



Research Article

TIME-FREQUENCY ANALYSIS OF EEG DATA TO DISTINGUISH DIFFERENT MENTAL STATES BY USING GLOBAL WAVELET SPECTRUM

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ABSTRACT

The electroencephalography (EEG) is a way to study the individual's electrical activity of the brain. It is non-invasive technique to analyze brain signals which help to identify that either signals are showing normal or abnormal activity of the brain i.e. Different emotional states and mental diseases. The signals of EEG are non-stationary means the frequency of signals changes over time. To study these non-stationary signals, wavelet transform is used to classify EEG segment for seven different subjects. In the proposed work, three dimensional global wavelet spectrum (GWS) are applied on seven EEG datasets to compare the results of different mental states of a person.

Keywords: EEG, global wavelet spectrum.

1. INTRODUCTION

This study is the extension of the work present in reference no [7]. Brain has a very tremendous importance in individual's life. It consists of millions of nerve cells that are interconnected with each other. All our actions, thoughts and activities are carried out due to electrical impulses that travel along neurons from the body to brain. These electrical signals are divided into five different waveform based on their frequency range which corresponds to different activities carried out by the subject. Generally, in normal persons, the frequency range of brain waves areas follows: [1]

Delta wave range 0 to 4 Hz, Theta wave range 4 to 8 Hz, Alpha wave range 8 to 12 Hz Beta wave range 13-30 Hz Gamma wave range 30-60 Hz

The abnormality in fluctuations of electrical signals show brain disorders such as epilepsy, autism spectral disorder (ASD) and other neurological diseases.[2]

The diagnosis of abnormality is an important issue. For this, various techniques have been introduced to measure brain activity to diagnose epilepsy or other neuro diseases

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such as functional magnetic resonance imaging (fMRI), magneto encephalography (MEG), positron emission tomography (PET), electroencephalography (EEG) etc.[7] Among all these methods EEG is one of the most widely used method to measure brain activity.

EEG signals possess meaningful information about the function of the brain by capturing electrical signals of the brain.[7] As EEG signals are non-stationary in nature and long term EEG measurements has a lot of data values which is difficult to review manually. Therefore time varying computation is needed to extract the useful information from EEG signals. For this purpose there are variety of mathematical methods to study the time series that contain non stationary power at many different frequencies. The most appropriate method to analyze localized variations of power within a time series is Wavelet Transform.[1]

Wavelet transform provides information on both the amplitude of any periodic signal within the series and time at which the amplitude of signal varies. (Torrence,2001). Wavelet transform is either discrete or continuous. In this paper, we used continuous wavelet transform to differentiate various mental states with the help of the wavelet power spectrum and global wavelet spectrum.

2. MATERIALS AND PROPOSED METHODOLOGY

1) Dataset obtained

The data used in this paper is obtained from "Epilepsy center in Bonn, Germany collected by Dr. Ralph Andrzejak" which is publically available on [http://epilptologiebonn.de/ Andrzejak et al.\(2001\)](http://epilptologiebonn.de/Andrzejak) and <https://www.kaggle.com/wanghaohan/confused-eeg/kernels>.

The datasets (A-E) containing 100 single channels and the datasets (a, c and m) containing 24 students data. Seven sets are selected for this study which are A, B, C, E, a, c and m. Set A represents Z001, set B represents O001, set C represents N001 and set E represents S001. Class Z shows healthy subject with eyes open state, class O is eyes closed state, class N is showing interictal activity, class S is seizure activity, set a represents data of attentive students, set c represents data of confused students and meditation is represented by set m .[7]

2) Wavelet transform

Wavelet analysis has a broad aspect to analyze signals in time-domain Dubravskacesta(2010). Wavelet transform is a mathematical tool for time-scale analysis, signal decomposition and signal compression .There are two types of wavelet transform which are: i) Discrete wavelet transform (DWT), ii) Continuous wavelet transform (CWT).

In this paper, we used CWT for wavelet power spectrum with Morlet wavelet function by the reference of Torrence(2001), which is defined as:

$$\psi_0(\eta) = \frac{-1}{\pi^4} e^{i\omega_0\eta} e^{-\frac{\eta^2}{2}} \tag{1}$$

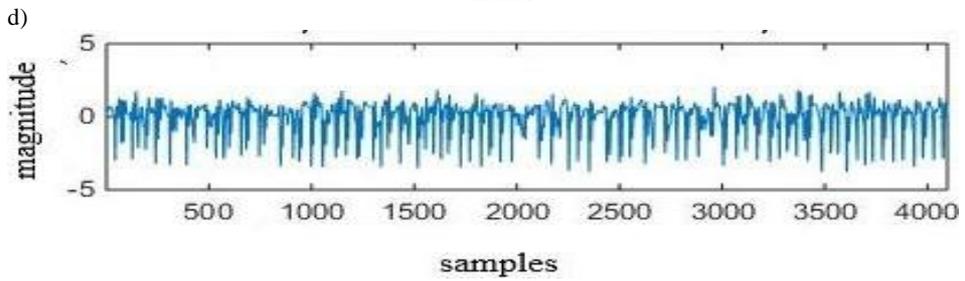
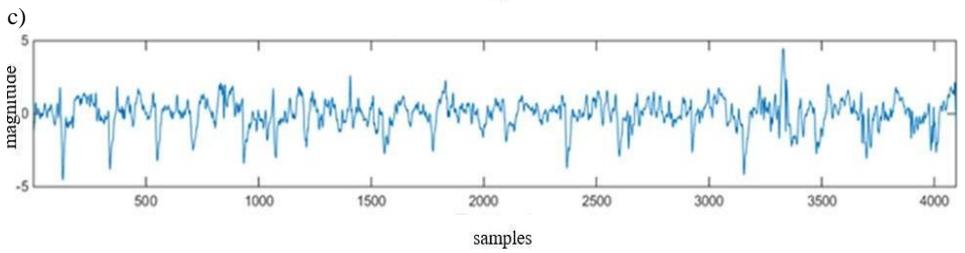
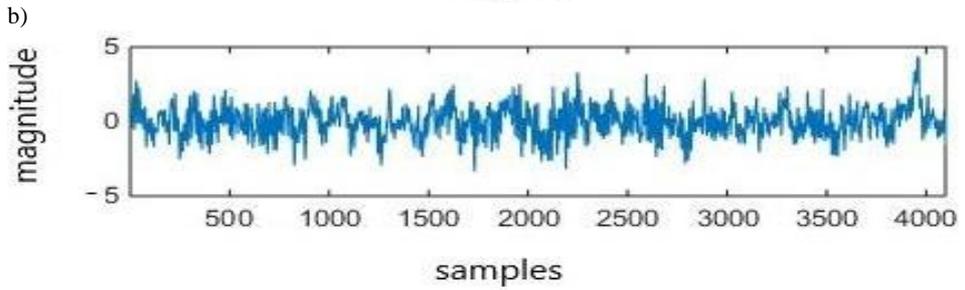
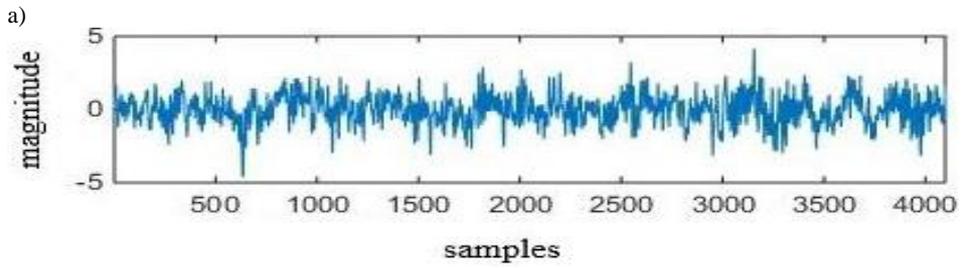
Where ω_0 and η represent frequency and time which has no dimension respectively.

Torrence(2001) defined the CWT of discrete sequence of EEG signal 'Sig_n' as a convolution of the data sequence with a scaled and translated version of the mother wavelet. Mathematically:

$$W(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} \text{Sig}_n \psi^* \left[\frac{(n-m)\delta t}{s} \right]$$

$$m = 0, 1, \dots, N - 1. \tag{2}$$

δt is sampling interval and s , are dilation & translation parameter used to change the scale & slide in time in that order with wavelet function ψ .



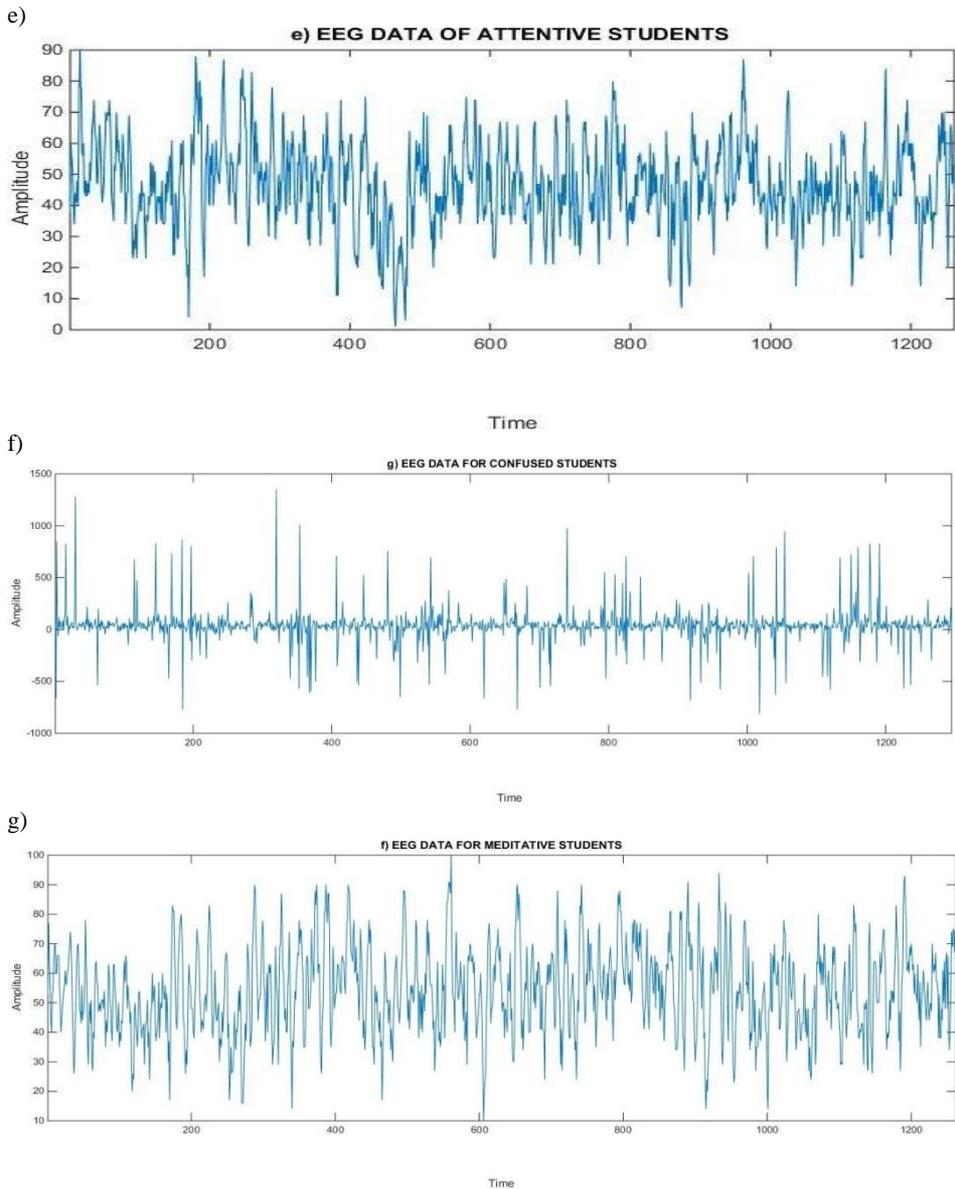


Figure 1. EEG signals a) Z001, b) O001, c) N001, d) S001, e) Set a, f) Set c, g) Set m

a) Three Dimension Global Wavelet Spectrum

Three Dimension Global wavelet spectrum provides a fair and consistent estimation of the true power spectrum of more than one time series of same subject. It is also helpful in comparing the region's temporal variability to the other regions which does not display long term changes : [7]

$$\bar{W}^2(s) = \frac{1}{N} \sum_{n=0}^N |W(s)|^2$$

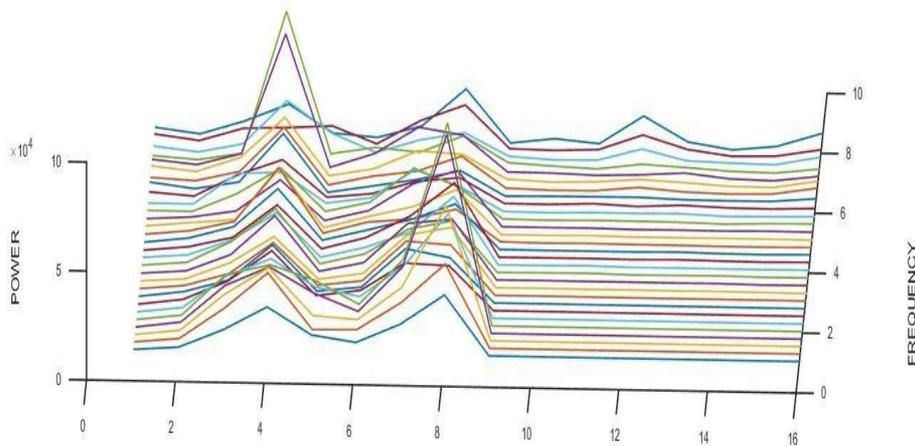
3. RESULTS AND DISCUSSIONS

The main results are compared in Figure 2, Figure 3, Figure 4, Figure 5 and Figure 6.

In Figure 2, comparison between attention and confusion states is shown. The pattern of data of sixteen students of Attention and Confusion may clearly be identified. In first eight students, it is clearly identified that student number four and eight are more attentive than others and student 9 is more confused. From the diagram it may be concluded that if the students are attentive than they are not confused. In Figure 3, comparison between confusion and meditation states is shown. The pattern of data of sixteen students of Confusion and meditation students may clearly be identified. In first eight students, it is clearly identified that few students are more confused than others. From the diagram it may be concluded that if the students are confused than they are not in good meditation states. In Figure 4, differences between attention and meditation states are examined. In Figure 5, attention, confusion and meditation states are differentiated by using EEG data. In Figure 6, comparison of 400 signals i.e. 0-100, 101-200, 201-300, 301-400 of four EEG datasets is shown which are N,O,Z and S respectively. Seizure activity is specified around period 4-8 Hz which is significantly different from other signals. To quantify the difference among datasets, the statistical feature (variance) of these signals is calculated in Table 1 which clearly shows the difference in epileptic patient before and after attack, healthy person with eyes open and eyes closed.

GWS OF SIXTEEN STUDENTS FOR COMPARISON OF MEDITATION/CONFUSION STATES

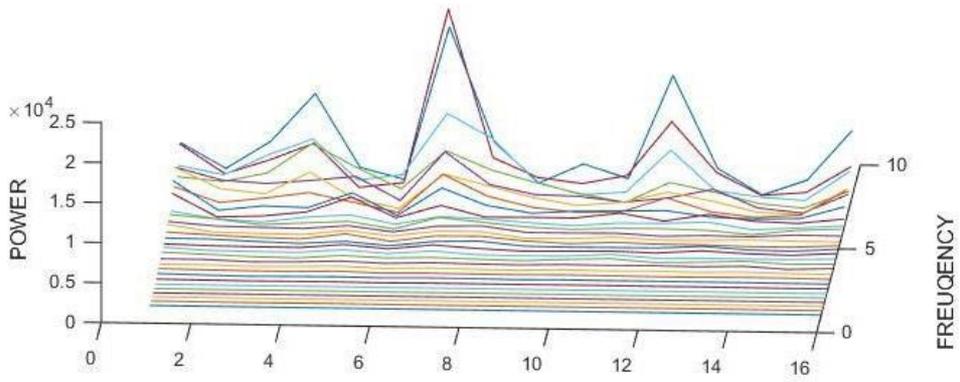
Figure 2. Comparison of data of sixteen students of Attention and Confusion states



EIGHT STUDENTS IN CONFUSED STATES
LAST EIGHT STUDENTS IN MEDITATION STATES

Figure 3. Comparison of data of sixteen students of Confusion and meditation states.

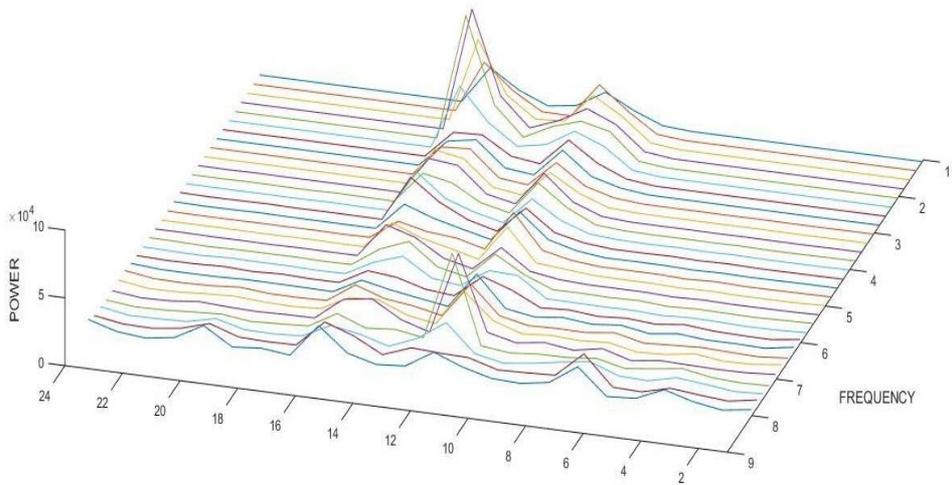
GWS OF SIXTEEN STUDENTS FOR COMPARISON OF MEDITATION/ATTENTION STATES



EIGHT STUDENTS IN ATTENTION STATES
 LAST EIGHT STUDENTS IN MEDITATION STATES

Figure 4. Comparison of data of sixteen students of Attention and Meditation states

GWS OF SIXTEEN STUDENTS FOR COMPARISON OF MEDITATION/CONFUSION/ATTENTION STATES



FIRST EIGHT STUDENTS IN ATTENTION
 SECOND EIGHT STUDENTS IN CONFUSED STATES
 LAST NINE STUDENTS IN MEDITATION STATES

Figure 5. Comparison of all three states i.e. attention, confusion and meditation

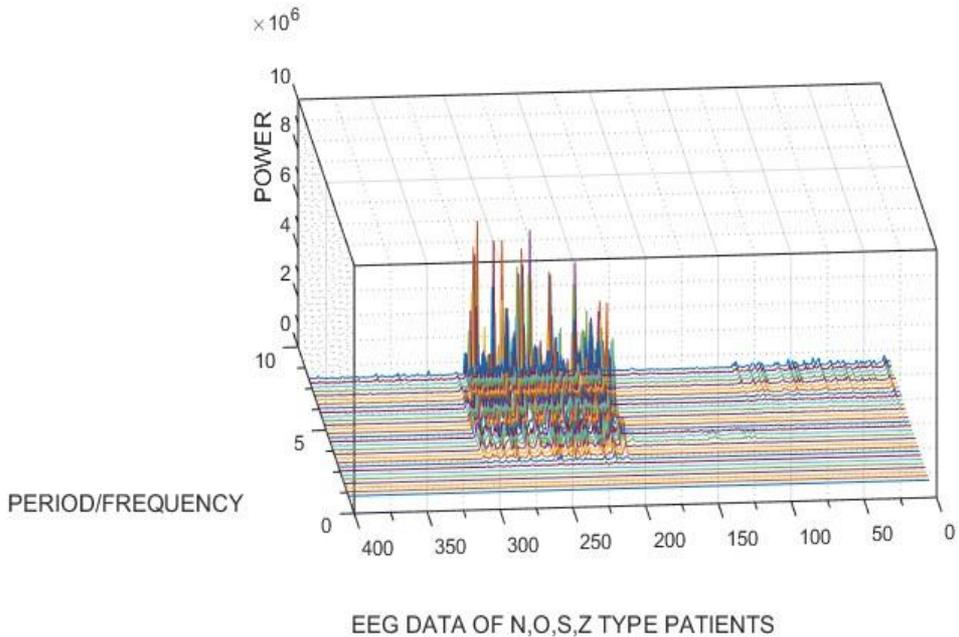


Figure 6. GWS of 100 signals of four EEG datasets: N,O,S and Z

Table 1. Variance of EEG signals S001, Z001, N001, O001

Brain waves	S001	N001	Z001	O001
Alpha	4.1656e+003	321.5280	157.6744	328.8349
Theta	1.1900e+003	148.0828	151.0412	174.5409

4. CONCLUSION

In this study, Attentive, Meditative and Confused states, healthy and epileptic persons, eyes open and eyes closed conditions, and ictal and interictal spikes are distinguished using EEG data based on wavelet analysis. Wavelet analysis is applied to characterize EEG signal frequency component along with time localization on seven EEG datasets. GWS clearly indicated by different pattern the difference in activities of examined groups within the specific components.

Conflict of Interest

The authors declare that they have no conflict of interest

REFERENCES

- [1] M. Teplan, (2002) Fundamentals of EEG measurement, Measurement Science Review, Volume 2, Section 2, 1-11.

- [2] I. Omerhodzic, S. Avdakovic, A. Nuhanovic, K. Dizdarevic (2013) Energy distribution of EEG signals: EEG signal wavelet-Neural network classifier, *World Academy of Science, Engineering and Technology*, 61, 1190-1195.
- [3] K. Asaduzzaman, M. B. Reaz, F. Mohd-Yasin, K. S. Sim, M. S. Hussain, (2010) A study on discrete wavelet-based noise removal from EEG signals, *Adv Exp Med Biol.*,680:593-9.
- [4] A. A. Mashakbeh (2010), Analysis Of Electroencephalogram To Detect Epilepsy, *Int. Journal Of Academic Research*, vol. 2, pp. 63-69.
- [5] A. S. Patil,G. G. Kulkarni (2012), Extraction of Features from EEG Signal to Determine Seizure, *International Journal on Advanced Electrical and Electronics Engineering*, (IJAEED), Volume-1, Issue-1, 109-112.
- [6] Torrence C, Compo GP (1998) A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society* 79: 61-78.
- [7] Zakaria K., Huma S. and Choudry A.A (2019), EEG data analysis by wavelet power spectrum and global wavelet spectrum, *International Journal of Scientific and Engineering Research* 10(3):1058-1066.
- [8] S. B. Wilson, R. Emerson (2002), Spike detection: A review and Comparison of algorithms, *Clin. Neurophysiol.*, vol. 113, pp. 1873-1881.
- [9] H. Adeli, Z. Zhou, N. Dadmehr (2003), Analysis of EEG records in an epileptic patient using wavelet transform, *J. Neurosci. Meth.*, vol. 123, no. 1, pp. 69-87.
- [10] L. D. Iasemidis, L. D. Olson, J. C. Sackellares, R. S. Savit (1994), Time dependencies in the occurrences of epileptic seizures: A nonlinear approach, *Epilepsy Res.*, vol. 17, pp. 81-94.
- [11] J. F. Annegers, E. Wyllie, Lea, Febiger (1993), *The epidemiology of epilepsy, The Treatment of Epilepsy*, Philadelphia, Pennsylvania, pp. 157-164, 1993.