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EEG SIGNAL ANALYSIS RELATED TO SPEECH PROCESS THROUGH BCI DEVICE EMOTIV, FFT AND STATISTICAL METHODS

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ABSTRACT

The electroencephalography is a method used for measuring the electrical impulses that are generated on the cerebral cortex by using electrodes located in different positions, but keeping a standard distribution. In this work, EEG signals related to speech process were acquired by the Emotiv EPOC+®, this device is a low cost electroencephalogram that have 16 electrodes but only six were used (F7, F8, FC5, FC6, T7, T8). The aim of this research is to analyze if there are measurable and quantifiable differences among neutral EEG signals and vowels EEG signals from to imagine or to think any vowel by using DSP techniques, like Filters or Fourier Transform, along with statistical method that allow verify the truthfulness of previously mentioned difference. The aim of this research is to analyze if there are measurable and quantifiable differences among neutral EEG signals and EEG signals from the imagination or the thinking of any Spanish vowel by using DSP techniques, like Filters or Fourier Transform, along with statistical methods that allow verify the truthfulness of the previously mentioned difference. The analysis performed in this work makes evident the differences among the thinking of five Spanish vowels and the control signal, concluding that the recognizing of these is possible due to measurable features that are different from each other.

Keywords: brain-computer interface (BCI), EMOTIV, electroencephalography, imagined speech, fast fourier transform, non-stationary signal, analysis of variance.

INTRODUCTION

Communication is the process by which information is transmitted from one place to another by using different methods and elements. This process is one of the most useful tools that humans have for interacting with their peers and developing a variety of tasks in a determined environment.

The most common forms of communication are the visual and verbal interaction by using gestures and speech respectively; nevertheless, some people with disabilities have difficulties for performing these tasks, such people with body or facial paralysis.

Nowadays are technological developments in the design and implementation of devices that try to solve communication problems in people with some disabilities in motor or cognitive abilities have been. As one solution, devices that work by using brain signal have been proposed and developed.

Some researches use Brain-Computer interface devices [1], based on the blood pressure changes that occur in the cranial area, as is the case of [2], which can identify with 80% accuracy the commands "yes" and "not", others acquire the signals generated from the thought of movements, as presented in [3], achieving a rating of 65% for the movements of upper limbs, in the same way, there are works about the imagined speech, as it can be appreciated in [4] where try to identify two monosyllables with a recognition rate equal to 61% and in [4, 5] where Hidden Markov Models are used for making the separation of classes of two imagined Korean vowels with 86% of accuracy.

These works show the effort that has been made to advance in the search for alternatives for the actual communication systems of human being, whether natural or artificial, in addition, besides of general interest in to analyze all the data that our brain is capable to generate, for example in [6, 7] where an identification of patterns in alcoholic subjects was realized and in [7] with the diagnosis of epilepsy patients, by measuring components of high frequency in the brain waves.

Most recent developments include devices that operates with EEG signals, this devices ranging from purely educational purposes like in [8], emotion recognizing as is presented in [9], basic robotic manipulation through mental commands like in[10]and some advances in the letters and signs recognition as is exposed in [11].

One of these devices, that have been an interesting innovation in the last years, is the Emotiv EPOC+®, a low cost electroencephalogram [12], this device was designed as a teaching and mental training device capable to help people with problems in the interaction with his environment using only body movements. It is commonly used by simple commands such as facial movements as shown [13], or detection of moods, for example, stress or concentration as shown in [14]. Also, its versatility has made of this an instrument used in many scientific field, such as medicine, neurology, psychology and sleep study [15].

The aim of this research is to analyze and identify the differences in EEG signals between a neutral pattern of thought and the signals obtained from the imagination of a vowel, with de data of six sensors responsible for

measuring the areas related to the speech. This computation is performed by implementing the Fourier transform for obtaining frequency data of all the samples, then a statistical method called ANOVA was used for proving that the samples have measurable differences among each other.

In this paper the first part is about the topics related to EEG signals and its applications, showing some articles and researches that implement different methods and devices to capture signals of this type. In the second part the methods and materials that were used are described, as well as its justification and individual and combined importance to develop the work. Third section shows the obtained results from the implementation of ANOVA, which gives numerical support to the differences among the acquired patterns. In the last part, the conclusions obtained with the development of this work are exposed, posing a future perspective which allows giving a bigger margin of study for this topic.

MATERIALS AND METHODS

Materials

BCI Device Emotiv EPOC+®

Brain-computer interface devices are systems that transform the signals generated by brain activity, which generally are electrical or electromagnetic, in orders or control commands that can be interpreted by machines or computers.

The main idea of the development of these devices is to allow the interaction between the user and their environment by using the activity generated in the brain, without using external peripherals or signals that belong to muscular movements [1].

For this work, the headset Emotiv EPOC+® was used, this device has 16 electrodes (14 for the acquisition task and the other 2 for reference) that are distributed according the international 10-20 system which is used for electroencephalography. These electrodes are specifically located for acquiring the data of the brain activity without capturing muscular signals, for example the motor cortex. Figure-1 shows the distribution map of Emotiv electrodes.

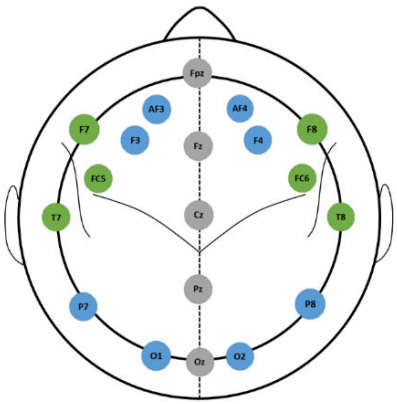

Figure-1. Distribution map of Emotiv electrodes.

The Table-1 shown the nomenclature of each electrode according international standards, also has a brief description of Brodmann areas associated to each sensor and its main function.

Table-1. Nomenclature of the electrodes and its related Brodmann areas.

Sensor		Brodman's area	Main functions
AF4	AF3	Granular Frontal	Emotions
F7	F8	Triangular	Semantic
F3	F4	Intermediate Frontal	Eye movements
FC5	FC6	Opercular	Syntax
T7	T8	Middle Temporal	Auditory process
P7	P8	Occipitotemporal	Visual Memory
O1	O2	Parastriate	Visual perception

According to the Table-1 the device is capable to capture the signals individually, allowing the selection of signals that we want to measured. Also the device has another features like wireless connection with the computer [16], acquisition of raw signals [17] and is portable [18].

METHODS

Signals acquisition

Measures of the brain waves of three test subjects were performed; all of them were in stress-free environments. For the acquisition process the steps of the algorithm shown in Figure-2 were followed.

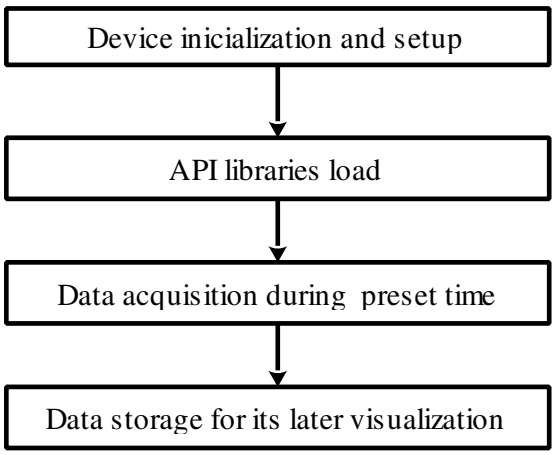

Figure-2. Acquisition process diagram.

The Figure-3 shows an example of the signals acquired through Emotiv® device, specifically the sensors that are related to the processes in the brain regarding to speech skill.

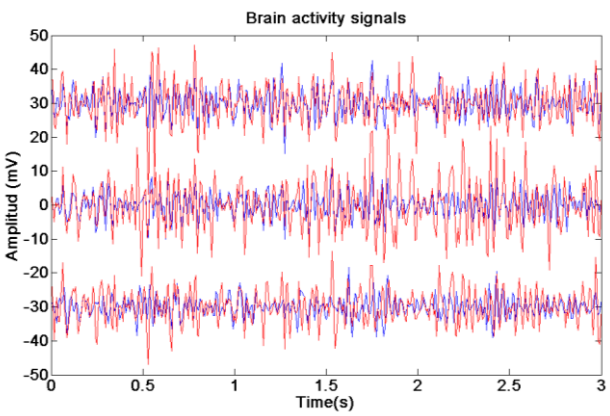

Figure-3. Acquired EEG signals with the EMOTIV Epoc ®.

Digital signal processing

Six sensors related to the speech and language process were selected, these are: F7, F8, FC5, FC6, T7, T8. In this manner, the study was adjusted for the more suitable signals with the aim of find a difference between neutral and vowel signals.

Processing was performed in two stages; the first one is a filtering stage for extracting the data that is relevant for our work and the other is a transformation stage where the Fast Fourier Transform is applied.

Filtering

The brain has five types of waves with different frequencies bands, these waves are Delta, Theta, Alpha, Beta and Gamma and are distributed in an interval between 1 and 100 Hz, as is depicted in the Table-2.

Table-2. Brain waves and its frequency bands. [19]

Wave	Frequency (Hz)	Brief description
Delta	0.5-3.5	Deep sleep
Theta	4-7	Sleepiness
Alpha	8-12	Relaxation
Beta	13-30	Active consciousness
Gamma	31-100	High attentional control

We can say that speech is a conscious process [20], because its need certain grade of concentration and stimuli because this need certain grade of concentration and stimuli for processing the received and response data. For this reason the beta wave was selected, and like this signals are only present in a specific frequency band, is necessary to perform a filter with a pass-band between 13 and 30 Hz as was mentioned in the Table-2.

The chosen filter was an IIR filter, specifically a Butterworth filter, because it has a soft response in the pass-band, this ensures that the amplitudes of the allowed frequencies don't change. In the other hand, the filter has two disadvantages, it is slow in the stop-band and has a non-linear behaviour in the phase, but nevertheless these features aren't critical because the reconstruction of the signal is not required. The digital filter was realized in MatLab® and its expression is shown in the equation 1.

$$|H(\omega)^2| = \frac{1}{1+(\frac{\omega}{\omega_0})^{2n}} \quad (1)$$

Where,
ω = Angular frequency
ω_0 = Cutoff frequency
n = Filter order

The Figure-4 shows an example of the acquired signals as well as the filtering process. An amplitude reduction for some time intervals can be seen, but the form of the signal is the same.

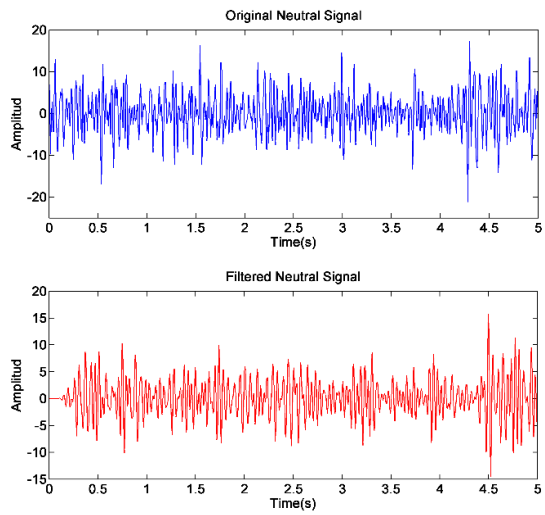

Figure-4. Neutral signal from F7 channel.

Fast Fourier Transform (FFT)

Fast Fourier transform is a computation method for the Discrete Fourier transform. The method used by Matlab is known as Cooley-Tukey algorithm, exposed in the equation 2. This method has one special condition, the data length have to be equal to any power of 2; typically are 512, 1024 and 2048.

$$X(k) = \sum_{r=0}^{\frac{N}{2}-1} x[2r]W_N^{2kr} + W_N^{2k}\sum_{r=0}^{\frac{N}{2}-1} x[2r+1]W_N^{2kr} \quad (2)$$

Where,

N = Data series length
r = Sample index
k = Integer value between 0 and $\frac{N}{2}-1$
W_N= Complex expression: $e^{\frac{-j2\pi kn}{N}}$

This technique is one of the most important and useful tools in fields like engineering, science and mathematics, because is a domain transformation that allow to process temporal signals in frequency domain, which implies some advantages like dimension reduction, feature extraction and normalized data lengths. The principal advantage of this algorithm is its speed, because de DFT needs at least N^2 operations, like additions and multiplications of complex expressions, while the FFT only needs N(log(N)) operations because of its design.

The Figure-5 shown the specters of the same signals, but the upper graphic are the original signal and the other is the filtered signal. The second graphic shows the amplitude values for the range of 12 to 31 Hz are the only ones present.

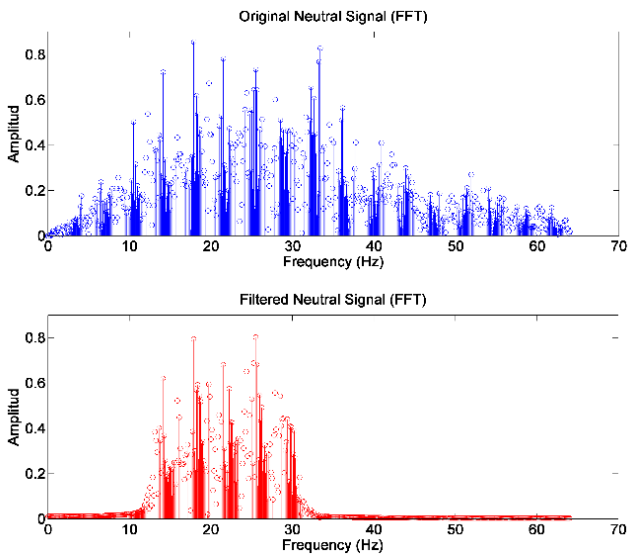

Figure-5. FFT of neutral signal (blue) and the same signal but filtered (red).

Analysis of variance

Analysis of variance or ANOVA, is a statistical method based on the computation of variances for determining if different samples have big differences, or otherwise their average values don't change, which means that samples are very similar each other. This model analyzes groups of two or more data series, each series represent an independent sample, conformed by various observations of the same event. The normal linear model of ANOVA, describes that the data groups have a normal distribution with different averages, in this way the model only require the computation of variances and averages of each group. The most common model is depicted in the equation (2).

$$y_{i,j} = \mu_j + \varepsilon_{i,j} \quad (3)$$

Where,
i = Experimental unit index
j = Group's index
$y_{i,j}$ = Observations
μ_j = The average of each group
$\varepsilon_{i,j}$ = Normal distribution of random errors with zero average.

If the model result is zero or near to this value, the hypothesis is put into a doubt, which means that the samples are different. In the practice, the achieving of a value equal to zero is not possible, for this reason a proximity value have to be defined, this value is known as significance. If this value is less than 0.05, the hypothesis is nullified, and with this, the difference among the data is confirmed.

RESULTS

As a first results, were obtained a group of datasets related to the thinking of Spanish vowels, as well as a methodology for the acquisitions of bio potentials associated with cognitive process like speech.

From the data acquired of three test subjects were obtained the results consigned in the Tables 3, 4 and 5. These data are the significance value generated by the ANOVA test, making a comparison among neutral or control signals and signals related to the thought of a vowel.

When a significance value is less than 0.05 the hypothesis is nullified, that means that the variation of the amplitudes for the same frequency in a vowel signal is different respect to a neutral signal. For interpreting tables, the results highlighted are considered as non-success cases. In the table 3 the results of the test subject 1 are shown. It is evident that the best success cases, in terms of the difference among the vowel and neutral patterns, are presented in the F7, F8 and FC6 channels.

Table-3. Significances table of test subject number 3.

Channel	Vowel signals				
	A	E	I	O	U
F7	1,82E-25	1,17E-30	2,13E-40	2,57E-16	4,61E-07
F8	4,58E-12	2,70E-09	1,17E-16	7,14E-16	1,15E-04
FC5	0,7501	0,6263	0,0796	0,0254	0,1833
FC6	2,49E-10	9,13E-09	2,10E-13	3,00E-16	1,14E-04
T7	0,8263	0,3738	0,0262	0,2682	0,2271
T8	0,0241	0,0503	0,0490	0,0001	0,1994

The Figure-9 shows an example of box plot the data of test subject 1.

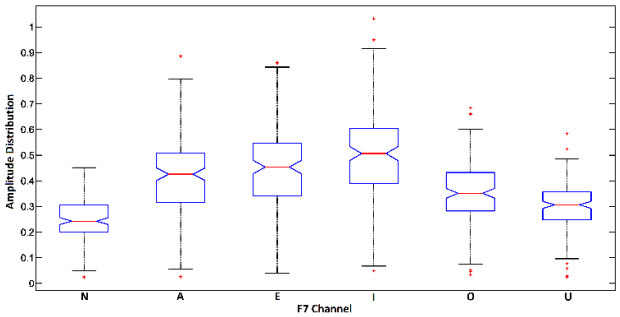

Figure-6. Box plot for F7 channels. Test subject 1.

This box plot contains specifically the amplitudes of F7 channel, and can be seen that the F7 data are different for each vowel, this means that amplitude distribution between a neutral signal and vowel signal is different, and with this information is possible to find accurate patterns for each signal. With the same idea were calculated the values in the table 4.

This case is like the one shown in the above table, because have three channels that showed significant differences but located in different places (F8, FC6 and T8).

Table-4. Significances table of test subject number 2.

Channel	Vowel signals				
	A	E	I	O	U
F7	0,56717	0,57120	4,55E-12	1,24E-09	3,33E-02
F8	5,34E-16	9,43E-19	0,03037	0,02936	6,80E-11
FC5	0,92683	0,15361	0,00376	0,05374	9,08E-07
FC6	2,90E-07	1,29E-14	1,58E-17	5,77E-06	2,42E-55
T7	1,36E-15	3,30E-29	1,71E-04	0,4419	1,11E-10
T8	0,0071	0,0018	3,22E-05	7,44E-07	1,34E-09

Finally, the Table-5 includes data related to the last test subject; this data has a different behavior in comparison to the previous two. In first place, most channels achieved values under the significance level, for almost all the vowels and the amount of non-success cases are the same as the test subject number two, but consistently distributed. For the test subject 3, the success cases are located in the F7, F8, FC5, FC6 and T8 channels. The only that is similar, taking into account the data dispersion, is the channel T7.

Table-5. Significances table of test subject number 3.

Channel	Vowel signals				
	A	E	I	O	U
F7	5,29E-16	0,0170	8,41E-20	4,51E-09	5,53E-16
F8	1,83E-08	0,0366	6,25E-07	0,2823	0,0010
FC5	6,73E-10	0,8442	3,60E-10	7,96E-07	1,14E-05
FC6	5,99E-17	2,03E-06	9,91E-18	2,90E-11	1,72E-14
T7	9,96E-17	0,2275	1,02E-10	0,2691	0,0706
T8	2,68E-10	0,0882	5,25E-09	6,19E-04	1,43E-06

CONCLUSIONS AND FUTURE PERSPECTIVES

Fourier transform allows to analyze signals in the frequency domain, which implies two main advantages, the first one is the extraction of information present in the signals frequencies and this information is relevant because is not time-dependent, the second advantage is to achieve a reduction in the amount of data to be analyzed.

F7 and F8 were the only channels that showed consistency among the three test subjects, these channels are related to the semantic process, in other words, with the interpretation and identification of linguistic signs of specific language.

Channels with the worst performance were FC5 and FC6, which are responsible for sensing the processes attached to the syntax, according to this is possible that this error of this channel may be because the development of sentences is more complex than the sign recognizing.

It's difficult to find a common pattern for the three different subjects with EEG signals related to the communication process, specifically with the speech, because the response of different subject for the same thought of a vowel does not have a direct relation.

As a future work, a vowel detection system using EEG signals and artificial intelligence algorithms, like neural networks, could be implemented. These algorithms will be trained with data extracted from measured signals.

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