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Decoding Grasp Types with High Frequency of Local Field Potentials from Primate Primary Dorsal Premotor Cortex*

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Abstract—**Recently, local field potentials (LFPs) have been successfully used to extract information of arm and hand movement in some brain-machine interfaces (BMIs) studies, which suggested that LFPs would improve the performance of BMI applications because of its long-term stability. However, the performance of LFPs in different frequency bands has not been investigated in decoding hand grasp types. Here, the LFPs from the monkey's dorsal premotor cortices were collected by microelectrode array when monkey was performing grip-specific grasp task. A K-nearest neighbor classifier performed on the power spectrum of LFPs was used to decode grasping movements. The decoding powers of LFPs in different frequency bands, channels and trials used for training were also studied. The results show that the broad high frequency band (200-400Hz) LFPs achieved the best performance with classification accuracy reaching over 0.9. It infers that high frequency band LFPs in PMd cortex could be a promising source of control signals in developing functional BMIs for hand grasping.**

I. Introduction

Brain machine interfaces (BMIs) could directly extract movement information from the neural activities of motor cortex and help the paralyzed patients to restore their lost motor functions. Hand grasping, one of the commonly used motor functions, is the most important for people to interact with the environment in daily life [1]. Harnessing the cortical motor-related activities to control robotic hand for restoring grasp motion is still particular challenging. Recently, some research groups in BMI have demonstrated different grasp types can be successfully classified from single unit activities (SUAs) [2, 3, 7]. However, most SUAs will gradually decay and disappear over one or two years later after the electrodes are implanted, which greatly limits the implementation of BMIs in grasp reconstructing. Compared with SUAs, local field potentials (LFPs) are likely more stable and can be recorded for a longer time [4]. Therefore, it is worthwhile to investigate the decoding power of LFPs for improving neural control of grasping.

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In the recent years, many studies have reported the representation of low-frequency band LFPs of object-specific grasp movement. Spinks *et al.* investigated low-frequency bands of LFPs (<50 Hz) from primary motor cortex (M1) and F5 and revealed high selectivity of the beta-frequency range during stable holding periods of grasping [5]. Asher *et al.* found that low-frequency LFPs (<100Hz) from posterior parietal cortex were also selective to different grasp types, despite that they are less informative than spike signals [6]. Similarly, low-frequency LFPs recorded from dorsal premotor cortex (PMd) and ventral premotor area (PMv) were used to discriminate two grasp types and an accuracy of 73% was achieved [7]. All these studies were focused on low-frequency components of LFPs. Although Zhuang and Bansal *et al* showed that grasp aperture can be decoded successfully from LFPs within 200-400 Hz [8, 9], no study had been reported to use high-frequency LFPs to decode grasp types to our knowledge. Without the knowledge about the relationship between grasp types and all frequency components of LFPs, it is hardly possible to take full advantage of such informative signals.

Therefore, this paper focuses on revealing the decoding power of high-frequency LFPs on grasp types. We designed an experimental paradigm, in which a monkey was instructed to perform grasping tasks with four distinct hand gestures, and meanwhile LFPs were recorded from the PMd of the monkey. The patterns of low and high-frequency bands of the LFPs were analyzed and clear selectivity to grasp types was observed for both bands. Then we tested the decoding performance of individual frequency bands and found that the broad high (200-400 Hz) frequency band significantly outperformed other frequency bands. The average classification accuracy was over 90%, which had not been achieved in previous publications.

II. Materials and Methods

A. Behavioral Task and Data Acquisition

In the experiment, one adult male *Macaque mulatta* monkey was trained to grasp one of four objects with different shapes using his right hand following visual cues from the central location of the objects. The experimental paradigm was shown in Figure1A. Four objects used in the experiment were plate, cone, cylinder and ring respectively in Figure1B. Before the experiment, the monkey was given limited water. During the experiment, the monkey was seated on a chair in a dark room with his head restrained to face the four objects. At

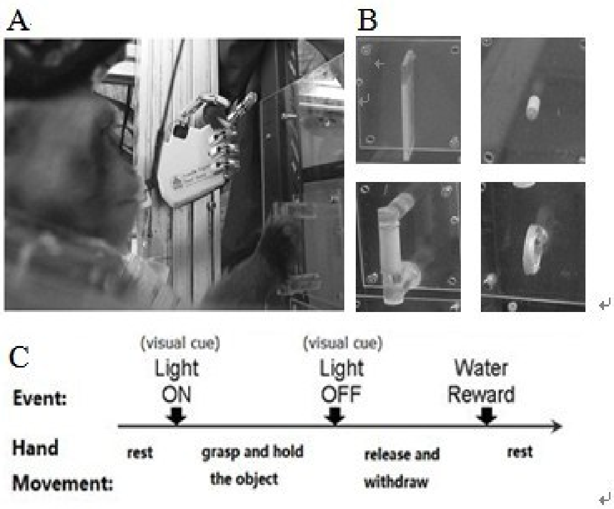

Figure 1. The grasping movement under visual cues of four differently shaped objects. (A) Monkey grasped objects according to the visual cue, at the same time, LFP signals were recorded from PMd cortex. (B) The four typical shaped objects, which were cylinder, plate, ring and cone respectively. (C) Experimental procedure of a trail in details, lasting about 4s.

the beginning of a trial, his hand was off the object. Once the visual cue , which is the background light of an object, was on (Light ON) , the monkey was required to grasp the corresponding object for 3 to 4 seconds, and then put its right hand back when the visual cue was off (Light OFF). The monkey could obtain drops of water as reward at the end of a successful trial. The experimental procedure is illustrated in Figure1C. The experimental paradigm only had two visual cues to control the start and the end of the grasp movement, which was easy to learn for the monkey.

After the monkey being well trained within this experimental paradigm, i.e., he could complete reach grasp movements correctly, a 96-channel microelectrode array (Blackrock Inc., USA) was implanted in the monkey's PMd cortex.

The monkey was allowed to recover from the surgery for one week before signal recording, and then we did the task as follows. Multi-channel neural signals from PMd and relevant external events were recorded synchronously when the monkey was performing reach-grasp movement. Signals were acquired and stored by a Cerebus multichannel data acquisition system (Blackrock Inc., USA) to filter 64channels of neural signal analogy and recorded them with 30 kHz sampling rate. 1-64channel recorded the signal from PMd. Each block lasted 10 minutes. And we randomly shuffled the positions of the four objects' to eliminate the effect of hand position and guaranteed that the collected brain signal was only related to the grasp gesture. In offline data processing, neural signals were down sampled to 1 kHz, and then filtered by a 2nd order digital Butterworth filter with band 0.3Hz to 450Hz to extract LFPs. In addition, the signal was also filtered by notch filter.

All the surgery and experimental procedures conformed to the Guide for The Care and Use of Laboratory Animals (China Ministry of Health) and were approved by the Animal Care Committee at Zhejiang University, China.

B. Data Processing

Before the time-frequency analysis, we needed to identify the frequency bands of the local field potential signals. Similar to previous studies, we divided the LFP signal into seven frequency bands, these bands corresponded to: δ(0.3-5Hz), θ-α (5-15Hz), β(15-30Hz), γ1(30-50Hz), γ2 (50-100Hz), γ3(100-200Hz) and a broad high-frequency band(bhfLFP, 200-400Hz) [9].

The power spectrum of each frequency band was estimated by multitaper spectral analysis, which had been successfully used in some other LFP studies [10]. To generate input features for classification, we partitioned the time period of LFP recording into contiguous 100ms windows and the power spectrum of each frequency band was integrated in each of these windows. The feature vector of each time window is the concatenation of the integrated power values of the current window and the previous nine windows, which are included to take 'memory' information into account.

C. Classification and Evaluation

A K-nearest neighbor (KNN) classifier was adopted here to decode the four types of grasp movements [2, 11]. Given a testing sample, the classifier predicts its corresponding grasp type based on the labels of its K nearest training samples in the feature space. The power spectrum of one second LFPs containing 10 bins after the visual cue was the input of the KNN classifier and the output of the classifier was one of the four types of grasp motions. Besides, 5 fold cross-validation was used here to evaluate the classification performance.

In addition, we calculated the confusion matrix in order to investigate the difficulty of different grasping types for the monkey, and the decoding accuracy varies with the number of channels and trials. When computing the decoding accuracy varies with the number of channels, we randomly chose a channel to decode the test set at first, then, adding another channel every time to decode the same test set, the result is the average of 10 calculations, based on 5 fold cross-validation in every calculation. Similarly, when computing the classification accuracy varies with the number of trails, we firstly chose a trail in each type of grasp motion in the same session and then randomly added another trail of each grasp motion type every time, the result is also the average of 10 calculations.

III. RESULTS

The following results are based on 4 sessions, including 568 conducted over a period of 1 month. The time intervals between successive sessions are 3 days, 20days and 2days..

After being well trained, the monkey could learn to start the grasp movement of 3s, after the Light ON, and held the object all the time before the Light OFF.

A. LFP time frequency

To test the hypothesis that, the power spectrum of LFPs can be used to decode grasp motions, we normalized the time-frequency map for LFPs from one channel. As we can see from Figure2, which clearly show the different LFPs patterns for four objects in one session, the variation of the LFPs power spectrum is evidently distinguishable between four grasp motions in the high frequency bands, namely between 100Hz to 400Hz.

Besides, the signal shown in the Figure 2 is during the time from the Light ON to Light OFF. Light ON marks the beginning of the visual cue, and Light OFF marks the end of grasp movement promoting the monkey to put hand back. The variation of high frequency bands averagely begin around 0.5s after the visual cue, which means the LFP signal is possibly related to the grasp movement of the monkey movement of grasping and holding.

Above all, it is consistent with the idea that the patterns of the power spectrum changed progressively across different grasp motion and using the power spectrum of LFPs to decode grasp motion is feasible.

B. LFP decoding results

Based on the analysis in part A, we performed KNN classification on the power spectrum of LFP signal to decode the types of grasp motions, and then calculated the classification accuracy of each frequency band in all sessions by executing the 5 cross-validation procedure and averaging. The average results of all the sessions in each frequency band are showed in Figure 3. The average classification accuracy can be obtained as high as 0.95 when we used the LFP signals from PMd in the broad high (200-400 Hz) frequency band. Both high frequency bands (100Hz-400Hz) and low frequency bands (0.3Hz-15Hz) show a certain decoding accuracy, while other frequency bands show low decoding accuracy.

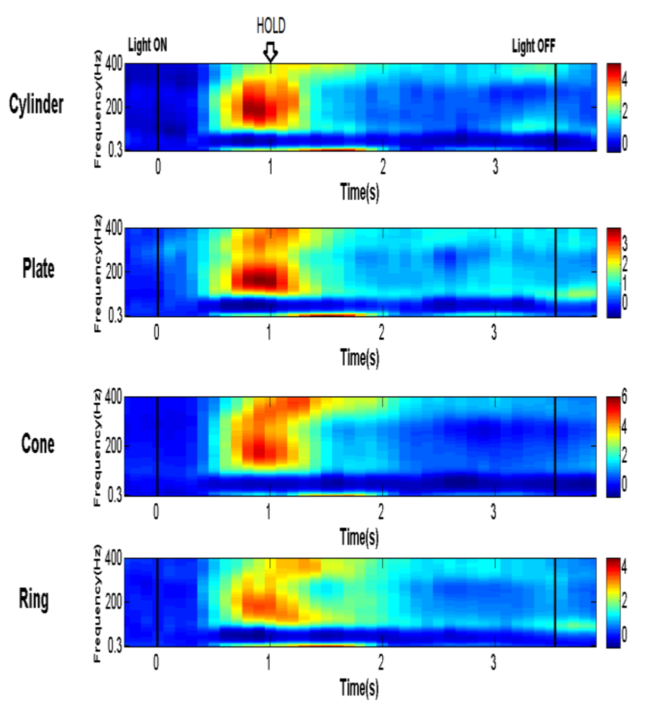

Figure 2. Time-frequency spectra of LFP signals for the four grasp types. The signals were from the same channel and aligned with the movement onset.

This finding suggests that the LFPs from PMd encoded a great amount of information related to object-specific grasp movements, and suitable for decoding the types of grasp motions, especially the broad high frequency band, which led to the highest decoding power of 0.95.

C. LFP robustness

For the purpose of investigating the difficulty of different grasping types for the monkey, we analysis the misclassification rate of four grasp types in all recording sessions and find out that although the misclassification rate of the four grasp motions is low, both cone and ring shaped objects are still easy to be misclassified, the misclassification nearly 10% of all sessions, see TABLE1, which is the confusion matrix of classified grasp motion and actual grasp motions. We used the decoding accuracy of broad high frequency band. There exist two possibilities leading to this result: 1.because the grasping gestures are similar between themselves, 2.because the brain electric signals patterns of these two grasping gestures are similar.

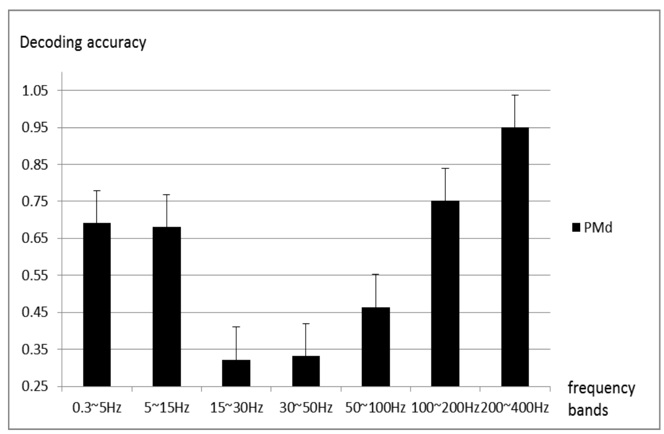

Figure 3. The decoding accuracies of the seven frequency bands of LFPs. The broad high frequency band (200-400 Hz) produced the highest decoding accuracy (95%).

TABLE 1 CONFUSION MATRIX FOR FOUR OBJECTS IN ALL SESSIONS(%)

Grasp motions	Cylinder	Plate	Cone	Ring
Cylinder	0.96	0	0.01	0
Plate	0.03	0.94	0.03	0.05
Cone	0.01	0.03	0.92	0.05
Ring	0	0.03	0.04	0.9

In addition, in order to optimize the decoding method we firstly need to understand the effect of number of channels on decoding power. We trained the KNN classifier by increasing the number of channels from PMd in the broad high (200-400 Hz) frequency band and $\gamma3$(100-200Hz)band, both having good decoding accuracy and the results can obtained in Figure 4, which including the results of 4 sessions. Consequently, we find that, although there is a gap between session 2 and session 3 for nearly 20days, the general tendency was similar to each other. When the channel number great than 30, the gain of decoding accuracy slows down significantly, which means that the added channels does not contributes a lot, or providing redundant information.

We also increased the number of trials in training set in the broad high (200-400Hz) frequency band and $\gamma3$(100-200Hz)band for the KNN classifier, which can be inspected in Figure 5. We find that the decoding accuracy quickly increases along with the number of trials increasing from 1 to 7. Generally, the decoding accuracy improved with number of trials increases, however 7-8 trials for training is enough to achieve good decoding power.

Overall results show that, apart from the characteristic of long-term stability of LFP signals, we can also utilize fewer channels and fewer trials to decode the grasp motions.

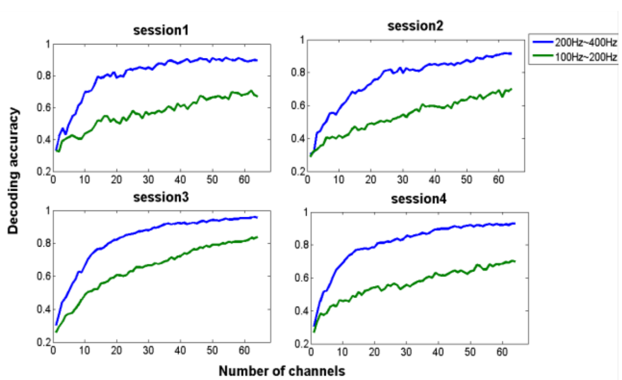

Figure 4. Decoding accuracy varies with number of channels for each sessions and 2 frequency bands(200Hz~400Hz and 100Hz~200Hz) When the number of channels reaches to 30, the decoding accuracy is acceptable

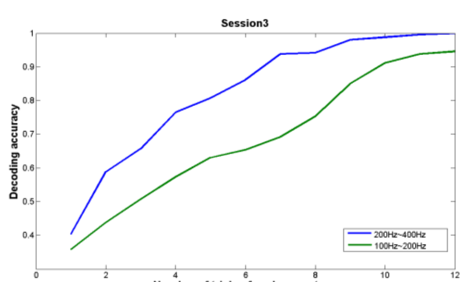

Figure 5. Decoding accuracy varies with number of trialsin session3 and 2 frequency bands(200Hz~400Hz and 100Hz~200Hz). When the number of trials reaches to 7, the decoding accuracy is acceptable.

IV. CONCLUSIONS

The results demonstrate that four different grasp types can be reliably distinguished in reach grasp movements using LFPs from the monkey's PMd cortex. In particular, the broad high frequency band of LFP outperformed other frequency bands by producing accuracies higher than 90%. This suggests that high-frequency LFPs are valuable for building BMIs to control prosthetic hands.

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