

Independent Component Analysis with Functional Neuroscience Data Analysis

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ABSTRACT

Background: Independent Component Analysis (ICA) is the most common and standard technique used in functional neuroscience data analysis.

Objective: In this study, two of the significant functional brain techniques are introduced as a model for neuroscience data analysis.

Material and Methods: In this experimental and analytical study, Electroencephalography (EEG) signal and functional Magnetic Resonance Imaging (fMRI) were analyzed and managed by the developed tool. The introduced package combines Independent Component Analysis (ICA) to recognize significant dimensions of the data in neuroscience. This study combines EEG and fMRI in the same package for analysis and comparison results.

Results: The findings of this study indicated the performance of the ICA, which can be dealt with the presented easy-to-use and learn intuitive toolbox. The user can deal with EEG and fMRI data in the same module. Thus, all outputs were analyzed and compared at the same time; the users can then import the neurofunctional datasets easily and select the desired portions of the functional biosignal for further processing using the ICA method.

Conclusion: A new toolbox and functional graphical user interface, running in cross-platform MATLAB, was presented and applied to biomedical engineering research centers.

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Keywords

Electroencephalogram; Functional Magnetic Resonance Imaging (fMRI); Graphical User Interface (GUI); Independent Component Analysis (ICA); Functional Neuroscience

Introduction

Biomedical signals are continuous and sophisticated with some artifacts. Signal processing techniques are used to obtain useful information from various biomedical signals for analysis, design, or diagnosis [1]. Biomedical engineering designed Biosignals, bioelectrical, and biomechanical systems, while physicians and health-care specialists used biomedical signals for detecting health problems. Researcher functioning on biomedical applications can process the biosignals according to their medical applications by different signal processing techniques [2,3].

In this paper, two of the most important neuroscience functional data Electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI) are analyzed with Independent Component Analysis

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(ICA). The EEG signal involves several correlated signals from different places on the scalp that translates the electrical activity of the brain [4,5]. The neural activity and related hemodynamic response function (HRF) can be detected in the brain by calculating the Blood Oxygenation Level-dependent (BOLD) signal [6]. The fMRI images are represented by a 4D dataset, which are sequences of 3D images obtained over time [7,8].

The ICA is a standard method, recently used to analyze data in brain computing interfaces by extracting clean signals from signal blends with artifacts [9] without any changes to the data, i.e., it doesn't add any further information to the signal. Additionally, the ICA is commonly denoted as the Blind Source Separation algorithm. The signals extracted by the ICA are described by the time course (TC) representing the evolution of neural activity over time. The output signal of the functional neural activity is the independent component (IC), which is statistically independent of any other signal [10].

The EEG signal is the weighted sum of brain activity depending on the signal path from the neuron cell to the electrodes. The recorded neuron potential from more than one electrode may be the same value; thus, the output signal is extremely correlated to the recorded neuron. The ICA is a mathematical method, leading to separating the EEG signals into mutually independent components of the scalp maps [11]. Sun et al. trained the ICA on real EEG signals and identified the independent sources statistically. The experimental results showed that the ICA approach had the ability for analyzing multichannel EEG by removing the artifacts and separating the mixed signals significantly [12]. Winkler et al. used real data to train the projected automatic method for signal component classification. The EEG signal components may be artificially split by an ICA method due to the big dimensionality of the data. Winkler et al. concluded that the proposed method worked as a good classifier

of the ICA components and removed the artifacts from EEG data efficiently [13]. Rejer and Gorski proved the benefits of applying ICA in rearranging the true brain sources and artifacts in some components as new mixtures [14], fast ICA deflation approach [15], and Infomax [16]. The results showed that all ICA algorithms improved the signal-to-noise ratio significantly [17].

The ICA can extract the task paradigm of the fMRI study that this task activation map is designed to capture the activity of the brain through a time series of the experiment [18-20]. Moritz et al. processed a real dataset from 10 individuals with the ICA of multislice fMRI data to study temporal and spatial characteristics of brain activation. The individuals were asked to perform the finger-tapping paradigm to map the sensorimotor cortex. The results showed the ICA method with information on the temporal configuration and spatial localization of the components [21]. Calhoun et al. proposed a new model for complex-valued fMRI datasets using ICA. They also showed an improved capability for separating the task-related activated functional variations with many activities of the functional voxel [22]. Bi et al. introduced a post-nonlinear ICA grouping of source signals, which is most appropriate for the mixed signals of the brain, and used real data from 38 and 32 mild cognitive impairment unhealthy and healthy individuals in resting-state networks, respectively. Further, they proved that the functional connectivity of resting-state networks in mild cognitive deficiency individuals was abnormal concerning the healthy individuals [23].

For neuroscience and especially functional neuroscience data, there are some software packages designed for processing and analyzing signals. However, they are sophisticated and need an expanse of time to learn about using these toolboxes by the physicians or healthcare specialists who work in this field. No package introduced the output results of two of the essential neurofunctional signals

Electroencephalogram (EEG), functional Magnetic Resonance Imaging (fMRI), and the Independent Component Analysis (ICA) technique in the same module. To the best of our knowledge, the presented tool is the first study in the literature in this field.

Many Graphical User Interface (GUI) software packages are presented for analysis and learning tasks in neurofunctional data analysis [24-27]. Delorme and Makeig developed Encephalography and local field potentials Analysis (EEGLAB, which is a MATLAB-based GUI package [28] to analyze EEG data for both ordinary and advanced EEG processing. The Electro and MagnetoEncephalography Lab (ELAN), as an advanced GUI tool, was developed by a group of scientists [29], picturing the topographical activation records based on EEG, Magneto Encephalogram (MEG), and local field potentials (LFP) signals.

The proposed tool was implemented for the non-invasive, electrophysiological EEG, and neuroimaging fMRI techniques, which are the major in detecting functional brain activity. This study is designed as a simple toolbox constructed on GUI via MATLAB. In this package, the functional data through low spatial resolution and high temporal resolution (represented in EEG) and the data through high spatial resolution and comparatively weak temporal resolution (described in fMRI) are designed on the same GUI page. The software package is more flexible and easier compared to the other analogous packages.

Material and Methods

This experimental and analytical study aimed to present a simple toolbox for Neurofunctional Data Analysis with the ICA algorithm. Many analysis techniques were designed and implemented for essential analysis packages in different types of functional neuroscience data [4,30]; however, these tools were complicated and inflexible in use. Also, they lacked in using the same analysis method with the neurofunctional dataset for a better compari-

son. The designed tool introduced the view and comparison in the same module, which is a very useful analysis and preferred by a lot of researchers in the functional neuroscience field.

Figure 1 summarizes the model of the designed package with a simple flow graph. The central part of the modeling design is based on the ICA techniques for both the EEG and fMRI raw data. The ICA was practical to bio-signals [4]. In the EEG, the ICA was used to evaluate the principal sources in a multi-lead EEG waveform; while in fMRI, ICA was used

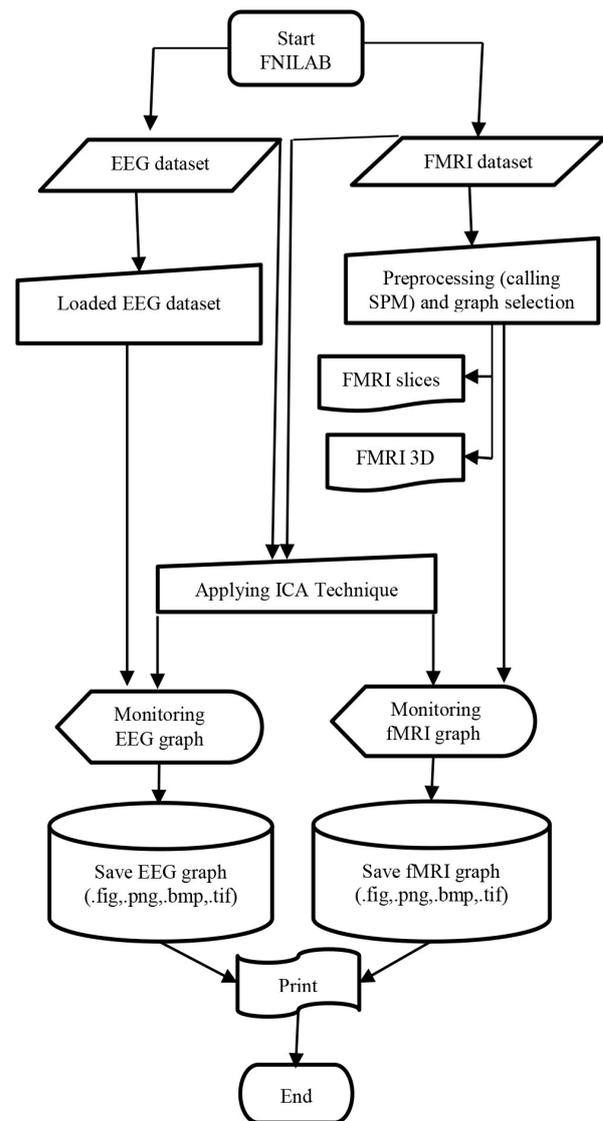


Figure 1: The flowchart of the designed functional neuroscience data analysis tool

to develop the recognition of active neural areas in the brain [30].

In the environment of EEG and fMRI data, the extracted components are purely statistical properties and examined based on their time course. The ICA can produce a modified signal mixture after removing the components showing artifacts and other non-brain processes [10].

Preprocessing steps must be done before applying the ICA algorithm to the neurofunctional data. The preprocessing includes “cleaning up” the data and throwing the artifact sources before the subsequent processing and analysis algorithms.

The EEG preprocessing steps must be done, in which many waveforms are picked up above the area of the scalp, while these different small waveforms are the product of a smaller number of neural sources. In this situation, the aim is not only to decrease the number of waveforms but also to produce more significant signals, in which various waveforms are acquired from electrodes located around the cortex. As a result, the EEG signals signify the grouping of principal neural sources.

Due to the difficulty in fMRI acquisition and a low Signal Noise Ratio (SNR) connected

with the BOLD signals, a preprocessing stage is needed for fMRI raw data. For preprocessing and analysis of fMRI data, some software tools are accessible that some of them are open sources, such as Statistical Parametric Mapping (SPM), Functional Magnetic Resonance Imaging of the Brain (FMRIB) software library (FSL), and analysis of functional neuroimages (AFNI). SPM [31] and FSL [32] are the most popular two packages.

The SPM is an open-source package in MATLAB, selected for the designed toolbox. The presented work used the SPM in the designed tool for pre-processing fMRI data.

The fMRI dataset must be preprocessed before fMRI data analysis using the ICA technique. The preprocessing stages are needed for eliminating unwanted noises or data from the dataset, improving the fMRI mapping, and arranging it for analysis.

In the proposed design, the fMRI dataset was preprocessed using the following steps: 1) realignment, 2) co-registration, 3) segmentation, 4) normalization, and 5) smoothing (Figure 1).

The essential package used with the preprocessing steps was shown in the SPM menu window in Figure 2.

The ICA algorithm can be consequently ap-

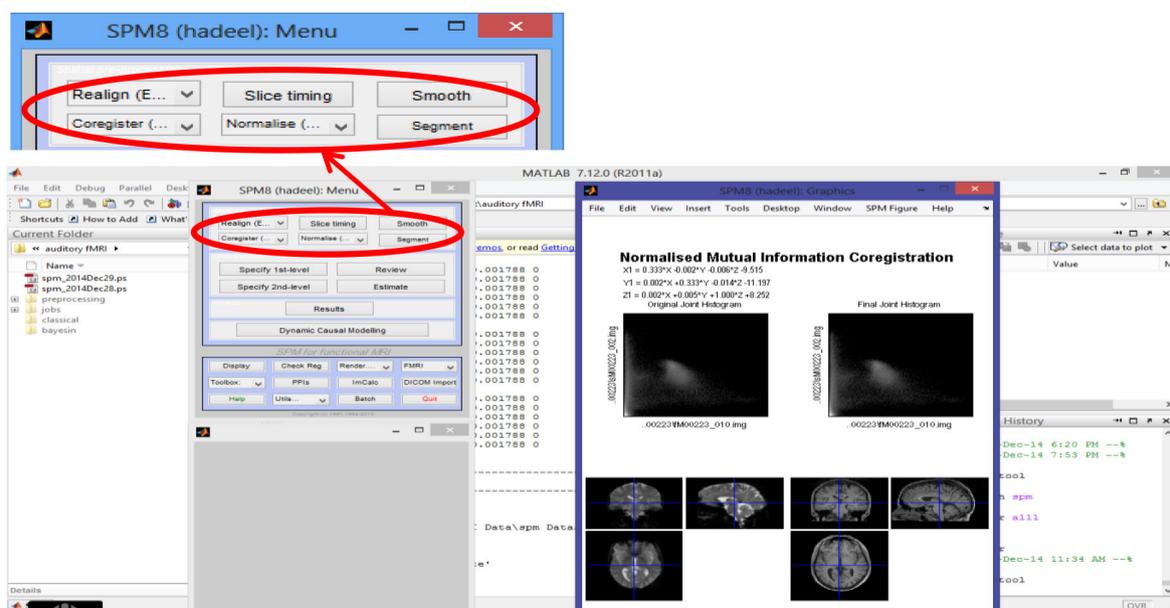


Figure 2: Statistical Parametric Mapping (SPM) main windows for the designed model.

plied after the preprocessing steps for both EEG and fMRI signals. The ICA aimed to convert the waveforms into some variables, which are statistically independent and non-gaussian. The ICA can catch noise sources, and these (components), i.e. converting mixed signals to independent components can be withdrawn from the waveform [2,3].

The features provided by the proposed visual package are as follows:

- **FMRI:**

a) Preparing fMRI data: converting DICOM file format [33] to ANALYZE [34] or Neuroimaging Informatics Technology Initiative (NIFTI) file format [35] for the preprocessing steps.

b) Preprocessing and fMRI data analysis: calling the SPM tool within the designed package.

c) Dealing with the ICA algorithm.

d) Showing fMRI data: displaying fMRI

brain images slice by slice, in which any number of fMRI slices can be directly selected from the pop-up menu.

- **EEG:**

a) Loading EEG data.

b) Dealing with the ICA.

c) Monitoring EEG dataset.

d) Saving the EEG graph after processing it with the ICA for further analysis and understanding.

Results

Two of the primary functional data, EEG and fMRI presented in the same GUI module (Figure 3). Screen capture of a module user session was designed as a simple toolbox running under GUI using MATLAB.

In the presented design, EEG data were pre-processed by removing the artifacts, filtering, epoch selection, and averaging. Ensemble averaging is a simple and powerful signal pro-

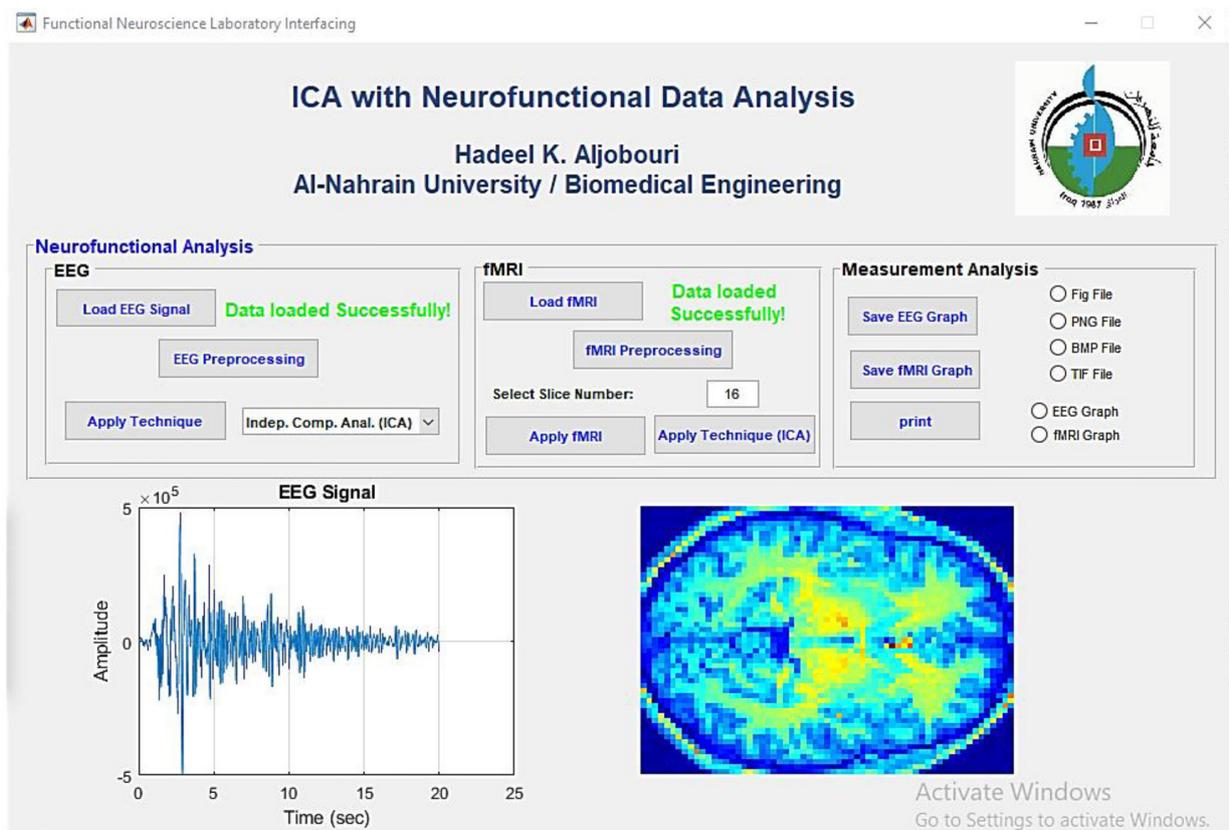


Figure 3: Screen capture of the designed tool running under MATLAB-based Graphical User Interface (GUI).

cessing method for decreasing artifacts when various observations of the signal are possible due to sensors or repeated stimuli of the same stimulus. In ensemble averaging, a group, or ensemble, of time responses is averaged together on a point-by-point basis that is an average signal constructed by taking the average, for each point in time, overall signals in the ensemble. Figure 4a shows the raw EEG waveform with a visual response presenting a small neural signal surrounded by the EEG. Figure 4b shows the visual evoked response (VER), which cannot be identified in the EEG waveform without averaging hundreds of in-

dividual responses of the EEG signal.

Different types of artifacts are associated with the EEG signal. A bandpass filter was used to remove lower and upper undesirable frequencies. Figure 5 shows an example of the bandpass filter on raw EEG signal, and the filter range was designed with (6 Hz) low and (12 Hz) high cutoff frequencies.

Two types of free datasets (one for EEG and the other for fMRI) were used in this study. The EEG signal was acquired from the PhysioNet data bank (2002). The presented toolbox had features of reading EEG data, experience information, and channel situation file in many

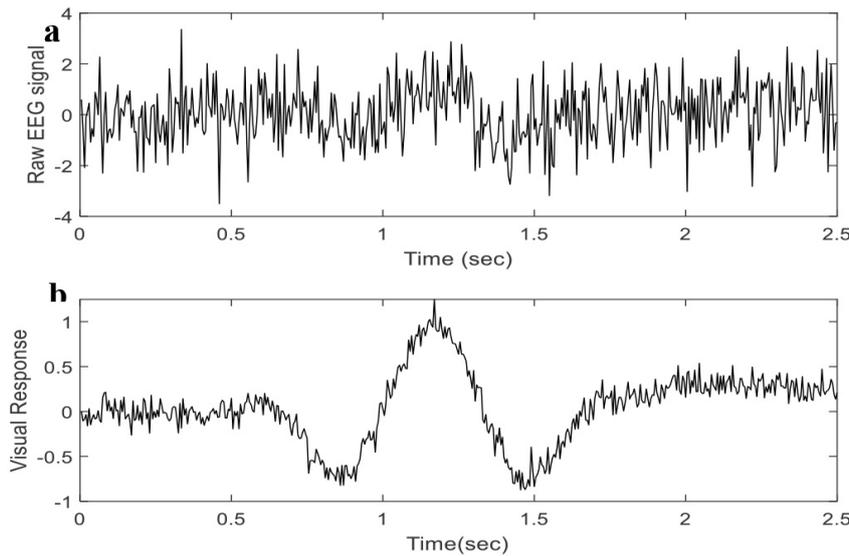


Figure 4: The effect of ensemble averaging on raw Electroencephalography (EEG) waveform. (a) raw EEG, (b) clear visual response.

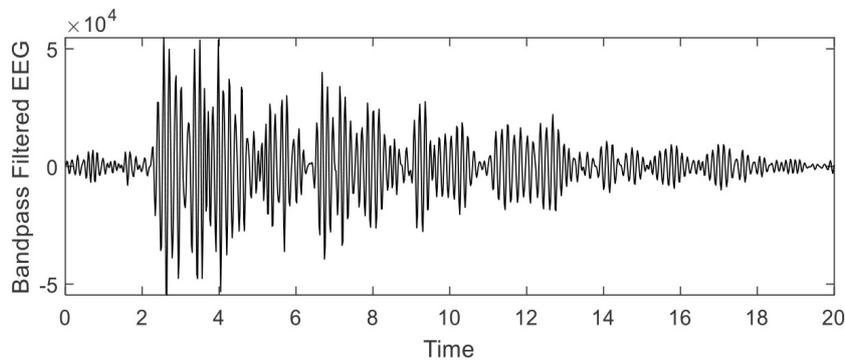


Figure 5: Bandpass filtered Electroencephalography (EEG) signal.

altered formats.

In this experiment, the free auditory fMRI dataset involves whole-brain BOLD/ Echo Planar Imaging (EPI) on an adjusted 2-tesla Siemens MAGNETOM vision system [36]. The experimental paradigm was alternated between two states as auditory stimulation “silence” and “talk”. When the raw fMRI data were successfully loaded, a new ‘info’ module was performed as seen in Figure 6. The ‘info’ module comprised the specifics of fMRI data:

- The dimension of data: the dimensionality of the data in X, Y, and Z dimensions as well as the whole number of fMRI slices designated as the whole brain.
- The total number of voxels: the whole number of voxels of the designated fMRI dataset.
- Analyzed voxels: the number of evaluating voxels after applying the threshold value.

Figure 7 shows a screen capture of the ICA user session for the fMRI dataset running under MATLAB. In fMRI, the ICA can examine for components associated with artifacts or blood flow dynamics. Thus, regions of interest (ROI) were first recognized. The separated data was reformatted as one dimension by stringing the image rows, or columns, from each slice.

The resultant data from each slice were organized as a single vector. The ICA was applied to the rearranged ensemble of slice vectors.

Therefore, each pixel was considered a different source, and each slice was an observation of that source.

If there are different intensity pixels in a non-random manner, this outputs one or more components in the analysis. The variable that records, such as the paradigm, is then used as a further accurate estimate of blood flow hemodynamics in the correlation analysis. The separated variable was used to assess the place of the paradigm.

Figure 7 shows the first three variables (components) from an independent component analysis applied to the ROI in Figure 3 representing the blood flow hemodynamics. A function was analogous to the paradigm shown in the first pattern. The second and third patterns show the artifacts, related to head motion or respiration.

Neurofunctional Tool Assessment

The neurofunctional tool was examined for validity and educational contributions and introduced to biomedical students and researchers as an efficient educational tool. The presented toolbox was evaluated at Al-Nahrain University, in which nearly 40 researchers and students were in the biomedical engineering department in both graduate and postgraduate studies.

The neurofunctional system was developed

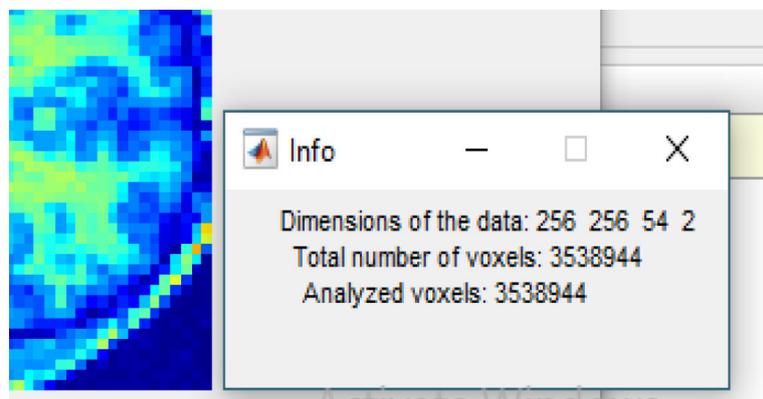


Figure 6: Example of the “info” window.

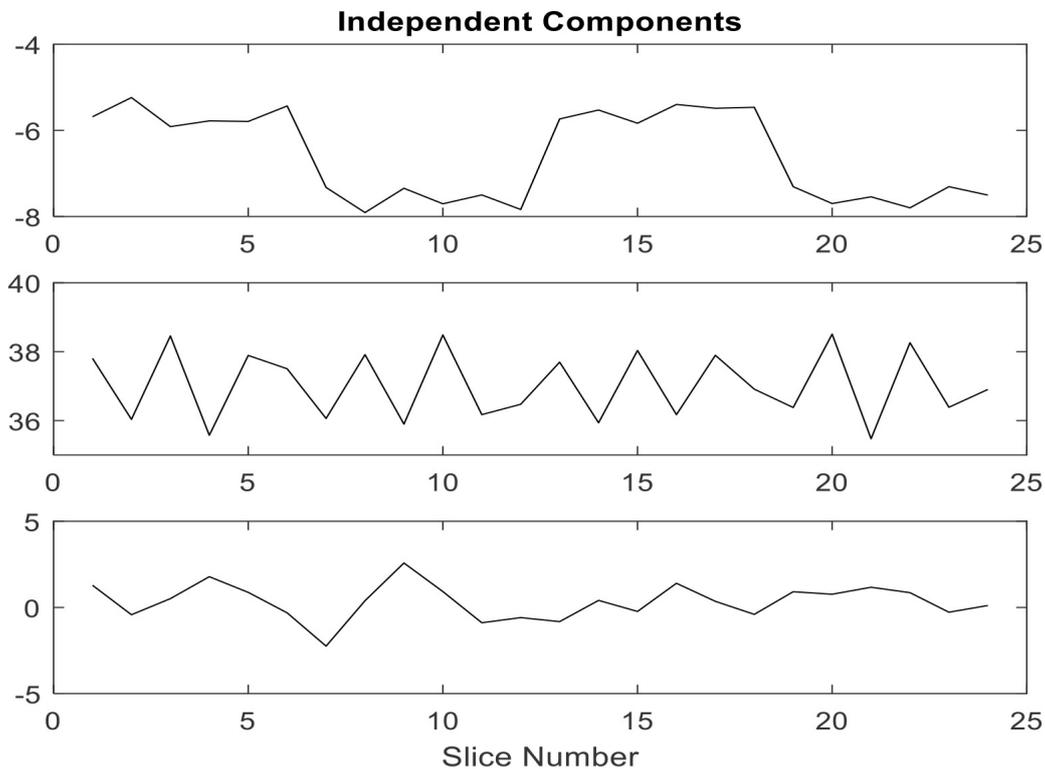


Figure 7: The first three variables from Independent Component Analysis (ICA) applied to functional Magnetic Resonance Imaging (fMRI) Region of Interest (ROI)

with an automatic window, including the evaluation form (Figure 8). The evaluation form included eight questions related to the efficiency and flexibility of the designed system. Five points (excellent=5, very good=4, good=3, fair=2, and very poor=1) were used as a scale to reflect how the participants evaluated this work. The statistical test answers were shown as the output results in Figure 9.

Discussion

The designed tool proposed a user-friendly graphical interface dealing with two of the most important functional signals, EEG, and fMRI. The ICA was modeled for the usage in the same package as the traditional biosignals analysis method.

All the presented packages in the literature dealt with either EEG or fMRI separately, and no package collected these two neurofunctional data in the same tool to analyze and compare

the output results. EEGLAB [28] processed EEG signals, while ELAN [29] processed EEG MEG and LFP signals in the same package. The REST [24], VCfMRI [26], SPM [31], and FSL [32] dealt with fMRI processing, the FSL used melodic ICA with fMRI analysis.

The presented package introduced a simple analysis of the EEG and fMRI using ICA in the same window. The proposed work was presented as part of the biomedical engineering instrumentation course; thus, it can be available for students or researchers using only a standalone application or executable file (.exe file) without installing the MATLAB platform.

In sum, the proposed functional toolbox provides the ability to deal with the available datasets efficiently. Also, the user could select the preferred portions of the functional biosignal, process, and analysis of the neurofunctional dataset using the standard ICA method. Finally, the results could be saved and visual-

Evaluation Form

Student ID

Question 1
Neurofunctional tool is easy to use
 Excellent Very good Good Fair Poor

Question 2
Tool is flexible & reliable
 Excellent Very good Good Fair Poor

Question 3
The extent of Neurofunctional impact to practical applications in the LAB
 Excellent Very good Good Fair Poor

Question 4
The extent of Neurofunctional tool meet the requirements of online learning
 Excellent Very good Good Fair Poor

Question 5
Skills & features you learned using Neurofunctional system
 Excellent Very good Good Fair Poor

Question 6
Response time of Neurofunctional system
 Excellent Very good Good Fair Poor

Question 7
How would you score the Neurofunctional system?
 Excellent Very good Good Fair Poor

Question 8
The structure of the Neurofunctional system is adaptable and appropriate for designing different tools based on biomedical applications
 Excellent Very good Good Fair Poor

Figure 8: Evaluation form

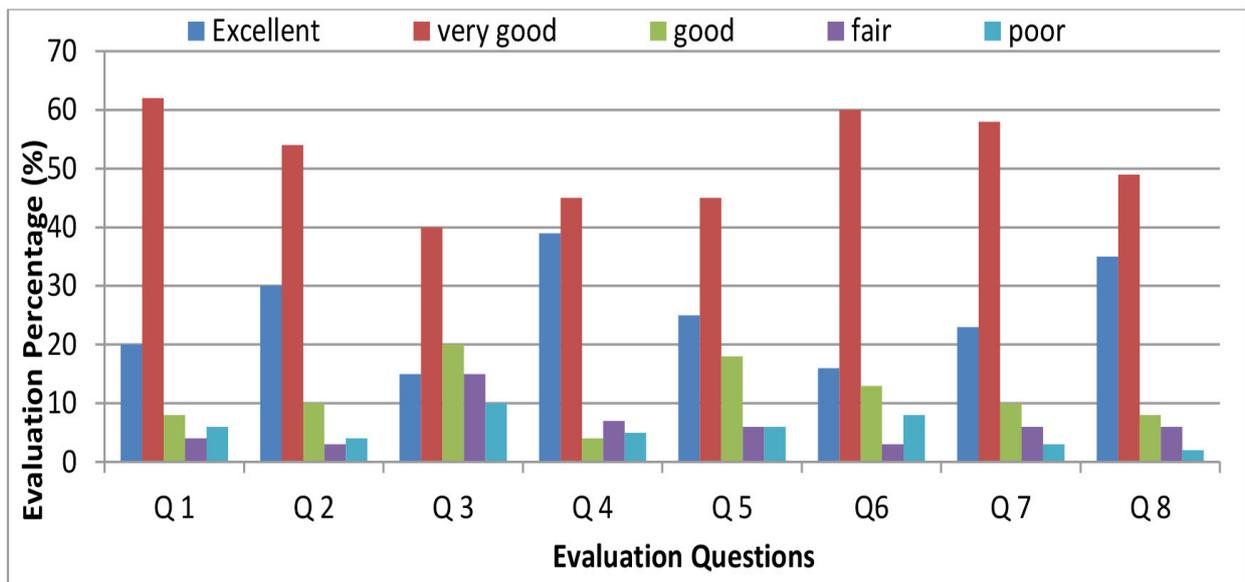


Figure 9: Test answers results

ized using plots only.

Conclusion

The presented graphical user interface tool can be used as a demonstration software package for programmers and engineers. Physicians and healthcare specialists can easily compare the functional results. The proposed tool can process and analyze EEG and fMRI datasets by 1) loading the raw EEG dataset, 2) preprocessing EEG signal by removing the artifacts, filtering, epoch selection, and averaging, 3) analyzing and processing EEG data using ICA to extract the most critical features of the EEG signal, 4) loading the raw fMRI data with .nii or .img and .hdr format, and watching images, such as slices of a brain or the whole brain as well as active areas detected in the brain, 5) fMRI preprocessing by calling the SPM package within the considered tool, 6) observing the loaded fMRI data as image slices by selecting many slices; thus, this package provides the capability of selection, which the number of slices can display the active zones in the definite region, and 7) analyzing and processing fMRI data using ICA to examine the components related to artifacts or task-related.

In sum, the users can import, select, process, and analysis the functional datasets using the ICA method, and save and visualize all the results using plots.

The proposed work is important in Iraq and neighboring countries due to a shortage in using the GUI for biomedical applications for researchers and educational laboratory purposes.

Ethical Approval

This study was conducted according to the approval of the research ethics committee of the Biomedical Engineering of Al-Nahrain University (02/ 2020).

Conflict of Interest

None

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