A Generic Machine-Learning Tool for Online Whole Brain Classification from fMRI

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Abstract

Objective. We have developed an efficient generic machine learning (ML) tool for real-time fMRI whole brain classification, which can be used to explore novel brain-computer interface (BCI) or advanced neurofeedback (NF) strategies. *Approach.* We use information gain for isolating the most relevant voxels in the brain and a support vector machine classifier. *Main results.* We have used our tool in three types of experiments: motor movement, motor imagery and visual categories. *Significance.* We show high accuracy results in real-time, using an optimal number of voxels, with a shorter delay compared to the previous method based on regions of interest (ROI). Finally, our tool is integrated with a virtual environment and can be used to control a virtual avatar or a robot.

1 Introduction

Real time fMRI is a promising risk-free non-invasive method for several reasons. Due to superior spatial resolution fMRI may be used to classify a much wider set of mental patterns than EEG. Thus, fMRI-based BCI may facilitate exploring new BCI paradigms. fMRI BCI paradigms can be used to localize underlying brain patterns and transfer the paradigms back to other, more accessible signals, such as EEG and near-infrared spectrography (NIRS) [1, 2]. fMRI-based BCI can also be used for training patients in BCI (e.g., before surgery), for rehabilitation sessions, or for pattern-based neurofeedback (NF) – in all these cases very specific brain areas may be targeted.

We have developed a generic efficient tool for online whole-brain classification from fMRI data. In contrast to other research [3], this tool is designed for real-time processing, normalization and multi-classification which can be extended to other algorithms within the Weka ML API [4]. This tool is also integrated with a virtual environment feedback to allow for engaging subjects in a wide range of scenarios and tasks, and can also be integrated with external devices such as a humanoid robot. In this paper, we show how our approach achieves high accuracy in three different mental tasks: motor motion, motor imagery, and visual categories.

2 The System

Imaging was performed on a 3T Trio Magnetom Siemens scanner as described in [5, 6], with a repetition time (TR) of 2000ms. Visual feedback is provided by a mirror, placed 11cm from the eyes of the subject and 97.5cm from a screen, which results in a total distance of 108.5cm from the screen to the eyes of the subject.

Dicom files[1] from the scanner are preprocessed by Turbo Brain Voyager (TBV, Brain Innovation, Netherlands). Since fMRI data tends to have non linear non-homogeneous drifts, we introduce a normalization process that has been verified to perform well online; given a raw value at voxel i and time t, $r_{i,t}$, and a sliding window of length w we derive a new value for each raw value:

$$r'_{i,t} = r_{i,t} - median(r_{i,t-w+1}, ..., r_{i,t}) \tag{1}$$

We have empirically established that a w of 40 TRs (80 seconds) is optimal in our case.

Our tool is integrated with the Unity game engine (Unity Technologies, California); in other studies this allowed subjects to control an avatar in a virtual environment or a humanoid robot [5]. The system allows easily configuring classification and interaction parameters during an experiment and playing back experimental sessions.

Training and applying classifiers in real-time requires that learning be executed faster than is generally done in the application of ML to fMRI. Our system is optimized for memory usage, processing speed, and classification speed. To achieve faster processing, we focus on several areas: (1) feature reduction, (2) feature selection, (3) redundant data reduction, (4) minimization of computational cycles and RAM consumption by using sparse data handling, (5) using RAM without having to access the disk drive, and (6) transferring data between processes using an inter-process communication method.

Our method is divided into two parts. In the first part, the subject is given instructions based on the experimental protocol and several runs are recorded as input to a machine-learning tool. In the second part, the subjects perform a task, our system classifies their intentions in real time, and the classification result is transmitted to an external device. In this study the task was similar to training, in order to evaluate BCI accuracy.

The 3D matrix of the entire brain area is composed of 204,800 voxels, which hold the raw blood-oxygen-level dependent (BOLD) derived values. Our TBV plugin transmits the raw data using an inter-process communication method to our application. The 3D matrix is flattened into a 1-dimensional vector, and the set of voxels is further reduced by setting an activity threshold, which removes voxels that belong to the empty space around the head that and are not part of the brain. We also remove any voxels that belong to the subject's eyes, reducing the number of voxels to approximately 26-30,000 voxels per TR.

For purposes of learning, we select only those voxels with highest information gain (IG) [7]. Labeled training examples, each represented as a vector recording the values of the selected voxels, are passed on to our learning algorithm: Weka's [4] implementation of multiclass [8] SVM [9], using default parameters. The result of the training phase is an SVM classifier that can classify previously unseen vectors.

In the second online stage we classify a vector every TR (2 seconds) and use the same noise reduction, eye filtering and normalization methods as in the training stage, selecting the same voxels based on the IG filtering performed at model training. Finally, the data is passed into the trained SMO model, and the classification result is then transmitted to the external device. The training process takes several minutes and the classification process uses 1-5% of the CPU and lasts approximately 50 milliseconds.

Here we compare our results with our previous study, in which we introduced a simple classification method used to successfully classify intentions of motor movement or imagery [5]. In that method, we manually localized the subject's relevant brain areas corresponding to activation of left and right hand and legs, and the algorithm selected online the class that corresponded to the ROI with maximum Z-score normalized averaged value.

[1] http://medical.nema.org/

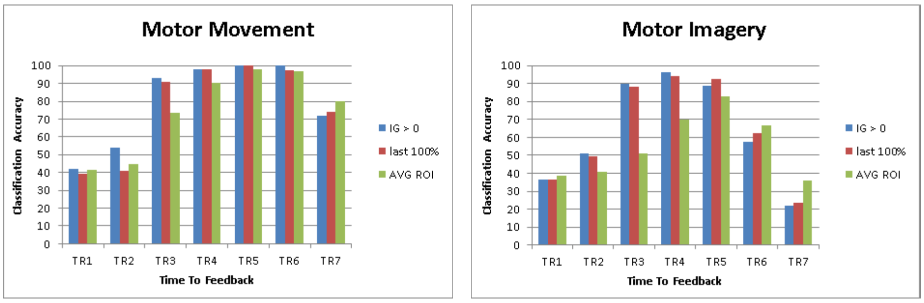

Figure 1: A comparison of MM and MI classification accuracy across six (MM) and three (MI) subjects, between ML and ROI. The ML results were obtained by using (a) all voxels with IG above 0 and (b) the smallest number of voxels that permit perfect classification of all training examples.

3 The Experimental Protocols

We tested our system in three areas: i) motor motion (MM, 5 subjects), ii) motor imagery (MI, 3 subjects), and (iii) visual categories (VIS, 5 subjects). In MM and MI, we classified left hand, right hand, and legs movement or imagery; subjects were allowed to move their fingers and toes in the MM condition. In VIS we had subjects watch four visual categories: faces, houses, tools, and a fixation screen that corresponds with idle viewing. In both the MM and MI studies the subjects see an avatar standing in the center of a three-door room. In each run of the cue-based experiment, the subjects received equal amount of triggers from each class, in a pseudo-random order. The total number of triggers was determined based on 10-12 minute run. For MM, MI, and VIS we used 30, 45, and 40 samples per class respectively (in MI one subject had performed the runs earlier in the research and had only 30 samples per class). We used only three runs for model training in MM due to a higher signal to noise ratio, while for MI and VIS we used four runs; the training and testing data were kept in a chronological order. Written informed consent was obtained from all volunteers, and the studies were approved by the Ethics Committee of the Weizmann Institute of Science.

Our results were obtained offline from recorded data. However, the calculation was simulated by our real-time system as if it were an actual real-time experiment; our system received and classified a new DICOM file every 2 seconds, as would be the case in a real-time study.

3.1 Results

Figure 1 compares average classification accuracy across subjects between ML and ROI. Classification accuracy coincides with the hemodynamic response: in TRs 1 and 2 the accuracy is around chance level, then it gradually increases with the best accuracy in TR 3 to TR 5-6 (6-12 seconds after the trigger), and gradually drops to chance level. The results indicate that identifying the most relevant features by using IG and classifying using SMO is superior to the ROI method. In MM above 90% accuracy can be achieved even at TR 3 (6 seconds after a cue), which is better than the 10 seconds delay in the ROI method. In MI, accuracy of 90% in TR3 and 95% in TR4 can be achieved, which is higher than the highest ROI accuracy at TR 5. Figure 2 provides the results of the VIS study, indicating 78% in TR3. Accuracy up to 87% can be reached with a longer delay. Finally, by reducing the voxel count (i.e., raising the IG threshold) to the smallest number of voxels that permit perfect classification of all training examples, we can achieve similar accuracy to that achieved by using all voxels with positive IG, but with greatly reduced computation time.

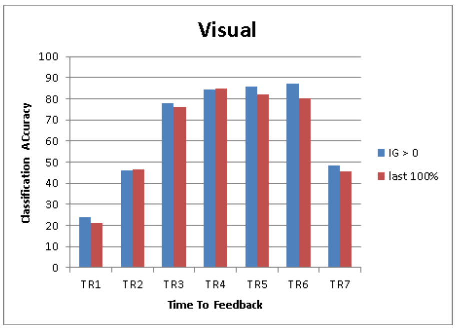

Figure 2: ML results obtained for VIS using (a) all voxels with IG above 0 and (b) the smallest number of voxels that permit perfect classification of all training examples

4 Discussion

Our results indicate that the system is robust across subjects, and efficient in classification time and CPU usage. We have identified multi-voxel brain patterns in the primary motor cortex, the fusiform face area (FFA), the parahippocampal place area (PPA), and the lateral occipital object area (LO). Future experiments may lead to identifying more complex brain patterns. We show successful classification in three different tasks in two several brain areas, using the same method. The fact that this system works online opens the door to new paradigms in BCI, NF, and brain rapid brain mapping.

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