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Analysis of fMRI data based on sparsity of source components in signal dictionary

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ABSTRACT

Blind Source Separation (BSS) methods, like Independent Component Analysis (ICA), show good performance in the analysis of fMRI data. However, the independence assumption used in ICA, may be violated in practice. Hence, it is important to develop algorithm which can fully exploit the characteristics of fMRI data and use more reliable assumptions. In this paper, we propose an fMRI data analysis method which exploits the sparsity of source components in a signal dictionary. The proposed method, derived as a two-stage method, is established by reformulating the blind separation problem as a sparse approximation problem. First, a priori selection of a particular dictionary, in which the source components are assumed to be sparsely representable. By choosing a particular dictionary (like wavelet dictionary), the source components, which can be well sparsified in the selected dictionary, are estimated more accurately. Second, the source components are extracted by exploiting their sparse representability. The extracted signal components are applied to find consistent task related (CTR) component, activation voxels of CTR, and performance of neural decoding. Numerical results show that compared to ICA based method, the proposed method can extract more useful information from fMRI data, and higher performance on voxel selection and neural decoding can be achieved by using the separated sources.

1. Introduction

Functional magnetic resonance imaging (fMRI), which is based on the blood oxygenation level dependent (BOLD) effect, has been one of the most widespread methods for investigating brain's functions. fMRI data analysis plays an important role in brain research to find the truth hidden behind the data. There are many fMRI data analysis methods [1,2] proposed in literatures so far. Generally, they can be categorized into two classes: model-driven methods and data-driven methods. The model-driven methods, e.g. general linear model (GLM) [3], need prior knowledge about the task function of fMRI experiment to work properly. However, data-driven methods [4] extract the intrinsic spatiotemporal structure of fMRI data with little prior knowledge.

Data-driven methods treat fMRI data analysis as blind source separation (BSS) problem. Two classical BSS methods widely applied in fMRI data analysis are independent component analysis (ICA) [5] and non-negative matrix factorization (NMF) [6]. In practice, it is important to control the validity of the mathematical assumptions of ICA and NMF based methods for fMRI data [7]. For ICA based methods, it is assumed that source components are independent each another. However, it is found that the independence assumption for ICA based method is too restrictive for fMRI data [8,9] recently. In [10], it has been argued that the underlying reason for ICA based methods to analyze fMRI data may be linked to their ability to handle sparse components rather than independent components. Recently, in [11], the author presented a view that ICA based method does select components for independence. It is an opposite view against [10]. However, an undeniable fact is that there is no a completely certain support on the rationality of independence assumption of ICA based method for fMRI data.

NMF based method utilities non-negativity assumptions on source components and their corresponding time courses to analyze fMRI data. However, the non-negativity constraint for time courses may be violated in practice. In fMRI experiment, the contribution of source component may increase or decrease during the task, which implies that time courses of source components may contain negative values. This limitation may weaken the performance of NMF based methods for fMRI data analysis.

Indeed, the fundamental objective of all kinds of blind separation methods is to devise a quantitative measure of contrast for source components. Note that sparsity of sources plays an important role in the performance of BSS methods, because sparsity

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greatly enhances the differences between the sources [12]. The sparser the sources are in the time or transformed domain, the more accurately that the sources can be estimated. Moreover, it has been found that first transferring the data into a representation in which the sources are assumed to be sparse greatly enhances the quality of the separation [13–15]. Inspired by this finding, we proposed a BSS method which exploits sparsity of sources in dictionary for fMRI data analysis.

In analysis of fMRI data, it is an important problem to find the source component, which are closely related to task. This consistent task related (CTR) component contains signals of brain activations. In order to accurately extract CTR components from fMRI data through the method exploiting sparsity in a dictionary, it is better to find a dictionary which can well sparsify CTR components.

In this paper, we use wavelet transform as the candidate dictionary. Wavelet transform is widely used in fMRI data analysis [16,17]. For sparsity in a dictionary based a priori fMRI data analysis, wavelet transform is advantageous since it is particularly suited to applications where the shapes and spatial extents of the interested signals cannot be well specified [18]. This advantage applies to fMRI data, because shapes and locations of activation areas in CTR component usually variate as the task function of experiment changes. Moreover, several studies have reported that activation signals in fMRI data can be sparsified by being represented with a small number of wavelet coefficients, while the power of white noise is uniformly spread throughout the wavelet space. Thus, in the wavelet domain, activation signals of fMRI data can be well sparsified [19].

Recently, a method was reported in [20] which presents a novel approach for detecting temporal activity in fMRI by decomposing the fMRI time courses into newly designed activelet basis that concentrates activity-related energy on few wavelet coefficients. These coefficients are then identified by means of a sparse search algorithm. Compared with the method proposed in this paper, the major difference is that the method in [20] is a temporal domain approach, while the proposed method is spatial-temporal domain method. In other words, the method in [20] decomposes the fMRI signal into sparse combination of activelets in time domain. While the proposed method blindly decompose the fMRI signals into spatial components (brain areas) associated with different temporal responses. These spatial components have sparse representation in some dictionaries, like wavelet dictionary. Then, the task-related spatial brain activation map is identified by finding the activated spatial components with CTR time course. The roles of wavelet transform in these two methods are very different.

With the wavelet dictionary and further exploiting the sparsity property of signal components in the selected dictionary, a blind separation process could be proposed to find the source components based on an alternate iteration optimization framework [21]. As we will show by numerical experiments, the proposed method is a reliable approach for voxel selection and neural decoding in fMRI data analysis.

The remaining part of this paper is organized as follows. In Section 2, we introduce the data model and the proposed method for fMRI data analysis. In Section 3, a simulated data set and two real fMRI data sets are used to evaluate the reliability and effectiveness of proposed method. Finally, in Section 4, some conclusions are presented.

2. The proposed method

2.1. Data model

For fMRI data, the data model for BSS methods can be illustrated by Fig. 1. The fMRI data is expressed by

$$\mathbf{X} = \mathbf{A}\mathbf{S} \tag{1}$$

where $\mathbf{X} = [\mathbf{x}_1^\top, \ldots, \mathbf{x}_i^\top, \ldots, \mathbf{x}_M^\top]^\top \in R^{M\times L}$ is the observed fMRI data with M denoting the number of observations and L denoting the number of voxels. $\mathbf{x}_i$ is the spatial distribution of voxels in observed fMRI data obtained at the ith sample instance. $\mathbf{S} = [\mathbf{s}_1^\top, \ldots, \mathbf{s}_j^\top, \ldots, \mathbf{s}_N^\top]^\top \in R^{N\times L}$ is the source components with N denoting the number of source components. $\mathbf{s}_j$ is the spatial distribution of voxels of the jth source component. Each value of $\mathbf{s}_j$ represents the relative amount a given voxel is modulated by the activation of the corresponding source component. $\mathbf{A} = [\mathbf{a}_1, \ldots, \mathbf{a}_j, \ldots, \mathbf{a}_N] \in R^{M\times N}$ is the mixing matrix and $\mathbf{a}_j = [a_j[1], \ldots, a_j[M]]^\top$ is the time course of jth source component. Generally, it is

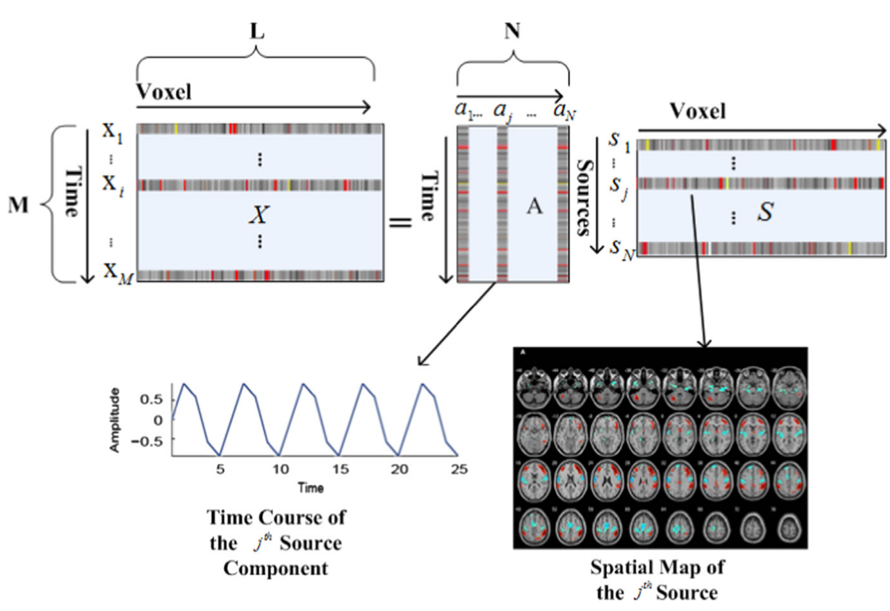

Fig. 1. Observed fMRI data as a mixture of different source components. Each source component (represented by source matrix **S**) represents a spatial distribution map of activated voxels. The observed fMRI data (represented by observation matrix **X**) is the linear mixing of all the source components. The mixing matrix **A** represents the contribution of the corresponding source components.