Common Spatial Pattern for the Classification of Imagined Geometric Objects

Fabio R. Llorella Costa[1], Gustavo Patow[1] and José M. Azorín[2]
[1]VIRViG, Universitat de Girona, Girona, Spain
[2]BMI-LAB, Universidad Miguel Hernández, Elche, Spain

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Abstract: Electroencephalographic (EEG) signals contain cognitive information, which can be used by Brain-Computer Interface (BCI) systems to control devices through thought. In this work we study the possibility of detecting the visual imagination of seven different geometric objects (triangle, circle, square, pentagon, line, hexagon and parallelogram). The power spectral density in the α band were compared offline with using common spatial pattern (CSP) and the variance of each channel, obtaining as a best result the calculation of the CSP plus variance in the α band and classifying the vector of features with a support vector machine (SVM), obtaining an average result of 52% accuracy and a kappa value of 0.43 in the classification of the seven geometrical shapes, reaching up to 83% and a kappa value of 0.78 for a single user.

1 INTRODUCTION

Classification of electroencephalographic (EEG) signals is not a simple task as they show a great variability in time, that is, they are non-stationary signals (Lo et al., 2009). BCI are non-invasive systems that are ultimately based on the classification of EEG signals. There exist BCI devices that can properly classify EEG signals for the control of different devices (Chen et al., 2015; Abiyev et al., 2016; Edlinger et al., 2011), but the vast majority of works that can be found in the literature use motor imagery or related signals, as the slow cortical potentials (SCP) (Mensh et al., 2004). This limits applications of BCI systems to applications of motor nature, i.e., where motor imagination can play an important role, as could be the movement of a wheelchair or a prosthesis (Ferreira et al., 2010; Galán et al., 2008; Guger et al., 2002). However, there are applications that are difficult to implement and ultimately are unnatural at the time of use.

Another problem encountered by non-invasive BCI systems is that, as EEG signals are difficult to classify, these systems can only discriminate few classes, usually between two and four classes, although it is true that There are studies where this number of classes is overcome using visual evoked potentials (SSVEP) (Song et al., 2017). However, for imagined signals, the four-class limit cannot usually be overcome. In this paper we have chosen to use techniques widely used in motor imagery classification, such as the common spatial pattern, which has offered good results (Wang et al., 2005; DaSalla et al., 2009) and has been used to classify support vector machines, also widely used in the classification of EEG signals (Singla and Haseena, 2013; Mariko and Junichi, 2014; Lotte et al., 2018). To extract the characteristics of the signals, we chose to use the variance of each channel, as it is a fast statistical technique. Currently, there are few works that offer light on how to build a BCI system that takes advantage of the opportunities that visual imagination can offer in the construction of BCI systems for people who have artistic interests or who want to use BCI systems to carry out design or drawing applications. Here we demonstrate the possibility of classifying seven imagined geometric objects with a high degree of accuracy. Being simple geometric objects, these can be used for the creation of a BCI system such as computer-aided design.

2 METHODS

2.1 Subjects

Three subjects (two female and one male) between 24 and 40 years of age, participated in this study. All sub-

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jects were right-handed and and they have not vision problems or neurological disorders. The experiment had the informed consent of the people.

2.2 Material

In this study, the *g.Nautilus* device of *g.tec* was used. The device consists of eight wet electrodes at a sampling rate of 250 Hz. We used the international 10-10 system to place the electrodes on the scalp. The electrodes used were: Oz, P3, POz, P4, PO7, PO4, PO3 and PO8, with AFz used as reference. We have used these electrodes because they are located in the occipital area, an area linked to vision and because other studies identified electrodes P4, PO4, PO3 and PO7 as good to classify signals coming from visual imagination (Bobrov et al., 2011). At the time of registering the impedance of the electrodes was below $10k\Omega$.

2.3 Experimental Paradigm

The paradigm used lasts a total of eight seconds. During the first second, a white cross is shown on a black background, indicating the start of the trial. The next two seconds show the geometric figure that the person must imagine, and in the last five the black screen appears and is left. This is when the person must imagine the figure that has been previously shown. The order the figures appear on the screen is random, so the user does not know what figure will appear and thus cannot anticipate it. This procedure is performed 20 times (14 trials each). Once the trials have been registered, the person makes a short break and re-registers other 14 trials, making a total of 280 trials (40 trials per geometric figure). The OpenVibe software was used to program of the paradigm, because it offers a simple and quick way to create these paradigms.

3 PROCESSING PIPELINE

In all BCI systems, there are differentiated phases, the first phase always being the pre-processing of the EEG signals, where the EEG signals are conditioned for the following phases. In this pre-processing, EEG signals are usually partitioned into pieces to be filtered in the frequency range and spatial filters are applied to eliminate the artifacts that they may contain.

The next phase is feature extraction. Features must contain the necessary information to be able to differentiate between the different classes that we want to classify.

The last phase is the classification, which will be responsible for associating the different feature vectors with the corresponding cognitive activity. In this work, we have used common spatial pattern, together with the variance of each component of the common spatial pattern in the feature extraction phase (Ramoser et al., 2000).

3.1 Data Processing

While the signals were being recorded, they were filtered by the hardware of the g.Nautilus device between 0.01 and 60 Hz with a pass banda filter, the order of the filter was six, and then a Notch filter between 48 and 52 Hz was also applied. Once the EEG signals were registered, they were partitioned into fragments of a second without overlapping, omitting the first second of the imagination task. Once the trials were partitioned, they were filtered in the α band, between 8 and 12 Hz (this band is important in visual imagery (Bobrov et al., 2011)) using a butterworth band pass filter of order six. All the processing of the EEG signals was done offline using MATLAB R2016a (Matlab, 2016).

3.2 Common Spatial Pattern

The CSP is a special filter that aims to maximize the variance between two different classes. Although this algorithm is usually applied between two classes, it can be extended to an arbitrary number N of classes. The objective of the CSP filter is to return a transformation matrix W with respect to a group of EEG data matrices X_i. The first step is to calculate the normalized spatial covariance matrices of X_i where i is the type of class being analyzed.

$$R_i = \frac{X_i X_i^T}{trace(X_i X_i^T)} \tag{1}$$

where T is the transpose operator and $trace$ is the sum of the diagonal elements.

Next, it is necessary create the covariance matrix.

$$R_c = \sum_{i=1}^{N} R_i \tag{2}$$

where N is the number of classes. Here, we used $N = 7$. The corresponding matrices of eigenvectors are:

$$R_i = V \lambda V^T \tag{3}$$

where V is the diagonal matrix of eigenvalues. Finally, W is constructed as:

$$Q = V \sqrt{\lambda^{-1}} \tag{4}$$

$$W = (V^T * Q)^T \tag{5}$$

To create the feature vector, we must transform the signals in the following way:

$$Z_i = W * X_i \tag{6}$$

where x_i is the set that contains the signals EEG that belong to class i. Finally is necessary calculate the variance for each component of Z_i:

$$f_i = log\,(var(Z_i(j)) \tag{7}$$

where j is the number of channels.

With this method we build feature vectors of dimension equal to the number of channels of the EEG signals. The advantage that this procedure has is that it creates small vectors and therefore does not need many trials to train the classifier, because if the size of feature vectors is very large, more trials will be needed (Trunk, 1979).

3.3 Classification

The last stage of the BCI systems is usually the classification of the vector of features that we have generated. Nowadays there are several types of classifiers that have been proven to be useful when classifying EEG signals, but one of the most used are the support vector machines (SVM). This type of classifier tries to identify the optimal hyperplane to separate the different classes, although currently we can find linear or non-linear SVMs: the difference lies in that, in the non-linear SVMs case, the data is mapped into higher dimensionality using a kernel function. This process is known as "implicit mapping" (DaSalla et al., 2007). In this work, we had used a Radial Basis Functions (RBF) (Teukolsky and Vetterling, 2007), the form of this kernel is show below:

$$K(x,x') = e^{-\gamma||x-x'||^2} \tag{8}$$

$$\gamma = \frac{1}{2\sigma^2} \tag{9}$$

where K is a kernel function of support vectors x and σ is a free parameter.

The classification has been done offline, using the k-fold cross validation algorithm. Data is partitioned into k groups, where $k-1$ groups are used to create the model (called *train*) and one group to test it (called *test*). Finally, all the results are averaged and the final accuracy is calculated. This process is intended to eliminate overfitting when training the classifier. In this work we used $k = 5$.

4 RESULTS

The results in Figure 1 were obtained by applying and without applying the CSP algorithm before calculating the variance of the channels. When the CSP was not applied, we calculated only the time variance of the EEG signal channels.

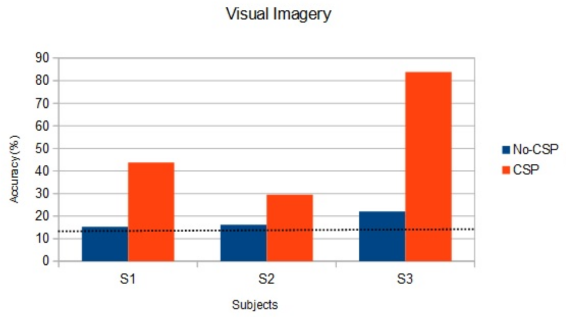

Figure 1: Result of applying CSP (orange) and without applying CSP (blue), the dotted line indicates value for a random selection.

It can be seen that applying the CSP algorithm results in more significant results than without applying it, obtaining a mean accuracy of 52% with CSP and 18% without applying CSP. The subject S3 is the best one, with an 83% of accuracy and a 0.78 kappa value. The accuracy of the subject S2 is the 30% and 0.20 kappa value, which is the lowest accuracy. It should be noted that in all three users the results are higher than we would expect if selections were random.

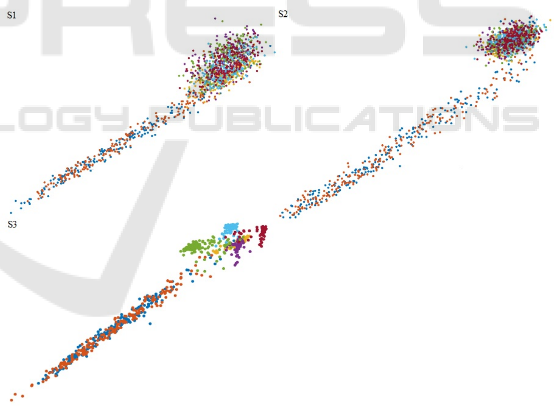

Figure 2: Distribution of the features depending on the geometric object. Dark blue: Triangle, Orange: Circle, Yellow: Square, Lilac: Trapeze, Green: Line, Light blue: Hexagon, Red: Parallelogram.

In Figure 2 we can see the distribution of the features according to each user, where the y axis is the P3 channel and the x axis is the PO4. These two channels seem to be the most appropriate to differentiate the geometric objects imagined. Subject 3 (S3) is where the accuracy of the classification is greater: in this subject it can be observed that the Pentagon, line, hexagon and parallelogram objects have a high separability rate, hence the accuracy is much higher than that of the rest of users. This can be attributed to the level of concentration of the user at the time of doing the test, or that the user has more facility to visualize imagined objects.

5 CONCLUSIONS

In this work we have demonstrated the possibility of using visual imagination for the construction of BCI systems, specifically using the imagination of simple geometrical figures. A methodology for this task has also been presented using the CSP filter together with the calculation of the variance of the transformations made with the CSP filter.

As future work it would be interesting to register more people, study what frequency range and which electrodes are better to perform the classification of the geometrical figures, and study the impact of the different geometrical shapes in the classification.

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