

## 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

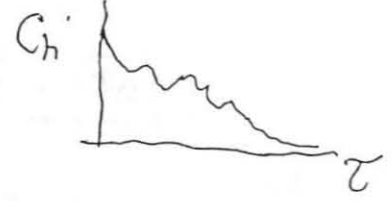
3. Correlation function

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

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:

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

- but might not converge @ low f.

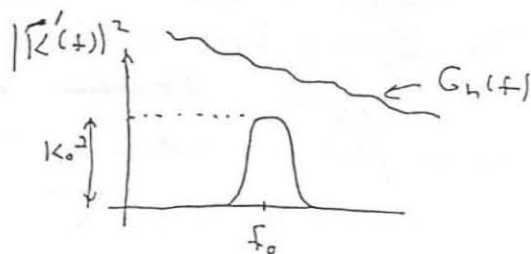
6. Filtering

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



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

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

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

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 near that  $f$ .

9. Wiener Optimal Filter:

a.  $h(t) = \underbrace{A}_{\text{unknown}} s(t) + n(t)$  ... 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: Suppresses ~~cross~~ frequencies where detector is

noisy ...  $\int_F h^*(f) S^*(f) df$  -- then cross correlate:  $G_h(f)$

$$W = \int h(t) S_F(t) dt = \int \frac{h^*(f) S^*(f) df}{G_h(f)}$$

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?