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Laminar Analysis of Movement Direction Information in Local Field Potentials of the Rat Motor Cortex

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Abstract— **Local field potentials (LFPs) have been proposed for use in controlling neural prosthetic devices because they can provide reliable motor and sensory-related information, and can easily be recorded over long periods of time. While studies have shown that directional information about motor movements can be inferred from LFPs, it is not known at what depth these signals should be recorded from in order to maximize the amount of movement information. Towards this end, we used a directional motor task in Long Evans rats, while sampling LFPs with an electrode consisting of 16 vertical recording sites that were evenly-spaced 100μm apart. This allowed for simultaneous recording of all layers of the motor cortex. The frequency components of LFPs were then analyzed using k-means clustering to determine directional information as a function of depth. Here we report our initial findings that superficial layers (II/III) of motor cortex may provide more information about movement directions then deeper layers (V).**

I. INTRODUCTION

Decoding intention from neural signals is a vital area of research in the development of neural prosthetics and brain machine interfaces (BMIs) [1], [2], [3], [4]. Recently there has been interest in local field potentials (LFPs) as a reliable way to chronically deliver control signals to BMIs [5], [6], [7]. Historically, BMIs have relied on extracellular action potentials which were recorded using microelectrodes targeted at the large pyramidal cells in layer V of cortex. However, this may not be the optimal depth for recording a control signal from field potentials, since the source of LFPs is derived largely from synaptic activity (and not the pyramidal cells). Here, we test the hypothesis that local field potentials, which reflect synchronized synaptic activity from a population of neurons, would decode better movement information in the arborized superficial layers.

Information analysis of LFPs was conducted using a non-parametric clustering algorithm that estimated the statistical similarity of LFP frequency components associated with leftward and rightward movements using data from all layers of the rat primary motor cortex. Our findings suggest that the superficial layers of the motor cortex may be optimal for determining the movement direction from LFPs. We also provide evidence, using current source density (CSD) analysis, that the better decoding may be due to the synaptic activity in the upper layers.

II. METHODS

A. Animal Procedures

Four Long-Evans rats weighing 275-300g (Charles River Laboratories) were used during this study. Surgery was performed where anesthesia was maintained through intraperitoneal injections of a mixture of 50 mg/ml ketamine, five mg/ml xylazine, and one mg/ml acepromazine at an injection volume of 0.125 ml/100 g body weight. Updates of ketamine 0.1 ml ketamine (50 mg/ml) were delivered intraperitoneally on an hourly basis to maintain anesthesia. Three bone screw holes were drilled and a craniotomy was performed over the neck area of primary motor cortex (MI) in the right hemisphere. The dura was cut and folded back to allow insertion of a single shank penetrating electrode with either 16 (n=3) or 32 (n=1) recording sites. The electrodes were inserted by hand until the top recording site was even with the brain surface. The recording sites were equally spaced at 100 μm (Figure 1). The probes were then secured using dental cement and the subjects were allowed 5-7 days to recover.

B. Behavioral Training

After surgery, rats were placed in a recording chamber that consisted of behavioral box with three nose pokes, a speaker, a video camera, a signal commutator and amplification system. The rats were initially trained to nose poke a hole and wait for a tone of 4 kHz to receive a food pellet. The time delay to the tone was gradually increased until the rats consistently waited for 550−800 msec during 85% of the trials. After which time, the second part of training began. Rats waited for the cue as before; however, now either a high (8 kHz) or a low (2 kHz) tone was played. Depending on the tone played, the rats had to move toward one of two holes located either to the left (2 kHz) or to the right (8 kHz) of the center hole. If they performed the correct movement, they received a 45mg food pellet as a reward. An error trial occurred when the rats nose poked the wrong side hole. In this case, rats were forced to repeat a trial until they performed it correctly to prevent the development of a side preference. The intertrial interval changed randomly, ranging between 15 and 30 sec. Rats were fed 15g of standard chow

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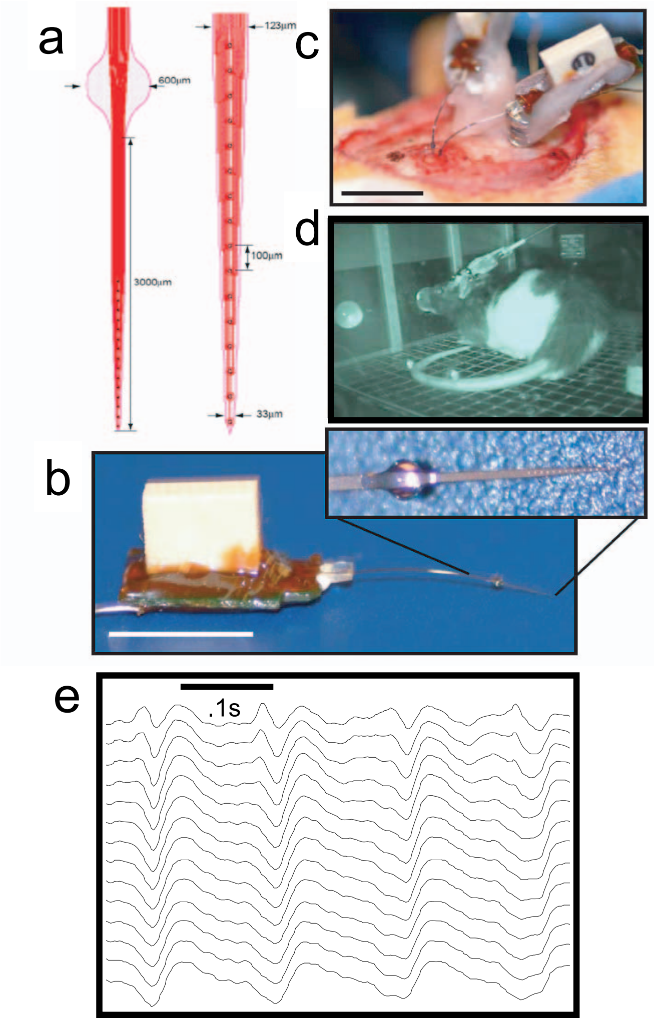

Fig. 1. Experimental Methods. (a,b) 16 channel silicon electrode. (c) surgical preparation, (d) recording chamber with awake behaving rat. (e) high voltage spindle of rat R1 recorded from 16 vertical sites.

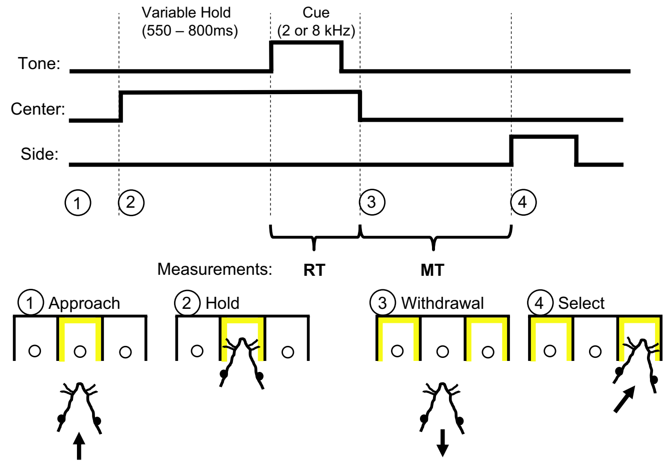

Fig. 2. Depiction of the behavioral paradigm used for training rats. Analysis was performed on 1s of data before and after movement initiation, shown here as event 3. Yellow lines indicate cued nosepoke. Circles illustrate approximate placement of photobeam detector.

at the end of each session, which kept them at 85% of free feeding weight.

C. Data Collection

LFP data were band pass filtered between 3 and 90Hz, and were digitally sampled at 500Hz (Plexon Inc, Dallas, TX). Digital events from all nosepokes, cues, and tones were simultaneously sampled with 150μs resolution and were synchronized with the field potentials. Action potentials were also recorded but not analyzed in this study.

D. Data Conditioning

For each training day, 2s of LFP data were extracted for each trial in the session. These 2s of trial data were centered (time t = 0s) upon movement initiation from the center nosepoke to a side side nosepoke (See event 3 of Figure 2), and spans 1s both before and after this event. The data windows were then sorted into "rightward" and "leftward" movements, depending on the direction of the selected side nosepoke. To avoid data contamination, all trials containing obvious noise artifacts were removed from the data set using the custom Matlab software (Mathworks, Natick, MA) and trials with movement times $>$ 2s were dropped. Finally, for each field potential, a multi-tapered time-frequency spectrum was calculated using the Chronux data analysis toolbox (version 1.0, http://chronux.org) for each trial. When calculating the $3-90$Hz spectrogram, a 300ms moving window was advanced at 20ms intervals across the 2s data window.

E. Movement Classification

The spectrogram data were used to determine if we could predict leftward and rightward movements. For each time step in the spectrogram, the mean power in 3 oscillation bands: Theta ($3-10$Hz), Beta ($10-30$Hz), and Gamma ($30-90$Hz) were used to form a 1x3 vector for each trial. A k-means clustering algorithm was implemented to separate the power bands of all n trials into two groups (left and right)[8]. Specifically, the algorithm divided all the trials of a session into two clusters that minimized the distances between each data point (x_n) in relation to the cluster center (μ_j). Written mathematically, the algorithm aims to minimize the objective function

$$J = \sum_{j=1}^{2} \sum_{n \in S_j} |x_n - \mu_j|^2, \tag{1}$$

where n is the number of data points in cluster S_j. This method was chosen as it is one of the simplest unsupervised learning algorithms for classification.

Following classification into two groups, we calculated the percent of correctly classified leftward and rightward trials. This approach allowed us to determine the ability to decode movements information from the LFP data. For example, if spectral content for both leftward and rightward movements is the same, or statistically indistinguishable (as should be before the tone), the algorithm will classify approximately

50% of the trials correctly. As the leftward and rightward signals become more distinguishable, the percent of correct classification increases. The percent correct for each recording site at each time step were visualized as a two dimensional heat map that ranged from 50-75% correct. The data was then smoothed using a 5x3 (site x time) point filter.

F. Current Source Density

Current source density was performed on the field potentials by first averaging the LFPs over several trials, and then applying a 10 point smoothing box filter to each signal. The DC offset of LFPs were remove by subtracting the mean of the first 20ms from every LFP signal. The LFP signals were then spatially differentiated twice using a 5th order geometric series. Finally, the data was smoothed in the spatial direction by interpolating 20 times between the laminar data points.

III. RESULTS

The cortical layers sampled at each recording site were estimated from the depth beneath the cortical surface as well as from the CSD profile of high voltage spindles [9]. We estimated that sites 1-8 (0-800μm) were layers II/III, and were labeled as "superficial", and that sites 8-16 (800-1600μm) were sampling from layer V, and were labeled "deeper" [10]. Current source density of high voltage spindles provided an additional online estimate of layers sampled (data not shown). Histology of one subject (R4) revealed that the electrode was placed too deep, so the neurophysiological data were not analyzed on this subject.

The rats learned the behavioral task in two stages. Motor learning, as measured by a significant decrease ($P < 0.05$, ANOVA) in the movement time, occurred during the first session. Associative learning, as measured by the percent correct nosepokes, occurred much later and stabilized above 80% correct after 8 sessions. For this analysis, we analyzed data for sessions after motor learning had occurred (sessions $2-11$). The mean (variance) reaction and movement times for all subjects were 385ms (132ms) and 367ms (130ms), respectively.

A. Movement Classification

Figure 3 shows the results of the k-means clustering algorithm for the LFPs recorded from the top 16 sites of the 3 rats analyzed in this study. This figure demonstrates that the superficial layers often provide more information about the movement direction than the deeper layers. Also, the most informative time point in the superficial layers precedes that of the deeper layers.

B. Current Source Density

We used current source density analysis to determine if the information contained in the superficial layers was locally generated (*e.g.* from synaptic activity), or if this was due to

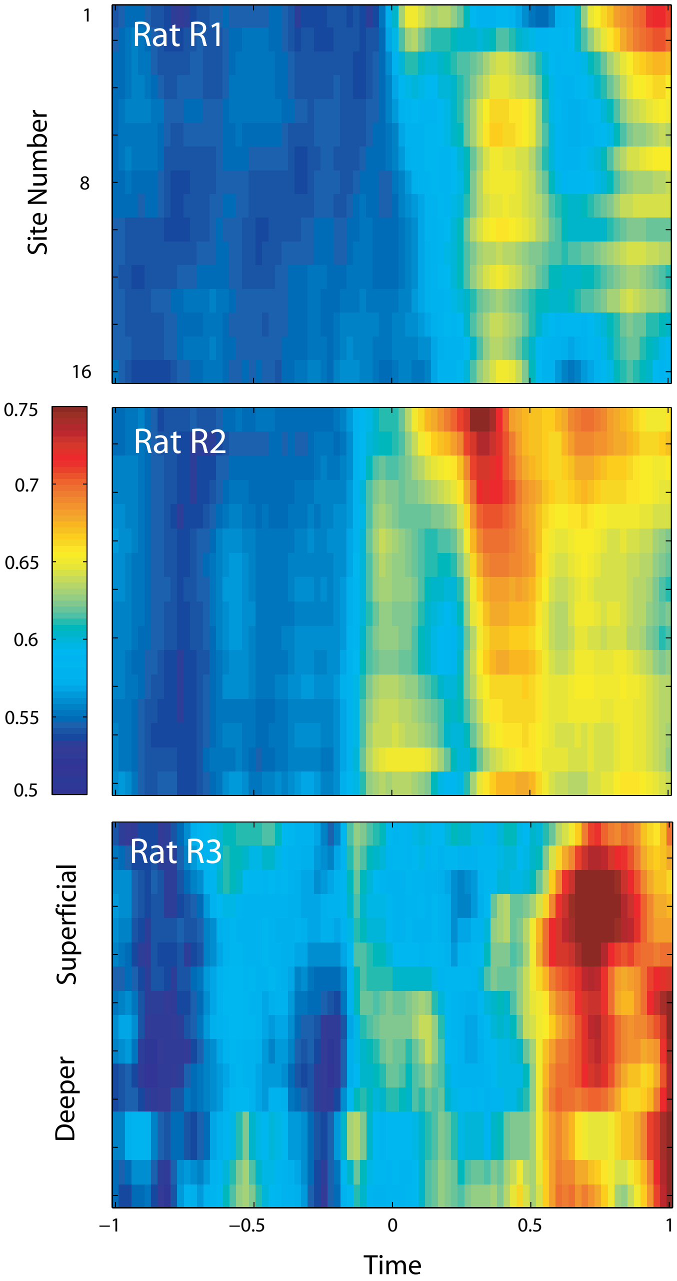

Fig. 3. Mean classification performance of three rats across session $2-11$. Color bar indicates the percent of trials that were correctly classified by the k-means algorithm. Time 0 indicates when the center nosepoke photobeam rejoined at the beginning of side direction movements. The Y axis, indicating the recording site that was used in the classification algorithm, is the same for all plots and is shown for rat R1. As expected, the decoding power was at chance (50%) during the hold time before the cue was presented. Notice that the superficial layers tend to classify the movement better than the deeper layers for all rats.

a far field perturbation (*e.g.* field changes in response to a remote brain structure).

Figure 4 shows a typical CSD profile of leftward and rightward events. The mean CSD of the first 16 trials for each movement on session 9 of rat R1 are displayed. Note that for the leftward movements the current sources are located in the superficial layers, while current sinks are located deeper in the cortex. Also the timing at which the source begins is synchronized with the onset of directional information. There is an absence of large current sink/source pairs for contralateral rightward movements. These data are consistent with the hypothesis that the directional information in LFP are driven from the synaptic activity in the superficial layers.

IV. DISCUSSION

The analysis presented here suggests that BMI systems which are implemented using local field potentials should target more superficial layers, rather than the traditional deeper layers of the motor cortex.

Both LFP and spike signals have advantages and disadvantages with regards to movement information. LFP signals are more stable than spikes and can more easily be obtained, but they lack the spatial and temporal resolution of unit recordings. Future devices may seek to combine spikes and LFPs to exploit their respective advantages and potentially provide complementary information to the device controller.

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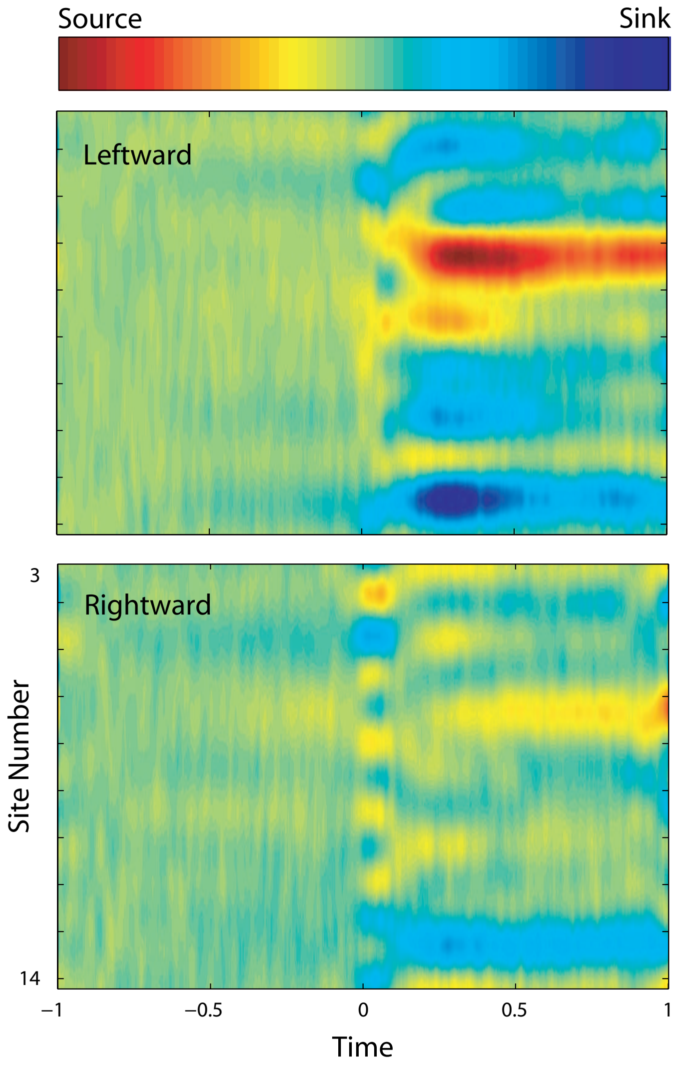

Fig. 4. Current source density analysis for session 9 leftward and rightward movements of rat R1. Color scale indicates the location of laminar current flow. The location of local current sinks and sources are shown as blue and red respectively. Note that directional differences are apparent in the local sources found in the superficial layers. Time axis is same as described in Figure 3. The two proximal and distal sites are removed as a result of the CSD calculation.

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