Spectral Analysis

How to process neural oscillatory signals

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Comprehensive Training
November 2015
Why spectral analysis?

- MEG signals contain a wide range of components
- Electrophysiology vs. BOLD: what is 'activity'?
Why spectral analysis?

- MEG signals contain a wide range of components
- Electrophysiology vs. BOLD: what is 'activity'?

BOLD fMRI example

Cross-correlation of BOLD with intra-cranial LFP recordings

Schöllvinck et al., PNAS (2010)
Basic concepts

- Frequency: (how fast?)
  - theta: (4-8 Hz)
  - beta: (13-25 Hz)
  - gamma: (80-120 Hz)

- Phase: (where?)
  - 0, π/2, π

- Power: (how strong?)

Time scale: 100 ms
Basic concepts

Cycle

Frequency (how fast?)

theta (4-8 Hz)

beta (13-25 Hz)

gamma (80-120 Hz)

Phase (where?)

π
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Power (how strong?)

100 ms
Basic concepts

Cycle

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Phase (where?)

\( \pi \rightarrow 0 \rightarrow \pi/2 \)

Power (how strong?)

100 ms
Basic concepts

Cycle

Frequency (how fast?)
theta (4-8 Hz)
beta (13-25 Hz)
gamma (80-120 Hz)

Phase (where?)
π, 0, π/2

Power (how strong)

100 ms
How to do it? Brainstorm!
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Which methods, which parameters do I choose?
Methods covered today

Two main groups:

• Estimation of spectral power (stationary) vs.
• Localization of Power in time & frequency
Methods covered today

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Usage:

- Quality check (noise level)
- Resting-state dynamics
- Extended task periods
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Usage:

• Quality check (noise level)
• Resting-state dynamics
• Extended task periods

Usage:

• Task-induced responses
• Transient oscillatory phenomena (HFOs)
Methods covered today

Two main groups:

- Estimation of spectral power (stationary) vs.
- Localization of Power in time & frequency

Stationary:

- Fourier transform
- Power spectral density (Welch's method)
Methods covered today

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**Stationary:**
- Fourier transform
- Power spectral density (Welch's method)

**Time-resolved:**
- Wavelet transform
- Filtering & Hilbert transform
Methods covered today

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• Estimation of spectral power (stationary) vs.

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Short introduction to cross-frequency coupling measures

Example signal

- Concepts will be illustrated using the following signal
Example signal

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- MEG source signal from visual cortex
- 4 seconds
- Sampling frequency: 600 Hz
Example signal

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- MEG source signal from visual cortex
- 4 seconds
- Sampling frequency: 600 Hz
- Visual stimulus
Contents

Stationary:

• Fourier transform

• Power spectral density (Welch's method)

Time-resolved:

• Wavelet transform

• Filtering & Hilbert transform
(Fast) Fourier Transform, FFT

- Transforms a signal from time to frequency domain.
- Hugely important in many fields of science and engineering.
- Not so powerful in its raw form for estimating spectral components in neural signals
- BUT: forms the basis for many of the following methods
(De-) **Composing** a signal

\[
\begin{align*}
\text{Time} & \quad 0 \text{ sec} & \text{Time} & \quad 1 \text{ sec} \\
\text{Wave 1} & \quad + & \text{Wave 2} & \quad + \\
\text{Wave 3} & \quad + & \text{Result} & \quad =
\end{align*}
\]
(De-) Composing a signal
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- FFT output is symmetric, second half usually removed
- Peaks in frequency domain correspond to an oscillatory component in time domain
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- Number of samples in time = number of samples in frequency (1/2 without 'negative frequencies')
- Higher sampling rate can resolve higher frequencies
Fourier Transform

- We can see a peak in the alpha band (8-12 Hz)
Fourier Transform

We can see a peak in the alpha band (8–12 Hz)

- Sometimes helpful to display frequency axis in log-scale (see next)
Linear- vs. Log-scaled spectrum

Compare:

1 or 2 cycles per second

50 or 51 cycles per second
Linear- vs. Log-scaled spectrum

Sinusoids linearly spaced from 1 Hz to 17 Hz
Linear- vs. Log-scaled spectrum

Sinusoids log spaced from 1 Hz to 17 Hz
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Fourier Transform

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- Sometimes helpful to display frequency axis in log-scale (see next)
- Power usually decreases at higher frequencies
  - 1/f phenomenon
  - Log-scaling the power axis
Fourier Transform

- We can see a peak in the alpha band (8–12 Hz)
- Sometimes helpful to display frequency axis in log-scale (see next)
- Power usually decreases at higher frequencies
  - $1/f$ phenomenon
  - Log-scaling the power axis
- Raw FFT can be very noisy
  - see next
Contents

Stationary:
  • Fourier transform
  • Power spectral density (Welch's method)

Time-resolved:
  • Wavelet transform
  • Filtering & Hilbert transform
Power spectral density
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Power spectral density

Repeated averaging over sliding windows decreases noise in the estimation.

Resulting spectrum is less noisy.
PSD: effect of window size

- Window length determines frequency resolution
- Smaller window: lower resolution, more averaging/less noise
PSD: effect of window size

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Time-frequency analysis

- Analysis of transient oscillatory activity
- Examples: auditory cortex / motor cortex
- Event-related synchronization vs. desynchronization

Spoken sentence, auditory cortex responses (Fontolan, Morillon et al., 2014)

Build-up of choice predictive activity in motor cortex (Donner et al., 2009)
Wavelet transform

Morlet wavelet (used in Brainstorm):

- Sine wave, power is modulated in time with a gaussian centered at time zero
- Serves as a 'template'
Wavelet transform

- Wavelet is swept over and 'compared with' the signal
- From this similarity measure we can estimate and plot the power over time
Wavelet transform

- Wavelet is contracted and expanded to estimate power over different center frequencies
Wavelet transform

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- Important: time and frequency resolution changes for different frequencies

  - Compare with PSD window length
Wavelet transform
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Wavelet transform

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- Remember the $1/f$ phenomenon: high frequencies tend to have less power.
Wavelet transform

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- Map can be normalized using a z-score based on the mean and std of a 'baseline period'.
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- Remember the 1/f phenomenon: high frequencies tend to have less power.

- Map can be normalized using a z-score based on the mean and std of a 'baseline period'.
Wavelet transform

- Map can be normalized using a z-score based on the mean and std of a 'baseline period'
- What is the right baseline?!?
Wavelet transform

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- What is the right baseline?!!
Wavelet transform

- Changing the parameters of the 'mother wavelet' affects time vs. Frequency resolution of the results
Wavelet transform

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Evoked vs induced responses
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- Averaging
  - 10 trials
Evoked vs induced responses

- Averaging
  - 10 trials
  - 20 trials
Evoked vs induced responses

- Averaging
  - 10 trials
  - 20 trials
  - 100 trials
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- Fourier transform
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Time-resolved:
- Wavelet transform
- Filtering & Hilbert transform
Hilbert transform

- Useful for estimating time-resolved power (or phase) in a pre-defined frequency band (e.g. Delta: 2–4 Hz)
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- Signal is first filtered in the specified band
Hilbert transform

- Useful for estimating time-resolved power (or phase) in a pre-defined frequency band (e.g. Delta: 2–4 Hz)
- Signal is first filtered in the specified band
- Envelope (power) is computed using the Hilbert transform
Hilbert transform

- 2 – 4 Hz
- 8 – 12 Hz
- 60 – 90 Hz
The hilbert transform can also extract the phase of the bandpassed signal in time.
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The Hilbert transform can also extract the phase of the bandpassed signal in time.

**Usage:** phase-locking value, stimulus-brain coupling, phase-amplitude coupling

* All of that later in the day
Hilbert vs. Wavelet

- Hilbert method in BST uses FIR filters
- Important: frequency response of the bandpass filter
Hilbert vs. Wavelet

- Hilbert method in BST uses FIR filters
- Important: frequency response of the bandpass filter
- Wavelets more localized around center frequency
Defining frequency bands

- 'Based on the literature': many definitions
Defining frequency bands

• Should I collapse over frequency bands or keep the full spectrum?
  • Information might be lost (peaks)
Defining frequency bands

- Should I collapse over frequency bands or keep the full spectrum?
  - Sometimes necessary for reducing dimensionality (e.g. in source space)
  - Can increase sensitivity (due to averaging)
Cross-frequency Coupling

- Cross frequency coupling (CFC):
  - Interaction between oscillations at different frequency bands

- Several synchronized neuronal assemblies in the brain:
  - Each supports a frequency band of the network rhythm

- Relationship between these frequencies:
  - Interaction between local neural circuits
  - Changing of intrinsic properties in each circuit

- G. Buzsaki. Cerebral Cortex, 1996
Types of CFC

- Phase-phase coupling
- Amplitude-amplitude coupling
- Phase-amplitude coupling

Jirsa et al., Front. Neurosci., 2013
Cross-frequency Phase-amplitude Coupling

- Phase-amplitude coupling

Canolty and Night, Trends Cogn Sci, 2010
Cross-frequency Phase-amplitude Coupling

• Phase-amplitude coupling

✓ Plausible physiological mechanisms
  • Low frequency phase reflects local neuronal excitability
  • High frequency power increases reflect:
    – A general increase in population synaptic activity (broad-band power increase)
    – Selective activation of a connected neuronal subnetwork (narrow-band power increase)

✓ Functional correlations

Canolty and Night, Trends Cogn Sci, 2010
Functional Correlations

- Several studies have been conducted in this field
  - Phase of the low-frequency theta (4 to 8 hertz) rhythm modulates power in the high gamma (80 to 150 hertz) band

Measuring Cross-frequency Coupling

- Several algorithms available
  - Each proper for a particular case
  - No single method has been elected as a preferred standard so far
### Measuring Cross-frequency Coupling

#### Available measures:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
<th>Reference</th>
<th>Limitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESC</td>
<td>The envelope to signal correlation</td>
<td>[Bruns and Eckhorn, 2004]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>PLV</td>
<td>Phase-locking value</td>
<td>[Vanhatalo et al., 2004]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>MVL</td>
<td>Mean vector length</td>
<td>[Canolty et al., 2006]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>GLM</td>
<td>The general linear model measure</td>
<td>[Penny et al., 2008]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>APSD</td>
<td>Amplitude power spectral density</td>
<td>[Cohen, 2008]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>CV</td>
<td>Coherence Value</td>
<td>[Colgin et al., 2009]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>KL-MI</td>
<td>Kullback-Leibler based modulation index</td>
<td>[Tort et al., 2010]</td>
<td>⭐️⭐️</td>
</tr>
<tr>
<td>ERPAC</td>
<td>Event related phase amplitude coupling</td>
<td>[Voytek et al., 2012]</td>
<td>⭐️⭐️⭐️</td>
</tr>
</tbody>
</table>

- ⭐️ Sensitive to coupling phase (Negative feature)
- ⭐️⭐️ Need long data length
- ⭐️⭐️ Only works on event-related datasets
- ⭐️⭐️⭐️ Potentially not capable of calculating coupling intensity
Summary

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