

Radboud University



Fundamentals of neuronal oscillations and synchrony

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Let's recap evoked activity



Let's recap evoked activity



repeated over many trials

averaged

What now?



Or what if the brain signal contains oscillatory components?



Outline

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

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Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

Spectral analysis

Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis Using simple oscillatory functions: cosines and sines



Spectral decomposition: the principle



Spectral decomposition: the power spectrum



Spectral analysis

Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis
Using simple oscillatory functions: cosines and sines
Express signal as function of frequency, rather than time

Technique: Fourier transform Concept: linear regression using oscillatory basis functions

Alternative techniques: Wavelets, bandpass filtering + Hilbert transform

Spectral analysis ~ GLM

 $Y = \beta * X$

- X set of (orthogonal) basis functions
- β_i contribution of basis function i to the data.
- β for cosine and sine components for a given frequency map onto amplitude and phase estimate.

Going from N time points to N cosine/sine components

Each cosine/sine pair reflects 1 frequency bin so ~N/2 frequencies can be estimated

Frequencies correspond to integer number of cycles of basis functions in time window





Time-frequency relation: frequency resolution

Frequencies correspond to basis functions with integer number of cycles in time window/epoch length (T) Rayleigh frequency = $1/T = \Delta f$ = frequency resolution



Consequence 1: each frequency bin reflects the signal's energy in a frequency band. Consequence 2: there's no such thing as an instantaneous frequency

Time-frequency relation: Nyquist frequency

The highest frequency that can be resolved depends on the sampling frequency $1/\Delta t = f_{sample}$ Nyquist frequency = $1/(2*\Delta t) = f_{sample}/2$



Consequence: Signal energy at frequencies in the original signal > Nyquist end up elsewhere in the spectrum (a.k.a. Aliasing, which is a special form of spectral leakage)

Spectral analysis

Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis
Using simple oscillatory functions: cosines and sines
Express signal as function of frequency, rather than time

Technique: Fourier transform

Concept: linear regression using oscillatory basis functions Each oscillatory component has an amplitude and phase Discrete and finite sampling constrains the frequency bins -> spectral leakage

Outline

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

 Signal components at frequencies not sampled with Fourier transform spread their energy to the sampled frequencies









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Spectral leakage in the frequency domain

- Signal components at frequencies not sampled with Fourier transform spread their energy to the sampled frequencies
- To fit edges, many basis functions may be needed (lot of distant spectral leakage)



Spectral leakage in the frequency domain



 Tapering = attenuating potentially problematic edges of the signal by multiplication with a 'taper function'











Multitapers

Make use of more than one taper and combine their leakage properties

Used for smoothing in the frequency domain

Instead of "smoothing" one can also say "controlled leakage"

Multitapered spectral analysis



Multitapered spectral analysis



Multitapers

Multitapers are useful for reliable estimation of frequency components with a bandwidth > spectral resolution
 Low frequency components are better estimated using a single (Hanning) taper

%estimate low frequencies	%estimate high frequencies
<pre>cfg = []; cfg.method = `mtmfft'; cfg.foilim = [1 30]; cfg.taper = `hanning';</pre>	<pre>cfg = []; cfg.method = `mtmfft'; cfg.foilim = [30 120]; cfg.taper = `dpss'; cfg.tapsmofrq = 8;</pre>
freq=ft_freqanalysis(cfg, data);	freq=ft_freqanalysis(cfg, data);

Outline

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

Typically, brain signals are not 'stationary'

• Divide the measured signal in shorter time segments and apply Fourier analysis to each signal segment









high bood 35



Frequency (Hz)

high baod 0 36











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Evoked versus induced activity





Noisy signal -> many trials needed



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The time-frequency plane



The time-frequency plane

The division is 'up to you' Depends on the phenomenon you want to investigate:

- Which time scale?
- Bandwidth?



time



Time versus frequency resolution



short timewindow

long timewindow



Wavelet analysis

Popular method to calculate time-frequency representations

Is based on convolution of signal with a family of 'wavelets' which capture the different frequency components in the signal

Convolution ~ local correlation

Wavelet analysis



Wavelet analysis

Wavelet width determines the time-frequency resolution Width is a function of frequency (often 5 cycles) 'Long' wavelet at low frequencies leads to relatively narrow frequency resolution but poor temporal resolution 'Short' wavelet at high frequencies leads to broad frequency resolution but more accurate temporal resolution



Summary

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

Time-frequency analysis

This morning/afternoon: hands-on

Time-frequency analysis on real data

Different methods

Parameter tweaking

Power versus baseline

Visualization