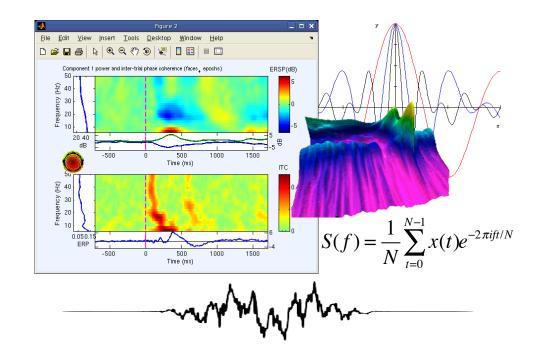
Time-Frequency Analysis of Biophysical Time series

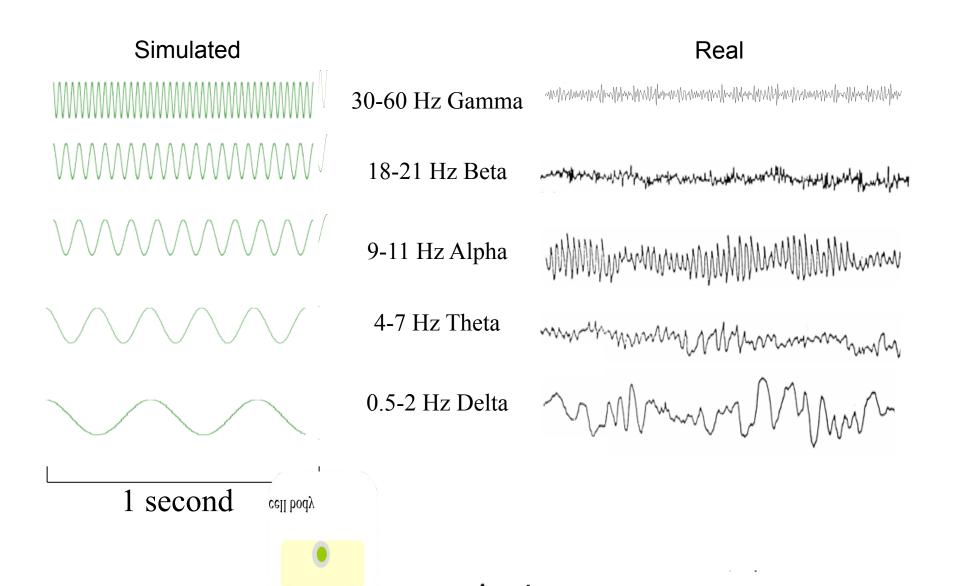
Tim Mullen

(with many contributions from Arnaud Delorme)

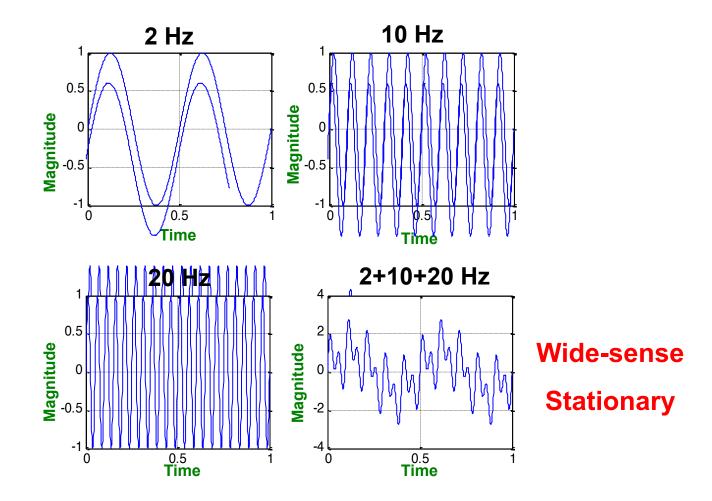




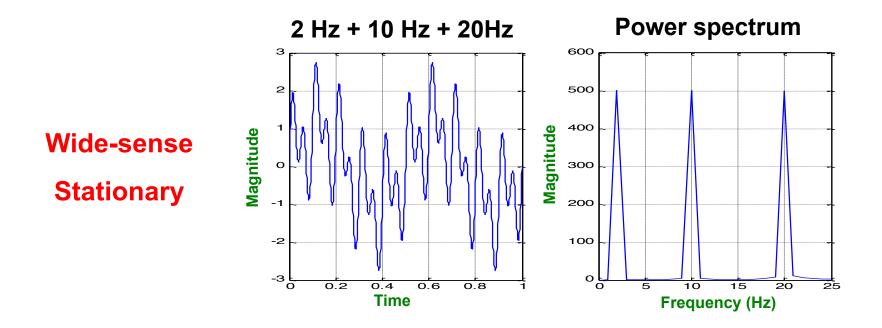
Common Oscillatory Modes in EEG



Wide-sense stationary signals



Wide-sense stationary signals



By looking at the Power spectrum of the signal we can recognize three frequency Components (at 2, 10, 20Hz respectively).

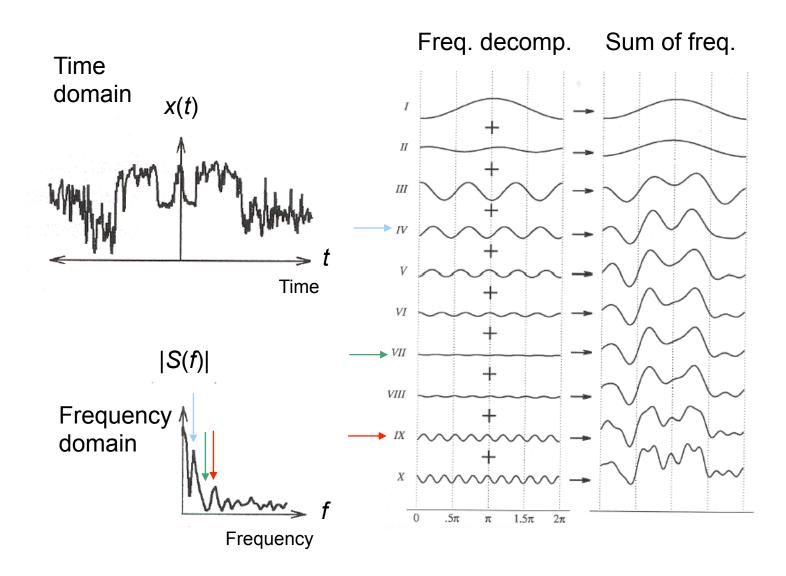
Fourier's Theorem

Any stationary, continuous process can be exactly described by an infinite sum of sinusoids of different amplitudes and phases.

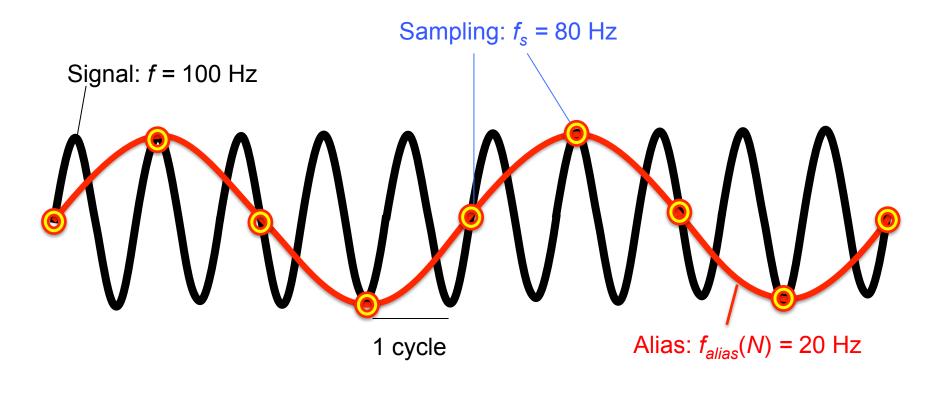


Jean Baptiste Joseph Fourier (1768 – 1830)

Fourier's Theorem



Aliasing and the Nyquist Frequency



Nyquist Frequency:

 $f_{N} = f_{s} / 2$

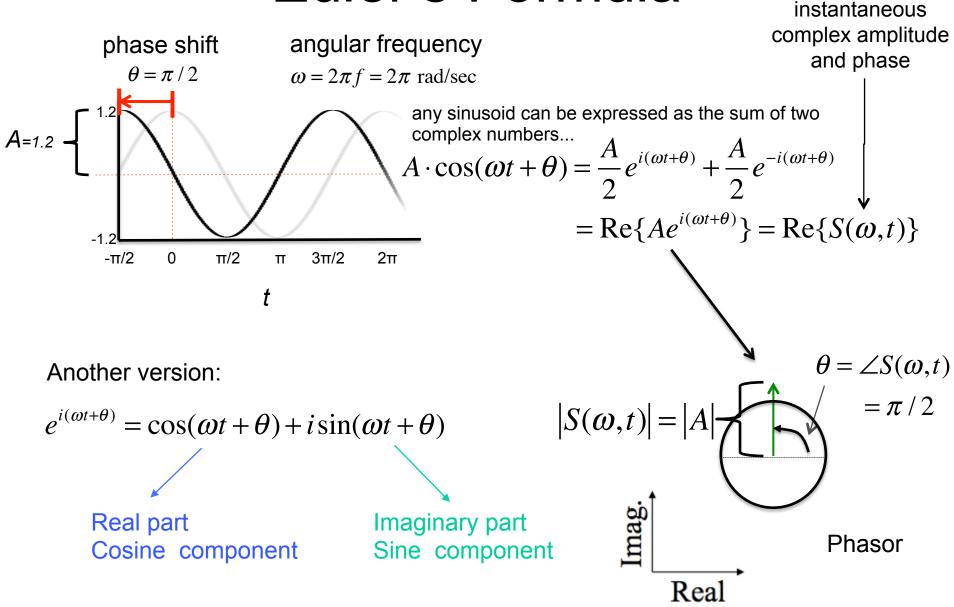
The maximum frequency that can be uniquely recovered at a sampling rate of f_s

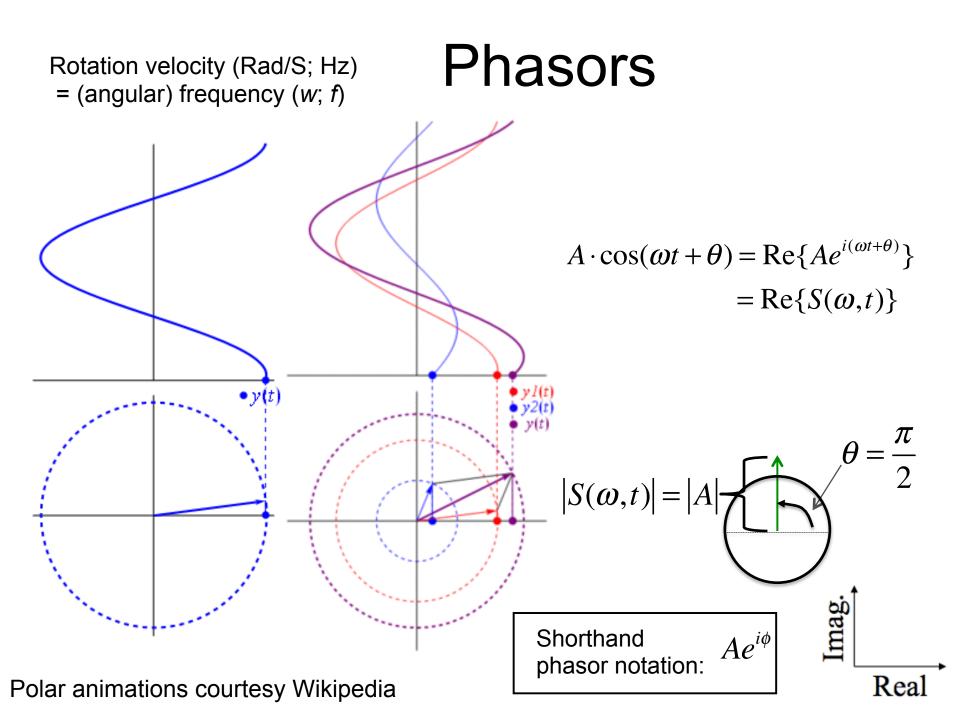
$$f_{alias}(N) = |f + Nf_s|$$

 $f_s =$ sampling rate

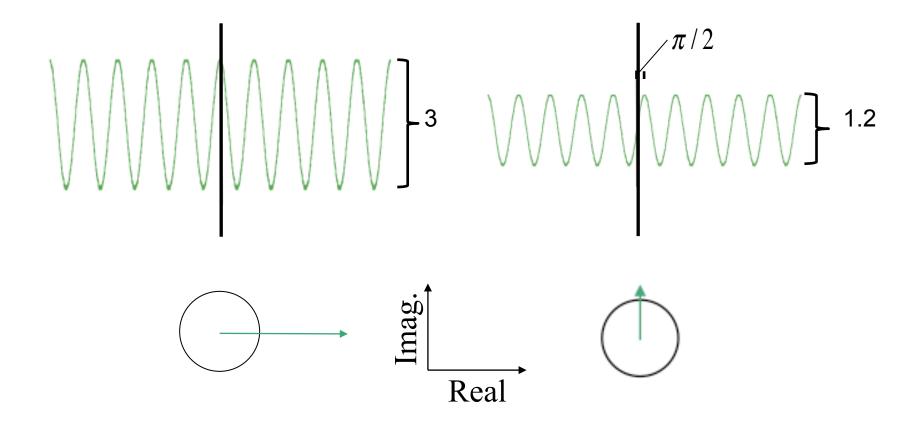
Quiz: What is *N* in the example above?

Euler's Formula

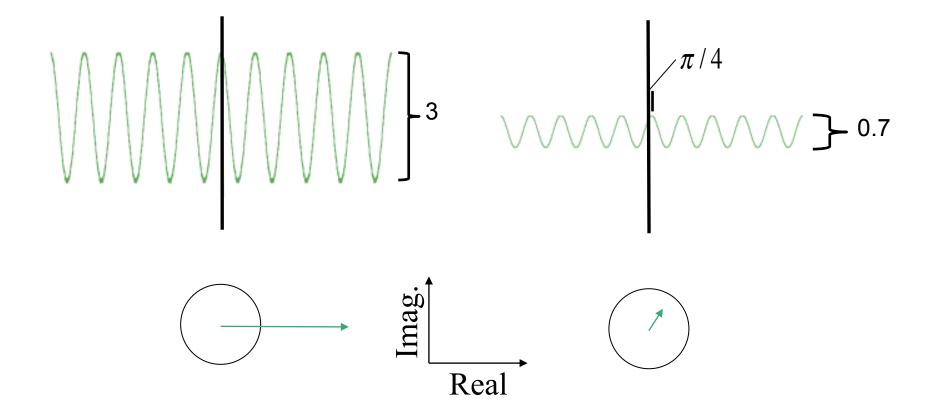




Phasors: Example



Phasors: Example



Discrete Fourier Transform

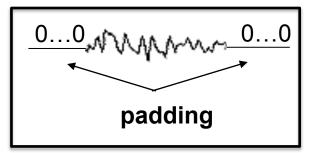
Time \rightarrow FrequencyFrequency \rightarrow TimeForward transformInverse transform $S(f) = \frac{1}{N} \sum_{t=0}^{N-1} x(t) e^{-2\pi i f t/N}$ $x(t) = \frac{1}{N} \sum_{f=0}^{N-1} S(f) e^{2\pi i f t/N}$

N = number of samples

Fast Fourier Transform (FFT)

Zero-padding

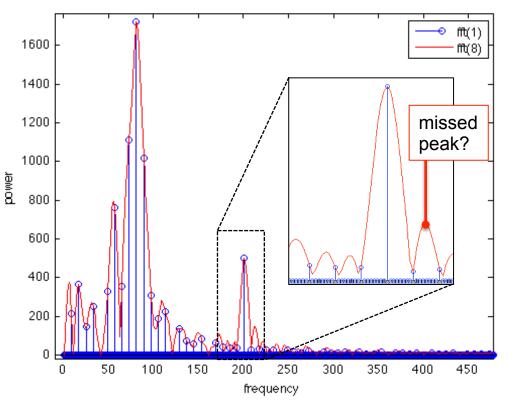
The DFT/FFT of a sequence of length N produces power estimates at N frequencies evenly distributed between 0 and the sampling rate (Fs) (or $\lfloor N/2+1 \rfloor$ frequencies between 0 and the Nyquist rate, Fn=Fs/2).



Padding the signal with Q zeros achieves the following:

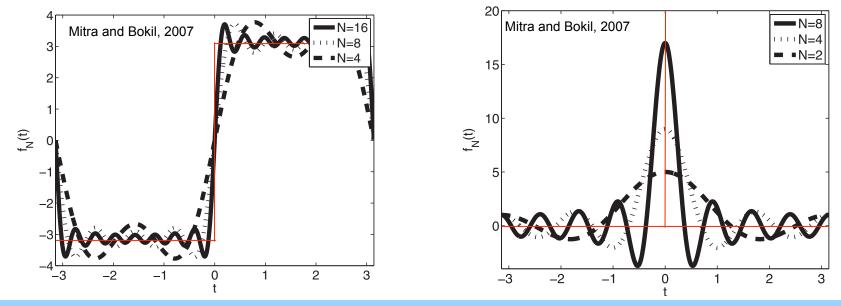
- 1) Allows enforcement of signal length as a power of two enabling FFT
- Increases the number of frequency bins between 0 and Fs from N to N+Q (intermediate points are sinc interpolates)

Zero-padding does not increase frequency resolution (number of independent degrees of freedom)



Tapering

Fourier's Theorem lets us exactly describe any continuous, stationary signal using an infinite weighted sum of sinusoids. Discontinuous functions can be infinitely *approximated*, but the approximation may be poor for finite sampling.



Gibbs Phenomenon "Rippling" effect due to discontinuities in signal (e.g. edges of the truncated signal)

- Infinite number of frequencies required to approximate discontinuities
- This means infinite (or very large) number of samples required (not possible)

What can we do?

Tapering

Smoothly decay signal to zero at endpoints to smooth discontinuity

EEG

Χ

ANN MARTIN

Taper

0

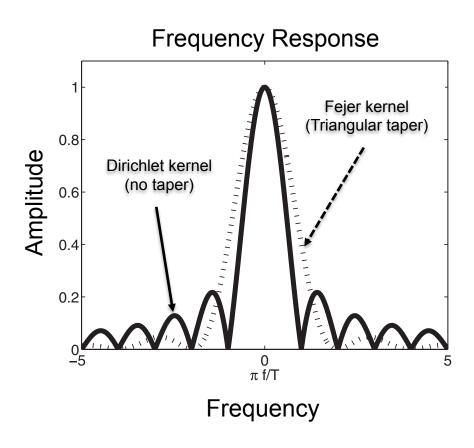
Tapered EEG

MAMM-

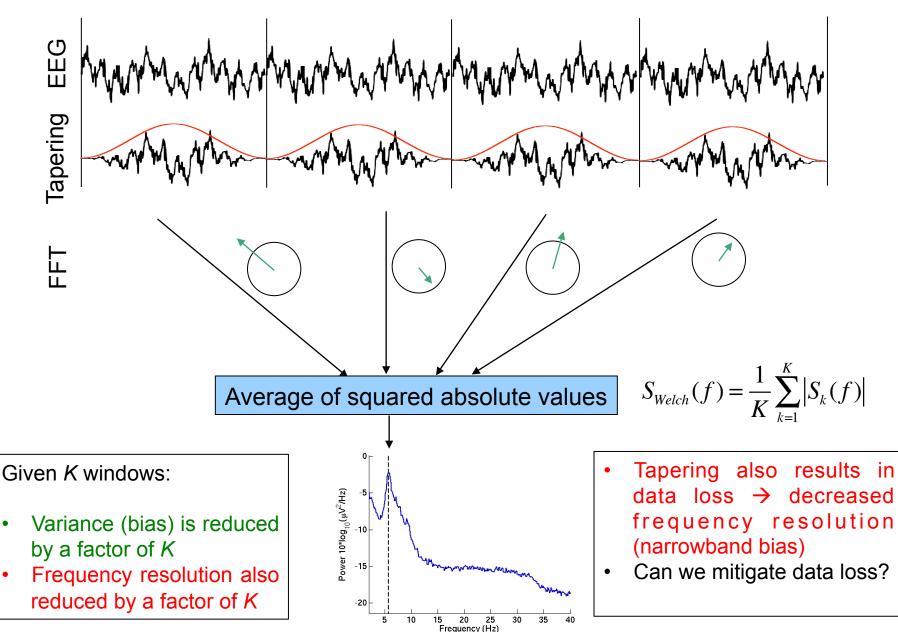
Tapering

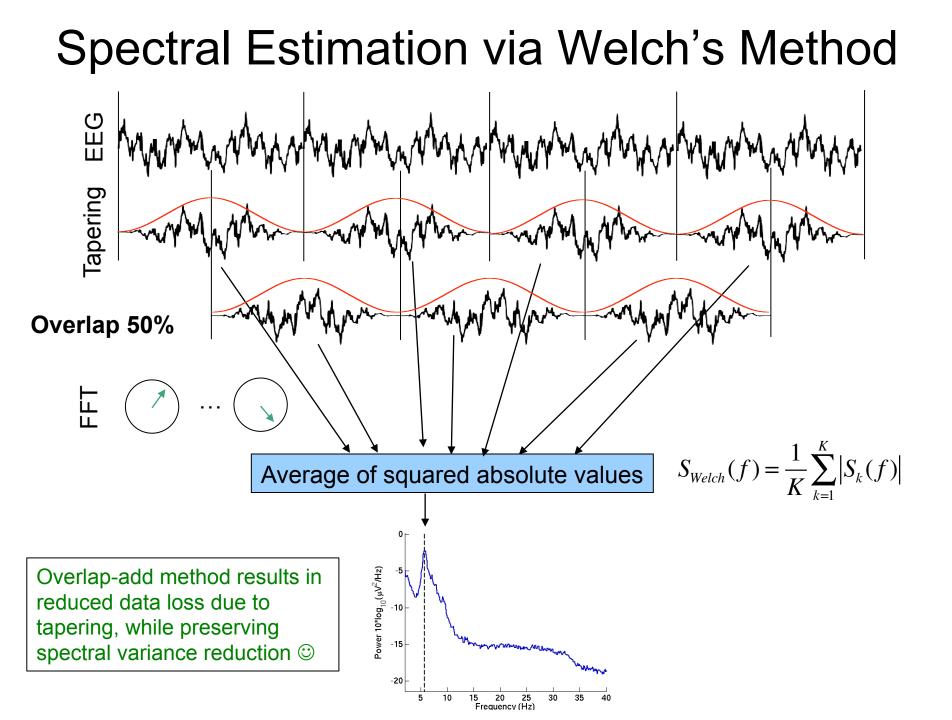
Tapering reduces the effect of the Gibbs phenomenon making it easier to identify "true" peaks in the spectrum from spurious ripple peaks (minimized broadband bias or "spectral leakage")

The cost is increased width of central peak (narrowband bias).



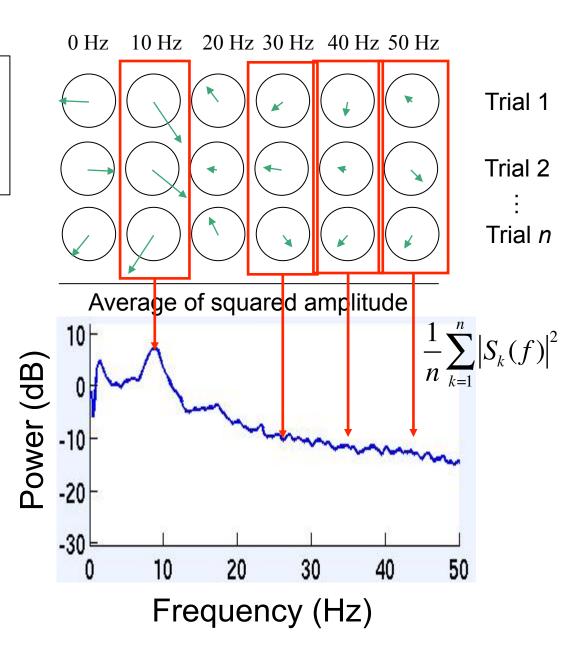
Spectral Estimation via Welch's Method





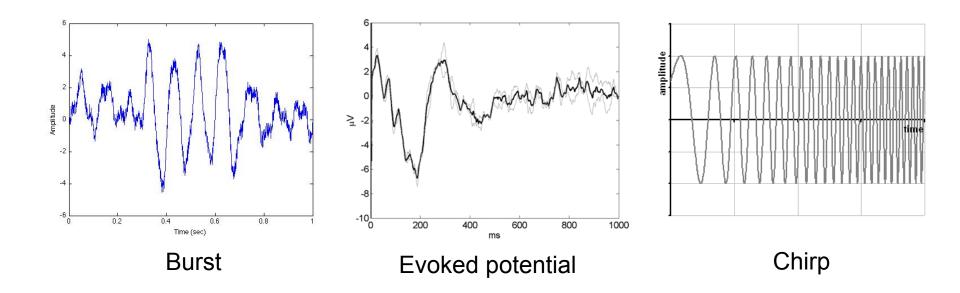
Trial Averaging

Averaging spectra over *n* independent trials leads to further reduction of variance by a factor of *n*

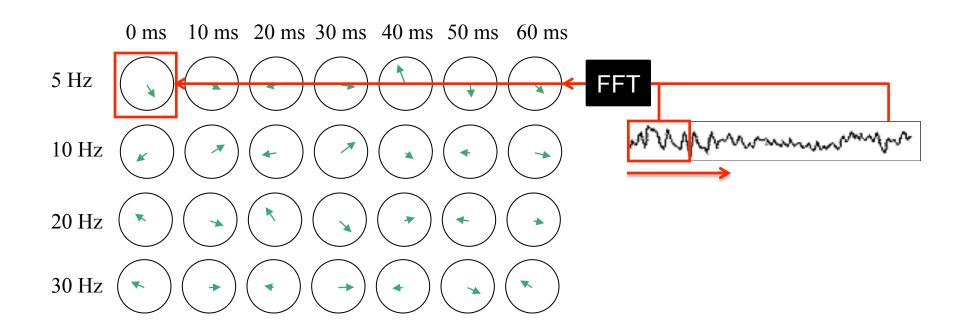


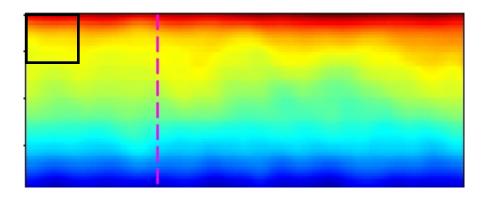
Non-Stationary Signals

Non-stationary signals include bursts, chirps, evoked potentials, ...

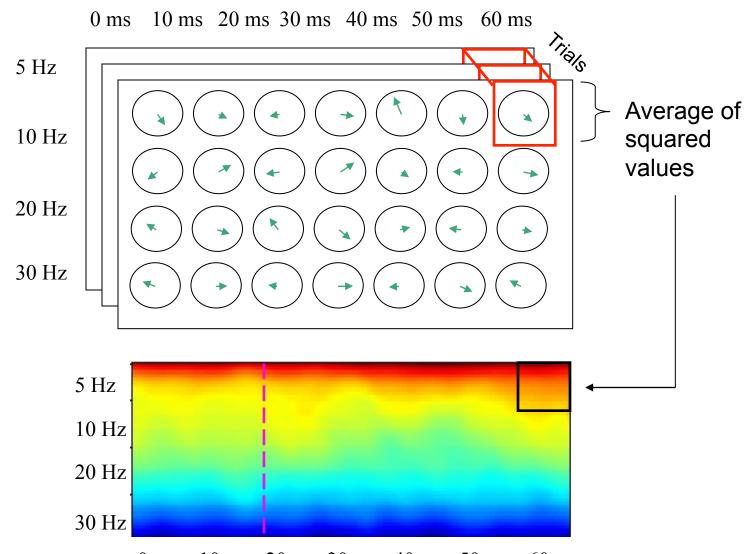


Spectrogram or ERSP



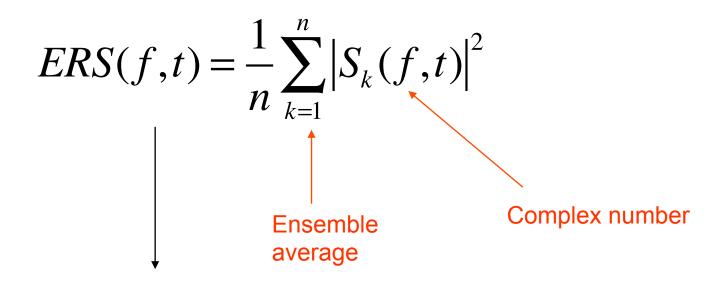


Spectrogram or ERSP



0 ms 10 ms 20 ms 30 ms 40 ms 50 ms 60 ms

Power spectrum and event-related spectral (perturbation)

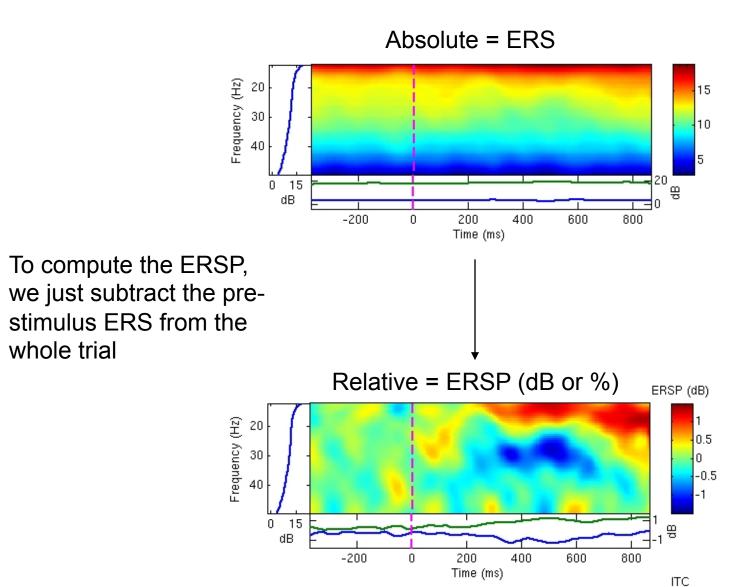


Scaled to dB 10Log₁₀

Here, there are *n* trials Each trial is time-locked to the same e

Each trial is time-locked to the same *event* (hence "event-related" spectrum) The ERS is the average power across event-locked trials

Absolute versus relative power



The Uncertainty Principle

There exists a lower bound to the *Heisenberg product*:

 $\Delta t \Delta f \ge 1/(4\pi)$

or $\Delta f \ge 1/(4 \pi \Delta t)$

e.g. here are two possible (Δf , Δt) pairs:

 $\Delta f = 1Hz, \Delta t = 80 \text{ msec}$ or $\Delta f = 2Hz, \Delta t = 40 \text{ msec}$

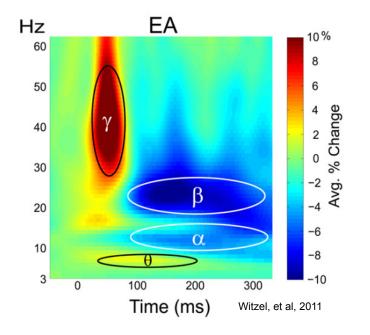


Werner Karl Heisenberg (1901 – 1976)

Note: Δf means "difference between successive frequencies" or the inverse of the frequency resolution. Ditto for Δt .

Time-Frequency Tradeoff

Natural biophysical processes may exhibit sustained changes in narrowband low-frequency oscillations along with rapidly-changing (e.g. "burst") high-frequency oscillations.

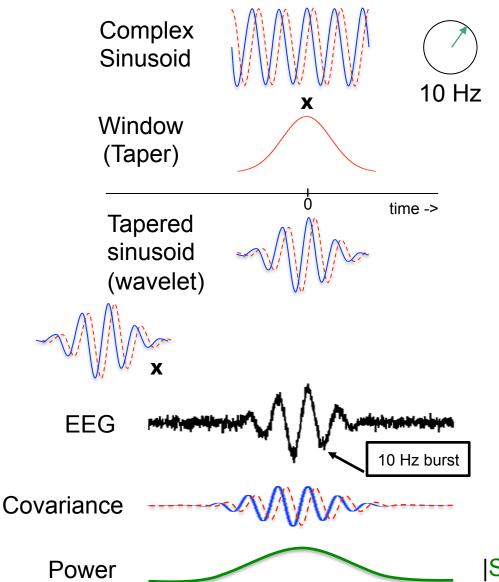


The Short-Time Fourier Transform has a constant temporal resolution for all frequencies.

Can we adapt the time-frequency resolution tradeoff for individual frequencies to improve spectral estimation?

Yes, we can!

Wavelet Analysis



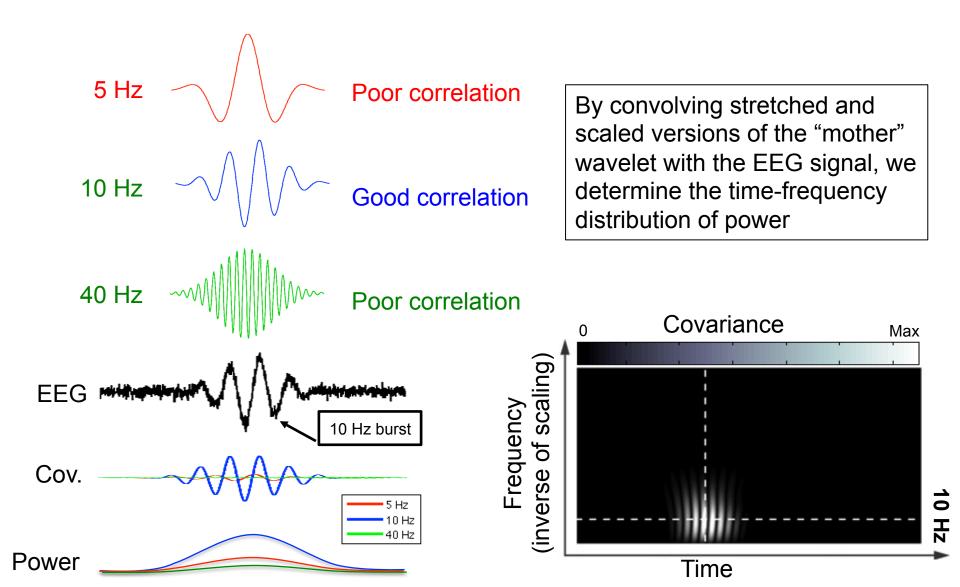
Real Part (cosine)

--- Imaginary Part (sine)

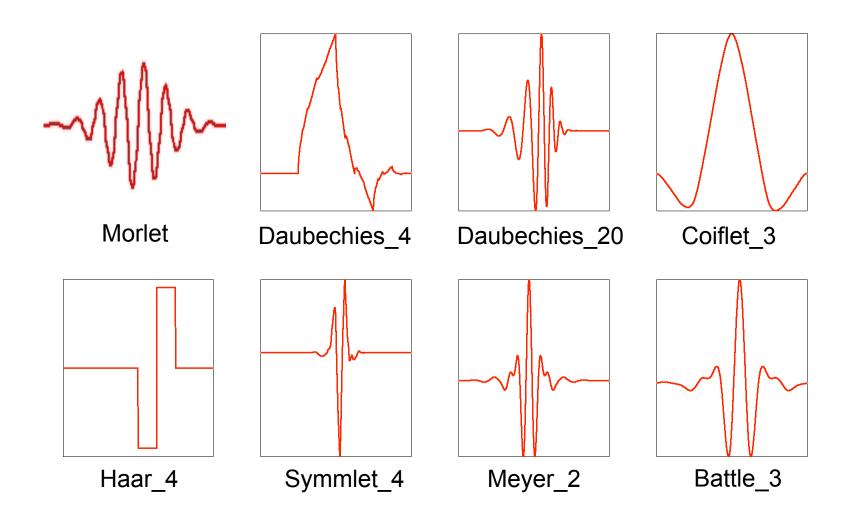
We estimate the timevarying power at 10 Hz by convolving EEG signal with a tapered 10 Hz complex sinusoid (Morlet wavelet)

 $|\mathsf{S}(f,t)| = |\mathsf{Re} + \mathsf{Im}|$

Wavelet Time-Frequency Image

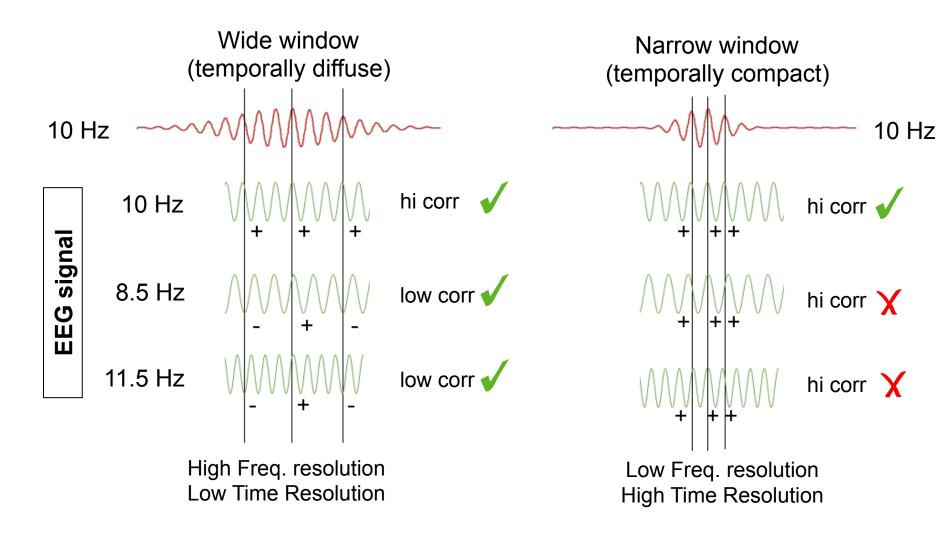


Some Wavelet Families

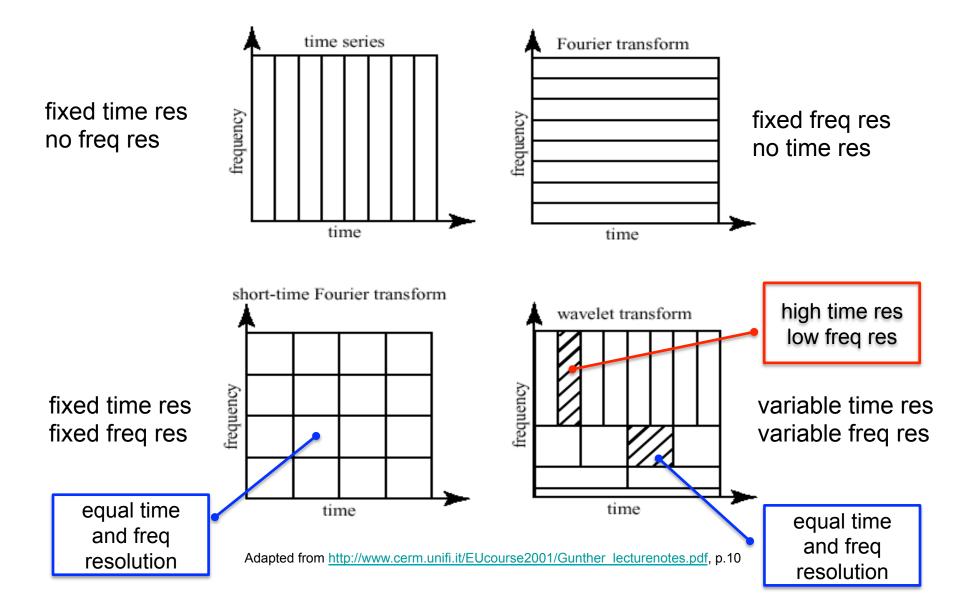


Trading Frequency for Time

(and vice versa)



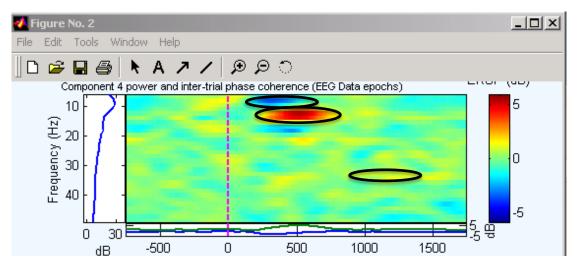
FFT versus Wavelets

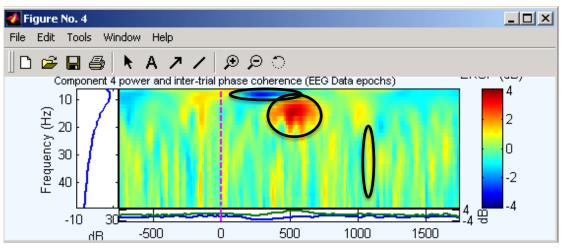


FFT versus Wavelets

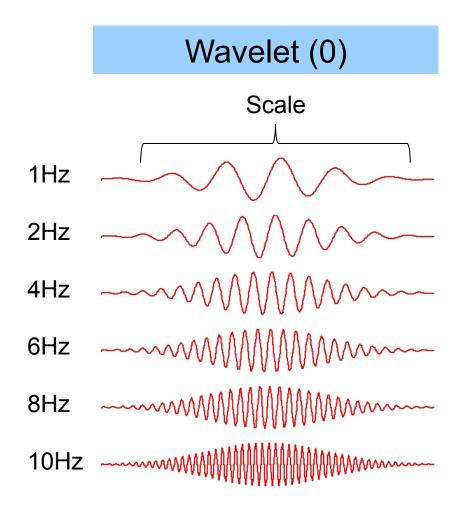
FFT (Wavelet(0))

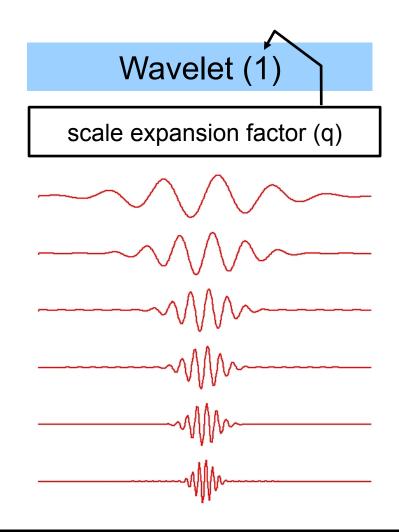
Wavelet (1)





Wavelet scale



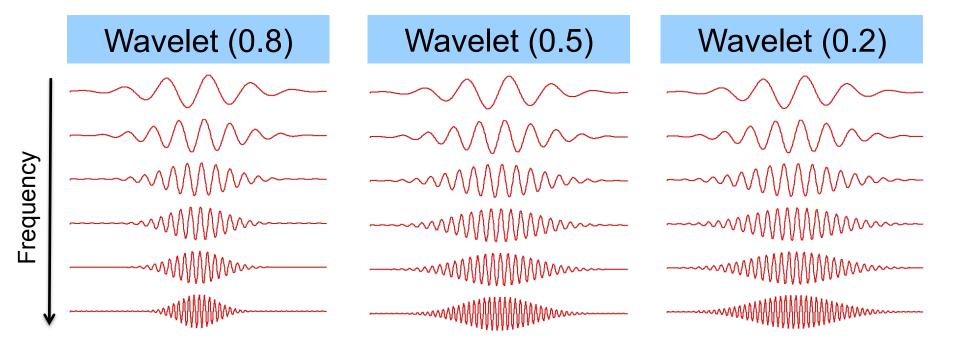


constant window size (time resolution) for increasing frequency \rightarrow increasing # cycles with frequency.

window size decreases by a factor of 2 for each octave (power of 2) \rightarrow constant # of cycles at each frequency

Wavelet scale expansion factor

Larger expansion factor produces larger scale decrements (increased time resolution, lower frequency resolution) for increasing frequency

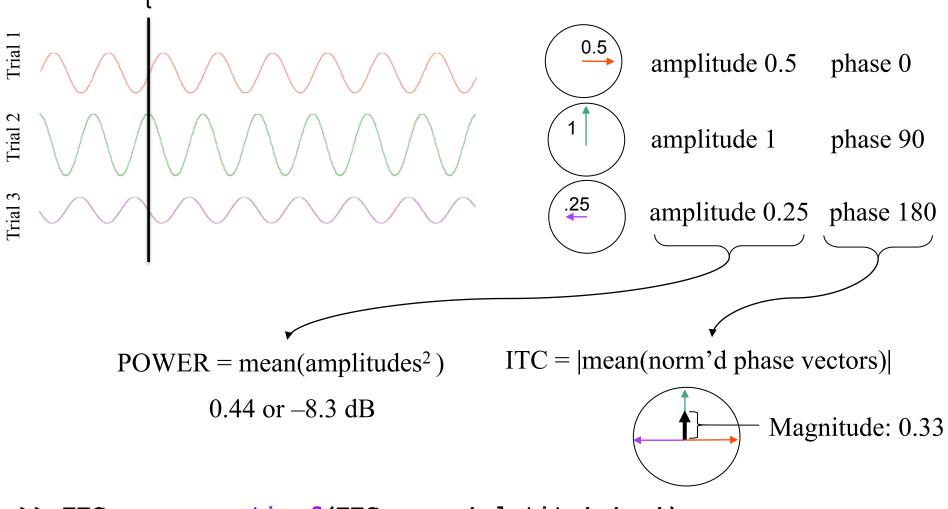


Number of cycles at highest frequency for an expansion factor of q:

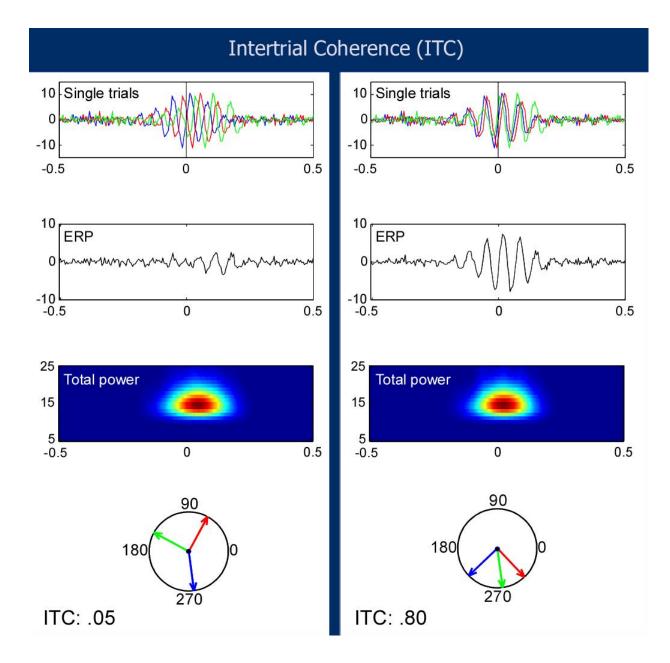
$$C_{\text{fmax}} = \frac{f_{\text{max}}}{f_{\text{min}}} C_{\text{fmin}} (1 - q)$$

Inter-Trial Coherence (ITC)

Tallon-Baudry, et al, 1996



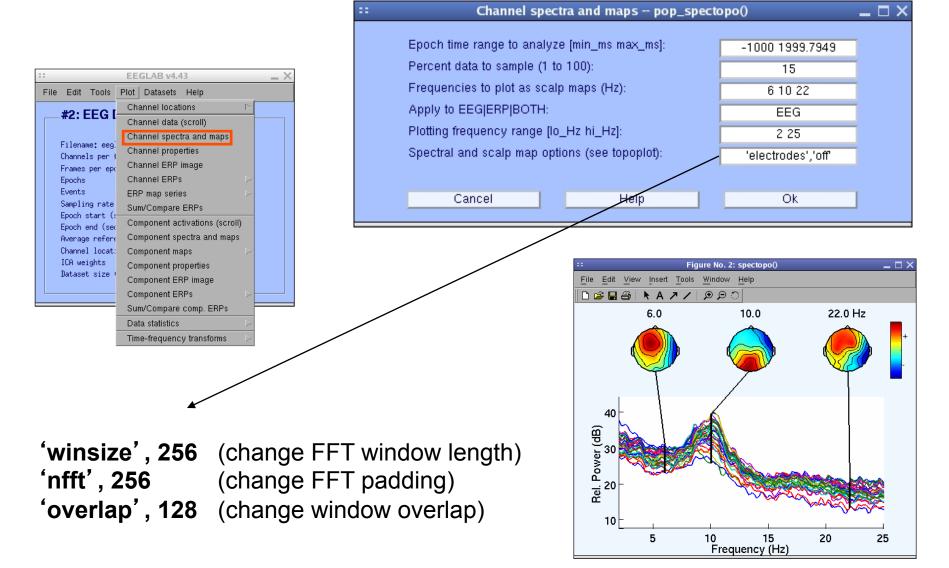
>> EEG = pop_newtimef(EEG,..., 'plotitc','on');

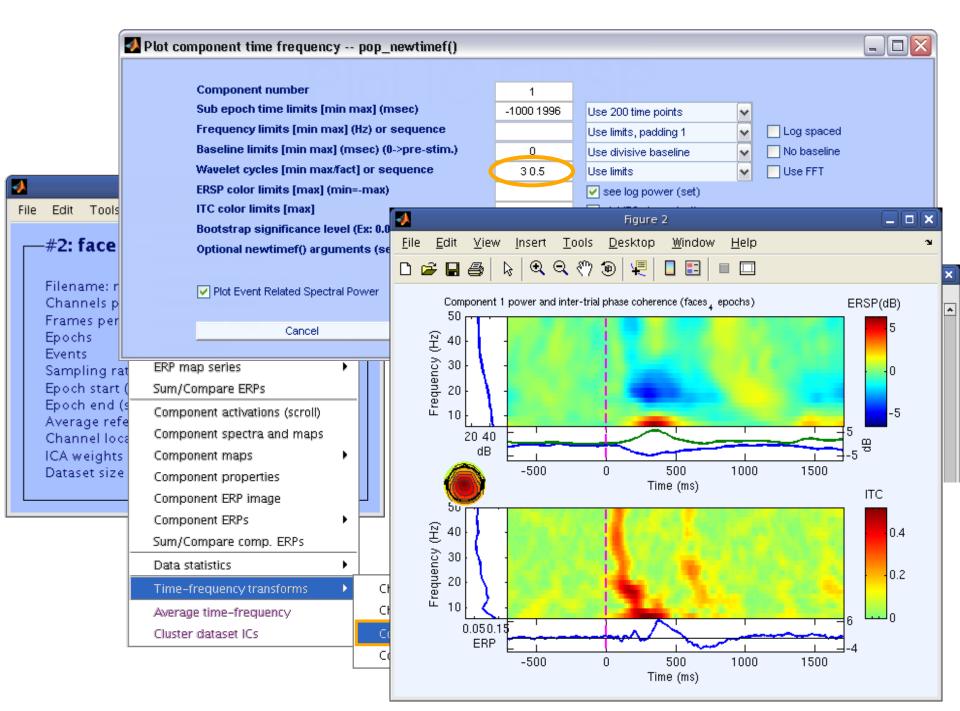


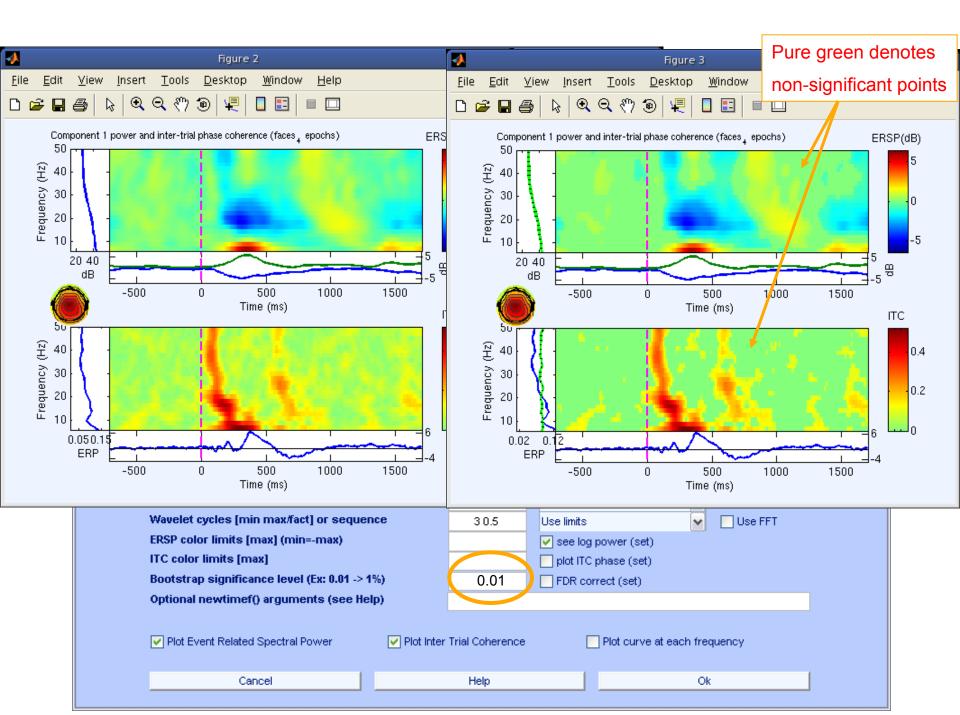
Time-Frequency Analysis of Biophysical Time series:

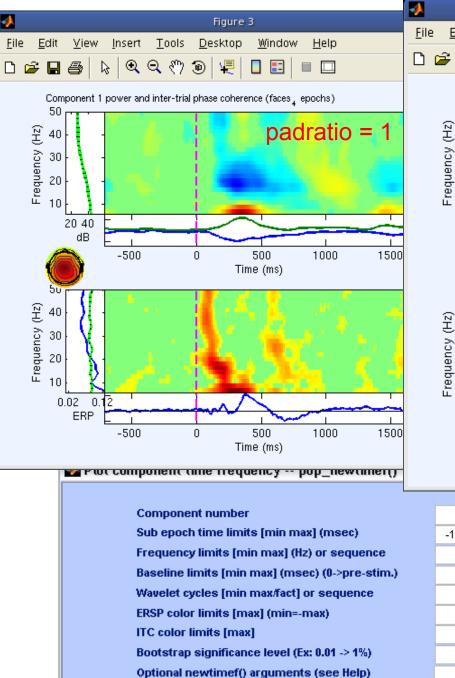
Practicum

Plot periodogram (spectrum) using Welch's method



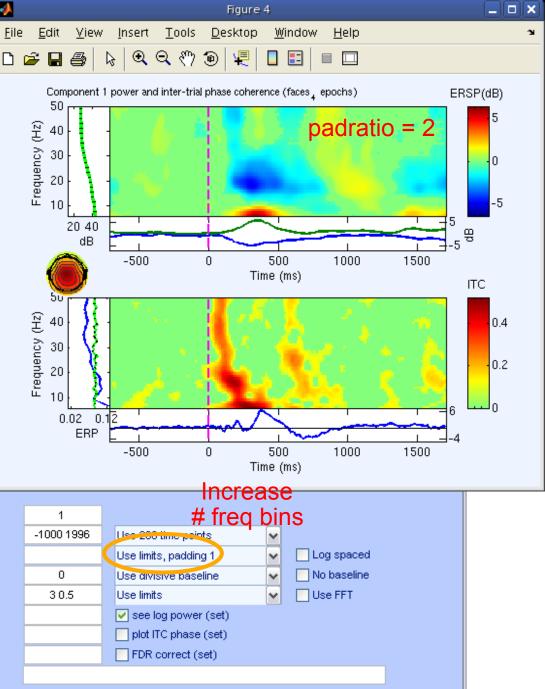


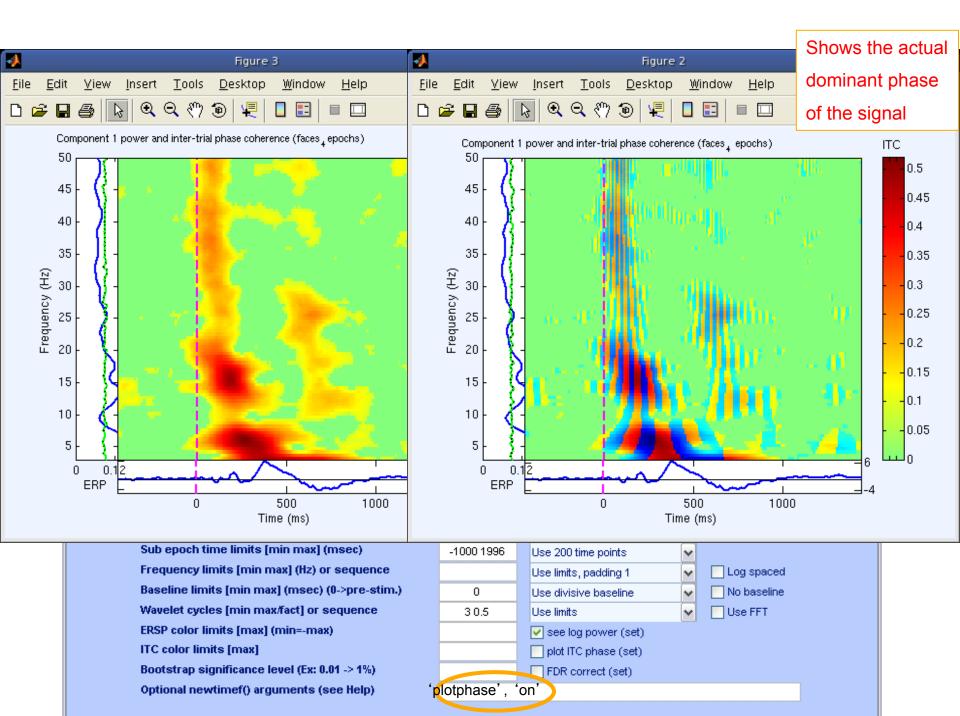


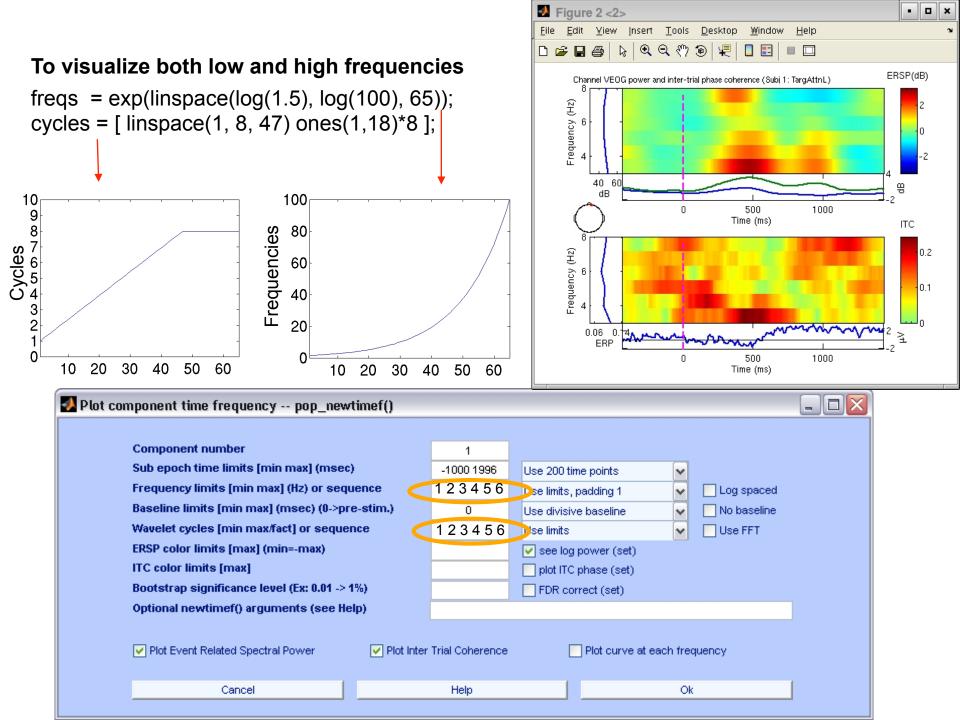


4

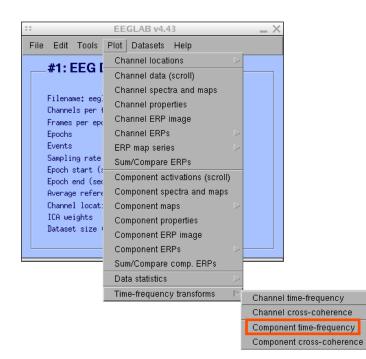
<u>F</u>ile

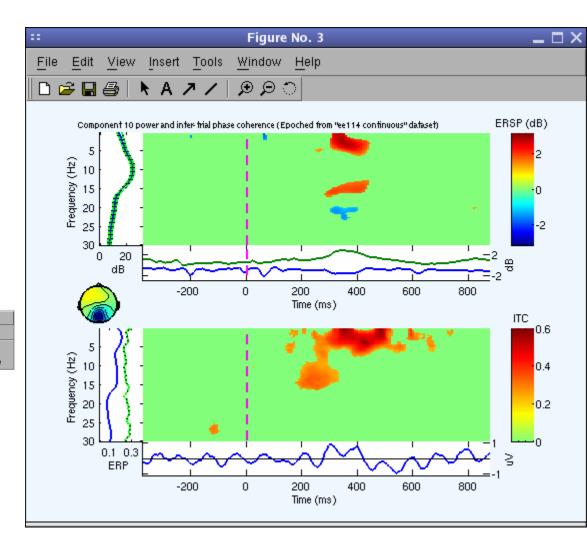






Component time-frequency





Exercise

• ALL

Start EEGLAB, from the menu: load <eeglab_root>/sample_data/ eeglab_data_epochs_ica.set or your own data

Novice

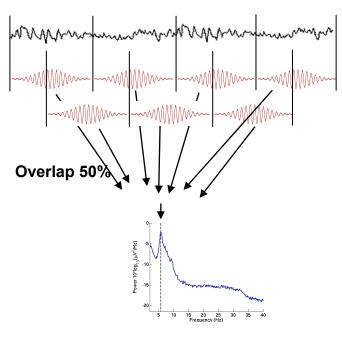
From the GUI, Plot spectral decomposition with 100% data and 50% overlap ('overlap'). Try reducing window length ('winsize') and FFT length ('nfft')

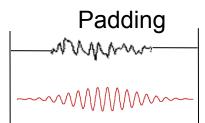
Intermediate

Same as novice but using a command line call to the *pop_spectopo()* function. Use GUI then history to see a standard call ("eegh").

Advanced

Same as novice but using a command line call to the *spectopo()* function.





Exercise - newtimef

Novice

From the GUI, pick an interesting IC and plot component ERSP. Try changing parameters window size, number of wavelet cycles, padratio,

• Intermediate

From the command line, use newtimef() to tailor your time/ frequency output to your liking. Look up the help to try not to remove the baseline, change baseline length and plot in log scale. Enter custom frequencies and cycles (2 slides back).

Advanced

Compare FFT, the different wavelet methods (see help), and multi-taper methods (use timef function not newtimef). Enter custom frequencies and cycles. Look up newtimef help to compare conditions. Visualize single-trial time-frequency power using erpimage.