TITLE: Analyzing time series of brain electrical activity through wavelet transform

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ABSTRACT

EEG (Electroencephalography) is deals with human brain. EEG signals more useful in neurology and play prominent role in study about activity of the brain. EEG study are mostly useful for diagnosis of Epileptic activity. But afterward it is also useful for understanding of cognitive process. The EEG technique read by neurologist who has taken specific training in the interpretation of EEGs. The purpose of the paper is to construct a base for the development of future methodology for reading and interpreting EEG correctly even in absence of qualified person. In present work, used EEG signals for analyzed electrical activity of brain at different condition of person: normal behavior of person (eyes open (a) and eyes close (b)), seizure free interval (epileptic zone (c) and hippocampal formation (d)) and the seizure activity (e) via continuous wavelet transform. Continuous Wavelet transform is known as mathematical tool which provides Multiresolution analysis. It is found that Morlet wavelet coefficients (low pass coefficient and high pass coefficient) clearly identify distinguishing features of the signals using matlab technique. After pin-pointing these robust features in the wavelet scalogram, systematically work on the autocorrelation property of the wavelet coefficients of the signal. This can help tremendously in the developing front telemedicine. Using EEG data extracted from University of Bonn, Germany, which is available in public domain [12]. So in present paper, continuous wavelet transform can be employed here for making precise analysis of electrical activity of brain at different condition. So the difference of EEG time series at different state represent by periodic nature and also find out behavior of the brain.

Keyword: - *Electroencephalograph (EEG), Matlab, Continue Wavelet Transform.*

1. INTRODUCTION

Human body is a wonderful machine given by God which is the most valuable gift. The brain provides intelligence to use our physical and mental capacity [1]. It is a need of human to diagnose the proper functioning of brain always, because throughout life, electrical signal generated by the brain presents not only image of the brain but also the eminence of the human whole body [2]. Nervous system contains many nerves. It is expanses from the brain to all part of the body. They carry signals in the form of tiny electrical signal. These electrical signal can be monitored through many scientific techniques. Using these techniques scientist see what was occurrence inside the brain without opening up their skull. EEG is the most useful scientific technique that measure the brain electrical activity over a short period, within 20-40 minute [3]. This technique is measured electrical activity through the firing of bundle of neurons [3, 4]. These neurons carry information in the forms of tiny electrical impulse and transmit over long distance to each neighbor neurons. The electrical potentials recordable on the scalp surface to be picked by EEG (electro encephalography). EEG is show result in form potential generated by many neurons at the same time. When potential generated by single neuron is far too small [5], which will present day research. In neurology, EEG mainly useful for diagnosis in the case of epilepsy, which gives detail information about epileptic activity and create clear abnormality [3]. It is also used for the studies of sleep and sleep disorder, tumors, stroke and other focal brain disorder [4]. Also using EEG, imagine that what a person have in which state. It may be in sleep, awake condition and anaesthetized etc. because in every situation each state shows different characteristic. Using EEG data researchers measure electrical activity and observe changes over split seconds of time. One important application of EEG is, from data shows how long it takes the brain to process various stimuli. This present work providing new insight in the Electroencephalography (EEG) signals using continuous wavelets transform [6, 7]. These work describes a computer model to provide a more accurate picture of the EEG signal processing using wavelets [8, 9, 10, 11]. Then matlab software have been used which provided a system oriented scientific decision making model [8, 9].

2. EXPERIMENTAL AND COMPUTATIONAL TECHNIQUE

2.1 EEG Data collection

In this present work, EEG data extracted from University of Bonn, Germany which is available in public domain [12]. For recording of EEG data multiple electrodes used and pasted on the scalp of brain. These electrodes is also connected with computer which provided brain signal in form of continuous multiple channel. The complete database is comprised of five set of dataset refereed as A to E. Each dataset contains 100 signal channel EEG segments of 23.6-sec duration. Set A consist of segment EEG when patients had open eyes in an awake state. Set B consists of those segment when person had closed eyes in sleep state. When in set C and Set D records those segments when brain have totally seizure free duration. Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. And set E only contained seizure activity. Here segments were selected from all recording sites exhibiting ictal activity. All EEG signals were recorded with the same 98- channel amplifier system, using an average common reference. After 9 bit analog to digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. Band-pass filter settings were 0.53–40 Hz (9 dB/oct.). Exemplary EEGs are depicted in Fig-1.

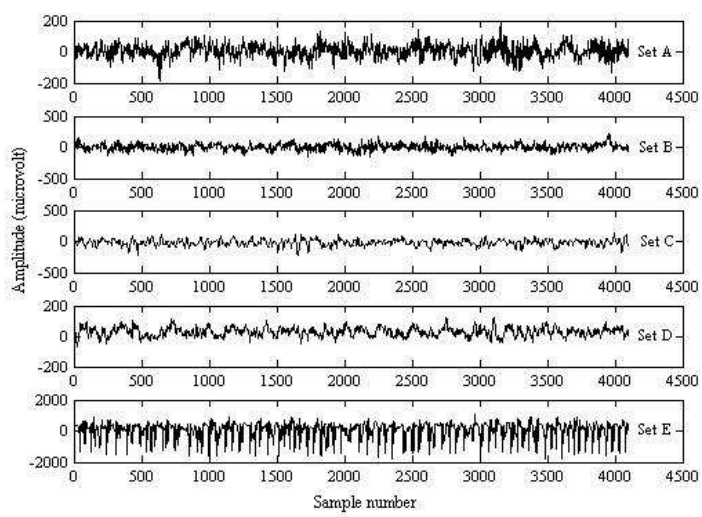


Fig -1: Exemplary EEG time series from each of the five sets. From top to bottom: set A to set E. Amplitudes of surface EEG recordings are typically in the order of some μV.

Here, taken EEG series cut out from multichannel EEG series. So discontinuities occurs between starting to end in EEG series. In these series total 4396 samples were first cut out from the continuous EEG recording with in this interval first 4096 samples was selected such a way that the amplitude difference of consecutive data points within range of amplitude differences of consecutive data point. Hence the making slopes of end to beginning of the series became indicate same sign. This algorithm depending upon windows functions for calculate the power spectrum.

2.2 Continuous wavelet Transform

The word wavelet is due to Morlet and Grossman in early 1980, first time they were used word ‘ondelette’ means a ‘little wave’. After some time it was transforms into ‘wave’ so it is known as ‘wavelet’. The continuous wavelet transform is defined as,

$$\psi_{\tau,s} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

Equation-1: CWT equation.

Where, **‘τ’** is translation parameters and **‘s’** is scale parameters [13, 14]. In CWT, one uses functions which are smooth, but do not have strictly finite extents. For example, the extensively used Morlet wavelet is a multiplication of a Gaussian function with a cosine wave, $\psi = C\, e - t^2 /\sigma \cos(\omega t)$; where ω and σ (sigma), width of the Gaussian are related [14, 15]. The fact that the Gaussian function provides a window to analyzing function cos (ωt), Morlet wavelet closely resembles window Fourier transform, which allow one to peak out local variation. In case of wavelet transform, continuous wavelet transform are over complete basis, hence in over complete basis redundancy is present. Often this property is quite useful in pin pointing weak features in data sets thereby making CWT a useful tool for data analysis [14]. So as per Equation-1, the transformed signal is a function of two variables, τ and s, the translation and scale parameters. The translation parameter is related to the location of the wavelet window, as the window is shifted through the signal. The scale parameter is defined as 1/frequency and relates to the zooming action of the wavelets. The wavelet coefficients are the function of both scale and time.

2.3 Pictorial demonstration

Pictorial demonstration of CWT is presented in Fig-2., N = 0 level represents the original signal. In level one i.e., N = 1 Morlet wavelet decomposition, the nearest neighbour averages and differences are calculated with the normalization factor of 1 / √2, which leaves half of the data in the form of low pass coefficients and other half in terms of level – 1 high pass coefficients. Subsequently, the same procedure can be applied once more to the low pass coefficients to decompose them into level - 2 high pass coefficients and level – 2 low pass coefficients. In total N level decomposition can be carried out.

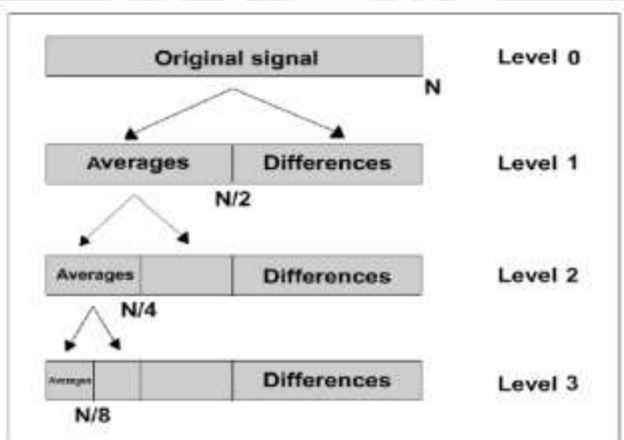


Fig-2: Pictorial demonstration of wavelet transform.

2.4 Autocorrelation

As the name suggests, auto – correlation measures the degree of correlation present in a time series with itself, over different time scales. The autocorrelation of a discrete process denoted by X_t for t = 1, 2,……., , can be represented as,

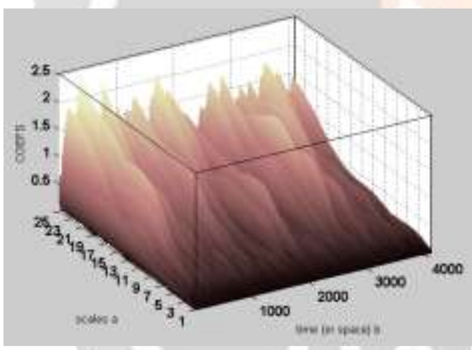
$$R(\tau) = 1 / (N - \tau - 1) \sum_{t=1}^{N-\tau} (X_t - \mu_1)(X_{t+\tau} - \mu_2) / \sigma_1\sigma_2$$

Where R (τ) denotes the correlation for lag τ lying within the range [0, τ_{max}], N = length of the time series, the max. value of lag allowed τ_{max} is chosen as 3N/ 4, μ_1 denotes the mean of the first half of series of the series ranging from X_1 to $X_{N-\tau}$, μ_2 denotes the mean of the other half of series of the time ranging from $X_{1+\tau}$ to X_N , where σ_1 and σ_2 are corresponding standard deviations of the two halves.

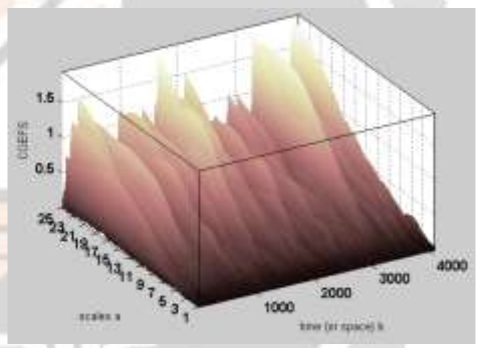
3. RESULTS

Here investigate that, analyzing electrical activity of brain between different five conditions of person through continuous wavelet transform using matlab software. The face that, continuous wavelets provide an over complete basis, rather than orthonormal basis set, make them ideal to extract subtle changes during rapid different activity [16]. The present work, describes a computer model to provide a more accurate picture of the EEG signal.

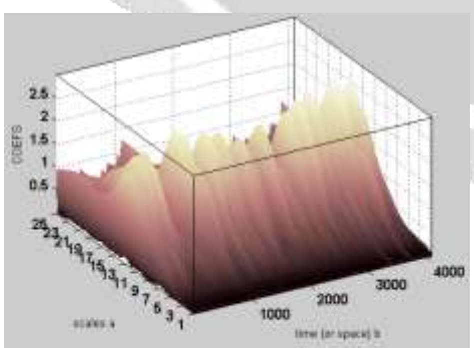
The wavelet scalogram of electrical activity of brain in five individual condition, as seen in Fig-3.



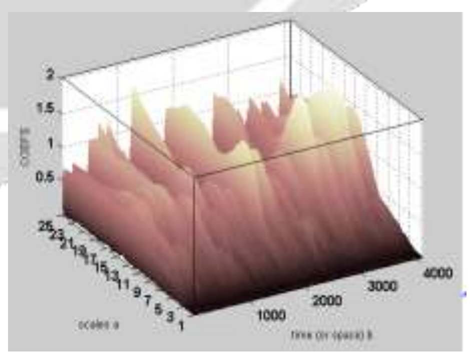
(a: open eyes)



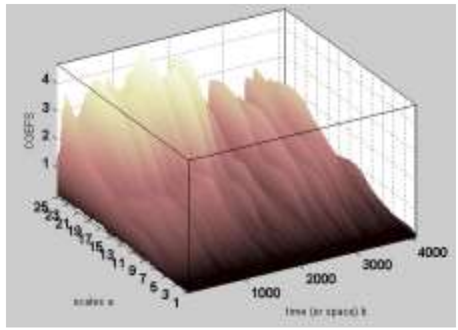
(b: closed eye)



(c: seizure free interval)



(d: hippocampal formation)



(e: during seizure)

Fig-3: Continuous wavelet transform scalogram of (a), (b), (c), (d) and (e) of electrical activity of brain in different condition using Morlet wavelet.

Now, CWT decomposition into form of low pass coefficient and high pass coefficient at 8th level,

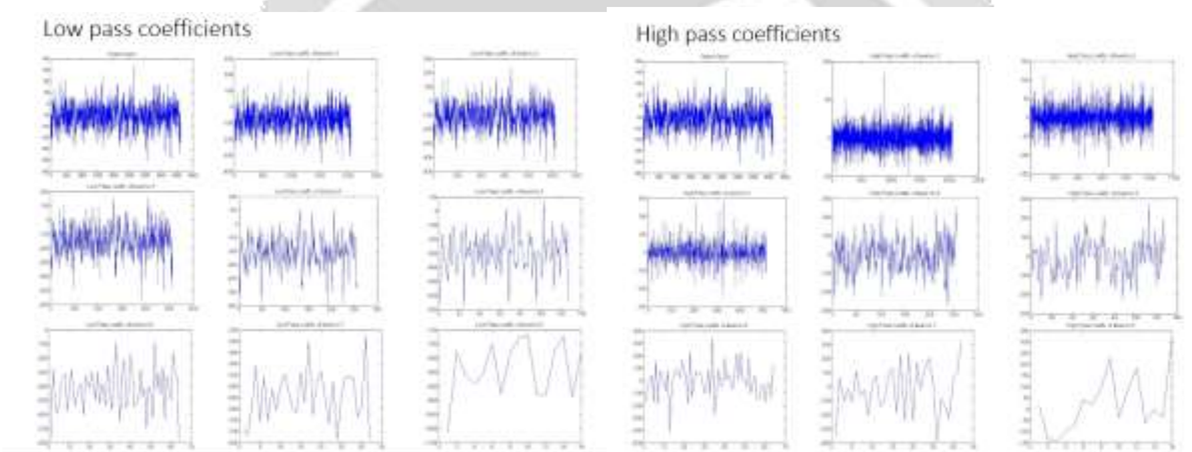
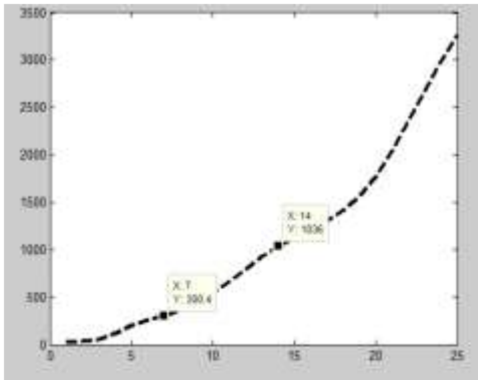


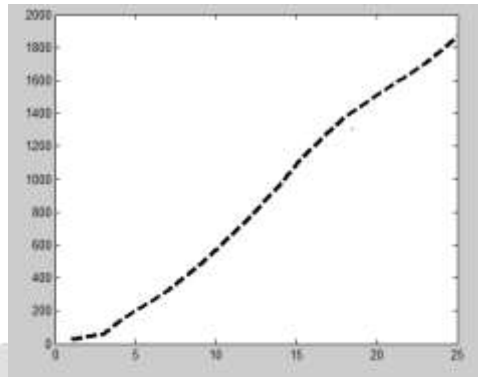
Fig-4: low pass and high pass coefficient.

the periodic variation capture in the scalogram, for a normal condition in awake state when eyes open (a) are visualize around 12 scale, when closed eye's (b) are seen around 13 – 14 scale, the seizure free interval time (c) are making around 9 – 12 scale, for hippocampal formation at opposite side of brain during as seizure free interval (d) are around 17 – 19 scale, whereas during seizure activity are seen around 12 – 14 and also shown at 22 – 24 scale, means give more periodic variation. At these scale, we get clear difference between normal, seizure free interval and during of seizure from the periodic variation of the dominant wavelet coefficient.

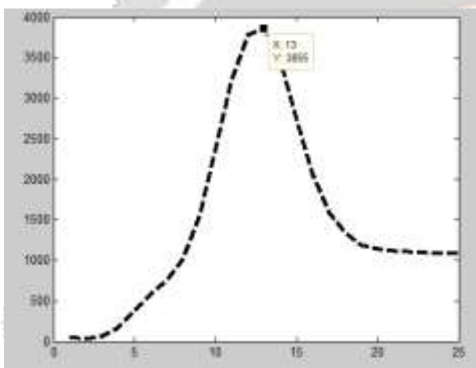
In order to properly study the scalogram behavior at different scales, we have *computed* the cumulative sum of the log of magnitude of wavelet coefficient over scale [17]. Their respective cumulative sums of five different condition of person are shown in Fig-5 respectively. And cumulative sum of log of magnitude of wavelet coefficient are shown in Fig-5 respectively. Here, logarithmic principle is used because it is used in find out clearer picture of different activity of brain.



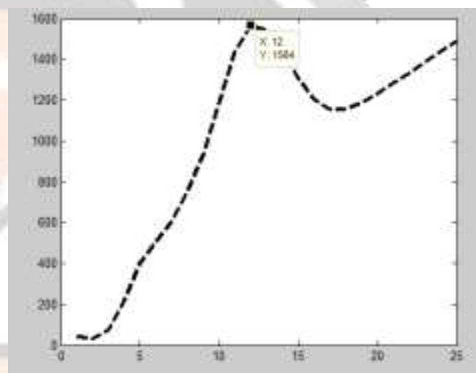
(a: open eyes)



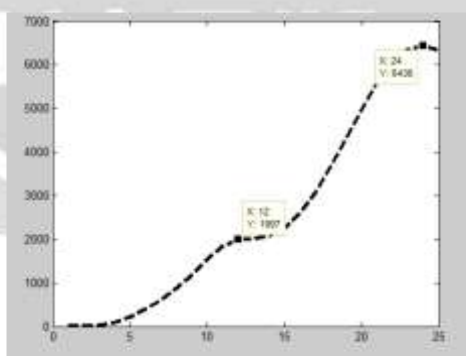
(b: close eyes)



(c: seizure free interval)



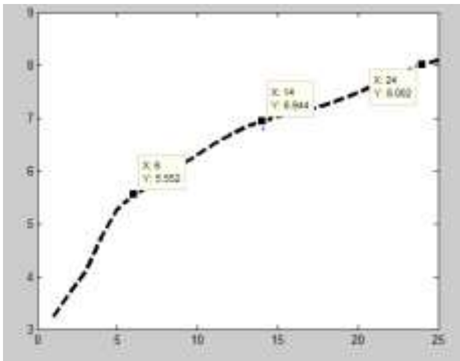
(d: hippocampal formation)



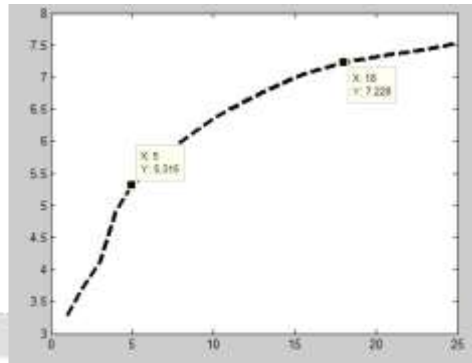
(e: during seizure)

Fig-5: plots of the cumulative sum of the CWT coefficients over 1 – 25 scale range for the electrical activity of brain.

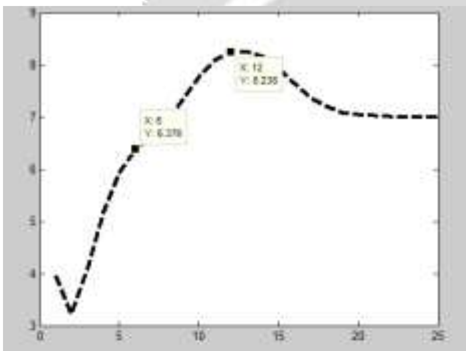
And cumulative sum of log of magnitude of wavelet coefficient are shown in Fig-6 respectively.



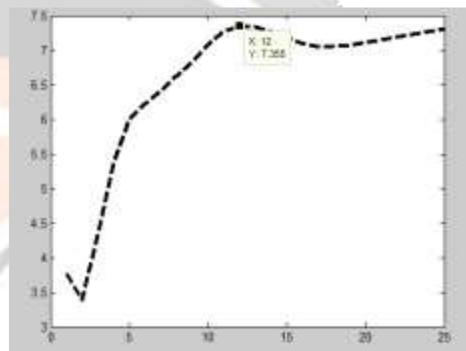
(a: open eyes)



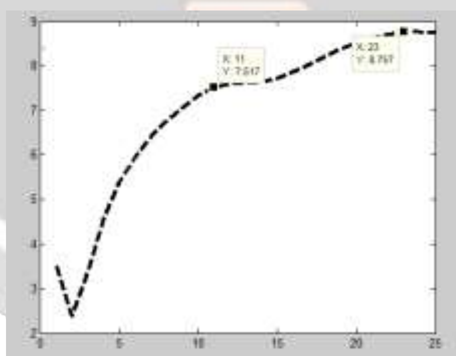
(b: closed eyes)



(c: seizure free interval)



(d: hippocampal formation)



(e: seizure activity)

Fig-6: Plots of the cumulative sum of log of magnitude of the CWT coefficient over 1 – 25 scale range.

It is very interesting note that, when compare Fig-5 and Fig-6, in First condition of awake state at Fig- 5(a), signal has little bit increase at scale 7 but when take a logarithmic algorithm, then it is clearly identified behavior of brain electrical activity that it is already start increased at scale 6 and also gives maximum value at scale 14. Same as second condition for sleeping state in Fig-5(b), if we see with neck eye there is not seen any pick but in Fig-6(b) behavior changed start at the scale 5 which clearly visualized. So we can say that logarithmic algorithm more useful in prediction of a nonlinear function. Hence here using five different condition at all signal channel, cumulative power show out of phase behavior between normal (for open and closed eye), seizure free interval (set c & d) and for the seizure (set e) at the scale 1-25 range. These both figures are decomposition of original signal, but Fig-6 gives more clear behavior than Fig-5 which clearly identified in both figure.

3.1 Correlation behavior of EEG series

We have calculated the autocorrelation of these coefficient corresponding to the scale of local maxima. A typical plot of autocorrelation is shown in Fig-7, which exhibits a strong periodic behavior. It is noteworthy that the recurrence pattern shows on each level but difference depend on no of variation in period and height of amplitude which indicate by max value.

From Fig-7, the autocorrelation plot suggested that the period of recurrence present between level 3 - 4 reach at periodic value near 0.1 for awake state at open eyes condition. During the relaxation (eyes closed) present between level 3-4 but it is given maximum amplitude value near 0.35 because of more excitation of neurons.so here we can say that during sleepy condition more electrical power consumed, resulted higher amplitude is shown.

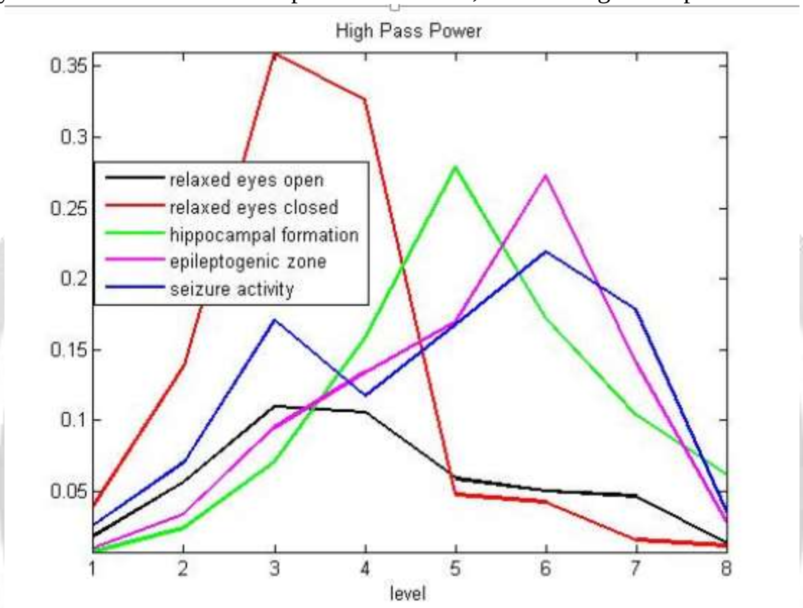


Fig-7: plot periodic behavior of five condition (set A-E) EEG series by autocorrelation.

Now for the seizure free interval, in the case of hippocampal formation, it is present near the 5th level, reached at peak value between 0.25 to 3.0 and for the epileptogenic zone present near to level 6th at the periodic variation of 0.25 to 3.0. And for seizure activity gives frequent variation in periodic waveform at different possible scale. Thus, from autocorrelation plot suggested that the period of recurrence pattern without seizure has one maximum peak but during a seizure more than one variation present in the periodic waveform at different energy level.

Using the Fig-7 found that electrical activity of brain in different condition of person showed different behavior in wavelet domain. So finally here we can say that, EEG analysis depending upon rhythmic high amplitude patterns which contributes to a localization of the epileptogenic zone.

4. CONCLUSIONS

Using CWT method doing symmetrical study about EEG signal on different possible scale. For making detailed study a low pass coefficient and high pass coefficient obtained through the Matlab software. The fact that these characteristic signatures are based on higher level average coefficient make them robust and less susceptible to experiment and statistical uncertainties. It is worth emphasizing that a straight forward averaging with arbitrary window sizes would not allow an independent separation of fluctuations and average behavior at multiple scales. It is observed that, scaling and translation are key point, which enable one to carry out a local analysis at desired scale and leads to independent wavelet coefficients devoid of redundancy. The CWT have pin pointed significant differences in EEG activity of different five condition of person like for normal (relaxed for open and closed eyes), seizure free interval (for epileptogenic zone and hippocampal formation), and during of seizure. The multi-resolution ability and over complete nature of the Continuous Morlet Wavelets are responsible in finding out these minute variation in the periodic activity of EEG. So finally making smooth study, CWT contribute major role in analysis of EEG signal.

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