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A Review on Analysis of EEG Signals

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Abstract: Electroencephalography (EEG) enlighten about the state of the brain i.e. about the electrical bustle going on in the brain. The electrical activity measured as voltage at different points of brain act as basis of EEG. These signals are generally time-varying and non-stationary in nature. These signals can be scrutinized using various signal processing techniques. In this paper, few statistical approaches to analyze EEG data are conversed.

Keywords: EEG signals, analysis, methods.

I. Introduction

The electric current produced by a normal human brain has order of a few microvolts. These voltage fluctuations are the result of ionic current that flows between brain and the neurons. The spontaneous activity of brain is observed for about 20-40 minutes. This results in generation of the EEG signals. The electric potential picked up by a single neuron is very small and thus it is impossible to detect. So the EEG determines the summation of the synchronous activity of a large number of neurons present in the brain. These neurons have similar spatial orientation to get determined. Also, the Brain Computer Interface is one of the most anticipative edges technology between humans and machines in today's era. Electroencephalogram-based BCI systems has turned out to be a raging field in the investigation of brain engineering and reintegration

There are four major types of EEG waves *viz.* alpha, beta, theta and delta waves. The nature and occurrence of these waves helps in identification of a number of diseases such as epilepsy, insomnia and many more. For instance, if high theta activity is present in an adult when awake then it must be suffering from some abnormal pathological conditions. The age and mental state also plays a vital role in the brain activity of an individual. This can be judged from the example that an alpha wave in an infant is completely normal but in fully grown adults, it might be a sign of some disease. The presence of spikes may be a sign of epileptic seizure or stroke.

The recording of EEG signals is simply done by placing electrodes on the scalp of the subject. The amplitude of EEG signal may vary from 10 to 100 micro volts with a frequency range of 1-100 Hz. The recordings may be mono polar or bipolar. In mono polar recording the electrode potential at an active electrode is measured w.r.t some reference point such as earlobe. The bipolar recording is simply a voltage difference between two active electrodes. The mono polar recording is a more popular method and is widely used.

The signal extracted from electrodes is called raw EEG signal. The raw EEG signal may include some non-cerebral signals called artefacts. These are actually contaminations in the signal. The EEG signals is contaminated by much other kind of signals for example: - movement related potentials, eye blinks, movement of facial muscles etcetera. Sometimes signals like ECG, EMG, EOG also gets mixed up EEG signals. These are called biomedical artefacts. These are the most difficult to remove as most of the times these resemble the actual EEG signal. Another category of artefacts are the environmental artefacts like line noise, pulse, electrode stabilization etc. The elimination of these artefacts is very important from the clinical point of view as minute mistake in the interpretation of the signal may turn fatal to the patient. Improvement in technology can easily decrease externally generated artefacts, such as line noise, but biological artefact signals must be removed after the recoding process.

Thus, a raw EEG signal undergoes various processes in order to become readable. The signal is filtered and various techniques to obtain actual signal are performed. The filtering of these signals is one area and analysis of these signals is represented by another area. The feature extraction is generally performed using statistical methods. And, after performing feature extraction, the signal is finally classified using support vector machines or the neural networks. A few statistical approaches for the analysis of EEG signals are discussed in next section.

II. Statistical Approaches For EEG Analysis

The statistical methods may be used as pre-processing or post-processing for an EEG analysis. Sometimes a combination of one or more methods is used to achieve better accuracy. Statistical analysis may include linear or non-linear methods to fulfil its purpose. A number of linear and non-linear methods have been applied to analyse the EEG signals. But some methods cannot be categorized as either of two methods. This section gives a brief account of such methods for example, wavelet transform, PCA and ICA.

1).Linear Methods

The first in this category consists of prediction methods. In the prediction methods a set of parameters is determined that would help to figure out the signal generation system. The linear prediction method mainly works in the time domain. Mathematically, a linear prediction model can be represented as

$$z(n) = -\sum_{m=1}^{p} a_m z(n-m) + x(n) \tag{1}$$

Where a_m, $m = 1, 2, \ldots, p$, are linear parameters, n represents the discrete sample time, and *x(n)* is the noise input. The discrete samples of time are normalized to unity. The given equation represents the autoregressive (AR) modeling of an EEG signal. The AR modeling method is the most commonly used linear prediction method. There are some other methods such as adaptive filters, moving average filters, weighted moving average filter, calculating randomness of signals and many more. However, these methods are not always guaranteed to be linear.

The linear prediction method was efficiently used in analysis, storage and transmission of EEG data [2]. This method gives a better view of background EEG activity. The autoregressive moving average (ARMA) method and multi variate AR (MVAR) approach are used as linear methods to analyze EEG signals in time domain.

2).Non-linear Methods

Much like linear models, the output in non-linear models is depends upon the output of previous models but non-linearly. A simple mathematical method to represent a non-linear model can be given by the following equation

$$x(n) = g(z(n-1), z(n-2), \ldots) + z_n h(z(n-1), z(n-2) \ldots) \tag{2}$$

Where, z(n) represents the input to the signal and x(n) represents the output. Also, the functions *h(.)* and *g(.)* denote some kind of nonlinearity in the signal. Generally, these functions represent non-linearity in mean and variance of signal, respectively.

This method is popularly known as generalized autoregressive conditional heteroskedasticity (GARCH) method [4] and was originally used for time-varying volatility. The drawback of GARCH method is that the sign symmetries are not entertained i.e., the inverse problem [1]. However, a number of alternatives are present to deal with this problem. In the field of EEG signals localization of sources deal with the issue and the method is called low-resolution electromagnetic tomography (LORETA) [6].

Other than GARCH method, some other methods such as Burg Method, Durbin Recursion and Yule-Walker method are used as non-linear, non-parametric methods. Short data sequences are efficiently analyzed using this method.

3).Short Time Fourier Transform

This method deals with the signal in spectral domain. The method provides a bridge between the Fourier analysis and wavelet transform.

The FT is not an appropriate method to be used when it comes to non-stationary signals. This is because FT does not provide simultaneous time-frequency analysis and cannot represent discontinuities at the corners. Thus the FFT algorithm is applied on such signals.

But a better approach is STFT, in which the signal is divided into small segments and the signal within this segment is assumed to be stationary. Statistically,

$$STFT_x^{(y)}(t,f) = \int_{-\infty}^{\infty} [x(t).\, y^*(t-t')].\, e^{-2\pi f t}\, dt \tag{3}$$

Where,
x(t) is the signal,
y(t) is the window function,
And the L.H.S represents the STFT of the signal.

The segmentation of signal is done using the window function that has equal width as the segment of the signal. The choice of window function depends upon the minimum frequency separation required to resolve two amplitude frequency components [7]. However, the size of window function also require a good trade-off between the frequency and time resolution as wider window function results in good frequency but poor time resolution and vice-versa. The solution to this problem is overcome by wavelet transform [5].

4).Wavelet Transform

Wavelet transform has good localization properties in time as well as frequency domain. The conversion of signal from time domain to the frequency domain gives a better understanding of the signal [3]. The wavelet transform is preferred to be implemented for analyzing EEG signals because of its dual property i.e. it can be used for discrete (Discrete WT) and analog (Continuous WT).

The DWT is appropriate for analysis and the synthesis of the signal whereas the CWT is more suitable to identify diseases. Wavelet Transform is a powerful tool to analyze EEG signals as there is an option to choose from many mother wavelets [10, 11]. Haar and Daubechies are the examples for the same. The choice of mother wavelet also affects the accuracy of the received output.

And then, sometimes, multi resolution analysis (MRA) is performed to achieve good time resolution and poor frequency resolution at high frequencies and vice-versa.

5).Principal Component Analysis

A different technique that has been utilised to analyse EEG signals is principal component analysis that aims at the dimensionality reduction of the system. However, it is a theoretical approach that that applies mathematical operations to obtain Eigen values but the method is extensively used for analysis of EEG and removal of artefacts from it. It is a powerful tool for analysing and for dimension reduction of data without loss of information [8]. The data is linearly transformed in such a way that only orthogonal components are retained. These orthogonal components provide maximum information about the signal. In particular it allows us to determine the principal directions in which data varies. These principal directions actually represent the data in the best possible manner. PCA combined with different techniques provide great results [12]. One more advantage of PCA is that it can be used for pattern recognition as well as compression of data without much loss of useful information.

6). Independent Component Analysis

PCA reduces the data into orthogonal components. But a better and improved approached is independent component analysis (ICA).

In this method higher order statistics such as kurtosis parameter are used to separate the components. Independent component analysis (ICA) separates EEG data into neural activity and artefact; once identified; such components can be deleted from the data. The orthogonality of the signal is not an issue in this method. It is dependent on two assumptions:

i) The source signals are independent of each other;
ii) The distribution of values in each source signal is non-Gaussian.

Independent Component Analysis is a strong tool to separate different data such as artefacts or spatially overlapping EEG activities [13]. But still, there are some limitations of ICA. Firstly, it can be applied to decompose the number of sources equal to the number of scalp electrodes used to collect the data. The number of factors contributing to the signal is generally unidentified. Secondly, for a small dataset, the temporal independence may not yield satisfying results. Thirdly, it is not always right to assume that cerebral and artifactual sources are spatially fixed. This is the principle assumption of ICA.

7).Empirical Mode Decomposition

Another statistical technique similar to principal component analysis is the Empirical Mode Decomposition. The data is taken in time-series. The principle of this method is to first decompose the signal into a sum of functions called intrinsic mode functions. The main characteristics of IMFs are given as follows:-

i) They should have same number of zero-crossings and extrema (or difference should not be more than one).
ii) They should be symmetric w.r.t. local mean i.e. mean values of upper and lower envelopes must be equal to zero.

The signal is thus decomposed into oscillating components which are further broken into lower and higher frequency components. Thus, it is not necessary for the signal to be stationary. Further, the results of EMD when applied to support vector machine yield even better results.

8).Fractional Dimension

This method is helpful in reducing the complexity of signals by means of their quantization. In this method, a set of points represent a bigger set of original values [16].

For a given set of S original values, the fractional dimension is given as

$$FD = -\lim_{\epsilon \to 0^+} \frac{\log N(\epsilon)}{\log \epsilon} \tag{4}$$

Where, $N(\epsilon)$ is the minimum number of circles with radius $\leq \epsilon$ required to cover S.

Fractional Dimension is more effectively used for short EEG time series [14]. This technique has greater accuracy than any other method.

III. Conclusion

The EEG signals have gained a lot of importance in the field of biomedical science in the past few decades. The advancement in technology and its ever increasing demands have encouraged the engineers to ascertain new methods for analyzing these signals. Some of the most widely used methods have been discussed in this paper. These methods can be further modified or combined with some other methods to get more appropriate results. Also, in the later stages, the support vector machines or the neural networks can be used for the classification of signal.

IV. References

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