Analysis of EEG Signals for Detection of Seizure Abnormalities

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Abstract
The human brain is like command center of human body .EEG is non-invasive technique of recording electrical patterns in your brain due to firing of neurons. The changes in pattern of EEG can be used to detect if any kind of disorders in human body like seizures, level of anesthesia injected during operations, awakefulness of a person, pattern of migraine etc. These disorders can be easily detected by doctors by observing the EEG patterns of the patients. The analysis of EEG signal for the detection of brain abnormalities is in itself difficult process. So a PC based automatic system is needed for the detection of brain abnormalities. Proposed work can be used as a useful tool in studying normal and abnormal seizure patients and the accuracy of the system with the different routine waves i.e. beta alpha theta delta can be checked for correct detection of seizure abnormality using a PC based system reducing the efforts of the doctors for diagnosing the disorder

Keywords- *EEG ; seizures ; artifacts ; wavelet transform*

INTRODUCTION

A disease is an abnormal condition that affects the body of an human**.** Any deviation from the normal structure of a body part or organ is displayed by a characteristic set of symptoms or signs. Electroencephalogram is used for detecting the brain disorders. Electroencephalogram is the recording of electrical activity of the brain from scalp. It measures the voltage fluctuations resulting from ionic current flows within the neurons of the brain. Diagnostic applications generally focus on the spectral content of EEG that is the type of neural oscillations that can be observed in EEG signals. EEG is commonly painless and harmless. And it does not pass any kind of electricity into your brain or body. The EEG signals are most commonly decomposed into five EEG sub-bands: delta, theta, alpha, beta and gamma. Alpha waves are rhythmic and its frequency range is from 8 to 13 Hz. The amplitude of the alpha wave is quite low. Each region of the brain has the characteristic of alpha rhythm but mostly it is recorded from the occipital and parietal regions most commonly. It oscillates between adult in awake and relaxed state with eyes closed.

Beta waves are very irregular and its frequency range is greater than 13 Hz. The amplitude of the beta wave is mostly very low. It is mostly recorded from temporal and frontal lobe. It oscillates from during deep sleep, mental activity and is related with remembering. Delta waves are rhythmic and its frequency range is about 4 to 7 Hz. The amplitude of the delta wave is quite high. It oscillates from the children in sleep state, drowsy adult and emotional distress in occipital lobe. Theta waves are comparatively slow and its frequency range is less than 3.5 Hz. The amplitude of the theta wave is between low-medium. It oscillates from adult and normal sleep in rhythm. Gamma waves are the fastest brainwaves in frequency and its frequency range is from 31 to 100 with the smallest amplitude.

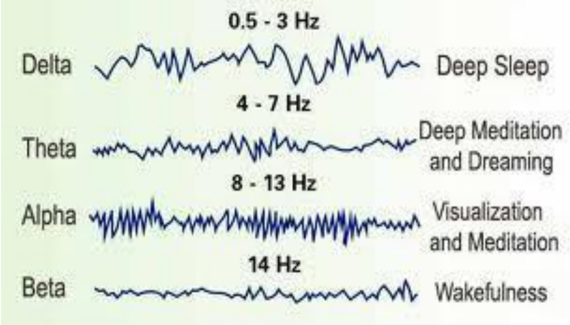

***Fig 1** Normal EEG waves*

In the proposed work the EEG signals are given as input to the pre processing code. From the pre processing the discrete wavelet transform are used to remove noises in it and the EEG signal are decomposed into five sub-band signals. The non linear parameters (time and frequency) were extracted from each of the six EEG signals (original EEG, delta, theta, alpha, beta and gamma). A genetic algorithm was used to extract the best features from the extracted time and frequency domain features. Then the classifier is used to classify the given EEG signal as normal or abnormal seizure signal
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LITERATURE REVIEW

Proposed system is designed after studying different methods for easy detection of normal and abnormal seizure waves , their accuracy and the most appropriate type of classifier .

In the paper, "Comparative Study of Wavelet-Based

Unsupervised Ocular Artifact Removal Techniques for Single-Channel EEG Data" the authors Saleha Khatun; Ruhi Mahajan; Bashir I. Morshed performed unsupervised wavelet transform (WT) decomposition technique which was systematically evaluated for effectiveness of OA removal for a single-channel EEG system.[1]

The authors Xinyang Li; Cuntai Guan; Haihong Zhang; Kai Keng Ang in the paper "Discriminative Ocular Artifact Correction for Feature Learning in EEG Analysis", to address the issues regarding loss of actual signal during artifact removal proposed a novel discriminative ocular artifact correction approach for feature learning in EEG analysis. Without extra ocular movement measurements, the artifact is extracted from raw EEG data, which is totally automatic and requires no visual inspection of artifacts.[2]

Here authors Abhijit Bhattacharyya; Ram Bilas Pachori in the paper "A multivariate approach for patient specific EEG seizure detection using empirical wavelet transform" , Investigate the multivariate oscillatory nature of electroencephalogram (EEG) signals in adaptive frequency scales for epileptic seizure detection. Methods: The empirical wavelet transform (EWT) has been explored for the multivariate signals in order to determine the joint instantaneous amplitudes and frequencies in signal adaptive frequency scales.[3]

The method proposed by authors Md Kafiul Islam; Amir Rastegarnia; Zhi Yang in paper "A Wavelet-Based Artifact Reduction From Scalp EEG for Epileptic Seizure Detection", is primarily based on stationary wavelet transform and takes the spectral band of seizure activities (i.e. 0.5 - 29 Hz) into account to separate artifacts from seizures.[4]

The authors Robert Keight, Dhiya Al-Jumeily, Abir Jaafar Hussain, Mohammed Al-Jumeily, Conor Mallucci in the paper "Towards the Discrimination of Primary and Secondary Headache: An Intelligent Systems Approach" considers the use of intelligent systems to address the long-standing medical problem of diagnostic differentiation between harmful (secondary) and benign (primary) headache conditions.[5]

In the paper "Analysis of EEG Signal for the Detection of Brain Abnormalities" the authors V.Kalaivani, V.Anusuya Devi classify the EEG signal as normal or abnormal. It is proposed to develop an automated system for the classification of brain abnormalities. [6]

The authors Hemant K. Sawant and Zahra Jalali in the paper "Detection and classification of EEG waves"analyse and classify EEG waves using using first the Discrete Wavelet Transform DWT, used for time-frequency analysis, followed by Fast Fourier Transform (FFT) that captures the rhythmic changes in EEG data. The process uses DWT for classifying EEG wave's frequencies, where as FFT is implemented to visualize these waves.[7]

In the paper "Classification of EEG Signals for Detection of Epileptic Seizures Based on Wavelets and Statistical Pattern Recognition" the authors D. Gajic, Z. Djurovic, S. Di Gennaro and Fredrik Gustafsson describe an automated classification of EEG signals for the detection of epileptic seizures using wavelet transform and statistical pattern recognition.[8]

PROPOSED SYSTEM

In the proposed system the first step is to collect database of EEG signals of X people with normal conditions and X people with seizure brain abnormalities and then grouping them according to ages. The artifacts in these signals are removed. The features in time and frequency domain like standard deviation, mean, band powers, energy etc are extracted. The dominant ones are selected and comparing these with the normal signals abnormalities are detected using discrete wavelet transform.

For signal processing MATLAB software is preferred because it is easy for signal Analysis, visualization and algorithm development. Also it supports to develop Graphical User Interface.

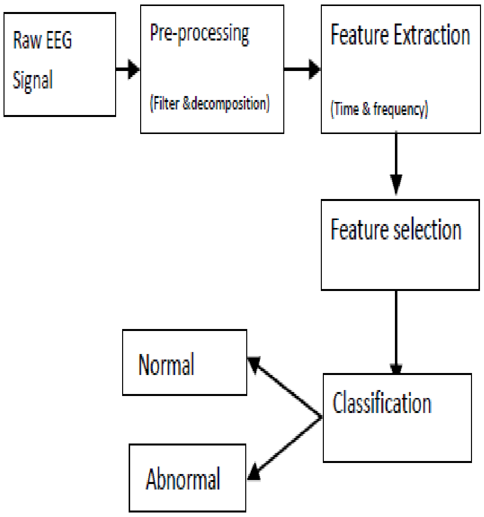


Figure 2 Frame work for analysis of EEG signal

EEG signal preprocessing

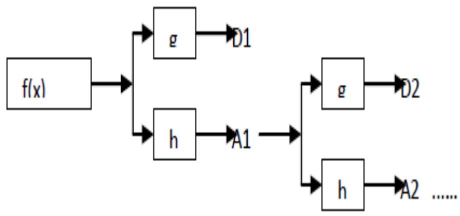


Figure 3 sub-band decomposition of a EEG signal by using Discrete Wavelet Transform

The figure 3 represents the Discrete Wavelet Transform which was used to decompose the EEG signal into its sub-band signals. The discrete wavelet function splits the signal into its detail coefficient (higher level frequency) and approximation coefficient (low level frequency). The approximation coefficient values are chosen because they mainly reduce the noises. After eight level of decomposition, the EEG was decomposed into five EEG sub-bands that approximate to delta (0-4Hz), theta (4-8Hz), alpha (8-15Hz), beta (15-30Hz) and gamma (30-100Hz).

Feature extraction

The extraction methods are used to reduce the dimensionality of features. Extracted features represent the characteristics of original signal without much of redundancy. The features can be extracted from the EEG signal in two different domains such as Frequency domain features (FDF) and Time domain features (TDF) .In the system proposed the feature extracted are power spectral density(pdf),min, max, standard deviation and entropy.

Simulation results

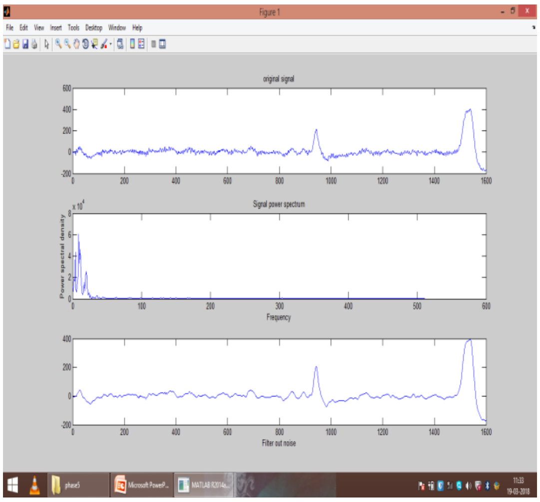


***Fig 4** 0riginal signal*

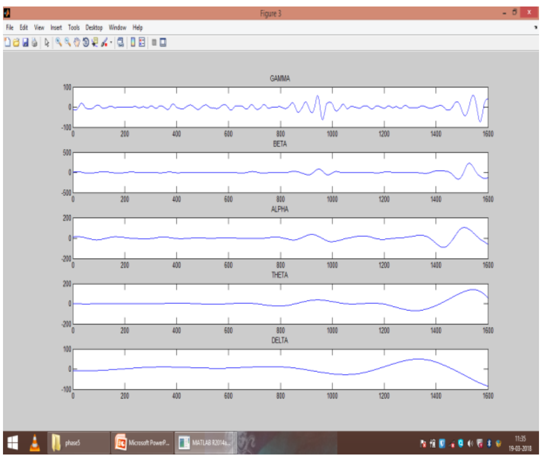


***Fig 5** Decomposed signals*

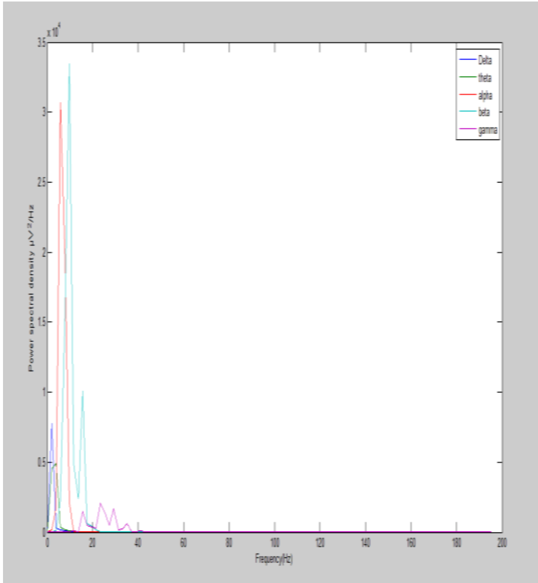
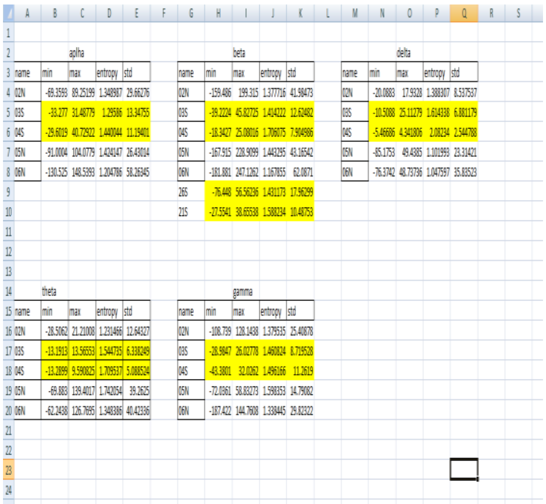


***Fig 6** Power spectral Density*



aplha

name	min	max	entropy	std
02N	-69.3593	89.25199	1.348987	29.66276
03S	-33.277	31.48779	1.29586	13.34755
04S	-29.6019	40.72922	1.440044	11.19401
05N	-91.0004	104.0779	1.424147	26.43014
06N	-130.525	148.5393	1.204786	58.26345

beta

name	min	max	entropy	std
02N	-159.486	199.315	1.377716	41.98473
03S	-39.2224	45.82725	1.414222	12.62482
04S	-18.3427	25.08016	1.706075	7.904986
05N	-167.915	228.9099	1.443295	43.16542
06N	-181.881	247.1262	1.167855	62.0871
26S	-76.448	56.56236	1.431173	17.96299
21S	-27.5541	38.65538	1.588234	10.48753

delta

name	min	max	entropy	std
02N	-20.0883	17.9328	1.388307	8.537537
03S	-10.5088	25.11279	1.614338	6.881179
04S	-5.46686	4.341806	2.08234	2.544788
05N	-85.1753	49.4385	1.101993	23.31421
06N	-76.3742	48.73736	1.047597	35.83523

theta

name	min	max	entropy	std
02N	-28.5062	21.21008	1.231466	12.64327
03S	-13.1913	13.56553	1.544735	6.338249
04S	-13.2899	9.590825	1.709537	5.088524
05N	-69.883	139.4017	1.742054	39.2625
06N	-62.2438	126.7695	1.348386	40.42336

gamma

name	min	max	entropy	std
02N	-108.739	128.1438	1.379535	25.40878
03S	-28.9847	26.02778	1.460824	8.719528
04S	-43.3801	32.0262	1.496166	11.2619
05N	-72.0361	58.83273	1.598353	14.79082
06N	-187.422	144.7608	1.338445	29.82322

***Fig 7** Feature Extraction*

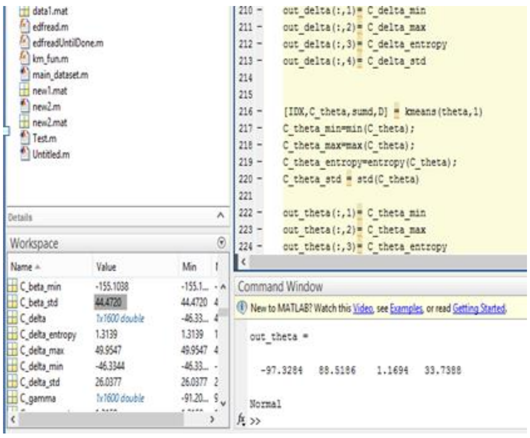


***Fig 8** Classification as normal or abnormal on the basis of dominant feature selected.(Here it is standard deviation)*

Observed results for changes in peak overshoots of normal and abnormal EEG waves.

These results were observed for 25 patients which approximately(mean) gave the values below.

Signals	Normal	Abnormal
Delta	15000	8000
Theta	7000	9000
Alpha	7000	31000
Beta	17000	6000
Gamma	4000	9000

The ranges of frequency for given power spectral density (uV^2/hz) remain the same for normal and abnormal signal.

Implementation issues and system reliability:

1.The data obtained from doctors is usually from software neurocompact and its conversion to mat file becomes an issue.

2.The results observed were appropriate for 17 patients out of 25 so the accuracy of the system goes around 68%.

CONCLUSION AND FUTURE WORK

The analysis of EEG signal for the detection of brain abnormalities is a difficult process. So the PC based automatic system is needed for the detection of brain abnormalities.

Complexity of EEG is reduced. A filtered out signal and power spectral densities for alpha bête theta delta gamma are obtained.

Proposed work can be a useful tool in studying normal and abnormal patients and the accuracy of the system with the different routine waves i.e. beta alpha theta delta can be checked for correct detection of abnormality.

The system can be extended further in future using kmeans to extract features like min,max,standard deviation etc, select the dominant one and then classify the signals as normal and the abnormal seizure ones and display the result using a GUI created which will be useful.

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