

# Classification of Cognitive States from fMRI data using Fisher Discriminant Ratio and Regions of Interest

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## ABSTRACT

*In recent decades, analyzing the activities of human brain achieved some accomplishments by using the functional Magnetic Resonance Imaging (fMRI) technique. fMRI data provide a sequence of three-dimensional images related to human brain's activity which can be used to detect instantaneous cognitive states by applying machine learning methods. In this paper, we propose a new approach for distinguishing human's cognitive states such as "observing a picture" versus "reading a sentence" and "reading an affirmative sentence" versus "reading a negative sentence". Since fMRI data are high dimensional (about 100,000 features in each sample), extremely sparse and noisy, feature selection is a very important step for increasing classification accuracy and reducing processing time. We used the Fisher Discriminant Ratio to select the most powerful discriminative features from some Regions of Interest (ROIs). The experimental results showed that our approach achieved the best performance compared to other feature extraction methods with the average accuracy approximately 95.83% for the first study and 99.5% for the second study.*

**Keywords:** functional Magnetic Resonance Imaging, Regions of Interest, feature selection, Fisher Discriminant Ratio.

## 1. INTRODUCTION

Investigating activities in human brain for disease detection is one of the challenges in the past decades. Many scientists tried to find some techniques to access the human's cognitive states through brain activation. Several techniques such as electro encephalography (EEG), magneto encephalography (MEG) and positron emission tomography (PET) also allow researchers to measure the brain activation. Generally, these techniques are concerned with the activity arising from a large group of neurons but they differ in what they measure, as well as in the temporal and spatial resolution. EEG and MEG techniques are based on the information of electrical and magnetic activity in the brain. They provide temporal resolution precisely while fMRI and PET techniques, which are based on the information of blood flow changes, provide a high spatial resolution. Since fMRI technology has the promise of achieving good performance for studying human cognitive processes, this article focuses on the classification issues related to fMRI which has taken an important position in the neuroimaging domain.

The fMRI technique is most commonly performed using blood oxygenation level-dependent (BOLD) contrast to study local changes in deoxyhemoglobin concentration in a brain [2]. Based on the diamagnetic property of oxygenated hemoglobin and paramagnetic property of deoxygenated hemoglobin, BOLD signals can help us to measure the activation of brain for generating three-dimensional images. Each image consists of a number of uniformly spaced volume elements, called voxels. Changes in voxel intensity across time can be used to infer when and where an activity is taking place. Multiple 2D images can be captured, forming a 3D image that may contain on the order of 15,000 voxels, each of which can measure the response of a 3x3x5 region of the brain. Images of 15,000 voxels can be acquired at the rate of one or two per second with high field (3 Tesla) echo planar imaging.

The analysis of fMRI data is made complex by a number of factors. First, the data are liable to a number of artifacts, such as those caused by head movement. Second, there are a number of sources of variability in the data, including variability between individuals and variability across time within individuals. Third, the dimensionality of the data is very large, which causes a number of challenges in comparison to the small datasets that many scientists are accustomed to working with. The major components of fMRI analysis are meant to deal with each of these problems [3]. They include:

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- Quality control: ensuring that the data are not corrupted by artifacts.
- Distortion correction: the correction of spatial distortions that often occur in fMRI images.
- Motion correction: the realignment of scans across time to correct head motion.
- Slice timing correction: the correction of differences in timing across different slices in the image.
- Spatial normalization: the alignment of data from different individuals into a common spatial framework so that their data can be combined for a group analysis.
- Spatial smoothing: the intentional blurring of the data in order to reduce noise.

Figure 1 illustrates the processing stream for analyzing fMRI data. The pre-processing step is necessary before using fMRI data as the input for classification. With exception of removing noises, standardizing the brain space and correcting head motion, this step was conducted to shift the time series so they can be considered to have been measured simultaneously.

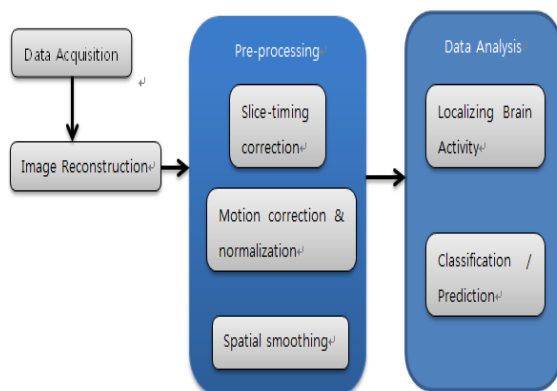


Fig. 1. fMRI stream processing [2]

The fMRI technology has been used to conduct hundreds of studies that identify which regions of the brain are activated when a human performs a particular cognitive function (reading, mental imagery, remembering) [4]. In this approach, researchers focus on mapping from a task to brain locations activated by this task. In contrast, many other researchers are interested in mapping from fMRI data to the human subject's cognitive states [12-17] which are known as clustering and classification problem. The goal of this approach is training machine learning classifiers to automatically detect the subject's cognitive state at a single time interval. This capability would be useful not only in tracking the hidden cognitive states of a subject performing a single, specific task but also in solving some medical diagnosis problems such as diagnosing Alzheimer's disease [5].

This problem is a challenge because it must solve the issue of extremely high dimensional, sparse and noisy data. In our case, we encountered problems where the examples are described by more than 80,000 features and we have only several dozens of examples per class. The fMRI data were collected when some human subjects were shown special pictures and simple sentences. Our target was training classifier for distinguishing cognitive states such as "observing a picture"

versus "reading a sentence" and "reading an affirmative sentence" versus "reading a negative sentence". At first, we chose some Regions of Interest (ROIs) which have a good performance when classifying the above cognitive states. After that, by computing the Fisher Discriminant Ratio of every feature in each ROIs, we selected the most powerful discriminative features. In the end, by using Gaussian Naïve Bayes classifier, our system achieved the average accuracy approximately 95.83% for the "observing a picture" versus "reading a sentence" study and 99.5% for the "reading an affirmative sentence" versus "reading a negative sentence" study.

The remainder of this paper is organized as follows. Section 2 describes approaches of others researchers and their achievements. Section 3 discusses about the proposed method. The data description and experimental results are detailed in Section 4. Section 5 is our conclusion.

## 2. RELATED WORK

Over recent years, various techniques were applied for analyzing fMRI data. Friston et al. and Bly used Generalized Linear Models (GLM) to perform a regression for each voxel [6,7]. GLM approach models the time series as a linear combination of several different signal components. Therefore, they can predict the signal value at every voxel based on properties of the stimulus and test whether activities in a brain region are systematically related to any of the known input functions. Hojen-Sorensen, Hansen and Rasmussen used Hidden Markov Models (HMM) to learn a model of activities in the visual cortex resulting from a flashing light stimulus [8]. Although the program was not told the stimulus, the on-off stimulus was recovered as the hidden state by the HMM. Jung et al. referred to Independent Component Analysis (ICA) as a useful method for fMRI analysis [9]. It has proven to be a powerful approach for detecting task-related activations, including unanticipated activations that could not be detected by standard analyses. Mc Keown et al. used Principle Component Analysis (PCA) to determine spatial factors that can be linearly combined to reconstruct the fMRI signal [10]. Haxby et al. showed that different patterns of fMRI activity were generated when a human subject viewed a photograph of a face, a house, a shoe, a chair [11]. Cox and Savoy applied Support Vector Machine and Linear Discriminant Analysis to a set of data to successfully classify patterns of fMRI activation evoked by the presentation of photographs of various categories of objects [12].

Since fMRI data is high dimensional, dimensionality reduction is typically performed before classification to improve the performance of system. The Principle Component Analysis (PCA) and the Regions of Interest (ROIs) are most widely used as feature selection method. PCA is a standard dimensionality reduction method that transforms high dimensional data onto a linear eigen-space learned from the training dataset. However, the performance of PCA is generally limited when the dimension of original data is much higher than the number of available training samples which is the common case of fMRI data. Therefore, many researchers tried

to apply the enhanced version of PCA or the combination of PCA and other techniques. T. Hoang et al. used incremental PCA (iPCA) to develop an incremental subspace tracking for reducing computation and storage requirements [13]. Y. Fan et al. applied PCA after extracting regional features which are formed by statistical information [14]. They achieved a very high accuracy by using nonlinear support vector machine (SVM) in lie detection study.

Brain regions that are relevant to the problem under study must first be selected from a background of brain activity [14]. It's believed that any mental task is activated in some special location of the brain, called Regions of Interest (ROIs). Instead of using all features of the entire brain, considering only specific ROIs can improve the performance of classifiers. Etzel et al. tried to solve classification problem of fMRI by using anatomical ROIs [15]. They selected all voxels containing in some specific ROIs to evaluate the performance of anatomical ROIs-based fMRI classification approach. Mitchell et al. and S. Bapi et al. selected the most active voxels per ROIs [16]. While Mitchell et al. could not reach a high accuracy for the Picture versus Sentence study, S. Bapi et al. had a good result with Early versus Late Learning study.

However, Mitchell et al. proposed another feature selection method by providing the definition of fixation condition [5]. This fixation condition contains data observed during the time that human subject is generally at rest. Therefore, their binary classification problem became the classification between three classes: two classes indicate the cognitive states of a human subject, the remaining one is fixation. They called the voxels which have ability to distinguish the target class from fixation condition as active voxels. They applied t-test for each voxel of each target class to measure the power of active voxels. This method had a good result with the highest accuracy compared to other methods proposed by Mitchell et al. [5].

Instead of using standard classifiers such as Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), Bernard et al. proposed a new group of classifiers, called Generalized Sparse Classifiers (GSC) to alleviate the over-fitting problem of standard classifiers [17]. They constructed a Spatial-Smooth Sparse Linear Discriminative Analysis (SSLDA) classifier to demonstrate the power of GSC. SSLDA reached a very high accuracy for the Picture versus Sentence study provided by Mitchell [5].

### 3. PROPOSED METHOD

In this paper, we propose an approach for classifying human's cognitive states from fMRI data using the Fisher Discriminant Ratio to select the most powerful discriminative features from some Regions of Interest (ROIs). By using Gaussian Naïve Bayes classifier, our approach performed the best performance compared to other feature extraction methods for the Picture versus Sentence study and Affirmative versus Negative sentence study.

#### 3.1 Regions of Interest

In order to localize the task-related regions, some researchers

tried to divide the entire brain into some Regions of Interest (ROIs). We followed Mitchell et al. [5] to mark up the brain with 25 anatomical Regions of Interest (ROIs). They included: calcarine sulcus (CALC), dorsolateral prefrontal cortex – left & right (LDLPFC, RDLPFC), frontal eye fields – left & right (LFEF, RFEF), left inferior frontal gyrus (LIFG), inferior parietal lobule – left & right (LIPL, RIPL), intraparietal sulcus – left & right (LIPS, RIPS), opercularis – left & right (LOPER, ROPER), posterior precentral sulcus – left & right (LPPREC, RPPREC), supramarginal gyrus – left & right (LSGA, RSGA), superior parietal lobule – left & right (LSPL, RSPL), temporal lobe – left & right (LT, RT), triangularis – left & right (LTRIA, RTRIA), supplementary motor areas (SMA), inferior temporal lobule – left & right (LIT, RIT). In order to create these ROIs, Mitchell et al. used structural image which captures the static physical brain structure at high resolution. For each subject, this structural image was used to identify the anatomical regions of interest, using the parcellation scheme of Caviness and Rademacher [18]. After that, the mean of fMRI images was co-registered to the structural image. Hence, individual voxels in fMRI images could be associated with the ROIs identified in the structural image. We applied Gaussian Naïve Bayes (GNB) classifier for each ROI to check the effectiveness of ROIs in our study. Based on the classification accuracy of each ROIs, we could find some specific regions of the brain that most related to the tasks of viewing a picture or reading a sentence. The details of this work will be described more in section 4.

#### 3.2 Fisher Discriminant Ratio

Fisher linear discriminant is one of efficient approaches for dimension reduction in statistical pattern recognition. Fisher discriminant ratio (FDR) is commonly employed to qualify the discriminatory power of individual features between two classes. In other words, it is independent of the type of class distribution. FDR value is defined as:

$$FDR = \frac{(m_1 - m_2)^2}{(\sigma_1^2 + \sigma_2^2)}$$

where  $m_1$  and  $m_2$  are respective mean values,  $\sigma_1^2$  and  $\sigma_2^2$  are respective variances associated with the values of a feature in two classes. For the features that have large differences between the means of two classes and small variances in each class, a high value of FDR will be obtained. It means that if two features have the same absolute mean difference and a different sum of variances, the one with the smallest sum of variances will get a higher FDR value. On the other hand, if two features have the same sum of variances and different mean differences, the one with larger mean difference will get a higher FDR value. This meaning of Fisher Discriminant Ratio is illustrated as Figure 2. We can imagine that features in each class are performed by a circle where the center is the mean and the radius is variance. Two circles are located more separately when distance between two centers is large and their radius are small. In our studies, we selected  $n$  features which have highest FDR values as the most discriminative power features from seven ROIs which are explained in experimental section. These selected features not only improve the performance of our

classifiers but also reduce the processing time compared to the method of using only ROIs and the method of computing FDR value of features from the whole brain.

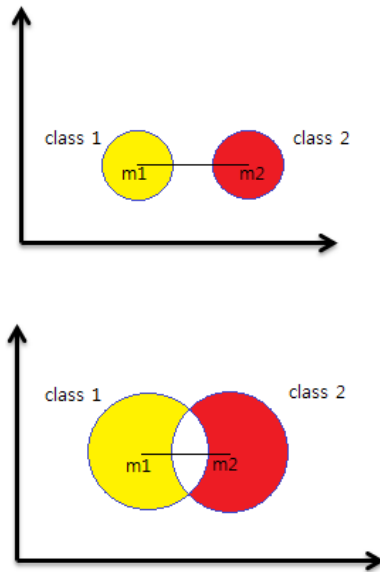


Fig. 2. Illustration of Fisher Discriminant Ratio

### 3.3 Gaussian Naïve Bayes Classifier

The Bayes Theorem is a statistical principle for combining prior knowledge of the classes with the new evidence gathered from data [20]. Bayes theorem is described as the following formula:

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)},$$

where  $X$  is attribute set and  $Y$  is the class variable. Based on this theorem, given attribute value  $X = x$  we can compute the probability of class  $Y = y$ . This conditional probability  $P(Y|X)$  is also known as the posterior probability for  $Y$ , as opposed to its prior probability  $P(Y)$ . We need to learn the posterior probabilities  $P(Y|X)$  for every combination of  $X$  and  $Y$  based on information gathered from training data. Hence, a test record  $XI$  can be classified by finding the class  $Y$  that maximizes the posterior probability.

In order to express the posterior probability, we need to estimate the class-conditional probability  $P(X|Y)$ . The Naïve Bayes classifier solved this problem by assuming that the attributes are conditionally independent, given the class label  $y$ .

$$P(X|Y = y) = \prod_{i=1}^d P(X_i|Y = y)$$

where each attribute set  $X$  consists of  $d$  attributes.

For the continuous attributes, we can estimate the class-conditional probabilities by using Gaussian distribution. This distribution is characterized by two parameters, its mean  $\mu$  and variance  $\sigma^2$ . For each class  $y$ , the class-conditional probability for attribute  $X$  is:

$$P(X = x|Y = y) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}$$

The Gaussian Naïve Bayes (GNB) classifier uses the training

data to estimate probability distribution over fMRI observations, conditioned on the subject's cognitive state. It classifies a new example  $x$  based on the posterior probability  $P(c_i|x)$  of cognitive state  $c_i$  given fMRI observation  $x$ .

$$P(c_i|x) = \frac{P(c_i) \prod P(x_j|c_i)}{\sum [P(c_k) \prod P(x_j|c_k)]}$$

Each distribution of the form  $P(x|c)$  is modeled as Gaussian using maximum likelihood estimates of the mean and variance derived from training data. Distributions of the form  $P(c)$  are modeled as Bernoulli using maximum likelihood estimates based on training data.

## 4. EXPERIMENTAL RESULT

### 4.1 Data Description

We used the StarPlus data collected by Mitchell et al. for validation [5]. This data were preprocessed to remove artifacts and noises using the FIASCO program. All voxel activity values were presented by the percent difference from their mean value during rest conditions. These preprocessed images were used as input to our classifiers.

fMRI data were collected many times for each human subject, performs a set of trials. During each trial, the subjects were shown a sequence of sentences and a simple picture. They also had to answer whether the sentences described the pictures correctly to ensure that they concentrated on their tasks. In half of trials, a picture was presented first, followed by a sentence and the remaining trials are vice versa with sentence was presented first, followed by picture. The experiments from six human subjects consist of a set of trials with 27 seconds of time interval for each one. Since fMRI images were captured every 500msecond, a total of 54~55 images were collected for each trial. The timing within each such trial is as follows:

- The first stimulus (sentence or picture) was presented at the beginning of trial (1<sup>st</sup> image).
- Four seconds later (9<sup>th</sup> image), first stimulus was removed, replaced by a blank screen.
- Four seconds later (17<sup>th</sup> image), second stimulus (different from the 1<sup>st</sup> one) was presented and remained for 4 seconds.
- The rest period of 15 seconds was added after removing second stimulus from the screen.

The pictures simply were geometric arrangements of symbols such as +, \*, @, \$, --. The sentences were partitioned into affirmative sentences and negative sentences such as "It is true that the star is above the plus" or "It is not true that the plus is above the star". Given a particular time interval of 8 seconds, we wished to train a classifier to distinguish whether the subject is viewing a picture or reading a sentence and distinguish whether the subject is reading an affirmative sentence or a negative sentence. For each subject, we trained a classifier of the form:

$$f: \text{fMRI-sequence}(t, t+8) \rightarrow \{\text{Class1}, \text{Class2}\}$$

where  $t$  is the starting time of stimulus.

Since the fMRI BOLD signal does not ‘disappear’ instantly when the stimulus is stopped, it is necessary to extend the time interval in order to capture the full fMRI activity associated with the stimulus. Therefore, although the stimulus was presented for only 4 seconds, a 8 seconds time interval was chosen to avoid lacking brain activity.

For the Picture versus Sentence study, each subject includes 80 samples, 40 samples for each label. For the Affirmative versus Negative Sentence study, each subject includes 40 samples, 20 samples for each label. Table 1 shows the number of all features of each subject. Generally, every sample includes approximately 80,000 features.

Table 1. Description of dataset

Subject ID	04799	04820	04847	05675	05680	05710
Number of features	79184	80240	75168	82160	80992	74144

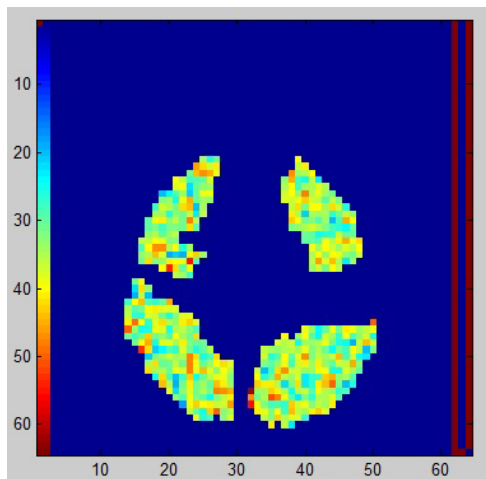


Fig. 3. Brain activation at z = 4 slice in trial 4

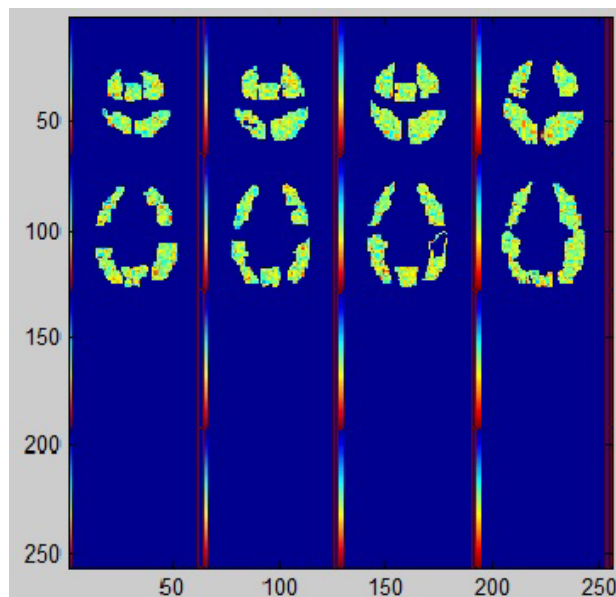


Fig. 4. fMRI image of the brain

Figure 3 describes a 2D slice image of the brain for trial 4.

Note that every fMRI image is a sequence of eight 2D slice images as shown in figure 4. Figure 5 describes the time series data of a single voxel. The red line indicates stimulus conditions including: fixation condition, sequence of picture – sentence with affirmative sentence, sequence of picture – sentence with negative sentence and ignorable data (condition = 0). The blue line indicates activation of this voxel. It seems that this activation signal does not follow the stimulus condition precisely. Hence, we cannot consider this voxel as a good feature for the tasks of viewing a picture and reading a sentence.

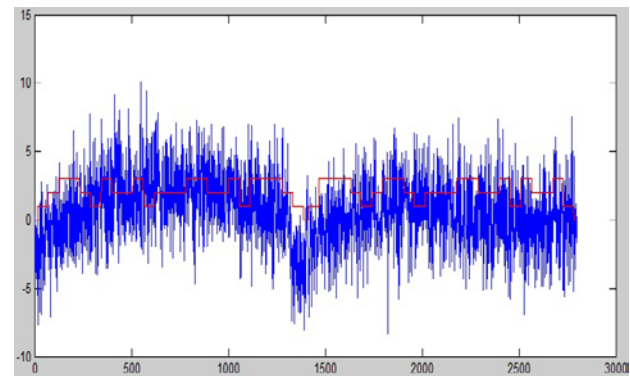


Fig. 5. Time course of single voxel

#### 4.2 Evaluation

We restricted our system to consider only some specific Region of Interest (ROIs), not the whole brain. Table 2 shows the classification accuracy of each ROIs by using GNB classifier. With a high accuracy for most of human subjects, CALC region seems to be the center region of the brain in the task of viewing picture and reading sentence. In our experiments, a set of ROIs: {CALC, LIPL, LT, LTRIA, LOPER, LIPS, LDLPFC} produced the best accuracy for our studies.

For evaluating the classification performance, we applied k-fold cross validation with k = 10. The average accuracy was computed and compared to other methods such as iPCA [13], ROIs, and the methods from Mitchell et al. [5] including Discrim, Active, roiActive and roiActiveAvg. Our proposed method will be described as ROIs+FDR with 250 features selected and performed by using GNB classifier. Table 3 shows the classification accuracy of our method for each human subject and the comparison with other methods. It is very surprising that the subject 04799 had the lowest accuracy with other methods but highest accuracy with our one. Subject 04847 has the highest accuracy with all methods. For all subjects, our proposed method had classification accuracy much higher than the others one. This performance proves that we detected the right patterns of the brain when activated by



the task of reading a sentence and viewing a picture.

Table 2. Classification accuracy of each ROI

ROIs / Subject ID	04820	04799	04847	05675	05680	05710
CALC	0.7125	0.8625	0.9375	0.8625	0.7875	0.8875
LIPL	0.65	0.5875	0.6875	0.5625	0.55	0.6125
LT	0.65	0.5875	0.7125	0.65	0.7125	0.6375
LTRIA	0.625	0.675	0.5875	0.575	0.6125	0.7
LOPER	0.6	0.7	0.7625	0.6	0.5625	0.6
LIPS	0.6	0.525	0.85	0.6375	0.725	0.5875
LDLPFC	0.5375	0.5125	0.7	0.55	0.5875	0.55

Table 3. Classification result of single subject

Feature Selection	04799	04820	04847	05675	05680	05710
All features	56.75%	57.5%	75%	58.75%	67.5%	70%
ROIs	61.5%	70%	97.5%	75%	80%	80%
iPCA	80%	80%	90%	88.75%	78.75%	85%
ROIs+FDR	100%	96.25%	100%	93.75%	90%	95%

Table 4. Average accuracy

Feature Selection	Average Performance
All features (80,000)	63.75%
Discrim(1440)	68%
roiActiveAvg(120)	73%
roiActive(240)	77%
ROIs(20,000)	77.3%
Active(240)	82%
iPCA(250)	83.75%
ROIs+FDR(100)	95.2%
ROIs+FDR(250)	95.83%

Table 5. Processing time

Method	0479	0482	0484	0567	0568	0571
	9	0	7	5	0	0
FDR	20.2	20.9	21.8	23.8	20.4	17.9
	9s	s	8s	6s	8s	5s
ROIs+FDR	4.88s	5.1s	4.72s	5.9s	5.77s	5.72s
DR						

Table 6. Affirmative vs Negative Sentence study

Methods	04799	04820	04847	05675	05680	05710
iPCA	75%	82.5%	77.5%	92.5%	80%	75%
ROIs+FDR	97.5%	100%	100%	100%	100%	100%

Table 4 shows the average accuracy of our proposed method and the comparison with the other one. The number in parentheses is the number of selected features. From our experiment, range of number of features from 200 to 400 will provide the best classification accuracy. In this range, the accuracy of Picture versus Sentence study always is more than 95.5%. We tried to reduce the number of selected features from 250 to 100 to check the power of our method with a limited number of features. In this case, the classification accuracy was still greater than 95% which was much better than other methods. Without using FDR, the accuracy was very low when we selected all voxels from ROIs. Without using ROIs, we had to compute FDR value for all features of the entire brain, so that the processing time was much slower than using ROIs+FDR as shown in table 5. Although the method of using FDR without ROIs had a similar accuracy to ROIs+FDR, we believe that ROIs+FDR is an optimal method.

For the Affirmative versus Negative Sentence study, our proposed method achieved a surprising result while Mitchell et al. [5] failed in this kind of study with a very low accuracy. Table 6 shows that with a limited number of samples (about 40 samples) our method had a perfect performance. iPCA also classified affirmative versus negative sentence successfully but

its accuracy is about 20% lower than our method even though the number of samples are same.

## 5. CONCLUSION

In this paper, we have presented a new approach for classifying specific cognitive states of a single subject from fMRI data. We only consider the following Regions of Interest: {CALC, LIPL,

LT, LTRIA, LOPER, LIPS, LDLPFC}. By selecting features with highest FDR values from these ROIs, we achieved a set of the most powerful discriminative features. Finally, we used Gaussian Naïve Bayes to train classifier dealing with the Picture versus Sentence study and Affirmative versus Negative Sentence study. The experimental results showed that our proposed method had a good performance with the highest accuracy compared to the other ones. In the future, we will apply this method to another kind of study and dataset in order to investigate the effectiveness of Fisher Discriminant Ratio and Regions of Interest in the problem of classifying human cognitive states. We will also extend to the problem of detecting multiple-subject cognitive states.

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#### REFERENCES

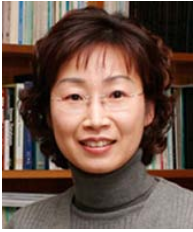
- [1] J. Ford, H. Farid, F. Makedon and L.A. Flashman, "Patient Classification of fMRI Activation Maps," *LNCS*, vol. 2879, 2003, pp. 58 – 65.
- [2] M.A Lindquist, "The Statistical Analysis of fMRI Data," *Statistical Science*, vol. 28, 2008, pp. 439 – 464.
- [3] R.A. Poldrack, J.A. Mumford and T.E. Nichols, *Handbook of functional MRI data analysis*. Cambridge University Press, 2011.
- [4] T.M. Mitchell, R. Hutchinson, R.S. Niculescu, F. Pereira, X. Wang and M. Just, "Classifying Instantaneous Cognitive States from fMRI data," *American Medical Informatics Association Symposium*, 2003, pp. 465 -469.
- [5] T.M. Mitchell, R. Hutchinson, R.S. Niculescu, F. Pereira, X. Wang, M. Just and S. Newman, "Learning to decode Cognitive States from Brain Images," *Machine Learning*, vol. 57, 2004, pp. 145 – 175.
- [6] B.M. Bly, "When you have a General Linear Hammer, every fMRI time-series looks like independent identically distributed nails," *Concepts and Methods in NeuroImaging Workshop*, 2001.
- [7] K.J. Friston, A.P. Holmes, K. Worsley, J.B. Poline, C.D. Frith and R.S.J. Frackowiak, "Statistical parametric maps in functional imaging: A general linear approach," *Human Brain Mapping*, vol. 2, 1995, pp. 189- 210.
- [8] P.A.d.F.R. Højen-Sørensen, L.K. Hansen and C.E. Rasmussen, "Bayesian modeling of fMRI time series," *Proc. Conf. Advances in Neural Information Processing Systems*, NIPS, 1999, pp. 754 - 760.
- [9] T. Jung, S. Makeig, M. McKeown, A. Bell, T. Lee and T. Sejnowski, "Imaging Brain dynamics using Independent Component Analysis," *Proc.IEEE*, vol. 89, 2001, pp. 1107 – 1122.
- [10] T. Jung, S. Makeig, M. McKeown, A. Bell, S. Kinderman and T. Sejnowski, "Analysis of fMRI data by blind separation into independent spatial components," *Human Brain Mapping*, vol. 6, 1998, pp. 160 – 188.
- [11] J.V. Haxby, M.I. Gobbini, M.L. Furey, A. Ishai, J.L. Astouchen and P. Pietrini, "Distributed and overlapping representations of faces and objects in ventral temporal cortex," *Science*, vol. 293, 2001, pp. 2425 – 2430.
- [12] D.D. Cox and R.L. Savoy, " Functional magnetic resonance imaging (fMRI) "brain reading": Detecting and classifying distributed patterns of fMRI activity in human visual cortex," *NeuroImage*, vol. 19, 2003, pp. 261 – 270
- [13] M.T.T. Hoang, Y.G. Won and H.J. Yang, " Cognitive States Detection in fMRI Data Analysis using incremental PCA," *ICCSA*, 2007, pp. 335 - 341 .
- [14] F. Yong, D. Shen and C. Davatzikos, "Detecting Cognitive States from fMRI Images by Machine Learning and Multivariate Classification," *Proceedings of the 2006 Conference on Computer Vision and Pattern Recognition Workshop*. 2006.
- [15] J.A. Etzel, V. Gazzola and C. Keysers, "An introduction to anatomical ROI-based fMRI classification analysis," *Brain Research*, vol. 1282, 2009, pp. 114 – 125.
- [16] R.S. Bapi, V.Singh and K.P. Miyapuram, "Detection of Cognitive States from fMRI data using Machine Learning Techniques," *IJCAI*, 2007, pp. 587 -592 .
- [17] N. Bernard, A. Vahdat, G. Hamarneh and R. Abugharbieh, "Generalized Sparse Classifiers for Decoding Cognitive States in fMRI," *Proceedings of the First international conference on Machine learning in medical imaging*, 2010, pp. 108 - 115.
- [18] J. Rademacher, A.M. Galaburda, D.N. Kennedy, P.A. Filipek and V.S. Caviness, "Human cerebral cortex: Localization, parcellation, and morphometry with magnetic resonance imaging," *Journal of Cognitive Neuroscience*, vol. 4, 1992, pp. 352 – 374.
- [19] S. Theodoridis, A. Pikrakis, K. Koutroumbas and D. Cavouras, *Introduction to Pattern Recognition – A MATLAB Approach*, Academic Press, 2009.
- [20] P.Tan, M. Steinbach and V. Kumar, *Introduction to Data Mining*. Pearson Addison Wesley, 2006.



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