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Abstract

Magnetoencephalography (MEG) and electroencephalography (EEG) are popular methods of noninvasively measuring the spatiotemporal characteristics of human neural activity. Both techniques record the effects of neural activity at the scalp with millisecond precision. The neural source is most often assumed to arise from a point dipole. However, the inverse problem of reconstructing the location and time course of sources is ill-posed and standard inverse methods have various shortcomings. Over-determined methods that parametrically fit a small number of dipoles do not allow for sources distributed in space and are limited by user assumptions of number and location of dipoles. Under-determined methods reconstruct activity over a large grid covering the brain. Within this framework, non-adaptive minimum norm techniques tend to have large localization bias. Adaptive minimum variance techniques have much less bias, but can fail if two or more sources are highly correlated in time. All techniques suffer from many sources of noise. Background on-going brain activity, stimulus equipment, and sensor noise can drown out brain signals of interest.

We present several algorithms for source localization of MEG/EEG data based on a probabilistic modeling framework. We assume a generative model of the sensor data that involves a summation of various contributions, including evoked brain sources of interest, background activity, and sensor noise. Each of the contributions can be written as a linear mixture of factors. In the case of the evoked sources of interest, the mixing matrix is the known forward field. For all other interference sources, the mixing matrix is unknown and learned. Additionally, all background activity and sensor noise are assumed to be

present in both a pre-stimulus period as well as post-stimulus, whereas evoked sources are only present in post-stimulus time. This helps to remove all noise contributions for improved source localization of the evoked sources of interest. The first general type of method presented here assumes that all the evoked and background factors are unknown and learned from the data, whereas the second general type assumes that the temporal dynamics of the denoised evoked factors are first learned from the data, and then fixed and subsequently localized. Performance of both algorithms in simulations and real data demonstrate significant improvement over existing source localization methods.