Bayesian Dictionary Learning for EEG Source Identification

Electroencephalography (EEG) signals represent the measured electrical activity on the scalp due to a flow of ionic current within the neurons of the brain. Unfortunately, EEG signals measured from a distinct electrode on the scalp, do not directly provide a measure of the activity within a local region of the brain [1]. Indeed, the EEG signals obtained from scalp measurements describe a mixture of all the simultaneously active potentials generated in the brain.

Let Y be the measured EEG signals, X the activations of the local brain regions, and A be the mixing matrix. Then the EEG mixing can often be described as a linear operation and we obtain Y=AX [2]. The inverse EEG problem is to identify both A and X from the EEG data Y. The matrix A contains relevant information about the spatial origin (localization) of the sources, and X provides information about the timing of events.

Estimating A and X turn out to be a challenging problem especially in the case of limited data or limited sensors [1]. Indeed, for low density EEG systems, the number of mixed sources is often greater than the number of sensors. In such a case, conventional methods based on blind source separation (independent component analysis (ICA)) do not work [1].

If A is given, and the number of active sources is sparse, i.e. X is a sparse, then X can be recovered using sparse optimization techniques such as:

Minimize || Y – AX||_2 + ||g(X)||_1,

where ||.||_p, denotes the p-norm, and g represents a function that promotes sparsity.
In general, we do not know A, and it has to be estimated. Unfortunately, in the case where X is not sparse, it turns out that it is hard to recover A. Recently, it was shown that the use of Multiple Measurement Sparse Bayesian Learning techniques makes it possible to recover a good approximation of A [2,3].

In this project, we are interested in a non-stationary situation, where the brain activity changes over time due the processing in the brain when the subject is exposed to non-stationary acoustic stimuli. In particular, in certain periods of time, the subject is exposed to very noisy speech, and in other situations there is almost no noise. The EEG signals are recorded on the scalp using low-density EEG equipment, i.e., the number of EEG electrodes is less than 32 (could be as little as 6). We are interested in finding the scalp map (A matrix) and the active sources X within a short time window (e.g., 10 seconds). Moreover, we are interested in being able to perform online adaptation of the matrix X and source vector X in order to track the functional connectivity and activity levels within the brain.
We have a database with real and synthetic EEG signals available, and we suggest to use the framework of [1] to simultaneously estimate A and X.
An additional challenge would be to make the system adaptive in order to track the evolution of A and X over time.

Proposed work plan:

1. Get familiar with sparse recovery techniques based on total variation, l_p, and other norms.
2. Get familiar with dictionary learning algorithms.
3. Implement a baseline system for estimating A and identifying the sources in X based on [1]. A more detailed description is provided in [4].
4. Use the baseline system on real EEG signals.
5. Extend the system with tracking capability.
6. Test the tracking capability on synthetic and real EEG data.

Literature:

1. O. Balkan et al.,"Covariance-domain dictionary learning for overcomplete EEG source identification", Available on Arxiv.2015.
2. P. Nunez et al., "EEG coherency. I statistics, reference electrode, volume conduction, Laplacians, cortical imaging, and interpretations at multiple scales." EEG and clinical neurophysiology, vol. 103, no.5, 1997.
3. Balkan et al., "localization of more sources than sensors via jointly-sparse Bayesian learning", Signal Processing Letters, IEEE., vol.21., no.2., 2014.
4. Balkan O. "Support Recovery and Dictionary Learning for Uncorrelated EEG Sources", PhD Thesis, UC San Diego, 2015.

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- Possible collaboration with industry.