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Classification of multi-modal data in a self-paced binary BCI in freely moving animals

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***Abstract*— The goal of the present article is to compare different classifiers using multi-modal data analysis in a binary self-paced BCI. Individual classifiers were applied to multi-modal neuronal data which was projected to a low dimensional space of latent variables using the Iterative N-way Partial Least Squares algorithm. To create a multi-way feature array, electrocorticograms (ECoG) recorded from animal brains were mapped to the spatial-temporal-frequency space using continuous wavelet transformation. To compare the classifiers BCI experiments were simulated. For this purpose we used 9 recordings from behavioral experiments previously recorded in rats free to move in a nature like environment.**

***Index Terms*— Multi-way analysis, tensor factorization, classification, wavelet transform, brain-computer interface (BCI), self-paced.**

I. Introduction

Based on neuronal activity recordings of the brain, Brain Computer Interface (BCI) aims to provide an alternative non-muscular communication pathway to send commands to the external world in individuals suffering from severe motor disabilities. Over the last decades several approaches and methods have been developed to improve neuronal signal decoding. Among others, recently multi-way analysis was considered as an effective tool for neuronal signal processing. Thanks to this approach data from several domains (e.g. space, frequency and time) can be treated simultaneously. In previous studies from our laboratory [1] multi-way analysis was applied to develop and implement a binary self-paced BCI designed to function in animals (rats) freely moving in a nature like environment. As opposed to the cue-paced systems, when the subject waits for the external cue that drives interaction, no stimulus is used by the self-paced BCI. The subject controls it at its own intention which is more adapted to the real-life applications. During the last years an increasing number of papers started to apply self-paced BCI paradigms [2]–[6]. However, the BCI performance reported in these articles is still not suited for practical application, in particular, because of high level of false system activation [4]. Moreover, results were obtained by the analysis of short recordings of several minutes. Variety of experimental paradigms and evaluation criteria [2], [4], [5], [7] makes complicated comparison of performances of self-paced BCI systems.

Series of long term BCI experiments (up to one hour duration) in freely moving animals were recently carried out in our laboratory [1]. Neuronal activity was monitored and recorded continuously using surface electrodes placed on the cortex of the animal (ECoG). To form a tensor of observation we map ECoG recordings to the spatial-temporal-frequency space using continuous wavelet transform (CWT). Despite of relative computational complexity, this method was chosen because of its high frequency resolution and absence of limitation in the temporal resolution in the higher frequencies [8]. Applying the N-way Partial Least Squares (NPLS) approach [9] a regression model predicting the intentional control was created. The NPLS is a statistical method for linear modeling. It corresponds to the generalization of ordinary PLS for tensor input/output variables. In comparison to other tensor-based methods that were recently applied in BCI studies [10]–[12] the NPLS involves class information performing tensor decomposition which significantly increases the efficiency of modeling. While the NPLS works without any prior knowledge, it can be efficiently applied to automatically identify models aiming to predict BCI events from recordings of neuronal brain activity. The main disadvantage of the generic NPLS is its significant memory consumption. To overcome this problem, recently the Iterative Multi-way Partial Least Squares (INPLS) [1] and the Recursive Multi-way Partial Least Squares (RNPLS) [13] were invented.

The NPLS algorithm is based on the data projection to the low dimensional feature space (space of latent variables), with further construction of linear regression. The binary BCI leads to the problem of two class discrimination. Although the PLS algorithm (as well as the NPLS and its derivations) was not inherently designed for classification, it is widely applied to solve this problem [14]. In particular in the studies [1], [15], and [16] NPLS linear regression was applied for classification using binary output variables. Otherwise PLS was used as a dimensionality reduction tool and coupled with different classifiers in the space of latent variables (for more details see [14]). The present paper has two main goals. The first one is to study the efficiency of different classifiers in the space of INPLS latent variables in

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the context of the binary self-paced BCI. As the second goal several mother wavelets were compared for their efficiency. To achieve these goals recordings from several series of long term experiments in rats freely moving in a nature like environment were used.

II. Data Description

Data was recorded by a neurophysiology team at CLINATEC/LETI/CEA, FRANCE, as described in details in [1]. The experiment was based on a simple reward task. A rat freely moving in a cage had to push a pedal to activate a food dispenser. The rat was trained to press the pedal without any clue or other conditioning stimulus. During a set of experiments ECoG signals from 14 surface electrodes implanted over the cortex of the rat were recorded. In addition the signal from the pedal was recorded simultaneously. The ECoG signals were recorded at sampling rates of 6.5 kHz or 13 kHz using Biomea system Biologic, Grenoble, France. Signals were sampled down to 1.3 kHz and band-pass filtered $[0.5; 500]$ Hz. The Common Average Reference (CAR) filter was applied to the signal, i.e., an average signal of all the electrodes was subtracted to exclude a "common source". Two series of experiments lasting from 10 minutes up to 1 hour were carried out in the same animal in July 2009 (4 recordings), and in October 2009 (5 recordings). For further details see [1].

III. Methods

A. Tensor representation of ECoG data

The BCI feature tensor was formed from the epochs extracted form the ECoG signals mapped to the spatial-temporal-frequency space using CWT (see Fig. 1). For each epoch j (determined by its final moment t), electrode c, frequency f and time shift τ, elements $x_{j,\tau,f,c}$ of the tensor $\underline{\mathbf{X}}$ are calculated as norm of CWT of ECoG signal. Frequency band $[10, 300]$ Hz with step $\delta f = 2$ Hz and sliding windows $[t-\Delta\tau, t]$, $\Delta\tau = 2$ sec with step $\delta\tau = 0.04$ sec were used for all electrodes.

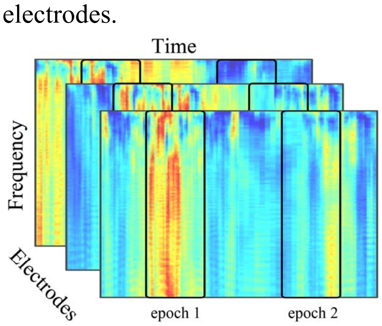

Fig.1. Multi-channel ECoG recording mapped by continuous wavelet transform (CWT) to the temporal-frequency-spatial feature space.

Upper bound of frequency band is conditioned by limitation of wireless data acquisition system which is under development in CLINATEC/LETI/CEA [17]. The resulting dimension of a point was $(146 \times 51 \times 14)$. The binary dependent variable was set to one, $y_j = 1$ if the pedal was pressed at the moment t, and $y_j = 0$, otherwise.

B. Wavelet optimization

To choose the most appropriate basis of decomposition, several mother wavelets ψ were compared: Meyer, Morlet, Symlet '7' and '8', 2nd and 10th orders Debauchies, Coiflets '5', and Haar. Their evaluations were made according to the maximum level of correlation between the absolute value of the wavelet's coefficients $C_\psi(\tau,s)$ over scale factors s and time shift $\tau \le 2sec$, and the signal of the pedal y: $R_\psi = \max_{s,\tau}\{\mathrm{corr}_t(|C_\psi(t-\tau,s)|, y(t))\}$, where s corresponds to the frequencies of the band $[10, 300]$ Hz and $y(t) \in \{0, 1\}$ represents the position of the pedal at the moment t.

C. Formation of training and test sets

The training data, namely the tensor $\underline{\mathbf{X}}$, representing electrical brain activity, and the vector $\mathbf{y}$ indicating the position of the pedal, were calculated using the first 10 minutes of the recording made in July 2009. Then this entire recording and 8 others were used to validate the classifiers. The total number of points in the training dataset was equal to 1400, including 400 event-related points (formed as random replication of 73 event situations from the training recording) and 1000 randomly selected non-event points.

D. Projection to low dimensional space

Because of the huge size of the tensor $\underline{\mathbf{X}}$ the INPLS algorithm was employed to project data to the low dimensional feature space. The number of factors (projectors) was set to 8 by ten-fold cross validation. The resulting latent variables were used for classification.

E. Classification algorithms

Different types of classification methods have been applied in BCI tasks [18]. Several linear and non-linear classifiers widely used in BCI research were chosen in this study. Then, they were compared using a given set of INPLS features.

Linear classifiers: *Linear Discriminant Analysis (Fisher's LDA)*, *INPLS regression with binarization.*

The INPLS algorithm generates a linear regression model in the latent variables space to predict $\hat{y}$ corresponding to the output variable y. For the binarization of $\hat{y}$ a scalar threshold was found using the training set according to the criterion of efficiency (described below).

Non-linear classifiers: *Quadratic Discriminant Analysis*, *Logistic Regression*, *Kernel Support Vector Machine* (radial basis function was chosen as a kernel, $\sigma = 1$).

Training of all classifiers was carried out using the training data set. Then the efficiency of the classifiers in the BCI task was estimated by simulation of BCI experiments using the test recordings.

F. Simulation of BCI experiments

To study generalization ability of all classifiers, simulating BCI experiments were carried out. Binary discriminators were applied offline to 9 recordings (lasting from 10 minutes to 1 hour). Decision (event or non-event) was making with Decision Rate 2Hz, i.e., every 0.5 sec. The system was blocked for 5 seconds after event detection to prevent multiple activations. Follow to [4] the real event was treated as detected if the time interval between the event and its detection did not exceed 1.5 seconds.

G. Performance evaluation

The performance of binary BCI is characterized by *True Positives (TP)* representing the amount of correctly detected events, *False Positives (FP)*, representing the amount of non-event situations detected as events, *True Negatives (TN)*, representing correctly detected non-events, and *False Negatives (FN)* representing the amount of missed events. On the basis of this characteristics, the statistics *True Positives Rate* (TPR = TP/(TP+FN)), and *False Positives Rate* (FPR = FP/(FP+TN)) are calculated. TPR characterizes the percentage of events which were successfully detected by the BCI system. FPR is the standard statistics to characterize the relative amount of false activation. Note that FPR statistics depend on decision rate and class ratio. It should be considered comparing BCI systems. Self-paced BCI involves a classification problem with highly unbalanced classes. To better characterize false activation of the self-paced BCI system, an additional characteristics, such as, *Positive Predictive Value* (PPV = TP/(TP+FP)), could be applied [19]. It reflects the ratio of correctly detected events to the amount of detections. To create a single value characterizing performance of the self-paced BCI system, in the present study an average value of TPR and PPV was used (Overall Performance (OP) = (TPR+PPV)/2). This statistic was introduced because the commonly used standard Classification Accuracy (ACC = (TP+TN)/(TP+TN+FP+FN)) or the Error Rate (ERR = 1-ACC) [19] fail to efficiently characterize performance of classifiers for highly unbalanced classes. Maximization of OP provided the set of parameters (thresholds of detection) for all classifiers.

IV. RESULTS

Mother wavelets were compared using 4 files representing the first series of experiments. The comparison of mother wavelets shows that second order Debauchies and Haar lead to a relatively low level of correlation, whereas the performance of all other wavelets is comparable. Meyer wavelet was chosen for the present study as mother function, due to its computational efficiency [8]. Results are shown in Fig. 2.

Table 1 summarizes the results of comparison of classifiers. For this purpose simulations of the self-paced BCI experiments were carried out using test recordings. BCI simulations show that the quadratic classifier applied to INPLS latent variables is the most efficient. Nevertheless, this method does not significantly outperform linear regression with binarization threshold. The values of Overall Performance for 9 test data sets and all classifiers are shown in Fig. 3.

V. DISCUSSION

Over the last decades numerous approaches and methods have been proposed for BCI. So far most BCI experiments were done with cue-paced (synchronized) approaches, self-paced BCIs seems to be much more suited for real-life application. Recent publications reported self-paced BCIs of good performance [15], [20]. Nevertheless, these self-paced BCI experiments were still carried out under highly restricted conditions which are not satisfactory for clinical applications. Our study is based on long term experiments (up to one hour) performed in freely moving animals in a noisy environment. In average feeding was taking about 40% of the experiment session, the rest of the time was spent by the rat in spontaneous activities. During simulation of online BCI experiments still 86% of correct detection of control intentions was achieved with only a moderate rate of false activation. These results were obtained using multi-modal neuronal signal processing improving extraction of useful information from the data. The projection to the low dimensional space with INPLS allowed the application of different classifiers which improved the BCI effectiveness.

Finally, a set of real-time experiments demonstrated the computational efficiency sufficient for on-line applications. The processing time of 0.5 sec buffer is not surpassing 0.1 sec (Intel Dual Core, 3.16 GHz; RAM 3.25 Gb). In parallel several mother wavelets were compared for the temporal-frequency data representation. This study does not reveal the essential difference between wavelet generative functions.

TABLE I

PERFORMANCE OF SIMULATED SELF-PACED BCI EXPERIMENTS WITH DIFFERENT CLASSIFIERS IN SPACE OF LATENT VARIABLES

	TPR (%)	PPV (%)	FPR (%)	ERR (%)	OP (%)	FP min^{-1}
INPLS	80 ± 14	87 ± 9	0,36 ± 0,16	0,91 ± 0,33	84 ± 11	0,42 ± 0,19
LDA	77 ± 13	81 ± 13	0,55 ± 0,21	1,21 ± 0,37	79 ± 13	0,64 ± 0,25
QDA	**85 ± 13**	**86 ± 9**	**0,45 ± 0,29**	**0,85 ± 0,31**	**85 ± 10**	**0,52 ± 0,34**
KSVM	76 ± 12	81 ± 13	0,57 ± 0,43	1,31 ± 0,43	79 ± 11	0,67 ± 0,50
Logit	83 ± 14	83 ± 11	0,52 ± 0,27	0,97 ± 0,31	83 ± 12	0,61 ± 0,31

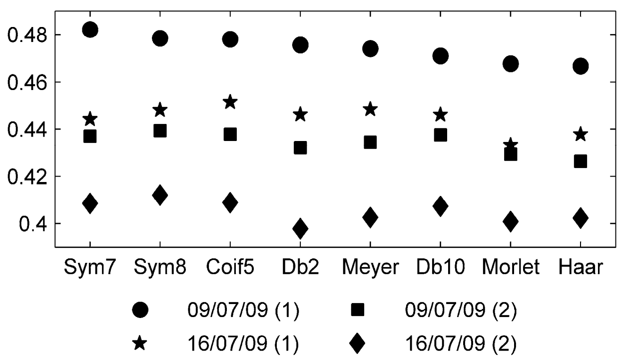

Fig. 2. Maximum of correlation between wavelet coefficients and the signal of the pedal.

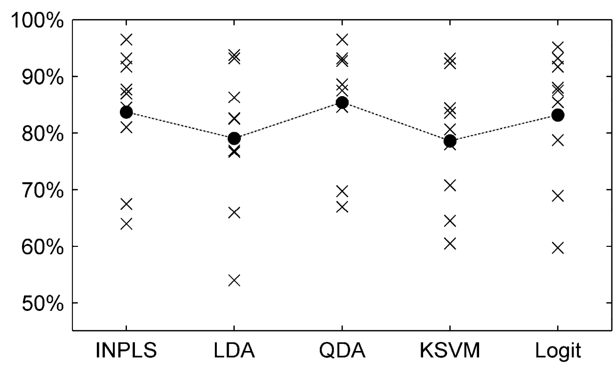

Fig. 3. Overall performance (OP) for series of simulated self-paced BCI experiments using different classifiers in space of INPLS latent variables. Black circles represent the average value over all the experiments.

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