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Selection of Cortical Neurons for Identifying Movement Transitions in Stand and Squat *

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***Abstract*—Neural signals collected from motor cortex were quantified for identification of subject's specific movement intentions in a Brain Machine Interface (BMI). Neuron selection serves as an important procedure in this decoding process. In this study, we proposed a neuron selection method for identifying movement transitions in standing and squatting tasks by analyzing cortical neuron spike train patterns. A nonparametric analysis of variation, Kruskal-Wallis test, was introduced to evaluate whether the average discharging rate of each neuron changed significantly among different motion stages, and thereby categorize the neurons according to their active periods. Selection was performed based on neuron categorizing information. Finally, the average firing rates of selected neurons were assembled as feature vectors and a classifier based on support vector machines (SVM) was employed to discriminate different movement stages and identify transitions. The results indicate that our neuron selection method is accurate and efficient for finding neurons correlated with movement transitions in standing and squatting tasks.**

I. Introduction

Researchers have been seeking methods to restore normal motor function for people who have lost their limbs due to amputation or who suffer from paralysis caused by neural impairments. The Brain Machine Interface (BMI) has been proposed as a plausible way to fulfill this objective [1]. Motor cortical neurons' activities characterized by spike trains and local field potentials acquired from electrodes inserted in cerebral cortex have been applied in BMI construction [2]. Starting from one-dimensional motion decoding in rats [3] and continuing with the development of signal acquisition and computing technology, increasingly sophisticated information about motor control has been obtained through neural signal recording and analysis. For instance, neural signals corresponding to monkey or human's reach and grasp movements have been used to control robotic hands or artificial arms [1, 4].

Spinal cord injury and other neural impairments may lead to dysfunction in lower limb motor control. The significance of developing an effective means to help those people regain standing and walking ability is obvious. However, in contrast to research investigating upper limb motor control, few studies have performed neural recordings related to lower limb movement [5]. One possible reason for this is that the areas corresponding to lower limb motor control in motor cortex are much smaller and deeper and hence more difficult to reach. Our previous studies have proposed a novel method for investigating cortical control of standing and squatting in conscious behavior monkeys [6], and preliminary results show a potential to develop cortically controlled direct lower limb prostheses based on BMIs.

Neural signals collected from motor cortex are quantified to detect specific movement intentions of subjects in a Brain Machine Interface (BMI). Neuron selection serves as an important procedure in this decoding process. Large numbers of neurons are recorded in an experiment, but only a certain percentage shows correlation with certain meaningful behavioral events. Neuron selection improves decoding performance by incorporating highly task-related neurons and avoiding insignificant neurons. Meanwhile, decreased required neuron number means less electrodes for recording and computational complexity for decoding algorithms [7, 8].

In this paper, we propose a neuron selection method for identifying movement transitions in standing and squatting tasks based on the analysis of spike train data acquired in [6]. A nonparametric analysis of variance, Kruskal-Wallis test [9], was used to evaluate whether the average discharging rate of each neuron changed significantly among different movement stages, thereby categorize neurons according to their active periods. Selection was performed with neuron categorizing information. Finally, the average firing rates of selected neurons were assembled as feature vectors and a classifier based on support vector machines (SVM) was employed to discriminate different movement stages and identify transitions. The results indicate that our neuron selection

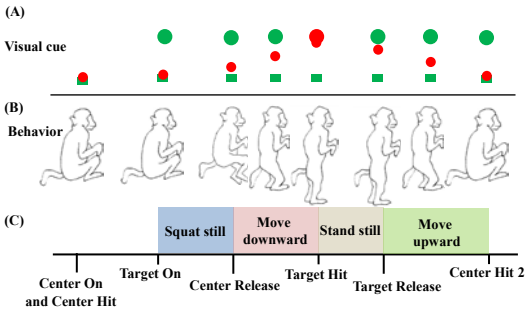

Figure 1. Illustration of behavior task procedure. (A) Visual cue sequence. A green box at the bottom represented center light. A red ball represented the marker attached on the ankle of the monkey. A green ball was shown as target object. (B) Behavior of the monkey in different motion stages. (C) Events and time intervals in a typical successful trial.

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method was accurate and efficient for identifying neurons correlated with movement transitions in standing and squatting tasks.

II. METHODOLOGY

A. Experimental Description

Two monkeys (Macaca mulatta, names: Hippie and Vivo) were trained to complete a series of visually guided stand and squat tasks on a special designed primate chair with a movable pedal in an experiment performed at Arizona State University (ASU). Visual cues were displayed as appearance and shifts of colored figures on a screen. A marker attached to the right ankle of the monkey was represented as a red ball onscreen.

Fig. 1 shows the procedure of the behavior task in a typical successful trial. A trial started with *Center On*, corresponding to the appearance of a green box on the bottom of the screen. To proceed, the monkey must squat properly and make the red ball touch the green box (*Center Hit*). A short time after *Center Hit*, a green ball emerged at the top of the screen (*Target On*) and the monkey was required to stand up and push down the pedal of the chair to move the red ball toward the target until their positions were matched (*Target Hit*). The onset of the lower limb motion during this phase was defined as *Center Release*. The monkey was trained to remaining standing for 400ms. Then, it was guided to retract both legs back (*Target Release*) and make the red ball move towards the center box. When the red ball touched the center box again (*Center Hit 2*), a trial was completed and the monkey was rewarded. Four typical movement stages could be extracted from a successful trial: (1) *Target on* to *Center Release* (TR), an interval during which the monkey squatted still; (2) *Center Release* to *Target Hit* (CH), during which the monkey moved its lower limbs downward; (3) *Target Hit* to *Target Release* (HR), during which the monkey stood still. (4) *Target Release* to *Center Hit 2* (TH2), during which the monkey moved its lower limbs upward. Abbreviations for these movement stages are listed in Table I.

TABLE I. ABBREVIATIONS FOR 4 MOVEMENT STAGES

Abbreviations	Time interval	Monkeys' state
TR	*Target On* to *Center Release*	Squat still
CH	*Center Release* to *Target Hit*	Move downward
HR	*Target Hit* to *Target Release*	Stand still
TH2	*Target Release* to *Center Hit 2*	Move upward

Five independent microdrivable electrodes (Thomas Recording) were inserted into the target areas corresponding to lower limb motor control in each monkey' s motor cortex. Cortical neural activities were recorded and pre-processed by a 64-channel neuron recording system (Plexon Inc., Dallas). After every 20-24 successful behavior trials (recorded as a set), the recording depth of each electrode was adjusted in order to approach neurons in different layers. The experiment paradigm and surgical procedures were approved by the Institutional Animal Care and Use Committee at ASU. Detailed description of the experimental apparatus, animal training, electrodes and data collection can be found in [6].

B. Neural signals processing and analysis

Neural potential waveforms from each electrode channel were processed using Offline Sorter (Plexon Inc., Dallas) to isolate a single neuron unit. For each recorded set, about 3~10 units were extracted. Each unit's average firing rate within TR, CH, HR, and TH2 was calculated separately. For each sorted unit, we investigated whether individual discharging patterns changed significantly during these intervals.

ANOVA (Analysis of Variance) was implemented as an easy tool for categorizing different neural activities. There are some prerequisites for ANOVA:

- Independence of observations – this assumption simplifies the statistical analysis.
- Normality – the distributions of the residuals are normal.
- Homogeneity of variances — the variance of data in groups should be the same.

However, the statistical features of spike train data violate these assumptions and some characteristics of data were missing from taking the ratio of recorded data when conducting ANOVA analysis [10]. Kruskal–Wallis analysis of variance is a non-parametric method for testing whether samples originate from the same distribution. It is used for comparing more than two independent or unrelated samples. Since it is a non-parametric method, Kruskal–Wallis test does not assume a normal distribution or homogeneity of variances, unlike its parametric equivalent ANOVA. These attributes accord with the statistic features of spike train data [9]. Due to fewer restrictions and a wider applicability, Kruskal-Wallis test could be an efficient method for detecting statistical changes of spike train among different time intervals related to certain behavior events.

Kruskal-Wallis test was applied to the datasets of neuron units' average firing rate within TR, CH, HR, and TH2. The null hypothesis was that a certain neuron's average firing rate followed the same distribution within these 4 intervals. The test statistic was given by:

$$H = \frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} - 3(N+1) \quad (1)$$

Where k was the sample number, namely the number of time intervals in this study. n_j ($j=1, 2 \ldots k$) was the sample size for the jth sample, namely the number of successful behavior trials in a dataset. $N=\Sigma^{n}_{j=1} n_j$. R_j was the sum of ranks for the jth sample. Since $H \sim \chi^2(k-1)$, for a given significance level α, if $H \geq \chi^2_{\alpha}(k-1)$ is true, the null hypothesis can be rejected. Thus the average firing rate of a certain neuron can be recognized as varying significantly between given motion stages. The Kruskal-Wallis test leads to significant results when at least one of the samples is different from the other samples. However, the test does not identify where the differences occur or how many differences actually occur. To overcome this shortcoming, we used multiple comparisons to determine during which paired intervals a neuron's discharging patterns

changed most significantly. When tests on all neurons were finished, we identified the active periods of each neuron and categorized them according to the test results. Data analysis programs were implemented in MATLAB (Mathwork Inc.).

TABLE II. NEURON SELECTION CRITERIA

Category number	Discharging rate changed during which two time intervals		Such neurons could be used for identifying:
1	TR	CH	Squatting still to start moving downward
2	CH	HR	Moving downward to standing still
3	HR	TH2	Standing still to moving upward
4	CH	TH2	Moving downward and moving upward

Neuron selection can be performed easily with categorized information. Our criteria of selecting neurons for decoding lower limb movement transitions are summarized in Table II.

The average firing rates within certain intervals of selected neurons were assembled as feature vectors for classification. An SVM classifier [11] was employed to discriminate different movement stages offline. Radial basis function was chosen as the kernel function of our SVM model in preference of its good learning performance and wider convergence region. The parameters of the kernel function were decided by N-fold cross validation. Both training and testing data set were selected randomly and normalized to the interval of [0, 1]. Neuron firing rate within 60 successful trials formed the training set and were divided into 4 parts to fulfill the cross validation. Another 60 successful trials formed the testing set. Lib-SVM [12] was adopted for SVM implementing.

III. RESULTS AND DISCUSSION

A. Neuron Categorizing

947 neurons were sorted from 94 datasets for monkey Hippie while 1011 neurons from 97 datasets for Vivo. Kruskal–Wallis test (α=0.05) and multiple comparisons were conducted on all sorted neurons. Table III summarizes the quantities of each neuron category in both monkeys.

TABLE III. THE QUANTITIES OF EACH NEURON CATEGORY AFTER KRUSKAL-WALLIS TEST AND MULTIPLE COMPARISONS

Category number	Discharging rate changed during which two time intervals		Quantities of neurons	
			Hippie	Vivo
1	TR	CH	424	486
2	CH	HR	229	261
3	HR	TH2	283	689
4	CH	TH2	368	618

From Table III, we can infer that there are neurons whose discharging patterns change within more time intervals, e.g., TR to CH and CH to HR. The complex linkage among neurons in motor cortex contributes to this phenomenon. Using the selecting method described above, the active stages of each neuron involved in lower limb motor control were identified.

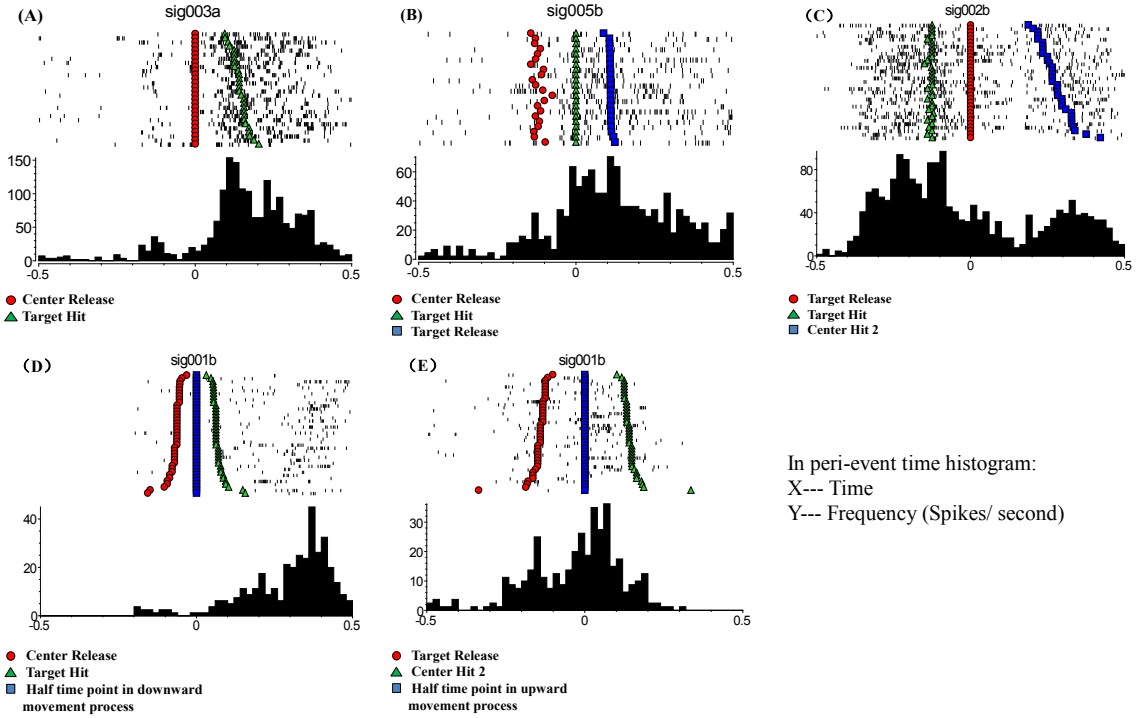

Figure 2. Peri-event raster and time histogram (bin size: 20ms) of 4 randomly selected neurons. In each peri-event raster, the relationship between spike timestamps and reference events in each successful trial is showed. The colored identifiers (circle, triangle and square) on peri-event raster subplots indicate certain event time point in each trial. (A) a neuron featured the transition from TR to CH; (B) a neuron featured the transition from CH to HR; (C) a neuron featured the transition from HR to TH2; (D)(E) a neuron which had different discharging patterns in downward and upward movement process. This neuron could be incorporated for discriminating downward and upward movement.

B. Validation of Neuron Selection

According to the results above, we randomly selected several neurons from each category and plotted the peri-event raster and time histogram to confirm the accuracy and reliability of our neuron selecting method, as shown in Fig.2.

The results in Fig. 2 show that the intuitive observations (peri-event raster and time histogram) of neuron activity match our categorizing method well. In Fig. 2 (A), the neuron's firing rate increased significantly after the event of *Center Release,* which featured the transition from TR to CH. In Fig. 2 (B), the neuron' s firing rate from *Target Hit* to *Target Release* was notably higher than that within the previous time interval, which featured the transition from CH to HR. Fig. 2 (C) shows a neuron which featured the transition from HR to TH2 with its firing rate decreasing dramatically after *Target Release*. Fig. 2 (D) (E) show a neuron identified by our categorizing criterion, which discharged quite differently in downward and upward movement processes. Furthermore, the peri-event histogram indicates this neuron was more active within upward movement. Obviously, this neuron can be incorporated in our study for discriminating upward from downward movement.

TABLE IV. CLASSIFYING ACCURACY WHEN INCORPORATING 4, 8, AND 16 SELECTED NEURONS' DISCHARGING RATE DATA IN SVM CLASSIFIER

Movement transitions		**Hippie**		**Vivo**	
		Neurons number	**Accuracy**	**Neurons number**	**Accuracy**
TR	CH	4	90.00%	4	63.00%
		8	92.50%	8	90.00%
		16	100%	16	100%
CH	HR	4	90.00%	4	63.00%
		8	87.50%	8	71.67%
		16	100%	16	90.00%
HR	TH2	4	95.00%	4	87.00%
		8	100%	8	85.00%
		16	100%	16	100%
CH	TH2	4	87.50%	4	87.00%
		8	87.50%	8	87.00%
		16	100%	16	93.00%

C. Movement Transition Classification

The accuracies of various movement transition discriminations with SVM classifier are summarized in Table IV. For comparison, we incorporated different numbers of neurons to form feature vectors. The neurons were chosen randomly within their corresponding category.

The results in Table IV suggest that neuron selection before classification can contribute to the performance of movement transition identification. Incorporating neurons without delicate selection, given the large size of the neuron dataset, would be foolhardy and decoding accuracy may be undermined. The results suggest that incorporating more neurons to form larger feature vectors may improve classifying accuracy at the cost of more temporal delay and memory consumption. Thus the trade-off should be carefully considered before implementation.

IV. CONCLUSION

In this study, we analyzed the spike train data correlated with lower limb motor control in standing and squatting tasks. Considering the absence of normality and homogeneity of variances in the spike train data, we applied the Kruskal-Wallis test to evaluate whether the average discharging rate of each neuron changed significantly among different motion stages and to categorize neurons according to their active periods. Neuron selection was accomplished based on category information and a SVM classifier was used to discriminate different movement stages.

The results indicate that our neuron selection method was accurate and efficient in finding neurons correlated with movement transitions in standing and squatting tasks and that such transitions can be identified accurately with the selected neurons' spike train data. Further application of our method in neural controlled lower limb prostheses may be feasible.

Future work includes applying the neuron selection method proposed in this paper on chronically recorded neural datasets and developing on-line decoding algorithms.

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