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Complexity Measures for Normal and Epileptic EEG Signals using ApEn, SampEn and SEN

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Abstract **-** There are numerous applications of EEG signal processing such as monitoring alertness, coma, and brain death, controlling an aesthesia, investigating epilepsy and locating seizure origin, testing epilepsy drug effects, monitoring the brain development, and investigating mental disorders; where data size is too long and requires long time to observe the data by clinician or neurologist.

EEG signal processing techniques can be used effectively in such applications. The configuration of the signal waveform may contain valuable and useful information about the different state of the brain since biological signal is highly random in both time and frequency domain. Thus computerized analysis is necessary. Being a non-stationary signal, suitable analysis is essential for EEG to differentiate the normal EEG and epileptic seizures. The importance of entropy based features to recognize the normal EEGs, and ictal as well as interictal epileptic seizures. Three features, such as, Approximate entropy, Sample entropy, and Spectral entropy are used to take out the quantitative entropy features from the given EEG time series data of various time frames of 0.88s, and 1s .Average value of entropies for epileptic time series is less than non epileptic time series.

Keywords— *Approximate Entropy;Sample Entropy; Spectral Entropy.*

I. INTRODUCTION

The neural activity of the human brain starts between the 17th and 23rd week of prenatal development. It is believed that from this early stage to throughout life electrical signals generated by the brain represent not only the brain function but also the status of the whole body. This assumption provides the motivation to apply advanced digital signal processing methods to the electroencephalogram (EEG) signals measured from the brain of a human subject.

EEG is a non-invasive testing method which contains a lot of information about the state of a patient's health. It also contains very useful information relating to the different physiological states of the brain and thus is a very effective tool for understanding the complex dynamical behavior of the brain. Since EEG is non-invasive, it can be recorded over a long time span which is very important for In fact, epilepsy monitors are widely used for monitoring incidental disorders like epileptic seizures which are not permanently presents in the recordings. In fact, epilepsy monitors are widely used for recoding EEG data for long periods of time for presurgical evaluation of epilepsy patients. These EEG recordings are visually inspected by highly trained professionals for detecting epileptic seizures. This information is then used for clinical diagnosis and possible treatment plans. Clearly, this is a very time consuming process and is very costly [12].

Approximately 1% of the world's population suffers from epilepsy, a disorder of the normal brain function, characterized by the existence of abnormal synchronous discharges in large ensembles of neurons in brain structures [2]. These discharges are often referred as "paroxysmal activity" and appear either during seizures (ictal periods) or between seizures (interictal periods) [2]. Epileptic seizures are manifestations of epilepsy, which are due to the sudden development of synchronous neuronal firing in the cerebral cortex and are recorded using the EEG, which is a measure of brain electrical activity. Epileptic seizures may occur in the brain locally (partial seizures), which are seen only in a few channels of the EEG recording, or involving the whole brain (generalized seizures), which are seen in every channel of the EEG recording. Clinical neurologists in daily practice commonly examine short recordings (usually 20-min recordings) of interictal periods. The most common forms of the interictal periods are the individual or isolated spikes, the sharp wave, and the spike-and-wave complex. These are perceived in the majority of patients with epilepsy. For this reason, interictal event detection plays a vital role in the diagnosis of epilepsy. However, during an isolated spike, the brain is not in a clinical seizure. A different EEG pattern is observed

during the ictal period consisting of rhythmical waveforms for a wide variety of frequencies, polyspike activity, and low-amplitude desynchronization, as well as spike-and wave complexes. Although interictal findings offer evidence of epilepsy, diagnosis of epilepsy is usually based on observed epileptic seizures. The interictal indications of epilepsy can be identified using a short period EEG recording. Visual seizure detection has not been proven very efficient. Automated seizure detection schemes facilitate the diagnosis of epilepsy and enhance the management of long-term EEG recordings [2].

the bi-domain sample entropy to predict termination of atrial abnormalities. Kannathal et al., have shown the importance of various entropies for detection of epilepsy (Kannathal, Lim, et al., [10], [12] introduced the detection of epileptic seizures using discrete wavelet transform and approximation entropy. Pravin Kumar [1], [4] have shown some study on wavelet entropy for epileptic seizure detection and discusses the detection of epileptic seizure using three entropies, namely, wavelet entropy (WE), spectral entropy (SEN) and sample entropy (SampEn) to exploit the important diagnostic information from EEG recordings. The stationority of the

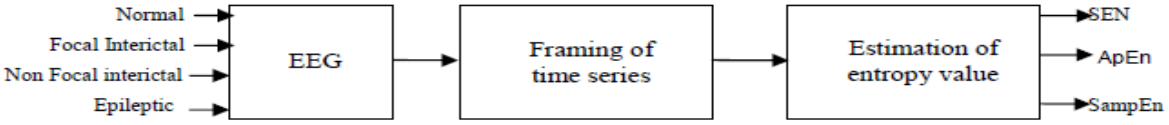

Fig.1 Schematic diagram for detection of entropy

Nonlinear measures like Sample entropy (SampEn), approximate entropy (ApEn) and Spectral entropy quantify the degree of complexity in a time series. Features are selected so that they capture the differences between the epileptic and normal EEG. Feature extraction process plays a very important role on the classification performance [12]. Here three non-linear features, such as; approximate entropy, sample entropy, and spectral entropy are used to extract quantitative entropy features from the given EEG time series.

II. LITRATURE REVIEW

Epilepsy, a chronic neurological disorder is generally characterized by the sudden and recurrent seizures [8], [9] [16]. It is an indication of hyper-synchronous activity of neurons in the brain [9]. Electroencephalography (EEG) signal is generally used as a diagnostic indicator for investigating brain activities under various physiological conditions. The synchronized seizure activity is reflected in the EEG signal where the neurologist has to closely monitor the recordings through visual inspection. Several features for the detection and prediction of epileptic seizures have been reported in the literature [9], [10], [14], [15], [17], [18]. It deploys single linear analysis to non-linear dynamical analysis for the detection of abnormalities. Most of the EEG based detection system involves time domain based feature extraction. In the recent years, studies based on measuring entropies have been applied for cardiovascular and other biological studies [13]. The randomness of non-linear time series data is well exploited using entropies and it helps in providing distinguishable variation for normal and abnormal biomedical signals. Richman [13] have discussed the physiological time-series analysis using approximate and sample entropy. Alcaraz and Rieta [5] introduced

EEG time series is also studied by considering time series of .88s, and 1 s samples. EEGs recorded from extra cranial and intracranial electrodes are considered, for this study. In the intracranial recordings, two seizure activities are prominent, one ictal activity and the other interictal seizure activity. Figure 1 shows the Schematic diagram of feature extractions from EEG signals.

III. EEG DATA SETS

EEG data is obtained from University of Bonn Germany, which is available in public domain. The complete datasets contain five sets of data referred as sets A–E. Each set contains 100 single channels EEG segments with-out any artefacts with 23.6 s. Sets A and B contain recordings obtained through external surface electrodes under normal eyes open and closed conditions. Sets C–E were recorded using intracranial electrodes exhibiting interictal and ictal epileptic activities. In particular, Set C recordings were obtained

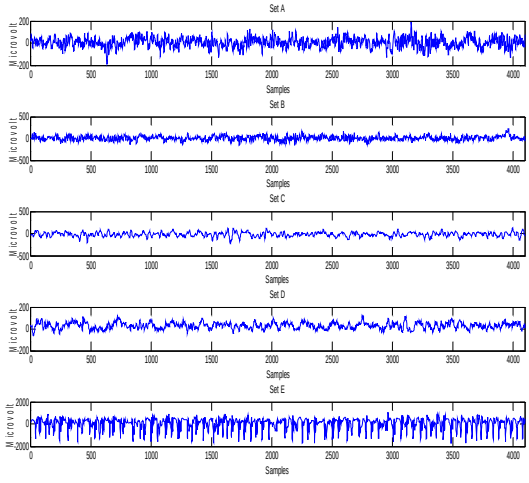

Fig.2 Sample recording of EEG Signal

from within epileptic zone during seizure free intervals that indicates focal interictal activity and Set D recordings were obtained from the hippocampal formation of the opposite hemisphere of the brain and it indicates the non-focal interictal activity [7]. Fig.2 shows the sample recordings of EEG obtained from Sets A–E. All EEG signals were recorded with the same 128-channel amplifier systems, using an average common reference, with 12A/D conversion bit rate of 12, sampling rate of 173.61 Hz [7].

IV. ENTROPY

Entropy is a measure of uncertainty. The level of chaos may also be measured using entropy of the system. Higher entropy represents higher uncertainty and a more chaotic system.

A. Sample Entropy

Sample Entropy $SampEn$ examines time series for similar epochs and assigns a non-negative number to the sequence, with larger values corresponding to more complexity or irregularity in the data [5], [6]. Two input parameters, a run length m and a tolerance window $\boldsymbol{r}$, must be specified for SampEn to be computed. $SampEn(m, r, N)$ is the negative logarithm of the conditional probability that two sequences similar for m points remain similar at the next point, where self-matches are not included in calculating the probability. Thus, a lower value of SampEn also indicates more self-similarity in the time series. SampEn is largely independent of record length.

Formally, given N data points from a time series $\{x(n)\} = x(1), x(2), ..., x(N)$, $SampEn$ can be defined as follows:

1. Form $\boldsymbol{m}$ vectors $X_m(1), \ldots X_m(N-m+1)$ defined by $X_m(i) = [x(i), x(i+1), ..., x(i+m-1)]$ for $1 \le i \le N-m+1$. (1)

   These vectors represent $\boldsymbol{m}$ consecutive $\boldsymbol{x}$ values, starting with the i^{th} point.

2. Define the distance between vector $X_m(i)$ and $X_m(j), d[X_m(i), X_m(j)]$, as the absolute maximum difference between their scalar components:

   $$d[X_m(i), X_m(j)] = \max_{k=0,\ldots m-1}(|x(i+k) - x(j+k)|) \quad (2)$$

3. For a given $X_m(i)$, count the number of $j(1 \le j \le N-m, j \ne i)$, denoted as B_i, such that the distance between $X_m(i)$ and $X_m(j)$ is less than or equal to r. Then, for $1 \le i \le N-m$

4. $$B_i^m(r) = \frac{1}{N-m-1} B_i \ , \quad (4)$$

   Define $B^m(r)$ as

   $$B^m(r) = \frac{1}{N-m} \sum_i^{N-m} B_i^m(r) \quad (5)$$

5. Increase the dimension to $m+1$ and calculate A_i as the number of $X_{m+1}(i)$ within r of $X_{m+1}(j)$ where j ranges from 1 to $N-m (j \ne i)$. We then define $A_i^m(r)$

6. $$A_i^m(r) = \frac{1}{N-m+1} A_i \ , \quad (6)$$

Set $A^m(r)$ as

$$A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r) \quad (7)$$

Thus, $B^m(r)$ is the probability that two sequences will match for m points, whereas $A^m(r)$ is the probability that two sequences will match for $m+1$ points. Finally, sample entropy can be defined as:

$$SampEn(m, r) = \lim_{N \to \infty} \left\{ -\ln \left[\frac{A^m(r)}{B^m(r)} \right] \right\} \quad (8)$$

Fig.3 (a)-(c) and Fig. 4(a)-(c) depicts the values of sample entropy obtained for normal with eyes open, focal interictal, non-focal interictal and epileptic seizures.

B. Approximate Entropy

Approximate entropy $(ApEn)$ is a statistic that can be estimated from the discrete-time sequences, especially for real-time applications [12], [19]. This measure can quantify the complexity or irregularity of the system. $ApEn$ Is less sensitive to noise and can be used for short-length data. In addition, it is resistant to short strong transient interferences such as spikes [19].

Let the data sequence containing N data points be $X = [x(1), x(2), \ldots x(N)]$. and let x(i) be the subsequences of X such that

$x(i) = [x(i), x(i+1), x(i+2), ..., x(i+m-1)]$, for $1 \le i \le N-m$, (9)

where m is the number of samples used for prediction

The distance between any two of the above vectors, $x(i)$ and $x(j)$ is defined as

$$d[x(i), x(j)] = \max_{k=0,...m-1} \left| x(i+k) - x(j+k) \right|$$

Where $|.|$ denotes the absolute value. Considering a threshold level of r , is equal to 0.2* SD, the number of times, $M^m(i)$, that the above distance satisfies $d[x(i), x(j)] \le r$ is found. This is performed for all i . For the dimension m ,

$$C_r^m(i) = \frac{M^m(i)}{N-m+1}, \text{for } i = 1, ..., N-m+1 \quad (10)$$

Then, the average natural logarithm of, $C_r^m(i)$ is found as $\psi_r^m = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_r^m(i)$ (11)

By repeating the same method for, $m+1$, the $ApEn$ will be given as,

$$ApEn(m,r) = \lim_{N \to \infty} (\psi_r^m - \psi_r^{m+1}) \quad (12)$$

However, the threshold value has to be set correctly. In some applications the threshold value is taken as a value between 0.1 and 0.25 times the data standard deviation.

C. Spectral Entropy

The spectral entropies use the amplitude components of the power spectrum of the signal as the probabilities in entropy calculations. Spectral entropy (SEN) [3], [9], [11], [13] is the normalized form of Shannon's entropy. It quantifies the spectral complexity of the time series. A variety of spectral transformations exist out of these the Fourier transformation (FT) is most probably the well known transformation method from which the power spectral density (PSD) can be obtained. The PSD is a function that represents the distribution of power as a function of frequency. For each frequency, the power level P_f obtained from Fourier Transform is summed and the total power $\sum P_f$ is calculated.

Normalization of p_f with respect to the total spectral power will yield a probability density function. Each frequency's power level is divided by the total power

$$P_f = \frac{p_f}{p_T} \quad (13)$$

Where p_T is total power, yielding in the end the total, $\sum P_f = 1$ Entropy is computed by multiplying the power in each frequency by the logarithm of the same power, $P_f \log(P_f)$ and multiplying the result by -1Total entropy is the sum of entropy computed over entire frequency range (0—100 Hz). Thus, the spectral entropy is given by,

$$SEN = \sum_f P_f \log\left(\frac{1}{P_f}\right) \quad (14)$$

Heuristically the entropy has been interpreted as a measure of uncertainty about the event at f . Thus, entropy may be used as a measure of system complexity. It measures the spread of data. Data with broad, flat probability distribution have high entropy. Data with narrow, peaked distribution will have low entropy. Fig.7 (a) and (b) shows the value of SEN obtained for sets A, B, C, D, E.

V. PERFORMANCES OF THE THREE ENTROPIES

The complexity of signal can refer to the unpredictability of a signal, and it can also refer to difficulties one has in describing or understanding a signal. For example irregular signal are more complex than regular ones because they are more unpredictable: and regular signal varying quickly appear to be more complex than those varying slowly because quick varying ones present more variations in a given period of time. This description of complexity means that the random numbers are more complex than periodical signals and that periodical signal with higher frequency are more complex than lower frequencies.

In this section, we demonstrate the performances of the three entropy definitions on measuring signal complexity by applying them to experimental EEG signals. During each computation, m is fixed to 2 and 3 and the width of boundary is set as r multiplied by the standard deviation (SD) of the original data set for sample and approximate entropy. The experiment is carried out for 500 data of different sets of different types of EEG signals. Average values of entropies are calculated from all datasets entropy and find as shown in Table I.

TABLE I : Average value of different entropy

Data sets	ApEn	SampEn	SEN
A	0.47	1.28	2.76
B	0.45	1.34	2.73
C	0.44	0.72	2.35
D	0.391	0.68	2.43
E	0.29	0.70	2.62

From the above table-1 it is clear that the average value of sample entropy for epileptic signal E, is less than non epileptic signal set A. and average approximate entropy for epileptic signal set E is less than normal EEG signal set A, and average spectral entropy for epileptic signal set E is also than for normal signal set A.

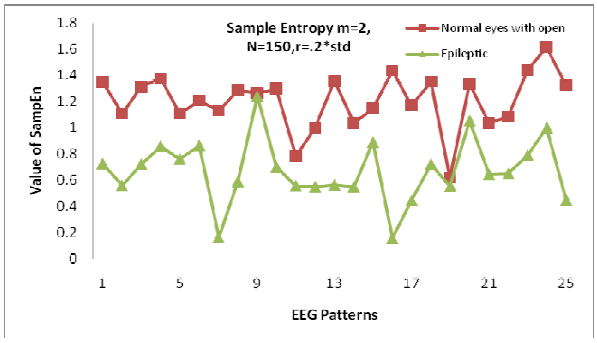

Fig.3(a) values of SampEn for Epileptic and Normal EEG with eye open.

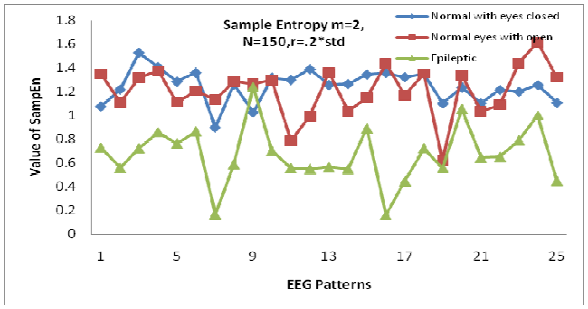

Fig.3(b) values of SampEn for Epileptic, Normal EEG with eye open and eyes closed.

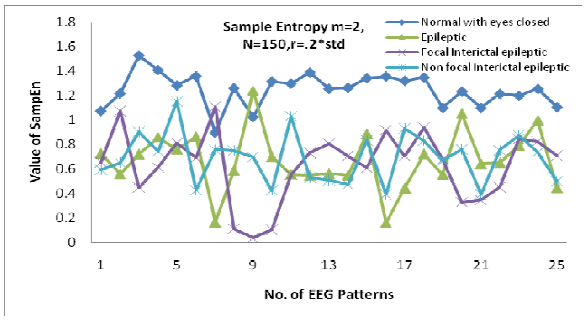

Fig.3(c) values of SampEn for Epileptic, Normal EEG with eyes closed,focal interictaland nonfocal interictal.

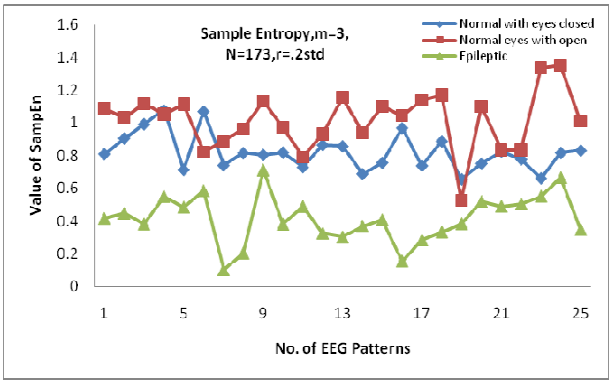

Fig.4(a) values of SampEn for Epileptic, Normal EEG with eye open and eyes closed.

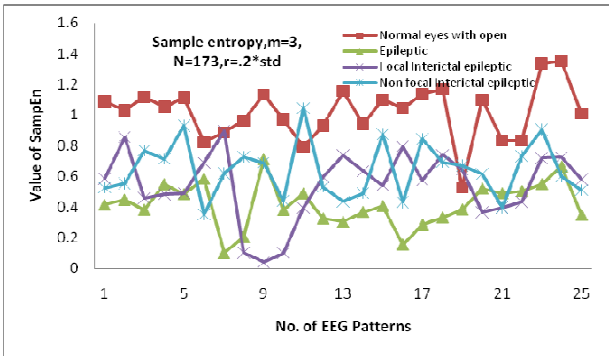

Fig.4(b) values of SampEn for Epileptic, Normal EEG with eyes open,focal interictaland nonfocal interictal.

From Fig 3(a)-(c) and Fig 4(a)-(b) the value of sample entropy for epilepic signal is low as compared to normal with eyes open and closed and as the length of signal is increasing from N=150 to N=173 samples the values of sample entopies are decereasing.

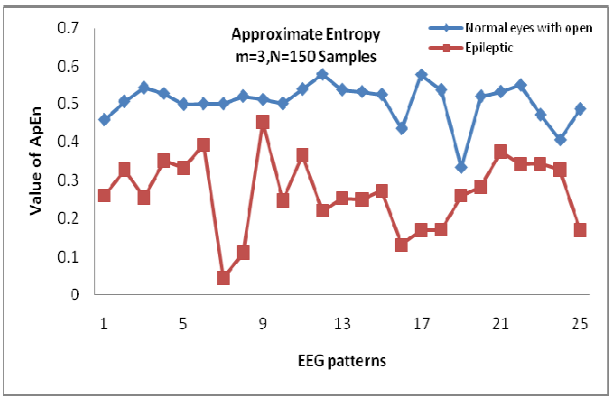

Fig.5(a) values of ApEn for Epileptic and Normal EEG with eye open

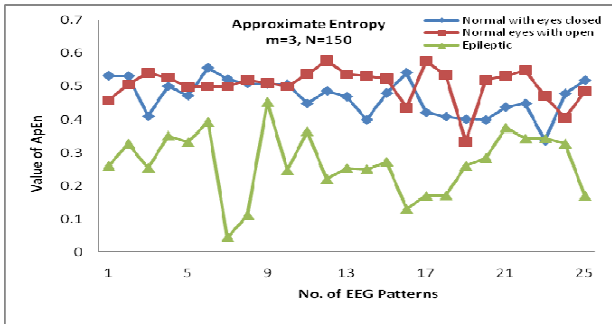

Fig.5(b) values of ApEn for Epileptic, Normal EEG with eye open and eyes closed.

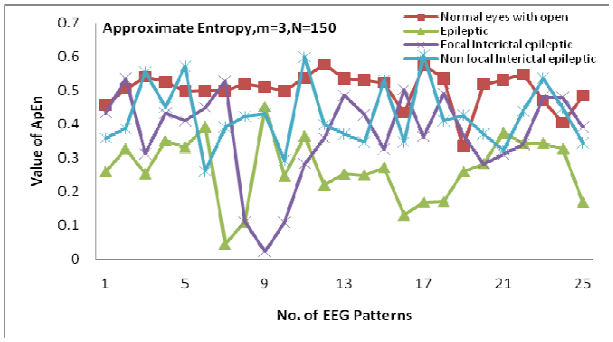

Fig.5(c) values of ApEn for Epileptic, Normal EEG with eyes open,focal interictal and nonfocal interictal epileptic.

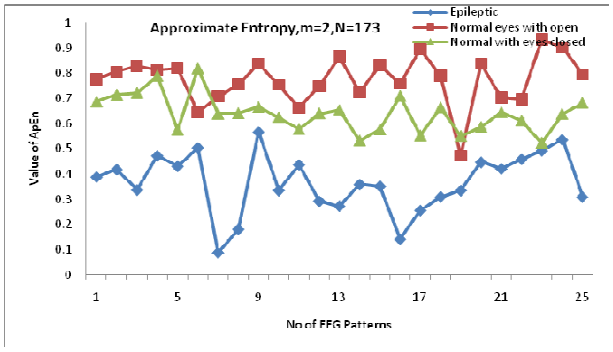

Fig.6(a) values of ApEn for Epileptic, Normal EEG with eye open and eyes closed

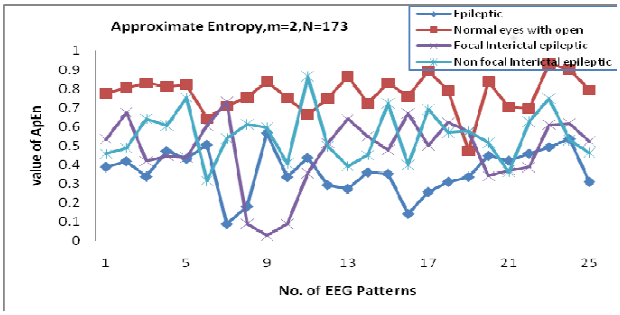

Fig.6(b) values of ApEn for Epileptic, Normal EEG with eyes open,focal interictal and nonfocal interictal epileptic.

Form Fig.5(a)-(c) and Fig 6(a)-6(b) values of Approximate entropy for epileptic data sets are low compared to normal data sets.

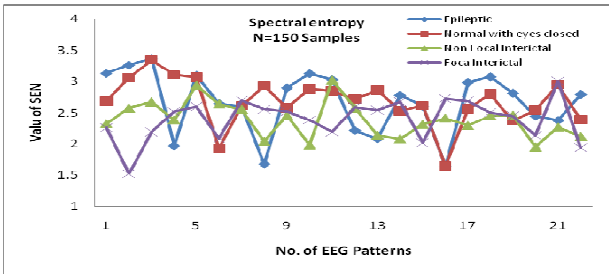

Fig.7(a) values of SEN for Epileptic, Normal EEG with eyes closed,focal interictal and nonfocal interictal epileptic.

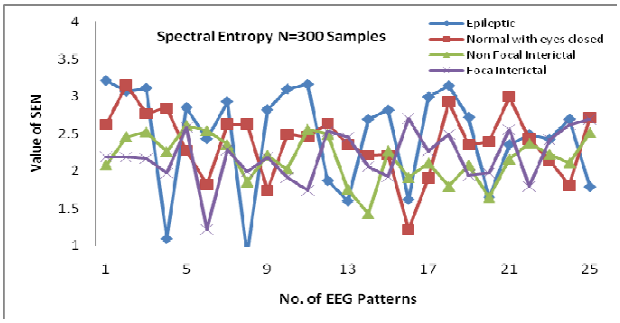

Fig.7(b) values of SEN for Epileptic, Normal EEG with eyes closed,focal interictal and nonfocal interictal epileptic.

Average value of spectral entropy for epileptic signal is less than non-epileptic signal.

VI. CONCLUSIONS

We calculate Approximate, Sample and Spectral Entropy to extract the features of EEG signals. These entropies quantify the complexity levels of the epileptic EEG and normal EEG. Our results confirm that there are significant differences between the epileptic EEG and normal EEG and shows that the degree of complexity for epileptic EEG signal is lower than that of normal EEG signals, so ApEn, SampEn and SEN could be helpful to distinguishing between epileptic EEG and normal EEG.

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