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fMRI Brain Decoding of Facial Expressions Based on Multi-voxel Pattern Analysis

Farshad Rafiei and Gholam-Ali Hossein-Zadeh

CIPCE, Control and Intelligent Processing Center of Excellence, School of Electrical and Computer, Engineering, College of Engineering, University of Tehran, Tehran, Iran

***Corresponding Author's E-mail:** Farshad_rafiei@ut.ac.ir*

Abstract

In a brain decoding study, using the functional magnetic resonance imaging (fMRI) data we determined the facial expression of the visual stimulus that the subject perceived. fMRI data acquired from a healthy right-handed adult volunteer who participated in three separate sessions. Participant viewed blocks of emotionally expressive faces alternating with blocks of neutral faces and scrambled images. Multi-voxel pattern analyses are then used to decode different expressions using the activity pattern of most active parts of brain. We used multi-class support vector machine (SVM) to distinct five brain states corresponding to neutral, happy, sad, angry and surprised. Results show that these facial expressions can be classified from fMRI data with the average sensitivity of 90 percent.

Keywords: *Brain decoding, facial expressions, Multi-voxel pattern analysis, Support vector machines.*

1. Introduction

Over the past decade, scientists working on fMRI analysis developed sensitive techniques for decoding the information represented in BOLD activity. Effectively decoding the information about the experimental stimuli (or tasks) from pattern of activity across an array of voxels various classifiers are utilized [1]. For instance classification based on linear discrimination, polynomial discrimination or classification based on RBF kernels were used for this purpose. Recent researches show that the efficiency of classification can be dramatically increased by taking into account the full spatial pattern of activity, measured simultaneously at many locations. This approach is called multi-voxel pattern analysis (MVPA); “an analytical technique that considers multiple decision voxels” [2]. Decoding of emotional expression of the face is crucial in human communication. Clinical and experimental researches in humans and non-human primates show right hemisphere specialization of brain activity [3-5]. Studies based on invasive recordings like electrical stimulation and microelectrode recordings have identified several intra hemispheric brain regions took part in facial expression processing [6]. These regions involve the temporal lobe [7], the basal ganglia [8], the mesial occipital and inferior parietal regions [9], the somatosensory cortex [10], and the amygdala [11].This paper examines brain decoding issue for facial expression stimulus using multi-voxel pattern analysis. Previous works didn’t use MVPA for this type of stimulus and most of them focused on the stimulus that apply separable cortical modules. A further pristine contribution of the present work is in the mask generation for brain while selecting the features. In the following we first explain our fMRI paradigm for facial expression decoding; then we will explain the data processing steps, and the

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regions of interest that we extracted, and classification approach. Finally the results are presented ad discussed.

2. Materials and Methods

Participant and Experimental Conditions

One healthy volunteer (29 years old, female) participated in our fMRI experiment. She was right-handed and reported no first-degree left-handed biological relatives. She wasn't a cigarette smoker and her visual acuity was more than 20/25.

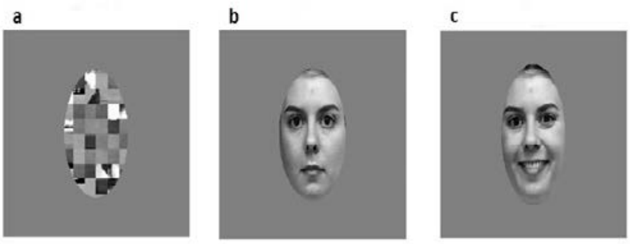

Figure 1. Images of paradigm. a) Scrambled image; b) Neutral image; c) Expressioned image (Happy)

The stimulus pictures were chosen from Cohn-Kanade AU-Coded Facial Expression Database available at: (**http://www.pitt.edu/~emotion/ck-spread.htm**) and then converted to grayscale pictures and modified for the experiment. We chose happy, sad, angry, surprised and neutral images and made a mask in MATLAB to extract only the face part of subjects in the images. An elliptically shaped mask was used for face extraction. Although the face size varies among stimuli pictures, the aspect ratio of ellipsoid mask is kept the same for all images.

The background intensity of images was set to gray (128 out of 256). Figure 1 shows examples of scrambled, neutral and happy images. For control condition, scrambled images were derived from neutral face images using MATLAB software. Examining what is specific to the processing of faces, we chose the mentioned baseline, which was made to control for the early visual operations involved in face-processing conditions. The scrambled images did not contain recognizable facial features. In spite of equating brightness of each scrambled image with the brightness of the face image from which it was derived, we did not equalize the local contrast or the spatial frequency distribution of the scrambled image to a specific value [6].

Our paradigm was presented to the subject using Cogent toolbox (http://www.vislab.ucl.ac.uk/cogent.php) in MATLAB. The images were projected on a screen placed in front of the MR scanner and subject viewed this screen from within the bore of the magnet by means of mirror placed on the head coil. The subject was informed to focus on the images when viewing the scrambled images. Moreover she was instructed to concentrate on each face's expression when watching other images. At the start of every run, seven scrambled images ensued by seven neutral faces were presented as a sham cycle. MR scans corresponding to sham cycle were discarded then in the analysis. Images were displayed continuously for 3 seconds. The subject was presented with alternating 27-s epochs of nine scrambled images, nine neutral faces, nine emotionally expressive faces, again nine scrambled faces and at last nine emotionally expressive faces. This process repeats, but this time for the remaining of the expressions and this way, we will have a complete run. Figure 2 shows the temporal pattern of paradigm. Our subject viewed eight of these runs, two during session one and three during each of the sessions two and three. Each run contained happy, sad, angry and surprised emotions along with neutral and scrambled conditions. The order of the emotion blocks was randomized and there was not any predetermined emotion order.

Data Acquisition

The subject underwent a MRI scanning for structural and functional imaging of her brain using a 3 Tesla Siemens (Trio) MRI scanner in medical imaging center of Imam Hospital, Tehran, Iran. A head coil with 32 channels was used for brain imaging. T1-weighted structural MRI images were acquired with MPRAGE pulse sequence (TE=3.44 ms, TR=1800 ms, TI=1100 ms, flip angle=7°, field of view=256x256 (mm), voxel size=1x1x1 mm^3). This produced a 3D image of 256x256x176 matrix size with isometric voxel size of one cubic millimeter. Also $T2^*$-weighted functional MRI images were acquired with EPI pulse sequences (TE=30 ms, TR=2000 ms, field of view=192x192 (mm), flip angle= 90°, voxel size=3x3x3.6 mm^3).

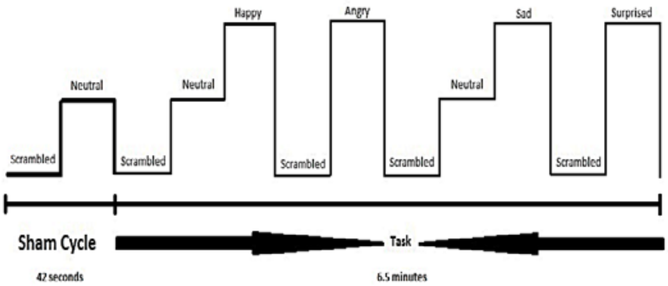

Figure 2. task schematic. This figure contains sham cycle and one of the tasks that is randomized orders of expressions in our paradigm.

The subject was asked to be relaxed inside the MRI scanner with open eyes and concentrate on each person's expression. However she was instructed not to think of anything while viewing the scrambled images.

fMRI Preprocessing and Statistical Map Generation

fMRI data processing was carried out using FEAT Version 5.90, part of fMRIB's Software Library (http://www.fmrib.oxac.uk/fsl). The raw data which was obtained from the scanner was imported to fsl. Volumes corresponding to sham cycle were deleted and functional images were aligned to the first scan. fMRI dataset was registered to our subject's anatomical image and the spatially normalized to Talairach atlas [12, 13]. Functional 3 dimensional images were smoothed by Gaussian spatial filter with FWHM of 5 millimeter. Eventually, each time point in all runs was coded to the corresponding intervals of expressions using general linear model. This helps us detecting the brain activated regions.

Feature (Voxel) Selection

A great deal on the number and quality of the variables (in this case, voxels) that are given to the classifier plays a significant role in the performance of pattern recognition application [14]. Variables that which contain little information or those contain information that is redundant can seriously affect the classification process and make the training data to overfit [15]. Therefore, applications related to pattern recognition include a "feature selection" step in which a subset or composite set of variables is opted. This set of variables should contain enough information to perform an efficient classification [14]. In this study, feature selection is equivalent to voxel selection. To reach effective pattern recognition, we should find a reasonable subset of these voxels to serve as input to the classifier. For this reason, we should have some persuading basis for believing that a given set of voxels will provide enough and efficient information about facial expressions.

One way to select features is to limit analysis to specific anatomical regions [16]. In this study we choose voxels that they were reported as most active parts of brain while the subject exposed to facial expression images. Using Talairach atlas in FSL we extracted these regions: parahippocampalgyrus, fusiform gyrus, inferior frontal gyrus, anteromedial temporal lobe, inferior frontal gyrus, inferior occipital gyrus, superior occipital gyrus, superior frontal gyrus, superior

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temporal sulcus, lateral occipital gyrus, inferior frontal gyrus, precentral sulcus, medial frontal/cingulate sulcus, lingual gyrus, angular gyrus, middle temporal gyrus and insula [3-7,17]. We used all these regions to create a single mask, and extract the voxels of these regions. This method limits our voxels (features) to about 12000 voxels. The activity of each of these voxels for each block of task is put in a 1x12000 feature vector. Therefore we will have 8 vectors corresponding to each of the four expressions and 16 for neutral faces containing about 12000 voxels (exactly 12327).

The choice of classifier in this paradigm is largely a matter of efficiency. Support vector machines (SVMs) were chosen as the classifier for this study, since they often work well with fMRI data. LIBSVM package (http://www.csie.ntu.edu.tw/~cjlin/libsvm) was used to perform the classification. Classification was done with SVM classifier using radial basis function (RBF) kernel and evaluation was handled by leave one out cross validation method which is the best option for small sample datasets like our case, and which avoids over-fitting or obtaining unreal optimistic results.

3. Results

Data is analyzed in a knowledge-based ROI approach. In this regard we extract 25 ROIs from Talairach structure atlases and we made vectors containing the voxels of them. The voxels of each area with the activation less than the threshold were set to zero in the feature vector and used in the classification. We have done an exhaustive search on the threshold magnitude in the range of 1 to 8 with 0.5 increments, corresponding to p-values of approximately 0.5 to 10^{-7} and we selected the best classification in the threshold magnitude equal to 3 (p-value=0.0013). We apply SVM classifier with RBF kernel function, as they are the first reasonable solution to nonlinear problems due to their discrimination ability and less complexity in comparison to other kernels. Also RBF kernel parameters (C, γ) have been optimized for our classification problem [18]. Table 1 shows the classification results achieved by applying the proposed method in section *II.D*.

Table1. Classification performance of the proposed method on fMRI data

Expression	Classification accuracy $\pm$ SEM (%)	
	Training Data	Test data
Neutral	96.4 ± 1.4	87.5 ± 8.2
Happy	100	100
Sad	92.9 ± 2.7	87.5 ± 12.5
Angry	100	87.5 ± 12.5
Surprised	92.9 ± 2.7	87.5 ± 12.5

Conclusion

In this paper we used multi-voxel pattern analysis (MVPA) to differentiate and classify fMRI brain activation maps of a subject exposed to facial expression stimuli. Different ROIs which was reported as the most active regions (reported in previous studies) were individually extracted. These ROIs were unified to make a single mask for an effective classification scheme. Using threshold for extraction of active voxels in determined voxels and taking advantages of nonlinear SVMs as the classifier enabled us to achieve very desirable classification across the activation maps of different facial expressions including neutral, happy, sad, angry and surprised. This study demonstrates that using most active regions of the human brain that was exposed to facial expressions leads to a successful classification, even in the presence of overlap between the activated regions of brain for different facial expressions.

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