A BRAIN COMPUTER INTERFACE USING EMOTIV-EPOC ON AN ARM ORTHOSIS CONTROL

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Abstract: This work aims at presenting the development of a brain computer interface (BCI) using the Emotiv-EPOC, a low cost, commercially available device to reading electroencephalographic signals (EEG), on an arm orthosis control, applying the motor imagery technique. The detection of two patterns during the imagination of movement is used to implement physical tasks that were simulated mentally. The motor imagery, representing user intention, results on the movement of a custom made arm orthosis, commanding it for flexion and extension movements, that will bring a better qualification for various tasks and better interaction with physical environment for disabled.

Keywords: Brain Computer Interface (BCI), Electroencephalogram (EEG), Emotiv-EPOC, Orthosis, Arm flexion/extension.

Introduction

The electroencephalogram is known as the electrical brain activity measured along the scalp. It corresponds to voltage fluctuations resulted from ionic current flows through the neurons of the brain. Especially, when any motor task is performed, such as hand or arm movements, changes in the electrical brain activity occur [1]. Several studies have shown that these changes can also be produced during the imagination of the body limb movement. This technique, named motor imagery (MI), occurs without any muscle activity, i.e., there is a related brain activity even without real movement [2, 3].

From this point of view, motor imagery presents a fundamental field of study, not only to understand how the brain works on different situations, but also helping disabled, working as a brain computer interface (BCI). However, the most of electroencephalographic systems are too expensive for daily use. A BCI system needs to be constructed based on a low-cost system, which could be available for everyone. One system is the Emotiv-EPOC [4], an equipment that has no electrodes in primary motor and somatosensory areas of the brain, which involve movement planning, and areas directly linked to motor imagery. However, it stands out for its versatility, size, ease of using and the low-cost compared to others [5].

Some authors have reported the use of this device to a wide range of applications as Evoked Potentials, P300 [6] and Steady State Visual Evoked Potentials (SSVEP) [7, 8]. With focus on motor imagery applications, in [9], the Emotiv-EPOC was used with OpenViBE acquisition software in order to capture Mu waves from left and right hand imagery movements with average recognition rate of 60.63% for right arrow and 45.93% for left arrow in an offline testing and single trial classification scenario.

The proposal of this work is based on developing a brain-machine interface system using the Emotiv-EPOC for measure the brain activity during a motor imagery task. A signal processing is executed to recognize user's intention of hand movement associated to the movement of an electro-mechanical orthosis, enabling the user to flex or extend the arm.

Materials and methods

The Emotiv-EPOC [4] is equipped with 14 electrodes in the international 10-20 system in the positions: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and, AF4, with two references. This device is wireless enabled and operates in 128 SPS (samples per second) with frequency range from 0.2 to 43Hz and two axis gyroscope.

A custom-made arm orthosis [10] was used as application for BCI control. The orthosis was designed and constructed based on a 3D printer concept. A linear actuator performs elbow flexion/extension movements according to user's intention. The first prototype was controlled by myoelectric signal, which defined movement direction. In the present project, the user intention is based on the EEG signal, acquired with Emotiv-EPOC.

The general setup of the entire system is shown in Figure 1. Emotiv-EPOC is used for EEG acquisition during a motor imagery process, defined in this study as right and left hand movements. The signal is pre-processed in the Emotiv-EPOC system, and then transferred to the computer. An algorithm written in the OpenViBE platform, an open source code dedicated to EEG processing and BCI design, recognizes user movement intention, which is sent to a microcontroller. The final application is an arm orthosis controlled by the designed interface. The performed movement is flexion or extension based on the side of the hand motor imagery. The recognition process can be described through four stage processing named as scenarios: acquisition, spatial filter, training, classifier (Figure 2).

The first scenario is responsible for data acquisition where the user is requested to imagine the movement of right or left hand, depending of the sign that appears in the monitor. The sign is an arrow, which appears pointing for the right or left, guiding the user to imagine the movement of the same hand side. Some pre-processing, as signal filtering, are applied into the device -hardware. Moreover, the acquired signal is filtered using a temporal filter for the frequencies between 8-30 Hz due to the range related to MI events; distinguish between alpha (8-14 Hz) and beta (14-30 Hz) waves.

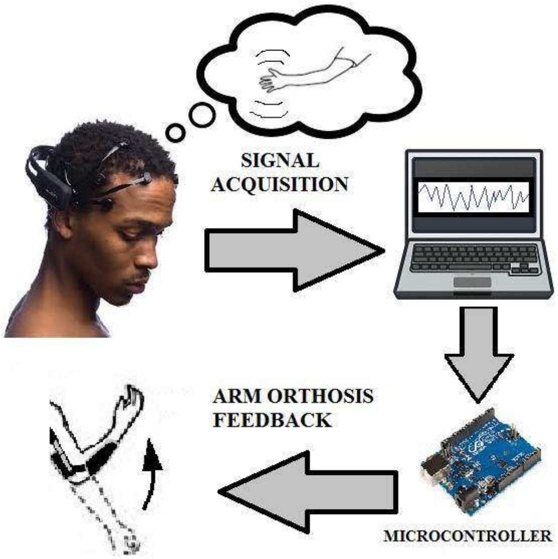

Figure 1 – General Project setup.

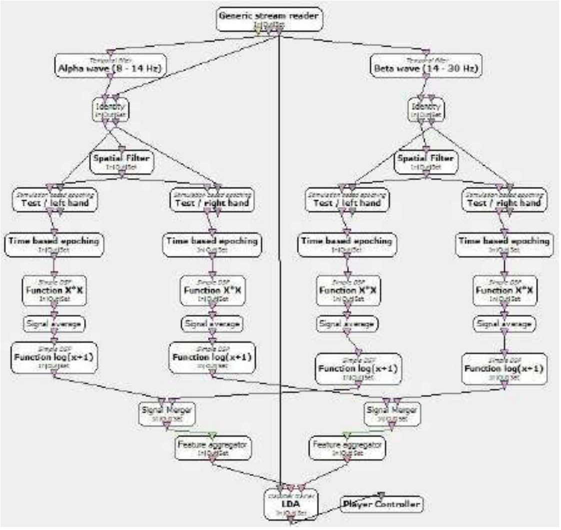

Figure 2 - Algorithm representation in OpenViBE to train LDA classifier.

An intermediate scenario is used to train a Common Spatial Patterns (CSP) filter that will be used in the further steps. This filter is a powerful tool that extracts specific feature of the signal supporting the classifier training [11]. Basically, the algorithm increases the signal variance for one condition, while minimizes the variance for other condition. In this way, the filter contributes to a better separation between the classes, which would be the right and left hand movements.

The next scenario is designed for classifier training. The chosen classifier is a Linear Discriminant Analysis (LDA), which works finding a linear combination of features that characterizes or separates two or more classes of objects or events [12]. A four-second period of signal data is selected and windowed in one-second size with 6.5ms shift. The signal window needs regularization to a normal distribution, due to the influence of CSP filtering process. The regularization is defined by a logarithm function. With a normal distribution, it is possible to create the feature vector matrix to feed the classifier [11].

The last scenario is responsible for recognizing the user intention and sending of the corresponding movement to a Virtual Server, Virtual-Reality Peripheral Network, which allows the OpenViBE information to be sent to other software/device. This output, representing user intention, is sent to a microcontroller that commands the arm orthosis motor. Arm orthosis flexion movement (Figure 3) is related to right hand MI, while the arm orthosis extension movement (Figure 4) is related to left hand MI.

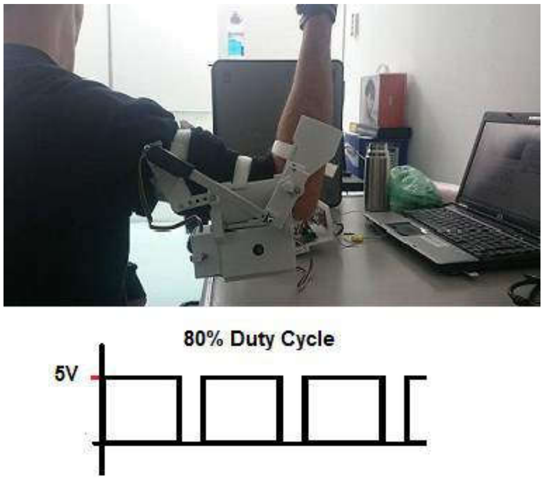

Figure 3 - PWM controlled arm orthosis for flexion movement.

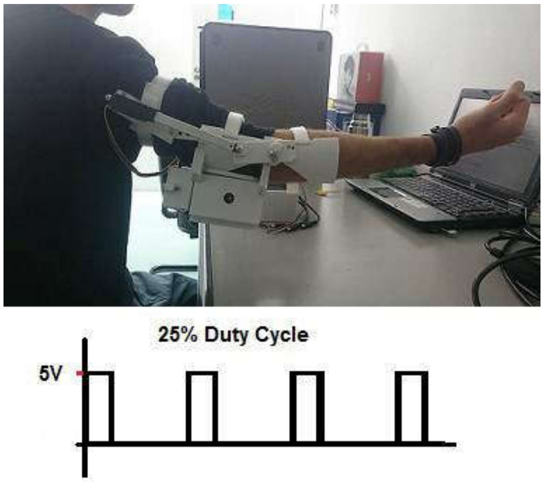

Figure 4 - PWM controlled arm orthosis for extension movement.

To move the arm orthosis, the system control uses a pulse width modulation (PWM) signal generated by the microcontroller. The correspondence between signal and movement is shown in Figures 3 and 4. The amount of pulse width variation corresponds also to the subject intention. The direction of the movement is controlled based on the side of the hand movement imagination, while the amplitude of movement depends on how much focus, is given for that action. This relation is mapped and embedded into the orthosis microcontroller, which receives the signals through USB port.

Experimental Procedure

The experimental protocol was approved by the research ethics committee (COEP - UMESP - No.1.361.875), and was conducted in three equal sessions. Five volunteers (average age 20), with no history of cognitive or neurological disorder were selected. They were given all the experimental procedures description and possible risks. Verbal and written consent were obtained prior to conducting experiments.

The Emotiv-EPOC electrodes were soaked in saline solution to improve the contact with the scalp and device performance, and the device was placed on the surface of the subject scalp.

During the sessions, to accomplish the tests, each subject was still in an environment with low light and isolated from distractions and audible noise. Moreover, they were orientated to not move any part of the body, which must remain relaxed. One part of greater interest is the face area, especially the eyes. Any muscle activation in this area can be registered by Emotiv-EPOC electrodes, representing noise. To deal with this problem, subjects were requested to minimize blinks and eye movements, focusing on the computer monitor.

During each session, there were presented to 40 arrows in the monitor, being 20 to the left and 20 to the right. Each arrow appearance has 1.25s of duration and the period between consecutive appearances was 3.75s, representing the period of time that the subject has to imagine the requested movement.

Results and Discussion

For the online performance analysis, the best result of the classifier among the three sessions was used for the orthosis control. Table I shows the accuracies attained for each subject. Subject 4 had a marginal performance, the others showed a high accuracy for one side, while the performance for the other side was almost near marginal. This difference between right and left side motor imagery accuracies could be proven applying the Wilcoxon Test with p=5%. Figure 5 is an example of the Confusion Matrix attained by subject 5. Since the electrodes had a good connection, the poor result could be explained by the subject's difficult to being concentrated and to imagine hand movement, and the needs for more subject's training. To overcome this limitation, the system confirms, for some cycles, the user intention before takes the corresponding action. Comparing with the work of [9], that applied very similar scenarios and platforms, the average recognition rate for left and right hand MI was higher (60.63% for right arrow and 45.93% for left arrow in an offline testing).

Table 1: Accuracies for online scenario (%).

Subjects	Left	Right	Average
Subj1	69	71	70
Subj2	76	72	74
Subj3	61	84	72.5
Subj4	43	73	58
Subj5	92	61	76.5

Figure 5 - Confusion matrix for online scenario.

In order to contribute with a better evaluation of the signals, leading to a correct movement correspondence, it was also analysed the 2D topographic map of the activated brain areas while the user was asked to imagine right and left hand movements. It can be seen in Figure 6, drawn with the aid of an interpolation technique, that there exists a huge area that is not covered by Emotiv-EPOC electrodes. Thus, since the main active areas, during the imagination process, were not present in the comprehensiveness of the device, there is the need to consider all the electrodes available in the analysis to ensure the recognition of the brain state. The figure also shows the corresponded user feedback screen, in which the bar is drawn based on the side of the imagined movement and the bar size means the amount of focus or attention given for imagination. For example, the bars drawn on the right side of each picture, represent motor imagery related to the right hand movement, and from the top to the bottom it can be noticed the increase of the bar size representing the increase of the user attention.

Conclusions

This work proposed an application of the Emotiv-EPOC on the control of an electronic device based on motor imagery brain signals. Although the performance had been higher than related previous work, the Emotiv-EPOC presents some limitation due to the lack of electrodes in the motor cortex areas. Even this, it was possible to use the proposed system to control the mechanism of the custom made arm orthosis via the developed brain-computer interface based on motor imagery. The commonly used electrodes in C3 and C4 areas, according to the 10-20 system, was not essential, since signals from these areas can be acquired by others electrodes near them. The resultant signal, although different from the originals, can be used to train the classifier and thus, being recognized as user intention and to command a system control. The proposed BCI proved to be more efficient than others as it is also possible to control the movement amplitude, while the accuracy error generated by the classifier was minimized by the confirmation strategy.

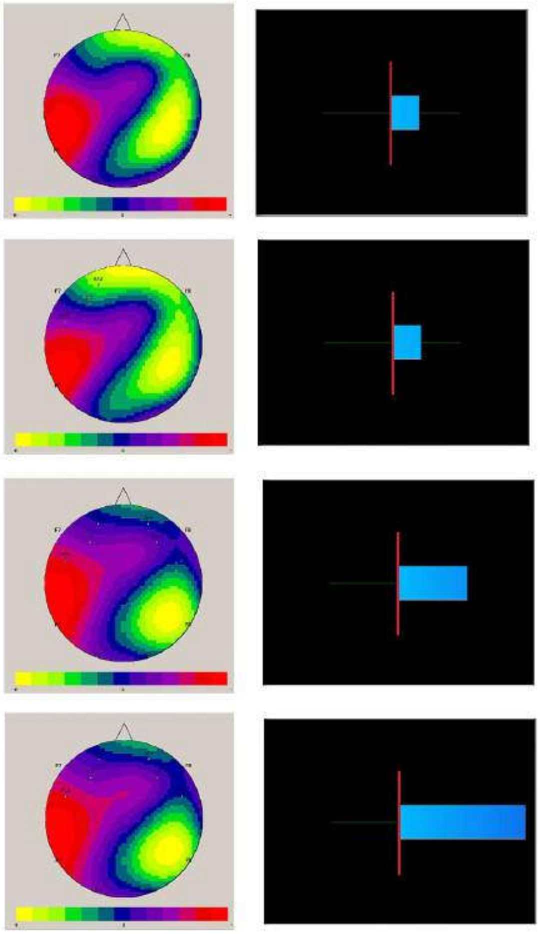

Figure 6 - 2D topographic map of the synchronization/desynchronization activation brain areas and corresponded user feedback screen.

Acknowledgements

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