DEVELOPMENT OF A LOW-COST SVM-BASED SPONTANEOUS BRAIN-COMPUTER INTERFACE

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Abstract: This paper describes a spontaneous non-invasive Brain-Computer Interface (BCI) using an inexpensive EEG device. The aim of this work is to determine the feasibility of using the Emotiv Epoc device in a BCI. BCIs provide a method for interaction with a computer for people with severe communication disabilities. The EEG signals of five healthy users have been registered and preprocessed. The Fast Fourier Transform (FFT) has been used to extract the relevant characteristics of the EEG signals. Frequency spectrum between 8 Hz - 30 Hz has been calculated. An offline analysis to the recorded data has been performed using a Support Vector Machine (SVM) as a classification algorithm in order to differentiate three and four mental tasks. Results of up to 71% classification accuracy for three tasks and 64% classification accuracy for four tasks were obtained, showing that the Emotiv Epoc is suitable to be used in a Brain-Computer Interface.

1 INTRODUCTION

A Brain-Computer Interface (BCI) provides a communication and control system that does not depend on the brain's normal neuromuscular output channels (Wolpaw, et al., 2002). A BCI is based on the use of the mental activity of a person to generate control commands in a device (Dornhege, et al., 2007). For this purpose, the brain activity of the user has to be registered and processed appropriately in order to distinguish between different cognitive processes or "mental tasks".

BCIs are an alternative to classical methods of human-machine communication, like a keyboard or a mouse. For that reason, this kind of interfaces are very useful for people with severe communication disabilities. BCIs have been used in different applications, from the control of a wheelchair (Galán, et al., 2008) to the control of a smart home (Guger, et al., 2008).

Brain activity can be registered in several ways, using invasive and non-invasive techniques. Using invasive techniques, the activity of a single neuron or a small group of neurons can be registered with microelectrodes arrays implanted directly in the brain. These techniques have been used to determine the intention of movements in animals (Carmena, et al., 2003) or to control a cursor on a screen (Serruya, et al., 2002). Non-invasive techniques use electrodes on the scalp to measure the EEG signals. For humans, non-invasive techniques based on EEG signals are more appropriate due to ethical aspects and medical risks.

Non-invasive BCIs can be classified as evoked or spontaneous. In an evoked BCI, the registered signals evidence the automatic response of the brain to certain external stimuli (Bayliss, 2003; Sirvent, et al., 2010). Nevertheless, the need for external stimuli limits the number of applications. In contrast, in a spontaneous BCI, the user performs the mental tasks of his/her own free will (Iáñez, et al., 2010).

Once the EEG signals have been registered, they have to be processed and filtered, and a classification has to be done in order to differentiate between the cognitive processes.

Table 1: Inexpensive EEG devices.

Price Range	Device	Channels
0€ - 200€	Neurosky MindWave Modular EEG OCZ Technology NIA	1 2-6 3
200€ - 500€	Emotiv Epoc	14
500€ - 1.000€	Neurobit Optima Neurobics Pendant EEG	2-4 2

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Figure 1: Sensor placement of the 14 data channels in the Emotiv Epoc, according to the 10/20 International System (left). Emotiv Epoc (centre). User with the Emotiv Epoc (right).

Different classification algorithms has been used in BCI experiments (Bashashati, Fatourechi, Ward and Birch, 2007). Among several of them, like Linear Discriminant Analysis (LDA) and Neural Networks (NN), Support Vector Machines (SVM) provide a powerful method for data classification (Garrett, Peterson, Anderson and Thaut, 2003). In this project, a SVM has been used as a classification algorithm.

Nowadays, several low-cost EEG devices are available for the consumer. They have a very affordable price by comparison with the professional EEG systems, whose prices vary between 10.000€ and 150.000€. Table 1 presents a list of inexpensive EEG devices. The Emotiv Epoc has been chosen in this experiment.

In recent years, there has been an increasing amount of literature on inexpensive BCI. The Emotiv Epoc device have been used from the control of a mobile phone (Campbell, et al., 2010) to the control of a car without using a steering wheel (AutoNOMOS project Freie Universität Berlin, 2011).

This paper describes a spontaneous non-invasive EEG-based Brain-Computer Interface using the Emotiv Epoc device. The BCI developed uses the Fast Fourier Transform (FFT) to extract the relevants characteristics of the EEG signals. The results of five voluntary users will be obtained using a Support Vector Machine (SVM) as a classification algorithm to differentiate between mental tasks. The aim of this experiment is to check the feasibility of using an inexpensive EEG device in a Brain-Computer Interface.

The rest of this paper is organized as follows. Section 2 describes the Brain-Computer Interface developed and the classifier used is introduced. In section 3, the experimental results are shown. Finally, Section 4 contains the conclusions.

2 BRAIN-COMPUTER INTERFACE

In this section, the Emotiv Epoc device is introduced. The procedure followed to register the EEG signals and to extract the relevant features of the signals is explained. The classifier used in this experiment is presented.

2.1 EEG Hardware

The EEG signals have been registered using the Emotiv Epoc headset (Figure 1, centre), released by the Emotiv Company (Emotiv Systems, 2011).

Emotiv Epoc is a wireless device composed of 14 channels and 2 reference electrodes, located according to the 10/20 International System (American Electroencephalographic Society, 1991) in the positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. CMS/DRL reference electrodes are located in the positions P3/P4 (Figure 1, left). Each electrode has to be moistened with a saline solution before being used. Once the device is placed on the scalp (Figure 1, right), the signal quality of the electrodes has to be checked. It has been seen that the signal quality decreases when the electrodes get dry.

The Emotiv Epoc device does not provide the impedance level of each channel. Instead, the contact quality of each sensor is represented by a colour code: Black – No signal; Red – Very poor signal; Orange – Poor signal; Yellow – Fair signal; Green – Good signal. This connection quality has to be checked from within the Emotiv Control Panel.

The headset transmits the EEG signals wirelessly to a Windows-based computer in the frequency of 2.4 GHz. The signals are filtered on the device

Table 2: Mental tasks.

Number	Name	Description
1	Rest	Countdown from 20 to 0
2	Arm	Imagination of a repetitive low circular movement of the right arm
3	Song	Mentally singing the “Happy Birthday” song
4	Math	Mentally performing the Fibonacci series
5	Object	Mentally rotating an object

before amplifying the data. A high-pass filter at 0.16 Hz cut-off frequency and a low-pass filter at 83 Hz are applied. The internal sampling rate is 2.048 Hz. Then, the data are filtered with a 5th order Sinc filter to notch out the 50 Hz and 60 Hz frequencies, and downsampled to 128 Hz.

2.2 Mental Tasks

Five cognitive processes or mental tasks have been considered in the experiment. These mental tasks have been taken into consideration due to the placement of the electrodes in the Emotiv Epoc. Table 2 shows the mental tasks considered.

2.3 Acquisition

A Matlab interface has been developed to register the EEG signals. The interface gives us options to connect and disconnect with the device, select the configuration of the test, and start/stop the test. The process used to register the data is as follows.

Each test is comprised of 25 trials, lasts 250 seconds and is repeated 4 times. There is a short pause between tests. Once the test is started, the mental tasks that the user has to perform are displayed. Each of the five tasks is showed randomly 5 times, and lasts 10 seconds (Figure 2). In the first 2 seconds, a cross appears to indicate the user that a new task is started; in the following 2 seconds, the image of the mental task to perform is displayed; in the last 6 seconds, the user performs the mental task. Once the test is finished, 120 seconds of each task have been recorded. A similar timing paradigm as the one described in (Guger, et al., 2001) is used to register the data.

Using the Emotiv Control Panel, it has been checked that the signal quality of each electrode was always good (green colour).

EEG signals were acquired at a sample frequency of 128 Hz. The EEG signals registered are processed in sequences of 1 second of length, including an overlap of 1/8 a second with the previous sequence. Once the data are recorded, they are preprocessed and a feature extraction algorithm is applied.

2.4 Feature Extraction

Before extracting the main characteristics of the registered data, a preprocessing has been applied to the signals. The DC offset in all channels is removed. Afterwards, the baseline of each electrode is removed, eliminating the mean value of the signal registered by each electrode. In this preprocessing, all 14 electrodes have been used.

Following this, a feature extraction algorithm is applied to the data in order to extract the main characteristics of the EEG signals, to facilitate the posterior classification. The algorithm used is based on the frequency domain. The Fast Fourier Transform (FFT) has been used to extract the relevant characteristics of the EEG signals. The frequency spectrum between 8 Hz and 30 Hz, with 2 Hz resolution (12 features), has been calculated in order to analyze the rhythmic activity variations. All the mental tasks are expected to be found in the EEG signals in the alpha (8 Hz – 12 Hz) and beta waves (12 Hz – 30 Hz). Each feature vector consists of 168 elements (12 features x 14 electrodes), obtaining 960 feature vectors by user.

Finally, a Surface Laplacian is applied in order to improve the signal/noise ratio in each electrode (Babiloni, et al., 2001).

2.5 Classifier

A Support Vector Machine (SVM) has been used in this experiment as a classification algorithm. SVMs are a very useful technique for data classification (Hsu, Chang and Lin, 2003). It uses a hyperplane or set of hyperplanes in a high or infinite dimensional space to distinguish between object of different classes.

A classification task usually consists in separating data into trainings and testing sets. Each instance

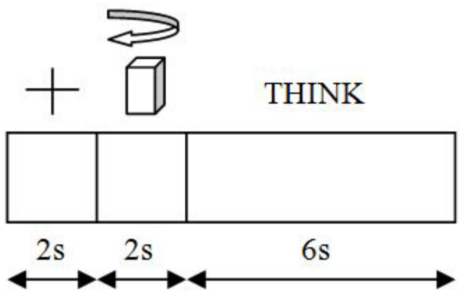

Figure 2: Time distribution of each task.

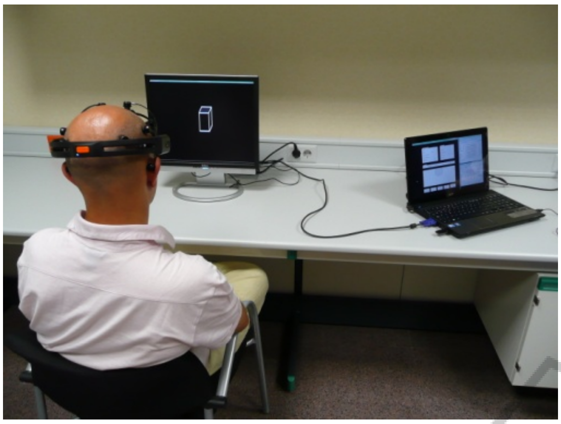

Figure 3: Image of a user performing the test.

in the training set contains a class label and several features. The aim of SVM is to create a model, based on the training data, which predicts the class labels of the test data given its features.

The accuracy of the SVM depends on the selection of the kernel type and the values of its parameters. In a Brain-Computer Interface project, the kernel generally used is the Gaussian or Radial Basis Function (RBF) kernel (Lotte, et al., 2007).

There are two parameters for an RBF kernel, the regularization parameter C and the parameter γ, which determines the RBF width. It is not known which C and γ are best for a specific problem. For that reason, some kind of parameter search has to be done. The aim of this search is to identify C and γ values so that the classifier can accurately predict the testing data. The best combination of C and γ is often selected by a grid-search using cross-validation with exponentially growing sequences of C and γ. The one with the best cross-validation accuracy will be selected.

3 EXPERIMENTAL RESULTS

In this section, the experimental results obtained are showed. The offline analysis performed to the registered data of five users is explained, using SVM as a classification algorithm.

3.1 Participants

For the experiment, the participation of five healthy right-handed male users with ages between 26 and 40 years old has been required. After informing the users of the requirements and tests involved, the volunteers agreed and gave their consent to take part in the tests. All users had normal vision and hearing, and no history of neurological or psychiatric disorders. All tests were done in an isolated room with the user sitting in front of a PC screen at a distance of 1 meter (Figure 3).

3.2 SVM Classification

An offline analysis has been done to the registered data. For this purpose, a Matlab application has been developed.

The results of five users have been calculated. Users 4 and 5 had not been previously involved in any BCI experiment. For every user, all the possible combinations of three and four tasks have been calculated. For each combination of tasks, data may be randomly extracted and separated into training data and test data. 75% of the data has been used as a training data, whereas the rest 25% is used as a test data.

As a classification algorithm, the Matlab interface of LIBSVM 2.9 library has been used (Chang and Lin, 2001). LIBSVM, developed by the National Taiwan University, is a free integrated software for Support Vector classification, regression, and distribution estimation. Features of LIBSVM include, among many other, multi-class classification, different SVM formulations and various type of kernels.

In this BCI experiment, a C-SVM with a Radial Basis Function (RBF) kernel has been used. To identify C and γ parameters values so that the classifier can more accurately predict the testing data, a grid-search using cross-validation with exponentially growing sequences of C (between 2^{-3} and 2^{12}) and γ (between 2^{-13} and 2^{1}) has been perform. For the classification of three tasks, values of C=512 and γ=0.0020 present the best results. Classifying four tasks, values of C=1.024 and γ=0.0020 have been selected.

Input values to the SVM were not normalized, because normalization did not improve the classification results.

3.3 Results

For each user and combination of three and four tasks, the mean value of the accuracy achieved after 10 iterations of the application has been calculated, in order to determine more accurately the success percentage in the classification. Average percentage of success for every set of tasks and user has been calculated. Tables 3 and 4 show the results obtained from the classification of three and four different tasks.

Table 3: Percentage of correct classification using 3 mental tasks.

Tasks	User 1	User 2	User 3	User 4	User 5	**Average**
Rest – Arm – Song	66.80	67.57	73.39	67.96	63.12	**67.77**
Rest – Arm – Math	74.08	72.80	72.78	67.55	67.18	**70.88**
Rest – Arm – Object	67.75	68.90	76.35	66.34	66.91	**69.25**
Rest – Song – Math	66.40	70.07	72.80	67.79	62.44	**67.90**
Rest – Song – Object	65.30	67.73	78.46	66.55	64.30	**68.47**
Rest – Math – Object	73.88	71.05	78.30	66.69	68.58	**71.70**
Arm – Song – Math	73.50	71.75	72.58	67.59	66.10	**70.31**
Arm –Song – Object	69.95	67.91	75.96	67.91	66.37	**69.62**
Arm – Math – Object	72.13	74.32	75.39	67.10	68.53	**71.49**
Song – Math – Object	71.83	71.21	76.35	68.05	66.86	**70.86**
Average	**70.16**	**70.33**	**75.24**	**67.35**	**66.04**	

Table 4: Percentage of correct classification using 4 mental tasks.

Tasks	User 1	User 2	User 3	User 4	User 5	**Average**
Rest – Arm – Song – Math	63.78	64.84	66.70	61.28	58.75	**63.07**
Rest – Arm – Song – Object	60.06	61.47	70.12	60.90	57.78	**62.07**
Rest – Arm – Math – Object	66.15	64.93	69.84	61.30	61.04	**64.65**
Rest – Song – Math – Object	62.38	63.45	70.57	61.38	58.60	**62.28**
Arm – Song – Math – Object	65.70	65.34	69.13	61.08	60.44	**64.34**
Average	**63.62**	**64.01**	**69.27**	**61.19**	**59.32**	

On average, involving both three and four tasks, user number 3 has achieved the best results. It is noted that user number 3 was the one with more experience in BCI experiments. In contrast, users 4 and 5, with no previous experience in BCI experiments, have obtained a low success percentage. This may probe that the more experience you have in BCI experiments, the better results you will obtain. Figure 4 shows the average accuracy of each user.

As regards sets of three tasks, the combination between the task “Rest – Math – Object” presents the greatest accuracy, with a 71.70%. As for sets of four tasks, the best results are classifying the tasks “Rest – Arm – Math – Object”, with a 64.65% of success. These combination of three and four tasks can be used as cognitive processes to classify in future works.

Furthermore, with the aim of obtaining more information in the classification, tables 5 and 6 show the average success percentage obtained by 5 users on each task, for each combination of three and four tasks. Results show that the task “Rest” has the greatest success percentage (77.16% using 3 tasks and 72.28% using 4 tasks) and the task “Math” has the second best success percentage (69.72% using 3 tasks and 62.77% using 4 tasks). This is reflected in the results showed in tables 3 and 4, where the combination of tasks that achieves the best results include these 2 tasks.

All results obtained indicate that an SVM classification together with the Emotiv Epoc as a register device can be used in a Brain-Computer Interface.

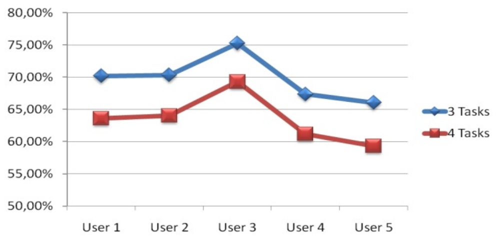

Figure 4: Average accuracy of each user.

4 CONCLUSIONS AND FUTURE WORK

A spontaneous non-invasive Brain-Computer Interface has been proposed. Using the Emotiv Epoc device to register the EEG signals, this BCI allows performing the classification of mental tasks. The feature extraction process using Fast Fourier Transform and the subsequent classification using a Support Vector Machine has been explained.

Results obtained in the classification have been showed. Success percentage for three and four tasks

Table 5: Average success percentage by 5 users on each task using 3 mental tasks.

Tasks	Rest	Arm	Song	Math	Object
Rest – Arm – Song	75.02	64.48	60.83	-	-
Rest – Arm – Math	76.76	64.70	-	67.86	-
Rest – Arm – Object	80.44	62.28	-	-	63.67
Rest – Song – Math	76.19	-	58.60	66.54	-
Rest – Song – Object	77.09	-	60.07	-	66.44
Rest – Math – Object	77.48	-	-	68.53	67.35
Arm – Song – Math	-	67.66	73.71	68.93	-
Arm –Song – Object	-	65.69	77.35	-	65.09
Arm – Math – Object	-	67.04	-	76.39	68.49
Song – Math – Object	-	-	73.86	70.05	66.86
Average	**77.16**	**65.31**	**67.40**	**69.72**	**66.32**

Table 6: Average success percentage by 5 users on each task using 4 mental tasks.

Tasks	Rest	Arm	Song	Math	Object
Rest – Arm – Song – Math	71.83	60.10	53.46	62.02	-
Rest – Arm – Song – Object	73.03	58.24	54.28	-	57.70
Rest – Arm – Math – Object	73.24	58.27	-	63.01	58.31
Rest – Song – Math – Object	71.01	-	53.81	62.13	61.70
Arm – Song – Math – Object	-	59.54	69.10	63.92	59.31
Average	**72.28**	**59.04**	**57.66**	**62.77**	**59.26**

indicates that the Emotiv Epoc is suitable to be used in a Brain-Computer Interface. As a future work, the implementation of an online application has been proposed. Also, is expected to perform different tests using volunteers with disabilities. In order to compare results and verify if there is any performance loss due to the Emotiv Epoc device, it is expected to test the same experiments with a high-quality research-oriented EEG system (gUSBamp g.tec). Finally, the use of a new set of tasks (for example, new motor tasks, tongue movement, mental calculation or word formation) are suggested, as well as the use of new classification algorithms.

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