A Study of Predicting Movement Intentions in Various Spatial Reaching Tasks from M1 Neural Activities

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***Abstract*—Understanding how M1 neurons innervate flexible coordinated upper limb reaching and grasping is important for BMI systems that attempt to reproduce the same actions. In this paper, we presented a study for exploring M1 neuronal activities while a non-human primate subject was guided to finish different visual cued spatial reaching and grasping tasks. By applying various configurations of target objects in the experiment paradigm, we can make thorough investigations on how neural ensemble activities represented subjects' intentions in different task-related time stages when target objects' properties, including shape, position, orientation, varied. Extracted neuron units were categorized according to their event related attributes. The prediction of subjects' movement intentions was completed with a support vector machine (SVM) based method and a simulated on-line test was performed to illustrate the validation of the proposed method. The results showed that, by M1 neural ensemble spike train signals, correct prediction of subject's intentions can be generated in certain time intervals before the movements were actually executed.**

I. INTRODUCTION

With the progress in Brain Machine Interface (BMI) related research, developing cortically controlled neural prosthetics for amputees or paralytics to regain upper extremity functions has become feasible. The ultimate goal of BMI is to create direct links between the nervous system and the external world by decoding neural signals to understand subjects' intentions [1]. Understanding how neurons in Primary motor cortex (M1) innervate flexible coordinated upper limb reach and grasp is important for implementing BMI systems that attempt to reproduce the same actions by decoding neuronal activities. Earlier studies investigated the neuronal firing patterns when the subjects were trained to reach different planar or spatial target in some typical tasks like Center Out [2]. More studies have demonstrated the feasibility of extracting several motor parameters during reaching and grasping process from the neural activities on non-human primates [3, 4]. Further, the success of a series of studies on neuronal ensemble control of prosthetic devices by human with tetraplegia [5, 6] have demonstrated the possibility for applying BMI on human subjects.

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BMI requires different forms of control commands. Both real-time estimation of arm/hand movement trajectories and discrete prediction of subject's movement intentions can provide important information for BMI systems. In [7], parametric and nonparametric classifiers were tested to assign individual trial responses to discrete direction classes based on neural ensemble data from M1 and premotor areas. In [8, 9], support vector machine (SVM) and Naïve Bayesian classifier were applied to detect rats' moving intentions and the SVM method outperformed in accuracy.

In this paper, we presented a novel study for exploring M1 neuronal activities while a non-human primate subject was guided to finish various visual cued spatial reaching and grasping tasks. Compared to previous work, our task design allowed more factors, including target positions, orientations, and shapes, to be taken into the analysis of neural activities jointly or separately. Within the experimental platform presented here, we can thoroughly investigate how M1 neural ensemble characterized the subject's movement intentions when it tried to reach designated target objects at different spatial positions as the visual cue launched and to form appropriate hand orientation and posture in grasping preparation period. After categorizing neuron units according to their event related attributes, we performed discrete prediction of subject's movement, which was completed with an SVM based method, and a simulated on-line test was performed to illustrate the validation of the proposed method.

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.

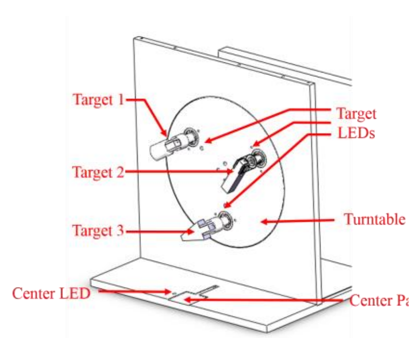

Fig.1 The experimental apparatus. 3 target objects with different shapes (ball, cuboid, and pyramid) were fixed on a turntable mounted on the front panel, and were driven by servo motors, with which their orientations can be quickly switched according to different task requirement. The position of the targets can be varied by adjusting the turntable.

A. *Behaviour Experiment*

A well-trained adult male Rhesus monkey (macaca mulatta) was guided to perform spatial reaching and grasping tasks. The monkey was comfortably seated in a primate chair in front of the experimental apparatus with its left arm restricted. The experimental platform is shown as Fig. 1, and details can be viewed in our previous publications [10].

The sequence of events for guiding the monkey to perform the tasks are shown in Fig. 2. Each movement trial started with a cueing of center LED on, instructing the monkey to place its hand on the center pad. After a fixed center holding time of about 500 ms, the light corresponding to an arbitrary target object was lit, cueing the monkey to release the central holding pad and reach for the corresponding target and make a whole-hand grasp contacting both sides of the object. When the monkey grasped the object firmly using a powerful grip and made contact with both sensors attached on the object, a successful trial occurred. Before the allowed movement time expired, the object light went off, indicating a successful trial. Then the monkey received a few drops of water as reward and returned its hand to the central holding pad to wait for the next trial. 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. The 3 target LEDs were also presented in pseudo-random order with equal probability. The time interval between *Target Light On* and *Center Pad Release* was defined as reaction time (RT) and that between *Center Pad Release* and *Target Hit* was defined as movement time (MT).

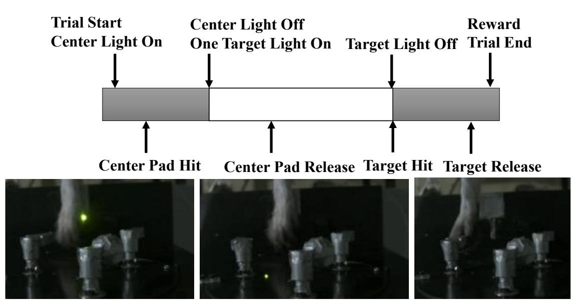

Fig. 2 Top: the sequence of events for guiding the monkey to perform the task and the trial epochs. Bottom: pictures of different stages in reaching and grasping movement.

B. *Neural Signal Recording and Pre-processing*

3 identical 32-ch Floating Microelectrode Arrays (FMA, Microprobes Inc.) were chronically implanted into the monkey's left brain hemisphere, 2 in the primary motor cortex (M1) arm/hand area [11] and 1 in the primary somatosensory cortex (S1), as shown in Fig. 3.

Neural signals were acquired by OmniPlex D (Plexon Inc.), a 128-channel neural data acquisition system (gain: 2×10^4, sampling rate: 40 kHz/channel). After passing a 250 Hz~6 kHz band pass filter, occurrences of spikes were marked by a threshold crossing method. Spike waveforms were sorted using Offline Sorter (Plexon Inc.) to isolate neuron unit. For every channel, about 1~5 units were extracted. Arm/hand movements and 3D trajectories of a marker on the monkey's hand were recorded by CinePlex (Plexon, Inc.), a video based motion capture system (4 cameras, sampling rate: 80 Hz).

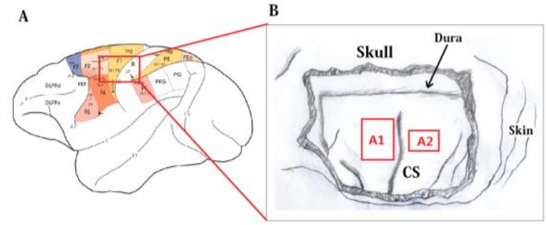

Fig. 3. The area for FMAs implantation. A) Lateral view of the frontal motor cortex (left hemisphere). B) Top view of the target area after craniotomy. A1 was the area for the 2 FMAs in M1. A2 was the area for the FMA in S1.

C. *Movement Intentions Prediction*

Here we demonstrate the method of predicting the monkey's movement intentions to reach different target positions in 3D space with M1 spike train data during RT.

On our experimental platform, thorough investigations on how neural ensemble activities represent subject' intentions by applying different configurations of the target objects and assignments of task sequences. Among the datasets, 2 in sequenced days were chosen for analyzing and here we only focused on the data from the 2 FMAs in M1 area. In these datasets, the 3 target objects were fixed at certain positions (cuboid: top, pyramid: bottom left, ball: bottom right); the monkey performed 30~40 successful trials for each orientation (45°, 90°, 135°) of each object. A non-parametric analysis of variance (Kruskal-Wallis test) [12] was applied on the datasets to test whether each isolated neuron units' firing rate during RT have significant difference when the monkey performed different reaching movements. Based on the results of Kruskal-Wallis test, neuron units were categorized according to their active period and event related attributions and divided into different subsets. The advantage brought by this step was that, with the categorized information, we can only incorporate highly task-related neuron units into the classifier input to improve its performance.

During RT, no actual movement occurred but the monkey was preparing for upcoming actions. We proposed an SVM based method [13] to map the M1 neural signals during RT to a specific movement direction (top, bottom left, or bottom right), ignoring the factors of orientation and shape. Because during RT, hand orientation and grip type for grasping has not formed and the movement intention was mainly related to target positions. Spike counts binned in a sliding 200 ms window incremented in 50 ms steps were used to form input vectors. The structure of input vectors is shown as Fig. 4.

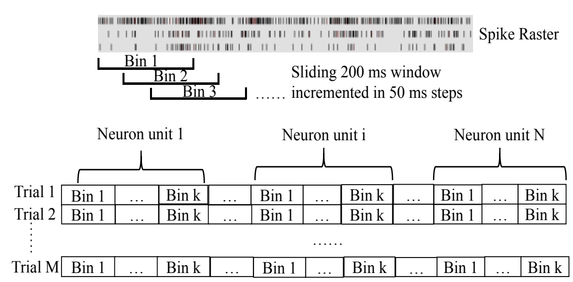

Fig. 4. The structure of input vectors for SVM

Each row in the input vector corresponded to a successful trial and can be written as:

$$\{r_{11},\ldots,r_{1k},\ldots,r_{i1},\ldots r_{ik},\ldots,r_{N1},\ldots r_{Nk}\} \quad (1)$$

In (1), r_{ik} denotes the spike counts of the i th neuron unit in the k th bin after the visual cue launched. N denotes the total number of units incorporated into the vectors. The value of N and k can be varied to observe the performance changes.

Radial basis function was chosen as the kernel function of our SVM model. The parameters of the kernel function were decided by 6-fold cross validation. The training set consisted of 150 successful trials in 3 classes, corresponding to the 3 possible intended directions. When finishing model training, a simulated online test was implement to test the performance of the proposed model. In this test, neural data was read from file to the workspace of MATLAB (Mathwork Inc.) sequentially to simulate the time flow in reality.

III. Results

A. Behaviour Results

In the 2 datasets from 2 sequenced days, the monkey performed totally 325 successful trials, 30~40 for each orientation of each target object. The average reaction time and movement time are shown as Table I.

TABLE I. AVERAGE REACTION TIME AND MOVEMENT TIME

Reaction time	Bottom left	0.379
	Bottom right	0.395
	Top	0.421
Movement time	Bottom left	0.357
	Bottom right	0.377
	Top	0.519

Average trajectories of the distal part of the upper limb across different trials were calculated, as shown in Fig. 5.

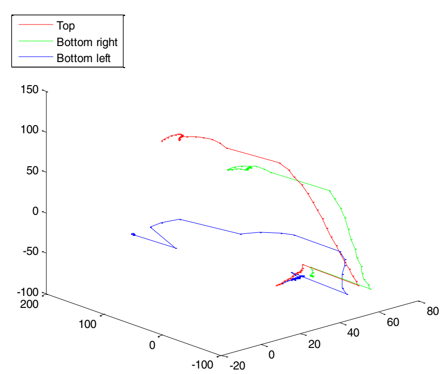

Fig. 5. Average trajectories of the distal part of the upper limb in 3 directions reaching movements (mm).

B. Neuron Units Categorizing

70 and 71 neuron units were isolated from the 2 FMAs in M1 area in each of these 2 datasets. 31 and 28 neuron units' firing rate during RT showed correlation to different directions, ignoring the factors of orientation and shape.

Peri-event raster and histograms of 2 typical units in such category are shown as Fig. 6. The figures were aligned on the onset of the cueing signal (Target On). In Fig.6, the firing pattern during RT of both the units (SPK 044b and SPK 042a) showed significant change when the monkey prepared to reach target at different positions.

C. Movement Intentions Prediction

Based on the neuronal categorizing information above, we incorporated 8, 16, 24 neuron units (N=8, 16, 24) in the input vectors for comparison. In each case, we also tested the performance of SVM when incorporated first 3, 6, 8, 10 bins (k=3, 6, 8, 10) into the input vectors. The accuracy for prediction in simulated on-line tests are shown as Fig. 7. The results indicated that data from earlier bins after the launch of visual cue contributed to the right classifying less than later bins. With only the first 3 bin data in RT, the accuracy was still quite low even incorporating more neuron units. Further, we tested the classifier's performance in situations when removing first several bins from input vectors and the results are shown as Fig. 8 (k=8~10, k=5~10). The results indicated that when using data from bins 5~10 in after visual cue launched, the movement intention prediction accuracy was quite close to that when using first 8 bins or 10 bins.

IV. Discussion

In reaching and grasping tasks, when visual cue was launched, the subject will make certain decision to control its arm/hand to reach the correct position. Meanwhile, the subject will adopt different postures (hand orientation, grip type) in order to make an effective grasp on target object after the initiation of movement. Such processes were characterized by certain neuronal activities. In cortical motor system, premotor cortex is responsible for movement planning while M1 neurons are related to movement execution. Final motor commands are delivered to muscle-skeleton system through neural pathways between spinal cord and cortical cortex. In fact, there is a time delay of about several hundred milliseconds between M1 neurons activation and actual movement initiation. So by characterizing the firing pattern of M1 neural ensemble with certain features and employing appropriate methods to perform classifying, correct prediction of subject's intentions before movement execution can be generated. The results in Fig. 7 and Fig. 8 proved the validation of our method. Moreover, these results also indicated that later bins in RT may contain more target direction related information while in first several bins, less M1 units were activated. Fig. 8 indicated the existence of redundancy in input vectors as Fig. 4. Potential method like Principle Component Analysis (PCA) can be applied to reduce the input dimensions.

With the platform described in part II, we can actually make thoroughly investigations on how M1 neurons innervate movement directions, arm/hand postures in reaching and grasping. In this paper, only a part of work was finished. But according to the methods and results above, a preliminary framework for movement intention prediction can be drawn. Data from highly event related neuron units contribute a lot to the accuracy of intention prediction. A calibration epoch is required for constructing classifying models using these data.

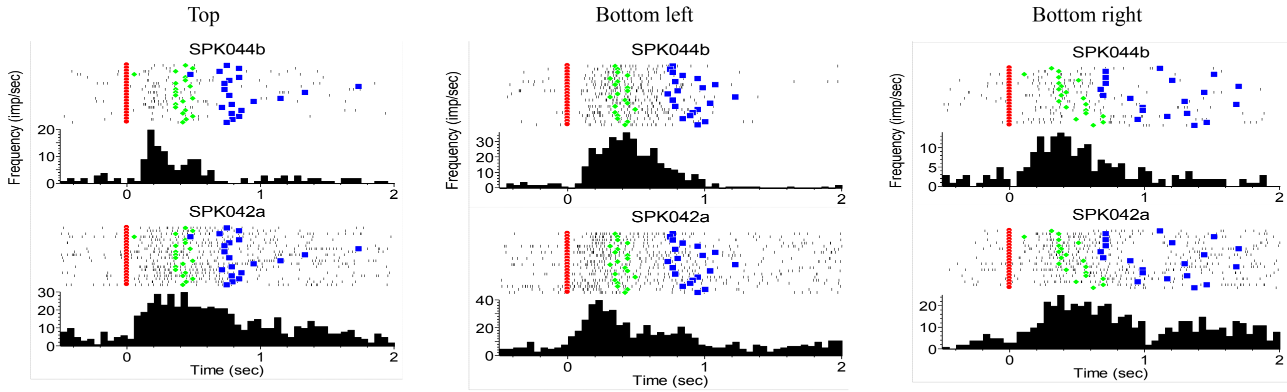

Fig. 6 Peri-event raster and histograms (bin: 50 ms) of 2 typical units whose firing rate pattern in RT changed significantly when the monkey prepared to reach targets at different positions. X: time (s), Y: Frequency (Spikes/second). In the figures, red dots indicated the onset of the cueing signal (Target On); green dots indicated the event of Center Pad Release; blue dots indicated the event of Target Hit.

Finally, well trained models are applied to conduct the intention prediction online.

In this work, only target position related information were used. Although we proposed that M1 neural activities during RT may be too earlier for predicting final postures of grasping, future work will still build more detail categorizes on recorded neuron units. Since the orientation of hand varied with time in the whole reaching and grasping process, final hand postures in grasping may be more correlated with neural activities in MT. We will also investigate the dynamic changes of neural activities from RT to MT.

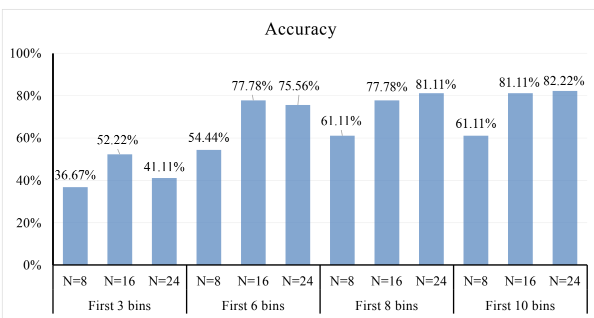

Fig. 7 SVM classification accuracy comparison when N and k were in different values in simulated online tests.

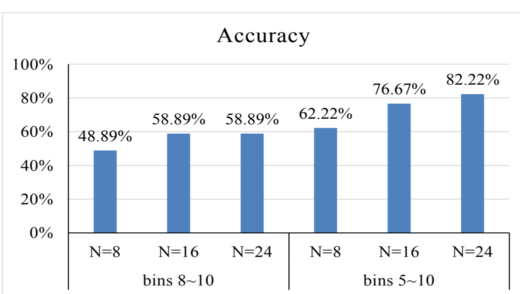

Fig. 8 SVM classification accuracy comparison when removing first several bins from input vectors. (k=8~10, k=5~10) in simulated online tests

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