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Controlling an Avatar by Thought Using Real-Time fMRI

O. Cohen[1,2], R. Malach[3], D. Friedman[1]

[1]*The Interdisciplinary Center, Israel;* [2]*Bar Ilan University, Israel;* [3]*Weizmann Institute of Science, Israel*

Correspondence: D. Friedman, The Interdisciplinary Center, P.O. Box 167, Herzliya, Israel. E-mail: doronf@idc.ac.il

Abstract. We have developed a BCI system based on real-time fMRI. Our approach is based on manually locating the regions of interest responsible for left-hand imagery, right-hand imagery, and feet imagery in the brain, and comparing the mean activity in these areas with their baseline values as a simple classification scheme. Six subjects were able to perform a cue-based task and a free choice task of controlling an avatar using finger and toe motion, and three of these subjects also performed the tasks using only motor imagery.

Keywords: Real-time fMRI, avatar, cue based, free choice, motor imagery

1. Introduction

We have developed a system for decoding mental patterns from fMRI data online, and use these decoded patterns to control an interactive virtual environment. Non-invasive BCIs are often based on recording brain activity using electrodes attached to the scalp, usually by electroencephalography (EEG). However, EEG signals are noisy and it is very difficult to localize the source of the activity that is detected, so the reliability and the information throughput of EEG-based BCI are limited. Motor imagery has also been used with EEG-based BCI for controlling virtual reality including controlling an avatar [Friedman et al., 2010], but the control is usually limited to two or three classes at most, and requires a lot of training. Therefore, we see potential for BCI research in fMRI-based BCI. The current cost and size of fMRI do not make it a viable option for application outside the research lab. Nevertheless, it can be used to explore new mental strategies, localize the corresponding brain areas, and be used to train subjects. Furtherhmore, fMRI-based neurofeedback has been suggested as a promising approach to rehabilitation [DeCharms, 2008]. Our approach goes beyond neurofeedback in using multiple regions of interest (ROIs) as BCI targets and providing virtual reality and even robotic feedback [Cohen et al., 2012].

2. Material and Methods

2.1. The System

Imaging was performed on a 3T Trio Magnetom Siemens scanner, and all images were acquired using a 12 channel head matrix coil. Three-dimensional T1-weighted anatomical scans were acquired with high resolution 1-mm slice thickness (3D MP-RAGE sequence, repetition time (TR) 2300 ms, TE 2.98 ms, 1 mm^3 voxels). For blood-oxygenation-level-dependent (BOLD) scanning, T2*-weighted images using echo planar imaging sequence (EPI) were acquired using the following parameters: TR 2000 ms, TE 30 ms, Flip angle 80, 35 oblique slices without gap, 20 towards coronal plane from Anterior Commissure-posterior Commissure (ACPC), $3 \times 3 \times 4$ mm voxel size, covering the whole cerebrum.

The data coming from the fMRI scanner is saved as Dicom files[1], and processed by Turbo BrainVoyager software (TBV, Brain Innovation, Netherlands)[2], which is a real-time processing, analysis, and visualization application that accepts input from an fMRI scanner. We have developed a system that integrates TBV and the Unity game engine[3] (Unity Technologies, California). Our system now includes a complete tool for running a wide range of real-time fMRI studies with different algorithms, experimental protocols, and virtual environments.

2.2. The ROI-based paradigm

The experiment is divided into three parts. In the first part the subject is given pseudo random motor-imagery instructions and the experimenter manually marks the regions of interest (ROIs) inside the most saturated regions for the three classes. In the second part the subject rests and the brain activity is recorded to serve as a baseline. In the third stage, we instruct the subject to imagine moving his limbs and collect the average values from each ROI every two

[1]http://medical.nema.org/
[2]http://www.brainvoyager.com/
[3]http://unity3d.com/

seconds. A classification is made using the Z-score formula and is calculated for each measured value by using the mean and standard deviation from the baseline period:

$$z = \frac{x - \mu}{\sigma}. \tag{1}$$

where x is the average raw value in an ROI in the current TR, μ is the mean raw value of the ROI in the baseline period, and σ is the standard deviation value of the ROI in the baseline period. The selected class is the one corresponding to the ROI with the maximal z-score value. The system then transmits the classification result to the Unity engine for rendering. Each ROI is mapped to a different action performed by the subject: turning left, right, or walking forward corresponds to left-hand, right-hand, or legs imagery, respectively.

2.3. Subjects and Experimental Conditions

Six subjects have performed a cue-based task that were intended to evaluate the BCIs accuracy, and a continuous free choice task: the subjects were represented by an avatar and were instructed to make the avatar reach a balloon. These subjects were allowed to use their fingers and toes while lying down in the scanner. Three of the subjects also performed the same tasks using only motor imagery. In the free choice tasks all subjects attempted at least one epoch (including 6 trials) with several temporal frequencies: a classification result was obtained every 2, 4, 6 or 8 seconds. The subjects filled in a questionnaire of 14 Likert-scale questions after each experimental session, and each subject went through a semi-structured interview at least once. The data is being further analyzed and will be reported in the full paper.

3. Results

In the cue-based task subjects reached 85–100 % accuracy. All subjects were able to control the avatar in all free choice conditions. We compared the number of steps that the subjects needed in order to reach the balloon with the minimum number of steps possible. All subjects were able to reach the balloon with the minimum number of steps at least once in all conditions (2, 4, 6 and 8 seconds, using both imagery and motion). The highest average accuracy is obtained when commands are sent every 6 seconds (using both imagery and motion).

4. Discussion

The results of this study indicate that subjects can learn to perform a free choice BCI task (controlling an avatar) using motor imagery, with very little training. The ROI-based method we have presented here is simple and computationally efficient. We are now extending it using machine learning techniques in order to identify more specific multi-voxel brain patterns that may lead to identifying more complex mental states and more classes.

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