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ANALYSIS OF BRAIN REGIONS AND EVENT RELATED POTENTIAL (ERP) ASSOCIATED WITH THE IMAGINATION OF ACTIONS BY EEG SIGNALS AND BRAIN-COMPUTER INTERFACE (BCI)

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ABSTRACT

Brain-computer interfaces (BCI) are devices designed with the aim of enable ways of interaction and communication in people with disabilities, and improve the execution of different tasks in healthy individuals. Thus arises the concept of imagined action, which consists of using different techniques of measuring and processing, capable of registering, extract and classify features related to changes that take place in the cerebral cortex, specifically the motor cortex, at the time of thinking about a movement or action. This work presents the results of analyzing EEG signals from the thought of an action, specifically to push an object, using domain transformation techniques, as well as a methodology that facilitated the registration of the mentioned event, obtaining as main contribution the characterization of areas with greater activation and variation of potential at the time to imagine the movement.

Keywords: EEG signals, brain-computer interface, event related potential, latency, gradient of potential.

INTRODUCTION

The current technological advances, have generated a dependence linked to the development of everyday activities that human performs. For this reason appears the human-computer interaction systems (HCI), whose objective is to allow the exchange of information, as a means of command for the resolution of any task through a computer system [1], [2].

Human-computer interaction tools, are complex systems whose development depends on particular applications, following this, during the last years elements known as brain-computer interfaces (BCI) have been popularized due to its operational characteristics, representing a bridge of communication between the user and the machine [3].

Although there are a wide variety of systems for the measurement of bio-potentials as characteristic elements for medical diagnosis and development of HCI-related applications, those that enable the measurement of EEG signals in a non-invasive way and have a high temporal resolution receive great attention by researchers and developers [4].

Within the technologies for these tasks, is the near-infrared functional spectroscopy (fNIRS) [5], [6] and the same systems of measurement of EEG signals. There are many applications of BCI systems. These technologies have been successfully used in communication, creation of art work, such as control interfaces of wheelchairs, and medical appliances for the prevention, detection, diagnosis and rehabilitation of diseases [7], [8].

The possibility of using brain activity to control applications, has opened the panorama to a number of developments, in where in addition to medical applications, those signals could be used as command posts in complex human-machine interfaces (HCI) [3], [9]. Examples as the presented in [10], performs a technical comparison between major BCI systems that are in the market nowadays, highlighting the Emotiv EPOC + system, which used in conjunction with mobile platforms could serve as a basis for the monitoring in real time of the actions carried out by users.

In general, the basis of all signal processing system is developed under the scheme of extraction and characterization of important elements present in these forms of wave [11]. For BCI systems, higher intensity signals occur when motor processes are performed by users. In this way, have been founded that the activity of the cerebral motor cortex, can be defined in specific frequency ranges [12].

Taking into account these characteristics, different control interfaces such as the one presented in [13], shows the use of BCI systems and the acquisition of EEG signals to control a Quadcopter in a three-dimensional space. More complex studies as that described in [14] shows possible analyses and features that can be extracted from a non-physical process. In this work, imagined speech is defined as imaginative process in the pronunciation of words, their decoding and recognition as previous stages in the construction of silent speech interfaces (SSI).

Another example related to the imaginative activities, is presented in [15], this work is about the brain activity produced by motor processes along with the imaginative processes. It is founded that the imaginative process of motor actions could be associated with the movements of the persons or the imagination of the movements of other people.

The work that is described throughout this document aims to provide the analysis of the EEG signals in an imaginative process, by using maps of ERP (Event Related Potentials), as a first approach to the development of control interfaces using BCI systems.

MATERIALS AND METHODS

In order to perform the analysis of the EEG signals associated with the imagination of actions, in this

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case the action of pushing a particular object, the methods and materials described below were used. The stage of acquisition was performed using stimuli and visual supports which enabled the focusing on the action that we wanted to measure.

Brain Computer Interface (BCI)

A BCI device is an element that allows human-machine interaction through the processing of signals generated by the brain activity during the execution or thinking of different tasks. They commonly have hardware and specialized software to carry out the capture, processing and classification of bioelectrical signals produced in the cerebral cortex, with the aim of turning them into commands or understandable instructions for a machine or computer.

Currently, there are developments and advances in the construction of this kind of device, one of these is the Emotiv EPOC+ which has 14 electrodes measuring with gold-plated and silver and 2 reference electrodes, positioned according to the international 10-20 for electroencephalography and according to that standard, the areas of the cortex or areas of Brodmann which is capable of recording are summarized in Table-1.

Table-1. Brodmann areas registered by Emotiv EPOC+.

Area of brain cortex	Electrodes	
Granular Frontal	AF3	AF4
Intermediate Frontal	F3	F4
Triangular	F7	F8
Opercular	FC5	FC6
Parastriate	O1	O2
Occipitotemporal	P7	P8
Middle Temporal	T7	T8

The potentials associated with conscious actions such as the intention of movement, are in the frequency band Beta, whose frequency range vary between 13 and 30 Hz, so the sampling rate of 128 Hz which has the device allows to cover a range of 0 to 64 Hz, achieving the capture of information relevant to the event that we wanted to analyze.

Event related potentials

Evoked potentials are variations or changes in the EEG signals that are direct indicators of the bio-electrical brain response to stimuli or cognitive, affective and motor events.

ERPs are tools of medical analysis, used to diagnose diseases such as epilepsy, Alzheimer's and other diseases that affect the central nervous system, causing the degeneration of mental faculties and probably cause dementia.

In comparison with normal EEG signals, the amplitude of an ERP is lower (1-30uV), and thus a processing is necessary for their quantification, which can be through averaging the signal or the application of statistical calculations. The analysis of the waveform that has an ERP takes into account three characteristics, latency, amplitude and distribution of potential in the scalp, in addition, is possible to make an analysis from relative latencies between its sub-components, through the implementation of algorithms of statistical separation, such as independent component analysis.

Latency is the point in time in which occurs the change of amplitude, i.e. the time of neuronal activation before a stimulus point. The amplitude of the ERP is linked to the neuronal activation produced by external or internal stimulus, and the distribution of potential is the pattern of change in the gradient of voltage by the excitation of neurons in an instant of time.

These potentials can be denoted with a letter N, as the N400, if are negatives, or positives represented with a letter P, as the P300.This type of notation indicates potential behavior, the number indicates the time in milliseconds between the stimulus and the peak amplitude. The ERPs are classified into two categories according to their latency, if it is less than 100 ms are exogenous and are influenced by physical events, on the other hand, are endogenous if they are superior to the mentioned value of latency, as example we have the P300, and are responses that vary in amplitude and time, depending on the mental activity that is not necessarily associated with a stimulation or physical signal.

Experimental acquisition

The experiment was performed taking into account the considerations set out below, the subject was in a room free of distractions and noise to prevent the registration of signs not desired, as well as facilitate the concentration of the volunteer in the task that he should do, the length of the recorded signals was the same throughout the experiment, in order to compare and analyze temporarily similar data. Finally, we used a visual support to allow the concentration of the volunteer and maintain the thought associated with to push an object in space and thus record signal associated with such activity.

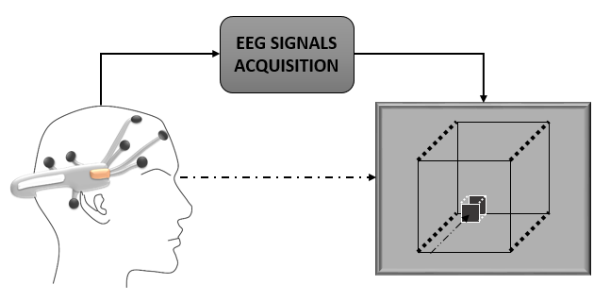

Figure-1. Scheme of the proposed experiment.

Bearing in mind the above conditions was the registration of EEG signals associated with the imagination of the action required, in a volunteer for 23 years. In addition, the electrodes which vary due to ocular artifacts (AF3, AF4, F7 and F8) were discarded with the aim of preventing that recorded samples were contaminated by real movements. In Figure-2 is depicted a sample of the signals with the selected sensors.

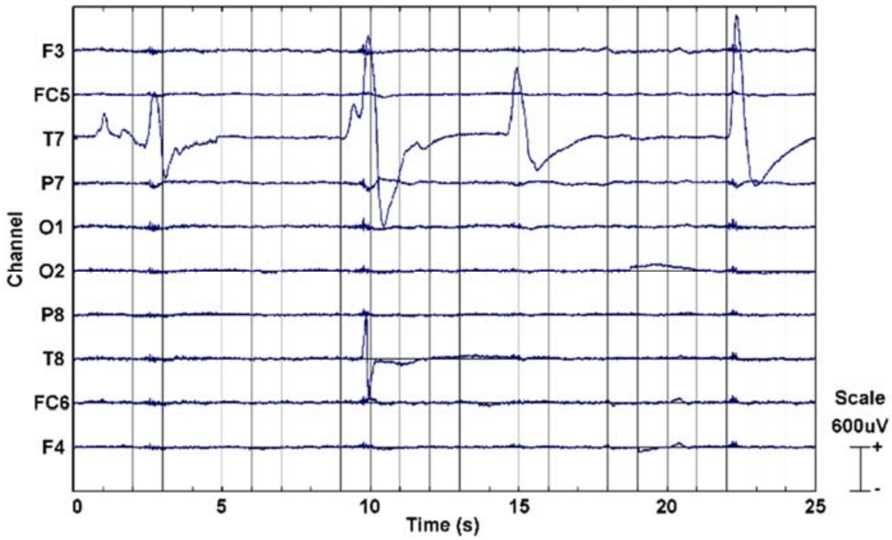

Figure-2. EEG signals related to "Push" action.

The duration of each one of the samples was 100 seconds, Figure-1 shows just a quarter of one of acquired signals, with 4 peaks of amplitude product of the imagined action, and the average duration of this variation is equal to 1 second.

RESULTS

For the analysis of the data captured during the experiment was used the complementary software of Matlab, EEGLab, getting the results that are shown below. The first result was the capture of EEG signals associated with the relaxation state of the volunteer, finding that variation of the signal is less than 30uV in the entire sample, as can be seen in Figure-3.

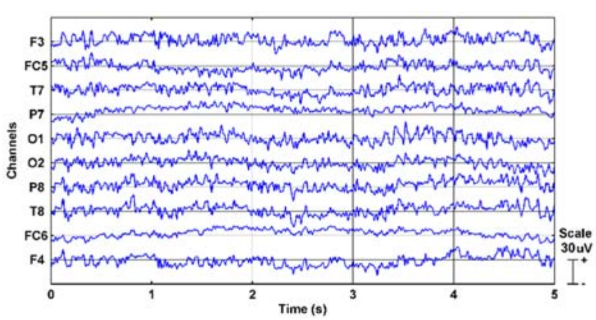

Figure-3. EEG sample of rest state.

On the other hand, the signal that was recorded in the imagination of the related action with pushing an object in three-dimensional space, as was depicted in Figure-1 presented a different behavior as shown in Figure-4.

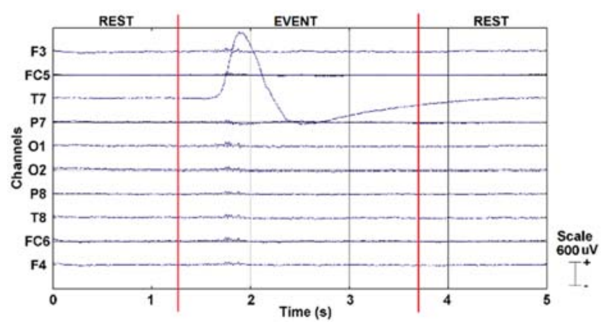

Figure-4. Segmentation of EEG signal for "Push" action.

In Figure-4 can be seen clearly the behavior that adopts the T7 channel signal when the volunteer thought in pushing an object, the response time was 1 second and the amplitude was 600uV, which is almost 20 times bigger that the presented in the EEG signals of relaxation state.

To develop a more accurate interpretation of what occurs in the cerebral cortex at the time of thinking in the suggested action, was performed the computation of ERPs generated by this activity, analyzing the variation through its amplitude and latency as shown in Figure-5. This Figure shows the change in the T7 channel (red) and in less extent its counterpart of the right hemisphere T8 (blue), which vary in the order of 10 to 15uV, potential with significantly lower values if they are compared with those obtained in Figures 2 and 4.

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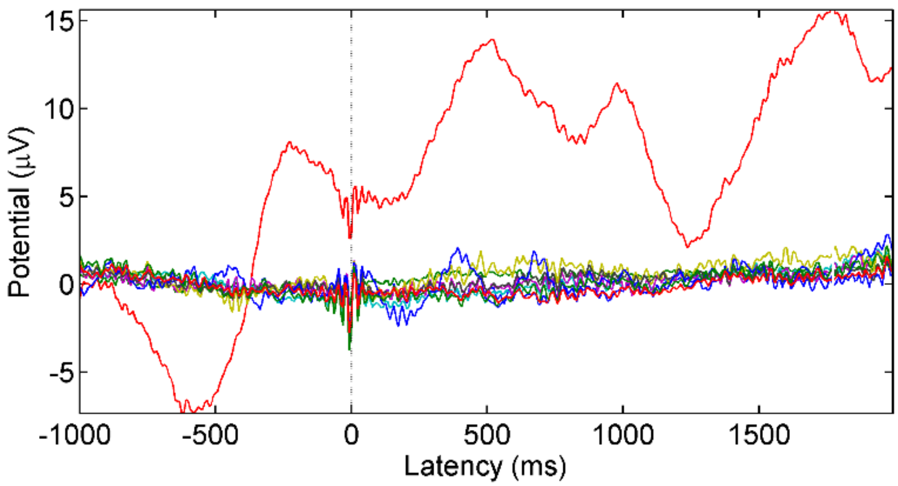

Figure-5. ERP of the imagined action "Push".

The highest potential values are presented in the latencies of 500ms with a value of 13uV, and 160ms with a little more than 15uV, which indicates that the neuronal activation in the area of Brodmann 21, which is measured by sensors T7 and T8 increases significantly and as shown in [16], [17], the middle temporal area is associated with the visualization of movements and non-verbal tasks. It is an endogenous positive ERP given its nature, and is associated with imaginary tasks of the motor area.

The color map for gradients variation is a useful tool at the moment of interpreting information associated with ERPs as the one presented in Figure 5.Figure 6 contains the distribution of potential that occurs on the scalp at the time to ask the volunteer to imagine the movement of an object in 3D space with their mind. To analyze the potential were taken 9 instants of time, equally distanced in 370 ms as shown below.

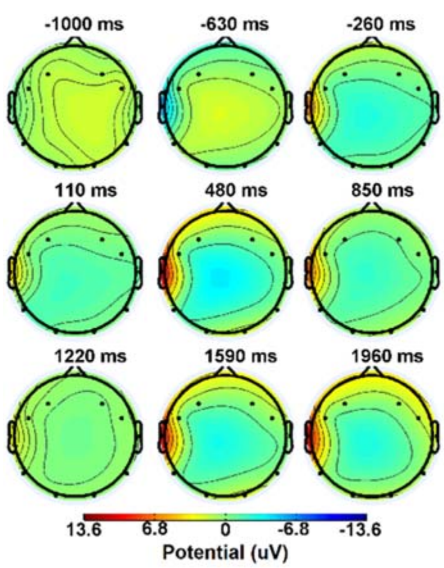

Figure-6. Mapping of ERPs.

This information shows a behavior according to the increase and appearance of peaks in the potential shown previously. Being specific, the two moments in Figure 6 which clarify the behavior of the signal are those of latency equal to 480 ms and 1590 ms, showing a positive change in the variation of the gradient related to the event that we were measuring.

CONCLUSIONS AND FUTURE PERSPECTIVES

Brain computer interface are low-cost acquisition devices, if it is compared with specialized medical equipment, allowing to register the biopotentials generated in the cerebral cortex during actions or specific thoughts, in this case the imagination of a movement. However, it has some drawbacks in terms of frequencies that can capture, because they only reach variations equal or lower to 64 Hz, so changes in frequency ranges such as those caused by the imagination of more complex actions, are hardly detected.

Evoked potentials maps allow to interpret in a graphical way the variation of the potential gradient in terms of time, improving the interpretation of the results obtained by the calculation of ERP, since it relates the variation of a specific signal, with the time and the area or areas in which takes place.

As a future work, it is proposed the use of other processing techniques, such as statistical separation through principal or independent component analysis for improving the feature extraction and its interpretation. Similarly the implementation of classification algorithms such as support vector machines and neural networks could improve the identification of changes in EEG signals for a particular event, without having to worry about the contamination in the signal by involuntary facial movements or noise in the capture device.

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