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Wavelet sub band entropy based feature extraction method for BCI

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Abstract

The study and analysis of the electrical activity of the brain is valuable in understanding the human mental state, intentions and will. This aids the development of Brain Computer Interface (BCI), facilitating communication between the human brain and computer, by converting the brain waves (EEG waves - Electroencephalography) into control signals. These control signals can then be used to trigger an external device, thereby enabling a seamless communication with the intelligent system. It unfolds various avenues for research and further applications in the realm of prosthetic device control, development of thought controlled intelligent systems and other complex interfaces. This will also be an aid to persons with disabilities or various other amputations. In this work, a novel feature extraction algorithm is proposed for extracting event related potentials from the EEG signals using wavelet sub band entropy which can be used in BCI applications. An attention index is defined which gives a measure of the amount of concentration or attention the subject has, upon focussing on a particular event or thought.

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Keywords: BCI, Wavelet sub bands, Entropy, Feature extraction, Evoked potential, EEG

1. Introduction

The idea of electricity being generated by the body goes back as far as 1798, when the Italian anatomy professor, Luigi Galvani claimed to have found out electricity in the muscle of a frog[1]. With the advent of modern day technology of amplification and data processing, the study of these signals opened new avenues of knowledge. Currently rapid development have been observed in this field of bio-signal processing. Motor cortex signal extracted from a group of neurons are captured and used to actuate external devices in many cases. Research groups led by Richard Andersen, John Donoghue, Phillip Kennedy, Miguel Nicolelis and Andrew Schwartz have achieved remarkable feats in this area[2]. Using EEG to interface human thoughts with a machine is one among the primary areas of ongoing research. Students of McMaster University has succeeded in bringing up an EEG controlled wheelchair prototype using real time BCI and fast machine learning algorithm[3]. Research in prosthesis field involving the development of a bionic limb has also progressed to a notable level. The *DEKA Arm* is a DARPA funded project aiming at the development of functionality for the disabled which is still under development[4]. Fully developed products that provide support

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for amputees are also becoming prominent. The i-limb ultra prosthetic hand is a powered device that can sufficiently mimic the grasping operation of the human hand[5].

An effective feature extraction algorithm is imperative to be able to successfully classify the various mental activities of the person for Brain Computer Interface applications. The EEG signal can be thought of as a superposition of the electrical activities pertaining to a large number of tasks. These brain activities are oscillations that gets synchronized by stimulation or while performing a particular task. The transition from a disordered to an ordered state results in event related oscillations and the spectral content of these oscillations change in a particular fashion. Analysis of these synchronizations can be efficiently done with the help of entropy based approaches since it can give a qualitative measure of disorderness in the states of brain oscillations. This approach has been successfully applied in medical studies, such as in epileptic seizures.

2. Methods

2.1. Data acquisition and analysis

Data acquisition of the raw EEG data was performed using NeuroSky Mindwave®, a single channel EEG acquisition device. The device incorporates a sensor located on the forehead, a reference that is clipped to the earlobe and a chip that does the pre processing of the raw EEG data acquired from the electrodes. It provides single channel raw EEG data along with Delta (0.1Hz to 3Hz), Theta (4Hz to 7Hz), Alpha (8Hz to 12Hz), Low Beta (12Hz to 15Hz), Mid range Beta (16Hz to 20Hz) and High Beta (21Hz to 30Hz) values. Raw EEG data with an ADC resolution of 12 bits and a sampling frequency of 512 Hz is provided[6].

NI LabVIEW ® provides an excellent platform for graphical programming. Signal processing and analysis was done on this Application specific Development Environment(ADE). It supports rapid prototyping and incremental development of applications, from measurement and automation to real time embedded and general purpose applications. An unmanaged dynamic linked library based on C is provided by NeuroSky to access the virtual COM port emulated by the headset. The interface with LabVIEW was done based on a LabVIEW - NeuroSky Driver for accessing the full functionality of the system level driver provided by NeuroSky®. A window of 512 raw EEG samples were read from the COM port at a time and processed in LabVIEW®.

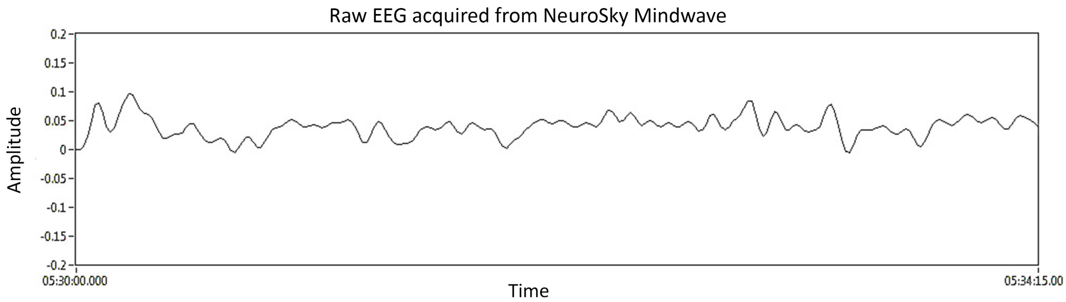

Fig. 1. Raw EEG signal acquired from NeuroSky Mindwave®, a 512 window sample

2.2. Evoked Potentials

EEG consists of brain activities that span several frequency ranges, which are normally in a disordered state. In the event of a particular brain activity such as attention, meditation, motor imagery or other perceptions, these disordered waves synchronize or gets ordered. This transition from a disordered to an ordered state, results in a resonance phenomenon due to the global synchronization of the EEG, giving rise to event related oscillations in several frequency ranges[7 8]. Başar et al (1980) put forth this hypothesis according to which EEG consists of the activity of an ensemble of generators producing oscillations in several frequency ranges[9]. The ERPs are reflected as changes in the temporal domain in EEG during a particular event.

2.3. Wavelet Decomposition

The theory of wavelets and filter banks have far reaching applications in the analysis of non - stationary signals. It is a powerful tool for feature extraction, signal denoising and compression. Using Fourier analysis, one can express a signal as the sum of an infinite series of sines and cosines. The major drawback in Fourier analysis is that it has no time resolution. The Fourier basis functions are localized in frequency alone, and not in time. Small frequency changes will hence produce changes everywhere in the time domain. Short Time Fourier Transform approach demands a constant time window which in turn affects the frequency resolution. Wavelets are local in both frequency and time, which is an advantage in many cases. Wavelet multi-resolution analysis is done in order to extract the various sub bands of the raw EEG signal for the analysis of event related potentials.

2.3.1. Wavelet Multi - resolution analysis

Multi-resolution analysis (MRA) is an efficient tool in analyzing the information content in signals at various resolutions or scales. It gives a hierarchical network of approximation and detail spaces. The idea of vector spaces is the underlying concept to this representation. A vector space of higher and lower resolutions exists for each scale of decomposition. The higher resolution finally yields the actual signal. The scaling function of wavelet is the basis of each of the decomposed vector spaces.

2.3.2. Mathematical formulation of Mallat's Fast Wavelet Transform algorithm

MRA defines a sequence of nested spaces of functions, $\{V_j\}$. Mathematically, this can be represented as:

$$\cdots \subset V_j \subset V_{j-1} \cdots \subset V_2 \subset V_1 \subset V_0 \subset V_{-1} \subset V_{-2} \cdots \tag{1}$$

The lower the index, smoother the functions that belong to the space. At each decomposition level, the approximation function becomes coarser. This sequence will, at the end, cover the space of the finite energy functions, $L^2(\mathbb{R})$. For $x(t) \in L^2(\mathbb{R})$ and $V_j = span\{\phi_j(t-k)\}$ at $j + 1^{th}$ level of decomposition,

$$x_A^{(j+1)}(t) = \left\langle x(t), \phi_{j+1}(t-k) \right\rangle \tag{2}$$

The approximated signal at each decomposition level is obtained by taking the inner product of the original signal with the scaling basis function corresponding to that scale. The two scale difference equation, which is central to Discrete Wavelet Transform (DWT) connects the finer and the coarser scales [10 11].

$$\phi_{j+1,l}(t) = \sum_k c_{k,l}\phi_j(t-k) \tag{3}$$

Where, the scaling function coefficients [10]

$$c_{k,l} = \left\langle \phi_{j+1,l}(t), \phi_{j,k}(t) \right\rangle \tag{4}$$

$$\phi_{j,k}(t) = \phi(2^{-j}t - k) \tag{5}$$

$$\phi_{j+1,l}(t) = \phi(2^{-(j+1)}t - l) \tag{6}$$

Let $\tau = 2^{-j}t - k$

$$\left\langle \phi_{j+1,l}(t), \phi_{j,k}(t) \right\rangle = \left\langle \phi\left(\frac{k+\tau-2l}{2}\right), \phi(\tau) \right\rangle \tag{7}$$

$$= \left\langle \phi\left(\frac{\tau}{2} - \left[l - \frac{k}{2}\right]\right), \phi(\tau) \right\rangle \tag{8}$$

$$= c_{l-\frac{k}{2}} \tag{9}$$

The above equation yields,

$$\phi_{j+1,l}(t) = \sum_k c_{l-\frac{k}{2}} \phi_j(t-k) \tag{10}$$

Substituting in 2, we get:

$$x_A^{(j+1)}(l) = \sum_k c_{l-\frac{k}{2}} x_A^j(k) \tag{11}$$

This can be interpreted as the convolution of the given signal, with the c_k values, followed by down sampling yielding the decomposed space. Using a similar approach in the detail space, we have:

$$x_D^{(j+1)}(l) = \sum_k d_{l-\frac{k}{2}} x_D^j(k) \tag{12}$$

where,

$$d_{k,l} = \left\langle \psi_{j+1,l}(t), \phi_{j,k}(t) \right\rangle \tag{13}$$

$\psi(t)$ is the wavelet function and d_k is the wavelet function coefficients. This is the basic idea behind *Mallat's Fast Wavelet Transform Algorithm*[12]. The choice of the wavelet depends largely on the signal under consideration. The wavelet should have high approximation ability.

2.4. Wavelet entropy based approach

The Entropy, H for a discrete random variable X is defined as[13]:

$$H(X) = -\sum_i P(X = a_i) log_b P(X = a_i) \tag{14}$$

Where a_i are the possible values of the random variable X. It reflects the degree of disorderness that the random variable possesses. Considering the non stationary characteristic of EEG signal and the event related potential, multi-resolution analysis of the signal has been done, which extracts signal in various frequency bands.

Wavelet packet decomposition performed on the raw EEG data with 5 levels yielded 64 sub bands, using Daubechies wavelet with 8 taps (db8). The energy in each of these bands, E_k is calculated as:

$$E_k = \sum_{j=1}^{8} x_j^2 \tag{15}$$

where, k is the index of the sub band and j is the number of data samples in each sub band.
The total energy of all the sub bands, E_{total} are calculated as :

$$E_{total} = \sum_{k=1}^{64} E_k \tag{16}$$

where, k is the index of the sub band.
Probability distribution for each level, p_k given by :

$$p_k = \frac{E_k}{E_{total}} \tag{17}$$

The wavelet sub band entropy, WS_k is given by :

$$WS_k = -p_k log_2(p_k) \tag{18}$$

Upon focussing or concentrating, the distribution of wavelet entropy along the sub bands was found to change in a particular fashion as long as the subject maintained that level of concentration. Sub bands W_{10} to W_{15} were found to have a significant change in the distribution pattern during the attention or concentration state. These 6 sub bands were extracted and the sub band entropy sum, WS_{sum} was calculated for these bands as:

$$WS_{sum} = \sum_{k=10}^{k=15} WS_k \tag{19}$$

The backward difference of the sub band entropy sum, ∇WS_{sum} was calculated to define an index to measure the level of attention.

$$\nabla WS_{sum} = WS_{sum}^{k} - WS_{sum}^{k-1} \tag{20}$$

2.5. *Attention Index*

A fraction of the backward difference of the sub band entropy sum was cumulatively added if it goes below a particular threshold and subtracted if it overshoots that threshold. This defines the *Attention Index*, A.

$$A_n = \begin{cases} A_{n-1} + \epsilon & , \mid \nabla WS_{sum} \mid \leq \eta \\ A_{n-1} - \epsilon & , \mid \nabla WS_{sum} \mid > \eta \end{cases} \tag{21}$$

where, n = 1, 2, 3, ... is the n^{th} window, ϵ = k∇WS_{sum}, k = 0.2, η is threshold value, 0.15 and $A_0 = 0$.
The algorithm is summarized in the block diagram shown in figure 2.

Since the value of WS_k lies between 0 and $\frac{1}{2}$, WS_{sum} has a lower bound given by 0 and the upper bound is determined by the number of wavelet sub bands under consideration. W_{10} to W_{15} has been used for calculating WS_{sum} i.e. number of sub bands(n) considered is six. WS_{sum} is bounded according to the relation:

$$0 \leq WS_{sum} \leq \frac{n}{2} \tag{22}$$

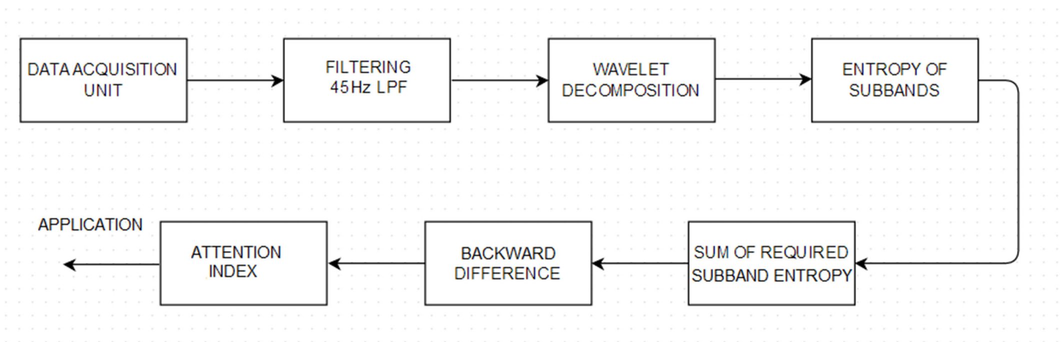

Fig. 2. General block diagram of the algorithm

2.6. *Testing*

The proposed algorithm for feature extraction of EEG can be used for performing various tests pertaining to cognitive analysis. An experiment to analyze the workload or amount of cognitive stress was carried out on various subjects.

The subject was asked to concentrate or focus on a particular object or thought and the attention index was analyzed. The measure of cognitive workload performed by the subject (here, the attention or concentration level) was used as a parameter for moving an object (a wireless toy car).

3. Results

The entropy based feature extraction was found effective in giving a measure of the attention level a subject has when he focusses on a particular thought. The signal processing algorithm can be implemented in a small DSP without much resources, thereby making it suitable for wearable systems. The algorithm in its crude stage works under the assumption that the neurons when fired in unity for a particular thought in mind, the entropy changes. This change in entropy is found and is quantified and can be even stored for future reference in case the same pattern occurs again. The algorithm is essentially immune to certain artifacts like popular noise source which has a particular fixed energy pattern (for example, a 50Hz sinusoid). As the entropy of these patterns are constant, the backward difference stage in the algorithm removes those noise patterns. The particular usefulness can be a problem if the user expects to extract non transient features since they are removed in the algorithm stage.

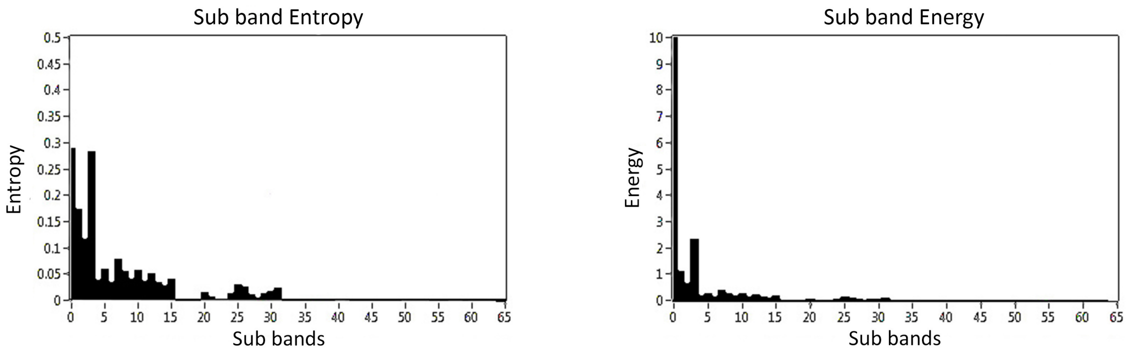

Fig. 3. Entropy and energy plots of the sub bands (bar plot)

In figure 3, it is evident that the wavelet sub band entropies and the corresponding sub band energies are prominent in the lower frequency levels. Significant changes in the sub band entropies were observed only from level 10 to level 15 while performing the test for attention index. The initial levels were discarded as it signifies the eye blink artifact, which should not be considered in our study.

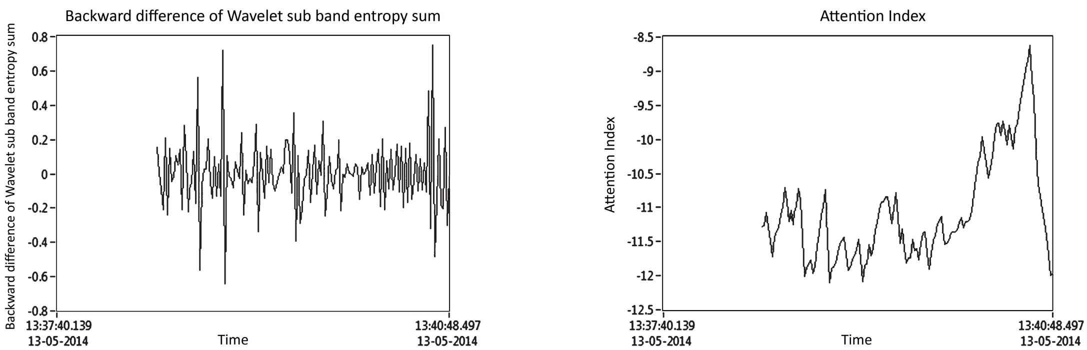

Fig. 4. Backward difference of the sub band entropy sum and the attention index

In figure 4, the backward difference of the wavelet sub band entropy sum for the sub bands from 10th to 15th level has been plotted in NI LabVIEW®, with the subject asked to concentrate on a particular thought. The initial portion of the plot represents the backward difference when the subject concentrated and the fluctuation is very less, which can be seen from the plot. The corresponding attention index is also seen to be increasing. The last part of the plot shows a sudden spike in the backward difference and a corresponding rapid downward slope in the attention index, indicating that the subject has lost focus in the thought.

4. Conclusion

In this work, a novel feature extraction algorithm for extracting EEG signals using wavelet sub band entropy sum has been proposed. This algorithm in conjunction with a proper ANN can create powerful feature extraction and classifying methods. The power lies in the extraction of the transient features which can be stored as a template for future reference. Features representing ERPs based on entropy has the advantage of representing the current mental state of the subject with precision. Wavelet sub band entropy can help in applications that require accurate results from less number of input channels. Choosing relevant sub band entropies pertaining to specific ERPs for analysis can aid many BCI platforms to meet their requirements.

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