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RESEARCH ARTICLE OPEN

EEG Feature Extraction Using Wavelet Techniques For Brain Computer Interface

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ABSTRACT*:*
The aim of this study was to compare methods for feature extraction and classification of EEG signals for a brain–computer interface (BCI) according to different mental task conditions. EEG data was obtained either from BCI data base or from EEG experimental recording. There were different methods for feature Extraction like temporal methods, frequential methods, and Time-frequency representations. Among these methods wavelet which was type of Time frequency representation method most popularly used for feature extraction.

Keywords:- Signal amplitude, Autoregressive parameters, Power spectral density, Short-time Fourier transform, Wavelets,

I. INTRODUCTION

Brain–computer interface (BCI) provides a direct communication channel between a subject's brain and a computer by using electroencephalogram (EEG) signals. The EEG signals are brain signals which will give the information regarding different mental task conditions such as movement imagination, geometric figure rotation, Arithmetic Tasks, relax etc. These are given below.

1.1 Movement Imagination:-
The subject was asked to plan movement of the right hand, movement of legs forward-backward etc

1.2 *Geometric Figure Rotation:-*
The subject was given 30 seconds to see a complex three dimensional object, after which the object was removed. The subject was instructed to visualize the object being rotated about an axis.

1.3 *Arithmetic Task:-*
The subject was asked to perform trivial and nontrivial multiplication. An example of a trivial calculation is to multiply 2 by 3 and nontrivial task is to multiply 49 by 78. The subject was instructed not to vocalize or make movements while solving the problem.

1.4 *Relaxed: -*
The subject was asked to relax with eyes closed. No mental or physical task to be performed at this stage.

II. EEG SIGNAL

Electroencephalogram is defined as electrical signal of an alternating type recorded from the scalp surface carried by metal electrodes and conducting media. EEG signal generally recorded by 10-20 electrode placement system. This is done by using the electrodes. Many BCIs use a special *electrode cap,* in which whole for electrodes are already in the right places, according to the international 10-20 system. It saves time because the electrodes do not have to be attached one by one. Typically, less than 10 electrodes are used in online BCIs with sampling rates of 100-400 Hz.

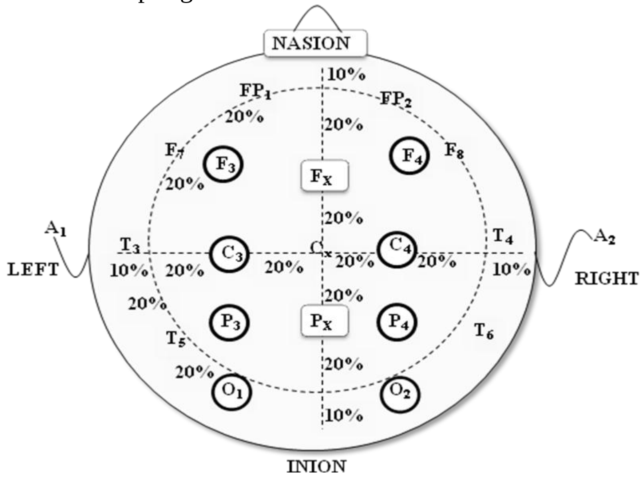

Figure 1: Electrode Placement System

III. DATA PROCESSING

3.1 Temporal methods

Temporal methods use time domain variations of the signals as features. These methods are particularly adapted to describe EEG signals with a accurate and specific time, such as the P300. P300 wave is a positive deflection in the EEG around 300 ms after visual or auditory stimuli for normal young adults.

3.1.1 Signal amplitude:-

The raw amplitudes of the signals from the different electrodes during EEG signal acquisition pre-processed. In such a case, the amount of data used is generally reduced by preprocessing methods such as spatial filtering or sub sampling. And Feature extraction done so as to read useful data from huge EEG signal data before being passed as input to a classification algorithm.

3.1.2 Autoregressive parameters:-

The EEG signals have non-stationary characteristics. In order to investigate their time varying properties they are divided into segments then the segments are analysed with an autoregressive model of order p.

$$X(t) = a_1X(t-1)+a_2X(t-2)+...+a_pX(t-p)+Et\ldots \quad (1)$$

Where a signal X(t), measured at time t, can be calculated as a weighted sum of the values of this signal at previous time, to which we can add a noise term Et (generally a Gaussian white noise)

Where the weights a_i are the autoregressive parameters which are generally used as features for

BCI and p is the model order.

AAR parameters assume that the weights a_i can vary over time, and are the most used variant of AR parameters.

It seems that AAR parameters would give better results than AR parameters for motor imagery classification, whereas they would give worse results for the classification of cognitive tasks such as mental computations, mental rotation of a geometric figure, etc.

It should be noted that it is possible to derive frequential information from the ai coefficient [24]

3.3 Frequential methods:-

EEG signals are composed of evoked potentials which are a set of specific oscillations known as rhythms. Evoked potentials are electrical signals measured on the surface of the head after stimulation administered by an appropriate external stimulus.During performing mental task the amplitude of these different rhythms vary. In BCI systems, steady state visually evoked potentials (SSVEP) used. SSVEP come from the visual cortex and are collected at the back of the skull and are oscillations with frequencies synchronized with the stimulus frequency. It is essential to exploit the frequential information embedded in the EEG signals. To this two main techniques, which are widely used, are: band power features and power spectral density features.

3.2.1 Band power features:-

Band power feature consists of band-pass filtering of signal in a given frequency band, then squaring the filtered signal and finally averaging the obtained values over a given time window It is also possible to log-transform this value in order to have features with a distribution close to the normal distribution. Band power features are generally computed for several frequency bands according to the mental states to be recognized. Such features have been used for motor imagery classification also for cognitive processing tasks.

3.2.2 Power spectral density:-

Power Spectral Density (PSD) features, called spectrum, gives distribution of the power of a signal between the different frequencies. PSD features can be computed, by squaring the Fourier transform of a signal or by computing the Fourier transform of the autocorrelation function of this signal. PSD features are probably the most used features for BCI, and have proved to be efficient for recognizing a large number of neurophysiological signals.

3.3 Time-frequency representations:-

In EEG signals used in a BCI have generally specific properties in both the time and frequency domain. Other methods, which are combination of both time and frequency domain, are also used to design BCI. These methods are based on various time-frequency representations such as the short-time Fourier transform or wavelets, and extract from the signals information that are both frequency and time domain

FT gives the frequency information of the signal but it does not tell us when in time these frequency components exist. This information is not required when the signal is stationary. So FT is not a suitable technique for non-stationary signal such as EEG signal.Short-time Fourier transform or wavelets, are capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal.

3.3.1 Short-time Fourier transform:-

In STFT, the signal is divided into small segments, where these segments of the signal can be assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window must be equal to the segment of the signal.

$$X(n, w) = \sum_{n=-\infty}^{+\infty} x(n).w(n).e^{-j\omega n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

In STFT first multiplying the input signal by a given windowing function w which is non-zero only over a short time period, and then compute the Fourier transform of this windowed signal. In discrete time, the STFT X (n,w) of a signal x(n) is Time-Frequency representation

In STFT has drawback that its window is of finite length, and no longer perfect for frequency resolution. If we use a window of infinite length, we get the FT, which gives perfect frequency resolution, but no time information. Narrow window gives good time resolution but poor frequency resolution. Wide window gives good frequency resolution but poor time resolution.

To overcome this drawback Wavelet analysis is used.

3.3.2 Wavelets Transform:-

A wavelet is a waveform of effectively limited duration that has an average value of zero. The wavelet analysis is done in a similar way to the STFT analysis, signal is multiplied with a function Ψ, similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal. The width of the window is changed as the transform is computed for every single spectral component, which is most significant characteristic of the wavelet transform.

$$\Psi_{a,b}(x) = \frac{1}{\sqrt{a}}\Psi\left(\frac{x-b}{a}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

Where, b is Shift Coefficient, and a is Scale Coefficient

$\Psi_{a,b}(x)$ is the sum over all time of the signal, multiplied by scaled and shifted versions of the wavelet function Ψ.

The advantage of wavelets is it has a good time resolution and poor frequency resolution at high frequencies for fine scale whereas it has good frequency resolution and poor time resolution at low frequencies for coarse scale. It possible to analyze the signal at different scales simultaneously, due to this advantage of wavelets it is useful for analyzing EEG signals. Various kinds of wavelets have been used for BCI as Daubechies wavelets, Coiflets, Biorthogonal wavelets. There are different methods of wavelet decomposition namely wavelet decomposition and wavelet packet decomposition.

A. Wavelet Decomposition:-

For many signals, the low-frequency content is the most important part, whereas high frequency content is not as much important.

In wavelet analysis there are approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

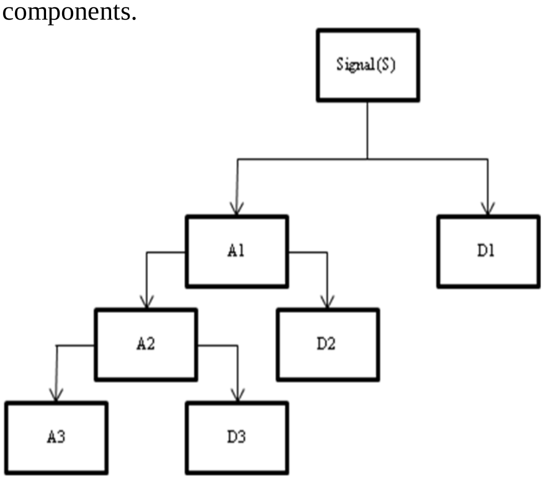

Figure 2: Wavelet Decomposition Tree (2 level decomposition)

The original signal, S, passes through low pass filter (approximation) and high pass filter (decimation). The decomposition process can be repeated, with successive approximations being decomposed, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.

A. Wavelet Packet Decomposition:-

When we have to consider both low frequency content and high frequency content we use wavelet packet decomposition.

In wavelet packet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated.

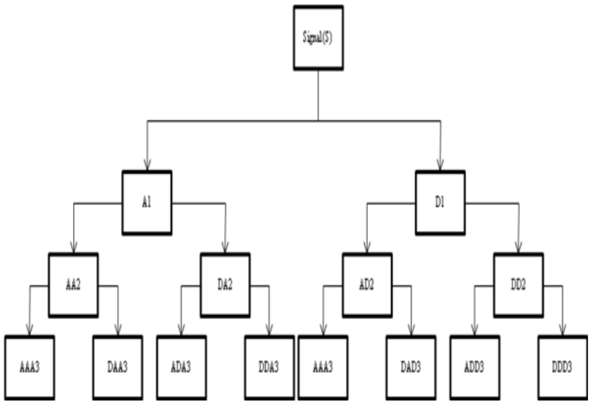

Figure 3: Wavelet Packet Decomposition Tree (2 level decomposition)

IV. APPLICATIONS

4.1 Controlling a wheelchair or an artificial limb by translating brain signals into control commands.

4.2 In playing Various Games on computer without operating computer.

4.3 A BCI provides an alternative means of communication and control for patients with Amyotrophic Lateral Sclerosis (ALS), a disease which leads to a shutdown of the patient's nervous system causing the person to lose all voluntary muscle control.

4.4 Robotics

V. CONCLUSION

As there are different methods for Feature Extraction of EEG signal. Since the EEG is non-stationary. So among these methods Wavelet transform is effective method for Brain computer interface as it provides more flexible way of time–frequency representation of a signal by allowing the use of variable sized windows, being broad at low frequencies and narrow at high frequencies. Thus leading to an optimal time - frequency resolution in all frequency ranges. Therefore, spectral analysis of the EEG signals is performing using the Wavelet transform.

The computational complexity and the feature vector size is successfully reduced to a great extent by using wavelet transforms Thus a wavelet transform is an elegant tool for the analysis of non-stationary signals.

Mathematical basis of the wavelet transform has also proved that EEG analysis based on wavelet transform coefficients can be used very efficiently for the estimation of EEG features. [28]

Also Wavelets are families of oscillating functions whose energy is localized in time, so making them well suited for feature extraction of non-stationary signals. Wavelet transform is used as a classifier of the EEG frequencies

There are different types of Wavelet Transform among them in most cases Daubechies Wavelets 'db4' used.

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