SEMI-BLIND INDEPENDENT COMPONENT ANALYSIS OF FUNCTIONAL MRI ELICITED BY CONTINUOUS LISTENING TO MUSIC

Tuomas Puoliväli[1], *Fengyu Cong*[1], *Vinoo Alluri*[1,2], *Qiu-Hua Lin*[3], *Petri Toiviainen*[2], *Asoke K Nandi*[1,4], *Elvira Brattico*[5,6], *Tapani Ristaniemi*[1]

1. Department of Mathematical Information Technology, University of Jyväskylä, Finland
2. Finnish Centre of Excellence in Interdisciplinary Music Research, University of Jyväskylä, Finland
3. School of Information and Communication Engineering, Dalian University of Technology, China
4. Department of Electronic and Computer Engineering, Brunel University, Uxbridge, Middlesex, UB8 3PH, UK
5. Cognitive Brain Research Unit, Institute of Behavioral Sciences, University of Helsinki, Finland
6. Brain and Mind Lab, BECS, Aalto University School of Science, Finland

ABSTRACT

This study presents a method to analyze blood-oxygen-level-dependent (BOLD) functional magnetic resonance imaging (fMRI) signals associated with listening to continuous music. Semi-blind independent component analysis (ICA) was applied to decompose the fMRI data to source level activation maps and their respective temporal courses. The unmixing matrix in the source separation process of ICA was constrained by a variety of acoustic features derived from the piece of music used as the stimulus in the experiment. This allowed more stable estimation and extraction of more activation maps of interest compared to conventional ICA methods.

Index Terms— independent component analysis, semi-blind, acoustic features, natural music, functional magnetic resonance imaging

1. INTRODUCTION

Independent component analysis (ICA), introduced by Comon [1], is a method for finding latent variables from multivariate data. After algorithmic improvements made by first Bell and Sejnowski [2] and then Hyvärinen and Oja [3], it was first applied by McKeown et al. [4] on blood-oxygen-level-dependent (BOLD) functional magnetic resonance imaging (fMRI) discovered by Ogawa et al. [5]. Even though fMRI has been the subject of increasing interest to study the human brain [6], little is known about fMRI elicited by natural, continuous, and long stimuli. The majority of existing studies present event-related or block designs, where the stimuli are short and artificial. For investigating neural processing of naturalistic stimuli, researchers have measured BOLD responses to simulated driving [7], watching movies [8, 9], listening continuous speech or music [10, 11], and doing simple sensory tasks [11]. In this study, fMRI elicited by a modern Argentine tango with rich structure is examined.

An fMRI recording is a series of high spatial resolution magnetic resonance imaging (MRI) volumes sampled on the order of seconds. Using ICA, independence of latent sources in either or both dimensions of fMRI, time and space, can be maximized [4, 12, 13]. In this study, spatial independence of the activated regions of the brain is maximized. Since real world data might more or less violate the model of ICA [14], introducing constraints to ICA algorithms may improve the data decomposition [15, 16, 17]. In this study, a similar approach to constrain the unmixing matrix of ICA that was proposed by Calhoun et al. [16] is used. What is novel in this study is that a variety of acoustic features are derived from the piece of music used as the stimulus in the experiment and are utilized to constrain the unmixing matrix of ICA.

2. DATA

Eleven participants with formal musical training participated in this study. Their average age was 23.2 years (standard deviation was 3.7 years), five of them were female, and all of them actively practised playing at least one musical instrument. None of the participants reported any neurological, hearing or psychological problems. The fMRI measurements were made using a 3-T (3.0T Signa VH/I General Electric) scanner at the Advanced Magnetic Resonance Imaging (AMI) Centre of Aalto University. The used stimulus was the modern tango *Adios Nonino* by Astor Piazzolla of duration 512 seconds and the sampling frequency of fMRI was 0.5 Hz. The first 26 seconds of the fMRI were excluded to avoid artifacts and the last 24 seconds due to applause in the piece of mu-

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sic. Thus, the final length of the analyzed fMRI data was 462 seconds. Refer to the study of Alluri et al. [10] for more information about the participants and the fMRI data.

3. SEMI-BLIND INDEPENDENT COMPONENT ANALYSIS

3.1. A systematic spatial ICA approach

Consider a real-valued linear and instantaneous mixing model

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

where $\mathbf{x} = (\mathbf{x}_1, \ldots, \mathbf{x}_m)^\top$ are mixtures of some unknown latent sources $\mathbf{s} = (\mathbf{s}_1, \ldots, \mathbf{s}_n)^\top$ and matrix $\mathbf{A}_{m\times n}$ giving the mixing weights. This is the basic model of ICA where noise is not explicitly modeled. In this study, the number of sources n is originally assumed to be less than the number of observations m, that is, the number of activated regions of the brain to be less than the number of MRI scans. To separate the fMRI data to signal and noise subspaces, and to account for possible problems of overlearning and overfitting [18], the dimension of data is reduced through

$$\mathbf{z} = \mathbf{V}^\top \mathbf{x} \tag{2}$$

where $\mathbf{V}_{m\times n}$ is a dimension reduction matrix from principal component analysis (PCA) and model order selection [19]. The objective of ICA is then to seek an unmixing matrix $\mathbf{W}_{n\times n}$ such that

$$\mathbf{y} = \mathbf{W}\mathbf{z} \tag{3}$$

where $\mathbf{y}$ is an estimate of the original sources. In this study, the unmixing matrix was found by iterating [20]

$$\mathbf{W}_\dagger = E\{\mathbf{z} g(\mathbf{W}^\top \mathbf{z})\} - E\{g'(\mathbf{W}^\top \mathbf{z})\}\mathbf{W} \tag{4}$$

$$\mathbf{W}_\ddagger = (\mathbf{W}_\dagger \mathbf{W}_\dagger^\top)^{-1/2}\mathbf{W}_\dagger \tag{5}$$

until convergence. The maximization of independence in equation (4) is about negentropy [20]. The nonlinear function $g(\cdot)$ was set $g(x) = tanh(x)$. Orthogonalization of columns of the unmixing matrix in equation (5) is needed to avoid finding any source more than once. Refer to the paper of Hyvärinen [20] for all details of the algorithm. The temporal courses of the activation maps (independent components) are obtained by projecting the estimated mixing matrix back to the time series of fMRI scans through the dimension reduction matrix $\mathbf{V}$ from equation (2) [21]:

$$(\mathbf{t}_1, \ldots, \mathbf{t}_n) = \mathbf{V}\mathbf{W}_\ddagger^{-1} \tag{6}$$

3.2. Reference signals to constrain the unmixing matrix

Six musical features were derived for reference from the piece of music used as the stimulus in the experiment. Since the same musical features were used for correlation analysis in the previous publication of Alluri et al. [10], with promising results, it was thought they would suit constraining the unmixing matrix of spatial ICA as well [16]. They were labeled as Fullness, Brightness, Timbral complexity, Key clarity, Pulse clarity and Activity, and obtained from a set of 25 acoustic features using PCA [10]. The musical features were downsampled to match the sampling frequency of fMRI (0.5 Hz) and convolved with a double-gamma hemodynamic response function (HRF) to account for the hemodynamic lag. The features Fullness, Brightness and Activity reflect spectral properties of the acoustic features in different frequency bands. Timbral complexity is associated with Wiener entropy of the spectrum of the acoustic features. Key clarity and Pulse clarity are estimates of their self-describing names. Refer to the study of Alluri et al. [10] for more information about the musical features.

3.3. Spatial ICA with multiple temporal constraints

To make full use of all the available prior information, a semi-blind ICA algorithm using multiple reference signals was designed following the early work done by Calhoun et al. [16]. Since the prior information in this study are the six musical features derived from the piece of music used as the stimulus in the experiment, we constrain the temporal courses of the activation maps. Denote the reference signals by $\mathbf{r} = (\mathbf{r}_1, \ldots, \mathbf{r}_k)$. In order to make any corrections feasible, the scale and polarity of the references and corrected temporal courses must match. Thus, to correct the ith temporal course using the jth reference, we apply the following formula,

$$\begin{aligned} \mathbf{t}_i^+ &= (1-\alpha)\cdot \mathbf{t}_i \\ &\quad + sign(c)\cdot \alpha \cdot \mathbf{r}_j \cdot std(\mathbf{r}_j)^{-1} \cdot std(\mathbf{t}_i) \end{aligned} \tag{7}$$

where $\alpha \in [0,1]$ sets the strength of correction, c is the correlation coefficient between $\mathbf{t}_i$ and $\mathbf{r}_j$ and $std(\cdot)$ is used to denote standard deviation. The strength of correction was chosen to be $\alpha = I^{-1}$ where I is the iteration number of the ICA algorithm. In this study, we set $i = j$ and $1 \le i \le 5$. The number of musical features was reduced to five through averaging the features Fullness and Activity, which showed a high correlation ($r > 0.9$). After the corrected temporal courses $\mathbf{t}_i^+$ are obtained, the projection in equation (6) is updated to constrain the unmixing matrix. The decreasing contribution of references to the source estimations set by $\alpha = I^{-1}$ was found to be very important. Because the nonlinear functions $g(\cdot)$ used in the negentropy based objective functions of ICA are sensitive to the underlying probability density functions of the sources, convergence could stop near the threshold if some of the references were not completely appropriate. This happened particularly for those subjects showing large difference between the modeled and actual HRF.

4. DATA PROCESSING

Before applying ICA, a digital filter and dimension reduction were applied on the fMRI data for the preprocessing. The purpose of the digital filter was to improve the SNR and to remove sources of no interest [22]. It was applied on temporal course of each voxel [23] and designed to meet the properties of the musical features. Because most of the power of the musical features was observed to be below .05 Hz, it was taken as the high cutoff frequency for the filter. The low cutoff frequency of .008 Hz followed the decision done in the previous publication of Alluri et al. [10]. The dimension reduction was done through PCA and model order selection. The model order was determined using the recently introduced GAP method [24] and happened to be the same, 46, for each participant.

Next, given an ICA algorithm, it was run for 100 rounds to allow stability analysis of the data decomposition, and selection of best estimates of the extracted activation maps and their respective temporal courses using ICASSO [25]. In order to produce more stable results, some of the rounds of ICA can be rejected. Using the prior information available, the suboptimal rounds of estimations of the mixing matrices of ICA can be detected. Here, the suboptimal results were determined through simple statistics with the six musical features. Namely, the maximal correlation coefficient between each musical feature and temporal courses of extracted activation maps was obtained. Those were then averaged to produce a single quality parameter for each round and used to remove the eighty worst of them. This step proved to be very important (see Table 1), since the mechanism for the best estimate selection implemented in ICASSO is sensitive to outliers.

After the best estimates of the extracted activation maps were obtained from ICASSO for each participant, Pearson correlation analysis was performed to select only those whose temporal courses were significantly correlated ($p < 0.01$) with the musical features for subsequent analyses; the rest were ignored. A Monte Carlo approach similar to the one described in [10] was used to find thresholds for detecting significant correlations. Finally, from the activation maps whose temporal courses were significantly correlated with the musical features, the ones appearing in the majority of participants were found through visual inspection. This was possible because the number of activation maps whose temporal courses were significantly correlated with the musical features was much less than their total number of 506 (11 participants $\times$ 46 activation maps).

5. RESULTS

See Fig. 1 for the average of task related activation maps which were showing activation in the bilateral auditory cortex and whose temporal courses were significantly correlated ($p < 0.01$) with the musical features. This kind of activation

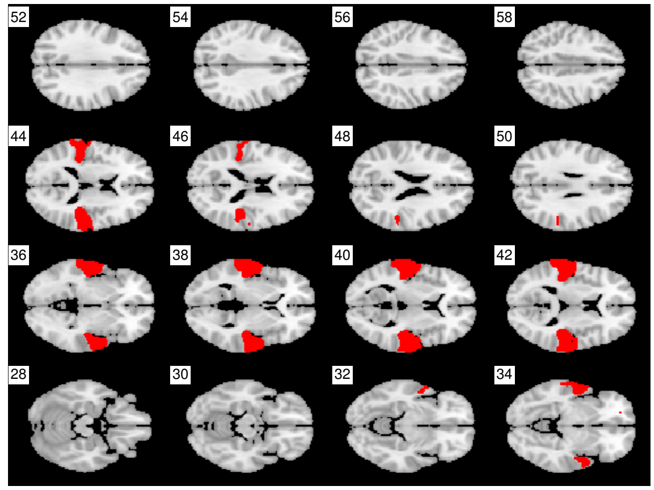


Fig. 1. Average of activation maps whose temporal courses were significantly correlated ($p < 0.01$) with the musical features Fullness, Brightness, Timbral Complexity and Activity. The single activation maps were normalized and their polarities made the same before the averaging. Red color is used to highlight those voxels whose values differed more than three standard deviations from the mean. The numbers marking the slices are their z-coordinates.

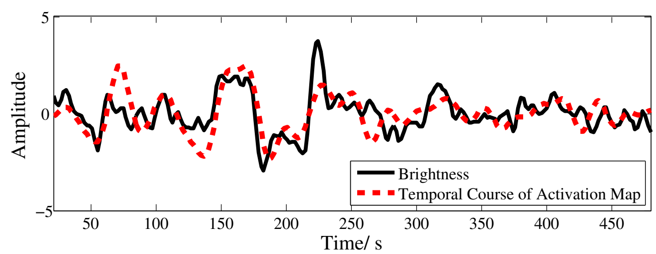
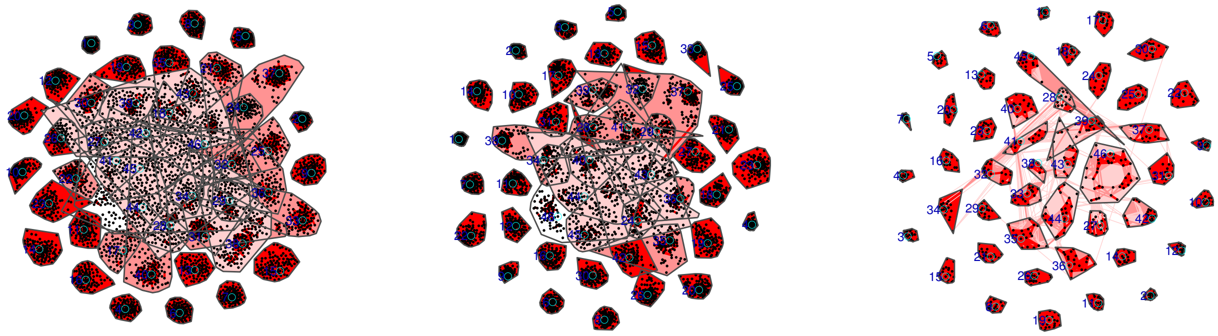


Fig. 2. The average of temporal courses which were significantly correlated ($p < 0.01$) with the musical feature Brightness under the activation map shown in Fig. 1. The single temporal courses were normalized and their polarities made the same before the averaging.

maps were found from 9 of the 11 participants. The total number of significant correlations was 20 (mean was 2 and standard deviation was 1.3 for participant-wise statistics). Feature Brightness had the most number (9) of correlations. See Fig. 2 for the average of those temporal courses. The overall results are summarized to Table 1. The results show about a fifty percent improvement in the number of found activation maps whose temporal courses were significantly correlated with the musical features when the available prior information was utilized in the unmixing process of ICA and in rejection of suboptimal estimations of the unmixing matrices before ICASSO. The stability of the data decomposition was remarkably improved when semi-blind ICA was used. This is illustrated in Fig. 3.



(a) (b) (c)

Fig. 3. Curvilinear component analysis (CCA) projections of activation maps extracted from one typical participant using different ICA methods and number of rejected rounds. The projections were obtained from ICASSO under the default settings. Compact and isolated clusters suggest stable estimates [25]. See (a) for the results of 100 rounds of standard ICA; (b) for the results of 100 rounds of semi-blind ICA; and (c) for the results of 20 best rounds of semi-blind ICA. Compare (a) and (b) to see the benefit of using prior information in the unmixing process of ICA and (b) and (c) to see the existence of detectable suboptimal estimations of the unmixing matrices.

Table 1. Comparison of performance of different ICA methods

ICA Method	Objective Function	Nonlinearity	Rejected Rounds	Mean IQ	Significant ICs
FastICA, standard	Negentropy	$g(x) = tanh(x)$	0	0.760	29
FastICA, semi-blind	Negentropy	$g(x) = tanh(x)$	0	0.844	32
FastICA, semi-blind	Negentropy	$g(x) = tanh(x)$	80	0.861	43

The column *Mean IQ* gives the mean of cluster stability indices (IQ) of the extracted activation maps suggested by ICASSO. The range of IQ is $[0, 1]$ and a higher IQ indicates better stability. The column *Significant ICs* the number of activation maps whose temporal courses were significantly correlated ($p < 0.01$) with the musical features.

6. DISCUSSION AND CONCLUSIONS

This study examined fMRI brain activity associated to continuous listening to a whole musical piece through semi-blind ICA. Our study was different from the previous designs of semi-blind ICA in two aspects. Firstly, we used multiple reference signals derived from the long and continuous piece of music used as the stimulus in the experiment. Secondly, the contributions of the reference signals to the source estimations were reduced as a function of the iteration number of ICA, whereas the contributions of the reference signals were fixed in [16]. Thus, the novelty of this study lies in using multiple musical features derived from the piece of music acting as the stimulus in the experiment to aid the source separation process of ICA, and in classifying and rejecting suboptimal estimations of the unmixing matrices before any further analysis. The presented approach gave much better results than what could be obtained using the conventional ICA algorithms (see Table 1). Much more activation maps whose temporal courses were significantly correlated with the musical features could be found. Also, the stability of the data decomposition was remarkably better.

Indeed, group ICA has been applied to study fMRI elicited by real world experiences [11, 26]. In this study, we applied ICA on individual subjects since it was unknown whether our fMRI data could meet the theoretical assumptions of group ICA or not. In the future, we plan to evaluate group ICA as well.

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