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Pre-processing Tool for EEG Signal Visualization

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Abstract: ***Electroencephalograph (EEG) -based studies that involve human subjects need a continuous monitoring of subject's state for a good data acquisition and research outcome. This paper presents a tool based on frequency domain features for EEG signals visualization. There are some acquisition softwares available but those come with the costly EEG amplifiers. Proposed method focusses on the enhanced presentation of the signal by a visualization tool. Change in frequency-domain features presents the change in state of the subject. Based on the variation in frequency band powers; algorithm displays the change in subject state data with different color codes using time and feature window. Segment length can be changed with user input and according to the prerequisite. Present work uses EEG data set obtained from UCI machine learning repository for evaluating algorithm.The tool is helpful in monitoring the subjects' state during data acquisition to maintain the quality of data acquired.***

Keywords: EEG features, Segmentation, Signal visualization

1. Introduction

Electroencephalography (EEG) is a common method used in cognitive neuroscience and other brain related research areas. These studies comprise a dense electrode system with the huge size of the acquired data which is difficult to handle. A standalone data visualization tool can work as a support system that performs pre-processing and provides visualization of the signal. The proposed method works as a pre-processing tool for EEG signal visualization that assigns the color coded labels to the signal based on its spectral properties. Algorithm takes a time window of 0.5 seconds successively without overlap to form a feature matrix and labels the signal with respect to corresponding feature matrix. This algorithm can be an aid to pre-process and visualize these epochs when subject's mental state shall be monitored during cognitive experiment or data recording.

Literature suggests various constant and adaptive segmentation methods depending upon the segment characteristics. Amplitude, slope, deflection width, standard deviation, variable threshold, fractal dimension, statistical characteristics are some of the features used in segmentation along with other time-frequency features[1][2][3]. EEG signal segmentation for signals obtained from rodent brains during injury and after recovery uses wavelet entropy feature [4]. Some suggested segmentation algorithms also find the variation in selected bands[5][6].

Many algorithms such as Genetic algorithm or Savitzky-Golay filter used Varri's famous method several times for segmentation. Varri's method utilize amplitude and frequency to find boundaries of the segment. Genetic algorithm uses Varri's method to determine the signal parameters[7]. Savitzky-Golay filter uses Varri's method to amend the signal parameter to get good segmentation results [8]. Another common approach for segmentation is the Equipartition principle that selects the segments based on their reconstruction errors but takes time when applied to long length signal.

Many applications use recursive band-pass filter, least mean square and auto-regressive models based adaptive algorithm to find signal features and events. Adaptive recursive band-pass filter based method estimates the filter coefficients to find the center frequency corresponding to each EEG wave[9]. Energy optimization and adaptive auto-regressive models are other methods to detect the events[10][11]. Markov model based segmentation method uses the least mean square adaptive algorithm to compute the coefficient of the model for segmentation[12]. Another suggested approach is rule based segmentation that compares the use of single and multiple features for the segmentation purpose[13].

Signal Segmentation is an important step in signal processing that serves many applications like Killer whale vocalization application that uses the Hilbert-Huang transform for segmentation of the desired signal[14]. Another application applies Hilbert transform to segment the neonatal physiological signals to estimate instantaneous respiration rate. Applications involving motor imagery task use reactive band identification method to identify subject specific band [15]. Other applications may include signal segmentation in the cognitive task, seizure and Brain-computer interface. In this paper, we segment the signal based on spectral features to estimate or visualize the change in state of mind. Further classification using the same spectral features, presents an extension to this work.

2. Material and Method

The proposed algorithm can perform segmentation using simpler features and minimum computational demands. The proposed scheme is different in various aspects as compared to other methods suggested in the literature. This scheme proposes an effective and economic visualization tool for EEG signals analysis and presentation. Algorithm utilizes the band powers of the EEG signal that vary with the cognitive state of the subjects and in accordance with the task offered to the subject. Figure 1 shows the detailed approach followed.

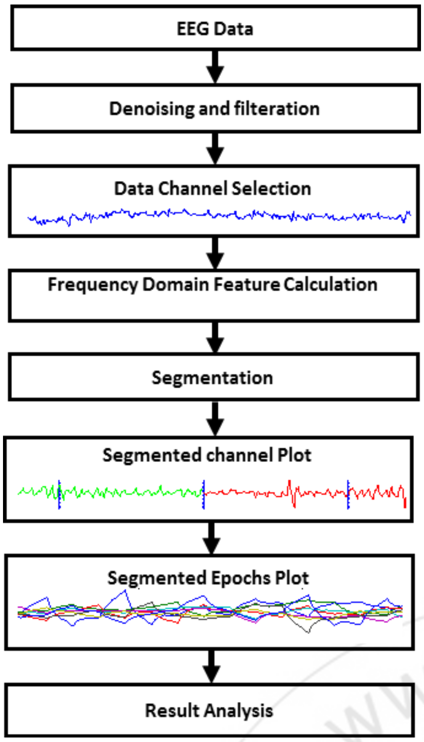

Figure 1: Methodology followed

2.1 Pre-processing

The current study uses the two datasets including EEG dataset and a synthetic signal. EEG data set is obtained from UCI machine learning repository to demonstrate the performance of the tool. The data set is of alcoholic and control subjects performing delayed matching task with three task conditions. The three task conditions comprise of displaying the images of single objects, successively matching objects and successively non-matching objects offering different cognitive load to the two classes of the subjects. Notch filter removes the power line interference at 50Hz frequency. Butterworth band pass filter performs the initial filtering in the range of 0.1-45 Hz. ICA-based blind source separation method removes the Muscle and Eye blink related artifacts and Wavelet-PCA based de-noising procedure ensure the advanced filtering.Another data includes a synthetic signal of sampling frequency 512 Hz with eight different frequencies generated in MATLAB.

2.1.1 Channel Selection

The tool provides a user interface for selecting the desired channel to visualize. Designed interface consists of a dialogue to enter the file name with the complete file path. And another dialogue appears for the channel number selection. Figure 2 shows the snapshots of the dialogue box.

2.1.2 Feature Calculation

Figure 2: Dialogue window for (a) data file name selection (b) channel number selection for visualization

Proposed EEG signal segmentation method uses the frequency domain features having low computational demand. Band power is an essential feature holding a significance and direct correlation with the state of mind of subject as mentioned in the literature[16]. Visualization of the band power variation showcases subject's state and accuracy during data acquisition in online as well as offline processing. There are five generalized EEG frequency bands commonly known as delta, theta, alpha, beta and gamma. Delta band denotes the deep sleep stage, Theta band gives the drowsy state of the brain that may be during meditation or sleep, Alpha frequency shows the wakefulness but relaxing state and Beta frequency represents the conscious state.
The frequency range of these bands may vary in different research applications. Table 1 shows the selected band range.

Table 1: Selected Frequency bands

EEG Frequencies	Frequencies (Hz)
Delta	0.1-3
Theta	4-7
Alpha	8-15
Beta	16-30
Gamma	31-45

Spectral features mentioned in the paper have their own significance related to the mental state of human subjects. Low frequencies generally relate to the state of drowsiness and higher frequency band powers show the state of mental activity or cognitive activity. This is about the general band power scenario, but in neuro-cognitive research, there exist results that contradict each other due to task condition and state of the subject involved. For example, alpha power is more when the subject is at rest with closed eyes and reduces as soon as subject opens his eyes. While some other studies show alpha power increase as subject processes irrelevant task. Considering another example of theta band; the lower theta power is correlated with drowsiness while upper theta power shows the cognitive performance. U. Melia et.al discusses the use of EEG features to correlate the two type of subjects with excessive daytime sleepiness and without daytime sleepiness subjects using delta band power, theta band power and mutual information features [17]. They characterize these subjects using EEG features. In another study author talks about anesthesia depth analysis which is a difficult measurement to perform[18]. Literature related to anesthesia depth analysis discusses various features of time, frequency, time-frequency, wavelet and bispectral domain that are being related to anesthesia depth or sedation.

The pattern of change in these features always exists that vary with the task condition given and subject involved. It is up to the researcher to make the interpretations based on visualization by means of the frequency variation and task condition given.

2.2 Methodology

Purposed segmentation algorithm follows the steps mentioned below:

1) Provides the dialogue for data file selection and data channel selection.
2) Performs the signal filtering.

3) Determines the frequency-domain features.

Power spectral density (PSD) represents the power distribution over different frequencies. There are two types of methods, i.e. non-parametric and parametric for PSD calculation. Non-parametric methods are used for signals like EEG, where very less is known about the signal ahead. These non-parametric methods can be further classified into two categories, one is the periodogram (direct methods) and correlogram (indirect methods). FFT based traditional method follows the approach as discussed below.

Let a data x(n) of finite length N, the Fourier transform of the data sequence x(n) is X(f) having length N:

$$X(f) = \sum_{n=1}^{N} x(n).e^{(-2*pi*(f-1)*(n-1)/N)} \quad (1)$$

Where 1 <= f <= N
Fourier transform multiplies to its conjugate to calculate the Power spectral density.

$$\mathrm{S(k)} = \left(\mathrm{X(k)} * \mathrm{Conjugate\ X(k)}\right) \quad (2)$$

Power spectral density from equation 2 represents the power distribution over different frequencies in the range of 0.1-45Hz. Features can be calculated using equation 2 for the selected frequency bands as shown in table 1.
FFT based methods show error in estimating power, which might cause a problem in classifying different frequency bands. Result evaluation section discusses this issue and presents the error in the calculation of band powers.

(4) Assigns value to the two segmentation windows i.e. time and feature window.

Algorithm uses two segmentation windows; time window and the feature window. Time window provides the time scale for segmentation while feature window assigns the segment labels to the data based on maximum selection rule.

$$\text{Feature Window} = \begin{bmatrix} \vdots \end{bmatrix} 5*1 \text{ for 1 second} \quad (3)$$

$$\text{Time Window} = [\quad \cdots \quad] 1*256 \text{ for 1 second} \quad (4)$$

(5) Performs segmentation.
Feature and time window computes the segment and displays the segmented data with different color codes. Algorithm works frame by frame on the data set and not on the full data instantly. This characteristic of the tool gives a clue about its use in the real-time analysis as well.

The next section discusses the results obtained with synthetic and real EEG signal using the proposed method and compare the results obtained using the FFT-based method.

3. Results

3.1. Evaluation using synthetic signal

This section presents a comparative analysis to validate the usability of signal band power features for EEG signal segmentation using two different approaches. As mentioned earlier, these features present the spectral changes in the signal, which is quite useful to observe the changes in the mental state of the subject over time. Detailed analysis requires more sophisticated features, but present work concerns the spectral changes for signal visualization. Evaluation process uses a synthetic signal to explain the results in another way.

Let us generate an eight-second signal x with 512 Hz sampling frequency. Signal consists of eight different frequencies 4, 8, 12, 16, 20, 24, 28 and 32 Hz. In this synthetic signal 4 Hz represents the theta, 8, 12 Hz represents the alpha, 16, 20, 24, 28 Hz represents the beta and 32 Hz represents the gamma as given in table 1. Figure 3 present the peaks detected for different frequencies.

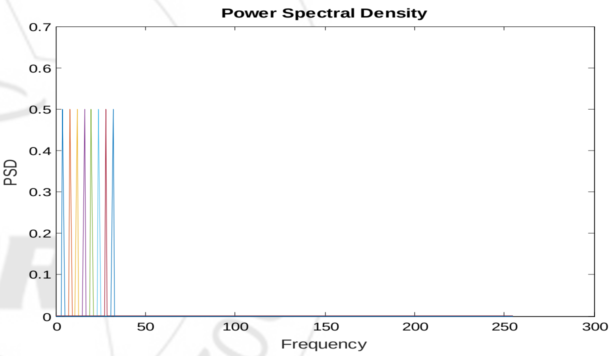

Figure 3: One sided Power spectral density for the synthetic signal.

Quantitative evaluation presents the calculated error in power estimation by the FFT-based method. The next step compares the exact and the estimated power to measure the estimation error in the power calculation. Table 2 presents the percentage error calculated. The result shows a decent accuracy obtained in calculating power and hence it voids the possibility of selecting a frequency dubiously.

Table 2: Calculation of power estimation error

Epoch Sequence Given	*Exact Power*	*Absolute Observed Powers*					*Power estimation error (%)*
		Delta	Theta	Alpha	Beta	Gamma	
epoch 1-theta	0.5	0.0919	**0.5001**	0	0	0	0.02
epoch 2-alpha	0.5	0	0.1226	**0.4998**	0	0	0.04
epoch 3-alpha	0.5	0	0.0001	**0.4998**	0.0001	0	0.04
epoch 4-beta	0.5	0	0.0001	0.1964	**0.4981**	0	0.38
epoch 5-beta	0.5	0	0	0.0002	**0.4998**	0	0.04
epoch 6-beta	0.5	0	0	0.0001	**0.4999**	0.0001	0.02
epoch 7-beta	0.5	0	0	0	**0.4999**	0.0001	0.02
epoch 8-gamma	0.5	0	0	0	0.0225	**0.4999**	0.02

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Figure 4 displays the results obtained with the proposed algorithm for the synthetic signal. The result shows the eight frequencies corresponding to the frequency bands given in table 1.

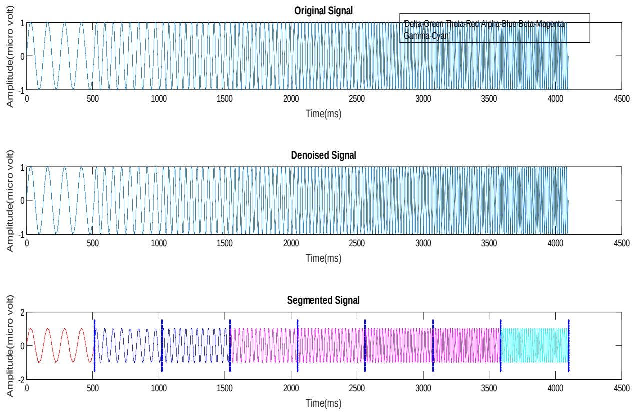
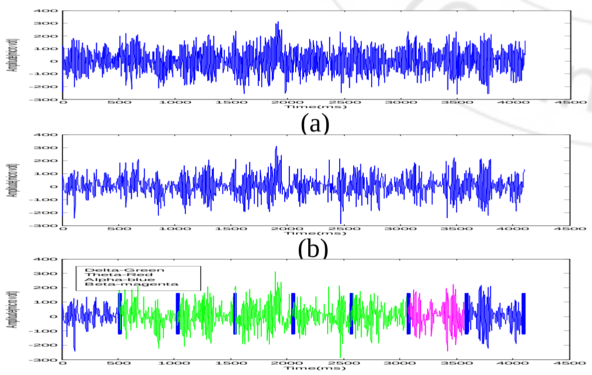


Figure 4: Algorithm evaluation using the synthetic signal. (Top) Original signal (Middle) denoised signal (Bottom) Segmented signal.

3.2 Evaluation using real EEG

This section presents the resultant visualization given by the tool; Figure 2 shows the snapshot of the tool. Dialogue box prompts for the file name selection and channel number selection. Algorithm performs the segmentation by taking 0.5 seconds segment however the user can select the length of the segment depending on the study under consideration. In EEG signal processing, the length of the signal segment or epoch considered has a great importance and is the reason that option of selecting epoch or segment length has been considered. Figure 5 shows the resultant segmented waveform with different color codes representing the different frequency bands for EEG data set of four seconds. In this way, the length of the signal represents the frequency variation over specified time segments



(c)

Figure 5: Algorithm evaluation using real EEG signal. (a) Original EEG signal (b) denoised EEG signal (c) Segmented EEG signal

4. Conclusion

This work presents a small standalone application for signal presentation and visualization based on spectral features. The assumption for the algorithm is that spectral features hold a correlation with the mental state of a person and resultant waveform presents the change in subject's state. Figure 4 and 5 show the output of the algorithm displaying the distribution of band powers over time scale. This visualization can assist in the data acquisition and data preprocessing and, hence saves time. This tool can assist in detecting the drowsiness over the time period of recording.

Algorithm works sequentially over segments using the time window; this feature presents a future perspective to make a real-time visualization tool. In future, we will try to make a robust application with other added features like multiple channel selection and automatic scaling.

5. Acknowledgement

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6. Conflict of interest

The authors have no conflict of interest to declare.

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