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Machine learning and uncertainty quantification for bioelectromagnetic inverse solutions and signal separation methods

Magneto- and electroencephalography (M/EEG) are non-invasive techniques that sense brain activity from outside the head, providing insights into the brain's functioning in health and disease. From a clinical perspective, it is desirable to localize pathological activity to the generating brain structures, for example to inform surgical planning in drug-resistant epilepsy. For this, the physical process mapping neuronal currents to the M/EEG sensors needs to be inverted. Typical inversion schemes (e.g., Haufe et al., 2011) provide only point estimates or degenerate posterior distributions (e.g., Cai et al., 2020) that are unsuitable for quantifying the uncertainty of the estimates. A similar situation is encountered for multivariate statistical machine learning algorithms such as independent component analysis (ICA) that decompose the data into artefact- and brain-related components (e.g., Sander et al., 2010,. Delorme et al., 2012; Lueschow et al., 2015). ICA has been shown to work in practice even if the experimental data do not meet the statistical criteria (most importantly, number of sources and stationarity) upon which it is based. Such model violations might introduce bias or variance in the decomposition and a quantification of the uncertainty of ICA decompositions is needed. Currently, there exists no approaches to provide well-calibrated posteriors in the context of M/EEG source localization or statistical source separation. Neither exist approaches that would address the M/EEG inverse problem as a supervised prediction problem using synthetic ground-truth data as inputs for neural networks.

The first part of the project will develop and validate novel M/EEG inverse source imaging techniques with well-calibrated built-in uncertainty estimates. We will generate realistic synthetic EEG data to serve as a ground truth using an existing simulation framework (Haufe and Ewald, 2019). In addition, public simulated data will be used. We will develop novel hierarchical Bayesian techniques for proper uncertainty modeling as well as supervised neural network (e.g. graph NN) based approaches that are equipped with built-in uncertainty estimates (e.g., Lakshminarayanan et al., 2017, Ardizzone et al., 2019). The quality of these approaches compared to resampling approaches. To this end standardized performance metrics will be developed.

In the second part, source separation techniques will be benchmarked to identify the conditions in which ICA can reliably isolate the stationary brain sources. From the simulation results, we aim to infer the detectability of brain sources in existing MEG data with the option to extend these datasets for further verification. A flexible tool to assess the stability of ICA decompositions shall be developed simulating cortical network structure with added white and non-white noise. The tool will incorporate classical methods such as resampling. Results from real data will be compared to the results obtained on simulated data using suitable metrics.

The project will leverage the expertise of the PIs and their extensive networks of collaborators. PTBs large database of MEG recordings is the result of two decades of neuroscience and clinical application research. Doctoral projects can be formally hosted at the novel professorship for machine learning and inverse problems (Dr. Haufe) at TU Berlin.

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