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.
Here, a simulation pipeline was created that systematically investigates parameters affecting the performance of brain connectivity measures. Based on this foundation, simulations were carried out to determine the role of a number of parameters that are known to influence the results of neural network analysis. Two of these parameters with particularly extensive impact, namely data length and regularization are presented here.

II MATERIALS and METHODS

Simulation pipeline

The simulation pipeline consists of four steps:

(1) M/EEG recordings are simulated, based on a network with an adjustable number of nodes and connections and user-definable parameters like signal-to-noise ratio (SNR), data length, number of trials, etc. In order to simulate volume conduction artifacts and spatial source mixing, the simulated EEG or MEG is calculated via forward-modeling using a spherical, template, or individual realistic head model.

(2) A discrete source analysis approach [1] was chosen as inverse method for source localization to retrieve time-dependent activity patterns for active brain regions. BESA Research 6.1 [2] provides built-in and user-defined source montages. The source model can be refined by a priori knowledge on the active network.

(3) Functional and effective connectivity estimators (e.g. Coherence, Imaginary Part of Coherence, Granger Causality and DTF) are calculated to reveal the simulated network.

(4) Performance of each estimator is calculated using Frobenius norm [3] and receiver operating characteristic [4] to measure the deviation between simulated and reconstructed networks.

Simulations:

Both simulations presented here, to analyze the influence of regularization constant and data length used a cortical network based on four dipoles that were placed in the source space as shown in figure 1.

Cortical activity: band-pass filtered white noise signal with additional time-lag of 10ms to simulate information flow from source 1 to source 2 and from source 3 to source 4.

Headmodel: concentric 3-sphere volume conduction model.

Noise: 20 dipoles randomly distributed in source space carrying white noise signal. EEG potentials were calculated and scaled to SNR levels of [0.1 .. 15].

Regularization: inverse source localization was performed using a truncated singular value decomposition (TSVD) with regularization factors ranging from 0% to 20%.

Data length: Recordings of 2s to 200s were simulated to analyze the effect of data length.

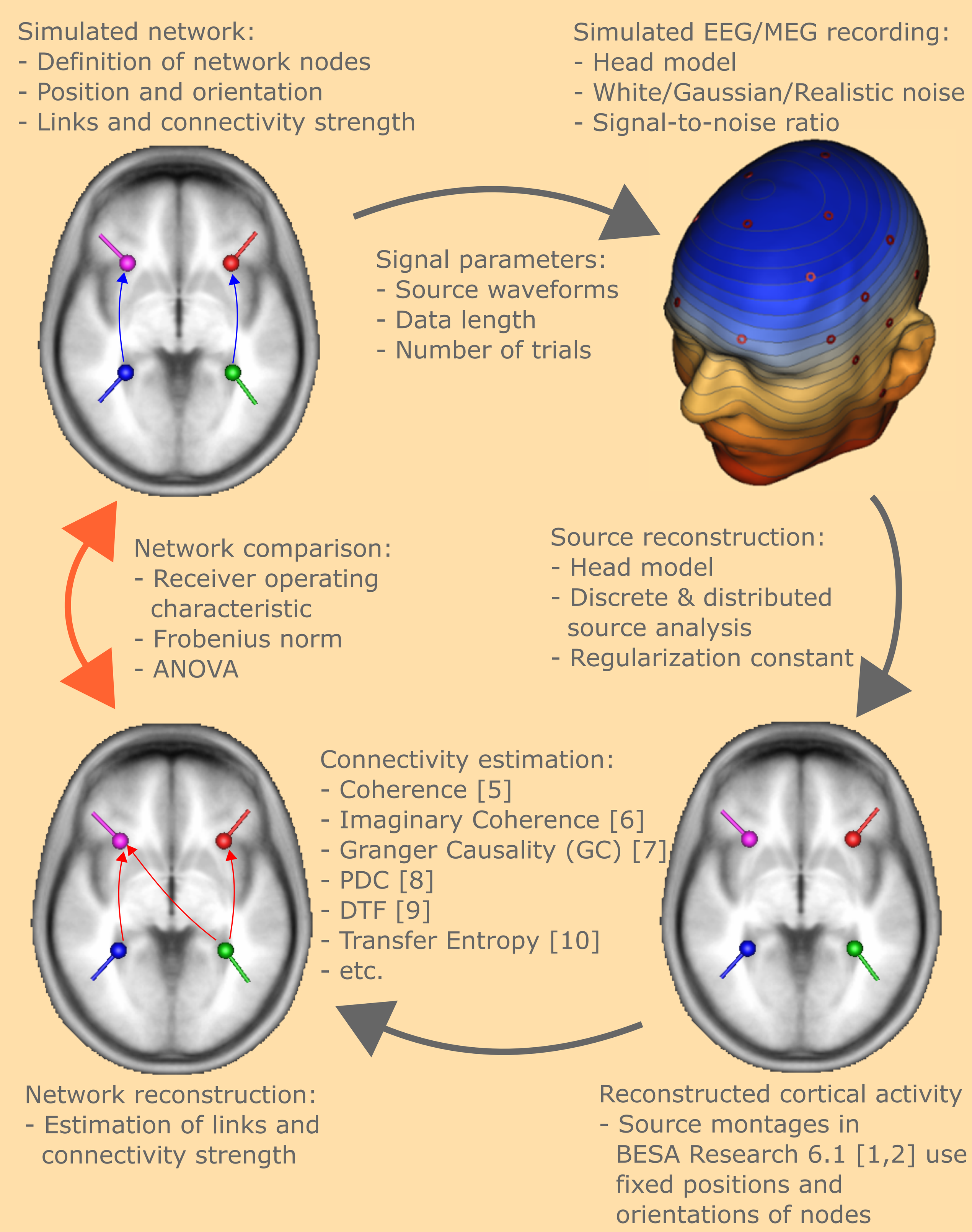

Fig. 1: Schematic sequence of simulation pipeline.

III RESULTS

Regularization

➤ Connectivity methods are affected differently to changes of regularization.

➤ GC provides the best results over all regularization factors in terms of accuracy and stability.

➤ Coherence shows an improvement in reconstruction for increasing regularization up to a certain limit. Further increase leads to a decline in network reconstruction. This value of optimal reconstruction is dependent on SNR, with higher SNR values requiring lower regularization.

➤ A decrease in reconstruction can also be observed for DTF and GC for high regularization (>15%) and high SNR.

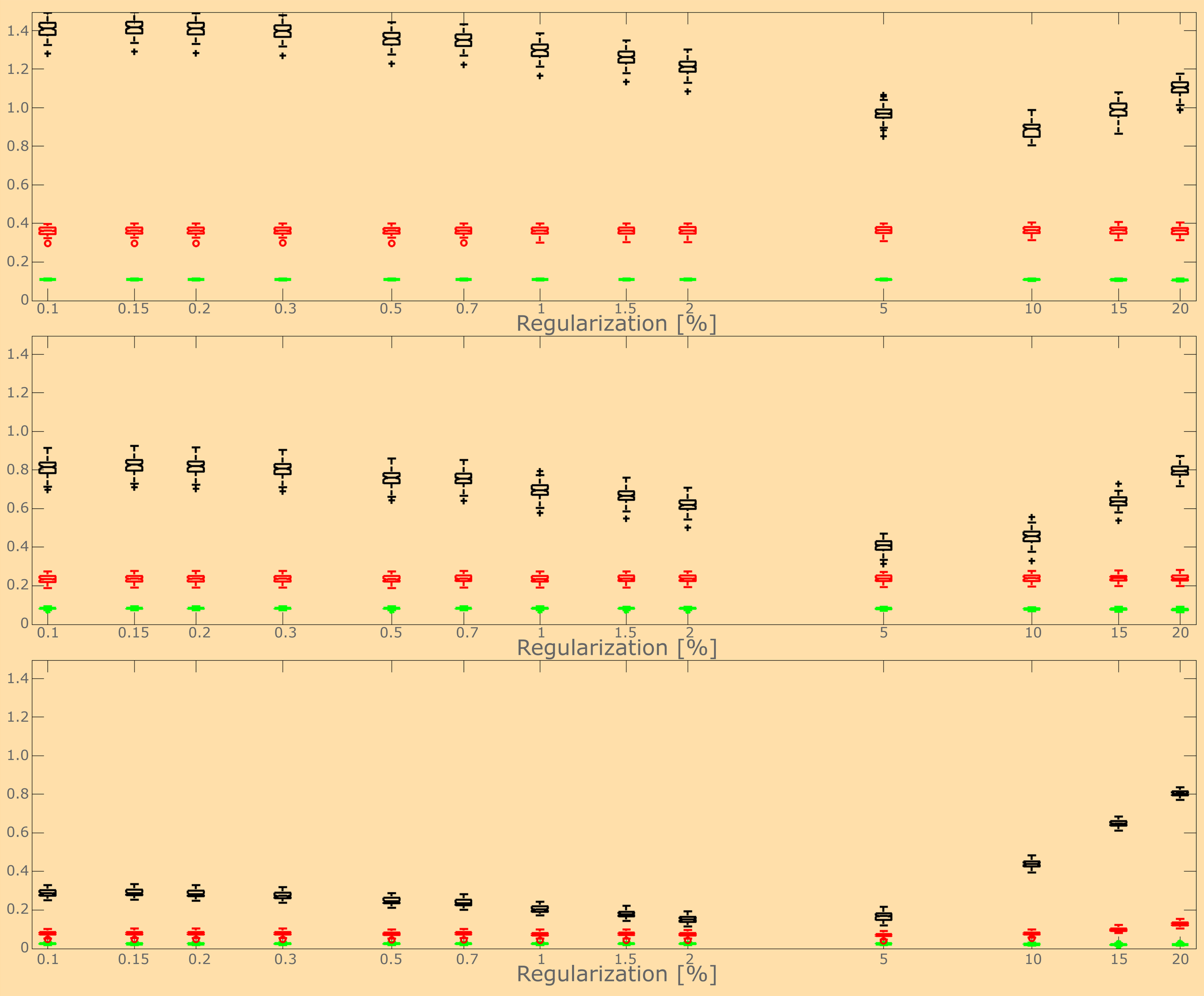

Fig. 2: Semilogarithmic plot of Frobenius norm vs. regularization for Coherence (black), DTF (red) and GC (green) at SNR values of 0.1 (top), 1 (middle), 10 (bottom).

Data Length

➤ All connectivity methods show an increase of accuracy and stability with an increase of data length.

➤ Accuracy converges towards a certain threshold, depending on SNR and connectivity method with GC outperforming DTF and Coherence.

➤ Variance decreases with higher data length, but average noise level does not decrease when having more data available.

➤ Long data epochs cannot compensate poor data quality.

➤ Coherence is more strongly impaired by shorter data than other methods.

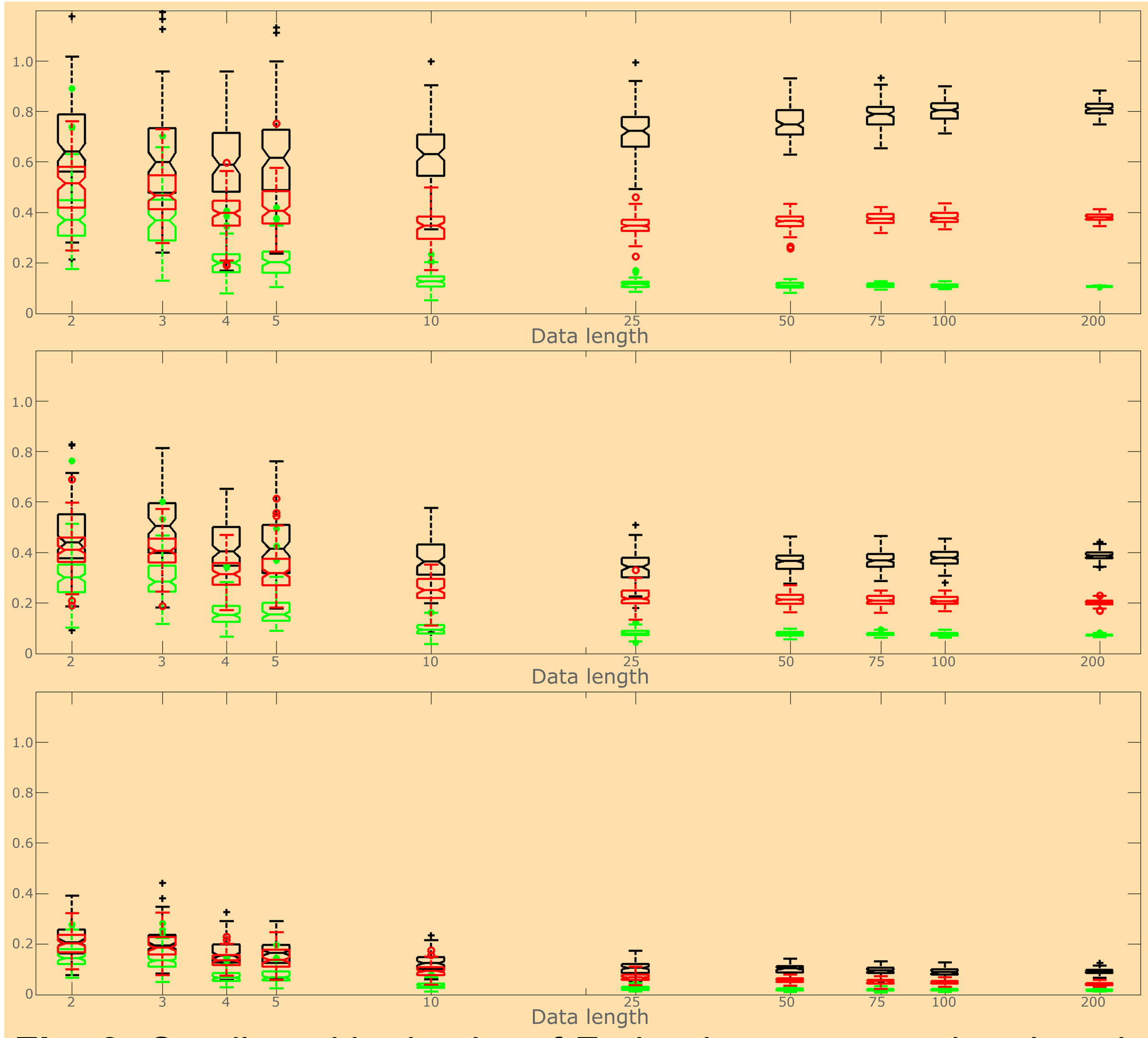

Fig. 3: Semilogarithmic plot of Frobenius norm vs. data length [s] of Coherence (black), DTF (red) and GC (green) at SNR values of 0.1 (top), 1 (middle),10 (bottom).

IV CONCLUSIONS and OUTLOOK

Results demonstrate that:

➤ GC generally provided more accurate and stable results compared to other methods.

➤ the degree of regularization chosen during inverse source reconstruction is crucial for network reconstruction and depends on data quality.

➤ long data epochs cannot compensate poor data quality.

Outlook:

Further simulations will be carried out, that will provide an initial insight on the performance comparison of different connectivity estimators. These evaluations will identify

➤ the influence of the number of active sources.

➤ the number of M/EEG sensors used for forward modelling and inverse source reconstruction.

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