High Performance BCI in Controlling an Avatar Using the Missing Hand Representation in Long Term Amputees

Ori Cohen[1,2], Dana Doron[3], Moshe Koppel[3], Rafael Malach[4], and Doron Friedman[1]

doronf@idc.ac.il, orioric@gmail.com

1 the Advanced Reality Lab, Interdisciplinary Center Herzliya (IDC H.), P.O. Box 167 Herzliya, 46150, Israel
2 the Department of Computer Science, Bar-Ilan University Ramat-Gan, 52900 Israel.
3 the Department of Brain Injury Rehabilitation, Sheba Medical Center, Tel-Hashomer, Israel.
4 the Department of Neurobiology, Weizmann Institute of Science, Rehovot 76100, Israel.

Brain-computer interfaces (BCIs) are especially important for those otherwise incapable of using their bodies to execute their intentions. For patient populations we need to address a major open question: can motor brain circuits that have been deprived of input following trauma still be used for controlling a BCI? In cases of long term amputation both efferent and afferent functions are abolished and may lead to deterioration of the relevant brain representations. Our study addresses this question by allowing a group of long-term amputees to control a computer generated avatar in real-time using their missing hand.

We have previously demonstrated that functional magnetic resonance imaging (fMRI), despite its dependence on sluggish hemodynamic signals, is capable of delivering BCI control and allows subjects to perform complex navigation tasks [1] or teleoperate a humanoid robot [2,3]. FMRI offers advantages of being risk-free, non-invasive, offering superior spatial resolution, and allowing us to tap the rich, functionally complex cortical organization of the whole brain – properties that are not matched by any other real time method currently available, including invasive methods. Thus, we suggest that real time fMRI, even though it is not a target platform for end user BCI by itself, can play a larger role in pushing the capabilities of novel invasive and non-invasive BCIs.

For patient populations there is no need to use motor imagery, and we asked the subjects to perform motor attempt in the missing limb, compared with motor execution by the fingers of the intact hand and by the toes. FMRI provides a highly detailed anatomical mapping of the brain activity, which allows us a quantitative comparison of the brain areas responsible for healthy and amputated limb control. The flexibility of our whole-brain machine learning-based approach [4] enabled the participation of neuronal populations in missing-hand motor actions, including voxels that are not typically associated with motor imagination or motor attempt.

Materials

Imaging was performed on a 3T Trio Magnetom Siemens scanner as described in [1], with a repetition time (TR) of 2000ms. We used our system based on whole brain machine learning [4] for training and real-time classification. Visual feedback was provided by a mirror, placed 11cm from the eyes of the subject and 97.5cm from a screen, which resulted in a total distance of 108.5cm from the screen to the eyes of the subject.

In order to verify that the amputee subjects are not using their stump we connected electromyogram (EMG) electrodes to the subjects' muscle area surrounding the stump. Subjects were instructed to move the fingers in the amputated arm and data (bandpass 1-5000 Hz; sampling rate 10000 Hz) obtained from the shoulder area was collected to validate that no muscle activity was involved in motor movement of the amputated arm. A comb band stop filter was used with a fixed value of 16Hz to remove repetitive noise that came from scanning 32 slices every 2000ms.

Method

Subjects: Seven subjects took part in the study: four control (2 male, mean age 28.5) and three amputees, all male (mean age 31.3), as follows: BZ is 40 years old, amputation above the elbow, 2 years after the accident. PW (Figure 1) is 26 years old, amputation below the shoulder, 1.5 years after the accident. BH is 28 years old, amputation below the shoulder, 2 years after the accident. All subjects reported suffering from mild to high levels of phantom pain. Each subject performed multiple sessions over consecutive days.

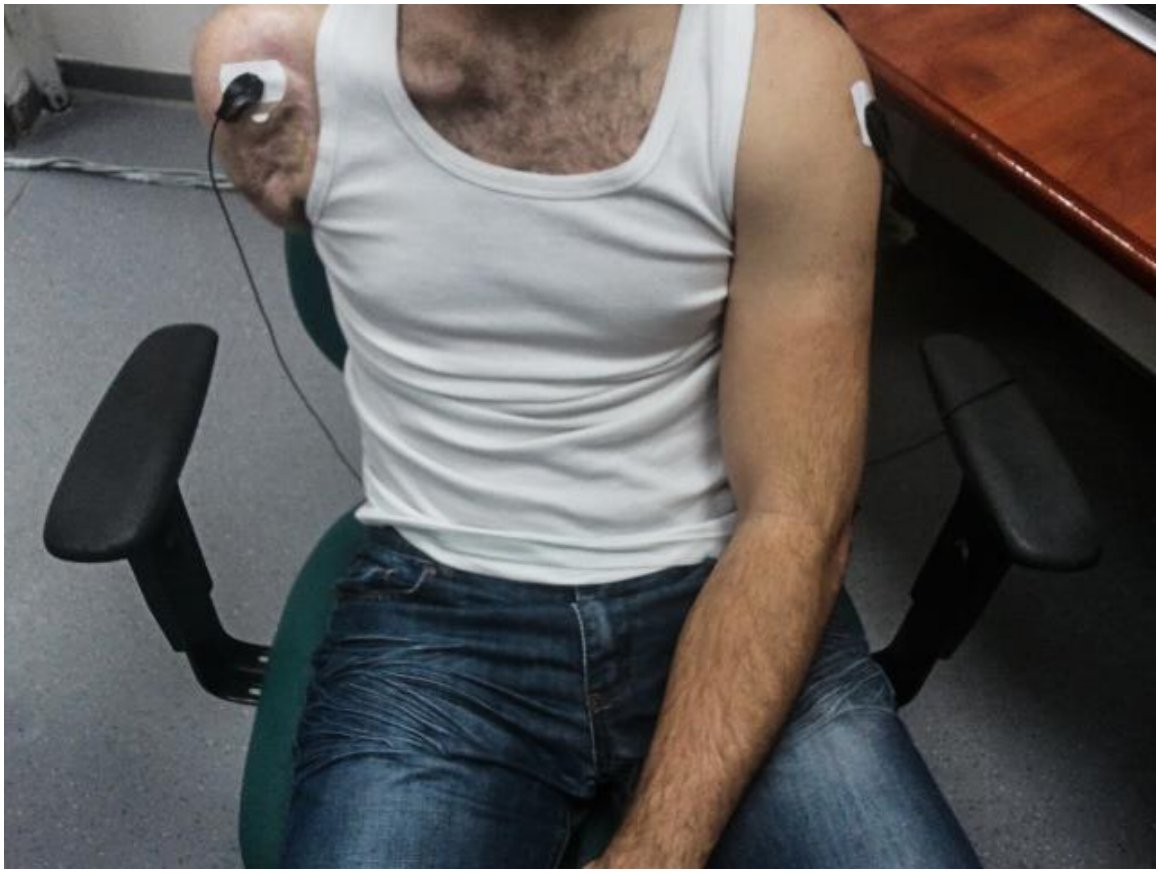

Figure 1: Amputee subject PW with the EMG electrodes connected to the shoulder.

Procedure: In the first part of this experiment, the subject sees an avatar standing in the center of a room (Figure 2a). In each trial the subject is given 40 pseudo-random auditory instructions (``left", ``right", ``forward", and ``rest"), 10 from each class, based on a motor-execution (or motor attempt) experimental protocol. Six seconds after each action, the subject is instructed to rest and during that time the avatar executes the pre-determined command that corresponds with the instruction (turning left or right, walking forward, and stopping). The rest duration varies between 8 and 10 seconds. We record between 3 to 4 sessions as input to a machine-learning tool [4]. For purposes of learning, we select only those voxels with highest information gain (IG). Labeled training examples are then passed on to our learning algorithm. The result of the training phase is a support vector machine (SVM) model that can classify previously unseen vectors. In the second part, the subjects perform a free-choice navigation task. Each subject was instructed to guide an avatar toward the end of a path by picking up as many discs as possible (Figure 2b). The avatar must "touch" a disc in order to successfully collect it, and then the disc changes to green. Our system classifies the subjects' intentions every TR (in our case 2 seconds) in real time. Selecting the same voxels based on the IG filtering performed at model training, the data is

passed into the trained SVM model, and the classification result is transmitted to the avatar (we use the Unity 3D engine for virtual environment feedback). Each trial lasted 696 seconds.

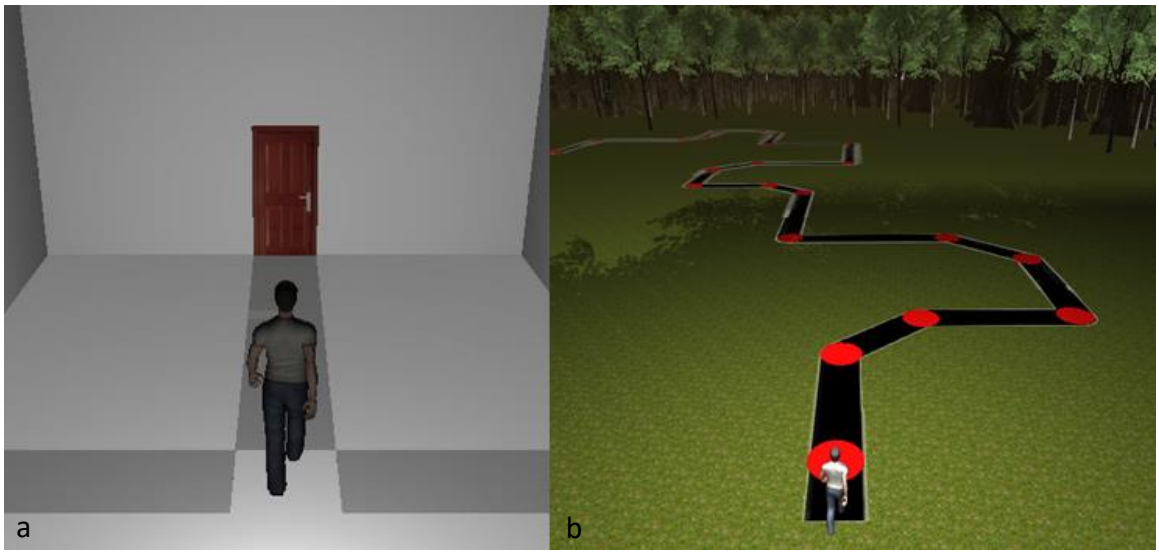

Figure 2: Snapshots of the virtual environment displayed on the monitor during the study. (a) An avatar standing in the center of a room. (b) The 3D virtual path scenario. The subject's avatar is seen standing at the beginning of the path.

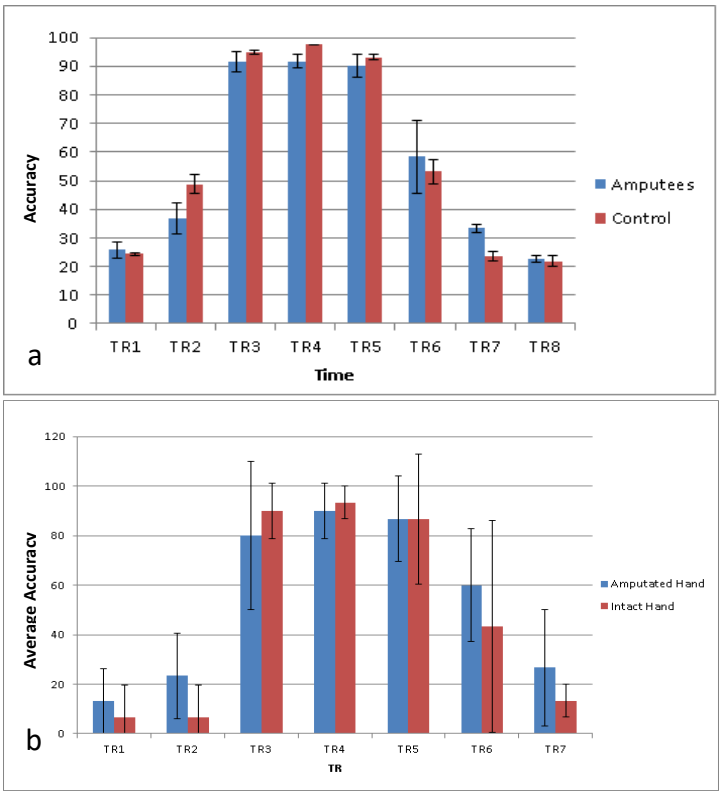

Figure 1: (a) Average classification accuracy in each TR for both groups. Accuracy was calculated from four available classes, with a chance level of 25%. (b) Average classification accuracy in each TR for amputated and intact hands . Error bars indicate the 95% confidence interval.

Results: Classification accuracy in the cue-based BCI task (Figure 3) and in the free-choice task (Figure 4) is promising, indicating that the degree of BCI control and performance with a missing limb is very high and comparable to the performance with the intact hand, and to the performance of control participants. In the free-choice task, the amputees showed similar trajectory patterns to the control group (Figure 5), and their performance was only slightly lower than controls (Figure 4).

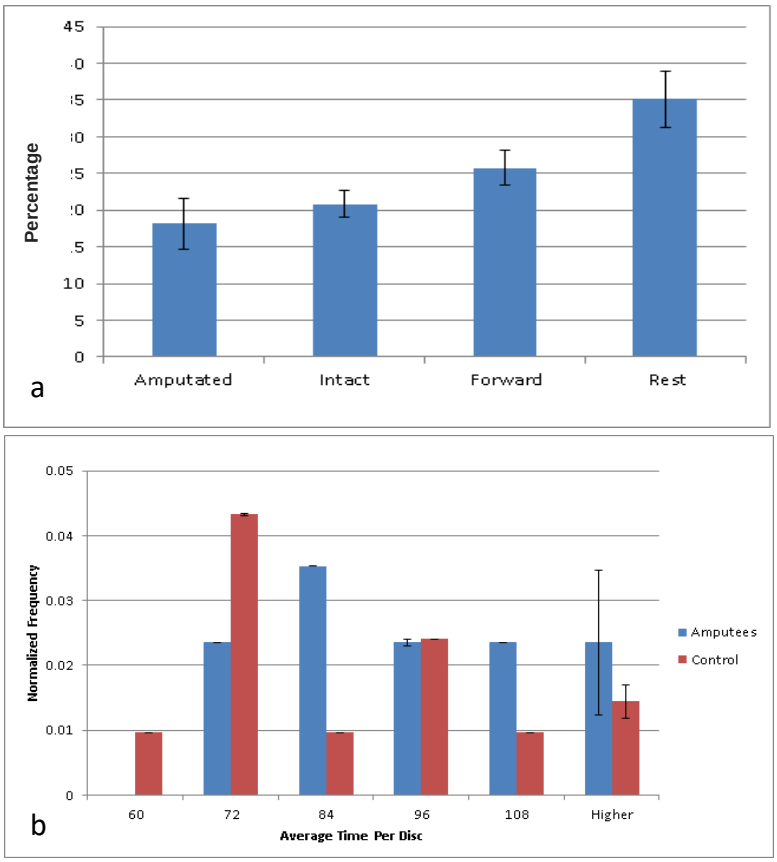

Figure 2: (a) Class usage percentage for the amputated group for each command out of 100%. (b) The distributions of the number of discs collected per group, based on the average time to collect a single disc. The Y-axis represents the normalized frequency and the X-axis represents each increment. Error bars indicate the 95% confidence interval.

A mixed effects for repeated measures statistical analysis taking into account subject, condition and accuracy indicated no significant difference between the groups in TR3 (amputees = 91.6%, control = 95%, p = 0.45) and higher performance (nearly significant) in controls at TR4 (amputees = 91.6%, control = 97.5%, p = 0.068) (Figure 3a). Figure 3b shows similar average classification accuracy in the amputee group for the intact- and missing-hand (3 subjects), taking into account the TR with maximum classification. Figure 4a shows average command usage in the free-choice trials, indicating similar usage patterns; i.e., the amputees had no bias toward the intact hand. A mixed effects for repeated measures statistical analysis taking into account subject, condition and performance, indicated that the control group performed slightly better in the free choice task, but the difference was not significant (p=0.158) (Figure 4b). A significant difference was found among the subjects (p = 0.024).

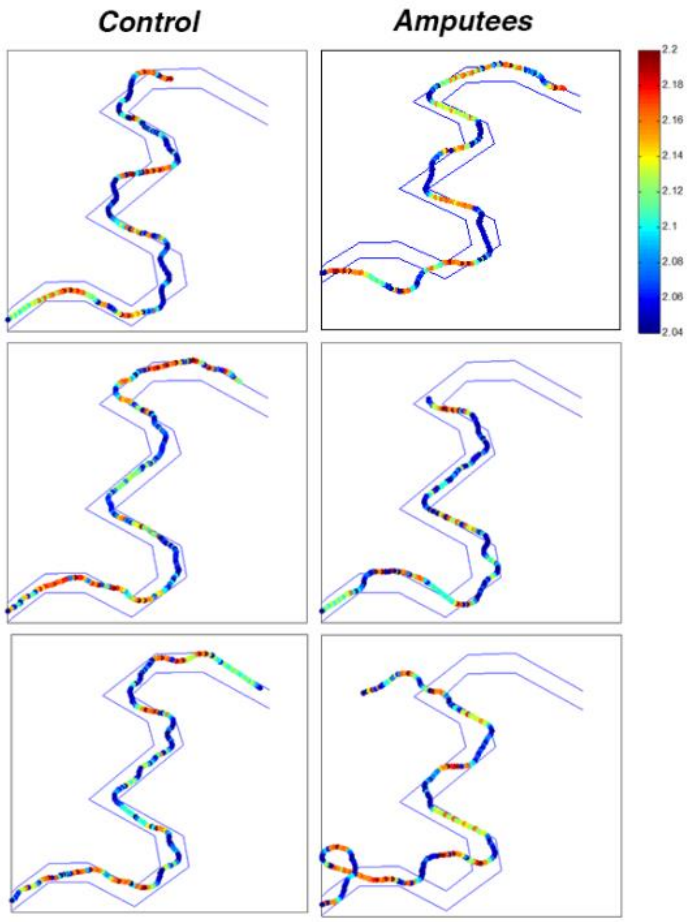

Figure 3: A visualization of the paths of the best performance navigation trial of six subjects. Left column: controls, right column: amputees. Warmer colors reflect higher speed.

Both subject populations were able to adopt a strategy that evoked motor-related brain regions. Nevertheless, an analysis of the voxels selected by the machine-learning platform for classification indicates larger variability in the amputee population and in some cases, there is evidence that the motor activation extended beyond the motor regions, as seen in Figure 6.

Conclusion: In our study [5,6] we used real-time fMRI to demonstrate a remarkably high performance of long term amputees in controlling a virtual avatar using their missing hand. Our whole-brain machine learning system was able to select the most relevant patterns for the task, without prior assumptions or information about those brain regions, converging on motor areas, for all subjects. We also demonstrate the utility of real-time fMRI for BCI: fMRI offers advantages of anatomical detail and brain coverage that are not matched by any other real time method currently available, including invasive methods. Thus we suggest the fMRI-based BCI can make a great contribution to BCI development, as well as to individual training and adaptation. fMRI-based BCI can be used to develop algorithms tailored to individuals following brain reorganization, and the algorithms can adapt to further neural changes following BCI training; issues that are crucial for clinical populations.

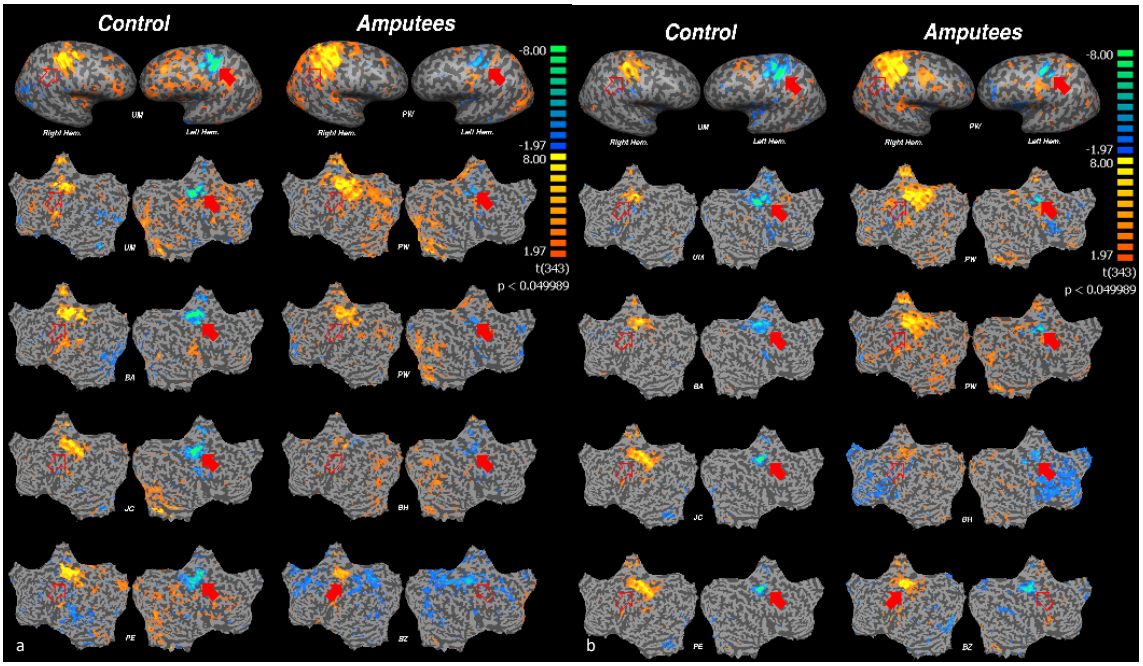

Figure 4: A gallery visualization of the left vs right contrast using a p<0.05 (uncorrected) for the (a) cue-based and (b) free-choice tasks, for all subjects from the amputees and the control group. The red arrows represent the dominant hand and intact hand for t

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