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Cortical surface alignment in multi-subject spatiotemporal independent EEG source imaging

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ABSTRACT

Brain responses to stimulus presentations may vary widely across subjects in both time course and spatial origins. Multi-subject EEG source imaging studies that apply Independent Component Analysis (ICA) to data concatenated across subjects have overlooked the fact that projections to the scalp sensors from functionally equivalent cortical sources vary from subject to subject. This study demonstrates an approach to spatiotemporal independent component decomposition and alignment that spatially co-registers the MR-derived cortical topographies of individual subjects to a well-defined, shared spherical topology (Fischl et al., 1999). Its efficacy for identifying functionally equivalent EEG sources in multi-subject analysis is demonstrated by analyzing EEG and behavioral data from a stop-signal paradigm using two source-imaging approaches, both based on individual subject independent source decompositions. The first, two-stage approach uses temporal infomax ICA to separate each subject's data into temporally independent components (ICs), then estimates the source density distribution of each IC process from its scalp map and clusters similar sources across subjects (Makeig et al., 2002). The second approach, Electromagnetic Spatiotemporal Independent Component Analysis (EMSICA), combines ICA decomposition and source current density estimation of the artifact-rejected data into a single spatiotemporal ICA decomposition for each subject (Tsai et al., 2006), concurrently identifying both the spatial source distribution of each cortical source and its event-related dynamics. Applied to the stop-signal task data, both approaches gave IC clusters that separately accounted for EEG processes expected in stop-signal tasks, including pre/postcentral *mu* rhythms, anterior-cingulate theta rhythm, and right-inferior frontal responses, the EMSICA clusters exhibiting more tightly correlated source areas and time-frequency features.

Introduction

Independent Component Analysis (ICA) has been widely applied to blind separation of statistically independent processes in time-varying event-related response data including functional magnetic resonance imaging (fMRI) and electroencephalographic (EEG) signals, without making use of a priori knowledge of the spatial distributions or temporal properties of the source processes summing to the observed responses (Hyvärinen, 1999; Makeig et al., 1996, 1997; McKeown et al., 1998). To identify functional processes shared by a group of subjects, several group-level ICA approaches have been proposed for fMRI analysis (see Calhoun et al., 2009 for a review). To integrate EEG data across subjects, on the other hand, some studies have concatenated the subject data temporally by assuming the recorded electrode channel locations to be spatially equivalent across individual subjects (e.g., Kovacevic and McIntosh, 2007; Marco-Pallarés et al., 2005; Vakorin et al., 2010), while other studies have used spatial concatenation, implicitly assuming that each stimulus presentation and/or task-related response has occurred at the same latency across trials (e.g., Eichele et al., 2008, 2009). The main feature of these approaches is to apply a single ICA decomposition to multi-subject data. However, it is well known that event-related EEG responses to stimulus presentations or time-locked to subject actions are in general not temporally consistent across trials, and their scalp topographies are not spatially consistent across subjects (for example, see Onton and Makeig, 2006; Onton et al., 2005). This is because the spatial projections of functionally equivalent cortical sources to the scalp electrodes can differ widely across subjects. As well, the peak latency, amplitude, and scalp distribution of all but the earliest brain responses to stimulus onsets can vary from one trial to the next within each subject, creating a data heterogeneity problem for multi-subject analysis.

An alternative approach to multi-subject ICA decomposition is to first perform single-subject ICA decompositions and then to cluster the resulting components into equivalence classes that share common

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spatiotemporal features (Langers, 2010; Makeig et al., 2002). However, a pair of either within- or between-subject derived independent components (ICs) may resemble and/or differ from each other in many respects — e.g., in their scalp maps, power spectra, event-related potential (ERP) time courses, and/or event related spectral perturbation (ERSP) and inter-trial coherence (ITC) time/frequency images (Makeig, 1993; Makeig et al., 2004). The issue of how to find equivalent IC clusters or categories across subjects is thus theoretically non-trivial and may be viewed as an indeterminate problem in the ICA EEG analysis model itself, whose optimal solution depends on the nature of biological consistency across individuals as well as methodological efficiency.

ICs have been commonly clustered into homogeneous groups by comparing their scalp topographies, and several studies have proposed and assessed methods for clustering ICs according to their cortical locations estimated from the scalp topographies (De Lucia et al., 2010; Delorme et al., 2007; Knyazev et al., 2011; Makeig et al., 2002; Marco-Pallarés et al., 2005; Milne et al., 2009; Onton et al., 2005; Pockett et al., 2007; Ponomarev et al., 2010). The source imaging methods applied in these studies are mainly performed in a two-stage manner, e.g. as supported by the EEGLAB software environment (Delorme and Makeig, 2004). First, ICA decomposes the data from a cognitive task of interest into temporally and in many cases functionally distinct IC processes. Then, to assist in anatomic and functional interpretation of the component process a source localization/imaging method is used to estimate the cortical locations of the individual ICs from their scalp maps given by the individual columns of the ICA unmixing matrix. For example, each component may be modeled as one (or occasionally two) equivalent current dipoles (e.g., Makeig et al., 2002; Milne et al., 2009; Onton et al., 2005; Pockett et al., 2007; Ponomarev et al., 2010; Zhukov et al., 2000), or as a current-source density distribution (e.g., Congedo et al., 2010; De Lucia et al., 2010; Delorme et al., 2007; Marco-Pallarés et al., 2005; Ponomarev et al., 2010).

However, identifying equivalent ICs by directly clustering either their scalp maps or equivalent dipole locations computed from the identified IC scalp maps may be prone to error; a group of ICs may have similar scalp maps but functionally different source locations, and functionally equivalent cortical sources may have quite different brain and scalp distributions. Fig. 1 illustrates this problem. Fig. 1 shows a simulated EEG source (top row) consisting of mixtures of two Gaussian-tapered cortical patches (occupying approximately 163.7 mm^2 in the superior parietal gyrus) based on a group-averaged inflated model in the left hemisphere cortex, and its projections onto the spherical topographies of five subjects using the FreeSurfer cortical area parcellation applied to five subjects' MR head images (MGH, Harvard Medical School, available from http://surfer.nmr.mgh.harvard.edu; Dale et al., 1999; Desikan et al., 2006; Destrieux et al., 2010; Fischl et al., 1999). FreeSurfer reconstruction has been widely used in EEG/MEG source imaging analysis over the last few years, e.g., in the MNE software (Hämäläinen, 2009) that computes cortically-constrained L2 minimum-norm current estimates from MEG/EEG signals, allowing group analyses to be computed in the same space.

Here, as shown in Fig. 1, by identifying and warping the subject cortical models to a common template (topmost), the prominent cortical sulci of the inflated cortical models of our five subjects (row 2) after co-registration of their major sulci. Below this are shown the locations on the five original fully-inflated (row 3) and native (not-inflated, row 4) cortical models for each subject, and below these, the scalp projection (scalp map) for each of these functionally equivalent sources, as computed using boundary element method (BEM) forward electrical head models constructed from an MR head image for each subject (Akalin Acar and Makeig, 2010). Because details of cortical topology and folding differ across the subjects, both the spatial locations and orientations of equivalent cortical areas and their scalp projections vary widely. The lowest two rows show the equivalent current dipole (Scherg and Von Cramon, 1985; Scherg and Voncramon, 1986) for each simulated component scalp map in a standard MNI template brain (Maintz and Viergever, 1998), computed using *dipfit*() (Oostenveld and Oostendorp, 2002) in EEGLAB, and sLORETA-computed source current density distributions in the individual subject cortical surface models (Pascual-Marqui, 2002). The topological (and presumed functional) equivalence of the five simulated sources is not apparent either from the component scalp maps, equivalent dipole source locations, or distributed sLORETA source current density estimates.

This inter-subject spatiotemporal heterogeneity of functionally equivalent cortical sources and their scalp projections raises an important question about how best to perform multi-subject source-level comparison in EEG studies. However, Fig. 1 also suggests a possible solution. Here, unlike the now conventional two-stage approach that localizes the cortical source of each IC from its scalp map, we use spatiotemporal EMSICA decomposition to decompose directly the continuous or concatenated trials EEG data into spatiotemporal components whose active source areas are identified by a distribution of cortical voxels on an MR-image derived model of the individual cortical surface. The so-identified active IC source areas are then spatially registered across subjects within a common spherical inflated-cortex model to which the individual cortical surface models have been warped and co-registered. Their event-related dynamics, in the form of ERSP and ITC images, are then co-registered on a common latency/frequency grid.

The Methods section below gives an overview of single-subject ICA approaches to EEG source localization and imaging, followed by a detailed elaboration of the spatiotemporal alignment scheme and its use for multi-subject comparison. The proposed cortical alignment scheme is applied to ICs identified in an experimental data set using two decomposition approaches, one a conventional two-stage approach using IC scalp maps contained in the temporal ICA unmixing matrix to estimate IC source densities (Makeig et al., 2002). The other is the Electromagnetic Spatiotemporal Independent Component Analysis (EMSICA) method that combined temporal ICA decomposition and source density estimation into a single spatiotemporal model estimation process (Tsai et al., 2006).

The experimental data were collected from eleven participants in a self performance-monitoring and -inhibition stop-signal paradigm (SSP) (Logan et al., 1984; Savostyanov et al., 2009). The results included spatiotemporal ICA component processes in visual, motor, frontal and anterior cingulate cortical areas. The significance of the cortical activation topographies and directions for future work on multi-subject EEG source imaging are highlighted.

Methods

The step-by-step procedure of our proposed multi-subject EEG source imaging analysis approach includes: (a) realistic single-subject forward electrical head modeling, (b) single-subject EEG data preprocessing and spatiotemporal independent source decomposition (either using ICA followed by source localization or projection of the data onto the cortical surface followed by EMSICA), followed by, (c) multi-subject cortical surface alignment, (d) event-related spectral perturbation (ERSP) and/or other measure computation using, if relevant, (e) trial-to-trial latency alignment, and finally, (f) IC source clustering.

Experiment design

Eleven healthy right-handed males (ages 26 ± 3 years) participated in a stop-signal (SSP) experiment to investigate brain active source areas and associate event-related power changes involved in rapid motor response initiation and inhibition. Participants were presented with a picture (a deer or a tank) at roughly 4-s intervals and were asked to respond to each picture by pressing one of two buttons using their right or left thumb, respectively, thereby choosing a weapon (a rifle or an anti-tank rocket launcher) to shoot at the target (Savostyanov et al., 2009). The 'deer' and 'tank' stimuli were presented