Analysis of EEG Spectrum Bands Using Power Spectral Density for Pleasure and Displeasure State

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Abstract. The technology of reading human mental states is a leading innovation in the biomedical engineering field. EEG signal processing is going to help us to explore the uniqueness of brain signal that carries thousands of information in human being. The aim of this study is to analyze brain signal features between pleasure and displeasure mental state. Brainwaves is divided into 5 sub frequency bands namely alpha (8 – 13 Hz), beta (13 – 30 Hz), gamma (30 – 100 Hz), theta (4 – 8 Hz) and delta (1 – 4 Hz). However, in this study, alpha and beta waves were analyzed to investigate the mental states. Twenty subjects were recruited from undergraduate engineering student’s education background in UniMAP with age ranging between 19 to 23 years old. The subject must be healthy and right-handed. The subject was required to view a series of pleasure and displeasure images for 10 minutes and take rest for 30 seconds between pleasure and displeasure view. Truscan EEG device (Deymed Diagnostic, Alien Technic, Czech Republic) with 19 channels were used to acquire EEG data with frequency sampling of 1024 Hz and impedance is kept below 5 kΩ. A bandpass filter was used to extract alpha and beta waves. The signal was segmented and PSD value using Welch and Burg method was calculated for both mental states. 7 statistical features (mean, mode, median, variance, standard deviation, minimum and maximum) were obtained from PSD value and used as an input for the classifier. K-Nearest Neighbour (KNN) and Linear Discriminant Analysis (LDA) were used to classify into two mental states. As a result, Welch method gives the highest classification accuracy which is 99.3 % for alpha waves followed by 97.5 % for beta waves from channel F4. It can be concluded that alpha waves are the most potential waves to be used in order to differentiate pleasure and displeasure features.

1.0 Introduction
A human brain is a complex nature and understanding the nature of interconnected neurons needs information signals from the brain. Electroencephalography (EEG) is non-invasive neurological diagnostic modalities which record brain signal. EEG data provide brain activity information. Different brain state depends on daily activity [1].

BCI is a technology advancement which enhances the communication between the human brain and external devices. The BCI reads different brain signals produced by the various parts of the human brain, interpret these signals into commands and actions for various applications [2]. The existence of BCI provides an alternative communication for anyone that suffers from any kind of neurological disorder that affects major muscle activity such as talking and swallowing [3] and allows them to communicate by distinguishing their brain signal.

The process of methodologies for EEG signal processing is divided into 4 stages which are data acquisition, preprocessing, feature extraction and classification. Data acquisition involves experimental protocol. Previous researcher has proposed different protocol in reading pleasure state [4].
During preprocessing stage, butterworth bandpass filter was implemented to filter into different sub-band frequency which in this research focus on alpha and beta waves for discriminating pleasure and displeasure mental state. As previous research [5] [6], suggest that the involvement of frontal cortex for beta and gamma waveform of brain is stable in reading emotion. Subsequently, in feature extraction, a linear feature extractor which are Power Spectral Density (PSD) was implemented and compared between two methods which are parametric (Burg method) and non-parametric (Welch method). Both of this method assumes the EEG signal is stationary random process in nature.

Lastly, in classification stage, The system learns to classify a set of features for a certain time duration to differentiate each mental states. Apparently, in this research, k-Nearest Neighbour (k-NN) and Linear Discriminant Analysis (LDA) were applied to compare the classification accuracy in discriminating two mental states.

2.0 Experiment
2.1. Subject
Twenty subjects aged between 19 to 24 years old have participated in this study. All subjects are right handed, good health condition and no mental history. This criterion of subject selection is compulsory to standardized subject’s state.

2.2. Experimental Set Up
EEG signal were recorded using Truscan EEG device by Deymed Diagnostic. 19 electrode cap channel was used in recording raw EEG signal. The EEG signals were recorded by Truscan software and display brain signals from 19 electrodes (F3, F4, T3, T4, C3, C4, P3, P4, FZ, CZ, PZ, Fp1, Fp2, F7, F8, T5, T6, O1 and O2). Electrode A1 and A2 act as a reference point. The electrode placement is according to the international 10- 20 system as shown in Figure 1. The signals were recorded in a quiet and calm environment where the subjects were asked to sit comfortably on a chair. The subjects were given 5 minutes to relax for pre-experimental procedures. The sampling frequency was set to 1024 Hz and the impedances were kept below 5 kΩ. The cutoff range signal was set as -80 to 80.

![Electrode placement according to 10- 20 international system](image)

2.3. Experimental Protocol
First, subject was required to fill in consent form and demographic form which contains questions related to the protocol of study. The process takes 10 minutes. Afterwards, subject was asked to sit comfortably on a chair in front of computer screen. The task is divided into three. Each task consists of a different set of picture. Task 1 consists a set of a picture to simulate pleasure, task 2 consist of the pictures to stimulate displeasure and task 3 consists of both pleasure and displeasure picture to compare which picture actually stimulate pleasure towards the subject. Subject requires to view each of the picture shown.
3.0 EEG Signal Processing

The recorded signal undergoes signal processing which comprises of 3 stages. Starting with preprocessing, feature extraction and lastly is classification. Based on Figure 2, shows the process for data analysis.

3.1 Preprocessing Method

Each raw signals have amplitudes of microvolts. Hence, preprocessing is required to denoise input raw data to maintain the information recorded. Butterworth bandpass filter with order 2 have been used to filter according to 2 sub-band frequency components which are alpha and beta.

3.2 Welch method

Welch method is applied to estimate power spectrum of determined time sequence. Data window is used in each sequence and enable it to overlap [8]. Let \{x_d(n)\} be the sequence, where \(d=1,2,3…L\) (signal intervals), \(M\) is interval length. Thus, power spectral density using Welch method is defined by,

\[
\hat{P}(f) = \left| \frac{1}{M} \sum_{n=0}^{M-1} x_d(n) w(n) e^{-j\omega f} \right|^2
\]

which \(U\) stands for normalization factor for power in window function

\[
U = \frac{1}{M} \sum_{n=0}^{M-1} |w(n)|^2
\]

Where \(w(n)\) stands for windowed data. Welch power spectrum is the average over modified periodograms defined by,

\[
\hat{P}_{\text{Welch}}(f) = \frac{1}{L} \sum_{l=0}^{L-1} \hat{P}(f)
\]

3.3 Burg Method

This method creates an estimation of reflection coefficients by minimizing the average of forward and backward linear prediction error fulfilling the Levinson Durbin recursion. The advantages of this method are estimating short data records and resolve closely space sinusoids in signal with low level [8]. PSD using the Burg method is defined by,

\[
P_{xx}(f) = \frac{e_P}{|1 + \sum_{i=1}^{p} a_P (i) e^{-2jfi}|}
\]

e_p indicates the total least square error and it is the sum of forward and backward prediction errors.

\[
\hat{e}_f(p(n)) = x(n) + \sum_{i=1}^{p} \hat{a}_p(i) x(n-i), \quad n = p + 1, ..., U
\]

\[
\hat{e}_b(p(n)) = x(n-p) + \sum_{i=1}^{p} \hat{a}_p(i) x(n-p+i), \quad n = p + 1, ..., U
\]
3.4. k-Nearest Neighbour (k-NN) Classifier

k-NN act as a linear classifier that within specified data point x, detects a hypersphere around it that comprises of K points and assign x to the class that has the largest number of representative inside the hypersphere [9]. The process occurs as k-NN finds k neighbourhood in training data and assign recurrent class in the neighbourhood of k. The value of k is quantified from 1 to 10. Subsequently, the value of k will be wide-ranging as per sequence number until 10. The highest value of classification rate with the value of k will be chosen without contemplating the average value for 10. However, in this study, the distance used is correlation and the rule set is random as it provides the highest accuracy to the given data.

3.5. Linear Discriminant Analysis (LDA)

Consist of a linear combination of variable [9]. The concept uses hyperplanes to differentiate training feature vectors shows for dissimilar classes. The orientation and location of this hyperplane are decided by training data. Additionally, for a two class problem, the class of unseen feature vector is based on which side of hyperplane the feature vector situated.

4.0 Results and Discussion

The results show characterization of alpha and beta waves using channel F4 during pleasure and displeasure state.

Based on Figure 3, it indicates that alpha waves in pleasure state is higher compare to displeasure state due to alpha waves are more dominant during relax mind as in pleasure state while the value of alpha wave decreases during displeasure state as the mind is not in relax phase anymore [10]. As for beta waves, in this study the value is not significant but significant value maybe obtain using advance feature extractor to extract better features.

Comparison of classification accuracy are tabulated in Table 1. K-NN and LDA classifiers were applied to classify two mental states.

| Feature extractor | Signal wave | Channel | k-NN (%) | LDA (%) |
|-------------------|-------------|---------|----------|---------|
| Welch              | α           | F3      | 12.09    | 37.14   |
|                    |             | F4      | **99.29**| 57.14   |
|                    |             | F3 & F4| 93.92    | 56.42   |
|                    | β           | F3      | 13.21    | 35.36   |
|                    |             | F4      | 97.50    | 61.79   |
|                    |             | F3 & F4| 91.43    | 57.14   |
| Burg               | α           | F3      | 96.07    | 60.00   |
|                    |             | F4      | 95.36    | 54.29   |
According to Table 1, it can be shown that highest classification accuracy is 99.3% by using Welch method for alpha waves followed by 97.5 % for beta waves from channel F4.

5.0 Conclusion
The method proposed in this study was based on feature extraction using PSD with Welch and Burg method for classifying pleasure and displeasure mental state. Two classifiers were compared which are $k$-NN and LDA to test the efficacy of proposed features. The advantage of using PSD is easy to applied. The simulation results indicate that alpha waves are most potential waves in discriminating pleasure and displeasure states. Also, the highest classification accuracy (99.3%) was achieved by using Welch method in channel F4.

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