A Canonical Correlation Approach to Exploratory Data Analysis in fMRI

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Abstract A computationally efficient data-driven method for exploratory analysis of functional MRI data is presented. The basic idea is to reveal underlying components in the fMRI data that have maximum autocorrelation. The tool for accomplishing this task is Canonical Correlation Analysis. The proposed method is more robust and much more computationally efficient than independent component analysis, which previously has been applied in fMRI.

INTRODUCTION

Most current techniques for fMRI analysis are based on an a priori model for the temporal hemodynamic response. An alternative approach is to use data-driven techniques. Instead of searching for activity that fits a temporal response model, data-driven methods explore the data searching for components with interesting structure. The strength with data-driven methods is that they can find components that cannot be modelled a priori. The main use of such methods is to detect unexpected components in the fMRI data, such as drifts and motion related artifacts. The most well-known methods for finding “interesting components” in data are *projection pursuit* and *Independent Component Analysis* (ICA). Both these methods search for projections of the data such that the new variables (components) will have distributions that are as far from gaussian as possible, under the constraint that the components are uncorrelated. ICA solves the *Blind Source Separation* (BSS) problem and has successfully been applied in fMRI [1].

Here, we propose an alternative method for BSS based on *Canonical Correlation Analysis* (CCA). This method searches for components that have maximum auto-correlation, under the constraint that they are mutually uncorrelated. The CCA-method gives similar results as ICA but it is more robust and much faster than conventional methods for ICA. Similar approaches for BSS by maximum autocorrelation has been proposed earlier, e.g. [2], but to our knowledge they have never been used in fMRI.

METHODS

Blind Source Separation Given an unknown linear mixture of a set of unknown, statistically independent signals, the goal of BSS is to estimate the mixing matrix and recover the original signals. The mixture can be written as $\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t)$, where $\mathbf{A}$ is the unknown mixing matrix and the components in $\mathbf{s}$ are the statistically independent source signals. The goal is then to estimate a matrix $\mathbf{W}$ such that $\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t)$ equals the unknown source signals in $\mathbf{s}(t)$ (except for scalings and permutations).

Canonical Correlation Analysis Consider two multidimensional random variables, $\mathbf{a}$ and $\mathbf{b}$ and the linear combinations, $a = \mathbf{w}_a^T(\mathbf{a} - \bar{\mathbf{a}})$ and $b = \mathbf{w}_b^T(\mathbf{b} - \bar{\mathbf{b}})$, of the two variables respectively. The largest correlation between a and b is the largest *canonical correlation* and is found by solving the following eigenvalue equation: $\mathbf{C}_{aa}^{-1}\mathbf{C}_{ab}\mathbf{C}_{bb}^{-1}\mathbf{C}_{ba}\hat{\mathbf{w}}_a = \rho^2\hat{\mathbf{w}}_a$, where $\mathbf{C}_{aa}$ and $\mathbf{C}_{bb}$ are the nonsingular within-set covariance matrices and $\mathbf{C}_{ab}$ is the between-sets covariance matrix. This gives N solutions where N is the minimum of the dimensionalities of $\mathbf{a}$ and $\mathbf{b}$.

BSS by CCA Consider the case where the source signals in $\mathbf{s}$ are one-dimensional signals, e.g. time signals, $\mathbf{s}(t)$. CCA can then be used for separating the mixed signals $\mathbf{x}(t)$ by finding the linear combination of $\mathbf{x}(t)$ that correlates most with a linear combination of $\mathbf{x}(t+1)$, i.e. the next sample. In other words, we let $\mathbf{a}(t) = \mathbf{x}(t)$ and $\mathbf{b}(t) = \mathbf{x}(t+1)$. The first canonical correlation component will then give a linear combination $y_1(t)$ of the mixed signals with maximum autocorrelation at lag one. The second canonical correlation component will give a new linear combination $y_2(t)$ with maximum autocorrelation under the constraint that it is uncorrelated to the first component, etc. In the case of a two-dimensional source signals, e.g. images, we let $\mathbf{a}$ be the pixel values and $\mathbf{b}$ be the mean of the surrounding pixel values.

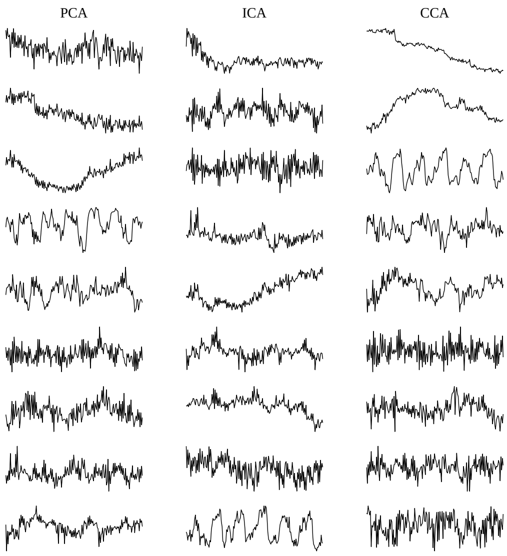

Figure 1: *Extracted time-courses for experimental fMRI data.*

BSS in fMRI FMRI data can be explored from both a temporal and a spatial point of view. In temporal analysis we are searching for interesting time-courses in the fMRI data. Examples are stimulus induced time-courses or time-courses containing pronounced drift or motion artifacts. In temporal data-driven fMRI analysis there are more voxels than time points, making the problem of recovering the underlying sources ill-posed. Therefore, preprocessing and relevant dimensionality reduction are required in order to reduce the number of mixtures. In spatial analysis we assume that each acquired fMRI image is a mixture of a set of underlying basis images. The basis images are assumed to reflect locations of independently occurring processes. Here, we try to recover the underlying basis images by linearly unmixing the acquired fMRI images. In this case there are significantly more samples of each mixture and therefore dimension reduction may not be necessary.

EXPERIMENTAL RESULTS

The PCA, Fast ICA and CCA methods were applied on experimental fMRI data. The experiment was a 180 time-points long mental calculation task where a volunteer added numbers. In the temporal analysis, all within-brain voxel time-courses were used as input to PCA. The nine first ’eigen-time-courses’ were subsequently used as input to ICA and the CCA. The resulting temporal components are shown in the figure. The CCA always give the same solutions, which is not the case with ICA. The solutions in the CCA approach are sorted by auto-correlation. In the table below the computational time in seconds for analyzing a single 128×128 fMRI slice with 180 time points are reported.

Method	Temporal	Spatial
PCA	40	30
Fast ICA	0.5	110
CCA	$<$0.01	5

Even though Fast ICA is a very fast implementation of ICA, the pure CCA method is obviously better in terms of computational complexity by at least an order of magnitude.

REFERENCES

[1] M. McKeown et. al. *Human Brain Mapping*, 6(3):160–188, 1998.

[2] P. Switzer and A. A. Green. Technical Report 6, Department of Statistics, Stanford University, 1984.