FLEXIBLE COMPLEX ICA OF FMRI DATA

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ABSTRACT

Data-driven analysis methods, in particular independent component analysis (ICA) has proven quite useful for the analysis of functional magnetic imaging (fMRI) data. In addition, by enabling one to work in its native, complex form, complex-valued ICA algorithms provide better estimation performance compared to the traditional approach that uses only the magnitude data. In the complex domain, circularity has been a common assumption even though most data acquisition methods collect fMRI data that end up being noncircular when saved in complex form. In this paper, we show that a complex ICA approach that does not assume circularity and also adapts to the source density is the more desirable one for performing ICA of complex fMRI data. We show that by adaptively matching the underlying fMRI density model, the analysis performance can be improved in terms of both the estimation of the task-related time courses and in the spatial activation.

Index Terms— Independent component analysis, fMRI, complex analysis, ICA

1. INTRODUCTION

Functional magnetic resonance imaging (fMRI) has contributed greatly to our understanding of the human brain by enabling researchers to study temporal and spatial changes in both the healthy and the diseased brain as a function of various stimuli. The MRI signal is acquired as a quadrature signal using two orthogonal detectors. The signal that is thus acquired in the complex frequency space (k-space) is inverse Fourier transformed into the complex image space. After this stage, most studies discard the phase and primarily use the magnitude images. However, processing of the fMRI data in its native complex form is attractive for a number of reasons [2]. In [3], we show on the average 20% increased sensitivity for detection of task-related components when compared to the magnitude only approach. Also, by using both the magnitude and phase of the time courses in fMRI data, one is likely to elucidate different networks while studying the brain connectivity as the magnitude and phase potentially activate different areas, or the link in such areas can be stronger when the phase and magnitude of the data are jointly processed. Using the phase information together with magnitude is also likely to lead to better localization of the origin of the signal by helping us to distinguish larger vessels from smaller ones.

Independent component analysis (ICA) has been shown to be quite effective for the analysis of fMRI data. By using a simple generative model based on linear mixing, ICA can minimize the constraints imposed on the temporal—or the spatial—dimension of the fMRI data, and hence provides valuable new insights, especially when studying paradigms for which reliable models of brain activity are not available. Thus, ICA emerges as a desirable alternate tool which promises to be quite valuable for analysis of the natively complex fMRI data as well.

Advantages of complex ICA for analyzing fMRI data in its native form has been noted recently [3, 5, 11]. However, the complex ICA algorithms implemented in these references all use a fixed nonlinearity, which is used to implicitly generate the higher-order statistics and assumes a fixed density model for the underlying fMRI sources. Some other well-known complex ICA algorithms, such as the complex FastICA algorithm [12] and circular Infomax algorithm [6], also assume a fixed nonlinearity function to match the underlying density model. For all the complex ICA algorithms presented here, the optimization criteria of them are based on maximum likelihood (ML)—which is equivalent to information maximization—and maximization of negentropy (MN) [1]. It can be shown that the two measures are equivalent when the demixing matrix is constrained to be unitary. For both ML and MN, the algorithms are optimal when the form of the nonlinear function used in the cost function matches the form of the probability density functions of the sources. Another important consideration when performing ICA in the complex domain is the circular/noncircular nature of the source distribution. Since very little is known about the nature of the fMRI sources, and in particular of the complex fMRI data, it would be much more desirable to use an adaptive algorithm such that the density model is estimated for each source adaptively. One such algorithm is introduced in [14] where a generalized Gaussian density model is used for the sources and the parameters of the model are estimated during the adaptation, estimation of the demixing matrix W. In this paper,
we show the application of the algorithm introduced in [14], the adaptive complex maximization of non-Gaussianity (A-CMN) algorithm to complex fMRI data and demonstrate the results using actual fMRI data for multiple subjects performing a motor task.

In the next section, we first give a brief review of complex statistics and ICA, and then introduce the A-CMN algorithm in section 3. In section 4, we explain the pre- and post-processing for the complex fMRI data and provide comparison of the performances of three competitive complex ICA algorithms when applied to fMRI analysis. We present our discussions in the last section.

2. COMPLEX ICA OF FMRI DATA

The probability density function (pdf) of a complex random variable $X = X_r + iX_im$ is defined through its joint density function $p_X(x) \triangleq p_{X_r,X_im}(x_r,x_im)$. A complex random variable $X$ is called circular in the strict-sense if $X$ and $X e^{j\theta}$ have the same pdf. A zero-mean random variable is called second-order circular (or proper) when its pseudo-covariance is zero, i.e., $E\{X^2\} = 0$.

In the ICA analysis of fMRI data, we assume independence of spatial brain activations (for spatial ICA), and write the complex ICA model as $X = \sum_{i=1}^N a_i s_i^2$ where the matrix $X \in C^{T \times V}$ is formed using the fMRI data such that the $i$th row is formed by flattening the volume image data of $V$ voxels into a row, and the rows are indexed as a function of time. The assumed mixing column vector $a$ represents the time course for the $i$th source and the independent source vector $s_i$ is the $i$th spatial map. The task of the ICA algorithm is to determine a weight matrix $W$ such that $y = Wx = Ps$, where $P$, a permutation matrix, represents the permutation ambiguity and $A$, a diagonal matrix, represents the complex-valued scaling ambiguity of ICA.

When performing complex ICA, most complex ICA algorithms assume that the sources are circular, such as the complex FastICA algorithm [12] and the Infomax algorithm that uses a circular nonlinearity [6]. It is desirable to relax the assumption of circularity so that the estimated source distributions are not constrained but also preprocessing inside the scanner is likely to lead to noncircular data [2, 8]. In addition, it is desirable to match the source distributions during the ICA estimation process. In the next section, we introduce such an adaptative ICA algorithm.

3. ADAPTIVE COMPLEX ICA ALGORITHM

The Adaptable complex maximization of non-Gaussianity (A-CMN) algorithm [14] uses a complex Generalized Gaussian distribution (CGGD) model for the underlying sources. The form of the CGGD density model is given as

$$p(s) = \frac{\beta(c)}{\sqrt{|C|}} e^{-|\eta(c) \hat{H} \bar{C}^{-1}s|^c}$$

where $s = [s \ s^*]^T$ is the augmented source vector, $\bar{C}$ is the covariance matrix of $s$, $\eta(c) = \frac{1}{\Gamma(\frac{2}{c})}$, $\beta(c) = \frac{\Gamma(\frac{2}{c})}{\Gamma(\frac{1}{c})}$ and $c$ is the shape parameter. Using this CGGD model, we can model both sub-Gaussian ($c > 1$) and super-Gaussian ($0 < c < 1$) sources can be modeled through the flexible shape parameter and we can model $b$th circular and noncircular sources through the estimation of the covariance matrix. The A-CMN cost function is defined as $J(y) = E\{(y y^*)^c\}$ where $y$ is the estimated source in a deflationary mode. The shape parameter $c$ and covariance matrix $C$ are estimated online using a maximum likelihood estimator. This on-line adaptation, modifies the cost function to match each source distribution and hence improves the overall performance.

4. RESULTS

4.1. fMRI data

The dataset used in this paper is from 16 subjects performing a finger-tapping motor task while receiving auditory instructions. The paradigm has a block design with alternating periods of 30s ON (finger tapping) and 30s OFF (rest). The experiments were performed on a 3T Siemens TRIO TIM system with a 12-channel radio frequency (RF) coil. The fMRI experiment used a standard Siemens gradient-echo EPI sequence modified to store real and imaginary data separately. The data was pre-processed for motion correction and spatial normalization into standard Montreal Neurological Institute space using the MATLAB Toolbox for Statistical parametric Mapping (SPM) [17].

4.2. ICA algorithms

Besides the A-CMN algorithm, for the comparison, we include the complex FastICA [12] algorithm and the circular Infomax algorithm [6] in our experiments. The cost function used in the complex FastICA algorithm is given by $J(y) = \log(\|y\|^2)$. In the circular Infomax algorithm, the score function is chosen as $[\mathrm{sign}(y)]^\frac{1-e^{-|y|}}{1+e^{-|y|}}$. Both algorithms assume that the sources are circular but have been shown to be robust choices for a number of applications including ICA of fMRI data [7].

4.3. Preprocessing

First, we apply quality map phase de-noising (QPMD) method presented in [15] to generate the mask to minimize the effects of noise in the phase of the fMRI data. The binary mask generated by QPMD identifies the good quality voxels in each
The two components we considered for this fMRI data set are the motor and the temporal components. The motor component is defined as the right motor activation area responding to the task, while the temporal component is the area activated in the bilateral temporal lobe. We observed that these two components have been consistently estimated by all three algorithms. To compare their performance, we consider three measures: 1) the number of activated voxels for the two components; 2) the maximum activation value for the two components; 3) for the motor (task-related) component, the correlation between the estimated time course and a model time course, which is generated by convolving a temporal model of the on-off task with a canonical hemodynamic response function.

To count the number of activated voxels for an activation map, we use WFU Pickatlas [16] to create the mask by selecting different areas of the brain. We create two masks for the right motor component and the bilateral temporal component. These masks include neuronal areas that are expected to be activated during the task as well as those in the temporal lobe. The areas included in each of the two masks are as follows: 1) right motor task-related: Brodmann areas 1, 2, 3, 4 and 6. 2) bilateral temporal lobe: Brodmann areas 20, 21, 22, 37, 38 and 42.

After the identification of the right motor and the temporal component, we count the number of voxels in the estimated components that overlap with the corresponding masks for each algorithm and each subject. The average number of activated voxels for all the subjects are displayed in Table 1 where RM denotes the right motor components and TMP denotes the temporal components. As shown in the table, the number of activated voxels estimated by A-CMN algorithm is the highest and the performance of circular Infomax is closely behind, and both perform better than complex FastICA.

The maximum activation values, thresholded by a Z-score value 2, are displayed in Table 2. Again, the A-CMN algorithm achieves the best performance with the circular Infomax algorithm closely behind. The complex FastICA algorithm obtains the lowest activation value for both of the two components. The correlations between the estimated time course and the model time course are displayed in Table 3. From this Table, the improvement on the estimation of the phase time
course by A-CMN algorithm is clearly observed. An example spatial map estimated by A-CMN algorithm is shown in Fig. ??, where both the magnitude time course and phase time course have correlation values as high as 0.86 with the model time course. As a comparison, one sample estimate by complex FastICA algorithm is shown in Fig.1. The two figures demonstrate that A-CMN algorithm can obtain much better results on the estimation of phase time course. Hence, based on the three performance indices, we note the importance of relaxing the circularity assumption of the sources and adaptively matching the underlying fMRI source model for improving the performance of the complex ICA of fMRI data.

Table 1. Number of voxels in activation area of components that overlap with the corresponding mask

<table>
<thead>
<tr>
<th></th>
<th>A-CMN</th>
<th>FastICA</th>
<th>Infomax</th>
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<tbody>
<tr>
<td>RM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No of voxels</td>
<td>728 ± 275</td>
<td>622 ± 310</td>
<td>667 ± 238</td>
</tr>
<tr>
<td>TMP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No of voxels</td>
<td>1855 ± 352</td>
<td>1782 ± 369</td>
<td>1829 ± 440</td>
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Table 2. Maximum Z-scores of the estimated components

<table>
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<th></th>
<th>A-CMN</th>
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<th>Infomax</th>
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</thead>
<tbody>
<tr>
<td>RM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum Z-score</td>
<td>12 ± 2.4</td>
<td>11 ± 4</td>
<td>12 ± 2.4</td>
</tr>
<tr>
<td>TMP</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Maximum Z-score</td>
<td>11 ± 2.1</td>
<td>9 ± 2.6</td>
<td>10 ± 2.3</td>
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Table 3. Correlation of the estimated time courses with model time courses

<table>
<thead>
<tr>
<th></th>
<th>A-CMN</th>
<th>FastICA</th>
<th>Infomax</th>
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<tbody>
<tr>
<td>RM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Magnitude</td>
<td>0.68 ± 0.24</td>
<td>0.64 ± 0.25</td>
<td>0.68 ± 0.26</td>
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<tr>
<td>Phase</td>
<td></td>
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<tr>
<td></td>
<td>0.69 ± 0.19</td>
<td>0.56 ± 0.24</td>
<td>0.6 ± 0.27</td>
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5. DISCUSSION

ICA is one of the most fruitful methods for the study of fMRI data and the use of phase information in addition to the typically used magnitude promises to provide new insights for the analysis. In this paper, we showed that by relaxing the circularity assumption and adaptively matching the density model, we can improve the performance of the analysis results for complex fMRI data using ICA. In particular, we demonstrated that the adaptive A-CMN algorithm provides a more flexible way to extract the intrinsic features of the noisy fMRI data. In addition, we addressed important issues when performing the ICA of fMRI data in its native, complex form, such as denoising and thresholding of the results for visualization.

6. REFERENCES