A Mutual Information-Based Approach to Estimate the Number of Meaningful Independent Components from ICA Decomposition of fMRI Data

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INTRODUCTION

The analysis of fMRI data is a challenging task, since the recorded signals have varied, unpredictable time courses, which represent summation of effects from hemodynamic changes as a result of neural activities, from subject motion and machine artifacts, and from physiological cardiac, respiratory, and other pulsations. The relative contribution and exact form of each of these components in a given session is largely unknown to the experimenter, suggesting a major role for exploratory data analysis (EDA). An additional difficulty in delineating functional correlates out of spatiotemporal fMRI datasets stems from the relatively small effect sizes in blood-flow-related phenomena. The difficulty in extracting information from raw data in neuroimaging is increased by the possibility that functional correlates of brain activity may relate to given behavioral paradigms in complicated ways. Adequate representations of multivariate datasets are expected to describe their essential structure and origin. Linear transformations are often envisaged as EDA due to their computational and conceptual simplicity. Independent component analysis (ICA) (1) is used in our experiments for exploratory analysis of fMRI data. The ICA model separates data into (sparse) maps (spatial modes), and associated time courses of activation. The spatiotemporal specificity of components in brain imaging datasets is outlined in relation with the strengths and weaknesses of data-driven versus hypothesis-driven paradigms in large real-life neuroimaging data analysis. The present contribution seeks for identification of meaningful independent components out of ICA decomposition of fMRI data. Mutual information (MI), an information-theoretic concept that constitutes a statistically natural measure of independence between distributions of random variables, is proven to give reliable information on the number of the underlying sources of meaningful brain activity in spatial ICA decomposition of fMRI data.

METHODS

Basically, two categories of data analysis are employed in neuroimaging to reveal statistical regularities in the data that can be associated with brain function, namely *hypothesis-driven* (*inferential*) and *data-driven* (*exploratory*) analysis. Most of imaging neuroscience relies on inferential hypothesis-led analysis, which makes use of spatially extended processes like statistical parametric mapping (SPM). The interpretation of functional brain imaging data requires by all means some assumptions on processing in the working brain that may not be entirely realistic and which precludes canonical methods of data analysis and experimental design. In data-driven analysis no statistical models on presupposed inferences need to specify. Multivariate data analysis relies on the covariance paradigm and is free of prior assumptions on activation functions. Contrary to inferential approach, EDA is capable to detect the functional activity without reference to the experimental protocol and can also reveal new components in the data. The covariance paradigms assess the temporal covariance between different brain regions during a particular task. Classical statistics leaning on analyzing small, homogeneous, stationary data by means of known distributional models and assumptions may prove inappropriate to deal with the problems raised by the analysis of large and complex data. It is also claimed that the difference between real-life large datasets and smaller ones consist not only in size but in qualitative terms as well (2).

Most often, fMRI data preprocessing includes principal component analysis (PCA) dimension reduction, which may discard some small but significant components. Accordingly, a means to estimate the number of meaningful independent components (ICs) in ICA decomposition suggests the adequate size of PCA reduction. Moreover, ICA yields components as independent as possible even if the assumption of source independence holds only loosely, and no intrinsic meaning is associated with them either. It is therefore compulsory to thoroughly check the validity of the assumptions on which ICA decomposition is based in order to evaluate the reliability and functional significance of the resulting components. A correct estimation of the number of ICs makes the interpretation task easier and more meaningful. Our approach is based on evaluating MI of the estimated ICs pair-wise and assessing a statistically significant change in its profile which presumably marks a qualitative change in pair-wise dependence (or independence). MI is symmetric, zero *iff* the factorization of the joint density holds, and it is strictly positive otherwise. Unlike the autocorrelation function, MI takes into account the whole dependence structure of the variables. Similarly to negentropy, MI has the invariance property to invertible linear transforms. Consequently, MI can be used as a metric between two patterns related to their degree of independence.

RESULTS AND DISCUSSION

Our fMRI data originated from a subject performing successive sessions of *12* runs, each run consisting of *24* s control blocks (fixation) followed by *24* s experimental block (round checkerboard flashes) during *216* s.. Data were collected from *35* slices of 64×64 voxels, with $TR=3$ s. The thickness of all slices was *3.75* mm and there was no gap in between, so that all voxels were $3.75\times3.75\times3.75$ mm^3, The scanner was an *Intera 3.0 T Philips Medical Systems* with SENSE coil both on and off; when on, the SENSE factors were *2* and *3*, respectively. Data processing was carried out in our integrated GUI-based ICA environment comprising Spatial and temporal smoothing were avoided for preserving all tiny components in data irrespective of their amplitude. The ICA algorithms comparatively used throughout were adapted from the extended infomax ICA algorithm (4), JADE algorithm (5), FastICA fixed-point algorithm (6), and EGLD Maximum Likelihood-based ICA algorithm (7). Data from each session were minimally preprocessed for preserving as much details as possible. In all cases, the most energetic components, which were ranked on the basis of percentage of variance accounted for in data space (PVAF), were in fairly good correlation $(r>0.8)$. We selected *6* components (fig.1) and generated components up to *72* having the same statistical proprieties (Fig.2) as the original fMRI data. The result was a set of *72* components consisting of *6* independent groups of sources, each composed of *12* uncorrelated but dependent components. The ICA estimated separation full-column rank matrix was inverted and used to linearly mix the so-formed fMRI "sources" (Fig. 2). Applying ICA decomposition, we found a significant change of MI pair-wise plots (Fig. 3) around MI=2%, which suggests *12* dependent components. Analyzing the means of MI for all ICA algorithms (Fig. 4), the result appears selfconsistent w.r.t ICA methods.

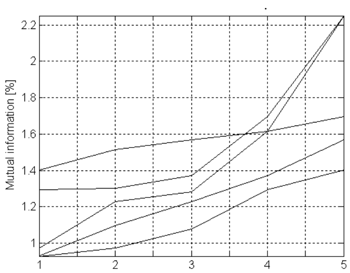

Fig.1 - fMRI independent sources.

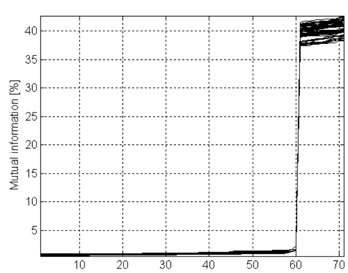

Fig. 2 - Artificially generated fMRI data.

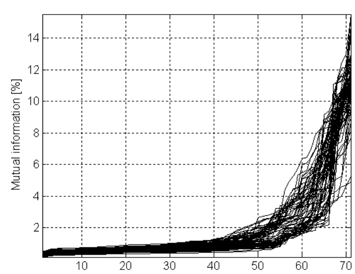

Fig. 3 – FastICA decomposition of data

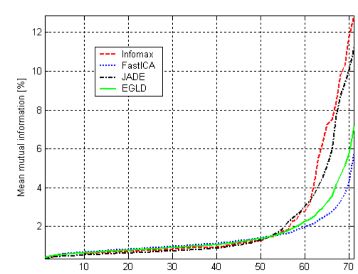

Fig. 4 - Mean mutual information.

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The contribution seeks for identification of meaningful independent components out of ICA decomposition of fMRI data. Mutual information, defined by means of Kullback-Leibler divergence, constitutes a statistically natural measure of independence between distributions of random variables. Generating synthetic components starting from selected real life fMRI data, it was proven that mutual informatiocontains reliable information on the number of the underlying sources of meaningful brain activity in spatial ICA decomposition of fMRI data sets.