

# Stochastic Structural Dynamics

## Lecture-21

### **Markov Vector Approach-1**

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## Recall

### Markov Property

- Refers to a property displayed by conditional PDF-s of random processes.

A scalar random process  $X(t)$  is said to possess Markov property if

$$P\left[X(t_n) \leq x_n \mid X(t_{n-1}) \leq x_{n-1}, X(t_{n-2}) \leq x_{n-2}, \dots, X(t_1) \leq x_1\right] \\ = P\left[X(t_n) \leq x_n \mid X(t_{n-1}) \leq x_{n-1}\right]$$

for any  $n$  and any choice of  $0 < t_1 < t_2 < \dots < t_n$ .

## **Diffusion process :**

A Markov process with continuous state and continuous parameter

## **Markov chain :**

A markov process with discrete parameter

- Mathematically, it is easier to deal with Markov chains.
- In vibration problems, however, we are interested in diffusion processes.

## Example

Let  $\{\Theta_i\}_{i=1}^n$  be an iid sequence of random variables.

Define

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

$$S_n = \Theta_n + \sum_{i=1}^{n-1} \Theta_i = \Theta_n + S_{n-1}$$

$S_n$  depends only upon  $S_{n-1}$  and not upon  $\{S_i\}_{i=1}^{n-2}$

$p(s_n | s_{n-1})$  is not a function of  $\{S_i = s_i\}_{i=1}^{n-2}$

$\Rightarrow S_n$  is Markov.

Also,  $p_{S_n}(s | S_{n-1} = u) = p_{\Theta_n}(s - u)$

## Simple random walk, absorbing and reflecting boundaries

The model  $S_n = S_{n-1} + \Theta_n; n = 1, 2, \dots$

represents the model for a simple random walk.

### Example 1

Consider an insurance company which starts business with an initial capital of  $X_0$  at time  $t = 0$ . Let

$Y_1, Y_2, \dots, Y_n =$  premiums received

$W_1, W_2, \dots, W_n =$  claims paid

Capital at time  $n$  is given by

$$X_n = X_0 + (Y_1 - W_1) + (Y_2 - W_2) + \dots + (Y_n - W_n)$$

At any  $n$ , if  $X_n < 0$ , the company is ruined and it

can no longer perform.  $X_n = 0$  is called an **absorbing barrier**.

## Example 2 Gambler's ruin

Two gamblers A and B with capitals  $a$  and  $b$  play a game  $n$  number of times.

Game ends when

A wins all the capital  $b$  from B

or A loses all his capital  $a$  to B

$X_n$  = capital gain of A at the end of  $n^{\text{th}}$  game.

$X = -a$  and  $X = b$  are absorbing barriers.

This is an example of random walk with

**two absorbing barriers.**

### **Example 3 Daily water level in a dam**

$b$  = capacity of dam

$X_n$  = volume of water in the dam on the  $n^{\text{th}}$  day.

$Y_n$  = inflow on  $n^{\text{th}}$  day.

$X_n$  executes a random walk in the interval 0 to  $b$

$X_n = 0$  &  $X_n = b$  are the **two reflecting barriers**.

## **Types of questions**

### **•Insurance company**

What is the probability of ruin of the insurance company for a given  $X_0$  ?

### **•Two gamblers**

What is the probability of ruin of A and B?

### **•Dam filling**

◦ What is the long-term equilibrium probability of water level in the dam?

◦ What is the PDF of empty periods and non-empty periods?



### Example

Verify if an iid sequence of random variables form a Markov process.

$$\bullet p(x_n | x_{n-1}, x_{n-2}, \dots, x_1) = p(x_n | x_{n-1}) = p(x_n) \quad [\text{Yes}]$$

### Example

Let  $X(t) = A + Bt$  where  $A$  and  $B$  are iid random variables.

Is  $X(t)$  Markov? [No]

### Example

Let  $A, B, C$  and  $D$  be random variables. Consider

$$\begin{Bmatrix} X(t) \\ Y(t) \end{Bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{Bmatrix} 1 \\ t \end{Bmatrix}$$

Investigate the conditions under which  $\begin{Bmatrix} X(t) \\ Y(t) \end{Bmatrix}$  is Markov.

## Complete specification of a Markov process

$$\bullet P(x_1; t_1) = P[X(t_1) \leq x_1]$$

$$\bullet P(x_1, x_2; t_1, t_2) = P[X(t_2) \leq x_2 \mid X(t_1) \leq x_1] P[X(t_1) \leq x_1]$$

$$\bullet P(x_1, x_2, x_3; \underline{t_1, t_2, t_3})$$

$$= P[X(t_3) \leq x_3 \mid \underline{X(t_2) \leq x_2, X(t_1) \leq x_1}]$$

$$P[X(t_2) \leq x_2 \mid X(t_1) \leq x_1] P[X(t_1) \leq x_1]$$

$$= P[X(t_3) \leq x_3 \mid X(t_2) \leq x_2]$$

$$P[X(t_2) \leq x_2 \mid X(t_1) \leq x_1] P[X(t_1) \leq x_1]$$

$$= \prod_{v=2}^3 P[X(t_v) \leq x_v \mid X(t_{v-1}) \leq x_{v-1}] P[X(t_1) \leq x_1]$$

$$\bullet P(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n) =$$

$$\prod_{v=2}^n P[X(t_v) \leq x_v \mid X(t_{v-1}) \leq x_{v-1}] P[X(t_1) \leq x_1]$$

## Complete specification

$$\bullet P \left[ X(t_\nu) \leq x_\nu \mid X(t_{\nu-1}) \leq x_{\nu-1} \right]$$

$$\& \underline{P \left[ X(t_1) \leq x_1 \right]} \forall n \& \{t_\nu\}_{\nu=1}^n$$

$$\bullet P \left[ X(t_\nu) \leq x_\nu, X(t_{\nu-1}) \leq x_{\nu-1} \right] \forall n \& \{t_\nu\}_{\nu=1}^n$$

- $P(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)$

$$= \prod_{v=2}^n P[X(t_v) \leq x_v \mid X(t_{v-1}) \leq x_{v-1}] \underline{P[X(t_1) \leq x_1]}$$

- Transitional PDF of  $X(t)$  [TPDF]

$$P[X(t_v) \leq x_v \mid X(t_{v-1}) \leq x_{v-1}]$$

- TPDF represents the evolution mechanism.

- $P[X(t_{n+1}) \leq x_{n+1} \mid X(t_n) \leq x_n, X(t_{n-1}) \leq x_{n-1}]$

$$= P[X(t_{n+1}) \leq x_{n+1} \mid X(t_n) \leq x_n].$$

$$\bullet P\left[X(t_{n+1}) \leq x_{n+1} \mid X(t_n) \leq x_n, X(t_{n-1}) \leq x_{n-1}\right]$$
$$= P\left[X(t_{n+1}) \leq x_{n+1} \mid X(t_n) \leq x_n\right]$$

$n + 1 = \text{Tomorrow}$

$n = \text{Today}$

$n - 1 = \text{Yesterday}$

Tomorrow's happenings depend on the what is happening today and  
and not on what happened yesterday!

**Recall : Model for dynamical systems using ODE - s**

$$\frac{dy}{dt} = h[y(t), t]; y(0) = y_0$$

Let  $t_2 > t_1$ .

$$y(t_2) = q[t_2, y(t_1), t_1]$$

That is, solution at  $t_2$  depends upon  $y(t_1)$  and not on  $y(\tau)$  ( $0 < \tau < t_1$ ).

Markov property can be viewed as the stochastic analog of the above property of ODE-s in deterministic systems

• Transitional probability density function [tpdf]

$$p(x_v; t_v | x_{v-1}; t_{v-1}) = \frac{\partial}{\partial x_v} P[X(t_v) \leq x_v | X(t_{v-1}) = x_{v-1}]$$

$$\underline{p(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)} =$$

$$p(x_n; t_n | x_{n-1}; t_{n-1}, x_{n-2}; t_{n-2}, \dots, x_1; t_1)$$

$$p(x_{n-1}; t_{n-1} | x_{n-2}; t_{n-2}, \dots, x_1; t_1)$$

$$\dots p(x_2; t_2 | x_1; t_1) p(x_1; t_1)$$

$$= p(x_n; t_n | x_{n-1}; t_{n-1}) p(x_{n-1}; t_{n-1} | x_{n-2}; t_{n-2})$$

$$\dots p(x_2; t_2 | x_1; t_1) p(x_1; t_1)$$

$$= \underline{p(x_1; t_1)} \prod_{v=2}^n \underline{p(x_v; t_v | x_{v-1}; t_{v-1})}$$

## Remark

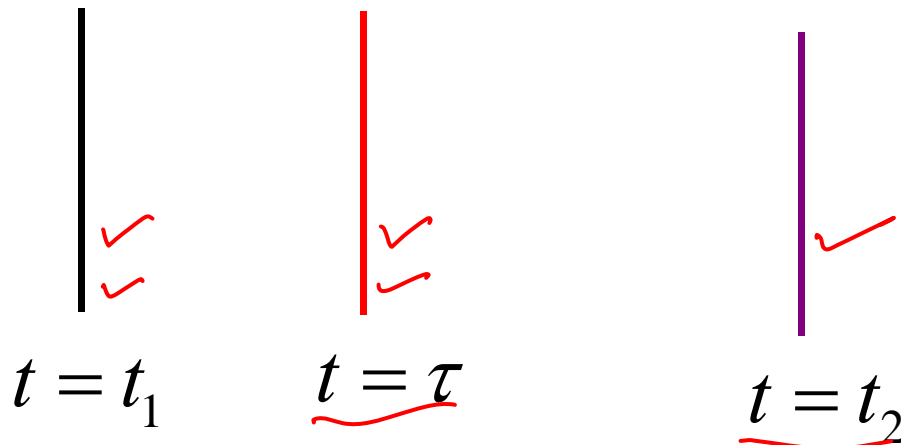
Markov process is also completely specified in terms of

- $p(x_v; t_v | x_{v-1}; t_{v-1}) \& p(x_1; t_1) \forall n \& \{t_v\}_{v=1}^n$
- $p(x_v; t_v, x_{v-1}; t_{v-1}) \forall n \& \{t_v\}_{v=1}^n$

$$\underbrace{p(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)}_{\text{Multi-dimensional jpdf}} = \underbrace{p(x_1; t_1)}_{\text{Initial pdf}} \underbrace{\prod_{v=2}^n p(x_v; t_v | x_{v-1}; t_{v-1})}_{\text{Product of transitional pdfs}}$$



# Chapman - Kolmogorov - Smoluchowski Equation



$$\begin{aligned}
 p(x_2, t_2; x_1, t_1) &= \underbrace{p(x_2, t_2 | x_1, t_1)} \underbrace{p(x_1, t_1)} \\
 &= \int \underbrace{p(x_2, t_2; x, \tau; x_1, t_1)} dx \\
 &= \int \underbrace{p(x_2, t_2 | x, \tau; x_1, t_1)} \underbrace{p(x, \tau | x_1, t_1)} \underbrace{p(x_1, t_1)} dx \\
 \Rightarrow \\
 \underbrace{p(x_2, t_2 | x_1, t_1)} &= \int p(x_2, t_2 | x, \tau; x_1, t_1) p(x, \tau | x_1, t_1) dx \\
 &= \int p(x_2, t_2 | x, \tau) p(x, \tau | x_1, t_1) dx \checkmark
 \end{aligned}$$

Consistency condition for the process to be Markov

$$p(x_2, t_2 | x_1, t_1) = \int p(x_2, t_2 | x, \tau) p(x, \tau | x_1, t_1) dx$$

for all  $t_1 < \tau < t_2$

### Question

How to utilize this result in characterizing response of randomly driven dynamical systems?

## Independent increment processes

Let  $X(t)$  be a random process with continuous state and continuous parameter (time  $t$ ).

Let  $t_1 < t_2 < \dots < t_n$  be  $n$  time instants.

Define  $X(t_1, t_2) = X(t_2) - X(t_1)$

$X(t_1, t_2)$  is called the increment of  $X(t)$  on  $[t_1, t_2)$ .

If, for all  $t_1 < t_2 < \dots < t_n$ , the increments  $X(t_1, t_2)$ ,  $X(t_2, t_3)$ ,  $\dots$ ,  $X(t_{n-1}, t_n)$  form a sequence of independent random variables, then the process  $X(t)$  is said to be a process with independent increments.

## Remark

Let  $X(t)$  ( $t \geq 0$ ) be a random process with independent increments.

Define  $Y(t) = X(t) - X(0)$  with ( $t \geq 0$ ). ✓

$Y(t)$  is a process with independent increments and also has the property  $P[Y(0) = 0] = 1$  //

Also,  $Y(t_{n-1}, t_n) = \underline{X(t_{n-1}, t_n)}$  and has the properties of increments of  $X(t)$ .

Without loss of generality, therefore, it may be taken that  $P[X(0) = 0] = 1$ .

Processes with independent increments possess  
Markovian property

$$\begin{aligned} \text{Define } Y(t) &= X(t) \text{ if } \mathbf{P}[X(0) = 0] = 1 \\ &= X(t) - X(0) \text{ if } \mathbf{P}[X(0) = 0] \neq 1 \end{aligned}$$

$$\Rightarrow Y(t_0) = 0$$

Consider  $t_n > t_{n-1} > t_{n-2} > \dots > t_1 > t_0 = 0$

and the associated random variables  $Y(t_n), Y(t_{n-1}), \dots, Y(t_1)$

$$Y(t_n) = \sum_{j=1}^n [Y(t_j) - Y(t_{j-1})]$$

$$= Y(t_1) - Y(t_0) + Y(t_2) - Y(t_1) \dots + Y(t_n) - Y(t_{n-1}) = Y(t_n)$$

Processes with independent increments possess

Denote  $Z_j = Y(t_j) - Y(t_{j-1})$

$\Rightarrow Z_j (j = 1, 2, \dots, n)$  are sequence of independent random variables.

$$Y(t_n) = \sum_{j=1}^n Z_j = Z_n + Y(t_{n-1})$$

$\Rightarrow Y(t)$  is Markov.

## Generalization : Markov property for vector random processes

Let  $X(t)$  be a vector random process with continuous state and continuous parameter (time  $t$ ).

Let  $t_1 < t_2 < \dots < t_n$  be the  $n$  time instants.

This defines  $n$  vector random variables

$$X(t_1), X(t_2), \dots, X(t_n).$$

The vector process  $X(t)$  is said to possess Markov property if the  $n^{\text{th}}$  order conditional joint PDF

$$\begin{aligned} & P \left[ X(t_n) \leq x_n \mid \underbrace{X(t_{n-1}) \leq x_{n-1}, X(t_{n-2}) \leq x_{n-2}, \dots, X(t_1) \leq x_1}_{\text{Markov property}} \right] \\ &= P \left[ X(t_n) \leq x_n \mid \underbrace{X(t_{n-1}) \leq x_{n-1}}_{\text{Markov property}} \right] \end{aligned}$$

for any  $n$  and any choice of  $t_1 < t_2 < \dots < t_n$ .

The  $m$ -dimensional vector random process

$$\mathbf{X}(t) = [X_1(t) \quad X_2(t) \quad \cdots \quad X_m(t)]^t$$

is said to be Markov if

$$P \left[ \bigcap_{i=1}^m \{X_j(t_n) \leq x_j\} \mid \mathbf{X}(t_{n-1}) = y_{n-1}, \mathbf{X}(t_{n-2}) = y_{n-2}, \dots, \mathbf{X}(t_1) = y_1 \right]$$

$$= P \left[ \bigcap_{i=1}^m \{X_j(t_n) \leq x_j\} \mid \mathbf{X}(t_{n-1}) = y_{n-1} \right] \forall t_n > t_{n-1} > \cdots > t_1$$

$$\underline{\text{TPDF}} = P \left[ \bigcap_{i=1}^m \{X_j(t_n) \leq x_j\} \mid \mathbf{X}(t_{n-1}) = y_{n-1} \right]$$

tpdf

$$p(\mathbf{x}; t \mid \mathbf{x}_0, t_0) = \frac{\partial^m}{\partial x_1 \partial x_2 \cdots \partial x_m} P \left[ \bigcap_{i=1}^m \{X_j(t_n) \leq x_j\} \mid \mathbf{X}(t_{n-1}) = y_{n-1} \right]$$



## Remarks

- A component of a vector random process (which itself is a scalar random process) need not have Markov property
- Different components of a Markov vector random process could be differentiable (in the mean square sense) to different levels.
- If a vector random process has independent random increments (vectorially), the components of the random process need not have independent increments.

# Consistency condition for a vector Markov process (CKS equation)

$$p(\tilde{x}_3; t_3 | \tilde{x}_1; t_1) =$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} p(\tilde{x}_3; t_3 | \tilde{y}; t_2) p(\tilde{y}; t_2 | \tilde{x}_1; t_1) dy_1 dy_2 \cdots dy_n$$

## Generalization : higher order Markov property

Let  $X(t)$  be a scalar random process with continuous state and continuous parameter (time  $t$ ).

Let  $t_1 < t_2 < \dots < t_n$  be  $n$  time instants.

This defines  $n$  random variables

$$X(t_1), X(t_2), \dots, X(t_n). \checkmark$$

$X(t)$  is said to possess 2<sup>nd</sup> order Markov property if

$$P\left[ X(t_n) \leq x_n \mid \underbrace{X(t_{n-1}) \leq x_{n-1}, X(t_{n-2}) \leq x_{n-2}, \dots, X(t_1) \leq x_1}_{\text{red underline}} \right]$$

$$= P\left[ X(t_n) \leq t_n \mid \underbrace{X(t_{n-1}) \leq t_{n-1}, X(t_{n-2}) \leq t_{n-2}}_{\text{red underline}} \right]$$

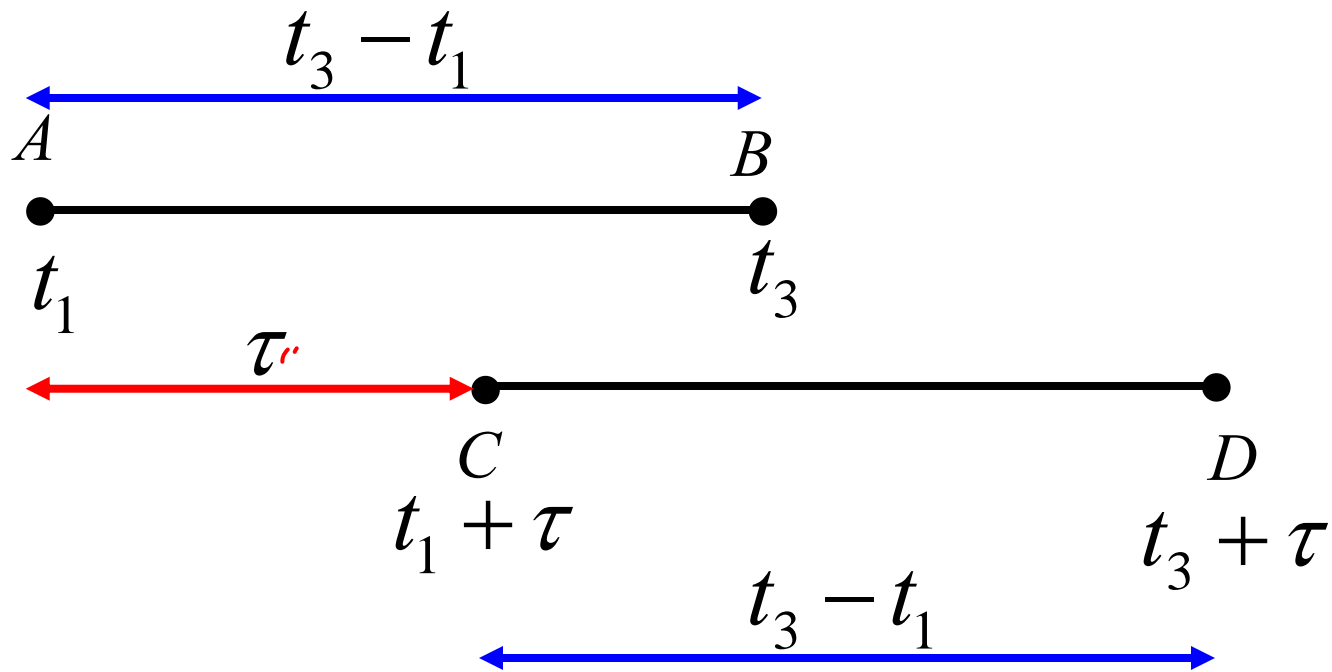
for any  $n$  and any choice of  $t_1 < t_2 < \dots < t_n$ .

The idea can be generalized to 3<sup>rd</sup> and higher orders.

## Markov process with stationary increments

$X(t)$  is said to be a Markov process with stationary increments if

$$p(x_3; t_3 + \tau | x_1; t_1 + \tau) = p(x_3; t_3 | x_1; t_1) \forall t_3 > t_1 \text{ \& } \tau$$



$$\begin{array}{l} \text{tpdf} \\ \text{from A to B} \end{array} = \begin{array}{l} \text{tpdf} \\ \text{from C to D} \end{array}$$

## Remarks

- $p(x_3; t_3 | x_1; t_1) = p(x_3; t_3 + \tau | x_1; t_1 + \tau)$

$\Rightarrow$  tpdf can be written as  $p(x_3; \tau | x_1)$ ;

$\tau =$  transistion time //

- $\lim_{\tau \rightarrow \infty} p(x_3; \tau | x_1) \rightarrow$   $p(x_3; \tau)$  ✓

- Stationary Markov random process is completely specified in terms of the tpdf.

- $X(t)$  is stationary  $\Rightarrow X(t)$  has stationary increments.

- $X(t)$  has stationary inrements need not mean that  $X(t)$  is stationary.

## Kinetic equation

Let  $X(t)$  be a scalar random process.

Let  $p_X(x;t)$  be the first order pdf of  $X(t)$ .

Can we derive a differential equation satisfied by  $p_X(x;t)$ ?

Here  $x$  and  $t$  would be the independent variables and  $p_X(x;t)$  would be the dependent variable. Thus the differential equation that we are looking for would be a partial differential equation.

Furthermore, can we also derive the PDE governing the  $n$ -dimensional joint pdf of  $X(t)$ ?

Notation:  $p_X(x;t) = p(x;t)$

Reference: T T Soong, 1973, Random differential equations in science and engineering, Academic Press, NY.

Consider the random variables  $X(t)$  &  $X(t + \Delta t)$

$$p(x, t + \Delta t) = \int_{-\infty}^{\infty} p(x, x'; t, t + \Delta t) dx'$$
$$= \int_{-\infty}^{\infty} \underbrace{p(x; t + \Delta t | x'; t)} \underbrace{p(x'; t)} dx' \dots (1)$$

Define  $\Delta X(t) = X(t + \Delta t) - X(t)$ .

$\langle \exp[iu\Delta X(t) | X(t) = x'] \rangle =$  Conditional characteristic  
function of  $\Delta X(t)$  given  $X(t) = x'$ .

Denote  $\Phi(u, t + \Delta t | X(t) = x') = \langle \exp[iu\Delta X(t) | X(t) = x'] \rangle$ .

$$\Phi(u, t + \Delta t | X(t) = x') = \int_{-\infty}^{\infty} \exp(iu\Delta x) \underbrace{p(x; t + \Delta t | X(t) = x')} dx \dots (2)$$

with  $\Delta X(t) = X(t + \Delta t) - X(t)$  such that  $\Delta x = x - x' \dots (3)$ .

$$\Phi(u, t + \Delta t | X(t) = x') = \int_{-\infty}^{\infty} \exp(iu\Delta x) p(x; t + \Delta t | X(t) = x') dx$$

$$\Rightarrow p(x; t + \Delta t | X(t) = x')$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-iu\Delta x) \Phi(u, t + \Delta t | X(t) = x') du \dots (4)$$

**Recall:**  $f(x+h) = f(x) + hf'(x) + \frac{h^2}{2!} f''(x) + \dots = \sum_{n=0}^{\infty} \frac{h^n}{n!} f^n(x)$

$$\Rightarrow \Phi(u, t + \Delta t | X(t) = x') = \Phi(0 + u, t + \Delta t | X(t) = x')$$

$$= \sum_{n=0}^{\infty} \frac{u^n}{n!} \frac{d^n}{du^n} \Phi(u, t + \Delta t | X(t) = x') \Big|_{u=0}$$

$$= \sum_{n=0}^{\infty} \frac{(iu)^n}{n!} \langle [\Delta X^n(t) | X(t) = x'] \rangle$$



## Recall : Characteristic function of a random variable

$$\text{Definition : } \underline{\varphi_X(\omega) = \langle \exp(i\omega X) \rangle} = \underline{\int_{-\infty}^{\infty} \exp(i\omega x) p_X(x) dx}$$

Here  $\omega$  is real valued. Thus,  $\varphi_X(\omega)$  is the Fourier transform of the pdf.

$$\text{It can be shown that } \underline{\frac{1}{i^n} \frac{d^n \varphi_X}{d\omega^n} \Big|_{\omega=0}} = \underline{\langle X^n \rangle}.$$

By using inverse Fourier transform, it follows that

$$p_X(x) = \int_{-\infty}^{\infty} \varphi_X(\omega) \underline{\exp(-i\omega x)} dx. \quad \checkmark$$

## Characteristic function of a random process

Definition :

$$\begin{aligned}\phi_X(u_1; t_1, u_2; t_2, \dots, u_n; t_n) &= \left\langle \exp \left[ i \sum_{j=1}^n u_j X(t_j) \right] \right\rangle \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \exp \left[ i \sum_{j=1}^n u_j x_j \right] p(x_1; t_1, x_2; t_2, \dots, x_n; t_n) dx_1 dx_2 \cdots dx_n //\end{aligned}$$

Here  $\{u_j\}_{j=1}^n$  is real valued.

$$\alpha_{j_1, j_2, \dots, j_n}(t_1, t_2, \dots, t_n) = \left\langle X^{j_1}(t_1) X^{j_2}(t_2) \cdots X^{j_n}(t_n) \right\rangle$$

$$\frac{\partial^m}{\partial u_1^{j_1} \partial u_2^{j_2} \cdots \partial u_n^{j_n}} \phi_X(u_1; t_1, u_2; t_2, \dots, u_n; t_n) \Big|_{\underline{\underline{\{u_j\}_{j=1}^n = 0}}} = i^m \alpha_{j_1, j_2, \dots, j_n}(t_1, t_2, \dots, t_n)$$

such that  $m = j_1 + j_2 + \cdots + j_n$ .

$$\Rightarrow p(x; t + \Delta t | X(t) = x') =$$

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-iu\Delta x) \left\{ \sum_{n=0}^{\infty} \frac{(iu)^n}{n!} \langle [\Delta X^n(t) | X(t) = x'] \rangle \right\} du$$

$$p(x; t + \Delta t | X(t) = x') = \sum_{n=0}^{\infty} \frac{i^n}{2\pi} \frac{1}{n!} a_n(x', t) \int_{-\infty}^{\infty} u^n \exp(-iu\Delta x) du$$

with

$$a_n(x', t) = \langle [\Delta X^n(t) | X(t) = x'] \rangle$$

$$= \langle [\{X(t + \Delta t) - x(t)\}^n | X(t) = x'] \rangle \dots (5)$$

= **Incremental moments**

$$p(x; t + \Delta t | X(t) = x') = \sum_{n=0}^{\infty} \frac{a_n(x', t)}{n!} \frac{1}{2\pi} \int_{-\infty}^{\infty} (iu)^n \exp(-iu\Delta x) du$$

$$p(x; t + \Delta t | X(t) = x') = \sum_{n=0}^{\infty} \frac{a_n(x', t)}{n!} \frac{1}{2\pi} \int_{-\infty}^{\infty} (iu)^n \exp(-iu\Delta x) du \cdots (6)$$

**Recall**

$$\int_{-\infty}^{\infty} \delta(x) \exp(iux) dx = 1$$

$$\Rightarrow \delta(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-iux) du$$

$$\Rightarrow \frac{d^n}{dx^n} \delta(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} (-1)^n (iu)^n \exp(-iux) du //$$

$$p(x; t + \Delta t | X(t) = x') = \sum_{n=0}^{\infty} \frac{(-1)^n}{n!} a_n(x', t) \frac{d^n}{dx^n} \delta(\Delta x) \cdots (7)$$

Substitute equation 7 in 1

$$p(x; t + \Delta t | X(t) = x') = \sum_{n=0}^{\infty} \frac{(-1)^n}{n!} a_n(x', t) \frac{d^n}{dx^n} \delta(\Delta x) \dots (7)$$

$$p(x, t + \Delta t) = \int_{-\infty}^{\infty} p(x; t + \Delta t | x'; t) p(x'; t) dx' \dots (1)$$

$$\Rightarrow p(x, t + \Delta t) = \int_{-\infty}^{\infty} \sum_{n=0}^{\infty} \frac{(-1)^n}{n!} a_n(x', t) \frac{d^n}{dx^n} \delta(\Delta x) p(x'; t) dx'$$

$$= \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} \int_{-\infty}^{\infty} \delta(\Delta x) a_n(x', t) p(x'; t) dx'$$

Recall  $\frac{d^n}{dx^n} \int_{-\infty}^{\infty} \delta(x - a) f(x) dx = \frac{d^n f(a)}{dx^n}$

$$p(x, t + \Delta t) = \sum_{n=0}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} [a_n(x, t) p(x; t)] \quad //$$

$$p(x, t + \Delta t) = \sum_{n=0}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} [a_n(x, t) p(x; t)]$$

$$= \underline{a_0(x, t) p(x; t)} + \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} [a_n(x, t) p(x; t)] \dots (8)$$

$$\underline{a_0(x, t)} = \langle \Delta X^0(t) | X(t) = x' \rangle = 1 \quad \checkmark$$

$$\Rightarrow p(x, t + \Delta t) - p(x; t) = \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} [a_n(x, t) p(x; t)]$$

$$\underline{\frac{\partial p}{\partial t}} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} [a_n(x, t) p(x; t)]$$

$$= \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \frac{d^n}{dx^n} [a_n(x, t) p(x; t)]$$

$$= \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{d^n}{dx^n} [\alpha_n(x, t) p(x; t)]$$

$$\frac{\partial p}{\partial t} = \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{\partial^n}{\partial x^n} [\alpha_n(x, t) p(x; t)] //$$

$$\alpha_n(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)]^n \mid X(t) = x \right\rangle; n = 1, 2, \dots$$

= Derivative moments

$$\lambda(x, t) = - \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{\partial^{n-1}}{\partial x^{n-1}} [\alpha_n(x, t) p(x; t)]$$

$$\frac{\partial p}{\partial t} + \frac{\partial \lambda}{\partial x} = 0 //$$

- Equation of conservation of probability

Similar to equation of continuity in fluid mechanics.

- Diffusion equation

- $\lambda(x, t)$  = amount of probability crossing  $x$  in unit time

## Remarks

- The equation  $\frac{\partial p}{\partial t} + \frac{\partial \lambda}{\partial t} = 0$  has infinite order with respect to the spatial coordinate.

Therefore, its application is severely limited.

### • Theorem

R F Pawula, 1967, IEEE Trans.

Information theory, IT-13, 33-41

If the derivative moment  $\alpha_n(x, t)$  exists for all  $n$  and is zero for some even  $n$ , then  $\alpha_n(x, t) = 0 \forall n \geq 3$ .



## Implication :

There exist two cases of equation

$$\frac{\partial p}{\partial t} + \frac{\partial \lambda}{\partial t} = 0. \text{ The one in which}$$

the order of the equation in  $x$  is infinite

and the other in which the order

is 2 or less. We would be interested in

applying the kinetic equation for

the case in which  $\alpha_n(x, t) = 0 \forall n \geq 3$ .

## Proof of the statement :

If the derivative moment  $\alpha_n(x, t)$  exists for all  $n$  and is zero for some even  $n$ , then  $\alpha_n(x, t) = 0 \forall n \geq 3$ .

Let  $n \geq 3$  and let  $n$  be odd.

$$\begin{aligned}\alpha_n(x, t) &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[ X(t + \Delta t) - X(t) \right]^n \mid X(t) = x \right\rangle \\ &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[ X(t + \Delta t) - X(t) \right]^{\frac{n-1}{2}} \left[ X(t + \Delta t) - X(t) \right]^{\frac{n+1}{2}} \mid X(t) = x \right\rangle\end{aligned}$$

Apply the Schwarz inequality

$$\alpha_n^2(x, t) \leq \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t^2} \left\langle \left[ X(t + \Delta t) - X(t) \right]^{n-1} \mid X(t) = x \right\rangle$$
$$\left\langle \left[ X(t + \Delta t) - X(t) \right]^{n+1} \mid X(t) = x \right\rangle.$$

$$\Rightarrow \alpha_n^2(x, t) \leq \alpha_{n-1}(x, t) \alpha_{n+1}(x, t) \quad \forall n \geq 3 \text{ \& } n \text{ odd} \dots (1)$$

Similarly it can be shown that

$$\alpha_n^2(x, t) \leq \alpha_{n-2}(x, t) \alpha_{n+2}(x, t) \quad \forall n \geq 4 \text{ \& } n \text{ even} \dots (2)$$

Let  $\alpha_r(x, t) = 0$  where  $r$  is an even integer.

Let  $n = r - 1, r + 1$ , and using

$$\alpha_n^2(x, t) \leq \alpha_{n-1}(x, t) \alpha_{n+1}(x, t) \forall n \geq 3 \text{ \& } n \text{ odd}$$

we get

$$\alpha_{r-1}^2(x, t) \leq \alpha_{r-2}(x, t) \alpha_r(x, t) \forall r \geq 4$$

$$\alpha_{r+1}^2(x, t) \leq \alpha_r(x, t) \alpha_{r+2}(x, t) \forall r \geq 2$$

Let  $n = r - 2, r + 2$ , and using

$$\alpha_n^2(x, t) \leq \alpha_{n-2}(x, t) \alpha_{n+2}(x, t) \quad \forall n \geq 4 \text{ \& } n \text{ even}$$

we get

$$\alpha_{r-2}^2(x, t) \leq \alpha_{r-4}(x, t) \alpha_r(x, t) \quad \forall r \geq 6$$

$$\alpha_{r+2}^2(x, t) \leq \alpha_r(x, t) \alpha_{r+4}(x, t) \quad \forall r \geq 2$$

$$\alpha_{r-1}^2 \leq \alpha_{r-2} \alpha_r \quad \forall r \geq 4$$

$$\alpha_{r+1}^2 \leq \alpha_r \alpha_{r+2} \quad \forall r \geq 2$$

$$\alpha_{r-2}^2 \leq \alpha_{r-4} \alpha_r \quad \forall r \geq 6$$

$$\alpha_{r+2}^2 \leq \alpha_r \alpha_{r+4} \quad \forall r \geq 2$$

Illustration:

Let  $\alpha_3 = 0$  and  $\alpha_n$  exist for all  $n$ .

$$\alpha_{r+1}^2 \leq \alpha_r \alpha_{r+2} \quad \forall r \geq 2 \Rightarrow \alpha_4^2 = 0$$

$$\alpha_{r+2}^2 \leq \alpha_r \alpha_{r+4} \quad \forall r \geq 2 \Rightarrow \alpha_5^2 = 0$$

$$\Rightarrow \alpha_r = 0 \quad \forall r > 3$$

$$\alpha_{r-1}^2 \leq \alpha_{r-2} \alpha_r \forall r \geq 4$$

$$\alpha_{r+1}^2 \leq \alpha_r \alpha_{r+2} \forall r \geq 2$$

$$\alpha_{r-2}^2 \leq \alpha_{r-4} \alpha_r \forall r \geq 6$$

$$\alpha_{r+2}^2 \leq \alpha_r \alpha_{r+4} \forall r \geq 2$$

Let  $\alpha_r = 0$  and  $\alpha_n$  exist for all  $n$ .

$$\alpha_{r+2}^2 \leq \alpha_r \alpha_{r+4} \forall r \geq 2 \text{ \& } \alpha_{r+1}^2 \leq \alpha_r \alpha_{r+2} \forall r \geq 2 \Rightarrow \alpha_n = 0 \forall n > r$$

$$\alpha_{r-2}^2 \leq \alpha_{r-4} \alpha_r \forall r \geq 6 \text{ \& } \alpha_{r-1}^2 \leq \alpha_{r-2} \alpha_r \forall r \geq 4 \Rightarrow \alpha_n = 0 \forall n < r \text{ \& } n \geq 3$$

**QED**

## Remarks

• For the case  $\alpha_n(x, t) = 0 \forall n \geq 3$ , the kinetic equation takes the form

$$\frac{\partial p}{\partial t} = -\frac{\partial}{\partial x} \left[ \alpha_1(x, t) p(x; t) \right] + \frac{1}{2} \frac{\partial^2}{\partial x^2} \left[ \alpha_2(x, t) p(x; t) \right]$$

This equation is known as the Fokker-Planck equation.

Here

$$\lambda(x, t) = \alpha_1(x, t) p(x; t) - \frac{1}{2} \frac{\partial}{\partial x} \left[ \alpha_2(x, t) p(x; t) \right].$$

- Initial condition:  $p(x; t = 0) = \underline{p_0(x)}$
- Boundary conditions: different possibilities exist.



## Boundary conditions

If  $X(t)$  takes values from  $-\infty$  to  $\infty$ , then the BCS are specified at  $\pm\infty$ . These boundaries are inaccessible.

$$\frac{\partial p}{\partial t} + \frac{\partial \lambda}{\partial t} = 0$$

$$\Rightarrow \int_{-\infty}^{\infty} \frac{\partial p}{\partial t} dx + \int_{-\infty}^{\infty} \frac{\partial \lambda}{\partial x} dx = 0$$

$$\Rightarrow \frac{\partial}{\partial t} \int_{-\infty}^{\infty} p(x; t) dx + \int_{-\infty}^{\infty} \frac{\partial \lambda}{\partial x} dx = 0$$

$$\int_{-\infty}^{\infty} p(x; t) dx = 1 \Rightarrow \int_{-\infty}^{\infty} \frac{\partial \lambda}{\partial x} dx = 0 //$$

$$\lambda(-\infty; t) = \lambda(\infty; t)$$

A stronger condition:  $\lambda(-\infty; t) = \lambda(\infty; t) = 0$  ✓

Still stronger condition:  $p(\pm\infty; t) = 0$  ✓

If  $X(t)$  can take values only in the bounded region  $x_1 \leq X(t) \leq x_2$ , then the Fokker Planck equation is valid in this region with

$$\frac{\partial p}{\partial t} + \frac{\partial \lambda}{\partial t} = 0 \Rightarrow \frac{\partial}{\partial t} \int_{x_1}^{x_2} p(x;t) dx + \int_{x_1}^{x_2} \frac{\partial \lambda}{\partial x} dx = 0$$

$$\Rightarrow \lambda(x_1;t) = \lambda(x_2;t) //$$

A stronger condition:  $\lambda(x_1;t) = \lambda(x_2;t) = 0$

Still stronger condition:  $p(x_1;t) = p(x_2;t) = 0$

✓  $\lambda(x_1;t) = \lambda(x_2;t) = 0$ : Reflecting boundaries

✓  $p(x_1;t) = p(x_2;t) = 0$ : Absorbing boundaries

## Remarks (continued)

- When  $\alpha_n(x, t)$  are independent of time, stationary solutions might exist such that

$\frac{\partial p}{\partial t} = 0$  and one gets the simplified equation

$$-\frac{\partial}{\partial x} [\alpha_1(x) p(x)] + \frac{1}{2} \frac{\partial^2}{\partial x^2} [\alpha_2(x) p(x)] = 0$$

leading to the solution  $\lambda(x) = 0$ .

## Generalization of the kinetic equation for the case of a vector random process

Let  $X(t) = \{X_1(t), X_2(t), \dots, X_m(t)\}^t$  be a  $m$ -dimensional vector random process.

Consider the vector random variables  $X(t)$  &  $X(t + \Delta t)$

$$p(\tilde{x}, t + \Delta t) = \int_{-\infty}^{\infty} p(\tilde{x}; t + \Delta t | \tilde{x}'; t) p(\tilde{x}'; t) d\tilde{x}'$$

$$\frac{\partial p(\tilde{x}; t)}{\partial t} = \sum_{n_1, n_2, \dots, n_m=1}^{\infty} \left[ \prod_{j=1}^m \frac{(-1)^{n_j}}{(n_j)!} \frac{\partial}{\partial x_j^{n_j}} \right] \left[ \alpha_{n_1, n_2, \dots, n_m}(\tilde{x}; t) p(\tilde{x}; t) \right]$$

with

$$\alpha_{n_1, n_2, \dots, n_m}(\tilde{x}; t) = \lim_{\Delta t \rightarrow 0} \left\langle \prod_{j=1}^m [X_j(t + \Delta t) - X_j(t)]^{n_j} \mid X(t) = \tilde{x} \right\rangle$$

# Next Lecture

- How to derive the Fokker Plank equation for response of dynamical systems driven by random excitations.
- How to solve them?