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Optimizing Brain Signal Classification through Computational Neuroscience with EMOTIV and Free Software

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Abstract. This study presents a method for the acquisition, preprocessing, and classification of brain signals aimed at brain mapping and the development of a brain-computer interface (BCI) using non-invasive electroencephalography (EEG). The proposed system is based on the hypothesis that imagined motor actions can be translated into control commands to displace a robotic prototype in four basic directions: right, left, push, and pull. For this purpose, raw biosignals were collected with EMOTIV headsets (EPOC X and Insight), exported in .csv and .edf formats, and subjected to a preprocessing pipeline including artifact removal, digital filtering (1–40 Hz), and statistical outlier detection to ensure data quality. The signals were then analyzed with different classification methods (J48 Decision Tree, RandomForest, NaiveBayes, and Support Vector Machines) to identify the most suitable model for BCI-based neurocontrol. Results show that RandomForest achieved the highest accuracy, reaching 100% with external test data, followed closely by J48 with 99.01%, while NaiveBayes and SVM demonstrated limited reliability under cross-validation. Finally, the methodology was validated through the neurocontrol of a robotic prototype using Arduino hardware, where participants successfully executed directional commands via mental activity. These findings demonstrate the feasibility of integrating consumer-grade EEG devices, free software, and machine learning techniques to develop robust and accessible BCI systems for assistive robotics. The contribution of this work lies in optimizing mental command recognition and highlighting the potential of EEG-based neurocontrol technologies to enhance mobility and autonomy in individuals with motor disabilities.

Keywords: Neurotechnology, Bio signals, Control Neuronal, Emotiv, Brain-Computer Interfaces, EEG, Computational Neuroscience, Mental Commands.

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1 Introduction

In a diverse and heterogeneous population, people with disabilities face discrimination, stigmatization, and other barriers that prevent them from participating in society on an equal basis with others. It is estimated that people with disabilities globally represent 15% of the world's population, that is, approximately 1,000 million people, according to the United Nations Development Coordination Office in its Disability Inclusion Strategy 2022-2025 plan [1].

According to studies carried out by the Rehabilitation Program of the Pan American Health Organization, there are 85 million people with disabilities in the Americas, of which only 2% receive solutions to their needs [2], emphasizing that mobility is a fundamental aspect of daily life that allows people to interact with their environment autonomously. However, individuals with severe motor disabilities face significant limitations in this area [3].

In Mexico, according to the 2020 Population and Housing Census, in Mexico there are 6,179,890 people with some type of disability, which represents 4.9% of the country's total population, where walking, going up or down; it is 48%; 44% see, even wearing glasses; 22% hearing, even using hearing aids; 19% bathe, dress or eat; 19% remember or be content and 15% speak or communicate. These percentages are greater than 100 percent for the population that presents more than one difficulty [4].

Brain-computer interfaces (BCIs) are technological devices that are based on the acquisition of brain signals and their subsequent processing, to perform actions or activities based on their interpretation. They are an attractive option to improve the quality of life of people with severe motor disabilities, by allowing them to communicate and send commands to external devices using only their electroencephalographic (EEG) signals [5], [6], [7].

The brain is the most complex organ in the body, it is responsible for various functions, such as movement, speech, processing emotions, among many others. A non-invasive way to study it is to employ a brain-computer interface (BCI). The main function of a BCI is to be able to convert the patient's conscious behavior into data for manipulation and, eventually, transform it into commands. The first step is to extract the signal using a neurological examination method called EEG, which consists of measuring the electrical potential. The brain signal is acquired by various electrodes placed on the head, usually using the International 10/20 System [2], [7].

The human body emits electrical signals that are essential for communication between different systems, particularly through nerve impulses that allow the emission of motor stimuli. In recent work he has developed non-invasive prototypes using a Raspberry Pi: Microcomputer used for programming and controlling the prototype. and an interface in Python**:** Programming language used to develop the interface and control system. These systems capture voltage signals using myoelectric sensors: Sensors used to capture electrical signals and control motors to reproduce different movements. The signals obtained are processed to generate spectrograms, which are used as inputs for the training of a neural network: Artificial intelligence model used to train and improve the accuracy of the prototype, achieving very good accuracy [5], [8], [9], [10].

Neuroimaging has the potential to provide detailed macroscale information on the functional and structural correlates of experience development. However, there are still some shortcomings. To address these shortcomings, methods of automatic and reliable collection of neuroimaging research knowledge have been proposed, supporting studies in brain science, brain-computer interfaces, and artificial intelligence. In addition, a set of tools have been developed to support basic research on neural functions in real-world environments, facilitating a more accurate analysis that is applicable to everyday situations [11], [12], [13].

In recent years, BCIs and assistive technologies have evolved significantly to improve the mobility and autonomy of people with motor disabilities. Research has explored different control strategies for smart wheelchairs, from conventional mechanisms to advanced systems based on brain signals.

An initial study developed an EEG-controlled system using the LabVIEW platform and Emotiv (edk.dll) libraries, in which signals related to emotions, participation/boredom, frustration and meditation were used to move an electric wheelchair. This prototype, tested on a patient with spastic paraplegia, focused on evaluating the quality of the recorded signals and demonstrated the feasibility of using non-invasive electrodes for assisted mobility [14].

Subsequently, Janani et al. implemented a system based on the NeuroSky MindWave headset, which analyzes alpha and beta waves to determine the user's level of attention and meditation, in addition to using blinks as signal interruptions. This approach allowed directional control (forward, backward, left, right) without the need for physical effort, evidencing the integration of cognitive and ocular parameters in control algorithmsSubsequently, Janani T. et al. implemented a system based on the NeuroSky MindWave headset, which analyzes alpha and beta waves to determine the user's level of attention and meditation, in addition to using blinks as signal interruptions. This approach allowed directional control (forward, backward, left, right) without the need for physical effort, evidencing the integration of cognitive and ocular parameters in control algorithms [15].

In parallel, Md. Abdullah Al Rakib et al. developed a smart wheelchair with voice activation and buttons, aimed at people with physical disabilities and older adults. Although it does not use EEG signals, this system stands out for offering an accessible control alternative, contributing to the diversification of interfaces and the inclusion of users with different levels of motor capacity [16].

Finally, Ayman A. Aly et al. proposed an adaptive neural network-based fixed-time tracking controller for an upper limb exoskeleton wheelchair robotic system. This work solved nonlinear dynamics and external disturbance problems by means of nonsingular integral terminal sliding mode adaptive control combined with wavelet neural networks, achieving high accuracy and stability in joint tracking [17].

Together, these studies reflect the transition from manual and voice controls to hybrid and advanced BCI systems that integrate EEG signal processing, neural control, and complementary robotic modules. This evolution shows a trend towards more autonomous, precise and adaptive devices, aimed at improving the quality of life of people with severe motor disabilities.

The purpose of this paper is to present a method of reading EEG signals aimed at brain mapping and the development of a brain-computer interface (BCI), using electroencephalography (EEG) signals applied to a robotic prototype. The proposal is based on the hypothesis that, when a subject imagines a movement, it is possible to translate this neural activity into commands that allow controlling the movement of the prototype in four basic directions: right, left, push and pull. To do this, a set of raw biosignals corresponding to mental instructions is generated, which are subjected to a filtering and preprocessing process in order to reduce noise and improve its quality. Subsequently, these signals were analyzed using different classification methods, with the aim of identifying the most suitable algorithm for the neurocontrol of robotic prototypes.

The rest of the paper is organized as follows: Section 2 introduces the methodology and tools used for EEG acquisition, preprocessing, and signal extraction with EMOTIV devices. Section 3 presents the experimental results, including dataset generation, brain mapping, and analysis of mental commands. Section 3.4 compares the performance of classification algorithms for command recognition, while Section 3.5 describes the integration of EEG-based neurocontrol with an Arduino-driven prototype. Finally, Section 4 summarizes the main findings and outlines future research directions.

2 Method and tools

2.1 EEG Signal Adquisicion, Extraction and Preprocessing

The proposed method facilitates non-invasive EEG biosignal acquisition using wireless EMOTIV devices, such as the EPOC X or Insight models. These devices enable brain mapping and real-time visualization of cognitive activity without requiring a license.

To perform the acquisition process, the following setup protocol is necessary:

- Official Software Installation: The official EMOTIV software (Launcher, BrainViz, EmotivPro, and EmotivBCI) is installed. This software is essential for connection management, 3D visualization of the brain (BrainViz), metric analysis, and controlling Brain-Computer Interfaces (BCI).
- Account Configuration: It is mandatory to create an account and obtain credentials (Username and Password) in the EMOTIV LAUNCHER to log in.
- Sensor Preparation: The headset sensors must be hydrated with a saline solution, such as a general purpose contact lens solution (e.g., ReNu).
- Connection and Adjustment: The device connects to the computer via Bluetooth or a universal USB receiver compatible with the Nordic protocol. The headband is adjusted to the skull, and the EMOTIV LAUNCHER application is used to monitor the quality of contact of the electrodes with the scalp. The goal is to ensure excellent EEG quality (all electrodes appear in green).

Once the signal quality is ensured, the extraction process begins. EEG signals are extracted and analyzed using EmotivPro. This software is licensed for data import, export, and conversion into various formats (such as .csv and .edf), event marking, and quick analysis to save recordings in the cloud. For this work, a file in EDF format is generated. This format is specifically used to store, edit, and analyze scientific data collected from laboratory experiments.

The preprocessing of the EEG signal is a crucial step to ensure data quality before any subsequent analysis. This process is implemented through a pipeline designed to eliminate artifacts and optimize the data for classifier analysis in the context of computational neuroscience. This development is performed in MATLAB using structures compatible with the EEGLAB toolbox for integration. The detailed preprocessing steps include:

- Acquisition Setup: EEG signals are acquired at a sampling rate of 250 Hz. A set of 14 channels of interest is defined (AF3, AF4, F3, F4, F7, F8, FC5, FC6, O1, O2, P7, P8, T7, and T8), corresponding to cortical regions associated with cognitive and motor processes.
- Incomplete Data Cleanup and Channel Loading: Data is imported from CSV files, preserving the original variable names to maintain traceability. A column selection is made based on valid channels, and rows containing incomplete data are removed using the function rmmissing().
- Detection and Elimination of Extreme Artifacts: An outlier detection procedure based on Z-scores is applied. Samples that exceed ±3 standard deviations are discarded, which drastically reduces extreme artifacts.
- Digital Filtering: To reduce noise and interference, Order 2 filters designed with butter() are applied in zero-phase mode (filtfilt()) to prevent temporal distortion: A High-pass filter (1 Hz) suppresses low-frequency components, such as DC movements or signal drift.A Low-pass filter (40 Hz) removes high-frequency noise, primarily of muscular origin.
- Exportation: The process concludes with the export of the processed data in two formats: Filtered CSV (compatible with Python/MATLAB workflows) and EEGLAB SET (for advanced analysis and event segmentation).

2.2 Neurocontrol with simulator

The following details the process for the installation, configuration, and collection of bio data using the Cortex API and Python, which is required for the simulator to function.

Table 1 Pseudocode: EMOTIV – Arduino Connection via Python

```
BEGIN
// 1. Verify and install dependencies
DISPLAY "Checking Python version..."
IF Python is NOT installed
   DOWNLOAD and INSTALL Python
END IF

DISPLAY "Installing required libraries..."
EXECUTE:
   pip install websocket-client
   pip install python-dispatch
   pip install cortex2
   pip install pyserial
   pip install serial

// 2. Environment setup
OPEN Visual Studio Code
LOAD folder 'cortex-example-master/Python'
INSTALL Python extension in VSC (if prompted)

// 3. Python code modification (live_advance.py)
OPEN file live_advance.py
IMPORT serial library
CREATE serial object:
   ser = serial.Serial('COMX', 9600)   // Replace COMX
with Arduino port

ADD write() method at line 221:
   action = data.get('action', '')
   ser.write(action[2].encode())

ADD EMOTIV credentials:
   client_id = "XXXX"
   client_secret = "XXXX"
CONFIGURE trained profile name in EMOTIV BCI
```

```
// 4. EMOTIV headset configuration
ASK: "Physical or virtual headset?"
IF physical:
   CONNECT headset to EMOTIV LAUNCHER
   CONFIGURE sensors and concentration level
ELSE IF virtual:
   CREATE virtual device in EMOTIV LAUNCHER
   CONFIGURE type and mental commands
END IF

// 5. Arduino hardware selection
ASK: "LED prototype or Cart prototype?"
IF LEDs:
   CONNECT circuits as per LEDs diagram
   UPLOAD Arduino LEDs code
   RUN system
ELSE IF Cart:
   CONNECT motors and digital pins as per Cart
diagram
   ADJUST speed (ENA and ENB between 1 and 255)
   UPLOAD Arduino Cart code
   RUN system
END IF

// 6. System execution
OPEN EMOTIV LAUNCHER
RUN live_advance.py
IF connection is successful:
   DISPLAY "System running successfully"
ELSE:
   DISPLAY "Error: Verify connection and trained
profile"
END IF

END
```

Python Library Installation: To begin, it is recommended to use a development interface such as Visual Studio Code, from which the following Python libraries must be installed using the PowerShell terminal:

- pip install websocket-client
- pip install python-dispatch
- pip install cortex2
- pip install cortex
- Python –m pip install PySerial

API and Credential Configuration: Once the libraries are installed, the Emotiv Python API, named "live_advance.py", must be opened in the Integrated Development Environment (IDE). This file is located in the GitHub repository. To run the program, it is essential to input two identification keys: the client_id and the client_secret. Additionally, the name of the profile created within the "Emotiv BCI" program must be provided. This data must be placed in the "main" method at the end of the Python code. If the user does not have an Emotiv BCI profile, they only need to access the application to create one.

Mental Control Training and Execution: The training is carried out using the headband (which can be physical or virtual) until the system manages to recognize and execute the four desired actions: left, right, push, and pull. It is important to note that for the system to operate correctly, two essential conditions must be met:

1. The profile must be registered both in the Python Script and in the "Emotiv BCI" application.
2. The Emotiv Launcher app must remain open during the process.

Through this training process, the movement of a virtual cube in the four directions is visualized within the Emotiv BCI application.

2.3 Prototype construction

The prototype construction focused on two phases: a basic validation circuit using LEDs and the final architecture for controlling direct current (DC) motors.

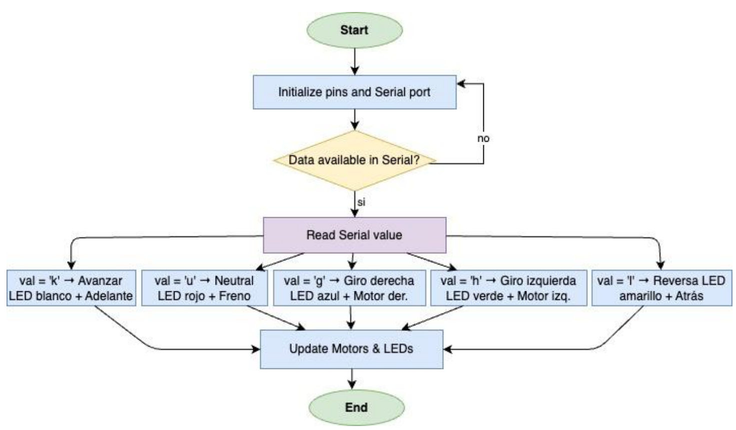


Figure 1 Flowchart for LED Ignition and Motor Control

Visual Validation Prototype (LEDs): For the initial validation of the interaction between the Emotiv headset and the Arduino hardware, a basic circuit with five LEDs was implemented, see Figure 1.

- The LEDs were connected to digital pins 3 through 7 of the Arduino.
- These pins were configured as outputs within the Arduino programming.
- The LEDs activate when the headset identifies one of the mental movements of the virtual cube (push, pull, left, right).
- The activation signal is sent at a rate of 9600 baud via the COM5 serial port.

Motor Neurocontrol Architecture: For the final control of the robotic prototype, an Arduino board was used, connected in parallel to an H-bridge (power controller). This architecture allows both power and control signals for the DC electric motors to be managed from a single microcontroller, see Figure 2. Electronic Circuit Connection Details are:

- *Power Supply and Common Reference:* The Arduino's 5V pin connects to the H-bridge's VCC pin, providing the necessary voltage for the control logic. Likewise, the Arduino's GND pin joins the H-bridge's GND, establishing a common reference that ensures correct signal transmission.
- *H-Bridge Enablement:* The H-bridge EEP pin connects to VCCs, enabling the controller and allowing the control signals to act on the motors.
- Direction Control and Motor Activation (Digital Output Pins): Arduino digital pins 8, 9, 10, and 11 are configured as outputs (OUTPUT). These pins send activation signals to the H-bridge inputs IN1, IN2, IN3, and IN4:
    1. Motor 1 is controlled via IN1 (pin 8) and IN2 (pin 9).
    2. Motor 2 is controlled via IN3 (pin 10) and IN4 (pin 11).
- Turning Mechanism and Polarity: Each pair of pins acts as a differential connection. The reversal of the signals between these pairs allows the direction of rotation of the motors to be changed, taking advantage of the H-bridge's property to invert the applied polarity.
- Power Conduction: The H-bridge outputs OUT1, OUT2, OUT3, and OUT4 are responsible for supplying electrical energy to the motors. Current conduction from these outputs occurs only when the corresponding inputs (IN1–IN4) receive the appropriate signals from the Arduino.
- Protection: Each motor receives two connections (positive and negative poles). This design is intended to prevent short circuits, ensuring that current flows only under the conditions set by the Arduino code.
- Software Dependence: The dynamic behavior (activation, direction, and speed) of the motors is ultimately determined by the source code loaded into the Arduino.

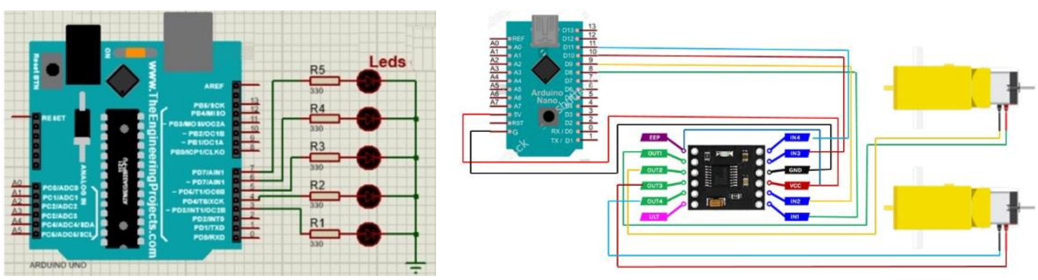


Figure 2 a) Electronic Circuit a) Visual motion activation (LEDs). b) Engine activation

This process allowed the construction of a robotic prototype that successfully responds to the mental commands of the headset, achieving the manipulation of forward, backward, left, and right movements.

3 Experimental Results

This study adhered to the ethical principles of the Regulations of the General Health Law on Health Research (General Health Council, DOF 02-04-2014), ensuring participant protection. EEG data collection was conducted at LNC-IACD under controlled conditions. Participants (ages 18–52, with no neurological or psychiatric history) were informed about the study and provided written informed consent in accordance with Articles 21, 22, and Chapter V. Privacy and data confidentiality were maintained (Article 16), and the protocol was approved by an ethics committee (Articles 41 and 43). Participants could withdraw at any time without consequences (Article 21). The EMOTIV EPOC X-14 Channel Wireless EEG Headset and Insight-5 Channel Wireless EEG Headset configuration method (Consult in [19] the protocol for configuration) allows it to be used to obtain the following.

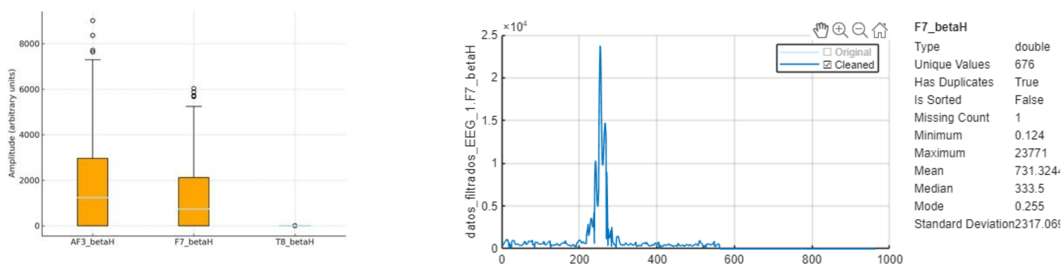
3.1 Biosignal Dataset

The data was collected from six participants, both male and female, aged between 18 and 25 para Get test data (open and close), and 15 participants, both male and female, aged between 20 and 30 years to obtain records of the four movements (push, pull, left and right), who reported no known mental health issues. All participants reside in the State of Mexico and the metropolitan area. The experiments were conducted at LNC-IACD. Each participant was prepared following a strict protocol for configuring the headband and recording EEG bio signals. The process required participants to transition between two mental states: meditation and concentration (Consult in [19] the protocol for configuration).

The raw data obtained from each user, each file generates an attribute corresponding to the time (timestamp), that is, the date and time of the sampling, the subsequent columns is the combination of the sensors or electrodes of the headband and the brain waves (Theta, Alpha, Beta Low, Beta High, Gamma) obtaining 72 or 25 characteristic attributes when using the 14 or 5 sensor headband. The generated dataset is in a public repository https://github.com/Gcortes7/COGNITIVESCIENCEDATA.git.

3.2 Biodata preprocessing

Figure 3a Compare the dispersion of the values in the AF3_betaH, F7_betaH and T8_betaH channels. However, it is done with all channels. It is observed that the frontal channels (AF3 and F7) show greater variability due to the influence of outliers, while the right temporal channel (T8) shows a more stable and concentrated distribution. These results confirm the need to apply cleaning processes in front channels and highlight the relative stability of the temporal records for the analysis of beta activity in BCI applications. Figure 3b shows the spectrum of the EEG signal on channel F7_betaH after data filtering and purging. A main energy peak is observed at low frequencies and a rapid attenuation in the rest of the spectrum, with a maximum value of 23,771 and a mean of 731.32.



(a) (b)

Figure 3 a) Comparison of EEG Signal Dispersion by Channel (High Beta). b) Spectrum of the EEG signal of the F7_betaH channel after filtering and filtering of data

Figure 4a Displays the spectral analysis of the T8_betaH channel after the application of a data filtering and cleansing procedure. This channel, located in the right temporal region, is relevant for sensorimotor integration and spatial perception, functions closely linked to the high beta band.

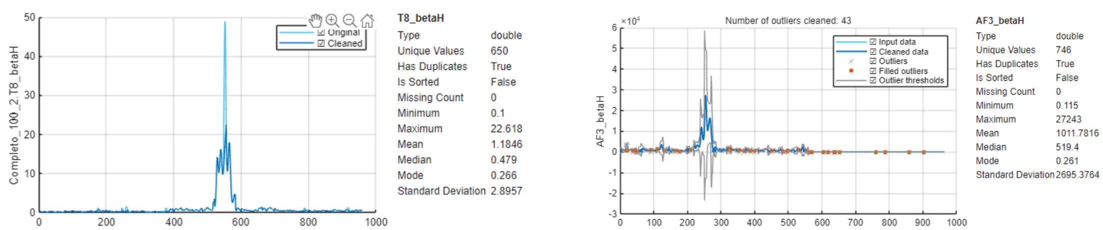


Figure 4 a) EEG signal from the T8_betaH channel after the cleaning and filtering process. b) EEG signal from the AF3_betaH channel before and after cleaning outliers.

The statistical results show a maximum value of 22.618, a mean of 1.18 and a median of 0.479, with a standard deviation of 2.89. This distribution indicates that most values are concentrated at low levels, while a few amplitude peaks generate dispersion. The cleaning applied allowed the physiological structure of the signal to be preserved, eliminating extreme irregularities and reducing the impact of outliers that could distort the interpretation.

Figure 4b It shows the processing of the AF3_betaH signal, in which a cleaning procedure was applied to eliminate outliers. The graph compares the original data (Input data) with the corrected data (Cleaned data), explicitly pointing out the detected outliers, the replaced values (Filled outliers) and the reference thresholds used for detection (Outlier thresholds).

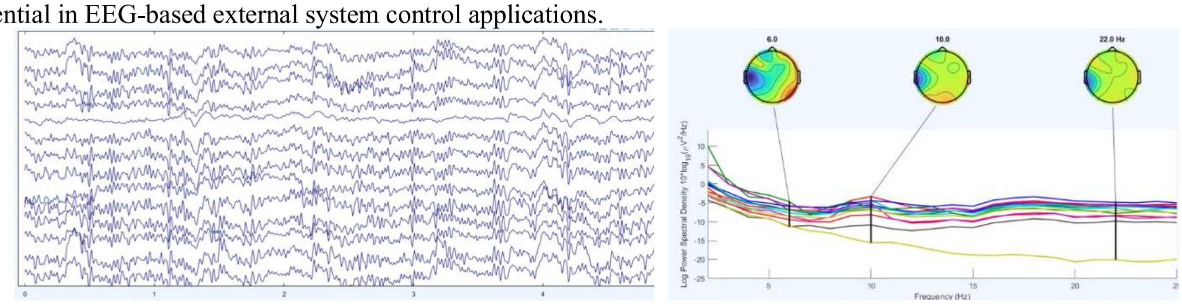
In total, 43 outliers were identified and corrected, which allowed the signal to be stabilized and its main structure to be preserved. This procedure is reflected in the reduction of extreme fluctuations without altering the general trend of spectral distribution.

The statistical values of the channel reinforce this interpretation: the maximum amplitude was 27,243, while the mean was 1011.78 with a standard deviation of 2695.37, which shows the influence of outliers on the dispersion of the data. After cleaning, the signal presents a more representative distribution of the real dynamics of brain activity, which facilitates its subsequent analysis.

3.3 Mapping the human brain

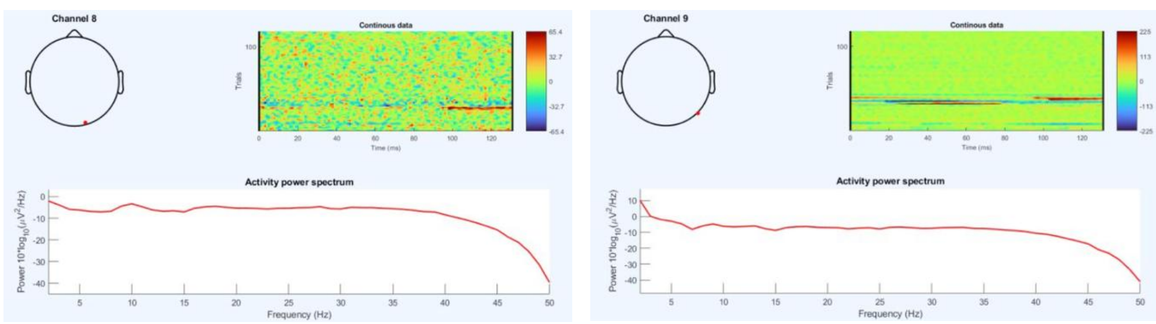
Spectral analysis confirms this predominance of alpha rhythms, complemented by theta activity (6 Hz) in posterior regions and low beta (22 Hz) components in frontal and central areas. This combination reflects the typical cortical dynamics of EEG at rest with eyes closed: neuronal synchronization in alpha, accompanied by theta and beta oscillations of lower intensity.

These findings demonstrate the ability of the Emotiv system to reliably record fundamental brain oscillations and underscore its applicability in brain-computer interfaces (BCIs). The consistent identification of alpha rhythms and their contrast with theta and beta activity constitutes a robust marker for discriminating states of relaxation, attention, and cognitive transition, strengthening their potential in EEG-based external system control applications.



(a) **(b)**

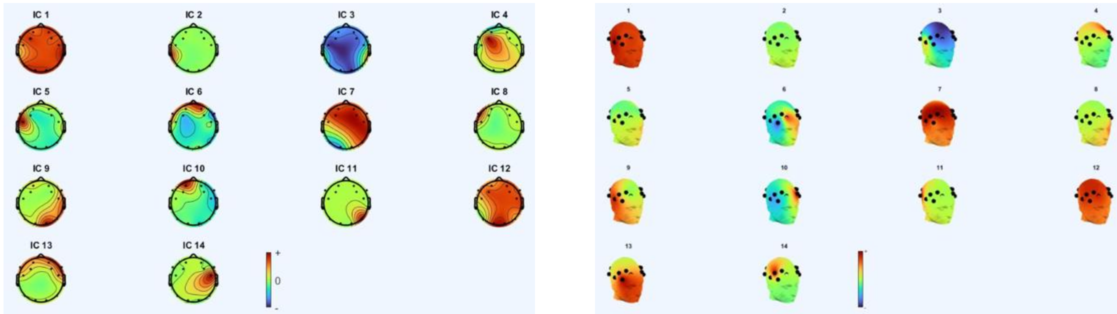
Figure 5 a) *EEG signals at rest with eyes closed, b) Power spectral density spectra per channel and topographic maps*



(a) **(b)**

Figure 6 *Channel 8 and channel 9 power spectrum during the standby condition with eyes closed*.

The spectral analysis of channels 8 and 9 shows a predominance of activity in the alpha range (8–12 Hz), congruent with the condition of resting with eyes closed and associated with neuronal synchronization in occipital and parietal regions. The similarity in power distribution between the two channels confirms the interchannel coherence and supports the interpretation of a relaxed waking state, although with slight variations attributable to the location of the electrodes. These results highlight the usefulness of the EEG signals obtained with the Emotiv headband as reliable markers in the detection of cognitive states, with direct BCI applications for the control of external devices.



(a) **(b)**

Figure 7 Decomposition into independent components (ICs) of the EEG recording, obtained by ICA (Independent Component Analysis) analysis. This procedure makes it possible to separate brain signals from possible noise sources and to spatially locate the contribution of each component in the scalp and in its three-dimensional projection.

Figure 7a presents the two-dimensional topographic maps of the 14 identified components. It is observed that several of them (IC1, IC7, IC11, IC12 and IC13) show wide activations in posterior and lateral regions, which is consistent with the predominance of alpha and beta rhythms in occipital and parietal areas during the resting condition with eyes closed. Other components, such as IC3 and IC10, exhibit negative distributions that could correspond to attenuated cortical activity or the identification of artifacts related to blinking or eye movement.

Figure 7b It shows the same fonts represented in three-dimensional form on the model of the head. This visualization confirms the spatial distribution of the components, evidencing that the main oscillations are concentrated in occipital and frontal regions, consistent with the dynamics expected in states of relaxed wakefulness. The homogeneous patterns of activation in IC1, IC7, and IC12 reinforce the interpretation that the acquisition system reliably captures the neural generators underlying the alpha and beta rhythms, while the variations observed in IC3, IC6, and IC10 reflect the ability of ICA analysis to isolate artifacts of non-cortical origin.

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Initially, the experiments were conducted in a controlled indoor environment, characterized by minimal external stimuli: no significant noise, stable natural daylight, and an overall tranquil atmosphere. Subsequently, additional measurements were taken in open-space conditions, allowing for the evaluation of how environmental variability affects user concentration and neural signal stability.

Each participant interacted with a virtual cube simulator via the Emotiv BCI interface, performing basic mental commands (left, right, push, pull) designed to evaluate their ability to intentionally modulate brain activity. This experimental design ensured that only participants without neurological impairments and with normal cognitive control were included, facilitating a reliable measurement of concentration and mental task performance. The analysis of the four mental commands (push, pull, left and right) obtained with the Emotiv BCI headband shows differentiated patterns of brain activation that allow discriminating between directional and imagined force movements.

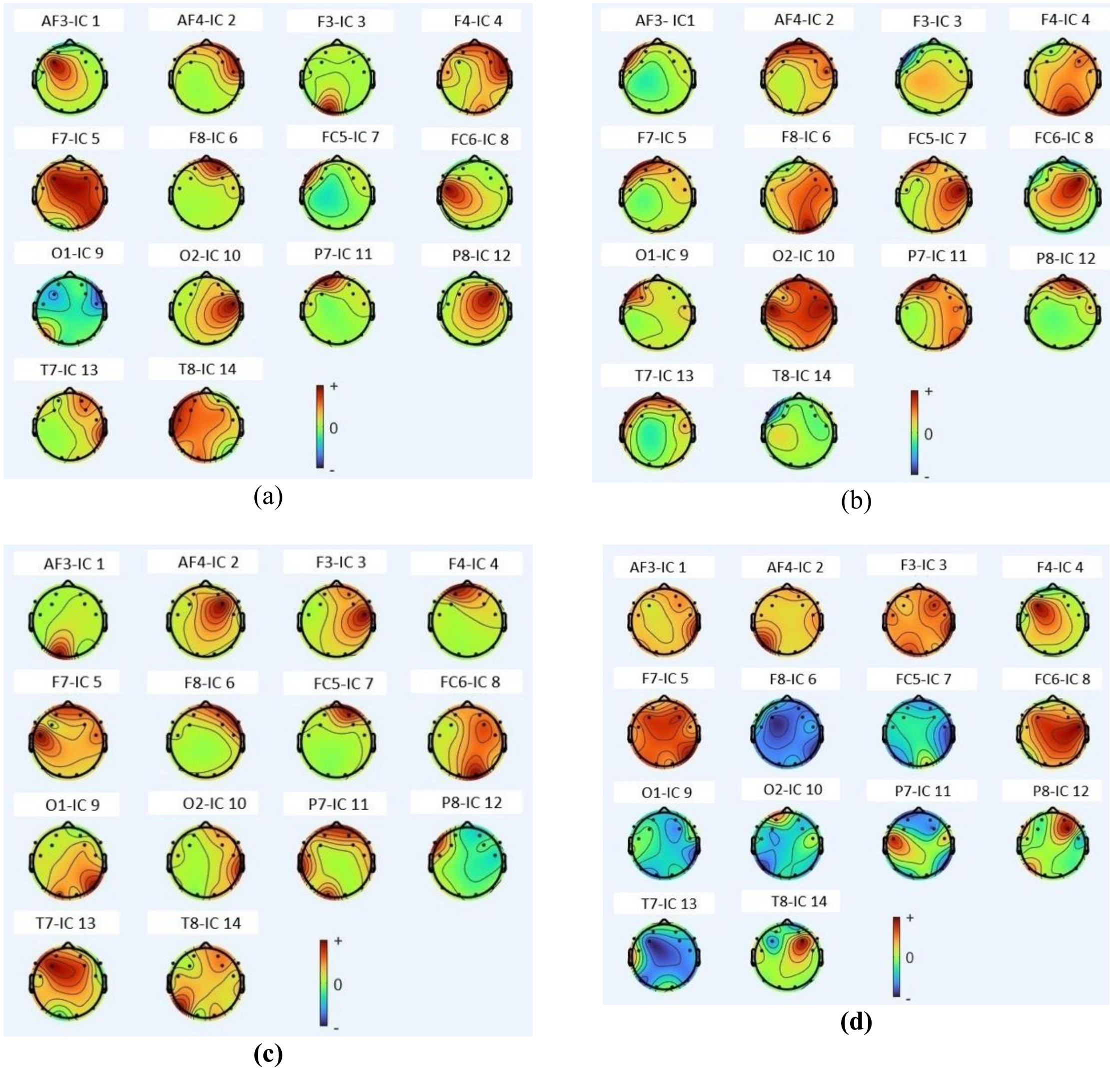


Figure 8 The graphs show EEG activity associated with the mental commands a) push, b) pull, c) left, and d) right, revealing frontal and central predominance in linear movements, and hemispheric lateralization in directional movements, with occipital-parietal alpha modulation as a marker of attention and motor imagery control.

Figure 8a and Figure 8b shows the EEG activity associated with linear force commands (push and pull), a predominant participation of the frontal and prefrontal regions (AF3, AF4, F3, F4, F7, F8) is observed, associated with cognitive effort, sustained attention and executive planning. These areas show increased activity in low and mid bands, reflecting the intentional control required to project linear forward or backward motion. At the same time, the parietal and occipital channels (O1, O2, P7, P8) register modulations in the alpha band (8–12 Hz), which is interpreted as a mechanism of visual inhibition and directed concentration. The similarity in the dynamics of these two commands reinforces their classification within a common category of "imagined force movements".

In contrast, Figure 8c and Figure 8d shows the EEG activity associated with lateral directional commands (left and right), show lateralized activation patterns. In the left command, a greater participation of the electrodes of the left hemisphere (AF3, F3, F7, FC5, O1, P7, T7) is registered, while in the right command a more marked activation is observed in the right hemisphere (AF4, F4, F8, FC6, O2, P8, T8). In both cases, alpha modulation in occipito-parietal regions reflects the attentional and inhibitory control necessary to sustain the command, while the participation of the central (FC5, FC6) and temporal (T7, T8) areas evidences the sensorimotor integration essential for the representation of lateral movementl.

3.4 **Comparative Evaluation of Classifying Methods**

Below are the findings derived from the evaluation of four classification algorithms —J48 (Decision Tree), RandomForest, NaiveBayes and SVM (SMO)— in order to identify the most appropriate model for the classification of control commands (pull, left, push, right). The dataset used shows an balanced distribution. To assess performance, the models were subjected to two main tests: a) Stratified cross-validation on 100% of the data. b) Evaluation with an external set of training and test equivalent to 70% and 30% of the data, respectively, see Table 1.

The Decision Tree model (J48) and SVM (SMO) showed outstanding and robust performance. In the cross-validation it reached an accuracy of 97.27% y 99.21%; respectively. When evaluated with the external test set, it achieving an accuracy of 98.80%, with only one error in 84 instances. The confusion matrix showed that the few errors were concentrated in incorrect classifications towards the push class. Its high generalization capacity positions it as one of the most promising methods for this task.

Table 1 *Performance in the external test suite*

Classificator	Stratified cross-validation			External Data Test 80-20		
	Accuracy	Instances		Accuracy	Instances	
		Successful	Incorrectas		Successful	Incorrectas
RandomForest	99.8%	511 / 512	1	100.0%	84 / 84	0
J48	97.27%	498 / 512	14	98.80%	83 / 84	1
SVM (SMO)	99.21%	508 / 512	4	98.80%	83 / 84	1
NaiveBayes	76.95%	394 / 512	118	73.80%	62 / 84	22

NaiveBayes was the model with the lowest performance. During the cross-validation it obtained an accuracy of 76.95%, while in the external test it reached only 73.80%. Its biggest weakness lay in the right class ranking, with a recall of 22.3% and 34.6% in each test, respectively. In addition, he presented recurrent confusions when classifying instances of right and pull as left. These results rule it out as a viable option for this type of application.

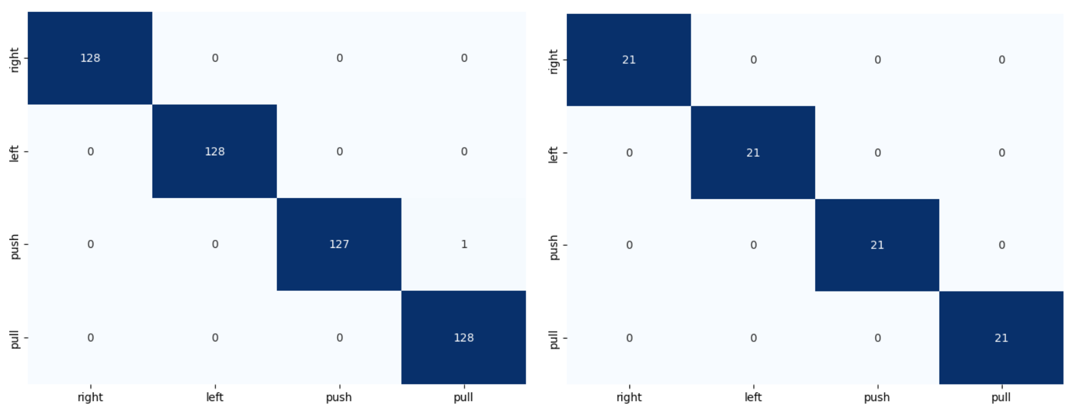


Figure 9 *Confusion matrix using RandomForest model. a) Cross-Validation*, b)External Data Test

Support Vector Machine (SVM) presented an ambivalent behavior. In the cross-validation it reached an overall accuracy of 99.21%; However, the detailed analysis showed a particularly low accuracy (59.6%) for the push class, generating a high number of false positives (more than 40% of the time). Despite this, in the evaluation with the external set, its performance improved drastically, reaching an accuracy of 98.80%, with only one error.

The RandomForest model also recorded a very competitive performance. In the cross-validation it obtained an accuracy of 99.80%, showing a high reliability in the prediction of most classes. Most of his mistakes consisted of classifying other instances as push. In the test with external data, the model achieved perfect performance with 100% accuracy, with out classification errors.

Figure 9a shows the confusion matrix shows a globally high performance of the RandomForest model during cross-validation, with success rates above 90% in most classes. The push category achieved the highest accuracy (99.2%). These results confirm the robustness of the model. Figure 9b shows the performance of the RandomForest model 100% during external Data Test, These results confirm the robustness of the model.

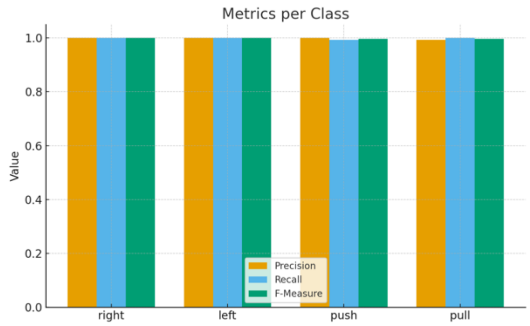
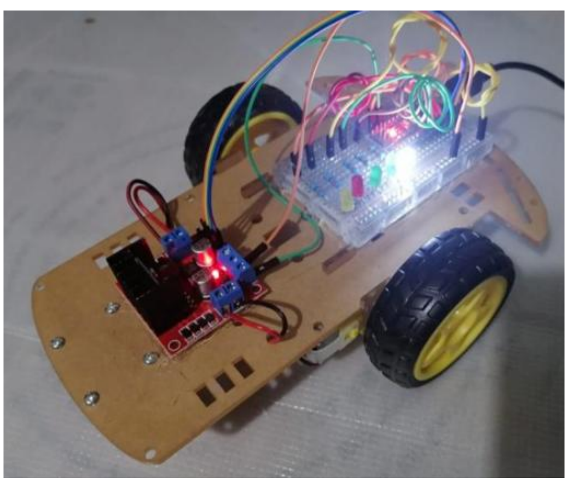


Figure 10 *Detailed Metrics by Class (Cross-Validation))*

The classifier exhibits near-optimal performance, achieving values close to 1.0 in precision, recall, and F-measure across all classes. The *right* and *left* classes show perfect metrics, while the *push* and *pull* classes present minimal deviations attributable to intraclass similarity. Overall, the results confirm a high generalization capability and significant robustness of the model for the evaluated classification task, see Figure 10.

3.5 Neurocontrol of the prototype

To demonstrate the functioning and efficiency of the neuro control, a prototype was built and neurocontrolled through the neuronal Diadem generating the data of the instructions received from the brain, see Figure 11. The process involved the installation, configuration, and calibration of the EMOTIV headband, collecting bio signals using the Emotiv API in Python, and building an electronic circuit for neural control of the prototype.



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mc data: {'action': 'neutral', 'power': 0.0, 'time': 1701810298.3352}
mc data: {'action': 'neutral', 'power': 0.0, 'time': 1701810298.4594}
mc data: {'action': 'neutral', 'power': 0.0, 'time': 1701810298.5836}
mc data: {'action': 'neutral', 'power': 0.0, 'time': 1701810298.7078}
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mc data: {'action': 'neutral', 'power': 0.0, 'time': 1701810301.813}
```

Figure 11 a) Neurocontrolled Prototype, b) Generated response

The initial prototype was validated through the implementation and testing of a basic circuit with LEDs, showing the ability of interaction between the Emotiv headband and Arduino hardware. Subsequently, a robotic prototype was built that responds to the mental commands of the headband, allowing the manipulation of forward, backward, left, and right movements.

4 Conclusions

The study and analysis of human brain behavior allow the development of different types of applications that can progressively become an aid for the development of daily tasks of the human being. With this premise, an Emotiv headband was used to monitor brain waves, for analysis and subsequent development of applications. The quantitative results obtained were graphed using the EMOTIV headband and the java toolbox (EEGLAB); in which it allows to visualize the grouping of a set of data by wave by means of a specific color, which can be interpreted by neurologists and that can be used to address problems that use neurofeedback techniques to train the human brain.

In comparison with the study published in [7], whose main focus went use two commands or responses, this solution uses four commands. However, the results obtained with the non-invasive EMOTIV device demonstrate the feasibility of using lower-density EEG signals with lower sampling rates to generate multiclass neural instructions applicable to robotic control.

The study published in [8] uses simulated device, this paper configure headset of 14 or 5 electrodes arranged according to the 10–20 system, along with data acquisition through EMOTIVBCI, the Cortex API, and BandpowerLogger, enabled the collection of sufficiently high-quality signals to discriminate the commands left, right, pull, and push. Additionally, the creation of a public repository in CSV format constitutes a relevant contribution to reproducibility and the future implementation of brain–computer interfaces aimed at assistive technologies. Overall, these results show that low-cost, non-invasive EEG systems such as EMOTIV can serve as practical alternatives for developing inclusive robotic solutions designed for individuals with motor disabilities.

The study presented in [9] uses alpha and beta channels as feature inputs. In contrast, this project applies cleaning and filtering techniques specifically to the F7_betaH, AF3_betaH, and T8_betaH channels, which substantially improve EEG signal quality by reducing dispersion caused by outliers, stabilizing the distributions, and preserving the essential physiological characteristics of brain activity. The results indicate that frontal channels are more susceptible to extreme peaks associated with cognitive effort and concentration, whereas temporal channels provide more stable recordings, although they remain sensitive to signal-cleaning processes.

These findings reinforce the importance of implementing cleaning processes in EEG recordings before their use in brain-computer interfaces (BCIs), as they ensure that classification algorithms work with more consistent and representative data. Consequently, outlier debugging and noise reduction not only improve the quality of spectral analysis, but also optimize the detection of cognitive states related to attention, concentration, and imagined motor control, strengthening the applicability of EEG in BCI-based control systems.
The study published in [12] employs brain mapping to identify the brain regions activated during task execution. In our work, the brain-mapping results allowed the identification of at least two differentiated activation patterns: (1) linear movements (push/pull), characterized by predominant frontal and prefrontal activation associated with overall cognitive effort, accompanied by parieto-occipital alpha modulation; and (2) lateral movements (left/right), distinguished by hemispheric lateralization consistent with the direction of the command, with greater involvement of occipito-parietal and ipsilateral temporal regions. These findings reinforce the viability of using low-density EEG to discriminate task-specific neural responses relevant to BCI-based command classification.
These findings are consistent with previous studies of motor imagination and confirm that the Emotiv headband allows for reliably discriminating between different types of mental commands. In the framework of BCIs, this differentiation is essential for the design of robust control systems, as it enables the precise classification of motor intentions in real time, a necessary condition for applications in rehabilitation, robotic assistance and control of external devices.

The study reported in [8] achieved 100% accuracy during the training phase because it relied on simulated data; however, its performance decreased during testing, indicating limited generalizability. In our experiments, classifiers based on decision trees—particularly J48 and RandomForest—demonstrated the best performance for command classification in the Emotiv BCI simulator, achieving accuracy levels close to or equal to 100% in external evaluations. In contrast, NaiveBayes proved unreliable, and SVM exhibited inconsistent behavior, showing improvement only when tested with unseen data. These results highlight decision tree–based models as the most robust and generalizable approach for this classification task.

The performance of the model for each of the four classes during the cross-validation phase, considering the Accuracy, Recall, and F-Measure metrics. The results show consistently high performance across all categories, reflecting the robustness of the classifier. However, a slight decrease in the recall of the pull class is observed, which indicates that the model was less effective in identifying all real instances of this class. Despite this variation, the global metrics show a balanced and reliable behavior, confirming the ability of the algorithm to adequately handle multiclass classification.

Finally, this paper has successfully demonstrated the development of a prototype controlled by an EMOTIV headset, the API of Cortex apps of EMOTIV, EMOTIV LAUNCHER, websocket-client, Python and Arduino through the generation of neural instructions. The implementation of this prototype opens the door to future improvements and applications in the field of mind-controlled robotics, offering a valuable starting point for further research and development.

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