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Classification of Individuals Based on Sparse Representation of Brain Cognitive Patterns: a Functional MRI Study

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Abstract— **Many neurological disorders can change patterns of brain activity observed in functional imaging studies. These functional differences may be useful for classification of individuals into diagnostic categories. However, due to the high dimensionality of the input feature space and small set of subjects that are usually available, classification based on fMRI data is not trivial. Here, we evaluate the use of a Sparse Representation Analysis method within a Fisher Linear Discriminant (FLD) classification method, taking functional patterns characteristic of different cognitive tasks as the data input. As a test dataset, with a clear 'gold-standard' classification, we attempt to classify individuals as young, or older, based only on functional activation patterns in a speech listening task. Thirty two young (age: 19-26) and older (age: 57-73) adults (16 each) were scanned while listening to noise and to sentences degraded with noise, half of which contained meaningful context that could be used to enhance intelligibility. Different functional contrast images were used within K-SVD to generate basis activation sources and their corresponding sparse modulation profiles. Sparse modulation profiles were used in a FLD framework to classify individuals into the young and older categories. The results demonstrate the feasibility of the general approach, and confirm the potential applicability of the proposed method for real-world diagnostic problems.**

I. INTRODUCTION

In the past two decades, functional resonance imaging (fMRI), has become a very popular way to study the 'brain at work', due in large part to its relatively good spatial resolution and its non-invasiveness. In fMRI studies, regional changes in blood-oxygen-level-dependent (BOLD) signal index how the brain is organized to perform particular cognitive tasks, and this can be compared between two groups, such as patients and normal controls [1]. Usually evoked activities between different cognitive conditions are compared [2, 3]. Marked variability within groups can make it difficult to determine whether groups differ reliably with respect to the localization and extent of the activation. Independent Component Analysis (ICA) is another method that has been used to make inferences about group-specific patterns of activity in recent years [4-6]. Unlike conventional analysis, ICA is a multivariate approach that uses high order statistics (independence) to find spatial patterns. Independence is a valid assumption in fMRI analysis, because the spatial networks of activations are typically known to be non-overlapping [7]. However, the theoretical assumption of independence of the patterns extracted by ICA algorithms is not guaranteed in practice. Daubechies *et al.* showed that using ICA algorithms, components are separated on the basis of spatial sparsity; therefore, other mathematical properties of brain fMRI data than independence should be used [8]. Sparsity is a natural characteristic satisfied by fMRI sources in the spatial domain [7]. K-Singular Value Decomposition (K-SVD) is a dictionary learning algorithm for sparse signal representation [9]. K-SVD can be used to represent large set of functional contrasts as sparse linear combination of small set of brain 'basis patterns'. K-SVD is the generalized k-means clustering process which iteratively updates basis patterns and sparse coding coefficients to better fit the data.

In the present study, we test potential application of K-SVD as a second-level analysis of an fMRI dataset involving young and older neurologically normal individuals. Here, we compare performance by young and older listeners on a speech comprehension task [10, 11]. Three functional contrasts are used. The first contrast compares responses to auditory stimuli (unintelligible noise) with silence. The second contrast compares response to sentences without a coherent meaning (e.g., "Her good slope was done in carrot") with the unintelligible noise. The third contrast compares responses to sentences with a coherent meaning (e.g., "Her new skirt was made of denim") and those without a coherent meaning. We use the sparse coefficients, which reflect group differences between functional contrast activation patterns, to automatically classify individuals as younger or older. Using these lower dimension coefficients, we overcome the problems of high dimensionality of the input feature space, and the small set of subjects that are usually available in classification based on fMRI data.

To the best of our knowledge, this is the first report of sparse representation of brain cognitive patterns to classify individuals. While we use young and old adults as a testbed to demonstrate the potential of the proposed sparse analysis approach to classify groups of subjects based on functional contrasts; the high classification accuracy confirms the potential applicability of the proposed method to neurological diagnostic disorders.

II. MATERIALS

A. Participants

Sixteen young (mean age: 21.1, range: 19-26, 11 female)

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and sixteen older (mean age: 64.2, range: 57-73, 11 female) adults were scanned. All subjects were native speakers of English, without any history of neurological illness, head injury, or hearing impairment. This study was cleared by the Queen's University Health Sciences Research Ethics Board, and written informed consent was obtained from all participants.[1]

B. Context Study

Subjects were asked to listen to sentences in the scanner and repeat what they were able to understand for half of the sentences. High-context and low-context sentences taken from those used by Davis *et al.* [10], were mixed with noise having the same long-term spectrum as the speech, and the same amplitude envelope of the utterance to be masked (Signal-Correlated Noise: SCN; [12]) at different Signal to Noise Ratios (SNRs): -5 dB, -3.5 dB, -2.5 dB, -1 dB, 0 dB, 2.5 dB. SCN on its own, silence, and clear high- and low-context sentences (without noise) were also tested. Behavioral performance was measured as the proportion of words correctly reported at each SNR. Sentence materials were designed such that comprehension was determined by the quality of the signal ("low context") or by quality of the signal, together with semantic knowledge ("high context"). Once deficits in hearing were controlled, the context benefit in older people was approximately as large as that in younger people [13]. Here, we hypothesize that, despite behavioral similarity, young and older subjects may be classifiable based only on the patterns of activity observed in functional contrast images. In this analysis, we do not consider information related to structural (anatomical) differences between the two groups.

C. Data Acquisition

The fMRI data were acquired using a 3.0 Tesla Siemens Trio MRI scanner with a 12-channel head coil in the MRI facility at Queen's University, Kingston, Canada. Each acquisition consisted of 32 contiguous slices with 4 mm thickness, field of view 211×211 mm, in-plane resolution of 3.3×3.3 mm. The repetition time (TR) was set to 9 sec and the acquisition time was 2 sec. This sparse GE-EPI imaging technique allowed for stimuli to be presented in the silent gaps between scans. Total functional imaging time was 48 minutes. Auditory stimuli and the visual 'repeat' instructions were presented to the participants using E-Prime v.1.2 and a NEC LT265 DLP projector. Participants viewed the screen via a mirror system mounted on the head coil [11]. The audibility of stimuli for young and older groups was equated by choosing SNRs such that word-report performance on low-context sentences was matched. Accordingly, SNRs from -5 dB, -3.5 dB, -2.5 dB, -1 dB, and 0 dB were used for younger people and -3.5 dB, -2.5 dB, -1 dB, 0 dB, and +2.5 dB for older adults.

D. Data Preprocessing

The fMRI data were preprocessed using Statistical Parametric Mapping software (SPM8, Wellcome Department of Cognitive Neurology, London, UK). MR images (DICOM images to which the Siemens motion correction algorithm had been applied) were converted to NIFTI format before preprocessing. Preprocessing steps included realignment, coregistration and the segmentation-normalization of SPM8. Data were spatially smoothed using Gaussian kernel of 8 mm. Single-subject general linear models were created by coding the condition to which each scan of the session belonged (i.e., whether it followed the presentation of silence, signal-correlated noise, or a high- or low-context sentence at different SNRs (including clear speech). The hemodynamic response function was selected as the basis function. Three functional contrasts were calculated: SCN vs. silence identifies those brain regions that process the acoustic properties of sound stimuli. Word meaning responses were assessed by comparing the low-context sentences vs. SCN. Sentence meaning responses were assessed by contrasting high- and low-context sentences.

III. Methods

A. K-Singular Value Decomposition

Each of the previously described functional contrast images was separately used as an input signal to the K-SVD to obtain patterns of brain activation. K-SVD is the generalization of the k-means algorithm, which decomposes the input matrix (Y) into a linear combination of dictionary elements using the fewest number of non-zero coefficients [9]. In other words, it solves the following minimization problem:

$$\min_{D,x}\{\|Y-DX\|_F^2\} \text{ subject to } \forall i, \|x_i\|_0 \le T_0. \quad (1)$$

In this equation $Y=[y_1, y_2, ..., y_N] \in R^{V\times N}$ is the observation matrix, where y_i is the vector containing functional contrast of subject i, $X=[x_1, x_2, ..., x_N] \in R^{K\times N}$ is the sparse modulation matrix, and $D=[d_1, d_2, ..., d_K] \in R^{V\times K}$ is the over-complete dictionary containing K signal atoms. Each of these atoms represents a pattern of brain extracted from the subjects' functional contrasts. V, N, and K are the number of voxels, subjects and brain patterns respectively, $||.||_F$ is the Frobenius matrix norm and T_0 is the number of non-zero elements in each linear combination [9].

To find the sparsest representation of input contrasts, K-SVD iteratively updates the vectors x_i and each column of the dictionary in two steps [9]. Assuming a fixed dictionary, in the first step, an N minimization problem of the following format is solved using the Orthogonal Matching Pursuit (OMP) algorithm [14].

$$\min_{x_i}\{\|y_i-Dx_i\|_F^2\} \text{ subject to } \forall i, \|x_i\|_0 \le T_0,\ i=1, 2, ..., N \quad (2)$$

In the second step, for each column of the dictionary (d_k), the representation error (E_k) is computed and using SVD decomposition the updated dictionary column ($\hat{d}_k$) is

[1] The same dataset with similar description is used in [17].

obtained;

$$E_k = Y - \sum_{j \neq k} d_j x^j, \quad E_k = U \Delta V^T, \quad k = 1, 2, \ldots, K \qquad (3)$$

where x^j is the jth row in X. The first column of U is chosen as $\hat{d}_k$ and the first column of V multiplied by $\Delta(1,1)$ is chosen as the updated x^k. These steps are run for a finite number of iterations (See [9] for more details). In this study, the number of iterations was set to be 20, the number of brain patterns (K) was set to be 16, and number of non-zero elements (T_0) in each linear combination was set to be 8[2].

B. *Automatic Classification*

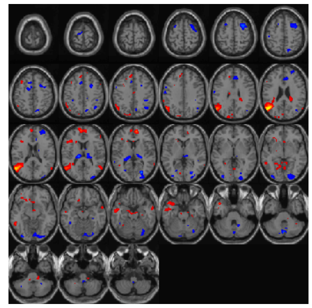
Classification based on fMRI data is not trivial, due to the high dimensionality of the input feature space and small number of subjects (16-30, approximately) that are usually available. In order to overcome these problems, we used the sparse mixing coefficients as input features. These low-dimension coefficients enable us to make inferences about how each subject's functional contrast is modulated by a source. Also it can be found whether one group shows stronger component modulation than another. We used a Fisher Linear Discriminant (FLD) classifier to classify subjects. FLD is a linear discriminant function $f(x)=<\omega.x>+b$ with the parameter vector ω and the scalar b. It tries to find a linear combination of features (x) that discriminate between two classes. The weights of this linear combination are given as $\omega = S_w^{-1} (\mu_1 - \mu_2)$, where μ_1 and μ_2 denote the respective means of the first and second classes, and S_w is the within-class scatter matrix [15]. The data were split into training and test sets and classification performance was averaged on each test set. In each measurement, 70% of the whole dataset (11 young and 11 older subjects) were used to train the classifier and the remaining subjects were taken as the test set. In the training phase, dictionary atoms and sparse-coding coefficients were obtained from the K-SVD analysis on 22 subjects. The columns of the sparse-coefficient matrix, i.e. x_i, were used as input features to train the classifier, in order to group the 22 subjects into two classes (young and older adults). In the test phase, the dictionary atoms were used to compute the classifier's input features for the test subjects. In other words, the sparsest representation of $Dx_i = y_i$ was computed approximately, using an OMP algorithm. In this equation, D is the dictionary matrix generated from the training dataset, y_i is the vector of contrast of the test subject, and x_i is the vector of sparse coefficients for each of the test subjects[3].

IV. Results

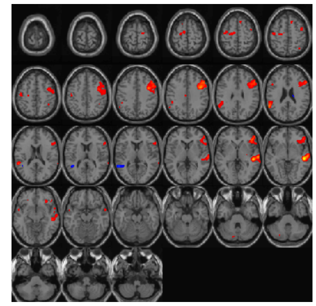
The goal of our sparse fMRI data analysis is to examine whether sparse coefficients could be used to accurately classify young and older adults on the basis of cognitive data from a speech perception experiment. Statistical difference of sparse coefficients and classification accuracy were selected to evaluate the performance of the method.

[2] http://www.cs.technion.ac.il/~elad/Various/KSVD_Matlab_ToolBox.zip

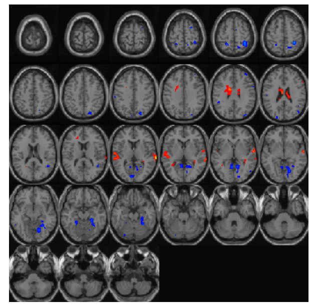
[3] http://cmp.felk.cvut.cz/cmp/cmp_software.html.



(a)



(b)



(c)

Contrast	p-value
High vs Low	0.0307
Low vs SCN	0.0025
SCN vs Silence	0.0237

(d)

Figure 1. The most discriminative pattern for (a) contrast comparing high-context sentences to low-context sentences, (b) contrast comparing low-context sentences to SCN, (c) contrast comparing SCN to silence, and the p-values on of a two-sample t-test on their corresponding sparse coefficients.

A. *Separability of Sparse coefficients*

A two-sample t-test on the sparse mixing coefficients was performed for each functional contrast. There were two significant components (p-value < 0.05) for the contrast of SCN vs. rest and contrast of high-context sentences vs. low-context sentences; but there were three significant components (p-value < 0.05) for the contrast of low-context sentences vs. SCN. Fig. 1 shows the most significant component for each of the contrasts together with the p-values of a two-sample t-test on their corresponding sparse coefficients.

B. *Classification*

Performance of the classification procedure was measured by repeatedly splitting the data into training and test sets and averaging classification performance on each test set. The process of splitting the data was done 50 times (each time selecting different 11 young and 11 older subjects as the training set and the remaining subjects as the test set), and the classification procedure was run 5 times, randomizing the order of subjects in the training dataset each time. We calculated the False Positive (FP), False Negative (FN), True Positive (TP) and True Negative (TN) values and took the classification accuracy, i.e. the ratio between TP and TN values to the total number of outcomes, as the performance metric. We selected the sparse coefficients based on the mean difference (p-values) they created between two groups. The coefficients were sorted by their corresponding p-values in an ascending order $([x_{p1}, x_{p2}, \ldots, x_{pK}]$, $p_1 \leq p_2 \leq \ldots \leq p_K)$. Each time, M of them were chosen

(x_{p1}, x_{p2}, ..., x_{pM}), and classification was performed. To further evaluate the classification performance, we plotted the Receiver Operating Characteristic (ROC) curves and calculated the Area Under the Curves (AUC). Detection reliability ρ [16], which is defined based on AUC as $\rho = 2\times AUC\text{-}1$ was obtained. The accuracy is scaled to obtain $\rho=1$ for perfect detection, and $\rho=0$ for failure in detection. Fig. 2 shows the detection reliability for each of the functional contrasts across numbers of features used ($M = 1, 2, ..., K$). As might be expected, using more coefficients does not imply higher detection reliability, because some of the obtained patterns of activities and their associated coefficients are similar between the two groups. Fig. 3 shows the best classification accuracy obtained for each of the functional contrasts. Results show that the young and older subjects can be classified based on their patterns of brain activation. Considering the fact that the number of subjects is low and the dimensionality of the input features is quite high, the results are promising. Fig. 2 and Fig. 3 show that the contrast comparing low-context sentences to unintelligible noise (SCN) can classify the two groups with an accuracy of more than 80%.

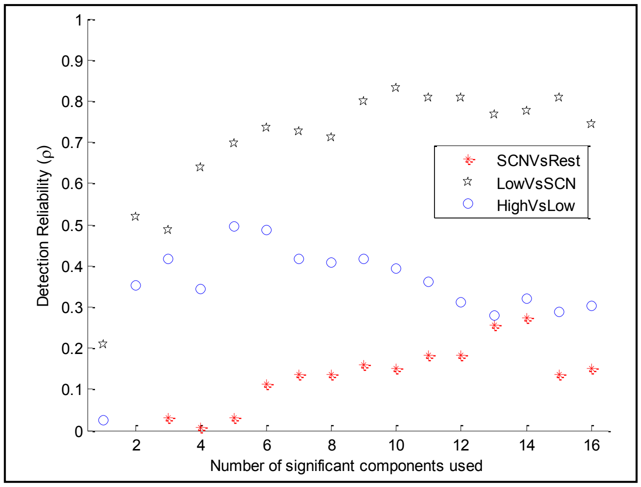


Figure 2. Detection reliability for each of the functional contrasts across numbers of features used. The contrast of comparing low-context sentences to unintelligible noise (SCN) can classify the subjects with higher reliability.

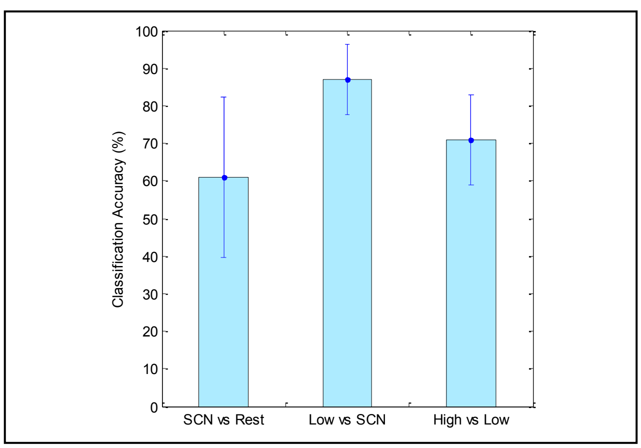


Figure 3. Best classification accuracy obtained for each of the functional contrasts.

V. CONCLUSION

Using a K-SVD method together with a linear classification algorithm, we have demonstrated that cognitive patterns can be used to classify individuals in the absence of behavioural differences. To demonstrate the potential of the proposed framework, a dataset comprising functional images of cognitively normal subjects in two age groups was used. Feasibility of the approach was shown by examining the age-related differences in the functional patterns of activation in healthy subjects. In future studies, we plan to apply the method for diagnosis of brain disorders.

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