

## **Computational Methods** (PHYS 2030)

**Instructors:** Prof. Christopher Bergevin (cberge@yorku.ca)

**Schedule:** Lecture: MWF 11:30-12:30 (CLH M)

**Website:** <http://www.yorku.ca/cberge/2030W2018.html>

## Fourier analysis

- Deep history throughout mathematics, physics, engineering, biology, .....
- Backbone of modern signal processing and linear systems theory
- Lays at foundation of many modern methodologies in medical imaging (e.g., MRI, CT scans)
- Builds off the basic idea of a *Taylor series* (which posits we can describe a function as an infinite series of polynomials)

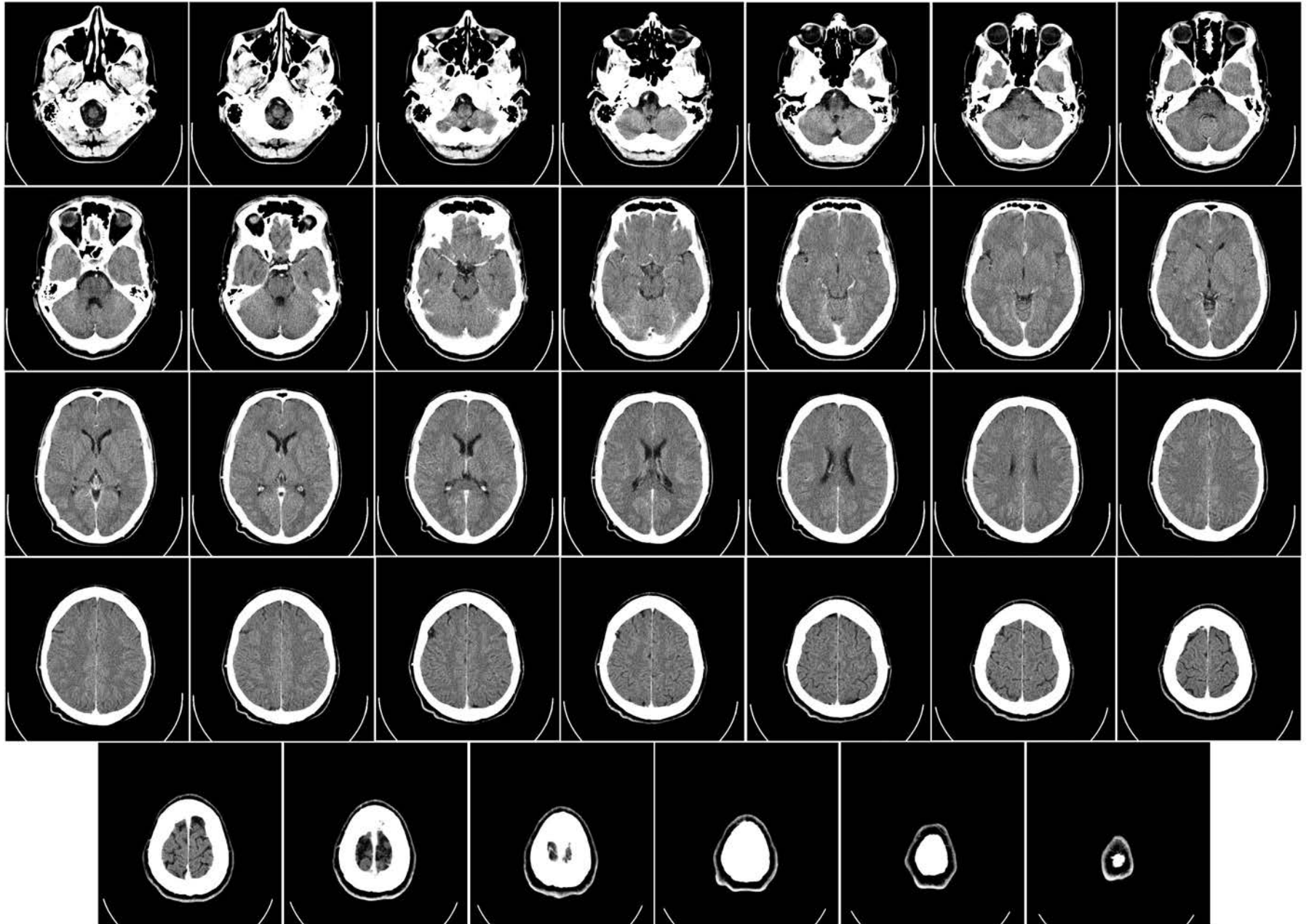
Basic idea: Represent ‘signal’ as a sum of sinusoids



Joseph Fourier (1768-1830)

Note: We focus on 1-D here for clarity, but these ideas generalize to higher dimensions (e.g., 2-D for images)

## Motivation: Medical Imaging (e.g., NMR/MRI)

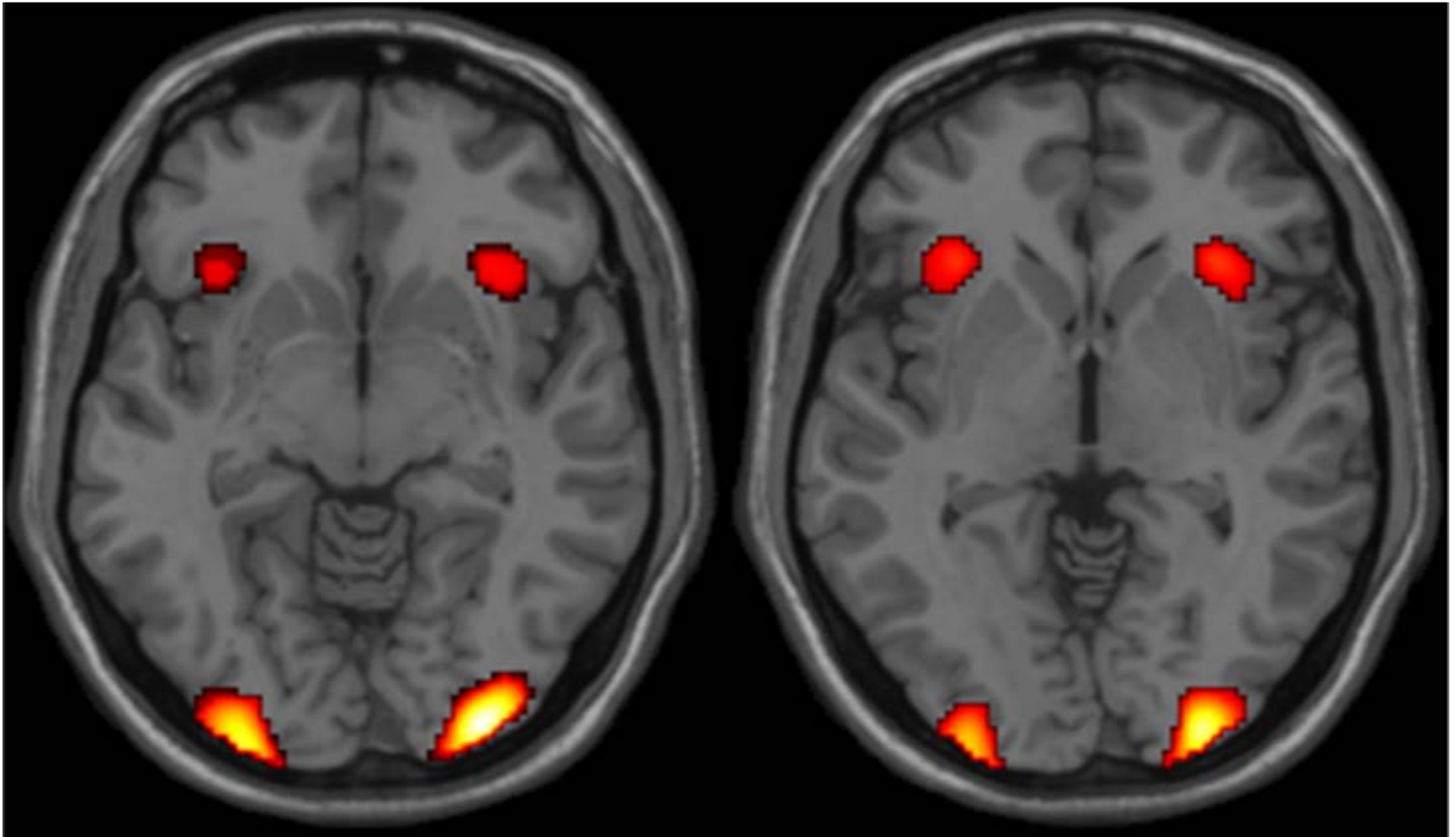


## Motivation: Medical Imaging (e.g., NMR/MRI)



→ A key foundation for imaging is a Fourier transform (“k-space”)

Motivation: Medical Imaging (e.g., NMR/MRI)





## Motivation: Medical Imaging (e.g., NMR/MRI)





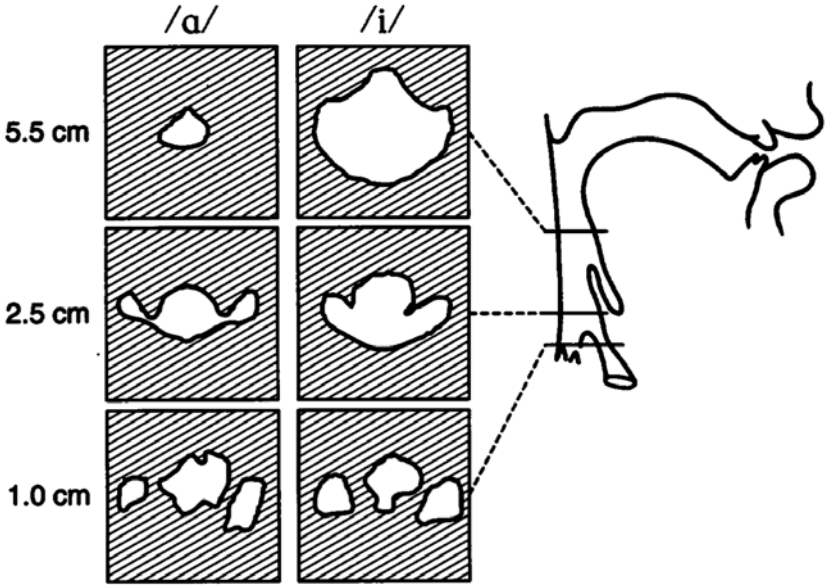
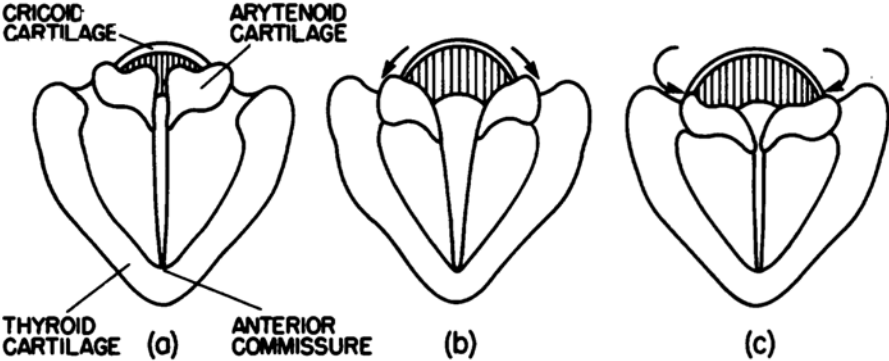
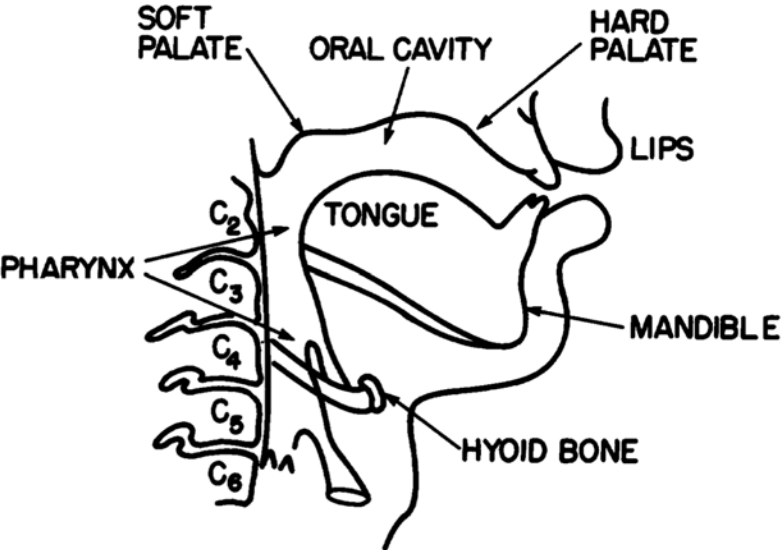
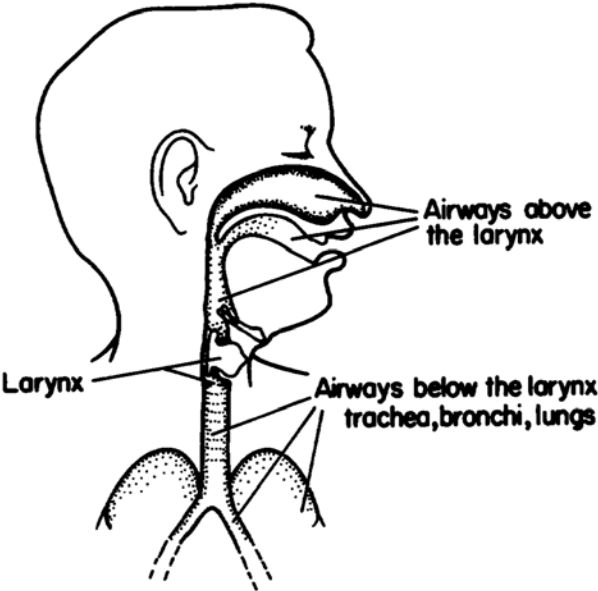






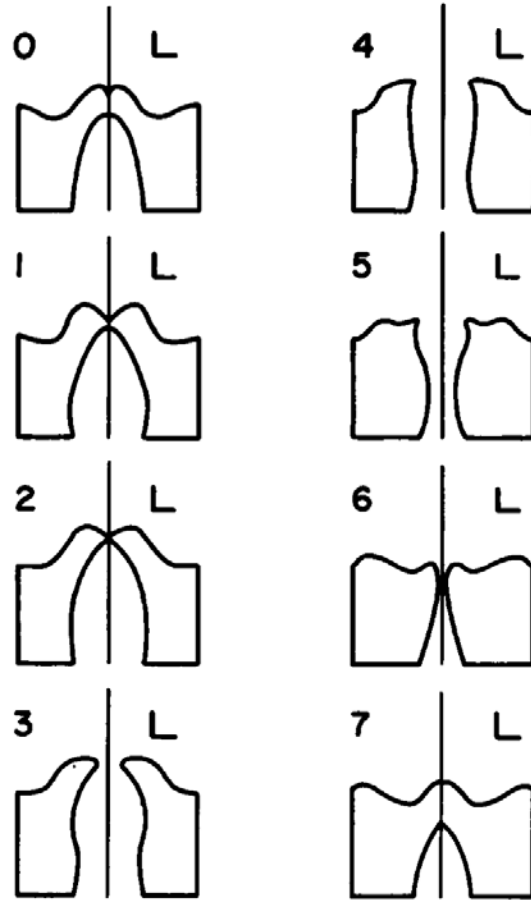


Motivation: Speech

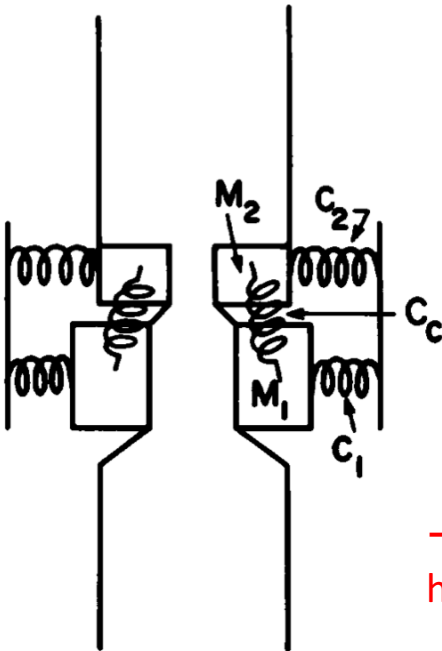


# Motivation: Speech

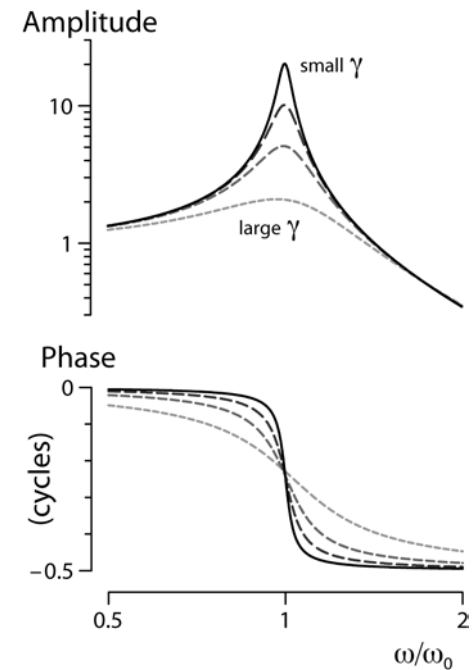
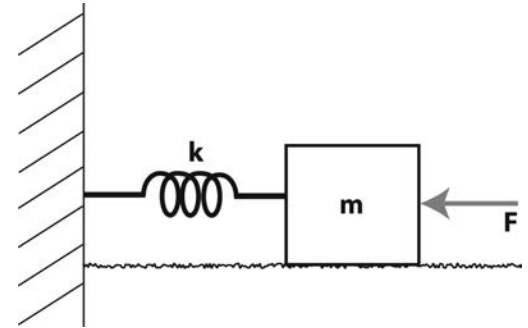
Snapshots of vibrating vocal folds



Simple two-mass model for the vocal folds

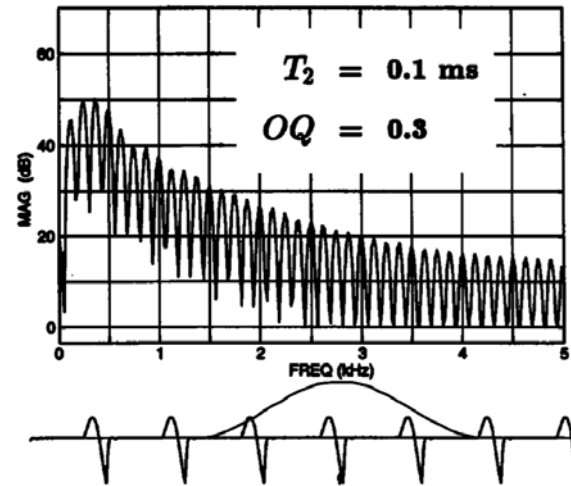
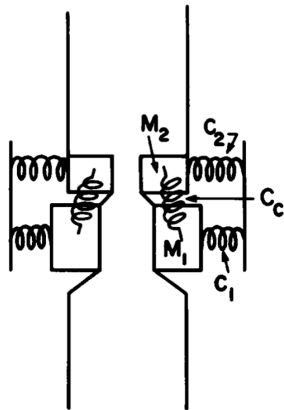
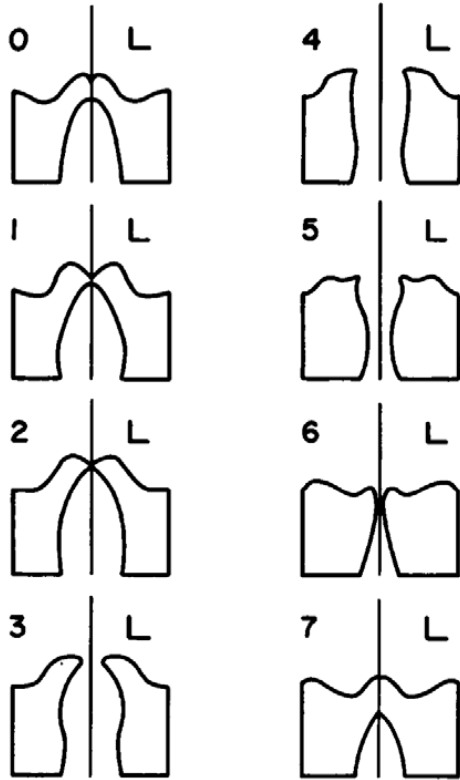


→ Vocal folds behaves like a harmonic oscillator (HO)!



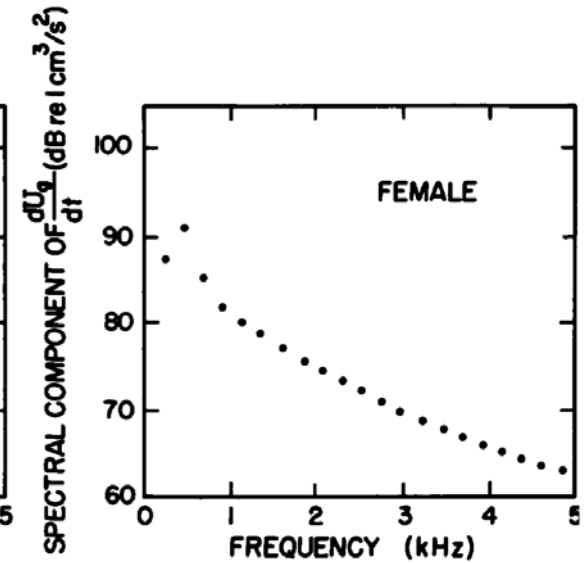
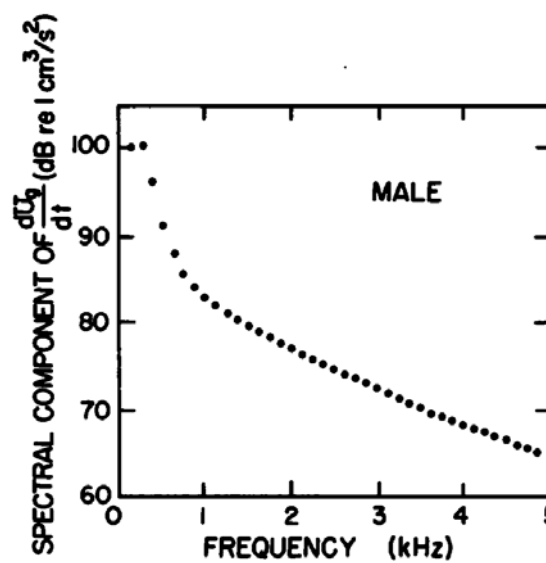
Reminder: We can describe HO in terms of 'spectral' response

## Motivation: Speech



Key idea:  
Spectrum  
→ x-axis is frequency [Hz]

→ Vibrating vocal folds give off 'buzzy' sound due to harmonics



→ Males have lower 'fundamental' (due to more massive vocal folds)



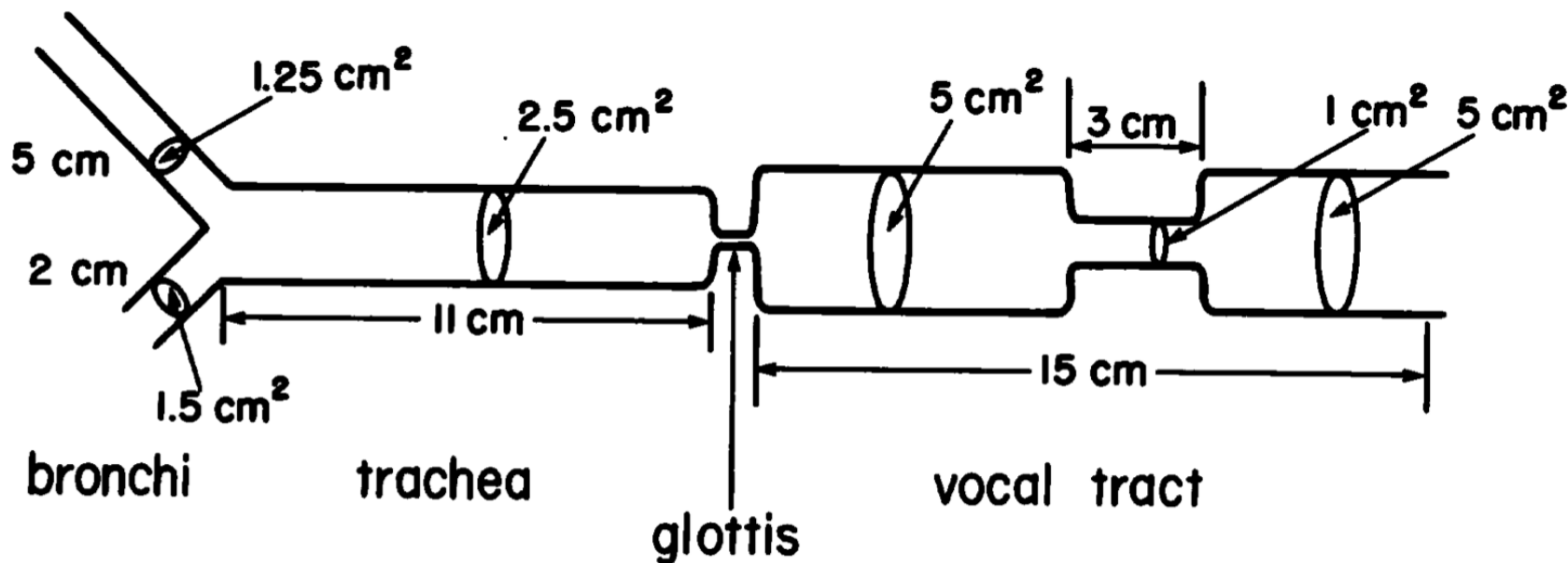
## Motivation: Speech

Pressure source  
(lungs)

Vibration source  
(vocal folds)

Filter  
(vocal tract)

Output  
(mouth)

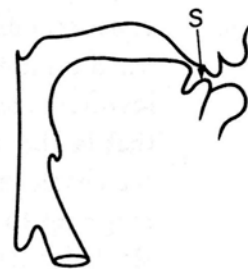


→ Complex acoustic process is boiled down to a relatively simple/tractable framework of 'sources' and tubes!

## Motivation: Speech

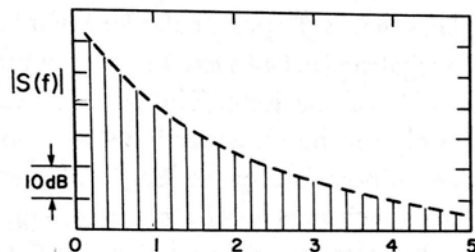


Vowel

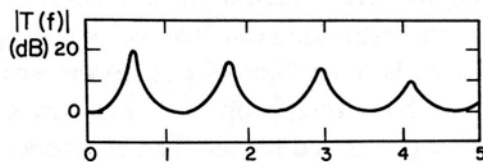


Consonant ('sss')

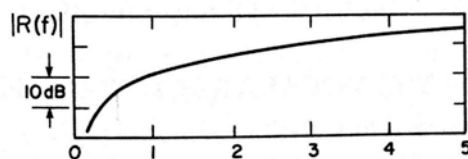
Source  
(vocal folds)



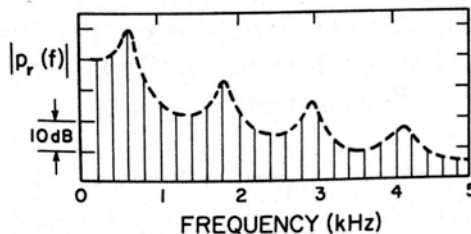
Filter I  
(vocal tract)



Filter II  
(radiation)



Speech signal

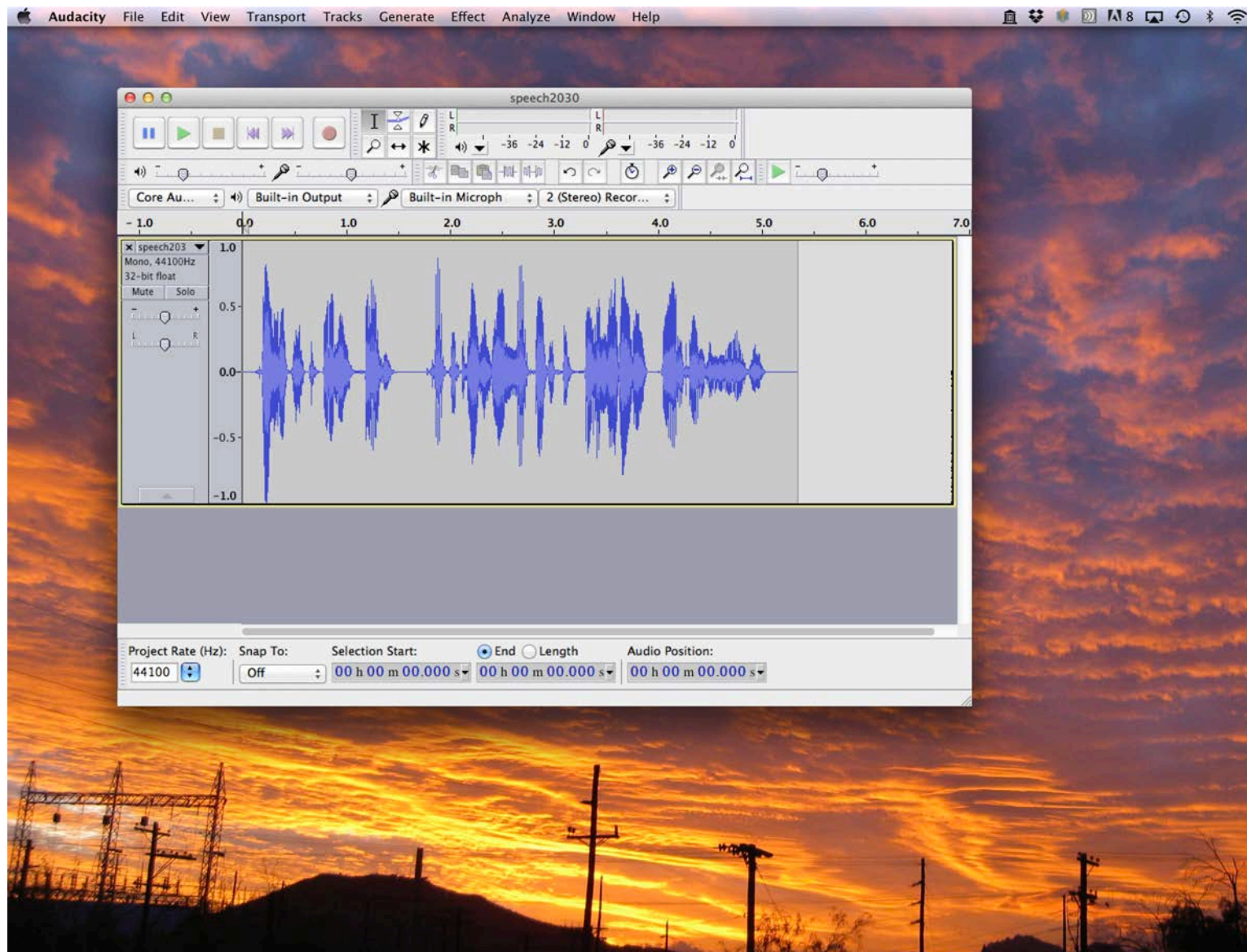


- Vibrating vocal folds make 'broadband' sound
- Vocal tract shapes that sound
- Resulting 'shape' emphasizes features which we then pick up with our ear (e.g., formants of vowels)

→ But what does it mean for everything to be a function of frequency?

**Figure 3.1** Sketches indicating components of the output spectrum  $|p_r(f)|$  for a vowel and a fricative consonant. The output spectrum is the product of a source spectrum  $S(f)$ , a transfer function  $T(f)$ , and a radiation characteristic  $R(f)$ . The source spectra are similar to those derived in figures 2.10 and 2.33 in chapter 2. For the periodic source,  $S(f)$  represents the amplitudes of spectral components; for the noise source,  $S(f)$  is amplitude in a specified bandwidth. See text.

## Aside: Recording sound



Note: Many freeware programs exist for recording sound (Matlab lets you do it on PCs)



## Aside: Recording sound

- Several basic ingredients:
  - sound source
  - microphone
  - A/D converter (e.g., laptop, Arduino)
  - software (e.g., Matlab, C, LabView, ....)
  
- Think about physically what each 'step' does (e.g., microphone transduces by either inductive or capacitive changes, thereby creating an electric current)
  
- Sound (i.e., pressure fluctuations) are thereby converted to voltage signals
  
- For a 'mono' signal, this is a 1-D system (i.e., voltage is a function of time)
  
- A continuous signal when digitized becomes discrete (i.e., 'sampled')

## Aside: Discrete vs Continuous

Start w/ some  
familiar ideas:

➤ Quantum vs. Classical mechanics

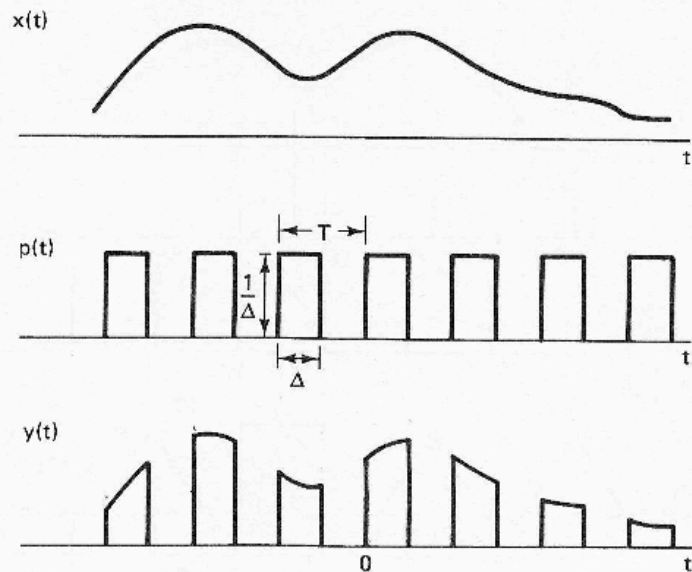
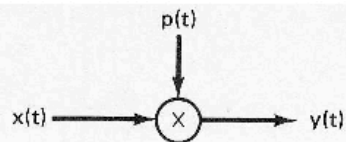
➤ Wave-particle duality

➤ Statistical mechanics

1. We 'live' in a world that is simultaneously discrete and continuous

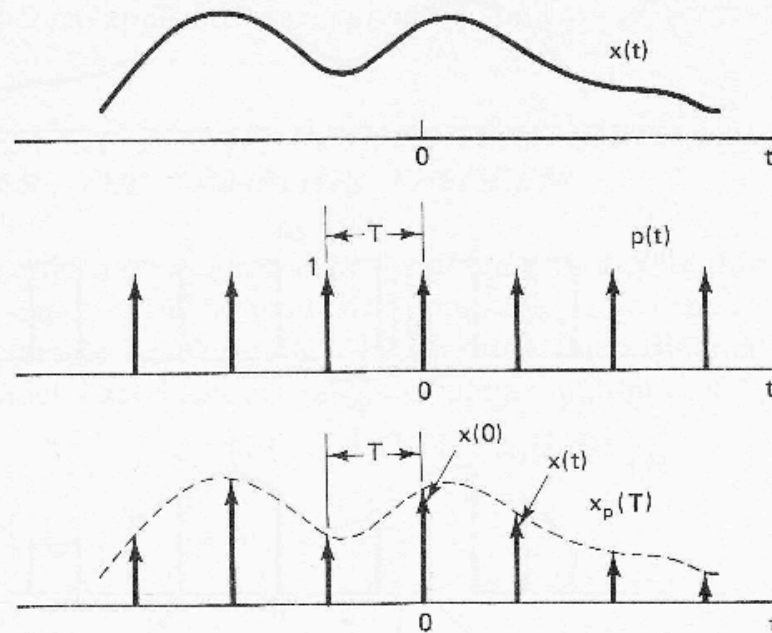
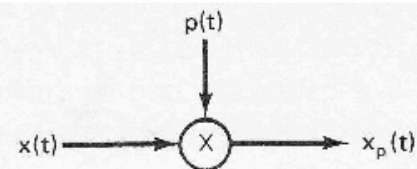
2. Such a reality flavors how we 'measure' anything

## Aside: Sampling



**Figure 8.2** Pulse amplitude modulation. As  $\Delta \rightarrow 0$ ,  $p(t)$  approaches an impulse train.

‘Snapshots’ (i.e., sampling)



**Figure 8.3** Pulse amplitude modulation with an impulse train.

Very short snapshots’  $\rightarrow$  Delta functions



## Aside: Sampling

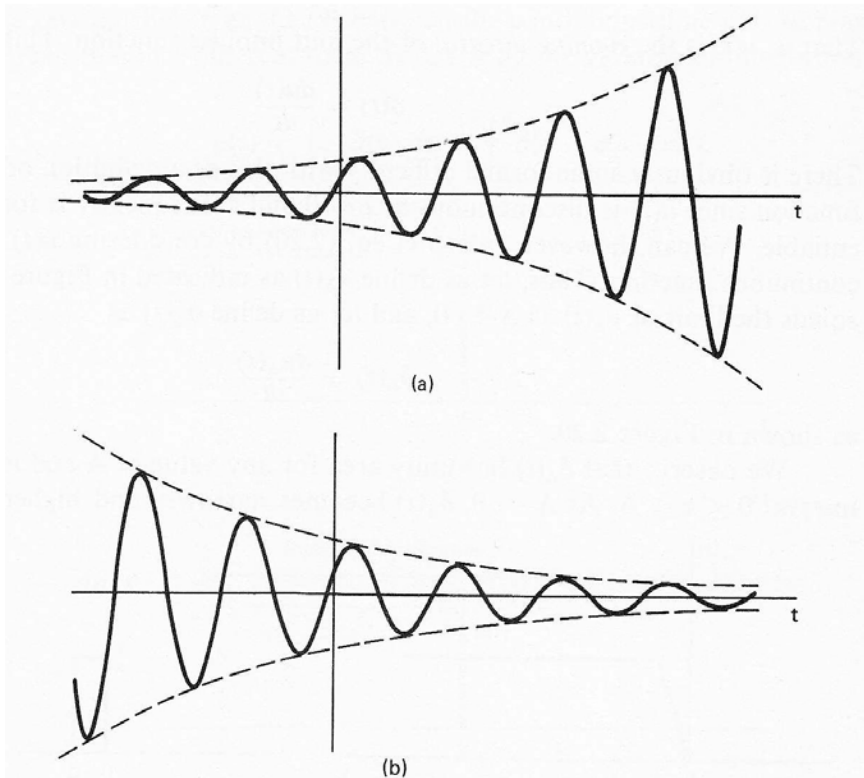


Figure 2.17 (a) Growing sinusoidal signal  $x(t) = Ce^{rt} \cos(\omega_0 t + \theta)$ ,  $r > 0$ ; (b) decaying sinusoid  $x(t) = Ce^{rt} \cos(\omega_0 t + \theta)$ ,  $r < 0$ .

Continuous signal (analog)

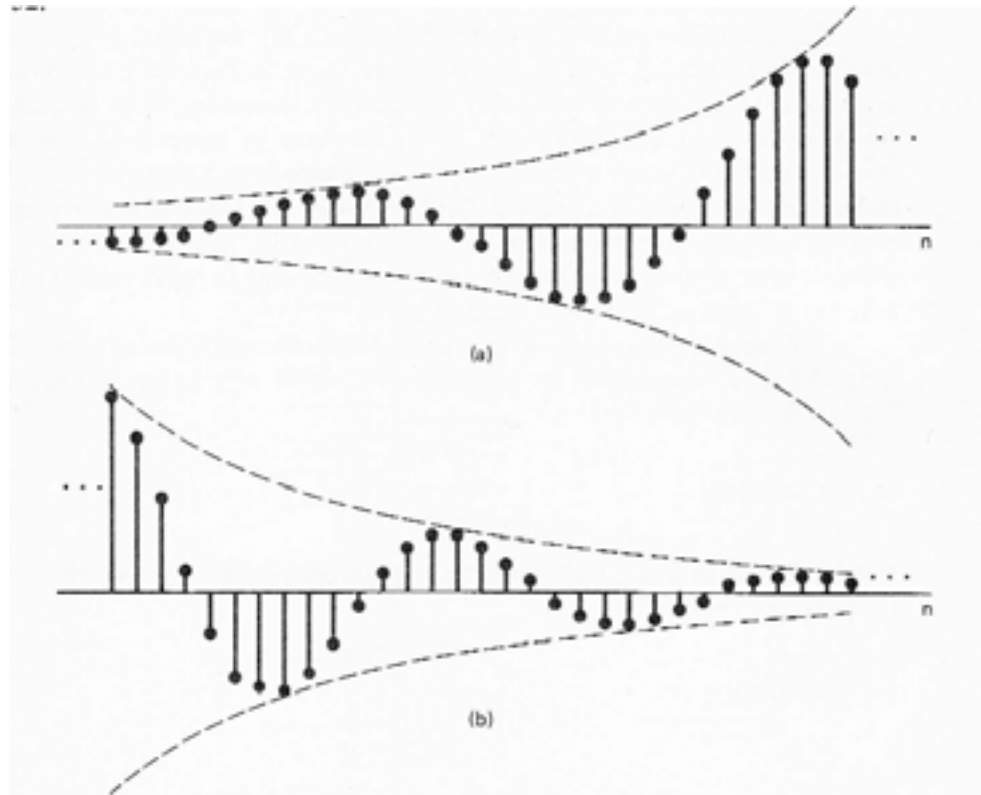


Figure 2.32 (a) Growing discrete-time sinusoidal signal; (b) decaying discrete-time sinusoid.

Discretized signal (digital)

→ Typically when we measure a signal, we measure a discretized version of such (which is both similar and different!)

## Aside: Sampling

- Note that there is some sort of timing associated with our sampling
- That is, there is a *sampling rate* associated with converting from analog to digital

ex. compact discs use a sample rate (SR) of 44.1 kHz

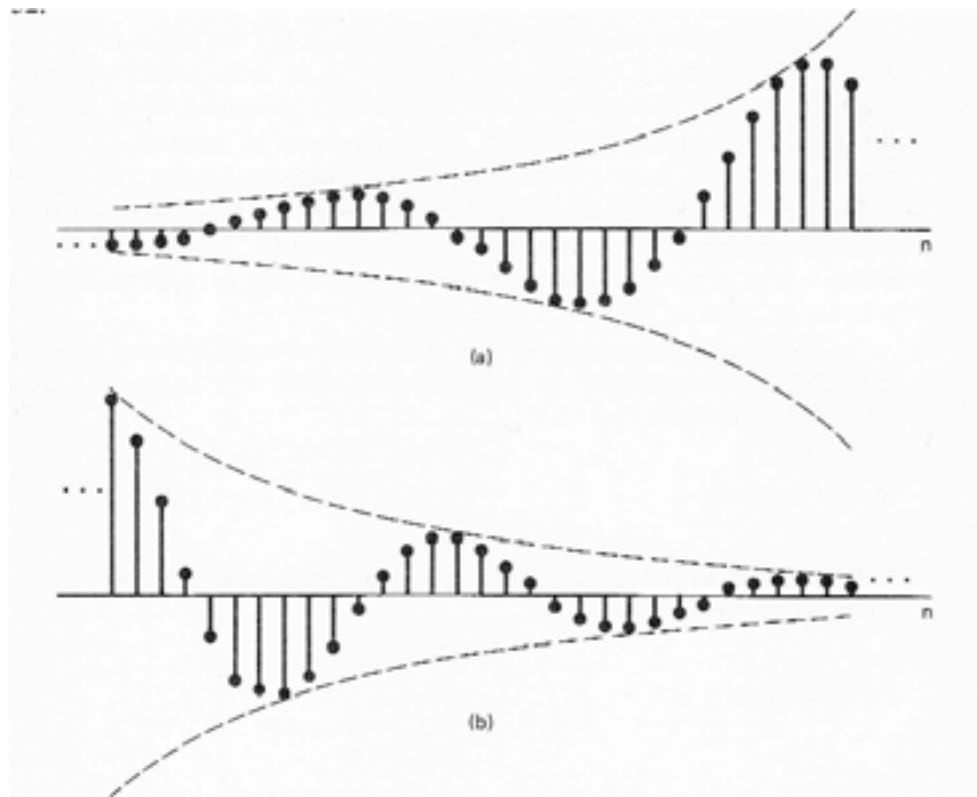
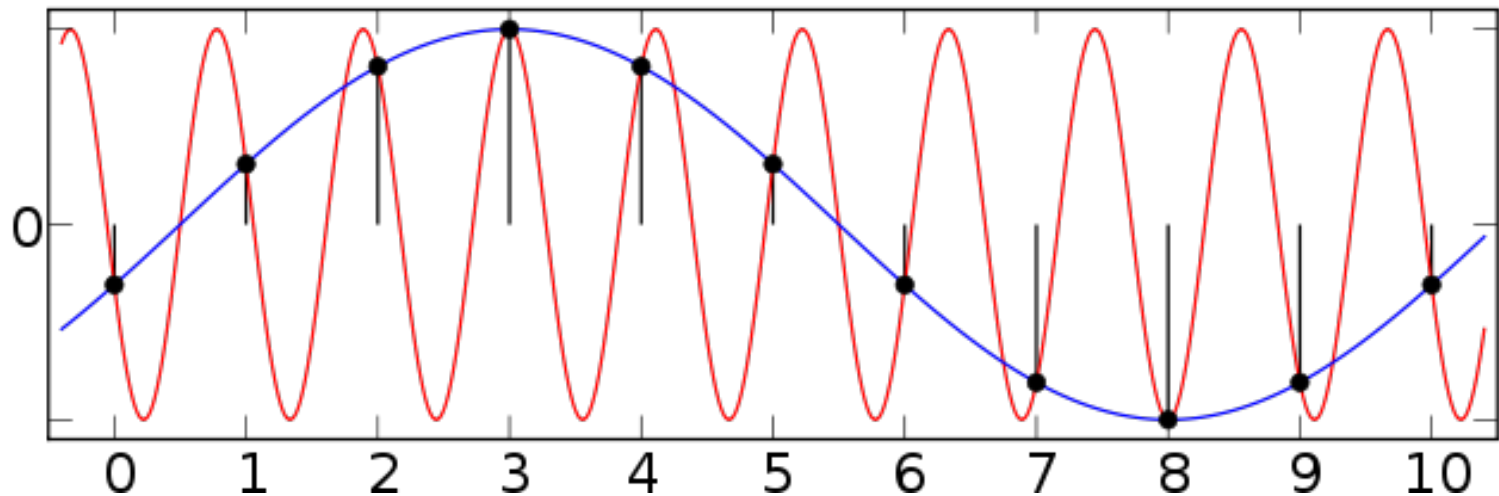


Figure 2.32 (a) Growing discrete-time sinusoidal signal; (b) decaying discrete-time sinusoid.

- The faster we sample, the more information we capture (to a point)

## Aside: Aliasing

- Be careful that your sample rate is not too low...

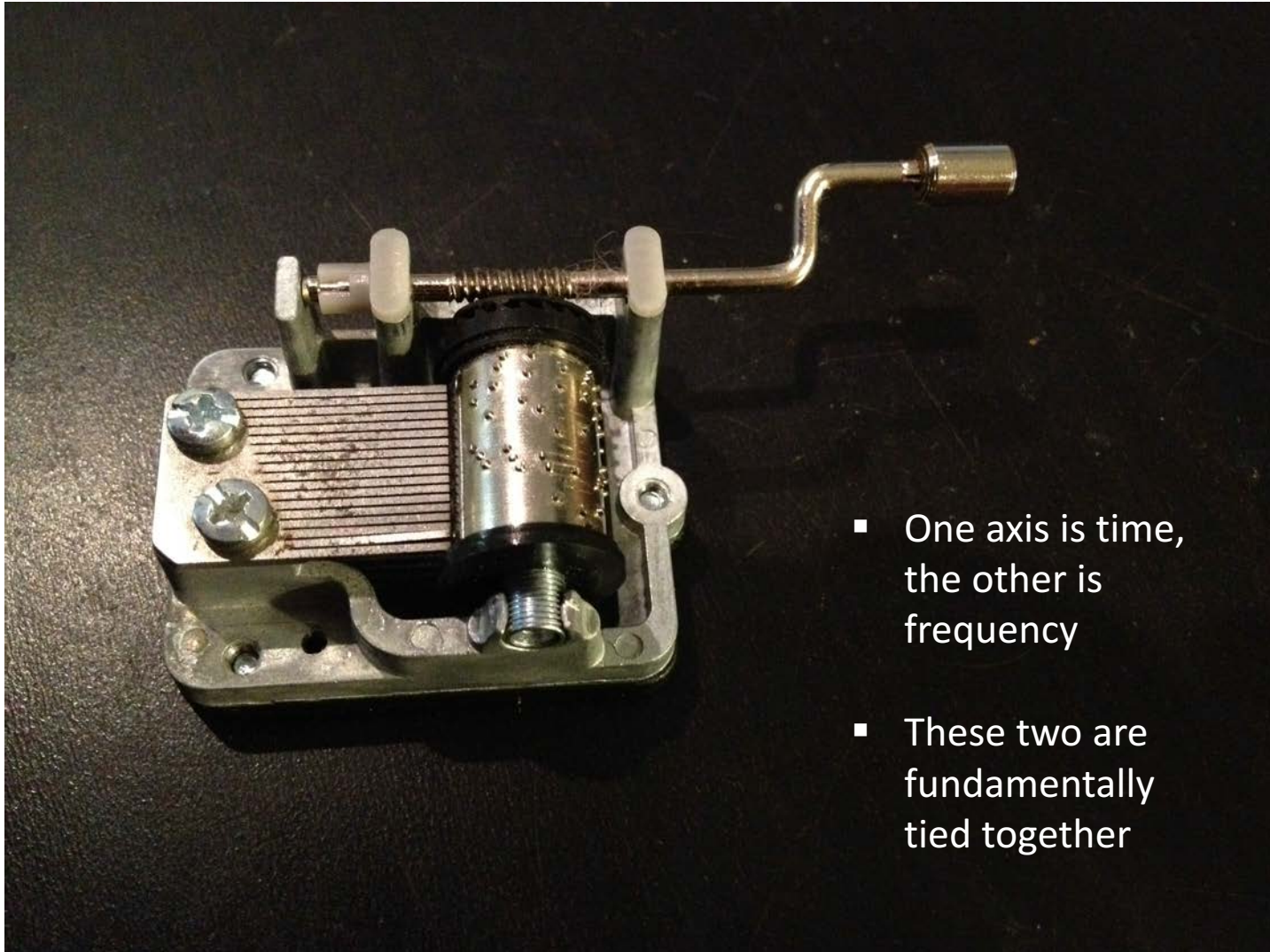


→ “Aliasing”

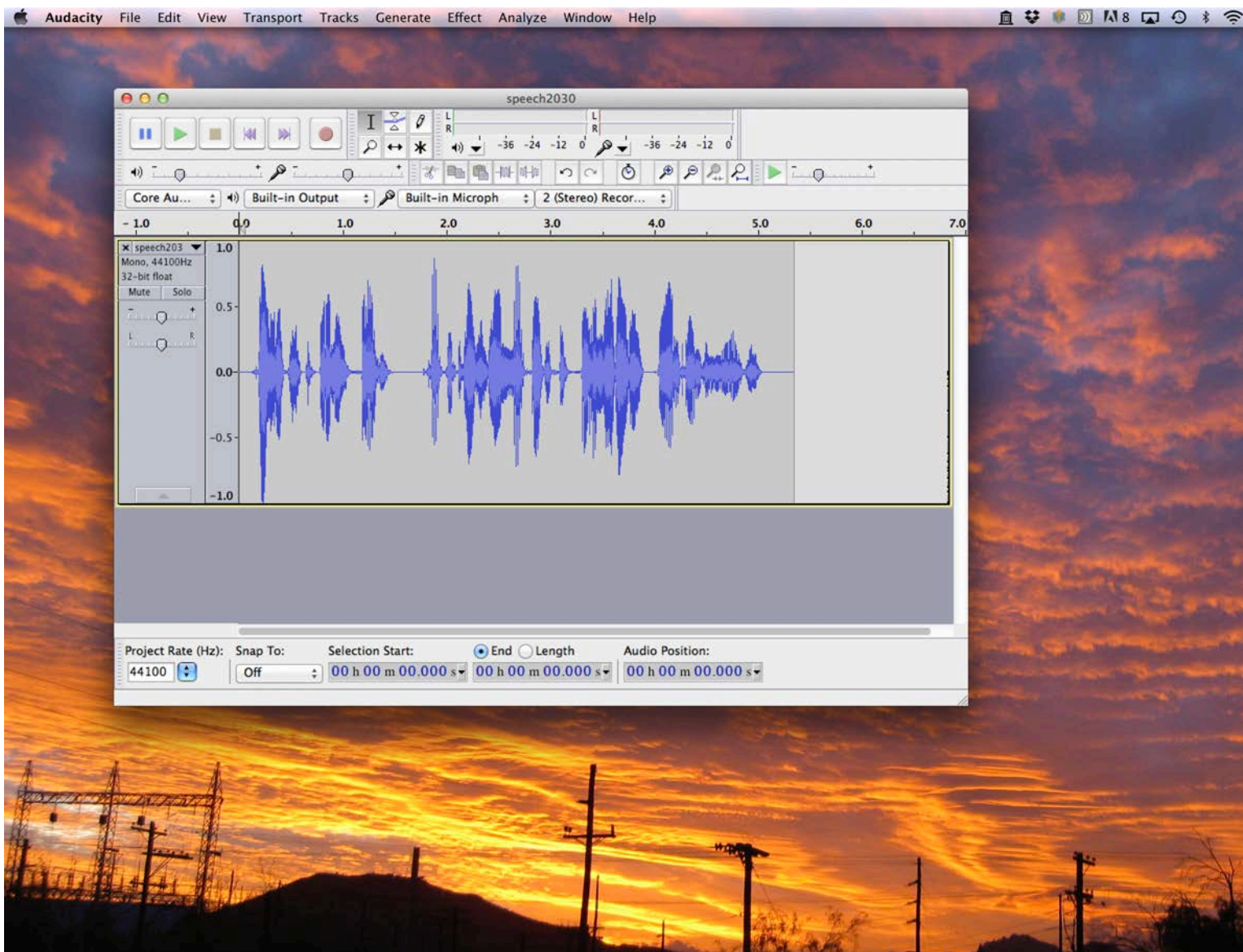


## Key idea: Fourier transform

- Allows one to go from a time domain description (e.g., our recorded mic signal) to a spectral description (i.e., what frequency components make up that signal)



- One axis is time, the other is frequency
- These two are fundamentally tied together



→ We are going to perform a specific type of spectral analysis called the 'Short Time Fourier Transform' (STFT) to make what is called a *spectrogram*

```

function y = makeSpectrogram(file)
% ### EXspectrogram.m ###          10.27.14
% Reads in wav file created via separate program (e.g., Audacity) and makes a spectrogram
% NOTE: make sure sample rate specified here matches that used when recording the data!

% -----
P.SR= 44100; % SR data collected at [Hz]
P.windowL= 2048; % length of window segment for FFT {2048}
P.overlap= 0.8; % fractional overlap between window, from 0 to 1 {0.8}
P.maxF= 8000; % max. freq. for spectrogram [Hz] {8000}
fileN= './spectrogram2030.jpg'; % filename to save image to
% -----
pts= round(P.windowL*P.overlap); % convert fractional overlap to # of points
disp(sprintf('Assumed sample rate = %g kHz', P.SR/1000));
A= wavread(file);
spectrogram(A,blackman(P.windowL),pts,P.windowL,P.SR,'yaxis'); % create spectrogram and plot (via
built-in function)
axis([0 size(A,1)/P.SR 0 P.maxF])
colorbar

% -----
% save picture to file as a jpg w/ a user-specified resolution
REZ= '-r180'; % resolution for exporting colormaps to jpg
print('-djpeg',REZ,[fileN]);

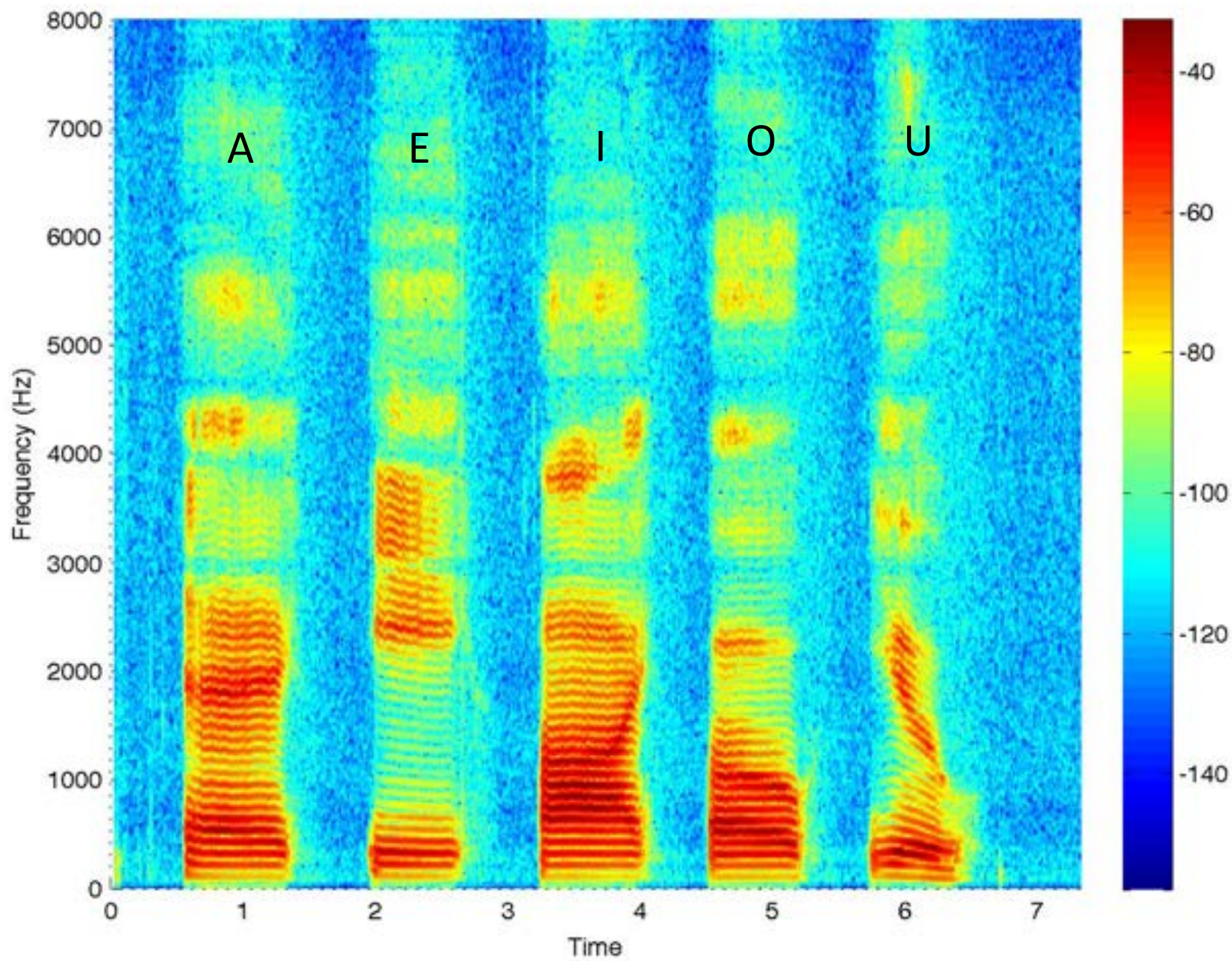
% NOTE: to play back the audio, type:
% > sound(A,SR)
% where SR is the appropriate sample rate (e.g., fiddle with if you want to
% change the pitch)

% NOTE: To save an array (A) to .wav file, type:
% > wavwrite(A,SR,16,filename);

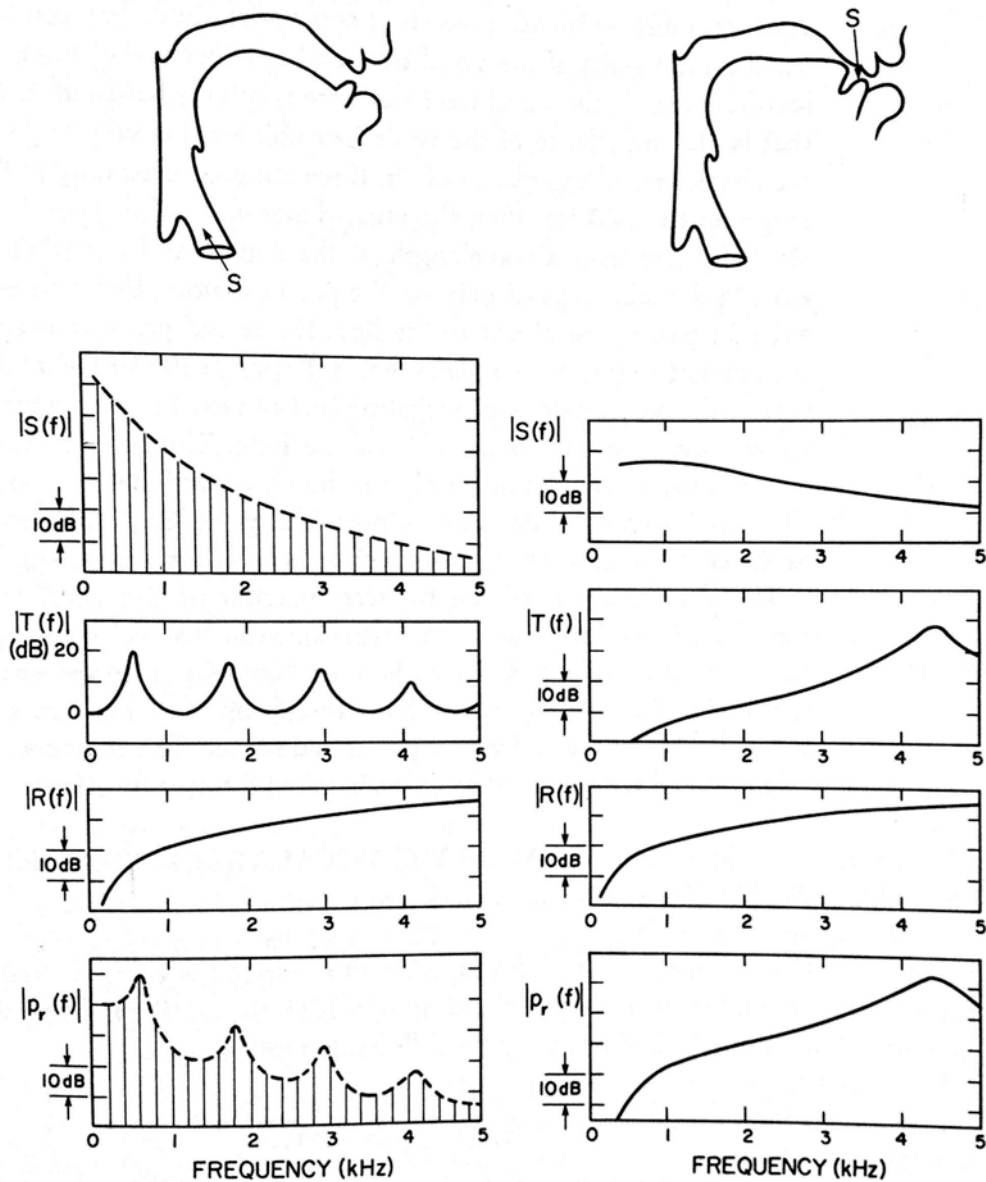
```

→ Requires pre-recorded sound file

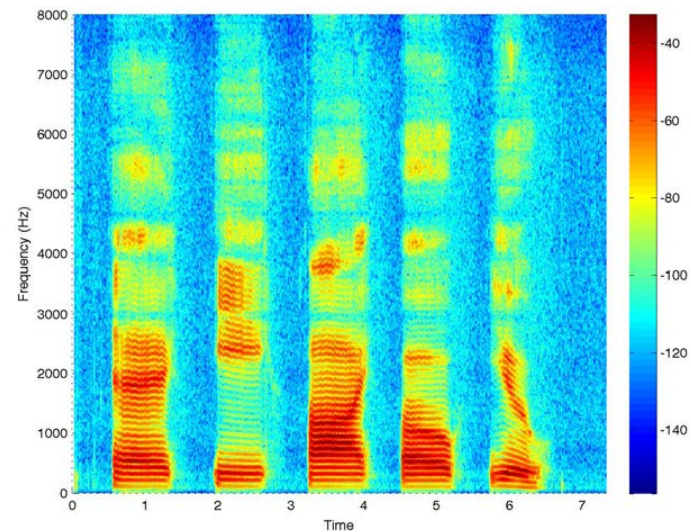


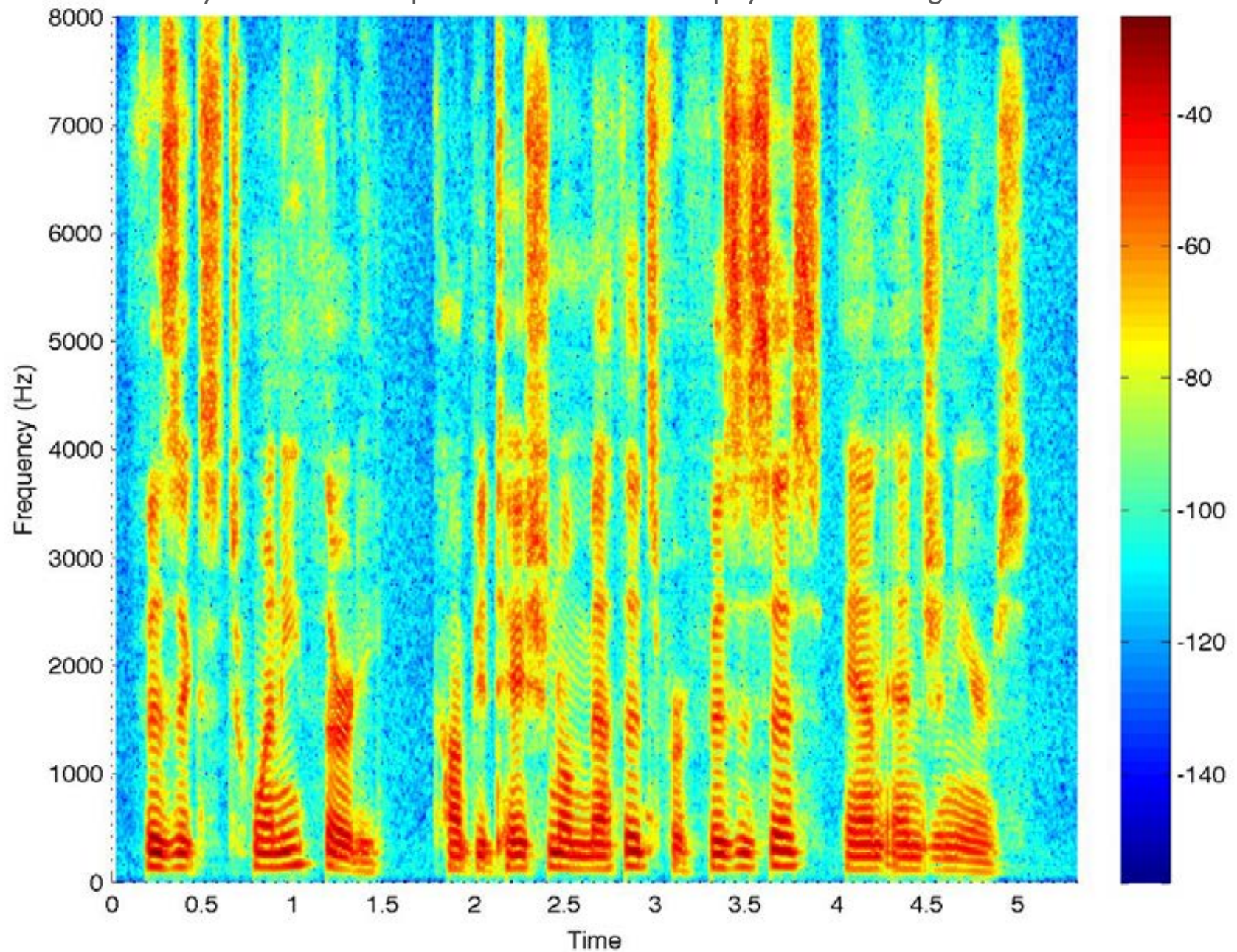




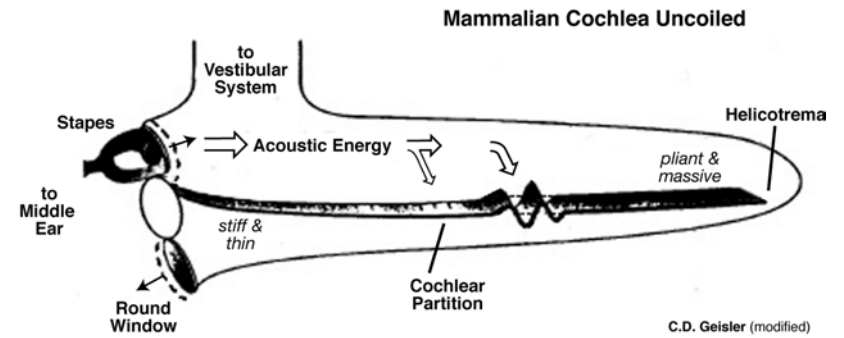
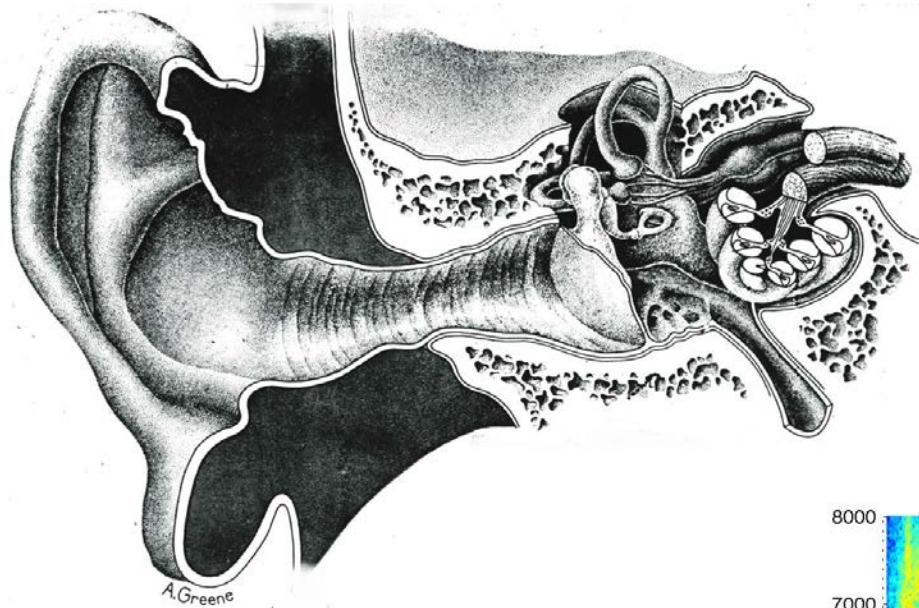


**Figure 3.1** Sketches indicating components of the output spectrum  $|p_r(f)|$  for a vowel and a fricative consonant. The output spectrum is the product of a source spectrum  $S(f)$ , a transfer function  $T(f)$ , and a radiation characteristic  $R(f)$ . The source spectra are similar to those derived in figures 2.10 and 2.33 in chapter 2. For the periodic source,  $S(f)$  represents the amplitudes of spectral components; for the noise source,  $S(f)$  is amplitude in a specified bandwidth. See text.

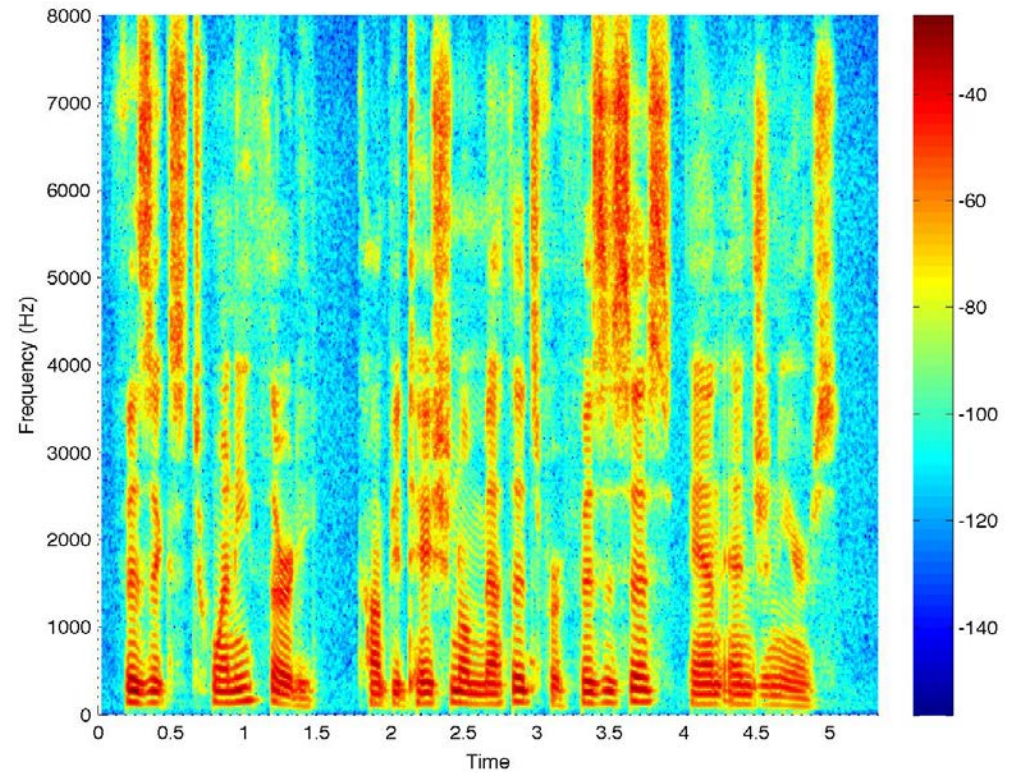








→ The ear's main job is to do this sort of spectral decomposition!



```

% ### EXfourier2D.m ###      10.27.14
% Shows a dynamic reconstruction of an image stemming from adding
% successively higher order terms from a 2D Fourier transform
% [source: Richard Murray, York CVR]
clear;
% -----
fileI= 'Einstein.tif';      % image to analyze
N = 4; % set number of radial sections per step
rstep= 1/2; % set radial step size going outward (larger means smaller steps)
delay= 0.1; % animation delay [s]
Mmovie= 0; % make a movie version (avi) (0-no,1-yes)
% -----
im = double(imread(fileI)); % load image
imft = fftshift(fft2(im)); % compute 2D FFT
% +++
dim = size(im,1);
ftmax = max(abs(imft(:))); % determine largest amplitude (for scaling)
[r,t] = matrt([ dim dim ]); % make distance map (via external function)
f = find(t<0);
t(f) = t(f)+pi;
t = t/pi;
rmap = floor(power(r,rstep)/.6);
dmap = rmap+t;
F = ceil(N*max(dmap(:)));
% +++
imC = uint8(127*[ im/255 500*abs(imft)/ftmax ]); % write initial frame (whole image and FFT)
figure(1); clf; colormap(bone)
image(imC); drawnow;
% +++
% make movie as well
if Mmovie==1
    obj = VideoWriter('fourier_synth_einstein.avi'); % open movie file
    open(obj); writeVideo(obj,imC);
end
% +++
% step through frames
figure(2); clf; colormap(bone);
for f=1:F
    mask = (dmap<(f/N)); % create low-pass filter mask
    imftmask = imft.*mask; % filter image by applying mask in freq. domain
    immask = real(ifft2(ifftshift(imftmask)))/255; % inverse Fourier transform
    imC = uint8(127*[ max(min(immask,1),0) 500*abs(imftmask)/ftmax ]); % update image
    image(imC); drawnow; pause(delay);
    if (Mmovie==1), writeVideo(obj,imC); end
end

```

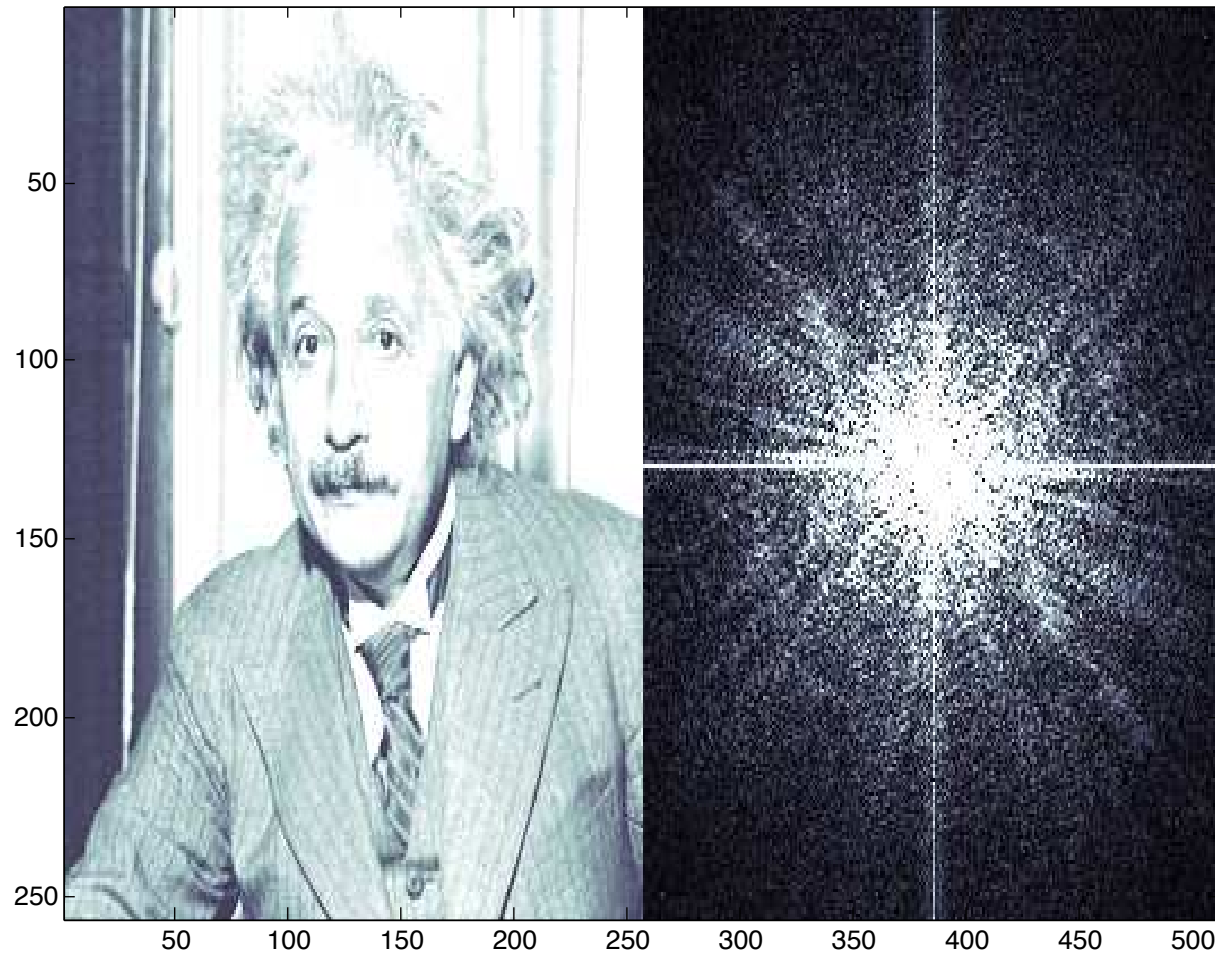
As an example, Fourier transforms are not limited to 1-D

→ Requires several 'sub' functions

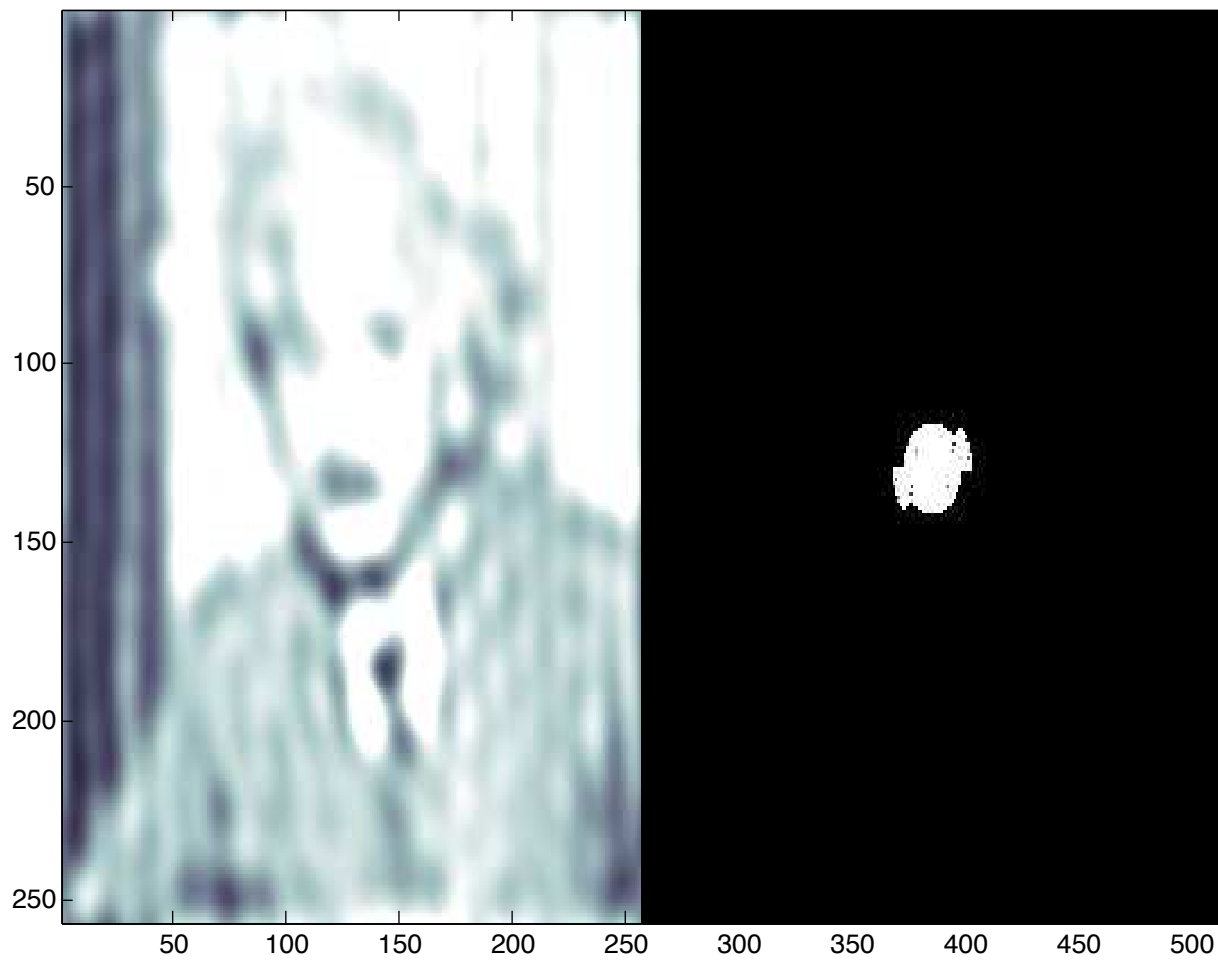


'Spatial domain'

'Frequency domain'



Note: Only  $\frac{1}{2}$  of the information is shown on the right (amplitude only; phase not shown)



→ 'Low-pass filtered' version of the image

## Fourier series

Intuitive connection back to Taylor series:

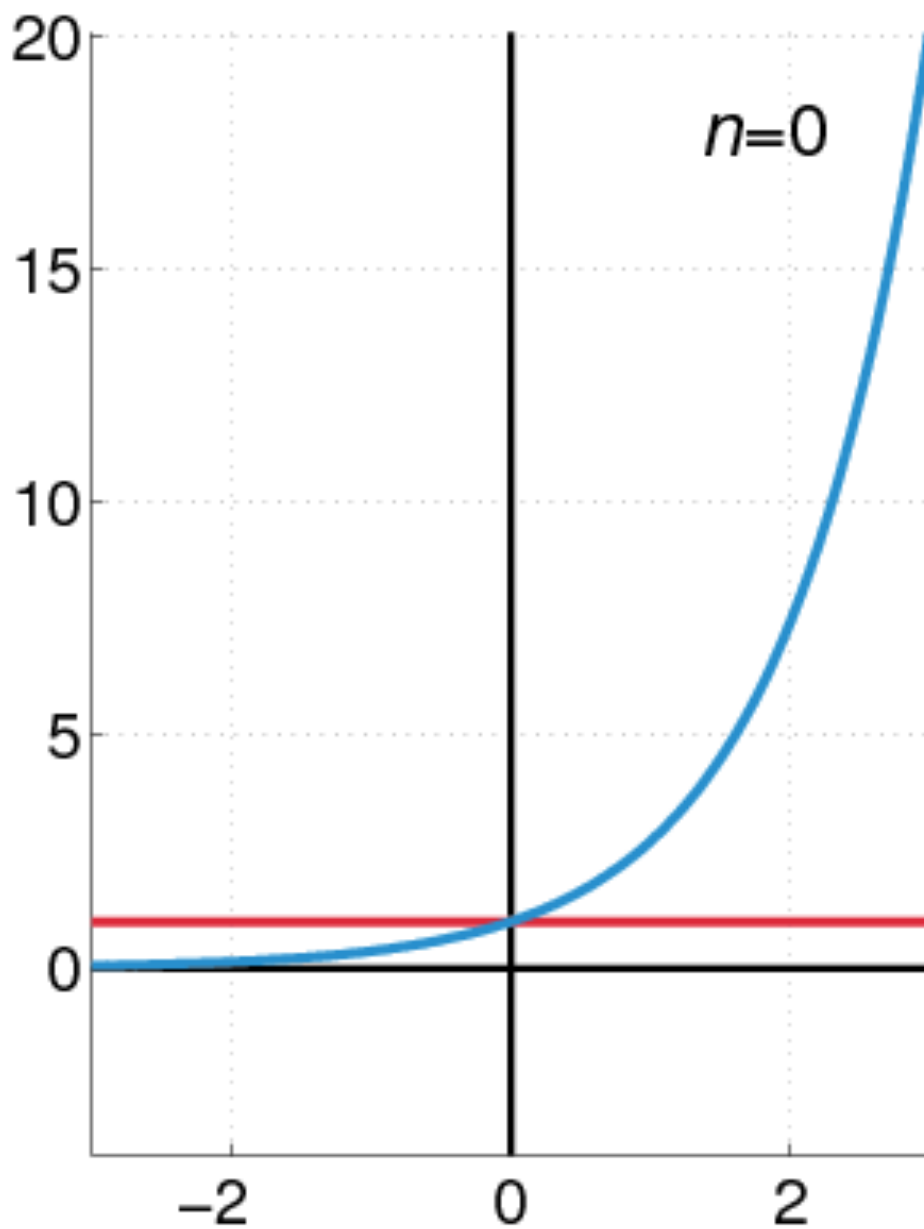
$$y(x_1 + \Delta x) \approx y(x_1) + \sum_{n=1}^N \frac{1}{n!} \left. \frac{d^n y}{dx^n} \right|_{x_1} (\Delta x)^n. \quad (\text{D.2})$$

$$\begin{aligned} f(x) &= f(x_o) + f'(x_o)(x - x_o) + \frac{f''(x_o)}{2!}(x - x_o)^2 + \cdots + \frac{f^{(n)}(x_o)}{n!}(x - x_o)^n + \cdots \\ &= \sum_{n=0}^{\infty} \frac{f^{(n)}(x_o)}{n!} (x - x_o)^n \end{aligned}$$

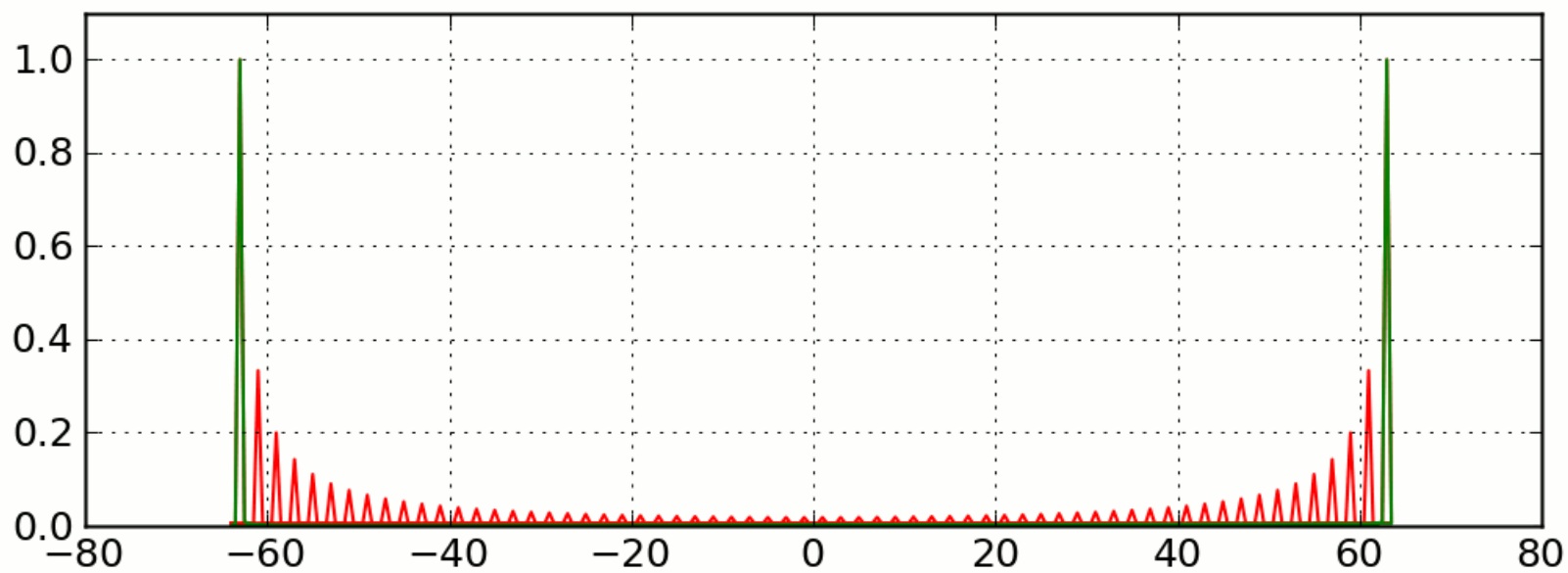
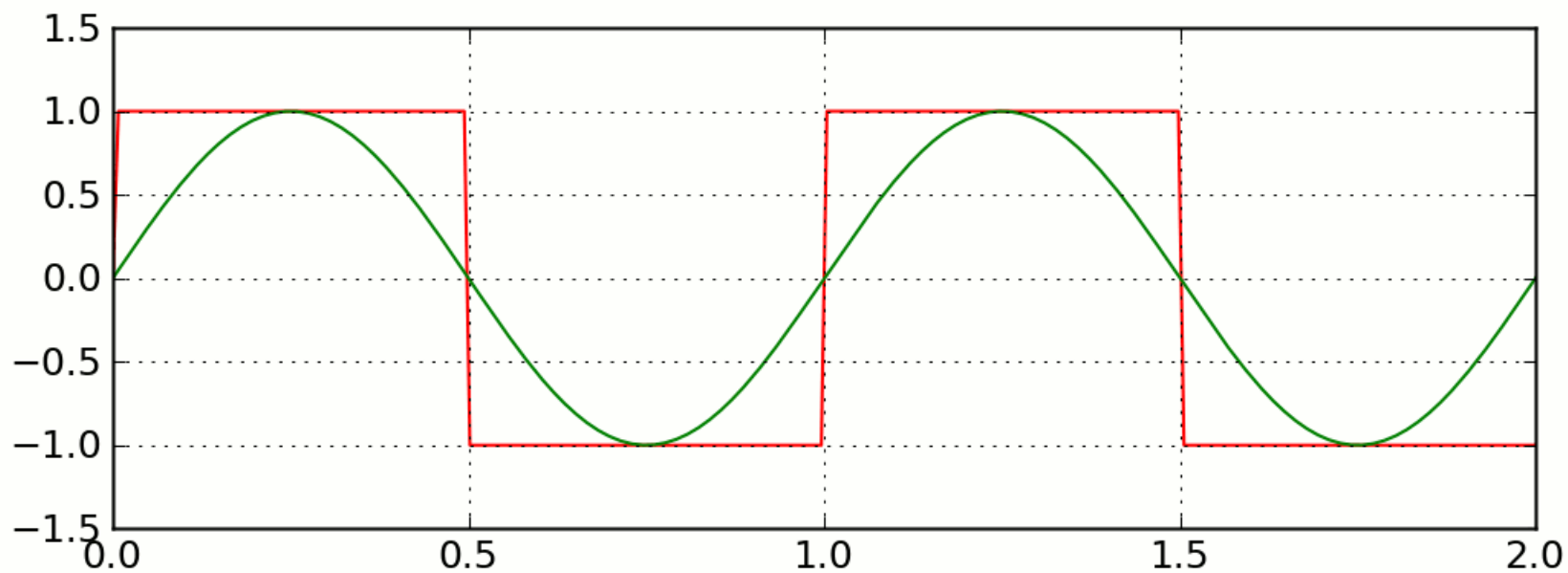
Taylor series → Expand as a (infinite) sum of polynomials

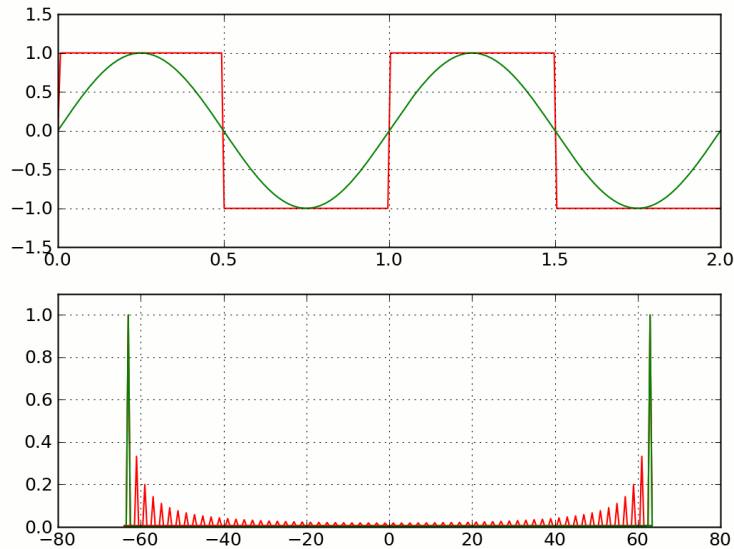
Different Idea: Fourier series → Expand as a (infinite) sum of sinusoids

“The exponential function  $e^x$  (in blue),  
and the sum of the first  $n+1$  terms of  
its Taylor series at 0 (in red).”









“Animation of the additive synthesis of a square wave with an increasing number of harmonics.”

“The six arrows represent the first six terms of the Fourier series of a square wave. The two circles at the bottom represent the exact square wave (blue) and its Fourier-series approximation (purple).”



## Fourier series

$$\begin{aligned} f(t) = & a_0 + a_1 \sin(\omega t) + b_1 \cos(\omega t) + \\ & + a_2 \sin(2\omega t) + b_2 \cos(2\omega t) + \\ & + a_3 \sin(3\omega t) + b_3 \cos(3\omega t) + \dots \end{aligned}$$

$$\begin{aligned} = & A_0 + A_1 \sin(\omega t + \phi_1) \\ & + A_2 \sin(2\omega t + \phi_2) \\ & + A_3 \sin(3\omega t + \phi_3) + \dots \end{aligned}$$

$$= \sum_{n=0}^{\infty} A_n \sin(n\omega t + \phi_n)$$

$$= \sum_{n=0}^{\infty} B_n e^{in\omega t} \quad \text{where } B_n \in \mathbb{C}, \quad i = \sqrt{-1}$$

Complex #s are much  
more compact and  
easier to deal with

# Summary

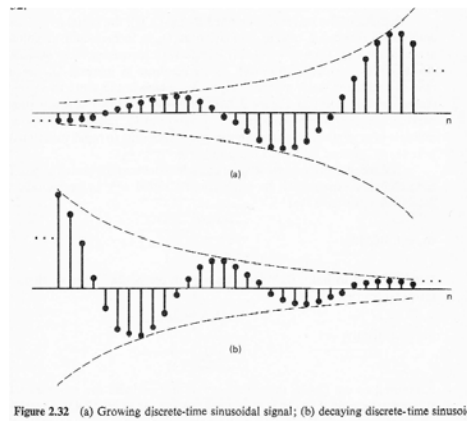


Figure 2.32 (a) Growing discrete-time sinusoidal signal; (b) decaying discrete-time sinusoid.

