33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Classification of Multichannel ECoG Related to Individual Finger Movements with Redundant Spatial Projections

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Abstract— **We tackle the problem of classifying multichannel electrocorticogram (ECoG) related to individual finger movements for a brain machine interface (BMI). For this particular aim we applied a recently developed hierarchical spatial projection framework of neural activity for feature extraction from ECoG. The algorithm extends the binary common spatial patterns algorithm to multiclass problem by constructing a redundant set of spatial projections that are tuned for paired and group-wise discrimination of finger movements. The groupings were constructed by merging the data of adjacent fingers and contrasting them to the rest, such as the first two fingers (thumb and index) vs. the others (middle, ring and little). We applied this framework to the BCI competition IV ECoG data recorded from three subjects. We observed that the maximum classification accuracy was obtained from the gamma frequency band (65-200Hz). For this particular frequency range the average classification accuracy over three subjects was 86.3%. These results indicate that the redundant spatial projection framework can be used successfully in decoding finger movements from ECoG for BMI.**

I. Introduction

In the past few years a number of research groups focused on decoding individual finger movements from invasively recorded neural activity [1,2,3]. The motivation for such an effort is to build a hand prosthetics that can be controlled solely by brain activity in the scope of a brain machine interface (BMI). Achieving such a detailed decoding performance was possible by invasive assessment of brain activity as it provides higher spatial and temporal resolution and signal to noise ratio (SNR) compared to noninvasive techniques such as EEG.

In a recent study, individual finger movements were decoded from single unit activity (SUA) recorded from monkey subjects with penetrating electrodes in the M1 hand area [1]. The firing rates from multiple electrodes were used in conjunction with an artificial neural network (ANN) to decode the finger movements. They reported 95.5% average asynchronous decoding accuracy for individuated finger and wrist movements across three monkeys. In [4], another modality, local field potential (LFP) that is recorded from rhesus monkeys with four 4x4 penetrating electrode grids in primary motor cortex, was used to classify dexterous grasp movements. The subjects are instructed to open and close three different types of switches. They used frequency domain features of 10 visually selected LFP channels with an ANN for classification. The average classification accuracy was reported as 81% for decoding three different dexterous grasping tasks.

Recently, finger movement decoding problem was studied using human subjects where the neural activity was assess with electrocorticography from 64 channels [5]. Shenoy and his colleagues used 3 different band features for each channel constituting a predictor space of 192 features. A linear programming machine which is a sparse support vector classifier was used for selecting a subset of features and giving decisions. They showed that an average 5-class error of 23% is possible across 6 subjects.

In this paper we tackle the same problem of classifying of the movements of five fingers using ECoG. We employ a recently introduced redundant spatial projection framework based on common spatial patterns (CSP) algorithm for feature extraction from ECoG data for the identification of individual finger movements [6]. The redundant spatial projection framework enables the application of binary CSP to the multiclass finger decoding problem we tackle. We utilized a support vector machine (SVM) classifier to map the extracted spatial features into class labels. We use the ECoG data recorded from three subjects to demonstrate the efficiency of our decoding strategy.

The rest of our paper is organized as follows. First, we explain the redundant spatial feature extraction and classification framework. Then, we describe the ECoG data set and provide the details of the decoding experiments we executed. Finally we present our results and conclude.

II. Methods and Materials

A. Multiclass CSP with Hierarchical Grouping

The ECoG data is generally recorded with subdural electrode grids from epileptic patients. A majority of electrodes is likely overlap with cortical regions out of the hand area of the motor cortex. Consequently, a small number of recording channels carry finger movement

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related information. As in any learning process the generalization capacity of the model decreases with increasing dimensionality of the input data. Therefore, a dimension reduction algorithm needs to be employed to decrease the dimensionality. Although, it is possible to select channels manually as in [2], such an approach is cumbersome and one can easily eliminate an informative channel. In this study, we applied the common spatial patterns (CSP) [7] algorithm on band pass filtered multichannel ECoG signals to reduce them into a few virtual channels for dimension reduction and improve the SNR of spatially correlated ECoG data. The CSP is a subspace technique which is widely used among BMI community in binary decision problems for feature extraction. The spatial filters are a weighted linear combination of recording channels which are tuned to produce spatial projections maximizing the variance of one class and minimizing the other. We computed the spatial projection using

$$\mathbf{X}_{\mathbf{CSP}}[n] = \mathbf{W}^{\mathbf{T}}\mathbf{X}[n] \quad (1)$$

where the columns of W are the eigenvectors representing each spatial projection and $X[n]$ is the multichannel ECoG data. The eigenvectors of the CSP algorithm are estimated via generalized eigenvalue decomposition by contrasting the covariance matrices of the first class (i.e. thumb finger) and the second class (e.g. one of the finger data that is not the first class, here thumb finger) of a two class training data set.

Since we are tackling a multiclass problem, here we used the strategy of [6], to apply the CSP to the five-class finger movement data. In more detail, we constructed several spatial filters tuned to contrast pairs of finger movements such as 1 vs. 2; 1 vs. 3; 2 vs. 4 etc. Moreover, the spatial projections were extended to the group-wise contrasts of fingers such as {1, 2} vs. {3, 4 and 5} within the same spirit of [6]. Here, we expect that the adjacent fingers will have similar neural representations which can be used in improving the SNR of the spatial covariance matrices while computing the projections. A schematic diagram of decoding algorithm is presented in Fig. 1.

B. SVM

For each of the spatial projection, we constructed an SVM classifier with a radial basis function (RBF) kernel and probabilistic output. To construct the classifier, we used libsvm [8] which is a publicly available toolbox. The SVM parameters g (kernel parameter) and C (cost or regularization parameter) were set to 0.25 and 100.

We constructed 10 pair-wise classifiers which contrasts one finger movement to another. In addition we used adjacent fingers as a hierarchy rule and contrasted two fingers vs. the others with the expectation that consecutive fingers are correlated in their neural representation. For this particular setup five spatial projections and five corresponding classifiers were constructed. In total there are 15 spatial projections (10 paired, 5 group-wise) and related SVM classifiers. Each classifier provides a probability output p for a feature set being one class and (1-p) of being in the other. We employed an error correcting output code (ECOC) step to post process the outputs of redundant classifiers and provide a final decision [9, 10]. This last step was accomplished by multiplying the vector representing the log scaled classifiers output with the ECOC decoding matrix M of KxL with entries $m_{i,j} \in \{0, 1\}$ where L (=30) is two times the number of binary classifiers and K is the number of classes (i.e., 5 finger movements). The index corresponding to the maximum value of the ECOC output was selected as the predicted finger of the test data.

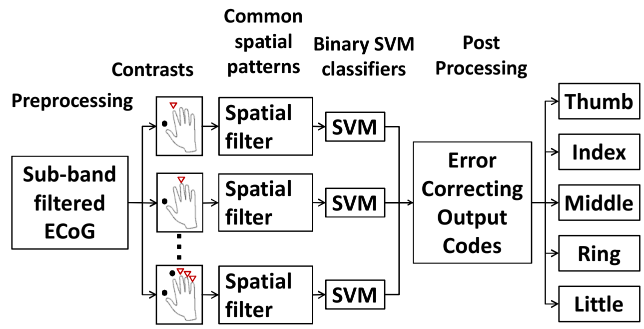

Fig. 1. The ECoG signal is bandpass filtered and a redundant set of contrasts were constructed to compute CSP for pair wise and group wise discrimination. The resulting spatial projection features are fed into corresponding SVM classifiers. The pair-wise and group-wise SVM results are fused using ECOC strategy to get the final classification decisions.

C. ECoG Data

We used multichannel ECoG data of BCI competition IV which is recorded from three subjects during finger flexions and extensions [11]. The electrode grid was placed on the surface of the brain. Each electrode array contained 48 (8x6) or 64 (8x8) platinum electrodes and was embedded in silicon plastic and has a diameter of 4 mm. They were separated with 1 cm distance from each other. Synamps2 amplifiers (Neuroscan, El Paso, TX) were used amplify the ECoG signal and digitize it with 1000 Hz frequency. The finger index to be moved was shown with a cue on a computer monitor placed at the bedside. Each cue lasted two seconds and was followed by a two-second rest period during which the screen was blank. The subjects moved one of their five fingers 3-5 times during the cue period. The experiment continued for 10 minutes for each patient.

To reduce the data rate we low pass filtered the ECoG data with a 220Hz cutoff frequency and down sampled it to

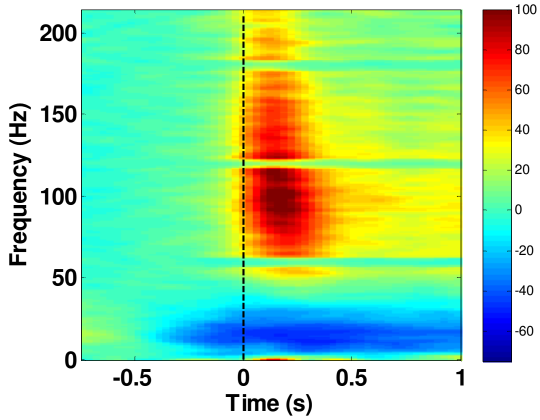

Fig. 2. The average time frequency map computed from all subjects using the most reactive channel set selected for each. The t-f surface was normalized to the energy in the first 500ms interval to identify modulated frequencies. Positive values represent energy increase and negative the decrease with respect to the baseline.

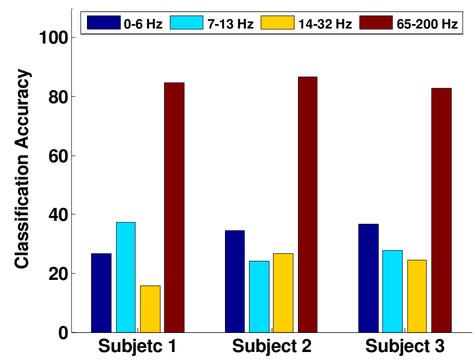

Fig. 3. The classification accuracies in each frequency band for three subjects. The highest accuracies are obtained from 65-200 Hz band features in all subjects.

500Hz. In order to identify the reactive frequency bands we implemented time-frequency analysis of ECoG data using short time Fourier transform. We aligned the ECoG data according to the movement onset covering a period of 750ms before the onset and 1000ms after it. We normalized the t-f plane to the energy in the first 500ms period of the idle state. We provide a t-f map representing the group average of most reactive channels in each subject in Fig. 2. We observed a broadband energy increase in 65-200Hz frequency band with the onset of movement. The energy in 7-32Hz decreased before the onset of the movement. We also observed energy increase in 0-6Hz band with the onset of the movement.

Based on these observations, the ECoG data of each subject was subband filtered in 0-6, 7-13, 14-32 and 65-200Hz frequency bands. We used one second data following movement onset for spatial feature extraction. Next, each band was transformed into four virtual channels with CSP algorithm by taking the first and last two eigenvectors. The variance of each channel was computed in all aligned data to get 4 dimensional feature vectors for each trial. Finally, the variances are log transformed and used as input features to SVM classifiers.

III. Results

We used a 10 times 10 fold cross validation procedure to estimate the classification accuracy of our system. In Fig. 3, for each frequency subband we present the classification accuracies. In all subjects, the gamma (65-200Hz) band provided the highest decoding accuracy. The average classification accuracy over all three subjects was 86.3%. In two subjects the second highest classification rate was obtained from 0-6Hz band whereas for the first subject the alpha (7-13) Hz resulted to the second highest rate. Interestingly, the 14-32Hz band provided consistently the minimum classification accuracy on all subjects. Although this band was modulated with the movement, it did not provide any information about the index of the executed finger movement but the cognitive state.

In Fig.4 we present the confusion matrix of our redundant classification system in gamma band and the correlation matrix of five-finger sensor data. The confusion matrices show that the misclassifications generally occurred between fingers 4 and 5. We note that for subject 2 and 3 the finger sensor data was also correlated between fingers 4 and 5 but not for subject 1. The misclassification for subjects 2 and 3 can be explained by the correlated movements of last two fingers. Interestingly, for the first subject despite the uncorrelated sensor data, the misclassification occurred once again between the last two fingers. This can be justified with the assumption of correlated neural representation of the adjacent fingers. The confusion matrices of other subjects also support this assumption. In contrary, for subject three, although the sensor correlation of adjacent fingers was high the misclassifications between the first four fingers were very low. This indicates that the neural representations of the first four fingers were distinguishable. However, the sensor measurements were somehow correlated which may originate from a *mechanical* cross talk of adjacent finger movements due to the hand anatomy of this particular subject. We note that, although very small, the misclassification occurred generally between the adjacent fingers. It should be noted that the correlated neural activity between adjacent fingers also improved the classification rates in the redundant case as the groupings improved the SNR of the common pattern shared by the adjacent fingers.

In order to quantify the gain we obtained with the redundant decoding strategy we compared it to the case where only paired (non-redundant) spatial projections and

TABLE I

The classification results for paired wise (non-redundant) and redundant decoding strategies in 65-200 Hz frequency range.

	Paired	Redundant
Subject1	80.7	86
Subject2	82.8	89.4
Subject3	78.9	83.4
Mean	*80.8*	***86.3***

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classification were executed. In Table I, we show the classification accuracy for 65-200Hz frequency bands for the redundant and paired (non-redundant) decoding strategies. We observed that in all subjects the redundant decoding strategy provided better results with respect to the paired one. These finding are in accordance with [10] where the same technique was used to decode movement direction from LFPs recorded in motor cortex. In average the paired solution provided 80.8% classification accuracy. We note that hierarchical structure noticeably increased the decoding performance of our system.

IV. CONCLUSION

In this paper we applied a redundant spatial projection framework based on CSP to classify ECoG data accompanying individual movements of 5-fingers. We studied the classification performance of different frequency subbands of ECoG data. We observed that the gamma (65-200Hz) provided the highest decoding accuracy with an average rate of 86.3% over three subjects. In all subjects we studied, the misclassifications generally occurred between fourth and fifth fingers. The overall trend of misclassifications was towards adjacent fingers. This indicates that neighboring fingers are likely represented by overlapping neural activity. The non redundant classification technique based on pairwise discrimination between finger movements provided on average 80.8% classification accuracy. Our results indicate that the redundant spatial projection framework can be successfully used in decoding finger movements for a BMI.

ACKNOWLEDGMENT

This study was supported in part with the University of Minnesota Interdisciplinary Informatics Grant (UMII) and national scientific research council of Turkey (TUBITAK).

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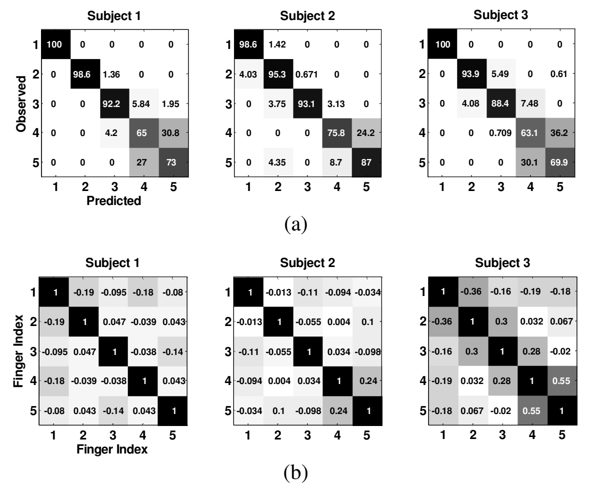

Fig. 4. (a) Confusion matrices for subject 1, 2 and 3. Note that the majority of misclassification occurred between ring finger (4th) and little finger (5th). Almost perfect separation was obtained for the thumb (1st). (b) The correlation matrices of finger position sensor signals for all subjects. . The color map is constructed according to absolute value of the correlation.

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