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Brain-machine interface control using broadband spectral power from local field potentials

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***Abstract*—Recent progress in brain-machine interfaces (BMIs) has shown tremendous improvements in task complexity and degree of control. In particular, closed-loop decoder adaptation (CLDA) has emerged as an effective paradigm for both improving and maintaining the performance of BMI systems. Here, we demonstrate the first reported use of a CLDA algorithm to rapidly achieve high-performance control of a BMI based on local field potentials (LFPs). We trained a non-human primate to control a 2-D computer cursor by modulating LFP activity to perform a center-out reaching task, while applying CLDA to adaptively update the decoder. We show that the subject is quickly able to readily reach and hold at all 8 targets with an average success rate of 74% ± 7% (sustained peak rate of 85%), with rapid convergence in the decoder parameters. Moreover, the subject is able to maintain high performance across 4 days with minimal adaptations to the decoder. Our results indicate that CLDA can be used to facilitate LFP-based BMI systems, allowing for both rapid improvement and maintenance of performance.**

I. Introduction

Brain-machine interfaces (BMIs) have undergone dramatic improvements in functionality, from simple modulation of individual neurons [1] to control of a robotic arm with multiple degrees-of-freedom [2]. Despite these impressive results, the difficulty in achieving proficient control can limit the clinical viability of BMIs. In addition, changes in neural signal quality recorded over time can further complicate the user's ability to maintain proficient control. To address these issues, prior work has shown that decoder adaptations performed during closed-loop BMI operation can facilitate rapid performance improvements [3]–[6] as well as maintain proficient control [7]. However, these adaptive approaches have yet to be implemented with local field potential (LFP) signals, which measure the sum of local synaptic currents flowing across extracellular space. For instance, in a recent closed-loop LFP study, Flint et al. used a static decoder but did not apply any decoder adaptations to aid performance improvement [8].

In this study, we used decoder modifications during closed-loop control, which we refer to as closed-loop decoder adaptation (CLDA), to achieve rapid initial performance BMI improvements. We trained a non-human primate to perform a center-out reaching task with a cursor controlled via LFP activity. We employed an assistive training paradigm [2], [9], [10] that gradually increased the difficulty of control, while simultaneously using a CLDA algorithm to recalibrate the decoder. This combined approach allowed the subject to reach and hold at all 8 targets with volitional control within 20 minutes. On subsequent days, the subject was able to readily perform the task at the start of the session without any further assist.

II. Methods

A. Electrophysiology

One adult male rhesus macaque (macaca mulatta) was used in this study. One microwire array of 128 teflon-coated tungsten electrodes (35 μm diameter, 500 μm wire spacing, 8×16 array configuration; Innovative Neurophysiology, Durham, NC) was chronically implanted in each brain hemisphere, targeting the arm areas of primary motor cortex (M1) and dorsal premotor cortex (PMd). All procedures were conducted in compliance with the National Institute of Health Guide for Care and Use of Laboratory Animals and were approved by the University of California, Berkeley Institutional Animal Care and Use Committee.

B. Behavioral Task

The subject was head-restrained in a primate chair and performed a self-paced 2-D center-out reaching task to 8 circular targets (1.7 cm radius) uniformly spaced about a 13 cm diameter circle. Initially, the subject was trained to perform the task using a Kinarm (BKIN Technologies) exoskeleton with the right arm. During subsequent BMI operation, the subject's arms were confined within the primate chair as he performed the task under neural control.

Reach targets were presented in a block structure of 8 targets with pseudo-randomized order within each block. Fig. 1 shows an illustration of the task setup. Trials were initiated by moving the cursor to the center target and holding for 400 ms. The subject had an unlimited amount of

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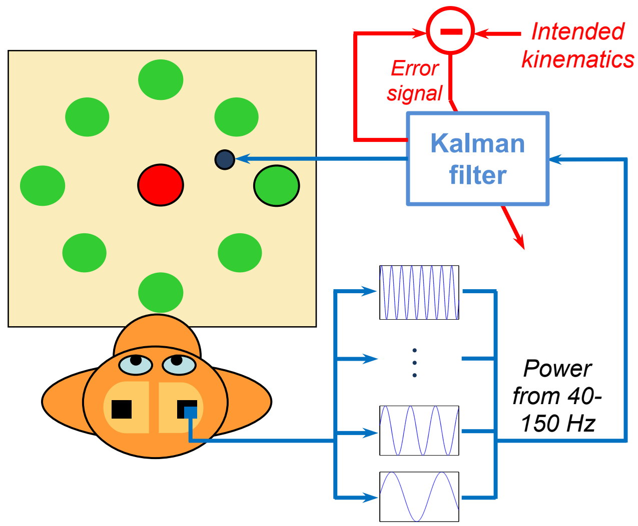

Fig. 1. BMI experiment setup. The log spectral power in consecutive 10 Hz bands from 40-150 Hz is estimated from each raw LFP channel. These neural features are translated into cursor control via a Kalman filter. The filter parameters are periodically updated using the SmoothBatch CLDA algorithm.

time to enter the center target to initiate a trial. Upon entering the center, the reach target appeared. After the center-hold period ended, the subject was cued to initiate the reach via target flash, after which he was required to move the cursor to the peripheral target and hold for 300 ms to receive a liquid reward. Failure to hold at the center or target, or reach the target within the time limit, restarted the trial without reward.

C. *Feature Extraction and Decoding Algorithm*

LFP signals were recorded and sampled at 1 kHz using a 128-channel MAP recording system (Plexon Inc., Dallas, TX). The multi-taper method [11] was used to extract estimates of the power in consecutive 10 Hz bands from 40–150 Hz in 20 randomly chosen channels from the right hemisphere. Spectral estimation was performed every 100 ms using a sliding window of 200 ms of raw LFP activity.

The logarithms of these spectral power estimates, across multiple frequency bands and LFP channels, were passed as neural features into a Kalman filter (KF) decoding algorithm in order to implement closed-loop BMI control. The KF assumes the following state transition and state evolution models:

$$x_t = Ax_{t-1} + w_t \quad (1)$$
$$y_t = Cx_t + q_t \quad (2)$$

where $w_t \sim N(0, W)$ and $q_t \sim N(0, Q)$ are Gaussian noise terms, and x_t and y_t are vectors representing the kinematic state of the cursor and the features being passed into the decoder (respectively) at time-step t. The transition matrix A models how the cursor kinematics evolve from one time-step to the next, while the observation matrix C relates cursor kinematics to neural features. The state vector x_t was defined to include the position and velocity of the cursor along both the horizontal and vertical directions of the screen. We refer the reader to [12] for the actual KF equations that estimate x_t from y_t at each time-step.

D. *Closed-loop Decoder Adaptation (CLDA)*

We initialized the decoder ("seed" decoder) using data collected as the subject performed natural reaches with his arm in the exoskeleton. We then used the SmoothBatch CLDA algorithm [5] to update the decoder while the subject performed BMI control. The SmoothBatch algorithm periodically computes new values of the KF observation model matrices (C and Q) using collected neural activity and an estimate of the subject's intended cursor kinematics. To estimate intended kinematics, we employed the method

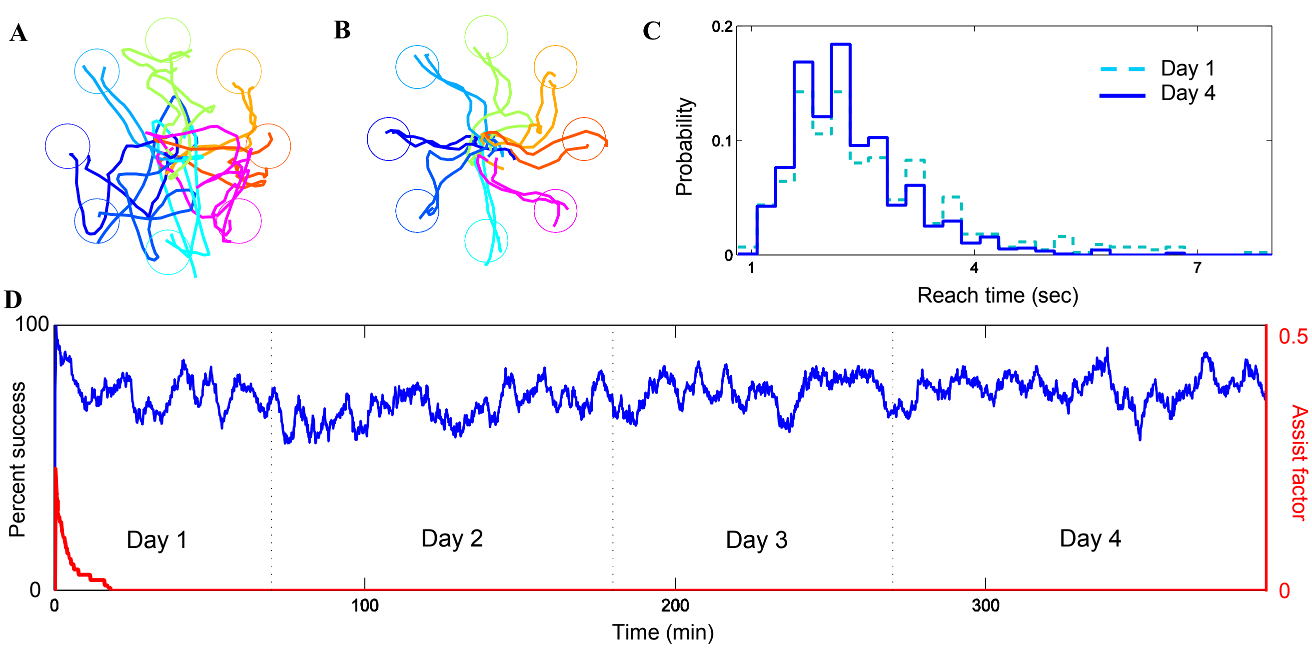

Fig. 2. Cursor trajectories to each target on day 1 (A) and day 4 (B). (C) Distribution of reach times for day 1 and day 4. (D) Percent of successful trials over time, for each day. Red line marks the assist factor.

developed by Gilja et al. [6], which assumes that the subject's intent is to always reach straight towards the current target at each time step.

In order to prevent abrupt changes in decoder parameters, SmoothBatch combines new parameter estimates with current parameter values using a weighted sum:

$$C^{(i+1)} = \beta C^{(i)} + (1-\beta)\hat{C} \quad (3)$$

where i denotes the i^{th} decoder update, $\hat{C}$ represents a new estimate of C from recent data, and $\beta \in (0,1)$ determines the speed of decoder adaptation (the update rule for Q is analogous). β was initially set such that the update "half-life" (the time after which the influence of a new estimate $\hat{C}$ is reduced to half) was approximately 2-3 min. The half-life was gradually increased to 15 min as the subject became more proficient and further decoder changes were unnecessary.

E. Training paradigm and decoder fitting

In conjunction with CLDA, we employed an assistive training paradigm previously used in [10]. After the initial decoder seeding, the subject underwent a secondary training phase during which the cursor control was partially directed towards the target. Specifically, the cursor trajectory was computed using:

$$\overrightarrow{v_{out}} = a \cdot \overrightarrow{v_{assist}} + (1-a) \cdot \overrightarrow{v_{user}} \quad (4)$$

where $a \in [0,1]$ is the time-varying "assist factor", $\overrightarrow{v_{out}}$ is the output trajectory shown on the screen, $\overrightarrow{v_{assist}}$ is a vector with a speed of 0.8 cm/sec that points to the current target, and $\overrightarrow{v_{user}}$ is the decoded output of the Kalman filter. We initially set $a = 0.25$, which was then manually reduced based on the subject's performance. At $a = 0$, the cursor was entirely controlled by the subject.

F. Performance evaluation

Overall BMI performance was assessed by calculating the subject's success percentage (the percentage of initiated trials that resulted in a reward) over time. In addition, the accuracy of cursor trajectories was evaluated using the following metrics:

1) Reach Time (RT): The time elapsed between leaving the center and entering the target.
2) Normalized Path Length (NPL): The distance traveled between leaving the center and entering the target, divided by the straight-line distance.
3) Movement Error (ME): The average deviation perpendicular to the reach direction [6].
4) Movement Variability (MV): The standard deviation of movement errors perpendicular to the reach direction [6].

III. Results

A. Behavioral performance

The subject performed the task under neural control for four consecutive days. Typical unassisted cursor trajectories during day 1 and day 4 are shown in Fig. 2A,B. Qualitatively, cursor trajectories appear to become straighter over time. The distribution of reach times for the first and last day are shown in Fig. 2C. The distribution on day 4 has a higher concentration of low reach times than on day 1, indicating more consistent and faster reaching trajectories.

The trial success percentage over time, based on a 5-min moving window, is shown in Fig. 2D. The average success rate across all days is 74% ± 7%. The high initial performance was a result of the assistive training procedure. Assistive training was only used during the first 20 minutes of day 1 (see red line in Fig. 2D). After assistive training, the subject maintained proficient control of cursor. On days 2–4, the subject was able to immediately operate the BMI without assist. Moreover, the subject maintained a high level of performance across days.

We used four additional methods (Section II-E) to quantify the quality of the cursor trajectories. Although the

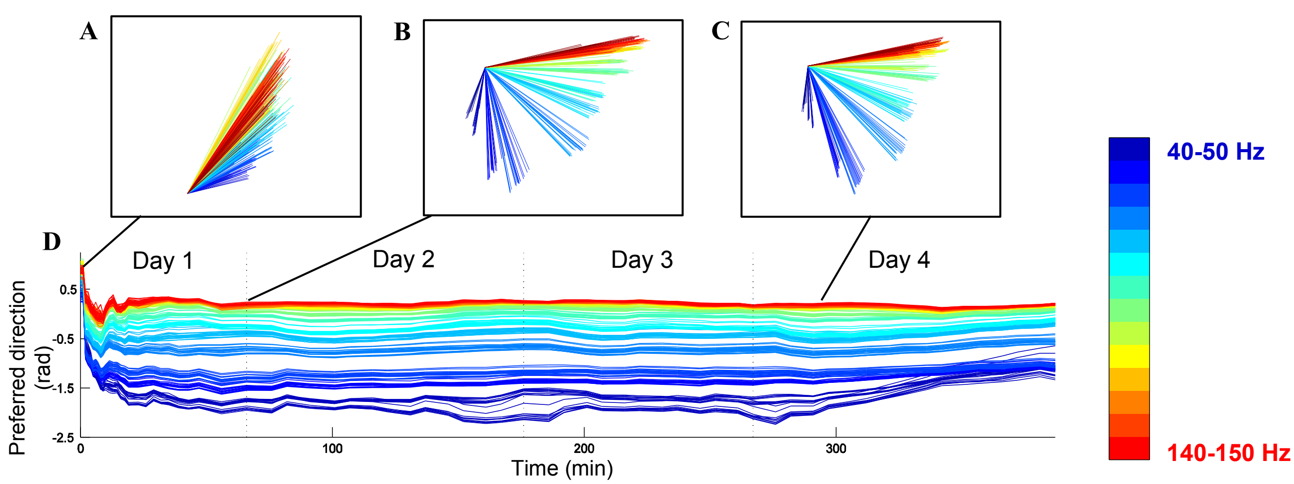

Fig. 3. (A-C) Velocity tuning for each channel/frequency pair initially (A), after day 1 (B), and on day 4 (C). Each line is colored based on frequency, with blue being lowest (40-50 Hz), and red representing the highest frequency band (140-150 Hz). The evolution of the preferred directions over time is shown in (D).

day-to-day changes were small, all four metrics steadily decreased over time (ME: -0.14 cm/day, r = -0.03, p = 0.07; MV: -0.25 cm/day, r = -0.08, p < 1e-3; NPL: -0.13 units/day, r = -0.11, p < 1e-9; RT: -96 ms/day, r = -0.10, p < 1e-6). Overall, these metrics show that the subject demonstrated improved ability to control the cursor over the course of the experiment.

B. Changes in decoder parameters

We examined the evolution of the velocity tuning of each channel/frequency feature, from the initial seed to the final decoder, by tracking the changes in the terms in C that correspond to velocity. The x and y velocity terms, plotted as a vector, at various points in time are shown in Fig. 3. Each vector represents the direction of cursor velocity that elicits an increase in power of the corresponding channel/frequency feature. The angle of the vector is referred to as the preferred direction (mathematically defined as $PD = tan^{-1}(C_y/C_x)$, where C_y and C_x are the velocity coefficients of that feature in the C matrix). The preferred directions for each channel/frequency feature as a function of time are shown in Fig. 3D. The tuning parameters changed drastically during the initial assistive training, but mostly converged to stable values as the subject obtained full control of the cursor.

IV. Discussion

In summary, we implemented a closed-loop decoder adaptation algorithm that rapidly enabled proficient control of a LFP-based BMI system. CLDA has been previously used in spike-based BMI to rapidly improve from low initial performance [3]–[5] and also to maintain long-term performance [7]. Gilja et al. used a decoder adaptation method (ReFIT-KF algorithm) to demonstrate accurate 2-D control in primates that approached the performance of natural arm control [6]. For field potential activity, Ashmore et al. recently applied CLDA on an electrocorticography (ECoG) based BMI in which accurate control was obtained after 4-5 days, and maintained over 28 days [10]. Here, we show that CLDA can also be applied to LFP activity to rapidly improve closed-loop BMI performance.

In this study, we continued the decoder adaptation throughout the entire experiment to track any changes to the LFP activity. Our results show that the decoder parameters converged rapidly in the first day and remained largely stable across days. This indicates that the decoder will likely continue to work without further adaptation or recalibration after the first day. This is important from a clinical perspective since this alleviates the need for the subject to perform a structured task each day in order to recalibrate the decoder.

Comparing the initial seed and final decoder parameters, we found significant differences between the two decoders, even though the initial seed was fitted from data collected while the subject performed the same center-out task (albeit with natural arm movements). This suggests that the subject's BMI control strategy may be fundamentally different than his strategy for natural arm control, especially since during BMI the subject's arm was constrained such that the same reaching motions were not possible. Given this observation, it may be possible that high performance can be achieved irrespective of the initial seed. In fact, Orsborn et al. used the SmoothBatch CLDA algorithm to successfully boost performance from a variety of "non-biomimetic" initial seeds [5]. This is another important aspect for clinical viability, as natural arm movement data may not be available for patients with severe disabilities. Therefore, in future work, we will test whether CLDA can be used to improve the closed-loop performance of LFP-based BMIs when starting from non-biomimetic decoder initializations.

References

[1] E. E. Fetz, "Operant Conditioning of Cortical Unit Activity," *Science*, vol. 163, no. 3870, pp. 955–958, Feb. 1969.

[2] M. Velliste, S. Perel, M. C. Spalding, A. S. Whitford, and A. B. Schwartz, "Cortical control of a prosthetic arm for self-feeding," *Nature*, vol. 453, no. 7198, pp. 1098–1101, May 2008.

[3] D. M. Taylor, S. I. H. Tillery, and A. B. Schwartz, "Direct Cortical Control of 3D Neuroprosthetic Devices | Science/AAAS," *Science*, vol. 296, no. 5574, pp. 1829–1832, Jun. 2002.

[4] G. J. Gage, K. A. Ludwig, K. J. Otto, E. L. Ionides, and D. R. Kipke, "Naive coadaptive cortical control," *J Neural Eng*, vol. 2, no. 2, pp. 52–63, Jun. 2005.

[5] A. L. Orsborn, S. Dangi, H. G. Moorman, and J. M. Carmena, "Closed-loop decoder adaptation on intermediate time-scales facilitates rapid BMI performance improvements independent of decoder initialization conditions," *IEEE Trans Neural Syst Rehabil Eng*, vol. 20, no. 4, pp. 468–477, Jul. 2012.

[6] V. Gilja, P. Nuyujukian, C. A. Chestek, J. P. Cunningham, B. M. Yu, J. M. Fan, M. M. Churchland, M. T. Kaufman, J. C. Kao, S. I. Ryu, and K. V. Shenoy, "A high-performance neural prosthesis enabled by control algorithm design," *Nat. Neurosci.*, vol. 15, no. 12, pp. 1752–1757, Nov. 2012.

[7] Z. Li, J. E. O'Doherty, M. A. Lebedev, and M. A. L. Nicolelis, "Adaptive decoding for brain-machine interfaces through Bayesian parameter updates," *Neural Comput*, vol. 23, no. 12, pp. 3162–3204, Dec. 2011.

[8] R. D. Flint, Z. A. Wright, and M. W. Slutzky, "Control of a biomimetic brain machine interface with local field potentials: Performance and stability of a static decoder over 200 days," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2012, pp. 6719 –6722.

[9] L. R. Hochberg, D. Bacher, B. Jarosiewicz, N. Y. Masse, J. D. Simeral, J. Vogel, S. Haddadin, J. Liu, S. S. Cash, P. van der Smagt, and J. P. Donoghue, "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372–375, May 2012.

[10] R. C. Ashmore, B. M. Endler, I. Smalianchuk, A. D. Degenhart, N. G. Hatsopoulos, E. C. Tyler-Kabara, A. P. Batista, and W. Wang, "Stable online control of an electrocorticographic brain-computer interface using a static decoder," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2012, pp. 1740 –1744.

[11] P. Mitra and H. Bokil, *Observed Brain Dynamics*, 1st ed. Oxford University Press, USA, 2007.

[12] W. Wu, Y. Gao, E. Bienenstock, J. P. Donoghue, and M. J. Black, "Bayesian population decoding of motor cortical activity using a Kalman filter," *Neural Comput*, vol. 18, no. 1, pp. 80–118, Jan. 2006.