Classification of Hand Movement Direction based on EEG High-Gamma Activity

Carlos A. Loza, Gavin R. Philips, Mehrnaz Kh. Hazrati, Janis J. Daly and Jose C. Principe

Abstract— **The Electroencephalogram (EEG) is a non-invasive technique used in the medical field to record and analyze brain activity. In particular, Brain Machine Interfaces (BMI) create this bridge between brain signals and the external world through prosthesis, visual interfaces and other physical devices. This paper investigates the relation between particular hand movement directions while using a BMI and the EEG recordings during such movement. The Common Spatial Pattern method (CSP) over the high-γ frequency band is utilized in order to discriminate opposite hand movement directions. The experiment is performed with three subjects and the average classification accuracy is obtained for two different cases.**

I. Introduction

Patients with severe limb control disabilities caused by stroke, injuries or especial diseases like amyotrophic lateral sclerosis (ALS) [1] could improve their communication capabilities by using a BMI which records brain electrical activity and translates it to the control commands of robotic prosthesis, actuators or a virtual environment [2]. BMI might also help patients by expediting the rehabilitation process through providing biofeedback and keeping them motivated.

Electroencephalogram (EEG) is a superior noninvasive technique with high temporal resolution for recording scalp brain activity. Specifically, EEG-based BMI systems have been proofed effective to classify limb movement, e.g. left hand, right hand, foot and tongue [3], making them a potential suitable noninvasive rehabilitation technique.

Recent studies have shown the usefulness of raw EEG data to decode "grasp and hold" information [4] as well as hand movement flexion and extension [5]. Furthermore, after performing particular signal processing algorithms on the digital spatio-temporal EEG sequence, it has been possible to discriminate hand movement direction [6].

However, the usage of BMI is yet limited in clinical applications mainly because of the limitation in the number of tasks to be classified and the long training sessions that one requires in order to achieve satisfactory results. Moreover, in terms of classification of hand movement in humans, the scenario is more complicated due to the inherent motion involved in the tasks. Nevertheless, kinematics such as velocity, position and direction could provide additional information about the brain activity during such movement.

One of the algorithms used in EEG-based BMI literature is the CSP method; in this paper we applied this technique to extract the most discriminative information from 58 recorded EEG channels in a predefined paradigm, when subjects move a robotic hand in a random order in four different directions.

In this work we studied a particular EEG band known as high-γ (65-85 Hz) and the fact that particular hand movement directions might be encoded in that frequency band. The results are consistent with the previous neurological studies. On the other hand, very low frequency EEGs, also called slow cortical potentials (SCP), were reported originally in [7] in a BMI paradigm. However, in most cases, months of training are required to enable patients to control the prosthesis accurately; thus we did not focus on this particular scenario. In 2009, Wang and Makeig investigated posterior parietal cortex (PPC) role to decode intended movement direction [8]. Their results show that noninvasive neuronal activity recording over this region is associated with different movement directions. At the same time, Waldert et al. decoded hand movement direction from both Magnetoencephalography (MEG) and EEG signals. They reported power modulations in filtered MEG in the low-frequency band, but not from the beta and high gamma bands. In order to detect the healthy subject's hand/arm direction from EEG, the research group in Graz extracted features from EEG power between 5Hz and 30Hz, followed by a spatial filtering using the Common Spatial Pattern algorithm [9]

The rest of the paper is organized as follows: Section II introduces the CSP technique; section III describes the experiment we performed along with practical considerations. Section IV presents and analyzes the results while section V provides the conclusions of the study and further directions of research.

II. Common Spatial Pattern Method

CSP has been widely used in EEG literature to decode motor activity (see [10],[11],[12],[13]). It is considered part of the family of spatial filters for EEG and is based on the simultaneous diagonalization of covariance matrices. It was first proposed in [14] and outside the EEG literature, it is also known as the Fukunaga-Koontz transform (FKT).

Let X represent a trial of the band-pass filtered spatio-temporal EEG discrete sequence, i.e. $X \in \mathbb{R}^{E \times T}$, where E is the number of electrodes and T is the number of sampled time points. Next, the spatial covariance matrix, (1), is estimated using the correlation matrix biased estimator:

Carlos C. Loza, Gavin R. Philips, Mehrnaz Kh. Hazrati and Jose C. Principe are with the Computational NeuroEngineering Laboratory (CNEL), University of Florida, Gainesville, FL. (email: cloza@ufl.edu, gavin.philips@ufl.edu.com, M.hazrati@ufl.edu, principe@cnel.ufl.edu)

Janis J. Daly is with the Department of Neurology, University of Florida, Gainesville, FL. (email: janis.daly@neurology.ufl.edu)

This work is supported by UF opportunity fund # 00098693 and NIH NINDS R01-NS063275.

$$C_i = XX'/trace(XX') \quad (1)$$

where $i = 1,2$ represents a particular class in the training set. Due to the estimator, C_i will be a positive semidefinite (p.s.d) matrix; hence, their sum will be p.s.d as well, (2).

$$C = C_1 + C_2 \quad (2)$$

Now, we define the P matrix as (3).

$$P = \lambda^{-1/2}U \quad (3)$$

where U is the matrix containing the eigenvectors of C and λ is the diagonal matrix with the corresponding eigenvalues. Next, we perform whitening on C, (4).

$$PCP' = P(C_1 + C_2)P' = S_1 + S_2 = I \quad (4)$$

where the transformed covariance matrices are (5-6):

$$S_1 = PC_1P' \quad (5)$$

$$S_2 = PC_2P' \quad (6)$$

Both transformed covariance matrices share the same eigevectors, however, their eigenvalues must add up to one. Therefore, performing diagonalization on each individual transformed covariance matrix results in (7-9):

$$S_1 = B\lambda_1B' \quad (7)$$

$$S_2 = B\lambda_2B' \quad (8)$$

$$\lambda_1 + \lambda_2 = I \quad (9)$$

Now, in terms of discriminability, the eigenvector with the largest eigenvalue for S_1 corresponds to the eigenvector with the smallest eigenvalue for S_2. Therefore, the matrices P and B perform the whitening and further diagonalization needed for discrimination of two classes in the least squares sense, respectively; this results in (10),

$$W = P'B \quad (10)$$

Consequently, the spatially filtered sequence, Z, is (11),

$$Z = W'X \quad (11)$$

For discrimination and dimensionality reduction purposes, in the literature, it is common to introduce the parameter m as the number of columns taken from Z, i.e. the first and last m columns. Intuitively, the CSP algorithm creates a new joint space where the most discriminant directions correspond to the first and last m columns of the matrix W. Most of the times, this parameter is chosen in a heuristic manner depending on the classifier and trying to avoid overfitting. For a thorough analysis involving the free parameter m and FKT, refer to [15].

Due to the least squares approach for discrimination, the most obvious feature to be chosen is the variance from each direction in the joint space; hence, each element of the feature vector is equal to (12)

$$F_p = log(var(Z_p)) \quad (12)$$

where p takes values from 1 to $2m$. The log-operator is used to approximate a normal distribution.

III. Experiment

For our study, we recorded EEG data from 3 different subjects during actual hand movement and provided visual feedback through a simple and intuitive interface.

A. Setup

Our analysis was performed on data recorded at the Brain Rehabilitation Research Center (BRRC) of the Malcolm Randall VA Medical Center, located in Gainesville, Florida. Furthermore, the EEG sequences were recorded using a 64-channel Neuroscan SynAmps RT EEG amplifier and a ADC of 24 bits. Also, the sampling frequency of the recordings was 250 Hz. During each interval, as prompted by a visual cue through a monitor, the subject moves his right hand in four different directions while holding a modified InMotion ARM robot, also known as MIT MANUS.

At the start of each trial, a target appears on screen in one of four directions: North, South, East, and West. In addition, the order of presentation was randomized in order to discourage predisposition towards any direction. The target remains on screen for five seconds as the subject moves his hand in the desired direction. At that point, the target disappears from the screen, the subject returns his hand to center, and then rests until the next target is presented five seconds later. The timeline for a single trial is shown in Fig. 1. We performed the experiment with 3 subjects, all right-handed and over 50 years of age. For each subject, a total of 28 trials in each direction were recorded.

B. Data Processing

Due to the fact that the movement is always performed using the right hand, only the electrodes corresponding to the midline of the scalp and its left hemisphere were used, i.e. a total of 33 channels: FP1, FPz, AF3, F7, F5, F3, F1, Fz, FC5, FC3, FC1, FCz, T7, C5, C3, C1, Cz, TP7, CP5, CP3, CP1, CPz, P7, P5, P3, P1, Pz, PO7, PO5h, PO3h, POz, O1, Oz.

The next step was to visually inspect the EEG recordings and discard the trials where disconnected electrodes were noticed as well as blinks and other common artifacts. Due to the presence of a high-amplitude, low-frequency trend (around 0.1 Hz), the spatio-temporal EEG discrete sequences were first pre-processed using a first order linear adaptive filter [16] with constant input equal to 10, and a stepsize parameter of 2×10^{-4}. Additionally, the high-pass -3 dB point of the adaptive filter is located around 0.25 Hz. We chose this approach instead of regular highpass filtering mainly because the adaptive filter successfully suppresses the low-frequency component while keeping the original EEG recording intact. It is likely that the low frequency trend is due to an external artifactual source rather than the brain activity. In addition, the main focus of this paper is the high-γ band, and not the low frequency part of the spectrum. For each subject, a particular time window (1.5 seconds to 2 seconds) is chosen during the movement task. Then, before applying the CSP algorithm, we specified a particular frequency band of interest. For our case, due to previous studies done by Waldert et al., we chose the 62 Hz to 87 Hz band. Additionally, an elliptic filter was used along with a zero-phase filtering scheme in order to avoid transient effects.

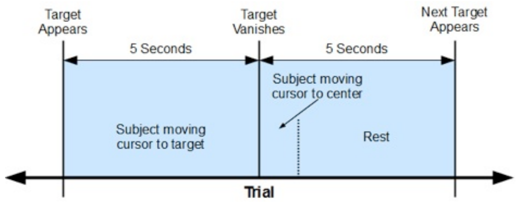

Figure 1. Timeline for a single trial of the experiment.

Fig. 2 shows an example of the projected samples in the new joint space when $m = 1$, i.e. first and last columns of Z for all the trials of Subject 1. Then, the feature vector is computed using (12). Classification was computed on opposite directions, i.e. North - South and East - West. Ideally, the resulting features have means located diametrically opposite of each other; thus, a Fisher Linear Discriminant classifier was used. For testing purposes, we used the cross-validation method known as "Leave-one-out" which means that, for N samples, we chose N-1 for training and performed classification over the sample that was not used for training. This procedure was repeated N times and, at the end, the results were averaged for each subject. Fig. 3 depicts the block diagram of our experiment.

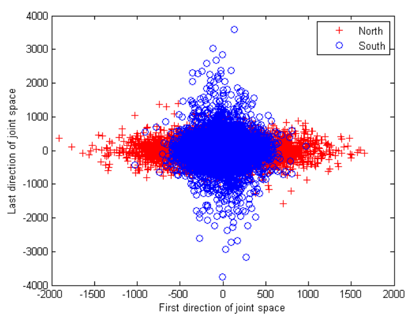

Figure 2. EEG time samples projected in the most discriminant directions of the new joint space.

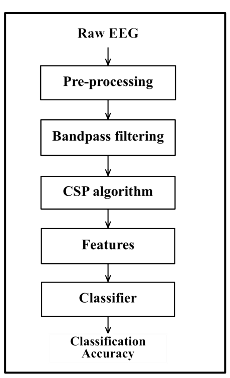

Figure 3. Block diagram of the proposed method.

IV. Analysis of Results

As previously mentioned, we implemented our algorithm on the EEG data in a two-class scheme; specifically, for the North - South case, an average classification of 83.5% was achieved, while, in contrast, for the East - West scenario, we obtained 62.5%. Table I illustrates the means and standard deviations of classification accuracy for each subject. In terms of sensitivity and specificity, we obtained 78.7%, 87.9%, 66% and 59% of classification accuracy for the classes North, South, East and West, respectively. These results were computed using $m=1$ for the free parameter in the CSP algorithm. This choice conveyed the best average classification accuracies. For instance, Table II shows the results for different values of m. These results agree with [17], where discrimination in terms of hand direction was encoded in the high-γ band and in the low part of the spectrum; specifically in the 0 Hz - 7 Hz band.

TABLE I. Average classification accuracy in percentage for cross-validation experiments

Subject	North - South	East - West
Subject 1	93.02 ± 25.78	60.61 ± 49.62
Subject 2	80.56 ± 40.14	56.82 ± 50.11
Subject 3	77.08 ± 42.47	70.00 ± 46.29

TABLE II. Average classification accuracy in percentage per subject for different values of m

Subject. Directions	$m = 1$	$m = 2$	$m = 3$
Subject 1. North - South	93.02	93.02	90.70
Subject 1. East - West	60.61	57.58	63.64
Subject 2. North - South	80.56	77.78	72.22
Subject 2. East - West	56.82	61.36	54.55
Subject 3. North - South	77.08	68.75	72.92
Subject 3. East - West	70.00	60.00	66.00

Our hypothesis can be tested using the spatial patterns from the CSP algorithm. Namely, the first and last rows of the inverse of the matrix W. Fig. 4 shows the results for both scenarios and indicates clear differences for the North - South case, while on the other hand, more evident and common patterns between classes East and West are obtained. Specifically, for North vs. South, the frontal-central and the motor cortex regions display the most significant changes in terms of activation.

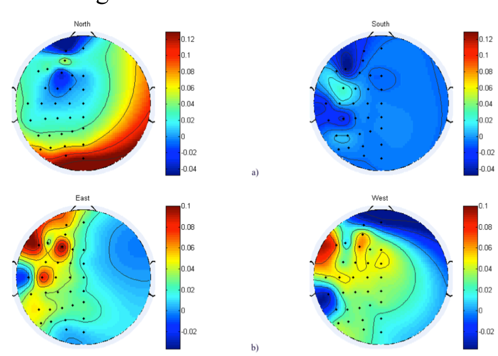

Figure 4. CSP Spatial Patterns for a) North - South case (Subject 1) and b) East - West case (Subject 2).

V. Conclusion and Further Work

This paper dealt with the implementation of a BMI where hand movement direction can be distinguished through proper analysis of brain signals. One of the purposes of the aforementioned BMI is to aid physically disabled subjects who go through physical therapy in order to recover motor abilities. The system was implemented by focusing on the EEG high-γ band and by finding an optimal linear projection (CSP) that discriminates two conditions in terms of second-order statistics.

The results show a clear difference between North vs. South and East vs. West discrimination; which suggests that the 62 Hz to 87 Hz band encodes more discriminant information for particular hand movement directions. In addition, it is also remarkable that the high-γ band provides relevant information; especially considering that its SNR is inherently low and the band is relatively close to the 60 Hz power line artifact. For instance, Fig. 5 shows EEG data recorded from electrode C3 for a single trial during movement after bandpass filtering. It is clear that there is modulation for this particular band; thus, it is not possible that this is a result of a constant 60 Hz artifact.

Additionally, it has been reported by Darvas et al. [18] that Electromyogram (EMG) interference is likely to occur over the high-γ band during EEG recordings that involve motion. Hence, in order to ascertain that our algorithm decodes neuronal activity, we applied the CSP technique in a windowed scheme, i.e. the experiment was computed for consecutive non-overlapping time windows during which we only focused on the activity recorded by the electrodes over the left primary motor cortex.

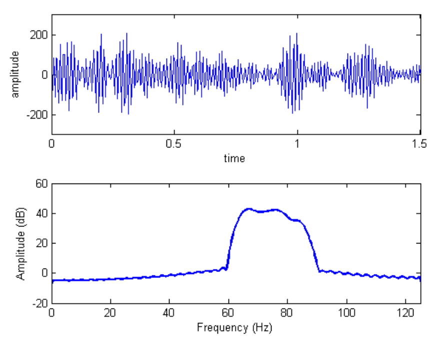

Figure 5. Upper figure: EEG sequence after bandpass filtering for the task North. Lower figure: power espectral density estimation. Subject 1.

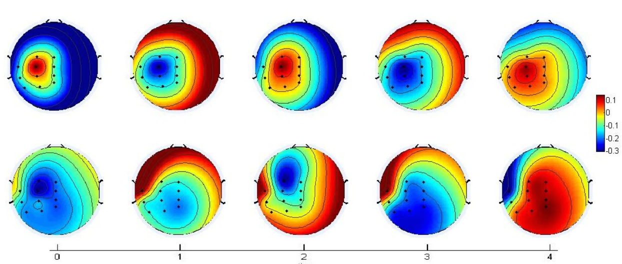

Figure 6. CSP Spatial patterns for consecutive non-overlapping 1-second time windows. First row: East direction. Second row: West direction. Subject 1.

Fig. 6 shows the results using 1-second windows during target reaching. We can appreciate that there is more significant and localized discriminability (around electrode C3) during the first seconds, i.e. pre-movement, and movement, while the discriminant activity starts to become more scattered by the end of the task, i.e. post-movement and rest. This suggests that brain activity is being decoded and used for discrimination and also agrees with the results shown in [19] regarding high-γ activity over the motor cortex at movement onset.

Future work will analyze different discriminant methods not only based on second-order statistics. Moreover, we will interpret the current results and perform further studies about how the high-γ band could be combined with other well known EEG spectral bands.

REFERENCES

[1] E. Sellers, E. Donchin, “A P300-based brain-computer interface: Initial tests by ALS patients,” *Clinical Neurophysiology,* vol. 117, no. 3, pp. 538 - 548, Mar 2006.

[2] J.R. Wolpaw et al., “Brain-computer interface technology: a review of the first international meeting,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, Jun. 2000.

[3] G. Pfurtscheller, D. Flotzinger, C. Neuper, “Differentiation between finger, toe and tongue movement in man based on 40 Hz EEG,” *Electroencephalography and Clinical Neurophysiology,* vol. 90, no. 6, pp. 456 - 460, Jun 1994.

[4] M. Kh. Hazrati, and A. Erfanian, “An On-line BCI for Control of Hand Grasping Sequence and Holding Using Adaptive Probabilistic Neural Network,” *30th International Proc. IEEE EMBS*, Canada, pp. 1009-1, 2008.

[5] A. Vuckovic and F. Sepulveda, "A Four-class BCI Based on Motor Imagination of the Right and the Left Hand Wrist, Applied Sciences on Biomedical and Communication Technologies", ISABEL 08, 2008

[6] S. Wladert et al., “Hand Movement Direction Decoded from MEG and EEG,” *The Journal of Neuroscience,* vol. 28, no. 4, pp. 1000 - 1008, Jan. 2008.

[7] N. Birbaumer et al., “The Thought Translation Device (TTD) for Completely Paralyzed Patients,” *IEEE Transactions on Rehabilitation* vol. 8, no. 2, pp. 190 - 193, 2000.

[8] Y. Wang and S. Makeig, “Predicting Intended Movement Direction Using EEG from Human Posterior Parietal Cortex,” *Foundations of Augmented Cognition. Neuroergonomics and Operational Neuroscience,* vol. 5638, pp. 437 - 446, 2009.

[9] G. Clauzel et a., "Offline Decoding of Hand Movement Directions from Non-Invasive EEG"International Journal of Bioelectromagnetism Vol. 13, No. 2, pp. 90 –91, 2011

[10] J. M-Gerking, G. Pfurtscheller, H. Flyvbjerg, “Designing optimal spatial filters for single-trial EEG classification in a movement task,” *Clinical Neurophysiology,* vol. 110, pp. 787 - 798, May 1999.

[11] H. Ramoser, J. M-Gerking, G. Pfurtscheller, “Optimal spatial filtering of single trial EEG during imagined hand movement,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 4, Dec. 2000.

[12] B. Blankertz et al., “Optimizing Spatial Filters for Robust,” *IEEE Signal Processing Magazine, IEEE,* vol. 25, no. 1, pp. 41-56, Jan 2008

[13] K. Ang et al., “Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface,” *International Joint Conference on Neural Networks, IEEE,* pp. 2390 - 2397, Jun. 2008.

[14] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2nd ed. New York: Academic , pp. 31 - 32. 1990.

[15] S. Zhang and T. Sim, “Discriminant Subspace Analysis: A Fukunaga-Koontz Approach,” *Transactions on Pattern Analysis and Machine Intelligence, IEEE,* vol. 29, no. 10, Oct. 2007.

[16] W. Liu, J. Principe and S. Haykin, *Kernel Adaptive Filtering: A Comprehensive Introduction*, John Wiley, 2010, pp. 3 - 7.

[17] N. Robinson et al., “A Wavelet-CSP Method to Classify Hand Movement Directions in EEG based BCI System,” *International Conference on Information, Communications and Signal Processing, IEEE,* pp. 1 - 5, Dec. 2011.

[18] F. Darvas et al., “High gamma mapping using EEG,” *Neuroimage,* vol. 49, no. 1, pp. 930 - 938, Jan. 2010.

[19] T. Ball et al., “Movement related activity in the high gamma range of the human EEG,” *Neuroimage,* vol. 41, no. 2, pp. 302 - 310, Jun 2008.