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Movement Direction Decoding with Spatial Patterns of Local Field Potentials

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Abstract— **We show that movement direction can be decoded with high accuracy using the spatial patterns extracted from multichannel local field potentials (LFPs). Two monkeys were trained to execute center-out movement in 8 directions. During the task the LFP activity was recorded with two 64 channel grids from the pre- and primary motor areas. The LFP signals were decomposed into 4 sub-band components in the 0-4 Hz, 4-10 Hz, 14-30 Hz and 48-200 Hz frequency ranges. The sub-band activity was post processed with regularized common spatial patterns algorithm and fed to linear discriminant analysis for final classification. Directions of movement were estimated using a redundant hierarchical classification strategy that tested groups of directions against diametrically opposite groups. The grouping of directions was based on the spatial correlation that we observed between LFP signals corresponding to neighboring movement directions which is similar to the cosine tuning profile of single neurons. We found that the decoding power for 8 directions was 80% and 92% for the two subjects, respectively, in 0-4Hz frequency band. Our best result of 92% nearly doubles the accuracy of the best results reported in the literature with similar set-ups. These results indicate that spatial patterns in LFP can be used to construct high accuracy brain computer interfaces.**

Keywords: Local Field Potential; Direction Decoding; Spatial Patterns; Neural Prostheses.

I. INTRODUCTION

Neural Prosthetics (NPs) aim to restore the motor functions of handicapped subjects by recording and processing the electrical activity of the brain. Noninvasive NPs typically rely on electroencephalogram (EEG) signals and have minimal clinical risk. Previous research shows that they are limited by poor signal to noise ratio (SNR) and spatial resolution and low information transfer rates. On the other hand, invasive NPs that use single unit activity (SUA) are limited by the instability of the recordings, the complexity of the processing and their inappropriateness for ambulatory systems. EEG and single cell recordings are sensitive to neural activity over different spatial scales: centimeters for EEG and microns for single unit activity. The local field potential (LFP) lies between these two scales and reflects the activity of a small population of neurons. Since LFP reflects the activity of an ensemble of neurons it is not as susceptible to long term recording problems as SUA. Indeed, recent results, e.g., [1], established that despite the fact that LFP is recorded with penetrating electrodes like SUA, the signal is more stable over time due to its larger scale. The ability to acquire stable brain signal recordings and extract complex brain activity from such signals are key to practical free-paced NP.

Although LFP signal acquisition techniques have been available for over a decade, the initial results were not encouraging in regard to the decoding of movement parameters, e.g., [2]. Indeed, it was originally believed that, as in EEG, the LFP lacked specificity as it sums activity over many neurons. More recently, [3] described low band modulation of motor cortex local field potentials during a directional reaching task. This study has been supported by the recent findings of [4] on LFP recorded from the posterior parietal cortex. This latter study showed that LFP carried directional information in higher frequency bands. However, the studies of the relation between LFPs and movement parameters have so far followed methods of analyses directly borrowed from SUA studies, in particular methods based on directional tuning functions. Most neurophysiological studies on motor control have been inspired by the work of Georgopoulos and colleagues in the last twenty years. Hence, it is not surprising that current studies of movement-related LFPs have been performed using the same analytic paradigm that has been used with single unit activity for many years, e.g., [5, 6, 7].

By breaking away from SUA-inspired approaches, we will show that spatial feature extraction techniques from oscillatory components of LFP signals can be used to decode movement direction and offer high information transfer rates. In particular, we observed evidence of cortical spatial organization of brain activity corresponding to different movement directions within primary (M1) and dorsal pre-motor cortex (PMd). This observation motivated us to implement the Common Spatial Patterns (CSP) algorithm to reduce dimensionality and extract parsimonious patterns from the neural activity for direction decoding [8]. The rest of the paper is organized as follows. Below we describe the experimental paradigm and data acquisition setup. Next we detail our signal processing strategy and finally provide experimental results from two subjects.

II. METHODS

A. Experimental set up and Data Acquisition

Two male rhesus monkey subjects (Macaca mulatta), H564 and H464, were trained in an instructed-delay center-out task to perform a point-to-point movement to visually displayed targets using a manipulandum. The animals were seated on a primate chair with their non-performing arm and head restrained. Under all task conditions, the subjects executed two-dimensional horizontal reaching movements with the manipulandum from a central location to one of eight targets equally spaced around a circle of radius ~9cm. To begin a trial the subject placed the feedback cursor inside a circular window (radius ~1cm) at the center of the display and held it for a control period of 800 ms (also referred to as the center-hold period). After this, a peripheral circular target was displayed pseudo-randomly at one of the eight locations and remained visible for 500-700 ms serving as a cue for the subject. The target locations were randomized within sets of eight, and the subject had to complete correct movements in all eight directions before moving onto the next set. Following the disappearance of the cue there was a memory delay of 800-1000 ms after which the target reappeared, thus serving as a 'GO' signal. Successful movements were to be completed within 1000 ms and finally the subject had to hold the cursor for 800 ms within the target circle (radius ~1cm) to obtain a juice reward. Fig. 1 shows the timeline for each trial. The cursor position was sampled and stored at 200 Hz via a personal computer that was also used to control the behavioral task (using Visual Basic). The LFP recordings were performed using two 10x10 Utah microelectrode arrays (4 mm x 4 mm in size, with an inter-electrode spacing of 400 µm; I2S Micro Implantable Systems (formerly Cyberkinetics Neurotechnology Systems, Inc.), Salt Lake City, Utah, USA). In both monkeys one array was implanted in M1 and one in PMd. LFP data were filtered between 0.3 Hz and 500 Hz and sampled at 1 KHz.

Using visual inspection, we eliminated the channels containing artifacts, such as power line noise from the analysis. The remaining channels were low pass filtered with 220Hz cut off frequency and down-sampled to 500Hz for further analysis. A total of 508 and 1109 trials were available for subjects one and two, respectively. The sessions for both monkeys were recorded over three days, with a gap of one week between sessions 1 and 2 and one day between sessions 2 and 3.

B. Signal Processing

As an initial step a time-frequency analysis was implemented to identify reactive frequency sub-bands. For this particular purpose the time-frequency surface was normalized relative to the power level in the baseline. This analysis was implemented for channels in M1 and PMd and averaged over trials. A representative time-frequency map of M1 for subject H564 is shown in Fig.2. We observed consistently distinct patterns in four different frequency bands; 0-4 Hz, 4-10 Hz, 14-30 Hz and 48-200 Hz. The LFP activity was sub-band filtered in these frequency ranges, down sampled to 100Hz and post processed for feature extraction. Although the LFP activity was high pass filtered with 0.3Hz cut-off frequency at the hardware level we observed DC wanders in several trials. Therefore before sub-band filtering the DC trend was removed from the entire recording. This minimized baseline shifts that appeared as outliers in the low frequency band data. Following sub-band filtering step, the envelope of the signal was computed in high frequency bands with Hilbert transform. The envelope of the signal was low pass filtered with a FIR filter with a cut-off frequency of 30Hz to prevent aliasing during down sampling operation. After inspecting the mean activity in each band for each direction we observed that the 0-4Hz frequency band was modulated across directions. The mean LFP activity for a representative channel for 4 different directions is depicted in Fig.3.

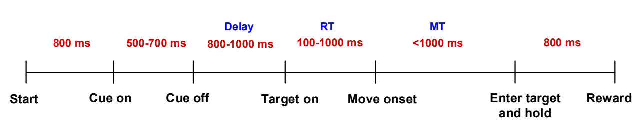


Fig.1. Time-course of trials in the instructed-delay center-out task.

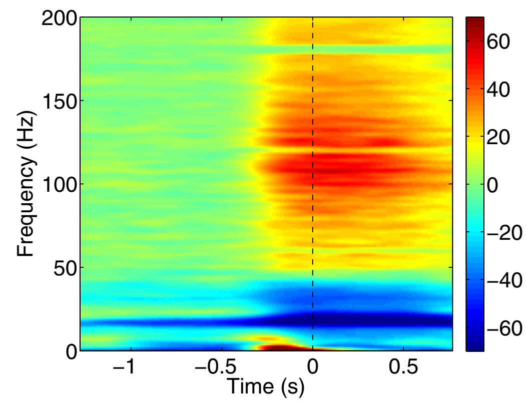


Fig.2. (a) Time frequency map of LFP recordings in M1 during the instructed-delay center-out task. The data were aligned to the onset of the movement (Time=0). The color map represents the change of power with respect to the baseline (not shown in the figure).

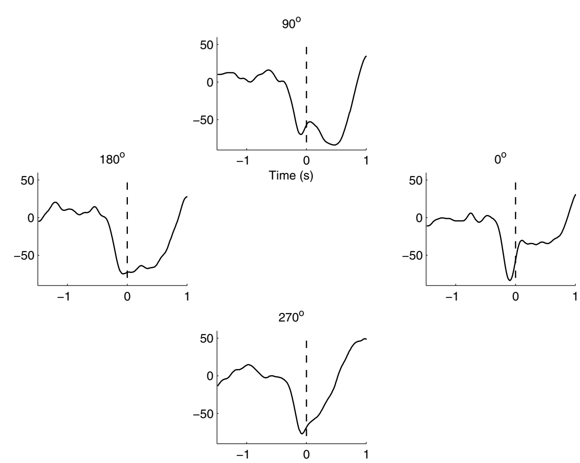


Fig.3. The mean LFP activity of 0-4Hz frequency band for different movement directions indicated in deg. The vertical line represents the movement onset.

As seen in Fig.3, the mean LFP activity had distinct patterns for different movement directions. In addition, we observed that the correlation between channels changed depending on movement direction. As a consequence, we used the Common Spatial Patterns (CSP) algorithm of [8] to extract features that were based on spatial organization in 0-4Hz frequency band. The CSP algorithm is widely used in multichannel EEG processing in binary classification paradigms. The CSP algorithm uses the correlation in spatial domain within a class while simultaneously discriminating this correlation pattern from that of another class.

C. Feature Extraction and Classification

Since we are tackling a multi class problem we utilized a one against other strategy to apply CSP to the multiclass classification problem at hand. We constructed several CSP filters tuned to discriminate between two distinct conditions, such as 0^0 vs. 180^0, 0^0 vs. 90^0, 90^0 vs. 180^0 etc. For each direction pair, six CSP features were computed and a Fisher linear discriminant classifier was constructed. Note that in a pairwise strategy *(K-1)K/2* binary classifiers need to be trained (*K*=8). We will refer this method as "Pairwise" discrimination strategy in the rest of the paper. To enhance our decoding performance, we used a redundant hierarchical classification strategy. The strategy was based on the error correcting output codes (ECOC) method [9]. It tested each group of directions from a series of groups of two to four neighboring directions against a corresponding group of directions. That latter group consisted of the diametric opposite directions to each of the directions in the group under consideration. The grouping of directions was based on the spatial correlation that we observed between LFP signals in different channels corresponding to neighboring movement directions. This spatial correlation structure is reminiscent of the cosine tuning profile of single neurons and is reported in an upcoming publication [in preparation]. A schematic diagram representing the ECOC strategy is shown in Fig.4. The final classification decision was implemented using a decoding matrix M of KxL with entries $m_{ij} \in \{-1, 0, 1\}$ where L is the number of binary classifiers and K is the number of classes.

Let $x \in \mathbb{R}^C$ represent the multi-channel LFP observations where C is the number of channels. The CSP method projects the multichannel data using spatial filters in $W \in \mathbb{R}^{CxC}$.

$$x_{CSP}[n] = W^T x[n] \tag{1}$$

The spatial filter W is found by calculating the generalized eigenvectors:

$$\Sigma_1 W = (\Sigma_1 + \Sigma_2) WD \tag{2}$$

Here Σ_1 and $\Sigma_2 \in \mathbb{R}^{CxC}$ are the estimates of the covariance matrices of the band-pass filtered multi-channel LFP signal for two different directions (e.g., 0^0vs 180^0). The diagonal matrix D contains the eigenvalues of Σ_1 and the column vectors of W are the spatial filters of the CSP projections. See [10] for details.

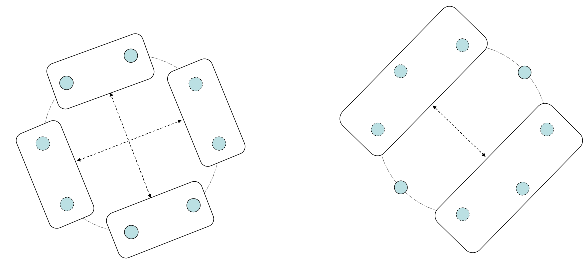


Fig.4. Grouped directions for ECOC. The hierarchical structure was constructed by grouping the neighboring directions. Two members (left), three members (right).

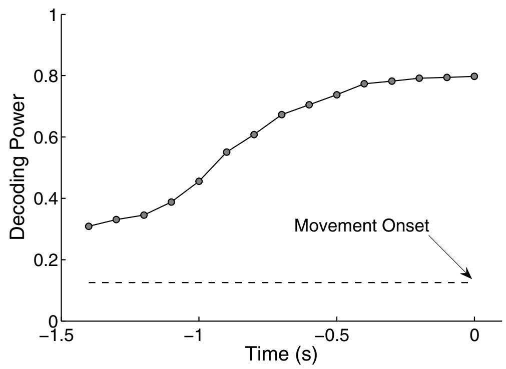
The CSP can be applied to non-centered correlation matrices or centered covariance matrices that are calculated from bandpass filtered LFP channels. The covariance matrix computation removes the mean of the signal for centering purposes. Removing the mean eliminates negative or positive shifts from the baseline that may appear in slowly changing cortical potentials and that could be informative. Indeed, we observed slowly varying characteristics in the 0-4 Hz frequency range. These variations can be exploited by using non-centered correlation matrix data. The use of non-centered data was also shown to be advantageous in processing slow cortical potentials or event related synchronization (ERS) and desynchronization (ERD) patterns, recorded with EEG [11]. The CSP algorithm based on correlation matrix is called regularized CSP (rCSP).

The LFP activity in one second time windows was used to extract features and train the classifiers. This window was shifted along the time axis with 100 ms intervals. The classification was implemented for 15 time points (=1.5 s). The classification started 1.5 s prior to the movement onset. The last classification time point used the first second of post movement data. The accuracy of the overall system was defined in terms of decoding power (DP) which is the ratio of correctly classified directions to all directions.

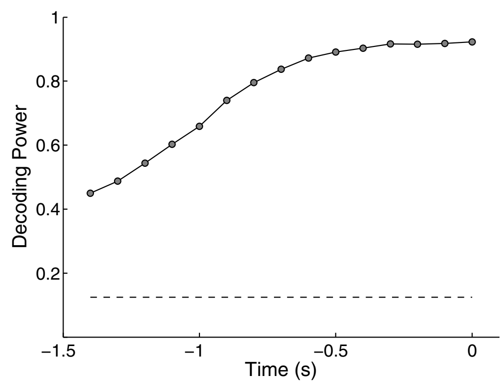
A 10x10 fold cross-validation method was utilized to test the classification accuracy of the system. This procedure was implemented for each time shift. In this study we used the LFP data from three sessions for both subjects.

III. RESULTS

We found that the decoding power of our system for 8 directions of movement reached 0.80 and 0.92 for monkey H564 and monkey H464, respectively. The distribution of DP versus time for both subjects is shown in Fig.5. We note that the DP slightly increased in the pre-movement period and reached its maximum value when the classification decision is based on the first second of post movement data. *These preliminary results showed better decoding power than those that have been reported in the literature; with our best initial result nearly doubling the accuracy of the best results obtained in similar set-ups*. Note also that the results with monkey H464 are superior to those reported in [3] despite the fact that the results of [3] were only estimates obtained by combining 6



(a)



(b)

Fig.5. Time-varying decoding power of 8 movement directions for (a) the first and (b) second monkey. Time point zero represents movement onset. The horizontal dashed line in each plot indicates chance level (=0.125).

sessions to classify the movement directions. In this study we used three sessions. Combining multiple sessions has the effect of reducing the effect of LFP variability due to other activity of the monkey, context and monkey state.

Finally, we examined the contribution of the elements of the classification procedure by repeating the analysis with or without ECOC and performing CSP using the correlation matrix (rCSP) or the covariance matrix (CSP). Table 1 provides the DP for the different setups. We found that the best classification accuracy was obtained using rCSP fused with ECOC. In particular, the rCSP and ECOC combination provided 13% and 8% improvements in decoding power with respect to the baseline Pairwise - CSP method for monkey H564 and monkey H464, respectively. We note that for both subjects using rCSP improved the DP. This indicates that the slow DC changes play a critical role in decoding the movement directions.

IV. Conclusion

LFP's are stable and robust brain signals that reflect the (synaptic) activity of neurons in the local vicinity. We show that movement direction can be decoded with a high degree of accuracy using the spatial patterns extracted from multi-channel LFP. Eight center-out movement directions were

TABLE I. The decoding power of 8 directions for different setups in 0-4 Hz frequency band.

	ECOC		Pairwise	
Subject	rCSP	CSP	rCSP	CSP
H564	***0.80***	0.75	0.70	0.67
H464	***0.92***	0.89	0.90	0.84

decoded using a redundant hierarchical classification strategy fused with error correcting output codes. The algorithm tested groups of directions against diametrically opposite groups. The grouping of directions was based on the spatial correlation that we observed between LFP signals corresponding to neighboring movement directions. The decoding powers of 8 directions for the two subjects were 80% and 92%, respectively, in 0-4Hz frequency band. These results indicate that the rCSP approach fused with ECOC is likely to be important for the implementation of practical and reliable neural prostheses for which robust brain signals that are stable over long periods of time are essential.

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