Journal of Neuroscience Methods 283 (2017) 72–82

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Research paper

A new method for independent component analysis with priori information based on multi-objective optimization

Yuhu Shi, Weiming Zeng*, Nizhuan Wang, Le Zhao

Lab of Digital Image and Intelligent Computation, Shanghai Maritime University, 1550 Harbor Avenue, Pudong, Shanghai, 201306, China

HIGHLIGHTS

- A new model of ICA-R was established based on multi-objective optimization.
- A new fixed-point learning algorithm was proposed to solve the model.
- An adaptive weighted summation method was introduced into the model.
- The ability of function detecting was improved on the single and group level.

ARTICLE INFO

Article history:
Received 3 August 2016
Received in revised form 26 March 2017
Accepted 26 March 2017
Available online 29 March 2017

Keywords:
Independent component analysis
Priori information
Multi-objective optimization
Adaptive weighted summation method
Fixed-point learning algorithm

ABSTRACT

Background: Currently the problem of incorporating priori information into an independent component analysis (ICA) model is often solved under the framework of constrained ICA, which utilizes the priori information as a reference signal to form a constraint condition and then introduce it into classical ICA. However, it is difficult to pre-determine a suitable threshold parameter to constrain the closeness between the output signal and the reference signal in the constraint condition.
New method: In this paper, a new model of ICA with priori information as a reference signal is established on the framework of multi-objective optimization, where an adaptive weighted summation method is introduced to solve this multi-objective optimization problem with a new fixed-point learning algorithm.
Results: The experimental results of fMRI hybrid data and task-related data on the single-subject level have demonstrated that the proposed method has a better overall performance on the recover abilities of both spatial source and time course.
Comparison with existing methods: At the same time, compared with traditional ICA with reference methods and classical ICA method, the experimental results of resting-state fMRI data on the group-level have showed that the group independent component calculated by the proposed method has a higher correlation with the corresponding independent component of each subject through T-test.
Conclusions: The proposed method does not need us to select a threshold parameter to constrain the closeness between the output signal and the reference signal. In addition, the performance of functional connectivity detection has a great improvement in comparison with traditional methods.

1. Introduction

Independent component analysis (ICA) is a well-established method that has been widely applied to study of functional magnetic resonance imaging (fMRI) data (Calhoun et al., 2001a, 2001b; Stone et al., 2002; van de Ven et al., 2004), since it was first introduced for fMRI data analysis by McKeown et al. (1998). As a data-driven blind source separation technique, ICA does not require any priori information. But some additional priori information about the desired independent components may be available in practice, and more and more researches have suggested that it can improve the capacity of ICA to analyze the fMRI data by incorporating priori information into the estimation process when it is available (Calhoun et al., 2005; Lin et al., 2010; Rasheed et al., 2009). There are many reasons to account for that why incorporating priori information in an ICA model can refines its performance. For example, compared with the classical ICA, we can extract only the interested independent components (ICs) without extracting all the ICs, so that it avoids computing uninteresting components and facilitates subsequent applications, and the computation time and storage requirements required by ICA are reduced simultaneously (Barros

* Corresponding author at: College of Information Engineering, Shangha Maritime University, 1550 Harbor Avenue, Pudong, Shanghai, 201306, China.
E-mail address: zengwm86@163.com (W. Zeng).

http://dx.doi.org/10.1016/j.jneumeth.2017.03.018

et al., 2000; Lu and Rajapakse, 2005); The most important thing is that the incorporation of priori information in the ICA can improve the quality and accuracy of the separation of interested components (Calhoun et al., 2005; Lin et al., 2010; Rasheed et al., 2009).

So far, several methodologies and algorithms have been proposed in the literatures to solve the problem of priori information in an ICA model. For example, based on the framework of constrained ICA which introduced constraints into the classical ICA with augmented Lagrangian multiplier method by Lu and Rajapakse (2005, 2000), a method named ICA with reference (ICA-R) was proposed which incorporated the priori information into the ICA model as reference and then a Newton-like learning algorithm was used to solve the constraint optimization problem (Lu and Rajapakse, 2006, 2001). Meanwhile, a semi-blind spatial ICA utilizing the spatial information with fixed-point learning algorithm was proposed under the framework of constrained ICA by Lin et al. (2010, 2007). In addition to the above two methods, a great number of other extension methods have been proposed (Li et al., 2010; Mi, 2014; Mi and Xu, 2014; Sun and Shang, 2010; Valente et al., 2009; Zhang, 2008). Existing studies have demonstrated that these methods have better performance due to the use of all kind of prior information, such as temporal priori information (Calhoun et al., 2005; James and Gibson, 2003), spatial priori information (Lin et al., 2010; Li et al., 2007a), or spatio-temporal priori information (Rasheed et al., 2009; Wang et al., 2014).

However, in the traditional ICA with reference algorithms (Lin et al., 2010; Lu and Rajapakse, 2006), it is difficult to pre-determine the threshold parameter ξ since ICs are blind, so the choice of a suitable ξ is quite dependent on the experience of applying ICA-R. Improper ξ often leads to two possible consequences. When ξ is beyond the upper bound of the feasible range, the output may produce an undesired IC; on the contrary, when ξ is smaller than the lower bound of the range, the output cannot produce any IC. Therefore, special effort has to be made to determine a proper parameter. Recently, a multi-objective optimization strategy has been applied to estimate ICs in the ICA with reference which has circumvented the selection of threshold parameter ξ (Du and Fan, 2013), but the weight parameter in this method is determined by manual operation. In this paper, we establish the model of ICA with priori information as a reference on the framework of multi-objective optimization without the choice problem of threshold parameterξ, in which mean square error is used to constrain the closeness between the output signal and the reference, and then an adaptive weight summation method is adopted to solve this multi-objective optimization problem with a new fixed-point learning algorithm. We will prove the superiorities of the proposed method through several experiments.

The remainder of this paper is organized as follows: Firstly, we present the relevant materials and the detailed contents of the proposed method. Then the hybrid data and real data experimental tests are designed to evaluate the performance of the proposed method compared with ICA-R methods and classical ICA where FastICA is used in this study. 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. Material and methods

2.1. Independent component analysis with reference (ICA-R)

In order to be incorporated into the estimated process of ICA, priori information is often used as reference in the model, and then some distance criteria should be defined to measure the closeness between the output signal and the reference. Several functions can be used to formulate as the distance criterion, such as mean square error or correlation (Huang and Mi, 2007). In the classical ICA, the contrast function is used to measure the independence of the output signal, which can be achieved by minimizing their mutual information or maximizing their non-Gaussianity measured by negentropy or kurtosis. In most cases, negentropy is usually used as the contrast function (Comon, 1994), so it is used in our study, and a flexible and reliable approximation of negentropy is used since the entropy of the output signal is unknown in practical (Hyvarinen, 1998). Then the problem of ICA-R can be modeled in the constrained ICA framework as a constrained optimization problem as follows:

$$\textit{Maximize } J(y) \approx \left\{E\left[G(y)\right] - E\left[G(v)\right]\right\}^2$$

$$\textit{Subject to } g(y) = \varepsilon(y, r) - \xi \leq 0 \text{ and } h(y) = E\left[y^2\right] - 1 = 0 \qquad (1)$$

where y is the output signal, $J(y)$ is the contrast function used to measure the independence of y. $G(\cdot)$ is a non-quadratic function (Hyvarinen, 1999), and v is a Gaussian random variable. r is a reference signal, $\varepsilon(y, r)$ is a distance criterion, and ξ is a threshold parameter which needs to limit the distance such that the desired output signal should be the only one satisfying the inequality constraint. The equality constraint $h(y)$ is used to compel the output signal have a unit covariance. To solve this optimization problem, the inequality constraint is transformed into equality constraint, $\hat{g}(y) = g(y) + c = 0$ via introducing a slack variable c. Then, the augmented Lagrange method is utilized to search for the solution by a Newton-like learning algorithm (Lu and Rajapakse, 2006) or a Fixed- point learning algorithm (Lin et al., 2007) and so on.

2.2. The proposed method

Multi-objective optimization is a process of optimizing two or more conflicting cost functions simultaneously. For multi-objective optimization problems, an optimal solution for one cost function is often not optimal for the others; there usually exist a set of trade-off solutions, referred to as the Pareto optimal set (Marler and Arora, 2004), which cannot be improved in one cost function without hurting the others. To solve a multi-objective optimization problem, we usually need to find the Pareto optimal set or its subset, and then evaluate which specific trade-off solution is more appropriate to the problem under study. In this paper, we formulate the ICA-R as the following multi-objective optimization problem.

$$\textit{Maximize } J(w_i) \approx \left\{E\left[G(Y_i)\right] - E\left[G(v)\right]\right\}^2 \textit{ and Minimize } \varepsilon(w_i) = E[Y_i - R_i]^2$$

$$\textit{Subject to } \|w_i\|^2 = 1 \qquad (2)$$

where $J(w_i)$ is the negentropy of the estimated independent component $Y_i = w_i^T\tilde{X}$, and $\tilde{X} = \left(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right)$ denotes the whitened X. $G(\cdot)$ can be any non- quadratic function (Hyvarinen, 1999), and $G(v) = \log(\cosh(v))$ is used in this paper. v is a Gaussian random variable with zero mean and unit variance, so $E\left[G(v)\right] = \int_{-\infty}^{+\infty} \log(\cosh(v)) \cdot \exp\left(-v^2/2\right)/\sqrt{2\pi}dv \approx 0.374567$. R_i denotes a spatial reference signal, and $\varepsilon(w_i) = E[Y_i - R_i]^2$ is specifically defined as the mean squared error to measure the closeness between Y_i and R_i in that both Y_i and R_i have zero mean and unit variance. A solution of the multi-objective optimization problem of Eq. (2) yields an optimal unmixing column vector w_i constrained to $\|w_i\|^2 = 1$.

Among the methods for finding a multi-objective optimization problem's solution, optimizing a linear weighted sum of the cost functions is an efficient method for the general multi-objective optimization problem if the weights are strictly positive and add