Movement Direction Decoding using Fast Oscillation in Local Field Potential and Neural Firing during Instructed Delay in a Center-Out Reaching Task

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Abstract

We explore the fast oscillation (15-33Hz) of Local Field Potential (LFP) and firing patterns of single units in motor cortex with respect to a monkey's hand-movement direction. Our work examined, during the instructed delay period, various approaches to couple the LFP and firing rates to the encoding of movement direction by counting the number of spikes per unit time within different phases of fast oscillation of the LFP. We found that the coupled rates within certain phases have higher (though not statistically significant) decoding accuracy than the rates over the whole instructed delay period which was reported in previous work.

Keywords: motor cortex, neural decoding, local field potential, fast oscillation, firing rate.

1 Introduction

Fast β-oscillations(15-33Hz) of Local Field Potential in motor cortex tend to appear most often during preparatory stages, e.g. instructed delay periods in center-out reaching tasks, and tend to ceased with motor execution [1, 2, 4, 5, 6]. The transitory nature of this oscillatory phenomenon could imply that β-oscillations play a role in the motor planning and intention. While accurate decoding of movement direction based on neural discharge (i.e. firing rates) around movement onset is commonly achieved [3], the same decode is much less accurate when based on neural discharge computed solely from instructed delay periods.

We hypothesize that LFP β-oscillations may modulate the movement direction encoding properties of neural discharge during instructed delay periods. In this paper, we test this hypothesis and explore different approaches to couple LFP and spikes in decoding algorithms. In particular, we tested if firing rates within oscillatory/non-oscillatory period, or at different phases of the oscillatory activity have different encoding properties. Our ultimate goal is to find ways of associating spikes and LFP activity such that more accurate decoding of movement parameters is obtained than in the case of exclusive use of neural discharge information.

2 Methods

2.1 Experiment and Data Acquisition

A Macaque monkey viewed a computer monitor and gripped a two-link, negligible-friction manipulandum on a tablet parallel to the floor. The monkey's task was to move the manipulandum to control a cursor from a central position to one of four possible targets (radially positioned at $0^o, 90^o, 180^o, 270^o$) displayed on the monitor. Each experimental trial consisted of three epochs: 1. a "hold" period (start trial to instruction) during which the monkey kept holding the cursor at the center of screen of monitor for 500ms; 2. an "instructed delay" period (instruction to go cue) during which one of the targets appeared but cursor was still restrained at the center (for a random length in the range 1-1.5sec, 1.27(Mean)±0.14(SD)); 3. a "movement" period (go cue to movement onset) initiated by target blinking. For the data analyzed here, there are 406 (125+87+102+92 in four directions) trials.

During the trials, the monkey's hand position was recorded at 72kHz. Utah Array (10×10 tapered electrodes) was implanted in the monkey's arm area of primary motor cortex to record neural discharge (spikes) and LFPs. The spikes were digitized at 40kHz and LFPs were sampled at 1000Hz. In the experiment, we obtained good recording at 7 electrodes: three of which have spike recording of only one neuron; the other four have spike recording of two neurons. Totally, we have 7 sequences of LFP data and 11 sequences of spike timing data.

2.2 Identification of LFP fast β-Oscillatory Periods

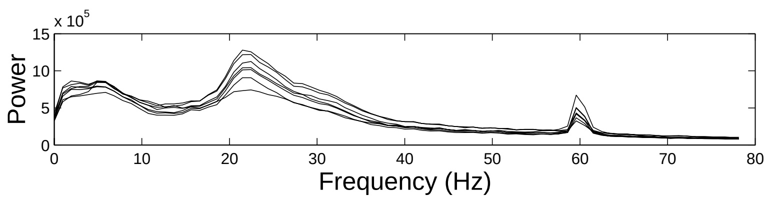


Figure 1: All electrodes show high power in the frequency band 15-33Hz

The averaged power spectrum of all LFPs is shown in Fig. 1. We see that all 7 LFPs have similar power spectra and that high power occurs often in the range 15-33Hz. Oscillations in this bandwith are here referred to as fast beta-oscillations. We apply a bandpass filter to extract the oscillations within this frequency band in order to improve the signal-to-noise ratio of this signal. A *Kaiser* filter is employed with lower cutoff frequencies at 15Hz and 33Hz (near 0dB) and higher cutoff frequency only at 24Hz (near 1dB). The maximum allowable error or deviation between the frequency response of the output filter and its desired amplitude for each band is set as 2%. All the parameters were chosen to have a localized (i.e. short) filter so that it is able to find the local properties in time domain. All the LFP data (during instructed delay period) were filtered by the above Kaiser filter. Figure 2 shows one typical LFP sequence and its filtered version.

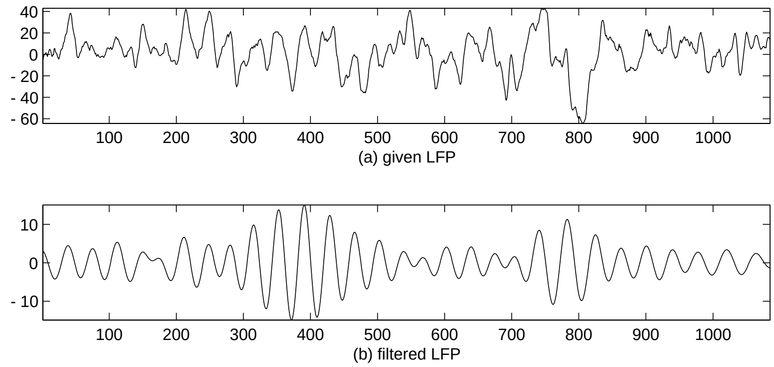


Figure 2: (a) one typical LFP signal, (b) filtered LFP by the given Kaiser filter.

In Figure 2, we can see that the peak-to-peak amplitude of the filtered beta-oscillations is not constant, but has a transitory nature. Consequently, an appropriate definition of oscillatory activity is needed to identify these oscillatory events in time. Similarly to Murthy and Fetz's [5, 6], an oscillation episode is here defined as three or more consecutive cycles (start and end at zero-crossings) of LFP data whose oscillation amplitudes are outside the interval $+-c\sigma$, where σ is the standard deviation of the LFP and c is a constant to be specified. One typical oscillation detection for $c = 1$ is shown in Figure 3. A LFP signal may have more than one oscillation episodes. We define *oscillatory period* as the union of all oscillation episodes and *non-oscillatory period* as its complement.

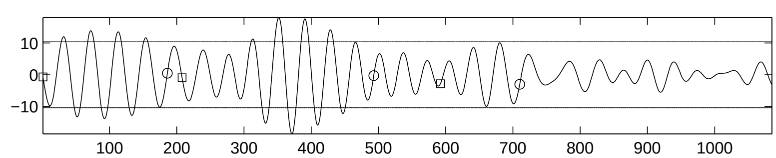


Figure 3: The instructed delay period of one electrode: the curve is a filtered LFP sequence; the two straight lines are oscillation thresholds ($c = 1$), the squares/circles are the start/end points for each oscillation episode.

2.3 Movement Direction Estimation

In [3], the monkey's hand movement directions were encoded by firing rates within instructed delay period, where all spikes were used without selection. Assume both the direction $k \in \{1, 2, 3, 4\}$ and firing rate vector $\vec{x} = (x_1, \cdots, x_{11}) \in \mathbf{R^{11}}$ are random variables, where

$\{1, 2, 3, 4\}$ stands for $\{0^o, 90^o, 180^o, 270^o\}$ and x_c is the firing rate [1] over instructed delay of cth cell, $c = 1, \cdots, 11$. In contrast to this, we exploited the oscillatory properties of LFP and applied them to make selection on the spikes. Given the oscillation episodes, we calculated the firing rate x_c of each cell over the oscillatory period or non-oscillatory period.

Each trial contains a pair of movement direction and firing rate vector. Given moving direction k, conditional probability $p(\vec{x}|k)$ of firing rate vector $\vec{x}$ can be simply modeled as a multivariate Gaussian distribution [3]:

$$p(\vec{x}|k) = \frac{1}{(2\pi)^{\frac{n}{2}}(\det(R_k))^{\frac{1}{2}}} e^{-\frac{1}{2}(\vec{x}-\vec{m}_k)^T R_k^{-1}(\vec{x}-\vec{m}_k)}, \tag{1}$$

where n = 11 and the parameters R_k and $\vec{m}_k$ can be estimated from the given data. Due to the limited number of trials, we assumed that R_k's are diagonal in order to avoid overfitting in the parameter estimation. If the firing rate within oscillatory period was used, we chose all the trials which have at least one oscillation episode for each LFP, while if within non-oscillatory period, we chose all 406 trials. The chosen trials are nonempty and valid for the modeling and estimation. Leave-one-out cross-validation was adopted here to test the validity of fitted model: the parameters in the model were fitted by training data, then the movement direction in the test trial (with firing rate $\vec{x}$ in oscillatory/non-oscillatory period) was estimated by MLE (Maximum Likelihood Estimation), i.e.

$$\hat{k} = \operatorname*{argmax}_k \, p(\vec{x}|k). \tag{2}$$

The successful estimation ratio (SER) is the number of successful direction estimation on test trial of all rounds divided by the number of valid (chosen) trials.

[1] number of spikes over a period divided by the length of that period

3 Results

3.1 Firing rate within oscillatory or non-oscillatory period

In [3], without coupling with LFP, firing rate was calculated within the whole instructed delay period. The successful estimation ratio was obtained as:

$$\text{SER} = 0.594.$$

Our main goal is to find positive association between LFP, and spikes, then couple them to obtain higher SER than the above result (0.594).

In the definition of oscillation episode, three consecutive cycles seems reasonable, but the threshold for the amplitude is controversial. Here we argued to range c from 0 to 1.6 to accommodate both loose and tight criteria for such definition. Table 1 shows the successful estimation ratio as a function of different c's using firing rate within oscillatory period. 1.6 is an appropriate upper bounds for c because if c is larger than 1.6, we would have too few valid trials. Note that when $c = 0$, the oscillatory period is *almost* the same as the whole instructed delay epoch (it is *almost* because the oscillation epsiode is defined to have both ends on zero-crossings).

c	0	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6
# of valid trials	406	406	406	404	401	385	339	271	214
SER	0.591	0.586	0.586	0.572	0.554	0.532	0.558	0.506	0.472

Table 1: The first row: the threshold parameter c; the second row: the number of valid trials; the third row: the successful estimation ratio.

If the firing rate is calculated within non-oscillatory period, the number of valid trials is always 406. We can also get the successful estimation ratio in Table 2. Note that if $c < 0.4$, the non-oscillatory period is too short to be used. Consequently, we only calculate for $c \geq 0.4$

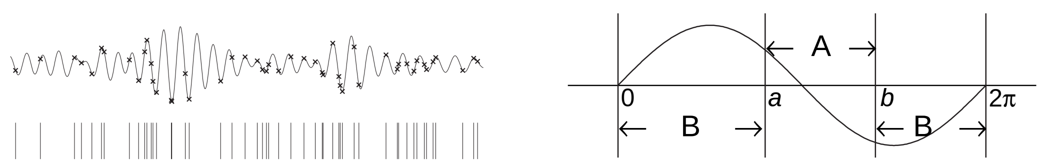
c	0.4	0.6	0.8	1.0	1.2	1.4	1.6
SER	0.308	0.382	0.493	0.520	0.547	0.569	0.567

Table 2: successful estimation ratio using firing rate within non-oscillatory period

From Table 1 and 2, we found that firing rate within neither oscillatory nor non-oscillatory period provides higher SER. This suggests that neither of the periods has the positive association with spikes on the encoding of the hand movement direction. One basic trend is that the larger the period size, the higher the SER, which may result from the overfitting in the Gaussian model of each direction. To avoid this issue, we always let $c = 0$ in the following analysis and only consider the spikes within oscillatory epsiodes.

3.2 Firing rate within certain phase subset

We tested to encode the hand movement direction using firing rate within oscillatory or non-oscillatory period, yet did not acquire better decoding for the direction estimation. To explore the property of LFP one-step deeplier, we consider the phase information each spike (in oscillatory period) contains, where the correspondence between the spike and its phase in LFP signal is depicted in Fig. 4 (a).



(a) (b)

Figure 4: (a) Each spike (vertical stick) corresponds (the same time instant) to one point (crossed) in LFP signal, whose phase ($\in [0, 2\pi)$) is defined as the phase of the spike. (b) Illustration of phase partition. $\mathbf{A}$ is the phase set from a to b; $\mathbf{B}$ is its complement.

Here we choose 10 bins for each phase cycle (from 0 to 2π) and we test the estimation performace using firing rates within its subsets. Although there are only 10 discrete bins, the total number of subsets is virtually very large. Here we only consider the sub-intervals (within $[0, 2\pi)$ or across the boundries). Therefore each cycle can be partitioned to two subsets $\mathbf{A}$ and $\mathbf{B}$ (depicted in Figure 4 (b)), where

$$\begin{cases} \mathbf{A} = [a, b), \mathbf{B} = [b, 2\pi) \cup [0, a) & \text{if } a \leq b \\ \mathbf{A} = [a, 2\pi) \cup [0, b), \mathbf{B} = [b, a) & \text{otherwise} \end{cases} \tag{3}$$

In the Methods section, we described that the oscillation threshold c was chosen as 0, so the spikes within oscillatroy period should all have the corresponding phases. Since there are 10 bins in each cycle, the partition phase points $a, b \in \{0, 0.2\pi, 0.4\pi, \cdots, 2.0\pi\}$. Firing rate vector $\vec{x} = (x_1, \cdots, x_{11})$ is calculated within subset **A** defined in Eqn. (3). The SERs of all kinds of **A** are shown in Table 3 (a). If $A = \{0, \cdots, 0.6\pi, \pi, \cdots, 1.8\pi\}$, SER $= 0.606$, which is slightly larger than 0.594 (SER without coupling of LFP).

(a)

a\b	**0**	**0.2π**	**0.4π**	**0.6π**	**0.8π**	**1.0π**	**1.2π**	**1.4π**	**1.6π**	**1.8π**	**2.0π**
0		0.436	0.470	0.502	0.517	0.532	0.539	0.579	0.591	0.579	0.591
0.2π	0.569		0.451	0.493	0.532	0.527	0.532	0.552	0.589	0.569	0.569
0.4π	0.574	0.586		0.443	0.478	0.510	0.515	0.557	0.562	0.569	0.574
0.6π	0.564	0.584	0.584		0.424	0.485	0.490	0.525	0.552	0.567	0.564
0.8π	0.554	0.562	0.567	0.571		0.416	0.470	0.525	0.554	0.567	0.554
1.0π	0.552	0.571	0.569	0.589	**0.606**		0.411	0.507	0.527	0.557	0.552
1.2π	0.571	0.559	0.576	0.589	0.584	0.581		0.431	0.502	0.547	0.571
1.4π	0.542	0.537	0.549	0.567	0.569	0.564	0.571		0.401	0.500	0.542
1.6π	0.490	0.502	0.534	0.547	0.547	0.552	0.544	0.581		0.473	0.490
1.8π	0.414	0.478	0.515	0.525	0.530	0.534	0.552	0.574	0.596		0.414
2.0π	0.591	0.436	0.470	0.502	0.517	0.532	0.539	0.579	0.591	0.579	

(b)

a\b	**0**	**0.2π**	**0.4π**	**0.6π**	**0.8π**	**1.0π**	**1.2π**	**1.4π**	**1.6π**	**1.8π**	**2.0π**
0		0.557	0.586	0.576	0.586	0.567	0.579	0.584	**0.601**	0.586	0.591
0.2π	0.584		0.571	0.574	0.584	0.564	0.564	0.584	0.584	0.579	0.584
0.4π	0.589	0.584		0.564	0.571	0.557	0.549	0.576	0.574	0.586	0.589
0.6π	0.586	0.586	0.591		0.554	0.567	0.557	0.584	0.586	0.579	0.586
0.8π	0.569	0.569	0.589	0.581		0.547	0.542	0.562	0.589	0.571	0.569
1.0π	0.581	0.591	0.594	0.594	**0.611**		0.544	0.589	0.596	0.586	0.581
1.2π	0.599	0.599	0.594	0.596	0.591	0.581		0.569	**0.608**	**0.608**	0.599
1.4π	0.569	0.571	0.581	0.584	0.596	0.581	0.589		0.564	0.557	0.569
1.6π	0.596	0.589	0.569	0.581	0.586	0.579	0.581	0.591		0.549	0.596
1.8π	0.547	0.567	0.569	0.567	0.576	0.584	0.584	0.591	0.586		0.547
2.0π	0.591	0.557	0.586	0.576	0.586	0.567	0.579	0.584	**0.601**	0.586	

Table 3: (a) SER of firing rate within subset **A**, where a and b range from 0 to 2π; (b) SER of firing rate within subset **A** and whole oscillatory period. The boldfaced are the ratios that are larger than 0.6.

In all above approachs, movement direction k was encoded by 11 dimensional vector $\vec{x}$. Two issues arise here: 1. are the 11 dimensions enough for the model? 2. if we have higher dimensional vector, will the SER be improved (higher)? One way to test these is to combine the firing rate within subset **A** and whole oscillatory period. i.e. $\vec{x} = \{x_1, x_2, \cdots, x_{22}\}$, where firing rate vector $\{x_1, \cdots, x_{11}\}$ is over **A** and $\{x_{11}, \cdots, x_{22}\}$ is over whole instructed delay. The SERs in this coding scheme are shown in Table 3 (b).

Compared (b) with (a) in Table 3, 22 dimensional vector acquires higher SERs. Particularly, when $A = \{0, \cdots, 0.6\pi, \pi, \cdots, 1.8\pi\}$, SER obtains the maximum 0.611. Also, when $A = \{1.2\pi, 1.4\pi\}$, SER = 6.08 is the second largest. Combine these two best cases, we are expecting to get even higher SER. Here we mean that $\{x_1, \cdots, x_{11}\}$ is firing rate vecotr over subset $\{0, \cdots, 0.6\pi, \pi, \cdots, 1.8\pi\}$, and $\{x_{11}, \cdots, x_{22}\}$ is over subset $\{1.2\pi, 1.4\pi\}$. For this new difinition of $\vec{x}$, we have SER = 0.613.

4 Discussion

We have described a new approach to couple neural discharge (spikes) and LFP. We found that firing rates computed from neither oscillatory nor non-oscillatory LFP periods allowed higher accuracy in the decoding of movement direction. That was true for all choices of threshold in the definition of oscillation episode. Decoding of direction based on the spike phase with respect to the beta-oscillations provided slightly decoding improvement within some particular phase range. This suggests that the neural discharge does associate with the beta-oscillation phase for the encoding of hand movement direction, although the current supporting evidence is still weak.

While attempting to improve direction decoding by exploring the association between LFPs and spikes, we have applied simple mathematical techniques in encoding model Estimation. The adopted models may suffer from the assumption on Gaussian distributed firing rates conditioned on movement direction, since the rate is always non-negative and its density histogram may be skewed. Although preliminary results employing non-symmetric distributions(for example, Gamma distribution) showed no substantial differences, more detailed investigation is needed. In terms of pure partitioning, other advanced mathematical techniques, such as Support Vector Machine, could be exploited here. Our future work will focus on the search for associations between LFPs and spike activity and on the development of related mathematical modeling methods.

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