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Scientific articles

**FIMALOF, una interfaz gráfica de usuario para el tratamiento de
señales cerebrales y localización de fuentes**

***FIMALOF, a graphical user interface for brain signal treatment and source
localization***

***FIMALOF, uma interface gráfica de usuário para processamento de sinais
cerebrais e localização de fontes***

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Resumen

Las señales electroencefalográficas (*EEG*) necesitan ser tratadas y procesadas debido a que contienen diferentes tipos de distorsiones. Generalmente, se suelen emplear softwares especializados para tal propósito. En el presente trabajo se describe una nueva interfaz gráfica de usuario, FIMALOF (Filtrado, Mapeo y Localización de Fuentes), que consiste en un conjunto de programas que realizan tareas específicas para el tratamiento de señales cerebrales, incluyendo filtros digitales. También incluye técnicas de descomposición de señales, como el análisis de componentes independientes (*ICA*, Independent Component Analysis en inglés), *ICA*-filtros pasa-baja, descomposición empírica de modos. Asimismo, permite generar señales electroencefalográficas (*EEG*) sintéticas mediante una relación matemática basada en las características eléctricas del cerebro. Con esta señal *EEG* sintética se pueden probar y validar los filtros implementados para verificar su correcto funcionamiento. La interfaz también es capaz de procesar señales *EEG* reales. De esta manera se presenta una herramienta, alternativa a las existentes, para poder llevar a cabo el procesamiento de señales *EEG*.

Keywords: interfaz gráfica de usuario; filtrado; *ICA*; *EMD*.

Abstract

The electroencephalographic (*EEG*) signals need to be treated and processed due to the fact that they contain different artifacts. Generally, specialized software tools are used for that purpose. In the present work, a graphical user interface (GUI), FIMALOF (Filtering, Mapping and Source Localization) is introduced, which consists of a group of programs that do specific tasks for brain signals treatment, including digital filters, and decomposition signals techniques such as Independent Component Analysis (*ICA*), *ICA*-Low-pass filters, and Empirical Mode Decomposition (*EMD*). Moreover, it is possible to generate *EEG* synthetic signals through a mathematical relationship based on the brain's electrical characteristics. The synthetic *EEG* signals allow validating the proper functioning of the implemented filters. The interface is able to process real *EEG* signals. Thus, the software tool is introduced as an alternative to existing solutions, in order to process the *EEG* signals.

Keywords: graphical user interface; filtering; *ICA*; *EMD*.

Resumo

Os sinais eletroencefalográficos (EEG) precisam ser tratados e processados porque contêm diferentes tipos de distorções. Geralmente, software especializado é usado para essa finalidade. Este artigo descreve uma nova interface gráfica de usuário, FIMALOF (Source Filtering, Mapping and Localization), que consiste em um conjunto de programas que executam tarefas específicas para o processamento de sinais cerebrais, incluindo filtros digitais. Também inclui técnicas de decomposição de sinais, como análise de componentes independentes (ICA), filtros passa-baixa ICA e decomposição de modo empírico. Ele também permite a geração de sinais eletroencefalográficos (EEG) sintéticos por meio de uma relação matemática baseada nas características elétricas do cérebro. Com este sinal de EEG sintético, os filtros implementados podem ser testados e validados para verificar seu correto funcionamento. A interface também é capaz de processar sinais reais de EEG. Desta forma, é apresentada uma ferramenta, alternativa às existentes, para poder realizar o processamento de sinais de EEG.

Palavras-chave: interface gráfica do usuário; filtrado; ACI; EMD.

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Introduction

Electroencephalography (*EEG*) is a widely used technique for studying the brain. It consists of recording brain activity, both normal and abnormal. However, the acquired signals are often contaminated with various types of noise or distortions, called artifacts. These artifacts can be classified as physiological, such as eye movements, muscle movements, heart rate or sweating, among others; and technical, such as electrode disconnection or power line interference (Nayak and Anilkumar, 2022). All these distortions must be eliminated since they might hide important physiological information. Therefore, different filtering techniques are used to eliminate them, ranging from the simplest ones, such as digital filters, whether low-pass, high-pass, band-pass, or band-stop, to the most complex ones, such as signal decomposition techniques.

One of the techniques to suppress different types of distortions (artifacts) is independent component analysis (*ICA*). With it, it is possible to separate *EEG* signals into different components, in which ideally some will only have the brain signal and distortions or artifacts of different types (Jiang et al, 2019). However, there are some artifacts that are not so simple to identify, such as muscle artifacts, which can appear in many components



and are also usually mixed with physiological signals in the same component, so, for their elimination (Santillán et al., 2017), a combination of *ICA* with low-pass filters and state space models is proposed. Another recently used technique is *Empirical Mode Decomposition (EMD)* (Huang and Attoh-Okine, 2005), which eliminates noise and the trend of the signals to which it is applied. In *EMD*, a single input signal is decomposed into *N* modes (*Intrinsic Mode Functions*, *IMF*), where the first contains the highest frequencies and the last contains the lowest.

Currently, there are a variety of graphical user interfaces capable of analyzing, filtering, and calculating different time and frequency similarity measurements between signals. One of them is *EEGLAB* (Swartz Center for Computational Neuroscience, 2022; Delorme and Makeig, 2004). This tool allows you to import data, apply low-pass, band-pass, or band-stop *FIR* (finite impulse response) filters, depending on the frequency(s) to be eliminated or analyzed. The *EEGLAB tool* turns out to be very useful for those who already know how to work with it. However, there might be problems when you are not familiar with the tool and when you must convert the formats of the input signals so that they can be read with the software. On the other hand, there are also other graphical user interfaces such as: *Brain Visualizer*, which provides a real-time, three-dimensional visualization of the brain (Excellent brain EEG visualizer, 2022), thus offering something additional to the public; *Curry 8 SBR* software presents a signal and image processing package as well as source analysis for event-related potentials or ERP (Compumedics Neuroscan, 2022). Additionally, there is *LORETA KEY*, which allows, from EEG signal data, to perform a distributed source reconstruction using a three-layer-based spherical head model (Fieldtrip, 2022). Additionally, Niso et al. (2013) created *HERMES*, a graphical interface used to determine the connections between signals and activated areas in the brain, as well as for calculating correlation, coherence, Granger causality, among other notable parameters. These interfaces, although useful for specific applications, have drawbacks such as high costs, they are often not very intuitive for the user, or sometimes an extra license must be paid to use them. For this reason, and with the aim of offering a more intuitive and didactic tool, an improvement of the FIMALOF (Source Filtering, Mapping and Localization) graphical user interface was developed, as described in Santillán et al. (2018), whose objective is to provide a tool that not only filters the signals using digital filters or the signal decomposition techniques described above (*ICA*, *ICA* with low-pass filter, *EMD*), but also filters synthetic signals created with a mathematical model, with which the parameters that characterize the signal

are known and therefore the source identification algorithms can be validated and consciously altered to test and validate the filters. The signal created can be entered into the same interface to be filtered, and it also lays the foundation for future use as a tool in the field of work of doctors, particularly those who perform this activity in remote areas that do not have technological devices for recording and analyzing *EEG* signals and being able to detect any alteration or damage to the brain in time.

Materials and methods for the development of the graphical interface

We will begin by describing the general operation of each element involved in developing the FIMALOF interface.

Digital filters

In order to filter brain signals and then locate sources, various digital filters were implemented. First, a low-pass filter was developed, which can eliminate frequencies above a specified cut-off frequency (f_c), and preserve those below it (Malvino, 2000). The range from 0 to f_c is called the passband. Later, high-pass filters were implemented, which act in the opposite way to low-pass filters. That is, they will preserve signals whose frequencies are above f_c while eliminating those below it. Another filter that is very commonly used in brain signal processing is the band-pass filter, which allows signals whose frequencies are between a lower cut-off frequency (f_{c1}) and an upper cut-off frequency (f_{c2}) to pass, attenuating the rest. The difference between both cut-off frequencies is known as is known as bandwidth (B). It is inversely proportional to the Q factor, which, together with the bandwidth, defines the selectivity of the filter. There is also a central frequency (f_0), which corresponds to the frequency with the maximum amplitude. Finally, band-stop filters (also known as Notch) were developed, frequently used to suppress distortions from the power line (50 or 60 Hz). In general, like the Band-pass filters, Notch filters have two frequencies (f_{c1} and f_{c2}), but unlike these, notches will remove signals between both frequencies. The Q factor is calculated in the same way as in the band-pass, and the central frequency is the main frequency that needs to be suppressed. All these filters can be designed in different approximations. Four of these approximations are briefly described below. The first one is the Butterworth approximation, which is characterized by having a flat response in the pass band and a monotonic decay in the eliminated band, the slope decays at a rate of $20 n$

dB/decade or $6n$ dB/octave, where n is the order of the filter (Malvino, 2000). The next approximation is the *Chebyshev I*, it presents ripples in the pass band (A_p), whose amplitude can be selected by the user and is generally given in dB. A faster decay than the Butterworth filters characterizes this filter. However, it presents ripples in the pass band, reflecting non-zero attenuations in the frequency band where they should be zero (Malvino, 2000). Depending on the user's needs, this type of approximation will be chosen, making a compromise between the fast decay in the eliminated band and the attenuation due to the ripples in the pass band. The following approximation developed was the *Chebyshev II* or *inverse Chebyshev*, which presents ripples in the eliminated (or stop) band, denoted by A_s (defined by the user, also given in dB and less than A_p) and has a flat pass band. The advantage of this filter is that the pass band will not present a decrease in amplitude, while its disadvantage is that in the eliminated band there will be less attenuations. Finally, the Elliptic approximation is characterized by the presence of ripples in both bands: pass and eliminated. This implies that attenuations will occur at the passband frequencies and that part of the signal will remain at the stopband frequencies. The major advantage of this approximation is that with a lower order, a response similar to that obtained with a higher order approximation can be achieved.

Independent component analysis

The objective of *ICA* is to estimate the independent components from the following model (Santillán et al., 2017):

$$\mathbf{y}(k) = \sum_{l=1}^m c_l s_l(k) = \mathbf{C}\mathbf{s}(k), (1)$$

Where, $\mathbf{y}(k) = [y_1(k), \dots, y_n(k)]^T$, corresponds to the signals acquired by the measurement system, k indicates the time; n is the number of *EEG* electrodes; $\mathbf{s}(k) = [s_1(k), \dots, s_m(k)]^T$, denote the m independent components; and $\mathbf{C} = [c_1, \dots, c_m]$ is the mixture matrix of size $n \times m$. According to (1), there are two unknowns and only one known variable ($\mathbf{y}(k)$). Therefore, it is necessary to take into account the *ICA* assumptions, described in (Santillán et al., 2017).

One of the most commonly used algorithms for calculating independent components in *MATLAB* due to its fast convergence and ease of implementation is *FastICA* (Santillán et al., 2017). In the present interface, *FastICA* is the algorithm used to obtain independent

components. Components with artifacts are removed and clean signals are reconstructed using the new set of artifact-free components and the mixture matrix.

Empirical decomposition of modes

This technique: empirical mode decomposition allows the input of a univariate signal, $y(k)$, to be decomposed into a series of intrinsic mode functions (IMF), $IMF_i(k)$, and a residual denoted as $r_N(k)$, which can be a constant or considered as the trend of the input signal. Mathematically, it is expressed as (Huang and Attoh-Okine, 2005) :

$$y(k) = \sum_{i=1}^N IMF_i(k) + r_N(k). (2)$$

The procedure for identifying and extracting IMFs is called *sifting*. Each IMF must satisfy two fundamental conditions. The first is that the number of extremes and the number of crossings between the upper envelope and the lower envelope (defined by the local maxima and minima, respectively) must be less than two.

For this purpose, the local extremes (maxima and minima) are identified, which determine the upper and lower envelopes. Then, the average value is calculated, $m_1(k)$, between both curves. This average value is subtracted from the input signal to extract the first IMF candidate, known as proto-IMF, denoted as $pIMF_1(k) = y(k) - m_1(k)$. The proto-IMF is the new input signal and the *sifting process* is applied iteratively to it. To avoid a high number of iterations, as well as losing the physical meaning of the IMFs, two criteria are used to stop the process, which are detailed in (Huang and Attoh-Okine, 2005). When both criteria are satisfied, after i iterations, the first IMF ($IMF_1(k)$, which contains the highest frequency of the signal) is obtained:

$$IMF_1(k) = pIMF_{(i-1)}(k) - m_i(k). (3)$$

The first *IMF* is separated from the rest of the input signal as follows:

$$r_1(k) = y(k) - IMF_1(k). (4)$$

With this, $r_1(k)$ is the new input to the sifting process. The algorithm stops when the residual is a constant or corresponds to the signal trend.

Combination of ICA and low-pass filters

Since muscle artifacts cannot be completely eliminated by using low-pass filters or *ICA* alone, the present interface features a combination of *ICA* with low-pass filters, as described in (Santillán et al., 2017). This combination begins with the application of *ICA* to the input signals. The independent components are obtained and, from these, those that

contain physiological information mixed with muscle artifacts or that contain purely artifacts are selected by visual inspection. A low-pass filter is applied to the selected components to prevent the independent components from containing a mixture of physiological signals with artifacts. If there are independent components that, despite being filtered, still contain artifact residues, these will be eliminated. The filtered *EEG* signals are reconstructed using the new set of artifact-free independent components, together with the previously defined mixture matrix **C**.

Source Identification Method

One of the commonly used methods to validate the identification of a source is through the generation of the same in the form of a synthetic source. To do this, the direct problem of source identification is solved, which is based on a conductive medium model already studied in Morín et al. (2019).

A representation of this model considers the head in two conductive layers, where the innermost Ω_1 represents the brain and the next Ω_2 represents the other conductive layer that must group intracranial fluid, skull and scalp, S_1 represents the separation surface between Ω_1 and Ω_2 , S_2 the surface of the scalp. From certain conditions and since conductive layers are considered, it is possible to apply, for the modeling some of Maxwell's laws, this condition and some restrictions make it possible to find that the electrostatic potential u satisfies the following boundary problem, when the source is located in the cerebral cortex:

$$\Delta u_1 = 0 \quad \text{in } \Omega_1$$

$$\Delta u_2 = 0 \quad \text{in } \Omega_2$$

With the boundary conditions:

$$u_1 = u_2 \quad \text{on } S_1$$

$$\sigma_i \frac{\partial u_1}{\partial n_1} = \sigma_2 \frac{\partial u_2}{\partial n_2} + j \cdot n_1 \quad \text{on } S_1$$

$$\frac{\partial u_2}{\partial n_2} = 0 \quad \text{on } S_2$$

From this, two main problems can be stated and solved: The direct and inverse problems (Morín et al., 2019). For the direct problem in 2 dimensions, it will be assumed that the source $g = j \cdot n_1$, which restricted to S_1 , denoted as $g(\theta)$, is known and described by

Fourier series and the potential (measurement) produced by such source is calculated (Kirsch, 1996). To do this, it is proposed: $g(\theta) = \sum_{k=1}^{\infty} g_k^1 \cos k\theta + g_k^2 \sin k\theta$. Where the Fourier coefficients are given by $g_k^1 = R_1 \int_{-\pi}^{\pi} g(\theta) \cos k\theta d\theta$ and $g_k^2 = R_1 \int_{-\pi}^{\pi} g(\theta) \sin k\theta d\theta$. The potentials are sought in the following form

$$u_1(r, \theta) = \sum_{k=1}^{\infty} a_k^1 r^k \cos k\theta + b_k^1 r^k \sin k\theta$$

$$u_2(r, \theta) = \sum_{k=1}^{\infty} (a_k^2 r^k + b_k^2 r^{-k}) \cos k\theta + \sum_{k=1}^{\infty} (c_k^2 r^k + d_k^2 r^{-k}) \sin k\theta$$

According to the boundary conditions, by developing and simplifying, the potential generated by $g(\theta) = \sum_{k=1}^{\infty} (g_k^1 \cos k\theta + g_k^2 \sin k\theta)$, is expressed in the form:

$$V(\theta) = u_2|_{s_2} = u_2(r, \theta)$$

$$= \sum_{k=1}^{\infty} \left(\frac{2g_k^1 (R_1^{k+1} + R_2^k)}{k[(\sigma_1 - \sigma_2)R_1^{2k} + (\sigma_1 + \sigma_2)R_2^{2k}]} \right) \cos k\theta$$

$$+ \sum_{k=1}^{\infty} \left(\frac{2g_k^2 (R_1^{k+1} + R_2^k)}{k[(\sigma_1 - \sigma_2)R_1^{2k} + (\sigma_1 + \sigma_2)R_2^{2k}]} \right) \sin k\theta$$

where $a_k^1 = \frac{g_k^1 (R_1^{2k} + R_2^{2k})}{k[(\sigma_1 - \sigma_2)R_1^{2k} + (\sigma_1 + \sigma_2)R_2^{2k}]R_1^{k-1}}$, $b_k^1 = \frac{g_k^2 (R_1^{2k} + R_2^{2k})}{k[(\sigma_1 - \sigma_2)R_1^{2k} + (\sigma_1 + \sigma_2)R_2^{2k}]R_1^{k-1}}$

This expression can be considered as the (electroencephalographic) measurement produced by the source, where: g_k^1 and g_k^2 are the Fourier r coefficients of g and since it was considered from the beginning that the head would be represented by concentric spheres, we can agree that the radius of the brain is R_1 , R_2 the radius of the head, σ_1 and σ_2 are the average conductivities of the brain and head respectively, θ indicating the position of each electrode located on the scalp. With this relationship, the aforementioned synthetic EEG signal is generated, which allows the implemented interface to be validated.

Results

The graphical interface was implemented in *MATLAB*, which is shown in Figure 1.

The FIMALOF interface includes several buttons, distributed according to their functionality: Four for digital filters (low-pass, high-pass, band-pass and band-reject), three for signal decomposition techniques (*ICA*, *ICA* -low-pass filter and *EMD*) and an additional one to perform format conversion. It is also possible to select the language, either Spanish or English, in addition to having a button that allows generating a synthetic *EEG* signal created from the mathematical model previously described. If a source to be filtered is selected and is generated from the contour problem, it will be necessary to generate a V measurement (synthetic measurement), which will be expressed by Fourier series in the conductive medium model. Due to the structure, a synthetic *EEG* signal will be generated that can be filtered through this interface. If the user enters data out of range, the graphical interface will display an alert, informing the user that the range is out of limit and must to be entered again.

Figure 1. FIMALOF main GUI



Source: Own elaboration.

Below are some special functions used in the interface.

a) Sub-interface: format conversion

The main screen of the interface contains a button for format conversion, which allows converting files from .edf, .cnt and .mat formats to the .mat format compatible with FIMALOF. This conversion is necessary for FIMALOF to be able to load and read the signals. It is important to mention that within the interface there are two types of conversion from .edf to .mat. This is because, on the one hand, it is possible to determine the channels that come from the *EMOTIV Epoc + (14-channel EEG* measurement system plus two reference channels, (*EMOTIV* , 2024)), while on the other hand, there are other systems whose channels with EEG signals may vary, but still have the original .edf format.

b) Sub-Interface: Filters

In the case that the user selects to apply a low-pass filter from the main interface, the user must enter the necessary parameters for each type of approximation, such as: sampling frequency (F_s), cut-off frequency (F_c), order (Order), A_p , for the case of *Chebyshev I* and elliptical type filters, A_s , for the case of *Chebyshev II* and elliptical type filters, the number of the initial sample to start processing (Start Point) and the number of seconds to be analyzed (Seconds). Subsequently, the channels to be filtered must be selected, which can be part of four possible configurations that are currently being considered in the interface: Configuration 1, corresponding to *EMOTIV* (14 channels); Configuration 2, of 19 channels, corresponding to the 10-20 system; Configuration 3, of 32 channels, corresponding to the modified 10-20 system; Configuration 4, corresponding to 128 channels. In this case, the user may choose those required for analysis and processing.

Once the user has selected the channel(s) to be filtered, the EEG signals are loaded into the interface. As mentioned above, the data must be in .mat format in order to be used in FIMALOF. If they are in another format, the conversion is done with the “Convert Data” sub-interface, with which the data is converted to .mat, so that they can be processed. Immediately after the information to be filtered is loaded, the selected channels are graphed in the upper right, and a standardization is done (unit variance and zero mean value). Subsequently, the filter approximation(s) is/are selected. In the lower left, the frequency response of each selection is graphed in the color corresponding to the approximation. The selected filter(s) is/are applied and the filtered signals are graphed in the upper right. In the lower right, the power spectrum of a chosen channel is graphed.

Thus, once the different approaches have been applied, the user will be able to determine which of them provides the best filtering results for the *EEG* signals, according to the frequency band that he/she wishes to analyze later. The above is done in an analogous way for all filters, which have been improved from the previous version of the FIMALOF interface. In the present version, the saving of signals was added, in addition to generating warning messages to the user when the data entered by him were not done properly, informing him how they can be written. For more details on the operation of the filtering part, refer to (Santillán et al., 2018).

c) Sub-Interface: ICA

As mentioned above, with ICA it is possible to decompose the n input channels into m independent output components. From these, the one(s) containing artifacts are selected to remove them, and thus reconstruct the clean signals.

The graphical interface for *ICA* is shown in Figure 2. In this case, the user must enter the value of the sampling frequency, the start of the signal, and the number of signals to be cleaned in seconds. For this particular case, the channels to be filtered are not selected, since *ICA* works with all the input channels to produce the m independent components. Once the data have been entered, the signals to be filtered are loaded, and the computation method of the *fastICA* algorithm is chosen. In the “Basic Parameters” panel there are: “defl” with which the independent components will be calculated one by one; and “symm”, which will calculate all the components in parallel. The default value is “defl”. The number of components to be taken can be entered. By default, the same number of channels will appear, that is, the size of the signals is not reduced.

Figure 2. Interface corresponding to ICA



The interface is divided into several sections:

- Basic Parameters:** Includes input fields for 'Fs' (128), 'Punto de Inicio' (1), and 'Segundos' (10).
- Control de Convergencia:** Includes 'Epsilon' (0.0001), 'Max. Núm. Iteraciones' (1000), and 'Max. Núm. Precisión' (100).
- Parámetros Básicos:** Includes a dropdown for 'Aproximación' (set to 'defl') and an input for 'Número de ICs' (14).
- No Linealidades:** Includes dropdowns for 'No linealidad' (set to 'pow'), 'Ajuste de Precisión' (set to 'pow'), and 'Estabilización' (set to 'on'). It also has input fields for coefficients 'a1' (1), 'a2' (1), and 'mu' (1).
- Buttons:** Includes 'Cargar Data', 'Graficar Data', 'Normalizar', 'Aplicar ICA', 'Seleccionar IC's a remover', 'Graficar Espectro', 'Actualizar', and 'Guardar'.

Source: Own elaboration

In the “Nonlinearities” panel are the non-linear functions that are used to obtain **C** (mixture matrix); such as “pow3”, “tanh”, “gauss” and “skew” (Hyvarinen and Oja, 2000). These functions are also used to have a 'Precision Adjustment'. The 'Stabilization' can be enabled or not. The default value is 'on', indicating that a stable version will be used to obtain the independent components more effectively. The coefficients 'a1' and 'a2'; and 'mu', which correspond to the step size must also be entered. These parameters have a default value equal to 1. The parameters to control the convergence are shown on the right side. The default values are “Epsilon”=0.0001, at which the algorithm stops; “Max. “No. Iterations” = 1000, a parameter related to the maximum number of iterations to estimate each independent component; and “Max. No. Precision” equal to 100, which has to do with the maximum number of iterations to adjust the algorithm.

Once all the corresponding data has been entered, the fastica algorithm is applied, the components are obtained and, from among them, those that are considered contaminated with artifacts in both the time and frequency domains are chosen by visual inspection. Once selected, they are eliminated to suppress the different types of artifacts they contain. All the previously described input data can be updated as many times as the user considers necessary. Finally, the results can be saved for future comparison and analysis.

d) Sub-Interface: ICA-LPF

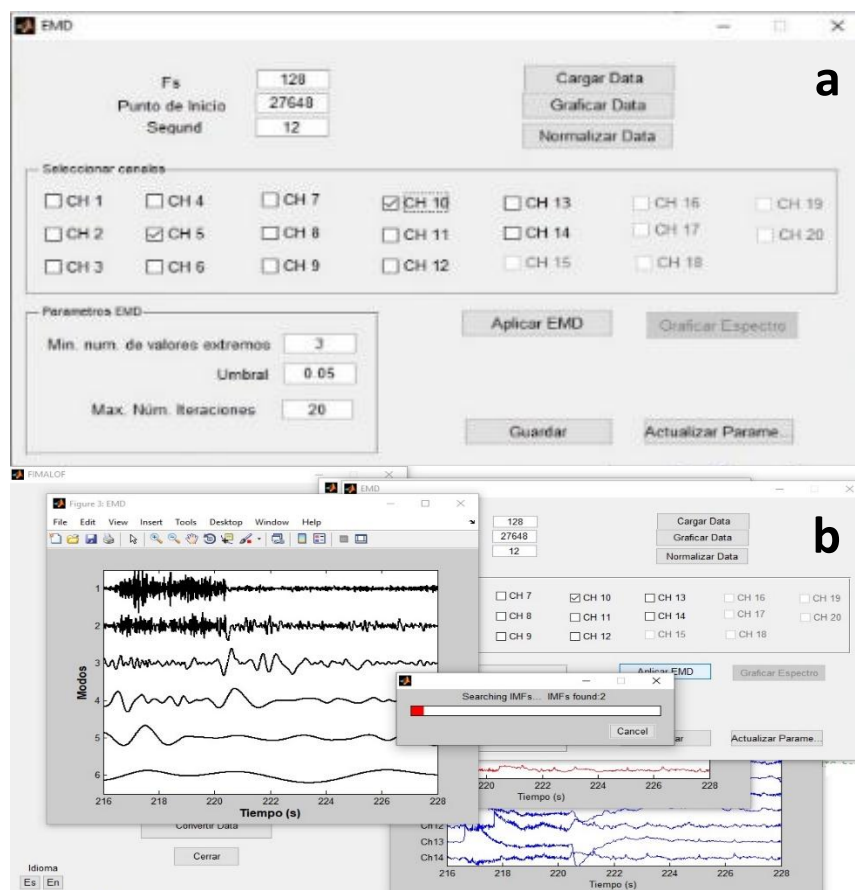
The interface of the ICA-LPF combination is similar to that of ICA, in which a button is added that is used to select the components with muscle artifacts and thus apply a low-pass filter to them. The selected components are filtered with a sixth-order *Butterworth low-pass filter*, with a $f_c=30\text{Hz}$, which is previously determined internally. The new series of

components, which contains the filtered and unfiltered ones, are shown in a figure to select among them those that still have muscle or other artifacts. The *ICA-LPF combination* allows the elimination of muscle artifacts in a more efficient way than using *ICA* alone.

e) Sub-Interface: EMD

Figure 3a shows the sub-interface corresponding to *EMD*. The parameters to be entered by the user, in addition to the sampling frequency, the starting point, and the number of seconds, are: The maximum number of iterations to obtain the *IMFs*, the threshold value used to stop the algorithm, as described in previous sections and the type of interpolation to use (cubic or linear). It is also possible to choose the channel to be filtered with *EMD*, one at a time, first choosing the configuration, as in the case of digital filters. Each basic parameter has a default value. Once the values have been entered, *EMD* can be applied to the selected channel, its spectrum can be graphed and those *IMFs* that are considered to be contaminated with some type of artifact can be selected. As in the previous interfaces, the results can be saved. Figure 3b shows an example of how the *IMFs* of one of the chosen channels can be viewed .

Figure 3. a) EMD interface, showing the parameters to be selected; b) example of how the IMFs (modes) of one of the selected channels are observed.



Source: Own elaboration.

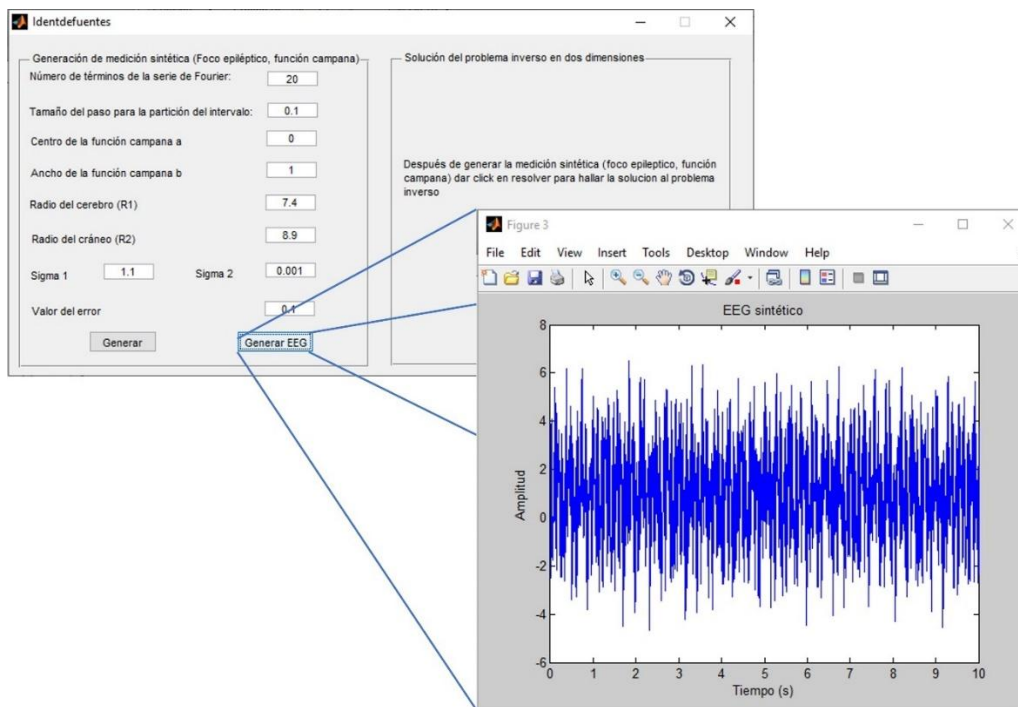
f) Subinterface: Source Identification

Finally, the mathematical models used for the *Identdefuentes* subinterface used for source localization are implemented. This consists of generating an *EEG signal* through the mathematical model of the conductive medium, described above (Santillán et al., 2021). In the source identification interface, the data such as the number of terms in the Fourier series, the value of the step size for the interval partition, the central point and the width of the bell function, the radius of the brain and the skull, sigma 1, sigma 2 and error are requested. This information is used to generate an epileptic type source where the head is represented by two concentric circles; sigma1 and sigma2 are the conductivities of the media. The data corresponding to the bell function are due to the representation of the epileptic focus. Then, by clicking on *Generate*, the graph of the source and its corresponding Fourier series is

displayed. At the same time, the graph of the exact measurement and the error measurement produced by the source are also generated; both measurements obtained by solving the electroencephalographic boundary problem. Subsequently, the *Generate EEG* signals and *Solve buttons* are enabled, and by clicking on *Generate EEG* a synthetic EEG is produced from the previously obtained measurement. This synthetic EEG will contain frequencies of 3.5Hz, 11Hz and 60Hz, emulating an absence epileptic event, alpha waves and the technical artifact of the power line, respectively.

By clicking the “*Generate a synthetic measurement*” button, the subinterface shown in Figure 4 opens. As can be seen, values such as the number of terms of the Fourier series, the value of the step size for the interval partition of θ , which goes from $-\pi$ to π , the value of the position of the center of the bell function (which was chosen to emulate an epileptic focus) that approximates the source, the value of the width of the bell function that approximates the source (Morín et al., 2019), the value of R1, R2, of the conductivities (“Sigma 1”, “Sigma 2”) and the error value are entered. This subinterface shows two buttons, the *Generate button* which is used to create the source previously established within the code, and with which the synthetic EEG can be generated, using the “*Generate EEG signals*” button. The interface provides the required synthetic EEG signal, saves it, and displays it on the screen, thus making it possible to apply the desired filtering, as shown in Figure 4.

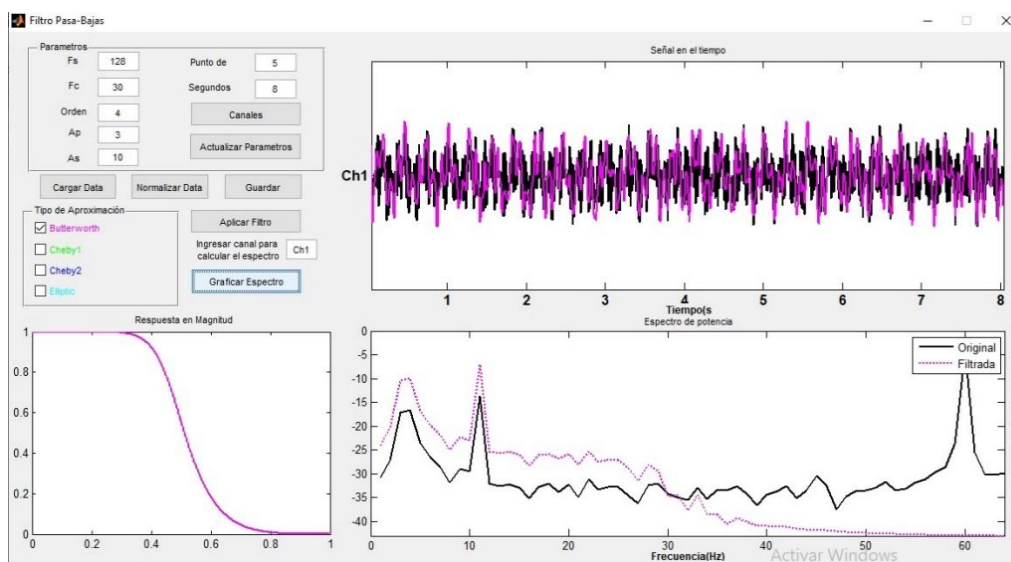
Figure 4. Subinterface corresponding to the generation of a synthetic measurement. The information requested from the user to generate the EEG signal is shown here.



Source : Own elaboration.

Figure 5 shows an example of the use of a low-pass filter applied to a synthetic EEG signal containing a frequency of 3.5 Hz (Panayiotopoulos et al., 2010), 10 Hz (alpha signal) and 60 Hz (power line artifact). Random noise was added to this signal to simulate more realistic conditions. The generated signal is automatically stored, allowing its reuse in the interface for additional filtering processes. As can be seen in Figure 5, a fourth-order Butterworth filter was applied with a $f_c=30$ Hz. The signals in black are the original ones, and in magenta, they are the filtered ones, both in time and frequency. In both cases, it is possible to observe a difference, noting that the frequencies above 30 Hz have been eliminated.

Figure 5. Example of using a low-pass filter applied to a synthetic EEG.



Source: Own elaboration

Discussion

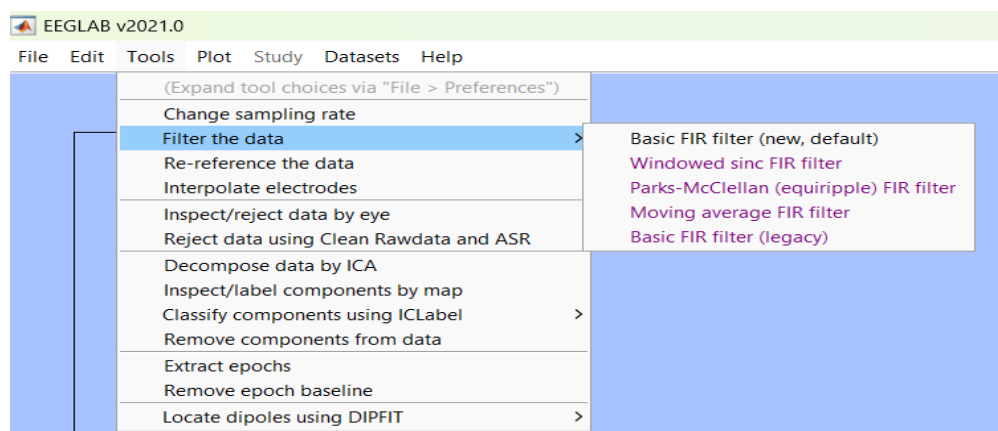
Advantages: This interface offers easy accessibility and handling for the user because it is not necessary to have specialized knowledge for its use. On the other hand, the generation of synthetic EEG signals through the mathematical model of the conductive medium, in which we know the sources that generate those synthetic signals, allows a complete characterization of ideal EEG signals, which can be contaminated with random noise associated with different artifacts. These contaminated signals can be filtered from the different filters implemented in the interface to obtain a clean signal from which the sources generating ideal *EEG* signals can be identified. This represents an advantage for users and modelers that, to the authors' knowledge, do not offer other interfaces. Thus, with this interface, it is possible to generate signal data that represent alterations in the EEG that, in general, can be difficult to obtain, but with this methodology, it can contribute to the identification of neuronal alterations such as epilepsy, brain damage, or tumors. It is highlighted that this type of implementation, which uses mathematical models based on laws of Physics and advanced mathematics that support the theoretical framework of this work, are a robust technological development that are required for their use by a broader community, which will allow for more effective progress in the analysis, study and research of problems in the brain. It is worth noting that the interface can have a didactic use that will impact the communities of students and teachers of medicine, psychology, engineering and

sciences. The interface is developed in Spanish and English. The default language is Spanish. Thus, the proposed interface will be accessible to native speakers of this language, which is the second most spoken language in the world.

Comparisons: Comparisons are shown between *EEGLAB* and the proposed interface, FIMALOF, with the aim of showing the similarities and differences that allow us to conclude that FIMALOF is comparable with *EEGLAB*, which is widely used for signal processing. Thus, the interface described in this work could be considered an easy-to-use alternative for signal processing, synthetic signal generation, as well as source localization.

Figure 6 shows the filters that can be used with *EEGLAB*, which correspond to finite response filters (*FIR*) and *ICA*, compared to the FIMALOF interface, which can perform infinite response filters (*IIR*), as well as *ICA* and *ICA* combined with low-pass filters (see Fig. 1).

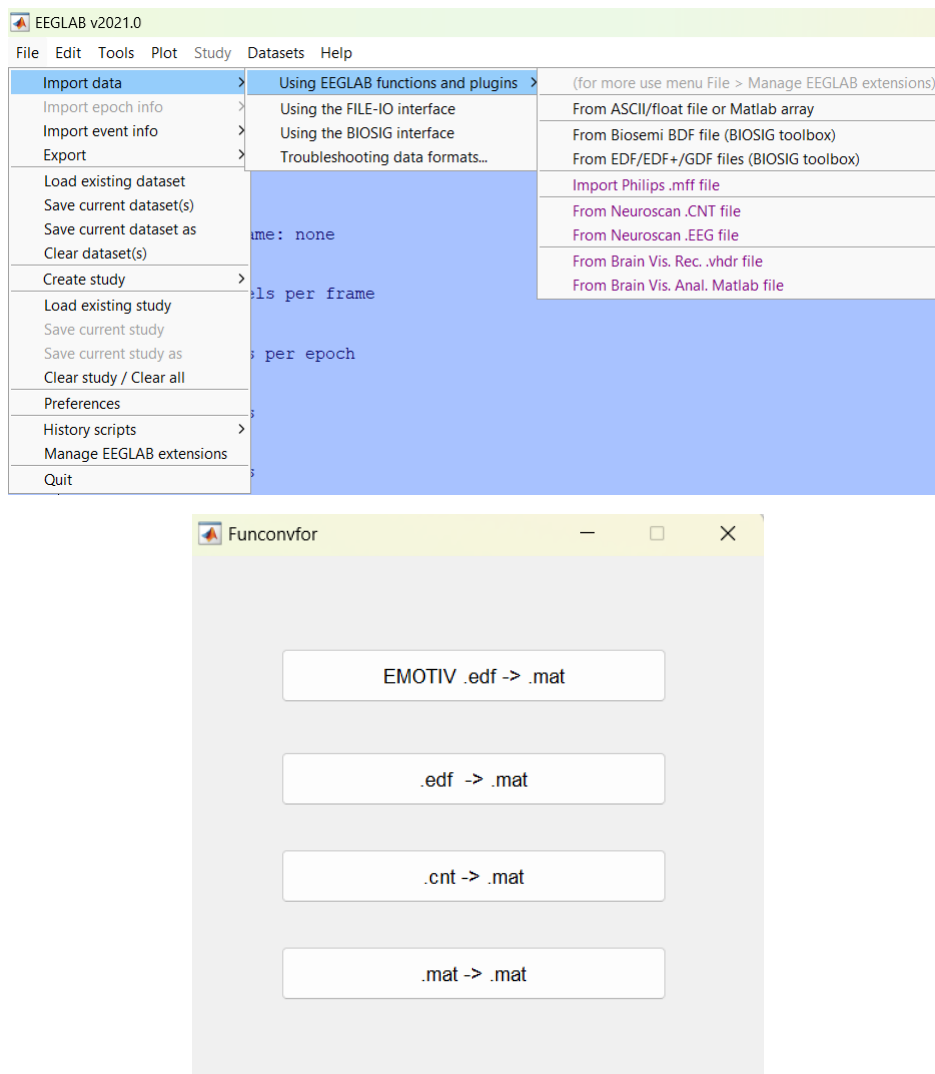
Figure 6. Part of the *EEGLAB* tool, showing the available filters to apply to EEG signals.



Source: Own elaboration, based on *EEGLAB*.

One of the problems that the user normally faces when using graphical interfaces is importing data. Figure 7 shows the different formats that can be loaded with *EEGLAB*, in addition to allowing the processing of signals previously located in the *MATLAB* workspace. Compared to the proposed interface, FIMALOF, it is also possible to import data in different types of formats, coming from various systems, as described in the results section in the format conversion sub-interface. Although *EEGLAB* is a very useful tool for importing data in a wide variety of formats, in FIMALOF it is easier to carry out such loading.

Figure 7. Formats that can be loaded with *EEGLAB* (top) and with *FIMALOF* (bottom).



Source: Own elaboration, based on EEGLAB.

To illustrate the potential of the interface, Figure 8 shows a comparison of signals before and after filtering. The top part shows the results using *EEGLAB*; the bottom part shows the results using *FIMALOF*. In both cases, 4 EEG signals were used, corresponding to channels FC5, T7, T8 and FC6, from second 6 to 8, where muscle artifacts were observed. In the case of *EEGLAB*, a *FIR* filter of 0.1 to 30 Hz was used. In the case of *FIMALOF*, a fourth-order Butterworth filter was chosen, with a cutoff frequency of 30 Hz.

While in *EEGLAB* only the filtered signals are displayed, *FIMALOF* also allows the frequency response of the applied filter and the power spectral density of the selected channel to be observed, providing a more complete view of the process.

Conclusions

A graphical user interface was developed for academic and research use implemented in *MATLAB*, intuitive and easy to use. This tool allows the filtering of *EEG* signals, as well as the identification of synthetic bioelectrical sources that emulate real sources. The generation of synthetic *EEG* signals, obtained through a mathematical model based on a contour problem, represents a significant advantage, since it allows the validation of both the implemented filters and the source identification algorithm, guaranteeing complete control over the generated signals. In addition, the interface is available in Spanish and English, making it accessible to a wider audience. It includes helpful messages in case the user enters parameters, and its ability to combine *ICA* with a low-pass filter significantly improves the removal of muscle artifacts compared to the use of *ICA* alone. The comparisons demonstrate the functionality and feasibility of FIMALOF as a highly comparable alternative to *EEGLAB*.

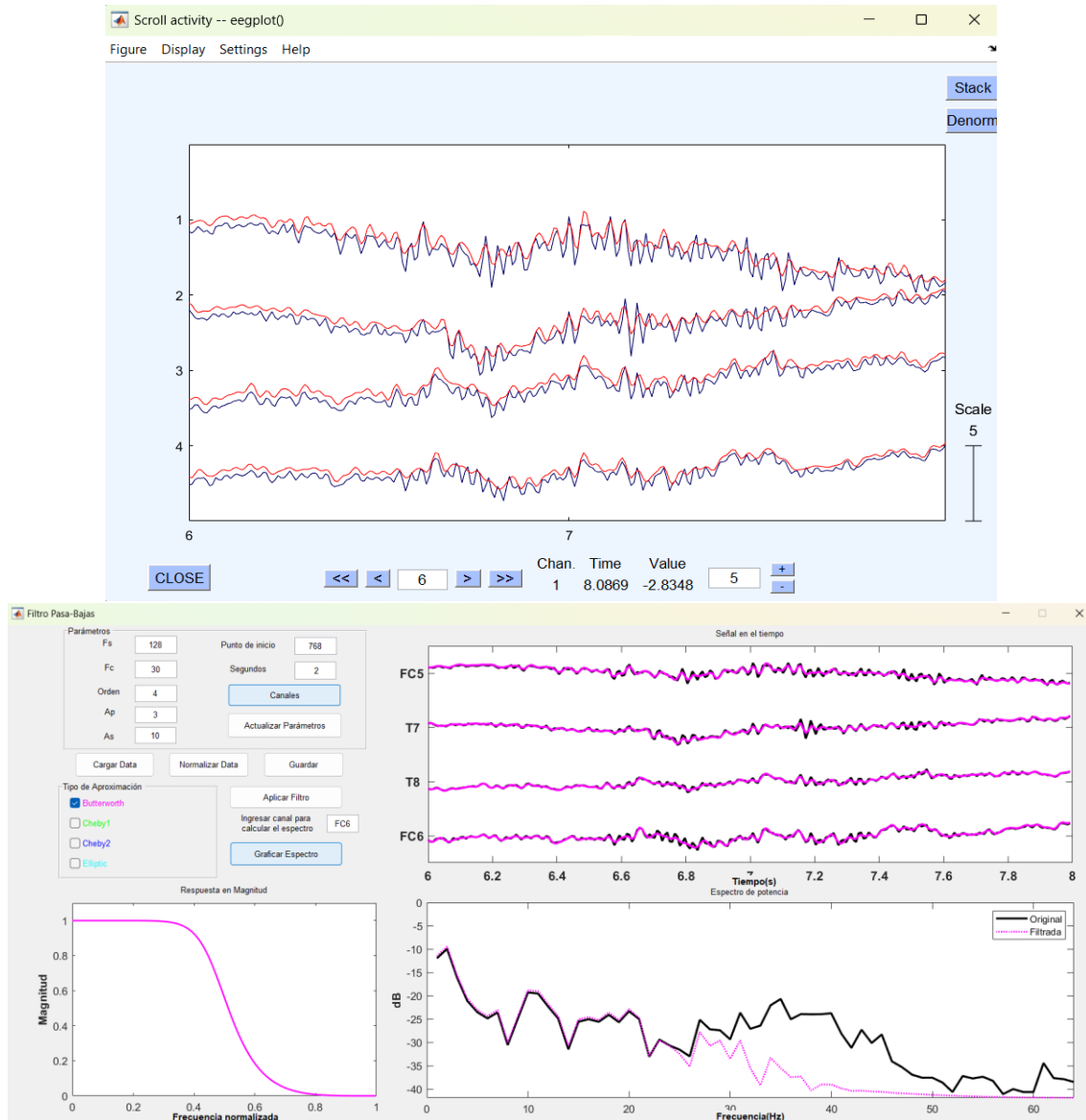
Future works

Future developments include automation in the removal of artifacts using *ICA* and *ICA-LPF*, identifying contaminated components automatically. In addition, topographic mapping, and statistical calculations of *EEG* signals are expected to be implemented. As for mathematical models, the aim is to emulate other neurodegenerative diseases, generating synthetic databases for analysis and filtering. This aim will allow preserving complete information of the *EEG* signals, suppressing noise, and hence, be useful for applications such as the development of brain-computer interfaces.

Possible improvements include expanding the source identification model, which currently operates in two dimensions. A model based on concentric spheres is planned for greater accuracy in future developments.

On the other hand, it is intended to develop an executable version of the interface that can be used by doctors and biomedical specialists without the need for knowledge of *MATLAB*. Likewise, work is being done on the incorporation of *wavelet*-based filtering techniques, which offer better time-frequency resolution and improve the analysis of *EEG* signals.

Figure 8. Top: Results of filtering 4 EEG signals using *EEGLAB*. Bottom: Results of filtering 4 EEG signals using *FIMALOF*. In both cases, 4 EEG signals corresponding to channels FC5, T7, T8 and FC6 were used, from seconds 6 to 8, where muscle artifacts were observed.



Source: Own elaboration, based on *EEGLAB*.

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