CLASSIFICATION OF FMRI DATA USING INDEPENDENT COMPONENT ANALYSIS

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Abstract:The application of Independent Component Analysis (ICA) algorithm to functional Magnetic Resonance Imaging (fMRI) data has been considered to be quite useful. In fact, the separation of original sources from the observed data (as in fMRI) is an important problem which ICA can solve efficiently. This article explains some basic principles about ICA and also shows some classification of fMRI data based on pure visual inspection. We have experimentally classified meaningful and noise signals. The study used real fMRI data acquired during the stimulation of the language processing cortex. The results were evaluated by activation maps and associated time courses. Based on the chosen results, a signal source was related to the task while two other sources reflected artifact-biased information.

Keywords: Functional Magnetic Resonance Imaging, Independent Component Analysis

1. INTRODUCTION

fMRI is a non-invasive technique that detects brain activity by measuring associated changes in blood flow whereas Magnetic Resonance Imaging (MRI) studies brain anatomy.

The neural activity makes changes to the oxygenated and deoxygenated hemoglobin concentration ratio and thus affects the local homogeneity of static magnetic field. To acquire fMRI data, it is necessary to scan brain repetitively so that the changes in blood oxygenation level dependent signal (BOLD) can be recorded [1]. The data could be acquired either in terms of external stimulation or without external stimulation (resting state data). The fMRI data has a structure of 4D matrix (3 spatial dimensions and time). For the purpose of Independent Component Analysis (ICA), the data are reshaped to 2D matrix with rows as time points and columns as individual voxels (or vice versa).

ICA is defined as a technique that decomposes a set of mixed data into maximally independent components assuming that we know very little, if anything, about the components or the way used to mix them [2]. In fMRI data each independent component (IC) produced by the ICA algorithm consists of a spatial distribution of voxel values (“spatial map”) and an associated time course. The time course corresponds mostly to the voxel of the highest activation. Fig.1 shows four independent components with their spatial maps and time courses. The observed signal is considered to be the sum of contributions of the independent components. Each component contributes to the data by the outer product of the voxel values in its spatial map with the activation values in its time course [3].

In a mathematical way this can be expressed as follows:

Let X be the T x M (T= number of time points (number of scans), M = number of voxels) matrix of the fMRI time series, S the N x M (N ≤ T = number of components) and A the T x N mixing matrix whose columns contain the time courses of components, so the ICA model can be written as:

$$X = A*S \qquad (1)$$

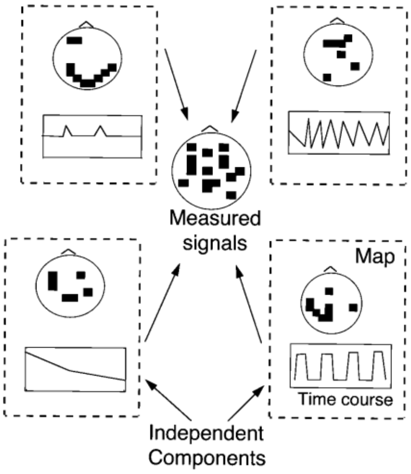

Figure 1: schematic of fMRI data decomposed into independent components. Each component extracted by the ICA algorithm consists of a spatial map ("a group of voxel values") and a single time course of activation. The time course corresponds mostly to the voxel of the highest activation.

2. METHODS FOR COMPONENT CLASSIFICATION

In fMRI data, some components indicate interesting forms of stimulus-induced or internal brain activity; others refer to artifacts or noise. Using ICA, we get components which are not sorted, so we can't recognize the most interesting ones from the other artifacts. The researcher is thus encountered by choosing the interesting BOLD-related components. In previous fMRI applications of ICA, many attempts have been done in order to select these interesting components. The simplest approach depends on visual inspection of IC spatial maps/time courses [4]. Generally, this approach has a drawback in that it is time consuming and also reliant on the knowledge of the experimenter. In this article, the method was used. The time courses and spatial maps of task-related components can already be expected. The other non-task related ICs are easily detected also by looking at each component spatial map and time course taking into account the general knowledge available from previous researches [5]. In this sense, some classification is considered to be done. The data were acquired from one subject.

Another approach is the automatic classification. It depends on using hyperplanes to define decision boundaries separating data points of different classes. The hyperplanes can be found after subdividing the ICs into maximally separated groups [6].

3. EXPERIMENT

The fMRI data contain 136 volume scans, with 46 slices for each scan. MATLAB-based toolbox, group ICA of fMRI toolbox (GIFT) [7] was used to process the data. Spatial maps and time courses for the independent components were extracted.

The task was performed by block design. The block design contains two phases: active phase (stimulation phase) and passive phase. They were alternating in a sequential way during the task. Each of them had duration of 24 seconds. There was a total of 8 stimulation epochs and 9 passive epochs with the start of a passive phase. During stimulation the subject was shown 6 sentences, each of which was displayed for 4 seconds. While reading the sentences they had to press a button if the sentence contained nonsense. During the passive phase the subject can only see strings of “X” or “O” characters (Like “XXXXX” or “OOOOO”). He was instructed to press the button only when he saw the X string.

According to the experiment, the language processing cortex should be activated during the stimulation period.

4. RESULTS

By looking at the ICs extracted from the data they can be classified into artifacts and sources of interest, based on observing time courses and spatial patterns. Each class is explained in detail with the corresponding components.

4.1. ARTIFACTS (UNINTERESTING SIGNALS)

This class includes motion-related sources like head movement. The time course changes slowly with sudden transient peaks. The spatial signal is highly expressed at the brain skull edges (also in white matter and ventricles) [8] .Fig.2 is an example of head movement signal.

Other artifacts are related to respiration and cardiac pulsation. These components are expressed mostly in the ventricles, white matter or in the regions with big veins [8]. The time series of these components may vary randomly. Fig.3 depicts such a kind of artifact.

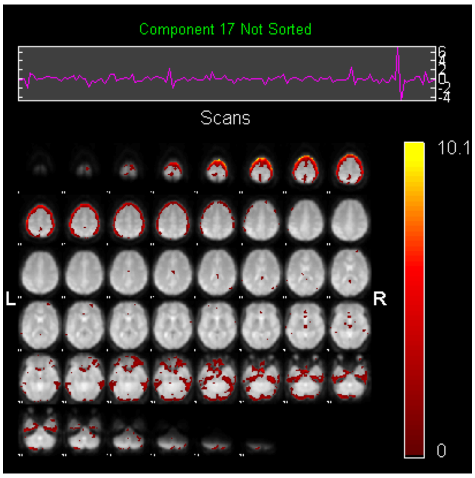

Figure 2: Artifact component: Head motion.

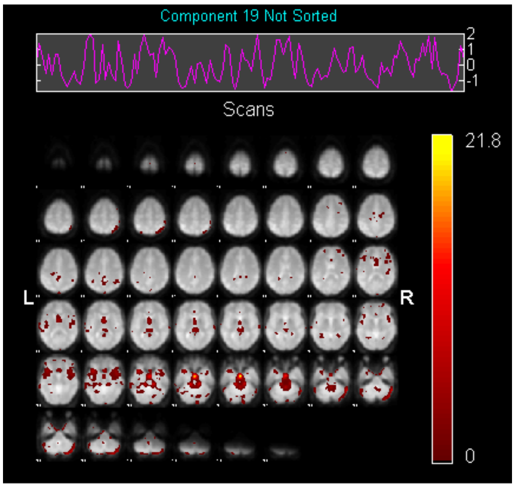

Figure 3: Artifact Component: Respiration or cardiac pulsation.

4.2. BOLD -SIGNAL COMPONENTS (INTERESTING SIGNALS)

The BOLD components are expressed in gray matter. The component in Fig.4 is related to the experiment. It is the response to the stimulation because it contains a periodic signal with active and passive epochs as the same like the stimulation signal. The two spatial peak activations (left frontal and left temporal) correspond exactly to the Broca and Wernike areas (Fig.5) which are known to be involved in language processing.

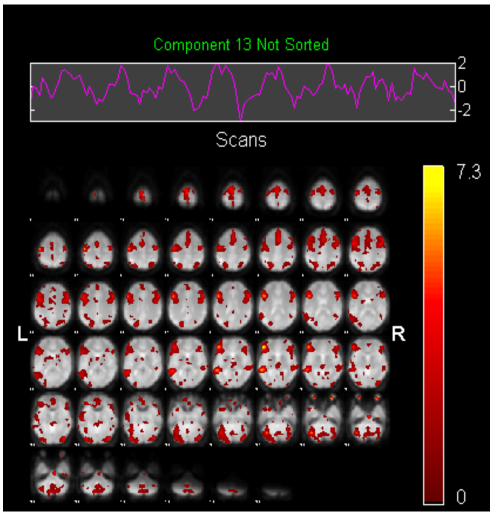

Figure 4: BOLD signal component.

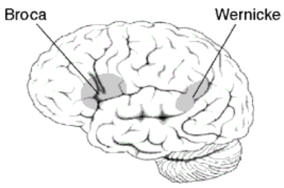

Figure 5: Broca and Wernicke areas. [9]

5. CONCLUSION

The application of ICA to fMRI data has been considered to be quite useful [5]. However, there is still much work to be done in the sense of taking full benefit of the information contained in the data. The aim of the paper was to state some essential characteristics about ICA and fMRI and to classify brain activations that were detected using ICA, by visual noticing of the independent components. The subject was instructed to read a text so that the language processing cortex was activated, and some components with different features were presented for the purpose of distinguishing the interesting signals from artifacts. The components with features corresponding to the experiment are considered to be interesting because it is related to the task. However, some other signals only indicate noise and so do not show any useful or meaningful information.

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