Low Cost Implementation of a Motor Imagery Experiment with BCI system and its use in neurorehabilitation

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Abstract— **the application of rehabilitation programs based on videogames with brain-computer interfaces (BCI) allows to provide feedback to the user with the expectation of stimulate the brain plasticity that will restore the motor control. The use of specific mental strategies such as Motor Imagery (MI) in neuroscientific experiments with BCI systems often requires the acquisition of sophisticated interfaces and specialized software for execution, which usually have a high implementation costs. We present a combination of low-cost hardware and open-source software for the implementation of videogame based on virtual reality with MI and its potential use as neurotherapy for stroke patients. Three machine learning algorithms for the BCI signals classification are shown: LDA (Linear Discriminant Analysis) and two Support Vector Machines (SVM) in order to determine which task of MI is being performed by the user in a particular moment of the experiment. All classification algorithms was evaluated in 8 healthy subjects, the average accuracy of the best classifier was 96.7%, which shows that it is possible to carry out serious neuroscientific experiments with MI using low-cost BCI systems and achieve comparable accuracies with more sophisticated and expensive devices.**

I. INTRODUCTION

The brain-computer interfaces (BCI) allow a wide spectrum of applications in both people with any disability condition as for completely healthy people. The interaction between the user and the BCI system does not occur arbitrarily: a series of signals generated by the specific mental task execution can be collected, processed and classified in order to build applications that can be neurocontrolled. To this end, the implementation of multiple signal processing and machine learning techniques to optimize the interaction processes by creating reliable protocols for conducting the online experiments is needed [1]. Motor Imagery (MI) is one specific mental strategy for BCI and the classification of different mental tasks used in this strategy is often a problem that requires the implementation of machine learning techniques in order to optimize the interaction between the user and a specific application [2]. It is believed that the MI, specifically in upper limbs can be registered mainly in two particular electrodes: C3 and C4 located in the motor cortex (follow the EEG 10-20 standard) [3]; however some researchers have demonstrated that this condition is user-dependent and only use the information from these electrodes could result in significant data loss for a BCI experiment with MI [4], [5]. Due to the commercial low-cost BCI systems often do not include the C3 and C4 electrodes; there are few investigations that use these sensors for the MI experiments, because the non-inclusion of these electrodes is often synonym of low accuracies in the final result of the classifier. Therefore, applications that use BCI systems with MI as mental strategy, usually require not only expensive interfaces (due to the amount of required electrodes), but also of a substantial investment in specialized software, limiting the use of the BCI systems [6]. Multiple BCI commercial systems exist in the market, which have being widely used for applications as videogames [7], multimedia applications and assistive devices [2]. One of the most used is the Emotiv EPOC, which is a neuroheadset composed by 14 electrodes distributed in the 4 lobules [8], this device has been successfully used to design applications in emotion recognition [1] and selective attention through visual stimulus such as steady state visual evoked potentials (SSVEP) [9]. However, since the sensor has not electrodes C3 and C4 located in the motor cortex where the movements are prepared, has not been used with success in experiments with MI [10]. Now, despite the variety of available software platforms to handling of electroencephalographic (EEG) signal from the BCI systems, only a few are open-source and contains the required tools for developing applications based on virtual reality [11] such as OpenViBe, an open-source software platform for the design, implementation and analysis of neuroscientific experiments based on BCI systems. The software consists of a set of modules that can be integrated with certain facility and efficiency to develop BCI functional applications, especially those that are combined with virtual reality systems [12]. There are four features that make OpenViBe an integrated platform for development neuroscientific experiments with BCI systems: a) modularity and reusability, b) user diversity, c) portability, d) virtual reality systems connectivity. This software has been previously used for EEG signal monitoring during a videogame intervention [13], BCI videogames based on virtual reality [12] and for the wheelchair control [10].

This paper proposes the use of a commercial BCI system, the Emotiv EPOC and the open source software OpenViBe for the MI-based experiment implementation and its potential use in neurorehabilitation therapies with stroke patients using virtual reality videogames. Recently, has been found that the use of rehabilitation therapies based on MI with BCI systems in stroke patients can induce significant changes in neural plasticity due to the use of feedback strategies with immersive virtual environments [14]. These therapies have some advantages in comparison with other techniques such as high temporal resolution of the signal, the

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portability of equipment, the non-invasive nature of the intervention and finally the fun component that have the specialized serious videogames for health [13]. In addition, the paper describes the support vector machines use, specifically the Nu-SVC [15] for two MI patterns classification: right and left hand movement imagination.

II. Neuromodulation with BCI Systems for Motor Rehabilitation

After stroke or brain injury, a large number of subjects do not regain the normal gait characteristics or the natural movements of the limbs. Some interventions use exercises for upper and lower limbs with the expectation of restore the motor control through of activity-dependent neuronal plasticity, which is widely bound with the synaptic connection changes in response to the external stimulus, generally correlated with the motor activity. The plasticity that has the central nervous system (CNS) has been documented by a large number of scientists as functional and structural adaptation of the neuronal mechanisms for learning new information and acquiring new skills [16]. This plasticity can involve modifications in the neuronal synaptic intensity in both brain and spinal cord, as fact the plasticity is the basis in which the cognitive and motor skills are acquired. After stroke, we can generate an extensive plasticity in the cortex and in other neural structures according to animal and human models [16]. BCI systems-based approaches could perform direct neurophysiological measures (i.e. EEG) to provide feedback to the user with the expectation that stimulate the brain plasticity that will restore the motor control [2]. The neurofeedback use can improve the cerebral function restoration and therefore the motor function [17]. The investigations point to three horizons: the identification of practice motor tasks that can produce a brain signal that can be used in rehabilitation, identifying the characteristics of brain signal that can be used in rehabilitation and the practicality (ease of use and precision) of the training session with BCI systems. For stroke patient survivors, the use of the BCI systems can help to improve the performance in the motor learning and the recovery of motor function, the use of specific mental strategies such as MI can serve as therapy for the retraining of the lost functions. [14].

III. BCI Application Scenarios

A. Acquisition Scenario

In this scenario we recollect the data coming from the user training. Once connected the Emotiv EPOC to the OpenViBe server, we add the channel selection box in where we enlist the set of channels used for the experiment, in this case are F3, F4, FC5, FC6, AF3, AF4, F7 and F8, which are the nearest electrodes to the motor and premotor cortex. The stimulation parameters are defined through the Graz Motor Imagery BCI standard [18], which contains the configuration of the quantity of samples per class, the labels for each class and duration time for visual feedback (the selected configuration was 20 samples per class for all the classifiers, two MI classes and feedback duration of 3.750 seconds). The outputs are connected to visualization box, which allow showing the visual stimulus; in this case, we use left and right arrows to generate the motor imagery tasks (left and right hand movement). The acquisition time is scheduled to take approximately time of 7-8 minutes (the first 30 seconds is signal without stimulus, in the second 33 the first stimulus appears and thereafter, every 11 seconds a random stimulus is represented until all 20 samples for each class).

B. Feature Extraction Scenario

The particular task observation (as imagining the hand movement) produce in the BCI systems a specific effect in the brain signals called Event Related Synchronization/ Desynchronization (ERS/ERD) in the electrodes that are close to neuromotor cortex. A powerful and widely used technique for the signal feature extraction in the BCI-EEG systems is the Common Spatial Patterns (CSP) [2]. The CSP analysis produces spatial filters that are optimal in terms of extracting the signals that are more discriminant between two conditions. The algorithm allows the identification of spatial filters that maximize the signal variance of one condition and at the same time minimize the signal variance with the other condition [19]. In the second scenario, we applied the CSP technique in order to extract the spatial filters for the training session signals, which are filtered in the bands related to the oscillatory rhythms Alfa and Beta (8 Hz- 30 Hz) where ERS/ERD are produced and after specific settings of the EEG epochs (segments) are performed. For this experiment we use an eight-order CSP filter which allows attributing to each of the eight channels, the best spatial components that maximize the difference between each class of MI. The result is a file that has the spatial filter configuration that will be used for classifier training and to carry out the online classification.

C. Classifier Training Scenario

This scenario is designed to training the classification algorithm using the training data and the CSP spatial filter obtained in the past scenario. The box *Time Based Epoching* allow to provide epochs in where their specific lengths can be configured, for this case the signal is split into blocks of 1 second with 0.125 seconds of interval (EPOC sample frequency 128 Hz and the block size is 16 samples. 16/128=0.125). This is performed in order to improve the computation of Power Spectrum Density (PSD), otherwise the spectrum would be coarse or rough; after this feature is added as a feature to the classifier. Then the classifier training is performed using the *Classifier Trainer* box which can be set to train LDA (Linear Discriminant Analysis) or SVM (Support Vector Machine) classifiers. For this work we performed probes using three classifiers in order: the LDA, the classical version of support vector machines called C-SVC with a lineal Kernel and a modified version of support vector machines called Nu Support vector Classification (Nu-SVC), which adds the Nu parameter that allow a control of the number of support vectors and margin errors. The parameter ν (0,1] is an upper bound on the fraction of margin errors to the training and a lower bound on the fraction of SVs. The cost function is:

$$J(w,\xi) = \frac{1}{2}\|w\|^2 - \nu\rho + \frac{1}{l}\sum_{i=1}^{l}\xi_i \quad (1)$$

Constraints:

$$y_i(w^T x_i + b) \geq \rho - \xi_i,\ \xi_i \geq 0, \forall_i = 1,\dots,l.\ \ \rho \geq 0 \quad (2)$$

Using the RBF Kernel:

$$K(x_i,x_j) = \exp\left(-\gamma\|x_i - x_j\|^2\right), \quad \gamma > 0 \quad (3)$$

From (1) ν ϵ (0,1] is a preselected parameter, l is the number of the training points and ρ is a margin parameter. The parameter *w* is a term the characterizes the model complexity and ξ is the EEG data. The Nu parameter was tuned to obtain the best classifier result. This parameter indicates a lower bound of the number of support vectors to use, given as a fraction of all calibration samples and a lower bound on the fraction of training samples that are errors (poorly predicted). Also, we applied the RBF (Radial Basis Function or Gaussian) Kernel that improves significantly la classifier accuracy of nu-SVC over the linear Kernel applied over the C-SVC classifier. The γ in the RBF-SVM allow to control the hiperplane separation shape, whereby the increase of this parameter usually increase the number of supported vectors; for this experiment we γ = 100. The result of this scenario is a configuration file of the trainer, which contains the algorithm parameters that will be used for the online classification carried out in the last scenario. To evaluate the best classifier is used cross-validation (K-fold Test) with 5 iterations, this parameter allow the computation of the accuracy of the classifier and prints it on console.

D. Online Classification Scenario

Finally, in this scenario we perform the online classification of MI tasks trained with the user. For this we loaded the obtain files in the previous scenarios (CSP filter training and classifier training). The signals are captured and the chosen channels are exactly the same used in the training user stage. For the use of the SVMs is necessary add a *Simple DSP* box that allow to move the signal through the x-0.5 function for the output values of the classifier are between 0 and 1. Once again the *Graz Stimulator* is used in order to provide feedback to the user in the online session. Since this scenario we perform the communication with any extern application, in this case, the videogame engine Unity for the communication with the virtual reality activity.

IV. Results

We carried out the experiment with eight young university students of masculine genre. Each user was instructed with the experiment routine just before to start. The interventions were performed always at morning (8:00 am. – 9:00 am.) in order to avoid accumulated stress factors or excessive sweating, also the users were asked to sleep well the night before in order to reduce problems with states of drowsiness during the operation of the experiment. Lastly the user was placed in front of the screen to start the training session. For each user, it was evaluated three classifiers: LDA, C-SVC with lineal Kernel and Nu-SVC with RBF Kernel. The figure 1 show a time-frequency map calculated of one user during a specific MI task, the maps cover the filtered frequency range (8 Hz- 30 Hz) and are performed over FC5 and FC6 electrodes in where we found the best latency of ERD/ERS neuromechanisms.

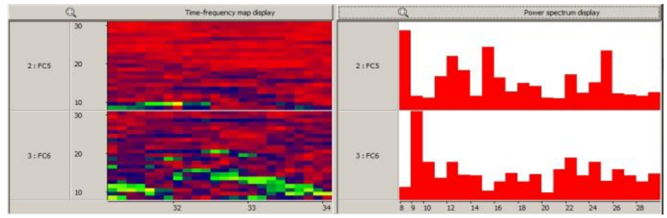

Figure 1. Spectrogram of a subject 1 in a motor imagery task

The captures are performed in one of the moments in which the user is exposed to MI training stimuli in a range of 4 seconds (in order to take a couple of seconds before). Finally the classification results for each user with each of the classifiers used for MI mental strategy are presented. The NU-SVC behavior with the RBF Kernel shows an outstanding performance over the rest of classifiers. The manual tuning of Nu parameter, allows that the results obtained in this work will exceed previous works with low cost BCI systems such as EPOC [20], [21] which always have been widely criticized for their low accuracy in punctual BCI mental strategies.

TABLE I. CLASSIFER ACCURACIES.

Subject	LDA (%)	C-SVC with Lineal Kernel (%)	Nu-SVC with RBF Kernel (%)
S1	68.1	67.3	95.7
S2	62.0	62.4	95.6
S3	73.3	73.3	97.9
S4	71.0	71.5	**98.5**
S5	66.7	71.2	97.2
S6	68.1	69.4	96.2
S7	59.4	59.4	95.3
S8	72.1	71.5	97.5
PROM	**67.6**	**68.3**	**96.7**

The Nu-SVC classifier using the RBF Kernel and the manual tuning of the Nu parameter allow increase more than 25 % in the classification accuracy with respect to the others classifiers. The figure 2 shows the average accuracy of the three classifiers for all eight users. This parameterization of the support machine through the Nu parameter provides a control over the number of supported vector and margin errors. Control the number of support vector has implications for: (1) run-time complexity, since the evaluation time of the estimated function scales linearly with the number of SVs [22], (2) training time, for instance, which we use the segmentation algorithm which increase the complexity with the vector support number, (3) possible data compression applications- ν characterizes the compression ratio: it suffices to train the algorithm only on the SVs, leading to the same solution, (4) generalization error bounds: the algorithm directly optimizes a quantity using which one can give generalization bounds. These, in turn, could be used to perform structural risk minimization over ν. Moreover, asymptotically, ν directly controls the number of support vectors, and the latter can be used to give a leave-one-out generalization bound [15].

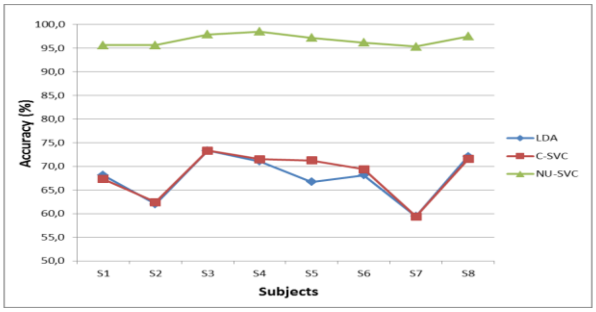

Figure 2. Classification results of MI patterns with the three classifiers

Finally we design a BCI videogame based on MI strategy for neurorehabilitation activities in stroke patients (especially in upper limb monoparetics), which is under evaluation in a local clinic. The videogame is based on the classic Duck Hunt for Nintendo, in where the user needs to imagine the movements of their right and left hands in order to shoot ducks to the right or left of the screen. After this promising result the next step is to test this approach in stroke patients.

V. Conclusion

This paper implements a mental strategy used extensively for the interaction with BCI systems, the motor imagery through a low cost wireless device using open source software. Despite of EPOC system limitations in terms of provide high quality signals for BCI application, the machine learning algorithms implementation such as support vector machines can offer high accuracies in bi-class problems (98%), comparable with experiments that use more academic and expensive BCI systems and with a greater number of electrodes. Even though the results show that it is possible to use low cost BCI systems such as EPOC to perform rigorous neuroscientific experiments, there are some problems directly related with the software that often prevent their use in more accurate applications and provide better user experience when specific mental strategies are used as motor imagery: the neuroheadset recording electrodes not fully cover the motor cortex on which are effectively recorded the ERD/ERS neuromechanisms necessary for MI tasks; further, due to the EPOC flexibility the locations of the electrodes are not fixed when the neuroheadset is worn, which increase the complexity in the experiment reproducibility with the same user. The BCI videogames use as a tool for neuromodulation in stroke patients is presented as a therapy with a high potential to stimulate the neural and CNS plasticity that restore the lost motor control. In future works we will evaluate the design videogame in groups of stroke patients in order to verify the effectiveness of therapy in the restoration of some motor skills.

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