Mapping human brain function: a comparison between Variational Bayes Techniques and LCMV Beamformer

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665

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Introduction:

In the last years several hierarchical Bayesian approaches to the MEG/EEG inverse problem have provided for a relevant contribution to the field of MEG/EEG source localization (Friston et al., 2008b; Wipf et al., 2010). While several methods show applicability under specific conditions, none is optimal without prior information. Meaningful results are bound to previously acquired information. In this work we used simulated MEG data to compare three Variational Bayes reconstruction algorithms implemented within the SPM software preprocessing framework (available from http://www.fil.ion.ucl.ac.uk/spm/): two approaches involving the search for optimal mixtures of anatomically defined priors (Greedy Search (GS) and Automatic Relevance Determination (ARD)) (Friston et al., 2008a) and a third approach using a single empirical prior based on the well established LCMV Beamformer technique (Van Veen et al., 1997), that we denominated Empirical Bayes Beamformer (EBB).
Our parameters of interest were:
1. Number of simulated dipoles (1 to 3),
2. Relative position between dipoles (bilaterally symmetric versus random locations)
3. Dipole time-course correlation level (high/low).
Each parameter configuration set was tested with 5 levels of SNR (from -30 to +10 dB) and 50 dipole position sets.

Methods:

Construction of simulations
Simulated continuous source activities were generated with a length of 0.8 seconds and a basis oscillating frequency of 10 Hz with added Gaussian frequency noise of sigma=3 Hz (Fig. 1). All the sources were represented by current dipoles randomly placed on 50 precalculated positions of the cortical mesh.
We considered one single source for a simple and univocal test of ground truth. Simulations with two and three sources have been considered under conditions of both low and high correlation to check how the correlation bias affects spatial accuracy of localization results and time-course reconstruction at high SNR.

Accuracy parameters
To evaluate the spatial accuracy of the three techniques a variant of the Free receiver Operating Characteristics (FROC) method was implemented (Darvas et al. 2004). The area under the curve of the function (True Positive Fraction vs Accumulated Number of Peaks) is considered for the results in (FIG. 2, 3), yielding a figure of merit we termed Spatial Accuracy Index (SAI). A similar approach has been adopted to evaluate the temporal accuracy of the reconstructed time-courses, termed Temporal Accuracy Index (TAI).

Results:

All methods showed decreasing performance as the number of dipoles increased (Fig. 3). EBB demonstrated both excellent spatial and temporal accuracy under high SNRs and low correlation.
As expected, EBB results became poorer under high correlation between dipoles. On the other hand, ARD and GS showed better performance than EBB under realistic SNRs and low sensitivity to dipole correlations. GS provided better temporal accuracy, while ARD showed a better spatial accuracy.

Conclusions:

Our results suggest that GS and ARD are recommendable when the data SNR is rather poor. Still, the spatial resolution of the aforementioned techniques converges to 10-15 mm even under increased SNR. If a higher SNR can be achieved by signal processing, EBB is the best choice for localization. It allows for a few millimeters spatial resolution under optimal signal conditions.

Modeling and Analysis Methods:

EEG/MEG Modeling and Analysis

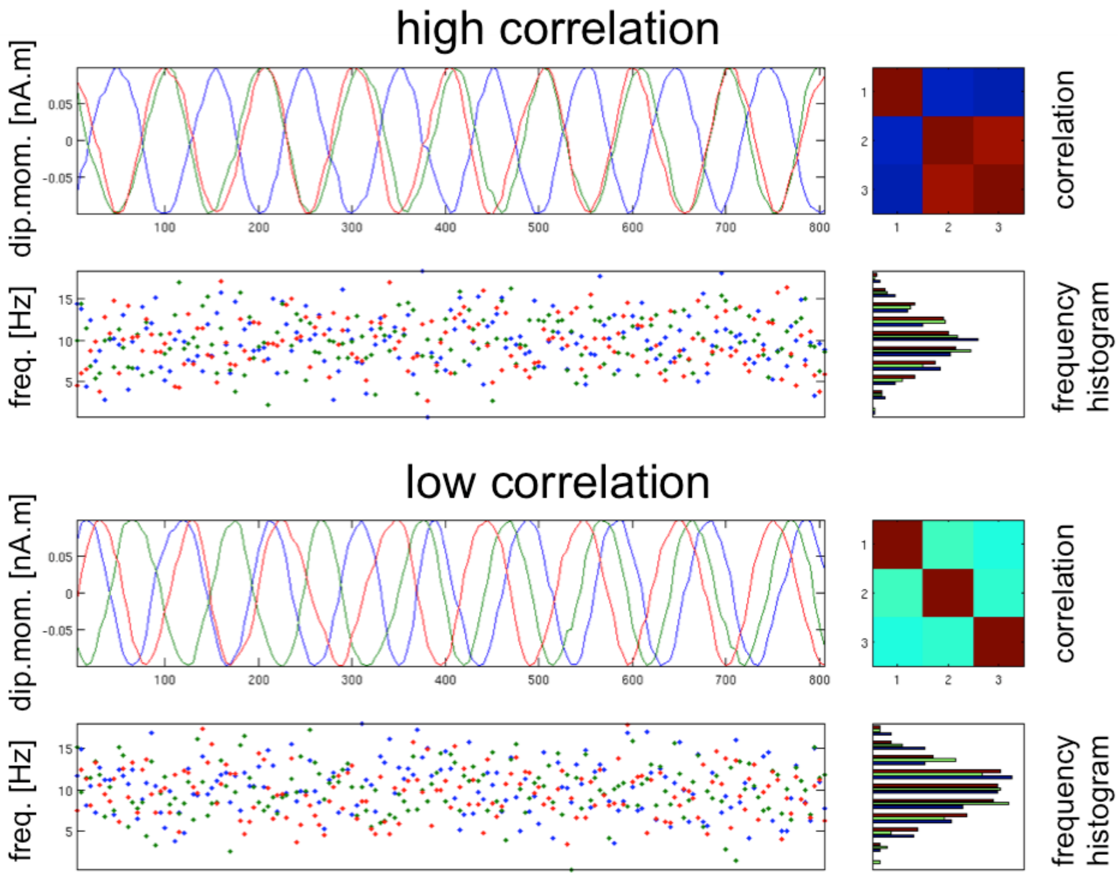

FIG. 1: Simulated time-courses were set to have either high (>0.8, higher panel) or low (<0.2, lower panel) correlation by adding instantaneous spurious frequency components (plotted under the respective basis time-courses).

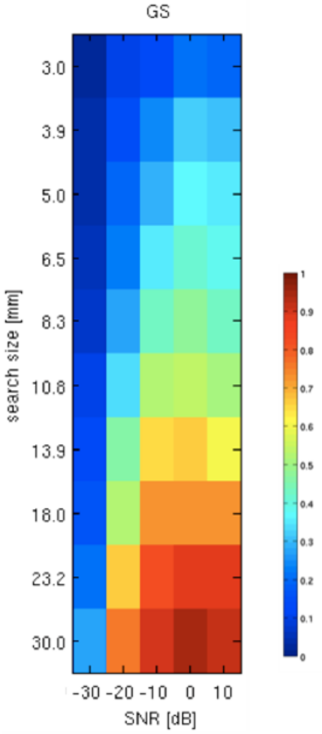

FIG. 2: Particular of FIG.3. with scale values. The color bar shows values for the SAIs which range from 1 (flawless localization) to 0 (total failure)

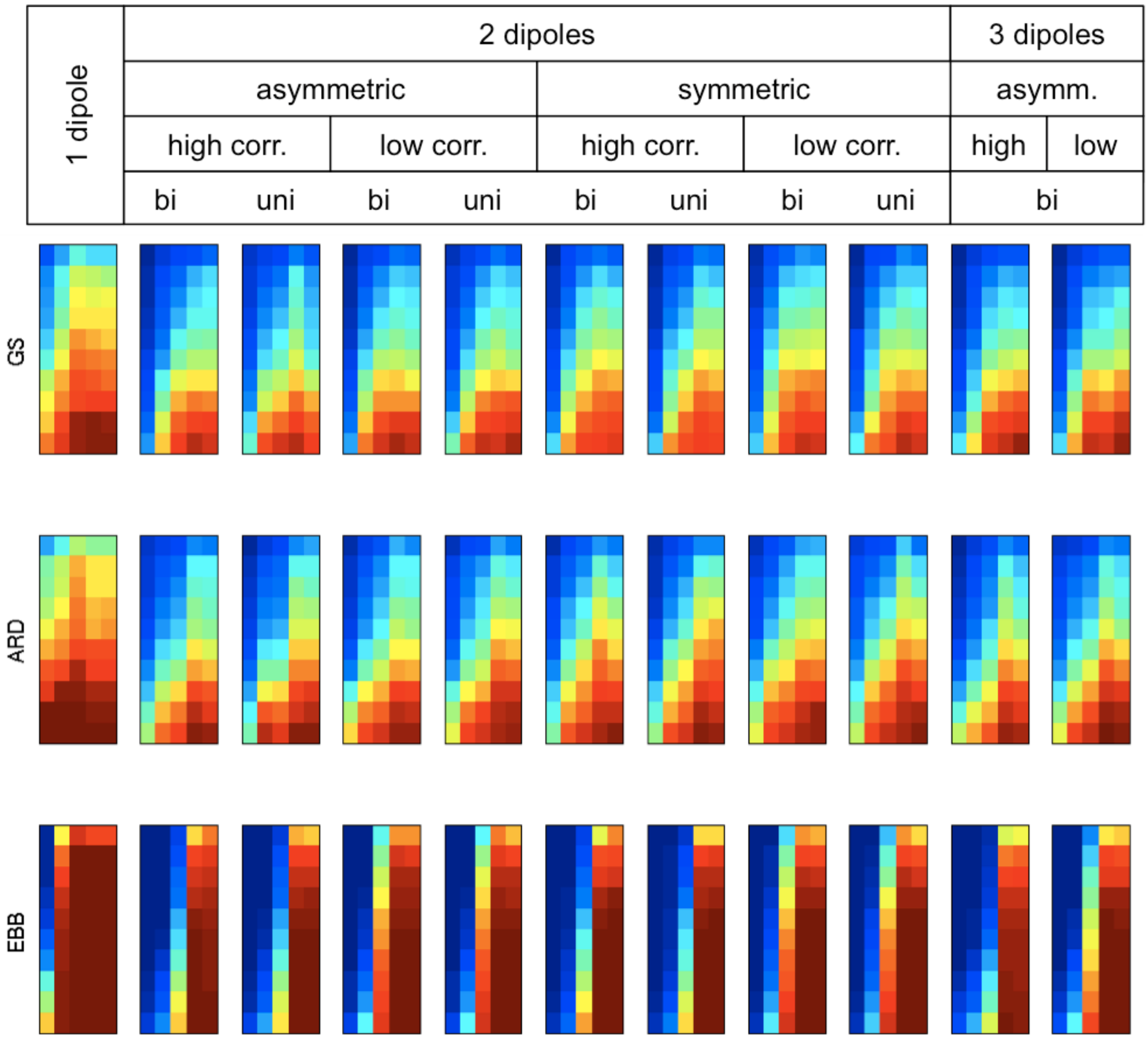

FIG. 3: Values for the SAIs with search-sizes ranging from 3 mm to 3 cm (Y axes, direction downward) and SNRs ranging from 10 dB to -30 dB (X axes, right to link)

Abstract Information

References

Darvas, F. (2004), 'Mapping human brain function with MEG and EEG: methods and validation' NeuroImage, vol 23, pp. 289-299.
Friston, K., (2008a). 'Bayesian decoding of brain images', Neuroimage vol. 39, pp. 181-205.
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Van Veen, B. D., (1997). 'Localization of brain electrical activity via linearly constrained minimum variance spatial filtering' IEEE Transactions on Biomedical Engineering vol 44, pp. 867-880.
Wipf. D., (2010) 'Robust Bayesian estimation of the location, orientation, and time course of multiple correlated neural sources using MEG' Neuroimage vol. 49, pp. 641-655.