UNIVERSIDAD DISTRITAL
FRANCISCO JOSÉ DE CALDAS

Visión Electrónica
https://doi.org/10.14483/issn.2248-4728

VISIÓN ELECTRÓNICA

A RESEARCH VISION

OpenBCI-Based Emotional Mapping Tool: Arousal and Valence Visualization

Herramienta de mapeo emocional basada en OpenBCI: visualización de Arousal y Valencia

Belman Rodríguez[1], Rafael Reyes[2], Jorge González[3], Sandra Camelo[4], Marcelo Herrera[5]

INFORMACIÓN DEL ARTÍCULO

Historia del artículo:
Enviado: 30/10/2025
Recibido: 01/11/2025
Aceptado: 17/11/2025

Keywords:
Arousal and Valence
EEG signals
Open BCI
PSD (Power Spectral Density)

Palabras clave:
Arousal y Valencia
Señales EEG
Open BCI
PSD (Densidad de Potencia Espectral)

ABSTRACT

This document details the development of a prototype created in Processing (Java) that enables real-time identification of Arousal and Valence values. The prototype utilizes electroencephalographic signals recorded from the Open BCI Cyton + Daisy system. The software receives the digitized amplitude data from EEG signals, and from these amplitudes, the PSD (Power Spectral Density) of each of these signals is obtained. Based on previous research, it has been established that through the processing and filtering of electroencephalographic data and the extraction of alpha and beta waves related to the power of certain electrodes (AF3, AF4, T7, and T8 of the Emotiv Insight), it is possible to estimate levels of arousal (emotional state of excitation and relaxation) and levels associated with positive or negative perceptions (emotional state of valence). For estimating Valence, electrodes AF3 and AF4 are used, comparing the alpha and beta power of these channels. Beta waves are associated with states of alertness or excitation, while alpha waves are more dominant in relaxation states. Therefore, the ratio between beta and alpha is a reasonable indicator of a person's arousal state. Finally, by analyzing the power between the electrodes located at F3 and F4, configured in the 10/20 standard, and extracting the spectral power in the alpha and beta bands, the Arousal and Valence values of the OpenBCI system are obtained.

RESUMEN

En este escrito se detalla el desarrollo de un prototipo desarrollado en Processing (Java) que permite identificar los valores de Arousal y Valencia en tiempo real;

1. Sound Engineer, MSc in Artificial Intelligence from Universidad Javeriana, PhD candidate in Neuromorphic engineering from Western Sydney University. j.rodrigueznino@westernsydney.edu.au

2. Multimedia Engineer, Universidad Católica de Colombia, Bogotá (Colombia). PhD in Public Health, Universidad Nacional de Colombia, Bogotá. Current position: Full-time professor at Universidad de San Buenaventura, Bogotá (Colombia). E-mail: rreyes@usbbog.edu.co.

3. Psychologist, Universidad Católica de Colombia, Bogotá (Colombia). PhD in Public Health, Universidad Nacional de Colombia, Bogotá. Current position: Full-time professor at Universidad de San Buenaventura, Bogotá (Colombia). E-mail: jgonzalez@usbbog.edu.co.

4. Psychologist, Universidad Católica de Colombia, Bogotá (Colombia). PhD in Public Health, Universidad Nacional de Colombia, Bogotá. Current position: Full-time professor at Universidad de San Buenaventura, Bogotá (Colombia). E-mail: psi.neurociencia@usbbog.edu.co.

5. Electronic engineer, Czech Technical University in Prague, Czech Republic. MSc in Radiocommunications and PhD in Acoustics, Czech Technical University in Prague, Czech Republic. Current position: Full-time professor at Universidad de San Buenaventura, Bogotá (Colombia). E-mail: mherrera@usbbog.edu.co. ORCID: https://orcid.org/0000-0003-2360-4184

Cite this article as: B. Rodríguez, R. Reyes, J. González, S. Camelo, M. Herrera, "OpenBCI-Based Emotional Mapping Tool: Arousal and Valence Visualization", Visión Electrónica, vol. 19, no. 2, 2025.

en estos se obtienen registros de señales electroencefalográficas del sistema Open BCI Cyton + Daisy. El software recibe como entrada, los datos digitalizados de amplitud de señales EEG y con estas amplitudes se obtiene la PSD o densidad de potencia espectral de cada una de estas señales. A partir de varios trabajos investigativos previos se establece que a partir del procesamiento y filtrado de los datos electroencefalográficos y la obtención de ondas alfa y beta relacionadas con la potencia de ciertos electrodos (AF3, AF4, T7 Y T8 de Emotiv Insight), es posible obtener valoraciones del nivel de excitación y relajación de una persona (estado emocional del Arousal) y también obtener niveles asociados a percepciones positivas o negativas (estado emocional de la Valencia). Para la obtención de una estimación de Valencia se emplean los electrodos AF3 y AF4, realizando una comparación entre las potencias de alfa y beta de dichos canales. En el caso de las ondas Beta, estas son asociadas con estados de alerta o excitación, mientras que las ondas alfa son más dominantes en estados de relajación. Por lo tanto, la relación entre beta y alfa es un indicador razonable del estado de excitación o arousal de una persona. Finalmente, con operaciones de potencia entre los electrodos ubicados en F3 y F4 configurados en el estándar 10/20 y extrayendo la potencia espectral en las bandas alfa y beta, se obtienen entonces los valores de Arousal y Valencia del sistema OpenBCI.

1. Introduction

Recent advancements in brain-computer interfaces (BCI) have enabled the development of systems that can monitor and interpret neural activity to understand emotional states. One such system is the Open BCI Cyton + Daisy, a versatile platform that allows for real-time acquisition and processing of electroencephalographic (EEG) signals. This document introduces a novel software prototype designed in Processing (Java) to identify Arousal and Valence levels using EEG signals recorded by the Open BCI system. The software extracts the power spectral density (PSD) of each EEG channel and utilizes known correlations between alpha and beta waves to estimate emotional states such as excitement or relaxation (Arousal) and positive or negative perceptions (Valence) [1].

Previous research has established that EEG signals, particularly the power in alpha and beta bands of specific electrodes, can serve as reliable indicators of emotional states. For instance, the electrodes AF3, AF4, T7, and T8 have been linked to changes in Arousal, while comparisons between alpha and beta powers in electrodes AF3 and AF4 are indicative of Valence [2]. The developed software integrates these findings and provides a direct, quantitative visualization of these emotional states within the Open BCI interface, offering a valuable tool for real-time emotion analysis and potentially enhancing applications in neuroscience research and psychological studies.

The system leverages the flexibility of open-source software to manipulate EEG data, enabling researchers to explore and program various methods for quantitative estimation of Arousal and Valence, which is a significant advantage over proprietary software that typically restricts data access [3]. This makes the prototype an innovative solution for researchers looking for customizable and extensible tools in the field of neurotechnology.

2. State-of-the-art

2.1. EEG in the Verification of Emotional States

Electroencephalography (EEG) has been widely used in research for the verification and classification of emotional states due to its non-invasive nature, good temporal resolution, and ability to capture real-time neural activity. EEG records electrical signals from the brain through electrodes placed on the scalp, which enables the detection of various brain waveforms—such as delta, theta, alpha, beta, and gamma waves—each associated with different cognitive and emotional states. For instance, alpha waves are typically related to relaxation, beta waves to alertness and active thinking, theta waves to meditation and drowsiness, and gamma waves to high-level cognitive functioning [4]. These characteristics make EEG an ideal tool for studying human emotions and cognitive states as it captures the precise timing of emotional responses.

2.2. Use of BCI Devices in Emotion Recognition Projects

Brain-Computer Interfaces (BCIs) have become central to emotion recognition research.

Modern BCI systems, which are primarily non-invasive, can identify and classify emotional states by processing the patterns of brain activity. These systems often integrate machine learning algorithms to analyze and categorize emotions based on the Power Spectral Density (PSD) of EEG signals, enabling high-precision detection of emotions in real time [5]. Recent research has shown that BCI devices can be successfully used to detect emotional states such as stress, excitement, and calmness by focusing on the temporal dynamics and frequency bands of EEG signals [6].

The application of BCI technology in emotion recognition is expanding across various fields, including healthcare, education, and human-computer interaction. Research studies now frequently utilize BCI devices combined with deep learning algorithms to improve emotion classification accuracy and adapt the systems to different user-specific characteristics [7]. This has resulted in the development of emotion-specific frameworks that use a wide range of features extracted from EEG signals, such as time-frequency, entropy, and multi-scale entropy domains [8]. Recent studies have shown that tracking EEG signals to complex process such as relaxation with different kind of stimuli (like Tibet sound stimulation) are possible through BCI technology [9].

2.3. Versatility in visualization of EEG Data in Emotion Recognition

The visualization of EEG data plays a critical role in understanding and interpreting emotional states. Most BCI systems use heatmaps, power spectra, or three-dimensional models to represent changes in brainwave activity and emotional states in real time. Visualization tools help in detecting the subtle variations in waveforms and provide a better understanding of how different regions of the brain contribute to emotional states [8]. Moreover, the use of multi-modal data visualization combining EEG with other physiological signals—such as skin conductance or heart rate variability—has shown promise in providing a more comprehensive view of the user's emotional state. This versatility allows researchers to correlate EEG patterns with external behavioral data, improving the robustness of emotion detection.

2.4. Brain Wave Analysis: Alpha, Theta, Beta, and Gamma Waves

The different types of brain waves captured through EEG have distinct roles in representing emotional and cognitive states.

- **Alpha Waves (8–13 Hz):** Typically associated with relaxation and reduced mental effort, alpha waves increase during states of calm and relaxation and decrease during mental exertion or heightened alertness.
- **Beta Waves (13–30 Hz):** Often linked to active thinking, problem-solving, and anxiety, beta waves are dominant during focused attention and are indicators of heightened cognitive activity.
- **Theta Waves (4–8 Hz):** Associated with meditative, drowsy, or trance-like states, theta waves are prevalent during deep relaxation and are often targeted in mindfulness research.
- **Gamma Waves (30–100 Hz):** Related to high-level information processing and cognitive functioning, gamma waves are less common in routine emotional assessments but are indicative of complex thought processes and peak performance [5][6][8].
- **Role of EEG Waveforms in Emotion Recognition:** The use of these waveforms in emotion recognition is crucial, as they provide insights into the underlying neural processes associated with various emotional states. For instance, changes in the ratio of alpha to beta power in frontal lobe electrodes have been used as indicators of stress and arousal, making EEG a valuable tool for assessing both the intensity and valence of emotions [5][7].

3. Methodology

The methodology for this project follows a structured approach to develop an EEG-based emotion recognition system using BCI devices and advanced data processing techniques. The primary objective is to create a robust system for identifying emotional states such as Arousal and Valence using the Open BCI Cyton + Daisy system and visualization techniques implemented in Processing (Java).

3.1. Data Acquisition

The first step involves setting up the Open BCI Cyton + Daisy system for EEG signal acquisition. The electrodes are placed according to the international 10-20 system, targeting regions like AF3, AF4, T7, and T8, which are known to provide reliable data for emotional state detection [4][5]. The EEG signals will be recorded at a sampling rate of 250 Hz, ensuring sufficient temporal resolution for identifying changes in different frequency bands such as alpha, beta, theta, and gamma waves.

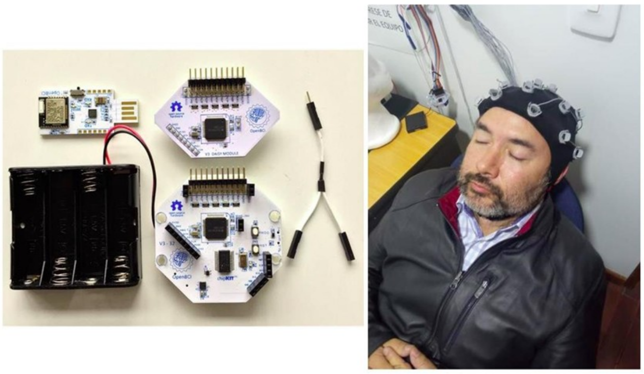
3.1.1. Subjects

A group of 10 participants (5 males and 5 females) will be recruited for the study. Each participant will undergo an emotion induction protocol, which involves exposure to visual and auditory stimuli designed to evoke specific emotional responses (e.g., videos, images, or music clips).

3.1.2. Instrumentation

The Open BCI Cyton + Daisy device will be used for EEG recording. Additional sensors such as heart rate monitors and skin conductance sensors may be used to provide complementary physiological data for a more comprehensive emotion recognition model.

Figure 1: OpenBCI Cyton + Daisy Module



Source: Own.

3.2. Preprocessing of EEG Data

The raw EEG data will undergo a series of preprocessing steps to eliminate noise and artifacts that may interfere with the accuracy of the emotion detection:

3.2.1. Filtering

A band-pass filter will be applied to retain frequencies between 0.5 Hz and 45 Hz, which encompass the most relevant brain wave frequencies for emotion analysis [10]. This step helps in removing DC offsets and high-frequency noise.

3.2.2. Artifact Removal

Independent Component Analysis (ICA) will be used to separate and remove artifacts such as eye blinks, muscle movements, and power line noise from the EEG data.

3.2.3. Segmentation

The cleaned EEG signals will be segmented into epochs of 2 seconds, each containing sufficient information for short-time Fourier transform (STFT) and other feature extraction techniques [6].

3.3. Feature Extraction

Feature extraction focuses on analyzing the power spectral density (PSD) of the EEG signals to quantify the power within different frequency bands—alpha, beta, theta, and gamma. These features will be used to estimate emotional states.

- **Time-Frequency Analysis:** Techniques such as Short-Time Fourier Transform (STFT) and wavelet transforms will be used to decompose EEG signals into their frequency components, facilitating the extraction of energy in the desired bands [4].

- **Spectral Features:** The PSD for each electrode channel will be calculated using Welch's method. The alpha-to-beta power ratio, which is known to correlate with emotional arousal and valence, will be considered a key feature [5].

- **Statistical Features:** Mean, variance, skewness, and kurtosis of the frequency bands will be computed to capture the statistical properties of EEG signals during different emotional states [7].

3.4. Classification of Emotional States

The extracted features will be used to train a machine learning model for classifying emotional states. A combination of traditional and advanced machine learning techniques will be explored.

- **Machine Learning Models:** The following classifiers will be evaluated for emotion classification: Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Random Forest. Additionally, deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks will be implemented to capture temporal patterns in EEG data [5].

- **Cross-Validation:** A k-fold cross-validation ($k = 10$) will be applied to ensure the robustness and generalizability of the models.

- **Performance Metrics:** The performance of the classifiers will be evaluated using metrics such as accuracy, F1-score, precision, recall, and the area under the ROC curve (AUC) [6].

3.5. Validation and Testing

The system will undergo extensive testing to validate its effectiveness.

- **Internal Validation:** The system's performance will be tested using simulated data and data from pilot trials to ensure it functions correctly under controlled conditions.
- **User Testing and Feedback:** End-users, including researchers and clinical professionals, will provide feedback on the usability and accuracy of the system.

3.6. Results

A software was developed in Processing (JAVA) which enables to identify the Arousal and Valence values in real-time. These are obtained from the EEG signals captured on the Open BCI Cyton + Daisy.

The software receives as input, the digitized amplitude EEG signal values. With these amplitudes, the PSD is obtained (Power Spectral Density) of each of these signals, according to Literature, specifically the research from Rafael Ramírez and Zacharias Vamvakousis from the University of Pompeu Fabra (Detecting Emotion from EEG Signals using the Emotiv Epoc Device). From the EEG data processing and further obtention of alfa and beta waves related to the energy power at some electrodes (AF3, AF4, T7 and T8 from the Emotic Insight), it is possible to obtain values at the excitation level and relaxation of a person (Arousal emotional state) and also to obtain associates levels to positive perceptions (or negatives), related to Valence. For obtaining Valence estimation, we employ AF3 and AF4 electrodes, realizing a comparison between alfa and beta power from these channels.

$$Valencia = \frac{\alpha_{F4}}{\beta_{F4}} - \frac{\alpha_{F3}}{\beta_{F3}} \tag{1}$$

Beta waves are associated to alert or excitation states, while alfa are more dominant in relaxation states. Therefore, relationship between beta and alfa is a reasonable indicator of the excitation or arousal of a person. On the other hand, according to the study of Hayfa Blaiech, Mohamed Neji (Emotion recognition by analysis of EEG signals), arousal is defined as:

$$Arousal = \frac{\alpha(AF3 + AF4 + F3 + F4)}{\beta(AF3 + AF4 + F3 + F4)} \tag{2}$$

Based on these operations of power between the electrodes located in F3 and F4, configured in standard 10/20 and extracting the spectral power in alfa and beta bands, Arousal and Valence values of the OpenBCI system as shown:

Figure 2: Distribution of the proposed heat flux for the thermal simulation across different aerospace materials.

Source: Own work.

Figure 3: Magnetostatic analysis showing current density distribution and directional magnetic flux.

Source: Own work.

3.7. Implementation of Advanced Features

Future iterations of the system will include the integration of AI-based classifiers, multi-modal data fusion (combining

EEG with other physiological data), and a refined emotion model based on continuous feedback from test users. Future work will have to deal with the development of classification algorithms based on AI for the precise estimation of Arousal and Valence characteristics.

Conclusions

The developed software can be integrated to the OpenBCI software and enables to give a quantitative measure of Arousal and Valence within the same user-interface.

The advantages of this development are associated to a direct real-time analysis within the user interface, enabling working with an open-source code for manipulating EEG signals, exploring and programming different methods of quantitative estimation of valence and arousal. Similar software are licensed and do not allow the manipulation of registered data of EEG.

Acknowledgments

This research is funded by Universidad de San Buenaventura and it encompasses the Faculty of Engineering and the Faculty of Psychology, and it is the outcome of a project related to Neurotechnology (a scientific line within the Doctorate´s Program of Applied Neuroscience and Behaviour).

References

[1] H. Blaiech, M. Neji, A. Wali, and A. M. Alimi, "Emotion recognition by analysis of EEG signals," in *13th International Conference on Hybrid Intelligent Systems (HIS 2013)*, 2013, pp. 312-318.

[2] R. Ramírez and Z. Vamvakousis, "Detecting emotion from EEG signals using the emotive epoc device," in *International Conference on Brain Informatics*, Springer, Berlin, Heidelberg, 2012, pp. 175-184.

[3] Koelstra, S., Muhl, C., Soleymani, M., et al., "DEAP: A Database for Emotion Analysis Using Physiological Signals," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18-31, 2012.

[4] "Emotion recognition with EEG-based brain-computer interfaces: a systematic literature review," *Multimedia Tools and Applications*, SpringerLink.

[5] "Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review," *Neural Computing and Applications*, SpringerLink.

[6] "Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review," MDPI.

[7] "EEG-Based BCI Emotion Recognition: A Survey," MDPI.

[8] T. Angsuwatanakul et al., "Multiscale Entropy as a New Feature for EEG and fNIRS Analysis," *Entropy*, vol. 22, p. 189, 2020. doi: `https://doi.org/10.3390/e22020189`

[9] M. P. Carvajal et al., "EEG Verification of Relaxation Processes with Tibetan Stimuli," in *XVIII Congreso Internacional de Electrónica, Control y Telecomunicaciones - CIECT XVIII*, 2023.

[10] N. Zhuang et al., "Emotion recognition from EEG signals using multidimensional information in EMD domain," *BioMed Res. Int.*, 2017.