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Real-Time Estimation and 3D Visualization of Source Dynamics and Connectivity Using Wearable EEG

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Abstract. This report summarizes our recent efforts to deliver real-time data extraction, preprocessing, artifact rejection, source reconstruction, multivariate dynamical system analysis (including spectral Granger causality) and 3D visualization within the SIFT and BCILAB toolboxes. We report the application of such a pipeline to EEG data obtained from wearable high-density (32-64 channel) dry EEG systems.

Keywords: Wearable EEG, Dry Sensors, Connectivity, Source Localization, Artifact Rejection, Visualization

1. Introduction

Dynamic cortico-cortical interactions are central to neuronal information processing. The ability to monitor these interactions in real-time may prove useful for BCI and other applications, providing information not obtainable from univariate measures, such as bandpower and evoked potentials. Wearable (mobile, unobtrusive) EEG systems likewise play an important role in BCI applications, affording data collection in a wider range of environments. However, reliable real-time modeling of neuronal source dynamics using data collected in mobile settings faces challenges, including mitigating artifacts and maintaining fast computation and good modeling performance with limited amount of data. Here we describe some of the wearable hardware and signal processing we are developing that attempt to address these challenges, contributing to the development of EEG as mobile brain imaging modality.

2. Material and Methods

Our data-processing pipeline is outlined in Figure 1. The pipeline is implemented in Matlab within our SIFT and BCILAB toolboxes, which are publically available as EEGLAB plugins [Delorme 2011]. All elements of the pipeline can be controlled "on the fly" via a control panel GUI.

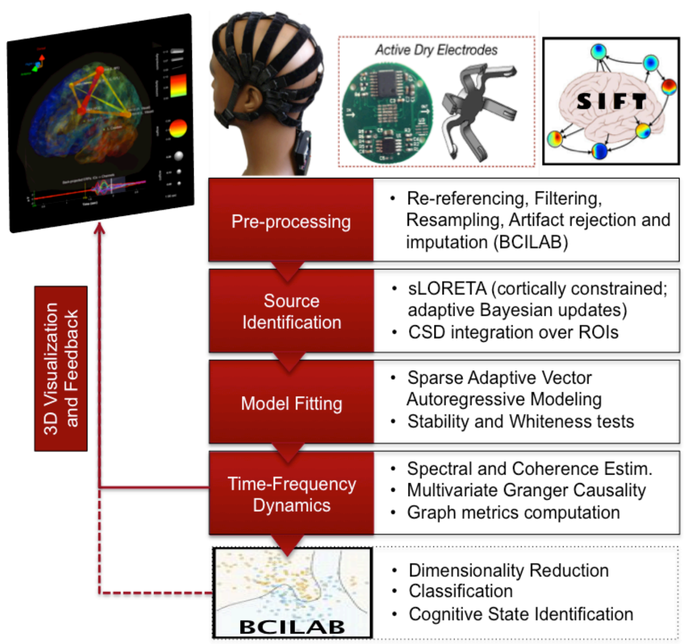

Figure 1. Real-time data processing pipeline. A Cognionics 64-channel system is depicted above with flexible active dry electrodes.

2.1. Wearable EEG Hardware

Cognionics has developed two new high-density (32 and 64 channel) dry wearable EEG systems. Harness and electronics are integrated into a compact and lightweight form-factor. Signals are digitized with 24-bit ADCs at 300 samples/sec and transmitted via Bluetooth. The headsets support a novel, flexible dry electrode consisting of a set of angled 'legs' made from conductive plastic, which flatten on impact. Typical sensor impedances are between 100k - 1M ohms and high input impedance circuitry on the headset ensure minimal signal degradation.

2.2. Preprocessing and Artifact Rejection

EEG data is streamed into Matlab, and an efficient online pre-processing pipeline is applied using BCILAB. Preprocessing elements include (though are not limited to) re-referencing, rejection of corrupted data samples or channels with bad channel imputation and/or high, low, or band-pass filtering. Short-time high-amplitude artifacts in the continuous data may be removed online, using a sliding-window Principal Component Analysis, by statistically interpolating any high-variance signal components exceeding a threshold relative to the covariance of a calibration measurement (here one minute of resting data). Each affected time point of EEG is then linearly reconstructed from the retained signal subspace based on the correlation structure of the calibration data.

2.2. Source Reconstruction

Following pre-processing, we estimate current source density (CSD) over a high-resolution cortical mesh. Our default forward model consists of a four-layer (skull, scalp, csf, and cortex) Boundary Element Method (BEM) model derived from the MNI "Colin 27" brain and computed using OpenMEEG [Gramfort 2010]. For inverse modeling, we have currently implemented anatomically constrained LORETA with a Bayesian MAP update rule for hyperparameter estimation [Trujilo 2004]. This approach is well suited for real-time adaptive estimation and automatically controls the level of regularization for each measurement vector. Additionally, we segment the source space into 90 regions of interest (ROIs) using Automated Anatomical Labeling [Tzourio-Mazoyer 2002]. The user can compute spatially averaged, integrated or maximal CSD for any subset of these ROIs.

2.3. Dynamical Systems Analysis

Preprocessed channel or source time-series are piped into SIFT and an order-p sparse vector autoregressive (VAR[p]) model is fit to a short chunk of recent data (e.g. 0.5-2 sec). The VAR coefficients are estimated using Alternating Direction Method of Multipliers (ADMM) with a Group Lasso penalty [Boyd 2011]. Model estimation is warm-started using the solution for the previous data chunk. The regularization parameter is initialized offline, by cross-validation on the calibration data, and adapted online using a simple heuristic based on two-point estimates of the gradients of the primal and dual norms. Model order is selected offline, by minimizing information criteria (e.g. AIC or BIC) on calibration data. Following model fitting and tests of stability and residual whiteness (autocorrelation function or Portmanteau), we obtain the spectral density matrix and any of the frequency-domain functional and effective connectivity measures implemented in SIFT. Graph-reductive metrics such as degree, flow, and asymmetry ratio can be applied to connectivity matrices. Finally, selected measures (power, connectivity, outflow, etc.) are visualized within an interactive 3D anatomical representation. These measures may also be piped to BCILAB as features for one of the 13 classification frameworks currently available.

3. Results and Discussion

We have tested our pipeline on 32- and 64-channel Cognionics systems in mobile settings. Preliminary results are encouraging. For a moderate number of ROIs (10-15), we obtain fast cLORETA convergence and good VAR model fit (stable with uncorrelated residuals, $p<0.05$). The VAR process spectrum exhibits characteristic EEG $1/f$ shape with theta, alpha, and beta peaks, including prominent occipital alpha gain and occipital-frontal Granger-causality at rest with eyes closed. On an Intel i7 4-core (2.3 Ghz) laptop, preprocessing and source reconstruction typically takes 50-80 ms, model fitting 50-70 ms, and visualization 200-300 ms. We are currently further validating the existing pipeline in simulations and in cognitive tasks where there is a measure of ground truth. Subsequent work will use source connectivity information as features for cognitive state classification within the BCILAB framework.

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References

Boyd, S., Parikh, N., Chu, E., Peleato, B., Eckstein, J. Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers. *Machine Learning* 2011;3(1):1-122.

Delorme, A., Mullen, T., Kothe, C., Akalin Acar, Z., Bigdely Shamlo, N., Vankov, A., Makeig, S. EEGLAB, SIFT, NFT, BCILAB, and ERICA: New tools for advanced EEG/MEG processing. *Computational Intelligence and Neuroscience* vol. 2011, Article ID 130714, 12 pages.

Gramfort, A., Papadopoulo, T., Olivi, E., Clerc, M. OpenMEEG: opensource software for quasistatic bioelectromagnetics, *BioMedical Engineering OnLine* 45:9, 2010

Trujillo-Barreto, N., Aubert-Vazquez, E., Valdes-Sosa, P.A., 2004. Bayesian model averaging in EEG/MEG imaging. *NeuroImage* 21, 1300:1319

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., Joliot M. Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. *NeuroImage* 2002;15: 273-289.