International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.171

A Study of Time Domain Features of EEG Signal Analysis

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***Abstract*—Electroencephalography is a non-invasive technique used to monitor brain activity and make a variety of neurological problems diagnoses. The electrical activity of the brain is measured using an EEG instrument, which converts chemical variations in the brain into voltage. With either the intracranial EEG method or the Scalp EEG approach, several electrodes are implanted at the right location on the brain to measure EEG signals. Analysis of electroencephalograms, or EEGs, has grown to be crucial for identifying many human disorders. The most crucial and straightforward step in processing EEG readings is using temporal frequency analysis to make a potential diagnosis. EEG signals are the important data for any type of analysis of brain activity. In this study, we first analysis the EEG signal characteristics that have been used in the literature for a variety of activities, then we concentrate on looking at EEG feature applications, and finally we talk about the potential and unresolved issues with EEG feature extraction. Everyone should assess the wide variety of EEG signal properties and their effects on BCI interfaces in order to improve the accuracy of different brain activity detection in the future.**

I. Introduction

The mass of nerve tissue that is known as the brain may be found in the frontal region of an organism. This mass is comprised of three different parts: the cerebrum, the cerebellum, and the brainstem[1]. The **human brain** is responsible for integrating sensory information and coordinating the activities of the muscles. The human brain is comprised of millions of neurons, each of which plays an important role in the process of controlling how the body reacts to both internal and external motor and sensory impulses. These neurons will serve as units for the flow of information between the body and the brain.

The signals that are produced by an electroencephalogram (EEG) are a representation of the electrical activity that occurs in the brain. Electroencephalography is a software program that may objectively link particular electroencephalographic (EEG) patterns to the activities of the central nervous system (CNS)[2], in addition to dysfunctions and disorders. The electroencephalogram (EEG) is a valuable modality that allows for the collection of brain signals related to a variety of states directly from the surface of the scalp.

EEG waves are the single most important source of information that can be used for successful detection. A feature is a distinguishing characteristic, a measurable quantity, and a functional element that is derived from a component of a pattern[14]. In the strictest sense, a feature is derived from a pattern piece. EEG signals are the singleimportant source of information that can be utilized in the detecting process.

It has always been difficult to identify cross-subject emotions based on brain imaging data, such as EEG, due to the poor generalizability of features across different people. This is especially true of electroencephalogram (EEG) data. As a result, it is essential to conduct in-depth research on the degree to which different EEG metrics may differentiate between the emotional information of different people.

A distinguishing characteristic, a measurable quantity, and a functional element produced from a section of a pattern are all examples of features[3]. The purpose of extracted features is to minimize the amount of significant signal-embedded information that is lost. In addition to this, they cut down on the number of resources that are needed to accurately describe a large amount of data. This is necessary in order to remove the possibility of requiring information to be compressed, to reduce the cost of processing information, and to simplify the implementation process. In recent years, several methods, including wavelet transforms (WT), time frequency distributions (TFD), Eigenvector methods (EM), Fast Fourier Transforms (FFT) and auto regressive methods (ARM), have gained popularity in the process of extracting features from electroencephalogram (EEG) recordings. The analysis of EEG signals has been the subject of a significant number of studies. EEG signals make it feasible to perform an examination of the brain activity of a person in real time.

In the past, determining an acceptable EEG characteristic was an essential aspect of the investigation of this phenomenon. This research presents a mathematical approach to the problem of extracting features from EEG data. It focuses specifically on the extraction of features from EEG signals.

II. Time domain Features

EEG is a time series signal which is a function of amplitude of electrical activities of the neurons and time [19] . EEG signals can be analyzed in various domains like Time, Frequency and time-frequency. Time domain features are extracted from the EEG signal by time domain analysis. The time domain features can be extracted from raw or preprocessed EEG signals. This time domain features extracted from EEG signal is highly relevant to describe the mental states of the person under study. Time domain feature are quick at easy to extract from the EEG signals. Time domain analysis consist lower computational complexity compared with frequency and time-frequency domain analysis. Time domain features are extensively used in medical and engineering research, since these features do not require any complicated transformation and

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easy to implement. time domain features are widely used because of the classification effectiveness in low noise situation. The major drawback of the time domain features is , it assumes the EEG signal as a stationary signal. But in reality EEG signals are non-stationary signals (varying with time) .

Simplest time domain features are mean, median, variance, standard deviation, kurtosis, skewness which are statistical in nature. The linear time domain features are mean amplitude, peak amplitude, RMS amplitude , peak to peak amplitude , wave form duration and zero crossing rate. The non-linear time domain features are fractal dimension, correlation dimension, sample entropy, approximate entropy, Hurst exponent, Lyapunov exponent , fuzzy entropy etc., In this paper we are discussing briefly some of the popular time domain features

Various Features

2.1.Mean

Mean is the average of the values of all data points of the signal[4].

$$\mu = \frac{1}{N}\left[\sum_{i=1}^{N} x_i\right] \tag{1}$$

2.2Median

Median is the middle value of a signal data when all the values are arranged in ascending or descending order.

$$\text{Median} = \begin{cases} x\left(\frac{n+1}{2}\right), if\ n\ is\ odd \\ \frac{x\left(\frac{n}{2}\right)+x\left(\frac{n}{2}+1\right)}{2}, if\ n\ is\ even \end{cases} \tag{2}$$

2.3 Variance

Variance is a measure of dispersion of the signal data.It is the average of the squared differences from the mean.

$$\sigma^2 = \frac{1}{N}\left[\sum_{i=1}^{N} (x_i - \mu)^2\right] \tag{3}$$

2.4 Standard deviation

The standard deviation is a measure of how the data is spread out from the mean value and is computed as the square root of the variance. A high standard deviation indicates that the signal data are widely dispersed from its mean value[5], while a low standard deviation indicates that the signal data are nearer to the mean value

$$\sigma = \sqrt{\frac{1}{N}\left[\sum_{i=1}^{N} (x_i - \mu)^2\right]} \tag{4}$$

2.5 Skewness

Skewness is a statistical feature which measure the degree of asymmetry of a distribution. positively skewed or right skewed distribution has a long right tail which indicating an excess of low values. Negatively skewed or left skewed distribution has a long-left tail which indicating an excess of high values.

$$SKew(x_i) = \sqrt{\frac{\frac{1}{N}\left[\sum_{i=1}^{N}(x_i-\mu)^3\right]}{(\sigma^3)}} \tag{5}$$

2.6 Kurtosis

Kurtosis describes the shape of the distribution of the signal data[7][11]. Datasets with high kurtosis tend to have a high peak (more values) near the mean, decline rapidly, and have heavy tails. Datasets with low kurtosis tend to have a low peak or flat top (less values) near the mean, decline gradually and have light tails

$$kurt(x_i) = \frac{N\left[\sum_{i=1}^{N}(x_i-\mu)^4\right]}{\left[\sum_{i=1}^{N}(x_i-\mu)^2\right]^2} \tag{6}$$

2.7Zero-crossing rateZCR

The zero crossing rate (ZCR) measures how many times the waveform crosses the zero axis[8][10]. In other words, it is the number of times the signal changes value, from positive to negative and vice versa. It can be obtained counting how many times both following conditions are fulfilled for a signal X(t):

$$\{X(t)<0 \text{ and } X(t+1)>0\} \text{ or } \{X(t)<0 \text{ and } X(t+1)>0\},$$
$$|X(t)-X(t+1)| \geq \epsilon, \tag{7}$$

whereϵ is a threshold to avoid miscounting zero crossing due to noise.ZCR can be interpreted as a measure of the noisiness of a signal

2.8Peak amplitude

The peak amplitude of a sinusoidal waveform is the maximum positive or negative deviation of a waveform from its zero reference level.

Peak Amplitude = $max[X_n]$ (8)

2.9Peak to peak amplitude

Peak to peak amplitude is the difference between maximum value (positive amplitude) and minimum value (negative amplitude) of the signal x(n).

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Peakto peak = $max[X_n] - min[X_n]$ (9)

Hjorth parameters

2.10Activity

Activity gives a measure of the squared standard deviation of the amplitude of the signal. [9][15[[16][17].High value activity indicates higher frequency components presence and low value activity indicates the presence of lower frequency components.

$$\text{Activity} = variance[x(t)] \quad (6)$$

2.11 Mobility

Mobility is calculated as the ratio of the standard deviation of the slope of the signal to the standard deviation of the signal, expressed per unit of time.

$$\text{Mobility} = \sqrt{\frac{variance[x^1(t)]}{variance[x(t)]}} = \sqrt{\frac{variance\left(\frac{dx_i}{d_t}\right)}{variance x_i}} \quad (7)$$

2.12 Complexity

The measure of complexity of a signal is determined by its similarity to a pure sine wave. This measure is calculated as the number of standard slopes generated during the average time it takes to generate one standard amplitude.

$$\text{Complexity} = \frac{mobility[x^1(t)]}{mobility[x(t)]} = \frac{mobility\left(\frac{dx}{dt}\right)}{mobility(x)} \quad (8)$$

2.13 K-complex

K-complex is a distinct pattern in an EEG signal, consisting of a sharp negative waveform immediately followed by a positive component , with a total span of at least 0.5 seconds[6].

2.14 Energy E

Energy is the total of the squared magnitudes of all the components of a signal [12][13].

$$\text{Energy} = \sum_{i=1}^{N} |x_i|^2 \quad (9)$$

III. Materials and Methods

3.1Subjects and Data Acquisition

The EEG data is acquired from the 10 healthy yoga practitioners from different age groups.The group of yoga practitioners , who practiced yoga daily for 3 years (Surya namaskar,Asanas:Tadasana, vrikshasana,paschimottanasana,ustrasana, Mudras : chin mudra,Pranayama: Nadisuddhi)were compared with a group with no experience in yoga. Group of yoga practioner (4 F, 6 M) between 22 to 47 years old and group of non practioner (5 F, 5 M) between 21 to 52 years old participated as the study subjects. The subjects are 6 students, 5 unemployed, 9 in technical, professional and white collar occupations. The subjects had no history of any type of mental disorder and none of them take any medical treatment. The experimental procedure was clearly explained to the subjects.

3.2 EEG Recordings

EEG recordings were taken from the subjects using a 18channel RMS with a sampling frequency of of 256 Hz in aa electrically shielded room. The AC frequency of 50 Hz. Was eliminated by a line filter.The arrangement of active electrode on the scalp (FP2-F4, F4 -C4 ,C4 -P4, P4 -O2, FP1-F3, F3 -C3, C3 -P3,P3 -O1 , FP2-F8 , F8 -T4 , T4 -T6 , T6 -O2 , FP1-F7 , F7 -T3 , T3 -T5 , T5 -O1) according to the International 10-20 system of electrode placement, referenced to the linked ear lobe electrodes. The recorded duration for each subject in both groups is 2 minutes. During the entire duration of these experiments.subjects were entirely relaxed in an awake state with eye closed throughout the entire duration of this experiment. The subjects were seated in normal position. The real time signals obtained from the subjects are non-stationary, random and non-linear. The data acquired from these methods were further pre-processed for removing noise.

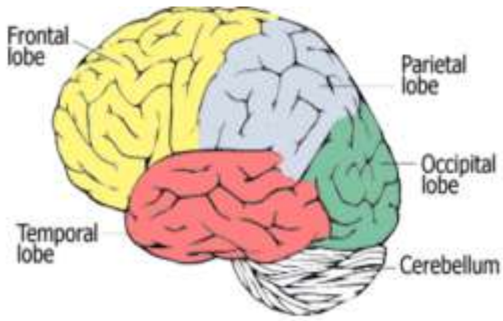

Fig. 1 Brain lobes

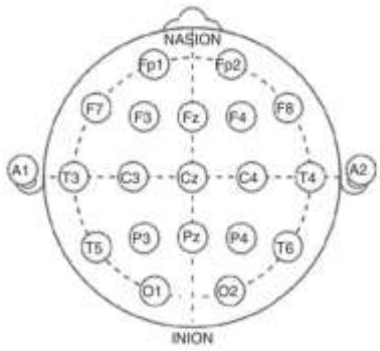

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Fig 2. International 10–20 system for standardized EEG electrode locations on the head.(C = central, P = parietal, T = temporal, F = frontal, Fp = frontal polar, O = occipital, A = mastoids) [18]

IV. RESULT

The EEG data waves has been analyzed in both yoga and non yoga conditions and the result shown below.

TABLE 1 TIME DOMAIN FEATURES OF CONTROL GROUP (INDIVIDUAL SUBJECTS)

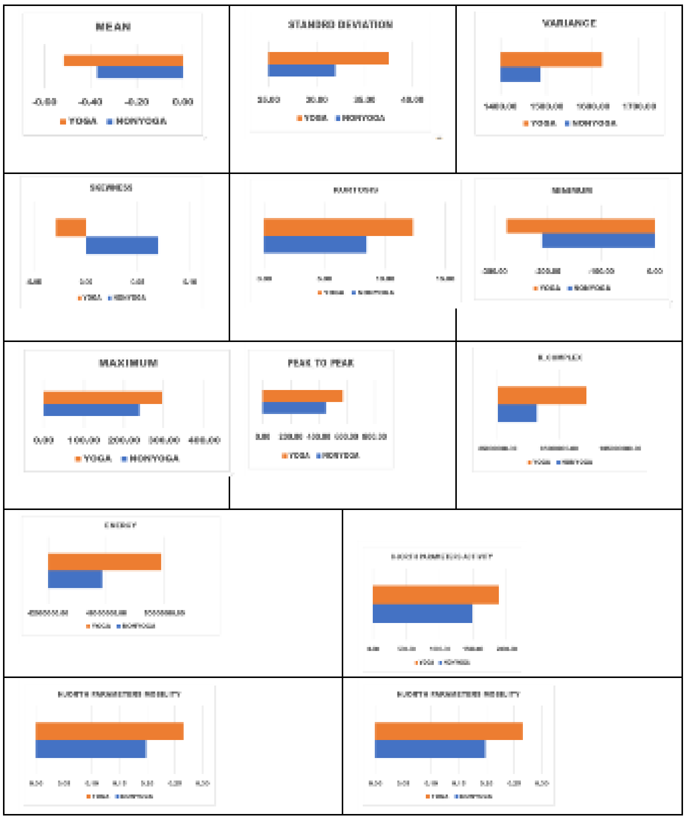
Features	s1	s2	s3	s4	s5	s6	s7	s8	s9	Sampls10
Mean	-0.49	-0.49	-0.57	-0.02	0.50	-0.58	-0.47	-0.52	-0.48	-0.59
Standard deviation	38.45	38.14	20.25	50.33	-40.47	56.33	27.56	45.77	43.24	40.09
variance	1526.74	1484.10	482.61	3003.57	-2239.84	3980.46	821.99	2130.40	2036.13	1648.73
skewness	-0.01	-0.03	0.00	0.79	0.75	-0.30	-0.56	0.19	-0.01	-0.13
kurtosis	0.29	1.95	5.26	39.32	-15.15	26.56	7.55	4.40	13.54	1.00
Minimum	-177.19	-201.88	-135.69	-421.13	296.88	-474.75	-215.75	-242.75	-303.31	-234.38
Maximum	170.88	188.38	149.13	692.00	-207.56	465.88	166.38	266.63	285.81	204.94
peak_to_peak	348.06	390.25	284.81	1113.13	-504.44	940.63	382.13	509.38	589.13	439.31
k_complex	93810842.03	91190573.79	29662346.21	184553884.7	-137623847	244575979	50509641	130900063	125107061	101309554
Energy	46909356.88	45599073.5	14836719.31	92284063.06	-68816038.5	122296249	25258244	65454320.5	62557153.3	50660631.4
Hjorth parameters Activity	1526.74	1484.10	482.61	3003.57	-2239.84	3980.46	821.99	2130.40	2036.13	1648.73
Hjorth parameters Mobility	0.33	0.33	0.17	0.11	-0.15	0.11	0.23	0.33	0.21	0.31
Hjorth parameters Complexity	1.67	1.72	3.25	6.50	-5.56	8.03	2.75	1.88	2.67	2.00

TABLE 4.2TIME DOMAIN FEATURES OF STUDY GROUP(INDIVIDUAL SUBJECTS)

Features	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Mean	-0.45	-0.71	-0.52	-0.44	-0.52	-0.52	-0.49	-0.51	-0.50	-0.52
Standard deviation	51.98	45.84	34.52	28.78	37.09	37.09	24.51	22.53	44.79	48.46
variance	3068.30	2268.38	1263.23	871.48	1549.97	1549.97	602.91	513.81	2099.46	2414.36
skewness	-0.27	-0.34	-0.08	0.33	0.04	0.04	0.03	0.02	-0.03	-0.02
kurtosis	14.20	8.84	2.94	4.73	44.52	44.52	1.42	1.46	0.52	0.22
Minimum	-516.38	-378.88	-184.31	-146.88	-430.69	-430.69	-138.31	-120.75	-208.69	-210.00
Maximum	472.25	353.44	183.69	192.56	552.06	552.06	143.25	126.63	198.25	196.81
peak_to_peak	988.63	732.31	368.00	339.44	982.75	982.75	281.56	247.38	406.94	406.81
k_complex	1.89E+08	1.39E+08	77621459	53550099	95238972	95238972	37050226	31577431	1.29E+08	1.48E+08
Energy	94264764	69701882	38815134	26778254	47623757	47623757	18528899	15793088	64503096	74177689
Hjorth parameters Activity	3068.30	2268.38	1263.23	871.48	4221.80	1549.97	602.91	513.81	2099.46	2414.36
Hjorth parameters Mobility	0.27	0.27	0.23	0.24	0.19	0.20	0.30	0.29	0.31	0.34
Hjorth parameters Complexity	2.41	2.24	1.85	1.88	3.48	3.14	2.04	2.08	1.76	1.70

TABLE4.3 AVERAGE FEATURES OF STUDY GROUP AND CONTROL GROUP

Features	Nonyoga Average	Meditation
Mean	-0.37	-0.52
Standard deviation	31.97	37.56
variance	1487.49	1620.19
skewness	0.07	-0.03
kurtosis	8.47	12.34
Minimum	-210.99	-276.56
Maximum	238.24	297.10
peak_to_peak	449.24	573.66
k_complex	91399609.73	99553185.55
Energy	45703977.21	49781031.90
HjorthparametersActivity	1487.49	1887.37
Hjorth parameters Mobility	0.20	0.27
Hjorth parameters Complexity	2.49	2.26



IV. CONCLUSION

Using a wide range of approaches, the purpose of this study was to evaluate the time domain properties of the EEG signal. They are consequently helpful in identifying whether an EEG signal possesses random oscillations, periodicity, or synchronicity. By analysing the EEG signals' temporal domain features, researchers are able to identify irregularities in the signals themselves.

An examination of the time domain aspects of the EEGs of non yoga and yoga practitioners is planned for a later stage of this research project. It is possible to identify the important aspects that have been influenced by yoga and meditation.

DOI: rp-9788770040723.171

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