

Evaluating Neural Interaction in Motor Cortex during Reach-to-grasp Task from the Spike Train Data

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Abstract—In this work, we recorded the spike train data from a rhesus monkey's motor cortex while it was trained to perform reach-to-grasp task at different directions and orientations. The neurons were divided into several classes according to their neuronal activities, and each class of neuron encoded a kind of functional parameter, such as direction-related, orientation-related and so on. Then we applied the generalized partial directed coherence (PDC) to evaluate the neural interaction. This method is a frequency domain measure established on the multivariate vector autoregressive model (MVAR). Since MVAR works primarily for continuous data, the spike trains were converted into the time series of the instantaneous firing rate prior to the MVAR estimation. The results indicated that the neural interactions commonly existed among neurons, and there were different network topology and coupling strength of the neural interaction corresponding to different targets. And also, our study still provided the more evidence for the hypothesis that there probably existed a common pathway in motor cortex that controlled both direction and orientation during the reach-to-grasp task.

Keywords—neural interaction; Reach-to-grasp task; partial directed coherence

I. INTRODUCTION

The multiple-electrode recording technologies have allowed us to measure multiple spike trains from the neurophysiologic systems simultaneously. Although many data analysis methods have been proposed [1], it is still one major challenge to characterize the neural interactions among neuronal populations and their changes in response to the different stimulus or tasks. The spike trains have been considered as the multivariate point process due to their dynamic and stochastic property. Traditionally, the neural associations could be measured with cross correlation in time domain and coherence in frequency domain [1], and even the information flow could be assessed with the Granger causality [2], but most of them are only defined for the pairwise analysis of bivariate signals. Therefore, they couldn't be applied into the condition of multivariate process directly. To dealing with the issue of point process, one attempt is to develop the multivariate point-process model [3], while another choice is to convert the spike train into continuous time signals prior to the other analysis [4].

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Prehension movements involve three components: transport, manipulation, and hand orientation. It has been the main focus of researches to examine the relation between transport and manipulation [5], and very little study has directly studied the problem from the upper command level and investigated cortical control of hand orientation during reach-to-grasp. Our previous studies on the human subjects and the non-human primates have shown that the hand orientation is controlled as an individual channel of prehension movements [6, 7], and neurons encoding hand orientations and neurons encoding movement directions coexist in the same regions of the motor cortex, which indicates there probably exists a common pathway in motor cortex that controls both parameters [7].

In this paper, we described a further data analysis based on the works performed by Fan [7]. The spike trains were recorded from a rhesus monkey's motor cortex, while it was trained to perform active reach and grasp of targets with various directions and orientations. According to the statistical properties of neural activity, a systematic classification was carried out for all of the recorded neurons. Then the spike trains were converted into continuous time signals of the instantaneous spiking rate. To evaluate the neural interaction, we applied the partial directed coherence (PDC), which is a frequency domain measure for Granger causality based on modeling time series by multivariate vector autoregressive model (MVAR) [8, 9]. In contrast to the previous investigation [7], we aimed to evaluate the neural interaction in motor cortex and their changes corresponding to different target during the reach-to-grasp task.

II. MATERIALS AND METHODS

A. Experimental Description

The experiment was performed at Arizona State University (ASU). ASU Institutional Animal Care and User Committee approved the behavioral paradigm, surgical procedures and animal care.

The monkey was trained to perform the visually guided 3-D reach-to-grasp task, while the targets were composed by two different directions (left, right) and three different orientations (45°, 90°, and 135°). A successful trial started with central light

on cueing the monkey to place its hand on the central holding pad. After a random center holding time (CHT), a target light came on, cueing the monkey to reach for the indicated target and make a whole hand grasp. The target light would go off after a minimum target hold period. The monkey would return the hand to the central pad and wait for the next trial (Fig. 1A).

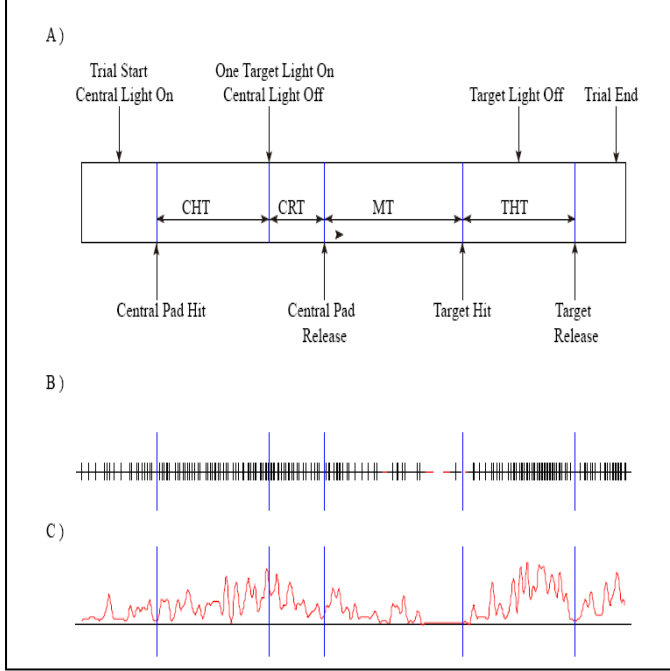


Figure 1. A) The sequence of events for the reach-to-grasp task and the trial epochs in this experimental setup. The cue reaction time (CRT) is the time from target light on to central pad release; the movement time (MT) is the duration from holding pad release to target grasp; and the target holding time (THT) is defined as the time from target hit to target release. B) A typical neuronal activity in the original spike train form during a complete trial. C) the resulting continuous-time rate signal constructed from the corresponding spike train in B).

During the experiment, a recording chamber was placed on the contra lateral hemisphere. The electrical activity of single motor cortical neurons was recorded with five independently driven microelectrodes (Thomas Recording). Each electrode made one penetration a day, and the recording depth was adjusted after one block (one successful block includes 108 successful trials, while 18 trials to each target condition) to record from different neurons. The complete description of experiment setup and data acquisition are also given in [7].

B. Data Pre-processing

A total of 979 motor cortical neurons were recorded. The preliminary data analysis included the classification of the neural function and the conversion from the spike train into continuous time signals.

The classification was based on the average neuronal activity in each behavioral epoch (Fig. 1A). Epoch firing rates were calculated for each neuron by counting the number of spikes recorded within each epoch and divided by the epoch duration. The firing rates during CHT were considered as the

baseline firing rates. A two-way analysis of variance (ANOVA) was used to analyze their statistical properties of neural activity before, during and after movements ($P < 0.05$). As a result, we divided all the neurons into several classes, while different classes encoded different functional parameters, including task-related, non-task-related and so on.

We then selected a set of typical block to evaluate the neural interaction. Since the spike trains are sparsely distributed in our recording, it is better to convert them into time series of the instantaneous firing rate like as [4], rather than convolving them a Gaussian kernel [8, 10]. The resulting rate profile and the original spike train contain the same temporal firing behavior of the neuron. Fig.1C is an instantaneous firing rate signal constructed from the corresponding spike train shown in Fig.1B.

C. Partial Directed Coherence

Granger causality is proposed in terms of predictability and temporal precedence, and its original form is a time domain concept and often considered for bivariate time series [2]. PDC is one of its extensions for the multichannel analysis [8, 9], and could be evaluated through fitting MVAR.

Let us consider $X(t) = (x_1(t), x_2(t), \dots, x_k(t))$ as the k -dimensional time series wherein x_k is the time series of instantaneous firing rate corresponding to the k^{th} neuron. Then the MVAR with model order p is defined as:

$$X(t) = \sum_{n=1}^p A(n)X(t-n) + \varepsilon(t) \quad (1)$$

where $\varepsilon(t) = (\varepsilon_1(t), \varepsilon_2(t), \dots, \varepsilon_k(t))$ is the vector to characterize white noise process, and

$$A(n) = \begin{bmatrix} a_{11}(n) & \dots & a_{1k}(n) \\ \dots & a_{ij}(n) & \dots \\ a_{k1}(n) & \dots & a_{kk}(n) \end{bmatrix}$$

is the coefficient matrix

with the element $a_{ij}(n)$ reflecting the linear interaction of $x_j(t-n)$ onto $x_i(t)$.

During the model estimation, we applied the Nutall-Strand algorithm to fit the MVAR parameters [11], and selected the Akaike Information Criteria (AIC) to find the proper model order p [12].

After Fourier-transforming, the PDC could be defined in frequency domain as:

$$\pi_{ij}(f) = \frac{a_{ij}(f)}{\sqrt{\sum_{i=1}^k |a_{ij}(f)|^2}} \quad (2)$$

where

$$a_{ij}(f) = \delta_{ij} - \sum_{n=1}^p a_{ij}(n) \exp(-i2\pi nf) \quad (3)$$

for $\delta_{ij} = 1$ if $i = j$ and 0 otherwise.

Here, we applied a normalized form of PDC called generalized PDC [13], the generalized PDC from time signal i to time signal j is given by:

$$\pi_{ij}(f) = \frac{\frac{1}{\sigma_i} a_{ij}(f)}{\sqrt{\sum_{i=1}^k \frac{1}{\sigma_i^2} |a_{ij}(f)|^2}} \quad (4)$$

where σ_i^2 is the variance of the $\mathcal{E}_i(t)$

In our study, we put the time period of the same task together during a whole record, and then estimated the MVAR respectively (including six different tasks). After obtaining the PDC, we calculated the direct coupling strength from neuron i to neuron j as

$$C_{ij}(f) = \int_{\Omega} \pi_{ij}(f) df \quad (5)$$

where Ω are the frequency ranges beyond the 5% significance level. We applied this measurement to characterize the direct interactions among these simultaneously recorded neurons. For comparing the results among different tasks, we then normalized the coupling strength value.

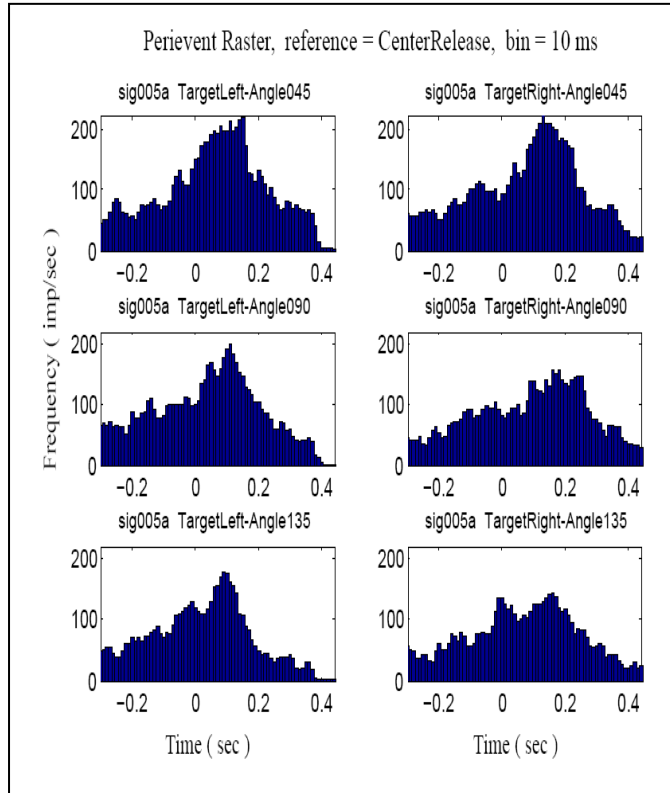


Figure 2. Perievent histograms of a motor cortical neuron encoding hand orientation during reaching and grasping the targets oriented at three different angles. The left column shows the neural activity during movements to the left target; the right column shows the neural activity during movements to the

right target. The three rows correspond to three levels of target orientations. Each raster illustrates the discharge pattern of the neuron during 18 trials of movements to each target fixed at the same orientation. The rasters were ordered by the trial sequence. Time zero was aligned at central pad release (movement onset). The histograms were calculated with a bin of 10 msec.

III. RESULTS AND DISCUSSION

There were 568 out of 979 (58%) neurons that were found to be task-related among the whole recorded motor cortical neurons. We then further classified them into movement-relation-only, orientation-relation-only, both-orientation-and-direction, and orientation-direction-interaction. Their detailed distribution and location could be found in [7].

Fig. 2 shows perievent histograms of a typical motor cortical neuron during movements to fixed targets oriented at three different angles. From the illustration, we could find that the neuronal activity of this motor cortical neuron kept the similar firing patterns between the two movement directions (while comparing between the left column and right column), and the significant changes were observed across the movements to the three different target orientations (while comparing among the three rows).

The data set used to evaluate the neural interaction came from a typical block. We estimated the MVAR for each task. Fig. 3 shows the typical example of the overall changes for the interaction among neurons. There were eleven neurons recorded simultaneously, and they were divided into four classes (Note that in this example, there was no neuron that related to orientation-direction-interaction). In this example, it was quite obvious that the changes were both taken place for the network topology and the coupling strength of the neural interaction. However, there was not any distinct rule. And also, we could find that the existence of neural interaction among the neurons encoding either the same or the different functional parameters. Even the neurons of non-task-related (yellow color in the Fig. 3) had the information flow with the neurons of task-related. In our previous study [7], we hypothesized that there probably existed a common pathway controlling both functional parameters of the direction and orientation. And the finding in this study would provide the more evidence for the hypothesis.

IV. CONCLUSION

In this study, we have demonstrated the use of PDC in evaluating the neural interaction from the spike train data, with the specific application to the motor cortex during the reach-to-grasp task. PDC can detect the direct interactions in multivariate system, and it can also identify the direction of these interactions with respect to the Granger causality.

Our results revealed that the neural interaction commonly existed among neurons with different functional parameters in motor cortex, and there were different network topology and coupling strength of the neural interaction corresponding to different targets during the reach-to-grasp task. This research

will advance our knowledge on the cortical control of hand orientation and arm movement, and provide information to develop the decoding algorithm that translates the neural signals to control the neuroprosthetic device under real life situation of reach-to-grasp.

Additional study involves establishing the new experiments that extend the recording time for the same neurons under the same tasks. And this may enhance the ability to explore the pattern of dynamic interaction among neurons.

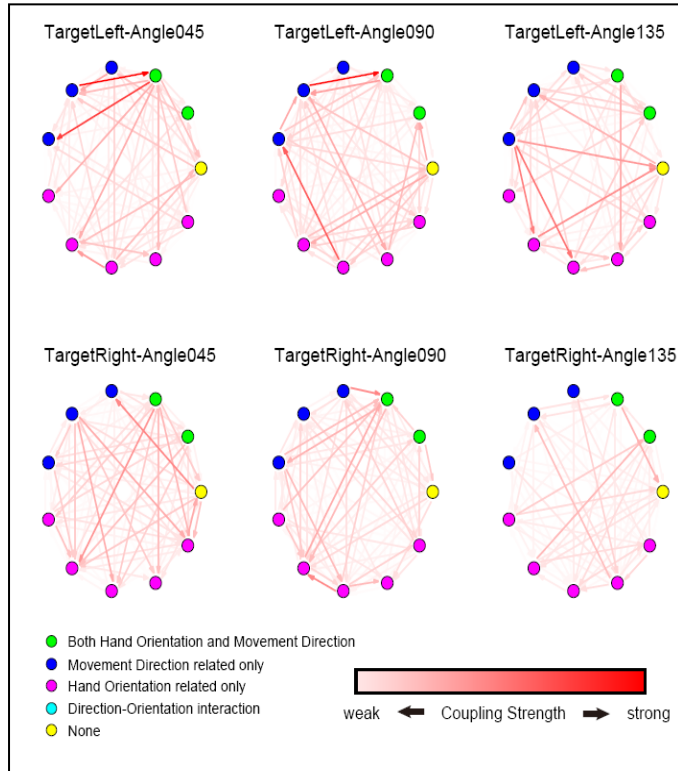


Figure 3. The estimated network architecture for six different tasks. The nodes represent the simultaneously recorded neurons, while different colors indicate the different kinds of neuron we classified (None means it's a non-task-related neuron). The lines represent the neural interaction, which arrows indicate the directions of information flow and the red degrees illustrate the relative coupling strength (the values are normalized to 0~1), the color bar is given at the lower right corner.

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