Adaptive decoding using local field potentials in a brain-machine interface

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Abstract— **Brain-machine interface (BMI) systems have the potential to restore function to people who suffer from paralysis due to a spinal cord injury. However, in order to achieve long-term use, BMI systems have to overcome two challenges – signal degeneration over time, and non-stationarity of signals. Effects of loss in spike signals over time can be mitigated by using local field potential (LFP) signals for decoding, and a solution to address the signal non-stationarity is to use adaptive methods for periodic recalibration of the decoding model. We implemented a BMI system in a non-human primate model that allows brain-controlled movement of a robotic platform. Using this system, we showed that LFP signals alone can be used for decoding in a closed-loop brain-controlled BMI. Further, we performed offline analysis to assess the potential implementation of an adaptive decoding method that does not presume knowledge of the target location. Our results show that with periodic signal and channel selection adaptation, decoding accuracy using LFP alone can be improved by between 5-50%. These results demonstrate the feasibility of implementing unsupervised adaptive methods during asynchronous decoding of LFP signals for long-term usage in a BMI system.**

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

I. INTRODUCTION

Brain-machine interface (BMI) systems hold much promise in offering a solution for people with spinal cord injury, who want to regain mobility [1-3]. Previously, we demonstrated a BMI system that allows a non-human primate to achieve self-motion by using single-neuron (spike) activities to control a mobile platform [4].

However, BMI systems still suffer from two unsolved challenges. The first is signal degeneration over time when using high frequency action potential, or spike, signals for decoding. Although spike signals result in accurate and stable decoding in the short term, the number of channels carrying such signals decreases over time [5], and have led to concerns over the long-term reliability of BMI systems. To this end, some groups have proposed local field potential (LFP) signals to be used as an alternative [6-7], or in conjunction with [8], spike signals in neural decoding.

The second major issue in BMI systems is non-stationarity of the signals. Gradual changes in tuning of signals have been reported [9], and could arise due to neural plasticity, micro-motion of the electrodes, or changes in environmental properties. Many groups have proposed methods for adapting or recalibrating the decoding model [10-11]. However, most of these studies were performed using task-oriented experimental design (e.g. center-out tasks), which has fixed targets that can be used as a reference point when adapting the model. BMI systems for the purpose of enabling self-motion, on the other hand, need to achieve reliable continuous asynchronous decoding with no fixed target.

In this study we present a method for adaptive decoding using only LFP signals, which does not presume prior knowledge of the target locations. Although targets were present during the experiments, adaptation of the model was performed entirely using decoded direction as the only reference. We show that such unsupervised continuous adaptation led to higher decoding accuracy and can be implemented in future asynchronous BMI control systems.

II. METHODS

A. Neural signal acquisition and processing

Floating microwire arrays (32 channels each) were implanted in the left primary motor cortex of one adult male rhesus monkey. Wideband neural signals from 64 channels were recorded at 12.5kHz. The raw signal was processed every 0.1s, first using a fast fourier transform that converts the signal to the frequency domain, and subsequently the mean scalar LFP power between 200-400Hz [7] for each channel was calculated.

B. Behavioral task and experimental design

The monkey was seated on a robotic platform, and was trained to move towards a reward (usually a piece of fruit held by a trainer). The platform was either controlled by joystick signals when the monkey moved a joystick using its right hand (joystick control), or by decoded LFP signals (brain control) (figure 1A). The joystick was removed during brain control. For each trial, the monkey was required to move in one of 4 directions – forward, left, right, or stop. It received a reward upon successful completion of either moving forward by 2m, turning left by 90^{o}, turning right by 90^{o}, or staying still for at least 5s. A trial was considered successful if the monkey was able to complete the task in less than 15s. Each session consisted of 20 trials, 5 in each direction.

This study was based on two datasets collected on separate days. The first dataset was recorded during 5 sessions of joystick control, and the second during 4 sessions of brain control. For offline analysis, the first session from the joystick control dataset was considered as the training session and the rest as test sessions. During the first (training) session for brain control, a randomized decoding model was used and the platform was pre-programmed to move towards the reward direction 90% of the time. The assumption was that since the monkey was well-trained in brain control experiments, it would attempt to use its brain signals to move the platform, and the collected signals could be used to build a decoding model for subsequent test sessions. No adaptation algorithm was implemented during online decoding for this dataset.

C. Decoding methods

We employed a multi-class classifier (discrete decoding) to perform continuous decoding and control. The classifier generated control signals for the robotic platform every 100ms. Linear discriminant analysis (LDA) was used for classification of movement directions, both during online decoding and offline analysis. A four-class LDA was implemented; LFP signals were decoded into the same four categories as the behavior task – forward, left, right and stop. Decoding was performed every 0.1s, based on the mean LFP between 200 and 400 Hz during the preceding 0.5s.

D. Adaptive algorithm

Offline analysis was performed for both sets of data to compare the decoding accuracy with and without the use of adaptive algorithms.

Two types of adaptation were tested. The first adaptation required an update of the signals used for creating the model (signal adaptation). When both of the following criteria were met, LFP signals used for decoding at that time step was used to replace the oldest set of signals in the decoding model:

1) Posterior probability of decoded direction > 0.99
2) No. of previous directions that matches current direction > 5

In this way, the size of the model used for decoding remained constant, but was constantly recalibrated during the decoding process. The threshold values of 0.99 and 5 were selected empirically, and these criteria were used to reduce the rate of incorrect recalibration.

The second type of adaptation involved the update of the selected channels, or features, that were used in decoding (channel adaptation). The channels were initially selected based on correlation (corr>0.8) of the neuronal tuning curves between the first and second half of the training session. We tested how decoding accuracy changed either with periodic updates to channel selection before the start of each session, or with constant channel adaptation with each occurrence of signal adaptation as described above. The threshold of 0.8 was again selected empirically.

E. Data analysis

To compare and quantify differences in the channels' LFP tuning properties between various training and test sessions, we first estimated the probability distribution of the LFP signals for each direction class, and then calculated the Kullbakc-Leibler (KL) distance between the probability distributions.

Offline calculation of decoding accuracy was determined in two ways. When the joystick was present, the ground truth direction was determined from the joystick signal. When the joystick was absent, the ground truth direction was regarded as the direction of the reward, with the assumption that the monkey was always trying to move towards the target. In both cases, accuracy was calculated as the percent of decoded directions that matched the ground truth directions.

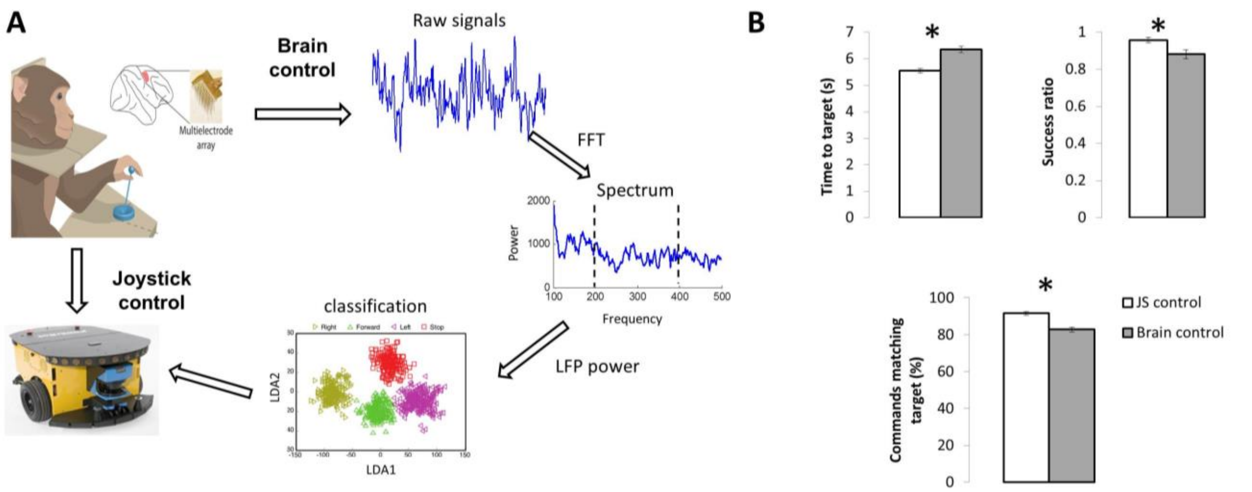

Figure 1 – (A) Schematic for processes involved in joystick and brain control. (B) Behavioral results during both joystick and brain control. Brain control resulted in significantly longer time to reach target, decreased success ratio, and decrease percent of commands matching target direction. (*one-way ANOVA, p<0.05)

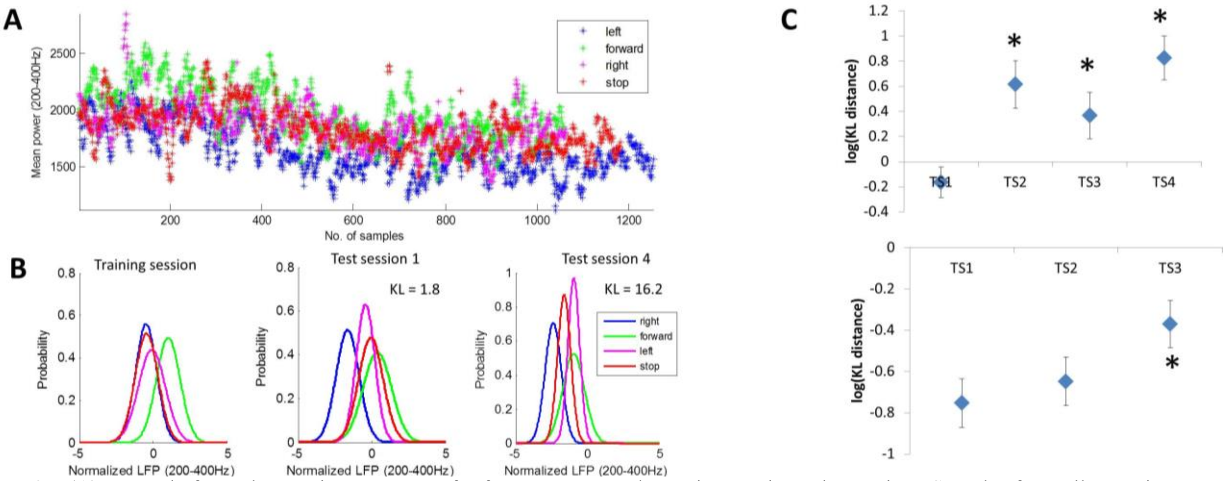

Figure 2 – (A) Example from changes in LFP power for four movement classes in one channel over time. Samples from all 5 sessions were combined in this figure. (B) Probability distribution curves of LFP power from the same channel as in (A) during various training and test sessions. (C) Plot of KL distances between probability curves for each test session (TS) compared to the training session, for joystick control (top panel) and brain control (bottom panel). *One-way repeated measures ANOVA, p<0.05.

III. Results

A. Behavioral performance

The behavioral performance of the monkey was assessed based on two factors – time taken to reach the target, and ratio of success trials. Although the monkey was able to reach the reward majority of the time (88%) using brain control, it resulted in a significantly longer time per trial, and a lower success ratio compared to joystick control (Figure 1B). These results indicate that the control of the mobile platform was more difficult for the monkey during brain control using LFP signals compared to joystick control. The percent of commands sent to the platform that matched the direction of the reward was less during brain control compared to joystick control (Figure 1B), indicating that a significant proportion of LFP signals we incorrectly decoded, which led to poorer behavioral outcome.

B. Change in tuning of LFP signals

We observed significant changes in LFP tuning over time. An example of the changes in LFP power from one channel during joystick control is shown in figure 2A. There was a gradual decline in 200-400 Hz power in this channel for all four movement classes over time, and the mean power at the end of the experiment was lower than in the beginning. Furthermore, there was a change in tuning properties as well (Figure 2B). During the training session, this channel appeared to be selective for forward movements, but by the last test session, this selectivity was reduced, and the channel became more selective for right movements instead.

Using KL distance, we quantified the global changes in tuning across all channels between the training session and test sessions, for both joystick and brain control (Figure 2C). For joystick control, there was a large and significant increase in KL distance after the first test session, indicating that the tuning properties of LFP signals across channels has changed significantly. Although a slight increase in KL distance was also seen for brain control over time, the increase was much less compared to joystick control, indicating that LFP tuning changed less during test sessions for brain control.

C. Adaptive vs. Non-adaptive Decoding

For joystick control, offline analysis showed that decoding accuracy without adaptation led to a rapid decrease to below 50% after the first test session. Model adaptation using fixed channel selection resulted in significant improvements in decoding accuracy for all test sessions. When a periodic channel adaptation before the start of each session was incorporated, a further improvement in decoding accuracy up to 50% was observed (Figure 3A). However, constant channel selection update resulted in worse decoding accuracy compared to fixed channel selection.

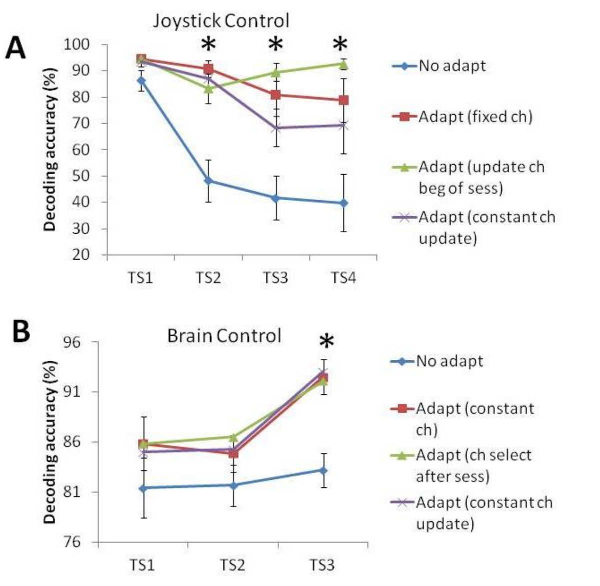

Figure 3 – Comparing decoding accuracies for various test sessions (TS) when using a static decoding model and when using adaptive methods, for both joystick control (A) and brain control (B). Adaptive decoding resulted in higher decoding accuracies in both cases. (*significantly different from no adapt, one-way repeated measures ANOVA, p<0.05)

Offline analysis for the brain control dataset showed that decoding accuracy was maintained at around 80% for all test sessions (figure 3B, 1B), even without adaptation. However, when signal adaptation was implemented, a higher decoding accuracy of 92% was achieved during test session 3 (Figure 3B). In this case, channel adaptation did not have an effect on the decoding accuracy when used in combination with signal adaptation.

IV. Discussion

This study showed that LFP power alone can be used as a decoding signal for closed-loop BMI applications, though control was more difficult compared to joystick control. Offline analysis using datasets from both joystick and brain control indicates that an unsupervised adaptive decoding method could improve decoding accuracy compared to a static model.

The first interesting observation is that LFP signals could vary and change greatly within a short period of time. Although all 5 sessions in the joystick control dataset were recorded in less than an hour, and the behavioral task remained the same during that period, the tuning of LFP power for some channels was very different at the end of the experiment compared to the beginning. Therefore, changes in LFP signals can occur on the order of minutes, which are generally not seen in spike recordings. Due to these changes in LFP tuning, there was a large drop in decoding accuracy during offline joystick control analysis using a static model.

We showed that one way to mitigate the effects of such non-stationarity in LFP signals is to constantly recalibrate the decoding model through signal adaptation. In this manner, any gradual shifts in LFP tuning could be captured in the updated model. The main novelty in our method is that instead of using the target location as the ground truth reference for adaptation, we used the actual decoded signal as the reference target. Therefore, adaptation can be implemented in an unsupervised manner without prior knowledge of the target location, which would be the case in asynchronous continuous usage of the BMI system.

Decoding accuracy for brain control dataset was maintained at around 80% even without adaption. This result is congruent with the much smaller changes in global tuning of LFP power during brain control compared to joystick control. The reason behind the smaller change in LFP tuning during brain control remains unclear. The upward trend in the change in KL distance during test sessions of brain control indicates that there were changes in tuning in the later test sessions compared to the training session, but these changes were small and not significant enough to affect decoding accuracy. However, if such trends continued, decoding accuracy using a static model may have dropped for later test sessions. This hypothesis will be tested in future experiments. In any case, offline analysis showed that the decoding accuracy for brain control was further improved when adaptive decoding was implemented, and it can be inferred that if such methods were used during online brain control it would have led to improved behavioral outcomes.

Feature selection often greatly affects decoding accuracy. For joystick control, periodic channel adaptation in addition to signal adaptation further improved decoding accuracy by 10% during the last two test sessions compared to signal adaptation alone. However, for brain control, updating channel selection did not greatly affect decoding. These results show that periodic channel adaptation may be useful for long-term BMI usage following large and significant global changes in LFP tuning.

One major limitation of this study is that analysis of adaptation was performed entirely through offline analysis. For the joystick control dataset, changes in tuning of LFP signals may not be directly correlated with behavior and the effects of learning was not captured, since the monkey was not using LFP for control. However, such offline analysis is still useful for comparing various forms and strategies used for adaptive decoding. Future studies would implement such adaptation methods during long periods of online testing to measure their efficacy and reliability compared to using a static model. Changes in tuning of control-relevant LFP signals can be studied in greater detail as well. Nonetheless, these results demonstrate the feasibility of using LFP signals for BMI applications, and adaptive decoding without prior knowledge of the target location. Such methods hold promise for development of BMI systems that allow for long-term continuous use without the need for periodic re-training of the decoding model based on target-oriented tasks.

References

[1] M. Velliste, et al., “Cortical control of a prosthetic arm for self-feeding.,” *Nature*, vol. 453, no. 7198, pp. 1098–101, Jun. 2008.

[2] L. R. Hochberg, et al., “Reach and grasp by people with tetraplegia using a neurally controlled robotic arm.,” *Nature*, vol. 485, no. 7398, pp. 372–5, May 2012.

[3] F. Galán, et al., “ A Brain-Actuated Wheelchair: Asynchronous and Non-Invasive Brain-Computer Interfaces for Continuous Control of Robots”, *Clinical Neurophysiology*, vol. 119, pp. 2159–2169, 2008.

[4] R. So, et al., “Neural representations of movement intentions during brain-controlled self-motion”, *Conf. Proc. 7th International IEEE/EMBS Conference on Neural Engineering (NER)*, pp. 228–231, 2013.

[5] J. C. Barrese, et al., “Failure mode analysis of silicon-based intracortical microelectrode arrays in non-human primates.,” J. Neural Eng., vol 10, no 6, pp. 066014, 2013

[6] K. So, et al., “Subject-specific modulation of local field potential spectral power during brain-machine interface control in primates.,” *J. Neural Eng.*, vol. 11, no. 2, p. 026002, Apr. 2014.

[7] Y. Li, et al., “Decoding grasp types with high frequency of local field potentials from primate primary dorsal premotor cortex.,” *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2012, pp. 1691–4, Jan. 2012.

[8] S. D. Stavisky, et al., “A high performing brain-machine interface driven by low-frequency local field potentials alone and together with spikes.,” *J. Neural Eng.*, vol. 12, no. 3, p. 036009, Jun. 2015.

[9] K. Ganguly, et al., “Reversible large-scale modification of cortical networks during neuroprosthetic control.,” *Nat. Neurosci.*, vol. 14, no. 5, pp. 662–7, May 2011.

[10] V. Gilja, et al., “A high-performance neural prosthesis enabled by control algorithm design.,” *Nat. Neurosci.*, vol. 15, no. 12, pp. 1752–7, Dec. 2012.

[11] B. Jarosiewicz, et al., “Advantages of closed-loop calibration in intracortical brain-computer interfaces for people with tetraplegia.,” *J. Neural Eng.*, vol. 10, no. 4, p. 046012, Aug. 2013.