Predicting Hand Orientation in Reach-to-grasp Tasks Using Neural Activities from Primary Motor Cortex

Peng Zhang, Xuan Ma, *Student Member, IEEE*, Hailong Huang, Jiping He, *Senior Member, IEEE*

***Abstract*—Hand orientation is an important control parameter during reach-to-grasp task. In this paper, we presented a study for predicting hand orientation of non-human primate by decoding neural activities from primary motor cortex (M1). A non-human primate subject was guided to do reaching and grasping tasks meanwhile neural activities were acquired by chronically implanted microelectrode arrays. A Support Vector Machines (SVMs) classifier has been trained for predicting three different hand orientations using these M1 neural activities. Different number of neurons were selected and analyzed; the classifying accuracy was 94.1% with 2 neurons and was 100% with 8 neurons. Data from highly event related neuron units contribute a lot to the accuracy of hand orientation prediction. These results indicate that three different hand orientations can be predicted accurately and effectively before the actual movements occurring with a small number of related neurons in M1.**

I. Introduction

Brain-Machine Interface (BMI) is a promising way to restore voluntary movements and somatosensory sensations in paralyzed patients and amputees. In a BMI system, motor commands can be recorded and decoded through electrodes in the brain to control an advanced artificial limb and sensory sensations can be restored by intracortical microstimulation (ICMS) on neural tissues almost simultaneously. Sophisticated hand control is a peculiar characteristic of higher primates and the hands play a central role in interacting with the world, so restoring the functions of upper limbs is a main objective in BMI researches. Reaching and grasping are two basal functions of upper limbs and their executions need engage many cortical areas. Among these areas, primary motor cortex (M1) plays a central role[1] and electrical stimulation of small regions or even single neurons in M1 can facilitate the movements of upper limb[2, 3]. Using neural population activity in primary motor cortex (M1), researchers reconstructed continuous 2D and 3D arm and hand position [4-7]. Andrew Schwartz et.al showed that monkey with both arms restricted can learn to use these signals to control a robotic arm for self-feeding[8]. Further, L. R. Hochberg reported successful applications of BMI in human[9, 10]. Two people with tetraplegia can control a robotic arm to perform three-dimensional reaching and grasping movements through BMI.

The achievements above showed great promise for restoring motor functions of upper limb by BMI, but improving accuracy and effectiveness is still quite significant in BMI researches. Neuron selection is an efficient path to improve BMI performance[11] and computational complexity of decoding algorithms can be decreased by incorporating only task-related neurons.

In this paper, we present a study for predicting hand orientation of non-human primate by decoding neural activities from M1. A non-human primate subject was guided to do reaching and grasping tasks meanwhile neural activities were acquired by chronically implanted microelectrode arrays. A nonparametric analysis of variance, Kruskal-Wallis test[11], and a task-related analysis[12] were employed to evaluate correlation between neuron units and hand orientations. Base on the above results, different number of related neurons were selected to predict hand orientation using SVM based method[13]. The results indicate that hand orientation can be predicted accurately and effectively with only a small number of related neurons.

II. Methods

All the experiments and surgical procedures relating to this study were approved by the Institutional Animal Care and Use Committee at Huazhong University of Science and Technology.

A. Animal

One male Rhesus macaques, weighing 8.0 Kg and 5 years of age, was used in these experiments.

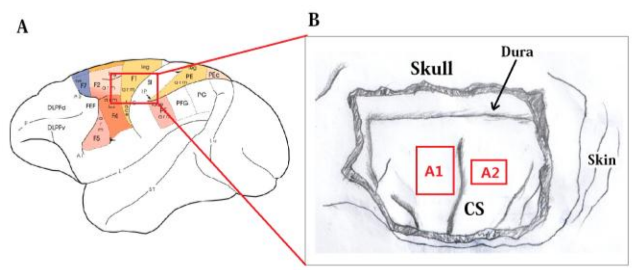

Fig.1. The area for FMAs implantation. A) Lateral view of the frontal motor cortex (left hemisphere). B) Top view of the target area after craniotomy. A1 was the area for the 2 FMAs in M1. A2 was the area for the FMA in S1

* Resrach supported by National Natural Science Foundation of China (61233015), and 973 Project of China (2013CB329506).

Peng Zhang, Xuan Ma are with the Neural Interface & Rehabilitation Technology Research Center, Huazhong University of Science and Technology, Wuhan, China.

Hailong Huang is with the Department of Rehabilitation Medicine, Tongji Hospital, Tongji Medical College, Huazhong University of Science and Technology, Wuhan,China.

Jiping He is with the Center for Neural Interface Design, Harrington Department of Bioengineering, Arizona State University, Tempe, AZ 85287, USA. He is also with the Neural Interface & Rehabilitation Technology Research Center, Huazhong University of Science and Technology, Wuhan, China (phone: +86-27-87793916; fax: +86-27-87793916; e-mail: jiping.he@asu.edu).

B. Electrode Array Implantation

The animal was implanted with three Floating Microelectrode Arrays (FMA, Microprobes, Inc.) in the left brain hemisphere. Two FMAs were implanted in the arm and hand representations of M1 and the other one was implanted in the primary somatosensory cortex (S1) corresponding to hand sensing, as shown in Fig. 1.

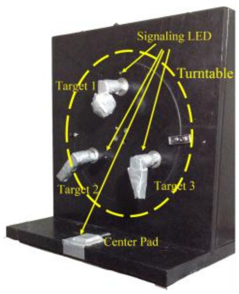

Fig.2 The experimental apparatus. The apparatus mainly contained a center pad in the below and three target objects with different shapes (ball, cuboid, and pyramid) on the front panel. Each target object had three orientations (45°, 90°, 135°) and three positions(top, left bottom, right bottom). The orientation and position of target objects can be quickly switched according to different task requirements.

C. Behavior Tasks

The monkey was comfortably seated in a primate chair with its left arm restricted and performed spatial reaching and grasping tasks with its right hand guided by a home-made experimental apparatus. The experimental apparatus is shown in Fig.2 and details can be viewed in[14].

The tasks were mainly guided by the LEDs in the experimental apparatus and the sequence of the tasks is shown in Fig.3. Each trial began with a cueing of center light on, instructing the monkey to fixate on the center pad. After a center holding time (CHT) of 500ms, the center light went out meanwhile one arbitrary target light went on, cueing the monkey to reach for the corresponding target and make a whole-hand grasp contacting both sides of the object. After a target holding time (THT), the target light went out. The monkey would return the hand and a reward of a few drops of water would be delivered. This was a successful trial and then a new trial would begin. If the monkey broke fixation during the center pad holding or grasped the wrong target, the trial was aborted, and a new trial would begin. The orientation of each target object was adjusted in pseudo-random order among 3 values (45°, 90°, 135°) with equal probability in every five or six successful trials.

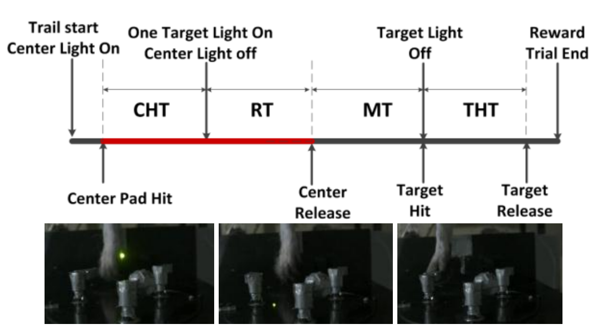

Fig. 3 Top: the sequence of events for the behavior task and the trial epochs. Bottom: pictures of "Center pad hit", "Center release" and "Target hit".

D. Data Recording and Analysis

Neural signals were recorded through the FMAs by OmniPlex system (Plexon, Inc.) when the monkey performed behavior tasks. For each channel, neural signals were amplified (gain 20,000×), bandpass filtered between 250 and 6 kHz, and digitized at 40 kHz. Then a threshold crossing method was employed to mark the occurrences of action potentials (spikes). Neural signals were saved to the hard drive disk in real-time with behavioral event time points. To isolate single neuron units of each channel, neural signals were spike-sorted offline using Offline Sorter (Plexon, Inc).

In this paper, we mainly analyzed signals from the two FMAs implanted into the M1 to predict the monkey's hand orientations. Hand orientation depends on the shape and orientation of objects during reach-to-grasp task[15, 16] and this also can be seen in Fig.4. To accurately analyze the relationship between target orientation and neural activity, the dataset used in this study was acquired from tasks which target position and target shape were constant but target orientation was changed. Table 1 shows the details of behavior dataset used in this study.

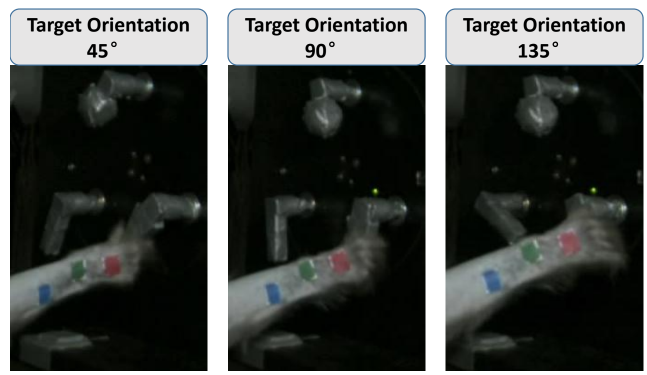

Fig. 4 The monkey grasped target with different orientations. Different hand orientation was performed when the monkey grasped target with different orientations.

From Fig.3 we can see that each trail was divided into four behavioral epochs: center holding time (CHT), cue reaction time (RT), movement time (MT) and target holding time (THT). In the CHT, the monkey fixated hand on the center pad without movements or movement intentions and the neural activities in this epoch were considered as a baseline. In the RT, even still no actual movements occurred, the monkey was preparing for upcoming actions and the relevant neurons began discharging. So the neural activities in the CHT and RT which were marked red in Fig.3 were suitable for extracting movement intention and were chosen to decode hand orientation in this paper.

A non-parametric analysis of variance (Kruskal-Wallis test)[11] was used to evaluate whether changes in the average firing rate of each isolated neuron unit in RT were significantly modulated by target orientation. Then a task-related analysis[12] was applied to test the correlation between neuron units and behavior events. The firing rates during CHT were considered as the baseline firing rates. We defined a neuron unit as a task-related unit if its average firing rates within the RT was at least 2SDs greater than its baseline firing rate. Based on the results of Kruskal-Wallis test and task-related analysis, neuron units were categorized and selected to be incorporated into the classifier.

An SVM classifier was employed to map neural signals to a specific target orientation. Spike counts in a time period of 300ms after the Target Light On event (this period is similar with RT) have been extracted from selected neuron units. In particular, spike counts were extracted from each unit in each trial using fixed analysis windows of 50ms which progressively slid over the reference period with a moving step of 50ms to form input vectors. Normalization was done with respect to the maximum spike counts among all trials. Radial basis function was chosen as the kernel function of our SVM model for its good performance and the parameters of the kernel function were decided by 6-fold cross validation. The neuron activities recorded during the behavior tasks were labeled in 3 categories corresponding to three levels of target orientations and used as training or testing data set for the classifier. 19 trials randomly selected from each category were used to train the classifier and the remaining trails were for testing. Different number of neurons were chosen within their corresponding category and used to compare the influence of neuron selection in hand orientation predictions. Data analysis programs were implemented in MATLAB (Mathwork Inc.).

TABLE I. BEHAVIOR DATASET

Target Position	Target Shape	Target Orientation	The number of trails (For training /For testing)
right bottom	pyramid	45°	39 (19/20)
right bottom	pyramid	90°	42 (19/23)
right bottom	pyramid	135°	44 (19/25)

III. RESULTS

A. Behavior Results

In this dataset, the monkey performed totally 125 successful trials and the average reaction time and movement time are shown as Table II. The average RT was more than 300ms, so the time period of 300ms after the Target Light On event which was used to extract spike counts for the SVM classifier was appropriate. Using this time period we can predict hand orientation before the actual movement occurring.

TABLE II. AVERAGE REACTION TIME AND MOVEMENT TIME

Reaction time(sec)	45°	0.3168
	90°	0.3682
	135°	0.3988
Movement time(sec)	45°	0.2895
	90°	0.2923
	135°	0.4202

B. Neuron Units Categorizing

78 neuron units were sorted from this dataset. Kruskal–Wallis test (α=0.05) and task-related analysis were conducted on all sorted neurons. Table III summarizes the quantities of each neuron category in three orientations. Maybe it was because the locations of electrodes were just in the relevant area corresponding to hand and arm movement; most of the neurons were task-related and modulated by target orientation.

TABLE III. THE QUANTITIES OF EACH NEURON CATEGORY

Category number	Target Orientation	Quantities of neurons
1	45°	65
2	90°	70
3	135°	63

Fig.5 shows perievent histograms of 2 exemplary units in such category. The three columns correspond to three levels of target orientations. Each raster illustrates the firing pattern of the unit during 39 trials of reaching and grasping a target with specific orientation. The two units discharged sparsely during the CHT, but discharged frequently just before the event of center release indicated that the units were related to the task. The significant changes of firing pattern in RT among different target orientations indicated that the units were modulated by target orientation.

C. Movement Intentions Prediction

Table IV summarized the accuracies of various target orientation predictions with SVM classifier. When 2 neurons were selected, the accuracy of target orientation prediction was 94.1%. More neurons were selected, higher accuracy can be achieved. When 8 neurons were selected, the accuracy can be 100%. These results suggest that neural selection before classification can contribute to the performance of target orientation prediction and more neurons may get higher classifying accuracy. But increasing the number of neurons may not always be appropriate, computing time and memory consumption should be considered too. Moreover, 2 neurons can get the accuracy of 94.1% and this accuracy may have met demands of some situations.

TABLE IV. CLASSIFYING ACCURACY WITH DIFFERENT NUMBER OF NEURONS IN SVM CLASSIFIER

Target Orientation	Neurons number	Accuracy
45° **90°** **135°**	2	94.1%(64/68)
	4	98.5%(67/68)
	8	100%(68/68)

IV. DISCUSSION

Reach and grasp are two basic functions of upper-limbs and hand orientation is an important component of grasping function. In this paper, an SVM classifier has been used to predict different hand orientations from the activity of M1 motor neurons during reach to grasp tasks. Different number of neurons and a time period of 300ms after the Target Light On event were selected and analyzed; the classifying accuracy was 94.1% with 2 neurons and was 100% with 8 neurons using window width of 50ms. Data from highly event related neuron

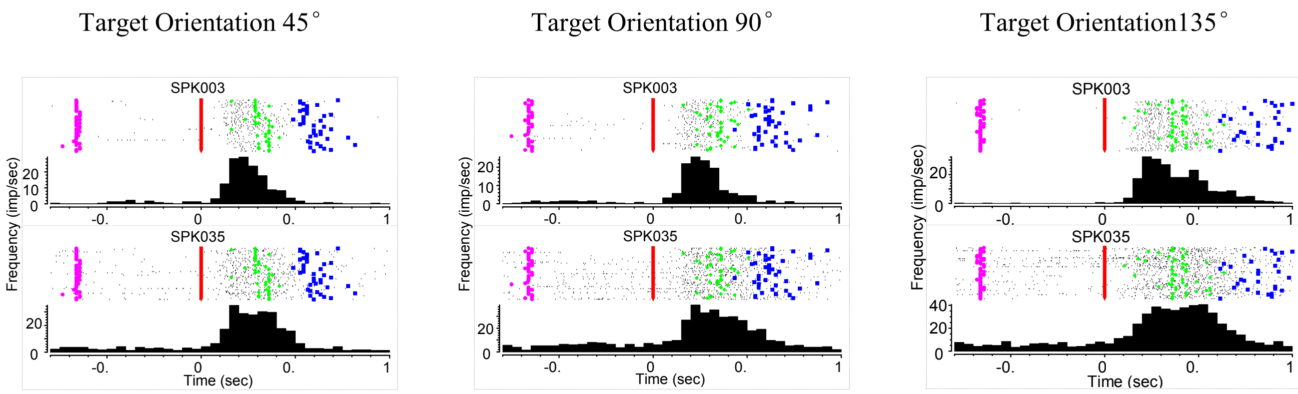

Fig. 5 Peri-event raster and histograms (bin: 50ms) of 2 exemplary units encoding hand orientation during reaching and grasping the targets oriented at three different angles. Time zero is aligned at Target On (the onset of RT and indicated by red dot in the figure) . Purple dot indicated the event of Center Pad Hit; green dot indicated the event of Center Pad Release; blue dot indicated the event of Target Hit.

units contributed a lot to intention prediction accuracy. These results indicate that three different hand orientations can be predicted before the actual movements occurring with a small number of neurons. Accuracy of 100% can be achieved by selecting 8 neurons while there are still about 60 other neurons which also are task-related not be selected. These "redundant" neurons may also modulate the hand orientation, because the hand orientation decoded in this task is discrete but it changed continually in actual movements. These neurons may modulate hand orientation of different angle in different time during the reach to grasp tasks or these neurons are just redundant to ensure the stability of movements.

In this work only fixed window width of 50ms was used in the SVM classifier, selection of different time windows or other parameters may further enhance the performance of orientation prediction. There are another two factors (target position and target shape) in the behavior tasks need to be decoded and future work will focus on the two factors and develop on-line neural decoding algorithms for reaching and grasping activities.

Acknowledgment

The study is supported by National Natural Science Foundation of China (No. 61233015) and China 973 Project (No. 2013CB329506). This study has received kind and generous supports from *Neural Interfaces and Rehabilitation Technology Research Center* of *HUST* and *Experimental Animal Center* of *Wuhan University*. Authors wish to express sincere thanks to Dr. Wei Jiang, Dr Mingbo Nie in Tongji Hospital, Wuhan for their devoting to monkey surgery.

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