Robust and Efficient High-resolution Beamformer Reconstruction of Magnetoencephalographic Brain Imaging Data Using Low-Resolution Sparse Bayesian Learning

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Introduction:

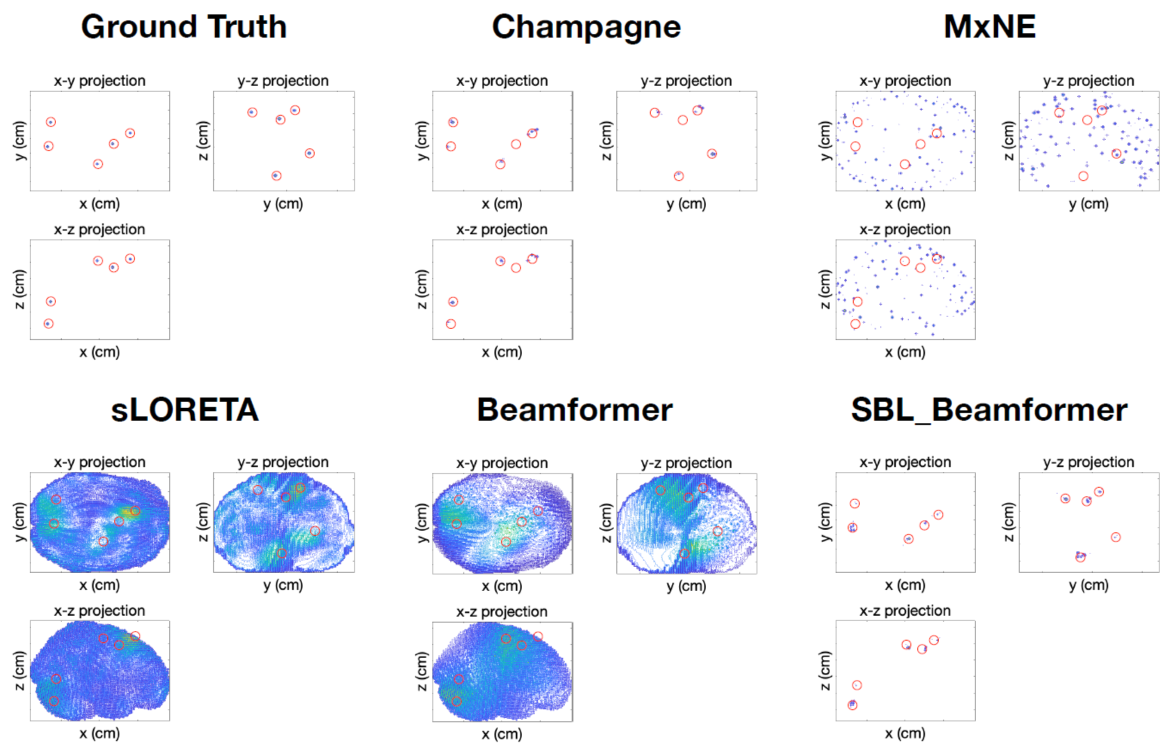
High-resolution, robust, and fast estimation of correlated electromagnetic brain activities has long been a challenge in the field of magnetoencephalography (MEG). One class of suitable methods, minimum variance beamformers[1], use spatial filters that pass source signals in particular locations while suppressing noise and interference. However, reconstruction quality deteriorates depending on the degree of source correlation, limiting functional connectivity analysis. Several algorithms have been shown to improve robustness to correlation but are of limited practical value due to the need for a prior information[1], limitation to scalar sources[2], or excessive computational time[3]. Sparse Bayesian methods, shown to be excellent in learning sparse models from over-complete feature sets, can improve robustness to source correlation without these limitations. We propose a new multi-resolution method explicitly incorporating robust data covariance estimation by sparse Bayesian learning (SBL) followed by adaptive beamforming, referred to as SBL Beamformer.

Methods:

Our novel algorithm improves correlated source reconstruction by estimating the data covariance at low resolution using sparse Bayesian learning followed by parallelized minimum variance beamformer reconstruction at high-resolution. The algorithm was tested against several representative benchmarks (Champagne[4], MxNE[5], sLORETA[6], and the minimum variance beamformer[7]) using challenging simulated source configurations and time courses. SBL Beamformer was implemented using the NUTMEG library in the MATLAB environment.

Results:

Our results demonstrate that SBL Beamformer is robust at handling multiple correlated sources while suppressing the effect of interference and noise. In simulations, SBL Beamformer demonstrates improved runtime efficiency and increased reliability of localization, while maintaining performance in correlated environments. In a representative example MEG simulation (figure) with five point sources (with inter-source correlation of 0.9 at 10 dB), SBL Beamformer demonstrated improved localization accuracy and power estimation compared to the four benchmark algorithms. Computation time for Champagne, MxNE, sLORETA, Beamformer, and SBL Beamformer was 879.4 s, 758.3s, 24.7s, 160.7s and 61.3s.



Conclusions:

Improving robustness to correlated source activity is expected to significantly improve functional connectivity analysis in MEG. Many previous modifications of the minimum variance beamformer have shown limited utility in this regard[1,2,3]. The SBL Beamformer addresses the issue of source correlation by employing sparse Bayesian learning at low resolution to robustly estimate the data covariance prior to high-resolution beamformer reconstruction. This multi-resolution procedure results in a reconstruction method that is both efficient in terms of computational time and robust to correlation. We expect that MEG functional connectivity analysis will be improved across a wide variety of studies by utilizing the SBL Beamformer rather than the conventional minimum variance adaptive beamformer, Champagne, sLORETA, or MxNE.

Highlights:

High-resolution beamforming with robust low-resolution data covariance estimation using sparse Bayesian learning is able to efficiently reconstruct correlated neuronal activity in magnetoencephalography measurements. This novel method, termed SBL Beamformer, showed improved performance compared to several commonly used reconstruction algorithms.

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