

Control of a Biomimetic Brain Machine Interface with Local Field Potentials: Performance and Stability of a Static Decoder Over 200 Days*

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Abstract— Brain-machine interfaces (BMIs) have the potential to restore lost function to individuals with severe motor impairments. An important design specification for BMIs to be clinically useful is the ability to achieve high performance over a period of months to years without requiring frequent recalibration. Here, we report the first successful implementation of a biomimetic BMI based on local field potentials (LFPs). A BMI decoder was built from a single recording session of a random-pursuit reaching task for each of two monkeys, and used to control cursor position in real time (online) over a span of 210 days. Performance using this BMI was similar to prior reports using BMIs based on single-unit spikes for 2D cursor control. During this ongoing study, target acquisition rates remained constant (in 1 monkey) or improved slightly (1 monkey) over a 7 month span, and performance metrics of cursor movement (path length and time-to-target) also remained constant or showed mild improvement as the monkeys gained practice. Based on these results, we expect that a stable, high-performance BMI based on LFP signals could serve as a viable alternative to single-unit based BMIs.

I. INTRODUCTION

As brain-machine interface (BMI) applications have grown more sophisticated, questions have arisen as to the optimal signal source to control them. Recent biomimetic BMI designs (i.e., those based closely on the brain's normal physiology) have generally inferred movement from trains of single-unit action potentials, or spikes. This BMI design can decode endpoint kinematics [1], and control computer cursors [2, 3] or robots [4, 5]. Offline movement decoding has also been accomplished using local field potentials (LFPs) in place of spikes [6-9]. Advantages of LFPs over single-unit spikes include potentially greater longevity [10, 11], lower sampling rates, requiring less power and generating less heat in an implantable device, and eliminating the need for spike sorting. However, only one prior study has used intracortical LFPs in an online BMI, and that was as a binary gating signal [12].

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Most previous studies with online BMIs used decoders that were trained within a few days to a week. Evidence that offline movement decoding can still be performed after months to several years has been presented [13-15]; however, the same studies reported the complete loss of spike signals for a majority of channels. Meanwhile, the effects of signal degradation on actual online BMI control (in the absence of decoder retraining) remain unknown.

In this study, we describe the first reported use of a biomimetic BMI decoder based purely on LFPs to control a computer cursor online. This decoder was built from a single recording session and remained virtually unmodified through the course of 210 days of testing.

II. METHODS

A. Behavior

All experiments were approved by the Institutional Animal Care and Use Committee of Northwestern University. Two rhesus macaques (C and M) were trained to perform a random-target pursuit task while grasping a two-link manipulandum. The position of the manipulandum controlled a cursor on a monitor placed at arm's length from the monkey. Successful trials consisted of acquiring a series of 6 randomly positioned targets, and holding within each for 0.1 s to obtain a liquid reward. The workspace of possible target locations measured 20 cm X 20 cm, and the task covered all of this space. Targets were 2 cm X 2 cm squares. Cursor diameter was 1 cm. The task was self-initiated and self-paced.

B. Recording and online LFP control

In each monkey, following behavioral training, we surgically implanted a silicon 96-electrode array (Blackrock Microsystems) into the arm region of primary motor cortex contralateral to the arm used in the behavior. All electrodes were 1.5 mm long. Details of the surgical procedure have been described elsewhere [16].

All recordings were performed using a 96-channel MAP system (Plexon, Inc, Dallas TX). LFP signals were band-pass filtered from 0.5 Hz to 500 Hz, then sampled at 1000 Hz. Position of the manipulandum was also sampled at 1000 Hz. A velocity decoder for each monkey was built from a single 10-minute hand-control file. Monkeys were able to achieve approximately 100 rewards in this amount of time (i.e., 600 targets acquired). We extracted 6 features from each field potential signal: the local motor potential (LMP; a sliding average in the time domain of 256 ms length), and the

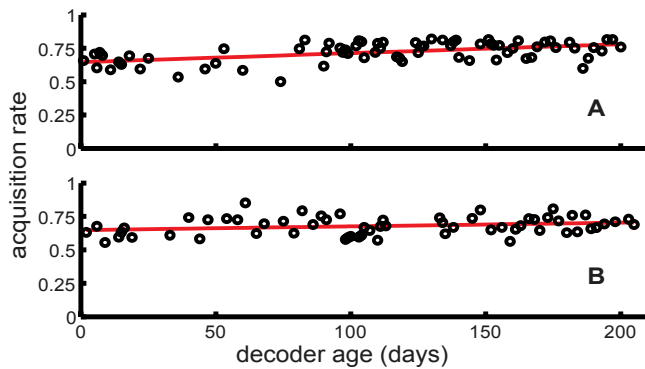


Figure 1. Target acquisition performance vs. decoder age. Black circles, performance for 1 recording session; red line, best linear fit. A, monkey C. Pearson’s correlation coefficient $r=0.51$ ($p<10^{-5}$). The slope of the best-fit line was 0.001. B, monkey M. Pearson’s correlation coefficient $r=0.25$ ($p=0.05$). The slope of the best-fit line was 0.0.

power in 5 frequency bands (0-4, 7-20, 70-115, 130-200, and 200-300 Hz). For each band, we computed the log of the power in each bin relative to the log of the mean power in the band over the entire file, to provide a sample every 50 ms. We chose a subset of features for decoding based on the absolute value of the correlation coefficient ($|r|$) between each feature and the endpoint velocity. We ranked features in descending order of the mean of $|r|$ over both output dimensions, and used the top 150 features for decoding. The decoder itself was constructed using a Wiener cascade model [17]. A set of causal linear filters (10 lags) was fit between the LFP features and the x- and y-velocity of the manipulandum. The outputs of the Wiener filter were then convolved with a static nonlinearity [18] implemented by fitting a third order polynomial between the filter outputs and the velocities.

The online LFP BMI (“brain control”) was implemented using custom software to calculate the LMP and frequency-based features online, apply the Wiener cascade decoder,

and obtain predicted cursor velocity, which was integrated to provide cursor position. Targets for the online version of the random-pursuit task were 4 cm on a side (target surface area was 4% of the workspace).

In some sessions, we observed a large amount of noise on particular channels during visual inspection of the signals prior to the start of brain control. When this occurred, features corresponding to these noisy channels were removed from the decoder by setting their weights to zero. We did not retrain the decoder, or include additional channels to compensate for this loss of information.

C. Evaluating BMI performance

We used three measures to assess the quality of cursor control: (1) target acquisition rate (rewarded/total trials), (2) normalized cursor path length, and (3) normalized cursor time-to-target. Normalized path length, a measure of path straightness, is the length of the cursor path between consecutive targets, divided by the straight-line Euclidean distance between the targets. Normalized time-to-target is the elapsed time from target presentation to target acquisition, divided by the distance travelled in that trial. See [3].

III. RESULTS

Both monkeys performed LFP brain control two or three days per week. On the other 2-3 days per week, they participated in a different study with a spike-based BMI (results not shown). To date, we have recorded 72 and 61 LFP control days for monkeys C and M, respectively, over the course of 210 days.

A. Target acquisition performance was stable, or slightly improved, over time

Fig. 1 shows the rate of target acquisition for monkeys C

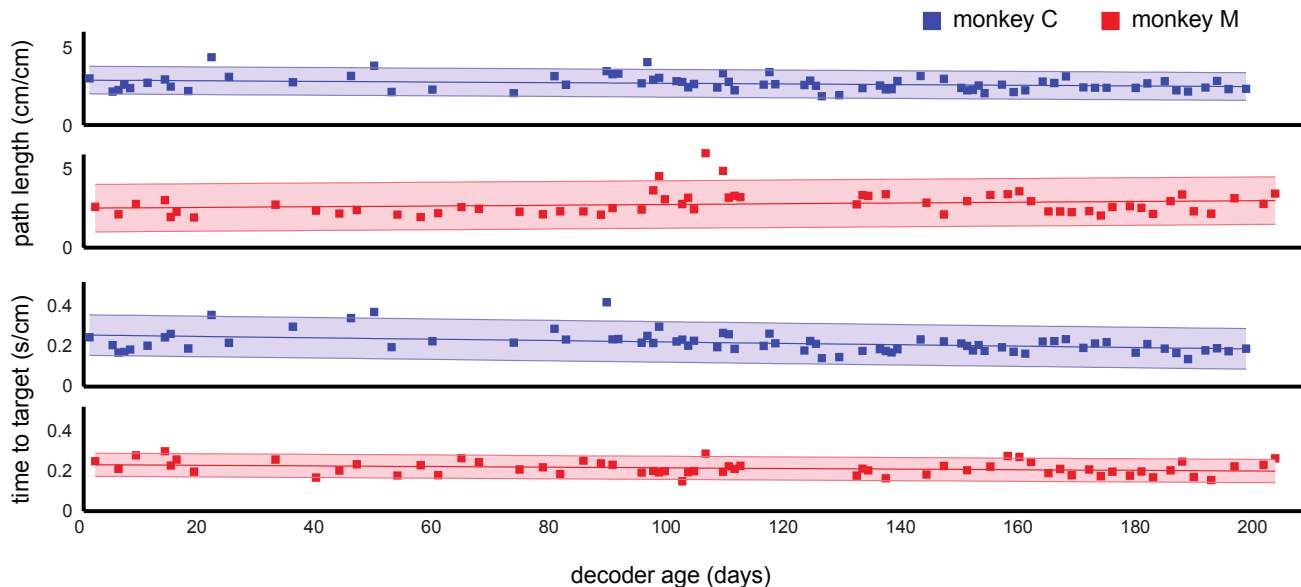


Figure 2. Performance metrics across days. Blue: monkey C, red: monkey M. Each point is the median across trials for the metric for one day. The solid colored lines represent the best-fit line through the median values, shaded areas demarcate a 95% confidence interval around the line.

(Fig. 1A) and M (Fig. 1B). Across days, the mean rate of successful target acquisition was $72 \pm 8\%$ for monkey C (126 ± 25 total trials/day), and $68 \pm 7\%$ for monkey M (122 ± 30 trials/day). For monkey C, there was a small but statistically significant positive correlation between acquisition rate and the number of days since the decoder was built (decoder age, Fig. 1A), indicating that, for this monkey, performance improved with practice. For monkey M (Fig. 1B), the acquisition rate was not significantly correlated with decoder age.

B. BMI performance metrics showed improved control over time

For each day, the median over successful trials was calculated for path length and time-to-target (Fig. 2). The medians of path lengths taken over all days were 2.63 and 2.78 for monkeys C and M, respectively. The overall median of time-to-target values was 0.22 s/cm for each monkey. For monkey C, both metrics exhibited a weak but significant negative correlation with decoder age (path length: $r=-0.25$, $p=0.03$, time-to-target: $r=-0.38$ s/cm, $p=0.0008$, Pearson's correlation, see Fig. 2), indicating that cursor paths tended to straighten and reach the targets more quickly. Monkey M showed no significant correlation between path length and decoder age, and a weak negative correlation between time-to-target and decoder age (path length: $r=0.19$, $p=0.14$; time-to-target: $r=-0.27$, $p=0.04$, Pearson's correlation, see Fig. 2). As with target acquisition rate, these metrics demonstrated either no change, or improvement over time.

Removal of features corresponding to noisy channels occurred in only 21 out of 133 sessions between both monkeys. Nearly all (18/21) of these sessions took place during months 2-4 of recording. In the 3 most recent months, only one such adjustment has been made for monkey M, and none have been necessary for monkey C.

C. Monkeys C and M differed in distribution of movement information

An examination of the decoders used for brain control shows that despite similar performance, monkey M and monkey C represented movement information differently within the LFP signals. Of the 150 features chosen (see Methods), 47% and 21% were from the LMP for monkeys M and C, respectively. The delta (0-4 Hz) band supplied 33% and 22% of features, respectively. The gamma bands supplied a significant proportion of features, with 0% and 14% from the 70-115 Hz band (for M and C), 11% and 17% from the 130-200 Hz band, and 9% and 23% from the 200-300 Hz band. The least informative band was the 7-20 Hz band, which supplied 0 and 3% of chosen features for monkeys M and C, respectively. Thus, information about movement was more broadly distributed in monkey C than in monkey M, whose feature set was dominated by the LMP.

IV. DISCUSSION

These results represent clear evidence that online, biomimetic BMI control using LFP signals is feasible and accurate. LFP-based control performance was comparable to

that of spike-based BMI control in the random target-pursuit task (for example, in [3], time-to-target was 0.33 s/cm and path length was 3.67, averaged over both monkeys). This is, to our knowledge, the first time such control has been demonstrated with LFPs. It is likewise the first demonstration of long term (7 month) stability in online BMI control achieved without recalibration of a decoder built on day 1 of the study.

All measures of BMI performance remained stable, or improved slightly over at least 7 months using the same decoder. Previously, Chao et al. [19] found no decline in their ability to decode movement kinematics offline over the course of 250 days using subdurally-recorded signals. The present work extends these earlier results to intracortically recorded LFPs and, importantly, confirms them in actual online BMI control. The ability to operate a BMI without frequent decoder recalibrations would increase the user-friendliness of a neuroprosthesis, which would benefit patients directly by reducing the need for caregiver assistance.

Ganguly et al. [2] demonstrated highly stable spike-based online decoding of movement over the course of 19 days, but their method of isolating stable single units was even more labor-intensive than spike sorting and would not likely be practical for a clinical application. Their decoders were also recalibrated each day.

LFPs are attractive as BMI signal sources for several reasons, including the stability described above. While we did remove channels in some sessions due to obvious noise contamination, this could easily be automated and would not require input from a BMI user. As mentioned above, LFPs would likely incur lower computational and power costs. Moreover, we have observed previously that LFPs can be used to decode movement in the absence of spikes [11], suggesting that LFPs may provide sufficient longevity to operate BMIs for clinically-useful durations, i.e., decades.

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