Performance comparison of functional and effective brain connectivity methods

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I INTRODUCTION

Connectivity analysis of neuroimaging data has played a key role in understanding the functional architecture of the brain. To reveal dynamic interactions between cortical areas that form the basis of cortical functions, a wide range of functional and effective connectivity methods are applied.

With this simulation study, we want to benchmark a method's ability to reconstruct cortical networks and also highlight how certain characteristics of EEG and MEG data sets can potentially affect connectivity analysis.

II MATERIALS and METHODS

Simulation pipeline

The simulation pipeline was designed to be able to create and analyze data sets with well defined properties. It consists of three steps:

1. Simulation of an EEG/MEG recording based on a configurable cortical network:
The number of nodes as well as their positions, orientations and connectivity strength of links between two nodes are specified. To account for volume conduction effects, the signal of EEG/MEG sensors is calculated via forward-modeling using various head model.
Cortical background noise is added via dipoles that are randomly distributed in the cortex. These noise sources carry either white, Gaussian or realistic noise. The desired SNR was achieved by scaling the noise signal in the frequency domain.
2. Inverse source reconstruction:
Since source mixing heavily affects connectivity analysis, inverse source reconstruction methods are applied prior to connectivity estimation. BESA Research 6.0 [1] provides a discrete source analysis approach using source montages [2].
3. Connectivity analysis:
Functional and effective connectivity estimators are calculated to reveal the simulated network. Performance of each estimator is calculated using Frobenius norm [7] and receiver operating characteristic (ROC) [8] to measure the deviation between simulated and reconstructed networks.

Simulations

To ensure stability and convergence the number of iterations performed was evaluated. Furthermore, the effect of SNR on connectivity estimators was tested.
Both simulations use a network based on four dipoles (Fig. 1). Time-courses of each node were generated by adding a band-pass filtered white noise signal to time-courses consisting of white noise only.
EEG potentials where calculated at 31 electrode positions.

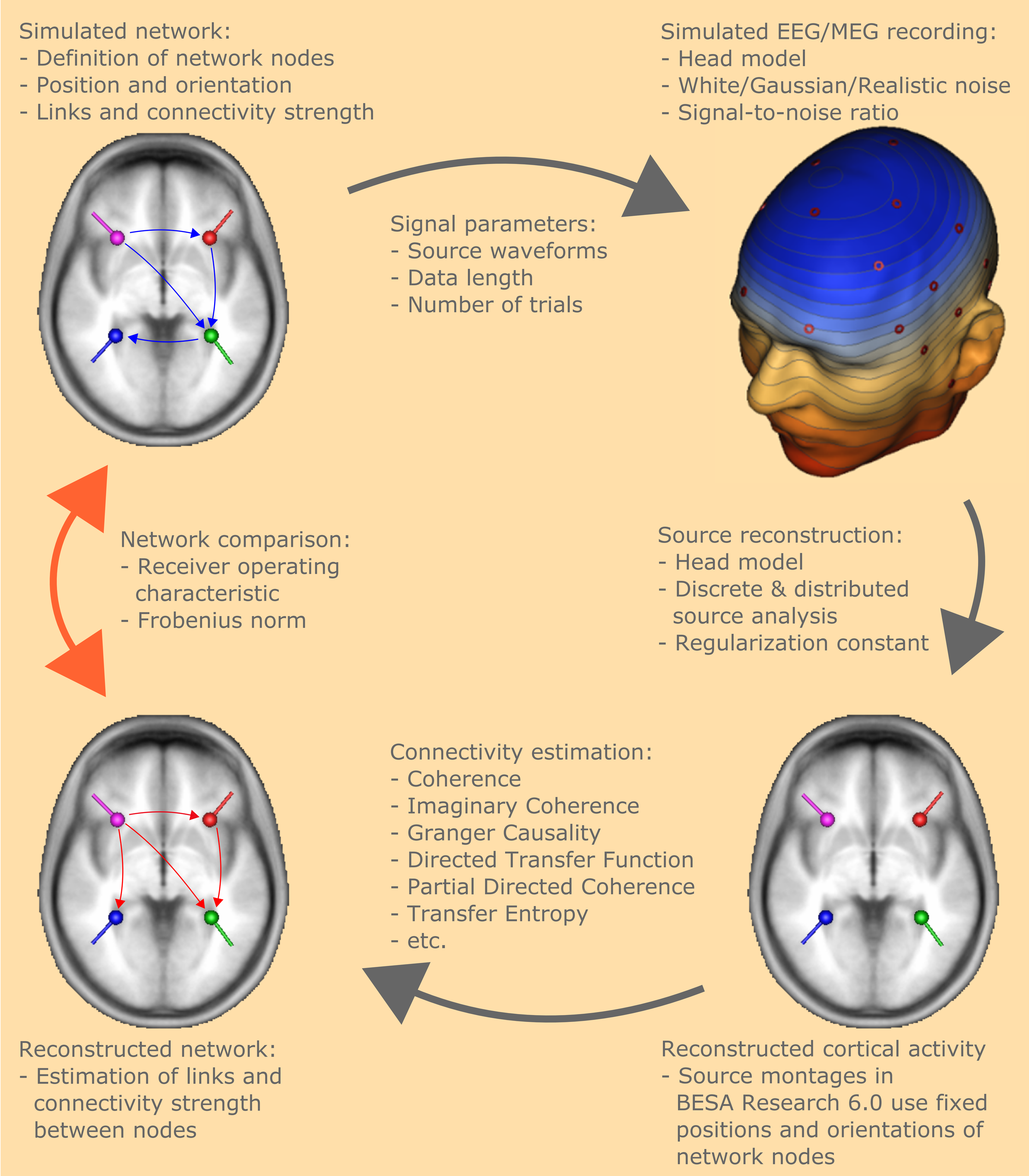

Fig. 1: Schematic sequence of simulation pipeline.

III RESULTS

Convergence and stability

- ➢ Results with varying number of iterations [10 20… 100] showed that Frobenius norm (Fig. 2), as well as AUC converges to the same limiting value for all iterations.
- ➢ Most stable results are provided from 50 iterations upwards, as boxplots show a more symmetric distribution with a larger number of iterations.
- ➢ Subsequent simulations were required to consist of 100 iterations.

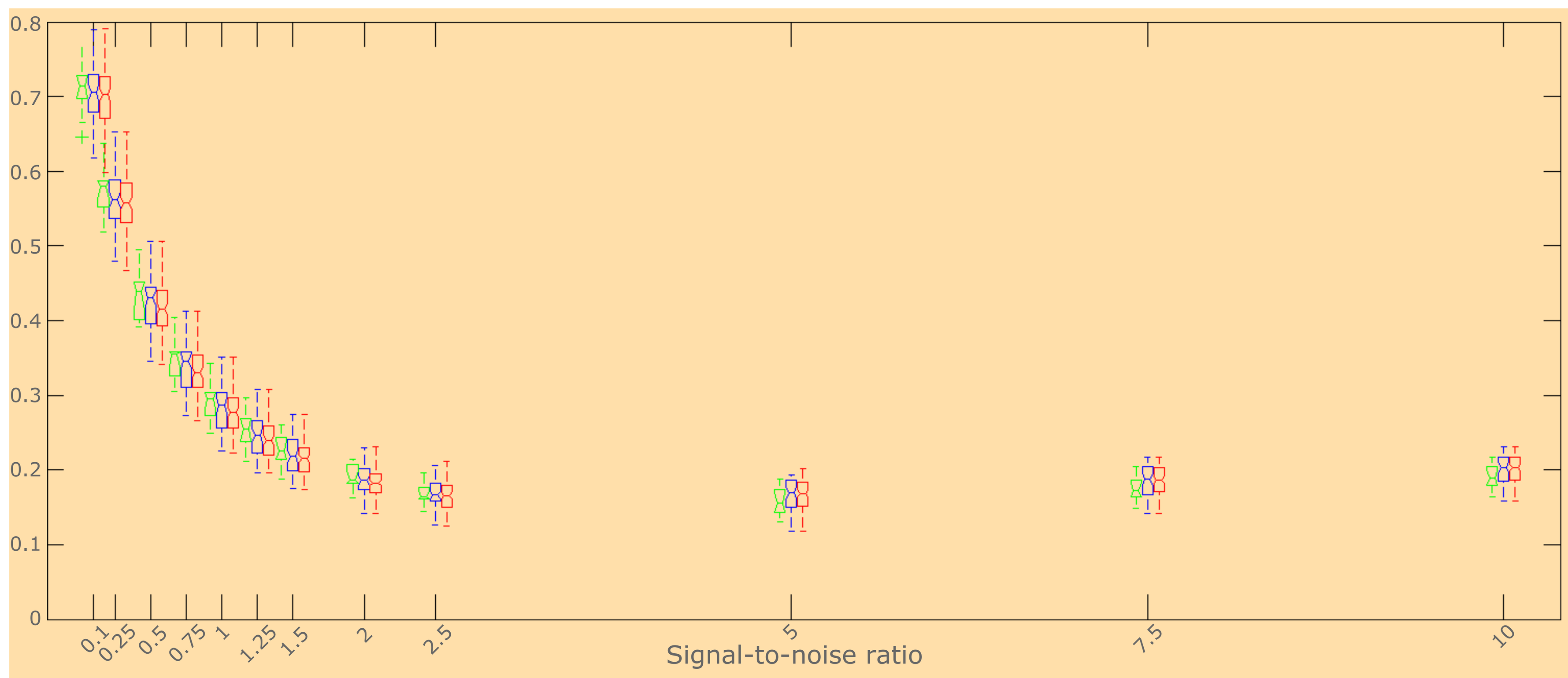

Fig. 2: Comparison of Frobenius norm of Coherence between 10 (green), 50 (blue) and 100 (red) number of iterations.

Effect of SNR

- ➢ Frobenius norm values show a non-linear increase of accuracy over all connectivity methods with an increase of signal-to-noise ratio (Fig. 3).
- ➢ Results also highlight that Coherence is more strongly impaired by lower SNR levels [0.1 – 2.5] than other methods.
- ➢ As expected, and as a validation of the pipeline, cortical network can be reproduced best by methods based on Granger Causality.

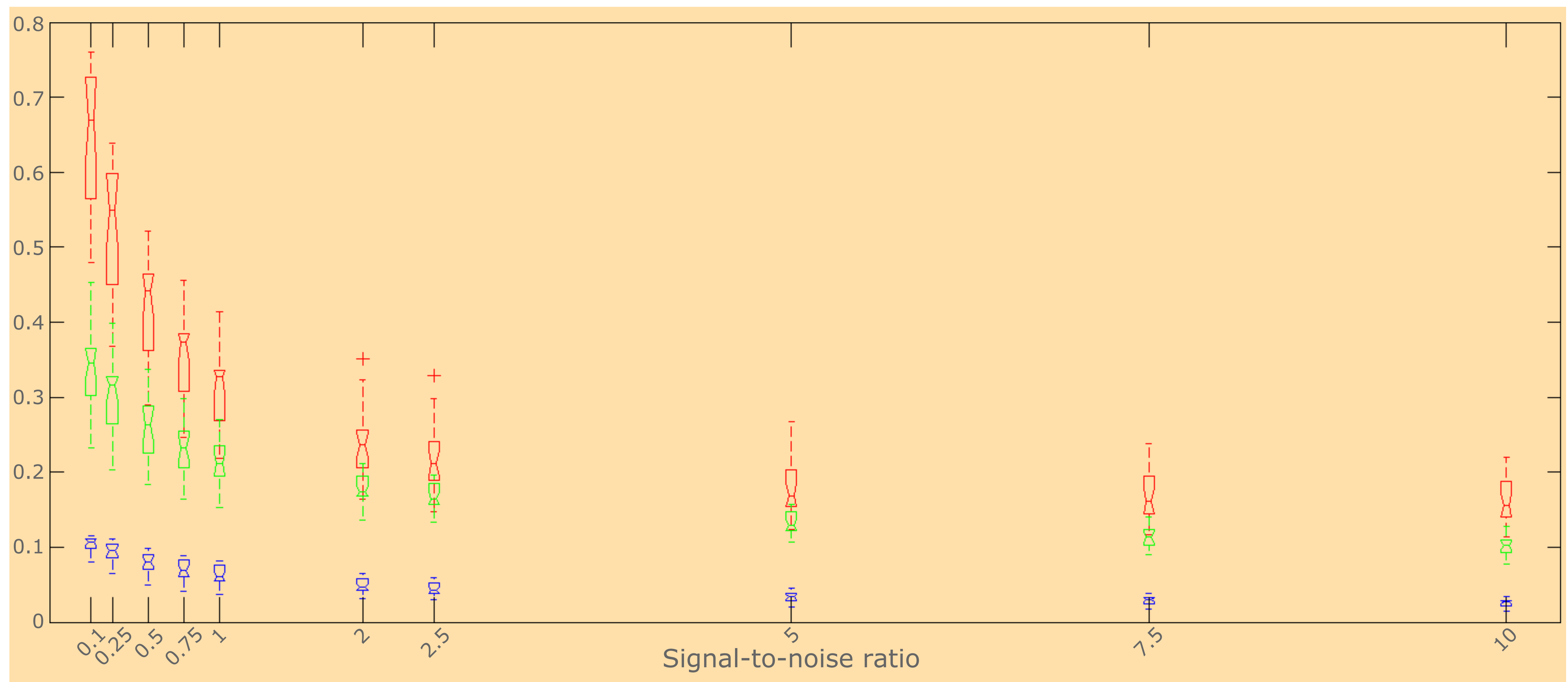

Fig. 3: Frobenius norm of Coherence (red), Directed Transfer Function (green) and Granger Causality (blue).

IV CONCLUSIONS

Results demonstrate that ...:

- ➢ the number of iterations has to be selected large enough to achieve stable and converging results.
- ➢ Coherence is more affected by low SNR than other methods.
- ➢ Causality was better able to cope with low SNR values.
- ➢ Frobenius norm values show an increase of accuracy with increasing SNR over all connectivity methods.

Outlook:

Further simulations to investigate additional parameters on the performance of connectivity estimators:

- ➢ Influence of altering the value of the regularization constant required for inverse source reconstruction.
- ➢ Differences in reconstructed cortical networks with EEG compared to MEG recordings.

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