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FACIAL GESTURE CHARACTERIZATION FROM ELECTROENCEPHALOGRAPHIC SIGNALS

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ABSTRACT

Study of the activity of human brain has advanced plenty since the development of electroencephalogram. A few decades ago, Brain Computer Interfaces (BCI), which allow direct communication between the brain and computer systems, seemed to belong only to science fiction. For example, today a limb of the body can be replaced by a robotic limb and it can be controlled using current nerve impulses. Analysis and interpretation of electroencephalographic signals represents a challenge since everyone responses differently to the same stimuli depending on several factors such as age, sex, diseases, among others.
In this article the implementation of a BCI for the acquisitions of electroencephalographic signals is performed by using sensors present on the EMOTIV INSIGHT headset to visualize, process and analyze signals emitted by the brain when someone is performing certain facial gestures, with aiming to characterizing them using correlation analysis.
This study evaluates the strength of a relationship between the signals produced by the same facial gestures and different test subjects. The correlation analysis, despite being a statistical method, proved to have significant results, obtaining an average of 20.91% of strong relationships and 34.18% of moderate relationships

KEYWORDS: Facial gesture, Brain Computer Interface (BCI), electroencephalographic signals, correlation, signal processing.

1. INTRODUCTION

Brain-machine interfaces (BCI) were conceived in 1973 by Jacques Vidal at UCLA (University of California, Los Angeles). But it was not until the early 1990s when the first human tests were done. In recent years, thanks to technological and scientific advances, BCI systems have been successfully developed.

Currently, many researchers have developed applications that allow BCI to be manipulated by simply using eye gestures and events (closing the eyes or varying the flicker frequency) to move a robot or a small robotic vehicle (Monge and Aracena, 2015 and Zeng, 2018) or for use in home automation (Villegas y Rojas, 2019).

On the other hand, other works have focused on finding a relationship between human emotion and brain signals, for which it has been shown that facial expressions can be used to detect a person's emotional state, the movement of certain points or regions of the face can be used to determine a relationship between emotions and facial expressions (Pantic, and Rothkrantz, 2000 and Esfahani and Sundararajan, 2011).

In both cases, the characterization of the gestures is important since it would allow to recognize the typical attributes, characteristics and parameters generated by the facial gestures in the EEG signals and to differentiate these signals, from those obtained with thoughts of action, imagination of movement or emotions.

The objective of this work is to characterize different facial gestures (neutral, closed eyes, smile, frown, clench teeth and surprise) by correlation analysis.

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The contribution of this work is to determine whether it is possible to use commercial encephalographic signal acquisition devices with a limited number of sensors such as EMOTIV INSIGHT (with 5 sensors) to characterize the signals that come from facial gestures, for future application in BCIs both execution and recognition of emotions.

The present work is divided into different sections, of which a brief explanation will be given.
In Background a brief description is made of the concepts involved in the development of a BCI from the acquisition to the processing of the data.

The Methodology presents the instruments, methods and techniques used for the acquisition and processing of the data, as well as the description of the experiment performed starting from the configuration of the devices to the processing.

In Results, the values obtained in the analysis of correlation of the gesture with the highest percentage of correlation between all the sensors are presented concisely, the rest of the graphs of the gestures are presented in the Annexes section. In addition, we discuss what the values obtained represent and the percentage of correlation between the different subjects when performing each gesture.

Conclusions present what was achieved in this work and in Future Work suggestions to continue or resume research.

2. BACKGROUND

Even these days, there is no exact definition of what is called BCI, but according to Abdulkater, et al (2015): A BCI is a direct communication path between a human brain and computer systems. "That is, a technology that records brain activity and acquires signals that reflect the user's intention and interactions with a computer or machine by sending commands to perform some actions.

To record the data, one of the most used techniques can be used, electroencephalography that records brain signals from specific regions of the head by fixing electrodes along the scalp (Pun, et al, 2006 & Li and Lu, 2009).

The electroencephalogram (EEG for its acronym in English Electroencephalogram) is an electrophysiological monitoring technique that allows to record the electrical signals that our brain emits due to the exchange of information produced by neuronal activity, its result is electroencephalography, which is defined as a representation Graph over time of the potential difference between two sites in the scalp caused by brain electrical activity.

EEG signals can be electrical, electromagnetic or of any other type that occur on the cranial surface (Buzsaki, 2006). In addition, they have unique characteristics and vary from person to person according to age, sex, level of education, among other factors. They can also be altered according to the state in which the person is, whether concentration, relaxation, interest, sleep, etc.

The skull attenuates these signals so that only large populations of active neurons can generate enough electrical potential to be recorded by the electrodes located in the scalp.

To standardize the placement of surface electrodes using cranial references, the international positioning system 10-20 was created (Figure 1). Which is an international standard defined by the FISE (International Federation of Electroencephalography Societies) that describes in which location of the skull the electrodes should be placed, for measurement by means of an Encephalogram (Homan, et al 1987)

This system is based on the relationship between the location of the electrode and the area of the cerebral cortex located under it. The numbers "10" and "20" refer to the fact that the distance between the neighboring electrodes can be 10% or 20% of the total distance between the front and back, or from right to left of the skull. Each zone was assigned a letter, to identify the lobe in which the sensor is located, and a number, to identify the hemisphere of the sensor. If the number is even, the electrode positions belong to the right hemisphere of the brain, if the number is odd, they belong to the left hemisphere. Table 1 relates each lobe to its identifier. This table shows that, although there is no central lobe, the name is used for identification (Gómez, 2016).

Table 1. Nomenclature of electrodes according to the 10-20 system

Electrode Identifier	*Lóbulo*
F	*Frontal*
T	*Temporal*
C	*Central*
P	*Parietal*
O	*Occipital*

For clinical studies, a minimum of 21 electrodes is recommended. For the purposes of this work, since it is not considered a clinical case, only the 5 electrodes present in the data acquisition device (EMOTIV INSIGHT) will be used.

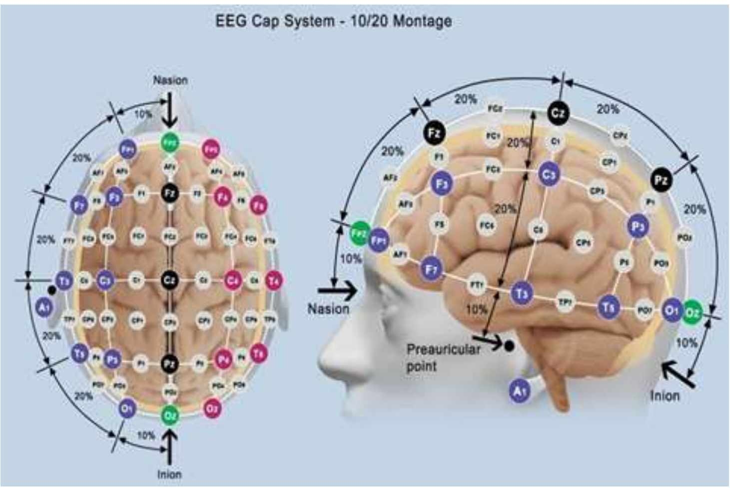

Figure 1. Electrode position according to the 10-20 system for EEG

It is also important to identify the areas of Broadmann, regions of the cerebral cortex defined based on the arrangement of the cells that constitute the cerebral cortex. These areas are related to brain functions.

The relationship between brain functions and Broadman areas allows us to classify which important sensors to use to develop applications related to different brain functions. For example, in Figure 2 it is observed that what is related to the execution functions is most strongly in the frontal area, related to the visual system, in the occipital area, and related to movements, in the central area of the brain.

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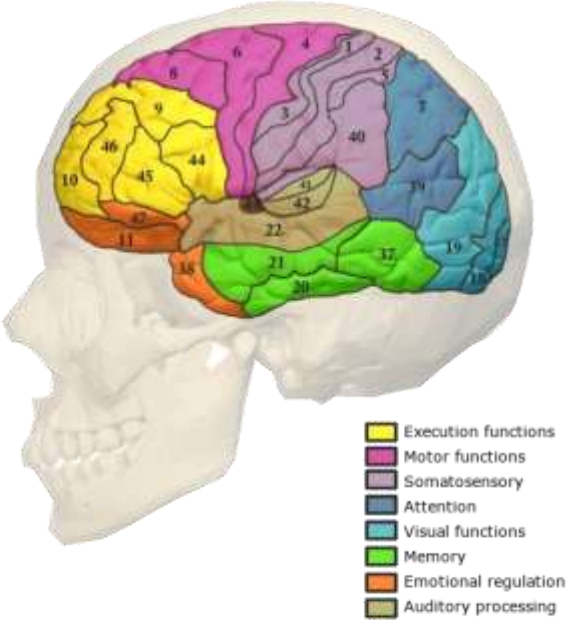

Figure 2. Brodmann areas

The use of BCI based on the electroencephalogram has demonstrated several advantages such as: the one that is a non-invasive, low-cost, portable and easy-to-use method; But this method has some disadvantages such as the difficulty for the acquisition and preprocessing of the signals, the extraction of the characteristics and the classification of the EEG data, since the signal processing must be done in real time to generate a response to reasonable speed.

Therefore, it is recommended to treat the signals before extracting their characteristics, using some preprocessing method. This implies from, reorganizing the data, for example, extracting some point of interest without making any other modification or removing some elements of an electrode with poor quality, to a filtering or transformation that facilitates the subsequent analysis by modifying the raw data of the EEG (Gómez, 2016).

Regarding the techniques for extracting characteristics of the EEG signals, these can be divided into three main groups, which are: 1) the methods that subtract temporary information from the signal, 2) methods that extract frequency information, and 3) hybrid methods, based on time-frequency representations, that take advantage of both temporal and frequency information (Lotte, 2008).

Temporal methods use the temporal variations of the signals as characteristics; These are particularly adapted to describe neurophysiological signals with a precise and specific time signature, among these are instantaneous statistics and autoregressive models.

Frequency domain techniques study how many simple signals make up those signals, using other signals (eg, sinewaves) to isolate frequency components of the signal, the Fast Fourier Transform (FFT). it is one of the most applied techniques in the treatment of the signals, although they are also used, for example, the Short Time Fourier Transform (STFT) and the spectral power density (PSD per its acronym in English Power Spectral Density).

Time-frequency techniques are considered hybrid since they take advantage of both temporal and frequency information, these allow the treatment of non-stationary signals. These techniques include the Wavelet transform, the Hilbert-Huang transform (HHT for its acronym in English Hilbert-Huang Transform).

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3. METHODOLOGY

For the characterization of facial gestures by means of EEG signals, the process described in the system of Figure 3 was followed.

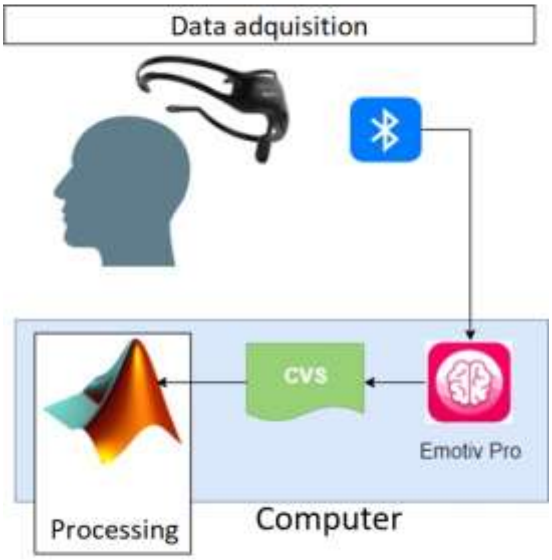

Figure 3. Diagram of proposed gesture characterization system using EEG

For the acquisition of data, the EMOTIV INSIGHT device (Figure 4) was used, which is a personal, portable and wireless EEG reader. This equipment can be used for various applications such as therapy, personal development, BCI, among others.

The INSIGHT has five semi-humid hydrophilic polymer sensors that allow reading brain waves without the need to use any gel or adhesives to read the sensors, although it is recommended to keep them moist with a solution of water and glycerin.

Figure 4. EMOTIV INSIGHT

The INSIGHT has a sampling rate of 128 samples per second per channel, a resolution of 14 bits. Its frequency response is between 0.5 and 43 Hz with a pair of 50 and 60 Hz band eliminator filters. It includes a 5th order digital sync filter. Wireless connectivity is achieved through Bluetooth.

The sensors included correspond to positions AF3, AF4, T7, T8 and PZ of the 10-20 system with references in the CMS and DRL positions (Figure 5).

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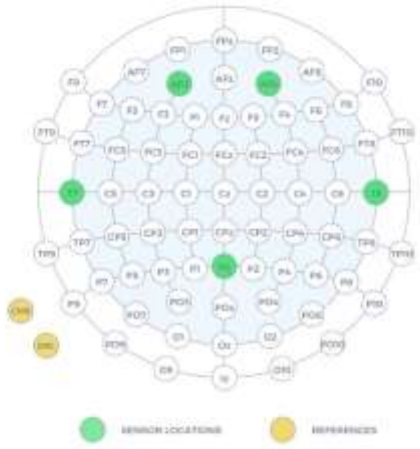

Figure 5. Insight sensors position

The experiment consisted of placing the device to 10 individuals and asking them to replicate a series of gestures for 15 seconds, with 5 seconds of rest between each gesture.

The individuals were 6 men and 4 women between the ages of 20 and 40, these were surveyed to know the factors that can change the EGG signals generated by their brain. These data are presented in Table 3. Hence, it was obtained that 9 are right-handed and 1 left-handed, 8 only dominate the Spanish language (native language) and 2 consider themselves bilingual, in addition 6 of them know how to play an instrument while that others do not know how to play any, most of them completed a master's degree and work in the area of education.

The gestures they made were: neutral gesture, eyes closed, smile, frown, surprise and clench your teeth. These gestures are predefined in the EMOTIV BCI software, which is a free version of the company's program that allows you to perform some basic functions with the device.

In order to extract the raw data, the free trial of the EMOTIV PRO program was used, the full version of the company's program that allows the data to be recorded while performing a sequence of gestures and subsequently exported to other formats, one of which is the CSV.

For the data processing the Matlab program will be used, with which it is possible to perform various matrix operations and data analysis. The signals obtained from the INSIGHT pass through a 5th order filter, which was taken by preprocessing the data.

To determine how similar the data of the different gestures are, the test subjects chose to perform a statistical test using the correlation analysis. This test, in combination with a preprocessing of the data has proven to be effective in the characterization of facial gestures and ocular events (Ovalle, 2019).

Correlation analysis is an information analysis technique that allows you to see the relationship between two or more variables, indicates strength and direction. This is observed by Pearson's correlation coefficient, a measure that represents the linear relationship between two quantitative random variables. This coefficient is normally represented with the letter r and is defined by equation (i):

$$r = \frac{S_{xy}}{S_x S_y} \quad \text{(i)}$$

Depending on their value, the following relationships can be obtained when r = 0, the variables are independent, when r> 0 has a direct linear relationship and when r <0, there is an inverse linear relationship. With this it is observed that when r is equal to 0, the variables are independent, however, if r approaches 0 there may be other

types of nonlinear relationships, which can be treated using nonlinear regression. The strength of the relationship is determined based on the following limits in Table 2.

Table 1. Limit values of r. Source: Heredia (2017).

r value		Relationship between the variables
Lower limit	Upper limit	
-1.0 a -0.5	1.0 a 0.5	Strong
-0.5 a -0.3	0.3 a 0.5	Moderate
-0.3 a -0.1	0.1 a 0.3	Weak
-0.1	0.1	Very weak

4. RESULTS

Each participant of the experiment was explained what it would consist of and trained in the performance of the gesture using the BCI program so that they knew exactly how the program identified it. Meanwhile, INSIGHT was placed and adjusted, ensuring that all sensors were in place.

The program provides an interface that allows you to adjust the sensors with a color code and a percentage of contact, where gray indicates that there is no signal; red, bad signal; yellow, low signal; Green, good sign. It was tried that all the participants initiated the experiment a good quality of contact between the sensors of between 90% and 100%. However, as the test progressed, some sensors will ask for connection, so the test subjects were asked to keep their heads as fixed as possible.

The subjects performed different gestures for 15 seconds, although only the first seconds had relevant data. The gestures they made were, neutral gesture, eyes closed, smile, frown, clenched teeth and surprise. During data collection, the system allowed a marker to be set when a gesture would be initiated.

Of the 10 participating subjects, only relevant samples were obtained from 8, the other 2 samples were discarded due to high noise levels.

For each gesture, a graph of the signal against time was prepared with the samples of all participants. As mentioned in the methodology, the signal from the INSIGHT device is already filtered, and when a second filter is applied in a considerable loss of data, it was decided to leave the data to maintain the greatest amount of data in the signal. What was done was a normalization of the data by subtracting the average value.

For the correlation analysis it was decided to use the AF3 sensor as a reference for the correlation since according to its area of Broadman it is related to the emotions that are reflected in the facial gestures.

Once this information is clarified, the case with better results is shown, which corresponds to the frown gesture in Figure 6.

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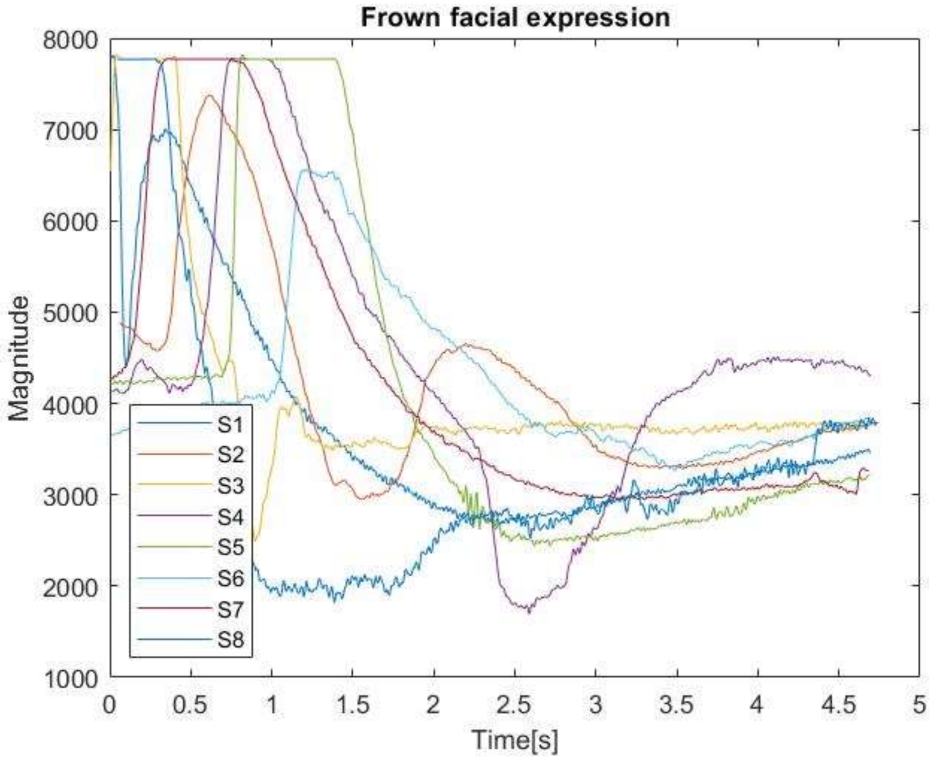

Figure 1. Time vs magnitude graph of frown facial expression in AF3 sensor

To analyze the relationships given between the different subjects, the demographic data of each subject will be presented in Table 3. It should be noted that most of the test subjects know each other and keep in touch either by work or friendship.

Table 2. Demographic data of the test subjects. Source: Own Creation

Subject	Gender	Age	Dominant hand	Languages	Musical instrument	Sector
1	Female	27	Right	Native	0	Engineering
2	Male	28	Right	Native	0	Medicine
3	Male	43	Right	Bilingual	2	Engineering
4	Male	30	Right	Native	1	Engineering
5	Male	39	Right	Native	2	Engineering
6	Male	33	Left	Native	1	Administration
7	Female	32	Right	Native	0	Engineering
8	Female	27	Right	Native	0	Administration

With the plotted signals, the correlation analysis was carried out, (MATLAB 2019), using the CORRPLOT command. The result is presented in Figure 7.

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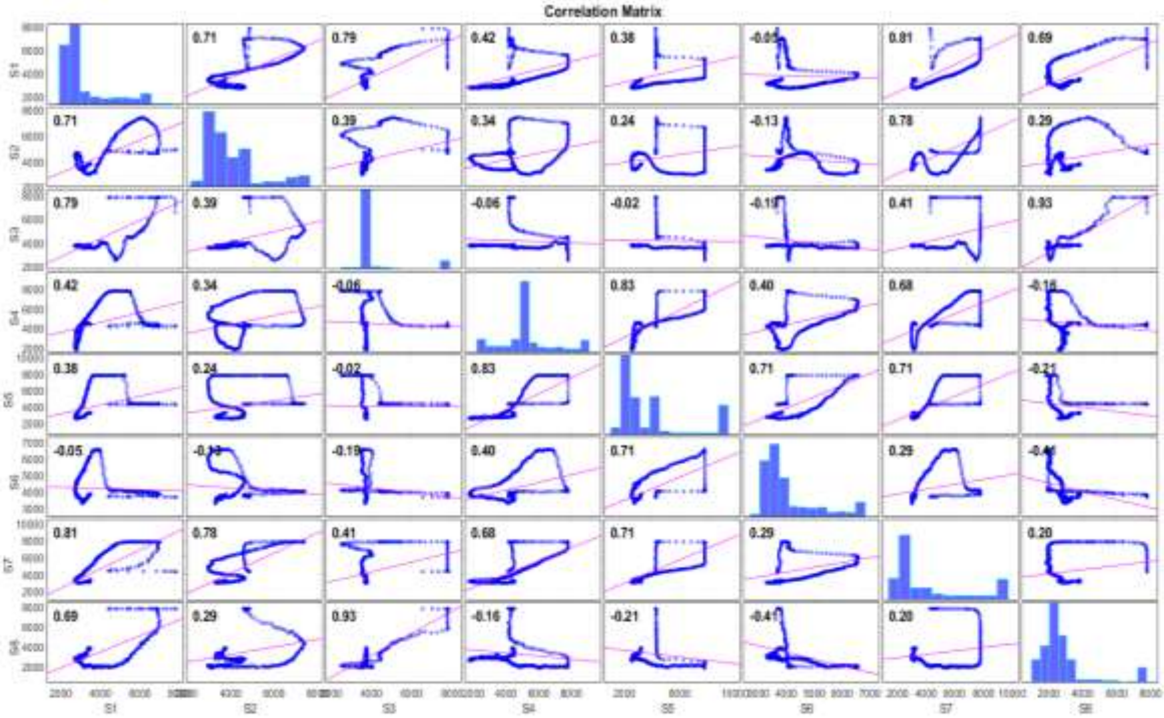

Figure 2. Correlation matrix of frown facial expression in AF3 sensor

The values obtained from the correlation are presented in Table 4.

Table 3. Correlation values of frown facial expression in AF3 sensor. Source: Own Creation.

				Frown				
S1	1	0.7067	0.7853	0.4190	0.3810	-0.0538	0.8128	0.6905
S2	0.7067	1	0.3938	0.3431	0.2436	-0.1271	0.7803	0.2945
S3	0.7853	0.3938	1	-0.0624	-0.0178	-0.1935	0.4075	0.9307
S4	0.4190	0.3431	-0.0624	1	0.8251	0.4000	0.6827	-0.1579
S5	0.3810	0.2436	-0.0178	0.8251	1	0.7072	0.7059	-0.2057
S6	-0.0538	-0.1271	-0.1935	0.4000	0.7072	1	0.2911	-0.4126
S7	0.8128	0.7803	0.4075	0.6827	0.7059	0.2911	1	0.2042
S8	0.6905	0.2945	0.9307	-0.1579	-0.2057	-0.4126	0.2042	1
	S1	S2	S3	S4	S5	S6	S7	S8

There are 28 possible combinations (or cases) for each gesture because there were 8 subjects in the test, therefore, it is observed that most of the relationships for the frown gesture turned out to be strong, 35.7%, a 21.4% of the relationships were moderate and only 10.7% of the relationships were very weak. These were the case among the subjects: 1-6, 3-4 and 3-5.

When separating the subjects based on their demographic data, it is observed that those who have the strongest relationships, for the gesture of frowning, are those who are in the same age range that in this case is between 27 to 33 years, Since these individuals do not take many years, it can be concluded that their brains behave similarly when they make a gesture, although this is not always the case. Since the individuals with the lowest correlation rate were subject 3 and subject 5 that differ in ages by a range similar to that of the group with a strong correlation relationship. The women in the group presented a strong to moderate relationship, while for men the majority of the correlation relationships were moderate to weak.

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With respect to the other gestures, a brief analysis of the results obtained will be carried out, based on the signals obtained from the AF3 sensor as in the previous example. In the annexes section, the graphs and tables corresponding to this data are presented.

In the neutral gesture, most of the correlation relationships were moderate (60.7%), very weak relationships only occurred in 10.7% of cases, with combinations between subjects, 2 - 7, 3 - 7, and 4 – 6

With eyes closed, cases with a strong relationship were 42.8%, and moderate relationships occurred in 32.1% of cases. While very weak relationships were only 7.1% of cases, with combinations between subjects, 4-6, and 5-6.

With the smile, 57.1% of the cases presented a moderate relationship, and 17.6% had a very weak relationship, with the combinations between subjects 1 - 3, 1 - 8, 2 - 7, 3 - 4, and 5 - 7.

For the gesture of clenching the teeth, 35.7% of the relationships were weak and 32.1% were strong. Although most relationships are weak this gesture is not something common to perform, since it comes from the English word "Clenching" which means firmly clenching the upper and lower teeth and is commonly an involuntary act that people perform at night for various reasons. In this case, 7.1% of the cases presented a very weak relationship, with the combinations between subjects 3 - 7 and 3 - 8.

For the surprise gesture, the majority of the correlation relationships were moderate (35.7%), however, it highlights that 32.1% of the relationships were very weak, which may be mainly due to the fact that the signal from subject 1 had a lot of noise, So in this case he presented 6 combinations with a very weak relationship. Leaving out subject 1, the remaining combinations were between the subjects: 2 - 3, 2 - 8, 3 - 5, and 4 - 8.

5. CONCLUSIONS

This paper presented a way to characterize the facial gestures of neutral, eyes closed, smile, frown and clench teeth and surprise by obtaining electroencephalographic signals by means of a BCI.

Using the correlation analysis, it was shown that the EEG signals generated by different individuals when performing facial gestures are related, although with a different level of strength, which in most cases proved to be mostly moderate.

On average there were 20.91% of strong relationships, 34.18% of moderate relationships and only 12.24% of very weak relationships.

Regarding the relationship with the test subjects and their demographic data, it can be seen in the results that subject 3, 6 and 7 have the highest incidence in very weak relationships. Among these subjects a very evident characteristic is shared, they turn out to be near the highest age of the sample used, so it could be inferred that the behavior of the signals is mainly affected by age, although it is not the only feature at that this variation can be attributed.

It was confirmed that EMOTIV INSIGHT is a viable option for the detection of the signals that come from performing the facial gestures described and that the correlation analysis despite being a statistical method presents significant, although inconclusive, results.

In addition, the areas of opportunity that this research has were detected, which are detailed in the next section for future consideration.

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6. ANNEX

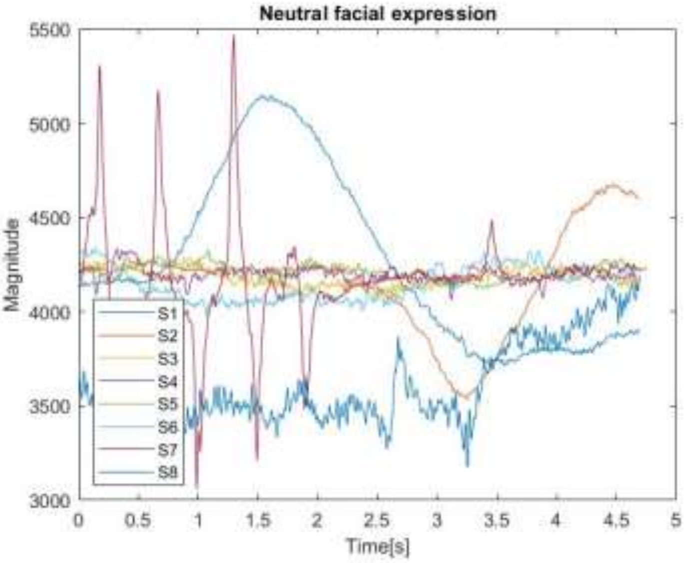

Figure 3. Time vs magnitude graph of neutral facial expression in AF3 sensor. Source: Own Creation

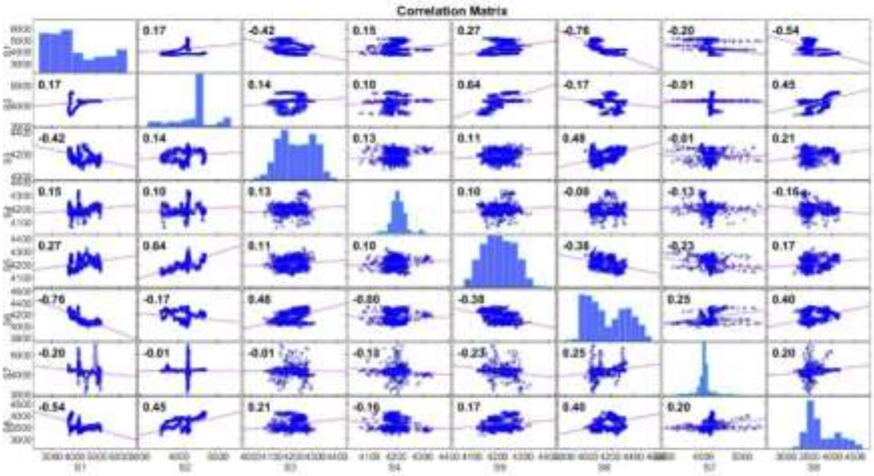

Figure 4. Correlation matrix of neutral facial expression in AF3 sensor. Source: Own Creation

Table 4. Correlation values of neutral facial expression in AF3 sensor. Source: Own Creation

Neutral								
S1	1	0.1682	-0.4165	0.1517	0.2701	-0.7630	-0.2026	-0.5389
S2	0.1682	1	0.1434	0.1033	0.6442	-0.1731	-0.0072	0.4502
S3	-0.4165	0.1434	1	0.1349	0.1118	0.4827	-0.0109	0.2142
S4	0.1517	0.1033	0.1349	1	0.1032	-0.0050	-0.1285	-0.1592
S5	0.2701	0.6442	0.1118	0.1032	1	-0.3761	-0.2315	0.1664
S6	-0.7630	-0.1731	0.4827	-0.0050	-0.3761	1	0.2469	0.4042
S7	-0.2026	-0.0072	-0.0109	-0.1285	-0.2315	0.2469	1	0.1961
S8	-0.5389	0.4502	0.2142	-0.1592	0.1664	0.4042	0.1961	1
	S1	S2	S3	S4	S5	S6	S7	S8

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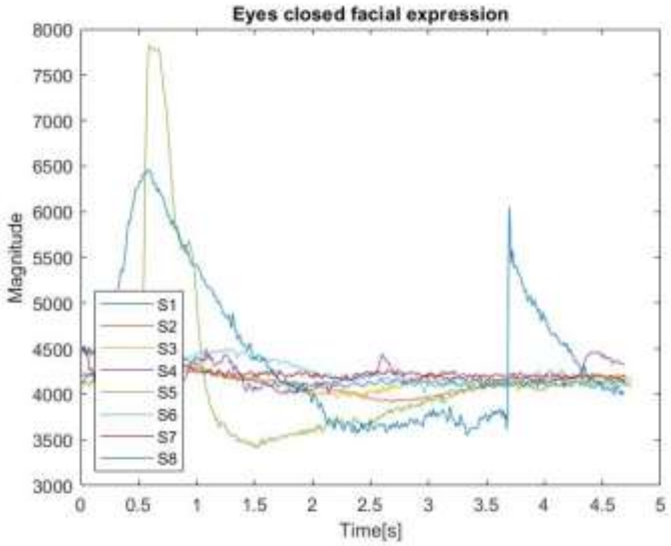

Figure 5. Time vs magnitude graph of eyes closed facial expression in AF3 sensor. Source: Own Creation

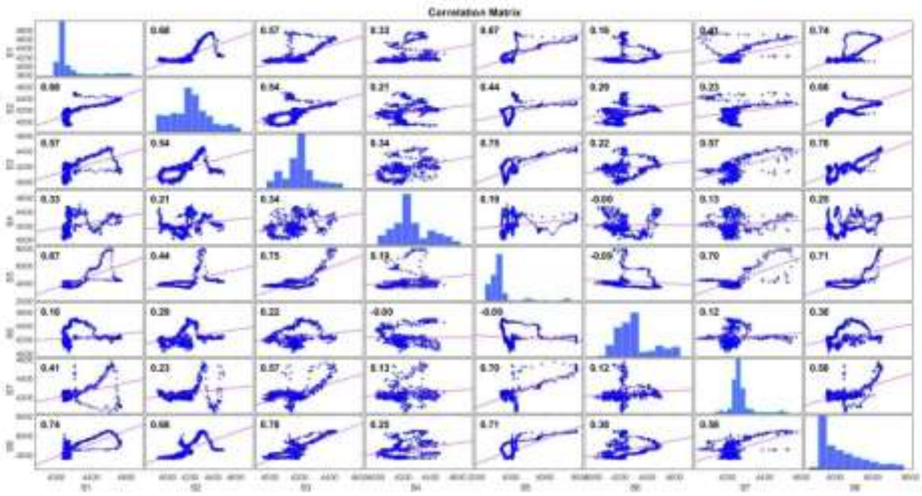

Figure 6. Correlation matrix of eyes closed facial expression in AF3 sensor. Source: Own Creation

Table 5. Correlation values of eyes closed facial expression in AF3 sensor. Source: Own Creation

Eyes closed								
S1	1	0.6786	0.5712	0.3265	0.6747	0.1558	0.4109	0.7419
S2	0.6786	1	0.5366	0.2137	0.4380	0.2917	0.2337	0.6833
S3	0.5712	0.5366	1	0.3437	0.7482	0.2157	0.5659	0.7830
S4	0.3265	0.2137	0.3437	1	0.1906	-0.0013	0.1265	0.2540
S5	0.6747	0.4380	0.7482	0.1906	1	-0.0950	0.6990	0.7071
S6	0.1558	0.2917	0.2157	-0.0013	-0.0950	1	0.1226	0.3783
S7	0.4109	0.2337	0.5659	0.1265	0.6990	0.1226	1	0.5756
S8	0.7419	0.6833	0.7830	0.2540	0.7071	0.3783	0.5756	1
	S1	S2	S3	S4	S5	S6	S7	S8

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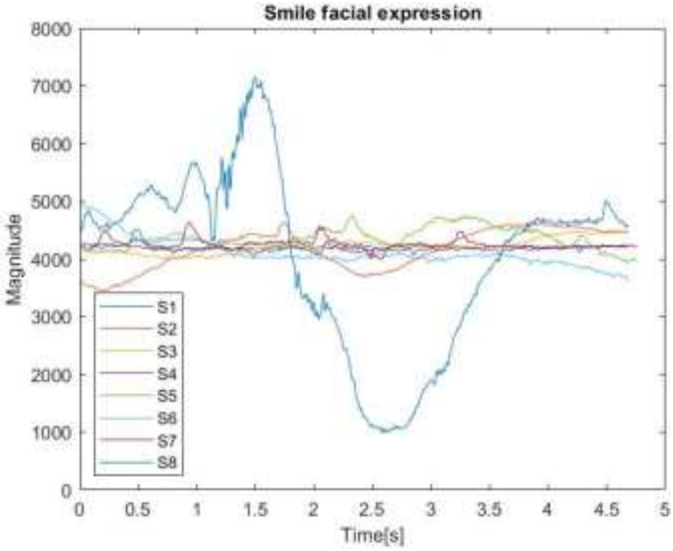

Figure 7. Time vs magnitude graph of smile facial expression in AF3 sensor. Source: Own Creation

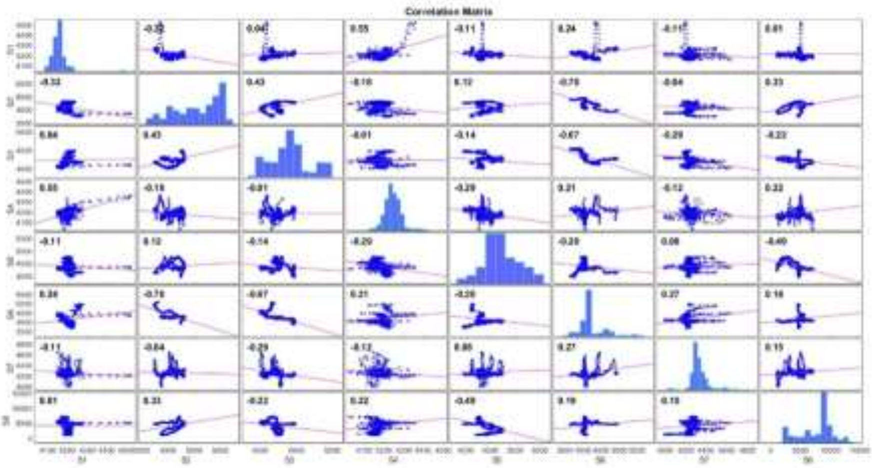

Figure 8. Correlation matrix of smile facial expression in AF3 sensor. Source: Own Creation

Table 6. Correlation values of smile facial expression in AF3 sensor. Source: Own Creation

Smile								
S1	1	-0.3246	0.0406	0.5528	-0.1075	0.2433	-0.1077	0.0066
S2	-0.3246	1	0.4335	-0.1767	0.1236	-0.7012	-0.0442	0.3291
S3	0.0406	0.4335	1	-0.0078	-0.1351	-0.6717	-0.2931	-0.2250
S4	0.5528	-0.1767	-0.0078	1	-0.2879	0.2051	-0.1239	0.2234
S5	-0.1075	0.1236	-0.1351	-0.2879	1	-0.1991	0.0848	-0.4869
S6	0.2433	-0.7012	-0.6717	0.2051	-0.1991	1	0.2676	0.1889
S7	-0.1077	-0.0442	-0.2931	-0.1239	0.0848	0.2676	1	0.1469
S8	0.0066	0.3291	-0.2250	0.2234	-0.4869	0.1889	0.1469	1
	S1	S2	S3	S4	S5	S6	S7	S8

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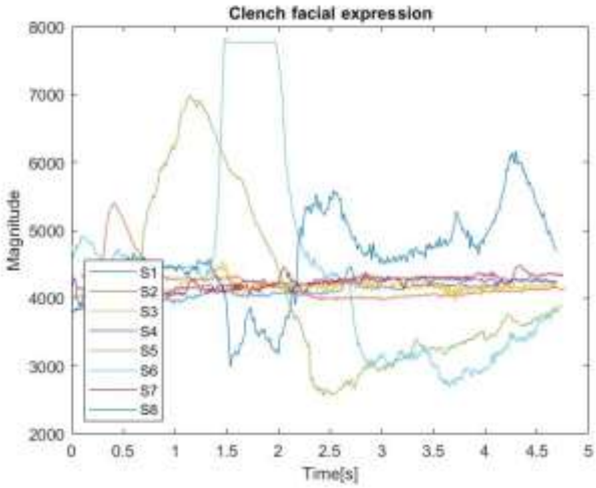

Figure 9. Time vs magnitude graph of clench facial expression in AF3 sensor. Source: Own Creation

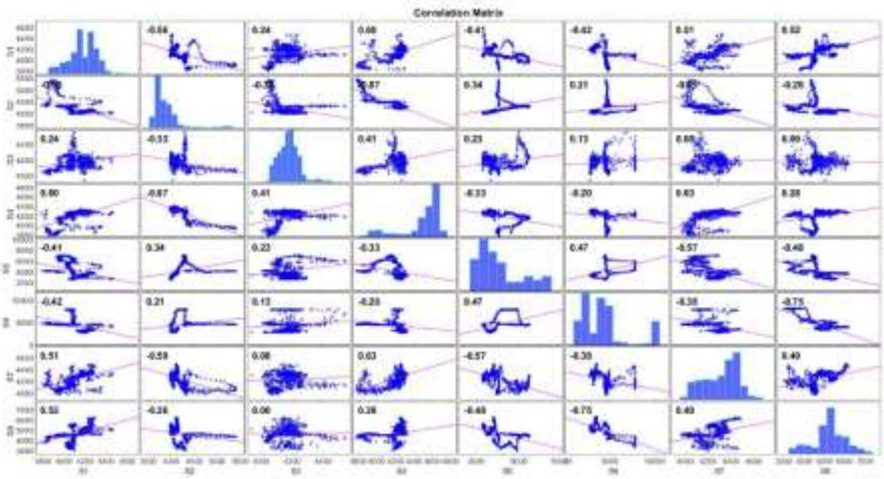

Figure 10. Correlation matrix of clench facial expression in AF3 sensor. Source: Own Creation

Table 7. Correlation values of clench facial expression in AF3 sensor. Source: Own Creation

Clench								
S1	1	-0.5624	0.2446	0.5954	-0.4096	-0.4199	0.5140	0.5239
S2	-0.5624	1	-0.3343	-0.8663	0.3387	0.2121	-0.5891	-0.2640
S3	0.2446	-0.3343	1	0.4118	0.2320	0.1257	0.0777	0.0028
S4	0.5954	-0.8663	0.4118	1	-0.3274	-0.2037	0.6304	0.2765
S5	-0.4096	0.3387	0.2320	-0.3274	1	0.4684	-0.5679	-0.4768
S6	-0.4199	0.2121	0.1257	-0.2037	0.4684	1	-0.3786	-0.7483
S7	0.5140	-0.5891	0.0777	0.6304	-0.5679	-0.3786	1	0.3995
S8	0.5239	-0.2640	0.0028	0.2765	-0.4768	-0.7483	0.3995	1
	S1	S2	S3	S4	S5	S6	S7	S8

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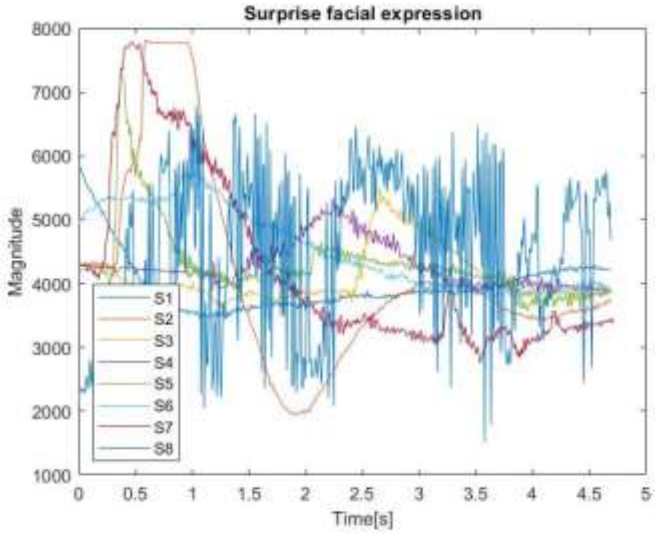

Figure 11. Time vs magnitude graph of surprise facial expression in AF3 sensor. Source: Own Creation.

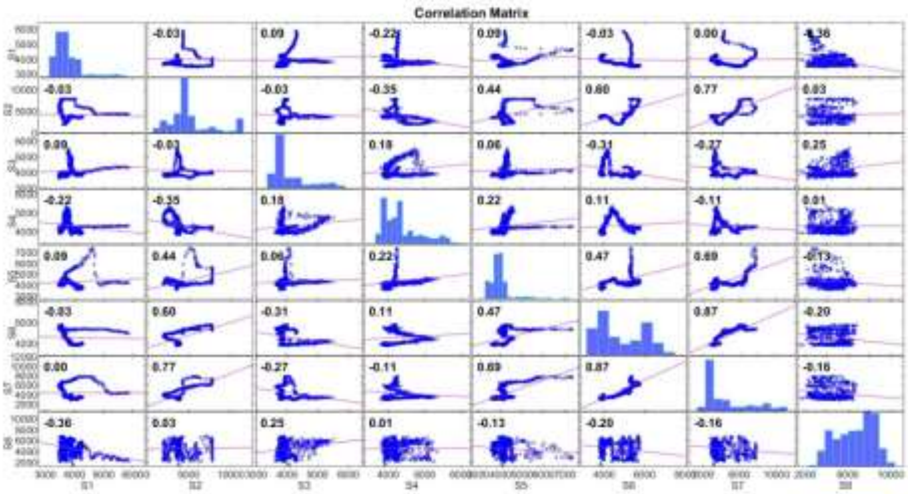

Figure 12. Correlation matrix of surprise facial expression in AF3 sensor. Source: Own Creation

Table 8. Correlation values of surprise facial expression in AF3 sensor. Source: Own Creation

Surprise								
S1	1	-0.0312	0.0854	-0.2207	0.0853	-0.0335	0.0011	-0.3552
S2	-0.0312	1	-0.0288	-0.3518	0.4385	0.5959	0.7733	0.0315
S3	0.0854	-0.0288	1	0.1776	0.0625	-0.3052	-0.2718	0.2462
S4	-0.2207	-0.3518	0.1776	1	0.2175	0.1078	-0.1108	0.0119
S5	0.0853	0.4385	0.0625	0.2175	1	0.4684	0.6897	-0.1297
S6	-0.0335	0.5959	-0.3052	0.1078	0.4684	1	0.8706	-0.2050
S7	0.0011	0.7733	-0.2718	-0.1108	0.6897	0.8706	1	-0.1561
S8	-0.3552	0.0315	0.2462	0.0119	-0.1297	-0.2050	-0.1561	1
	S1	S2	S3	S4	S5	S6	S7	S8

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