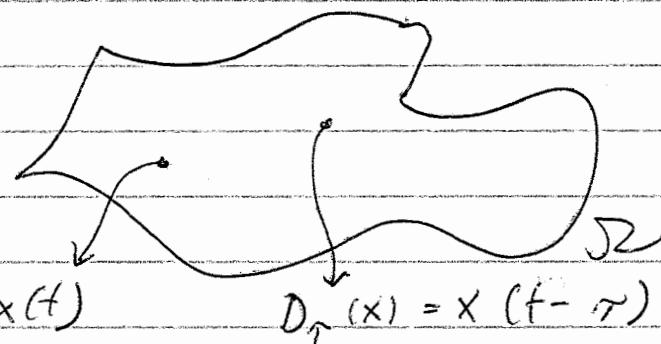


1. Power Spectra

The general problem: characterize a "noise" $x(t)$.



We typically have access to multiple samples at different start times. So, to set off the ground; assume

a) Stationarity : If $D_\tau(x) = x(t - \tau)$,
then $p(D_\tau(x)) = p(x)$

b) Ergodicity $\langle \rangle_S = \langle \rangle_\tau$

for "all" functions on $p(x_1, p(y), \dots)$

c) For suff. large T , $x(t)$ and $x(t + T)$ are independent.

Note that defining $p(x)$ takes some care.

In discrete case; define

prob. ($x(t)$ between $x_i + \Delta x$ and

$x(t_2)$ " $x_2 + \Delta x$, "

:

$x(t_k)$ " $x_k + \Delta x$) = $P(x_1, \dots, x_k) (\Delta x)^k$

2

and these prob's need to be defined in a self-consistent way, for all $\{x_1, \dots, x_k\}$, $k=1, 2, \dots$

Similarly in continuous time

We can always take $\langle x(t) \rangle_{\mathcal{R}} = 0$, since

ergodicity \Rightarrow it is a constant, & we can re-parametrize if $\langle x(t) \rangle_{\mathcal{R}} = \mu \neq 0$.

But of course sample mean may not be 0.

In view of results of last § (maxent + C.L.T.), we will take \mathcal{R} to be a Gaussian, but parameters of the Gaussian may not be known. Then, extend.

Since $\langle x(t) \rangle_{\mathcal{R}} = 0$, it is not a useful descriptor

what about $C_x(\tau_1, \tau_2) = \langle x(\tau_1)x(\tau_2) \rangle_{\mathcal{R}}$?

Now $C_x(\tau_1, \tau_2) = \langle x(\tau_1 + t)x(\tau_2 + t) \rangle_{\mathcal{R}}$ (say t)

so $C_x(\tau_1 + t, \tau_2 + t) = C_x(\tau_1, \tau_2)$, and we can write

$$C_x(\tau_1, \tau_2) = C_x(\tau_1 - \tau_2), \text{ where } C_x(t) \equiv C_x(t, 0).$$

Also $C_x(\tau_1, \tau_2) = C_x(\tau_2, \tau_1)$, so $C_x(t) = C_x(-t)$.

This is the auto covariance. Auto corr. = $C_x(t)/C_x(0)$.

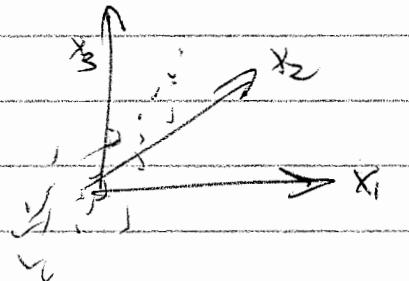
3.

Geometrically:

With $\mathbf{x} = (x_1, x_2, \dots, x_n, \dots)$,

$C_x(t)$ describes covariance of x_r and x_{r+t} , i.e.,

the shape of the ellipse



But a) translation-in-time symmetry \Rightarrow certain covariances must be equal

b) Some covariances influence others, e.g.

If x_3 and x_4 are highly correlated,
then x_4 and x_5 " "

and x_3 and x_5 must be somewhat correlated

c) Some correlations appear easier to measure

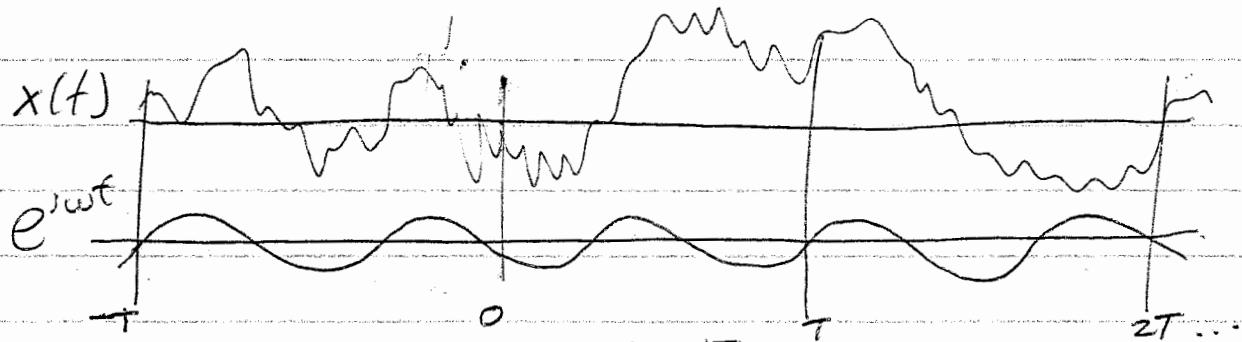
(x_k, x_{k+l}) than others $(x_k, x_{k+large})$.

So it is not clear how to do estimations -
e.g., how to put error bars on $C_x(t)$

What about trying to characterize $\tilde{x}(w) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$?

This should deal with time-translation. However;
 $\tilde{x}(w)$ is ill-defined:

4.



$$I = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt = \sum_{N=-\infty}^{\infty} \int_{NT}^{(N+1)T} x(t) e^{-j\omega t} dt$$

$$= \sum_{N=-\infty}^{\infty} F(x; \omega, T, NT) = \sum_{N=-\infty}^{\infty} F_N$$

F_N = a "Fourier estimate" at freq. ω , length T ,
start time NT , of $x(t)$

How are the F_N 's distributed?

$$F(x; \omega, T, T_0) = \int_{T_0}^{T_0+T} x(t) e^{-j\omega t} dt$$

$$u = t + T_0$$

$$= \int_0^T x(u - T_0) e^{-j\omega(u - T_0)} du$$

$$= e^{j\omega T_0} \int_0^T x(u - T_0) e^{-j\omega u} du$$

$$= F(D_{T_0}(x); \omega, T, 0) \cdot e^{j\omega T_0}$$

5.

But D is translation-invariant, so any statistic on x must = that statistic on $D_{T_0}(x)$.

So $F(x; \omega, T, T_0)$ must be distributed like

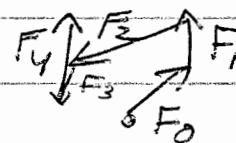
$$F(x; \omega, T, 0) \cdot e^{i\omega T_0}$$

But $F(x; \omega, T, T_0)$ must also be distributed like $F(x; \omega, T, 0)$ since when you set "wall clock" time to 0 is arbitrary.

So each $F(x; \omega, T, T_0)$ is distributed circularly-symmetrically in the complex plane.

But also, for T sufficiently large, "most" of the interval of $[NT, (N+1)T]$ is very far from the adjacent intervals, so "most" of each estimate F_N is independent of adjacent, & all other, intervals. [condition (c)]

Take $I = \sum_{k=0}^{K-1} F_N$, but the F_N 's consist of random-walk steps in the plane:



So, $\langle I_{K-1} \rangle = 0$ but

$$\langle |I_K|^2 \rangle = \langle \left| \sum_{n=0}^{K-1} F_n \right|^2 \rangle = \sum_{N,M=0}^{K-1} \langle F_N F_M \rangle = K \langle |F_0|^2 \rangle$$

6.

So $I_{KT} = \int_0^{KT} x(t) e^{-j\omega t} dt$ has mean 0, and variance proportional to K (fixed T).
 Proportionality depends on T .

Since T is arbitrary (but large),

I_{KT} must have variance proportional to KT .

Conversely, we expect that

$$\lim_{T \rightarrow \infty} \frac{1}{T} \left\langle \left| \int_0^T x(t) e^{-j\omega t} dt \right|^2 \right\rangle \text{ exists.}$$

This is the power spectrum. Units: $\text{X}^2 \cdot T, \text{ or, } \text{X}^2 / \text{Hz}$

$$P_X(\omega) = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle \left| \int_0^T x(t) e^{-j\omega t} dt \right|^2 \right\rangle = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle |F(x, \omega, T, t_0)|^2 \right\rangle$$

Because of ergodicity (b), can replace $\langle \dots \rangle_T$ by $\langle \dots \rangle_{t_0}$.

Because of limited correlation length (c), can replace $\langle \dots \rangle_{t_0}$ by

$$P_X(\omega) = \lim_{T \rightarrow \infty} \frac{1}{N} \sum_{n=0}^{N-1} \frac{1}{T} |F(x, \omega, T, nT + t_0)|^2$$

Note the difficulties with a "plug-in" estimation

- can't make $T \rightarrow \infty$

- with data of length L , reciprocity between

- length of segment T , & max # of segments. L/T

- tradeoff b/w frequency resolution $\Delta\omega$ and N ,
 since $T \geq L/\Delta\omega$.

What if there is a deterministic component in $x(t)$, namely,

$$x(t) = x_p(t) + x_N(t)$$

$\underbrace{\quad}_{\text{"periodic"}}$ $\underbrace{\quad}_{\text{"noise"}}$

$$F(x; \omega, T, T_0) = F(x_p, \omega, T, T_0) + F(x_N, \omega, T, T_0).$$

$F(x_N, \omega, T, T_0)$ behaves as above.

But $\langle F(x_p, \omega, T, T_0) \rangle$ typically not 0.

With $T = mP$, P a period of $x_p(t)$, and $\omega = \frac{2\pi h}{P}$

$$\begin{aligned} \langle F(x_p, \omega, T, T_0) \rangle &= \int_{T_0}^{mP+T_0} x_p(t) e^{-i \frac{2\pi h}{P} t} dt \\ &= m \int_{T_0}^{P+T_0} x_p(t) e^{-i \frac{2\pi h}{P} t} dt \end{aligned}$$

$$= T \cdot \frac{1}{P} \int_{T_0}^{P+T_0} x_p(t) \bar{e}^{\frac{2\pi h}{P} t} dt$$

$= T \langle \tilde{x}_p \rangle_h$, i.e., proportional to h^{th} .

F.C. of x_p .

So, the defining limit of the R.S. does not exist.

8-

However, can write

$$P_{X_n}(w) = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle |F(x; w, T, T_0) - \langle F(x; w, T, T_0) \rangle|^2 \right\rangle$$

Since $\langle F(x; w, T, T_0) \rangle$ typically not known,

it has to be estimated from data. Using standard
debiased variance estimate,

$$P_{X_n}(w) = \lim_{\substack{T \rightarrow \infty \\ n \rightarrow \infty}} \frac{1}{n-1} \sum_{n=0}^{N-1} \frac{1}{T} \left| F(x; w, T, nT + T_0) - \frac{1}{n} \sum_{n=0}^{n-1} F(x; w, T, nT + T_0) \right|^2$$

Why do we not need to consider the more general

$$W_{X_n}(w_1, w_2) = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle F(x; w_1, T, T_0) F(x; w_2, T, T_0) \right\rangle,$$

or even

$$W_{X_n}(w_1, w_2, \Delta T) = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle F(x; w_1, T, T_0) F(x; w_2, T, T_0 + \Delta T) \right\rangle?$$

Previous (p. 4-5) argument shows that shifting the start-time T_0 by, say, ΔT and choosing a new sample $D_{\Delta T}(x)$ multiplies the value of $F(x; w, T, T_0)$ by $e^{iw_1 \Delta T}$.

Similarly, value of $F(x; w_2, T, T_0)$ is multiplied by $e^{iw_2 \Delta T}$.

So the product is multiplied by $e^{i(w_1 + w_2) \Delta T}$.

9.

So there will only be a nonzero expectation if, for all σ ,

$$e^{i(\omega_1 + \omega_2)\sigma T} = 0, \text{ i.e., } \omega_1 + \omega_2 = 0, \text{ i.e.,}$$

$$W_x(\omega_1 - \omega) \equiv P_x(\omega) \left[\sin \frac{F(x, -\omega, T, T_0)}{F(x, \omega, T, T_0)} \right]$$

However, $B_x(\omega, \omega_2) \equiv$

$$\lim_{T \rightarrow \infty} \frac{1}{T} \langle F(x, \omega_1, T, T_0) \overline{F(x, \omega_2, T, T_0)} F(x, \omega_1 + \omega_2, T, T_0) \rangle$$

make sense. "Bispectrum".

What about multi-channel data?

Cross-spectrum:

$$C_{XY}(\omega) = \lim_{T \rightarrow \infty} \frac{1}{T} \langle F(x, \omega, T, T_0) \overline{F(y, \omega, T, T_0)} \rangle$$

No need to consider two frequencies.

If we can estimate P , we can estimate C_{XY} :

$$\begin{aligned} \langle \overline{(X+Y)(X+Y)} \rangle &= |X|^2 + |Y|^2 + X\bar{Y} + Y\bar{X} \\ &= |X|^2 + |Y|^2 + 2 \operatorname{Re}(X\bar{Y}) \end{aligned}$$

$$\begin{aligned} \langle \overline{(X+iY)(X+iY)} \rangle &= |X|^2 + |Y|^2 + iY\bar{X} - iX\bar{Y} \\ &= |X|^2 + |Y|^2 + 2i\operatorname{Im}(X\bar{Y}) \end{aligned}$$

10.

So,

$$\operatorname{Re} C_{XY}(w) = \frac{1}{2} [P_{XY}(w) - P_X(w) - P_Y(w)] \quad \left. \right\} \text{ formal}$$

$$\operatorname{Im} C_{XY}(w) = \frac{i}{2} [P_{X+Y}(w) - P_X(w) - P_Y(w)] \quad \left. \right\}$$

So an estimator for P will lead to an estimator for C ; bias will be easy to calculate.

$$\text{Coherency} = \frac{C_{XX}(w)}{\sqrt{P_X(w)P_Y(w)}} \quad \text{Complex } \# | \leq 1$$

$$\text{Coherence} = | \text{Coherency} | .$$

Given $P_X(w)$, can we calculate a "typical" $x(t)$?

Draw from the moment distib speckledly $P_X(w)$.

Naive approach: segment a sand of length L , startig at $t=0$, sampled \in resolution Δt .

$F(x, w, \phi, L)$ is a complex # $\in \langle |F|^2 \rangle = L P_X(w)$, symmetrically distributed, i.e.

$\operatorname{Re} F$ has variance $\frac{1}{2} L P_X(w)$

$\operatorname{Im} F \sim \sim \frac{i}{2} L P_X(w)$

$\operatorname{Re} F + \operatorname{Im} F$ are independently distributed

p.

So, choose $\text{Re } F(\omega) + \text{Im } F(\omega)$ independently from

$$\frac{1}{\sqrt{2\pi} V} e^{-F^2/2V}, V = \frac{1}{2} L P_X(\omega)$$

Do this for a sufficient set of ω so that one can write

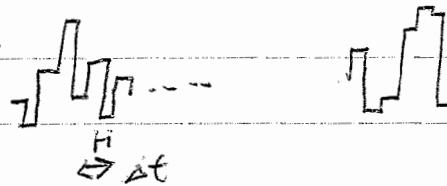
$$x(t) = \frac{1}{\sqrt{L}} \sum_{\omega = -\frac{1}{2\Delta t}}^{\frac{1}{2\Delta t}} F(\omega) e^{i\omega t}, \text{ constant value from } n\Delta t \\ \text{in steps of } \frac{1}{\Delta t} \quad (N = \frac{L}{\Delta t}) \quad (\text{from } n\Delta t \text{ to } (n+1)\Delta t)$$

Note $F(\omega=0)$ or $f(\omega=\frac{1}{2\Delta t})$ must be real, &

$$F(-\omega) = \overline{F(\omega)}$$

The $\frac{1}{\sqrt{L}}$ is to ensure that $\int_0^L x(t) e^{-i\omega t} dt = \sqrt{L}$

This makes a signal that looks like



Problem 1: its power spectrum, at intermediate freqs, doesn't agree in $P_X(\omega)$

2. It is periodic in parallel L .

Solution: use a larger L than you need. Then $\Delta\omega$ is smaller.

12. Properties of the Power Spectrum

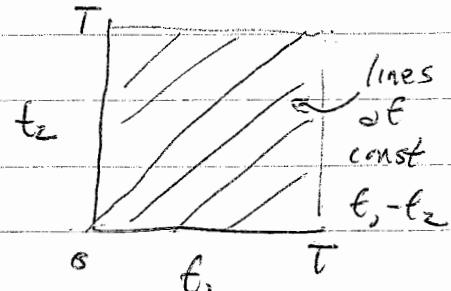
Relation to auto covariance

$$\text{From } P_x(\omega) = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle \left| \int_0^T x(t) e^{-j\omega t} dt \right|^2 \right\rangle$$

$$= \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle \left(\int_0^T x(t_1) x(t_2) e^{-j\omega t_1} e^{+j\omega t_2} dt_1 dt_2 \right) \right\rangle$$

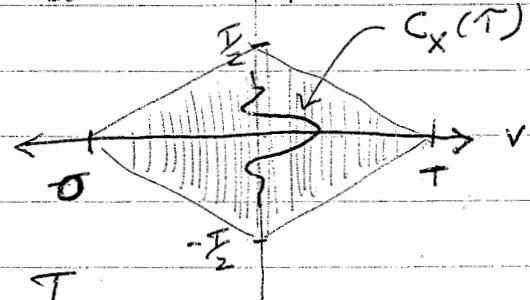
$$\gamma = t_1 - t_2$$

$$\nu = \frac{1}{2}(t_1 + t_2)$$



$$P_x(\omega) = \lim_{T \rightarrow \infty} \frac{1}{T} \left\langle \sum_{\gamma, \nu} x(\nu + \frac{\gamma}{2}) x(\nu - \frac{\gamma}{2}) e^{-j\omega \gamma} d\nu d\gamma \right\rangle$$

$$= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{\gamma, \nu} C_x(\gamma) e^{-j\omega \gamma} d\nu d\gamma$$



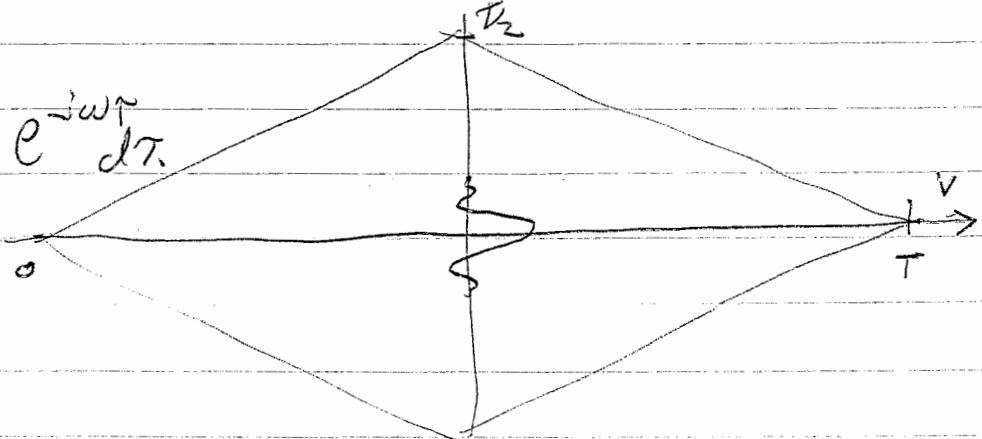
Once T is large enough

so that most of $C_x(\gamma)$

has been covered, by, say $|\gamma| \leq \frac{T}{1-\epsilon}$

then $\frac{1}{T} \int_0^T d\nu$ is within $1-\epsilon$ of 1, where $C(\gamma) \neq 0$.

$$\text{So } P_x(\omega) = \int_{-\infty}^{\infty} C_x(\gamma) e^{-j\omega \gamma} d\gamma.$$



13.

Analogous rel's for bispectrum & cross-spectrum.

$$\left(\text{to } \langle x(\tau_1)x(\tau_2)x(-\tau_1-\tau_2) \rangle \right) \left(\text{to cross-covariance} \right)$$

Superposition property: If $x(t) + y(t)$ are independent,

$$P_{x+y} = P_x + P_y$$

[cross-terms in det. of P.S. $\rightarrow 0$]

Weaker condition:

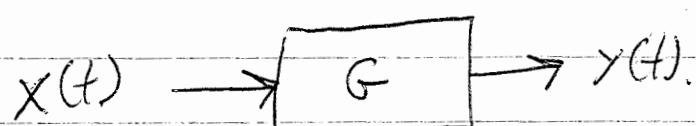
If $x(t)$ and $y(t')$ are uncorrelated - $P_{x+y} = P_x + P_y$.

Uncorrelatd: $\langle x(t)y(t') \rangle = 0$

Independent: $\langle A(x)B(y) \rangle = \langle A(x) \rangle \langle B(y) \rangle$

In either circumstance, $C_{XY}(w) = 0$.

Rel. to linear filtering:



$$F(w, y) = \hat{f}_y(w) F(w, X).$$

$$\begin{aligned} \hat{f}_y(w) &= \lim_{T \rightarrow \infty} \frac{1}{T} \langle |F(Y, w)|^2 \rangle \lim_{T \rightarrow \infty} \frac{1}{T} \langle |G_{\text{real}} F(X, w)|^2 \rangle \\ &= |\hat{f}_X(w)|^2 P_X(w) \end{aligned}$$

14.

Implications:

$$\bullet |G(\omega)|^2 = \frac{P_Y(\omega)}{P_X(\omega)}$$

Note phase of $G(\omega)$ cannot be determined

- Analysis of connectivity

- Can think of any Gaussian noise as a result of

$$W(t) \rightarrow \boxed{G} \rightarrow P_X(\omega)$$

\downarrow

$$P_W(\omega) = 1$$

provided $|G(\omega)| = \sqrt{P_X(\omega)}$

Though it may not be clear if phases can be assigned to $G(\omega)$ so that

$$\int g(\omega) e^{j\omega t} dt$$

is causal & finite.