

5/3/2016

ELE 730 QIC890-T33

lecture 1

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Tue

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Lectures: EIT 3141, Tuesdays 8:30-11:20am

Part 1: 8:30-9:45am

Part 2: 10:00-11:20am

Office Hours: Th 3-4 pm, QNC 4104.

Problem Sets 4-5, 50% . $S(t) = S(0) \times (1-t) \times 0.1$ if $t < t_s$, 0 if $t > t_s$

Final Exam. 50%

key words syllabus.

Tue.

• Noise?

What is Noise?

Is Noise Bad or Good?

What are the synonyms of "Noise"?

- randomness deviations
- error
- fluctuations ...

Noise \equiv Spontaneous fluctuations in currents, voltages and other physical quantities of a system under test.

→ "limits" an ultimate sensitivity in any measurement

In 1998, R. Landauer "The noise is the signal." Nature 392, 658 (1998)

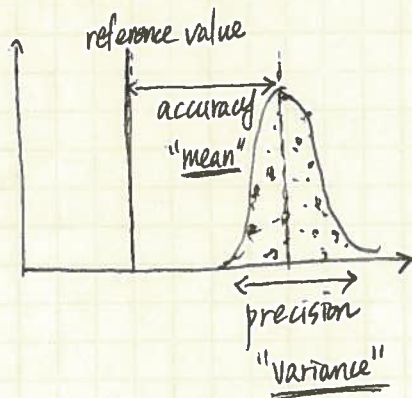
• Why do we have "noise" in a system data?• ~~noise~~• Noise: "statistical" quantity• \Rightarrow does not make sense to argue a single event at a certain time• Precision vs Accuracy

precision = a description of "random errors"
a measure of statistical variability

the degree to which repeated measurements under unchanged conditions to show the same results
"reproducibility", "repeatability"

vs accuracy = a description of "systematic errors"
a measure of statistical bias

the degree of closeness of measurements of a quantity

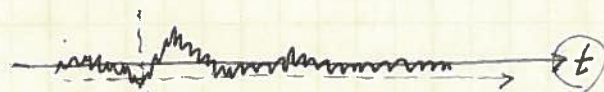


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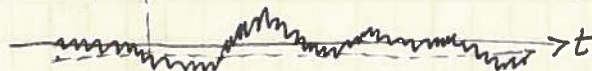
Two kinds of Statistics

sys.

[1]

 $x^{(1)}(t)$

[2]

 $x^{(2)}(t)$

[3]

 $x^{(3)}(t)$ time-average
"experimentalist"

[N]

 $x^{(N)}(t)$ ensemble average at t'
"theorist"① Time-average ("experimentalist's statistics")

$$\overline{x^{(i)}(t)} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x^{(i)}(t) dt \quad \text{mean = 1st-order time-average}$$

$$\overline{x^{(i)}(t)^2} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} [x^{(i)}(t)]^2 dt \quad \text{mean square = 2nd-order time-average}$$

$$\phi_x^{(i)}(\tau) \equiv \overline{x^{(i)}(t) x^{(i)}(t+\tau)} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x^{(i)}(t) x^{(i)}(t+\tau) dt$$

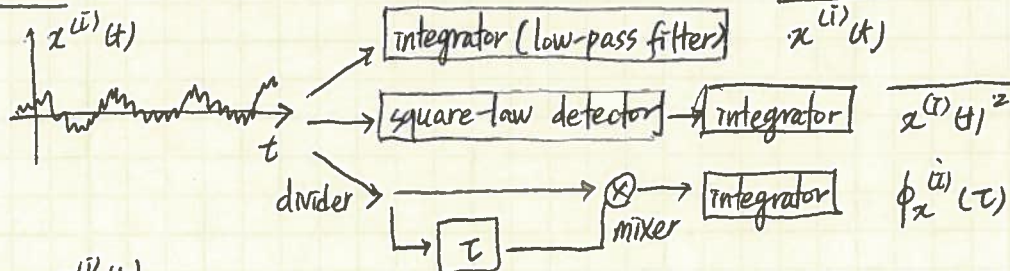
original
noise waveformdelayed
noise waveform

auto-correlation function

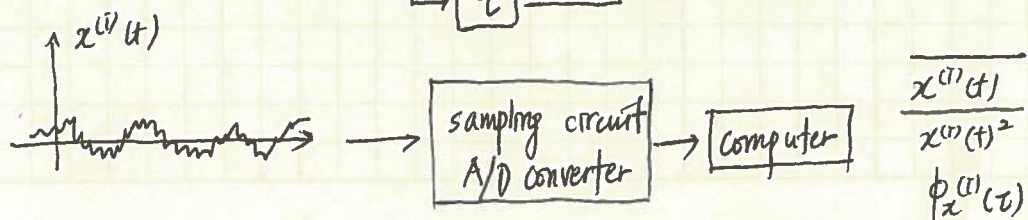
auto-correlation fn = time average of the original and delayed noise waveform.

When $\tau=0 \Rightarrow$ "mean square"= the correlation btw values of the process at different times of " τ "How to measure?

① Analog



② Digital



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② Ensemble-average (= "theorist's statistics") "given t "

$$\langle x(t_1) \rangle = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N x^{(i)}(t_1) = \int_{-\infty}^{\infty} x_1 p_1(x_1, t_1) dx_1 \quad \text{mean} = 1\text{st-order ensemble average}$$

↑ probability density fn.

$$\langle x(t_1)^2 \rangle = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N [x^{(i)}(t_1)]^2 = \int_{-\infty}^{\infty} x_1^2 p_1(x_1, t_1) dx_1 \quad \text{mean square} = 2\text{nd-order ensemble average}$$

$$\langle x(t_1)x(t_2) \rangle = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N x^{(i)}(t_1)x^{(i)}(t_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 p_2(x_1, x_2; t_1, t_2) dx_1 dx_2$$

• $p_1(x_1, t_1)$ = first-order probability density function

Covariance = a measure of how much 2 random variables change together

cf) correlation coeff. = normalized version of the cov.

$p_1(x_1, t_1) dx_1$: probability that x is found in the range between x_1 and $x_1 + dx_1$ at t_1

• $p_2(x_1, x_2; t_1, t_2)$ = second-order joint probability density function

$p_2(x_1, x_2; t_1, t_2) dx_1 dx_2$: probability that x is found in the range btw x_1 and $x_1 + dx_1$ at t_1 and x is found in the range btw x_2 and $x_2 + dx_2$ at t_2

(Theory) Fokker-Planck equation: calculation of probability distributions

⇒ obtain the probability density functions p_1 and p_2 .

Q: How can we close the gap between "Time-Average" and "Ensemble-Average"?

When is "theoretical predictions from ensemble averaging" equivalent to "experimental results" from time averaging?

Need (Introduce) "Ergodicity" & "Statistical stationarity"

→ equivalent when and only when the system is a so-called "ergodic ensemble"
ensemble averaging and time averaging are identical for a statistically-stationary system
different for a statistically-nonstationary system

Introduce "Ergodicity" & "Statistical stationarity"

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Ergodicity

in mathematics, a dynamical system has the same behavior averaged over time as averaged over the space of all system's state (phase space)

in statistics, a random process for which the time average of one sequence of events is the same as the ensemble average.

When do we need "ergodicity"?

we have only 1 sample fn of a stochastic process instead of the entire ensemble

if the process is ergodic,

even w/ 1 sample fn, all statistical information can be derived from time averaging

~~is not~~
① Ergodic in the mean

$$\bar{x(t)} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t) dt = \langle x(t) \rangle$$

↑
calculation w/ a particular member $x(t)$ & time averaging

↑
ensemble-average.
using the "1st-order" PDF $P_1(x, t)$

↑
~~time~~-independent.

↑
∴ constant

∴ ergodicity of mean implies the stationarity of the mean
(vice versa doesn't hold the truth.)

② Ergodic in the autocorrelation

$$\phi_x(\tau) = \overline{x(t)x(t+\tau)} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)x(t+\tau) dt = \langle x(t)x(t+\tau) \rangle$$

↑
calculation w/ $x(t)$

↑
using the 2nd-order PDF.

HW Q

Consider the example of the processes which are ergodic in the mean,
the autocorrelation
or/and
both.

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statistically-stationary process vs. statistically-nonstationary process.

$\langle \underline{x(t_1)} \rangle, \langle x(t_1)^2 \rangle$: independent of the time t_1

left ↓ not true

$\langle x(t_1) x(t_2) \rangle$: independent of t_1 & t_2
but dependent on $|t_2 - t_1|$

"concept of ensemble average" is valid,
but not time average.

no preferred begin in time

Wiener-Khinchine theorem

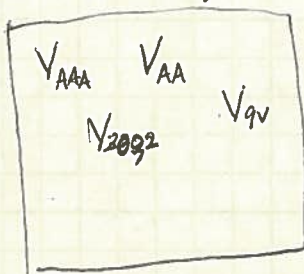
A stochastic process is wide-sense stationary

if its mean value is constant

and its autocorrelation function depends only on $\tau = t_2 - t_1$
time difference.

← "revisit - later"

Example statistically-stationary process



suppose select a battery at random & measure Voltage
 $v(t)$ = a member from selected from a
certain sub-group of constant
battery voltage

$$\langle \underline{v_{AAA}}(t) \rangle \approx 1.5 \text{ V indep. of time } t_1$$

$$\langle v_{AAA}^2(t) \rangle \approx \text{constant}$$

$$\langle \underline{v_{AAA}}(t_1) \underline{v_{AAA}}(t_2) \rangle \approx \text{constant}$$

∴ statistically stationary

Is this ergodic? No, why?

Example statistically-stationary & ergodic?

$$x(t) = \sin(\omega t + \theta)$$

↑ random variable,

$$0 \leq \theta \leq 2\pi$$

$$P(\theta) = \frac{1}{2\pi}$$

ergodic in the
mean?

Proof

$$\overline{x(t)} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-T/2}^{T/2} \sin(\omega t + \theta) dt \approx 0, \quad \text{time-average}$$

$$\langle x(t) \rangle = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N x^{(i)}(t) \\ = \int_{-\infty}^{\infty} x(t) P(\theta) d\theta = \int_{-\infty}^{\infty} \sin(\omega t + \theta) \frac{1}{2\pi} d\theta \approx 0$$

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Fourier Analysis time-domain vs frequency-domain

When $x(t)$ is absolutely integrable, i.e., $\int_{-\infty}^{\infty} |x(t)| dt < \infty$,

the Fourier transform of $x(t)$ is defined by, $X(i\omega) = \int_{-\infty}^{\infty} x(t) e^{-i\omega t} dt$,

the inverse Fourier transform is $x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(i\omega) e^{i\omega t} d\omega$ (Pf) $\frac{1}{2\pi} \int_{-\infty}^{\infty} X(i\omega) e^{i\omega t} d\omega$

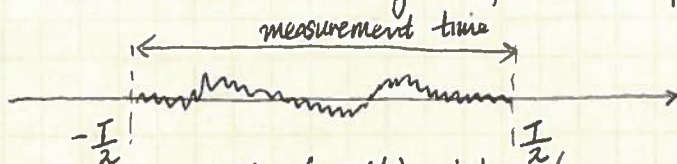
Does the Fourier transform of a statistically-stationary process exist?

No. Why? $\int_{-\infty}^{\infty} |x(t)| dt$ is not absolutely integrable

\therefore No. Fourier Transform exists

How to overcome this problem?

Since the measurement time is finite,
we can introduce "the gated function" $x_T(t)$



$$x_T(t) = \begin{cases} x(t) & |t| \leq T/2 \\ 0 & |t| > T/2 \end{cases}$$

Fourier
Transform

$$X_T(i\omega) = \int_{-\infty}^{\infty} x_T(t) e^{-i\omega t} dt$$

$$x_T(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X_T(i\omega) e^{i\omega t} d\omega$$

Now $\int_{-\infty}^{\infty} |x_T(t)| dt < \infty$, absolutely integrable

\therefore the Fourier transform of the $x_T(t)$ exists.

if $x(t)$ is real,

$\text{Re}(X(i\omega)) = \text{even fn of } \omega$

$\text{Im}(X(i\omega)) = \text{odd fn of } \omega$

$$X(i\omega) = X^*(-i\omega)$$

Lists of Theorems

- ① Parseval Theorem
- ② ~~Wiener~~ Energy Theorem
- ③ Wiener-Khinchine Theorem

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1. Parseval Theorem

$$x_1(t) \longleftrightarrow X_1(j\omega)$$

$$x_2(t) \longleftrightarrow X_2(j\omega)$$

consider the "auto correlation" fn

$$\begin{aligned} \int_{-\infty}^{\infty} x_1(t) x_2^*(t) dt &= \int_{-\infty}^{\infty} dt x_1(t) \frac{1}{2\pi} \int_{-\infty}^{\infty} d\omega X_2(j\omega)^* e^{-j\omega t} \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} d\omega X_2(j\omega)^* \left[\int_{-\infty}^{\infty} dt x_1(t) e^{-j\omega t} \right] \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X_1(j\omega) X_2(j\omega)^* d\omega \end{aligned}$$

consider the "auto correlation" fn

$$x_1(t) = x_T(t+\tau) \quad x_2(t) = x_T(t)$$

$$\begin{aligned} \int_{-\infty}^{\infty} x_T(t+\tau) x_T(t) dt &= \frac{1}{2\pi} \int_{-\infty}^{\infty} |X_T(j\omega)|^2 e^{j\omega\tau} d\omega \\ &\quad \uparrow \int_{-\infty}^{\infty} x_T(t+\tau) e^{-j\omega t} dt = X_T(j\omega) e^{j\omega\tau} \end{aligned}$$

$$\begin{aligned} &\int_{-\infty}^{\infty} x_T(t+\tau) \frac{1}{2\pi} \int_{-\infty}^{\infty} X_T(j\omega) e^{j\omega\tau} d\omega \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X_T(j\omega) \left[\int_{-\infty}^{\infty} x_T(t+\tau) e^{-j\omega t} dt \right] d\omega \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X_T(j\omega) X_T(j\omega)^* e^{j\omega\tau} d\omega \end{aligned}$$

2. Energy theorem

If $\tau=0$,

$$\boxed{\int_{-\infty}^{\infty} |x_T(t)|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X_T(j\omega)|^2 d\omega} = \text{the total energy}$$

$X_T(j\omega)$ = the (complex) amplitude of the harmonic component ($e^{j\omega t}$)
in a gated fn $x_T(t)$

$|X_T(j\omega)|^2$ = the energy density of this harmonic component
with units of energy per Hz

$$\int_{-\infty}^{\infty} |x_T(t)|^2 dt = \text{the total energy.}$$

= increases linearly with T for a statistically-stationary process

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3. Wiener-Khinchine theorem

Consider the ensemble-averaged autocorrelation ftn.

① statistically-stationary process

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\infty}^{\infty} \langle x_T(t+\tau) x_T(t) \rangle dt = \lim_{T \rightarrow \infty} \frac{1}{2\pi} \int_0^{\infty} \frac{2\langle |X_T(i\omega)|^2 \rangle}{T} \cos(\omega\tau) d\omega$$

: statis

② statistically-nonstationary process

$$\frac{1}{T} \int_{-\infty}^{\infty} \langle x_T(t+\tau) x_T(t) \rangle dt = \frac{1}{2\pi} \int_0^{\infty} \frac{2\langle |X_T(i\omega)|^2 \rangle}{T} \cos(\omega\tau) d\omega$$

Wiener-Khinchine theorem: the autocorrelation function of a wide-sense stationary random process has a spectral decomposition given by the power spectrum of that process.

$$\langle \phi_x(\tau) \rangle = \frac{1}{2\pi} \int_0^{\infty} S_x(\omega) \cos(\omega\tau) d\omega$$

$$\langle \phi_x(\tau, T) \rangle = \frac{1}{2\pi} \int_0^{\infty} S_x(\omega, T) \cos(\omega\tau) d\omega$$

$$S_x(\omega) = 4 \int_0^{\infty} \langle \phi_x(\tau) \rangle \cos(\omega\tau) d\tau$$

$$S_x(\omega, T) = 4 \int_0^T \langle \phi_x(\tau, T) \rangle \cos(\omega\tau) d\tau$$

↑
HW
proof

$$S_x(\omega) = \lim_{T \rightarrow \infty} \frac{2\langle |X_T(i\omega)|^2 \rangle}{T}$$

Fourier Transform pairs

stationary

$$\langle 2\phi_x(\tau) \rangle \leftrightarrow S_x(\omega)$$

non-stationary

$$\langle 2\phi_x(\tau, T) \rangle \leftrightarrow S_x(\omega, T)$$