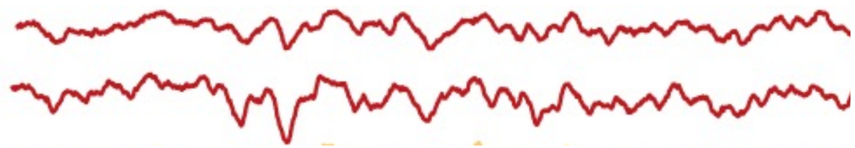
# Oscillations and Frequency Decomposition

# Brain Oscillations

<u>Rhythmic voltage fluctuations</u>



- How are oscillations recorded?
- Where do oscillations come from?
- Why should we be interested in them?
- What is frequency decomposition?
- What are the important features of an oscillatory signal?
- Short demos of analysis of spectral data

# Brain Oscillations

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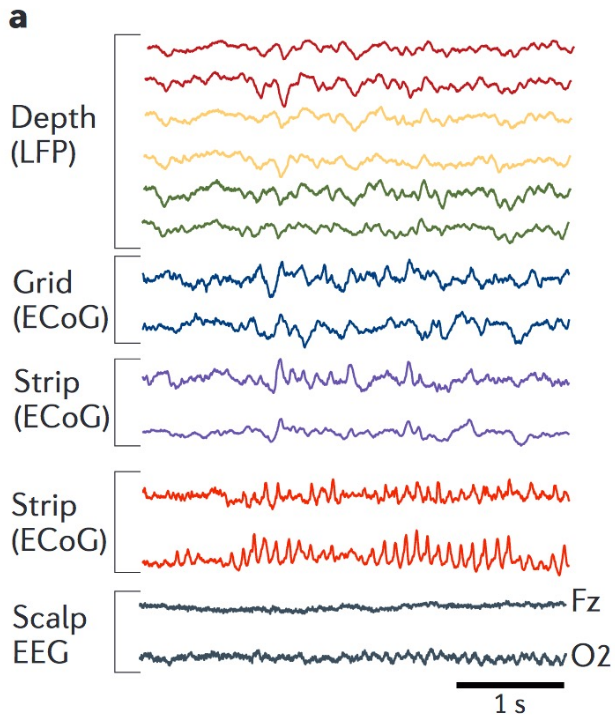
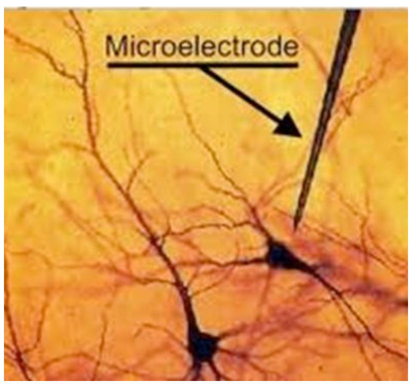


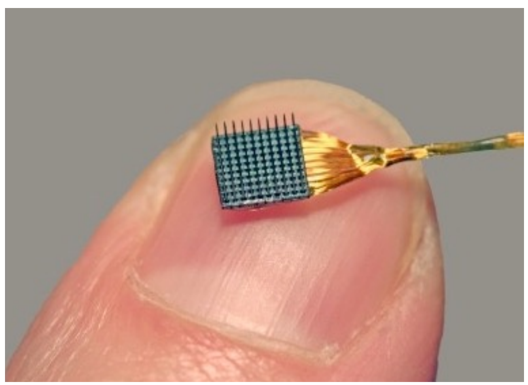

Buzsaki et al., 2012

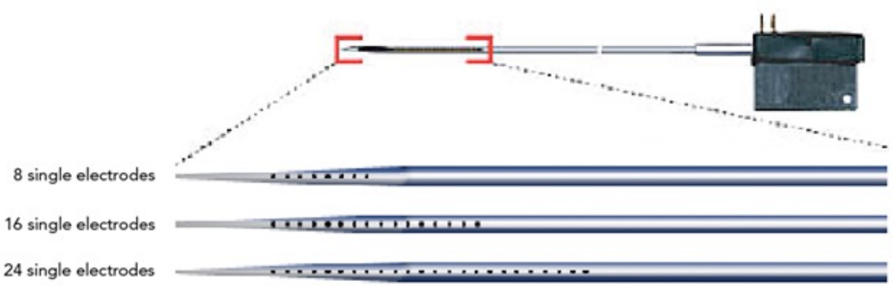
# Brain Oscillations

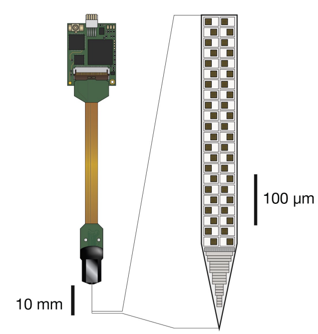
<u>Rhythmic voltage fluctuations</u>

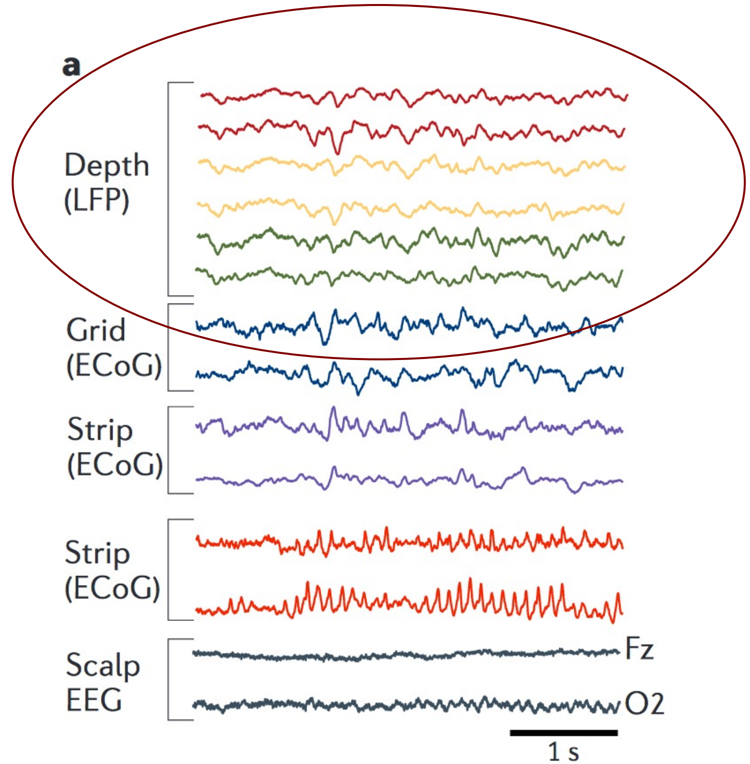
- Recorded *in* the brain – Local Field Potential (LFP)





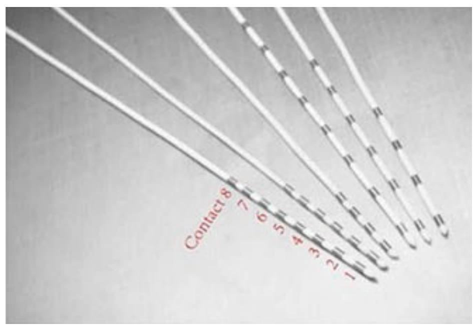

Buzsaki et al., 2012

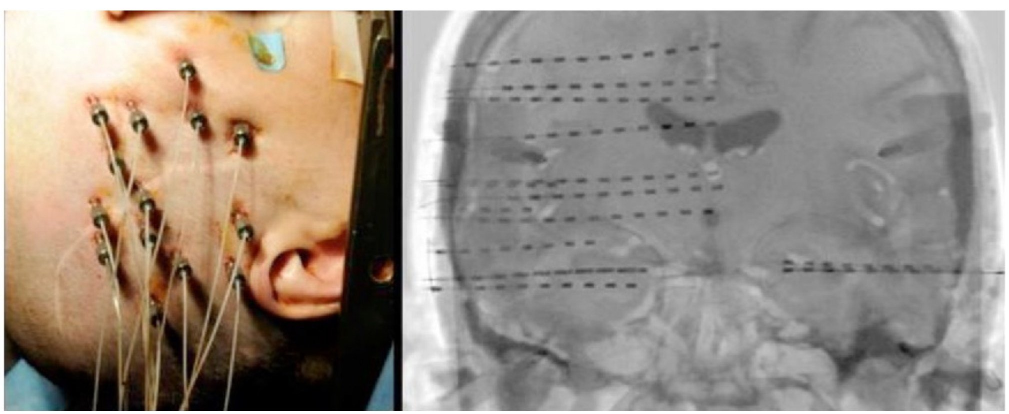
# Brain Oscillations

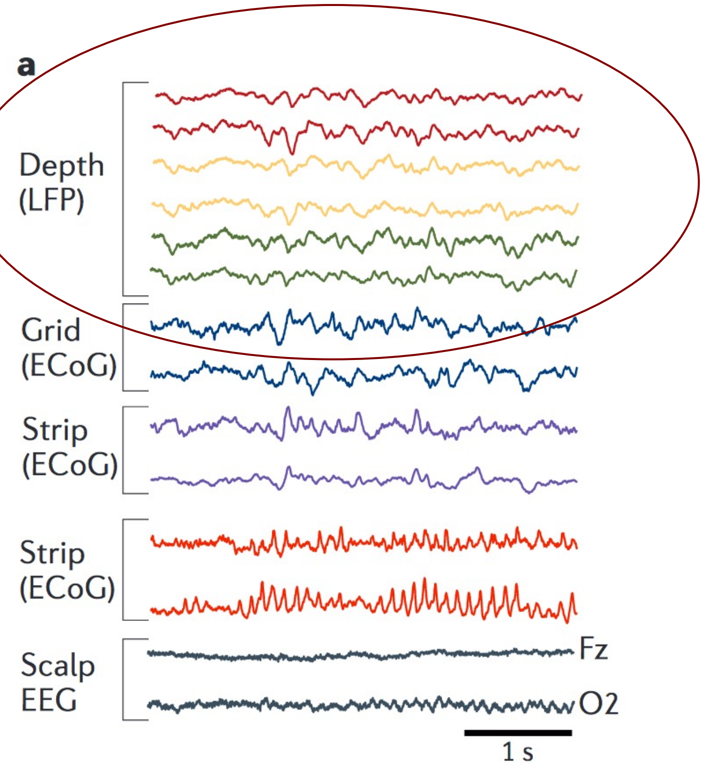
<u>Rhythmic voltage fluctuations</u>

- Recorded *in* the brain – Local Field Potential (LFP)

*"Stereo EEG"*






Buzsaki et al., 2012

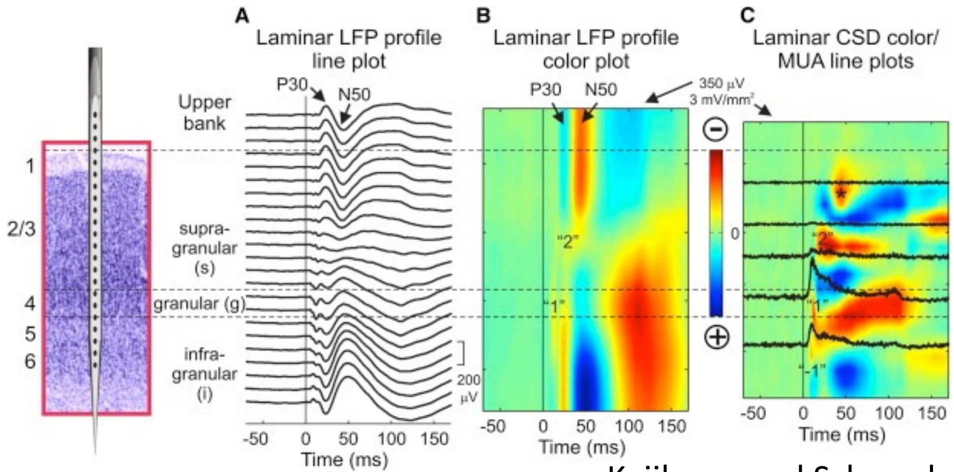
# How local are LFPs?

200–400 µm (Katzner et al., 2009, Xing et al., 2009)
600-1000 µm (Berens et al., 2008)
2–3 mm (Nauhaus et al., 2009, Wang et al., 2005)
~5 mm (Kreiman et al., 2006)
vertically over centimeters (Schroeder et al., 1992)

LFPs can vary across cortical layers

*Current Source Density (CSD) analyses can reconstruct laminar organization

*CSD = 2$^{nd}$ spatial derivative of LFP*



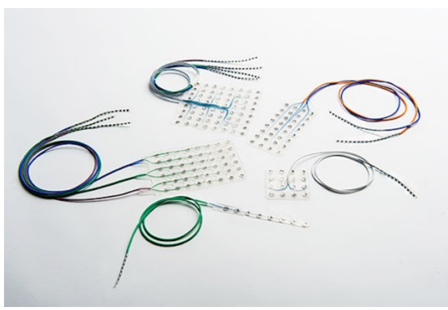

Kajikawa and Schroeder, 2011

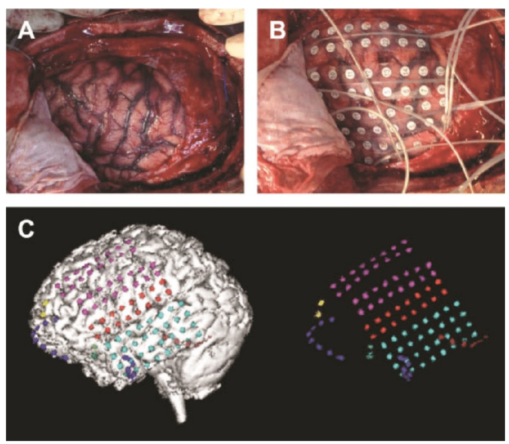
Also includes *volume conduction* from distant sources

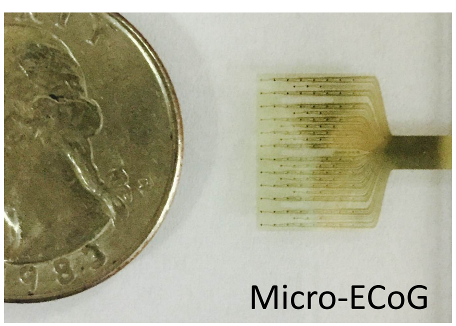
# Brain Oscillations

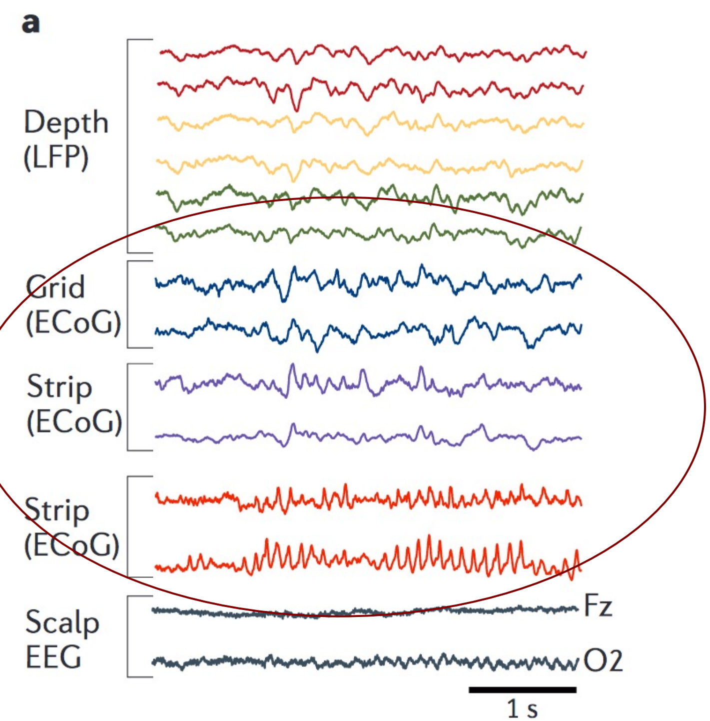
<u>Rhythmic voltage fluctuations</u>

- Recorded *in* the brain – Local Field Potential (LFP)
- Recorded *on* the brain – Electrocorticography (ECoG)





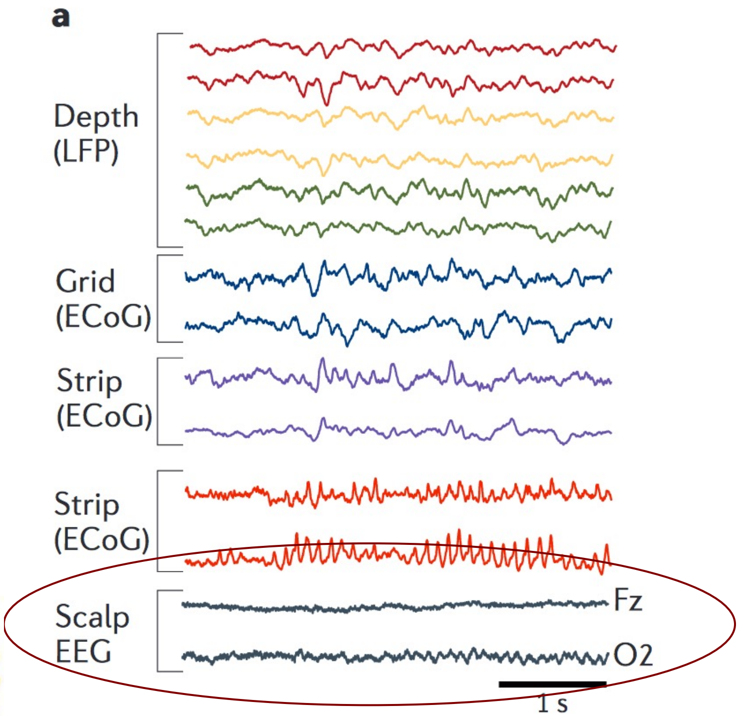




Buzsaki et al., 2012

# Brain Oscillations

<u>Rhythmic voltage fluctuations</u>

- Recorded *in* the brain – Local Field Potential (LFP)
- Recorded *on* the brain – Electrocorticography (ECoG)
- Recorded *near* the brain – scalp electroencephalography (EEG)




Buzsaki et al., 2012

as well as magnetoencephalography (MEG)

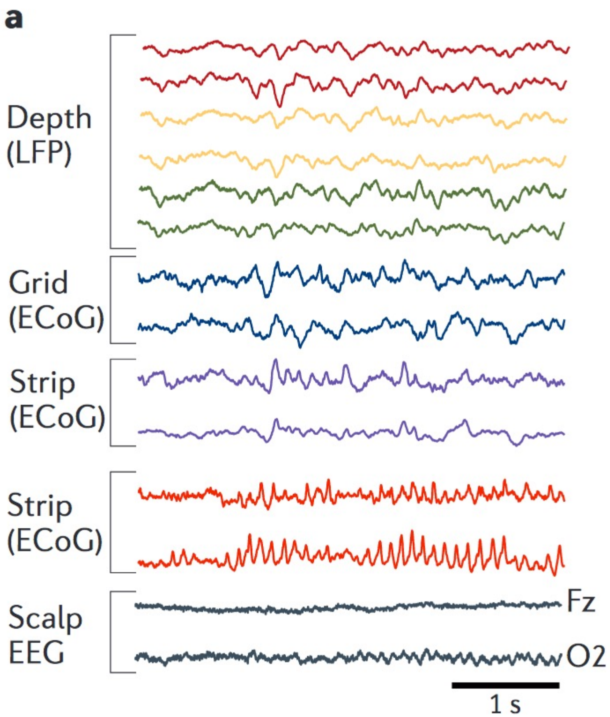
# Brain Oscillations

<u>Rhythmic voltage fluctuations</u>

Multiple sources:

Neuron spiking, subthreshold membrane potential fluctuations (axons, dendrites, soma, also glial cells), synaptic activity, calcium transients, etc.

*The brain is a dynamic environment of charged particles moving in and out of different compartments with specialized gating mechanisms*




Buzsaki et al., 2012

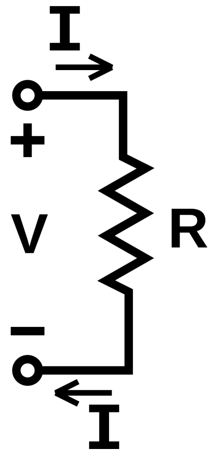
gating mechanisms are voltage sensitive -> dynamical system that produces oscillations

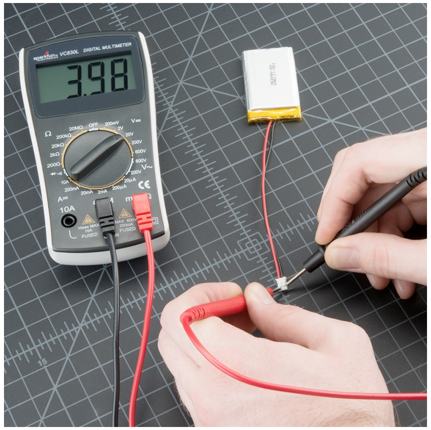
# Brain Oscillations

Rhythmic voltage fluctuations

Flow of charged particles -> *current*

$V = IR$




Voltage = electrical potential between two points

All voltages are recorded with respect to a *reference*

# Why are we interested in brain oscillations?

- Changes correlate with important brain processes
  (e.g. sensory, motor, cognitive, emotional events)

  Oscillations may play an role in computation themselves, or through interactions with neuron populations

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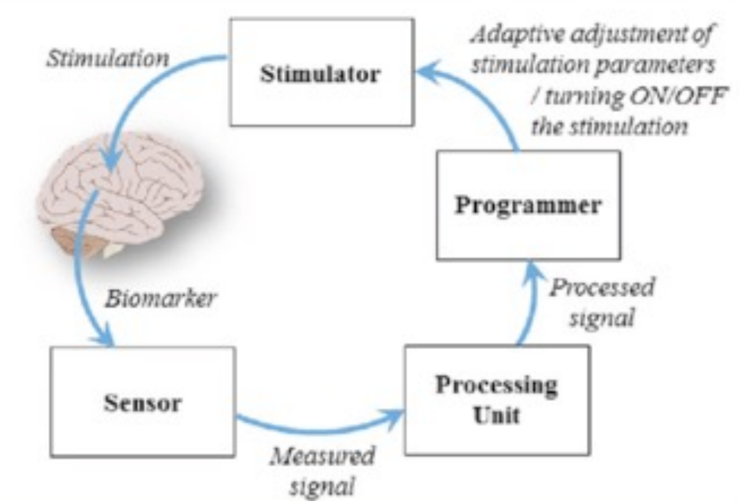

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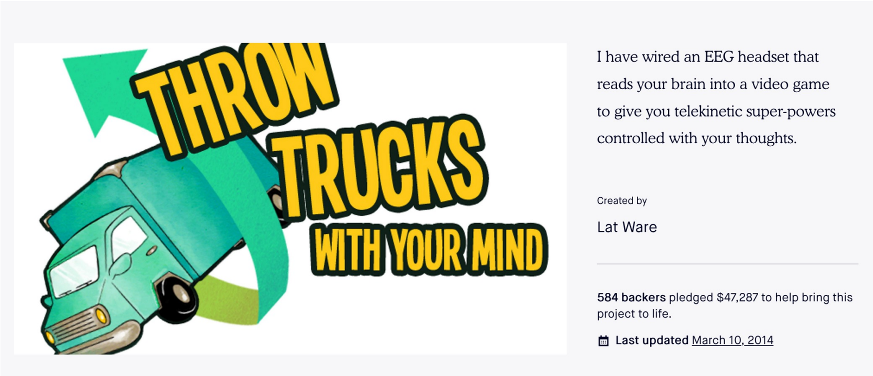
- Can be volitionally controlled

  Potential applications in brain-machine interfaces



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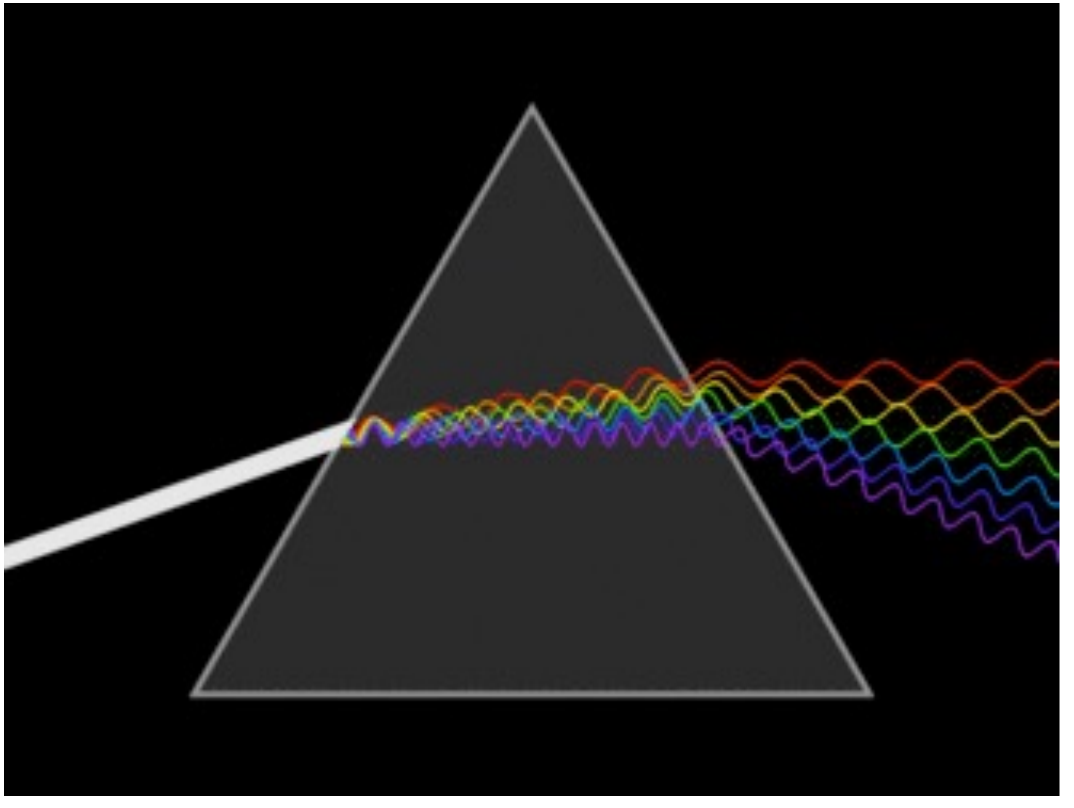
  Potential applications in brain-machine interfaces and biofeedback-based therapies

# Recorded signals are composed of multiple frequencies

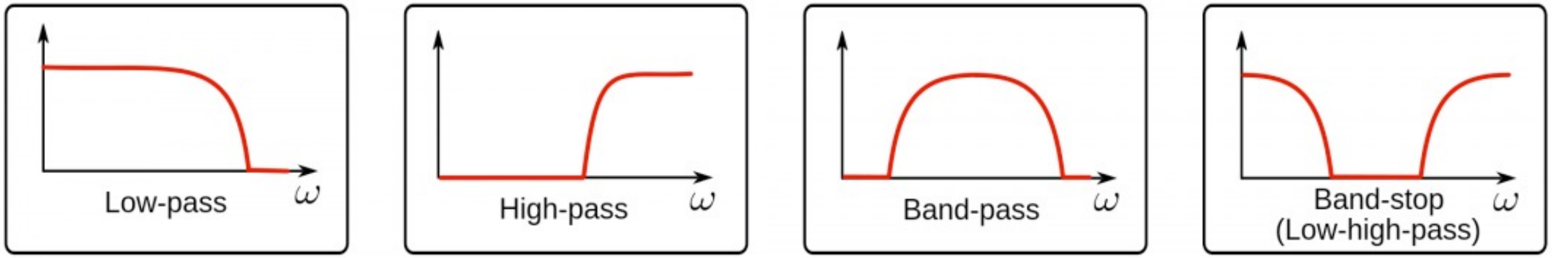


# Recorded signals are composed of multiple frequencies

Signals of different wavelengths can be extracted using various methods:

1. *Bandpass filters* – extract signal in certain frequency *bands* of interest

Types of filters:




aka. Notch filter

Most commonly used: Finite Impulse Response (FIR) filters

Names you may see: Butterworth*, Chebyshev, Bessel

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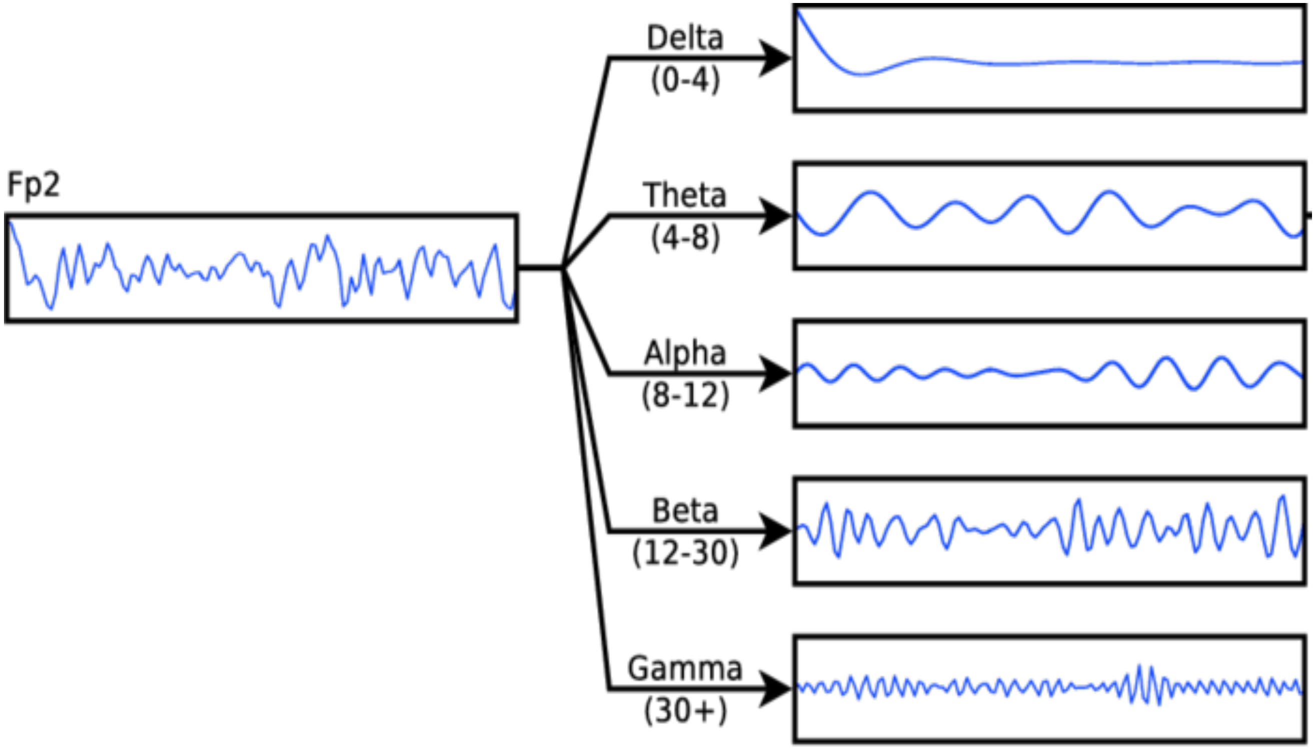
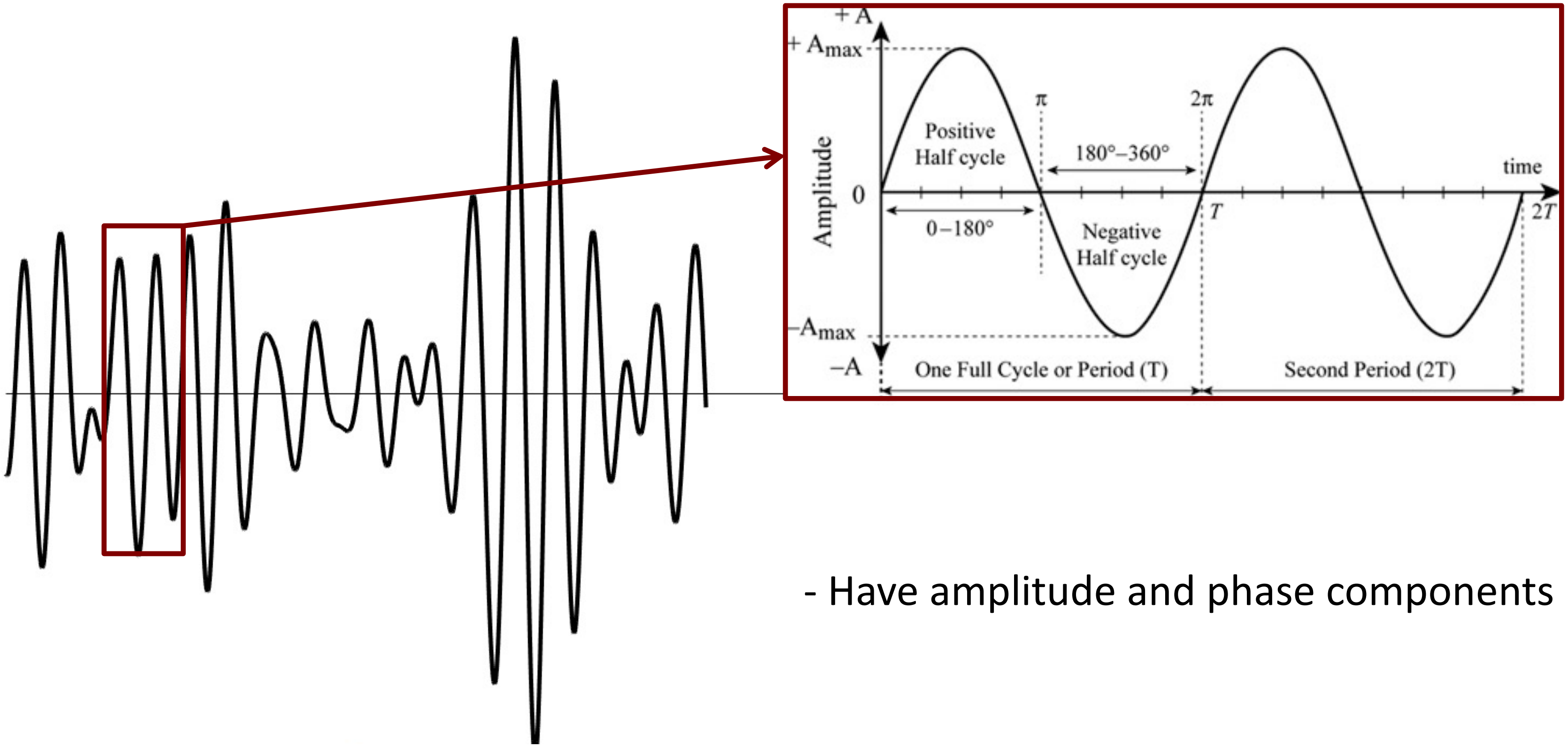
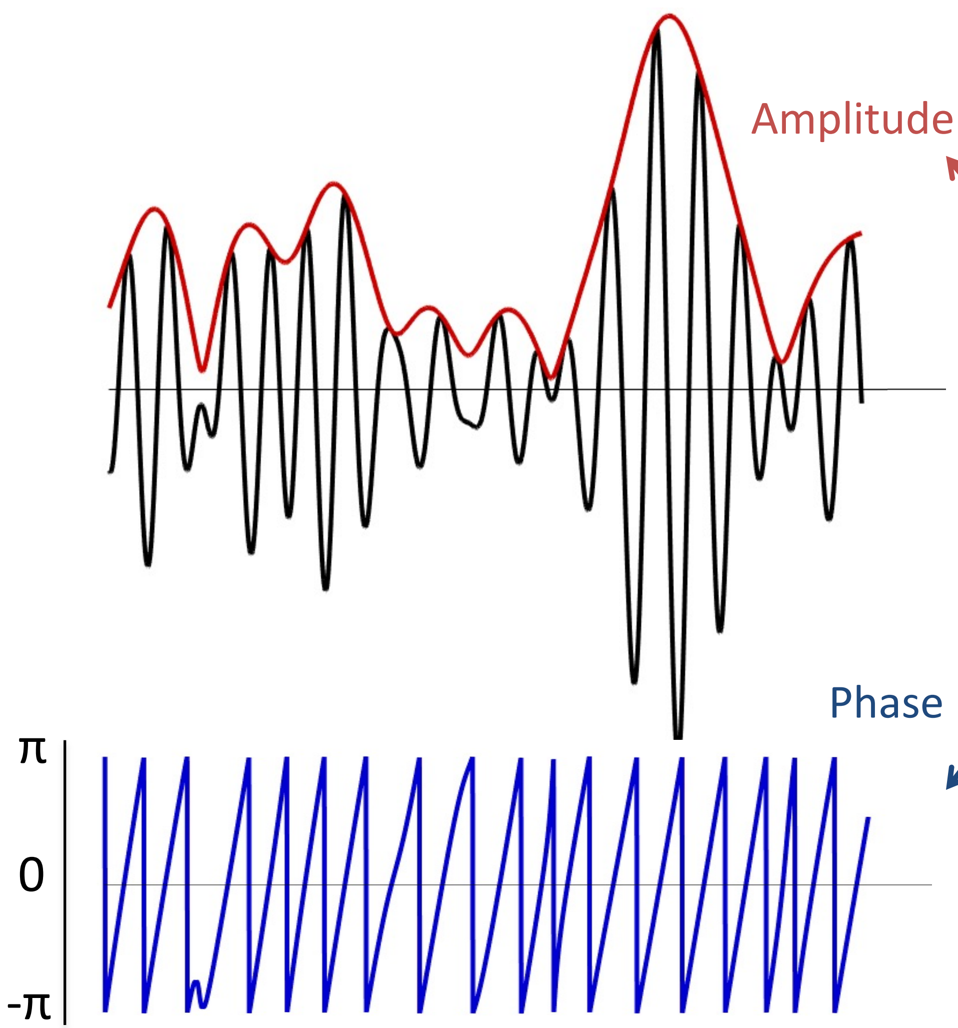


# Oscillations in a frequency band are sine waves




- Have amplitude and phase components

# Oscillations in a frequency band are sine waves




Can also be represented as a complex number:

$$a + bi$$

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Signals of different wavelengths can be extracted using various methods:

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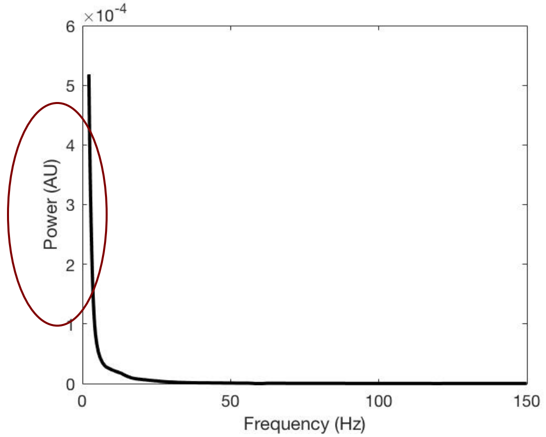
2. *Frequency decomposition* – extracts signal in all wavelengths within frequency range of interest

*Power spectral density plot (PSD)*




- Commonly use arbitrary units (AU) or decibels

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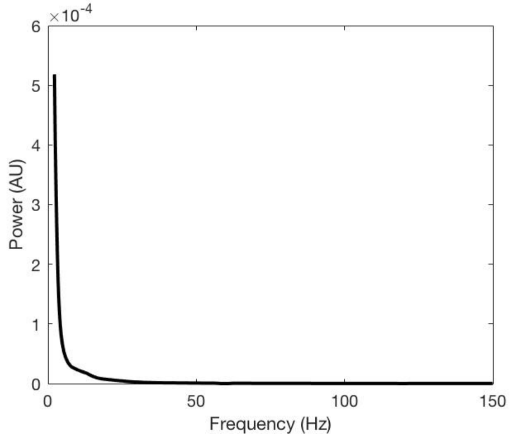
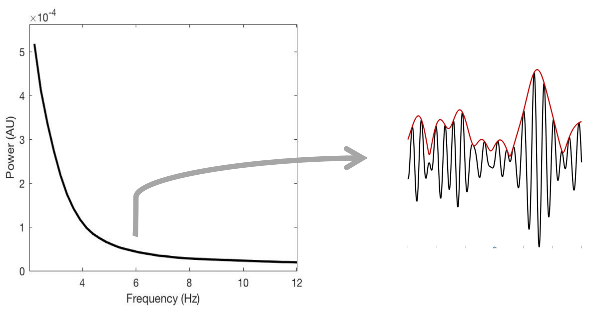



- Commonly use arbitrary units (AU) or decibels
- Power = amplitude squared



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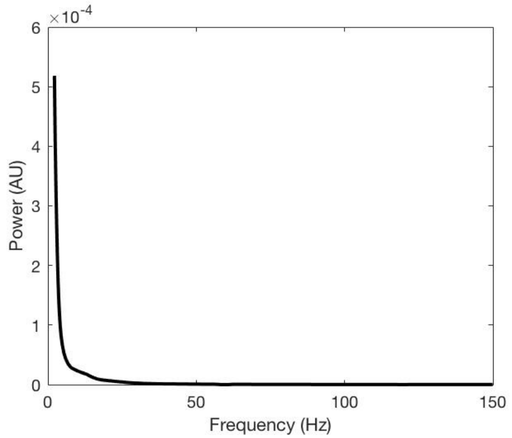


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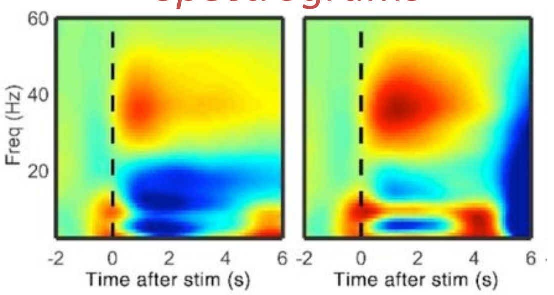
- Information is only in the frequency domain

*Spectrograms*



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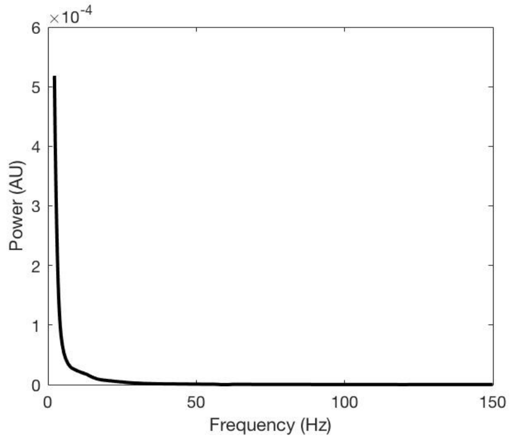


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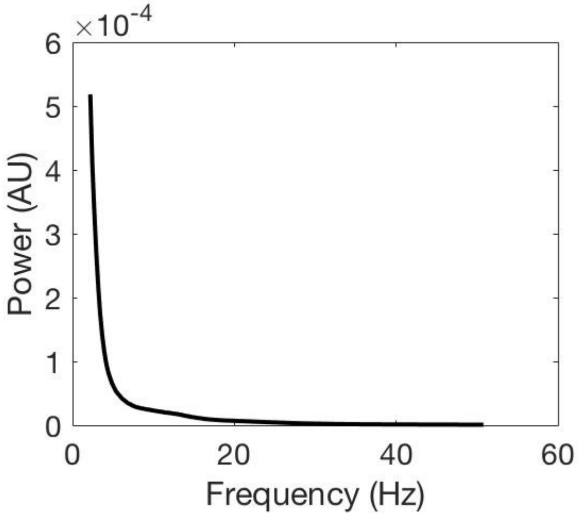
- ~1/f shape

# Neural signals have 1/f power spectral densities




- Actually c ($1/f^x$), where x is approximately 0.5 – 1.5
  *Power law* distribution

- Power decreases exponentially with frequency

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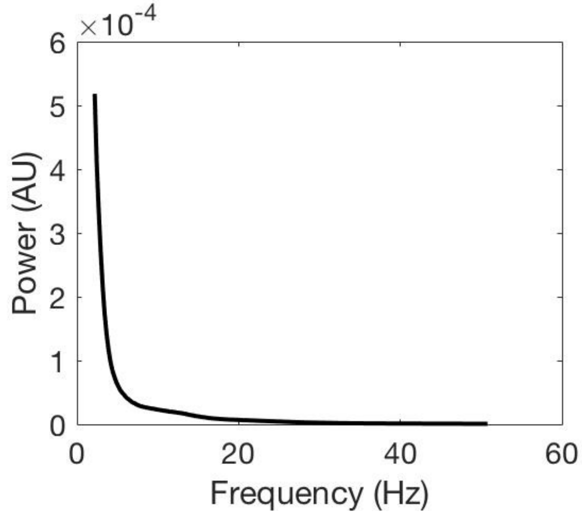


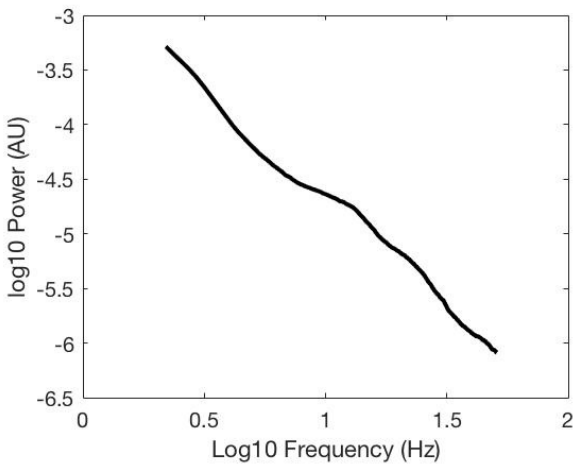


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- PSDs are often plotted on a log scale

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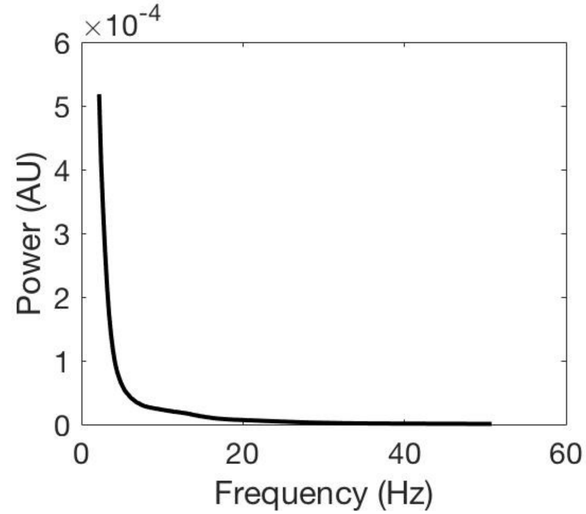


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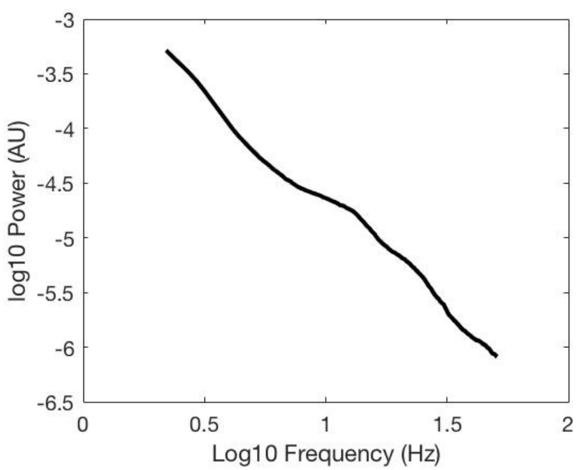
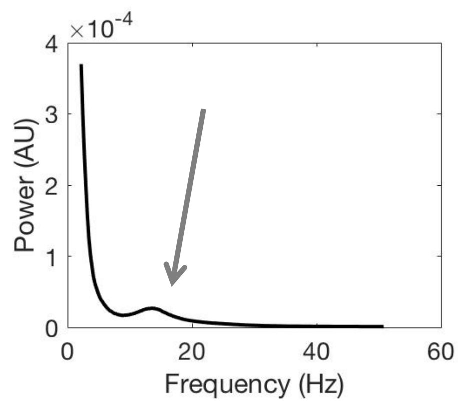
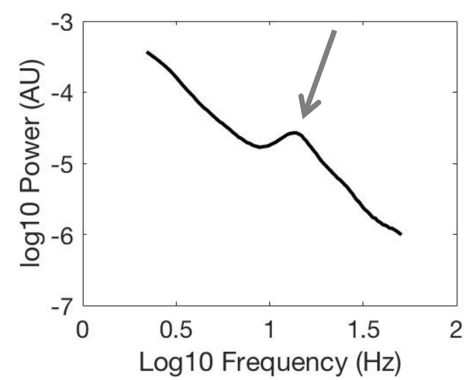
- Deviations from 1/f curves indicate frequencies with strong oscillations
  *usually within canonical bands*



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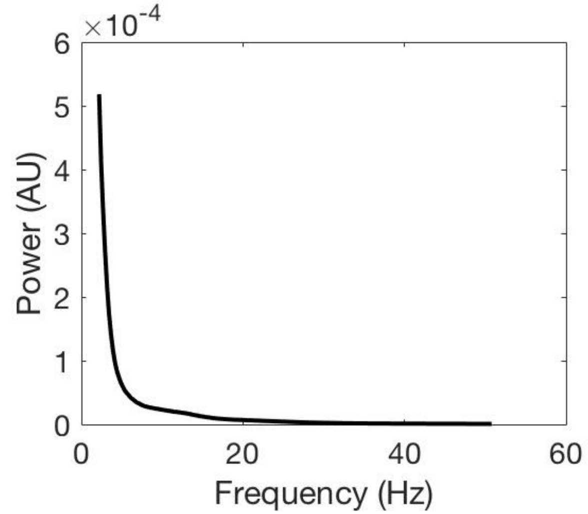


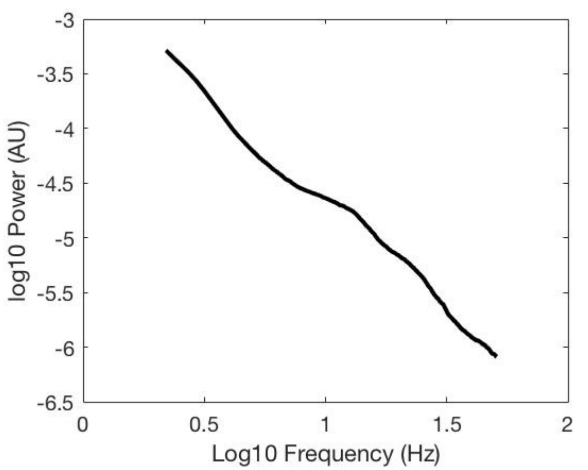


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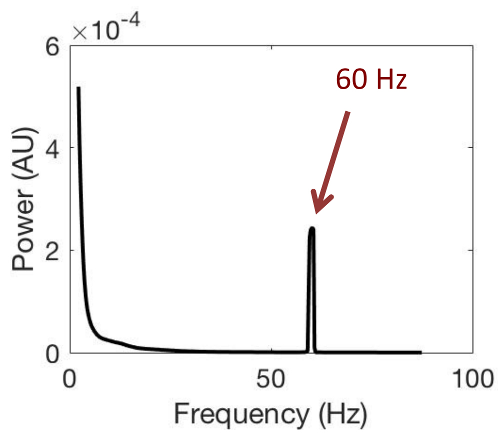


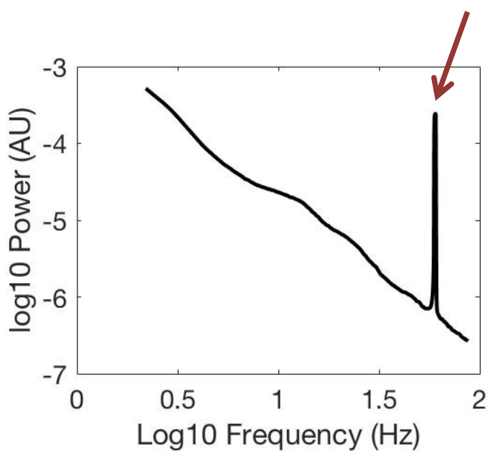

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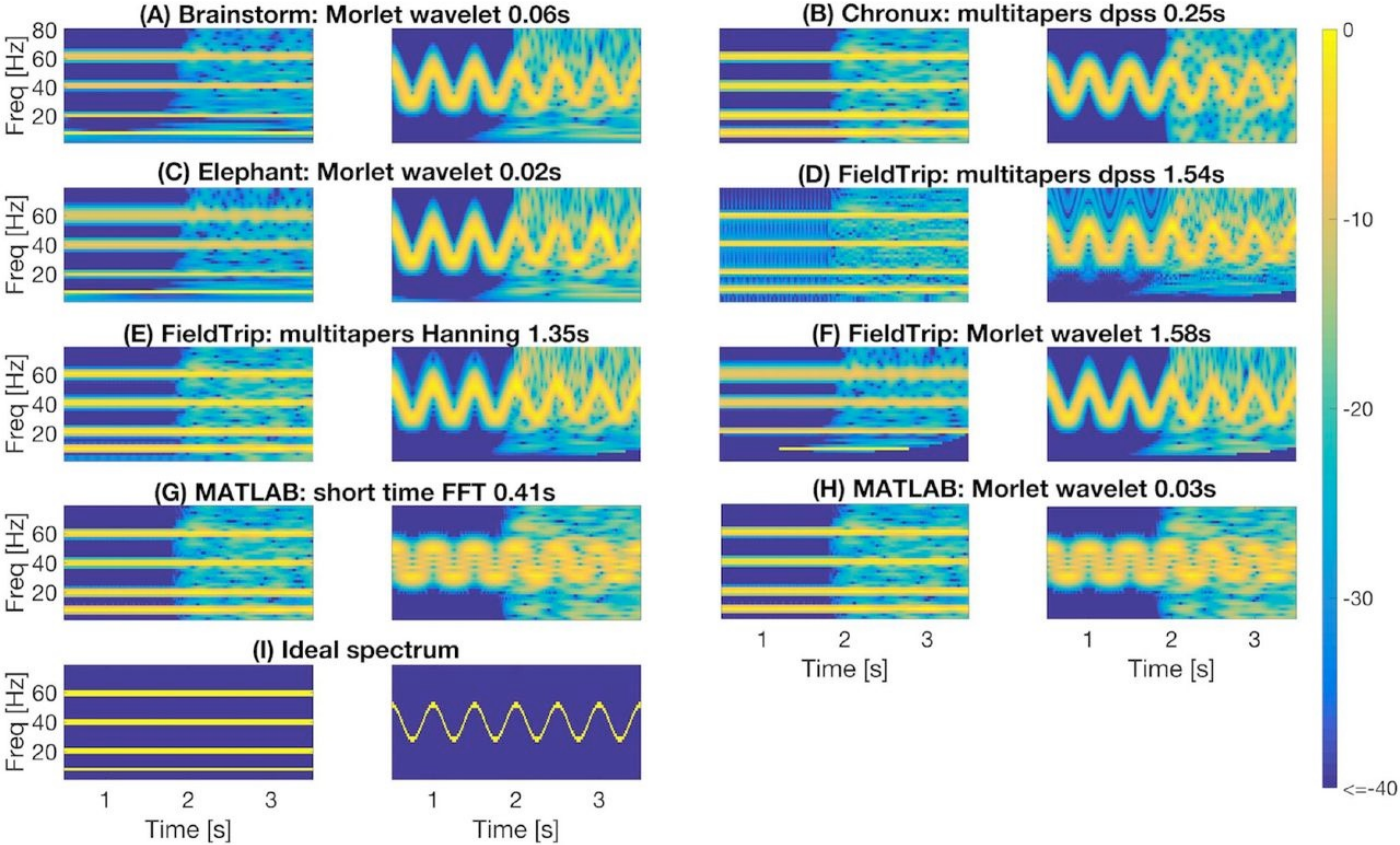
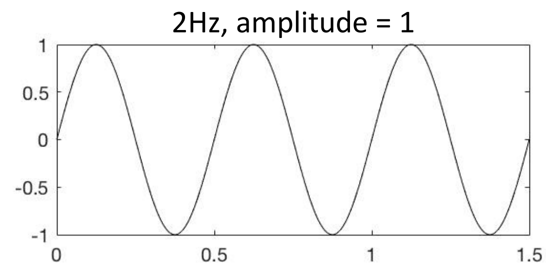
Signals of different wavelengths can be extracted using various methods:

1. *Bandpass filters* – extract signal in certain frequency *bands* of interest
   FIR filter
2. *Frequency decomposition* – extracts signal in all wavelengths within frequency range of interest
   Fourier Transform (Matlab users: fft.m)
   Wavelet convolution
   Multitapers (Matlab users: try Chronux toolbox)
   Bandpass -> Hilbert Transform (hilbert.m)




Unakafova and Gail, bioRxiv 2019

# Demo – decomposing spectral data




Start with a synthetic signal:

To make a sine wave signal:

Define parameters for your sine wave

amp = amplitude (e.g. 1)

freq = frequency (e.g. 2Hz)

t = time vector (x-axis)

- you'll need give the time vector a *sampling frequency* that is at least 2x your highest frequency of interest (Nyquist theorem)

*try this:* Fs = sampling frequency = 1000 Hz (= 1kHz)

L = length of your time vector (e.g. 5000 samples)

**time = (1:L).*(1/Fs)**

t

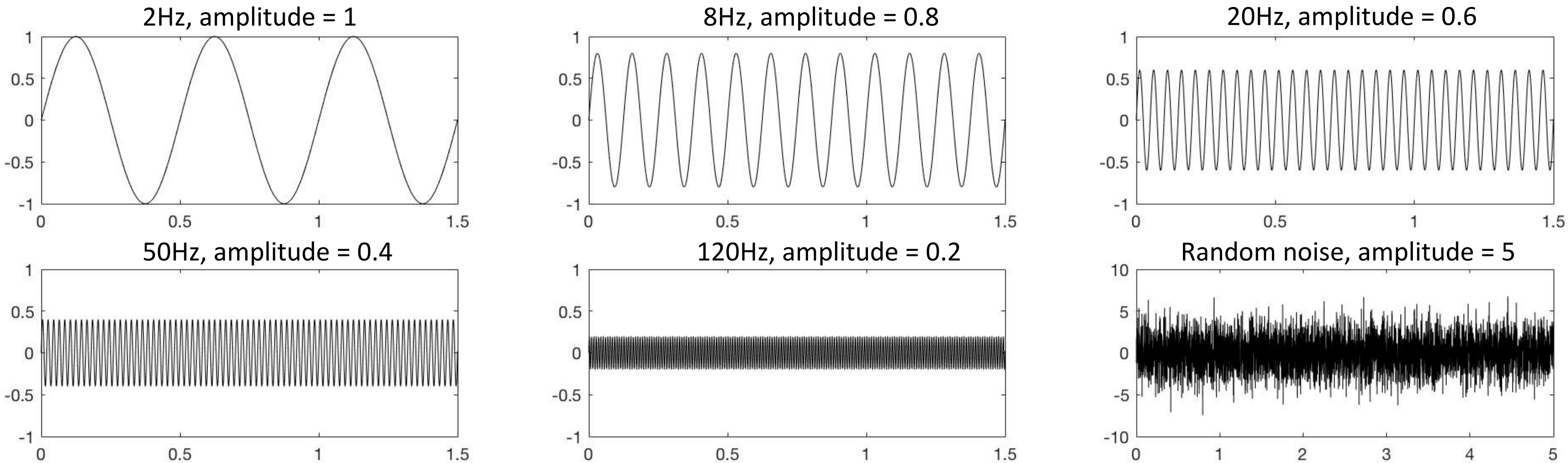
1x5000 double

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 | 1.0000e-03 | 0.0020 | 0.0030 | 0.0040 | 0.0050 | 0.0060 | 0.0070 |
| 2 | | | | | | | |
| 3 | | | | | | | |
| 4 | | | | | | | |
| 5 | | | | | | | |

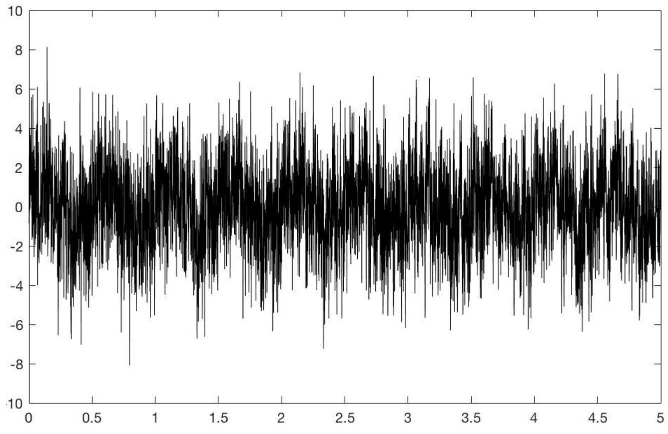
sinewave = amp*sin(2*pi*freq*t)

# Demo – decomposing spectral data

Start with a synthetic signal: different sine waves superimposed, with noise:




Summed signal:



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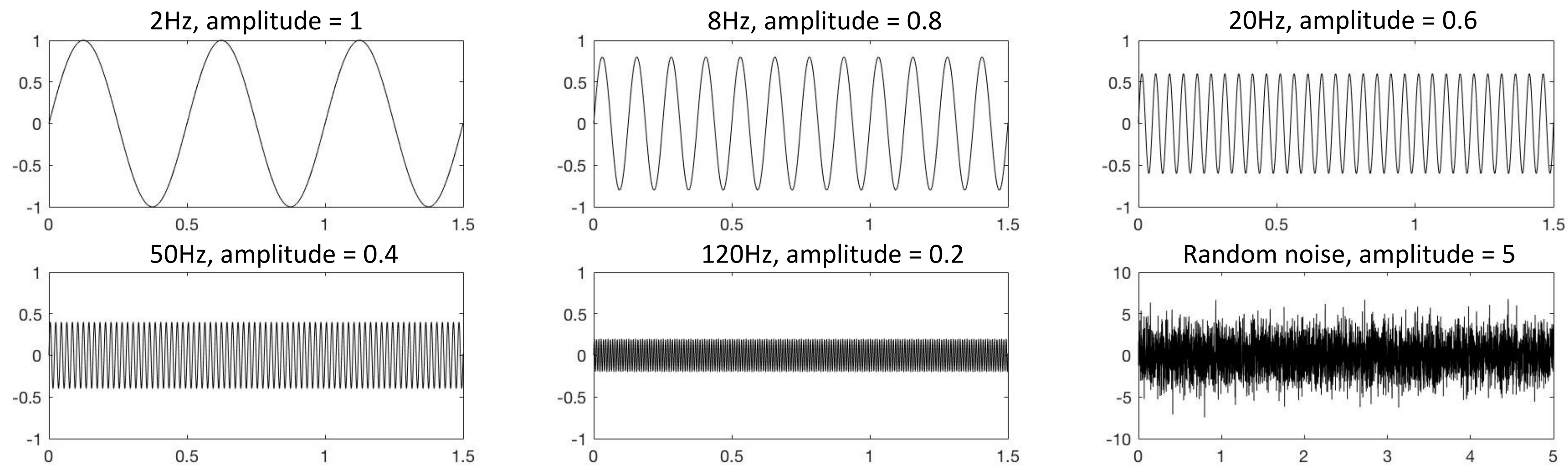
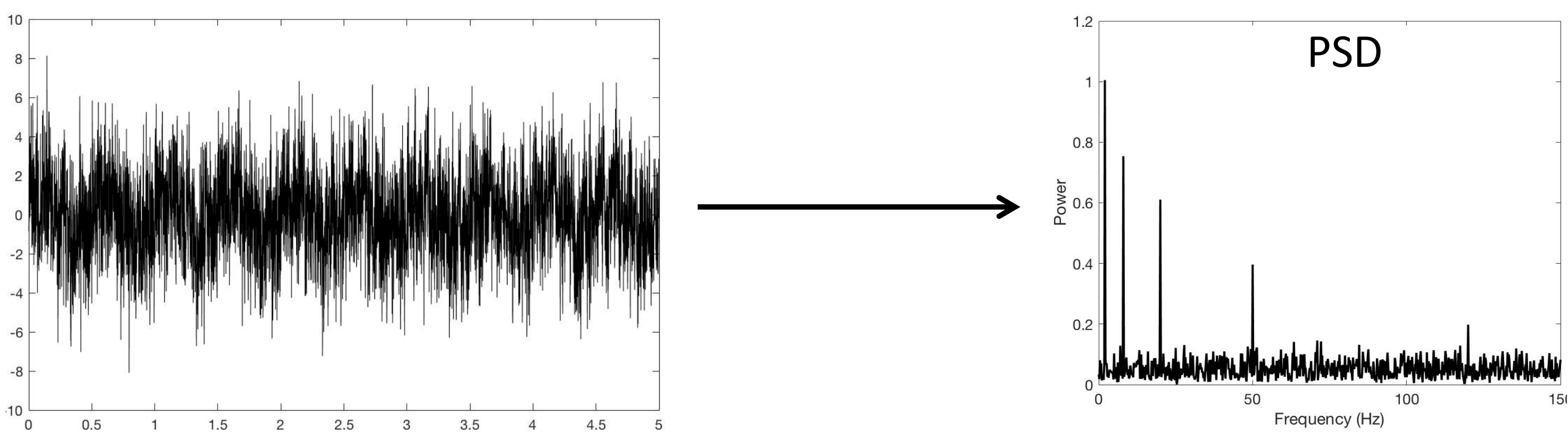
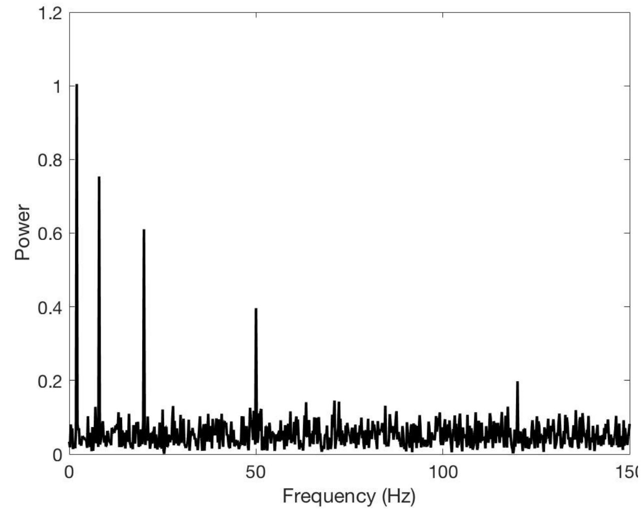


# PSD



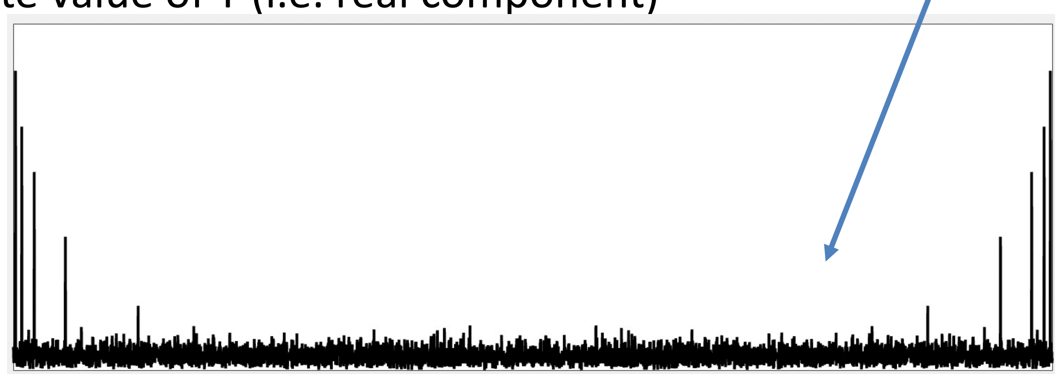

Fourier Transform (Matlab users: fft.m)

Y = fft(summed_sinewaves)

Y is a vector of complex numbers! (a + bi)

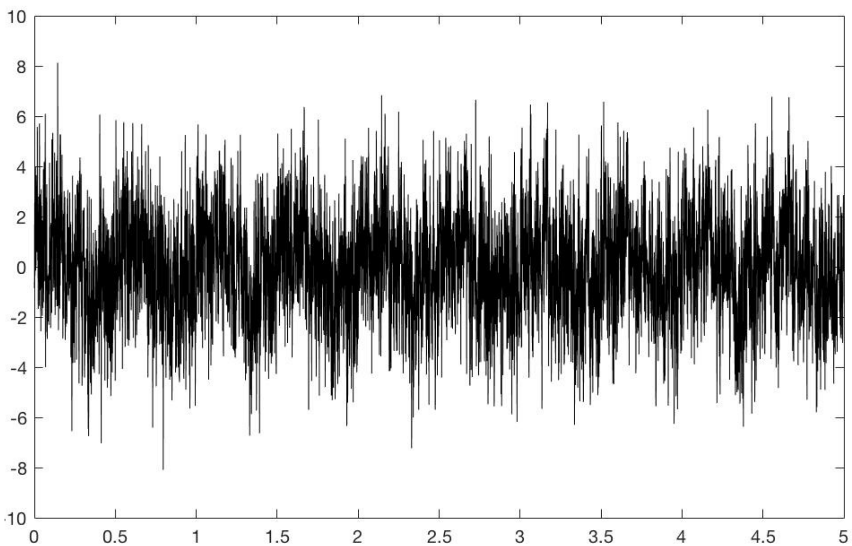
Plot the absolute value of Y (i.e. real component)

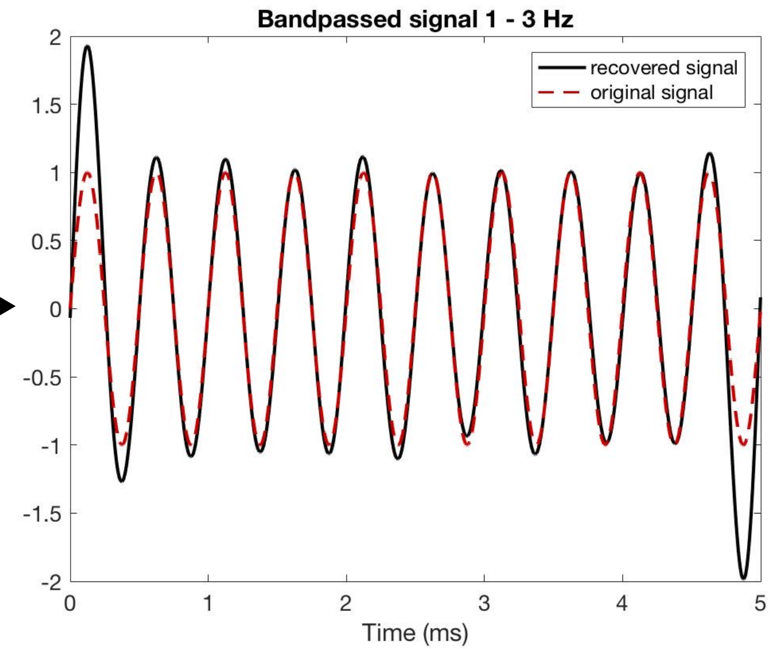
"negative frequencies"



# Demo – decomposing spectral data

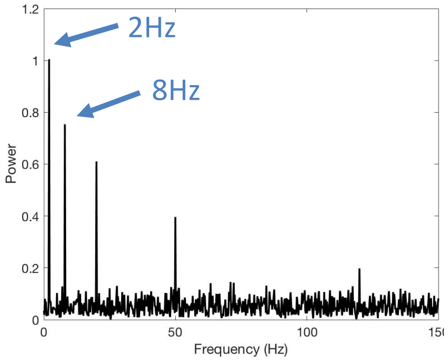
Original signal



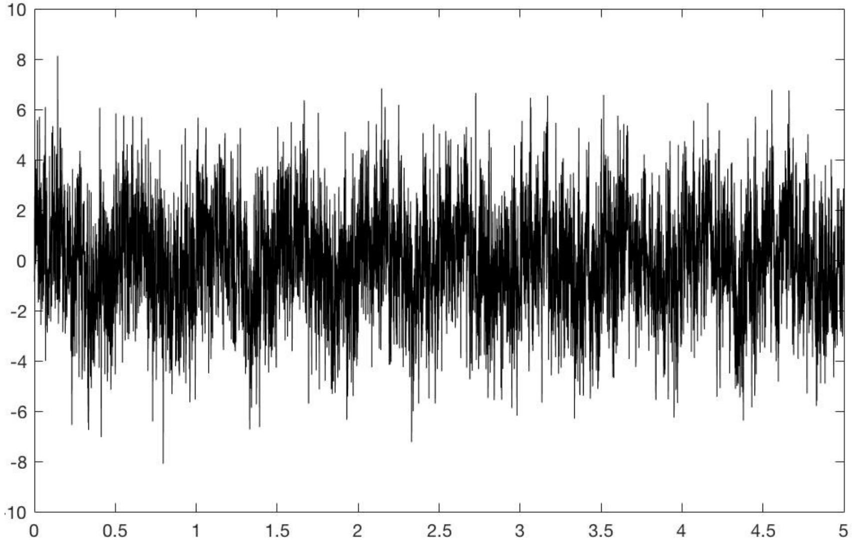



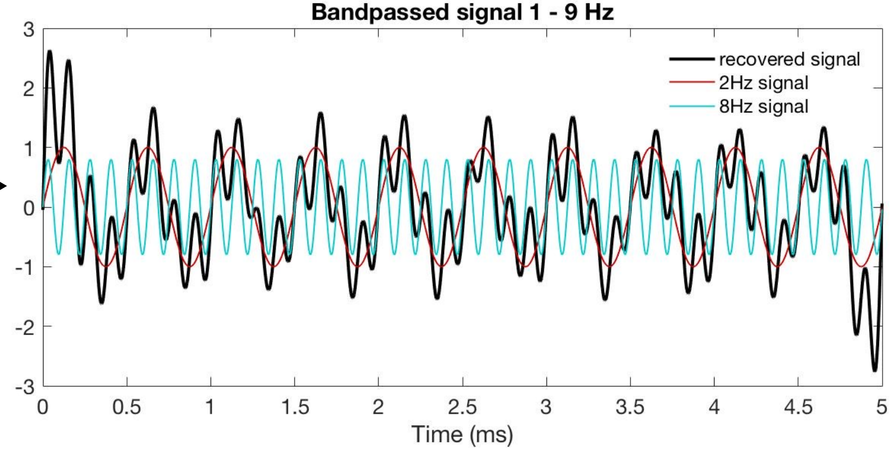

Bandpass filter recovers sine waves of a specified frequency

# Demo – decomposing spectral data




Original signal

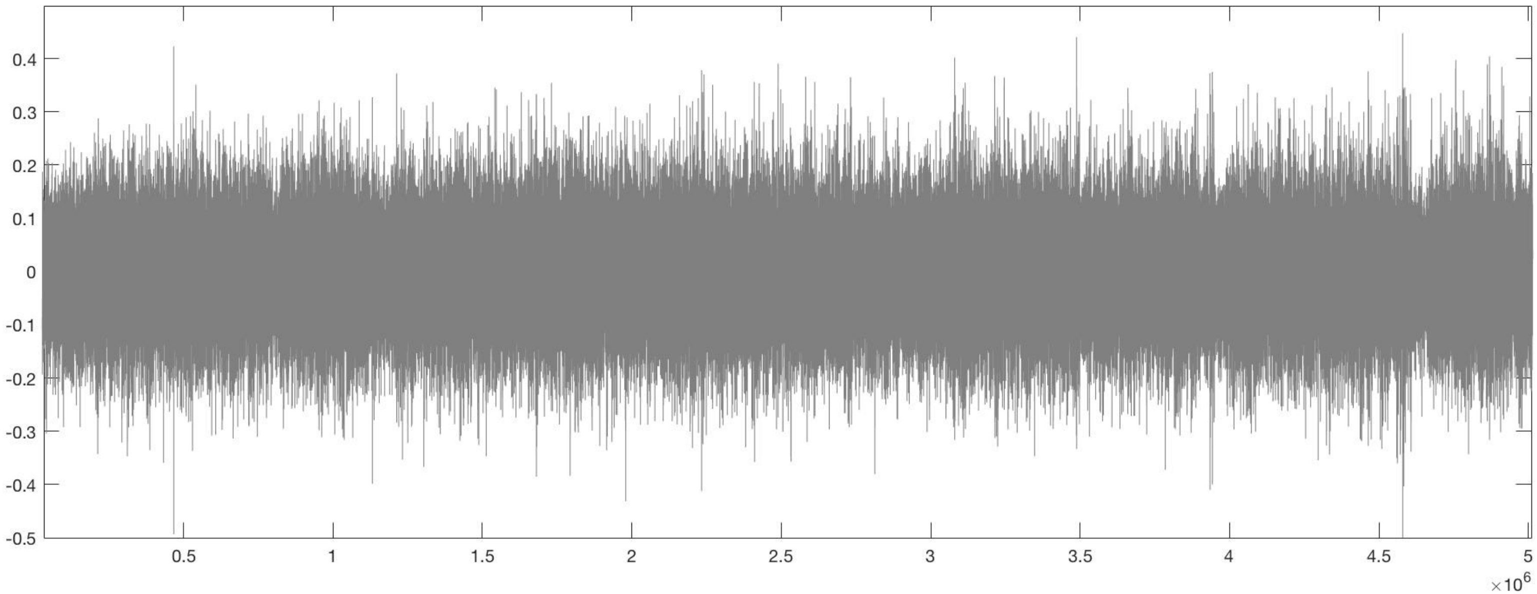




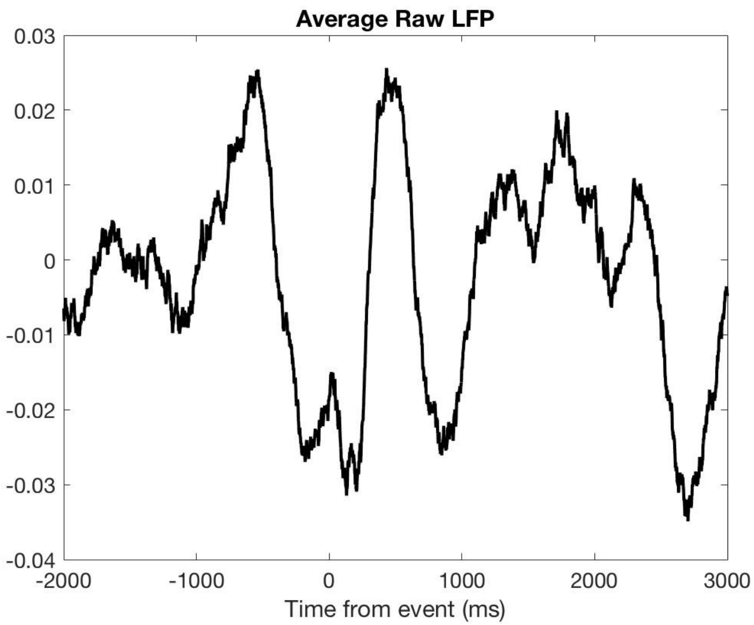

Bandpass filter recovers sine waves of a specified frequency

# Demo – decomposing spectral data

Now let's work with real data



# Demo – decomposing spectral data

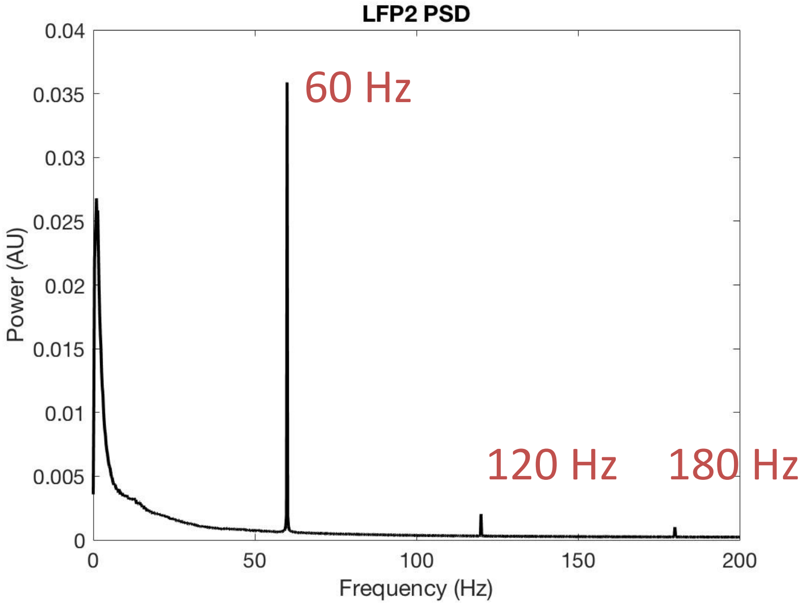



## Event Related Potential (ERP)

Unclear origins, but very common

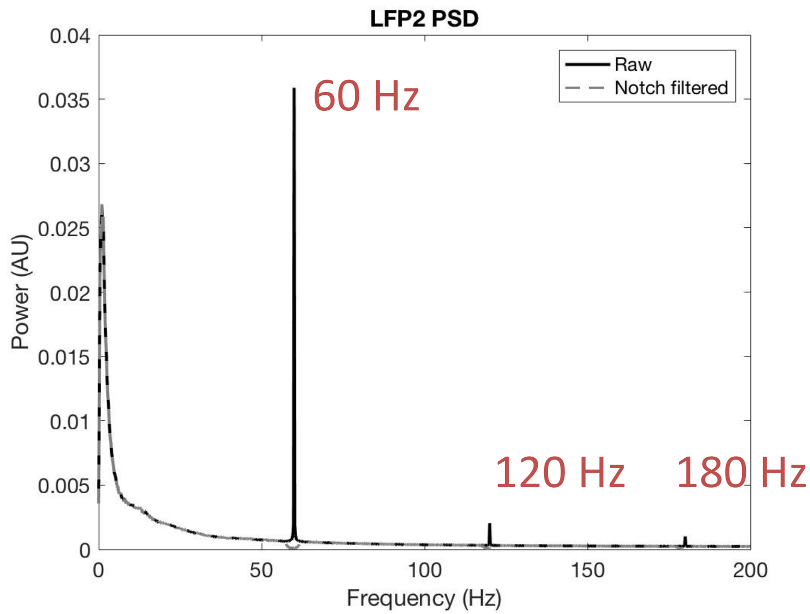
- One model proposes they are elicited by an event, and separate from background oscillations
- One model proposes they are phase resets of these oscillations

# Demo – decomposing spectral data




Next we can look at the PSD

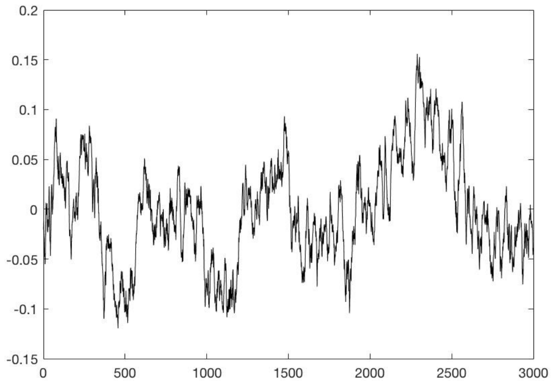
# Demo – decomposing spectral data

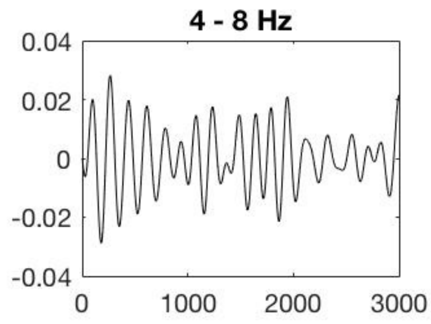


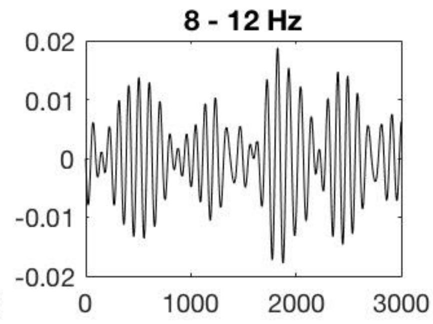

Apply a *notch filter* at 60Hz and harmonics

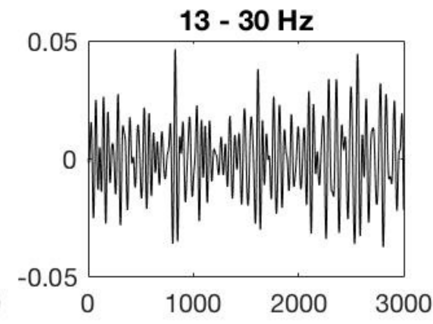
*This is a common preprocessing step

# Demo – decomposing spectral data

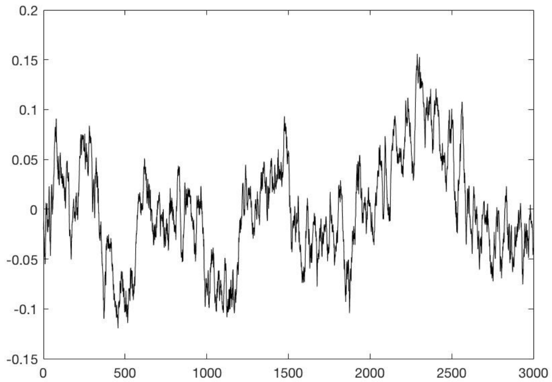


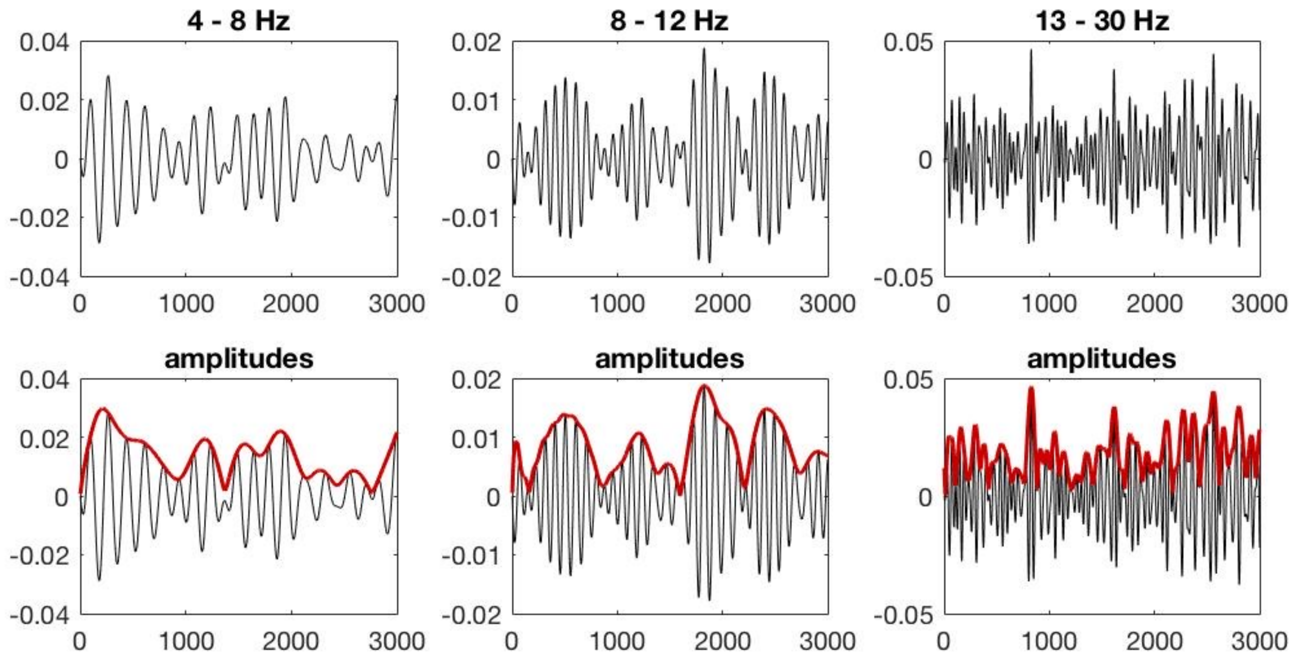



# Demo – decomposing spectral data



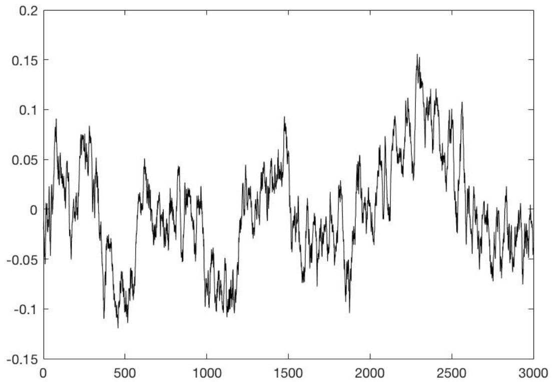

Bandpass -> Hilbert Transform

Hilbert will give you a
vector of complex numbers!
(a + bi). Here **a** is the original data; **bi** is the Hilbert transform containing amplitude and phase information

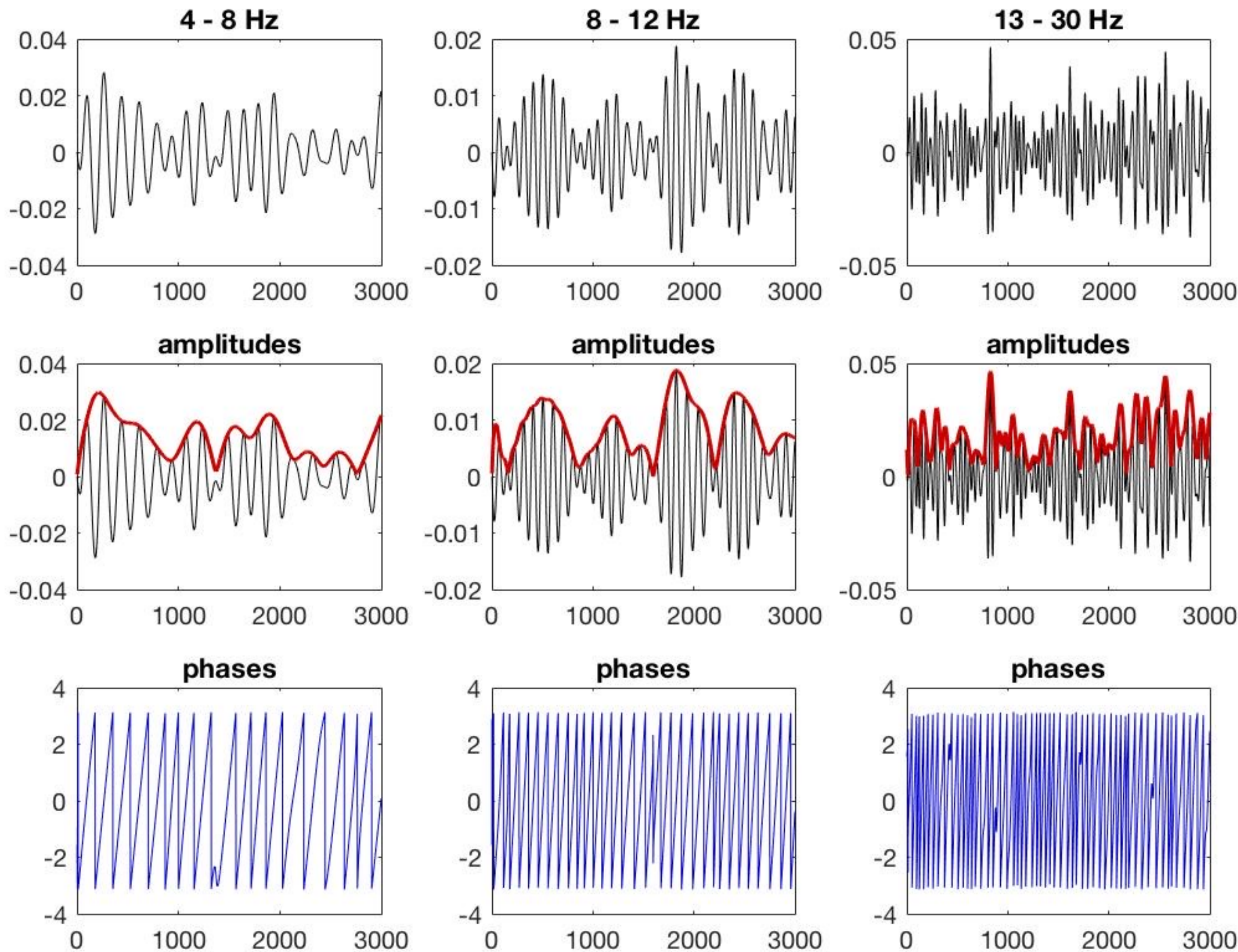
Hilbert is able to calculate an <u>instantaneous</u> amplitude and phase of a signal

To get the *analytic amplitude*,
take the absolute value of the transformed data

# Demo – decomposing spectral data




Bandpass -> Hilbert Transform



**HW7: Frequency decomposition**

You have recorded a local field potential with the following parameters:

Sampling frequency 1kHz

The vector in the attached data set includes the voltage trace of the LFP from your session, as well as timestamps, in ms, for a recurring event.

1. Plot the power spectrum of these data, including frequencies from 1 to 150 Hz (*Hint*: the spectrum will look smoother if you first divide the data into trials, or another time epochs, and plot the average. Make sure your x-axis is in Hz!). Then remove electrical noise (60Hz) and its first harmonic with a notch filter and overlay a plot of the filtered power spectrum.
2. Plot the mean event related potential (ERP) in response to the event indicated by the timestamps, working from the notch-filtered data. Use a window from -500ms before each event to 1500ms after.
3. Bandpass your signal in the following frequency ranges, and for each
   (a). plot a length of the data equal to 4 seconds
   (b). perform a Hilbert transform and separately plot the analytic amplitude and phases for the same length of data:
   4-8 Hz (theta)
   8-12 Hz (alpha)
   13-30 Hz (beta)

   *Hints:* There are a number of different filters that will bandpass a signal. Below is code for building a