Brain-Computer Interface

Implementation and Study of Algorithms for Processing and Classification of EEG signals

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***Abstract*— This article is the study of algorithms that are part of the signals processing chain of a Brain-Computer Interface (BCI) based on signals of electroencephalogram (EEG) and motor imagery (IM). The EEG signals processing chain was performed using a bandpass filter, a spatial filter via Common Spatial Patterns (CSP). The signals classification is performed using the Linear Discriminant Analysis (LDA) algorithm. A public dataset was used to evaluate all the processing chain. Two classification scenarios were considered: binary (one-against-one) and the multiclass scenario (one-against-all). The results are also compared regarding the removal or not of artifacts of the type eye blink obtained via electrooculography (EOG) signals.**

***Keywords*— BCI; EEG; LDA; CSP.**

I. INTRODUCTION

Several factors may cause cell death and degeneration, to a greater or lesser extent, of the nervous system, degenerative diseases in addition to other factors such as accidents or some kind of disorder capable of affecting the brain's communication with other parts of the body, as in [1].

By definition, a BCI system is collaboration between the brain and a device that allows the signals from the brain to control any outside activity, to totally or partially replace the lost functions, through which these signals can express an idea or control an external object by means of artificial channels, as described in [2].

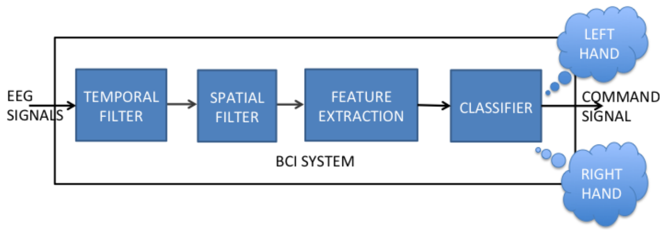

Fig.1 – A typical signal processing chain of a BCI system.

There are some ways to measure the brain activity by the BCI system. In this work it is used the electroencephalogram (EEG) signals. The EEG signal is the electric field resulting from pyramidal neurons population in the cortex region. The EEG procedure represents a non-invasive alternative, and it is relatively inexpensive with a good temporal resolution. In the Fig.1. there is an example of a typical processing chain of a BCI system.

A large quantity of algorithms has been developed in recent years with the purpose of performing the pre-processing of EEG signals robustly applied in BCI based on motor imagery, as in [3]. Among them, we highlight: the temporal filters, with the purpose of selecting the frequency bands related to motor imagery and the spatial filters to improve signal-to-noise ratio (SNR) EEG signals.

The feature extraction and classification steps will be described in detail in the section II.

II. MATERIALS AND METHODS

The dataset used in this study were obtained from the BCI Competition IV. It was organized by the Graz University of Technology, Austria.

A. Description of Dataset 2a

This dataset consists of 22 channels of EEG signals and 3 channels of EOG from 9 subjects. The signals acquisition was done during an interval of time in which they performed four different motor imagery tasks. The tasks include the imagination of movement of the left hand (class 1), right hand (class 2), feet (class 3) and tongue (class 4). Each individual held 2 sessions per day, where each session consisted of the set of 72 attempts for each class.

The experimental protocol consisted of acquisition of EEG signals of individuals sitting in front of a screen. At the beginning of each trial, a fixed cross was showed in the center of the screen. At the same time a short audible signal was emitted. After 2 seconds, an arrow pointing up, down, left or right corresponding to one of the classes (right hand, left hand, tongue and feet) indicated by 1.25s the task to be performed. The subjects performed the task of motor imagination until the cross disappear in the center of the screen, what happened after 6s. This procedure was repeated after a period.

The signals were filtered between 0.5 and 100Hz and a notch filter (50Hz) were used to remove the interference from the electrical power. The signals were sampled at 250 Hz.

The signals available on the dataset were obtained according to the characteristics described above. The software MATLAB and EEGLAB toolbox was used to implement the algorithms. The choice of these algorithms was based in

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literature, which also allowed us to compare the results with those obtained in these works, see [3] and [4].

B. Methods

The dataset was divided in different epochs. Each epoch consists of samples drawn from a time interval where the motor imagery event was being performed. It is used the samples at intervals that started 1s after the appearance of the cue and ended 1s before the disappearance of the cross.

For each time, a band-pass filter with passband between 8Hz and 35Hz filtered the EEG signals. The aim of selecting only the frequency bands within the band μ e β is removing the artifacts of low signal frequency.

After signals filtering, they passed through a removal of EOG artifacts. These artifacts may impair the performance of the feature extraction step, and for this reason, we chose to apply an automatic removal of EOG artifacts immediately before applying the process of feature extraction.

The epoch resulting from each processing step were divided into 2 groups. The first, composed of 72 epochs extracted from the first session, they were used for the classifier training. In addition, the 72 epochs extracted from the second session were used for the classifier validation.

The algorithm chosen to play this role was known as CSP, or Common Spatial Patterns and, in a scenario in which only two classes are considered, we find a transformation which, to be applied over the original signals, makes sure that the temporal variance components is the resulting maximum at intervals corresponding to one of the classes, and minimum at intervals corresponding to another [8].

To use the CSP algorithm in a multiclass scenario, the alternative chosen was to find four arrays, each one taking two classes, the first of them being formed by one of the four classes and the other by all the other classes, in an approach known as "one-against-all" (where the CSP is applied k times, and k the number of classes considered). Each application of CSP results in a set of 22 spatial filters, but only those with the largest and the smaller m eigenvectors are considered. With spatial filters obtained, the next step was to perform the filtering of signals in the windows of training and remove the features to train the classifier. In this way, the features (Z) were obtained from the EEG signals (X) in the following way:

$$f = log_{10}\left(\frac{var\ B^T X}{\sum(var\ B^T X)}\right) \tag{1}$$

where B is an array whose columns are the spatial filters obtained by the CSP algorithm and X is an epoch of filtered EEG signals between 8Hz and 35Hz, whose columns are samples of all channels. The operation $var\ B^T X$ returns the temporal variance of each component in. $B^T X$.

With the feature extraction complete, each window of the EEG was represented by a vector and the set of these vectors were used to train the classifier based on LDA. For the translation module/classification of the features in classes, a classifier based on LDA (Linear Discriminant Analysis) was used.

For a scenario of binary classification, this technique consists in finding a projection w that maximizes the following function:

$$J(w) = \frac{(m1 - m2)^2}{s_1 + s_2} \tag{2}$$

Where mi and si are respectively the mean and standard deviation of the distribution of x examples of class I designed by wTx. There is a closed solution for w, which makes this classifier quick and simple to train, one of the reasons why it was chosen to be used in the translation module. The training of the classifier complete, this was used to classify the 72 windows of the set of validation.

This step of validation performed, where for each example presented the classifier should assign one of the four possible classes. With the results obtained, each class assigned by the classifier was compared with the class to which it really belonged. From these, the table of the rate of correct answers and confusion matrix was assembled.

III. RESULTS AND DISCUSSIONS

Using the processing procedures discussed earlier, the trials for validation of the classifier were performed. In the trials both scenarios were considered: binary and the multiclass, in addition to this, trials with and without the removal of artifacts EOG were performed.

The results obtained in this are referring to the settings using the temporal filter with cutoff frequency of 8 to 35Hz and 10 special filters obtained by means of the CSP, corresponding to 5 major and 5 minor eigenvalues.

TABLE I - Result obtained in the scenario of binary classification without the step of removing artifacts in the EOG.

Accuracy (%)								
Individual	1/2	1/3	**1/4**	**2/3**	**2/4**	**3/4**	**Average**	**Error**
1	88.89	94.44	97.92	97.22	98.61	81.94	93.17	6.55
2	61.80	68.06	75.9	84.03	77.08	75.69	73.72	7.73
3	90.97	91.67	96.53	95.14	97.62	77.78	91.66	7.32
4	73.61	79.17	86.81	87.50	87.50	65.28	79.97	9.13
5	52.78	66.67	66.67	64.58	63.89	56.25	61.80	5.85
6	63.89	61.81	61.81	61.11	60.42	65.28	62.3	1.83
7	87.50	97.82	90.28	97.92	95.83	82.64	92.0	6.25
8	95.54	64.58	89.58	76.39	80.56	75.69	80.39	10.97
9	96.11	91.67	95.14	75.69	72.22	78.47	84.88	10.6
Average	79.01	79.55	84.49	82.17	81.55	73.22	79.99	7.36
Error	16.28	14.53	13.28	13.70	14.42	8.94	12.03	2.77

As observed in Tables I and II, we can perceive that the mechanism of removal of the artifacts did not provide significant improvements in the performance of the classifier. In general, it didn't influence considerably in the hit rate in individuals, however, for some of the individuals the performance was improved, as for the individuals 1, 5 e 6.

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Individual	1/2	1/3	1/4	2/3	2/4	3/4	**Average**	**Error**
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2	61.80	68.06	75.9	84.03	77.08	75.69	73.72	7.73
3	90.97	91.67	96.53	95.14	97.62	77.78	91.66	7.32
4	73.61	79.17	86.81	87.50	87.50	65.28	79.97	9.13
5	52.78	66.67	66.67	64.58	63.89	56.25	61.80	5.85
6	63.89	61.81	61.81	61.11	60.42	65.28	62.3	1.83
7	87.50	97.82	90.28	97.92	95.83	82.64	92.0	6.25
8	95.54	64.58	89.58	76.39	80.56	75.69	80.39	10.97
9	96.11	91.67	95.14	75.69	72.22	78.47	84.88	10.6
Average	79.01	79.55	84.49	82.17	81.55	73.22	79.99	7.36
Error	16.28	14.53	13.28	13.70	14.42	8.94	12.03	2.77

However, this result has influence of sample extraction at intervals where the influence of artifacts were small and after the analysis by experts, the windows with greater contamination of the EOG were discarded

TABLE III - Result obtained in the scenario of multiclass classification with the step of removing artifacts in the EOG.

Accuracy (%)						
Individual	**Left Hand**	**Right Hand**	**Feet**	**Tongue**	**Average**	**Error**
1	90.28	77.78	79.17	70.83	79.51	8.05
2	1.39	19.44	100.0	16.67	34.38	44.46
3	75.00	83.33	52.78	76.39	71.88	13.24
4	36.11	8.33	91.67	29.17	41.32	35.58
5	41.67	26.39	58.33	27.78	38.54	14.89
6	63.89	44.44	25.0	43.06	44.10	15.89
7	83.33	50.0	91.67	83.33	77.08	18.48
8	43.06	52.78	97.22	48.61	60.42	24.86
9	75.00	47.22	95.83	5.56	55.90	39.03
Average	56.64	45.52	76.85	44.60	55.90	23.83
Error	28.40	24.94	25.90	27.48	17.32	12.89

Analyzing the matrices of confusion, we realized that for starters multiclass error rates increase, as shown in table III. In addition, we have that the ICM system presents a greater ease to distinguish the imagination of the movement of the hand with the imagination of the movement of the upper limb in relation with lower limbs and tongue. However, the difficulty of the BMI system to distinguish between the movement of the left and right hands and between the tongue and the foot movement is noticed, as in TABLE IV.

In the experiments carried out, a large variation in performance of the system in accordance with the parameters was noticed. However, there was a better adequacy of certain individuals the specifications applied to the system, such as the cutoff frequency, filters used, etc; or, for certain individuals (for exemple 1, 3, 7 e 9) accuracy were higher than for other considering the system specifications.

TABLE IV - Confusion matrix for the individual 1 multiclass scenario with the step of removing artifacts in the EOG.

	Left Hand	**Right Hand**	**Feet**	**Tongue**	**Accuracy (%)**
Left Hand	65	4	3	0	90.28
Right Hand	14	56	2	0	77.78
Feet	5	0	57	10	79.17
Tongue	2	0	19	51	70.83

IV. CONCLUSIONS

In this article was conducted a study of methods used in applications of brain-Machine Interface. For this purpose, we studied and applied simple techniques that allowed us to obtain satisfactory results that are close to the results obtained in other studies that used the same database of EEG signals, such as, for example, [7].

The variations of system parameters, such as the frequency of cut, were performed empirically in order to adapt and provide a better outcome of performance observed in the rates of correct answers. In the study developed, the processing was carried out offline, with the only purpose of evaluating the performance of algorithms used.

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