# Functional Elements and Networks in fMRI

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**Abstract**. We propose a two-step approach for the analysis of functional magnetic resonance images, in the context of natural stimuli. In the first step, elements of functional brain activity emerge, based on spatial independence assumptions. The second step exploits temporal covariation between the elements and given features of the natural stimuli to identify functional networks. The networks can have complex activation patterns related to common task goals.

## 1 Introduction

Functional magnetic resonance imaging (fMRI) is one of the most successful methods for studying the living human brain. Traditionally, its analysis relies on artificially generated stimuli, coupled with generic statistical signal processing, in clear hypothesis-driven setups. The rising interest in natural stimuli studies calls for the development of new processing approaches.

In this work we propose a two-step method, illustrated in Fig. 1, where independent component analysis (ICA) finds spatially independent functional elements, whereas nonparametric dependent component analysis (DeCA[1]) collects them into networks related to the natural stimulation.

Related canonical correlation approaches have been previously suggested for fMRI [1, 2, 3]. Yet, no method has dealt with natural stimuli, since all experiments rely on non-overlapping block designs. Furthermore, the novel framework introduced in this paper extends the interpretability of the functional elements and networks.

## 2 Material and Methods

The experiments use a dataset from a recent competition organized by the University of Pittsburgh [4]. The analyzed data consists of fMRI recordings of one subject viewing a short movie clip, together with a set of features describing the stimulus.

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[1]DeCA generalizes canonical correlation analysis (CCA).

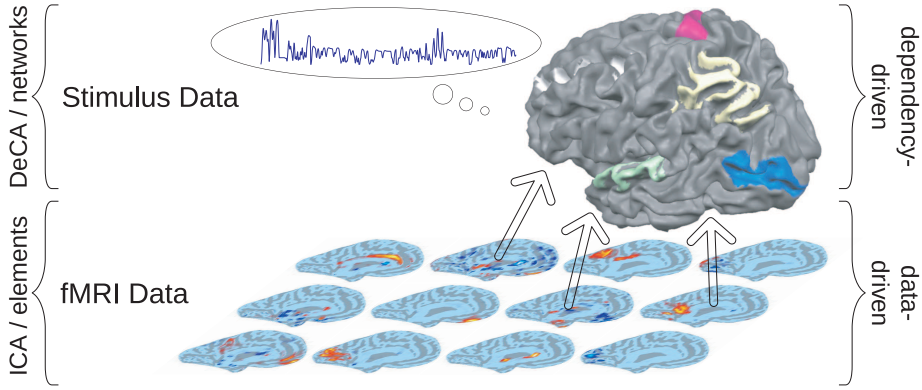



Fig. 1: The proposed framework: elements of functional brain activity emerge from the data via ICA. Functional networks are revealed by DeCA, based on covariation between the elements and task goals, encoded as features.

### 2.1 Natural Stimulus fMRI Recordings

The fMRI data consisted of 20 minutes of continuous measurements. Whole head volumes were acquired with a 3T scanner using an EPI sequence (TR=1.75s, TE=25ms, slice=3.5mm, FOV=210mm, flip=76°), resulting in $64 \times 64 \times 34$ voxels per volume, for 858 time points. We retained only the 641 time points, which contained actual movie viewing.

Preprocessing provided by the competition organizers included motion correction, slice time correction, linear trend removal, and spatial normalization of the volume data. Then the cortical surface was extracted and morphed into a smooth inflated surface containing 238735 vertices.

### 2.2 Features of Natural Stimulus Data

The movie clip was described with 29 features. Some of the features were quantitative, such as *brightness* or *rms sound*, measuring image intensity and root-mean-square sound amplitude, respectively. On the other hand, most of the features were more qualitative, *e.g.*, *laughter* and *sadness*, based on subjective ratings given by the viewers. Strong correlation redundancy among the features was removed. Brain activity related to observing other people's actions is of particular interest, so we combined the original actor-specific features (*e.g.*, *Al* and *Brad*) into a single new feature *people* by taking their maximum value. We left out features related to places (*e.g.*, *kitchen* and *backyard*).

The resulting set of 9 features was *attention*, *brightness*, *faces*, *food*, *language*, *laughter*, *rms sound*, *sadness* and *people*, shown in Fig. 2. Each feature was normalized to have zero mean and unit variance.


Fig. 2: The 9 features of natural stimuli as functions of time.

### 2.3 Independent Component Analysis

Independent component analysis (ICA) [5] is one of the most popular methods for solving the blind source separation (BSS) problem in a purely data-driven manner. BSS consists of finding solutions to the mixture $\mathbf{X} = \mathbf{AS}$, where only the observed data $\mathbf{X}$ is known. ICA assumes only statistical independence of sources $\mathbf{S}$, and full rank of mixture $\mathbf{A}$. Independence is considered here in the spatial domain, and the mixing reveals the temporal activation patterns of the corresponding sources [6].

We used a reliable ICA approach, proposed in [7], based on multiple runs of FastICA [5], in a bagging framework, *i.e.*, with resampled data and randomized initializations.

Suitable parameter values for FastICA were selected heuristically, based on performance, overfitting avoidance, and computation requirements. We used *tanh* nonlinearity in *symmetric* mode looking for 25 independent components in the 50 dimensional whitened space. The bootstrapping used a sampling of 25% with correlation threshold of 0.8 and power 4 (see [7] for details on implementation). The reliable ICA included 100 runs and mean representatives of the 25 most reliable components were selected as potential functional elements.

### 2.4 Nonparametric Dependent Component Analysis

To build functional networks from the independent elements, we find the underlying factors that are common for both, the independent components of brain activity, and the features of natural stimuli. A classical method for this task is the canonical correlation analysis (CCA) [8], which has been shown to maximize mutual information for Gaussian data [9]. Since we study independent components, which are far from Gaussian, we resort to nonparametric dependent component analysis (DeCA) [10]. It maximizes a dependency estimate between two datasets $y$ and $z$:

$$f(\mathbf{w}_y, \mathbf{w}_z) = \sum_{i=1}^{N} \log \frac{q_{yz}(i)}{q_y(i)q_z(i)} \quad ,$$

where $\mathbf{w}$ are the parameters that define the components (linear projection directions), and $q$ denote Parzen estimators of the density of the projected data. The summation is taken over the samples. Intuitively, if the two projected datasets would be near to independent, the estimator of joint density $q_{yz}$ would roughly factorize to the product $q_y q_z$ of the marginals, resulting in zero cost. DeCA looks for projections that are as far from this situation as possible. Multiple components were computed in a deflation manner.

Similarly as in reliable ICA, DeCA was run 20 times using different initializations. The best solutions according to the cost function were selected, and averaged over projections that had the same profile.

## 3 Results

Fig. 3[2] shows the set of reliable independent components. As expected, the components represent spatially independent functional regions of the brain. For example, component with index 3 (IC3) corresponds to the sensory auditory areas in the superior temporal lobes, whereas IC20 corresponds to the anterior cingulate gyrus. Individual interpretation of all the components is out of the scope of this paper.

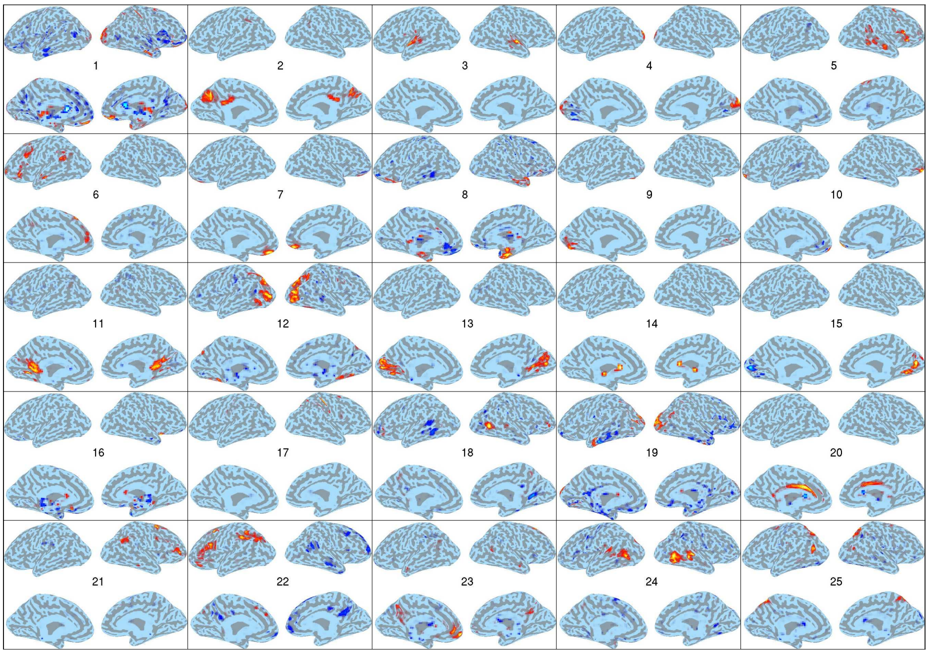
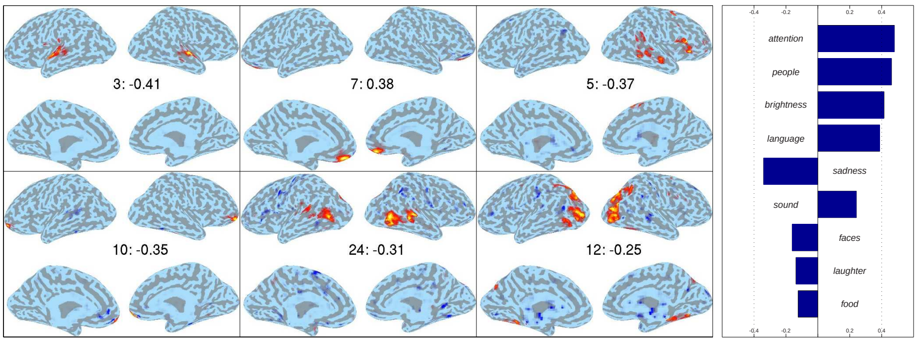



Fig. 3: Overview of 25 independent components representing spatially independent functional brain regions. The index of each component is shown in the middle of each square. Lateral and medial views of both hemispheres of the inflated cortex are shown. The cortex anatomy in light gray shades and the activation pattern superimposed with dark (yellow and blue gradients in color version).

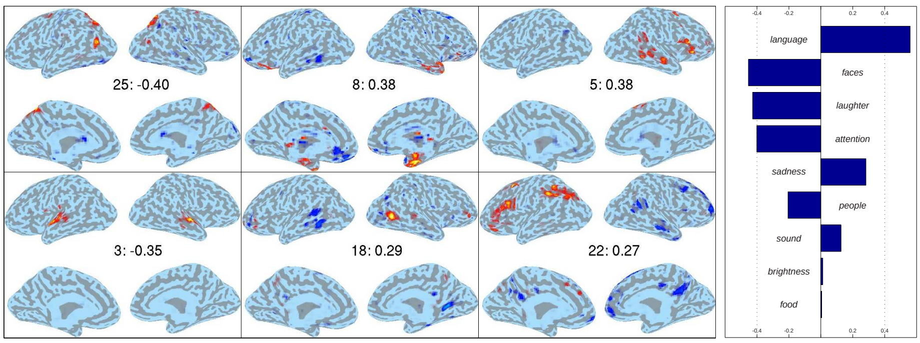
[2]A color version of the paper is available online.

Figs. 4 and 5 show two illustrative functional networks, corresponding to two dependent components identified by the method. In both cases, 6 independent components are shown in decreasing order of their absolute loading values. High absolute loading value means that the corresponding IC contributes significantly to the network. Respectively, Figs. 4(b) and 5(b) show the loadings of the stimulus features, where high values mean that the network is strongly related to the corresponding features.




(a) (b)

Fig. 4: (a) The 6 ICs (from Fig. 3) corresponding to the highest loadings in the first dependent component. The loading value is shown in the middle of each square. (b) Respective loadings of the stimulus features.




(a) (b)

Fig. 5: (a) The 6 ICs (from Fig. 3) corresponding to the highest loadings in the fourth dependent component. (b) Respective loadings of the stimulus features.

The first network comprises brain areas that individually correspond to, *e.g.*, auditory (IC3), visual (IC12), and multi-modal integration (IC24). This suggests that the functional role of the whole network is related to combining information from many sensory inputs. Indeed, the four highest scoring features of the dependent component are *attention*, *people*, *brightness* and *language*.

The second network includes areas related to, *e.g.*, language processing (IC3 and IC5) and face recognition (IC8). Additional information can again be drawn from the four highest scoring features *language*, *faces*, *laughter* and *attention*.

## 4 Discussion

ICA is commonly used in fMRI studies to identify, in a blind manner, spatially independent functional elements of brain activity. With complex stimuli, or complex brain functions, individual elements may not be directly relatable to the stimulus goals. In this paper, we introduced a two-step approach using ICA and DeCA to construct networks of functional brain activity, based on covariation between the networked activity and combinations of stimulus features. Interpretation of the functional role of the complex network is based on its constituent spatial elements, as well as on relations between the network's global temporal activity and the stimulus features.

The method was tested on fMRI recordings of brain responses to natural stimuli. The found networks seem plausible, considering the limited and very subjective nature of the available stimulus features. Some elements were a part of several networks, with different functional contribution to each network's common task. More controlled studies are being planned to verify the results and to further develop the approach.

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