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Long-Term, Stable Behavior of Local Field Potentials During Brain Machine Interface Use

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Abstract— **Local field potentials (LFPs) have the potential to provide robust, long-lasting control signals for brain-machine interfaces (BMIs). Moreover, they have been hypothesized to be a stable signal source. Here we assess the long-term stability of LFPs and multi-unit spikes (MSPs) in two monkeys using both LFP-based and MSP-based, biomimetic BMIs to control a computer cursor. The monkeys demonstrated highly accurate performance using both the LFP- and MSP-based BMIs. This performance remained high for 11 and 6 months, respectively, without adapting or retraining. We evaluated the stability of the LFP features and MSPs themselves by building, in each session, linear decoders of the BMI-controlled cursor velocity using single features or single MSPs. We then used these single-feature decoders to decode BMI-controlled cursor velocity in the last session. Many of the LFP features and MSPs showed stably-high correlations with the cursor velocity over the entire study period. This implies that the monkeys were able to maintain a stable mapping between either motor cortical field potentials or multi-spike potentials and BMI-controlled outputs.**

I. Introduction

Brain machine interfaces (BMIs) offer the potential to help people paralyzed from spinal cord injury, ALS, or stroke regain function. A few preclinical studies of invasive BMIs in tetraplegic patients use action potentials (spikes) from individual neurons as inputs. Yet it remains uncertain whether current technologies will be able to record from spikes from many neurons for the decades that a successful implant will require. Local field potentials (LFPs) are thought to represent summed potentials from thousands of neurons. Therefore, it has been hypothesized that they could provide robust, long-lasting control signals for neural prosthetic devices. Indeed, LFPs contain nearly as much information about movement as do spikes [1,4, 5, 11, 14] and retain this information when spikes are absent on the same electrodes [4]. Multi-unit spikes (MSPs), here defined as unsorted threshold crossings [6], are also thought to represent signals from multiple neurons. As such, they may also provide better longevity than single units.

Another consideration in BMI design is the frequency with which BMI decoders require recalibration. Less frequent recalibration would allow more time for the user's brain to learn the mapping between neural activity and BMI output. In this study we assess the long-term stability of LFPs and MSPs during control of a computer cursor using a static decoder of LFPs over 11 months. We also investigated the performance of BMIs using a static decoder of MSPs over 6 months. Both decoders were biomimetic, i.e., trained on the normal physiological function of the cortical signals.

We provide evidence here, for the first time, that the relationship between individual LFPs and BMI output remains remarkably stable over 11 months. We also show that individual MSPs remain surprisingly stable for almost 6 months. Previously it had been shown that spikes remain stable during natural movement and spike-based BMI control over a period of a day and 19 days respectively [3,7]. From a BMI perspective this is significant because it implies that decoder re-training may be necessary only infrequently when using either LFP-based or MSP-based BMIs. This property of the signals should allow BMI users to improve and stabilize control of BMI outputs more quickly and easily. Further, this neural stability supports the concept that the brain learns BMIs similar to a natural motor skill.

II. Methods

A. Behavior and recording

All procedures were approved by the Northwestern University Institutional Animal Care and Use Committee. All neural and behavioral data were recorded using a 96-channel Multiple Acquisition Processor (Plexon, Inc, Dallas, Tx). Monkeys used a 2D robotic manipulandum to move a computer cursor to random target locations. We simultaneously recorded intra-cortical LFPs and spikes from the primary motor cortices of 2 rhesus macaques contra-lateral to the moving arm using surgically-implanted, 96-channel silicon electrode arrays (Blackrock Microsystems). We calculated the end-point position of the hand from the manipulandum's joint angles (sampled at 1 kHz) and down-sampled to 20 Hz for analysis. LFP signals were band-pass filtered from 0.7 Hz to 300 Hz (or 0.7 Hz to 170 Hz on 32 of the channels) and sampled at 1 kHz.

B. Decoder Training

We used ten minutes of reaching activity to build the static online control decoder for each monkey. For each LFP channel, we calculated the local motor potential (LMP) [11, 13] using a 256-ms moving average of the LFP signal, overlapping by 206 ms, to provide a sample every 50 ms. In addition to the LMP, we computed the spectral power of

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each LFP channel by applying a 256-ms Hanning window (overlapped by 206 ms) and squaring the amplitude of the windowed signal's discrete Fourier transform. We averaged spectral power within the following frequency bands: 0-4 Hz, 7-20 Hz, 70-115 Hz, 130-200 Hz, and 200-300 Hz and used the logarithm of this power for features. To reduce the likelihood of over-fitting, we reduced the dimensionality of the input space as in prior studies. We computed the absolute value of the correlation coefficient (|R|) between each feature and the velocity in each dimension, and selected the 150 features with highest mean |R| as inputs to a Wiener cascade decoder [17]. The Wiener cascade included 10 lags, for a total filter length of 0.5 s. Multi-unit spikes were high-pass filtered at 300 Hz and sampled at 40 kHz. The threshold on each channel was set by visual inspection at the beginning of the first MSP session and kept constant for the duration of this study. The mean thresholds over all channels were 3.8 and 4.9 standard deviations above baseline for monkeys C and M, respectively. We used MSP firing rates in 50-ms bins as the inputs to a Wiener cascade filter (including 10 causal lags).

C. Brain control using LFPs and MSPs

Monkeys performed online control (brain control) in the random target pursuit task by moving the cursor to a randomly-located, 4x4-cm square target within 10 s of target appearance, and holding for 0.1 s to obtain a liquid reward. Success rate was defined as the number of successful trials divided by the total number of trials.

Brain control using either LFPs or MSPs was done approximately 2-3 times per week for 30-50 minutes each day, alternating between LFP and MSP brain control within and across days. MSP control sessions started approximately 5 months after monkeys had started LFP control. Monkeys' arms were not restrained during brain control. They did make small movements, however, these were not consistent from session to session for the same cursor movement.

D. Analysis of LFP and MSP Feature Stability.

To assess the stability of the signals themselves, we built Wiener decoders of cursor velocity for each of the 150 features and ~85 units included in the fixed decoders used for LFP and MSP brain control, similar to Carmena et al. [2] and Chestek et al. [3]. These sets of single feature decoders were built for each experimental session of LFP and MSP brain control. The decoders were then tested on 10 minutes of brain control data from the very last LFP and MSP BMI sessions. We defined the performance of the single feature decoders as the correlation coefficient (R) between predicted and actual brain controlled velocity. We used the single-feature R values as a method to assess the stability of the relationship between each feature and the brain-controlled output. Essentially, the single-feature R values measured the contribution of each feature to decoder performance during brain control over time. Because the decoder mapping was overdetermined and nonlinear, there was no a priori reason to assume that an individual feature would consistently maintain its relationship with the output.

III. RESULTS

Over the study period, modulation of both LFP features and MSPs maintained a largely stable relationship with BMI outputs. This is first evident from the stability of brain control performance, assessed through metrics that include path length, time to target and success rate. Averaged across monkeys and time, path length was 2.9 times that of a perfectly straight reach, and time to target was approximately 0.2 s/cm, comparable to levels reported in the literature for spike-based brain control [9, 14]. Success rate during online LFP and MSP brain control remained stable for11 and 6 months, respectively (Fig.1).

LFP and MSP signal stability became further evident when assessed through offline single feature decoding performance (Fig. 2). Many features had high R values that were stable or increased throughout the study. This was especially true in the LMP features, and also in a few of the high gamma and delta features. Most features that were not highly correlated at the beginning stayed that way. The

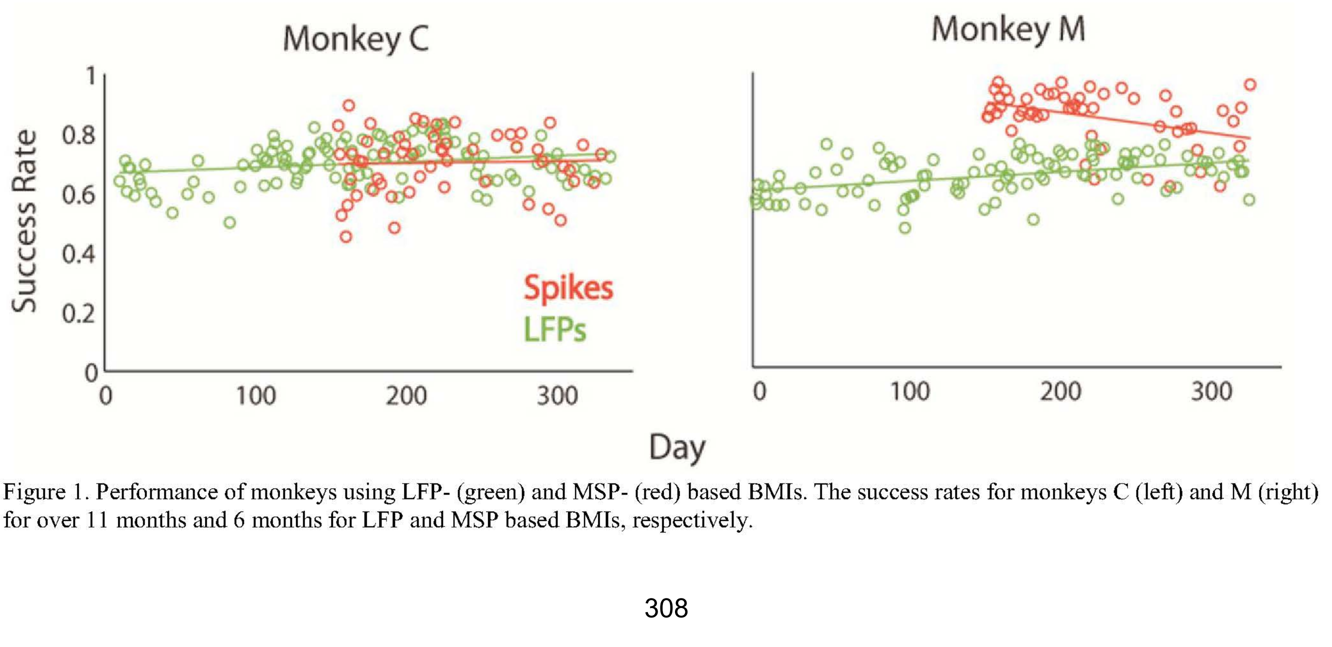

Figure 1. Performance of monkeys using LFP- (green) and MSP- (red) based BMIs. The success rates for monkeys C (left) and M (right) for over 11 months and 6 months for LFP and MSP based BMIs, respectively.

single feature decoders however, were particularly sensitive to perturbations in the recording setup. Fig. 2 notes each time a disruption occurred to the recording setup (e.g., a channel becoming intermittently noisy due to wear in a cable or connector). These perturbations affected the BMI output in such a way as to completely change the relationship between individual LFP features and BMI output (blue vertical bands). After accounting for these disruptions, the LFP-output relationship would return to its original state. Thus, single feature decoding performance ultimately remained stable for this period for both MSPs and LFPs.

IV. DISCUSSION

BMI performances using LFPs and MSPs were largely stable for 11 and 6 months, respectively. Moreover, many of the LFP and MSP signals themselves remained stable during this period of BMI use. This is far greater signal stability than has been demonstrated to date [3, 7, 15]. This signal stability persisted despite the facts that 1) the monkey learned to use other decoders in the interim and 2) we had to remove some channels from the decoder due to recording noise. This was especially true of the local motor potential, a few of the high-gamma bands, and a number of the MSPs. The stability of the MSPs, in particular, was surprisingly high.

These results may have implications in the design of BMI decoders. Since neural signals remain stable in relation to output on the order of months to years, it would only be

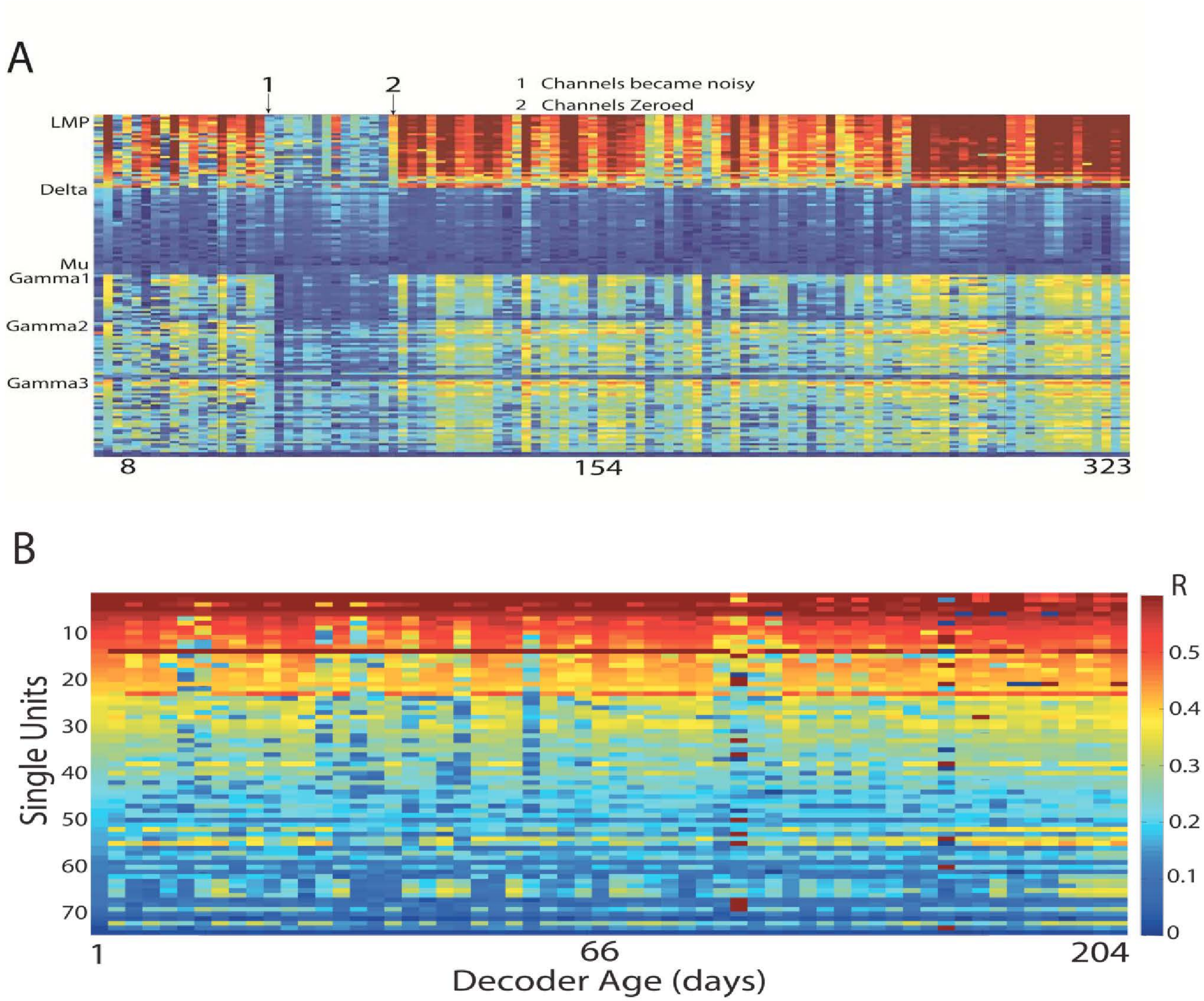

Figure 2. Performance of single feature (A) LFP decoders and (B) MSP decoders for Monkey C. Color denotes the correlation coefficient (R) between the output of the single feature decoder and the actual brain-controlled velocity in the last session. Numbered arrows in (A) note times of changes in single feature performance due to hardware malfunction (i.e., channels becoming noisy (1) due to worn cables or connectors) over the study period. Those channels were subsequently removed from the BMI decoder (2) by zeroing out the corresponding weights in the Wiener decoder of the BMI.

necessary to retrain BMI decoders every few months or so. Thus, there may not be a need to continuously adapt decoders algorithms; rather, it may be advantageous to adapt in early learning phases, then let the brain adapt to the decoder in later phases. Indeed, we saw gradual improvement (over weeks to months) of BMI performance in one of our monkeys.

This study demonstrates that both LFPs and MSPs can provide stable and high-performance control signals for BMIs. Thus, both multi-unit spikes and LFPs hold promise as BMI inputs. It remains to be seen whether MSPs and/or LFPs will deliver on their potential for greater longevity than single-unit spikes.

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