COMPUTER METHODS AND PROGRAMS IN BIOMEDICINE 122 (2015) 362–371

journal homepage: www.intl.elsevierhealth.com/journals/cmpb

A novel fMRI group data analysis method based on data-driven reference extracting from group subjects

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ARTICLE INFO

Article history:
Received 17 March 2015
Received in revised form
9 August 2015
Accepted 1 September 2015

Keywords:
Group-independent component analysis
Functional magnetic resonance imaging
FastICA
A priori information
Intrinsic reference

ABSTRACT

Group-independent component analysis (GICA) is a well-established blind source separation technique that has been widely applied to study multi-subject functional magnetic resonance imaging (fMRI) data. The group-independent components (GICs) represent the commonness of all of the subjects in the group. Similar to independent component analysis on the single-subject level, the performance of GICA can be improved for multi-subject fMRI data analysis by incorporating a priori information; however, a priori information is not always considered while looking for GICs in existing GICA methods, especially when no obvious or specific knowledge about an unknown group is available. In this paper, we present a novel method to extract the group intrinsic reference from all of the subjects of the group and then incorporate it into the GICA extraction procedure. Comparison experiments between FastICA and GICA with intrinsic reference (GICA-IR) are implemented on the group level with regard to the simulated, hybrid and real fMRI data. The experimental results show that the GICs computed by GICA-IR have a higher correlation with the corresponding independent component of each subject in the group, and the accuracy of activation regions detected by GICA-IR was also improved. These results have demonstrated the advantages of the GICA-IR method, which can better reflect the commonness of the subjects in the group.
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1. Introduction

Independent component analysis (ICA) has been successfully applied to the study of functional magnetic resonance imaging (fMRI) data as a data-driven method [1,2] since it was first introduced for single-subject fMRI data analysis by McKeown et al. [3]. ICA attempts to separate independent sources that have been mixed together. Based on different modeling assumptions, the conventional ICAs can be used to analyze the fMRI data in three different dimensions, namely, the spatial [4,5], temporal [6,7] and spatiotemporal dimensions [8]. This paper concerns ICA for the spatial dimension (spatial ICA, sICA), which models the fMRI data as a linear mixture of spatial independent components.

In some cases, ICA is used for multi-subject fMRI data analysis, often referred to as group ICA (GICA) [9]. The fMRI data of multiple subjects are typically grouped in three different ways with different hypotheses imposed upon the multi-subject fMRI data, including spatial concatenation, temporal

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http://dx.doi.org/10.1016/j.cmpb.2015.09.002
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concatenation and tensor concatenation. The spatial concatenation method concatenates the multi-subject fMRI data along the spatial dimension assuming that all of the subjects have common temporal information in each corresponding independent component (IC) [10]. The temporal concatenation method concatenates the multi-subject fMRI data along the temporal dimension with an assumption that all of the subjects have common spatial independent components (ICs) [11–13]. The tensor probabilistic ICA concatenates the original multi-subject fMRI data along a separate third dimension with the hypothesis that different subjects have common group spatial ICs and time courses but a subject-specific magnitude [14,15]. The temporal concatenation method works better than the spatial concatenation method for fMRI data analysis because the temporal variations in the fMRI signal are larger than the spatial variations [16]. A comparison of the temporal concatenation method and tensor probabilistic ICA method indicates that the temporal concatenation method works better for most fMRI studies [17]. Thus, only the temporal concatenation GICA will be considered in this paper.

As a blind source separation technique, classical ICA is not dependent on any a priori information, but some works have suggested that incorporating a priori information into the estimation process can improve the potential of ICA as a method for fMRI data analysis [18]. Several algorithms and methodologies have been proposed to account for a priori information on an ICA problem, such as a constrained ICA [19,20], ICA with a reference (ICA-R) [21,22] and other extension work [23,24]. Existing studies have demonstrated that these methods have better performance due to the use of a priori information, such as temporal a priori information [25], spatial a priori information [26,27], or spatiotemporal a priori information [28,29]. There are several reasons to incorporate a priori information into an ICA model when available. For example, compared to the classical ICA, ICA-R takes advantage of the a priori information to extract only the desired independent sources without extracting the whole data set of sources, and therefore, this method avoids computing the uninteresting sources and facilitates subsequent applications [30]. In addition, the incorporation of a priori information improves the quality and accuracy of the separation of interested components, and the computation time and storage requirements are reduced simultaneously [31].

However, the existing approaches with a priori information usually consider only specific knowledge on the sources, such as a specific template of spatial activation or a particular feature of a source. While this knowledge about the sources is not always known, how to extract the underlying information from the existing data itself is an important consideration. Recently, the group independent components (GICs) computed by GICA have been used to guide ICA on the single-subject level, and this method is able to obtain subject specific ICs with stronger independence and better spatial correspondence across different subjects in addition to higher spatial and temporal accuracy [32]. To the best of our knowledge, currently, there are no reports on how to obtain some information from each subject in the group and incorporate this information into the GICA extraction procedure for multi-subject fMRI data analysis on the group level, especially when no obvious or specific knowledge is available on an unknown group of sources. In this paper, we present such a method, which we have called GICA with intrinsic reference (GICA-IR).

The remainder of this paper is organized as follows: the relevant knowledge and theory of the GICA-IR method will first be presented followed by the simulated data, hybrid data and real data experimental tests, which were designed to evaluate the performance of GICA-IR compared with FastICA. Finally, the results and analysis will be presented together with interpretations and conclusions related to the advantages and limitations of this new data analysis method.

2. Materials and methods

2.1. Independent component analysis

The classic ICA model assumes that the source signals are not observable, statistically independent, and non-Gaussian. Let $\mathbf{X} = (\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_T)'$ be the $T \times V$ fMRI data observed from a single subject, where $\mathbf{X}_i (i = 1, \ldots, T)$ is a column vector of size $V \times 1$, T is the number of time points and V is the total number of voxels within a brain image acquired at each time point. The noise-free ICA of single-subject fMRI [3] can be expressed as

$$\mathbf{X} = \mathbf{MS} \tag{1}$$

where $\mathbf{S} = (\mathbf{S}_1, \mathbf{S}_2, \ldots, \mathbf{S}_N)'$ is a $N \times V$ matrix with each row representing the spatial map of a source signal, which is also called the independent component, $\mathbf{S}_i (i = 1, \ldots, T)$ is a column vector of size $V \times 1$ and N denotes the number of source signals. M is a $T \times N$ unknown mixing matrix that mixes the N independent source signals to generate the observed fMRI images, where each column of M representing the time course of a source signal. The goal of ICA is to estimate an $N \times T$, unmixing matrix $\mathbf{W} = (\mathbf{W}_1, \mathbf{W}_2, \ldots, \mathbf{W}_N)'$ with $\mathbf{W}_i (i = 1, \ldots, N)$ is a column vector of size $T \times 1$, such that $\mathbf{Y} = (\mathbf{Y}_1, \mathbf{Y}_2, \ldots, \mathbf{Y}_N)'$ computed by the following equation is a good approximation of the true sources $\mathbf{S}$

$$\mathbf{Y} = \mathbf{WX} \tag{2}$$

An error term representing residual variability in the observed data can be added to $\mathbf{X} = \mathbf{MS}$, which leads to the probabilistic ICA model [33,34]. The most commonly used ICA algorithms included Infomax [35], FastICA [36] and so on.

2.2. Independent component analysis with reference

To incorporate the reference into ICA, a distance criterion is defined to measure the closeness between the output signal $\mathbf{y}$ and reference signal $\mathbf{r}$, and we denote the distance as $\varepsilon(\mathbf{y}, \mathbf{r})$, where $\mathbf{y}$ and $\mathbf{r}$ are column vectors with the same number of voxels in the brain. Several functions can be used as $\varepsilon(\mathbf{y}, \mathbf{r})$, e.g., mean square error (MSE), correlation or negative correlation. Then, the problem of ICA-R can be modeled in the constrained ICA framework as a constrained optimization problem

$$\begin{aligned} &\text{Maximize} \quad J(\mathbf{y}) \\ &\text{Subject to } g(\mathbf{y}) \le 0 \quad \text{and} \quad h(\mathbf{y}) = E[\mathbf{y}^2] - 1 = 0 \end{aligned} \tag{3}$$

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