Influence of Movement Speed on Plan Activity in Monkey Pre-motor Cortex and Implications for High-Performance Neural Prosthetic System Design

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Abstract—**The success of human motor prosthetics will largely depend on increasing system performance by maximizing the movement-related information that can be recorded from cortical neurons. This will in turn depend on successfully combining information from different neurons, and across times for the same neuron. Here we investigate neural activity that occurs prior to reaching movements, and attempt to understand how this activity varies with the speed of the upcoming movement. We recorded pre-motor cortex neural activity from a rhesus monkey trained to perform delayed-reaches to targets at two different speeds. We found that movement speed information is present in action potential emission rates and 20-40 Hz local field potential power during a "plan" period preceding movement. We then further analyzed the action potential data to determine the accuracy at which trial conditions, including the speed of the upcoming movement, can be estimated from neural data. System performance is expected to increase when plan-period speed information is included in prosthetic estimation algorithms.**

Keywords—**Brain-machine interface, neural coding and decoding, motor control, reaching arm movements.**

I. INTRODUCTION

In recent years there has been a growing prospect of helping disabled patients by translating neural activity from the brain into control signals for prosthetic devices. It is now possible for monkeys to move computer icons solely by activating neural populations that participate in natural arm movements [1-3]. "Locked-in" patients have also demonstrated the ability to move icons with cortical neural activity [4].

While these proof-of-concept systems can perform simple icon tasks when driven by activity from tens to hundreds of neurons, there is intense interest in improving system performance so that naturalistic arm movements are possible. System performance can be increased by recording from more neurons or by extracting more information from each neuron.

We recently proposed an estimation algorithm that combines *plan* activity, which is neural activity present before or even without natural arm movements, with *peri-movement* activity, which is neural activity present during natural arm movements [5-7]. Combining neural activity from these two temporal epochs increases the total movement-related information available per neuron. This algorithm can also improve system performance by allowing plan activity and peri-movement activity from different brain areas to be combined, thereby increasing the total number of recordable neurons (Fig. 1).

If plan activity is to be used to drive neural prosthetics, whether acting alone or in conjunction with peri-movement activity, then it is critical to understand the relationship between plan activity and the impending movement. Plan activity in the motor cortices is known to vary with the direction and distance of an upcoming reach [8], suggesting that the intended endpoint can be estimated from plan activity, and used to constrain the estimate of movement trajectory based on peri-movement activity. This goal is complicated by the likelihood that plan activity may not depend on direction and distance alone. Plan activity can be influenced by arm orientation [9, but also see 10] and path [11]. This raises the idea that plan activity could be used to estimate more than just reach endpoint, and also reveals the possibility that reach endpoint might be mis-estimated if the influence of other factors is not taken into account. With the goal of better understanding the relationship between plan activity and movement, we asked whether plan activity in dorsal pre-motor cortex (PMd) is "tuned" only for direction and distance, or whether it also depends upon movement speed.
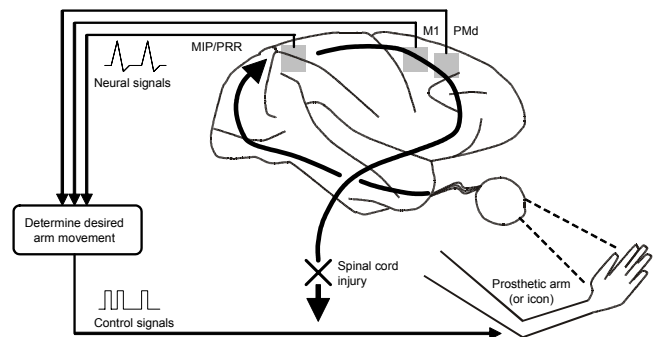

Fig. 1. Neural prosthetic arm/icon system. Target information from the eye is transformed into plans (medial intra-patietal area [MIP], parietal reach region [PRR], and PMd) and commands (motor cortex [M1] and PMd) to move the arm. If these commands cannot reach the musculature (e.g., spinal cord injury), electrical neural activity can be recorded with electrode arrays (gray squares) and processed with signal-processing algorithms to determine the desired arm movement. Control signals then guide a prosthetic arm, or computer icon, toward the desired target.

II. METHODOLOGY

Animal protocols were approved by the Stanford University Institutional Animal Care and Use Committee. We trained a rhesus monkey (*Macaca Mulatta*) to perform delayed center-out reaches to visual targets presented on a fronto-parallel screen [12]. We then trained him to reach to the same target locations but at two different speeds, depending on the color of the target (see Fig. 2). Green targets elicited "slow" reaches and red targets elicited "fast" reaches. Reaches exhibited the roughly bell-shaped velocity profiles characteristic of natural reaches. Slow reaches had peak speeds of ~40-100 cm/s and fast reaches had peak speeds of ~70-150 cm/s, depending on the reach distance (3-12 cm). For a given distance, peak reach speeds for the two distances formed largely separate distributions that overlapped slightly (see Fig. 3). Reach durations were ~100-250 ms depending on distance and speed.

We recorded 3D arm position (60 samples/s, ~0.1 mm resolution), eye position (240 samples/s, ~0.5° resolution), and single-neuron action potentials (spikes) with high-impedance microelectrodes while monkeys performed behavioral tasks under computer control. We termed the direction eliciting the largest spike-emission rate in a preliminary experiment (Fig. 2) the "preferred" direction, and the direction opposite the "null" direction. We then ran the experiment along this preferred-null axis (6-33 reaches
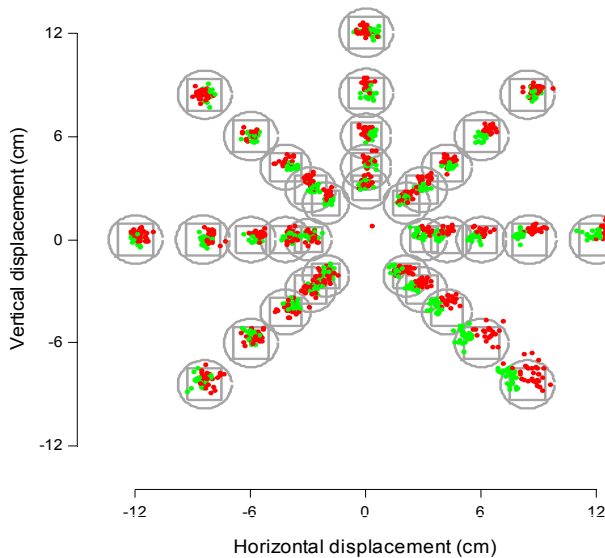

Fig. 2. All endpoint data from one preliminary experiment with end points colored according to reach speed (red-fast, green-slow). A monkey was trained to touch a central target (0 cm, 0 cm for 400-500 ms), colored according to the speed of the requested reach, and hold this central target for 500-900 ms (plan interval) while an identically colored target jittered locally around an endpoint location (gray squares). Then, when the target stopped jittering, the monkey reached at the requested speed to touch and hold the target (within gray circle) to receive a liquid reward. Each dot indicates the endpoint location of one reach trial. One of the 35 possible target locations was pseudo-randomly selected on each trail. The monkey typically fixated the target beginning shortly after its appearance until the reach was completed.
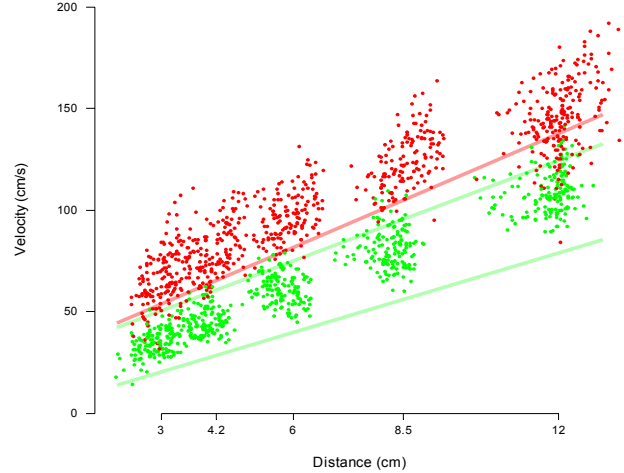

Fig. 3. All peak speed data from one preliminary experiment. Peak speed was computed on-line and must fall within the indicated speed boundaries to successfully complete the trial. Green lines bound the acceptable range for slow reaches; the red line delineates the slower bound for fast reaches. Each red/green dot indicates the peak speed of a fast/slow trial, respectively. All peak speed data (successes and failures) from one main experiment are shown.

to each of 2 directions × 5 distances × 2 speeds = 20 conditions). We computed spike rates by dividing the number of spikes in the plan interval by the time of the plan interval and statistical tests were performed on the spike rates associated with each behavioral condition. We neglected the first 200 ms after stimulus onset to avoid visual-target onset transients.

Prior research has reported that local field potentials (LFPs) in M1 and PMd also exhibit plan activity, revealed as an increase in 20-45 Hz frequency band power after an instructive cue but prior to a go cue [13]. This activity was previously found to be largely independent of the specifics of the upcoming movement, such as distance and direction [13]. We recorded LFPs (2-100 Hz) simultaneously with the single-neuron data described above and estimated the power-spectral density using the Thomson multi-taper spectral analysis method [14-15]. Statistical tests were performed on 20-40 Hz power using 200 ms sliding windows, in each of which the process was assumed stationary.

We performed simulations to assess how well movement speed and direction can be estimated from plan-period spike rates, using one trial of data per neuron. Modeling the distribution of spike rates for each condition as Gaussian, we employed maximum likelihood methods (similar to [7]) to determine the highest probability movement speed and direction for a given spike rate. We obtained performance curves using leave-one-out cross-validation. Since neurons were recorded one at a time inter-neuron correlations were not considered. Simulated trials were assembled and decoded many hundreds of times to assure that performance estimates had converged. Poisson modeling of spike counts was also tested but did not perform as well as Gaussian modeling of spike rates.

A. Action Potentials

We recorded 29 neurons from pre-motor cortex (putatively caudal PMd) and from near the M1/PMd border. Fig. 4 shows the average spike rate of one PMd neuron for reaches to one target location. The spike rate is significantly higher during the plan period (time between arrows) before slow reaches than before fast reaches. This illustrates our first main result: the speed of the upcoming movement systematically alters the plan-period spike rate. Fig. 5 plots the response from another neuron across all conditions. For this neuron the plan period spike rate was always greater before fast reaches than before slow reaches. The effect of movement speed on plan spike rate varied by neuron, and it was not uncommon for the "preferred" speed to vary with direction or distance.

A 3-way ANOVA ($P < 0.01$) revealed that the plan activity of 79% of neurons showed either a main effect of direction or an interaction involving direction, 66% showed either a main effect of distance or an interaction involving distance and 83% showed either a main effect of speed or an interaction involving speed. Thus, for the majority of neurons, the speed of the upcoming movement influenced spike-rate plan activity. The impact of speed on spike rate was typically as great as that of distance or direction.

B. Local Field Potentials

We examined the influence of movement speed on LFP plan activity recorded from 22 cortical sites. Fig. 6 shows the average LFP response from one PMd site before reaches executed at two different speeds. For this plot, data are collapsed across all distances and both directions. For much of the plan period, the 20-40 Hz power is significantly higher before slow reaches than before fast reaches. This illustrates our second main result: the speed of the upcoming movement systematically alters the 20-40 Hz LFP power
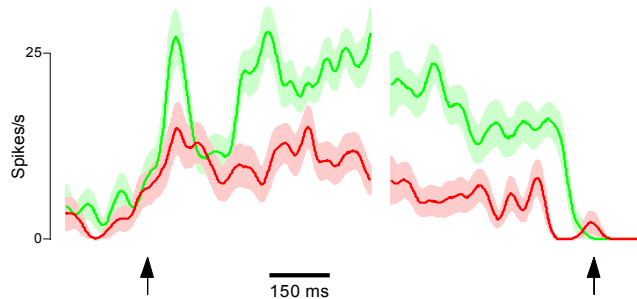

Fig. 4. Action potential response time-course for one PMd neuron to repeated reaches to the same location at two movement speeds. Red and green traces indicate spike rate response (mean ± SEM) for 20 fast and slow reaches, 3.0 cm in the up and left direction. Arrows mark the onset time of the visual reach target (left) and the onset time of the reaching arm movement (right). The gap in the traces is due to the variable-length plan period. To align all trials to target onset as well as to movement onset some data is included in traces on both sides of the gap. Data were smoothed with a 15 ms standard deviation Gaussian. (Neuron B16)
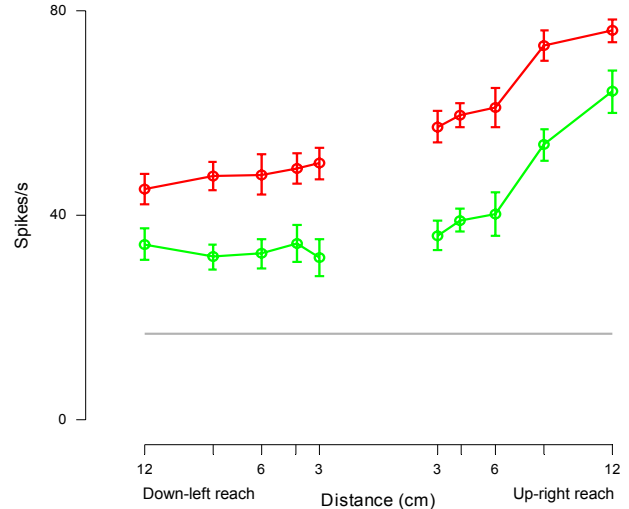

Fig. 5. Action potential response tuning curves for one PMd neuron. Red and green traces indicate spike rate (mean ± SEM) for repeated fast and slow reaches to five distances in two directions (22 repetitions). The gray line marks the baseline activity level. (Neuron B29)

during the plan period. Interestingly, other sites show the opposite pattern, with greater responses before fast reaches.

An ANOVA ($P < 0.05$) based on the 20-40 Hz LFP power during the plan period (200-400 ms after target onset) revealed that 4/22 sites showed a main effect of direction, 3/22 sites showed a main effect of distance, and 10/22 sites showed a main effect of speed. A non-parametric Friedman test of the data resulted in a nearly identical set of sites showing significant effects for speed. We also tested a later part of the plan period (300-500 ms) to better insure the avoidance of visual-target onset transients (e.g., the large hump of activity following the target presentation in Fig. 6) and found an even larger number of sites (16/22) with a significant main effect for speed. The ANOVA also revealed that a small number of sites exhibit an interaction effect between either two or all of the factors. Interestingly, while there was no consistent preference across sites for one speed over the other, all sites did show a distinct time evolution in power, with the preference sometimes switching later in the plan period. In summary, the speed of the upcoming movement influences the LFP plan activity at a large proportion of sites.

C. Estimating Movement Speed and Direction

Given the influence of movement speed and direction on plan activity discussed above, it is not surprising that these parameters can be estimated from neural activity. The primary question is how many neurons must contribute plan activity to attain a certain level of performance. To address this question we asked how well we could predict the direction (12.0 cm reaches in the preferred or null direction) and speed (fast or slow) of reaches given just the spike rate during the plan period. Computational simulations showed that it is possible to correctly classify 93% of the simulated reaches with activity from 18 neurons. Chance performance
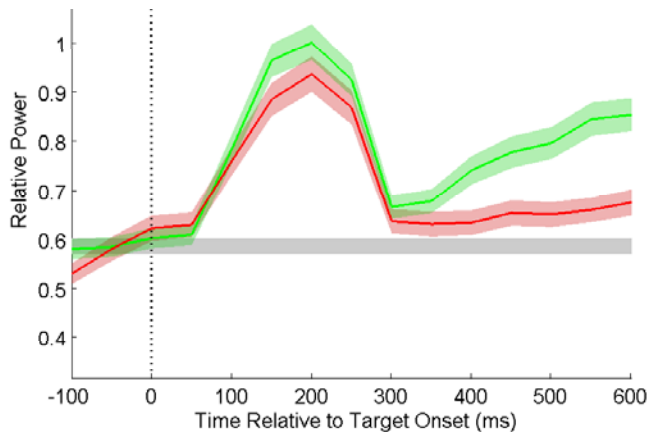
Fig. 6. LFP response time-course of one PMd site. Red and green traces (mean ± SEM) indicate the 20-40 Hz power for repeated fast (321 repetitions) and slow (325 repetitions) reaches, respectively. Data from reaches in both directions and to all five distances are grouped together according to instructed reach speed. The visual target appears at 0 ms and the movement cue appears after 500 ms. Spectrograms are computed with a 200 ms sliding window with the right edge corresponding to time on the abscissa. (LFP site B17)

is 25%. Of the 29 neurons recorded, the first five used a different range of plan periods. Our performance analysis was thus based on the latter 24, of which six did not improve overall performance due to the effects of low trial counts and outliers on leave-one-out cross-validation.

It is also possible to estimate movement distance from plan activity. However, errors in estimating target distance were common due to the close spacing of our targets, which sometimes led behavioral performance to overlap. As direction, distance and speed are all continuous variables, future work will attempt to provide estimates of movement parameters on a continuous scale.

IV. DISCUSSION

We recorded neural activity from pre-motor cortex of a rhesus monkey trained to perform delayed-reaches to targets at two different speeds. We found that the delay-period spike rate and 20-40 Hz LFP power co-vary with upcoming movement speed. Simulations demonstrate that spike-rate plan-period activity from a small neural ensemble is sufficient to predict movement speed and direction with good confidence. It should also be possible to estimate speed from plan-period LFP activity and then combine spike-based and LFP-based speed estimates to achieve even higher levels of performance.

When used with an algorithm that combines plan and peri-movement information, plan activity could provide a powerful "probabilistic prior" stating that the upcoming movement is quite likely to be at a particular speed (e.g., fast or slow) and directed toward a particular endpoint. Peri-movement activity could then be interpreted accordingly resulting in prosthetic system performance superior to that possible with peri-movement activity alone.

V. CONCLUSION

High-performance neural prosthetic systems must efficiently use all available movement information. We report here that speed information is present in PMd plan-period neural activity. We propose that combining this action potential and LFP plan-period speed information with peri-movement information can improve performance.

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