An Approach for Fusion between EEG and fMRI Data

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Introduction Localizing neural activity in the brain, both in time and in space, is a critical challenge to understanding brain function[1]. Researchers have developed a number of techniques to explore this problem. FMRI and EEG are commonly recognized as two core non-invasive functional brain imaging technologies. EEG is a direct measurement of the bioelectrical activity and fMRI is a measurement of the metabolic activity (hemodynamic response) coupled to neural activity. Here, we present an independent component analysis (ICA) approach to fuse ERP and fMRI signals and show using simulations and data collected during an auditory oddball task that incorporating multiple channels improves the results.

Methods

Paradigm and data acquisition Twenty two healthy participants, including 14 male, 8 female, were recruited at Hartford Hospital, all with normal hearing, no central nervous system disease history and capable of performing the task well during training before the scanning session. Each received fMRI and EEG for auditory oddball paradigms on the same day in two different sessions, Three stimuli are presented - the standard stimulus of a 0.5kHz tone with a probability of 0.8, the target stimulus of a 1kHz tone and the novel stimuli of random digital each with a probability of 0.1. fMRI scans were acquired on a Siemens Allegra 3T (TR=1.5s, TE=27ms, 3.75*3.75*4mm3, 29 slices) and preprocessed by SPM2, finally resulting in 53*63*46 voxels. The ERP data were collected using an SA bioelectric amplifier system, preprocessed to reduce ocular artifacts and electromyographic and constructed for trials in which target stimuli were clearly recognized, resulting in 250 time points[1].

Joint multi-channel ERP/fMRI analysis As an advanced and important statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals, Independent component analysis is widely used in blind source separation that attempts to decompose a data set into maximally independent components.[2] Here, we use a joint ICA method to access the fused components that reach both spatial and temporal independence maximally. Each data type is first reduced to a feature first. Then we use the following generative model for the data: $X^{(m)} = AS^{(m)}$, $m=1:M$ by assuming each modality are jointly spatial or temporal independent m is the modality index, $S^{(m)}$and $X^{(m)}$ are the $S{\times}V$ source and data matrix for modality , respectively. We use an algorithm based upon information maximization, and thus maximize the logarithm of the likelihood given above to estimate W given data from all modalities using natural gradient updates to write the update rule for two modalities as $\Delta \mathbf{W} = \eta \left\{ \mathbf{I} - 2\sum_{m=1}^{M} \mathbf{y}^{(m)} \left(\mathbf{u}^{(m)}\right)^T \right\} \mathbf{W}$, where $y^{(m)} = g(u^{(m)})$ and $g(x) = 1/(1+e^{-x})$ and is the nonlinearity chosen as the sigmoid function [1].We compute features for fMRI activities (FMRI) and ERP activities from (1) the cz channel (ERP_CZ), (2) the 1st component of all the channels (ERP_1ST) after a principle component analysis (PCA), (3) all the channels (ERP_ALLCHANs), (4) the pseudo inverse of the 1st component reconstructed back to all the channels (ERP_1STRE), (5) the pseudo inverse of the first 10 components back to all the channels (ERP_1ST10RE), (6) the pseudo inverse of 90% components back to all the channels (ERP_90PRE). Then we perform a joint ICA analysis algorithm between features of fMRI and 1) to 6) to estimate the fused fMRI and ERP sources.

Simulation We present the effectiveness of jICA method and compare the difference of results from between ERP entries by adding known virtual sources with specific noise into the original fMRI and EEG data. In our simulation, the virtual source for fMRI was created into a two dimensional spatial map of 53*63 voxels (Figure 1a), as the same size of the real data, while the virtual ERP sources are a sine wave for single-channel methods or sine waves combined with mulsti-channel EEG scalp distribution map (Figure 1b-1d) [3]. In order to compare the detectability of different channels, we also tune the dipolar location on the scalp potential map. All the hybrid data are normalized and interpolated before applying jICA to separate the sources.

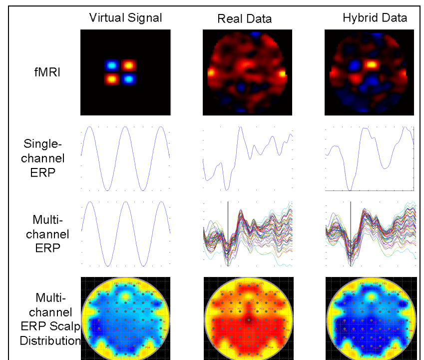


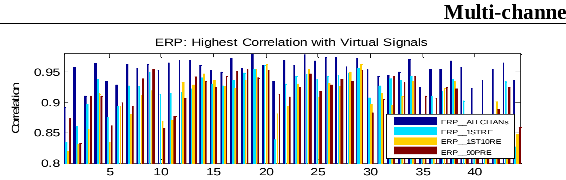
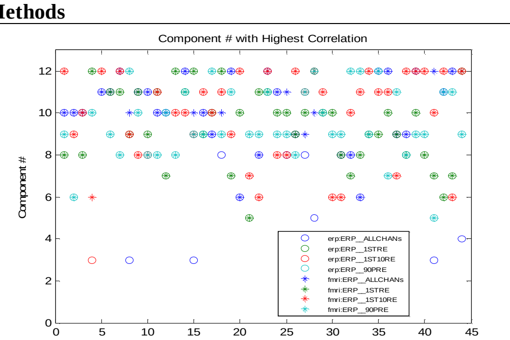
Figure 1. a-c. the generation of hybrid data for fMRI, single-channel ERP and multi-channel ERP, by adding virtual signal with random effect to the real data. **d**. the multi-channel ERP signals in spatial domain with interpolation at the time point t=190ms, i.e. the black vertical lines marked in **c**.

Results The number of components in the jICA analysis was estimated to be 12 based on the minimum description length criteria[1], and 13 for the simulation analysis. The components were ranked by their contribution to the average ERP time courses by first regressing the components onto the average ERP data, then computing the maximum absolute peak of the fitted time courses. Regions in the fMRI component were scaled to Z values and a voxel was colorized if it was greater than Z = 2.5. For the simulation, the correlations between virtual sources and independent components for all six methods were calculated and compared. The highest correlations for both ERP and fMRI data were determined. For all six methods, the ERP components match separate peaks on the average time courses very well. Also, by observing ERP and fMRI components together, different peaks at ERP time courses shows a high correlation with different regions of activities at fMRI maps, which presents an obvious spatialtemporal dynamics of auditory oddball target response. For example, the P3 component is proved to be associated with fMRI activity in thalamic regions and posterior superior parietal lobe areas. By the comparison of simulation (table 1), we found that the matching ratio of components with the highest correlation to the virtual sources is 82.978%. With multi-channel information (method 2-6) the ERP components correspond better to the sources than those retrieved from the single channel (ERP_CZ). Also, with dipolar located close to cz channel it works better than other distributions.

Discussion In our work, an improved method to obtain spatiotemporal information of AOD response is provided by fusing single/multi-channel EEG and fMRI hemodynamic target-related signals. The method uses and PCA for data reduction, pseudo calculation for data reconstruction and jICA for capturing relationships between different modalities. Therefore, we are able to enhance the visualization of neural activity responses and the revelation of the correlation between EEG and fMRI signal recorded correspondingly.

Reference 1) Calhoun et al NeuroImage, 2006;30:544-553 2) Hyvarinen, ICA, JW&S 2001 3) Moosmann et al, INT J PSY 2007.

Table 1 The highest correlation between virtual sources and independent components and the matching of the component numbers

Methods	ERP	FMRI	Multi-channel Methods	
ERP_CZ	0.8854 Comp #13	0.8967 Comp #13		
ERP_1ST	0.8717 Comp #9	0.8939 Comp #9