

391  
sp 11  
L7.1

- a) quick review of FFTs
- b) FFT "facts"
- c) properties of FFT's

a) review

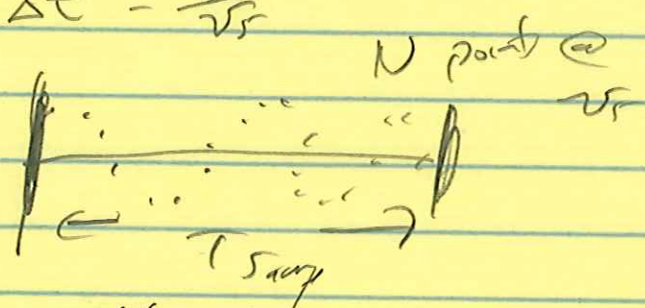
i) all real <sup>world</sup> data is discretely sampled.  
Data taken in equal time steps is called  
a "time series"

Data taken @ equal position steps can  
be substituted an analyzed similarly

ii) time series are sampled @ a constant  
rate  $v_s$  (or @ constant spacing  $\Delta x$ )

iii) once the experimenter choice  $v_s$   
and  $N$ , the # of samples in a  
sample is set & given by

$$T_{\text{sample}} = N \Delta t = \frac{N}{v_s}$$



also lowest freq observable is:

$$\Delta v = \frac{1}{T_{\text{sam}}} = \frac{v_s}{N}$$

391  
Sp 6  
L7.2

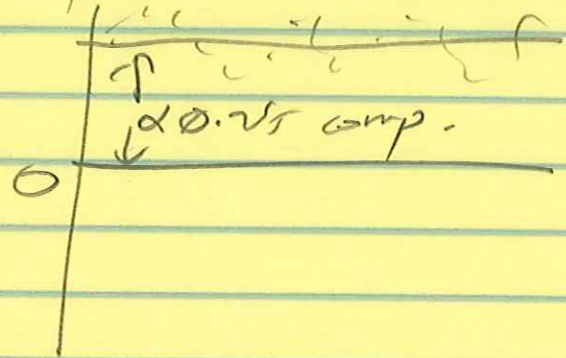
iii) continued

Fourier analysis will then give  
coefficients for  $f_{avg}$

$$\left( \cos, 1\Delta V, 2\Delta V, 3\Delta V, \dots, \frac{N}{2}\Delta V \right)$$

↑  
the Nyquist

iv) 0.25 coeff. gives  
the "DC component" or offset



b) FFT (Fast-Fourier Transform) "guts"

i) To Fourier series?

note  
 $x(t)$  is a  
"func basis"

$$x(t) = A_0 + A_1 \cos(1.2\pi \cdot \Delta V \cdot t + \phi_1) + \dots + A_{\frac{N}{2}} \cos\left(\frac{N}{2} \cdot 2\pi \cdot \Delta V \cdot t + \phi_{\frac{N}{2}}\right)$$

or in complex notation:

$$x(t) = C_0 + \sum_{j=1}^{\frac{N}{2}} \left[ C_j e^{ij2\pi \Delta V t} + C_j^* e^{-ij2\pi \Delta V t} \right]$$

3π  
5π/6  
L7.3

this is critical to understanding F.C.'s

F.C.'s, (c<sub>j</sub>'s) belong to their respective freqs, e.g.

$$c_a, c_a^* \longleftrightarrow e^{i(2\pi a/N)t}$$

the "orthogonals"

if we use particular frequencies  $j \cdot \Delta t = j \cdot \frac{2\pi}{N}$  because together they form an "orthonormal set"

$$\sum_{\text{cycle}} \cos(2\pi \nu_a t + \phi_a) \cdot \cos(2\pi \nu_b t + \phi_b) = \begin{cases} \phi & \text{if } \nu_a \neq \nu_b \\ \text{const} & \text{if } \nu_a = \nu_b \end{cases}$$

Only true for members of the orthonormal set and for summation over a complete cycle

{ draw on board and ask for a volunteer to come up, ~~do~~ steps for checking orthogonality }

c) new material: <sup>estimating</sup> FFTs + properties

3π  
5p 6  
L7.4

ii)

how do we mathematically estimate  $c_j$ 's?

for the  $n^{\text{th}}$   $c_j$ :

$$C(v_j) = \Delta t \sum_{l=0}^{N-1} v(t_l) e^{-i2\pi \frac{j}{N} l}$$

inner loop over time basis  $\rightarrow$  ortho. basis fctn of freq.  $\frac{j}{N}$  are extracted @ pt.  $l$

our outer loop then steps through each successive basis fctn (our "Fourier frequencies")

$$\left[ j = \frac{-N}{2} + 1, \frac{-N}{2} + 2, \dots, 0, 1, 2, \dots, \frac{N}{2} \right]$$

orthogonality ensures that each inner loop picks out only the same frequency of <sup>the</sup> signal components

iv) If we know  $c_j$ 's, we can synthesize  $v(t)$  from them

Inverse  
FFT  
 $v \rightarrow t$

$$v_c(t) = \sum_{n=0}^{N-1} c_n e^{+i2\pi \frac{n}{N} l} \quad \text{IFFT} \rightarrow \text{pt. } l$$

(must now outer loop over all times)

Matlab  
lecture 8  
FF

### c) FFT properties

**Linearity**: If  $h(t) = \alpha f(t) + \beta g(t)$

$\hat{h} = \text{FFT of } h$        $\hat{h}(\omega) = \alpha \hat{f}(\omega) + \beta \hat{g}(\omega)$

**Translation**: if  $h(x) = f(x - x_0)$   
then

$$\hat{h}(k) = e^{-ikx_0} \hat{f}(k)$$

$k = \text{wave number}$ ,  $\hat{h}(k) = \text{FFT}(h(x))$

**Differentiation**  $h(t) = \frac{d}{dt} f(t) \Rightarrow$

$$\hat{h}(\omega) = i\omega \hat{f}(\omega)$$

further  $\frac{d^n}{dt^n} f(t) = (i\omega)^n \hat{f}(\omega)$

derivatives become simple multipliers, easier to code:

see example

3a  
 wk  
~~L7.5~~  
 SPT  
 L7.1

c) conf.

Differentiation

$$h(t) = \frac{d}{dt} f(t)$$

$$\Rightarrow \vec{h}(\omega) = i\omega \vec{f}(\omega)$$

further:  $h(t) = \frac{d^n}{dt^n} f(t) \Rightarrow$

$$\vec{h}(\omega) = (i\omega)^n \cdot \vec{f}(\omega)$$

derivative  $\Rightarrow$  multiplication  
 (easier to code!)

(example in applied E+M)

curl  $\vec{E}$   
 say  $\nabla \times \vec{E} = -\mu \frac{\partial}{\partial t} \vec{H}$

note

$E$  = electric field in 3D (eg  $f(x,y,z,t)$ )

$H$  = magnetic field " " " "

one of Maxwell's eqs.

curl  $\vec{E}$  looks like  $\nabla \times \vec{E} = \begin{vmatrix} \hat{x} & \hat{y} & \hat{z} \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ E_x & E_y & E_z \end{vmatrix}$

$$= \hat{x} \left( \frac{\partial E_z}{\partial y} - \frac{\partial E_y}{\partial z} \right) + \hat{y} \left( \frac{\partial E_x}{\partial z} - \frac{\partial E_z}{\partial x} \right) + \hat{z} \left( \frac{\partial E_y}{\partial x} - \frac{\partial E_x}{\partial y} \right)$$

hard to solve in computer  
can input let

3.1
4.1
4.2.6
5.6
4.7

$$\hat{E} = \text{FFT of } \vec{E} \quad \text{write both space \& time}$$

$$\hat{H} = \text{FFT of } \vec{h}$$

then can write (for example):

$$\vec{x} \text{ component } \rightarrow i\omega_z \hat{E}_z + i\omega_y \hat{E}_y = +i\omega_x \hat{h}_x$$

solve all these for Fourier for  $\omega$ 's

Convolution if  $h(t) = f(t) \otimes g(t)$

$$\text{then } \equiv \int_{-\infty}^{\infty} f(t-\tau) g(\tau) d\tau$$

$$\text{then } \hat{h}(\omega) = \hat{f}(\omega) \cdot \hat{g}(\omega)$$

$\Rightarrow$  windowing

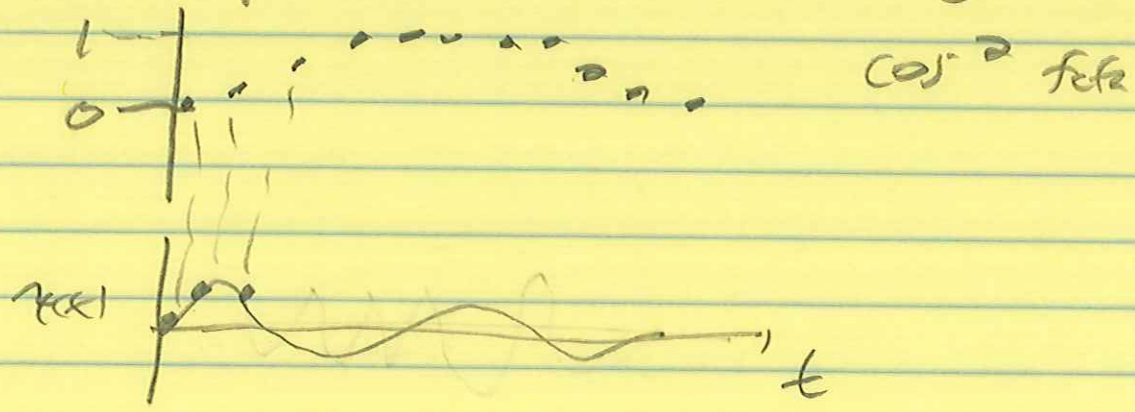
FFT we have looked at are really the convolution of the real signal and a windowing function. Say the box can



3.11  
 4.06  
 4.7.7  
 5.16  
 4.8

c) confd

Can choose to first convolve data with a specially-chosen windowing fcn,  $w(t)$



pt by pt mult of  $w(t) \cdot x(t)$

then  $\Rightarrow$  FFT

ML Lecture 8... n J

finally - show LPE trace for always

