

Processing of fMRI Images Based on ICA and Mathematical Morphology

Ali Akbar Pouyan, Seyed Mahdi Salehi

Abstract—Health monitoring and medical diagnoses are impossible without considering different images of organs and tissues. Further, those methods that focus on brain have a great importance because of role of brain in decision-making and control of any conscious and unconscious activity of humankind. Functional magnetic resonance imaging (fMRI) or functional neuroimaging is a new and efficient method for investigation about function of brain through any emotional, behavioral, mental and cognitive task. In this paper, with extending the independent component analysis (ICA) method using FastICA and Infomax as two common version of it, a novel idea based on mathematical morphology and Top-Hat transformations has been applied to improve and control the contrast of fMRI images after some time-consuming preprocessing steps. Higher degree of performance is achieved testing this method on a huge database of raw fMRI images for an emotional task. Quantitative and qualitative parameters and indices are used to confirm this modification in better recognition of active areas in human brain.

Index Terms— Functional Neuroimaging, fMRI, Independent Component Analysis (ICA), FastICA, Infomax, Mathematical Morphology, Top-Hat Transformations, Preprocessing.

1 INTRODUCTION

Functional Magnetic Resonance Imaging (fMRI) refers to the use of the technology of magnetic resonance imaging (MRI) to detect the localized changes in blood flow and blood oxygenation that occur in the brain in response to neural activity. fMRI is a modality for studying the brain function. This method uses Blood Oxygenation Level Dependent (BOLD) signal as a measure for detecting the neural activity. Since fMRI uses an indirect measure of neural activity, mathematical models are needed to analyze the data [1].

A typical fMRI scanning session lasts 1-2 hours and results in the collection of hundreds of megabytes of data. The theory and practicalities associated with processing that data are complex and evolving [2].

fMRI experiments can be done on many persons (called subjects) for several times (each time called a run or scan). Each scan has many slices, based on physics of fMRI and design and structure of fMRI test. Subject may be a volunteer or a patient that goes inside the fMRI Scanner many kind of clinical or research purposes.

Many fMRI experiments use a block design in which the subject is instructed to perform experimental and control tasks in an alternating sequence of 20-40 second blocks. The resulting activity is recorded for each volume element (voxel) of the brain. Analysis and process of fMRI images discriminate between active and inactive regions of brain for any kind of motor or sensor stimulus [3].

This discrimination is done by colored thresholding on areas of whole brain. Common form of fMRI image is an anatomical high-resolution image that superimposed (overlaid) with functional image of desired task. Activated areas of brain are emphasized and distinguished with color.

Any 3D image of whole brain has three 2D cross-sectional project images. These images include: Axial (view from top), sagittal (view from left) and coronal (view from back of head).

For example, amygdala [4] is a well known part of brain (as shown in fig 1 for axial and coronal view) thought to reflect the encoding and generation of responses to negatively and positively arousing cues and habituation of the human during visual processing of facial expression and special emotional activities including fear and sadness.

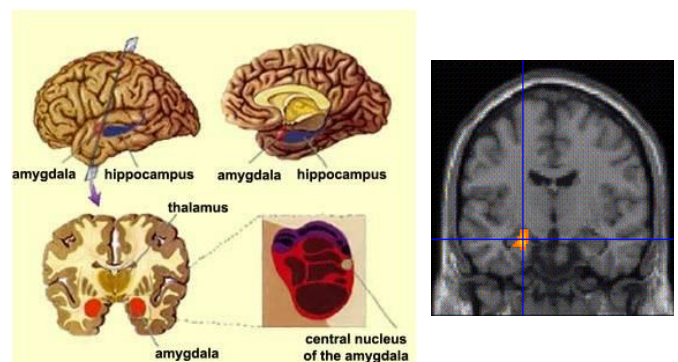


Fig. 1. The position of amygdala in brain for axial and coronal view

The remainder of this paper is organized as follows: in section 2, after mentioning stages of preprocessing for fMRI time-series, ICA is defined and two common version of it is explained. Section 3 goes with introducing mathematical morphology, its application, operations and transformations.

In section 4 our algorithm (our novel approach with morphology) is explained and in section 5, results has been shown

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and discussed. Many figures are shown, so the comparison between cases with and without morphological operations is possible. Conclusion is given in section 6.

2 ICA IN FMRI

Although many various methods like General Linear Model (GLM) [5], correlation [6], Principle Component Analysis (PCA) [7], wavelet [8] and Support Vector Machine (SVM) [9] are used for processing of fMRI time-series (images), one of most widely used method in this category is ICA. But, before introducing this method, it must be mentioned that all of these algorithms work on preprocessed fMRI images.

2.1 Preprocessing

Raw functional MRI time-series data obtained from an MRI scanner require several manipulations before statistical analyses can be performed. These manipulations include the following steps [10]:

1. Realignment

The goal is to align all functional images, so that the positioning of the brain in each image is the same. Typically, all functional images are aligned to the first functional image. The reason for doing this realignment is that subjects will move their head. There are 3 rotations (over the x, y, and z-axis), and 3 translations making a total of 6 parameters which fully describe the movement of the head over time.

2. Coregistration

The goal of Coregistration is to align the functional images with the anatomical image, so that the activation is superimposed onto the correct anatomical location.

3. Normalization

During normalization, the images of different subjects are warped in such a way those functionally homologous regions from different subjects are as close together as possible. Normalization involves changing the size of the brain using a linear 12 parameter registration (called an affine transformation) to match size and position of the template. In fig. 2 these parameters are shown. By masking the original image non-brain voxel is deleted and hence cannot affect this registration.

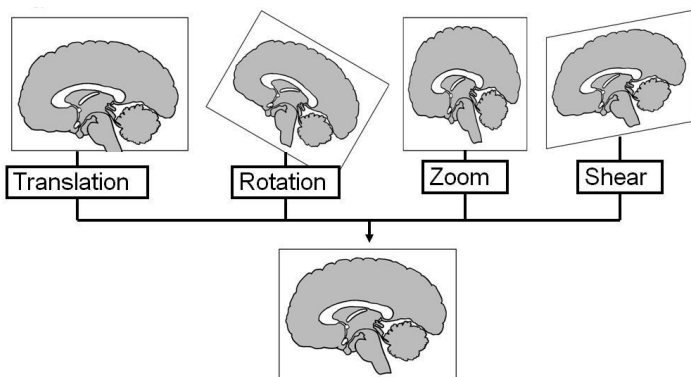


Fig. 2. Four kinds of changes in normalization along three axes

4. Smoothing

Smoothing involves blurring functional MRI images using (typically) a Gaussian filter, i.e. data is convolved with a Gaussian kernel. Smoothing is only applied when a group (between subjects) analysis is performed. By smoothing the image, the overlap of activation between subjects is increased. The size of kernel is determined by the full width at half maximum (FWHM). The FWHM is an indication of the distribution of the kernel values. After smoothing the image, the number of voxels and the size of the voxel (i.e. the sampling rate) remains the same. As shown in fig. 3 the resolution of the image becomes more less [11].

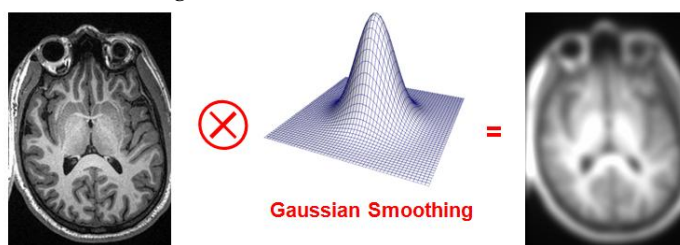


Fig. 3. Gaussian kernel for smoothing and its application

Preprocessing was performed using statistical parametrical mapping (SPM8; Welcome Trust Center for Neuroimaging, London, UK; www.fil.ion.ucl.ac.uk/spm) on MATLAB (Version 7.10., Mathworks, Natick, Ma USA).

2.2 ICA Method

ICA was introduced by Hyvarinen and Oja [12] for the first time and is a statistical technique that allows the extraction of signals of interest and not of interest without any prior information about the task. Thus ICA analysis could reveal characteristics of the brain function that cannot be modeled due to lack of prior information. This method also called as blind source separation (BSS).

Independent component analysis (ICA) has found a fruitful application in the analysis of fMRI data. ICA has been successfully utilized in a number of exciting fMRI applications including the identification of various signal-types (e.g. task and transiently task-related, and physiology-related signals) in the spatial or temporal domain.

The fundamental restriction in ICA is that the independent components must be nongaussian for ICA to be possible. Actually, without nongaussianity the estimation and evaluation of components is not possible at all.

The classical measure of nongaussianity is kurtosis or the fourth moment defined as:

$$kurtosis(x) = \frac{1}{M} \sum_{i=1}^M \left(\frac{x_i - \hat{\mu}_x}{\hat{\sigma}} \right)^4 \quad (1)$$

Mean (first moment), variance (second moment), skewness (third moment) also defined as below:

$$\hat{\mu}_x = \frac{1}{M} \sum_{i=1}^M x_i \quad (2)$$

$$\hat{\sigma}^2(x) = \frac{1}{M} \sum_{i=1}^M (x_i - \hat{\mu}_x)^2 \quad (3)$$

$$skewness(x) = \frac{1}{M} \sum_{i=1}^M \left(\frac{x_i - \hat{\mu}_x}{\hat{\sigma}} \right)^3 \quad (4)$$

Kurtosis can be either positive or negative. Random variables that have a negative kurtosis are called subgaussian, and those with positive kurtosis are called supergaussian. The value of zero for kurtosis is equal to a Gaussian distribution.

However, a second very important measure of nongaussianity is given by negentropy. Negentropy is based on the information theoretic quantity of (differential) entropy. Entropy is the basic concept of information theory:

$$H(\mathbf{Y}) = - \sum_i p(\mathbf{Y}=\mathbf{a}_i) \log p(\mathbf{Y}=\mathbf{a}_i) \quad (5)$$

And negentropy is defined like:

$$J(\mathbf{Y}) = H(\mathbf{Y}_{Gauss}) - H(\mathbf{Y}) \quad (6)$$

Calhoun in [13] represents a good example of ICA application for source separating. Input of ICA method is a mixed signal and output consists of 6 different signals as shown in fig 4.

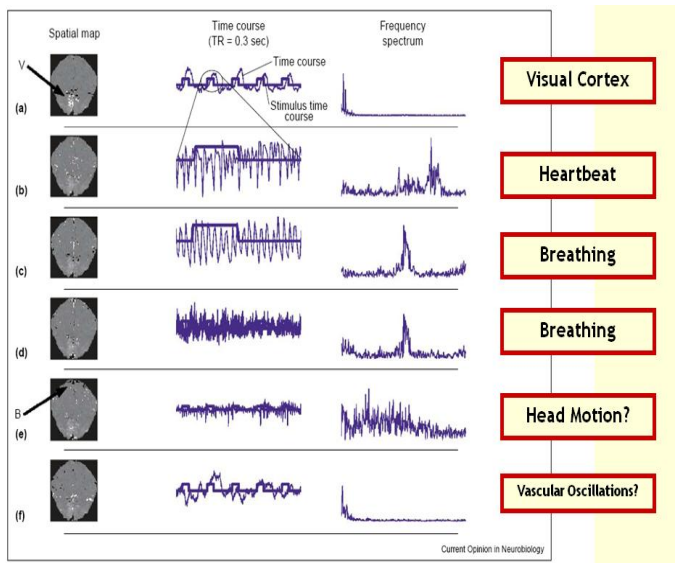


Fig. 4. Source (signal) separation using ICA

2.3 FastICA

At first, we shall show the one-unit version of FastICA. By a "unit" we refer to a computational unit, eventually an artificial neuron, having a weight vector \mathbf{w} that the neuron is able to update by a learning rule [14].

The FastICA learning rule finds a direction, i.e. a unit vector \mathbf{w} such that the projection $\mathbf{w}^T \mathbf{x}$ maximizes nongaussianity.

Nongaussianity is here measured by the approximation of negentropy $J(\mathbf{w}^T \mathbf{x})$.

The FastICA is based on a fixed-point iteration scheme for finding a maximum of the nongaussianity of $\mathbf{w}^T \mathbf{x}$. It can be also derived as an approximate Newton iteration. Denote by g the derivative of the nonquadratic function G . The basic form of the FastICA algorithm is as follows:

1. Choose an initial (e.g. random) weight vector \mathbf{w} .
2. Let $\mathbf{w}^+ = E \mathbf{x} g(\mathbf{w}^T \mathbf{x}) - E g'(\mathbf{w}^T \mathbf{x}) \mathbf{w}$
3. Let $\mathbf{w} = \mathbf{w}^+ / \|\mathbf{w}^+\|$
4. If not converged, go back to 2.

The g function can be defined as:

$$g_1(u) = \tanh(a_1 u) \quad g_2(u) = u \exp(-\frac{u^2}{2}) \quad (7)$$

The independent components can be estimated one by one. The algorithm finds directly independent components of (practically) any nongaussian distribution using any nonlinearity g .

2.4 Infomax

This method is based on maximizing the output entropy (or information flow) of a neural network with non-linear outputs [15]. Assume that \mathbf{x} is the input to the neural network whose outputs are of the form $\Phi(\mathbf{w}^T \mathbf{x})$, where Φ some non-linear scalar function and the w_i are the weight vectors of the neurons. One then wants to maximize the entropy of the outputs:

$$L_2 = H(\Phi_1(\mathbf{w}_1^T \mathbf{X}), \dots, \Phi_n(\mathbf{w}_n^T \mathbf{X})) \quad (8)$$

It is proved that the principle of network entropy maximization or "Infomax" is equivalent to maximum likelihood estimation. This equivalence requires that the non-linearities Φ used in the neural network are chosen as the cumulative distribution functions [16].

3 MATHEMATICAL MORPHOLOGY

Mathematical Morphology is a subject concerning with the shape of an object based on set theory and geometry and has been widely used in image processing and pattern recognition. Morphological operations work with two sets. One set is the image to be processed. Another set is called structuring element. By using a structuring element to operate on a signal, the information of a signal (shape, size, etc) can be extracted. Different results can be reached, if different structuring elements are designed to operate on an image.

3.1 Operations

Two operations (Dilation & erosion) are defined:

$$A \ominus B = \min_{u,v} A(x+u, y+v) - B(u,v) \quad (9)$$

$$A \oplus B = \max_{u,v} A(x-u, y-v) + B(u,v) \quad (10)$$

Dilation is the maximum pixels set union when structuring element overrides image, while erosion is the minimum pixels set union when image is overlapped by structuring element. Dilation expands image set and erosion shrinks it. Based on these two, we can define opening and closing operations:

$$A \circ B = (A \ominus B) \oplus B \quad (11)$$

$$A \bullet B = (A \oplus B) \odot B \tag{12}$$

Opening smoothes bright small regions of image and closing eliminates dark small holes. Opening and Closing operators can be interpreted as sliding structuring element along the image from beneath and above respectively.

3.2 Transformations

Top-Hat transformations are defined as below [18]:

$$Top - Hat (A) = A_{TH} = A - (A \circ B) \tag{13}$$

$$Bottom - Hat (A) = A_{BH} = (A \bullet B) - A \tag{14}$$

Top-Hat is usually used to extract bright image features and Bottom-Hat is used to extract black image features.

4 PROPOSED METHOD

4.1 Block Diagram

In this section, the block diagram of proposed method is shown (fig. 5).

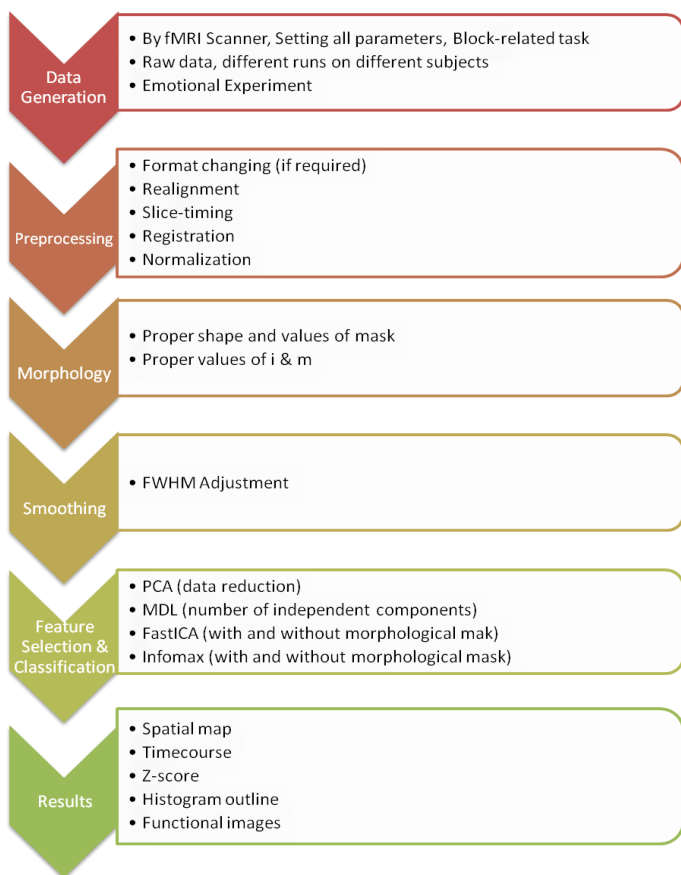


Fig. 5. Block diagram of proposed method

As one can see in this chart, our contribution based on morphology is inserted before smoothing stage.

In Feature selection & classification level, first of all, we use PCA for dimension reduction. PCA is a multivariable statistical analysis technique that seeks the linear combinations of the original variables such that the derived variables capture maximum

variance.

We propose using standard information theoretic methods for estimating the number of components from the aggregate data set. These methods make a decision based upon the complexity or information content of the data. The number of sources can be estimated using minimum description length (MDL) criterion. These criteria have the following form:

$$MDL(N) = -V (ML - N) \Psi(\hat{\theta}_n) + \frac{1}{2} \left(1 + NL + \frac{1}{2}(N - 1) \right) \ln V \tag{15}$$

Where V is the number of voxels, M is the number of subjects, Ψ is the log of the maximum likelihood estimate of the model parameters (and is estimated from the fMRI data), ML is the number of time points following the first reduction stage and N is the number of sources. The estimate for the number of sources is determined from the minima of the above functions with respect to N . In our case the output can be seen in Fig. 6 equal to 20.

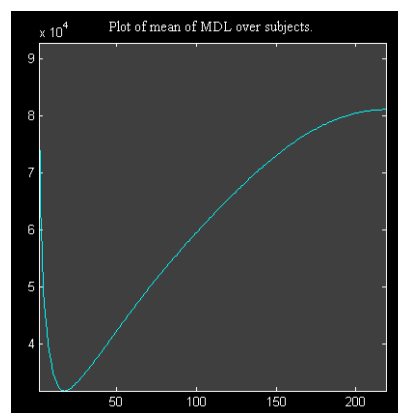


Fig. 6. Number of Components determined by MDL algorithm is 20

4.2 Enhancement by Morphology

Morphology has not been widely used in fMRI Image Processing. Only uses of dilation or opening operators are reported for elimination of isolated voxels that marked as active areas [17].

One good idea of image enhancement is enlarging the contrast between the bright and dim regions of image. Top-Hat transformation extracts bright image regions and Bottom-Hat transformation extracts dim image regions corresponding to the used structuring element. Therefore, one way of image enhancement is adding the bright image regions on and subtracting the dim image regions from the original image:

$$A_o = A + A_{TH} - A_{BH} \tag{16}$$

As another idea, bright and dim image features may exist at different scales of image. If the bright and dim image features at all scales could be extracted and used in (16), the original image could be enhanced more efficiently. So we make a sequence of multi scale structuring elements with the same shape and increasing sizes in (17). In our case and for many medical images, we use disk-shaped mask.

$$B_i = B \oplus B \oplus \dots \oplus B$$

← i times →

So we have:

$$A_{TH_i} = A - (A \circ B_i)$$

$$A_{BH_i} = (A \bullet B_i) - A$$

and (16) can be rewritten as:

$$A_o = A + A_{TH_i} - A_{BH_i}$$

And final form of formula is

$$A_o = A + m(A_{TH_i} - A_{BH_i}) \tag{21}$$

As i controls the size of mask and m controls the quality of output contrast of image. In this trial and error m may be any real positive number. For $i=n=1$, (21) equals to simpler form of its own i.e. (16).

It is noteworthy that we must clearly specify our goal using (21) for contrast enhancement. In first row of Fig. 7, the output of method has a better looking, but does not chase any specific target. in other rows, we improved contrast of input images for various diagnosis tasks.

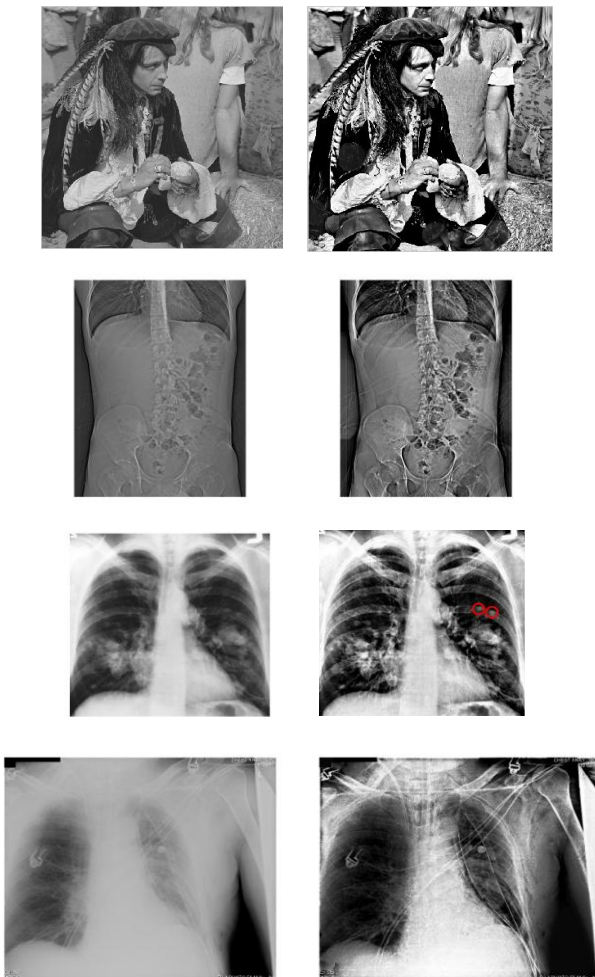


Fig. 7. Result of some images after applying formula (21) with $i=1$ and $m=1.2$ and disk-shaped mask with radius=25.

(17) These tasks include better diagnosis in CT image, finding nodules in lung, clarity in ending of cateter tubes.

$$\tag{18}$$

$$\tag{19}$$

$$\tag{20}$$

5 RESULTS AND DISCUSSION

Our database is from fmridc.org coded as 2-2000-1119F [19] that consists records of fMRI experiment for 20 subjects. 10 scan is taken from each subject and every scan has 220 slices. Task is emotional and activates the amygdala area.

For 20th slice of first run of subject 3, the application of morphological Top-Hat transformations is shown as sample. In fig. 8 through fig. 10, cross-sectional images as input with output for 4 different circular masks (radius =3, 5, 7, 15) are shown.

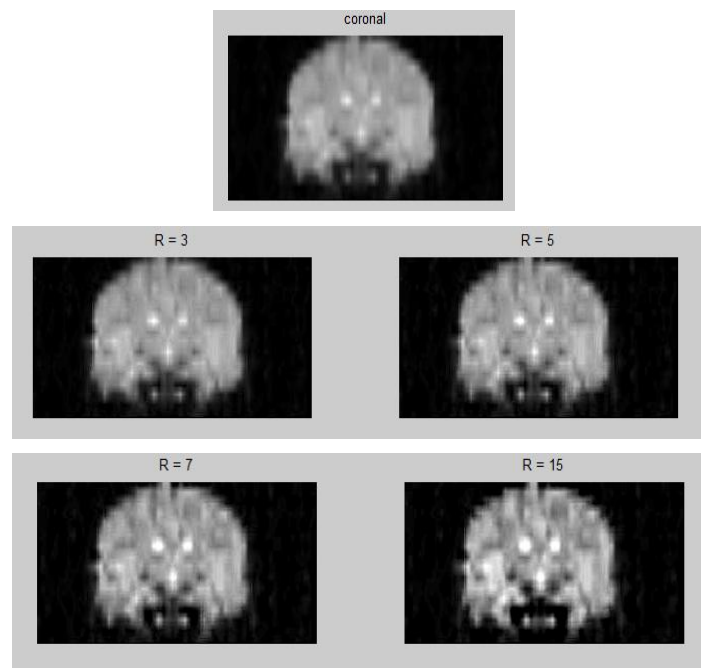


Fig. 8. Morphological Top-Hat transformations for coronal image of a slice (mask is disk with radius = 3, 5, 7, 15)

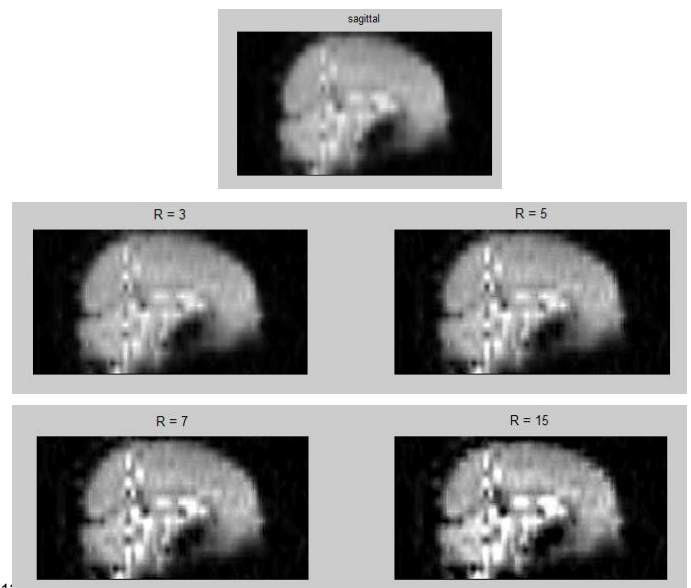


Fig. 9. Morphological Top-Hat transformations for sagittal image of a slice (mask is disk with radius = 3, 5, 7, 15)

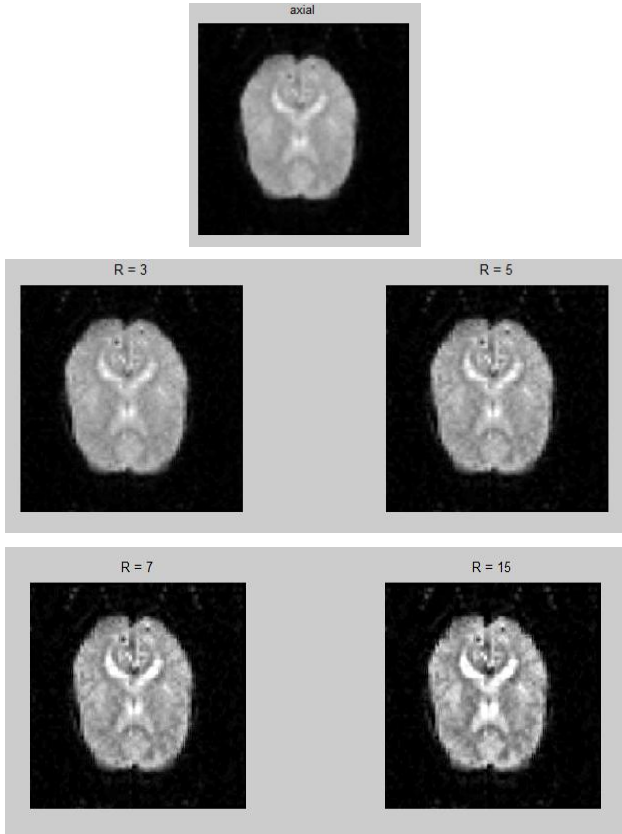


Fig. 10. Morphological Top-Hat transformations for axial image of a slice (mask is disk with radius = 3, 5, 7, 15)

Component ranking is based on consistency across multiple runs and subjects. Here two indices are used. Let the number of subjects be N , number of subject run M , component number T , for each individual-level, the mean component across multiple runs and distance parameter are defined:
 $i = 1$ to N , $j = 1$ to T , $k = 1$ to M

$$m_{jk} = \frac{1}{N} \sum_{i=1}^N C_{ijk} \quad (22)$$

$$d_{jk} = \frac{1}{N} \sum_{i=1}^N |C_{ijk} - m_{jk}| \quad (23)$$

Based on (22) and (23), mean and mean/std are defined:

$$m_j = \text{mean}(d_j) \quad (d_j : \{d_{j1}, \dots, d_{jM}\}) \quad (24)$$

$$t_j = \frac{\text{mean}(d_j)}{\text{std}(d_j)} \quad (d_j : \{d_{j1}, \dots, d_{jM}\}) \quad (25)$$

These two indices are very useful in ranking of independent components that make the fMRI image. In fig. 11, all 20 components are sorted via their value of mean/std and mean pa-

rameters. There is a very minor difference between the results. In Fig. 12, the corresponding image made by 3 most important independent components is given. Final result for FastICA and Infomax with and without morphology is shown in fig 13 and fig 14. Best output is achieved for fastM7 and fastM5 (using morphology with R=5 and R=7).

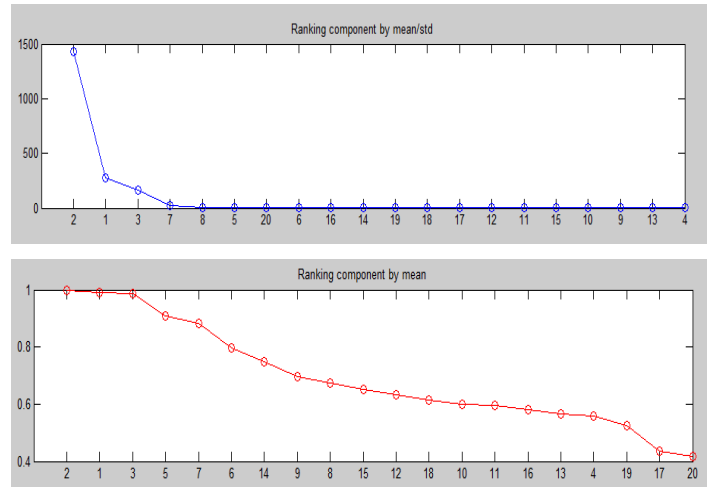


Fig. 11. Components sorted by their descending values of mean/std and mean parameters

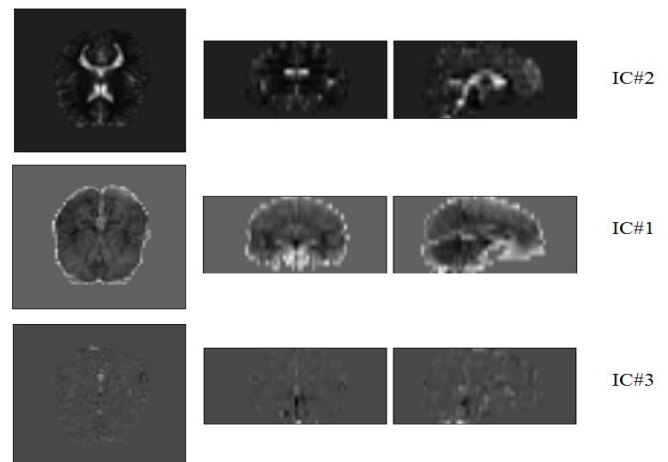


Fig. 12. Part of whole fMRI image corresponding to 3 IC

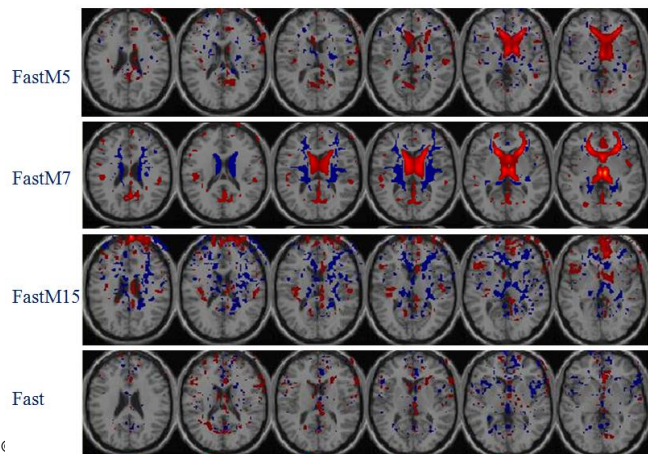


Fig. 13. Output images for FastICA method with and without morphological transformations.

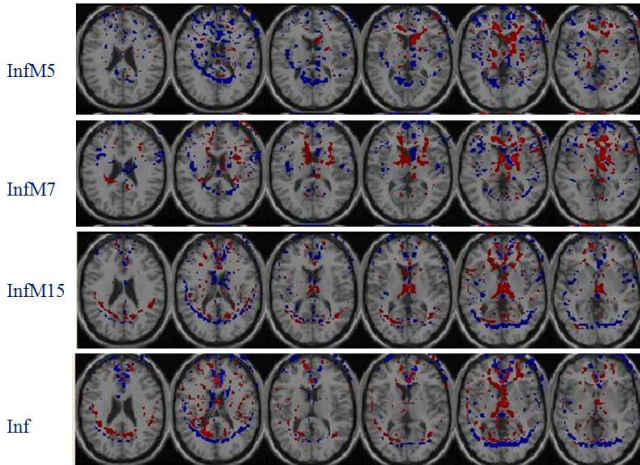


Fig. 14. Output images for Infomax method with and without morphological transformations

Fig. 15 shows the histogram (based on Z-Score) for 3 IC. With decrease in importance of IC, values are aggregated around zero.

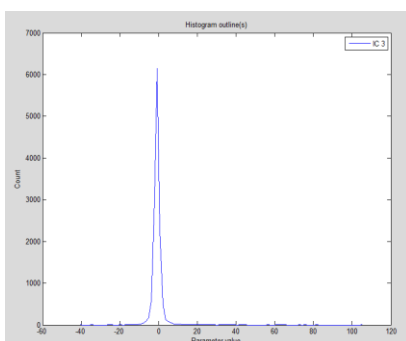
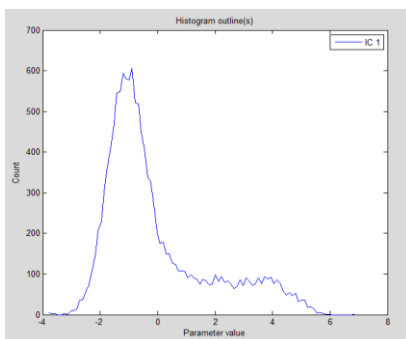
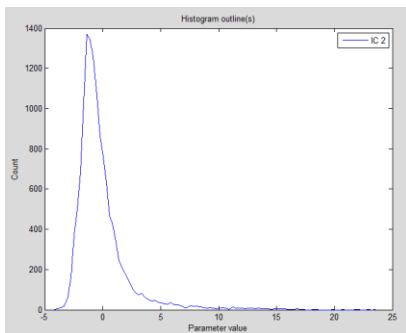


Fig. 15. Outlier histogram for 3 most important independent components

6 CONCLUSION

The most important contribution of this paper is some modification based on of morphological Top-Hat transformation for improving contrast of any kind of images.

We have outlined our proposed method based on this modification and test and compare the results of applying method with and without using morphology.

As a future work and extension of this idea, we focus on automation of this method for selecting the shape and size of morphological mask adaptively.

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