International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 8 (2015) pp. 21139-21149
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An Energy Spectral Density Computational Scheme For Brain Computer Interface

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Abstract

A Brain-Computer Interface (BCI) is a precise type of human-computer interface that facilitates unswerving communication between human and computers by scrutinizing Electroencephalogram (EEG). The efficiency of the BCI depends on the Information Transfer Rate (ITR) and ITR depends on precise feature extraction. The paper presents a scheme to compute energy spectral density of the EEG. The scheme was applied on arbitrary five pairs of channels of EEG. It precisely calculates energy spectral density (ESD) for each unique frequency value present in EEG. It also localizes highest ESD component for each channel.

Keywords: Brain Computer Interface, Electroencephalogram, Information Transfer Rate, Energy Spectral Density.

Introduction

A conventional medical survey points out that the presence of congenital neuromuscular disorder for one in three thousand five hundred of the biosphere's inhabitants. The neural malady such as Amyotrophic Lateral Sclerosis (ALS), normally denoted as Lou Gehrig's disease, is a rapidly spreading lethal neuromuscular ailment that assaults nerve cells and communication paths between spinal cord and brain. These grievances direct to an enforced assent of abridged life quality which consequences to rely on custodians and incur an escalating societal expenditure. A category of synthetic strategies realize neural prostheses to compensate the dysfunctional mechanisms of dented nervous system and corporeal structures are derived from an emerging expanse referred as Neuro Prosthesis. The driving signal for the aforementioned systems is acquired from physiological movements of the patients. This restraint necessitates developing an alternate regulatory archetype referred as Brain-Computer Interface (BCI).

A Brain Computer Interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles. Presently two approaches are pursued in the design of BCI systems Synchronized and Self-paced [1]. In the synchronized approach, which forms the traditional approach to the design of BCI systems, the user can only perform the control in certain time intervals that are specified by the system. A Self-paced BCI (SBCI) is constantly available for a user to use; The performance of SBCI systems is usually summarized by two measures:

1. The correct detection rate of Intentional Control (IC) commands (denoted as the true positive (TP) rate)
2. The amount of false activations during No Control (NC) periods (Periods for which the user does not wish to exert control).

The second feature that distinguishes BCIs is whether they utilize invasive (i.e., intra-cranial) or non-invasive techniques to record the electrical signals from the brain. The first feature that distinguishes BCIs is whether they utilize invasive (i.e. intra-cranial) or non-invasive methods of electrophysiological recordings. BCIs can also be classified based on electrode montage schemes on cortical areas of brain. Non-invasive systems primarily exploit electroencephalograms (EEGs) to control computer cursors or other devices. This approach has proved useful for helping paralyzed or 'locked in' patients develop ways of communication with the external world. However, despite having the great advantage of not exposing the patient to the risks of brain surgery, EEG-based techniques provide communication channels of limited capacity. Their typical transfer rate is currently 5–25 bits. Invasive BCI approaches are based on recordings from ensembles of single brain cells (also known as single units) or on the activity of multiple neurons (also known as multi-units). Figure 1shows a conventional BCI system.

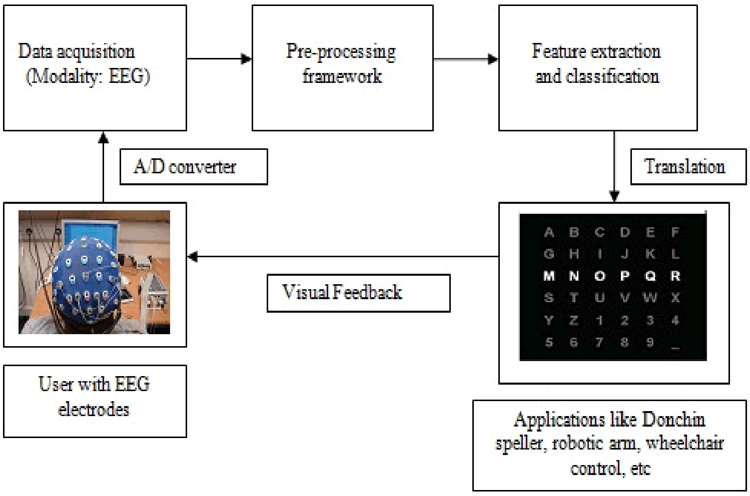

Figure 1: A conventional BCI system

The electrodes placed on the head of the user to record the electrical activity of brain Electroencephalography (EEG) signals from the scalp, ElectroCorticoGraphy (ECoG) signals from the brain or neuronal activity recorded using microelectrodes implanted in the brain. Several important factors should be considered in the design of the application specified as follows,

1. Time to learn
2. Performance Speed
3. Number of errors user can make
4. Retention ability of users
5. Subjective satisfaction

Evoked Potentials (VEPs) are small changes in the brain signal, generated in response to a visual stimulus such as alphabets display. They display properties whose characteristics depend on the type of visual stimulus. Visual Evoked Potentials (VEPs) originate from neurons in the cortex, outer layer of brain and exhibit oscillating, event-related potentials in its nature. These signals are responses to visual stimulants and extensively used in neuropsychological studies. The main components of ERP's are exogenous and endogenous. Physical stimuli are referred as exogenous components. These components include a Negative waveform around 100ms (N1) and a Positive waveform around 200 ms after stimulus onset (P2). Visual Evoked Potentials fall into this category. Endogenous components are components which are influenced by cognitive factors. These potentials reflect the visual information processing mechanism in the brain. With reference to the knowledge of brain electrophysiology, potentials generated corresponding to rapidly repetitive stimulations is referred as steady-state VEP (SS-VEP). Specifically transient VEP (TVEP) is a true transient response to a stimulus when the relevant brain mechanisms are in resting states and independent of previous trials. If the stimulus presentation rate is shorter than the duration of a TVEP, the potentials generated for each stimulus will overlap each other to yield SSVEP, which corresponds to brain's steady state excitability. The analysis of the TVEP is based on temporal methods such as template matching, whereas SSVEP detection is usually performed by frequency analysis such as power spectral density estimation.

By presenting florescent tubes flashing at 13.25 Hz through operant conditioning methods, the users can control the amplitude of the steady-state visual evoked potential (SS-VEP). This method of control may be considered as continuous as the amplitude may change in a continuous fashion. Either a horizontal light bar or audio feedback is provides when electrodes located over the occipital cortex measure changes in signal amplitude. If the VEP amplitude is below or above a specific threshold for a specific time period, discrete control outputs are generated. After around six hours of training users may have an accuracy rate of greater than 80% in this application. When the SS-VEP is used as a natural response virtually no training is needed in order to use the system. The main drawback of this system is flicker induced fatigue to users.

Features describing the complexity of brains signals can be classified into time series features, spatial features and frequency features [17]. Time series features includes the

1. Average of the signal (offset)
2. Linear trend of the signal
3. Absolute minimum and maximum values
4. Number and order of local minimum and maximum values
5. Weight factors describing the matching and positions of predefined patterns and slopes of predefined patterns.

The spatial features refer to placement of sensors or electrodes. By estimation of Energy Spectral Density (ESD) of the signal, time series can be described by its spectral characteristics. The ESD can be used to identify the important frequency components that change with psychological activities of the user. For BCI signals the spectral analysis is an important method, as the brain generates the task-dependent activity in relatively small frequency components. Feature Classifies are categorized into Linear and Non Linear. In terms of robustness, linear classifier holds edge over non linear. This advantage is attributed to tuning less number of free parameters, less prone to over-fitting. However, linear systems are ineffective in the presence of artifacts, but this can be managed by using regularization. The influence of the following parameters is limited by regularization:

1. Strong Noise
2. Classifier complexity
3. Irregularity of the decision vector.

This paper is organized as follows: Section II briefs the related works carried out in EEG processing for brain computer Interface. Section III proposes a scheme to compute energy spectral density of the acquired EEG signal and Section IV narrates the results accomplished from the implementation of the scheme.

Related Works

This section presents a detailed literature survey various feature extraction schemes associated BCI.

[4] proposed an integrated driving scheme derived from combining two brain signals P300 and steady-state visually evoked potential (SSVEP) for a novel hybrid brain computer interface to increase spelling speed. It yielded sub area/location and row/column spelling paradigms to realize two brain patterns and the target item was identified by 2-D coordinates. The scheme was tested for fourteen subjects and accomplished an information transfer rate was 53.06 bits/min and exhibited higher spelling speed compared with the P300 and SSVEP spellers. [5] proposed an online semi-supervised P300 BCI speller system founded on self-training least squares support vector machine (LS-SVM) classifier. This mode allows the user can feed characters through selective attention. Upon fed by every character input the classifier is steadily improved at backend with the unlabeled EEG data. The low computational complexity algorithm was validated by P300 Speller BCI data achieving the spelling accuracy of 85% and an average online semi-supervised learning time of 3 minutes.

[6] suggested a modified stimulus presentation paradigm-the half checkerboard paradigm (HCBP) for a hybrid P300 speller. The scheme uses electrooculography and electroencephalography signals elicited by 8 X 9 matrixes and an alphanumeric character selection. The scheme was weighed up against checkerboard paradigm through online test. It provided higher information transfer rate for 16-character-long test text. [7] proposed an automatic and dynamic data collection scheme for P300 based BCI speller. The data collection principle is a threshold based regulatory mechanism and the threshold value is continuously updated with each additional measurement by presuming each probable character is the target character. The novelty of the proposed Bayesian technique offers participant independent and probability based metric as the stopping criterion.

[8] suggested an unique visual stimulus program offering hierarchy of flash sets made up of Variable number of objects. The optimal hierarchy of flash set computational problem was perceived as a low computational complexity stochastic control problem solving for a given statistical language model. The scheme demonstrates that the average time per output character at 85% accuracy is reduced by over 50% using our variable-flash-set approach as compared to traditional fixed-flash-set spellers. [9] amended variations in conventional P300 BCI speller interface by reducing number of stimulus repetitions to accomplish increased information transfer rate. It incorporates a custom-built dictionary into the classification system. This system was tested on 14 healthy subjects and fifteen words of four letter length were used as test text. Incorporating the dictionary, the mean accuracy at five trials increased from 72.86% to 95.71%. By adjusting letter positions on the A to Z interface and using the modified interface and the mean information transfer rate of 55.32 bits/min was accomplished.

[10] investigated an alternative prospect to conventional BCI system by proposing P300-based BCI system in ambulatory condition. The study was based on experimental data recorded with seven subjects executing a visual P300 speller-like discrimination task while simultaneously walking at different speeds on a treadmill. Multiple artifact removal schemes were suggested to substantiate the feasibility of the proposed scheme. [11] Offered a SSVEP based self-paced BCI speller and the speller does not require any training from the user or from the signal processing part. The

system exhibits swift response to non-calibrated and untrained user input. It was tested on eight healthy subjects who had no prior experience with the application. The average accuracy and information transfer rate are 92.25% and 37.62 bits per minute, which is translated in the speller with an average speed of 5.51 letters per minute.

[12] Pointed out the drawback in evaluation of a BCI approach by information transfer rate (ITR) a classifier performance quantifier. It proposed a novel metric built on classifier and control interface characteristics to compute BCI Utility. The metric was tested on P300 speller and a P300 speller with an error correction system (ECS), for different values of accuracy of the classifier and recall of the ECS and the results outsmarted the ITR measure. [13] Identified the drawback associated with designed by Farwell-Donchin's P300 speller in 1988. The study paradigm uses a 6 X 6 matrix of letters and numbers is displayed, and the subject focuses on a target character while rows and columns of characters flash. This paper had demonstrated a presence of human perceptual error in the Farwell-Donchin paradigm and suggested a, a new region-based paradigm. The experimental results revealed better accuracy of the proposed paradigm over the Farwell-Don chin paradigm.

[14] proposed an unsupervised algorithm to enhance P300 evoked potentials by estimating spatial filters. It projects the raw EEG signals into the estimated signal subspace. The proposed scheme was evaluated on three subjects recorded data. The results shows that Bayesian linear discriminant analysis classifier is efficient and accurate. [16] realizes an online-adaptive-learning method to for P300-based brain computer interfaces to address calibration problem. It automatically captures subject-specific EEG characteristics during online operation. It invokes to learn a generic model termed subject-independent model offline from EEG of a pool of subjects to capture common P300 characteristics leading to new model termed subject-specific model. The online adaptation is based on EEG recorded from the new subject and the corresponding labels either by subject-independent model or the adapted subject-specific model, The method was tested on 10 healthy subjects and achieved 2-4 min online adaptation (spelling of 10-20 characters).

The literature survey reveals the main issue of importance associated with existing BCI systems as the necessity of an effective feature extraction scheme. The survey also presents a view of the various types BCI systems, various types of control signals, various visual stimulus paradigms, and existing feature extraction schemes.

Methodology

The EEG signal, representing the neural activity of the brain, which includes rhythmic responses and evoked responses can be defined by Equation (1).

$$X(t) = X_R(t) + X_E(t) \qquad (1)$$

The component $X_R(t)$ results from superposition of potentials generated by cerebral activity, $X_R(t) = M_{\mathbf{B}}\ S_A(t)$. The component $X_E(t)$ corresponds to evoked potentials in response to presented stimuli, $X_E(t) = N_{\mathbf{B}}\ S_B(t)$, where $M_{\mathbf{B}}$ and $N_{\mathbf{B}}$ are mixing matrices and $S_A(t)$, $S_B(t)$ are contributive elicited potentials to rhythmic and evoked responses respectively[18].

An effective localization in space domain is a pre requisite for uniform approximation of neuro electric waveforms. This improves the efficiency of the feature extraction schemes. The Scheme employs the following steps to accomplish the objective.

A function was defined which acts as the indicator of the specific segment associated with EEG signal.

STEP 1: For a defined range, the selected function defines the segment.

STEP 2: The authenticity of the selected segments is verified by subjecting translated or shifted versions the function to orthonormal property.

STEP 3: The extracted segment is decimated by a specific indicator function to obtain sub segments.

STEP 4: The decimation process is iterated by generalized indicator function to obtain a group of sub segments.

STEP 5: The generalized indicator function is dependent on two parameters, Dilation parameter ‘j’, Translation parameter ‘k’.

STEP 6: It was observed that a larger ‘j’ provides a finer approximation with smaller segments.

The relationship between the derived segments can be established by the following scheme:

STEP 1: A different range is fixed.

STEP 2: Corresponding to this range another Indicator function is defined.

STEP 3: This Indicator function also yield the segment defined by the range.

STEP 4: By testing orthonormal property on the indicator function the trueness of segment is established.

STEP 5: It was found that segments yielded by the above selected two indicator functions are related with each other.

The data was collected from a right-handed and able-bodied participant of 37 years old. The EEG signal was recorded from 16 monopolar EEG channels (according to the International 10-20 system at Frontal, Frontopolar, Central, Temporal, Parietal regions). The signals were then converted to bipolar EEG signals since such electrodes are more likely to generate more discriminant EVP features than monopolar electrodes. The conversion was carried out by calculating the difference between adjacent EEG channels and resulted in the generation of 18 bipolar EEG channel pairs. Figure 2 shows the electrode placement scheme used for the EEG acquisition.

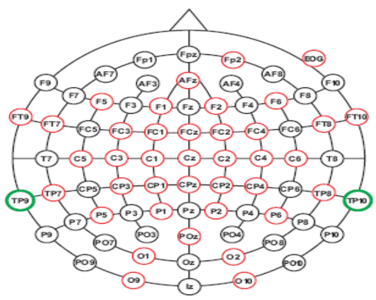

Figure 2: Electrode Placement Scheme

Results

Implementation of this algorithm on the recorded EEG for five electrode pairs montaged in temporal, parietal, occipital, frontal polar areas of the brain along with a comprehensive statistical relationship between the frequency and energy spectral density is shown in Figure 3, Figure 4, Figure 5 Figure 6 and Figure 7. These statistical values enable to localize maximum energy elicited for a specific stimulus. In graphical representations, X Axis represent Frequency in Hz and Y Axis represent ESD ($\mu V^2/Hz$)

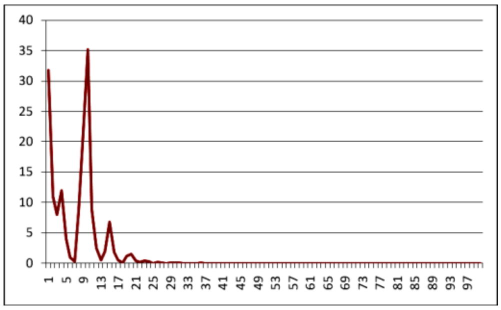

Figure 3: Energy Spectral Density for electrode pair C4-P4

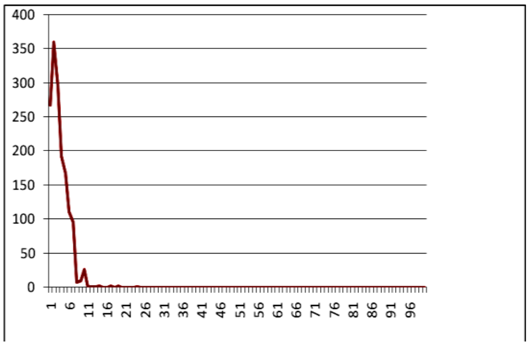

Figure 4: Energy Spectral Density for electrode pair FP2-F4

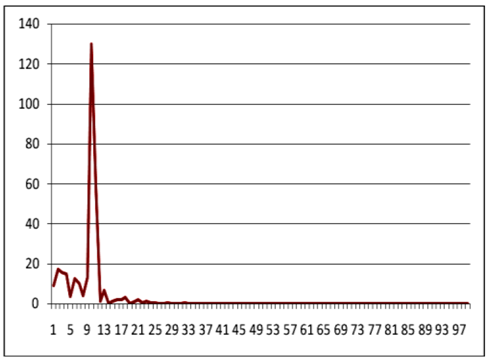

Figure 5: Energy Spectral Density For Electrode Pair P4-O2

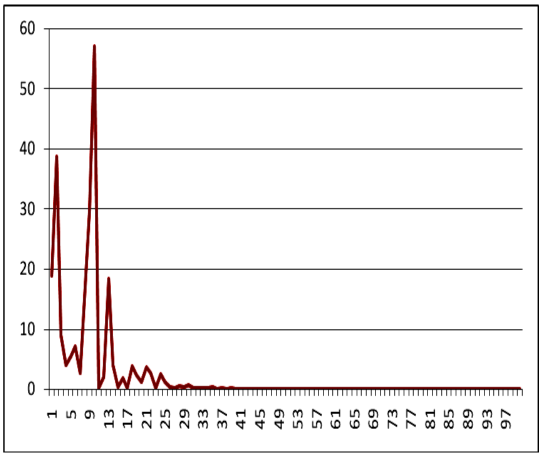

Figure 6: Energy Spectral Density for electrode pair T5-O1

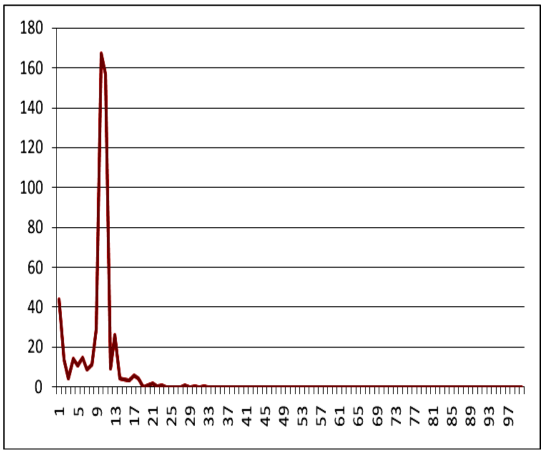

Figure 7: Energy Spectral Density for Electrode Pair T6-O2

Conclusion

The proposed scheme is a useful feature extraction tool as it explores the time as well as the frequency information of the signal. It shall be used in a number of synchronized BCI systems. This scheme was implemented on five pairs of channels C4-P4, FP2-F4, P4-O2, T5-O1, and T6-O2. The energy values support the hypothesis that proper channel selection for any user is necessary to obtain superior performance. Another inference also shows that the selected features are not necessarily located in the standard frequency bands. These results also indicate that a channel elimination methodology could be incorporated into the proposed method to further decrease the number of channels used for the operation of the system.

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