Characterization of facial and ocular gestures through electroencephalogram

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ABSTRACT

This article describes the characterization of facial and ocular gestures using the electroencephalogram (EEG) method connected with an EMOTIV EPOC+ Brainwear® device. This characterization is developed by the storage of raw data (unprocessed data) acquired by the device. The experiment was applied to nine subjects, considering that EEG explores neurophysiologically with high levels of statistical confidence the bioelectric activity in the brain in the condition of resting state such as wakeups or dreaming states. In contrast to non-resting states, the registered data showed a random and distinct activation of hyperpnea and intermittent luminous stimulus. Despite the reduced number of samples in the experiment, the results showed that the level of confidence was greater than 75%. The data was characterized and processed by a support vector machine (SVM).

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1. INTRODUCTION

There have had recent medical, academic or entertainment studies [1]–[3] of the brain and have permitted significant advances in paralysis or physical disability or in the development of devices in the video-game industry [4], [5]. The method of electroencephalography (EEG) is one of the most applied techniques for the recognition of brain activities. It is commonly used because of its non-intrusive technology that allows them extract efficiently data and implement their very easy-going devices and instrumentation.

The method of EEG was used to characterize the pattern of facial and ocular gestures by measuring different signals from nine subjects with different ages, appearances and socioeconomic status. All of this data was processed to obtain the basic signal characteristics such as amplitude, frequency and signal power. Then it was necessary applied operation as convolution and correlation to observe the behavior of the gestures through a box plot. At the end of the article, the results were classified using a support vector machine (SVM) technique and they were presented recognizing the classification percentage related to the specific gestures.

Several technological advances have been made in recent decades, advances in computers, mobile technology, hardware, software and even medical measurements applied in different parts of the body [6], [7] this can be used for the benefit of people who have more limitations in their daytime activity [8]. Electroencephalogram detection methods have had drastic changes throughout their history, since with small devices they can be successful compared to previously invented machines, which were more expensive and larger [9], [10] Unfortunately, this type of technology has not been applied to its maximum capacity, since it does not have a commercial appeal like other technological trends mentioned, in addition to being an analysis of one of the most unknown parts of the human body. In this paper, modern electroencephalogram technology will be used to demonstrate that this type of method can be used for various medical and social applications [11]–[14].

2. RELATED WORK

Electroencephalography is a non-invasive technique used to measure the electrical activity of the brain. It has become a useful tool in diagnosing neurological diseases. The main advantage of electroencephalography is that it allows real-time measurement of the electrical activity of the brain, and its information is valuable for diagnosing neurological diseases such as epilepsy, Alzheimer’s disease, and Parkinson’s disease. Additionally, another advantage is that it is a painless, non-invasive, and safe procedure for the patient user. On the other hand, electroencephalography also has some limitations. One of them is that the information it provides can be difficult to interpret. The electrical activity of the brain is very complex, and it can be challenging to distinguish between normal and abnormal patterns. Furthermore, electroencephalography cannot provide information about the structure of the brain, limiting its usefulness in some cases. Next, the three most commonly used types of applications are discussed.

2.1. Robotic motion control

In recent years, robotics has made enormous advancements in the field of human-robot interaction. The use of EEG as a tool for controlling robot movement has become increasingly common in robotics research. The combination of EEG technology and robotics allows for the control of robots through the user’s brain activity.

A literature review on EEG-based robotic motion control has shown effective improvement in user experience and human-robot interaction [15]. The ability to control robots through brain activity can improve movement efficiency and precision, and allow for a more intuitive and immersive user experience [16]. Furthermore, the integration of emotional signal processing techniques can further enhance human-robot interaction, allowing robots to respond to user emotions. This can have applications in areas such as healthcare, service robotics, and education. However, there are also limitations to the use of EEG for robot control. EEG signal processing can be complex and the precision of motion control can be affected by factors such as user fatigue or electromagnetic interference [17], [18].

2.2. Brain-computer interface

Brain-computer interface (BCI) technology has become increasingly popular in recent years as a means of enabling direct communication between the human brain and computers or other devices. The EMOTIV EPOC+ is a BCI device that has gained popularity in research and applications due to its ease of use, affordability, and non-invasive nature [19]. The device uses EEG technology to measure brain activity, allowing users to interact with computers or other devices using their thoughts.

Research on the use of the EMOTIV EPOC+ in BCI applications has shown promising results. Studies have demonstrated that the device can be used to control a variety of applications, including games, virtual environments, and robotic devices. The device has also been used in research to study brain activity and to develop new BCI algorithms and techniques [20].

Finally, for the classification corresponding to the mission of the document, it was done using power density spectrum (PSD) methods together with SVM in electrodes that highlighted greater changes in the tasks evaluated, in this particular case they were AF3 and AF4. Using this type of method, a maximum precision percentage of 87.84% was obtained, making this type of method desirable for the characterization proposed in this research. The author also made the classification using the Hilbert transform and the phase locking value (PLV) method and it was observed in the linear kernel of the document that a maximum precision percentage of 95.01% was obtained, this is due to the fact that the PLV method in comparison with the PSD handles all the data sessions as individual data, contrary to the PSD that handles them as the data of the 14 electrodes [19].

2.3. Body segmental dynamics control

Other studies have focused on a limited number of facial expressions using different types of headbands [21]. This article presents the use of the NeuroSky headband, which includes an electrode positioned on the user’s forehead to detect blink intensity and enable wheelchair movement. The authors chose blinking as the target signal because the headband provides three specific signals, including blinking. For the hardware section, the headband and a computer with a Bluetooth connection were required, while the software section utilized two programs: SolidWorks for 3D designs and LabVIEW for control and instrumentation of design applications [22]. The simulation and verification of headband input data were conducted using these two software programs.

To enable real-time monitoring, the authors developed a human-machine interface that employed a graphical interface designed with LabVIEW. The interface involved selecting the port to which the computer and headband are connected as slave/master for data reception and pressing the start button. Both software and hardware components work together as long as the connection is stable. Using simulation components and incoming data from the NeuroSky headband, the study showed a positive change in simulated motor angles based on the intensity of the blink and the person’s position. The authors note that these results can be useful for individuals with muscle paralysis who require such applications.

3. METHOD

Electroencephalography (EEG) is a non-invasive method of measuring and monitoring brain activity using electrodes connected to the scalp. These electrodes filter and amplify the output as a voltage signal, making EEG one of the most widely used methods for measuring brain waves. EEG devices are wearable, easy to transport, and less intrusive than other techniques.

The general system depicted in Figure 1 consists of two main components. Firstly, the EMOTIV EPOC+ headband is used to place electrodes according to the International 10-20 System, as can be seen on the left side of Figure 1. Secondly, as shown on the right side of the same figure, a general methodology is implemented for the acquisition and analysis of data. The EMOTIV EPOC+ headband is designed to be compatible with the 10-20 International System, which is widely used for electrode placement on the scalp. The general methodology includes a set of procedures and techniques that are used to acquire and analyze data from the EMOTIV EPOC+ headband.

The name of each electrode represents the central brain lobes [23] and the location in the cerebral hemisphere, the letters are determined as follows: F for frontal lobe, T for temporal lobe, O for Occipital Lobe and P for parietal lobe. The others letters and numbers locate some position in the hemisphere, specified such as: Z for half line and C for horizontal line. Also, the number identifies the location of the electrodes, even numbers for the right hemisphere and odd numbers for the left hemisphere.

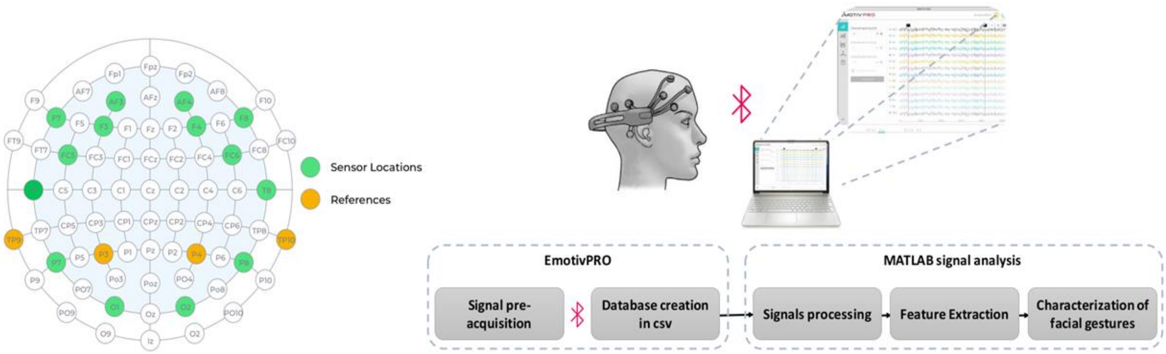


Figure 1. The general system includes electrodes positioned based on the 10-20 International System by the EMOTIV EPOC+, alongside the overall methodology

4. PROPOSED APPROACH

The methodology presented in this study is depicted in Figure 1. The experimental procedure involved using the EPOC+ device, which was connected to a local PC via Bluetooth using a USB transceiver provided by the manufacturer. The signals were acquired using the EmotivPRO program, which allowed recording, playing, and storing data in European data format (EDF) format and comma-separated value (CSV) file. A database was created by capturing the storage of facial and ocular gestures in different individuals. Fifty-four CSV files were acquired, with six recordings for each of the nine subjects.

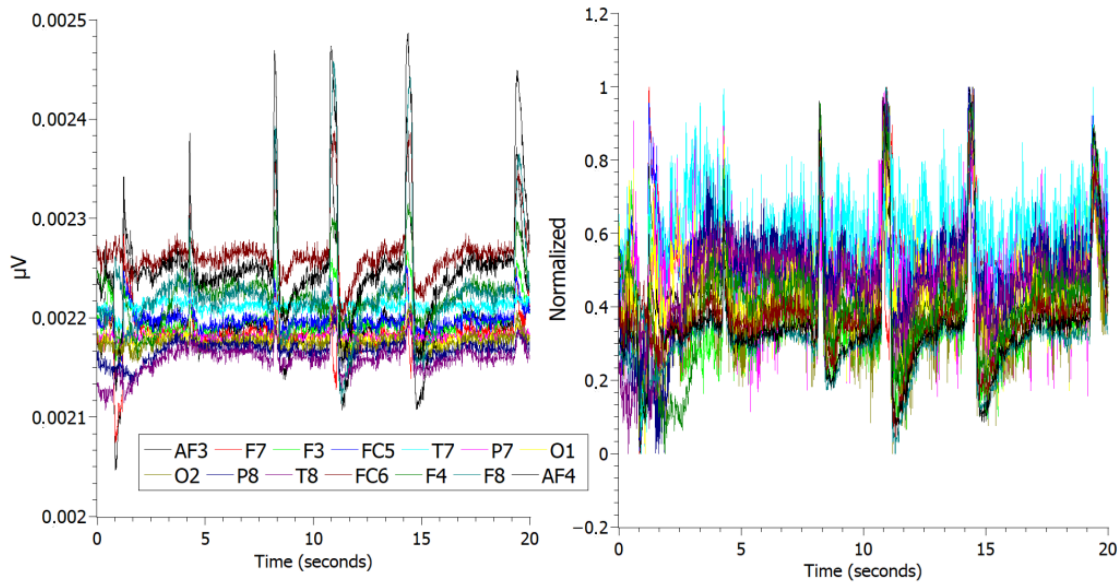
The recordings were then processed in MATLAB. It was found that the signals had an offset value, given by the same software used in the recording. The power spectral density of the signal was determined using the fast Fourier transformation (FFT) to facilitate frequency domain analysis and power estimation in each electrode. The box diagram was obtained statically to visualize the results and recognize gestures. Once the statistical processing of the results was completed, correlation and convolution operations were applied to insignificantly change the captures of the electrodes. The classification process was simplified by using a window function to limit the data, which is a condition for the FFT. The findings of this analysis are briefly presented in the document [24], [25]. Finally, to evaluate the performance of the existing characteristics for specific applications, a classifier based on support vector machines with the method of cross-validation was used. This method allowed checking the real classification percentage of the existing characteristics, which remained constant even when taking external data from the created database.

5. RESULTS AND DISCUSSION

As was described in the last section, database processing where all the files captured in .csv extension are passing through an offset suppressor described in the previous section, it begins with the processing of the database. All the CSV format files are taken and entered into a cycle where the process of eliminating the DC offset and the window function is carried out. The window function used is the flat surface window function. This type of window has a shape similar to that of a Gaussian sine and considerably reduces the data compared to other existing window types (Blackman and Hanning), as represented in Algorithm 1.

Algorithm 1. Signal processing algorithm
```
Read CSV database
Extract data electrodes
Data = 55
Chanel = 0
while Data ¡55 do
  while Chanel ¡15 do
    DC offset elimination
    Flat window
    Chanel++
  end while
  Data++
end while
Return databases processed
```

Figure 2 shows the pre-transformation of data that is carried out on the signal, in order to obtain the normalization of the input signal and to correlate the waves that have the same behavior but vary in scale, either due to scalp parameters, and skin moisture. In this way, algorithm 2, as shown in Figure 2(a), creates new data in the same .csv format and stores it in a new file folder, preserving the original data for reuse in case of any modifications to the database. This is illustrated in Figure 2(b).



(a) (b)

Figure 2. Input and output of data to the general system: (a) original signal and (b) resulting signal after removing the offset through the normalization process

Algorithm 2. Correlation and convolution process
```
Read CSV database
Electrode Selection 1
Data = 0
while Data ¡10 do
  Calculation of the absolute maximum
  Location of absolute maximum
  Data normalization
  Data reduction
  Data++
end while
Gx = 0
while Gx ¡10 do
  Convolution
  Correlation
  Gx++
end while
Return correlation average
```

The resulting signals were then processed using the FFT and the PSD techniques to determine if any of these characteristics could serve as determinant factors. To identify which electrodes were most significant in every facial gesture, a box plot with the PSD data was used in conjunction with descriptive statistical methods. This allowed for optimum frequency data, particularly with regard to cognitive values of the results, such as beta gamma, alpha waves, and so on.

The results are presented in Figure 3, which includes three distinct graphs: the spectrum magnitude of all electrodes, the power spectral density (PSD), and the Box diagram, which represents the power-to-frequency ratio expressed in [dB/Hz]. Specifically, the box diagram in Figure 3 illustrates the unique gesture of brow lifting, highlighting how the power levels of the electrodes differ when compared to other gestures. This visualization allows for a clear comparison and facilitates a better understanding of the electrical activity associated with specific facial movements.

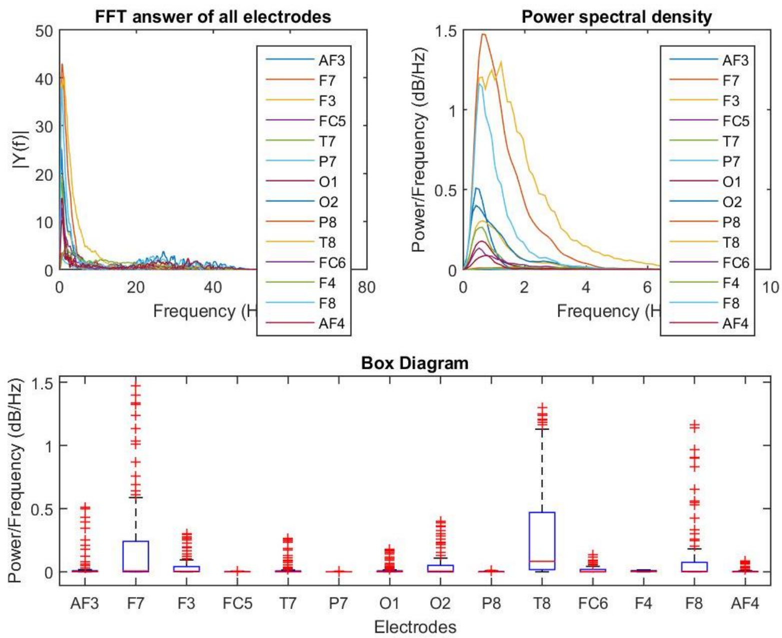


Figure 3. The sequential order of the process involves obtaining the FFT response of all electrodes and their respective power spectral density for a particular case

The term "*most prominent electrodes*" refers to those that exhibited the most significant and consistent activity during the experiments. The "*detection rate*" indicates how frequently the electrodes were detected during the tests. This process is repeated for each value in the database, and the resulting data is compiled in Table 1. For example, for the gesture of raising both eyebrows, the electrodes F7 and F8 were detected 66.6% and 88.8% of the time, respectively, during the tests.

In Table 1, the electrodes with the highest detection percentages were selected, even if they did not exhibit a significant change in their power or PSD. This is because such changes don't necessarily imply the same resulting signal. To better analyze these results, the correlation and convolution methods were applied to the processed signals as seen in Figure 2. The aim was to determine the level of similarity between the signals of all the detected electrodes.

Table 1. Electrodes that are most manifested in the tests carried out with their percentage of detection

Facial gesture	Manifested electrodes	Detection rate
Raise both eyebrows	F7, F8	F7: 66.6% F8: 88.8%
Chew on	F7, T7, F8, FC5, FC6	F7: 77.7% T7: 77.7% F8: 88.8%, FC5:77.7%, FC6: 88.8%
Look to the right	F7, T8, FC6, F8	F7: 77.7% T8: 55.5% F8: 100% FC6: 88.8%
Look left	F7, F8, FC6	F7: 88.8% F8: 77.7% FC6: 55.5%
Close the eyes	AF3, F7, F8, AF4	AF3: 66.6% F7: 100% F8: 88.8%, AF4: 66.6%
Flicker	AF3, F7, F8, AF4	AF3: 77.7% F7: 88.8% F8: 77.7% AF4: 77.7%

The process begins with the sum of convolution, which creates a new signal by combining two signals. Although the same procedure is used for each input signal from each selected gesture of the person, they must differ in order to avoid issues. To resolve this, an algorithm is designed to take the input signals and match them in the same time interval. It is important to note that the basic signal characteristics such as maximum and minimum amplitudes (which depend on the electrode response form) are different for each person. To correctly perform the convolution, it is necessary to normalize the input signals to ensure standard values from -1 to 1 are used. This normalization is also necessary to compare signals from different individuals.

The Algorithms 1 and 2 show the flow corresponding to the processing: it begins with the processed database and the electrode selection, then proceeds with data normalization, locating and calculating the absolute maximum, and aligning the response time across all nine data cycles. For some facial and ocular gestures, an amplitude more negative than the positive amplitude was observed, which needed correction by recalculating the maximum to ensure accurate correlation. Ultimately, the goal was to determine the location of this maximum to consider this time as the origin (or reference point) for all evaluated data.

To perform convolution, three signals from a specific electrode labeled as G1, G2, and Gx are selected from three different subjects. G1 and G2 are the best signals from the electrode according to the corresponding gesture and the database, while Gx is any other signal from the database. The convolution process involves creating a resulting signal C1 by convolving G1 and G2, and another resulting signal Cx by convolving G1 and Gx. G1 and G2 are considered constant signals because they are the best signals, and C1 is also constant and serves as the reference signal, or pilot signal. C1 is then correlated with Cx, which changes since it is the signal that is desired to find the corresponding correlation (Gx). After obtaining both resulting convolved signals, they are correlated. This correlation shows how well the two signals match or are related, and it ranges from -1 to 1, where -1 represents no correlation and 1 represents perfect correlation.

Then, this process will be repeated for each electrode or input signal from the database to obtain an average of all correlations with a unitary reference result and compare which electrodes have the worst or best correlation and how often this result is manifested. These results are recorded in Table 2. It is evident from the table that the electrode T7 has the lowest correlation with respect to the others and will be discarded for the following analyses. Additionally, it can be observed in the table that although T8 and FC5 have good correlation calculations, they are only manifested in one gesture, either facial or ocular, and their convolution or correlation could not be calculated with other gestures. These comparisons might be random or harmful for other analyses, and therefore, they will be eliminated from the data. Removing the comparison with these three electrodes will make the system faster and more accurate in characterizing the other electrodes or gestures (AF3, F7, FC6, F8, AF4) through SVM.

In order to verify that the characteristics of all gestures were correctly identified, it was necessary to classify the selected electrodes using the SVM method. This method is considered one of the most reliable for research related to electroencephalogram analysis or big data processing/transactions [26]. Only five electrodes were selected, normalized, and reduced to fewer input data (from 1,250 to 701) before being combined into a single row representing one input of either a facial or ocular gesture. Each row was labeled to indicate the corresponding gesture, resulting in nine input files for the classification process. These generated files had to be in a specific sparse format as defined by the creators of the SVM library used [27].

After obtaining the file for each individual, the data classification was performed using a cross validation function. This method involves dividing the data into two main sections: one for training and the other for testing. It is essential that the data in both sections remain independent throughout the process. The method splits the data into partitions, also known as "*folds*", depending on the K iteration (known as K-fold), and repeats the process until the last iteration. In this study, we used nine iterations, one for each individual evaluated, and applied the basic RBF core (short for radial basis function) with different constant values of C and gamma. The results are presented in Figure 4 and show the performance of a predictive model.

The S4 and S5 electrodes are located on the posterior region of the scalp, near the midline, in the occipital and parietal regions, respectively. They are commonly used in polysomnography to detect sleep patterns in the brain by measuring slow wave activity of sleep, which is activated in the deepest stages of sleep. Figure 4(a) shows the results of this activity. As the tests were carried out with participants in a conscious state, these waves did not represent relevant information compared to the evaluated gestures. Therefore, they were eliminated from the analysis, resulting in an increase in the percentage of clarity, as shown in Figure 4(b).

Table 2. Total correlation of each electrode and the number of times manifested with respect to each easy and ocular gesture

Electrode	Number of times manifested	Correlation result
AF3	2	0.78685
F7	6	0.69228
FC5	1	0.6214
T7	1	0.2591
T8	1	0.7821
FC6	3	0.6690
F8	6	0.68456
AF4	2	0.8425

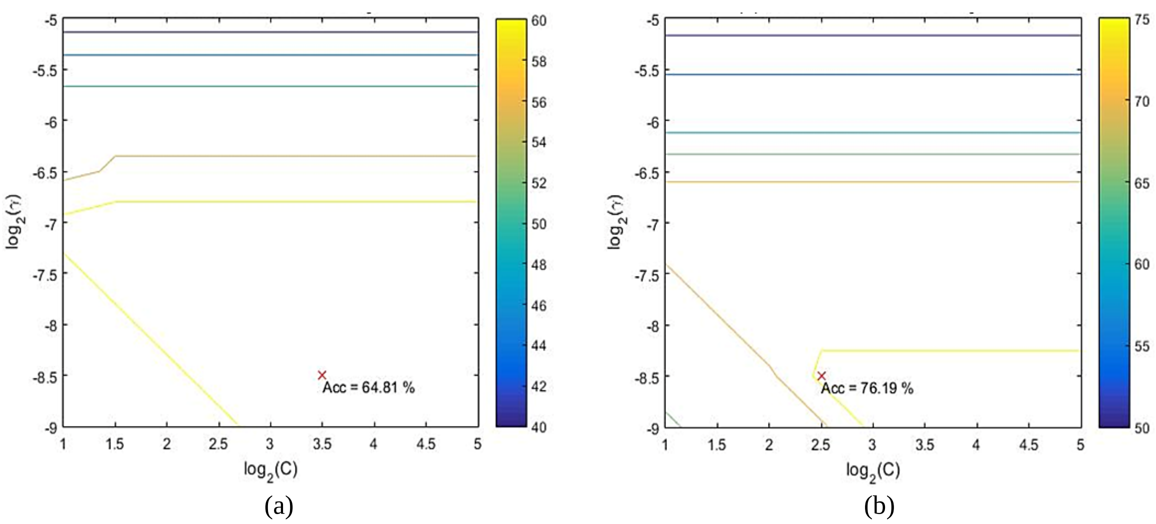


Figure 4. Performance of a predictive model: (a) resulting cross validation and (b) cross validation resulting from deletion of S4 and S5

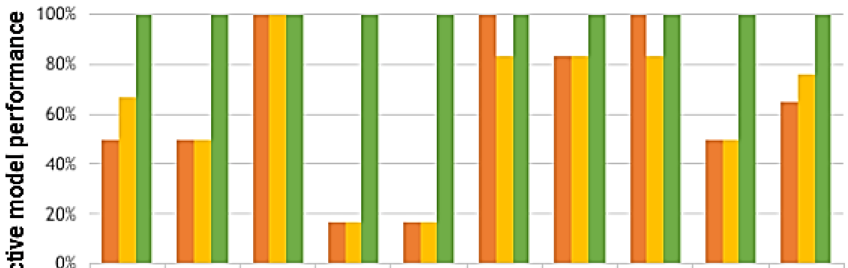
Figure 4(a) indicates that when a different input is given other than those from the database, this method matches the characteristics with an accuracy of 64.81%. To investigate why the cross-validation gave this number, an algorithm with the same function was created to visualize individual percentages instead of the overall average percentage. The individual percentages are important because it is necessary to identify which facial or ocular gesture in the database has no coherence with the number of electrodes applied. The individual results may differ significantly from the rest of the data in the database, and there is a possibility, albeit low, that lower percentages in the database may corrupt all classification systems. Table 3 displays the individual results for each subject used in the cross-validation classification.

With the data expressed in Table 3, it was demonstrated that subjects S4 and S5 had a smaller number of classified gestures, leading to a significant decrease in the overall classification percentage of facial or ocular gestures characteristics. In order to improve this classification, these subjects were eliminated, and the cross validation was executed again, with the results shown in Figure 4(b). With the elimination of subjects S4 and S5, the cross-validation accuracy increased from 64.81% to 76.19%, which is a significant improvement as cross validation ensures the classification of characteristics with other data outside of the database. The following bar plot shows the classification results in detail, with a distinction between the results of cross validation with the database of nine subjects (VC1), the results of cross validation with the decreased database (VC2), and the results of the classification method using SVM with constants C and gamma of VC1.

Table 3. Classification percentage of each subject

Subject	Classification percentage	Amount of classified gestures
S1	50%	3
S2	50%	3
S3	100%	6
S4	16.6667%	1
S5	16.6667%	1
S6	100%	6
S7	83.3334%	5
S8	100%	6
S9	50%	3
Average	62.96%	3.77

Figure 5 shows that when using SVM for training, the classification percentage is 100% in all cases (green color) because the test data was already included in the training of the system. However, if the test data were not used in the training phase, its classification would be unknown without using the cross-validation method. This graph also demonstrates how the data of individuals S4 and S5 in VC1 (orange tone) affected the overall results, as their percentage was significantly lower compared to the other subjects in the database. Thus, excluding these subjects from the classification training led to a final classification accuracy of over 75% (yellow tone) using a database of seven people.



	S1	S2	S3	S4	S5	S6	S7	S8	S9	Total
VC1	50%	50%	100%	17%	17%	100%	83%	100%	50%	65%
VC2	67%	50%	100%	17%	17%	83%	83%	83%	50%	76%
SVM	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Figure 5. Impact of cross-validation on the performance of a predictive model using SVM classification

6. CONCLUSION

In this article, it has been confirmed that EEG provides a viable option for measuring facial and ocular gestures. The instruments used for data collection were non-invasive, portable, and easy to use, compared to other methods described in the literature. Signal analysis was performed on the database using different types of processing to observe the characteristics of each gesture, such as amplitude, shape, power, and frequency, in order to obtain the best possible classification depending on the characteristics considered. It was noted that raw signals showed similarities in the correlation and convolution process, as observed in Tables 2 and 3. In contrast, the results obtained through FFT and PSD were only useful in differentiating which electrodes had more change than others and reducing the amount used for sorting.

For future work, it is recommended to conduct measurements on individuals with short hair. As confirmed in the analysis of results, the entire female database had low voltage values, making it difficult to distinguish any difference in frequency and power, resulting in a significant drop in the database throughout the signal analysis. Additionally, other reductions were made in the database during the use of SVM to observe how the results of cross-validation changed. This method was able to correctly classify the characteristics found in this project with a maximum percentage of 76%. Using these methods, it was possible to identify the main problems encountered in this research, such as the scarcity of input data and lack of recording sessions. For future classifications, it is necessary to have a broader database and, if possible, different measurement sessions. As seen throughout this document, values may look decent visually during recording but may be unusable for their intended purpose.

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