Detection of Brain Abnormalities using Hilbert-Huang Transform

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***Abstract*:- This paper presents the analysis of classifying between normal and abnormal patients using the featured based on Hilbert-Huang Transform of EEG Signal. By analyzing the EEG Signal from accessible database discrimination is achieved. The intrinsic function information which is in EEG Signal can be extracted with the help of s Hilbert-Huang Transform this information helps to get the local amplitude of the signal and frequency. Based on the information weighted frequency is calculated and the comparison between the intrinsic functions of normal and abnormal determinant is performed.**

Keywords: Weighted Frequency, Intrinsic Frequency, EEG, Hilbert-Huang

I. INTRODUCTION

EEG i.e. Electroencephalography it is a method providing information necessary for the classification, of normal and abnormal patients by doing proper diagnosis. The information can be obtained with the help of energy content and the frequency which is divided into delta theta alpha and beta. Normal and Abnormal patients' diagnosis can be done with the help of information obtained through the computerized Analysis. The methods efficient in classification of abnormal and normal patient are amplitude, frequency, and phase which are oscillatory information. These feature helps in comparison between normal and abnormal brain activities. Hilbert Transform not only gives spectral information but also gives analytical signal representation. The Aim and Objective of this paper is Coupling of EMD i.e. Empirical Mode Decomposition which is also called Huang Transform with Hilbert Transform to get the results of classification

II.RELATED WORK

The abnormality can be seen in the persons brain EEG Signal due to the disturbance or changes in the electrochemical activity of the neurons which leading to abnormal and synchronous discharges. The most difficult process is analysis of brain signals i.e. EEG Signals for brain abnormalities detection. So it develops a need of automatic

system which is PC based for brain abnormalities detection. Types of brain waves is shown in Fig.1 that are recorded on an EEG test it shows different state of wakefulness in which abnormalities are recorded .In this presented work discrimination is achieved by EEG signals database which is obtained from doctors or any freely accessible sources. MATLAB Software is used for implementing and testing of the Classification Algorithm which is proposed. So, using the features based on HHT i.e. Hilbert-Huang Transform the Classification of normal and abnormal activities can be done in this paper.

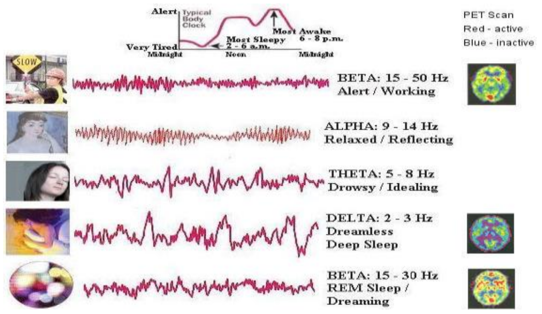

Fig .1. Wakefulness of person

Objectives:

- Obtain Normal and Abnormal EEG Signal from Data Base.
- Pre-Processing of EEG Signal.
- Develop Code for extraction of Features/Parameters like Standard Deviation, Mean, Band Powers, Energy etc.
- Development of code for Hilbert-Huang Transform.
- Classification of Normal and Abnormal Signal

III. METHOD

A. Hilbert Transform

With the help of EEG Signal Features the classification of the normal and abnormal activities of brain function is achieved using HHT i.e. Hilbert-Huang Transform. The analysis of different oscillatory modes such as energy and the frequency content of every brain wave is done. This can be achieved by tracking amplitude and frequency content of every signal whether normal or abnormal. By calculating the weighted frequency using the Hilbert transform discrimination between normal and abnormal patients is achieved. Huang Transform is used by coupling it with Hilbert Transform for getting the narrow banded signals.

B. Huang Transform

Huang transform is also known as EMD i.e. Empirical Mode Decomposition which is an signal processing technique this technique is used to extract the oscillatory modes which are

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embedded in a brain signal. The main advantage is that it does not require any linear or Stationary Data. This EMD mode is Data Driven Mode i.e. it does not require any resolution or harmonics. The amplitude and instantaneous frequency is defined by using Intrinsic Mode Functions. The Hilbert Transform can easily be applied to each and every single intrinsic mode. For the extraction of intrinsic mode the shifting process is done.

The proposed work contain following Steps,

1) The Signal Processing Technique named as EMD is used for extraction of the oscillatory mode without the requirement of linear or stationary data. As compared to wavelet mode why EMD is used here is it has no resolution and harmonics present. This decomposition technique is applied to EEG signal with the main objective of extracting intrinsic mode in EEG Signal
2) Tracking of the amplitude and instantaneous frequency is done by Hilbert Transform.
3) After Applying the HHT Algorithm based on the features extraction the classification is done between the normal and abnormal patients

Block Diagram

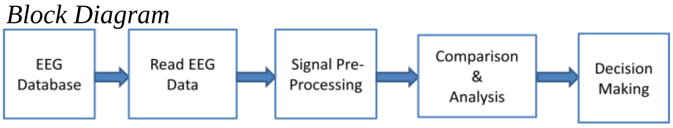


Fig.2. Block Diagram

In this work it is proposed to carry out the classification using Hilbert- Huang Transform of EEG Signals to Detect Brain Abnormality. The block diagram shown in Fig.2 represents the steps which are carried out i.e. The collected EEG Data Base is read first then Signal Processing is done after Comparison and Analysis the results are considered and decision making is done on normal and abnormal person.

III.II.I Pre-processing

EEG Matlab Software

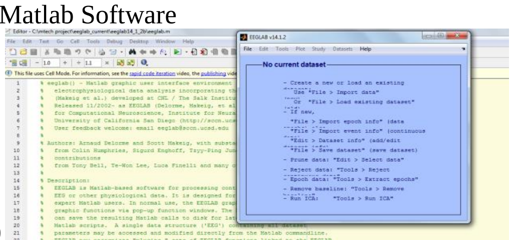
0 

Fig 3. EEG Matlab Software

The figure shows the first screen after running the EEGtoolbox when there is no data loaded

Importing Data

Import/Load Data

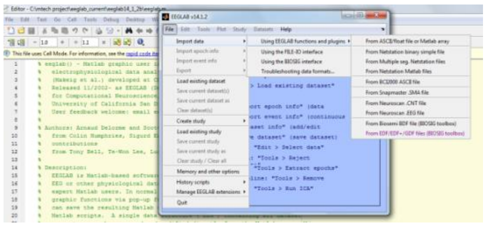


Fig4. Importing Data

The figure shows way to load data can be any Matlab,Binary.ACSII etc.

Load Dataset

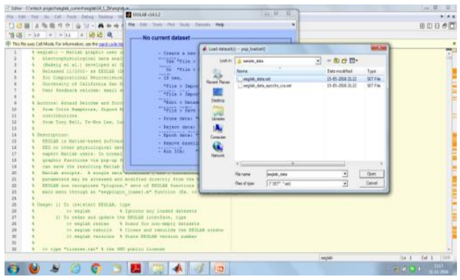


Fig 5. Loading Dataset

The figure shows that the dataset can also be loaded from existing data which is present in .set format

Data Information Scrolling Data

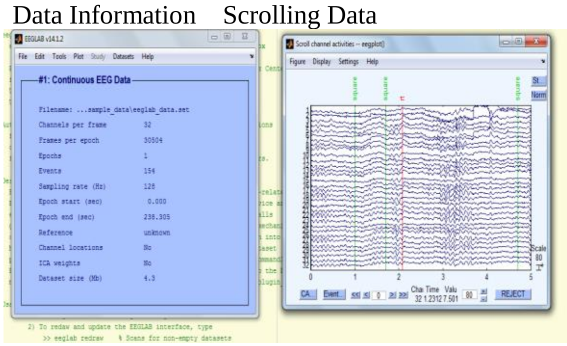


Fig 6. 32 Channel Data information

The figure shows 32 channel data information in the form of signals with time and value with respect X-axis and Y-axis.

Editing and Preprocessing

a) Edit/Select Data

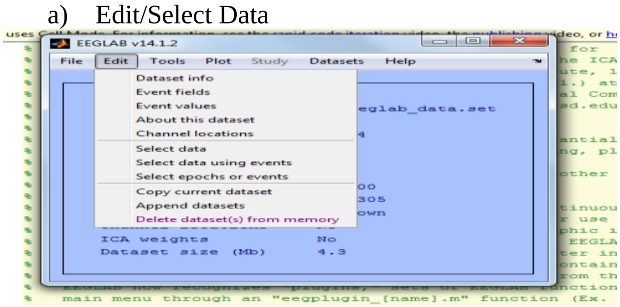


Fig 7. Editing Data.

The Figure shows that the data can be edited, event values, event fields and even sampling rate can be edited.

b) Pre-processing

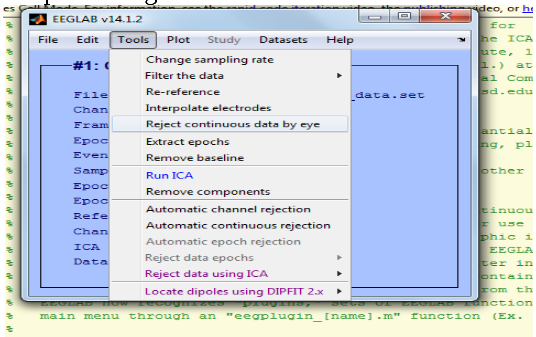


Fig 8. Processing Data

The figure shows various data processing techniques in tool

c) Rejecting Artifacts in Continuous Data

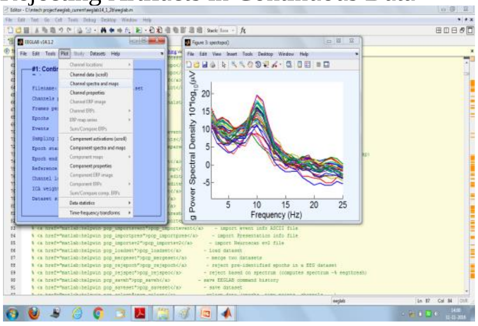


Fig 9.plot of power vs frequency

The figure shows channel spectra plot with respect to frequency. Every different color refers to different channel in total 32 channels 32 colors with pop spectopo() as command

d) Plot Data Spectrum and Maps

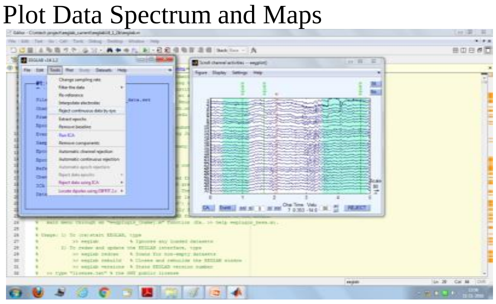


Fig 10. Rejection of Data

The figure shows we can reject particular data from signal and new data set can be created with marked regions being removed. There are two event types square and rt. Reaction time is given by rt we can see different reaction at different places. The time and value are represented at x axis and y axis it changes with the position on the signal.

e) Channel Statistics

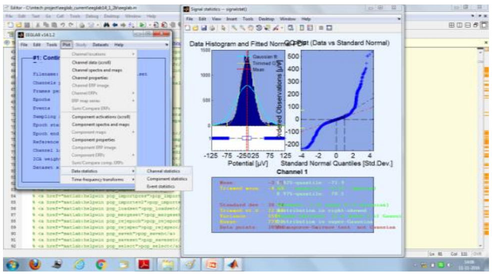


Fig. 11 Channel Statistics

Figure shows channel statistics with respect to Mean, Guassian and triimed.

2) Feature Selection

Feature extraction: The dimensionality of the features is reduced by using this feature extraction method. The Characteristics of Original signal without much redundancy is presented..

Time domain features: Statistical calculations are included in Time Domain Analysis. Mean, Median, Mode, Standard deviation, Maximum and Minimum are the time domain features.

IV. RESULT

1) Waveforms for EEG Normal Signal

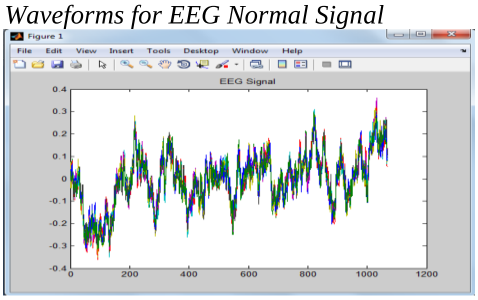


Fig. 12. Original Signal For Normal Signal 1

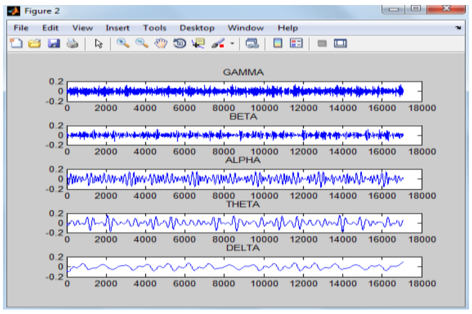


Fig 13. Different Ranges of Brain Waves in TD

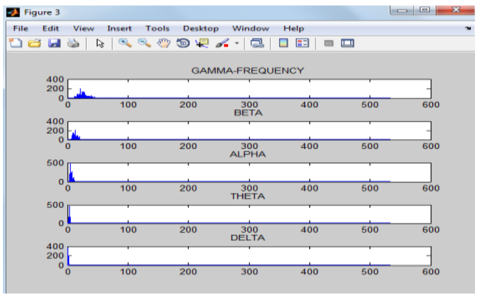


Fig 14. Different Ranges of Brain Waves in FD

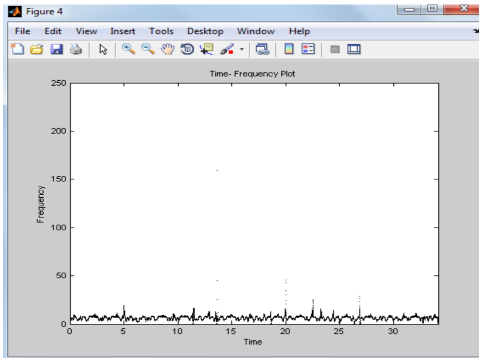


Fig 15. Time –Frequency Plot for Normal EEG

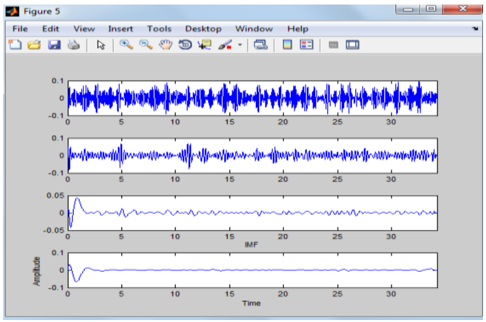


Fig 16. Amplitude Vs Time for Different Ranges

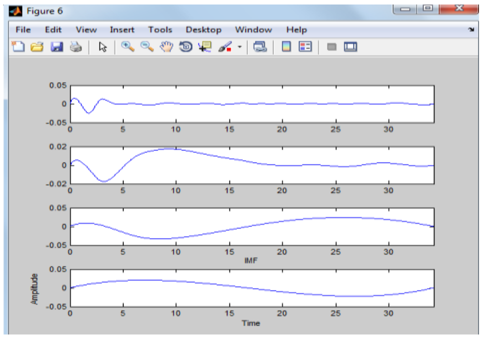


Fig 17. Amplitude Vs Time with IMF for

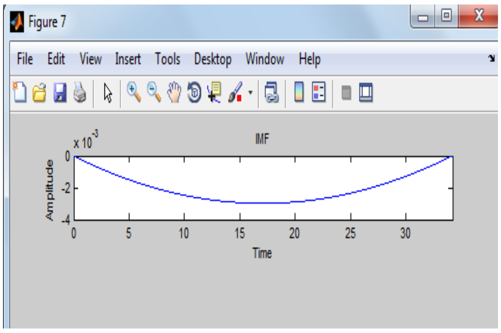


Fig 18. IMF Amplitude vs Time for Normal Signal

Table 1- Time Domain Features for Alpha Waves

EEGWaves	Min	Max	Entropy	Std.Deviation
Normal 1	-0.1677	0.1507	3.410	0.0619
Normal 2	-0.1715	0.1511	3.4115	0.0617
Normal 3	-0.1677	0.1507	3.4102	0.0619
Normal 4	-0.1677	0.1507	3.4101	0.0619
Normal 5	-0.1737	0.1528	3.3757	0.0606
Normal 6	-0.1677	0.1507	3.4102	0.0619
Normal 7	-0.1677	0.1519	3.3846	0.0595
Normal 8	-0.1912	0.1612	3.4156	0.0652
Normal 9	-0.1777	0.1656	3.5006	0.0724
Normal10	-0.1725	0.1594	3.4755	0.0719

Table 2- Time Domain Features for Beta Wave

EEG Waves	Min	Max	Entropy	Std.Deviation
Normal 1	-0.1349	0.1217	3.0148	0.0370
Normal 2	-0.1347	0.1257	3.0342	0.0375
Normal 3	-0.1349	0.1217	3.0153	0.0371
Normal 4	-0.1349	0.1217	3.0148	0.0370
Normal 5	-0.1246	0.1008	2.9762	0.0348
Normal 6	-0.1349	0.1217	3.0143	0.0371
Normal 7	-0.1401	0.1427	3.0735	0.0400
Normal 8	-0.1254	0.1382	3.0691	0.0394
Normal 9	-0.1361	0.1417	3.1478	0.0437
Normal 10	-0.1615	0.1468	3.1916	0.0458

Table 3- Time Domain Features for Delta Waves

EEG Waves	Min	Max	Entropy	Std.Deviation
Normal 1	-0.0998	0.1032	2.8523	0.0381
Normal 2	-0.0978	0.1033	2.9222	0.0381
Normal 3	-0.1002	0.1032	2.8537	0.0381
Normal 4	-0.0998	0.1032	2.8523	0.0381
Normal 5	-0.0958	0.1027	2.7933	0.0392
Normal 6	-0.0946	0.1032	2.8451	0.0380
Normal 7	-0.1004	0.1032	2.8529	0.0375
Normal 8	-0.1665	0.0981	2.8592	0.0677
Normal 9	-0.1827	0.1212	1.8698	0.0767
Normal 10	-0.1881	0.1226	2.8210	0.0867

Table 4-Time Domain Features For Gamma Waves

EEG Waves	Min	Max	Entropy	Std.Deviation
Normal 1	-0.1265	0.1362	3.1330	0.0411
Normal 2	-0.1265	0.1362	3.1352	0.0413
Normal 3	-0.1265	0.1362	3.1330	0.0411
Normal 4	-0.1265	0.1362	3.1330	0.0411
Normal 5	-0.1265	0.1362	3.1570	0.0418
Normal 6	-0.1265	0.1362	3.1340	0.0411
Normal 7	-0.1265	0.1362	3.1519	0.0424
Normal 8	-0.1265	0.1362	3.1504	0.0419
Normal 9	-0.1257	0.1362	3.1597	0.0425
Normal 10	-0.1262	0.1521	3.2026	0.0446

Table 5-Time Domain Features For ThetaWaves

EEGWaves	Min	Max	Entropy	Std.Deviation
Normal 1	-0.1862	0.1560	3.2323	0.0570
Normal 2	-0.1868	0.1559	3.2164	0.0563
Normal 3	-0.1862	0.1560	3.2321	0.0570
Normal 4	-0.1862	0.1560	3.2323	0.0570
Normal 5	-0.1849	0.1545	3.2363	0.0556
Normal 6	-0.1862	0.1560	3.2314	0.0569
Normal 7	-0.1862	0.1512	3.2172	0.0552
Normal 8	-0.1278	0.1416	3.0841	0.0420
Normal 9	-0.1488	0.1223	3.2789	0.0529
Normal 10	-0.1410	0.1239	3.3617	0.0519

1) Waveforms for Abnormal Signal

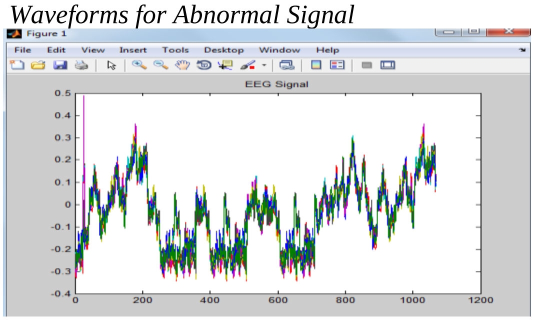


Fig 19. Original Signal for Abnormal Signal

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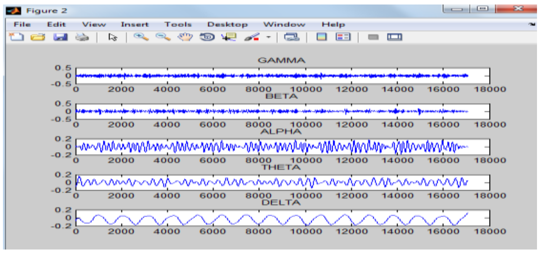

Fig 20. Different Ranges of Brain Waves in TD

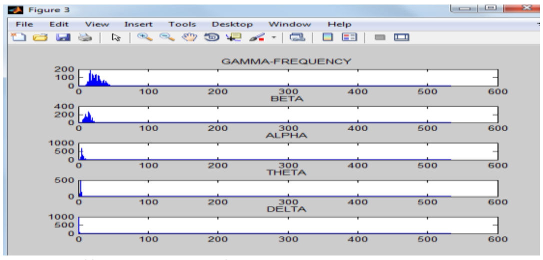

Fig 21. Different Ranges of Brain Waves in TD Abnormal Signal

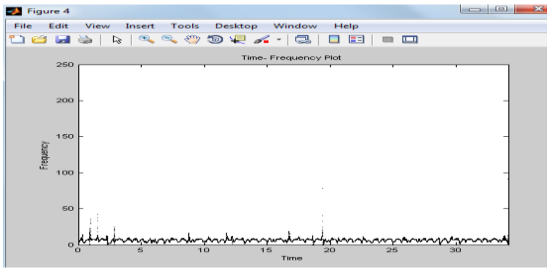

Fig 22. Time-Frequency Plot for Abnormal Signal 1

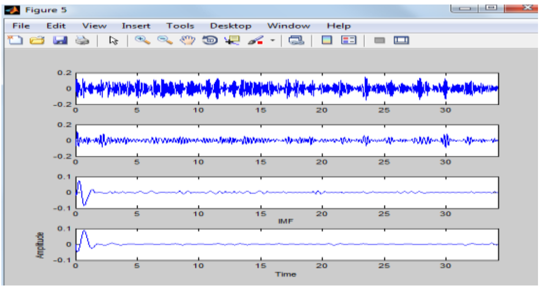

Fig 23. Amplitude Vs Time for Different Ranges in Abnormal EEG Signal1

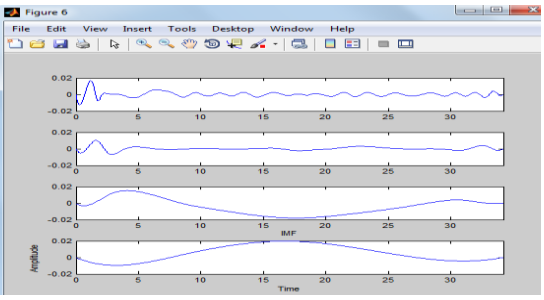

Fig 24. Amplitude Vs Time with IMF for Different Ranges in Abnormal EEG Signal 1

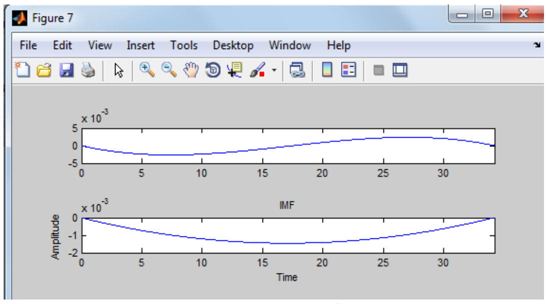

Fig 25. IMF Amplitude vs Time for Abnormal Signal 1

Table 6-Time Domain Features For Abnormal Alpha Waves

EEG Waves	Min	Max	Entropy	Std. Deviation
Abnormal 11	-0.1840	0.2068	3.5141	0.0725
Abnormal 12	-0.1839	0.2072	3.5264	0.0731
Abnormal 13	-0.1809	0.2050	3.5729	0.0775
Abnormal 14	-0.1827	0.2064	3.5524	0.0767
Abnormal 15	-0.1822	0.1771	3.4553	0.0710
Abnormal 16	-0.2033	0.1839	3.5451	0.0758
Abnormal 17	-0.1764	0.1753	3.4793	0.0718

Table 7-Time Domain Features For Abnormal Beta Waves

EEGWaves	Min	Max	Entropy	Std.Deviation
Abnormal11	-0.2414	0.2214	3.3813	0.0570
Abnormal12	-0.2509	0.1972	3.3617	0.0557
Abnormal13	-0.2257	0.2041	3.2918	0.0510
Abnormal14	-0.2260	0.2041	3.2947	0.0514
Abnormal15	-0.2234	0.1795	3.2890	0.0517
Abnormal16	-0.1549	0.1712	3.2375	0.0471
Abnormal17	-0.2237	0.1831	3.2789	0.0517

Table 8-Time domain feature extraction for delta waves

EEGWaves	Min	Max	Entropy	Std. Deviation
Abnormal11	-0.2134	0.1180	2.5338	0.0777
Abnormal12	-0.2127	0.1179	2.6311	0.0795
Abnormal13	-0.1882	0.1242	2.7136	0.0795
Abnormal14	-0.1857	0.1226	2.6454	0.0805
Abnormal15	-0.1912	0.1227	2.5008	0.0850
Abnormal16	-0.1936	0.1523	3.1195	0.0988
Abnormal17	-0.1870	0.1227	2.6425	0.0807

Table 9-Time domain feature extraction for gamma waves

EEG Waves	Min	Max	Entropy	Std.Deviation
Abnorma111	-0.2108	0.1769	3.2973	0.0532
Abnormal 12	-0.2108	0.1769	3.3042	0.0521
Abnormal13	-0.2051	0.1769	3.2452	0.0477
Abnormal 14	-0.2051	0.1679	3.2328	0.0472
Abnormal 15	-0.1445	0.1638	3.1698	0.0430
Abnormal 16	-0.3178	0.2827	3.3062	0.0537
Abnormal 17	-0.2189	0.1816	3.2254	0.0464

Table 10-Time domain feature extraction for theta waves

EEGWaves	Min	Max	Entropy	Std.Deviation
Abnormal 1	-0.1840	0.2068	3.5141	0.0725
Abnormal 2	-0.1839	0.2072	3.5264	0.0731
Abnormal 3	-0.1809	0.2050	3.5729	0.0775
Abnormal 4	-0.1827	0.2064	3.5524	0.0767
Abnormal 5	-0.1822	0.1771	3.4553	0.0710
Abnormal 6	-0.2033	0.1839	3.5451	0.0758
Abnormal 7	-0.1764	0.1753	3.4793	0.0718

V. DISCUSSION

After HHT Coding in MATLAB Software different results are obtained such as min and max of the respective signal, the entropy and Standard deviation , for the classification.

VI. CONCLUSION

For the diagnosis of epilepsy EEG Signal is very much important. For the detection of Brain abnormalities and brain disease and keeping the record of patient in long term and diagnosing huge amount of EEG data is needed. For detection of Epilepsy EEG Signal is must and the process is performed by experts in EEG labs of respective hospital this data is very private and secure. This HHT algorithm has the potential in classification of normal and abnormal activities using feature extraction method.

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