

3.1. Definitions

$x(t)$ N realizations $x^{(j)}(t)$, $j = 1, \dots, N$

(a) Ensemble averages

$$\langle x(t) \rangle = \lim_{N \rightarrow \infty} \frac{\sum_{j=1}^N x^{(j)}(t)}{N} = \int_{-\infty}^{\infty} x p(x, t) dx$$

$$\langle x^2(t) \rangle = \lim_{N \rightarrow \infty} \frac{\sum_{j=1}^N [x^{(j)}(t)]^2}{N} = \int_{-\infty}^{\infty} x^2 p(x, t) dx$$

$$\begin{aligned} \text{ACF } \langle x(t)x(t+\tau) \rangle &= \lim_{N \rightarrow \infty} \frac{\sum_{j=1}^N x^{(j)}(t)x^{(j)}(t+\tau)}{N} = \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 p_2(x_1, t; x_2, t+\tau) dx_1 dx_2 \end{aligned}$$

(b) Time averages:

$$\overline{x^{(j)}(t)} = \frac{1}{T} \int_0^T x^{(j)}(t) dt$$

$$\overline{[x^{(j)}(t)]^2} = \frac{1}{T} \int_0^T [x^{(j)}(t)]^2 dt$$

$$\overline{x^{(j)}(t)x^{(j)}(t+\tau)} = \frac{1}{T-\tau} \int_0^{T-\tau} x^{(j)}(t)x^{(j)}(t+\tau) dt$$

Theory: ensemble average

Experiment: time average advantageous

number of realizations N is not big enough

Def. 1 Ergodic process:

all ensemble averages = corresponding time averages at $T \rightarrow \infty$

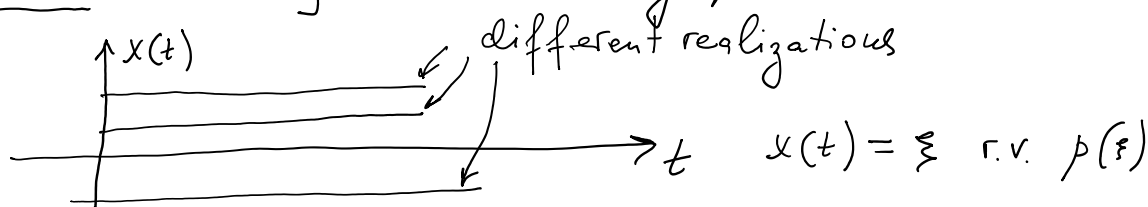
Def. 2. Weakly ergodic process (ergodicity in the wide sense)
(important in practice)

$$\left. \begin{aligned} \langle x(t) \rangle &= \overline{x^{(j)}(t)}, \quad T \rightarrow \infty \\ \langle x(t)x(t+\tau) \rangle &= \overline{x^{(j)}(t)x^{(j)}(t+\tau)}, \quad T \rightarrow \infty \end{aligned} \right\} \text{ for any } j, j=1, \dots, N$$

Theorem. Only stationary processes can be ergodic

Fact. "Most" of stationary processes are ergodic

Remark. Non-ergodic stationary process



$$\langle x(t) \rangle = \int_{-\infty}^{\infty} \xi p(\xi) d\xi \text{ does not depend on time}$$

$$\begin{aligned} \langle x(t)x(t+\tau) \rangle &= \int_{-\infty}^{\infty} dx_1 \int_{-\infty}^{\infty} dx_2 x_1 x_2 p_2(x_1, t; x_2, t+\tau) = \\ &= \int_{-\infty}^{\infty} dx_1 \int_{-\infty}^{\infty} dx_2 p(x_1) \delta(x_1 - x_2) x_1 x_2 \Rightarrow \int_{-\infty}^{\infty} dx_1 x_1^2 p(x_1) = \langle \xi^2 \rangle \end{aligned}$$

$$\text{However } \overline{x^{(j)}(t)} = \frac{1}{T} \int_0^T x^{(j)}(t) dt = x^{(j)} = \xi \text{ r.v.}$$

(3.2) Criteria of ergodicity

(a) role of Chebyshev inequality

$$x(t) = \langle x(t) \rangle + \xi(t), \quad \langle \xi(t) \rangle = 0$$

$$\overline{x(t)} - \langle \overline{x(t)} \rangle = \overline{\xi(t)}$$

Reminder. Chebyshev inequality. X r.v.

$$\Pr(|X - \langle X \rangle| \geq \varepsilon) \leq \frac{\sigma^2}{\varepsilon^2}, \quad \sigma^2 = \text{Var}\{X\} = \langle (X - \langle X \rangle)^2 \rangle$$

Our case: $\overline{x(t)}$ is random variable

$$\Pr\{|\overline{x(t)} - \langle \overline{x(t)} \rangle| \geq \varepsilon\} \leq \frac{1}{\varepsilon^2} \underbrace{\langle (\overline{\xi(t)})^2 \rangle}_{\sigma_T^2}$$

$$\text{If } \sigma_T^2 \rightarrow 0 \text{ at } T \rightarrow \infty \Rightarrow \overline{x(t)} \xrightarrow{\sigma_T^2} \langle \overline{x(t)} \rangle$$

Consider $x(t)$ stationary process, $\langle x(t) \rangle = \langle x \rangle$

$$\langle \overline{x(t)} \rangle = \langle x \rangle$$

$$\boxed{\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T x(t) dt = \langle x \rangle} \quad \text{if} \quad \lim_{T \rightarrow \infty} \sigma_T^2 = 0$$

(b) Time average in spectral representation

Any function $f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(\omega) e^{-i\omega t} d\omega$

$$\overline{f(t)} = \frac{1}{T} \int_{t_0}^{t_0+T} f(t') dt' = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(\omega) \underbrace{\frac{1}{T} \int_{t_0}^{t_0+T} e^{-i\omega t'} dt'}_{\text{}} d\omega \Rightarrow$$

$$= \left\{ \dots \right\} = \frac{1}{T} \frac{e^{-i\omega t'}}{-i\omega} \Big|_{t_0}^{t_0+T} = -\frac{1}{i\omega T} (e^{-i\omega(t_0+T)} - e^{-i\omega t_0}) =$$

$$= -\frac{e^{-i\omega t_0}}{i\omega T} (e^{-i\omega T} - 1) = -\frac{e^{-i\omega t_0} e^{-i\omega T/2}}{i\omega T} \underbrace{(e^{-i\omega T/2} - e^{i\omega T/2})}_{-2i \sin(\frac{\omega T}{2})} =$$

$$= \frac{\sin(\frac{\omega T}{2})}{\frac{\omega T}{2}} e^{-i\omega t_0} e^{-i\omega T/2} \left\{ \dots \right\}$$

$$\Rightarrow \boxed{\overline{f(t)} = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(\omega) \frac{\sin(\frac{\omega T}{2})}{\frac{\omega T}{2}} e^{-i\omega T/2} e^{-i\omega t_0} d\omega}$$

stronger damping of the high-frequency part of the spectrum

(c) spectral form of ergodicity criterion

$$\sigma_T^2 = \langle (\bar{x})^2 \rangle = \frac{1}{4\pi^2} \iint_{-\infty}^{\infty} d\omega d\omega' \underbrace{\langle \xi(\omega) \xi(\omega') \rangle}_{\substack{\text{previous} \\ \text{lecture}}} \frac{\sin(\frac{\omega T}{2})}{\frac{\omega T}{2}} \frac{\sin(\frac{\omega' T}{2})}{\frac{\omega' T}{2}} \times$$

$$\times e^{-i\frac{\omega T}{2} - \frac{i\omega' T}{2}} e^{-i\omega t_0 - i\omega' t_0}$$

$$= \int_{-\infty}^{\infty} G(\omega) \frac{\sin^2(\frac{\omega T}{2})}{(\frac{\omega T}{2})^2} \frac{d\omega}{2\pi}$$

Example 1. Finite spectrum at $\omega=0$, $0 < G(0) < \infty$

$$\sigma_T^2 \approx \frac{G(0)}{T} \int_{-\infty}^{\infty} \frac{\sin^2(\omega T/2)}{(\omega T/2)^2} \frac{d(\omega T)}{2\pi} = \left\{ y = \frac{\omega T}{2} \right\} = \frac{G(0)}{T} \int_{-\infty}^{\infty} \underbrace{\frac{\sin^2 y}{y^2} \frac{dy}{\pi}}_{\text{convergent integral}} \sim$$

$$\sim \frac{G(0)}{T} \sim \frac{1}{T} \rightarrow 0, \quad T \rightarrow \infty$$

Example 2. $G(\omega) \rightarrow \infty$, flicker noise

$$G(\omega) \sim G_0 \left(\frac{\omega_0}{|\omega|} \right)^\mu \sim \frac{1}{|\omega|^\mu}, \quad 0 < \mu < 1$$

$$\sigma_T^2 \sim \frac{1}{T^{1-\mu}} \text{ slow convergence } \sigma_T^2 \rightarrow 0, \quad T \rightarrow \infty$$

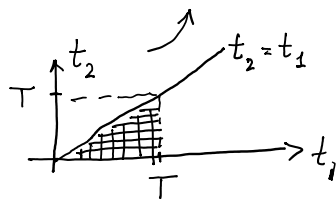
Example 3. $G(\omega) = G_0 \delta(\omega)$ non-ergodic stationary process, see example above

$$\sigma_T^2 = G_0 = \text{const}$$

(d) ergodicity criterion in time domain (Slutsky theorem)

$$\sigma_T^2 = \langle (\bar{\xi})^2 \rangle = \frac{1}{T^2} \int_0^T dt_1 \int_0^T dt_2 \underbrace{\langle \xi(t_1) \xi(t_2) \rangle}_{B(\tau); \tau = t_2 - t_1} =$$

$$= \frac{1}{T^2} \int_0^T dt_1 \left[\int_0^{t_1} dt_2 B(t_2 - t_1) + \int_{t_1}^T dt_2 B(t_2 - t_1) \right] =$$

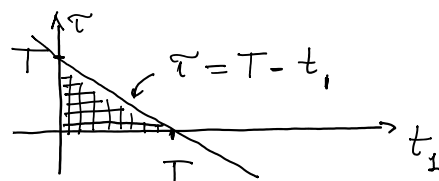


$$= \frac{1}{T^2} \int_0^T dt_2 \int_{t_2}^T dt_1 B(t_2 - t_1) + \frac{1}{T^2} \int_0^T dt_1 \int_{t_1}^T dt_2 B(t_2 - t_1) = \{ B(\tau) = B(-\tau) \}$$

$t_1 \leftrightarrow t_2$

$$= \frac{2}{T^2} \int_0^T dt_1 \int_{t_1}^T dt_2 B(t_2 - t_1) = \{ \tau = t_2 - t_1, \} =$$

$$= \frac{2}{T^2} \int_0^T dt_1 \int_0^{T-t_1} d\tau B(\tau) =$$



$$= \frac{2}{T^2} \int_0^T d\tau B(\tau) \int_0^{T-\tau} dt_1 = \frac{2}{T^2} \int_0^T (T-\tau) B(\tau) d\tau = \sigma_T^2$$

$$\boxed{\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T B(\tau) d\tau = 0}$$

Slutsky Theorem
(suff. and necessary
cond of ergodicity)

Example 1. Fractional Gaussian noise
 $B(\tau) \sim \frac{1}{\tau^\mu}$, $\tau \rightarrow \infty$, $0 < \mu < 1$

$$\frac{1}{T} \int_0^T B(\tau) d\tau \sim \frac{1}{T^{1-\mu}} \rightarrow 0$$

Example 2. $B(\tau) = \text{const} \cdot \cos \omega \tau$ (previous lecture)

$$\frac{1}{T} \int_0^T B(\tau) d\tau \sim \frac{\sin \omega T}{\omega T} \rightarrow 0$$

Remark We consider only ergodicity in the mean sense

$$x(t) = \langle x \rangle + \xi(t)$$

(e) 1-point generalization $f[x(t)]$

$$\overline{f_T[x(t)]}^T = \frac{1}{T} \int_0^T f[x(t)] dt$$

Example $\overline{x^2(t)}^T \rightarrow \langle x^2(t) \rangle$, $T \rightarrow \infty$

• Construct analogue of $B(t, t') = \langle \xi(t) \xi(t') \rangle$

$$\psi_f(t, t') = \iint_{-\infty}^{\infty} f(x) f(x') [p_2(x, t; x', t') - p(x, t) p(x', t')] dx dx'$$

• Chebyshev inequality

$$\Pr \{ |\overline{f_T(x)} - \langle \overline{f_T(x)} \rangle| \geq \varepsilon \} \leq \frac{\text{Var}[\overline{f_T(x)}]}{\varepsilon^2}$$

• For stationary processes

$$\psi_f(t, t') = \psi_f(\tau = t' - t)$$

$$\text{Var}[\overline{f_T(x)}] = \frac{1}{T^2} \int_0^T dt_1 \int_0^T dt_2 \psi_f(t_1, t_2) = \left\{ \begin{array}{l} \text{the same} \\ \text{procedure} \\ \text{as above} \end{array} \right\} \Rightarrow$$

$$\Rightarrow \boxed{\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T \psi_f(\tau) d\tau = 0} \quad \text{slutsky}$$

Example $f(x) = x^2(t)$

$$\psi_f(\tau) = \langle (x^2(t) - \langle x^2 \rangle) (x^2(t+\tau) - \langle x^2 \rangle) \rangle$$

(f) 2-point for stationary process

Let $\langle x \rangle = 0$

$$Q. \overline{x(t)x(t+\tau)}^T = \frac{1}{T-\tau} \int_0^{T-\tau} x(t)x(t+\tau) d\tau \rightarrow$$

$$\rightarrow \langle x(t)x(t+\tau) \rangle ?$$

$$A. \text{Var} \left\{ \overline{x(t)x(t+\tau)}^T \right\} \xrightarrow{T \rightarrow \infty} 0$$

Introduce ACF of $\eta_\tau(t) = x(t)x(t+\tau)$

$$ACF \equiv \psi_\eta(\sigma) = \langle \eta_\tau(t)\eta_\tau(t+\sigma) \rangle - \langle \eta_\tau(t) \rangle \langle \eta_\tau(t+\sigma) \rangle =$$

$$= \langle x(t)x(t+\tau)x(t+\sigma)x(t+\sigma+\tau) \rangle - \underbrace{\langle x(t)x(t+\tau) \rangle \langle x(t+\sigma)x(t+\sigma+\tau) \rangle}_{\langle x(t)x(t+\tau) \rangle}$$

$$\boxed{\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T \psi_\eta(\sigma) d\sigma = 0} \quad \text{Slutsky}$$

Remark 1 As a rule: $\langle \eta_\tau(t)\eta_\tau(t+\tau) \rangle \xrightarrow{\sigma \rightarrow \infty} \langle \eta_\tau(t) \rangle \langle \eta_\tau(t+\tau) \rangle \Rightarrow$
 $\Rightarrow OK$

Remark 2. Example of nonstationary process that is ergodic in the mean

$$x(t) = x_0 + a \cos \omega t, \quad a \text{ r.v.}, \langle a \rangle = 0, \quad x_0 = \langle x(t) \rangle = \text{const}$$

$$\text{Nonstationary: } \langle (x - x_0)^2 \rangle = \langle a^2 \rangle \cos^2(\omega t) \Rightarrow \text{Var}[x(t)] \text{ is time-dependent} \Rightarrow x(t) \text{ non-stationary}$$

However,

$$\overline{x(t)} = \frac{1}{T} \int_0^T (x_0 + a \cos(\omega t)) dt = x_0 = \langle x(t) \rangle \quad x(t) \text{ is mean ergodic}$$

$$\text{But } f(x) = x^2(t) = y(t)$$

$$y(t) = x_0^2 + 2x_0 a \cos \omega t + a^2 \cos^2 \omega t$$

$$\left. \begin{aligned} \langle y(t) \rangle &= x_0^2 + \langle a^2 \rangle \cos^2 \omega t \end{aligned} \right\} \Rightarrow \overline{y(t)} \neq \langle y(t) \rangle$$

$$\left. \begin{aligned} \langle y(t) \rangle &= x_0^2 + \langle a^2 \rangle \cos^2 \omega t \\ \overline{y(t)} &= x_0^2 + \frac{a^2}{2} \end{aligned} \right\} \Rightarrow \overline{y(t)} \neq \langle y(t) \rangle$$

II.4. Important classes of non-stationary processes

4.1. Nonstationary process with independent increments

Consider $x(t)$: sequence of time instants $t_1 < t_2 < \dots < t_n$

(a) Definition :

$$x(t_1), \underbrace{x(t_2) - x(t_1), x(t_3) - x(t_2), \dots, x(t_n) - x(t_{n-1})}_{\text{increment}}$$

are statistically independent

$$x(t_n) = x(t_1) + \sum_{j=2}^n [x(t_j) - x(t_{j-1})]$$

Remind : the stoch process is defined if we know all n -point probability densities for all n and all time instants

$$\begin{aligned} n\text{-point CF } \hat{p}_n(k_1, t_1; \dots, k_n, t_n) &= \langle \exp[i(k_1 x(t_1) + \dots + k_n x(t_n))] \rangle = \\ &= \langle \exp[i(k_1 + \dots + k_n)x(t_1) + i(k_2 + \dots + k_n)(x(t_2) - x(t_1)) + \\ &\quad + i(k_3 + \dots + k_n)(x(t_3) - x(t_2)) + \dots + i k_n (x(t_n) - x(t_{n-1}))] \rangle = \\ &= \langle \exp[i(k_1 + \dots + k_n)x(t_1)] \rangle \langle \exp[i(k_2 + \dots + k_n)(x(t_2) - x(t_1))] \rangle \\ &\quad \times \dots \times \langle \exp[i k_n (x(t_n) - x(t_{n-1}))] \rangle = \end{aligned}$$

$$= \hat{p}(k_1 + \dots + k_n; t_1) \hat{p}(k_2 + \dots + k_n; t_1, t_2) \dots \times \hat{p}(k_n; t_{n-1}, t_n)$$

$$\hat{p}(k, t) = \langle e^{ikx(t)} \rangle \quad \text{CF of } x(t)$$

$$\hat{p}(k, t_1, t_2) = \langle e^{ik(x(t_2) - x(t_1))} \rangle \quad \text{CF of increments of } x(t)$$

$$\hat{p}_2(k_1, t_1; k_2, t_2) = \langle e^{ik_1 x_1 + ik_2 x_2} \rangle$$

$$\hat{p}(k, t_1, t_2) = \hat{p}_2(-k, t_1; k, t_2)$$

(b) Gaussian process with independent increments
 $x(t)$ Gaussian

$x(t_2) - x(t_1)$ Gaussian

Reminder: Gaussian r.v. $\hat{p}_X(k) = \exp\left[i\mu k - \frac{\sigma^2 k^2}{2}\right]$

$$p_X(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$

$$\mu = \langle X \rangle$$

$$\sigma^2 \equiv \text{Var}\{X\} = \langle (X - \langle X \rangle)^2 \rangle$$

$$\langle X^u \rangle = \frac{1}{i^u} \left. \frac{d^u \hat{p}(k)}{dk^u} \right|_{k=0}$$

$$\hat{p}(k, t) = \exp\left[i\mu(t)k - \frac{1}{2}\sigma^2(t)k^2\right]$$

$$\hat{p}(k, t_1, t_2) = \langle e^{ik(x(t_2) - x(t_1))} \rangle =$$

$$= \exp\left[i\mu_\Delta(t_1, t_2)k - \frac{1}{2}\sigma_\Delta^2(t_1, t_2)k^2\right], \text{ where}$$

$$\mu(t) = \langle x(t) \rangle$$

$$\sigma^2(t) = \text{Var}\{x(t)\} = \langle (x(t) - \langle x(t) \rangle)^2 \rangle = \langle x^2(t) \rangle - \langle x(t) \rangle^2$$

$$\mu_\Delta(t_1, t_2) = \langle x(t_2) - x(t_1) \rangle$$

$$\sigma_\Delta(t_1, t_2) = \text{Var}\{(x(t_2) - x(t_1))\}$$

$$x(t_2) = x(t_1) + (x(t_2) - x(t_1)) \Rightarrow \sigma(t_2) = \sigma(t_1) + \sigma_\Delta(t_1, t_2)$$

↑
statistically independent

$$\Rightarrow \mu_\Delta(t_1, t_2) = \langle x(t_2) - x(t_1) \rangle = \mu(t_2) - \mu(t_1)$$

$$\sigma_\Delta(t_1, t_2) = \sigma(t_2) - \sigma(t_1)$$

PDFs $p(x, t) = \frac{1}{\sqrt{2\pi}\sigma(t)} \exp\left[-\frac{(x - \mu(t))^2}{2\sigma^2(t)}\right]$

$$p(x_2 - x_1; t_1, t_2) = \frac{1}{\sqrt{2\pi}(\sigma(t_2) - \sigma(t_1))} \exp\left[-\frac{(x_2 - x_1 - \mu(t_2) + \mu(t_1))^2}{2(\sigma^2(t_2) - \sigma^2(t_1))}\right]$$

Example 1. Wiener process (ordinary Brownian motion)
 $\mu(t) = 0$, $\sigma^2(t) = ct$, $c = \text{const}$

Applications: everywhere

Example 2 Scaled Brownian motion
 $\mu(t) = 0$, $\sigma^2(t) = ct^\alpha$, $\alpha > 0$, $c = \text{const}$

Applications: granular gases, hydrology, finance...

Remarks. 1) adding $\mu(t) \neq 0$ is trivial

2) terminology Wiener process $\sigma^2(t) = t$, $c = 1$