Inferring Large-Scale Brain Connectivity from Spectral Properties of EEG Recordings

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Introduction

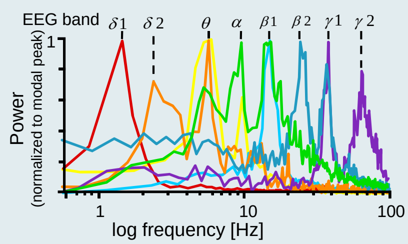
Power spectra from EEG recordings reveal that brain dynamics are multi-oscillatory with decoupled frequency bands [1] .

Large-scale connectivity in the brain is nonrandom, displaying a small-world topology [2].

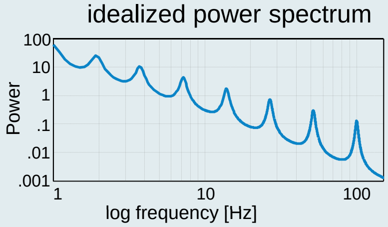
It is desirable to infer details regarding the connectivity of a neural network based on observation of its dynamics.

Goal: reverse-engineer a network with both a specified network topology as well as prescribed power spectrum.

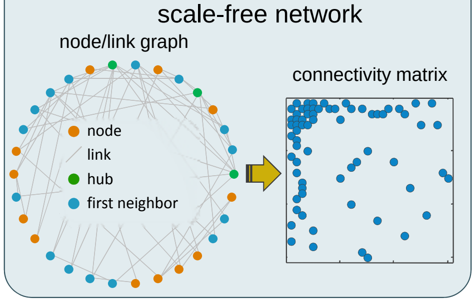
persistent LFP rhythms *in vitro*



idealized power spectrum

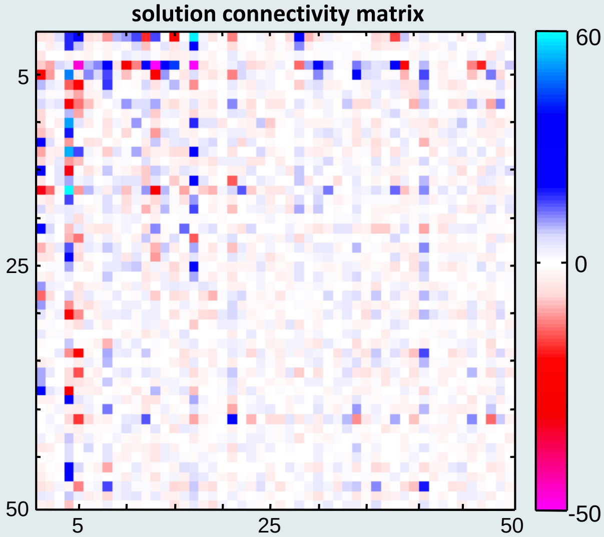


scale-free network

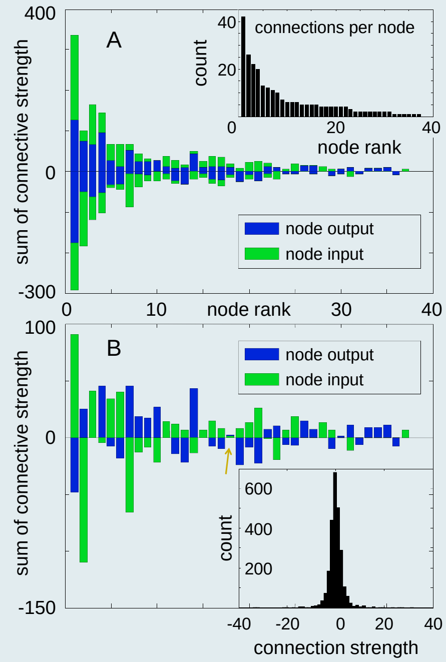


Results

solution connectivity matrix



Solution connectivity matrix shows a single realization for a network of 50 nodes produced with the iterative method sketched below. The eigenvalues of this matrix match identically with those which define the idealized power spectrum shown to the left, and the form of the connection strengths fits the scale-free network topology constraint (most connections have values approximately equal to 0, see **subfig. A & B**).



Subfigure A shows the sorted number of connections per node (node rank). **Figure A** Shows the sum of a node's excitatory (positive) and inhibitory (negative) connections, sorted by node rank (most connected node is rank 1, and so on). Excitatory/inhibitory totals are broken down into output (blue) and input (green) components. Node rank corresponds in trend to connective strength. **Figure B** shows the sum of the input and sum of the output to and from a node respectively. That is, the node rank 1 green bar in **B** is the sum of the node rank 1 green bars in **A**. **Subfigure B** is the histogram of connection strength for the network. Note that most of the connections are approximately equal to 0.

Conclusions: All reconstructed matrices exhibit globally balanced excitation and inhibition.

However, for each single node, the net excitatory and net inhibitory inputs are not balanced:

If a node receives more excitatory than inhibitory inputs from the network, it tends to provide more inhibition than excitation to the rest of the network; when a node receives more inhibition than excitation, it tends to provide more excitation than inhibition to the network.

The capability of inferring large-scale brain connectivity from EEG signals among other non-invasive techniques may be used in the near future to identify structural alterations of the brain underlying abnormal cognitive function. The application of our network-reconstruction algorithm may help uncover these anatomical alterations.

Future Work: Increase network size

Characterize common emergent properties across a large population of solution matrices

Investigate additional constraints on network construction, e.g. pure excitatory / inhibitory nodes, decoupling connective strength from node rank, etc.

Methods

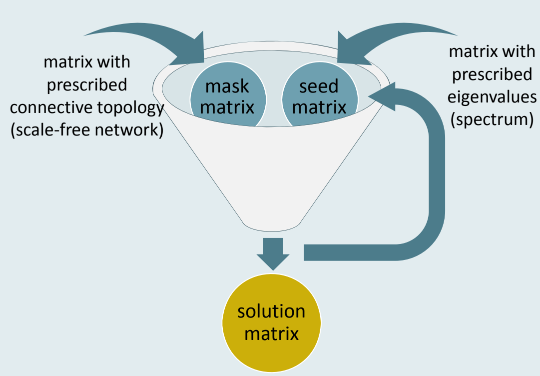
Inverse problem: reverse-engineer network from prescribed spectrum with scale-free topology as constraint

The eigenvalues of the connectivity matrix determine the average power spectrum

However, the power spectrum does not uniquely determine the connectivity matrix

Inverse eigenvalue problem: Using recently developed mathematical techniques [4] and constraints on the topology of the connectivity matrix, we reconstruct realizations from the family of solution matrices exhibiting the desired neural architecture and with (identically) the prescribed spectrum

iterative solution method



References

1. Buzsaki G: *Rhythms of the Brain, First ed*. Oxford University Press; 2006
2. Sporns O, Tononi G, Edelman GM: **Theoretical neuroanatomy: relating anatomical and functional connectivity in graphs and cortical connection matrices.** *Cereb.Cortex* 2000, 10(2):127-141.
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4. Chu MT, Golub GH: *Inverse Eigenvalue Problems: Theory, Algorithms, and Applications.* Oxford University Press; 2005.

Acknowledgments

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