

Neural Representations of Movement Intentions During Brain-controlled Self-motion

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Abstract—Using a brain-machine interface (BMI), a non-human primate (NHP) was trained to control a mobile robotic platform in real time using spike activity from the motor cortex, enabling self-motion through brain-control. The decoding model was initially trained using neural signals recorded when the NHP controlled the platform using a joystick. Using this decoding model, we compared the performance of the BMI during brain control with and without the use of a dummy joystick, and found that the success ratio dropped by 40% and time taken increased by 45% when the dummy joystick was removed. Performance during full brain control was only restored after a recalibration of the decoding model. We aimed to understand the differences in the underlying neural representations of movement intentions with and without the use of a dummy joystick, and showed that there were significant changes in both directional tuning, as well as global firing rates. These results indicate that the strategies used by the NHP for self-motion were different depending on whether a dummy joystick was present. We propose that a recalibration of the decoding model is an important step during the implementation of a BMI system for self-motion.

Keywords—brain-machine interface, non-human primate, decoding, spike activity, intracortical recordings

I. INTRODUCTION

Brain-machine interface (BMI) is a promising technology for restoring the motor functions of people with paralysis caused by spinal cord injury. Intact intracortical brain signals can be recorded for the control of prosthetic devices that will aid in functional tasks of daily living. Such prosthetic devices for humans have been developed for the control of computer cursors [1] and robotic arms [2-4]. One of the other main obstacles faced by paraplegics is the lack of independent mobility, or self-motion. Although EEG signals have been used for developing brain-controlled wheelchairs [5], intracortical spike activity has the benefit of providing faster, more precise control, and could also be easily integrated with other prosthetic systems that require high degrees of freedom. Here, using a non-human primate (NHP) model, we developed a BMI for brain-controlled self

motion, using single-unit cortical information to decode movement intentions.

The NHP was initially trained to perform self-motion tasks by using a joystick to control a mobile platform, while seated on top of it. Although the NHP had no difficulty switching to brain-control when a dummy joystick was present, good control of the platform was lost after removal of the joystick. This control was subsequently restored after the model for decoding was recalibrated using an intermediate step. The necessity for such a recalibration of decoding models has also been described in previous studies for other BMI applications [6-7].

In this study, we aimed to quantify the effects of using a recalibrated model for decoding during real-time brain-control and the changes in underlying neural activities that encode information related to movement intentions under various conditions. We argue that the strategies employed by the NHP during brain-control were different depending on whether a dummy joystick was present.

II. METHODS

A. Neural signal acquisition

A NHP (*Macaca fascicularis*) was implanted with 3 floating microwire arrays (32 channels each) in the left primary motor cortex. Wideband neural signals were recorded at 12.5 kHz and were high-pass filtered using a cut-off frequency of 300 Hz. Threshold (Thr) for spike detection was found using the formula:

$$\text{Thr} = 5\sigma; \sigma = \text{median}\{|x|/0.6745\},$$

where x is the filtered signal, and σ is an estimate of the standard deviation of the background noise [8].

Multiunit activity was used for decoding, and no spike sorting was performed after spike detection. The firing rates of neurons were recorded every 100ms, with a 500ms sliding window. Only channels with firing rates greater than 2Hz were considered for decoding.

B. Behavioral task

The NHP was trained to perform a behavioral task that required self-motion in a desired direction, while seated on a robotic platform. The NHP was able to maneuver the platform moving a joystick (joystick-control) with its right hand, and received a reward when it successfully performed one of four tasks - going forward by 2m, turning 90° left, turning 90° right, and staying still for at least 5s. A trial was considered successful if the NHP was able to complete the task in less than 15s.

C. Decoding methods

While the NHP was performing each of the movement tasks using the joystick, firing rates were recorded and used to create the first decoding model (one-step model) for online decoding.

Linear discriminant analysis was used for online classification of movement intentions in the same four categories as the behavior tasks – forward, left, right and stop. Decoding was performed at a rate of 10 Hz, based on the firing rates of detected spikes during the preceding 500 ms at each time point.

Online brain-control was first implemented with the use of a dummy joystick (dummy brain-control), and eventually the dummy was removed (full brain-control). In order to achieve full brain-control, an intermediate step was necessary to create a recalibrated decoding model (two-step model). During this step, the joystick was removed, and online decoding was implemented with a 50% correction

rate, i.e. the platform's direction of movement was changed to the position of the reward 50% of the time, regardless of the decoded direction. In this manner, the platform was able to reach the target under the time limit even with many errors in decoding. A higher percentage correction rate was not used so as to motivate the NHP to attempt to move in the direction of the reward. An inherent assumption is that the NHP always has the intention of moving towards the reward, which is mostly true after a long period of behavior training.

The recalibrated decoding model (two-step model) was created using neuronal firing rates measured during this intermediate session.

III. RESULTS

We compared the behavioral performances and neuronal firing patterns during joystick-control, dummy brain-control, and full brain-control.

A. Behavioral performance

The NHP's behavioral performance was assessed based on two factors – time taken to reach target, and ratio of successful trials. There was no significant difference in performance between joystick-control, dummy brain-control and full brain-control using the two-step model (figure 1). All three conditions led to high performance and good control of the mobile platform. However, full brain-control using the one-step model resulted in a 40% drop in success rate and a 45% increase in the time taken to reach the target during successful trials (figure 1). This difference in performance shows that the NHP was able to control the platform well using the one-step model when a dummy joystick was present, but the same model did not accurately decode movement intentions after the joystick was removed. Good control was only restored after a recalibration of the decoding model.

B. Neuronal response

Spike information from a total of 27 channels was used for online decoding and in this analysis. Other channels did not have spike activity, or the average baseline firing rates were below 2Hz. We compared neuronal firing rates for each channel during dummy brain-control and full brain-control using the two-step model, while the NHP was performing successful trials. Changes in neuronal firing during brain-control were quantified with and without the use of a dummy joystick. Figure 2 shows an example neuron's response during dummy brain-control and full brain-control. For this neuron, there was a change in directional tuning when switching between dummy and full brain-control. During dummy brain-control, the neuron had a selective response to the right movement, with a significant increase in firing rate only when the platform turned right. However, selectivity changed from the right to the forward movement after removing the dummy joystick, and firing rate increased most significantly when the platform moved

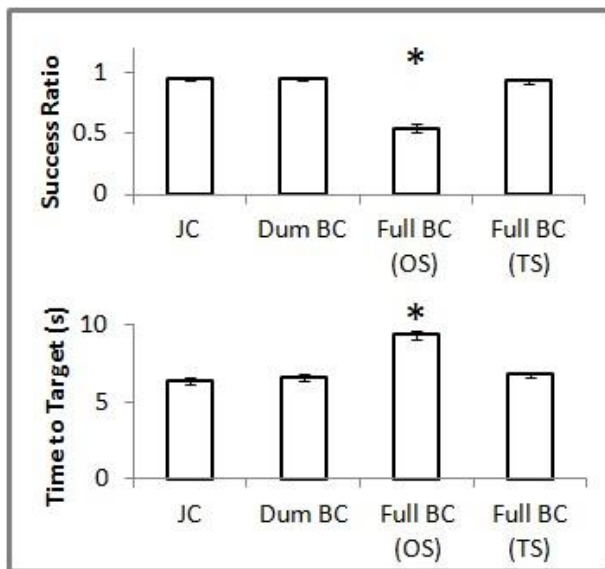


Figure 1. Behavioral results. Behavioral performance (measured in terms of success ratio and time taken to reach target) was similar for joystick control (JC), dummy brain-control (Dum BC) and full brain-control with two-step decoding model (Full BC TS). However, performance was significantly worse for full brain-control using the one-step decoding model (Full BC OS). (* $p < 0.05$, one-way ANOVA with post-hoc comparison.)

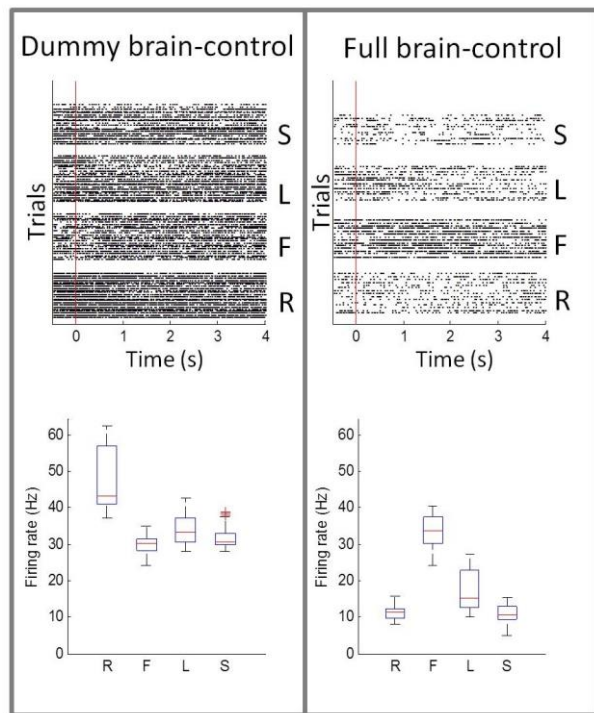


Figure 2. Neuronal response from an example neuron during dummy brain-control (dummy BC) and full brain-control using the two-step model (full BC). **(TOP)** Spike trains were aligned to the start of each trial for the four movement classes – right (R), forward (F), left (L), and stop (S). Firing patterns were consistent across trials. **(BOTTOM)** Quantification of the same data as the top figures. Firing rates were generally higher during dummy BC compared to full BC. Changes in relative firing rates respective to movement directions were also different. Firing rates were selectively tuned to the right movement during dummy BC, while selective tuning changed to the forward direction during full BC. The red asterisks indicate outlier points that were larger than 1.5 times the standard deviation.

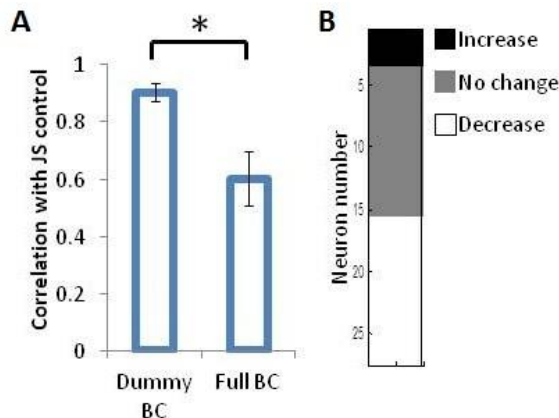


Figure 3. **(LEFT)** Correlation scores between directional tuning of dummy brain-control and joystick-control, and between full brain-control (two-step model) and joystick control. Correlation for full brain-control and joystick-control was significantly lower compared to correlation for dummy brain-control and joystick-control. **(RIGHT)** Proportions of neurons with global increase, decrease for no change in firing rates. These results show that there were both changes in relative neuronal firing rates for the four movement categories as well as global changes in firing rates after removing the dummy joystick.

forwards. In other words, there was a change in the relative difference in firing rate for the four movement categories when the dummy joystick was removed. If the one-step decoding model was used for full brain-control without the joystick, an increase in firing rate in this neuron during an intended forward movement would have been incorrectly classified as a right turn.

Furthermore, this example neuron exhibited a global decrease in firing rate during full brain-control (figure 2). The average firing rate of this neuron was much lower during brain-control without the joystick.

Since decoding was performed using information from all 27 channels, we aimed to understand changes in dynamics of the entire population of neurons. A correlation score was used to determine the similarity of directional tuning of each channel during dummy brain-control and full brain-control, as compared to joystick-control. The average correlation between joystick-control and dummy brain-control was 0.9, and the high score meant that tuning of the neurons did not change much between these two states. However, switching from dummy brain-control to full brain-control resulted in a significant decrease in correlation scores (figure 3A), indicating that for many channels, there were significant changes in the relative firing rate patterns. We also observed that 11.1% of neurons (3/27) had a global decrease in firing rate, while 44.4% of neurons (12/27) exhibited a global increase in firing rates (figure 3B).

Therefore, neurons exhibited changes in relative firing rates for the four movement classes, as well as changes in global firing rates when switching from dummy brain-control to full brain-control. Therefore, firing rates recorded from channels during full brain-control would not have given accurate decoding information regarding movement intentions if the same decoding model for dummy brain-control was used.

IV. DISCUSSION

A recalibration of the decoding model greatly improved the decoding of movement intentions and the control of the robotic platform during full brain-controlled self-motion. Our behavioral results showing the necessity of a recalibration step indicates that there were significant differences between the one-step and two-step decoding models, which led us to investigate the differences in the underlying neuronal firing during brain-control with and without the presence of a dummy joystick. Indeed, there were clear distinctions in neuronal responses under the two conditions, both in terms of directional tuning, as well as global firing rates.

A high correlation was found for the firing patterns between dummy brain-control and joystick control. This indicates that a similar strategy was employed by the NHP to control the mobile platform under these two conditions. Since the joystick was not removed, the NHP continued to use hand movements to manipulate the joystick when attempting to control the moving platform. If decoding accuracy was high, there would not have been a perceivable change when switching from joystick-control to brain-

control with a dummy joystick. Indeed, the behavioral results indicate that the NHP did not experience a major difference controlling the platform between the joystick-control state and brain-control state, as long as the joystick was still present.

However, after the joystick was removed, performance dropped significantly if the same decoding model was used. This effect shows that the NHP changed its strategy in attempts to maintain control of the platform. The intermediate session with a correction rate was designed to aid and motivate the NHP to control the platform with only brain signals. The second decoding model was built while the NHP used new strategies to control the platform without the presence of a joystick. Analysis of the neural responses shows that there were indeed changes in neural representations of movement intentions after removal of the joystick, reflecting this change in strategy. Therefore, the recalibrated model captured the new patterns of neuronal firing that the NHP adopted in an attempt to control the platform. With only one step of recalibration, the NHP was able to immediately regain control of the mobile platform, and accuracy in decoding movement intentions was restored.

In summary, our results indicate that the strategies employed by the NHP for brain-control were different depending on whether a dummy joystick was present. This change in strategy shows that neural representations of movement in the motor cortex are not static, and occasional recalibration of models used for decoding movement intentions may be necessary to achieve optimal control of a mobile brain-machine interface.

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