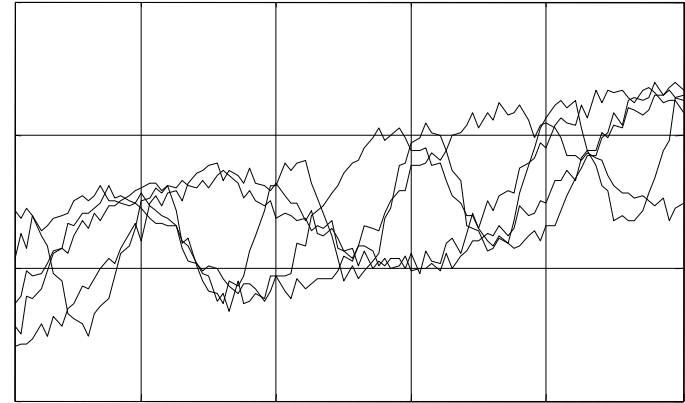
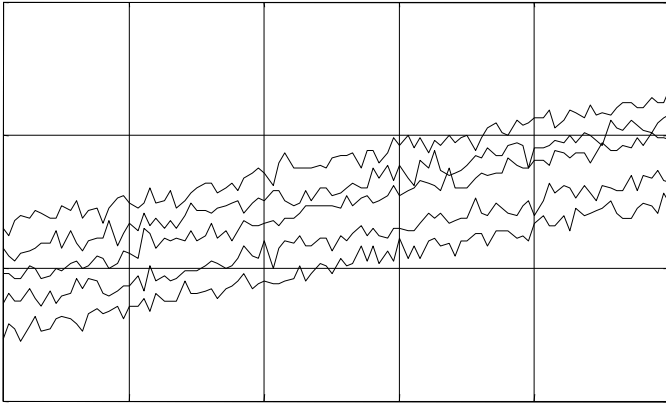
Statistics of Stochastic Processes

- Autocorrelation(自相关/自相关函数):
 - Two stochastic processes might have the same mean and variance



Statistics of Stochastic Processes

- Autocorrelation(自相关/自相关函数):
 - Two stochastic processes might have the same mean and variance



- For any two random variables $X(t_1)$ & $X(t_2)$ draw from the **complex** stochastic process $X(t)$, define the expectation of $X(t_1)X^*(t_2)$ as the **autocorrelation**:

$$R_X(t_1, t_2) = E\{X(t_1)X^*(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2^* f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

- Reflects the average degree of correlation between values taken at any two moments of the $X(t)$.
- $X^*(t_2)$ is the conjugate (共轭) of $X(t_2)$
- Note that, in this case, $R_X(t_1, t_2) = E\{X(t_1)X^*(t_2)\} \neq R_X(t_2, t_1) = E\{X(t_2)X^*(t_1)\}$

Statistics of Stochastic Processes

- Autocorrelation:

- For any two random variables $X(t_1)$ & $X(t_2)$ draw from the stochastic process $X(t)$, define the expectation of $X(t_1)X^*(t_2)$ as the **autocorrelation**:

Complex stochastic process:

$$R_X(t_1, t_2) = E\{X(t_1)X^*(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2^* f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

Real stochastic process:

$$R_X(t_1, t_2) = E\{X(t_1)X(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

- The autocorrelation can be complex or real valued, and can be positive or negative
- In general, the farther apart the time is, the weaker the correlation becomes, and the weaker the **absolute value of the autocorrelation** is.
- When the two moments coincide(重合), the strongest correlation (of this process) is obtained, therefore, **$|R_X(t, t)|$ is the maximum**

Statistics of Stochastic Processes

- Autocorrelation:
 - For any two random variables $X(t_1)$ & $X(t_2)$ draw from the stochastic process $X(t)$, define the expectation of $X(t_1)X^*(t_2)$ as the **autocorrelation**:

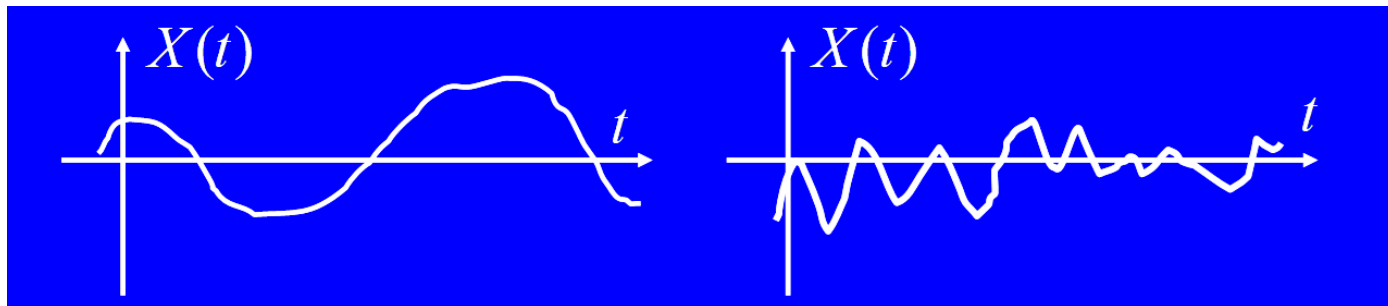
Complex stochastic process:

$$R_X(t_1, t_2) = E\{X(t_1)X^*(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2^* f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

Real stochastic process:

$$R_X(t_1, t_2) = E\{X(t_1)X(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

- The figure below is an example of 2 different therefore the correlation is stronger under the same conditions (same t_1 & t_2).



Statistics of Stochastic Processes

- Autocorrelation:

- For any two random variables $X(t_1)$ & $X(t_2)$ draw from the stochastic process $X(t)$, define the expectation of $X(t_1)X^*(t_2)$ as the **autocorrelation**:

Complex stochastic process:

$$R_X(t_1, t_2) = E\{X(t_1)X^*(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2^* f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

Real stochastic process:

$$R_X(t_1, t_2) = E\{X(t_1)X(t_2)\} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 f(x_1, x_2, t_1, t_2) dx_1 dx_2$$

- Application examples:**

- The channel information in the communication system changes with time. The information estimated at time t_1 (for example, the distribution of mobile phones in a cellular grid) is not necessarily consistent with the information at time t_2 .
- The farther the two moments are, the higher the degree of inconsistency.

Statistics of Stochastic Processes

- Autocovariance: the covariance of $X(t_1)$ and $X(t_2)$:

- For complex stochastic processes:

$$C_X(t_1, t_2) = E\{[X(t_1) - m_X(t_1)][X(t_2) - m_X(t_2)]^*\}$$

$$= R_X(t_1, t_2) - m_X(t_1)m_X^*(t_2)$$

$$R_X(t, t) = E\{|X(t)|^2\} \text{ \& } C_X(t, t) = \sigma_X^2(t)$$

$$\rightarrow \sigma_X^2(t) = E\{|X(t)|^2\} - |m_X(t)|^2$$

- For real stochastic processes (we will go on with real stochastic processes unless stated):

$$C_X(t_1, t_2) = E\{[X(t_1) - m_X(t_1)][X(t_2) - m_X(t_2)]\}$$

$$= R_X(t_1, t_2) - m_X(t_1)m_X(t_2)$$

$$R_X(t, t) = E\{X(t)^2\} \text{ \& } C_X(t, t) = \sigma_X^2(t)$$

$$\rightarrow \sigma_X^2(t) = E\{X(t)^2\} - m_X^2(t)$$

Statistics of Stochastic Processes

- Conclusion:

$$\begin{aligned} R_X(t_1, t_2) &= E\{X(t_1)X(t_2)\} \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 f(x_1, x_2, t_1, t_2) dx_1 dx_2 \\ C_X(t_1, t_2) &= E\{[X(t_1) - m_X(t_1)][X(t_2) - m_X(t_2)]\} \end{aligned}$$

Correlated? Orthogonal? Independent?

Given

$X(t_1), X(t_2)$ will be

$$C_X(t_1, t_2) = 0$$

?

$$R_X(t_1, t_2) = 0$$

?

$$f_X(x_1, x_2, t_1, t_2) = f_X(x_1, t_1)f_X(x_2, t_2)$$

?

Statistics of Stochastic Processes

- Conclusion:

$$\begin{aligned} R_X(t_1, t_2) &= E\{X(t_1)X(t_2)\} \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 f(x_1, x_2, t_1, t_2) dx_1 dx_2 \\ C_X(t_1, t_2) &= E\{[X(t_1) - m_X(t_1)][X(t_2) - m_X(t_2)]\} \end{aligned}$$

Correlated? Orthogonal? Independent?

Given

$X(t_1), X(t_2)$ will be

$$C_X(t_1, t_2) = 0$$

Uncorrelated

$$R_X(t_1, t_2) = 0$$

Orthogonal

$$f_X(x_1, x_2, t_1, t_2) = f_X(x_1, t_1)f_X(x_2, t_2)$$

Independent

Statistics of Stochastic Processes

- Statistics of Discrete type stochastic processes

$$m_X(t) = \sum_{i=1}^N x_i(t)p_i(t)$$

$$\sigma_X^2(t) = \sum_{i=1}^N [x_i(t) - m_X(t)]^2 p_i(t)$$

$$R_X(t_1, t_2) = E\{X(t_1)X(t_2)\} = \sum_{i=1}^N \sum_{j=1}^N x_i(t_1)x_j(t_2)p_{ij}(t_1, t_2)$$

$$C_X(t_1, t_2) = \sum_{i=1}^N \sum_{j=1}^N [x_i(t_1) - m_X(t_1)][x_j(t_2) - m_X(t_2)]p_{ij}(t_1, t_2)$$

Note that in Matlab, you can only use these equations to do the calculation, but the analysis is still based on the continuous type statistics.

Statistics of Stochastic Processes

- Example 3: Consider a stochastic process that change linearly with time: $Y(t) = at + X$, where X is an uniformly r.v distributed in $[-1,1]$; calculate the mean, variance, autocorrelation and autocovariance of $Y(t)$.

Statistics of Stochastic Processes

- Example 3: Consider a stochastic process that change linearly with time: $Y(t) = at + X$, where X is an uniformly r.v distributed in $[-1,1]$; calculate the mean, variance, autocorrelation and autocovariance of $Y(t)$.

Solution:

$$E(X) = 0 \quad D(X) = \frac{[1-(-1)]^2}{12} = E(X^2) - E(X)^2$$
$$m_Y(t) = E(Y(t)) = at + E[X] = at$$

$$D(Y(t)) = E((Y(t) - m_Y(t))^2) = E(X^2) = \frac{1}{3}$$
$$R_Y(t_1, t_2) = E\{Y(t_1)Y(t_2)\} = E\{(at_1 + X)(at_2 + X)\}$$
$$= a^2 t_1 t_2 + E(X^2) = a^2 t_1 t_2 + \frac{1}{3}$$

$$C_Y(t_1, t_2) = R_Y(t_1, t_2) - m_Y(t_1)m_Y(t_2) = a^2 t_1 t_2 + \frac{1}{3} - a^2 t_1 t_2 = \frac{1}{3}$$

Basic of Stochastic Processes – outline

- Definitions
- Distributions of Stochastic Processes
 - One-dimensional distribution
 - Two-dimensional and multidimensional distributions
- Statistics of Stochastic Processes
 - Mean, variance, correlation function, covariance function
 - For Discrete time Processes
- Stationary stochastic processes

Stationary stochastic processes(平稳随机过程)

- Stochastic processes can be divided into two categories: stationary and non-stationary.
 - Strictly speaking, all signals are **non-stationary**;
 - However, the analysis of stationary signals is much easier. For example, in an electronic system, if the main physical conditions that produce a stochastic process do not change in a certain time, or the change is so tiny that can be ignored, the signal can be considered as stationary:
 - For the noisy voltage signal of the receiver, due to the temperature change of the components in the beginning, the voltage is a **transient process** (non-stationary). After a short period of time, the temperature becomes stable, thus the signal can be considered stationary.

Stationary stochastic processes

- Strict Sense Stationary (SSS, 严格平稳)
 - If for any n , the n dimensional distribution of a stochastic process does not change with the start time, that is, when the time shifts, its n dimensional CDF/pdf does not change, then it is called Strict Sense Stationary (SSS).

- The 1-D pdf is time independent:

$$f_X(x, t) = f_X(x, 0) = f_X(x)$$

- The 2-D joint pdf is related to the time difference, not the absolute value of time:

$$f_X(x_1, x_2, t_1, t_2) = f_X(x_1, x_2, \tau, 0) = f_X(x_1, x_2, \tau), \tau = t_1 - t_2$$

Note that in some books, it is defined as $\tau = t_2 - t_1$, which will lead to a sign difference (+/-) in many of the theorems/equations we will learn later. However, in this course, the definition of the book will be used (see page 351, text book), and no reminder will be given later.

- Generalize to multidimensional:

$$f_X(x_1, \dots, x_n, t_1 + c, \dots, t_n + c) = f_X(x_1, \dots, x_n, t_1, \dots, t_n) \quad (5-1)$$

Stationary stochastic processes

- Strict Sense Stationary (SSS, 严格平稳)
 - For an SSS process, its **mean and variance are time-independent constants**, and the autocorrelation function is only related to the difference between t_1 and t_2 , instead of their absolute value.
 - The most basic feature of SSS is that the change of the start time will not affect its statistical properties, that is, it $X(t)$ has the same statistical properties as $X(t + \Delta t)$.
 - It is the strongest form of **Stationary**:
 - SSS is most likely not true for most real world applications
 - However, in most real world applications, what we care about are the first and second order moments (一二阶矩): **mean and autocorrelation**

Stationary stochastic processes

- Generalize to multidimensional:

$$f_X(x_1, \dots, x_n, t_1 + c, \dots, t_n + c) = f_X(x_1, \dots, x_n, t_1, \dots, t_n) \quad (5-1)$$

- Special case: *N*th-order stationary:

- If (5-1) holds for any $n \leq N$ only, it is called *N*th-order stationary
- SSS means that for any *N*, it is *N*th order stationary

- Example: 1st order stationary

- $f_1(x_1; t_1) = f_1(x_1; t_1 + \varepsilon) = f_1(x_1; 0)$
- That is, both **expectation** and **variance** are **time-independent** constants

$$\begin{aligned} E[X(t)] &= \int_{-\infty}^{\infty} x f(x, 0) dx = m_X \\ D[X(t)] &= E\{[X(t) - m_X]^2\} \\ &= \int_{-\infty}^{\infty} [x - m_X]^2 f(x, 0) dx = \sigma_X^2 \text{ (real valued)} \end{aligned}$$

Stationary stochastic processes

- Wide Sense Stationary (WSS, 广义平稳)

- $E[X(t)] = m_X$ Mean is time-independent
- $R_X(t_1, t_2) = R_X(t_1 - t_2) = R_X(\tau)$ Autocorrelation only related to τ

Note:

- For complex valued WSS processes:

$$R_X(\tau) = E\{X(t + \tau)X^*(t)\}$$
$$R_X(-\tau) = E\{X(t - \tau)X^*(t)\} = E\{X^*(t + \tau)X(t)\} \neq R_X(\tau)$$

- For real valued WSS processes:

$$R_X(\tau) = E\{X(t + \tau)X(t)\}$$
$$= E\{X(t)X(t + \tau)\} = E\{X(t - \tau)X(t)\} = R_X(-\tau)$$



- When the stochastic process is Gaussian distributed, the two equivalent.

In many practical problems, WSS is enough for analysis.

Therefore, we will mainly focus on WSS later

Stationary stochastic processes

- Example 4: A stochastic process $Z(t) = A\cos(\omega t) + n(t)$, where A and ω are constants, and $n(t)$ is a WSS normal processes with mean 0 and variance σ^2 . What is the one-dimensional probability density of $Z(t)$? Is $Z(t)$ WSS? SSS?

Multiple choices?

- A neither SSS nor WSS
- B SSS but not WSS
- C WSS but not SSS
- D SSS and WSS

Stationary stochastic processes

- Example 4: A stochastic process $Z(t) = A\cos(\omega t) + n(t)$, where A and ω are constants, and $n(t)$ is a WSS normal processes with mean 0 and variance σ^2 . What is the one-dimensional probability density of $Z(t)$? Is $Z(t)$ WSS? SSS?

Solution:

$$Z(t) \sim \mathcal{N}(A\cos \omega t, \sigma^2) \Rightarrow f_1(x, t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x - A\cos \omega t)^2}{2\sigma^2}\right)$$

$$E(Z(t)) = A\cos \omega t$$

\Rightarrow The mean is correlated with time t , obviously neither SSS nor
WSS

Reading

- This week:
 - Text book: 7.1
 - Red book: 2.1,2.2
 - Blue book: 6.1 - 6.4
- Next week:
 - Text book: 7.2
 - Red book: 2.3, 2.4, 3.1, 3.2.1
 - Blue book: 6.5 – 6.7

More examples:

- 1: Suppose that a stochastic process $X(t)$ follows: at any time t_1 , the $E(X(t_1)) = 0$, $D[X(t_1)] = \sigma^2 t_1$ for $X(t_1)$, and the $X(t_2) - X(t_1)$ is a Normal r.v with mean 0 and variance $\sigma^2(t_2 - t_1)$, and also independent with $X(t_1)$. Find the autocorrelation $R_X(t_1, t_2)$.
- 2: Suppose that an stochastic process $Z(t) = X\cos(t) + Y\sin(t)$, $-\infty < t < +\infty$. The X & Y are independent r.vs, and are equal to -1 and 2 with probability $2/3$ and $1/3$ independently. Is $Z(t)$ SSS? WSS?

Hint:

$$E(X) = E(Y) = (-1) \times \frac{2}{3} + 2 \times \frac{1}{3} = 0$$

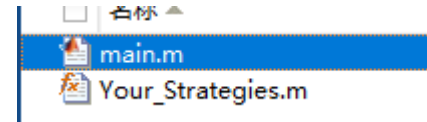
$$E(X^2) = E(Y^2) = (-1)^2 \times \frac{2}{3} + 2^2 \times \frac{1}{3} = \frac{2}{3} + \frac{4}{3} = 2$$

$$E(X^3) = E(Y^3) = (-1)^3 \times \frac{2}{3} + 2^3 \times \frac{1}{3} = -\frac{2}{3} + \frac{8}{3} = 2$$

$$E(XY) = E(YX) = E(X)E(Y) = 0$$

Experiment

- Go on for your Experiment 1 today
 - 关于extra的一些建议：
 - 满分是100分
 - 前面做好才是最重要的保障
 - 所谓的“submit the whole system with your strategy”，意思就是整个main函数，是需要自己写的
 - 所以，这个“whole system”，里面大部分的内容，大家均可以自由发挥，基本没有限制



Experiment

- Go on for your Experiment 1 today
 - 对experimental report 1的basic 2部分，请每个同学完成了8个图之后，叫译哲看一下。
 - 画4个分布的一共8个图，这4个分布都采用什么参数设置？
 - 大家自选参数设置就行（需要在实验报告里面说明选了什么参数）。只要运行能通过，就说明大家所自己选的参数是没有问题的。
 - 建议大家对程序进行仔细的调整，以画出一个比较漂亮的图。