Symmetric analysis of EEG and fMRI using nonlinear models: a Simulation Study

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***Abstract*—In this paper, we introduce a new method of symmetric analysis of Electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) data. We consider each signal as a projection of the real neural activations to find spatial sources and their related temporal sources. We use the sparsity of activated voxels as a constraint for solving the localization problem. Simulation results illustrate superiority of our method compared to the previous methods.**

I. Introduction

The purpose of EEG and fMRI integration is to achieve high spatial resolution of fMRI and high temporal resolution of EEG simultaneously. Multimodality analysis has been a focus of several research activities in recent years. The common purpose of these methods is to benefit from advantages of both modalities. Integration of EEG and fMRI is of particular interest because of the feasibility of their simultaneous acquisition.

Algorithms proposed to analyze EEG and fMRI can be divided in two groups. The first group uses a modality as an auxiliary data for analyzing the other modality data [1–4]. the second group called symmetric uses both EEG and fMRI data jointly to find spatiotemporal sources. In [5–7] methods based on independent component analysis (ICA) have been proposed. An approach in a variational Bayesian framework has also been proposed in [8]. These methods are based on linear models for EEG and fMRI.

Here, we use a nonlinear model for fMRI to jointly analyze EEG and fMRI and achieve higher resolutions in time and space. The proposed method is symmetric which means that it uses both of the EEG and fMRI data simultaneously to estimate spatiotemporal characteristics of the sources. To achieve symmetry, we have assumed that EEG and fMRI are two projections of the same activation map.

As fMRI models have shown that BOLD signal has a nonlinear relation with neural activations [9, 10], we have assumed that fMRI is a nonlinear projection of the activation map.

Sparsity which is a strong constraint for solving optimization problems is not obvious in the problem of EEG and fMRI fusion. We rewrite EEG and fMRI model to find sparse parameters which is the voxel activation and use sparsity to reach better results.

We have applied our new algorithm on simulation data of two sources generating EEG and fMRI signals. The proposed method extracts the time series of the sources in the resolution of EEG and their positions in the resolution of fMRI. Comparing with the most similar algorithms in the literature (Joint ICA and Parallel ICA), simulation results show superiority of the proposed method.

The paper is organized as follows. In Section 2, algorithms for temporal and spatial analysis are stated. Section 3 explains the generation of simulation data. Section 4 shows simulation results. Finally, conclusions are presented in Section 5.

II. Methods

Neural activations appear in different places and change in time. In medical imaging, we are interested in spatial and temporal specifications of the sources. The temporal and spatial analysis parts are executed separately although they have dependency. Temporal analysis leads to the identification of the time series of activations. The result of temporal analysis is used in the spatial analysis part of the method to find the locations of activations.

A. Temporal Analysis

In temporal analysis we use the ICA method to find the time series of activations. The EEG forward problem can be modeled with a linear equation.

$$M = G \times J + E \tag{1}$$

where M stands for the $e \times t$ matrix of observations recorded by the electrodes, J is the $n \times t$ matrix of the unknown source activations in dipoles, G is the $e \times n$ forward gain matrix, and E is the $e \times t$ error matrix. e, t, n are respectively the number of electrodes, time points, and sources. One of the recent methods of solving linear problems is the ICA. With the independence assumption of activations, we can use the ICA algorithms to find activation time series. To estimate the sources, we use the algorithm proposed in [11], which is based on the mean field approach. Source codes of this probabilistic ICA algorithm are available at [12].

B. Spatial Analysis

In this step, we model the electrode signals using the time series of activations. As depicted in (1), the EEG signal is a linear combination of activations. Forward gain matrix can be estimated from structural MRI using finite element method (FEM) or binary element method (BEM). We assume that a dipole exists in the center of each voxel so the gain matrix computed from FEM or BEM should be used to compute the forward gain for the center of each voxel. Each row of G related to each voxel is estimated as follows:

1) Find three nearest mesh vertices to the center of each voxel.
2) Compute the mean of the three related rows of the forward gain matrix computed from FEM or BEM.

We can assume that the electrical signal in each voxel is a linear combination of activations found in the temporal analysis step. We can model the dipole currents in (1) as:

$$\acute{J} = SM \times T_a \tag{2}$$

where SM is the $v \times n$ matrix for spatial map and T_a contains activation time series in its rows, and v is the number of voxels. In other words, SM maps the activations to the voxel signals. Here $\acute{J}$ is different from J in (1). J contains activation dipole currents but $\acute{J}$ contains currents of all assumed dipoles in the centers of voxels. It means that many rows of $\acute{J}$ is zero or noise. With this model, we can estimate the EEG signal in the electrodes using:

$$EstimM = G \times SM \times T_a \tag{3}$$

where SM is unknown and G is the known $e \times v$ matrix.

The fMRI data are nonlinear observations of the activations of the voxels. Here, we compensate nonlinearity in the fMRI data by increasing linear data correlation [13]. This algorithm is based on the fact that the inverse of the nonlinearities can be approximated by maximizing the linear correlations between the observations as proved in [13]. We consider each voxel of the fMRI data as an observation. The result of the nonlinear compensation is called LinfMRI in the rest of the paper. Also, we convolve the activation time series with the hemodynaic response function (HRF) using the HRF model suggested in [14], and resample it at the fMRI sampling intervals, called *BOLDSignal* in the rest of the paper.

With these assumptions, we can model the *LinfMRI* as a linear combination of the *BoldSignal*. Here, we choose the same spatial matrix of the EEG signal for computing the BOLD signal of each voxel from the *BOLDSignal*. This assumption is true as the neural activation is the same for the EEG and fMRI. Thus, we have:

$$LinfMRI = S \times SM \times BOLDSignal \tag{4}$$

where S is the unknown $v \times v$ matrix of scaling.

We use a simple descent gradient algorithm to find SM and S to minimize the error between the estimated signals and the observations for both of the EEG and fMRI signals in a loop. Although we have combined two modalities, the problem is

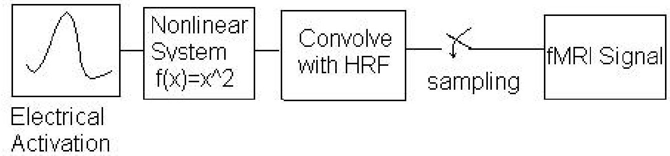


Fig. 1. A block diagram of fMRI signal generation

still ill-posed, therefore we use sparsity condition for the SM matrix. The SM rows represent the portions of activations of sources due to the related voxels. Because of the fact that in a brain study many voxels are inactive, many elements of SM are zeros, therefore it is a sparse matrix. We apply sparsity with l1 norm constraint for the error minimization as follows:

$$e_1 = M - G \times SM \times T_a \tag{5}$$

$$e_2 = LinfMRI - S \times SM \times BOLDSignal \tag{6}$$

$$ObjectFunc = \mu_1 e_1^2 + \mu_2 e_2^2 + \mu_s \sum_{i,j} |SM_{ij}| \tag{7}$$

III. Simulation

We test the proposed algorithm with the simulation data. For simplicity, we use two dimensional simulations which can be generalized to three dimensional simulations and real data.

The slice of the simulated brain has 100 voxels (10 by 10) with two sources in the 22nd and 78th voxels. The activation signals of the sources are 100msec long as shown in Figure 2. We put four electrodes in the four corners of the slice. We use a simple EEG forward gain matrix (G) and compute the signals of the electrodes as $e = Gs+n$. The value of G does not affect the algorithm, and in real data as described before it can be estimated from the structural MRI. In our simulation, each element of G is equal to the inverse of the distance between the center of the voxel and the related electrode.

We use the method of [1] to generate the fMRI signal. We compute the BOLD signal by convolving the square of the electrical activation signal with the HRF as follows [1].

$$h(t-\varepsilon) = \frac{(t/\tau)^{n-1} e^{-(t/\tau)}}{\tau(n-1)!} \tag{8}$$

where $n = 3$, $\tau = 1.25s$ and $\varepsilon = 2.5s$ as in the default settings of the BrainVoyagerQX software [1].

Each spike of neural activation produces an HRF shaped signal as a BOLD signal. The HRF is assumed 12s long and each fMRI sampling rate is 3s in our simulation so we have four temporal samples for each voxel (see Figure 1).

IV. Results

Results of the temporal and spatial estimation of the sources are shown in Figures 3(a) and 3(b), respectively. We have compared these results with three most similar methods in the literature, i.e., joint ICA [5, 6] called here jICA1 and jICA2, respectively and Parallel ICA [7] method called here pICA.

JointICA uses the ICA algorithm to separate sources from an observation matrix which is made of the EEG signals of the

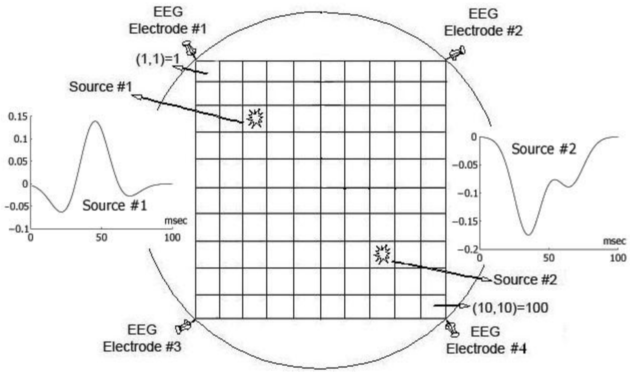


Fig. 2. Simulation Schematic

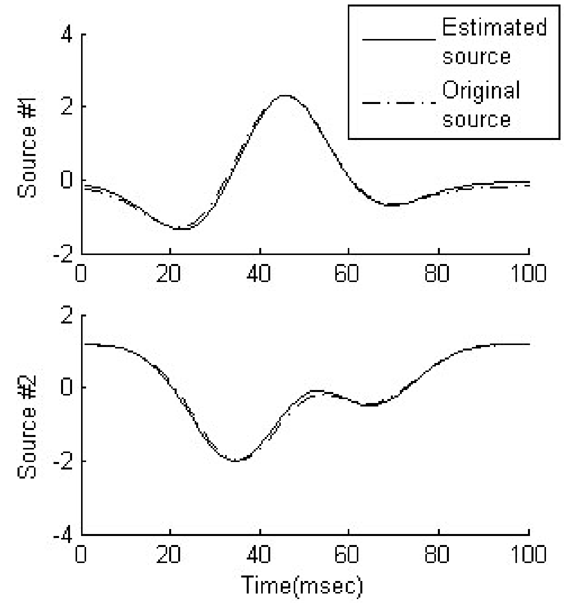
TABLE I
TEMPORAL AND SPATIAL CROSS CORRELATION FACTOR OF ORIGINAL SOURCES AND ESTIMATED SOURCES IN FOUR METHODS.

CC		jICA1 [5]	jICA2 [6]	pICA [7]	OurMethod
Temporal	Source1	0.9974	0.9842	0.7940	0.9440
	Source2	0.9961	0.9238	0.1370	0.9931
Spatial	Source1	0.2046	0.1205	0.0895	0.9338
	Source2	0.1097	0.1433	0.0752	0.9753

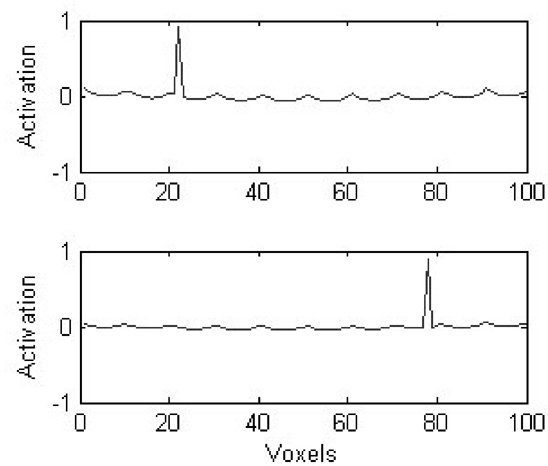
electrodes in rows concatenated with the fMRI spatial samples at different times.

The EEG signals of the electrodes can be considered as linear combinations of the neural activations. In comparison, the fMRI data are nonlinear combinations. Thus, the EEG signals are dominant. The results of the JointICA algorithm shows that the time series of the neural activations is found precisely, but the spatial activations related to the fMRI data are weakly estimated.

In parallel ICA, linear relations between the EEG and temporal activations and also between fMRI data and spatial activations are assumed. An extra assumption exists in the idea of the parallel ICA algorithm which is that the EEG and fMRI data are estimated linearly from the temporal and spatial series of the activations with the most correlated mixing matrix. This idea would result error in both temporal and spatial estimation. In the parallel ICA, EEG and fMRI are used to estimate different parameters therefore, the EEG signal is not the dominant data and the error propagates to both estimations.



(a)



(b)

Fig. 3. Sources estimation results. (a) Sources time series and (b) Voxel activation related to each source time series.

V. CONCLUSION

We have proposed a symmetric method for jointly analyzing the EEG and fMRI data using sparsity. Considering nonlinearity of the fMRI helps us to model the EEG and fMRI with the same sparse parameter. Using sparsity as a constraint for the error minimization of the model results in convergence of the optimization algorithm. Although our proposed method is simple, the simulation results illustrate superiority of our method compared to the previous methods.

One drawback of our method is that in the temporal estimation step we just used the EEG data. Add the fMRI data to the temporal estimation would increase the computational complexity as they are nonlinear observations of activations. Also, the fact that we have limited samples of the fMRI data versus the EEG data decreases the effects of fMRI data on temporal estimation process.

From another point of view, the proposed method is similar to GLM method. Its temporal and spatial parts can be considered as finding regressors from the EEG data and finding the activation levels from the GLM method. The difference between the proposed method and the GLM is that in the proposed method, both of the EEG and fMRI data are used to find the activation levels. In other words if we omit the EEG signal from the spatial part of the proposed method it would be equivalent to the GLM method. The most interesting point here is that never the GLM has been used to estimate the activation levels of all voxels simultaneously. As such, the GLM would not notice the sparsity of the activation maps, contrary to the proposed method which based on the integration of sparsity in the estimation of the activation maps.

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