

Basics of Signal Detection

Topics covered :

- Fourier Transforms (basic mathematical tool)
- Noise Spectral Density (characterising noise)
- Matched Filters (finding signals)
- Signal-to-Noise Ratio (SNR - signal detectability)

Topics not covered :

- Matches
- Template banks
- Parameter estimation
- Probability theory
- Detecting unmodelled signals
- Discretely sampled data (see handout: Ch 12, 13 of "Numerical Recipes")

Fourier Transforms

"Any" (reasonably behaved) function $x(t)$ can be written as a sum of sines and cosines, or equivalently as exponentials:

$$\cos 2\pi ft = \frac{e^{i2\pi ft} + e^{-i2\pi ft}}{2} \quad \sin 2\pi ft = \frac{e^{i2\pi ft} - e^{-i2\pi ft}}{2i}$$

Fourier transform definition:

$$x(t) = \int_{-\infty}^{\infty} \underbrace{\tilde{x}(f)} e^{i2\pi ft} df$$

where

$$\tilde{x}(f) = \int_{-\infty}^{\infty} x(t) e^{-i2\pi ft} dt$$

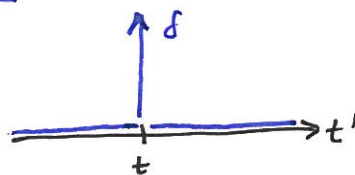
"Fourier transform of $x(t)$ "

Self-consistency check:

$$\begin{aligned} x(t) &= \int_{f=-\infty}^{\infty} \left[\int_{t'=-\infty}^{\infty} x(t') e^{-i2\pi ft'} dt' \right] e^{i2\pi ft} df \\ &= \int_{t'=-\infty}^{\infty} x(t') \left[\int_{f=-\infty}^{\infty} e^{+i2\pi f(t-t')} df \right] dt' \\ &= \int_{t'=-\infty}^{\infty} x(t') \underbrace{\delta(t-t')} dt' \\ &= x(t) \end{aligned}$$

Here $\delta(\cdot)$ is the Dirac delta function:

Roughly speaking:
$$\delta(t-t') = \begin{cases} 0 & t \neq t' \\ \infty & t = t' \end{cases}$$



more

rigorous definition:
$$\int_{-\infty}^{\infty} \delta(t-t') f(t') dt' = f(t) \quad \text{for any function } f.$$

Properties of the Fourier Transform:

① If $x(t)$ is real then $\tilde{x}(-f) = \tilde{x}^*(f)$ so we can focus on positive frequencies only, if we wish.

② Parseval's theorem (or Plancherel's theorem):

$$\int_{-\infty}^{\infty} \tilde{h}(t) \tilde{g}^*(t) dt = \int_{-\infty}^{\infty} \tilde{h}(f) \tilde{g}^*(f) df$$

③ The time and frequency domains are interchangeable - any calculation done with $x(t)$ can also be done with $\tilde{x}(f)$.

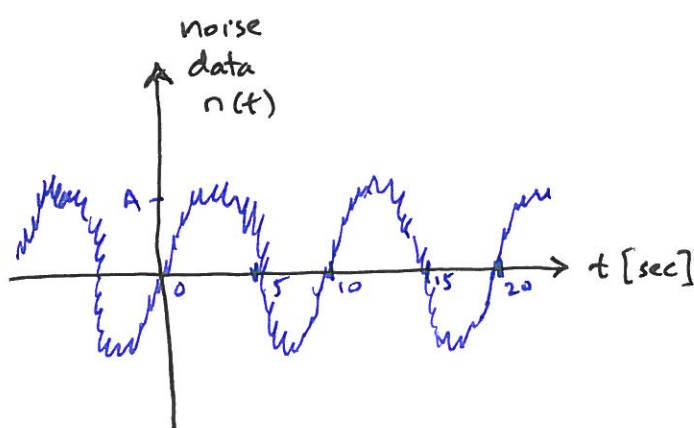
→ see Numerical Recipes, Ch 12 for more properties.

Why are Fourier Transforms useful in signal detection?

① Many signals and noise models have features which are simpler to model as functions of frequency than of time.

② Formulae in terms of frequencies are often simpler to write and faster to compute than their time-domain equivalents.

Toy Example: ~ Periodic Noise



$n(t) \approx$ sine wave with frequency $\sim 1/10$ sec + higher-frequency junk

$\approx A \sin(\underbrace{2\pi \times 0.1 \text{ Hz}}_{\text{Freq.}} t) + \text{higher-freq terms. (sines and cosines)}$

large amplitude "A"

Noise Power Spectral Density

The simplest case is noise that is stationary and Gaussian. Then $n(t)$ is fully characterised by its autocorrelation function $C(t)$:

$$C(t) \equiv E \left[n(t_0) n(t_0+t) \right]$$

\uparrow E : average over all noise realisations \leftarrow independent of start time t_0 ("stationary")

Toy noise example: 10 sec periodicity

if $n(t_0) > 0$ then probably $n(t_0 + 10s) > 0$ as well
 " " < 0 " " " " < 0 " "

We'll see it is more convenient to describe the noise in the frequency domain. Consider the Fourier transform, $\tilde{n}(f)$:

$$E \left[\tilde{n}(f) \tilde{n}^*(f') \right] = E \left[\int_{t_1=-\infty}^{\infty} n(t_1) e^{-i2\pi f t_1} dt_1 \int_{t_2=-\infty}^{\infty} n^*(t_2) e^{i2\pi f' t_2} dt_2 \right]$$

define new variable "t" by $t = t_2 - t_1$ to replace t_2

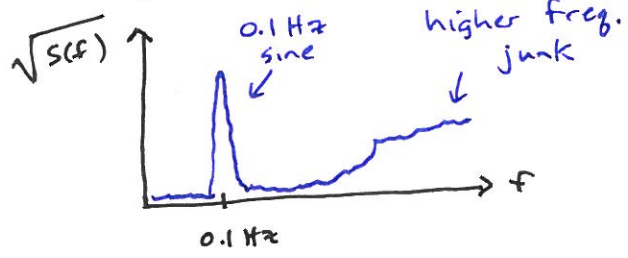
$$= \int_{t_1} \int_t E \left[\underbrace{n(t_1) n^*(t_1+t)}_{C(t)} \right] e^{-i2\pi(f-f')t_1} e^{i2\pi f' t} dt dt_1$$

$$= \underbrace{\left(\int_{t_1=-\infty}^{\infty} e^{-i2\pi(f-f')t_1} dt_1 \right)}_{\delta(f-f')} \underbrace{\left(\int_{t=-\infty}^{\infty} C(t) e^{i2\pi f' t} dt \right)}_{\text{Fourier transform of } C(t)}$$

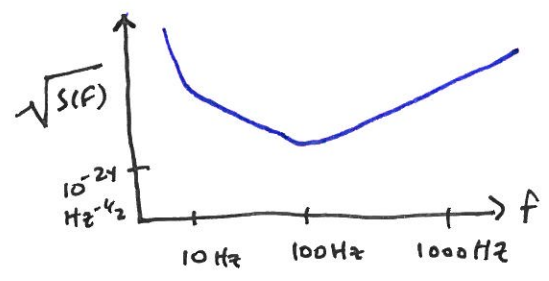
\Rightarrow call " $S(f')$ ", the noise power spectral density.
 [or $S(f')$]

$$\therefore E \left[\tilde{n}(f) \tilde{n}^*(f') \right] = \delta(f-f') S(f)$$

Toy Noise Example:



LIGO Noise:



BEWARE: Since $S(-f) = S(f)$, it is common to consider the one-sided spectral density $S_1(f)$, where

$$S_1(f) \equiv 2 S(f)$$

and work with $f > 0$ only. These notes stick with the two-sided spectrum $S(f)$ because it's simpler for the maths. The difference causes many factor of 2 errors in calculations!

Interpretation: $S(f)$ is the average value of $|\hat{n}(f)|^2$ - the squared noise in a given frequency bin.

Matched Filters

Suppose we know the signal $h(t)$ we're looking for. How do we determine if it is present in our noisy data?

$$d(t) = \underset{\substack{\uparrow \\ \text{data}}}{n(t)} + \underset{\substack{\uparrow \\ \text{noise}}}{h(t)} + \underset{\substack{\downarrow \\ \text{signal (may or may not be present)}}}{h(t)}$$

General approach: Integrate the data with a "filter function" $g(t)$:

$$\begin{aligned} \theta &= \int d(t) g(t) dt \\ &= \int \hat{d}(f) \tilde{g}^*(f) df \quad \downarrow \text{Parseval} \\ &= \underbrace{\int \tilde{n}(f) \tilde{g}^*(f) df}_{\text{noise response}} + \underbrace{\int \tilde{h}(f) \tilde{g}^*(f) df}_{\text{signal response}} \end{aligned}$$

Rule: Pick $\tilde{g}(f)$ to make the signal response as large as possible relative to the typical noise response. To be precise, pick \tilde{g} to maximise the signal-to-noise ratio (SNR) squared:

$$\begin{aligned} P^2 &\equiv \frac{(\text{signal response})^2}{\text{variance of noise response}} \\ &= \frac{\left(\int \tilde{h}(f) \tilde{g}^*(f) df \right)^2}{E \left[\left| \int \tilde{n}(f') \tilde{g}^*(f') df' \right|^2 \right]} \end{aligned}$$

$$\begin{aligned} \text{denominator} &= E \left[\int_{f=-\infty}^{\infty} \tilde{n}(f) \tilde{g}^*(f) df \int_{f'=-\infty}^{\infty} \tilde{n}^*(f') \tilde{g}(f') df' \right] \\ &= \int_{f=-\infty}^{\infty} \int_{f'=-\infty}^{\infty} \underbrace{E \left[\tilde{n}(f) \tilde{n}^*(f') \right]}_{\delta(f-f') S(f)} \tilde{g}^*(f) \tilde{g}(f') df df' \\ &= \int_{f=-\infty}^{\infty} S(f) |\tilde{g}(f)|^2 df \end{aligned}$$

ASIDE: A very common integral in these problems is the "noise weighted inner product". For two functions $a(t)$, $b(t)$

$$\langle a, b \rangle \equiv \int_{f=-\infty}^{\infty} \frac{\tilde{a}(f) \tilde{b}^*(f)}{S(f)} df$$

- Imagine $\tilde{a}(f)$, $\tilde{b}(f)$ as two vectors where f is the element of the vector. Then $\langle a, b \rangle$ is the frequency-by-frequency dot product with weighting $S(f)$ applied to down-weight frequencies with large noise contamination.
- The squared length or magnitude of a is

$$\|a\|^2 \equiv \langle a, a \rangle = \int_{-\infty}^{\infty} \frac{|\tilde{a}(f)|^2}{S(f)} df$$

So the denominator of the ρ^2 formula is

$$\begin{aligned} \text{denominator} &= \int_{-\infty}^{\infty} S(f) |\tilde{g}|^2 \cdot \frac{S(f)}{S(f)} df \\ &= \langle Sg, Sg \rangle \end{aligned}$$

The numerator of the ρ^2 formula is

$$\begin{aligned} \text{numerator} &= \left(\int \tilde{h}(f) \tilde{g}^*(f) df \right)^2 \\ &= \left(\int \frac{\tilde{h}(f) (\tilde{g}^*(f) S(f))}{S(f)} df \right)^2 \\ &= (\langle h, Sg \rangle)^2 \end{aligned}$$

So

$$\rho^2 = \frac{(\langle h, Sg \rangle)^2}{\langle Sg, Sg \rangle}$$

How do we select g ?

Note: ρ^2 is unchanged by an overall constant rescaling of g . Eg for $g \rightarrow \lambda g$ (λ constant) we get

$$\rho^2 \rightarrow \frac{(\langle h, \lambda Sg \rangle)^2}{\langle \lambda Sg, \lambda Sg \rangle} = \frac{\lambda^2 (\langle h, Sg \rangle)^2}{\lambda^2 \langle Sg, Sg \rangle} = \rho^2$$

So we can pick g to have unit length without loss of generality: $\langle Sg, Sg \rangle = 1$.

Then

$$p^2 = (\langle h, Sg \rangle)^2$$

↑ signal vector ↑ (unit) filter vector

We can maximise p^2 by choosing

$$Sg \propto h \Rightarrow g(f) = N \frac{h(f)}{S(f)}$$

← signal vector
← noise spectrum.
 normalisation constant
 (to get $\langle g, Sg \rangle = 1$)

The normalisation constant is defined by

$$1 = \langle Sg, Sg \rangle = N^2 \int \frac{|h(f)|^2}{S(f)} df = N^2 \langle h, h \rangle$$

$$\therefore N = \frac{1}{\sqrt{\langle h, h \rangle}} = \frac{1}{\sqrt{\int \frac{|h(f)|^2}{S(f)} df}}$$

Interpretation: our optimal filter g points in the direction of the noise-weighted signal vector.

compare: $\vec{a} \cdot \vec{b} = ab \cos \alpha \rightarrow$ maximised for $\alpha = 0$
(\vec{a} and \vec{b} parallel)

Our "matched filter" is therefore

$$Q = \int_{-\infty}^{\infty} \tilde{d}(f) \tilde{g}^*(f) df$$

$$= N \int_{-\infty}^{\infty} \frac{\tilde{d}(f) \tilde{h}^*(f)}{S(f)} df$$

$$= \frac{\langle d, h \rangle}{\sqrt{\langle h, h \rangle}} = \langle d, \frac{h}{\|h\|} \rangle$$

matched filter = "dot product of data vector with a unit-length signal vector."

Consider how $\hat{\theta}$ behaves when a signal is present:

$$d = n + h$$

$$\hat{\theta} = \frac{\langle d, h \rangle}{\sqrt{\langle h, h \rangle}} = \underbrace{\frac{1}{\sqrt{\langle h, h \rangle}} \int_{-\infty}^{\infty} \tilde{n}(f) \tilde{h}^*(f) df}_{\text{noise term}} + \underbrace{\sqrt{\langle h, h \rangle}}_{\text{signal term}}$$

The signal contribution is just p :

$$p^2 = (\langle h, Sg \rangle)^2 \xrightarrow{g = \frac{Nh}{S}} (N \langle h, h \rangle)^2 = \frac{\langle h, h \rangle^2}{\langle h, h \rangle} = \langle h, h \rangle$$

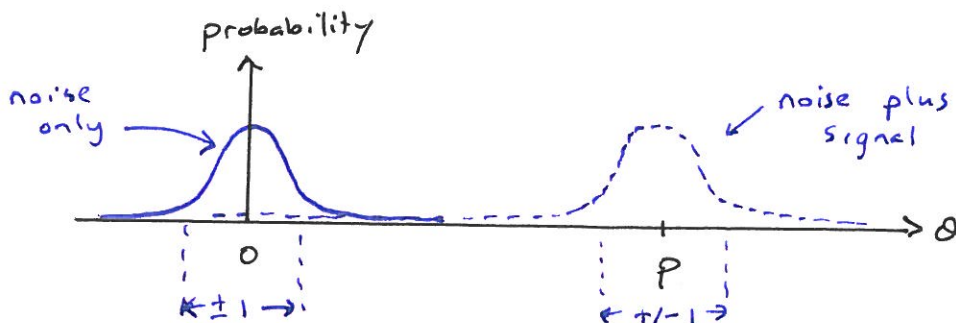
The noise contribution is a Gaussian with zero mean and unit variance:

$$E[\text{noise term}] = \frac{1}{\sqrt{\langle h, h \rangle}} \int_{-\infty}^{\infty} \underbrace{E[\tilde{n}(f)]}_{=0 \text{ for zero-mean noise}} \tilde{h}^*(f) df$$

$$\begin{aligned} \text{variance}[\text{noise term}] &= E[(\text{noise term})^2] \\ &= E\left[\frac{1}{\langle h, h \rangle} \int_{-\infty}^{\infty} \tilde{n}(f) \tilde{h}^*(f) df \int_{-\infty}^{\infty} \tilde{n}^*(f') \tilde{h}(f') df' \right] \\ &= \frac{1}{\langle h, h \rangle} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \underbrace{E[\tilde{n}(f) \tilde{n}^*(f')]}_{\delta(f-f') S(f)} \tilde{h}^*(f) \tilde{h}(f') df df' \\ &= \frac{1}{\langle h, h \rangle} \int_{-\infty}^{\infty} \frac{|\tilde{h}(f)|^2}{S(f)} df \\ &= 1 \end{aligned}$$

So when a signal is present

$$\hat{\theta} = \underbrace{p}_{\text{SNR}} + \underbrace{N(0,1)}_{\text{unit normal random number}}$$



It is conventional to write the formula for the SNR ρ in terms of the one-sided noise spectrum $S_1(f)$:

$$\rho = \langle h, h \rangle = \int_{-\infty}^{\infty} \frac{|\tilde{h}(f)|^2}{S(f)} df = 4 \int_0^{\infty} \frac{|\tilde{h}(f)|^2}{S_1(f)} df$$

$\underbrace{\int_{-\infty}^{\infty}}_{= 2 \int_0^{\infty}} \quad \underbrace{\frac{1}{S(f)}}_{= \frac{1}{2} S_1(f)}$