

Analysis of P300 detection with different configuration electrodes based on offline dataset

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ABSTRACT

Brain-Computer Interfaces (BCI) uses electroencephalography (EEG) signals recorded from the brain scalp to create a communication channel for the tetraplegia patient, between the brain and an output device by bypassing the conventional motor output path of spinal cord, nerves and muscles. The simulated experimental results in MATLAB for a given data set, shows that the implementation of the proposed algorithm achieves a very significant statistical accuracy in extracting and classifying P300 components. Most participants can learn to extract and classify the P300 wave with greater than 80% accuracy. One of the most important components of BCI for better accuracy is feature extraction of EEG signals. For which we used mean, variance Welch's power spectrum density and wavelet packet transform. Applying neural network classifier to the obtained feature vector gives maximum classification accuracy up to 93.5%.

KEY WORDS: Brain Computer Interface BCI, Electroencephalograph EEG, Wavelet packet Transform WPT, Neural Networks NN.

1. INTRODUCTION

Electroencephalograph (EEG) was recorded for the first time by Berger in 1929 by externally attaching several electrodes on the human scalp (David Millet, 2002). EEG is a technique used for recording the brain's electrical potentials, which are used to study the dynamics of neural information processing in the brain, and diagnose cognitive processes and brain disorders. Large data of EEG signal are obtained and it is not possible to analyze EEG recordings visually (Ubeyli, 2009). Therefore, there is a strong demand to extract information from EEG data for the proper evaluation, classification to understand the cognitive processes. The steps involved in the process of extracting relevant information from EEG data include signal acquisition, preprocessing, feature extraction and classification (Orhan, 2011). Extracting relevant feature vector is among the most significant steps for EEG data classification, because it has a direct impact on the systems classification performance (Iscan, 2011). If the extracted features are not expressive for a problem, then the classification performance will not be satisfactory. Even if the classification method is highly optimal for the problem but due to inadequate features, the algorithm may not provide good classification results. So, extracting suitable features from EEG recordings is mandatory to get high classification performance. Recently, a multi-disciplinary area—brain computer interface (BCI), involving researchers from, mathematics and neuroscience, neuropsychology, engineering, computer science, gained a lot of interest as it has the power and potential to provide control capabilities of limbs and communication to physically disabled subject with any motor movements (Wolpaw, 2002). In other words, it takes the brain signals using electrodes placed on head scalp to communicate with the external devices. Most of the research in BCI has been performed using electroencephalogram (EEG) signals. A good practical implementation of the BCI system require an efficient brain signal processing scheme that could filter the noises to extract features and perform classification with less computational time (Liang, 2006). Several methods have been proposed for feature extraction, which include time domain, frequency domain, and wavelet packet transform based features (Iscan, 2011). However, WT-based analysis is effective, because it deals better with non-stationary behavior of EEG recordings than other methods. Wavelet-based features, includes wavelet entropy (Rosso, 2001), Energy, Variance, Waveform Length. Details on the time domain, frequency domain and wavelet packet transform-based techniques and neural network classifier employed in EEG data classification for the offline analysis of cognitive tasks are provided in the Methodology section and the classification accuracy of these techniques are provided in the results section. The paper is structured as follows: "Methodology" section gives insight on signal acquisition, preprocessing, feature extraction and classification algorithm used. "Experimental results" section presents the results, and "Conclusion" section concludes the paper.

2. METHODOLOGY

Figure 1 illustrates that EEG signals are recorded and preprocessed using various preprocessing algorithm then features are extracted using feature extraction algorithm and finally those features are classified using neural network classifier.

Signal Acquisition: The dataset used for simulating are downloaded from the following website http://mmspg.epfl.ch/BCI_datasets. Aggregation techniques were applied on a population of five disabled and four able-bodied subjects for dataset (Hoffmann, 2007). The data was recorded from 32 electrodes placed at the standard positions of the 10-20 international system as in (Sharbrough, 1991) and from two mastoid electrode with sampling rate of 2048 Hz. The paradigm here consists of six images shown in Fig. 2, placed in 3 × 2 order. Each image is

flashed in random sequences. Data for each subject consists of four sessions taking at different interval. Each session consists of six runs taking for a period of 1 minute. Each runs consisted of 22.5 blocks in average. Each block consists of 22.5 target trials and 112.5 non-target trials. Each image is intensified for 100 ms, and inter stimulus interval (ISI) was 400 ms. However, Data for subject 5 (disabled) are not included in Table 1. It was not clear if the subject understood the instructions given by the speech therapist before the experiments. The level of alertness of the subject fluctuated rapidly during experiments. Venkatraman (2011), to optimize the operating parameters for an diesel engine with different mode of alternative fuels.

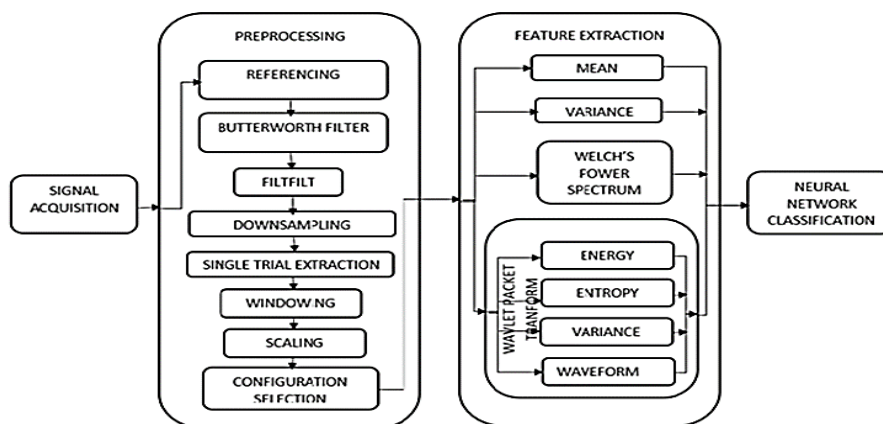


Figure.1.The architecture of the algorithm for P300 extraction

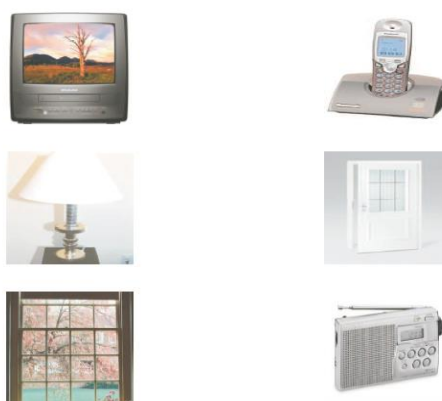


Figure.2.3 × 2 Single character paradigm

Preprocessing: Several preprocessing steps were applied to the data in the order stated below.

Referencing: The average signal of the two mastoid electrodes was used as reference for the electrode.

Filtering: A 2nd order forward-backward Butterworth filter was used to remove noise from the recording for zero phase distortion. Cut-off frequencies for band pass were set to 1.0 Hz and 15.0 Hz (Laurent Bougrain, 2012). The MATLAB function *butter* is used to compute the filter coefficients and the function *filtfilt* was used for filtering.

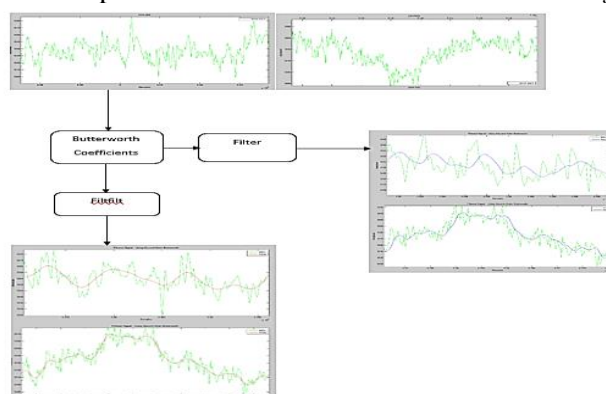


Figure.3.Raw EEG signal plot(Top), Block diagram for Filter(Center), filtered output graph using filtfilt and filter function.

Down sampling: The recording was down sampled from 2048 Hz to 32 Hz by selecting each 64th sample from the band pass filtered data.

Single Trial Extraction: From the data, Single trials of duration 1000 ms are extracted. It starts at the beginning of the intensification of an image, and ended 1000 ms after stimulus onset. Since ISI is 400 ms, the last 600 ms of each trial overlaps with the first 600 ms of the following trial.

Wind sorizing: Eye movement, eye blink, subject movement can cause large amplitude outliers in the recording. To reduce the noise, the data from each electrode were windsorized. The 90th percentile and the 10th percentile for the sample from each electrode were computed. Amplitude values lying above the 90th percentile and below the 10th percentile were replaced by the 90th percentile and by 10th percentile, respectively (Dixon, 1968).

Scaling: The samples were normalized by scaling the values to the interval[-1; 1].

Electrode Selection: There are four electrode configurations: The first configuration consists of 4 electrodes – Fz, Cz, Pz, Oz as shown in Figure. (a). The second configuration consists of 8 electrodes - Fz, Cz, Pz, Oz, P7, P3, P4, P8 as shown in Figure (b). The third configuration consists of 16 electrodes - Fz, Cz, Pz, Oz, P7, P3, P4, P8, FC1, FC2, C3, C4, CP1, CP2, O1, O2 as shown in Figure (c). The fourth configuration consists of 32 electrodes - Fz, Cz, Pz, Oz, P7, P3, P4, P8, FC1, FC2, C3, C4, CP1, CP2, O1, O2, FP1, FP2, AF3, AF4, F7, F3, F4, F8, FC5, FC6, T7, T8, CP5, CP6, PO3, PO4 as shown in Figure (d).

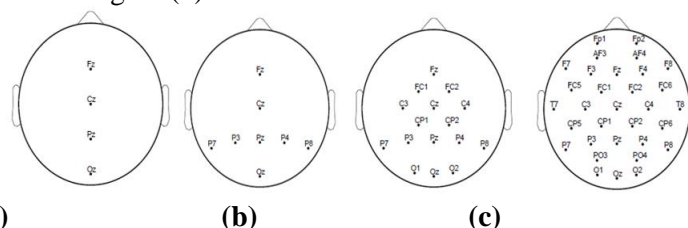


Figure.4. (a) 4 Electrodes (b) 8 Electrodes (b) 16 Electrodes (b) 32 Electrodes

Feature Extraction: Extracting a set of features from the sample and then encoding those features into a convenient form for comparison to classify. Here single trail consists of samples for 1000 ms for which we applied four techniques to extract the feature.

Arithmetic Mean: Measure of the central tendency either of a probability distribution of the random variable characterized by that distribution (Feller, 1950). It is given by Eq. (1) Here in this method since P300 is predominantly present in 300 ms to 800 ms (Ullsperger, 1985). We segregated the values in three blocks i.e 0 ms - 300 ms, 300 ms – 800 ms and 800 ms-1000 ms. Summation of the all the samples in each block over the number of samples is calculated.

$$x(m) = \frac{1}{n} \sum_{i=0}^n x_i - (1)$$

Variance: Measures how far a set of numbers are spread out from the expected value (mean). Here we consider means taken from the previous blocks and apply the Eq. (2) and find the variance.

$$Var(X) = \frac{1}{n} \sum_{i=0}^n (x_i - \mu)^2 - (2)$$

Welch's Power spectrum density: The method consists of dividing the time series data into (possibly overlapping) segments, computing a modified periodogram of each segment, and then averaging the PSD estimates. The result is Welch's PSD estimate (Welch, 1967). Welch's method is implemented in the MATLAB toolbox by pwelch function and is given by Eq. (3). The expected value of the PSD estimate is:

$$E\{P_{Welch}(f)\} = \frac{1}{FsLU} \int_{-Fs/2}^{Fs/2} |W(f - f')|^2 P_{xx}(f') df' - (3)$$

where L is the length of the data segments, $P_{xx}(f)$ is periodogram estimate of the PSD, $W(f)$ is the Fourier transform of the window function, U is the normalization constant present in the modified periodogram. We are able to plot the power spectrum and find the local maxima using the function findpeaks.

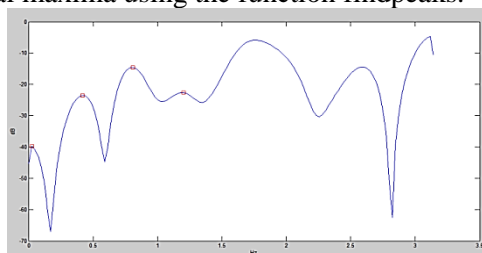


Figure.5. Welch's power spectrum density plot.

Wavelet packet Transform: The wavelet-packets transform was introduced by Coifman (Coifman, 1992). The WPT can be thought of as a tree of subspaces, with $\Omega_{0,0}$ represents the original signal space. In general notation, the

node $\Omega_{j,k}$, with k denoting the subband index within the scale and j denoting the scale, is decomposed into two orthogonal subspaces: a detail space $\Omega_{j,k} \rightarrow \Omega_{j+1,2k+1}$ and an approximation space $\Omega_{j,k} \rightarrow \Omega_{j+1,2k}$, this is shown in Fig. 1 with three levels of decomposition (Englehart, 1998). This is done by dividing the orthogonal basis $\{\phi_j(t - 2^j k)\}_{k \in \mathbb{Z}}$ of $\Omega_{j,k}$ into two new orthogonal bases $\{\psi_{j+1}(t - 2^{j+1}k)\}_{k \in \mathbb{Z}}$ of $\Omega_{j+1,2k+1}$ and $\{\phi_{j+1}(t - 2^{j+1}k)\}_{k \in \mathbb{Z}}$ of $\Omega_{j+1,2k}$ (Mallat, 2009), where $\psi_{j,k}(t)$ and $\phi_{j,k}(t)$ are the wavelet and scaling functions that are given in (Mallat, 2009) as

$$\phi_{j,k}(t) = \frac{1}{\sqrt{|2^j|}} \phi\left(\frac{t - 2^j k}{2^j}\right) \quad (4)$$

$$\psi_{j,k}(t) = \frac{1}{\sqrt{|2^j|}} \psi\left(\frac{t - 2^j k}{2^j}\right) \quad (5)$$

where 2^j is dilation factor, also known as the scaling parameter, measures the degree of scaling or compression. On the other hand, $2^j k$ is location parameter, helps to determine the time location of the wavelet.

Feed Forward Neural Network Classification: There are three phases to implement Artificial Neural Networks (ANN): design, training and execution. In design phase the architecture of the network is defined: number of layers, outputs and inputs, and the activation function of neurons as shown in Fig 7. In training phase, the weights of the network through a learning algorithm is defined. Finally the execution phase is executed using the fixed parameters of the neural network obtained during the learning phase (BehnamA, 2007). The relation between input pattern and output pattern can be any nonlinear function (BehnamA, 2007). In this work, feature vector is given as input data and target vector is given as target data and the data is divided into three parts: training - 70%, testing - 15%, validation - 15%. The mean square error denotes the performance of NN training.

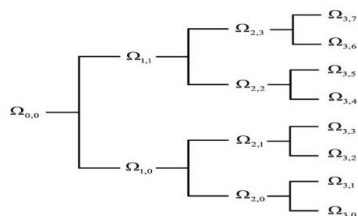


Figure.6.Wavelet packet transform – tree like structure

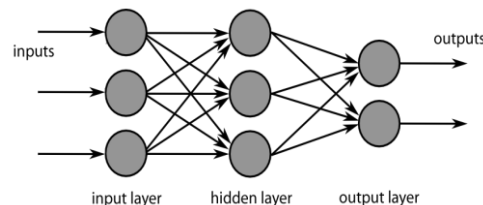


Figure.7.Neural Network Mesh

3. RESULTS

Experimental results are shown in table 1 for the offline data performs very well for electrode configuration with 4 electrode. In fact signal noise is less in this occipital region and P300 is predominantly present and easily extracted from this region. 16 electrode and 32 electrode also gives good accuracy but the computational speed has to be compromised which makes it difficult to use for online application with low end processor. Fz electrode gave an average highest accuracy (all subjects) of 85.3% and highest accuracy is also given by Fz : subject 6 - 89.5% and subject 8 - 88.5%. Accuracy and performance of the subject 8 is exceptionally well when compared to other subjects

Table.1. Accuracies for respective configurations for different subjects

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 6	Subject 7	Subject 8	Mean
4 Electrode	85.675	84.4	83.3	83.525	83.025	84	85.225	84.16429
8 Electrode	84.1	83.6875	83.2125	83.9	84.3625	83.5125	83.80357	83.79694
16 Electrode	84.29375	84.60625	82.8625	83.51875	83.09375	83.63125	84.23125	83.74821
32 Electrode	83.5875	83.84375	82.9125	82.87813	82.87813	83.64063	84.5	83.39866

4. CONCLUSION

This paper proposes simple preprocessing techniques, feature extraction and classification algorithms for the extraction of P300 from EEG signal for a given dataset. Furthermore, we can obtain average accuracy above 80% and a maximum accuracy up to 94% for an electrode for a given dataset and also the result demonstrated shows its effective for an offline data with good calculation speed of the algorithm making it feasible choice for the offline analysis of the data.

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