

Contents

1	INTRODUCTION	2
1.1	Review random variables	2
1.2	Random processes - Examples	2
1.3	Correlation and covariance functions	5
	DESCRIPTION:	
2	RANDOM VECTORS	10
2.1	Definition - Correlation and Covariance matrix	10
2.2	Linear transformations - Spectral shaping and factorization	11
2.3	The whitening concept	22
2.4	The Karhunen - Loève expansion	24
2.5	Binary Hypothesis testing	25
3	ESTIMATION THEORY	37
3.1	Mean Square Estimation	37
3.2	Linear Mean Square Estimation	47
4	CONVERGENCE OF SEQUENCES OF RANDOM VARIABLES	52
4.1	Convergence in distribution	53
4.2	Convergence in probability	55
4.3	Almost sure convergence	57
4.4	Convergence in the mean square sense	58
5	CONTINUOUS TIME STOCHASTIC PROCESSES	62
5.1	Stationarity	62
5.2	Mean square properties	66
5	PROCESSES THROUGH LINEAR SYSTEMS	77
5.1	Output statistics	78
5.2	Power spectral density and power spectrum	79
5.3	Mean-square periodicity and Fourier series	81
5.4	Input-output PSD's for linear systems	86

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Chapter 1

INTRODUCTION

1.1 Review random variables

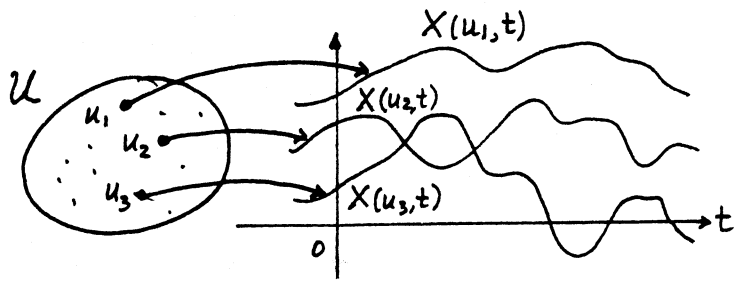
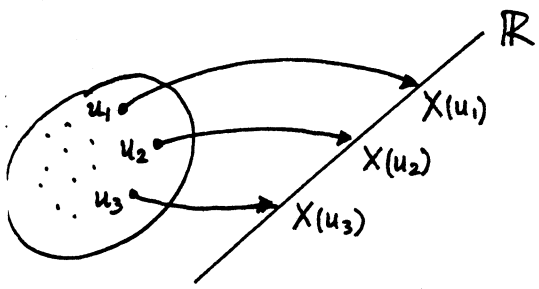
Recall the definition of a r.v. $X(u)$ as a mapping from a probability space $(\mathcal{U}, \mathcal{F}, \mathcal{P})$ to the real line, where \mathcal{U} is the space of all possible outcomes of an experiment, \mathcal{F} is the Borel field on that space and \mathcal{P} is the probability measure on \mathcal{F} .

F1-1

A random process is a mapping from a probability space to a set of functions.

1.2 Random processes - examples

We look at random processes (or stochastic processes) where the parameter space $t \in \mathcal{T}$ is discrete : $\dots, -2, -1, 0, 1, 2, \dots$ called a *random sequence*.



F1-1

Definition 1.2.1 A stochastic process is a collection of random variables

Examples of stochastic processes

1. Consider the free fall of a particle from some height H . If $h(t)$ is the distance travelled at time t and g is the gravitational constant then ideally

$$h(t) = H - \frac{1}{2}gt^2$$

Let T_h be the time it takes the particle to reach the ground or "hit" time. By solving $h(t) = 0$ we get

$$T_h = \sqrt{\frac{2H}{g}}$$

T_h is a random variable (r.v.) and $h(u, t)$ is a random process. It is a function of both $u \in \mathcal{U}$ and $t \in \mathcal{T}$.

If we fix the first argument $u = u_0$ then $h(u_0, t)$ is a deterministic function of t , called *sample path*. If we fix time $t = t_0$ then $h(u, t_0)$ is a random variable.

2. The voltage of an FM receiver of a randomly chosen station is a random process.
3. The prices in the stock market form a random process.

Recall the definition of a random variable $X(u, t); u \in \mathcal{U}, t \in \mathcal{T}$. With respect to the choice of the parameter space \mathcal{T} some cases of interest are :

1. for a finite set $\mathcal{T} = [1, 2, \dots, n]$ the random process is just a collection of r.v.'s $X(u, 1), \dots, X(u, n)$ which is formulated as a random vector

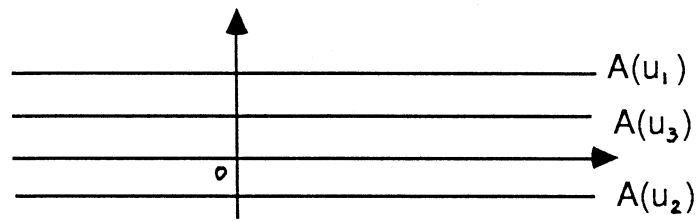
$$\underline{X}(u) = \begin{bmatrix} X(u, 1) \\ \vdots \\ X(u, n) \end{bmatrix}$$

2. if \mathcal{T} is a finite line segment

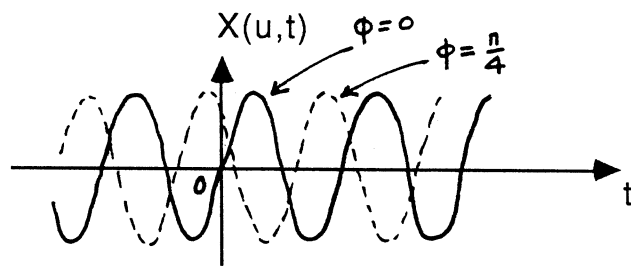
$$\mathcal{T} = \{t; 0 \leq t \leq T\}$$

then it is like observing a r.p. between time 0 and T .

3. Infinite line $\mathcal{T} \equiv \mathcal{R}$



F1-2



F 1-3

4. Countable set

$$\mathcal{T} = \{\dots, -3, -2, -1, 0, 1, 2, 3, \dots\}$$

in which case we get a random sequence

Note : It is not necessary that parameter t signify "time", it could be space. Looking at the range of $X(u, t)$ it can be the real line \mathcal{R} , or the space of complex numbers \mathcal{C} . Recall the definition of a complex r.v. :

$$Z(u) \stackrel{\text{def}}{=} X(u) + jY(u)$$

where $X(u)$ and $Y(u)$ are real r.v.'s

Examples

1. $X(u, t) = A(u)$, a random constant. For each outcome of the experiment we get a constant.

F 1-2

2. Sine wave with random phase

$$X(u, t) = \sin(2\pi ft + \phi(u))$$

where ϕ is a r.v. that could be uniformly distributed in $(0, 2\pi)$.

F 1-3

Further modelling is achieved by having the amplitude of the sine wave be a r.v. $A(u)$

$$X(u, t) = A(u)\sin(2\pi ft + \phi(u))$$

3. A random walk

F1-4

$$F(x_1, t_1, x_2, t_2, \dots, x_n, t_n) = \Pr\{X(u, t_1) \leq x_1, X(u, t_2) \leq x_2, \dots\}$$

4. We cannot describe the sample paths at all, neither in a mathematical nor visual way. Here we can only give statistical information about the process.

1.3.1 STATISTICAL DESCRIPTION

The most general kind of stochastic information for a process is obtained by the joint probability distribution function of a number n of samples $X(u, t_1), X(u, t_2), \dots, X(u, t_n)$ for any n and any set $\{t_1, t_2, \dots, t_n\}$, defined as:

Special cases:
First order:

$$F_X(x, t) \stackrel{\text{def}}{=} \Pr\{X(u, t) \leq x\}$$

or if this function is differentiable the joint density function

$$f_X(x, t) = \frac{\partial F_X(x, t)}{\partial x}$$

→ Second order

1.3.2 Correlation and covariance functions

A more advanced description of a random process involves second order statistics such as the joint PDF of two random variables obtained from the process by looking at time t_1 and t_2

$$F(x_1, x_2; t_1, t_2) = \Pr\{X(u, t_1) \leq x_1, X(u, t_2) \leq x_2\}$$

If this function F is differentiable then we can define the joint pdf as

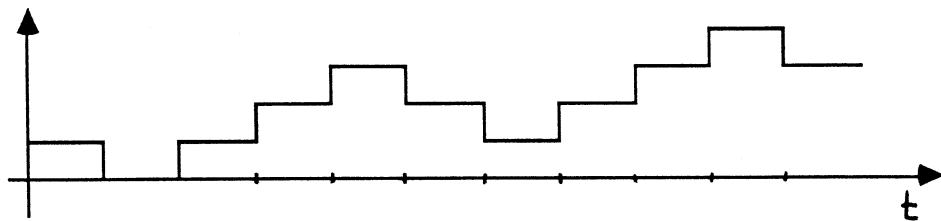
$$f(x_1, x_2; t_1, t_2) = \frac{\partial^2 F}{\partial x_1 \partial x_2}$$

This is typically too demanding so we usually settle for less. Moments are desirable quantities to obtain such as

1. The mean value of $X(u, t)$

$$m_X(t) \stackrel{\text{def}}{=} \mathcal{E}\{X(u, t)\}$$

which is a deterministic function of t



F 1-4

2. The correlation function

$$R_X(t_1, t_2) \stackrel{\text{def}}{=} \mathcal{E}\{X(u, t_1)X(u, t_2)\}$$

which is again a deterministic function of two arguments t_1 and t_2 . The above

F 1-5

definition for the autocorrelation holds for real $X(u, t)$. If $X(u, t)$ is a complex process then we define

$$R_X(t_1, t_2) \stackrel{\text{def}}{=} \mathcal{E}\{X(u, t_1)X^*(u, t_2)\}$$

where * means complex conjugate

3. The covariance function

$$K_X(t_1, t_2) \stackrel{\text{def}}{=} \mathcal{E}\{(X(u, t_1) - m_X(t_1))(X(u, t_2) - m_X(t_2))^*\}$$

by expanding we conclude that

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

Note : If $m_X(t) = 0$ then $K_x = R_x$ The above constitute second-order description of a random process, which very often is all we have or can calculate. In general knowing $m_X(t)$ and $R_X(t_1, t_2)$ says nothing about the underlying statistics which generated them. A notable exception is the *Gaussian* case that we will see later.

Examples :

1. $X(u, t) = A(u)$

$$\Rightarrow m_X(t) = m_A = \mathcal{E}\{A(u)\}$$

Note : Suppose that $m_A = 0$, ie the *ensemble* average of $X(u, t)$ is zero. Yet every time we do the experiment, (with probability 1 for continuous rv.'s) we see a constant number $\neq 0$! (for $-\infty < t < \infty$) Here the sample paths have little relation to the statistical averages of the process. Processes for which the sample path behaviour relates to ensemble quantities are called *ergodic*. (we will discuss them later)