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Analyzing EEG Source Connectivity with SCoT

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Abstract

In this article we demonstrate how to use SCoT[1], our source connectivity toolbox, to estimate connectivity on motor imagery data. We show both, multi- and single-trial analysis examples. The latter can be useful for feature extraction in brain-computer interfaces if reasonable regularization constraints are applied.

1 Introduction

Quantifying interactions in dynamic large-scale brain networks is an important and useful tool in neuroscience. The source connectivity toolbox (SCoT[1]) [3] is a Python package for estimating spectral effective connectivity between brain sources. SCoT extracts connectivity measures from vector autoregressive (VAR) models fitted to source signals. Typically, the sources are obtained by performing MVARICA [5] or CSPVARICA [3], which are based on independent component analysis (ICA) decomposition of VAR residuals.

Several brain-computer interface (BCI)-related studies have included connectivity features for classification [4, 2]. Although the tools in SCoT were originally designed for single-trial BCI feature extraction, they also support multi-trial data and are useful for functional and effective connectivity analysis of electroencephalogram (EEG) signals.

In this article, we demonstrate several ways to use SCoT on a motor imagery (MI) data set.

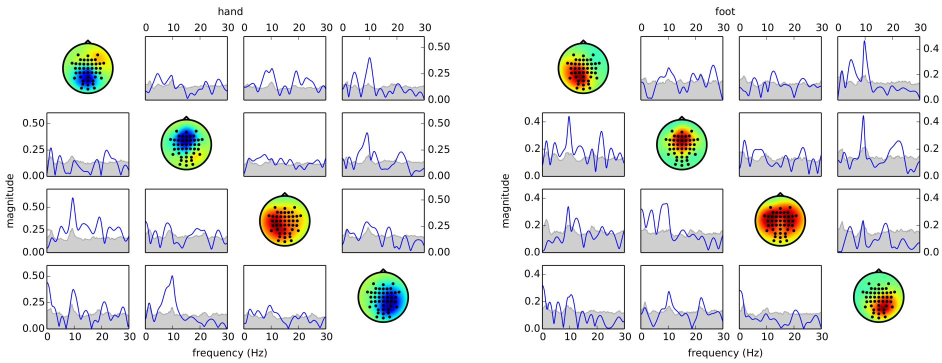

Figure 1: Multi-trial joint source/connectivity estimation. Left: hand MI, right: foot MI. Each plot shows the PDC spectrum of a source pair. The area shaded in gray is the one-sided 95 % confidence interval of the PDC under the null-hypothesis of no connectivity.

[1] `https://github.com/SCoT-dev/SCoT`

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2 Materials and Methods

SCoT Workflow SCoT provides routines for EEG source and connectivity estimation. Two estimation approaches are possible in SCoT. One approach is joint estimation, where sources and connectivity are estimated together. This is performed by applying MVARICA or CSP-VARICA to data where sources can be assumed to be spatially and temporally stationary. Alternatively, a two-step approach estimates sources and connectivity separately, possibly on different data sets. MVARICA or CSPVARICA can be employed in the source decomposition step by discarding their VAR estimates. In the second step, the unmixing matrix is used to obtain source activations. Connectivity measures are estimated from VAR models fitted to these source activations.

Example Data Set An example data set is available with SCoT. This data set contains a recording of 45 EEG channels from one healthy subject performing hand and foot MI.A total of 180 trials (90 trials per MI task) were recorded. In each trial the subject was cued to perform either MI task by an arrow pointing up (hand) or down (foot). The beginning of a trial was indicated by a fixation symbol appearing on the screen, and the motor imagery period started with the cue after 2.5 s. The motor imagery period was 4.5 s long and was followed by a 2.5–3.5 s break.

Usage Examples In this article, we demonstrate how to use SCoT to estimate and visualize connectivity on the example data set. We show how to perform joint estimation, multi-trial two-stage estimation, single-trial connectivity, and circular plots. In each case we measure connectivity with the PDC [1] in a 1 s window starting 2 s after the cue. For clarity of demonstration, we only use four sources in the first three examples and seven sources for the circular plots. We manually removed sources that were clearly related to artifacts (such as eye movement or neck muscle activity).

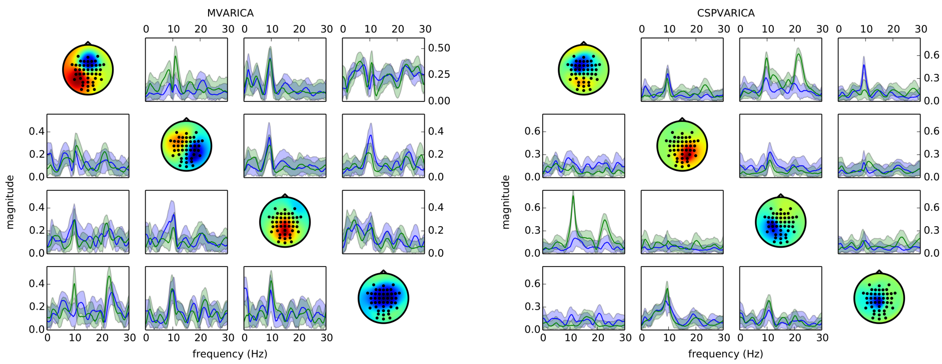

Figure 2: Multi-Trial Two-Stage Estimation. Left: MVARICA, right: CSPVARICA. Each plot shows PDC spectra of a source pair for hand MI (blue) and foot MI (green). The shaded areas correspond to the 95 % confidence intervals obtained by bootstrapping.

Interpreting the Results We show different spectral connectivity plots in Figures 1, 2, and 4, which are discussed in the results section below. These plots are arranged so that columns correspond to the origin, rows to the destination of connectivity, and source topographies are

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located along the diagonal. A high connectivity value in a plot generally means that there is causal interaction from the source in the same column to the source in the same row, at a certain frequency.

3 Results

Multi-Trial Joint Source/Connectivity Estimation Here, we performed joint estimation of sources and connectivity on all trials of each class separately. Figure 1 shows that slightly different sources are obtained for each class, which makes it difficult to evaluate class differences in connectivity.

Multi-Trial Two-Stage Estimation The idea of two-stage estimation is to re-use the source decomposition on different data sets, which allows us to evaluate changes in connectivity. We applied MVARICA and CSPVARICA to all trials of both classes to obtain source decompositions. Subsequently, we used the same sources for estimating the PDC under each class separately, as shown in Figure 2.

Single-Trial Estimation Single-trial estimation suffers from the *curse of dimensionality*, because the amount of data available in one trial is limited. SCoT solves this problem by supporting regularized VAR model fitting. Figure 3 shows how regularization improves estimates for a model order of 20. In this example, we have four sources and estimate connectivity on 100 time samples, which results in a total of 400 available data samples. The number of free parameters in the VAR model is 320 ($4 \cdot 4 \cdot 20$), which is a rather ill-posed fitting problem.

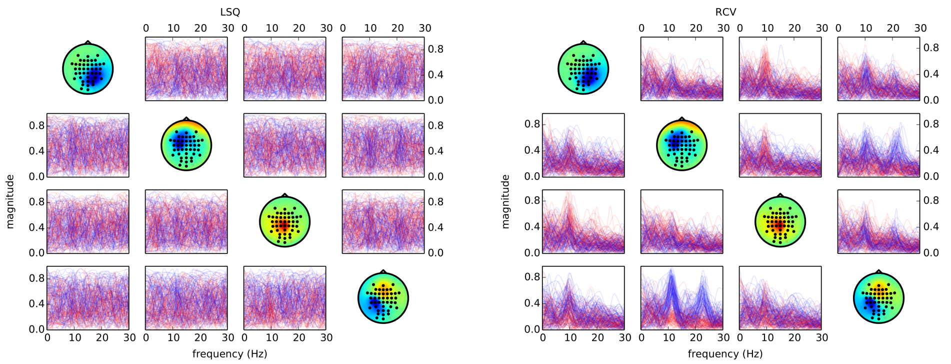

Figure 3: Single-trial estimation. Left: least squares fitting (LSQ), right: ridge regression (RCV). Lines correspond to individual trials, and the colors indicate the different classes (red: hand, blue: foot).

Circular Plots In this example, we show an alternative to spectral connectivity visualization. Instead of plotting the full connectivity spectrum, we show interaction only in selected bands. For this purpose, we averaged the PDC in the alpha (8–12 Hz) and beta (16–24 Hz) bands. If this average exceeds a threshold of 0.18 (alpha) or 0.25 (beta), we draw an arrow from the origin to the destination (Figure 4). Thus, these arrows indicate frequency dependent causal relations between sources.

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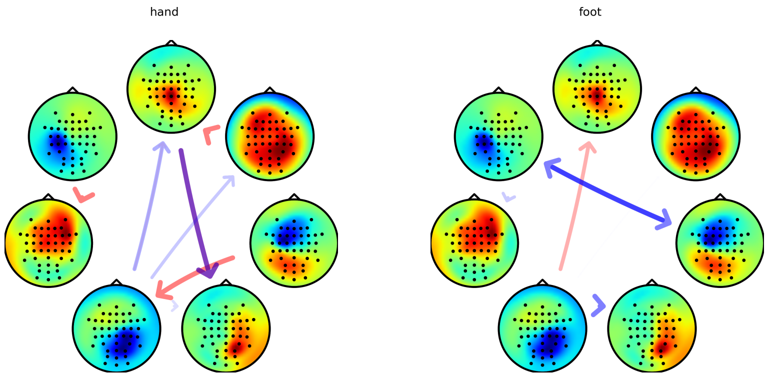

Figure 4: Circular plots. Left: hand MI, right: foot MI. These plots show the relative strength of connectivity (PDC in the alpha (8–12 Hz, red) and beta (16–24 Hz blue) bands. The width and intensity of the arrows indicates the strength of the connection.

4 Discussion and Conclusions

We demonstrated different approaches of source/connectivity estimation with SCoT. While joint estimation is the easiest approach, it is not suitable for evaluating changes in connectivity since sources change as well. Instead, the two-step approach allows us to evaluate changing connectivity between constant sources. Consequently, the two-step approach can be applied to single-trial estimation, which facilitates the use of connectivity features in BCIs [2, 3]. However, it is important to use regularization when fitting VAR models on low amounts of data.

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