



Donders Institute
for Brain, Cognition and Behaviour

Fundamentals of the analysis of neuronal oscillations

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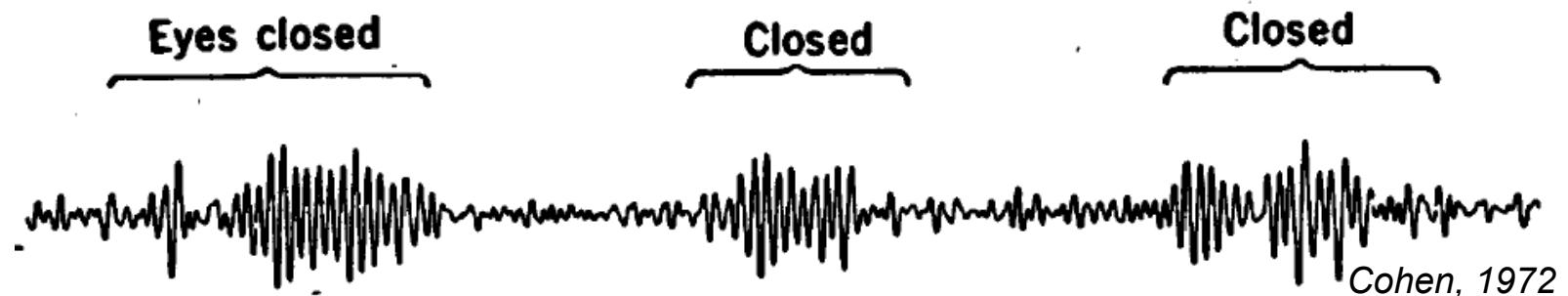


Separating sources

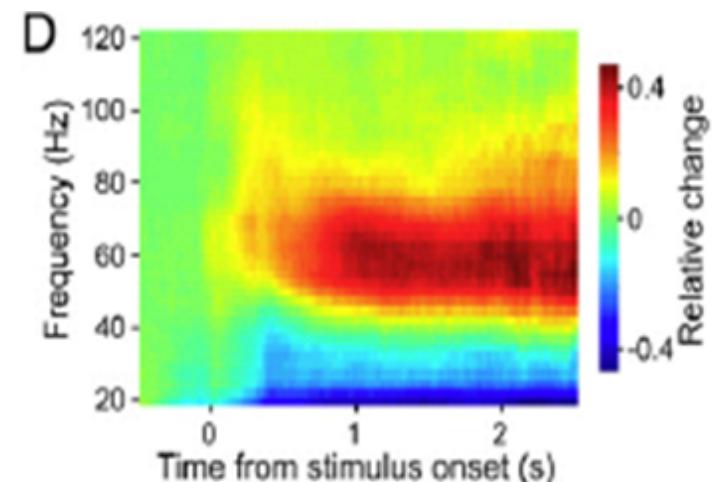
- Use the temporal aspects of the data at the channel level
 - ERF latencies
 - (ERF difference waves)
 - Filtering the time-series
 - Spectral decomposition
- Use the spatial aspects of the data



Brain signals contain oscillatory activity at multiple frequencies



Hoogenboom et al, 2006

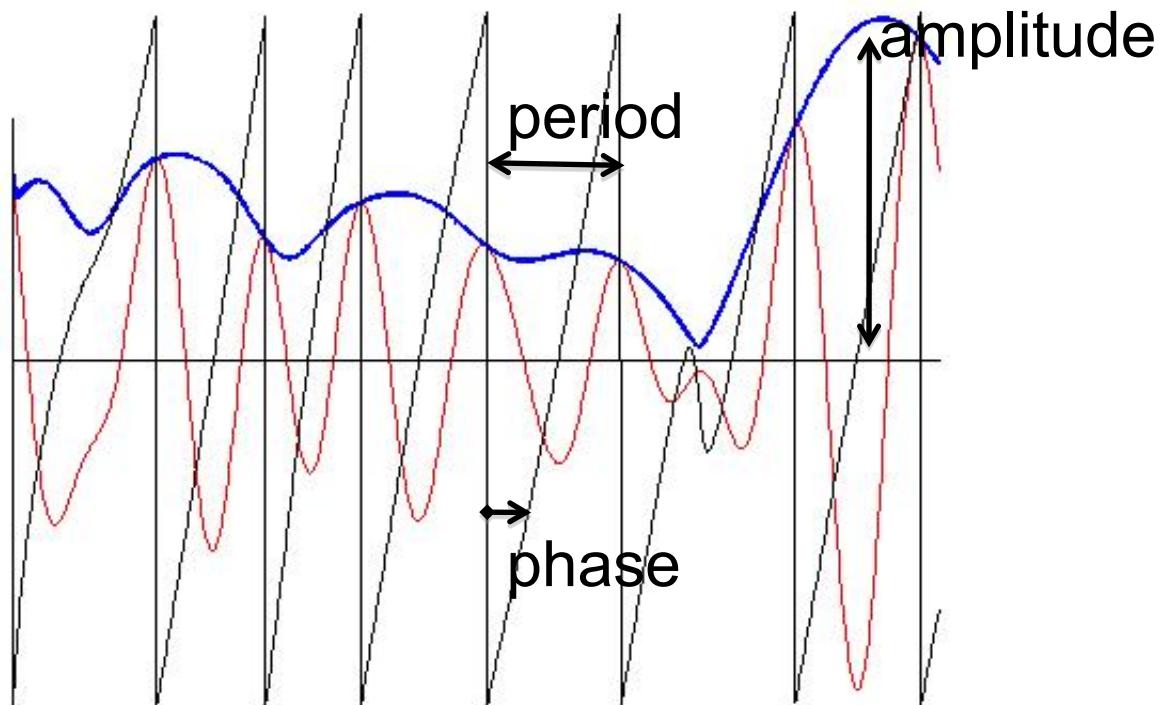




Outline

- Spectral analysis: going from time to frequency domain
- Issues with finite and discrete sampling
- Spectral leakage and (multi-)tapering
- Time-frequency analysis

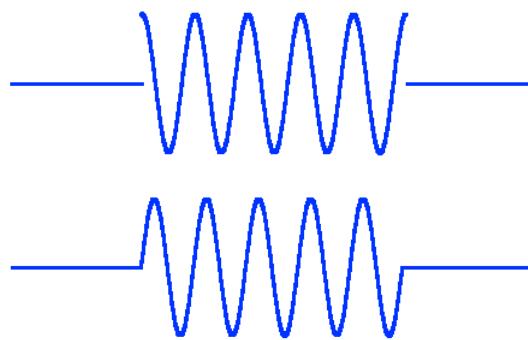
A background note on oscillations



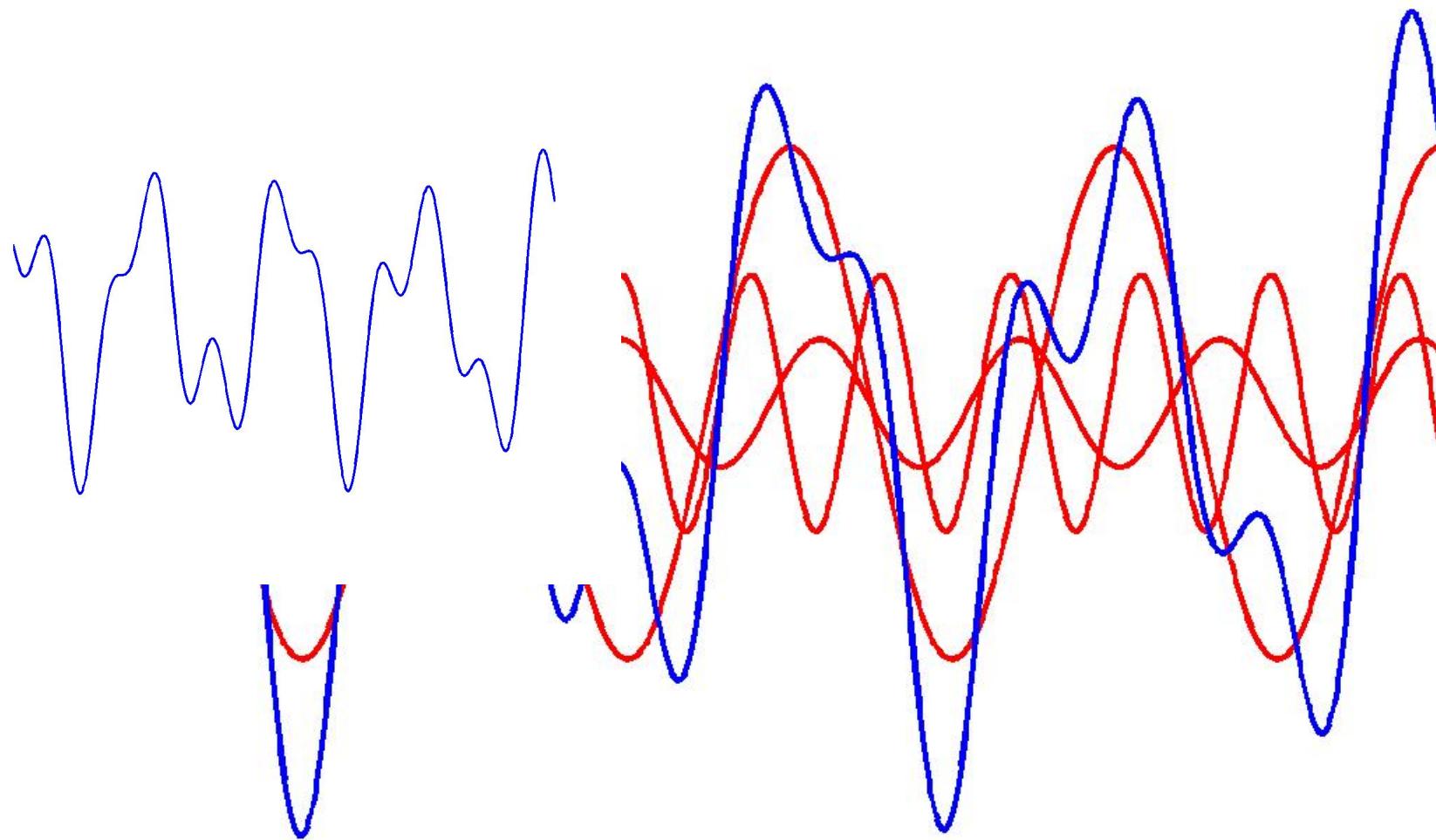


Spectral analysis

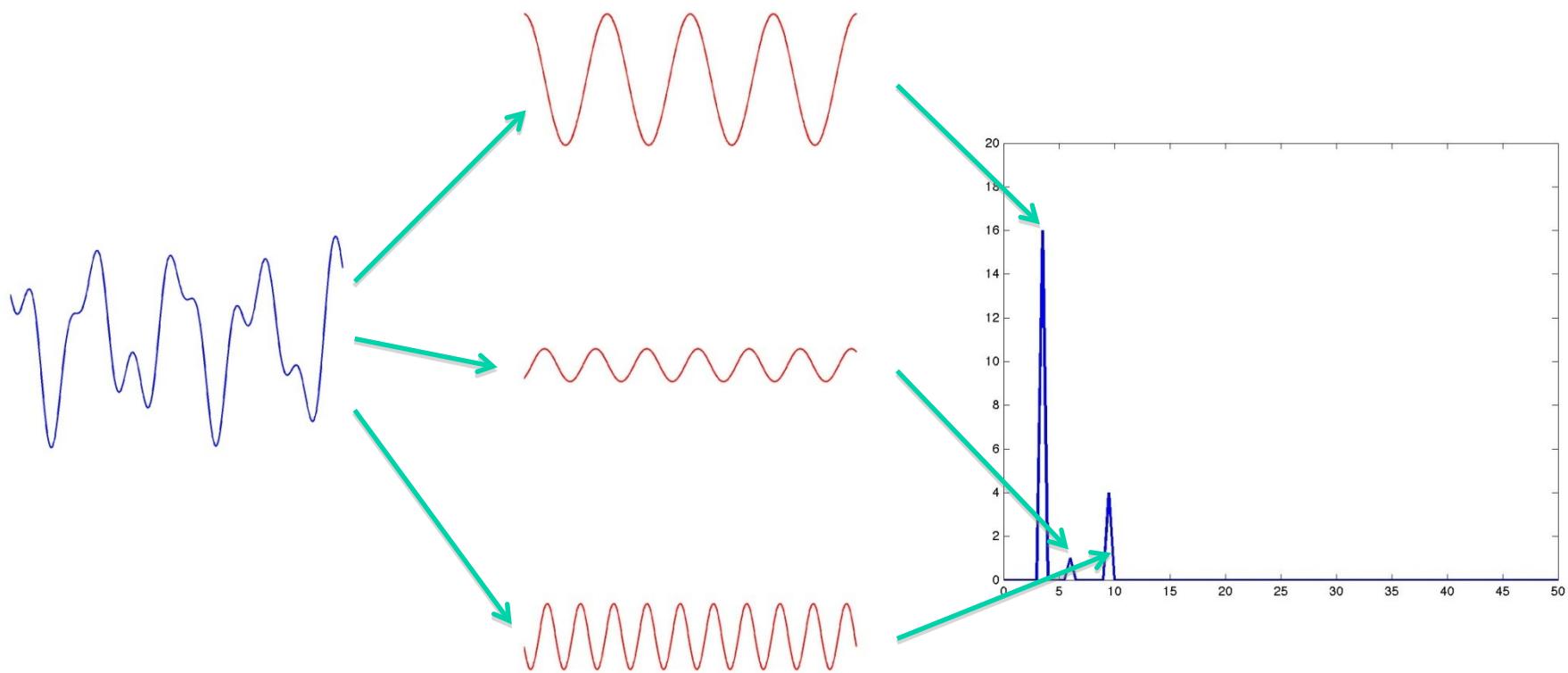
- Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis
- Using simple oscillatory functions: cosines and sines



Spectral decomposition: the principle



Spectral decomposition: the power spectrum



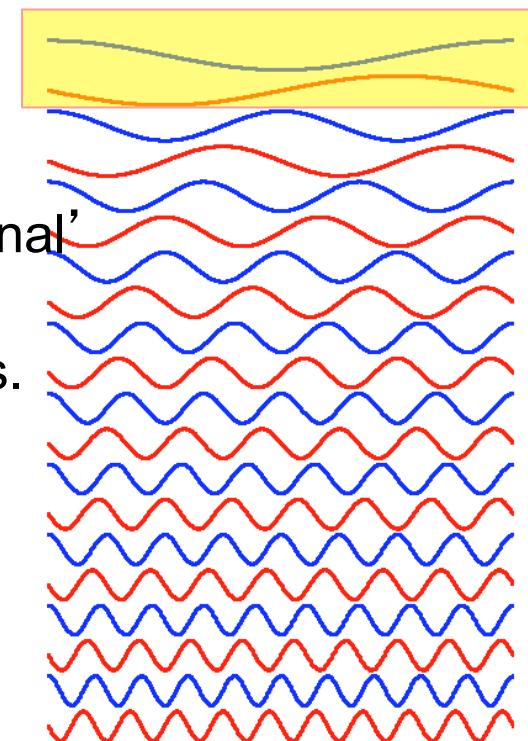
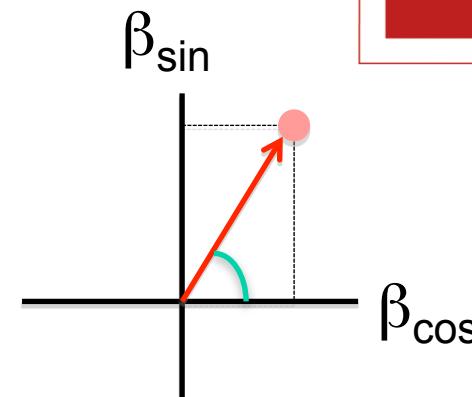


Spectral analysis

- 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
- Concept: linear regression using oscillatory basis functions

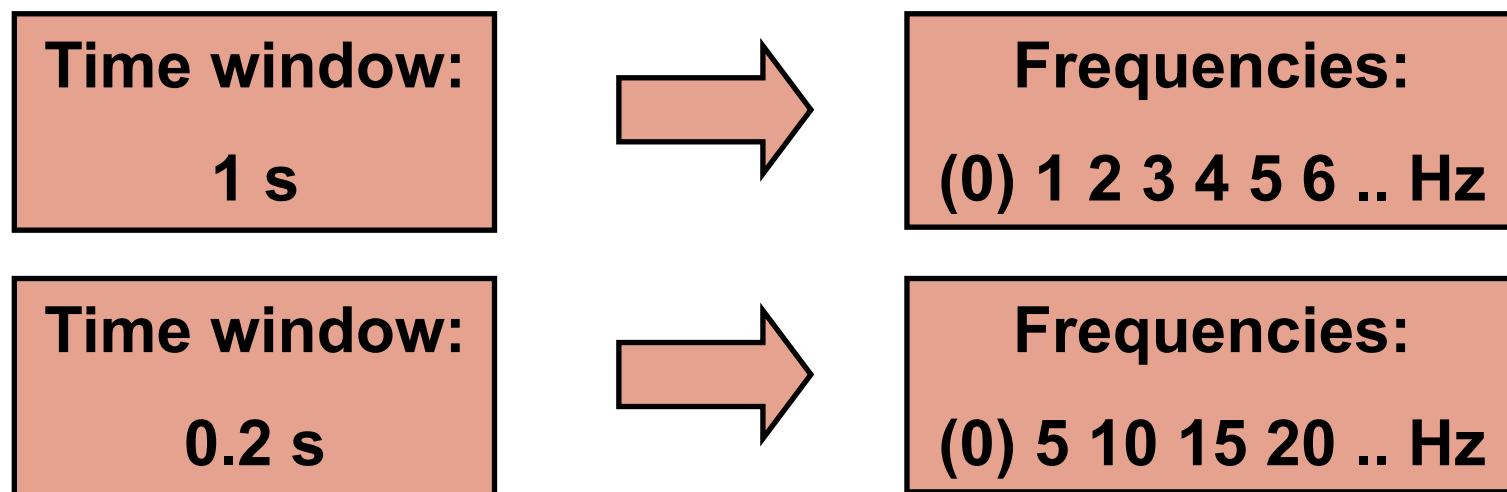
Spectral analysis ~ regression

- $\mathbf{Y} = \boldsymbol{\beta} \times \mathbf{X}$
- \mathbf{X} : set of basis functions
- β_i ~ ‘goodness-of-fit’ of basis function i with data
- $\boldsymbol{\beta}$ for cosine and sine components for a given frequency map onto amplitude and phase estimate.
- Restriction: basis functions should be ‘orthogonal’
- Consequence 1: frequencies not arbitrary -> integer amount of cycles should fit into N points.
- Consequence 2: N-point signal -> N basis functions



Time-frequency relation

- Consequence 1: frequencies not arbitrary -> integer amount of cycles should fit into N points (of length T).
- The frequency resolution is determined by the length of the data segments (T)
- Rayleigh frequency = $1/T = \Delta f = \text{frequency resolution}$

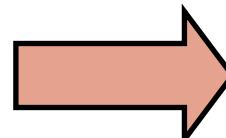


Time-frequency relation

- Consequence 2: N-point signal -> N basis functions
- N basis functions -> N/2 frequencies
- The highest frequency that can be resolved depends on the sampling frequency F
- Nyquist frequency = $F/2$

Sampling freq 1 kHz

Time window 1 s



Frequencies:

(0) 1 2 ... 499 500 Hz

Sampling freq 400 Hz

Time window 0.25 s



Frequencies:

(0) 4 8... 196 200 Hz

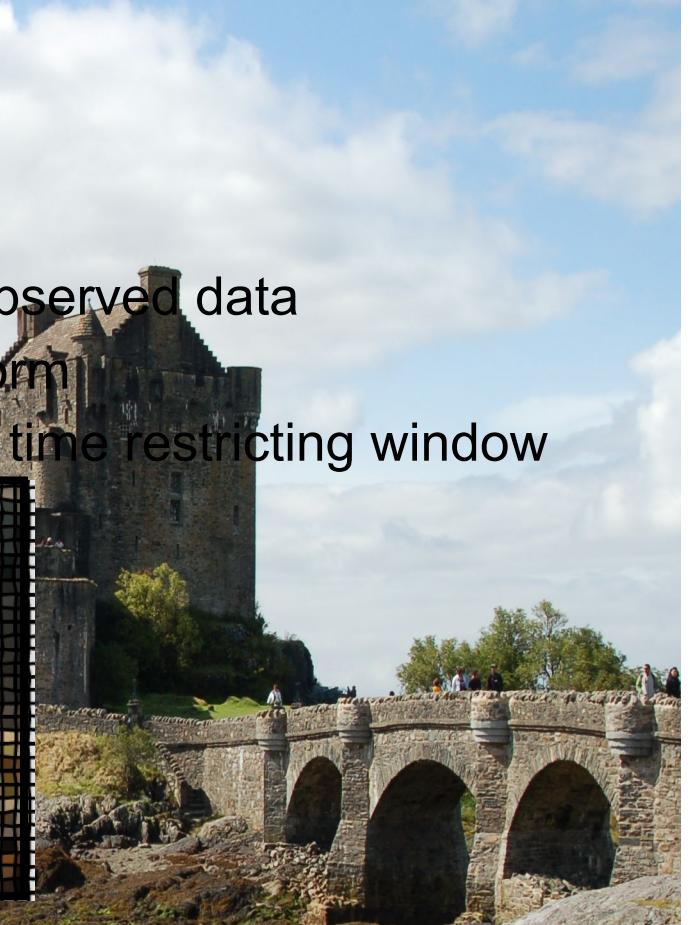
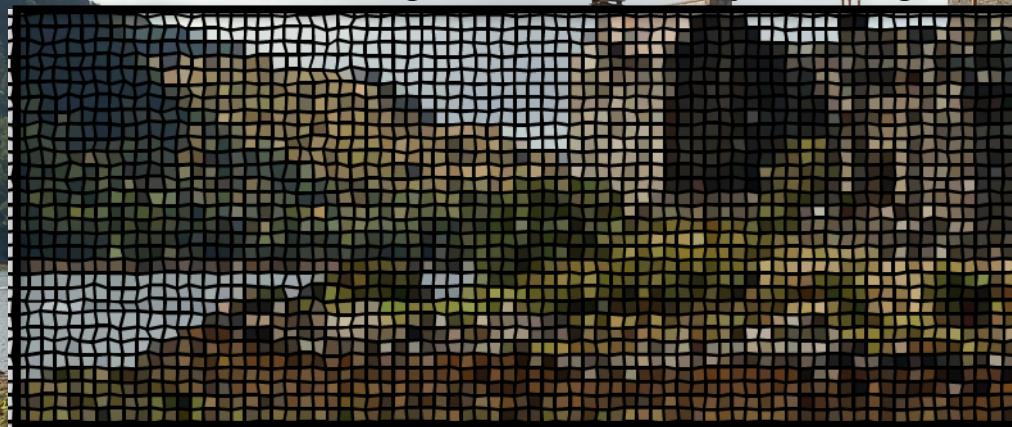


Spectral analysis

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

Goal and challenges

- Estimate the true oscillations from the observed data
- Limited time available for Fourier transform
- You are looking at the activity through a time restricting window

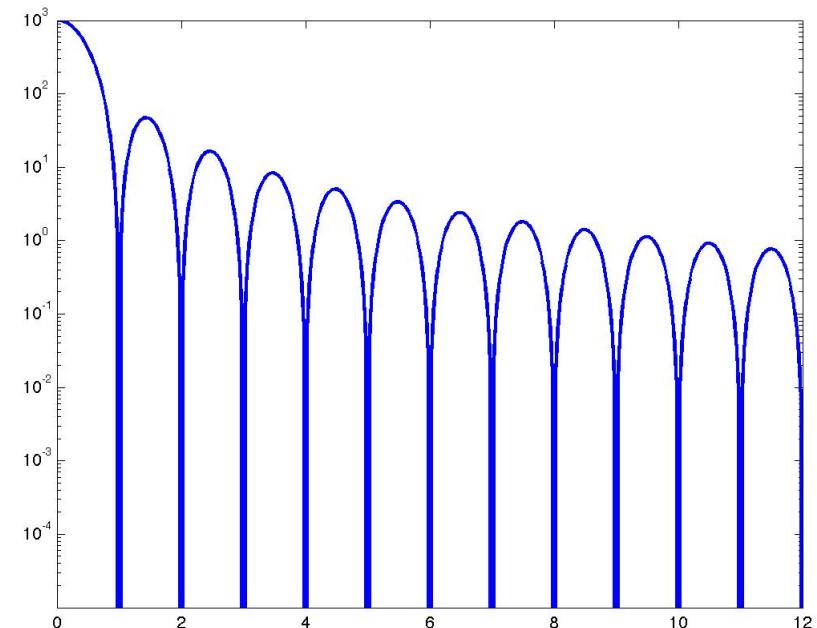
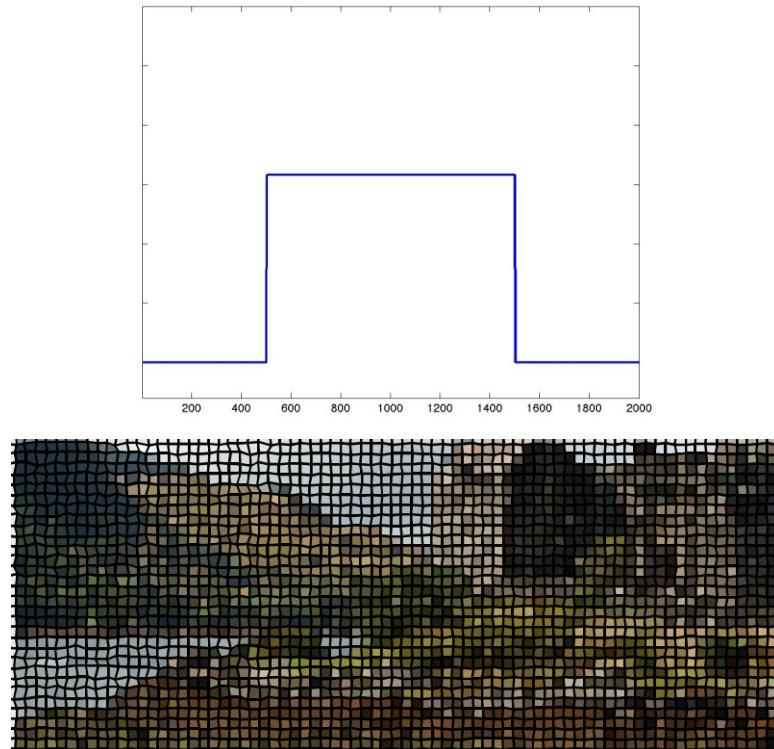


- This implicitly means that the data are ‘tapered’ with a boxcar
- Data are discretely sampled



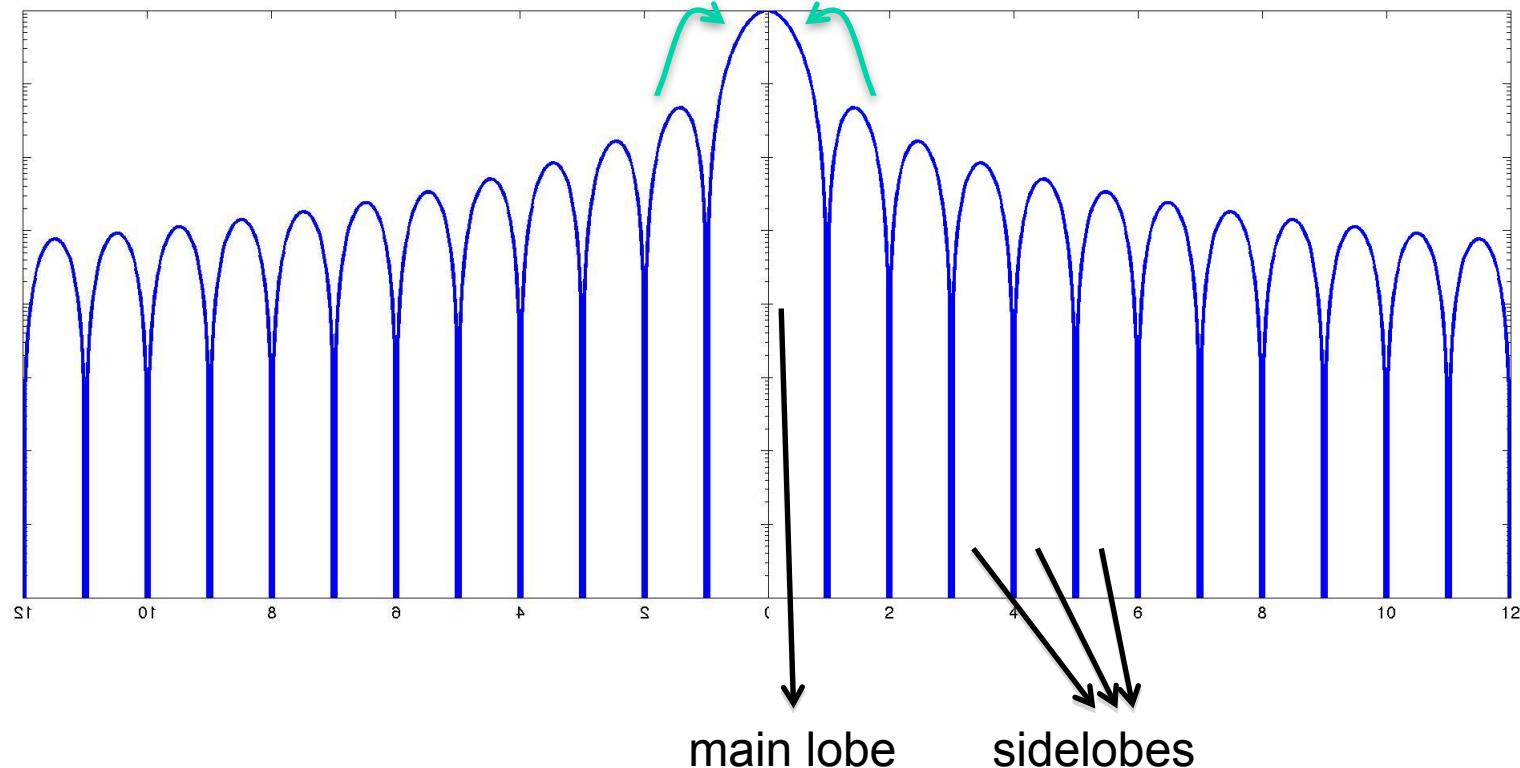
Spectral leakage and tapering

- True oscillations in data at frequencies **not sampled** with Fourier transform **spread their energy** to the sampled frequencies
- Not tapering = applying a boxcar taper
- Each type of taper has a specific leakage profile

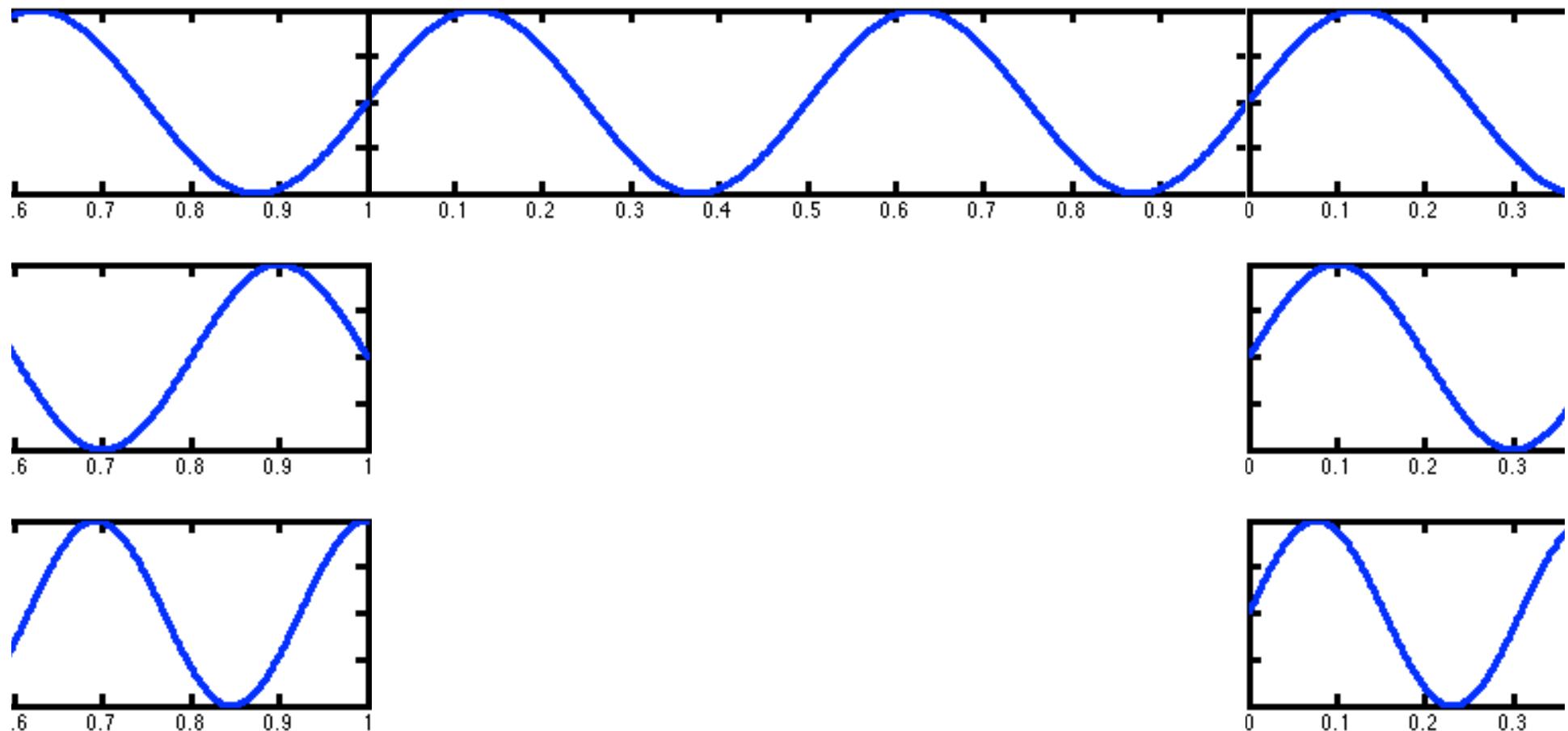




Spectral leakage

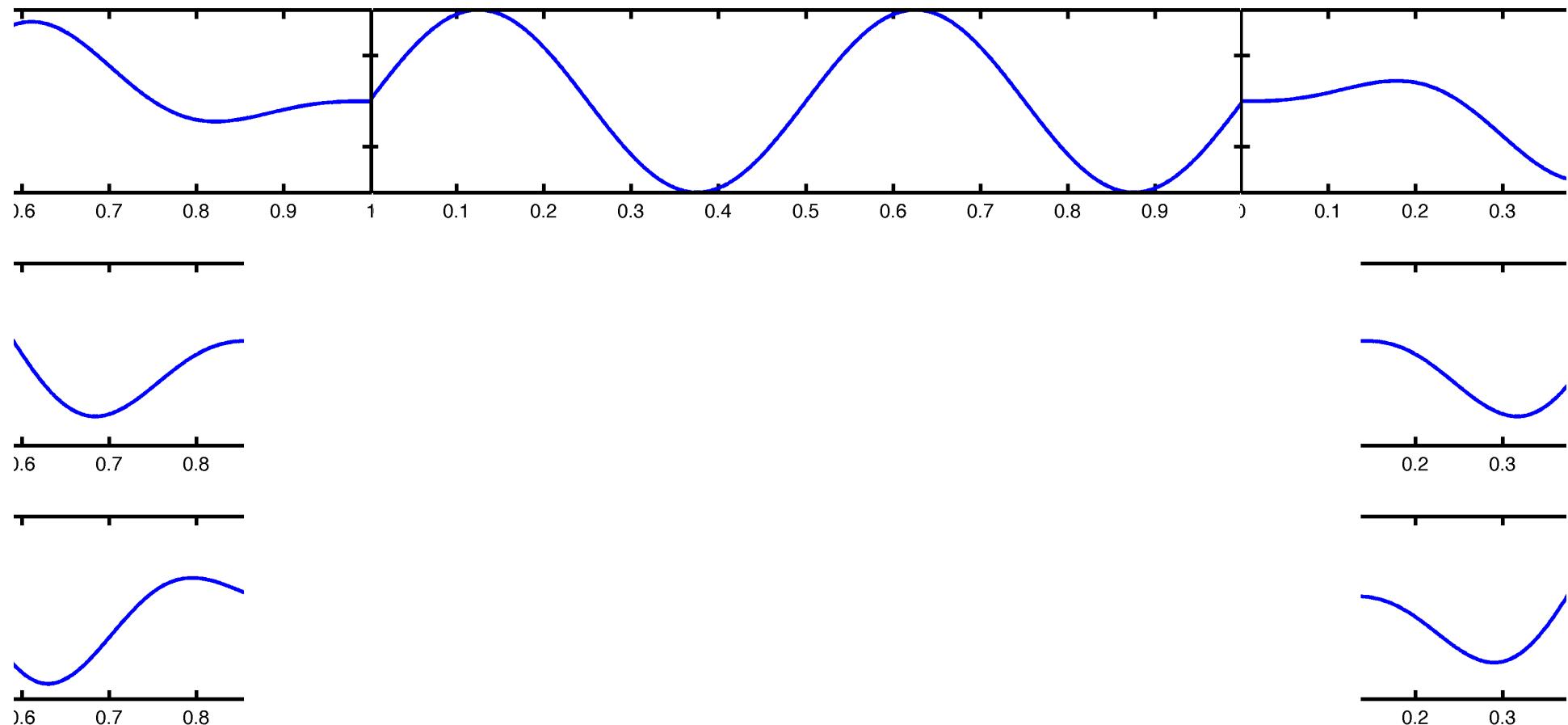


Tapering in spectral analysis



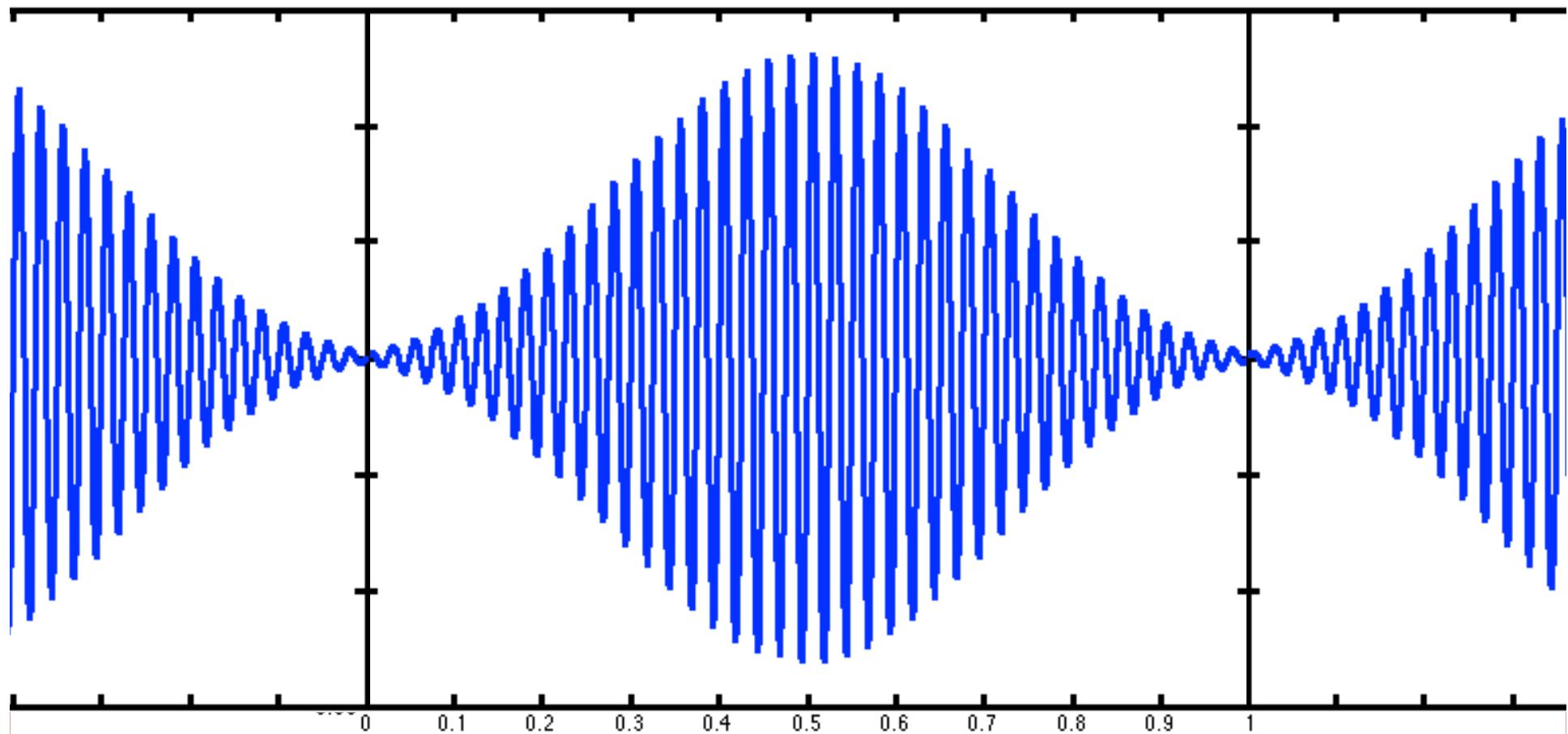


Tapering in spectral analysis



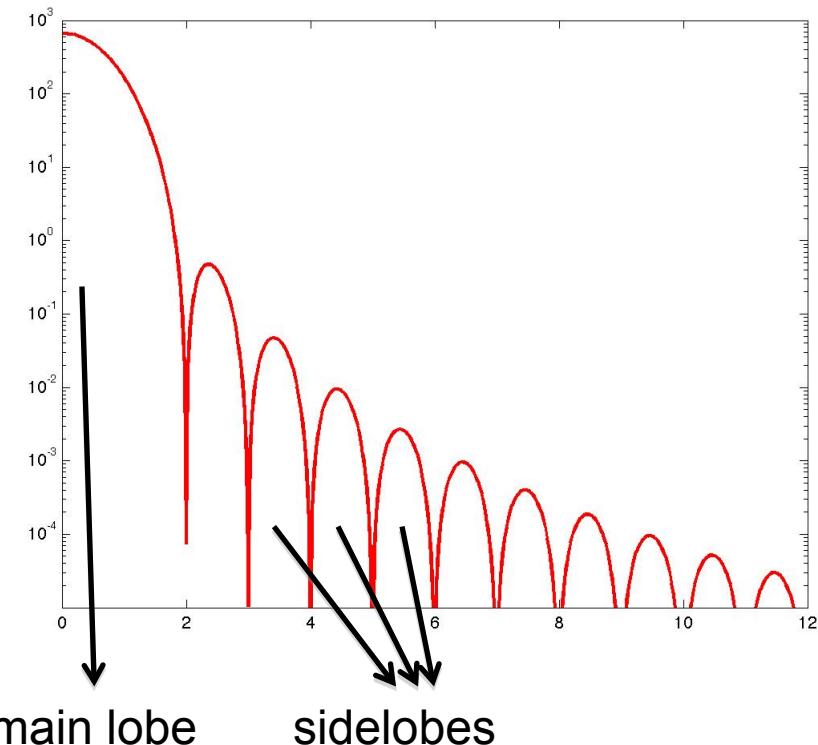
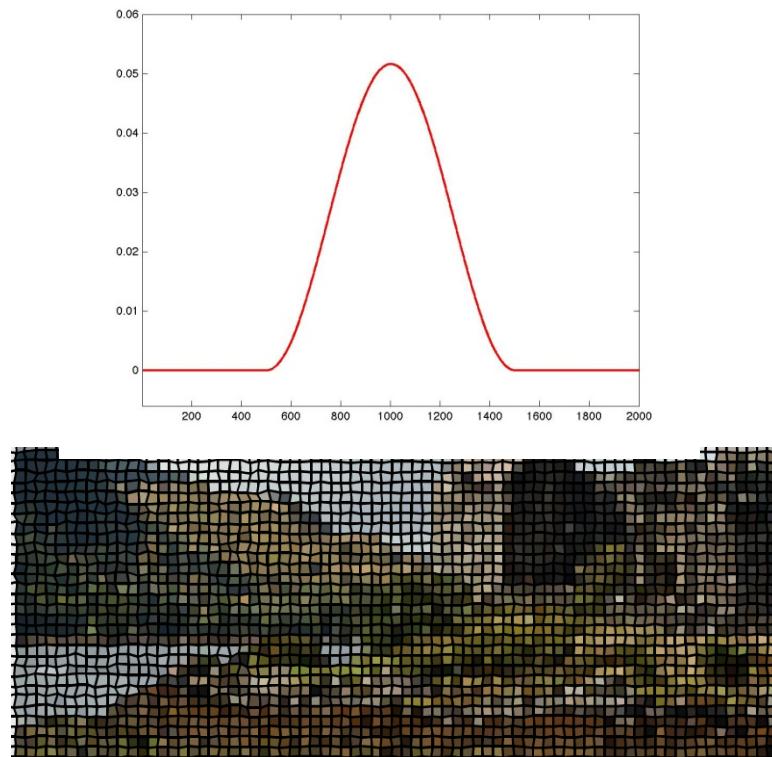


Tapering in spectral analysis



Spectral leakage and tapering

- True oscillations in data at frequencies not sampled with Fourier transform spread their energy to the sampled frequencies
- Not tapering = applying a boxcar taper
- Each type of taper has a specific leakage profile

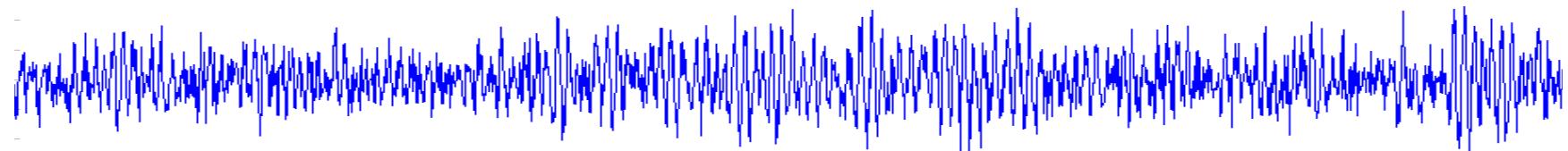




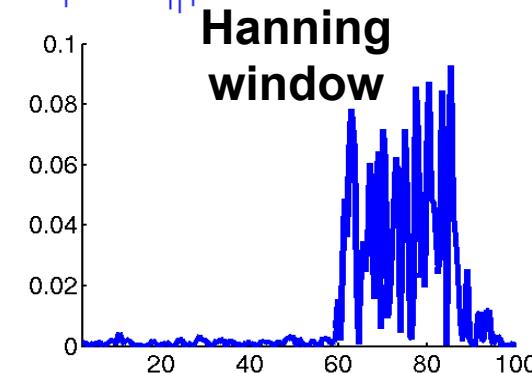
Multitapers

- Make use of more than one taper and combine their properties
- Used for smoothing in the frequency domain
- Instead of “smoothing” one can also say “controlled leakage”

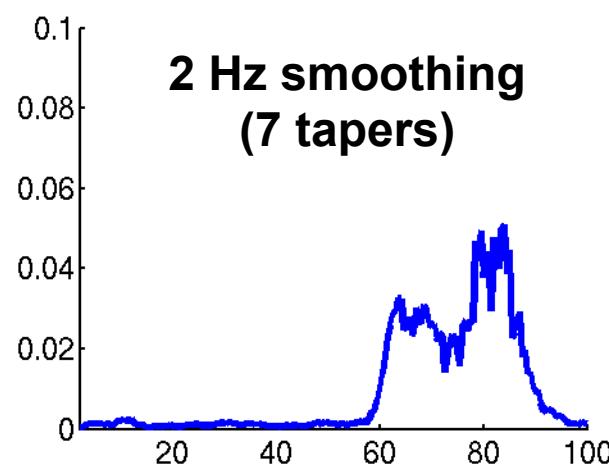
Multitapered spectral analysis



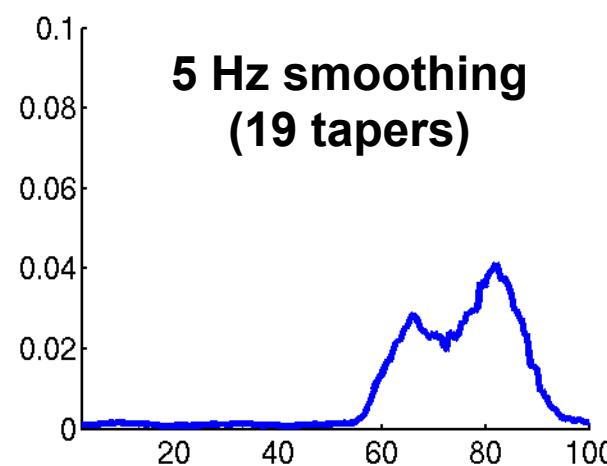
broadband activity
between 60-90 Hz



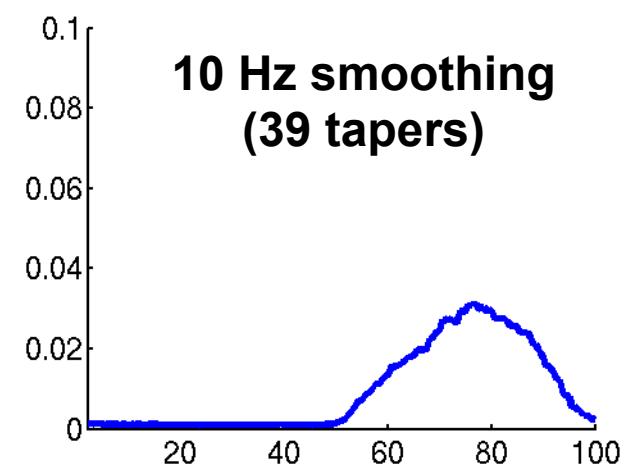
2 s



2 Hz smoothing
(7 tapers)

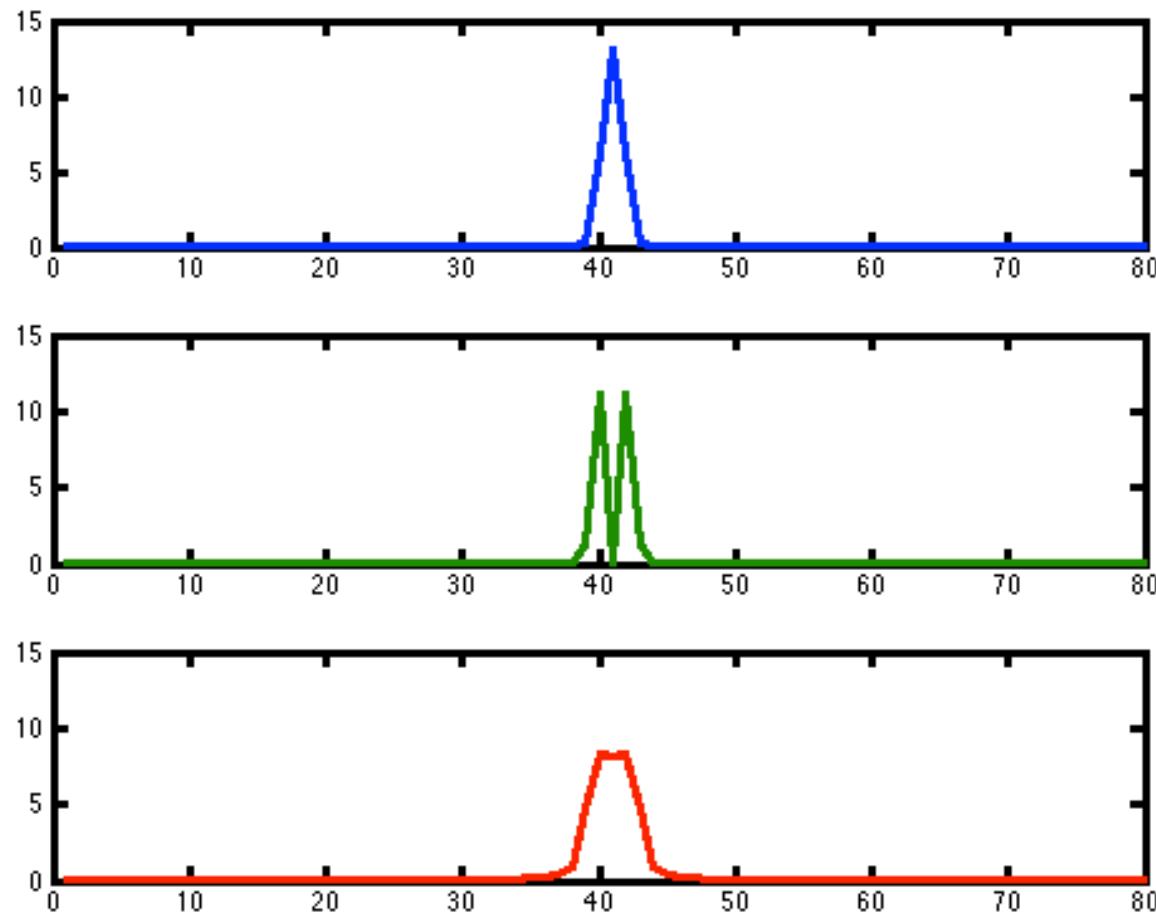


5 Hz smoothing
(19 tapers)

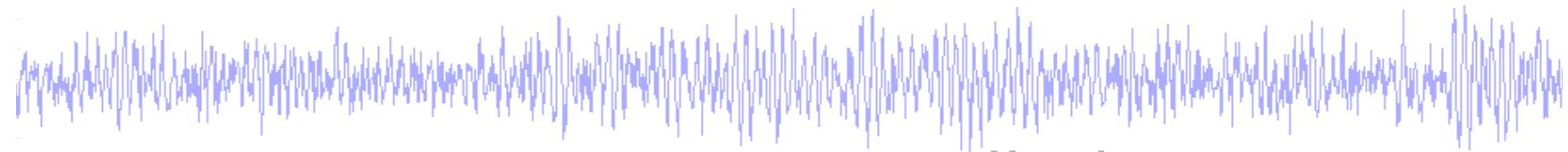


10 Hz smoothing
(39 tapers)

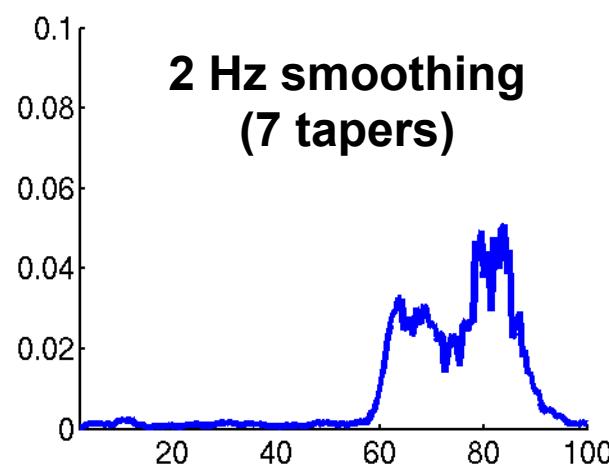
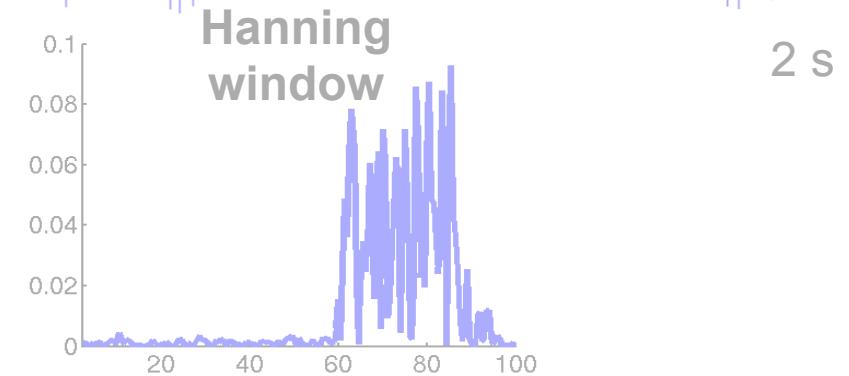
Multitapered spectral analysis



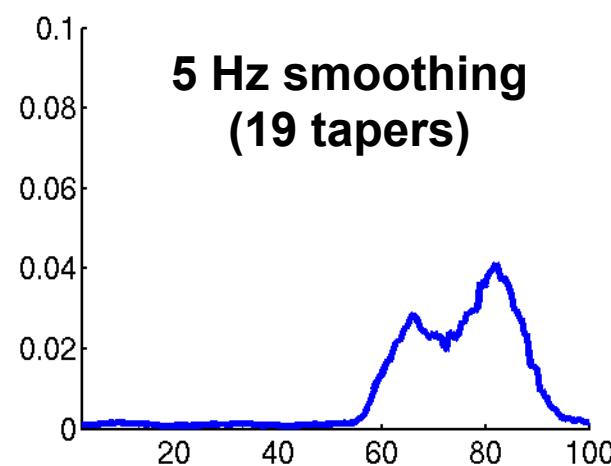
Multitapered spectral analysis



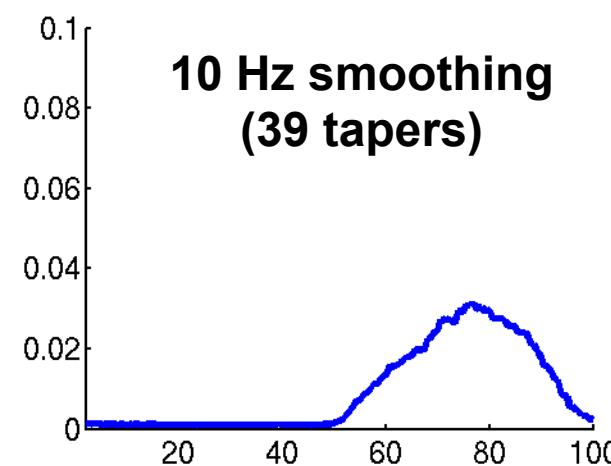
broadband activity
between 60-90 Hz



**2 Hz smoothing
(7 tapers)**



**5 Hz smoothing
(19 tapers)**



**10 Hz smoothing
(39 tapers)**



Multitapers

- Multitapers are useful for reliable estimation of high frequency components
- Low frequency components are better estimated using a single (Hanning) taper

```
%estimate low frequencies

cfg = [];
cfg.method = 'mtmfft';
cfg.foilim = [1 30];
cfg.taper = 'hanning';
.
.
.
freq=ft_freqanalysis(cfg, data);
```

```
%estimate high frequencies

cfg = [];
cfg.method      = 'mtmfft';
cfg.foilim      = [30 120];
cfg.taper       = 'dpss';
cfg.tapsmofrq = 8;
.
.
.
freq=ft_freqanalysis(cfg, data);
```



Sub summary

- Spectral analysis
 - Decompose signal into its constituent oscillatory components
 - Focused on ‘stationary’ power
- Tapers
 - Boxcar, Hanning, Gaussian
- Multitapers
 - Control spectral leakage/smoothing



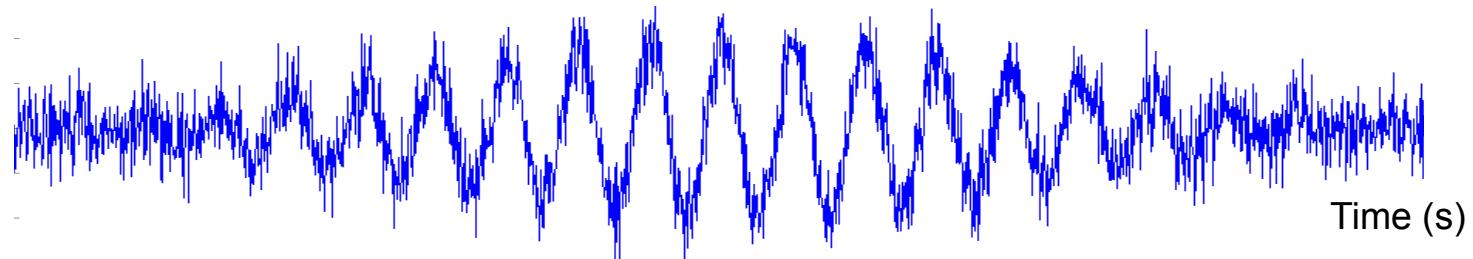
Time-frequency analysis

- Typically, brain signals are not ‘stationary’
- Divide the measured signal in shorter time segments and apply Fourier analysis to each signal segment
- Everything we saw so far with respect to frequency resolution applies here as well

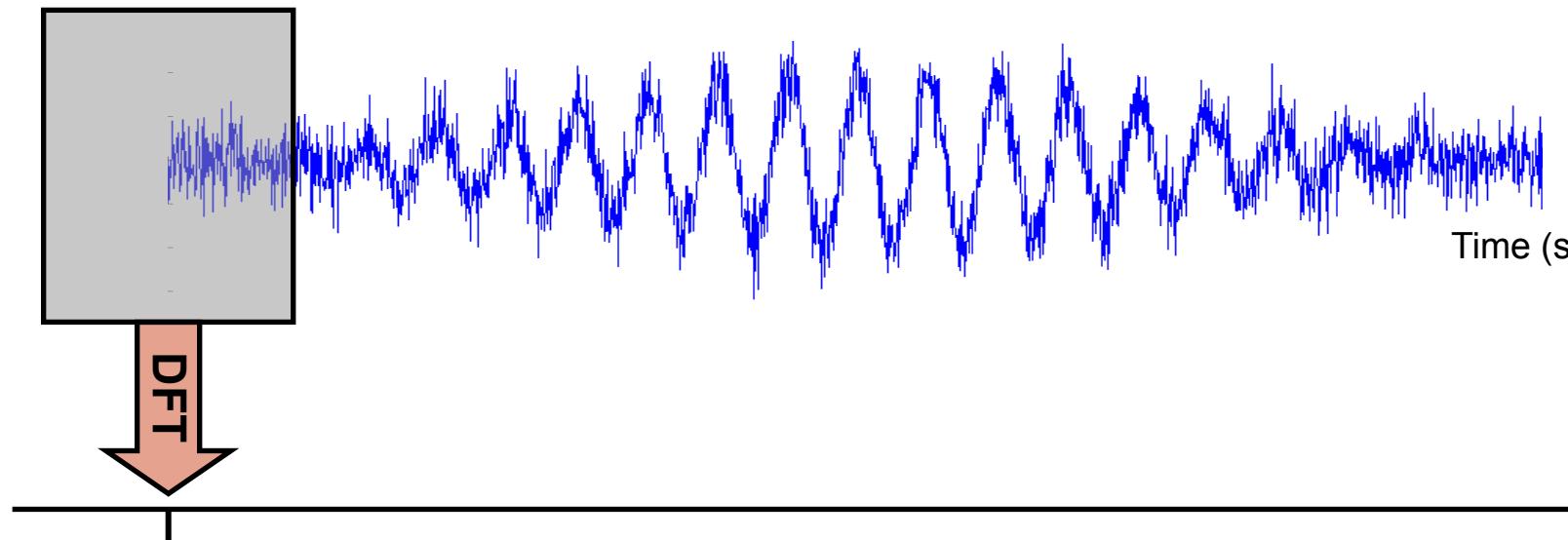
```
cfg = [];
cfg.method = 'mtmconvol';
.
.
.
freq = ft_freqanalysis(cfg, data);
```



Time frequency analysis

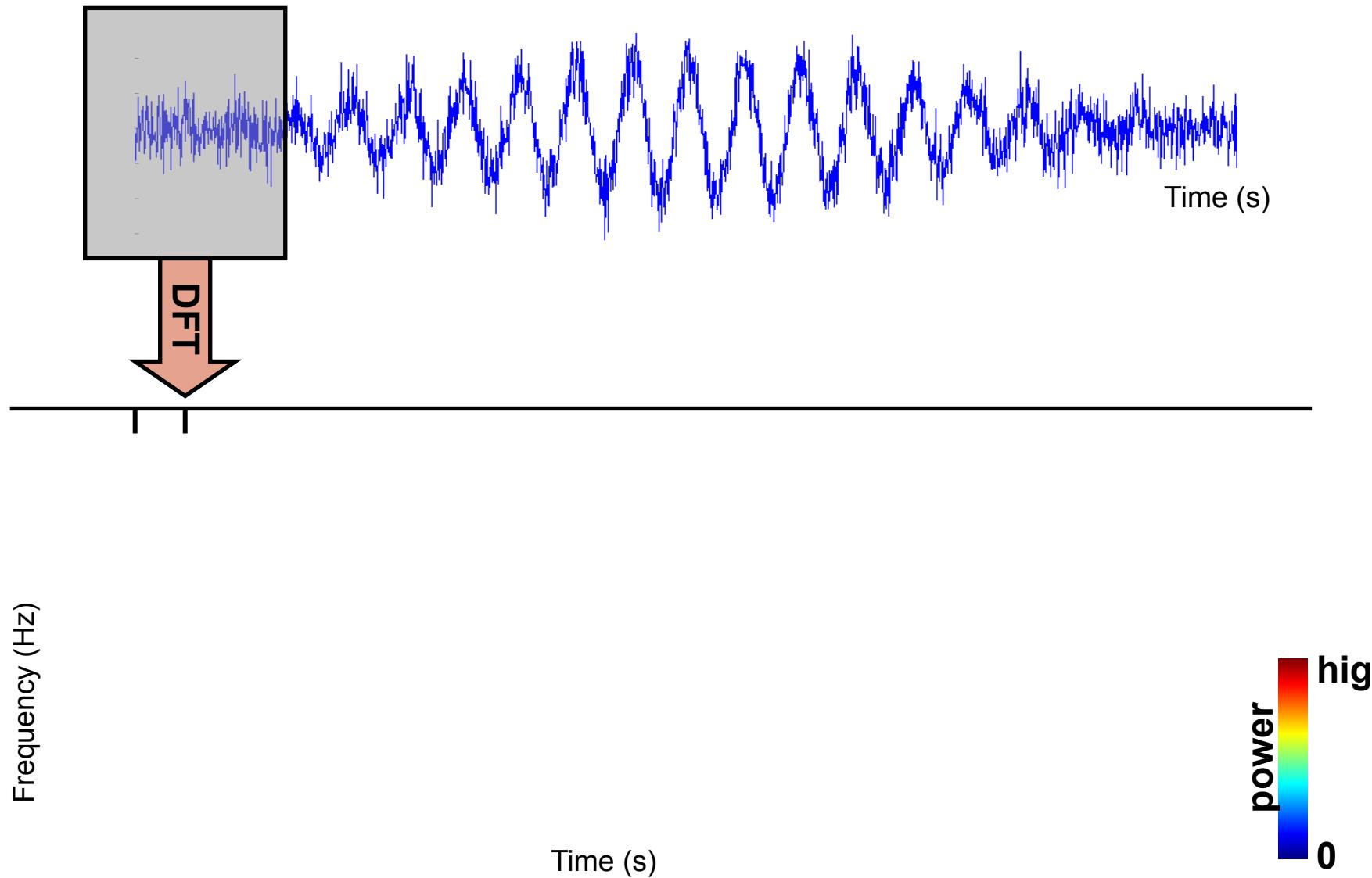


Time frequency analysis

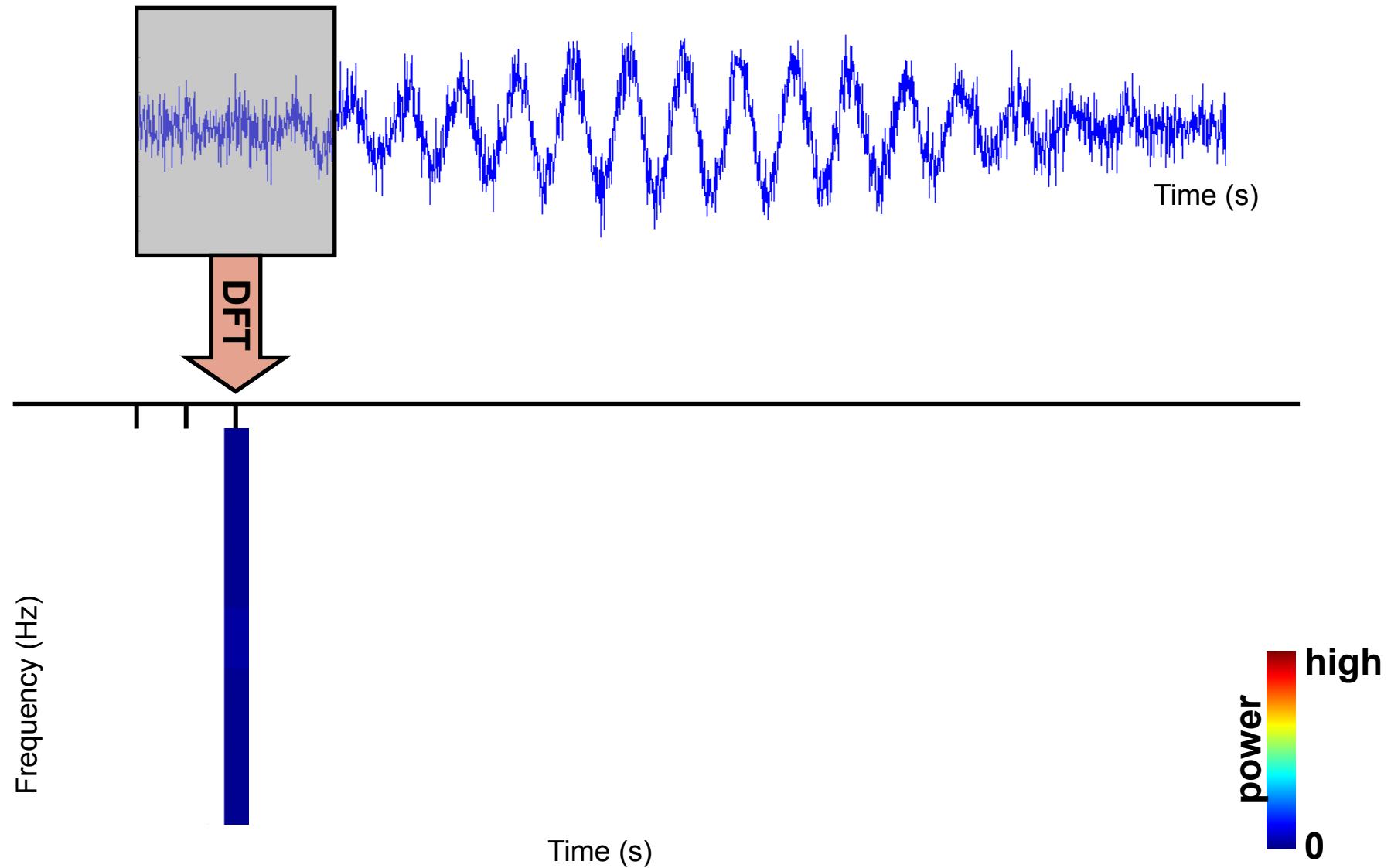




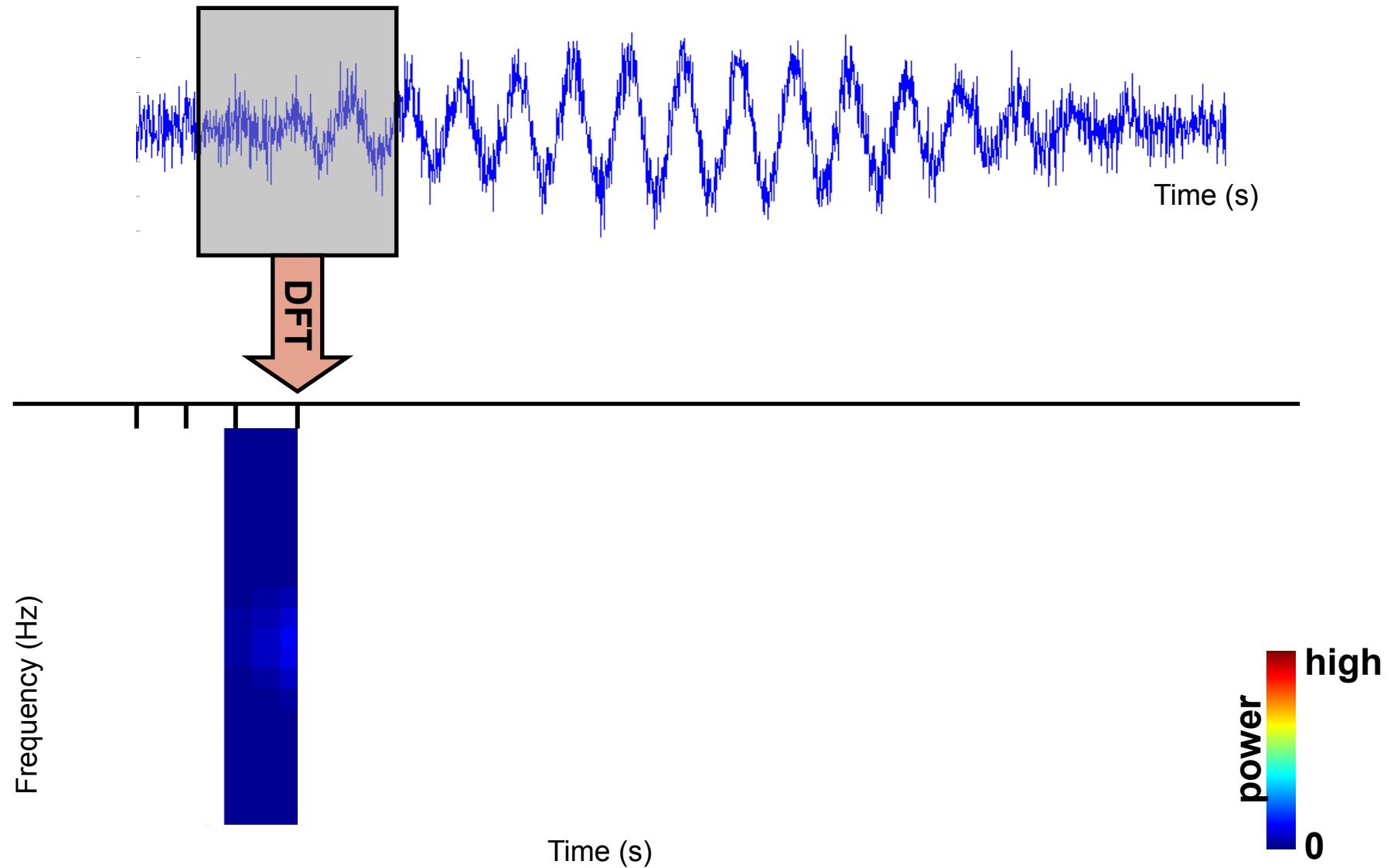
Time frequency analysis



Time frequency analysis

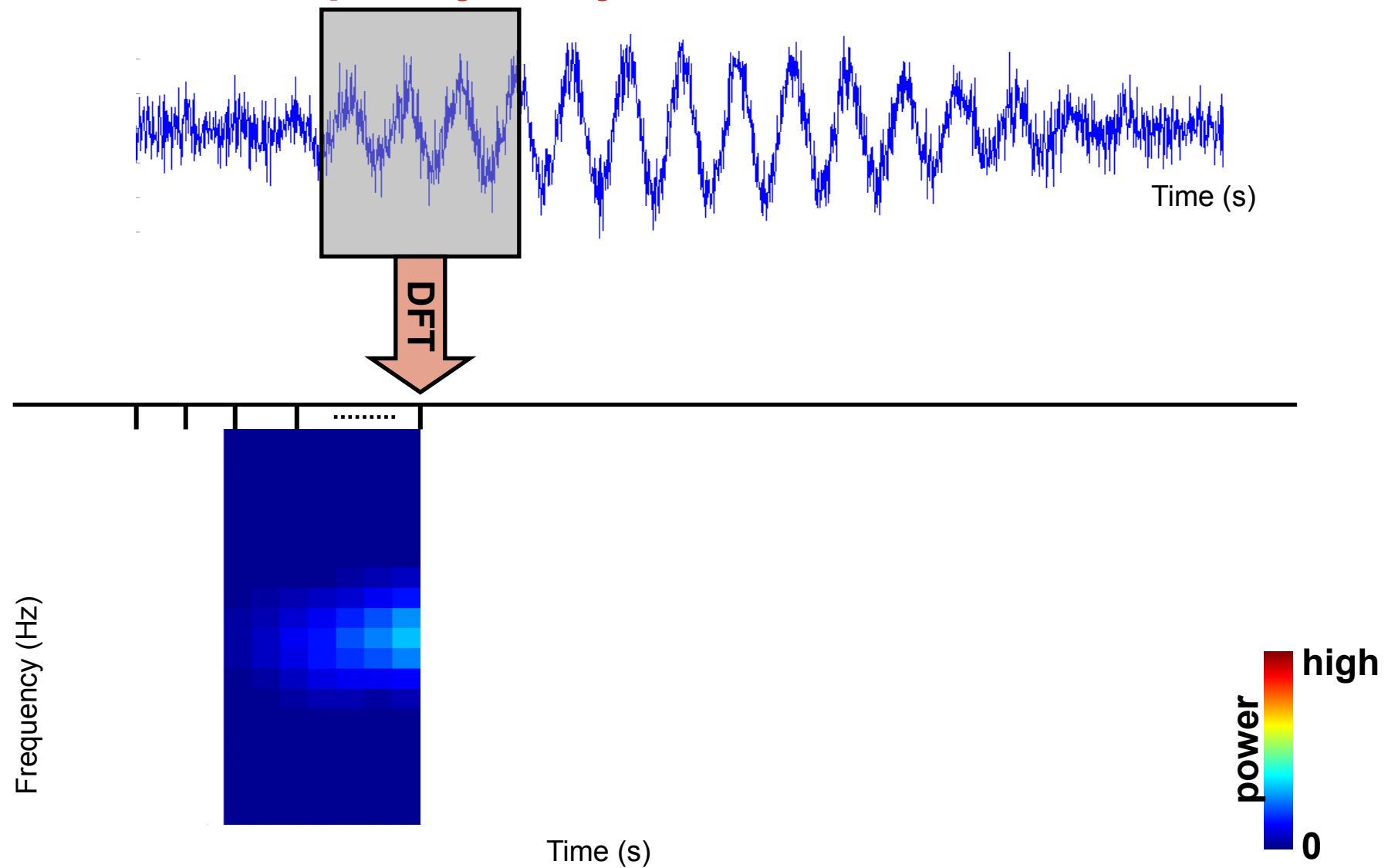


Time frequency analysis



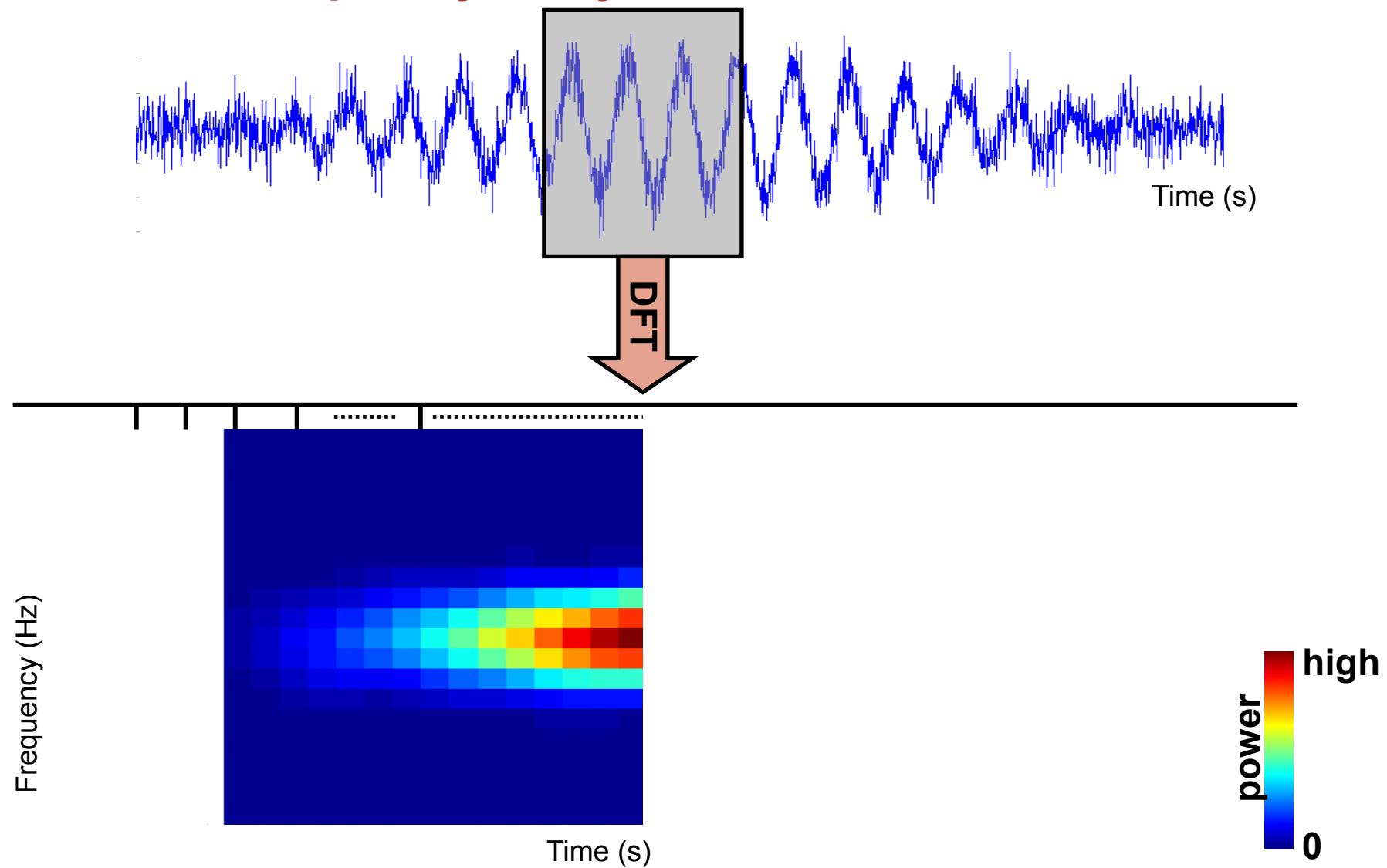


Time frequency analysis



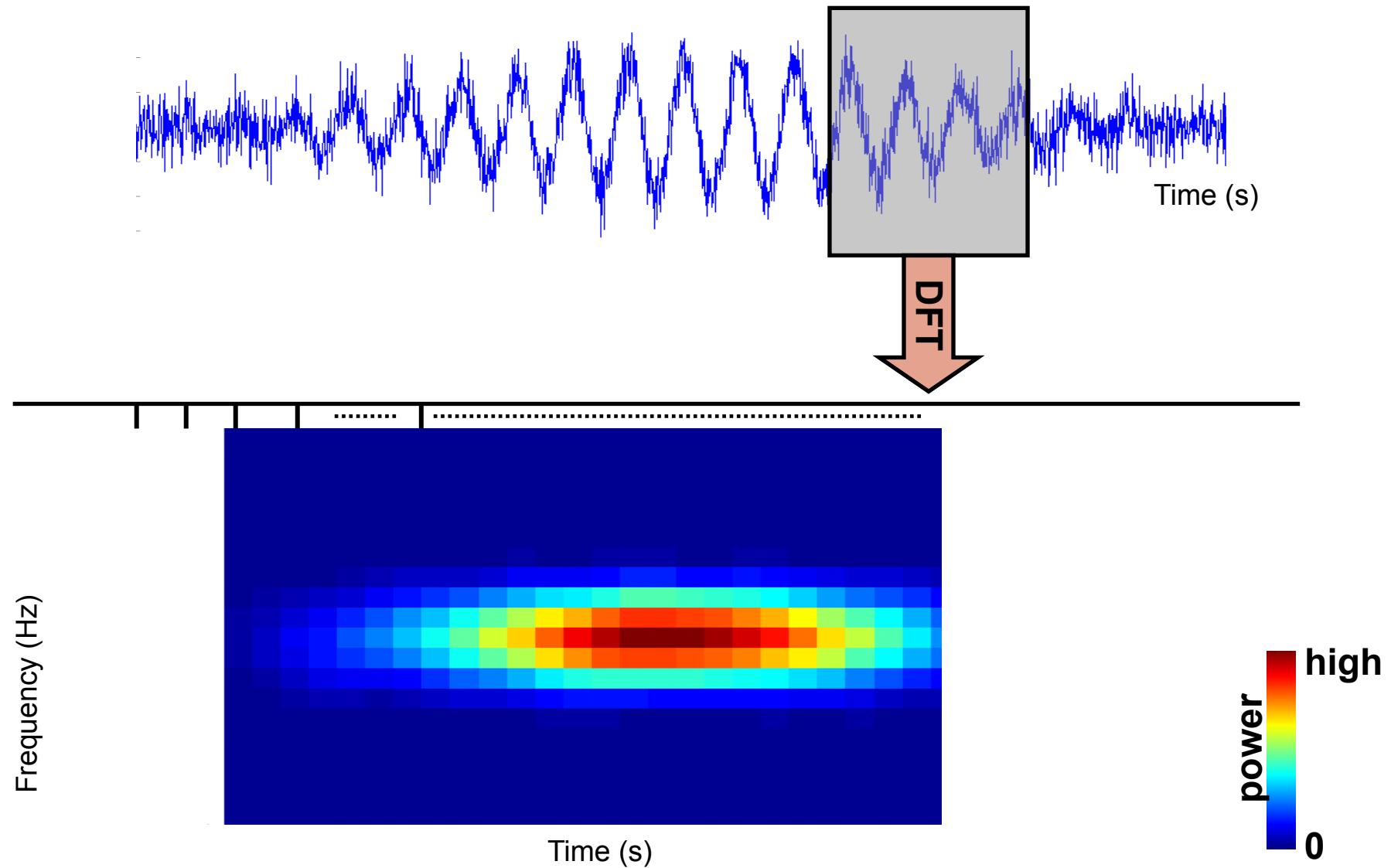


Time frequency analysis



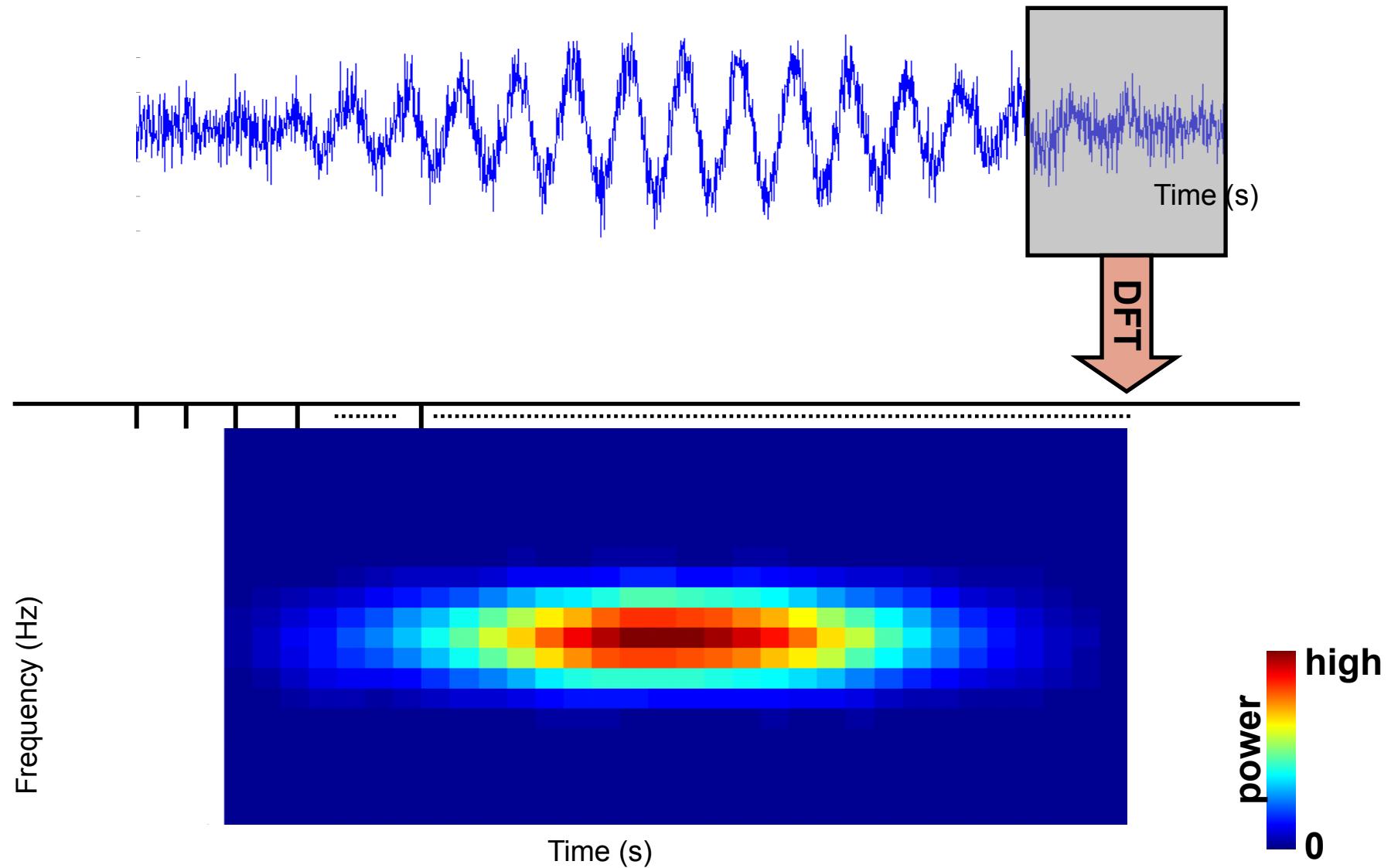


Time frequency analysis



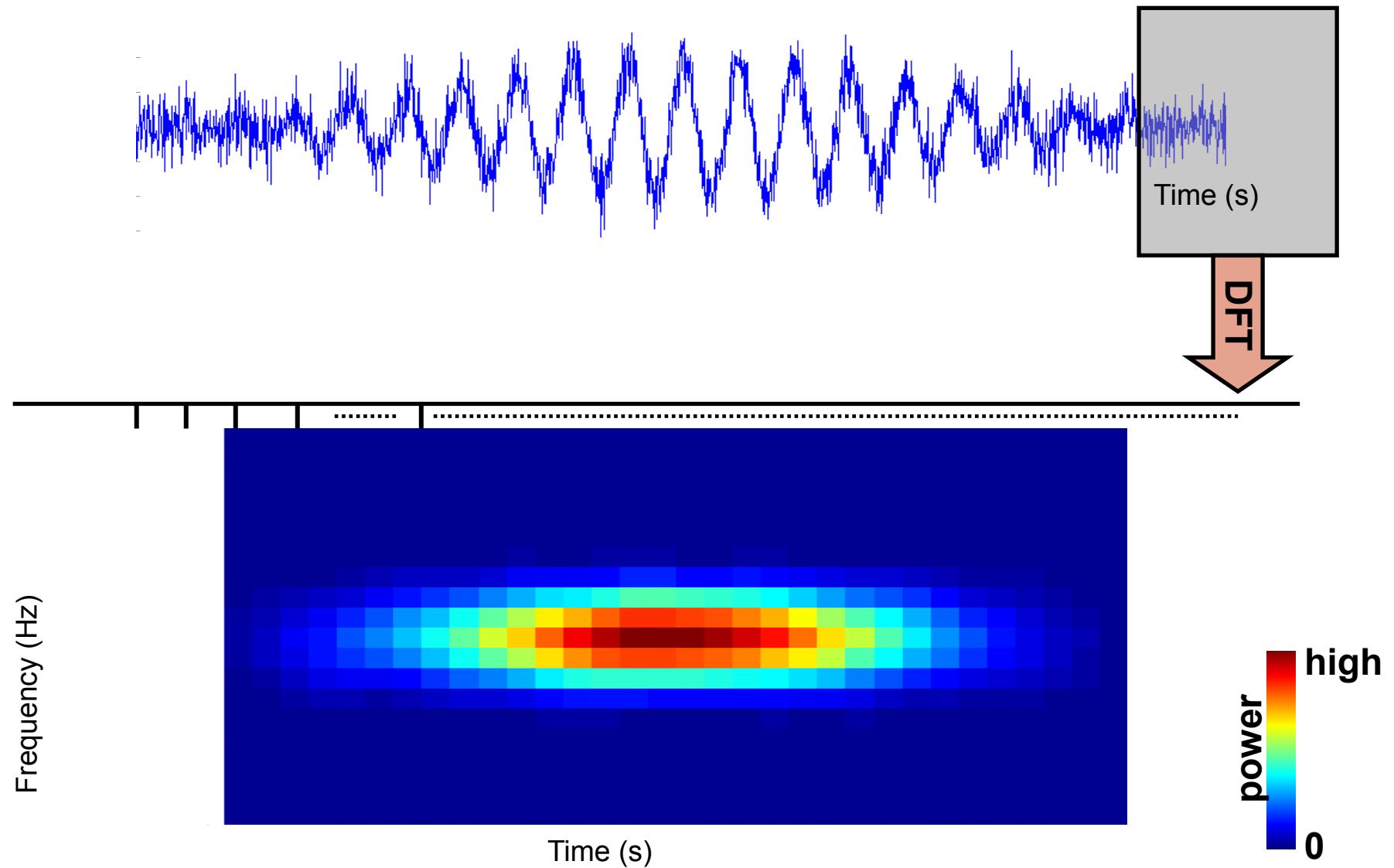


Time frequency analysis

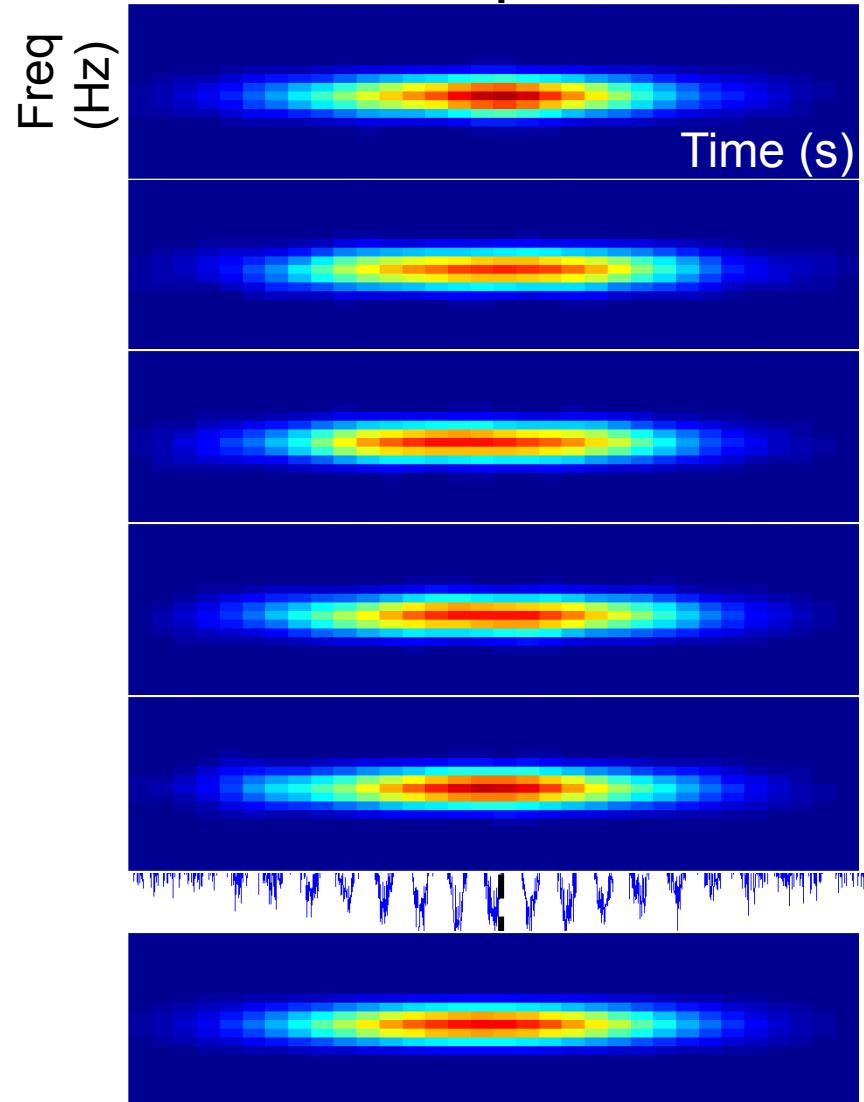
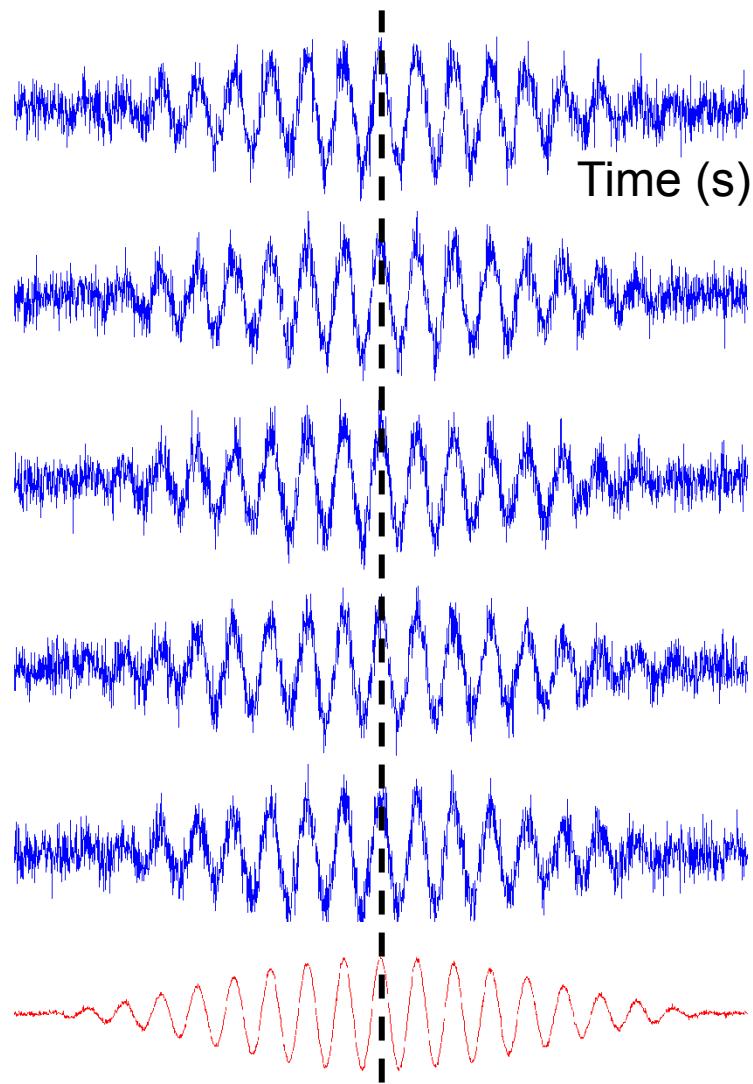




Time frequency analysis

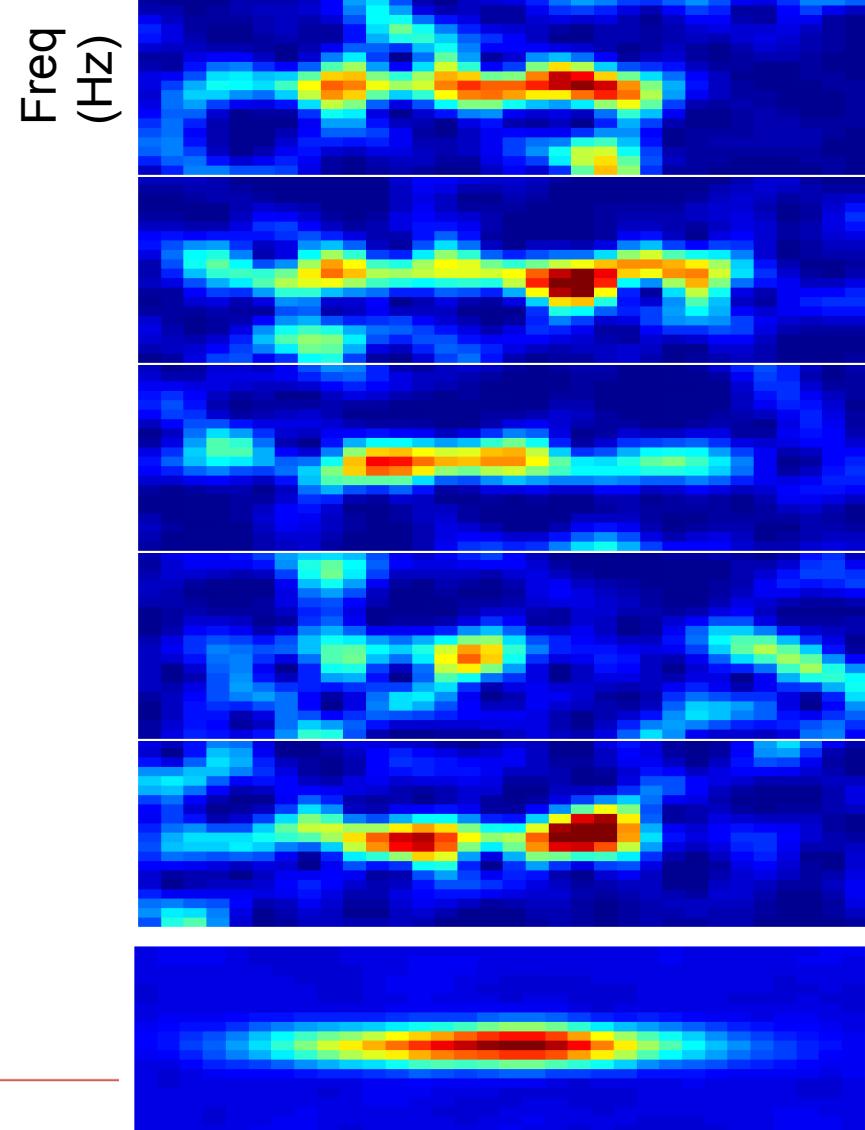
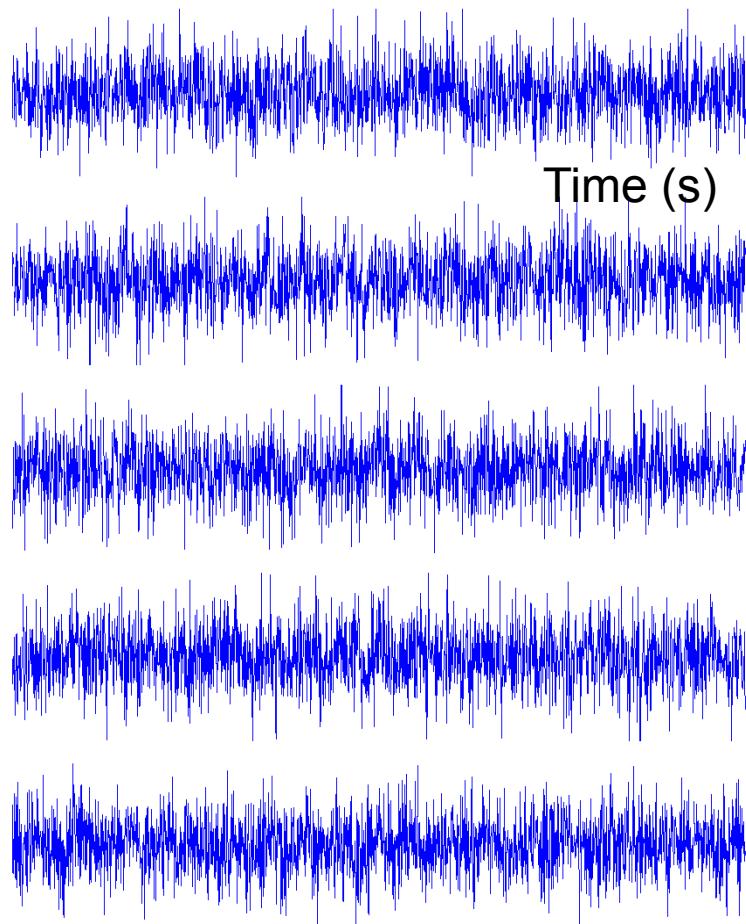


Evoked versus induced activity

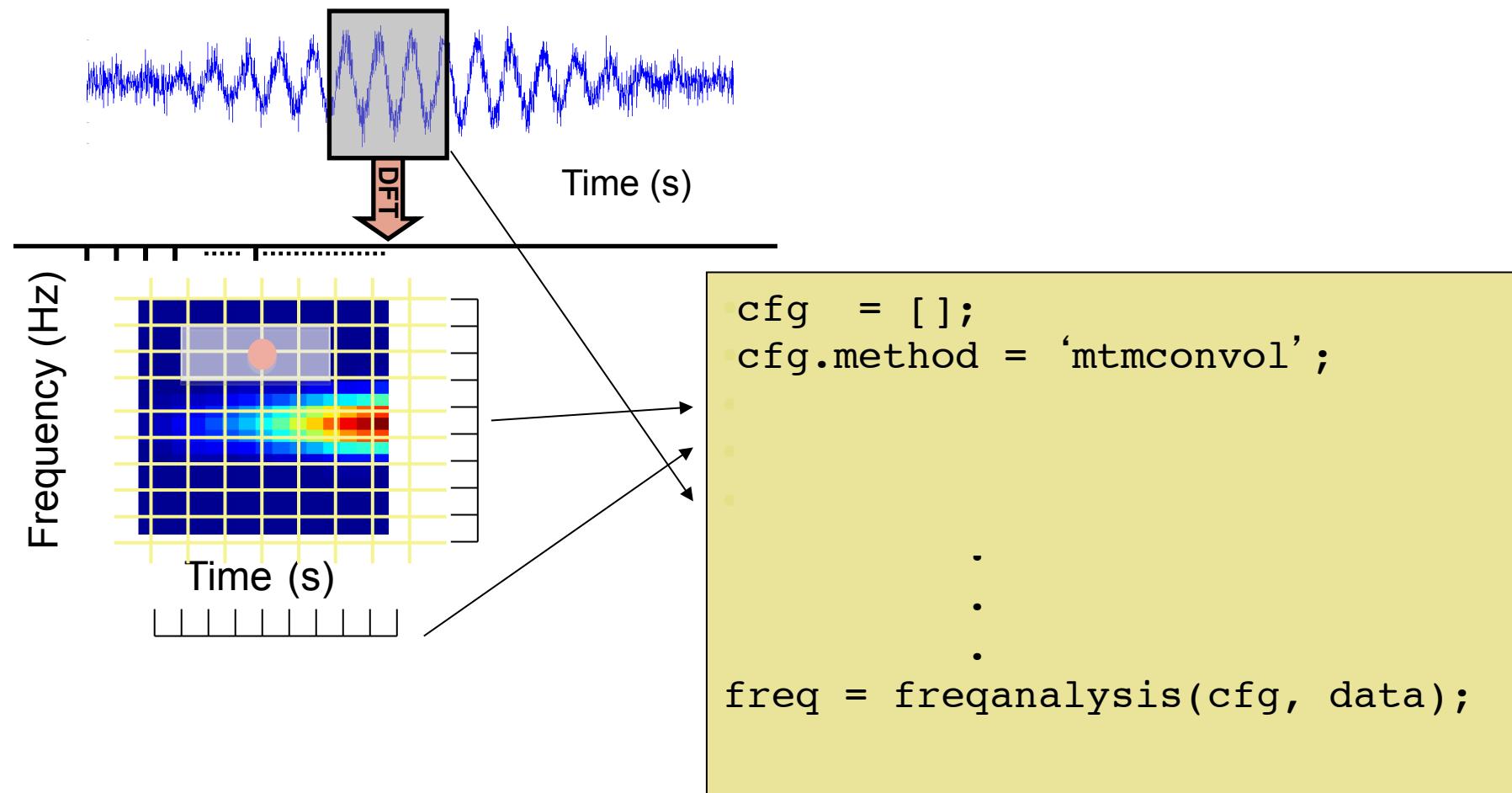




Noisy signal -> many trials needed

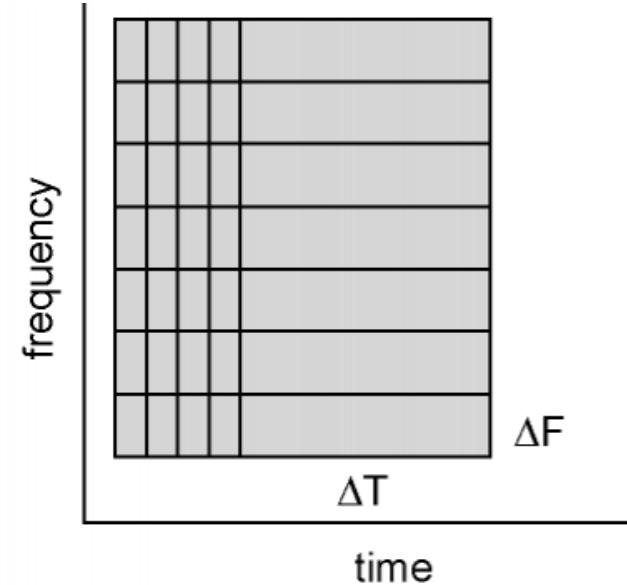


The time-frequency plane



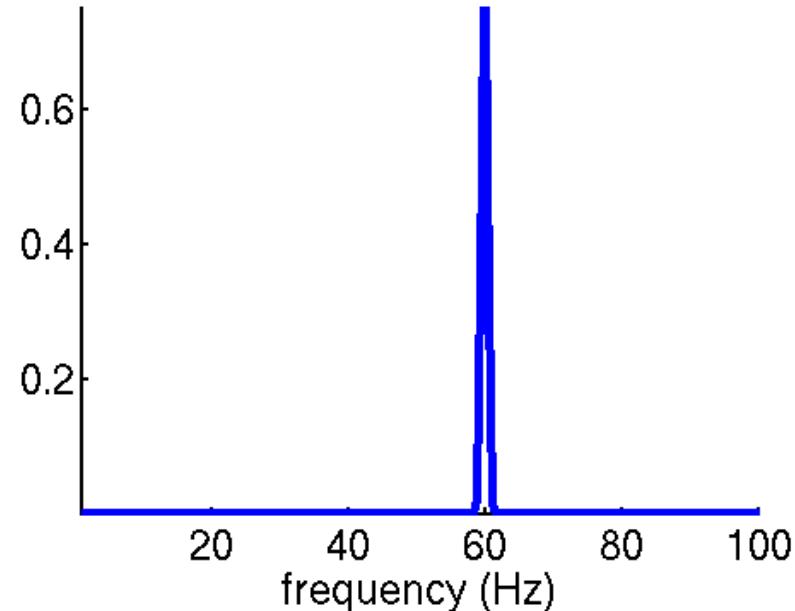
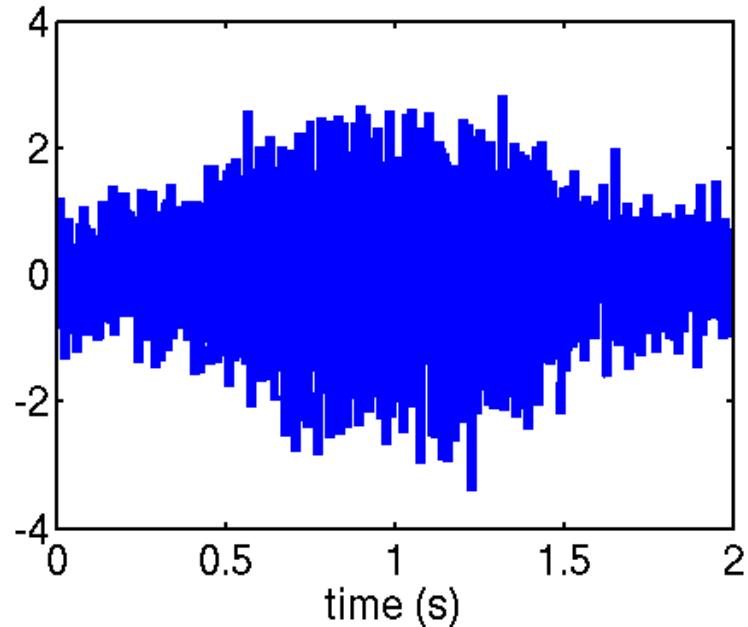
The time-frequency plane

- Division is ‘up to you’
- Depends on the phenomenon you want to investigate
 - Which frequency band?
 - Which time scale?

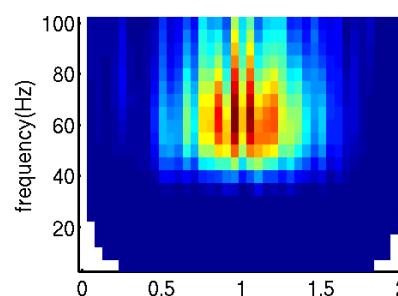


```
cfg = [];
cfg.method      = 'mtmconvol';
cfg.foi         = [2 4 ... 40];
cfg.toi         = [0:0.050:1.0];
cfg.t_ftimwin  = [0.5 0.5 ... 0.5];
cfg.tapsmofrq = [4 4 ... 4];
.
.
freq = freqanalysis(cfg, data);
```

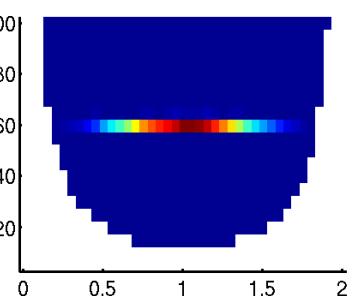
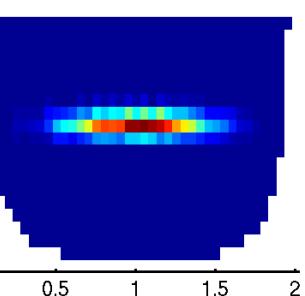
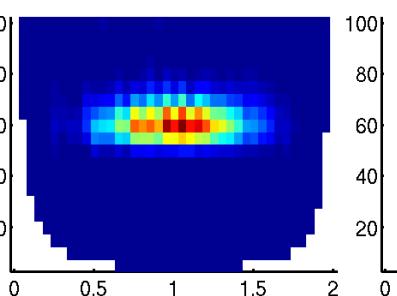
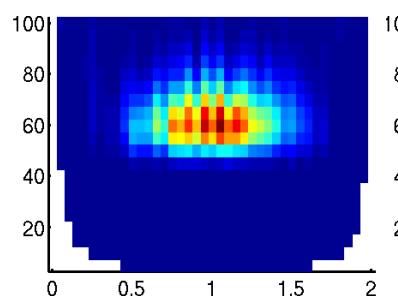
Time versus frequency resolution



short timewindow



long timewindow





Sub summary

- Time frequency analysis
 - Fourier analysis on shorter sliding time window
- Evoked & Induced activity
- Time frequency resolution trade off



Wavelet analysis

- Popular method to calculate time-frequency representations
- Is based on convolution of signal with a family of ‘wavelets’ which capture different frequency components in the signal
- Convolution ~ local correlation



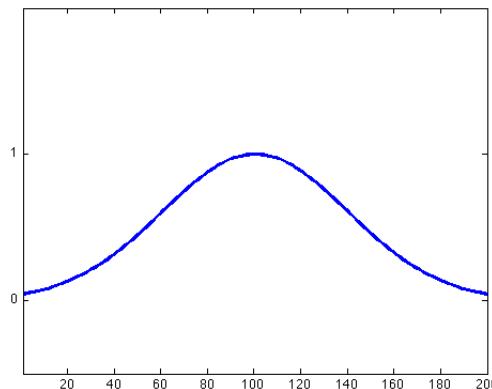
Wavelet analysis

```
cfg = [];
cfg.method = 'wavelet';
.
.
.
freq=ft_freqanalysis(cfg, data);
```



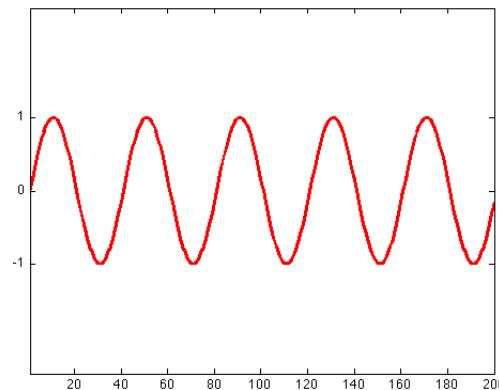
Wavelets

Taper

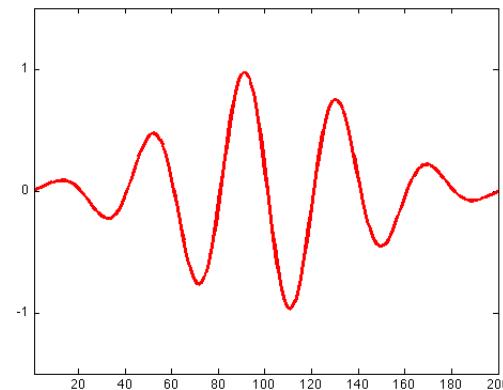


X

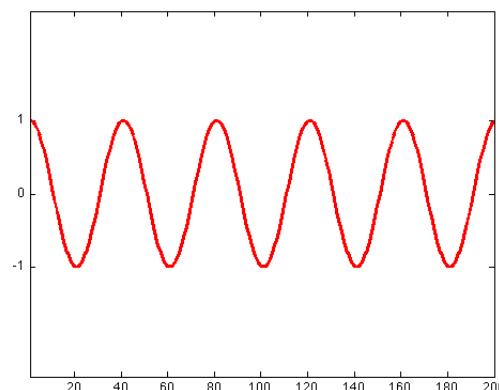
Sine wave



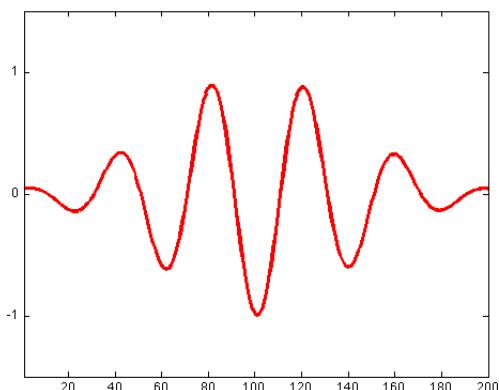
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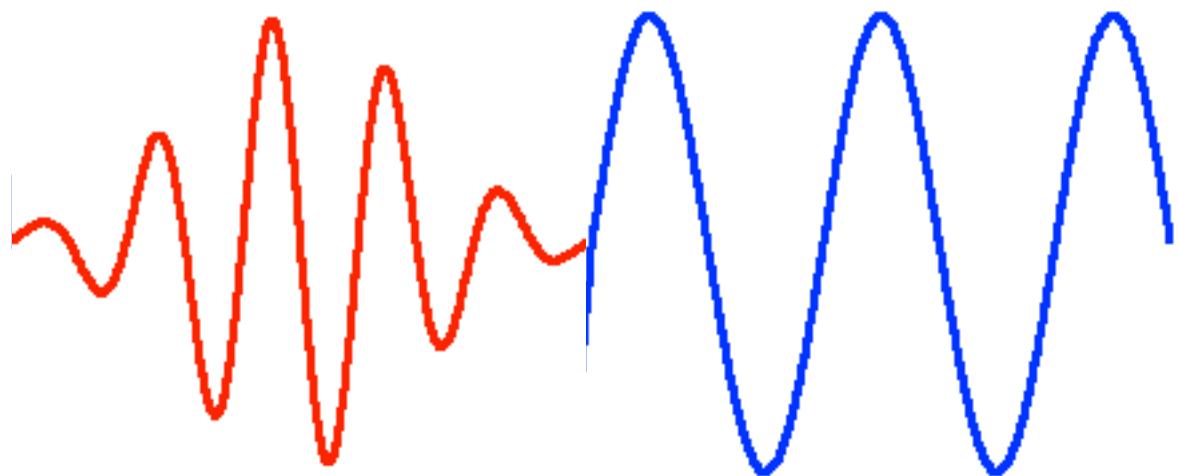


Cosine wave



=

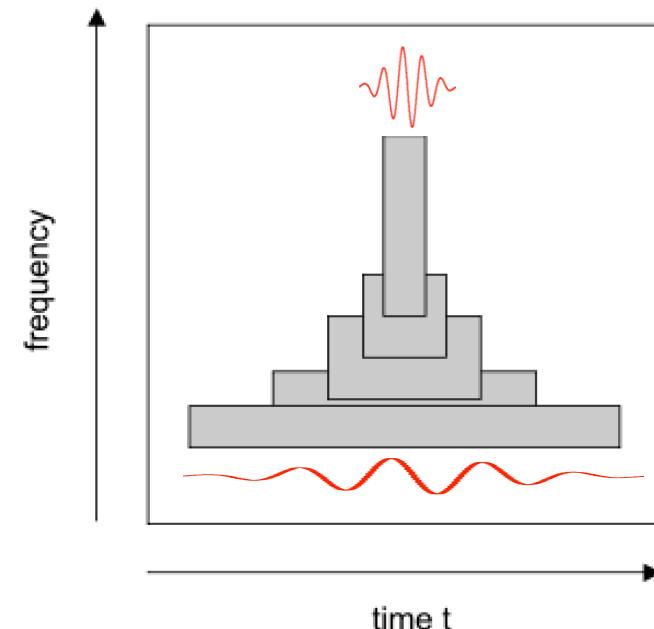




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Wavelet analysis

- Wavelet width determines time-frequency resolution
- Width 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





Wavelet analysis

- Similar to Fourier analysis, but
 - Computationally slow
 - Tiles the time frequency plane in a particular way with few degrees of freedom

```
%time frequency analysis with  
%multitapers  
  
cfg = [];  
cfg.method = 'mtmconvol';  
cfg.toi = [0:0.05:1];  
cfg.foi = [4 8 ... 80];  
cfg.t_ftimwin = [0.5 0.5 ... 0.5];  
cfg.tapsmofrq = [2 2 ... 10];  
.  
.  
freq=ft_freqanalysis(cfg, data);
```

```
%time frequency analysis with  
%wavelets  
  
cfg = [];  
cfg.method = 'wavelet';  
cfg.toi = [0:0.05:1];  
cfg.foi = [4 8 ... 80];  
cfg.gwidth = 5;  
.  
.  
.  
freq=ft_freqanalysis(cfg, data);
```

Summary

Spectral analysis

Relation between time and frequency domains

Tapers

Time frequency analysis

Time vs frequency resolution

Wavelets

Hands-on: Time-frequency analysis of power

Hanning window

fixed and variable length.

Wavelets

Multi-tapers

