A Graphical User Interface for EEG Analysis and Classification

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ABSTRACT: The Electroencephalogram (EEG) data measured from the human scalp represent a vital and non-invasive tool in many psychological and medical applications. This data can be concurrently recorded over tens of brain channels for extended periodsand for many participants. As a result, the resultant volume of the data acquired is large and require not only a significant storage area on the computer hard drive but analysing such amount of data to extracting useful information is painful as well. In this paper, we have developed a graphical user interface (GUI) to facilitate the preparation and analysis of the EEG data measured through the oddball test and for several participants. The design includes signal loading and preparation, signal classification and wavelet analysis. Results are displayed in detail in both numbers and figures. The designed GUI represents a significant approach in analysing any selected EEG by channel, trial or participant with the desired parameters and the targeted method of analysis. The analysis outcome can be performed easily and quickly. For one participant, when training both the LDA and the wavelet classifiers, in the LDA we obtained a sensitivity equal 57.448 and specificity 56.22 whereas in the wavelet classifier (coiflet1 filter), the sensitivity is 55.19 and specificity is 55.34. Here the LDA classifier gave better results.

KEYWORDS: Classification, EEG, ERP, GUI, Statistical analysis.

I. INTRODUCTION

Electroencephalogram (EEG) and Evoked Related Potential (ERP) signals are very weak potential recording from the scalp generated by the brain [1]. Their frequencies are in the range 0.5-100 Hz and their amplitudes can goes up to 100µV [2]. It gives a millisecond resolution of information for the study of human cognition states depending on the selection of the appropriate brain channels that reflect the cognition processes being studied. In most of the cases extracting useful information from the EEG require a conversion process on these signals to another useful form. The EEG is the normal measurement of these signals whereas the ERP is the measurement of these signals under an external stimulus such as the oddball test. The purpose of the stimulus is to extract important components (for example the P300) from the EEG when the participant attention raise suddenly. The first 1000ms of the EEG measured under stimulus contains the expected ERP components since the reaction of the participants starts in 300ms post stimulus. The P300 arise 300-600ms post stimulus [3]. Fig. 1 illustrates the EEG recording procedure with further processing towards ERP extraction and signal analysis.

The EEG is concurrently measured from tens of brain channels such as 64 or 128 for the same participant and for hundreds of trials in case of extracting the ERP components. As a result, the amount of data recorded is large and extracting a useful information from such amount of data is hopeless. Data needs to be sorted by participants, by channels and by trials as well. Single EEG trials need to be inspected by eye and unsuccessful trials (happen due to eye or muscle movement) should be excluded from the group of data [4].

In this paper, we have presented a Graphical User Interface (GUI) that can load and prepare the EEG for further analysis including the extraction of useful information from the huge amount of EEG data recorded and display the results in numbers and different sort of graphs. Our design is built on the available EEGLAB tool for EEG analysis and it adds statistics essential for these analyses. Our GUI toolbox simplifies EEG analysis for novice and experienced users.
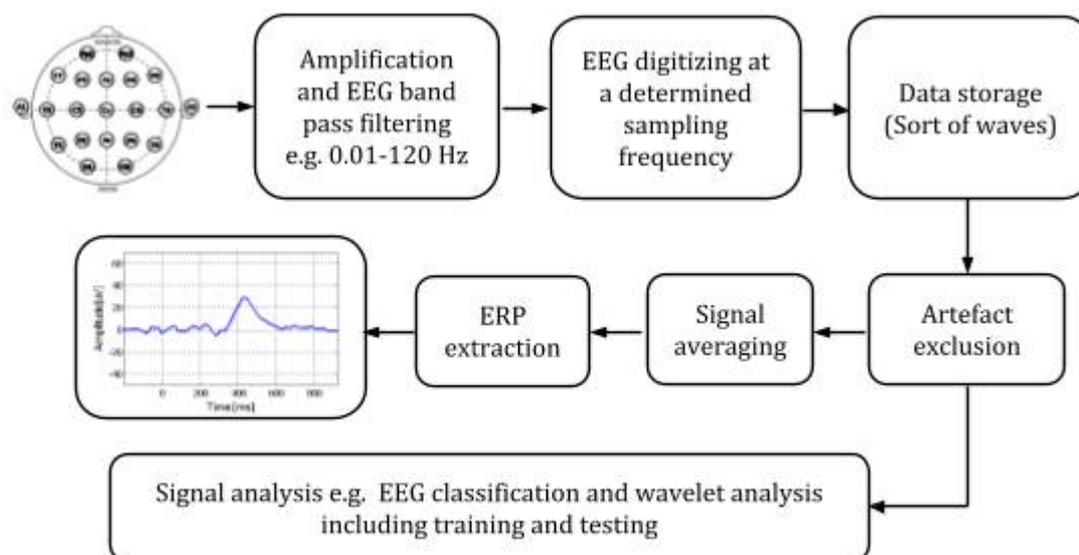
Fig. 1. In General, the EEG Recording Procedure with Further Processing Towards ERP Extraction and Signal Analysis

II. LITERATURE SURVEY

In [5] authors had developed a GUI for EEG recording during Transcranial Magnetic Stimulation (TMS). Their concerns were to develop a standard method to recover the TMS evoked potentials that often masked by the artifacts since the EEG is highly sensitive to artifacts. Another EEG based GUI is spotted in [6], the purpose of this GUI program is to enable the users to observe changes in brain neuro activity when compared to a previously defined electrographic state and behavioral. The procedures of the study was experienced on live animals. EEG Events were detected using the Short Time Fourier Transform (STFT), which show a short time epochs of the EEG. After 10 minutes of EEG recording and injection of pentylenetetrazol, the authors' spotted two high-amplitude bursts near 4 and 7 min. The two bursts were seizure events. In [7], a more complex GUI program was developed and called the SPM8. The design was built to perform in addition to the standard EEG preprocessing, three analysis tools. The first is the scalp-maps statistical analysis, EEG images in the time-frequency domain and the general linear model to reconstruct 3D source images. The authors employed the random field theory to correct the reconstructed images for multiple comparisons. The second tool was the Bayesian M/EEG source reconstruction with support to group analysis and simulation of EEG. The third analysis tool was the dynamic causal modelling (DCM) as a method that combine data analysis with neural modelling.

III. PROPOSED METHODOLOGY AND DISCUSSION

A. EEG recording

The EEG epochs were recorded through the oddball test according to the 10/20 international system and from 32-electrode cap. Data were collected from 19 participants. The Griffith University ethics number for human research was (PSY/92/09/HREC).

B. Algorithms Presented

In our GUI design, the EEG passes through optional pre-analysis steps including down sampling and EEG truncation. The down sampling reduces the number of EEG samples for faster analysis whereas the truncation keeps the first 1000ms of data. Further recording of the EEG is not necessary in ERP recordings since presenting the stimulus,

take a reaction to that stimulus are all happen in the first 1000ms of the recording. The classification algorithms employed are the Linear Discriminant Analysis (LDA) under the Fischer classification algorithm and the Wavelet Analysis (WA). The LDA is an approach used to find a linear combination of features that characterizes or separates two or more EEG epochs [8].

1.   LDA classifier
In brief, The LDA for two sets of data is firstly to compute the mean of entire data set as follows:

$$\mu_3 = \rho_1 \times \mu_1 + \rho_2 \times \mu_2 \qquad\qquad \text{eq.   (1)}$$

Where μ_1 and μ_2 are the mean of each data set and μ_3 is the mean of the entire data. ρ_1 and ρ_2 are the apriori probabilities of the classes, it assumed to be 0.5. Then the scatter measures computed as in equations (2) and (3):

$$S_w = \sum_j P_j \times (cov_j) \qquad\qquad \text{eq.   (2)}$$

For the two-class problem:

$$S_w = 0.5 \times cov_1 + 0.5 \times cov_2 \qquad\qquad \text{eq.   (3)}$$

The next step is to calculate the covariance matrices and the between-class scatter formula ending with finding the Euclidean distance, where the smallest Euclidean distance among *n* distances classifies the test vector as belonging to class *n*.

2.   DWT Classifier
The DWT is a powerful signal processing analysis tool. The key advantage of the wavelet transform is the ability to adapt to features in the spatial domain. Example of such features are the varying behaviour of frequency and signal discontinuities. The localization of wavelets allows processing the data in a region without affecting other data outside this region [9]. In this paper, 60% of data are selected to training the classifier and 40% for the real classification (testing).

IV. THE EEG GUI AND EXPERIMENTAL RESULTS

The EEG GUI is developed with MATLAB programming language for EEG presentation and statistical analysis: LDA classification and the discrete wavelet transform. It can be seen in Fig. 2.
It can be noticed from Fig.2 that the GUI contains several blocks of push buttons, static text, edit text, axes blocks and popup menus. The blocks are sorted into group in order to perform a specific task per group. The following explain the operation of our GUI:
Load the data by pressing LOAD DATA button then set the path of the provided data. The data will be loaded in a few seconds and the indicator "data?" changes to "data loaded" as shown in the figure. The next step is to down sample the EEG epoch to one of the available options: 32, 64 or 128 sample/sec according to the blue popup menu "sample rate" then pressing the "downsampling" button. The selected sampling rate will appear in the blue static text block. The "down conversion" step is optional to the user.Data truncation is another optional pre-analysis step in which the first 1000ms only is kept from the whole EEG epoch of 1536ms. The data truncation process is optional as well and the data can be restored to its original length as the user wish. Now the user can start plotting the EEG, use the LDA classifier, the wavelet panel, or do a comprehensive analysis. These are all explained in detail.
In the "sample EEG plot" panel, the user is able to see the EEG signal by selecting the participant (1-19), one of the scalp channels (F3,Fz, F4, C3, Cz, C4, P3, Pz, P9) and the trial number (1-295). By pressing the "plot orig data", the whole EEG epoch is plotted. There is an option to plot down sampled data or truncated data as well. It can be noticed

that two yellow buttons are presented in the GUI. These are used to save settings of parameters in order to repeat analysis later by pressing "save settings" and then "Restore".
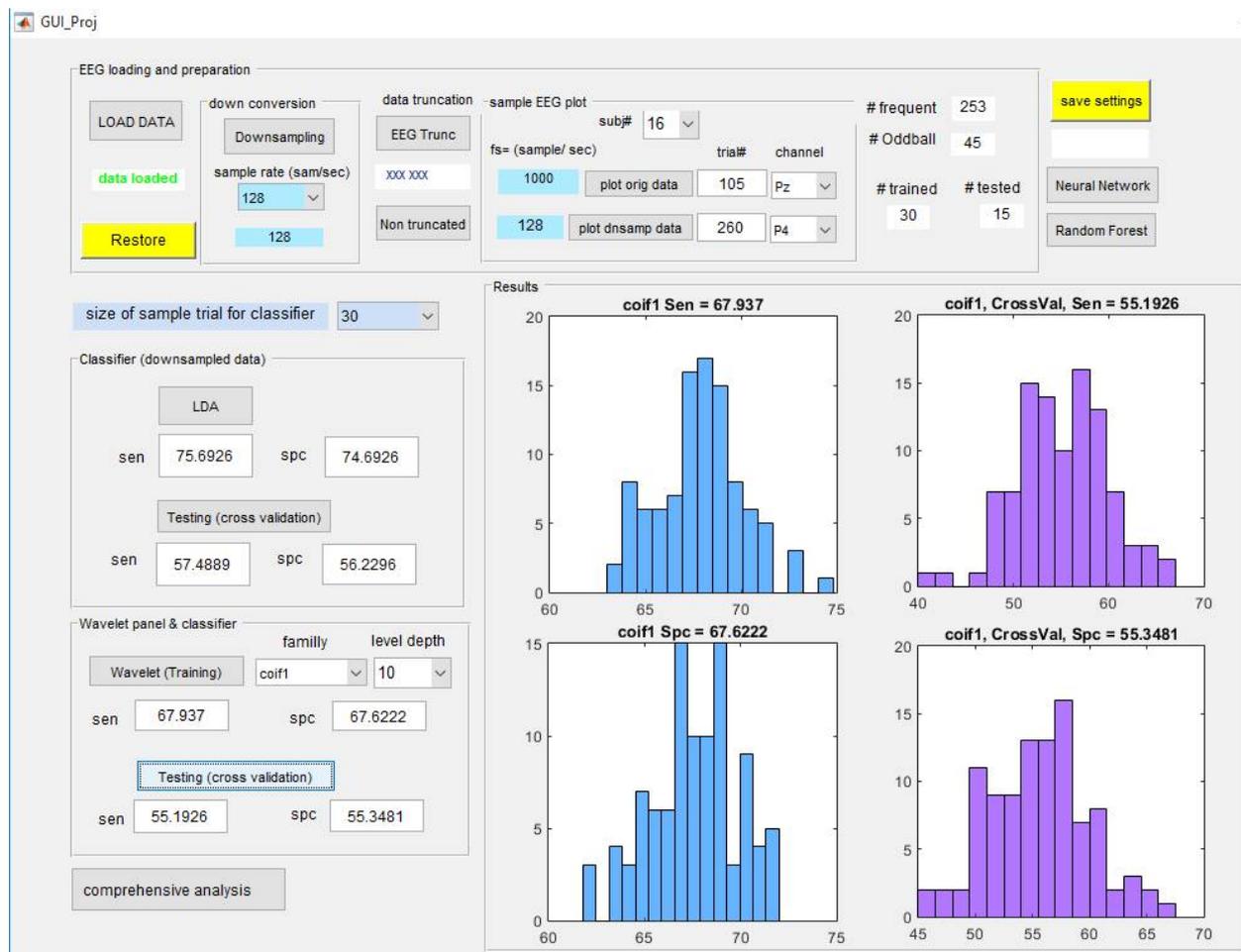

Fig.2: The EEG GUI Developed for EEG Presentation and Statistical Analysis

Linear Discriminant Analysis (LDA) button: the LDA require down sampling first otherwise a warning message appear advising to down sample the data. The EEG sensitivity and specificity are calculated under Fischer classification algorithm for a specific participant and results appeared in the allocated static box. Participant selection is done first, and then a sample trial of 20, 30, or 35 is need to be selected before data training. The histograms will appear on the axes blocks for trained data.Data testing is performed as a random selection on the rest of oddball trials for the same participant and on same random frequent trials (not used in the training step). The histogram of tested data is shown after pressing the button (Testing (cross validation)).

Discrete Wavelet Transform analysis: selecting a specific wavelet filter from the "family" popup menu and the depth of analysis from the "level depth" popup menu to perform the wavelet classification on the same participant and same sample trial. The histograms will appear as in the LDA on the same axes. The testing (cross validation) step is also available for untrained data.
The four indicators: #frequent, #oddball, #trained and #tested, show the total frequent trials, total oddballs, number of trained epochs and number of tested epochs respectively. When selection moves to another participant, those four

indicators show '-', where the new calculations appear as soon as classification started. In total, there are 8 indicators to show the sensitivity and specificity for the LDA and wavelet on trained and tested epochs.

The function of the "comprehensive button" is to combine both the LDA and the wavelet calculations in one press and save the results of SEN and SPC in the current folder measured at specific parameters. Two files will be generated exp.txt and exp2.txt. Those files contains the LDA and wavelet analysis for all participants including participant number and titles. However, only numbers are included in the files. The format of the contents is the same when the file is opened outside MATLAB. This helps using the file with another software package such as SPSS.

The following results is an example of the designed GUI, as in Fig. 2, 30 samples of data are used for the classifier, then a new 30 samples are tested for the cross validation. For participant 16, and after training both the LDA and the wavelet classifiers, in the LDA we obtained a sensitivity equal 57.448 and specificity 56.22 whereas in the wavelet classifier (coiflet1 filter), the sensitivity is 55.19 and specificity is 55.34. Here the LDA classifier gave better results.

V. CONCLUSION AND FUTURE WORK

This paper has presented a formal EEG GUI that include various EEG analysis and presentation tools. This GUI offer many options to the user for preparing the EEG samples required to perform the nominated task. From the classification tools included, the LDA classification sensitivity and specificity for both trained and tested data were clearly presented and it shows better classification results presented than the wavelet classifications. However, wavelet classifications depend in addition to the participants selected, to the wavelet filter family as well. Future trends will develop this GUI further adding additional classification tools such as neural network and random forest. The buttons are already prepared for these powerful tools as shown in Fig. 2.

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