Original Article

# Removing the Effect of Hemodynamic Response Function in Joint Factorization of EEG and fMRI Datasets

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## Abstract

**Purpose:** One of the most well-known multimodality techniques is the integration of EEG and fMRI datasets. Convolution of EEG signals with hemodynamic response function is one of the most important methods to consider the effect of HRF in the fusion of EEG and fMRI data. However, the latencies and amplitudes of ERPs and fMRI spatial components are affected by the low pass filtering effect of HRF in each trial.

**Materials and Methods:** In this paper, we have proposed a new method based on Advanced Coupled Matrix Tensor Factorization model to jointly factorize the EEG tensor and fMRI matrix while we simultaneously remove the effect of HRF through decomposition of fMRI dataset.

**Results:** Applying the proposed method to an auditory oddball paradigm of simultaneous EEG-fMRI recording, the well-known ERP of oddball paradigm and the corresponding fMRI spatial maps are estimated.

**Conclusion:** The results demonstrate that our proposed approach is strongly capable of extracting the ERPs and their corresponding fMRI spatial components, while simultaneously estimates the trial to trial variations of these factors with accurate amplitude and latency in each trial.

## 1. Introduction

Recently, the multimodality techniques are extensively used for the analysis of the brain functions due to their complementary natures. One of the mostly widespread multimodality approaches is the fusion of Electro-Encephalo-Graphy (EEG) and function Magnetic Resonance Imaging (fMRI) data. The temporal resolution of EEG signals is very high while, their spatial resolution is too low. On the other hand, the spatial resolution of fMRI recording is very fine and the whole brain is covered by fMRI scans, but the hardware limitations and the low pass nature of hemodynamic function result in poor temporal resolution of fMRI signals.

In many papers [1-3] Blood Oxygenation Level-Dependent (BOLD) signal is modeled as the convolution of neural signals with Hemodynamic Response Function (HRF). Although fMRI data is not the direct acquisition of neural activity, with its valuable high spatial resolution, the locations of brain activities can be directly inferred from fMRI scans.

Many algorithms have been developed in recent years to fuse EEG and fMRI data. In most of these methods, the data are formed as matrices and then the decomposition techniques are applied. For example, Canonical Correlation Analysis (CCA) [4], joint Independent Component Analysis (jICA) [5], and Independent Vector Analysis (IVA) [6] are among these

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approaches. In [7], the authors used CCA method for fusion of EEG and fMRI data in order to detect the covariation between the trial-to-trial Amplitude Modulations (AMs) of an auditory task involving implicit pattern learning. In [8] Calhoun *et.al.* used the IVA method to remove the fMRI gradient artifact from the simultaneous recording of EEG data with fMRI. In [9], jICA method is applied on an auditory oddball paradigm for fusion of EEG and fMRI data. Many other studies have investigated EEG and fMRI datasets separately and then evaluated the correlation between the results for further analysis [10].

The neuroimaging datasets convey many pieces of information and features about the whole brain. However, using the matrix factorization tools does not reveal the interdependency of these pieces of information [11]. For example, EEG is a multivariate data with different modes like channel, trial, time, spectrum and subject. Although the matrix factorization methods can extract the relation of two variants in the data, the other important features will be neglected due to the limitation of matrix representation. Using the other important dimensions of the neuroimaging data is possible by employing the tensor decomposition tools [12].

Tensors are arrays with more than two dimensions, which provide us with the natural representation of multivariate datasets. Beside their ability to represent data with true dimensions, we can obtain a unique factorization of data without imposing any additive constraint. Adding more dimension to the data is equivalent to addition of diversity to the model which has been proved by [13], as a reason for unique representation of tensor factorization methods. It has been proved in [14] and [15] that in comparison with matrix factorization approaches, tensor factorization algorithms have more relaxed conditions for unique decomposition. Therefore, beside their inherent ability for natural representation of multivariate data, their interesting uniqueness condition makes them very powerful tools for fusing the large datasets.

Tensor decomposition is a broad research area. The most famous decomposition methods are Canonical Polyadic decomposition, Tucker decomposition, and block term decomposition. There are also some other techniques that have been mentioned in [14] and can be used for specific problems. We have divided the literature of tensor decomposition applications on neuroimaging datasets into two categories: Single Modality and Multi-Modality. As an example for single modality approach, in [16], the authors use tucker decomposition to detect the change points of brain dynamic connectivity using EEG dataset. In this paper, we focus on multimodality approaches based on tensor factorization models.

There have been many studies investigating the application of tensor decomposition in neuroimaging data [17, 18]. However, only a few of them have studied EEG and fMRI. The recently coupled tensor factorization methods are employed for EEG-fMRI data fusion. The Coupled Matrix Tensor Factorization (CMTF) method beside its further extension, the advanced CMTF, has been used in many studies to investigate the common and uncommon information in multimodal datasets.

The authors in [19] have proposed the coupled matrix tensor factorization model. This model is capable of fusing multiple datasets, where they can be formed as matrix or tensor. Furthermore, one or two common factors can be selected to integrate the modalities. Due to the interesting features of CMTF method, it has had many applications for fusion of neuroimaging datasets [20].

The structural revealing method or advanced CMTF has been proposed in [21], which is one of the variants of CMTF model for joint factorization of a matrix and tensor. However, the ACMTF method can decompose the datasets into shared and unshared signatures, but CMTF model only considers the shared components. In [22], the author used ACMTF method to remove the ocular movement in the simultaneous acquisition of EEG data and the eye movements. In [23], Acar *et al.* analyzed the EEG and fMRI datasets of schizophrenia patients and the healthy control employing the ACMTF method. To have a common mode between EEG and fMRI data the subjects are arranged in a common dimension.

In [20], CMTF model is applied for some application in area of fMRI and EEG data fusion. For example, the author has employed CMTF method for localization of the brain dipoles using the data recorded by EEG electrodes and fMRI scans. Therefore, the spatial factor in two modalities is considered as the common factor.

Moreover, the author has utilized an extension of CMTF model that breaks the factors into shared and unshared blocks and estimates each block separately. The method is called discriminative subspaces [24]. In this method, the number of shared components must be known, while in ACMTF the number of shared components is estimated.

In [7], the author used the trial to trial co-variation of EEG and fMRI data as a common factor to analyze the data with CCA method. In [7], EEG data is convolved with HRF in order to share similar variations with fMRI and extract the common profile. This approach results in poor inference from the estimated temporal component of EEG data because they are the convolution of HRF and neural signals.

In this paper, we have employed the ACMTF model to simultaneously fuse EEG and fMRI dataset of an auditory oddball paradigm. The EEG signal is considered as a tensor with three dimensions in trials, epochs and channel topographies and fMRI dataset as a matrix with trials (Scans) and voxels as its two dimensions. Then, the trial mode is assumed to be the same across the two modalities. To remove the effect of hemodynamic response function, we have decomposed the fMRI signal by considering the effect of the HRF. This is obtained by modelling the BOLD signal as a matrix multiplication of the HRF convolutional matrix and the underlying trial to trial variation of neural signal. As a result, the common amplitude modulation in EEG and fMRI datasets are estimated across the trial mode while simultaneously we do not convolve EEG temporal signal with HRF. Consequently, as we use the tensor decomposition properties, we remove the effect of hemodynamic response function in simultaneous fusion of EEG and fMRI data, therefore we can extract the accurate amplitude and latency of brain activities in each trial.

The structure of this paper is as follows. In section II, a background of tensor decomposition methods and the ACMTF model are introduced and our method for removing the effect of hemodynamic response is explained. In section III, the experimental results are illustrated. A conclusion is then added to the paper, in section IV.

# 2. Materials and Methods

## 2.1.Tensor Decomposition

Multiway arrays known as tensors are matrices with higher dimensions. PCA, SVD and other matrix factorization tools decompose a matrix into two factors describing the features of data along its two dimensions. For multivariate datasets like EEG with many features such as, channel, trial, epoch, spectrum, etc., tensors are proper choices to extract the interdependency of underlying factors. Considering a multiway tensor $\chi$, there are various decomposition techniques with different properties. Canonical Polyadic Decomposition (CP) or PARAFAC is a strong method due to its uniqueness property. Besides CPD, Block Term Decomposition and Tucker decomposition are well-known methods in the literature.

Assuming $\chi \in \mathbb{R}^{I \times M \times N}$ as a three-way tensor, its CP decomposition is expressed as follow [18]:

$$\chi = \sum_{r=1}^{R} \lambda_r a_r \circ b_r \circ c_r \qquad (1)$$

where $a_r$ ,$b_r$ ,$c_r$ are the components along the first, second and third mode, respectively, R is rank of $\chi$ and $\lambda_r$ is the corresponding weight. The symbol "$o$" represents the vector outer product.

## 2.2. ACMTF

In ACMTF, the tensor data is factorized by the CP decomposition model and the matrix data is decomposed by SVD model:

$$f(A,B,C,V) = \|\chi - [[\lambda; A,B,C]]\|^2 + \|Y - A\Sigma V^T\|^2 + \beta\|\lambda\|_1 + \beta\|\sigma\|_1 \quad s.t. \quad \|a_r\| = \|b_r\| = \|c_r\| = \|v_r\| = 1 \quad for\ r = 1,\ldots,R \qquad (2)$$

In this objective function $\chi$ is a tensor with three modes in which A, B and C are its factors along mode 1, mode 2 and mode 3, respectively. Y is a matrix, which is coupled with $\chi$ in the first mode or dimension. $\lambda \in \mathbb{R}^{R \times 1}$ and $\sigma \in \mathbb{R}^{R \times 1}$ correspond to the weights of rank-one components in the third-order tensor and the matrix, respectively.

The objective function extracts the common profile A in (2) between two modalities and considers shared and unshared components. The shared components are obtained by estimation of $\sigma$ and $\lambda$. This is achieved by minimizing $\| \lambda \|_1$ and $\| \sigma \|_1$ to impose sparsity on the weights. As a result, the two components that are shared between modalities have simultaneous significant values in $\sigma$ and $\lambda$.

The common approach for optimization of loss function is based on Alternating Least Square (ALS) method, but the author in [19] applied non-conjugate gradient method due to its faster convergence in comparison to ALS approach. For this purpose, the gradient of objective function with respect to each unknown variable is computed and then updated using Pablano toolbox [25].

## 2.3. Modelling the Hemodynamic Response Function

A common factor between the EEG and fMRI datasets must be selected prior to the integration of two modalities. In this study, the trial factor is chosen to be common across the two datasets. This factor reflects the variation of brain activities in trial to trial mode. In order to fit the ACMTF model to our data, we form the EEG data in a tensor such that the trial to trial amplitude modulation is its first dimension; the event related potentials as its second dimension and the EEG channel topographies as its third dimension. Moreover, the hemodynamic response function is modelled with a convolutional matrix, which is multiplied by fMRI temporal signal in ACMTF model. Instead of convolving the EEG signal with the canonical HRF, this procedure helps to remove the effect of hemodynamic function. Then, the final model is represented as the model in (3) in which the trial to trial covariation of neural activities is common across the two modalities. Therefore, we can estimate the channel topographies and the ERPs of EEG signals with fMRI spatial components while the hemodynamic response does not have any low pass filtering effect on the latency and amplitude of the brain activities in each trial. As a result, the shared components illustrate the fMRI spatial maps corresponding to the EEG ERPs. We have:

$$f(T, T_e, M_e, M_f) = \left\| X - [[\lambda; T, T_e, M_e]] \right\|^2 + \left\| Y - HT \Sigma M_f^T \right\|^2 \qquad (3)$$

where, $X \in \mathbb{R}^{I \times M \times N}$ is the EEG tensor with dimension of trial×epoch×channel , $Y \in \mathbb{R}^{I \times P}$ is fMRI matrix with dimension of scans(Trials)×Spatial maps(Voxels), $T \in \mathbb{R}^{I \times R}$ is the trial to trial covariation of EEG and fMRI components, $T_e \in \mathbb{R}^{M \times R}$ is the ERP (epoch) factor of EEG data, $M_e \in \mathbb{R}^{N \times R}$ and $M_f \in \mathbb{R}^{P \times R}$ are channel topographies and fMRI spatial maps, respectively and $(.)^T$ denotes matrix transpose. H is a convolution matrix as follow:

$$H = \begin{bmatrix} h_1 & 0 & \cdots & 0 & 0 \\ h_2 & h_1 & \cdots & \vdots & \vdots \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ h_m & h_{m-1} & \vdots & \vdots & h_2 \\ 0 & h_m & \cdots & h_{m-2} & \vdots \\ \vdots & \vdots & \vdots & h_m & h_{m-1} \\ 0 & 0 & 0 & \cdots & h_m \end{bmatrix} \qquad (4)$$

Where, m is the length of HRF. Therefore, the dimension of H is $(m+l-1)\times(l)$, where l is the length of the temporal signal T. In most of the applications, HRF is modelled based on the double canonical Gamma function [26].

EEG tensor and fMRI matrix are illustrated in Figure 1.

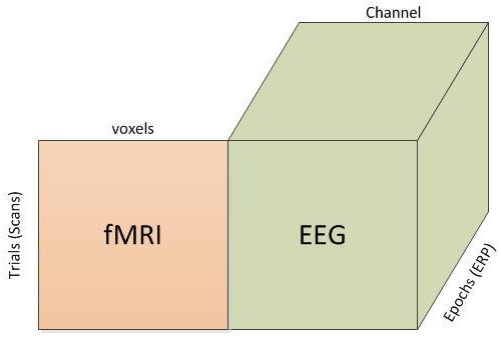



**Figure 1.** Applying ACMTF model for EEG-fMRI data fusion when the temporal signature is considered as the common factor

Based on this model, fMRI data is the matrix multiplication of HRF convolutional matrix and the underlying temporal variations. The gradients are obtained as follows:

$$\frac{\partial f}{\partial T} = -X_{(1)}\Lambda(M_e \square T_e) + T\Lambda(M_e^T M_e \times T_e^T T_e)\Lambda^T - H^T Y \Sigma M_f + H^T HT\Sigma M_f^T M_f \Sigma^T \quad (5)$$

$$\frac{\partial f}{\partial T_e} = -X_{(2)}\Lambda(M_e \square T) + T_e\Lambda(M_e^T M_e \times T^T H^T HT)\Lambda^T \quad (6)$$

$$\frac{\partial f}{\partial M_e} = -X_{(3)}\Lambda(T_e \square T) + M_e\Lambda(T_e^T T_e \times T^T H^T HT)\Lambda^T \quad (7)$$

$$\frac{\partial f}{\partial M_f} = -Y^T HT\Sigma + M_f \Sigma T^T H^T HT\Sigma^T \quad (8)$$

where, $\square$ denotes the Khatri-Rao product, $(.)^T$ is matrix transpose, $\Sigma$ and $\Lambda$ are diagonal matrices with $\sigma$ and $\lambda$ as their diagonal entries, respectively and $X_{(n)}$ is tensor X folded in its $n^{th}$ dimension.

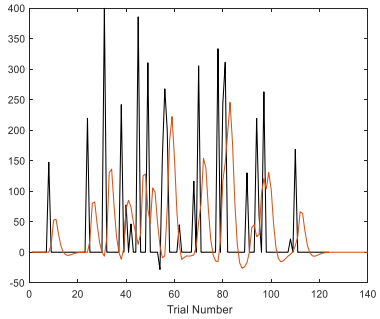
## 3. Results

The real dataset is an auditory oddball paradigm acquired from seventeen healthy subjects. The data acquisition procedure is completely explained in [27]. We have selected an interval (-100 milliseconds to 500 milliseconds) before and after stimulus onset.

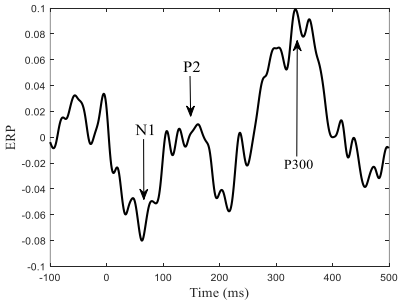
Before we apply the proposed method to real datasets, we have to choose the number of components for the model. In this paper, for the auditory oddball datasets, the number of components is chosen to be 2. This value is selected based on the Corcondia test [28]. The resulting trial to trial variations, ERP and the corresponding fMRI spatial map is shown in Figure 2.

After applying the proposed method, the four factors have estimated: The trial to trial variations, ERPs, EEG channel topographies and the fMRI spatial maps. Each of these factors have two components.

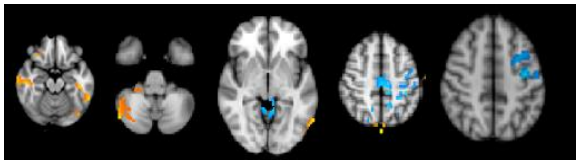
As it is depicted in Figure 2d., for EEG datasets, both components have significant weights in $\lambda$, while only one of these two components is significant in fMRI dataset, considering the value of $\sigma$. From the two significant components in EEG, only one of them is shared with the fMRI component.



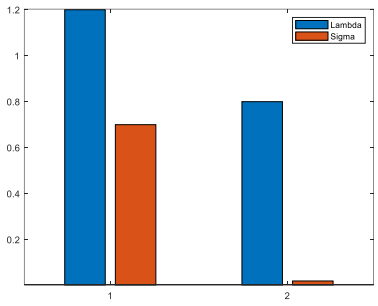

(a)




(b)



(c)




(d)

**Figure 2.** (a) The corresponding trial to trial variation of the ERP component and the fMRI spatial map. (b) The ERP component shows the well-known P300 component along with the N1 and P2. (c) The corresponding fMRI spatial maps. Blue color corresponds to negative values of z-score. (d) Only one component has significant value simultaneously in both EEG and fMRI

This component is the well-known ERP (P300) for oddball paradigm although some other ERPs such as N1 and P2 are also extracted in this component (Figure 2b.). The P300 component of oddball paradigm is extracted while we have concurrently estimated the spatial locations of this component across the cortex using the

fMRI dataset. The corresponding fMRI spatial maps in Figure 2c. show activities in left cerebral cortex, Lateral occipital cortex, Middle temporal gyrus, Precuneus cortex, cerebellum, right cerebral cortex, Precentral gyrus, Post central gyrus, Middle frontal gyrus, and cingulate cortex. These results are consistent with the results in previous papers [27, 28].

Figure 2a. depicts the trial to trial variation of brain activities. The black color is obtained by our proposed method through modelling the HRF in ACMTF model, while the red color signal is the trial to trial variation of components when the EEG signal is convolved with HRF and then the ACMTF model is applied.

## 4. Discussion

As it is illustrated by the figure, the true latency and amplitude of the ERP component in each trial is obtained by our proposed method, however, in the latter case these features are affected by the HRF signal. Considering the effect of hemodynamic response function in the model, we are able to estimate the ERPs with true latency and amplitude, while we have simultaneously localized the corresponding spatial maps in fMRI datasets.

These results demonstrate that our proposed method is more effective for analysis of trial to trial variations of brain activities in comparison with the traditional methods that convolve the EEG signal with hemodynamic response function. Our results demonstrate the effectiveness of the proposed method for removing the effect of hemodynamic response function in simultaneous factorization of EEG and fMRI datasets. While we are able to extract the well-known EEG event related potentials and the fMRI spatial locations corresponding to oddball paradigm, we are also able to estimate the trial to trial covariation of these factors with accurate amplitude and latencies in each trial.

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