High Performance in Brain-Computer Interface Control of an Avatar Using the Missing Hand Representation in Long Term Amputees

Ori Cohen[1,2,6], Dana Doron[3], Moshe Koppel[2], Rafael Malach[4], and Doron Friedman[1,5]

Abstract— **The ability to allow subjects, including paralyzed patients, to perform a task using brain-computer interfaces has seen a rapid and growing success. Surprisingly, however, it is still not known how far such performance can be improved - especially in cases of long term amputation where both efferent and afferent functions are abolished and may lead to deterioration of the relevant brain representations. Here we used real-time fMRI to demonstrate a remarkably high performance of long term amputees in controlling a computer generated avatar using their missing hand. The missing limb BCI performance showed similar levels both when compared to the intact hand and to control participants.**

I. INTRODUCTION

Advances in brain research have opened a number of promising opportunities to bypass motor deficits through brain-computer interfaces, including studies with disabled patients. Experimental demonstration of the feasibility of this approach has been documented in various modalities from non-invasive scalp recordings (e.g., [1]) to invasive multi-neuronal recordings following implantation (e.g., [2]). However, despite the rapid expansion of this field, it is unclear what the ultimate limits to BCI performance are. This issue should be divided into two independent aspects: the first is technical, and has to do with our ability to record neuronal signals at sufficient speed and detail to allow precise motor performance. The second question is biological and concerns the possibility that even if techniques for detailed recordings may be developed - the long term motor dysfunction may lead to deteriorated brain representations so that the information required for BCI will no longer be available. This is particularly problematic in the case of long term amputations, since in these cases not only the ability to move the missing limb is lost, but also all somato-sensory and proprioceptive inputs are abolished as well. Obviously, if such long term deterioration is the case, then the potential for successful BCI strategies, at least the ones that rely on direct recordings of motor commands, will be substantially limited, regardless of technical advances.

Here we addressed this question by allowing long term amputees to perform BCI study using real-time fMRI. The advantage of fMRI in this respect is that it 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. Furthermore, we have previously demonstrated that the fMRI, despite its dependence on sluggish hemodynamic signals is capable of delivering BCI control and allows subjects to perform complex navigation tasks [3]. Besides offering great promise to future BCI developments, our results open interesting new possibilities for rehabilitation using real time fMRI.

[1]O. Cohen and D. Friedman are with the Advanced Reality Lab, Interdisciplinary Center Herzliya (IDC H.), P.O. Box 167 Herzliya, 46150, Israel

[2]O. Cohen and M. Koppel are with the Department of Computer Science, Bar-Ilan University Ramat-Gan, 52900 Israel.

[3]D. Doron is with the Department of Brain Injury Rehabilitation, Sheba Medical Center, Tel-Hashomer, Israel.

[4]R. Malach is with the Department of Neurobiology, Weizmann Institute of Science, Rehovot 76100, Israel.

[5]corresponding author `doronf@idc.ac.il`

[6]corresponding author `orioric@gmail.com`

II. MATERIALS

Imaging was performed on a 3T Trio Magnetom Siemens scanner as described in [3], [4], with a repetition time (TR) of 2000ms. We used our system based on whole brain machine learning [5] 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.

Seven subjects took part: 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 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.

In order to verify that the amputee subjects are not using their stump we connected 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.

III. METHODS

A. Real-time Cue-Based BCI

In this experiment, the subject sees an avatar standing in the center of a room. In each trial the subject is given 40 pseudo-random auditory instructions ("left", "right", "forward", and "rest"); 10 from each class. 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. The classifier was trained once on three runs for each subject and the same model was used in every subsequent trial, over multiple days.

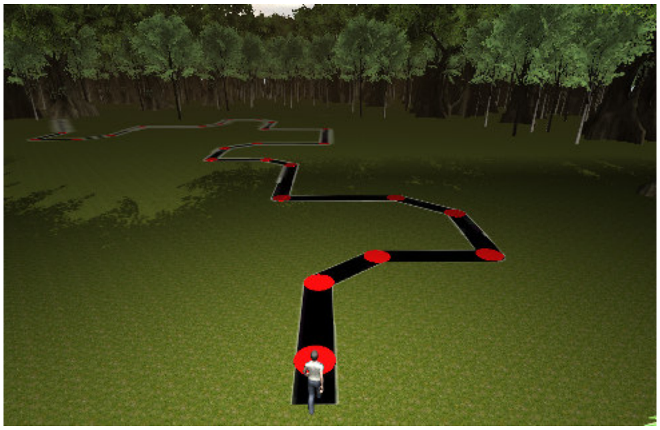

Fig. 1. The 3D virtual path scenario. The subject's avatar is seen standing at the beginning of the path.

B. Real-Time Free-Choice BCI

The same subjects participated in the a free-choice navigation task. Each subject was instructed to guide the avatar toward the end of the path by picking up as many discs as possible (Fig. 1). The classification result was then transmitted to the Unity 3D engine for virtual environment feedback. To successfully collect a disc the avatar must touch it and then the disc changes to green. Each trial lasted 696 seconds. The system provided feedback to the subject following each scan (in our case every 2 seconds), and between these updates the avatar kept performing the last instruction.

IV. Results

A. Real-time Cue-Based BCI

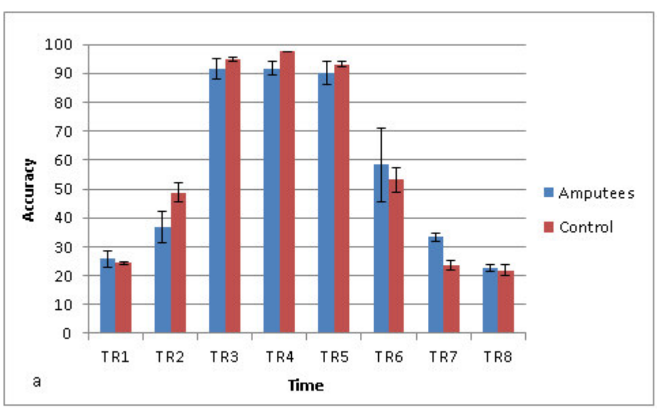

Fig. 2. Average classification accuracy in each TR for both groups. Accuracy was calculated from 4 available classes. The Y-axis represents the average classification accuracy and the X-axis represents the TR. Error bars indicate the 95% confidence interval.

Fig. 2 provides average classification results of the training and cue-based BCI sessions and indicates that the optimal accuracy, for 4 classes (left, right, forward, rest), is consistently achieved 6 seconds after a cue (due to the hemodynamic delay, and consistent with our previous findings [3]). The amputee group performance was similar to the control group. A mixed effects for repeated measure statistical analysis taking into account subject, condition, and accuracy, indicated that the difference between the groups at TR3 (amputees = 91.6%, control = 95%) was not significant (p = 0.45) and at TR4 (amputees = 91.6%, control = 97.5%) the difference is nearly significant (p = 0.068).

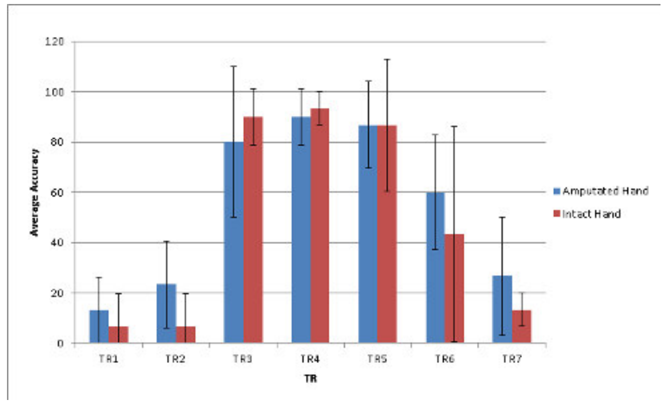

Fig. 3. Average classification accuracy in each TR for amputated- and intact hands. The Y-axis represents the average classification accuracy and the X-axis represents the TR. Error bars indicate the 95% confidence interval.

Fig. 3 compares the average classification accuracy of the intact hand with the missing hand. Taking into account the TR with maximum classification yields 93.3% and 90%, respectively, based on 3 subjects.

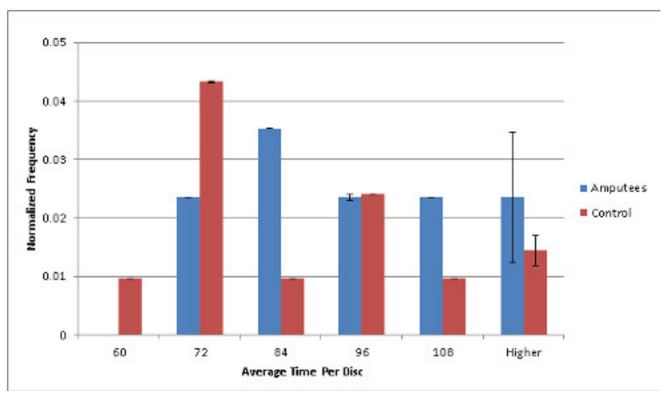

Fig. 4. The normalized amount of experiments in which the average time to pick up a single disc lies in each 12 second interval from 60 seconds upward, for both groups. The Y-axis represents the normalized frequency and the X-axis represents each increment. Controls participated in 1-2 additional runs and therefore picked up more discs than amputees, thus the frequency was normalized by the total amount of discs collected by each group. Error bars indicate the 95% confidence interval.

B. Real-Time Free-Choice BCI

In each trial i, performance was calculated by dividing the trial time t_i by the amount of collected discs d_i. Thus giving us the average time to collect a single disc in seconds (a lower result describes better performance); i.e.,$p_i = \frac{t_i}{d_i}$.

The optimal time for collecting a disc was determined in a pilot study using a joystick, and was 35 seconds per target. The task was repeated several times until it was completed without any mistakes and without using the 'rest' class to stop the avatar. The best time achieved by an amputated subject is 69.3 seconds and the best time by a subject who had both hands is 57.75 seconds, i.e., an overhead of 98% and 65%, respectively, beyond joystick performance. The average time included "rest" conditions that were part of the subjects' strategy, mostly when switching between commands; normalized results are displayed in Fig. 4. A mixed effects for repeated measures statistical analysis taking into account subject, condition, and performance indicated that the control group performed slightly better, but the difference was not significant (p=0.158). A significant difference was found among the subjects (p = 0.024).

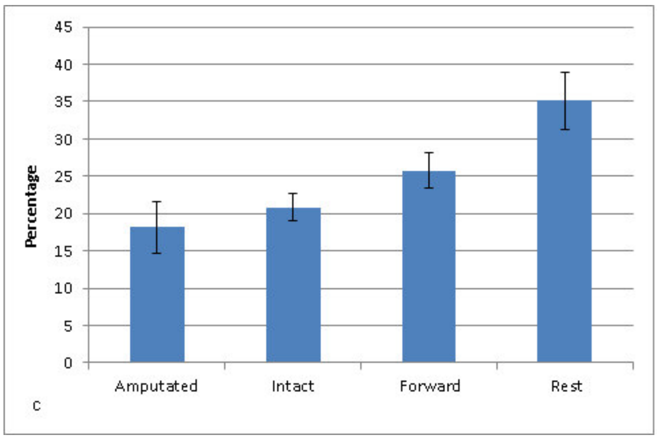

Fig. 5. Class usage percentage for the amputated group for each command out of 100%. The Y-axis represents the percentage usage and the X-axis represents the 4 commands. Error bars indicate the 95% confidence interval.

Fig. 5 shows average usage for each command in free-choice trials, indicating similar usage patterns in both groups; i.e., there was no bias for using the intact hand more than the missing hand in the amputees. As expected "forward" had more usage due to the nature of the path, which had longer distances between discs. The "rest" command was typically used when subjects switched between two commands.

Fig. 6 shows the best trajectories performed by 3 amputees and 3 control subjects. The speed is determined by the number of rest (null class) selections, and we see that both groups followed the same pattern, slowing down before turns.

V. Brain analysis

Fig. 7 shows a visual gallery of left vs right brain contrast overlayed on a flat brain using uncorrected p<0.05 in the cue-based task, and Fig. 8 presents the same data for the free-choice task. For subject 'PW' the inflated brain is a mapping of the flat brain immediately below it. The red arrows represent the dominant hand and intact hand for the control and amputees groups, respectively. Both subject populations were able to adopt a strategy that evoked motor-related brain regions, although this was not required by our

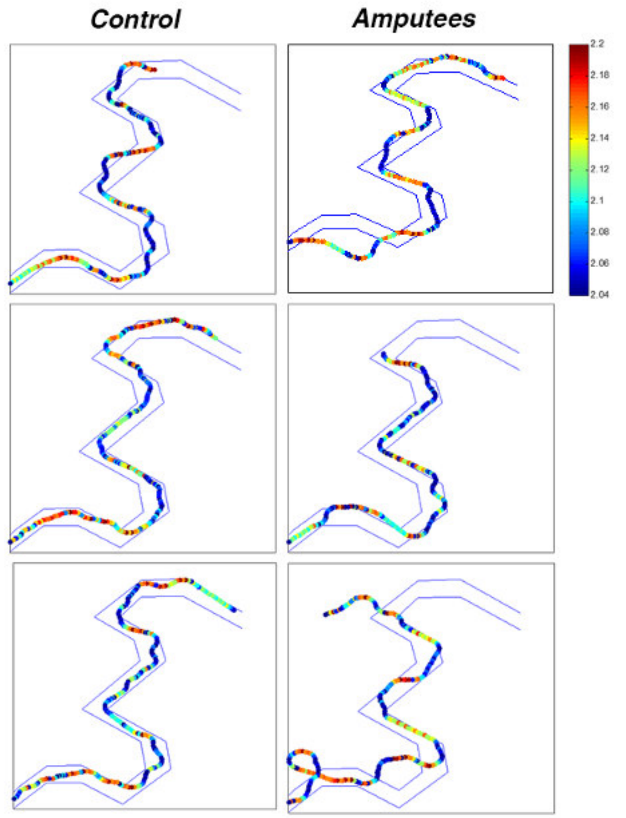

Fig. 6. A visualization of the paths of the best performance of six subjects. Left column: controls, right column: amputees. Colors reflect speed.

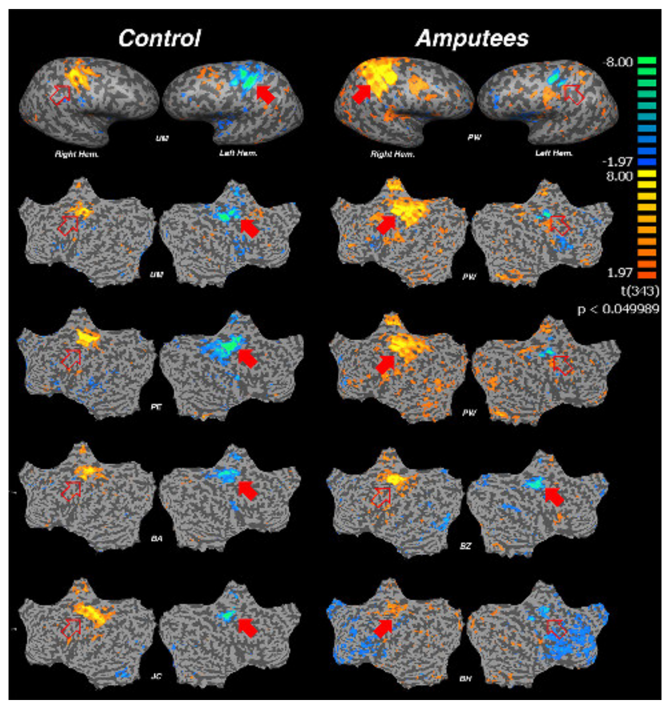

Fig. 7. A gallery visualization of the left vs right contrast using a p<0.05 for the cue-based task, for all subjects from the amputees and the control group.

whole-brain machine learning system. In other words, the system was able to select the most relevant patterns for the task, converging on motor areas, for all subjects, without prior assumptions or information about those brain regions.

In both tasks the patterns indicated by the arrows show that the motor activation of the dominant hand is stronger than the non-dominant hand in all subjects. In certain amputees the motor activations expand beyond the motoric area, and as expected the activations of the amputated hand is weaker than the intact hand. The mean beta values for the amputated hand are within the confidence interval of the intact hand; although slightly lower they are still higher than the mean beta values of the two other conditions in the same ROI, which allows for a good classification.

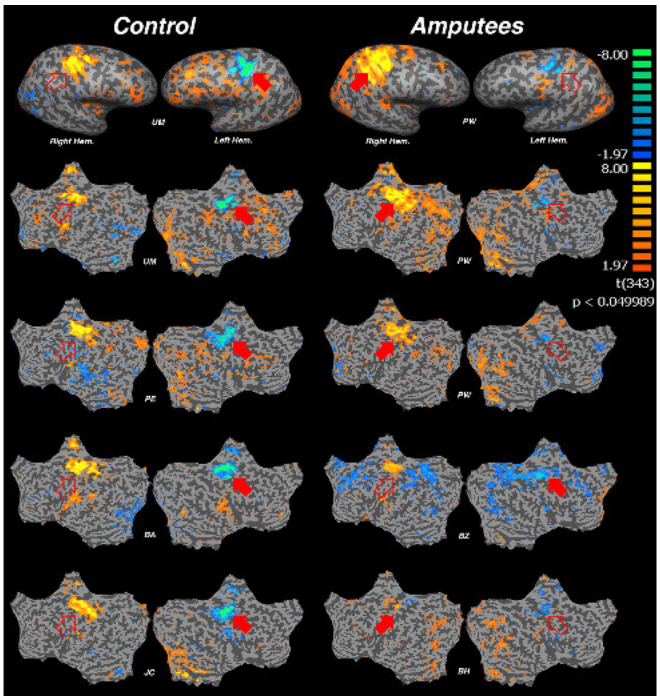

Fig. 8. A gallery visualization of the left vs right contrast using a $p<0.05$ for the free choice task, for all subjects from the amputees and the control group.

VI. Discussion

In this study we show that amputees can perform a BCI with their missing limb with very high accuracy, and that their BCI performance is comparable to that of able bodied 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.

VII. Acknowledgments

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