

LECTURE 2: RANDOM PROCESSES

Lecture by Kip S. Thorne

Assigned Reading:

- D. Pages 5-1 through 5-24 of “Chapter 5. Random Processes” from the textbook manuscript *Applications of Classical Physics* by Roger Blandford and Kip Thorne.

Suggested Supplementary Reading:

- a. L. A. Wainstein and V. D. Zubakov, *Extraction of Signals from Noise* (Prentice Hall, London, 1962; Dover, New York, 1970). [This wonderful book—a sort of biblical primer on the subject—is long since out of print. Kip will put his personal xerox copy on reserve in Millikan Library for a few weeks, along with the library’s only copy.]

Two Suggested Problems from Blandford and Thorne’s “Chapter 5, Random Processes”:

- 5.1 *Bandwidths of a finite-Fourier-transform filter and an averaging filter* [page 5-21]
5.2 *Wiener’s Optimal Filter* [page 5-22]. This is an especially important exercise, since the optimal filter underlies much of the data analysis to be done in LIGO.

Lecture 2

Random Processes

by Kip S. Thorne, 1 April 1994

This lecture actually consumed only half of the 90 minutes on 1 April; the completion of Lecture 1 consumed the other half.

This lecture was largely just a blackboard presentation of the key issues in Reference D [pages 5-1 through 5-24 of "Chapter 5. Random Processes" from the textbook manuscript *Applications of Classical Physics* by Roger Blandford and Kip Thorne]. Since that reference is included in Volume II, we here present, as a record of Lecture 2, only the scrawled notes from which Kip lectured.

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1. Example of RP: $I(t)$; $h(t) = C \cdot I_{pp}(t)$; $x(t)$ test mag

2. Sp Noise spectrum - VG show - what means? [Mean Removed]

↑ $h(f) \equiv \sqrt{S_h(f)}$

Like FT: $h(f) = \int_{-\infty}^{+\infty} h(t) e^{i2\pi ft} dt$

... no ... diverged; complex

Try $\lim_{T \rightarrow \infty} \frac{1}{T} \left| \int_{-T/2}^{+T/2} h(t) e^{i2\pi ft} dt \right|^2$ Same f & -f
→ follow

→ $G_h(f) \equiv S_h(f) \equiv [h(f)]^2 = \lim_{T \rightarrow \infty} \frac{2}{T} \left| \int_{-T/2}^{+T/2} h(t) e^{i2\pi ft} dt \right|^2$

[For Example $G_E(f) = \frac{4\pi}{\epsilon} \frac{dG}{dA dt df}$] Units: strain/√Hz

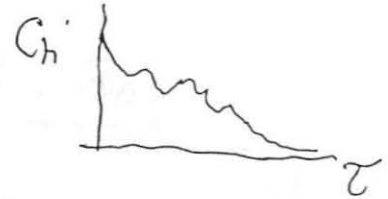
3. Correlation function

$C_h(\tau) \equiv \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-T/2}^{+T/2} h(t) h(t+\tau) dt$

4. Wiener-Khinchin Thm

$C_h(\tau) = \int_0^\infty G_h(f) \cos 2\pi f \tau df$

$G_h(f) = 4 \int_0^\infty C_h(\tau) \cos 2\pi f \tau d\tau$



5. Variance:

$C_h(0) = \int_0^\infty G_h(f) df = \overline{[h^2(t)]} = \sigma_h^2$

- but might not converge @ low f.

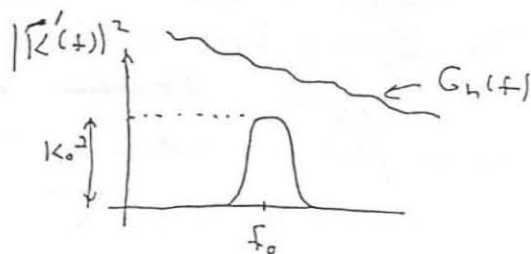
6. Filtering

a. $H(t) \equiv \int_{-\infty}^{+\infty} K(t-t') h(t') dt'$

b. If we were ~~not~~ worried to finite time: $H(f) = \hat{K}(f) h(f)$

c. For RP: $G_H(f) = \underbrace{|\hat{K}(f)|^2}_{\text{converges}} G_h(f)$

7. Band Pass Filter



$\int_{f_0 - \Delta f}^{f_0 + \Delta f} G_h(f) df$

$$\sigma_H^2(f) = \int_{f_0 - \Delta f}^{f_0 + \Delta f} |K'(f)|^2 G_h(f) df \approx G_h(f_0) \int_{f_0 - \Delta f}^{f_0 + \Delta f} |K'(f)|^2 df$$

$$\sigma_H^2(f) = \underbrace{[G_h(f_0) \cdot \Delta f]}_{\text{rms fluctuations of } h \text{ in bandwidth } \Delta f} \cdot K_0^2$$

a. Simple example of Bandpass filter:

$$H(t) = \int_{t-\Delta t}^t \cos[2\pi f_0(t-t')] y(t') dt'$$

$$\Delta f = 1/\Delta t$$

8.

Example: A line spike in spectrum ... large rms fluctuations over that Δf .

9. Wiener Optimal Filter:

a. $h(t) = \underbrace{A s(t)}_{\text{unknown}} + n(t)$... want to find $s(t)$ then do \rightarrow so how strong, A

Best way should be to cross correlate: $\int h(t) \cdot s(t) dt$

- Butter: Suppress ~~cross~~ frequencies where detector is

noisy ... $\int_{f_0 - \Delta f}^{f_0 + \Delta f} \frac{\overline{S'(f)}}{G_h(f)} df$ -- then cross correlate:

$$W = \int h(t) S_F(t) dt = \int \frac{\overline{h'(f) S(f)}}{G_h(f)} df$$

b. Signal contributes to W is S ; noise N is random @
 same mean \bar{N} : $W = S + N$.

$$\frac{S}{\bar{N}} = 4 \int_0^{\infty} \frac{|S(f)|^2}{G_n(f)} df$$

11. Known spectrum does not tell us $P(N)$, the probability
 dist'n of N . But if we know it is Gaussian, then

~~$$P(N) = \frac{1}{\sqrt{2\pi N}} \exp\left[-\frac{(N-\bar{N})^2}{2N}\right]$$~~

$$P(N) = \frac{1}{\sqrt{2\pi \bar{N}^2}} \exp\left[-\frac{N^2}{2\bar{N}^2}\right]$$

Key issue in L160 is

12. If instrument clean, then enough [not likely], noise
 is superposition of influences of many different things
 Central limit. then \Rightarrow Gaussian

13. Central issue will be: Gaussian or not?