Imaginary correlations in MEG recordings: Networks versus propagating waves

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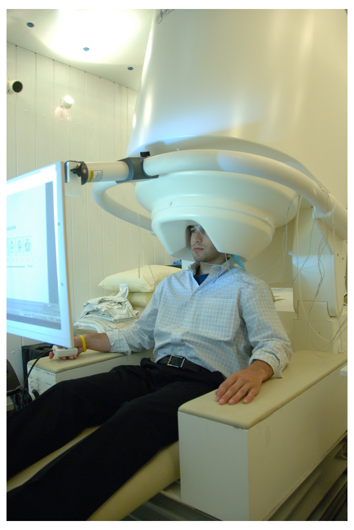
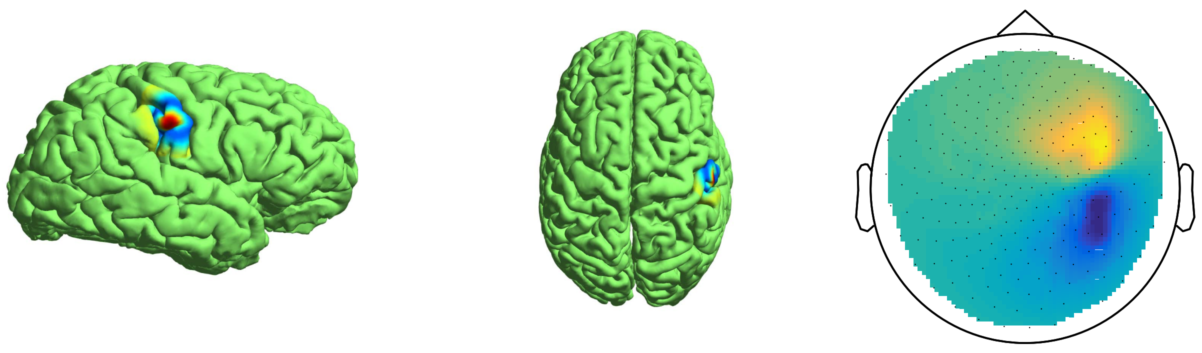
Introduction



- Electrical activity in neurons produces magnetic fields that are recorded outside the skull and used to calculate the source locations within the brain[1].
- The functional connectivity (FC) matrix quantifies statistical dependencies between time-series recorded at different channel-pairs, and is used to investigate the dynamical underlying brain structure.
- Since MEG signals reflect superpositions of cortical signals (volume-conduction), the channel-level FC matrix may contain spurious terms.
- It is claimed that imaginary FC is insensitive to volume-conduction[2] and only reflects genuine (phase-lagged) FC.
- We use an MEG volume-conductor model to compare the FC of simulated cortical activity with those of the ensuing channel activity[4].
- The results uncover a discrepancy between source- and sensor-level FCs.
- Since network-based analysis may provide faulty interpretations, we claim that MEG measurements are more naturally viewed as a spatiotemporal continuum sampled in space and time by the channels.

Simulation 1: Single Wave Propagation

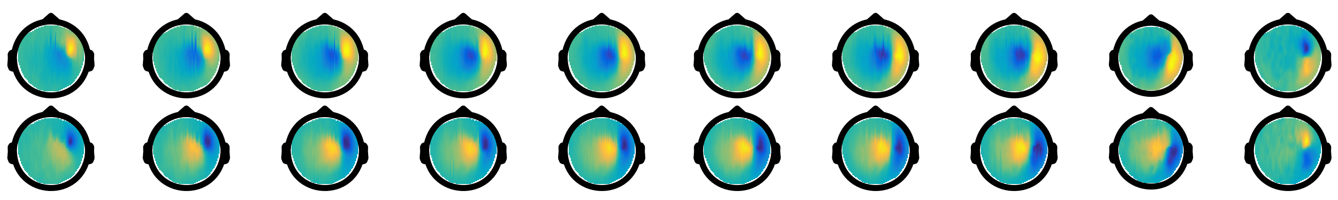


- We simulate a single source propagating wave $\mathbf{S}$ in the right hemisphere.
- The signal $\mathbf{S} \in \mathbb{R}^{N \times t}$, with $N = 131547$ mesh points and time index t, is gathered by the MEG sensors as

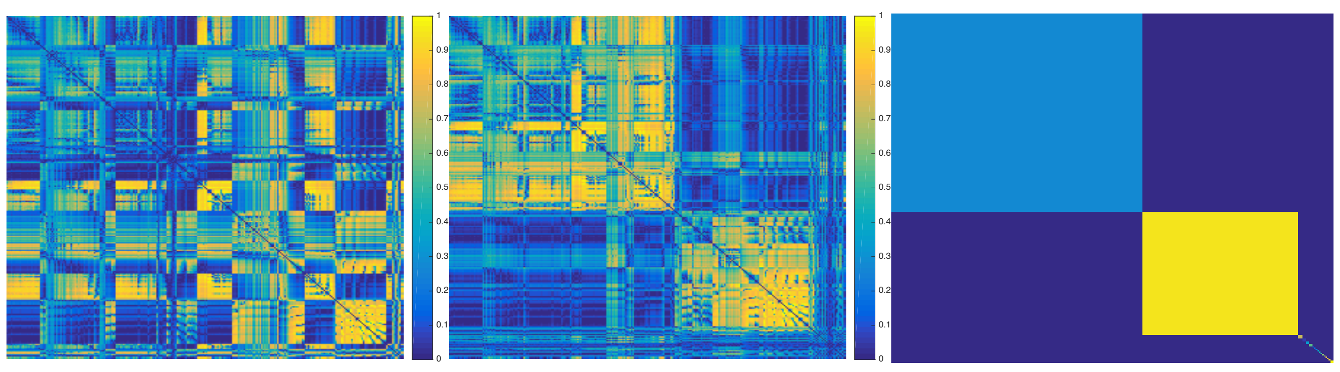
$$\mathbf{X} = \mathbf{GS} \tag{1}$$

where $\mathbf{G} \in \mathbb{R}^{273 \times N}$ is the leadfield matrix. $\mathbf{X}$ is Hilbert-transformed and the phase lag index (PLI)-based[3] correlation matrix is computed.

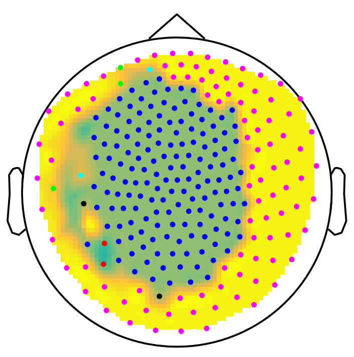
- As time evolves, at the sensor level the propagating wave is observed as a spiral wave:



Louvain Modularity at Sensor Level



- We conduct a network-based analysis on the simulated propagating wave and find 18 communities in the (273×273) FC matrix.

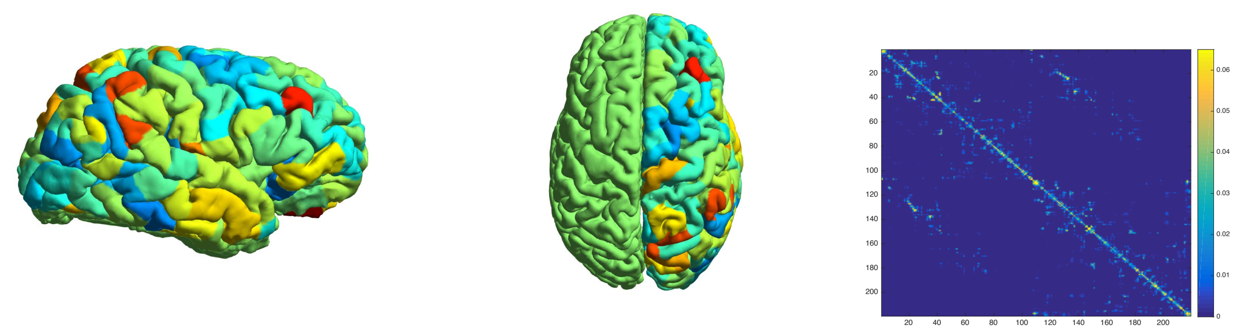


- Distribution of communities of simulated propagating wave in the alpha frequency band.
- The 6 most populated communities are highlighted for the sake of clarity.
- 90.5% belong to the 2 largest communities.

References

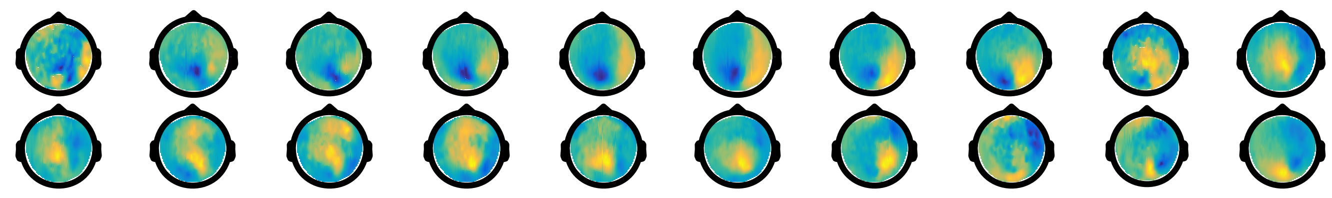
1. Hamalainen et al., Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. *Rev. Mod. Phys.*, 65(2), 1993.
2. Nolte et al., Identifying true brain interaction from EEG data using the imaginary part of coherency. *Clin. Neurophysiol.*, 115(10), 2004.
3. Stam et al., Phase lag index: assessment of functional connectivity from multi channel EEG and MEG with diminished bias from common sources. *Hum. Brain Mapp.*, 2007.
4. Stam et al., Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease. *Brain*, 132(Pt 1), 2009.

Simulation 2: Correlated Network

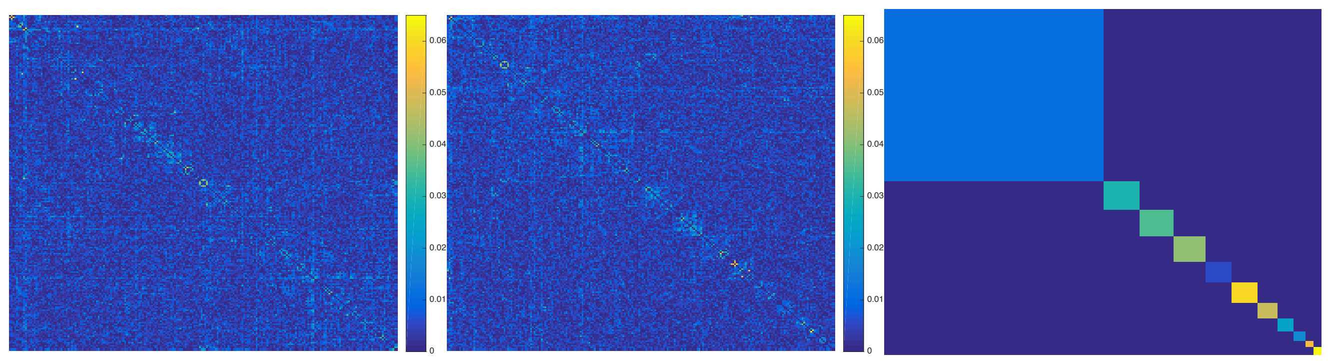


Correlated activity at source level and DTI structural connectivity (SC) matrix.

- We use a SC matrix obtained using DTI-based tractography. The parcellation is composed of 219 ROIs.
- Each network node implements a Hopf oscillator with delayed interactions.
- We conduct a network-based analysis on both the source signal $\mathbf{S} \in \mathbb{R}^{219 \times 1}$ and on the sensor level signal $\mathbf{X} \in \mathbb{R}^{273 \times 1}$. Time evolution of $\mathbf{X}$:

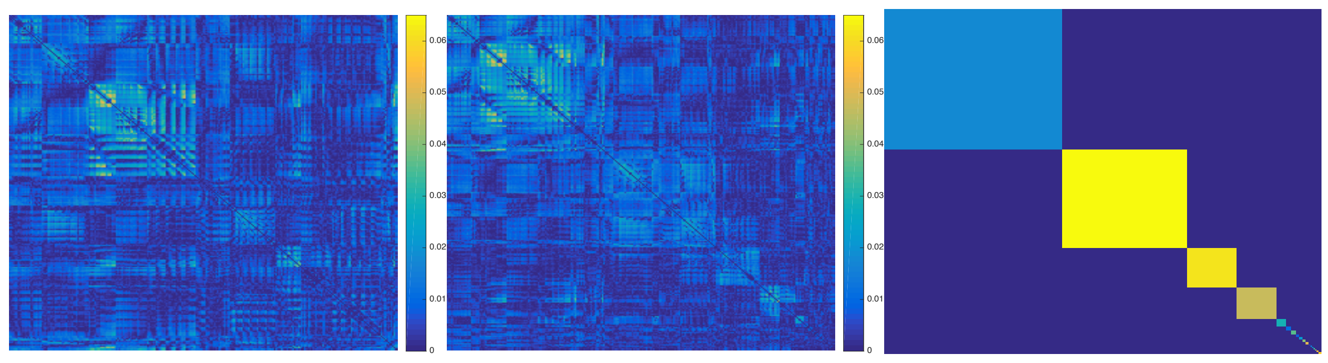


Louvain Modularity at Source Level

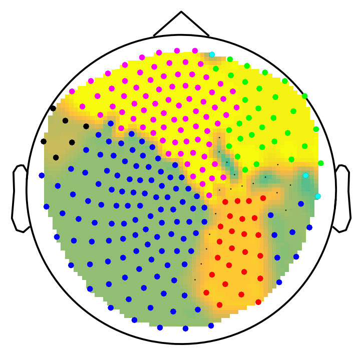


- The method detects 11 communities in the (219×219) source FC matrix.

Louvain Modularity at Sensor Level

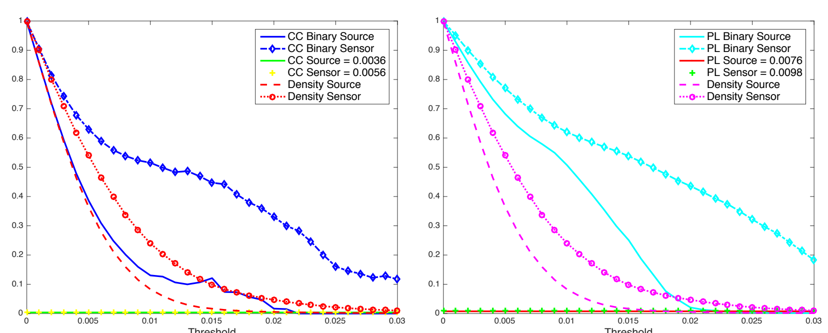


- With a network-based analysis at sensor level we find 18 communities in the (273×273) FC matrix.



- Distribution of communities at sensor level: the 6 most populated communities are highlighted.
- 85% belong to the 4 largest communities.

Network Measures: Source vs. Sensor Level



$$\hat{C}_w^{source} = 1.0058$$
$$\hat{C}_w^{sensor} = 1.0377$$
$$\hat{L}_w^{source} = 0.9945$$
$$\hat{L}_w^{sensor} = 0.7600$$

Clustering coefficient (CC) and average path length (PL) at source and sensor level. $\hat{C}_w = C_w / \langle C_w^{(surr)} \rangle$ and $\hat{L}_w = L_w / \langle L_w^{(surr)} \rangle$.

Conclusions

- A discrepancy is observed between source- and sensor-level FC matrices
- Information about the underlying SC is not obtained directly from sensor-level FC: network-based analysis may lead to fault interpretations
- MEG measurements more naturally viewed as a spatiotemporal continuum

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