Automated Characterization of Brain Tasks using FastICA Feature Extraction Algorithm

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ABSTRACT
Among the available imaging modalities, functional magnetic resonance imaging (fMRI) can provide the function of the brain based on the changes of local magnetic properties associated with the level of oxygenation and cerebral blood flow/volume. Independent component analysis (ICA) is a popular blind source separation (BSS) technique for the analysis of functional magnetic resonance imaging (fMRI) data and can be proved to work promisingly FastICA algorithm for feature extraction provide reliable results.

Keywords
functional MRI, ICA, data driven, support vector machine.

1. INTRODUCTION
Automated characterization of brain activities, and a concurrent attempt to interpret corresponding human thoughts, is an emerging research field. Specifically, automatic interpretation and classification of neuroimaging data may hold important keys for understanding the human mind, which has raised interests due to the potential commercial/clinical applications. Among the available imaging modalities, functional magnetic resonance imaging (fMRI) can provide the function of the brain based on the changes of local magnetic properties associated with the level of oxygenation and cerebral blood flow/volume [1][2] .

Region-of-interest (ROI)-based feature extraction scheme is developed to derive the feature vectors based on the individual-specific activation pattern. Six mental imagery tasks were used to test the developed method for automated identification of human thoughts. An automated method for the selection of optimal feature vectors was implemented based on the individual's specific patterns of brain activity. This type of 'data-driven' selection of feature vectors is more robust considering the variability of activation in comparison to 'hypothesis-driven' approaches, whereby the feature vector is selected from anatomically segmented brain regions [3]. The six mental tasks (with corresponding acronyms) are (1) right hand motor imagery (RH), (2) left hand motor imagery (LH), (3) right foot motor imagery (RF), (4) mental calculation (MC), (5) internal speech generation (IS), and (6) visual imagery (VI)[3].

2. RELATED WORK
This automated classification performance was compared depending on the feature vector selection methods. A general linear model (GLM) was adopted to define a neuronal activity and voxel-based or atlas-based approaches were adopted as feature vector selection methods. The classification results showed superior performance from the voxel-based feature selection method than the atlas-based method. Nonetheless, when multiple atlases were used to defined feature vector elements, the resulting performance was comparable to that of the voxel-based method with greatly reduced computational time.

The element of the feature vector was selected based on following two approaches: i.e., (1) data driven voxel-based selection and (2) atlas-driven region based selection.

2.1 Data-driven voxel-based selection
Any voxels whose level of neuronal activity was significantly active during the three scans or more were defined as an ROI of corresponding task. The levels of exclusively active voxels across the six ROIs were then used as elements of the feature vector. Here, a statistical significance (*i.e.,. p*-value) to define an active status of each voxel was automatically defined from a cross-validation (CV) scheme, in which the *p*-value presenting a maximum cross-validation accuracy during *k*-fold CV phase was used as an optimal statistical significance[1].

2.2 Atlas-driven region-based selection
The automated anatomical labeling (AAL) map and the Brodmann's area (BA) were used as the standardized atlas templates. Numbers of regions of the AAL and BA maps are 116 and 52, respectively), the beta weights of the active voxels within each of the atlas-defined functional areas were averaged and used as an element of the feature vector (*i.e.,* atlas-driven feature vector). Also, the combination of the ALL and BA map (*i.e.,* "AAL+BA") was also considered to define a feature vector. Again, the *k*-fold CV phase was applied to select optimal *p*-value and SVM parameters using the atlas based feature vectors.

For classification purposes, however, it is important to separate out task-specific activation areas so that they are as exclusive as possible. Therefore, we obtained a binary mask by including exclusively activated regions among the six ROIs. Consequently, the voxels within the mask were assigned as elements of a feature vector, which is an input for a classifier. The exclusively activated regions ($p<0.01$; z-score>2.58; [1].

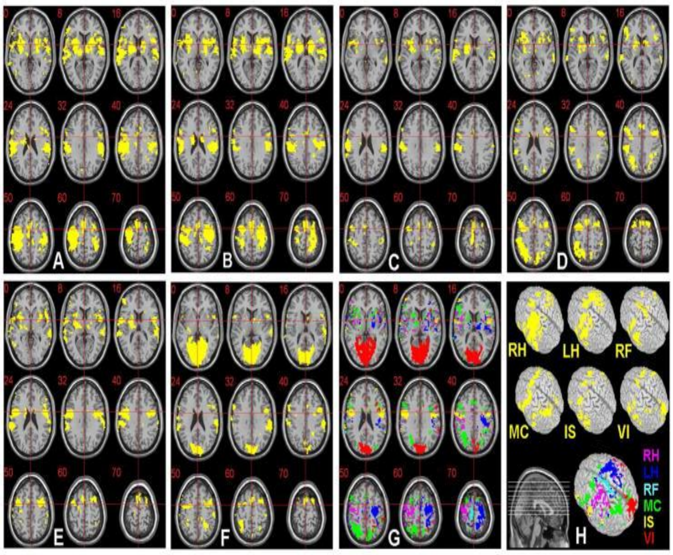

Figure .1 The ROIs ($p<0.01$; z-score>2.58; d.f.=49) obtained from the six imagery tasks performed by a male subject (S4) are shown as yellow-colored regions: (A) ROI for the right-hand motor imagery (RH), (B) left-hand motor imagery (LH), (C) right-foot motor imagery (RF), (D) mental calculation (MC), (E) internal speech generation (IS), and (F) visual imagery (VI). (G) The exclusively activated regions across (A) ~ (F) are displayed in different colors (labels in H) and are overlaid on the anatomical template.

The optimal ROIs and SVM parameters were determined from the maximum cross validation accuracy throughout p-values($p<0.05$, $p<0.01$, $p<5\times10^{-3}$, $p<10^{-3}$, $p<5\times10^{-4}$, and $p<10^{-4}$). These optimized parameters were applied to the subsequent classification of the testing data.

3. GENERAL LINEAR MODEL (GLM) APPROACH

The *general linear model* (GLM) is a statistical linear_model. It may be written as

$$Y=XB + U \qquad (1)$$

where **Y** is a matrix with series of multivariate measurements, **X** is a matrix that might be a design matrix, **B** is a matrix containing parameters that are usually to be estimated and **U** is a matrix containing errors or noise. The errors are usually assumed to follow a multivariate normal distribution. If the errors do not follow a multivariate normal distribution, generalized linear models may be used to relax assumptions about **Y** and **U**.

Using the optimally chosen SVM parameters during the *k*-fold

CV phase, the scans in the test set was automatically classified and corresponding target task was subsequently identified. Three types of automated classification tests were conducted based on the training and test sets used including (1) within-session test, (2) between-session test, and (3) between-subject test [1].

TABLE 1.

COMPUTATIONAL TIME (SEC) DURING EACH STEPS

	Feature Extraction	Training	Testing
	Within-session test		
Voxel	4748.8	82552.3	27.1
AAL	4430.8	8726.3	2.4
BA	4134.5	7070.0	1.6
AAL+BA	4258.4	14052.9	8.1
	Between-session test		
Voxel	34.1	513.2	0.18
AAL	35.2	33.2	0.01
BA	33.4	24.1	0.01
AAL+BA	33.4	69.2	0.06
	Between-subject test		
Voxel	428.0	48799.5	8.9
AAL	460.3	1473.2	0.3
BA	461.0	929.5	0.2
AAL+BA	473.1	4942.9	2.7

In the above method the performance of the automated classification of distinct human thoughts processes was evaluated depending on the feature extraction methods of data-driven approach to select active voxel, and atlas-driven approach to select active brain region. Overall, the performance from the data-driven voxel-based feature selection approach has shown consistently higher hit rates compared to the atlas-driven region-based feature selection approach.

4. PROPOSED SYSTEM

As it is seen that classification of distinct human thoughts processes was evaluated depending on the feature extraction methods of data-driven approach to select active voxel, and atlas-driven approach to select active brain region. In proposed system Independent component analysis (ICA) will be used which is a popular blind source separation (BSS) technique for the analysis of functional magnetic resonance imaging (fMRI) data and can be proved to work promisingly.

4.1 Independent Component Analysis

The aim of analyzing fMRI data by ICA, is to factor the data matrix into a product of a set of time courses and a set of spatial patterns .Some researchers extended ICA to allow for the analysis of multiple subjects. This analysis can simultaneously decompose group fMRI data into different component maps. [5]. At first in order to produce the observed matrix, each image which is acquired in each time point, is converted into a one dimensional row signal vector x_i $(i=1.....m)$, where i is the index of each time point, and is the m total number of time points. The length of the signal vector v is equal to the number of voxels per frame. The signal x_i is considered as a linear combination of the independent components, c_j $(j= 1....n)$

$$X_{ik} = \sum_{j=1}^{n} M_{ij} \,.\, C_{ij} \; (k = 1,....v) \qquad (2)$$

For implementation of spatial ICA analysis for fMRI data, algorithm such as FastICA (fixed-point ICA) have been proposed [4].Infomax & Jade these algorithms are also providing reliable results in their special area but FastICA algorithm on simulated group data and noted that the group ICA technique proposed in provided the best overall performance in terms of accurate estimation of the sources and associated time . This algorithm uses the concept of normalized differential entropy or negentropy[4].

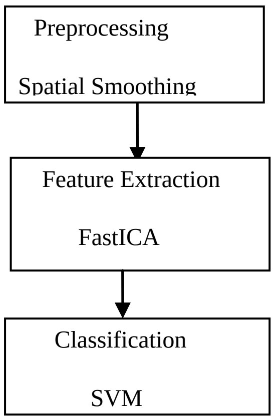

Fig-2. Block Diagram of Proposed System.

4.2 Preprocessing

Spatial smoothing smoothing means that data points are averaged with their neighbours. This has the effect of a low pass filter meaning that high frequencies of the signal are removed from the data while enhancing low frequencies.Advantage of spatial smoothing over temporal smoothing is that sharp "edges" of the images are blurred and spatial correlation within the data is more pronounced and also in multi-subject studies, individual brains are coregistered to each other to establish spatial correspondence between the different brains and here we are dealing with more subjects and six task.

Still, because of the substantial variation in individual brains, activated areas are rarely represented in exactly the same voxels. To increase the overlap of activated brain regions across subjects smoothing can be applied. Spatial smoothing results always in reduced spatial resolution of the data. Therefore, it is important to decide whether a precise localization of the activations is important.

4.3 Feature Extraction

As seen that for for feature extraction Fast ICA has been proposed because We use fMRI data from different subjects performing the tasks and instead of entering each subjects'

data into a separate ICA analysis, we use a group ICA technique to estimate one set of components and then back-reconstruct from the aggregate mixing matrix to obtain the individual subject maps. This method has the advantage of ordering the components in different subjects in the same way, which is a tedious task if individual ICA analyses are performed because unlike the general linear model (GLM) the group ICA technique allows for cross-subject variability test this can be performed using one of the algorithm i.e FastICA.

GIFT is a MATLAB-based ICA/BSS tool, that includes a number of analysis and visualization techniques in a user friendly graphical interface providing number of algorithms which was reported for a simulated set of fMRI-like data and actual fMRI data from a single slice out of which we are using FastICA. FastICA maximize the higher order statistics or the negentropy of the output to maximize the non-gaussianity of the estimated source using fixed-point iterations[6].

4.4 Classification

The concept of Support Vector Machine was introduced by Vapnik SVM is used for both classification and regression problems based on Statistical Learning Theory (SLT). SVM constructs models that are complex enough it contains a large class of neural nets, radial basis function (RBF) nets, and polynomial classifiers as special cases[7].

Support vector machine (SVM) is to be found good classifier in different studies of fmri. SVM outperforms in classification performance as well as in robustness of the spatial maps obtained (i.e. discriminating volumes. SVM indicate that it is feasible for either single subject classification or multiple subjects. The method is helpful to decode test among subjects.

Unlike other classifiers linear SVM, as the regularization clearly helps weigh down the effect of noisy features that are highly correlated with each other[8]. SVM appeared to have an edge over the other classifiers across different tasks. Sparse logistic regression has also been shown to be successful in voxel selection and classification. SVM has three major advantages over other classifier models: (i) the weights of the trained classifier can be used to rank the features (voxels); this is also true for the LDC (ii) SVM is robust and accurate; and (iii) SVM can be trained and run on thousands of feature in reasonable time, which is not true for most other classifier models[9].

5. CONCLUSION

This work will be considered as to provide good results using spatial smoothing, FastICA algorithm for feature extraction and SVM classifier among different subjects for the six task.Performance will be better in terms of accuracy and time.

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