Stable EEG Spatiospectral Sources Using Relative Power as Group-ICA Input

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Abstract

Within the last decade, various blind source separation algorithms (BSS) isolating distinct EEG oscillations were derived and implemented. Group Independent Component Analysis (group-ICA) is a promising tool for decomposing spatiospectral EEG maps across multiple subjects. However, researchers are faced with many preprocessing options prior to performing group-ICA, which potentially influences the results. To examine the influence of preprocessing steps, within this article we compare results derived from group-ICA using the absolute power of spatiospectral maps and the relative power of spatiospectral maps. Within a previous study, we used K-means clustering to demonstrate group-ICA of absolute power spatiospectral maps generates sources which are stable across different paradigms (i.e. resting-state, semantic decision, visual oddball) Within the current study, we compare these maps with those obtained using relative power of spatiospectral maps as input to group-ICA. We find that relative EEG power contains 10 stable spatiospectral patterns which were similar to those observed using absolute power as inputs. Interestingly, relative power revealed two γ-band (20–40 Hz) patterns which were present across 3 paradigms, but not present using absolute power. This finding suggests that relative power potentially emphasizes low energy signals which are obscured by the high energy low frequency which dominates absolute power measures.

Keywords

EEG • Spatiospectral ICA • Multisubject blind source separation

1 Introduction

The EEG signal is considered a stochastic process comprised of a mixture of distinct electrophysiological brain processes, where different frequencies become dominant during different cognitive states [1]. Within the last decade, multisubject blind source separation (BSS) techniques of EEG spectra have been developed and implemented for isolating these distinct EEG oscillations [2]. One multisubject technique gaining in popularity is spatiospectral group-ICA, conducted on the absolute power of spectral densities computed across multiple epochs [3]. We have recently identified spatiospectral sources derived using this method which appear (i.e. are stable) across different paradigms (i.e. resting state, semantic decision, visual oddball) [4].

Different EEG preprocessing steps could potentially influence the results of spatiospectral group-ICA. In order to explore this further, we compare the spatiospectral maps derived in our previous study using absolute power with those derived using relative power maps as inputs (i.e. the spatiospectral heuristic model [5]). This preprocessing step is particularly interesting based upon previous studies reporting that relative power fluctuations correspond more with the experimental task than absolute power fluctuations [6–8]. Within the current study we compute spatiospectral sources using relative power as input, and compare these sources to those derived in our previous study [4] using absolute power. In addition, we examine the degree in which the fluctuations of sources derived from relative or absolute power better correspond with the timecourse of experimental stimuli.

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2 Materials and Methods

2.1 EEG Data Acquisition

The scalp EEG data was acquired simultaneously with fMRI using an MR compatible 32-channel 10/20 EEG system (*BrainProducts, Germany*) with a 5 kHz sampling frequency. Two channels were used for ECG and EOG. Simultaneous fMRI data was acquired using a 1.5T Siemens Symphony Numaris. Informed consent was obtained from all subjects after the procedures were fully explained, and the study was approved by the local ethics committee. The equipment was identical during acquisitions of the three paradigms described below. For more detailed description of the paradigms, and acquisition parameters, see [4].

Resting-state paradigm: Fifty healthy subjects participated in a 15 min "resting-state" experiment (RST, 30 right handed men, 20 right-handed women; age 25 ± 5 years). Subjects were instructed to lie still within the fMRI scanner with their eyes closed, not to think of anything specific, and not to fall asleep.

Semantic decision paradigm: A block design semantic decision task (SDT) was performed by 42 healthy subjects (22 right-handed men, 2 left-handed men, 18 right-handed women; age 25 ± 5 years). The block stimulation design was implemented in order to elicit robust language network activation.

Visual oddball paradigm: An event-related visual oddball task (VOT) was performed by 21 healthy subjects measured in 4 inter-leaved sessions (13 right-handed men, 1 left-handed man, 7 right-handed women; age 23 ± 2 years).

2.2 EEG Data Preprocessing

EEG data were preprocessed using BrainVision Analyzer 2.02 (*BrainProducts, Germany*). Gradient artifacts were removed using template subtraction [9] and signals were resampled to 250 Hz (antialiasing filter included), and filtered with a Butterworth zero phase 1–40 Hz band-pass filter. Cardiobalistogram artifacts were removed by subtracting the average pulse artifact waveform from each channel [10] and signals were re-referenced to the average. For visual oddball EEG data, eye-blinking artifacts were removed by conducting a temporal ICA decomposition and removing eye-blink artifacts from the back-reconstructed time course [4].

2.3 Spatiospectral Group-ICA, Clustering of the Sources and Regression of the Timecourses

The preprocessed EEG signal from each lead was normalized such that the time course was normally distributed N(0, 1), and divided into 1.66 s epochs (i.e. the shortest repetition time of simultaneous fMRI acquisition [4]) without overlap. Each epoch was transformed to the spectral domain with fast Fourier transform (FFT), generating a vector (length = 67) of complex valued spectral coefficients between 0 and 40 Hz. Complex values were converted to relative power by taking the absolute value, squaring and dividing by the absolute power of the whole epoch. The output vector of 67 real relative power values comprised a 3D matrix $\boldsymbol{E}$ with dimensions n_t EEG epochs, n_c electrodes and n_ω spectral coefficients. The 3D matrix $\boldsymbol{E}(n_t, n_c, n_\omega)$ was transformed into a 2D matrix $\boldsymbol{E}(n_t, n_c * n_\omega)$ and used as input into spatiospectral group-ICA (Eq. 1) [3], returning a group mixing matrix $\mathbf{W}$ with dimensions $\boldsymbol{W}(n_t, m)$ and a group source matrix $\boldsymbol{S}$ with dimensions $\boldsymbol{S}(m, n_c * n_\omega)$. The dimension m is the number of decomposed ICs (m = 20).

$$\boldsymbol{E} = \boldsymbol{WS} \tag{1}$$

As described in [4], group-ICA was conducted followed by K-means clustering [11] (40 clusters) of the back-reconstructed individual spatiospectral maps for each paradigm. Forty output clusters were selected based on the elbow of residual variance and predictive residual variance curves for 2–250 output clusters (see Fig. S4 of our previous study [4]). Multiple linear regression was conducted between the timecourses of stable spatiospectral patterns in $\boldsymbol{W}$ and stimulus vectors, and statistically significant relationships were identified using one-sample t-tests computed on the regression coefficients.

3 Results

Twenty-one of the 40 output clusters were organized into 16 final K-means clusters (Fig. 1) whose spatiospectral patterns appear to be of physiological origin. Thirteen clusters were not included since their patterns consisted of single-frequency peak which appeared artefactual, and which was not present over the 3 paradigms. The remaining 6 excluded clusters contained less than 5% of single-subject patterns of at least one paradigm and are thus considered noise. Twelve of the sixteen patterns derived from relative EEG power were stable over all three paradigms (Fig. 1a, b). Of these twelve stable sources, ten appeared visually similar to patterns that were observed for absolute EEG power (Fig. 1a) [4]. Two stable γ-band patterns (Fig. 1b) were present with relative power but not with absolute power [4]. One cluster representing β-band activity (∼20 Hz) was present for SDT and VOT data but not RST (Fig. 1c). For the cluster number (cl. n.) 29, the spatial distribution of the pattern looks identical over paradigms, but the frequency peak within relative power maps appears to differ across paradigms (Fig. 2a). Three clusters contained maps (one θ-band and two γ-band patterns) which were present during RST but not SDT or VOT (Fig. 1d).

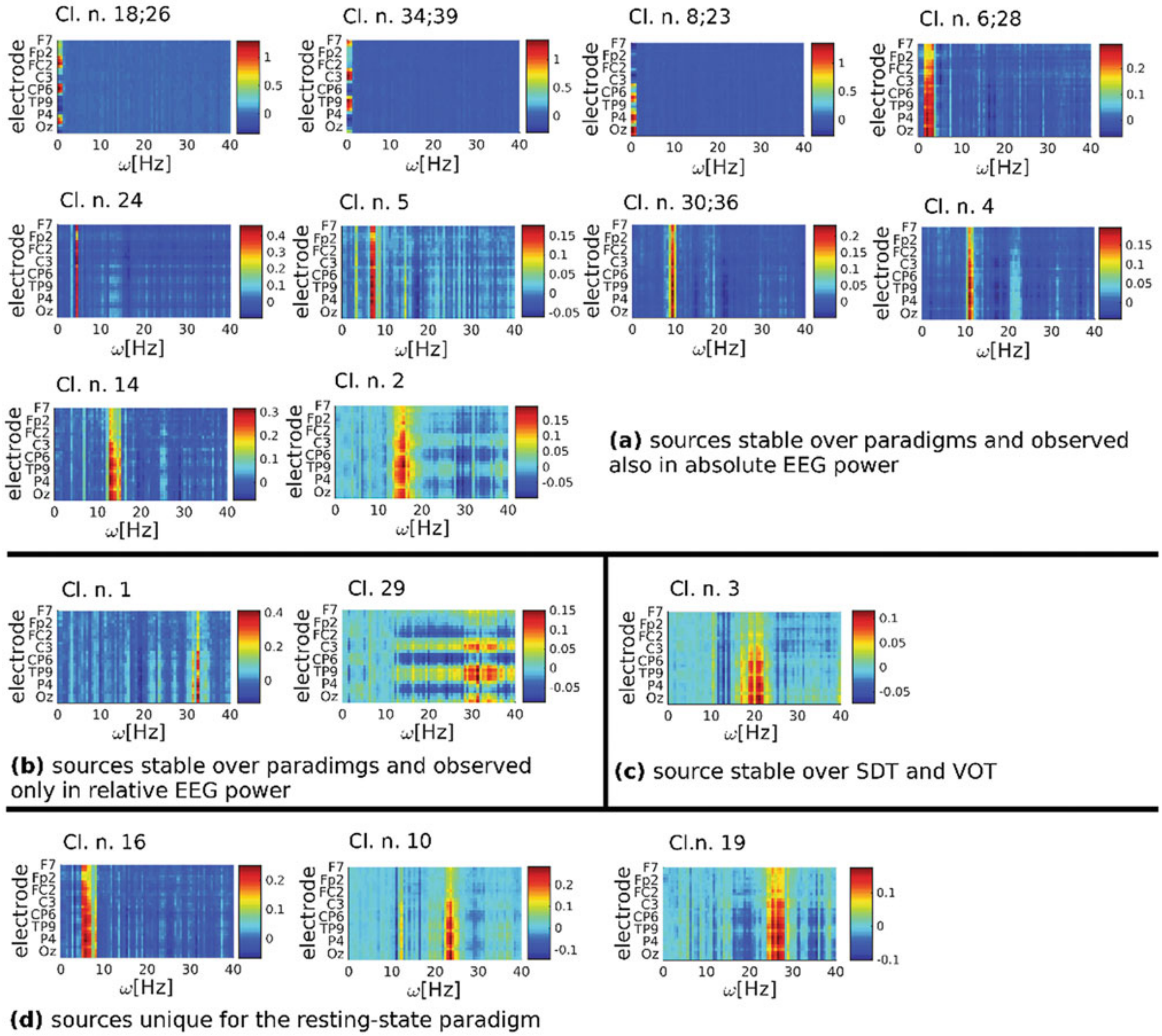

Fig. 1 Spatiospectral sources using relative EEG power as input to group-ICA

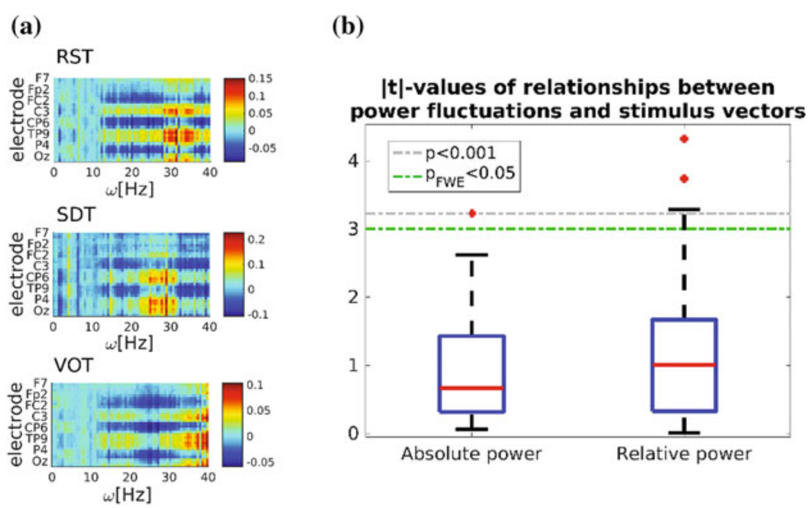

Fig. 2 **a** Similar spatial pattern and variable peaks in aggregated relative power of the cl. n. 29 over paradigms **b** relationships between timecourses of stable spatiospectral sources and stimulus vectors using absolute and relative EEG power as input to group-ICA

Although significant relationships with stimulus vectors were found for both power types, there appears to be no statistically significant difference in the distribution of |T|-values computed between the two (Fig. 2b). The difference between absolute or relative power relationships with the stimuli (Fig. 2b) is $p < 0.162$ based on two-sample t-test between distributions or $p < 0.150$ based on a 10 000 sample bootstrap test. |T|-values are not normally distributed, since the p-values of one-sample Kolmogorov-Smirnov tests are $p < 6.1 * 10^{-14}$ for the absolute power and $p < 1.8 * 10^{-12}$ for the relative power. Further research should be conducted to examine the potential influences of relative and absolute power map timecourses and stimulus timecourses.

4 Discussion

4.1 Novelty

The current study extends our recent study [4], by demonstrating that group ICA spatiospectral sources derived from relative power are stable across paradigms, and, we highlight the similarities and differences among relative and absolute power sources.

4.2 Absolute or Relative Power for Spatiospectral Group-ICA?

As previously shown for the absolute EEG power, we demonstrate here that relative EEG power also consists of stable spatiospectral patterns over paradigms. Although lower reproducibility of spatiospectral group-ICA estimates (using ICASSO [12]) has been observed and reported for sources derived from relative EEG power [4]. Ten stable sources were present within maps derived from absolute and relative EEG power, while two stable γ-band patterns (Fig. 1b) and 3 possibly physiological γ-band patterns (cl. n. 3, cl. n. 10 and cl. n. 19; Fig. 1c, d) were present with relative power but not absolute power. Relative power potentially emphasizes low energy signals which are obscured by the high energy low frequency which dominates absolute power measures.

We found significant relationships between stimuli and timecourses for both types of power values, with slightly higher t-values for relative power (although not statistically significant). This finding motivates further examination of task-related changes in EEG power fluctuations with relative and absolute power.

4.3 Limits and Possible Future Work

The spatiotemporal resolution (e.g. 30 electrodes and an epoch window time 1.66 s) can influence the group-ICA results and ultimately influence the relationship between the task and spatiospectral timecourses. Currently, we are capturing high-density (256-electrodes) EEG data where we will be able to decrease the epoch window time to durations that better capture evoked potential timing without undersampling. These findings can be compared with the present findings to better understand the influence of spatiotemporal resolution on group-ICA and the relationship between source timecourses and stimulus timing.

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