Journal of Neuroscience Methods 256 (2015) 106–116

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Computational Neuroscience

Online visualization of brain connectivity

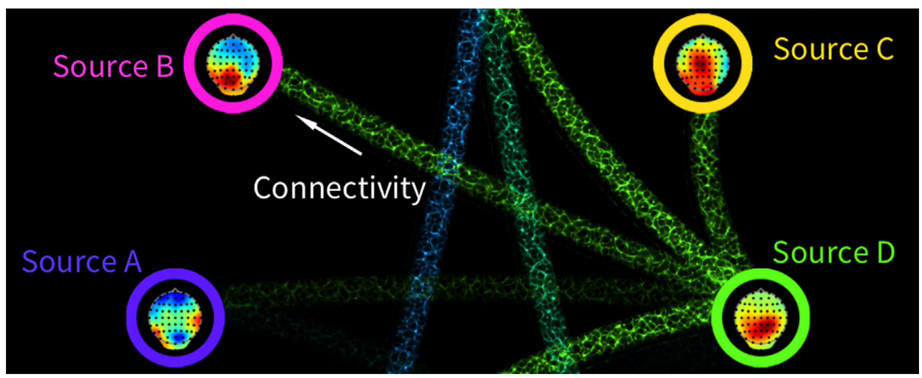
Martin Billinger[a,b,c], Clemens Brunner[a,d,*], Gernot R. Müller-Putz[a]

[a] Institute for Knowledge Discovery, Graz University of Technology, Inffeldgasse 13/IV, 8010 Graz, Austria
[b] Department of Otolaryngology, Hannover Medical School, Karl-Wiechert-Allee 3, 30625 Hannover, Germany
[c] Cluster of Excellence "Hearing4all", Hannover, Germany
[d] Department of Psychology, University of Graz, Universitätsplatz 2, 8010 Graz, Austria

HIGHLIGHTS

- We visualize source-based connectivity online based on multi-channel EEG recordings.
- This reveals dynamically changing causal interactions between cortical sources.
- We validate the feasibility of our approach with 12 participants.
- Our approach is based on Python and uses functionality from SCoT.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 26 May 2015
Received in revised form 26 August 2015
Accepted 27 August 2015
Available online 6 September 2015

Keywords:
EEG
Connectivity
ICA
Real-time
Visualization

ABSTRACT

Background: While visualization of brain activity has well established practical applications such as real-time functional mapping or neurofeedback, visual representation of brain connectivity is not widely used. In addition, technically challenging single-trial connectivity estimation may have hindered practical usage of connectivity in online applications.
New method: In this work, we developed algorithms that are capable of estimating and visualizing (effective) connectivity between independent cortical sources during online EEG recordings.
Results: The core routines of our procedure, such as CSPVARICA source extraction and regularized connectivity estimation, are available in our open source Python-based toolbox SCoT. We demonstrate for the first time that online connectivity visualization is feasible. We show this in a feasibility study with twelve participants performing two different tasks, namely motor execution and resting with eyes open or closed. Connectivity patterns were significantly different between two motor tasks in four participants, whereas significant differences between resting task patterns were found in seven participants.
Comparison with existing methods: Existing connectivity studies have focused on offline methods. In contrast, there are only a small number of examples in the literature that explored online connectivity estimation. For example, a system based on wearable EEG has been demonstrated to work for one subject, and the Glass Brain project has received considerable attention in popular sciences last year. However, none of these attempts validate their methods on multiple subjects.
Conclusions: Our results show that causal connectivity patterns can be observed online during EEG measurements, which is a first step towards real-time connectivity analysis.

* Corresponding author at: Department of Psychology, University of Graz, Universitätsplatz 2, 8010 Graz, Austria. Tel.: +43 316 3808526.
E-mail address: clemens.brunner@uni-graz.at (C. Brunner).

http://dx.doi.org/10.1016/j.jneumeth.2015.08.031
0165-0270/

1. Introduction

The human brain consists of a vast network of interconnected neuronal and glial cells. Each of the 20 billion neurons connects to about 7000 other neurons via chemical synapses (Drachman, 2005). Only by forming dynamic networks, groups of relatively simple neurons can perform complex tasks such as learning, moving a body, or writing a scientific paper. Hence, these connections are an important characteristic of the brain.

With steadily increasing computational power and improvements in neuroimaging techniques, scientists are now able to study brain connectivity at different temporal and spatial scales. While structural connectivity is only concerned with anatomical correlates, functional connectivity is related to correlated activity of neural networks. Inspecting functional connectivity in detail can reveal causal relations between correlated brain areas. This concept of directed connectivity is known as effective connectivity (Friston, 2011). Examples for connectivity research include anatomical tracing of white matter fibers (Wakana et al., 2004), measuring functionally coupled brain activity (Friston et al., 1993; Friston, 2011), and determining effective information flow among brain structures (Korzeniewska et al., 2003; Brookes et al., 2012).

Functional and effective connectivity can be estimated from various measures of brain activity such as functional magnetic resonance imaging (fMRI) (Smith, 2012), electroencephalography (EEG) (Michel and Murray, 2012), magnetoencephalography (MEG) (Brookes et al., 2012), functional near infrared spectroscopy (fNIRS), or positron emission tomography (PET) (Friston et al., 1993) in different temporal and spatial resolutions. In our work, we focus on EEG, because it is an inexpensive and portable technique that directly captures neural activity on a millisecond scale.

However, estimation of connectivity from the EEG faces two major challenges: (1) EEG channels are highly correlated due to volume conduction and a common reference, and (2) EEG sensor locations are not the actual sources of cortical brain activity. These challenges can be solved by measuring connectivity in the cortical source space rather than in the sensor space (Michel and Murray, 2012).

Routines for connectivity analysis are included in many popular EEG analysis tools such as EEGLAB and SIFT (Delorme et al., 2011), MNE-Python (Gramfort et al., 2013), and Fieldtrip (Oostenveld et al., 2011). However, most of these tools are designed for offline analysis. This means that they utilize multiple repetitions of the experimental conditions to increase time and frequency resolution of the connectivity estimates. In contrast, using connectivity in online applications such as brain-computer interfaces (BCIs) or real-time brain connectivity visualization requires more advanced estimation strategies.

Recently, we developed a framework for single-trial connectivity estimation (Billinger et al., 2013), where EEG channel data are transformed into the source space with independent component analysis (ICA) (Makeig et al., 1996) prior to connectivity estimation. We found that connectivity measures such as the direct directed transfer function (dDTF) were useful for classification of motor imagery tasks.

In this work, we go one step further and demonstrate online estimation of single-trial connectivity. We focus on connectivity visualization instead of implementing a BCI application. We extended the available tools to enable online validation of our single-trial connectivity estimation concept, which relies on distribution of modular computation units over processors and computers. This allows the system to process EEG signals fast enough for online application. Furthermore, we present a visualization strategy that engages multiple visual aspects (color, intensity, motion, and location) to concisely represent time-evolving connectivity patterns.

Since visualizing source-based connectivity in real-time is a novel approach, only few potential applications come to mind. For example, seizure prediction in epilepsy is a promising candidate since it has already been demonstrated that connectivity measures contain essential information to predict epileptic seizures (see van Mierlo et al. (2014) for a review). Specifically, previous studies have focused on offline detection of epileptic activity, but future applications could be based upon our methodology to process EEG connectivity online. This would allow the system to take suitable measures to prevent an epileptic seizure from fully developing – something that is only possible with an online approach. Other possible future applications include BCIs. We have already shown that connectivity features work in the context of BCIs (Billinger et al., 2013), and future work could focus on improving performance of connectivity-based features. More hypothetical applications include sleep stage analysis and biofeedback. The latter would directly benefit from our approach here, because it requires visualization of brain activity, which we provide in the form of source-based connectivity visualization.

2. Methods

2.1. Connectivity estimation

A common practice in connectivity estimation is to model the signals with a vector autoregressive VAR model. Such a model describes causal interactions in the time domain. Various spectral connectivity measures can be extracted from frequency domain representations of the model (Schlögl and Supp, 2006). In this manuscript, we will refer to the two steps of VAR model fitting and subsequent extraction of connectivity measures simply as connectivity estimation.

When performing multi-trial connectivity estimation, a large amount of data is available from many repetitions of the experiment. In a typical experiment with 64 EEG channels, 100 trials, and an estimation window length of 100 samples, a total of 640,000 data points are available for estimation. Thus, reliable estimates including statistical measures such as the mean and its confidence interval can be obtained in offline analyses. Fig. 1 shows an example of multi-trial partial directed coherence (PDC) (Baccalá and Sameshima, 2001) estimation.

In contrast, only a fraction of data is available in the single-trial case – typically only one short time window. This would amount to only 6400 data points in the previous example. In general, this is not sufficient for meaningful interpretation of connectivity estimates and leads to large inter-trial variance. However, this variance can be reduced by imposing constraints on the VAR model. In particular, regularization of the VAR model leads to more consistent single-trial estimates compared to unconstrained VAR models. We use ridge regression to regularize our VAR models, which imposes a penalty on the l_2-norm of the model coefficients. This in turn leads to smaller model coefficients and limits the influence of noise (Billinger et al., 2014). Fig. 2 illustrates the impact of regularization on single-trial connectivity estimation.

In this work, we extend our single-trial connectivity framework (Billinger et al., 2013, 2014) to support online visualization of connectivity. This framework is based on a two-step approach. In the first step, offline analysis is performed to initialize the single-trial analysis in the second step. In the initialization step, we decompose EEG channels into independent components. By manually selecting ICs that represent cortical sources, we derive an unmixing matrix that we can later use to extract signals from the same sources, but using new