# High resolution functional networks measured with MEG



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# Large-scale Networks in fMRI



Beckmann, Phil Trans Roy Soc B, 2005

### The same networks are recruited in task and rest



Smith et al., PNAS, 2009

## Large-scale Networks in MEG?

- What is happening at **faster** time-scales?
- What are the specific neuronal interactions?

## Large-scale Networks in MEG?

- What is happening at **faster** time-scales?
- What are the specific neuronal interactions?

- Can we use MEG to answer these questions?
  - excellent temporal res (millisecs)
  - good spatial res
  - non-invasive



# MEG: what functional connectivity (FC) measure should we use?

- Can NOT use raw zero-lag correlation as we do in fMRI (due to conduction delays)
- Need to use measures that are robust to non-zero lags
- e.g. Amplitude Coupling

- Detects if the amplitude (or power or envelope) time courses in particular frequency bands are correlated



Hipp et al.; Nat Neuro (2012) Brookes et al.; Neuroimage (2013)

# MEG FC: Amplitude Coupling



Hipp et al.; Nat Neuro (2012) Brookes et al.; Neuroimage (2013)

# MEG FC: Amplitude Coupling

• Resting state data



Significant beta band *amplitude correlation* between the left and right motor cortices

Brookes et al., Neuroimage, (2011)



Hipp et al. 2012 (Nat Neuro)

# MEG FC: Amplitude Coupling



Uncertainties in the source reconstruction induce zero-lag spatial correlations in source space



SOLUTION: remove all zero-lag correlations

- Orthogonalise **pairs** of raw time courses (regress one out of the other) **before** computing amplitude time courses *Hipp et al.; Nat Neuro (2012)* 

Brookes et al. ; Neuroimage (2013)

#### **Multi-region spatial leakage correction**

Can perform a multi-region orthogonalisation in one shot:



- finds the closest set of orthogonal vectors to the original timecourses
- any subsequent multi-variate analysis (e.g. regularised partial correlation) is possible

Colclough,...,Woolrich; Neuroimage, 2015

### **Network matrices from resting MEG**

#### 8 subjects' eyes open resting-state data

- alpha band (8-12 Hz) amplitude time-courses
- compute regularised partial correlation network matrices
  - thresholded at 5% FDR
- reveals a strongly inter-connected visual network

#### 38 cortical regions





No Spatial Leakage Correction

Multivariate Spatial Leakage Correction

Colclough, Smith ... Woolrich; Neuroimage (2015)

#### **Example Application: Heritability of MEG connectomes**

#### Human Connectome Project twin rest data





Colclough, Smith ... Woolrich; In submission

#### **Example Application: Heritability of MEG connectomes**

#### Human Connectome Project twin rest data

MEG - alpha band amplitude correlations (61 subjects)





Colclough, Smith ... Woolrich; In submission

### MEG Resting State Networks?



### MEG Resting State Networks?



### **MEG RSNs**

- RSNs found in MEG data using temporal ICA
- Eyes open, 10 subjects
- Good correspondence with
  fMRI ICA networks
- Found in beta band (except for DMN in the alpha band)



#### Brookes,..., Morris; PNAS (2011)

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### MEG: what FC measure should we use?

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- Phase coupling measures
  - Detect consistent phase differences between brain signals



# Phase Coupling Measures

 Detect consistent phase differences between brain signals



Spectral Methods

- estimated via multi-tapers or MAR models
- need to choose sensible taper size or model order

#### Phase Estimation Methods

- phase estimated on band-pass filtered data
- need to choose sensible freq bands

	Spatial Leakage Correction?	Partial?
Coherence	No	No
Imaginary coherence	Yes	No
Partial coherence	No	Yes
Phase Locking Value (PLV)	No	No
Phase Locking Index (PLI)	Yes	No

Colclough et al., How reliable are MEG resting-state connectivity metrics? Neuroimage, 2016

### MEG: what FC measure should we use?



Amplitude Coupling





Phase coupling: spectral methods



Marzetti et al, NI, 2013



Phase coupling: phase estimation methods



Ewald et al, Biomed Tech, 2013

It depends on the context!

### MEG: what FC measure in the resting state?

- Resting-state data from Human Connectome Project, 61 subjects with 3 sessions each
- Most consistent is amplitude correlations with spatial leakage correction (\*AEC)



Colclough et al., How reliable are MEG resting-state connectivity metrics? Neuroimage, 2016

#### **Time-varying functional connectivity**

#### Compute *sliding window* correlation network matrices

Sliding window (~10secs)



#### Non-stationary functional connectivity

#### Sliding window FC in fMRI:



#### Sliding window FC in MEG:



de Pasquale et al. (PNAS 2010)

#### Allen et al. (Cerebral Cortex 2012)

#### **Time-varying functional connectivity**

**BUT:** Sliding window correlation requires time window of sufficient length:

Sliding window (~10secs)



#### **Time-varying functional connectivity**

Instead pool data over disjoint time periods:





- Generative model, consisting of:
  - state time courses, x indicating which state the system is in at each time point



- Generative model, consisting of:
  - state time courses, x indicating which state the system is in at each time point
  - observation model which predicts the data, y, for a given state



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• Variational Bayes inference

#### HMM on MEG resting state data

- Can we use the HMM to infer *transient brain states* from resting MEG data?
  - Resting state data acquired with CTF 275 channel MEG system
  - 9 subjects, 10 minutes eyes open
  - Projection to source space using beamforming
  - HMM run on amplitude time courses (4 30 Hz)

### HMM on MEG resting state data



#### **State time courses**



#### **State Transition Probabilities**



#### **State Transition Probabilities**



DAN/DMN anticorrelation in fMRI (Fox et al., PNAS, 2005)?

#### **Relationship to EEG microstates?**

 Do the HMM states represent source space counterparts of EEG microstates?

 Quasi-stable topographies of EEG power over the scalp that remain stable for periods of ~100 ms



• EEG microstates correlate with BOLD RSNs (e.g. Musso et al. 2010, Britz et al., 2010, Yuan et al. 2012)

- Multivariate Normal (MVN) observation model requires use of amplitude time courses
  - what about working with raw time courses?
    - e.g. can we then find time-varying phase locking?
- Instead: Multivariate autoregressive model (MAR) per HMM state
  - captures different multi-region spectral properties for each state
  - e.g. PSD or coherence

MAR model: 
$$X_t = \sum_{i=1}^{p} W_i X_{t-i} + e_t$$

Vidaurre et al., Neuroimage, 2016

#### Are brain states modulated by task?

- Self-paced finger tapping task
  - 2 left/right MC parcels
  - 3 HMM states
  - 8 subjects
  - raw time-courses (1-50 Hz)
  - HMM with MAR observation model
- Do we see task-related HMM states?

(Note: HMM is run with **no** knowledge of task timings)

#### Spectral properties of each HMM state



significant state-dependent (time-varying)
 power spectra

Vidaurre et al., Neuroimage, 2016







Finger-tap (beta suppression) Post-finger-tap (beta rebound) Baseline



significant state-dependent (time-varying)
 power spectra

#### Vidaurre et al., Neuroimage, 2016



Finger-tap (beta suppression) Post-finger-tap (beta rebound) Baseline

#### **Cross**-Spectral properties of each HMM state



significant state dependent (time-varying)
 coherence (phase locking)

### HMM on resting fMRI data

Diego Vidaurre et al., In preparation

- HMM on fMRI data
- HMM on BIG data (stochastic learning)
  - e.g. HCP resting fMRI (~1000 subjects):



#### HMM on resting fMRI data



Diego Vidaurre et al., In preparation

### HMM on resting fMRI data



 Speed of state switching ("volatility") predicts behaviour

![](_page_41_Figure_3.jpeg)

![](_page_41_Figure_4.jpeg)

### Summary

- MEG functional connectomes can be computed using correlation between **power** time-courses
  - phase-locking measures are less sensitive (in resting state data)
  - beware spatial leakage!
- •MEG and HMM can identify brain states switch on ~100ms time-scales, much faster than previously shown
- The occurrence of brain states predicts task state and behavioural traits
- Further reading:

"Magnetoencephalography: From Signals to Dynamic Cortical Networks" edited by Supek and Aine

![](_page_42_Picture_8.jpeg)

![](_page_42_Picture_9.jpeg)

![](_page_42_Picture_10.jpeg)

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