Using Entropies for the Analysis of Brain Rhythms

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***Abstract*—Epilepsy is a chronic neurological disorder characterized by seizures. It involves abnormal discharging of neurons that effects smaller section of the brain, referred to as partial epilepsy or larger section of the brain resulting in generalized epilepsy. Sometimes these abnormal activities spread from smaller section to the larger section of the brain resulting in secondary generalized epilepsy. Hence, it is important to detect and control epileptic seizure in an early stage. In this work, we design a system that classifies interictal (period between the seizure) and ictal (after onset of seizure) signals by extracting subtle information from the EEG rhythms: gamma, beta, alpha, theta and delta. The following system also aims to determine the sensitivity of these EEG rhythms towards epileptic seizure. In this research, we have used entropy methods namely: Shannon entropy, approximate entropy and sample entropy to extract the subtle information from the EEG rhythms. Classifiers namely: k-nearest neighbor, support vector machine and linear discriminant analysis is utilized to distinguish interictal and ictal signals with a classification accuracy of 94%, 95.5% and 97.5%.**

***Index Terms*—Electroencephalography (EEG), EEG rhythms, epilepsy, entropy**

I. Introduction

Brain is a complex system that controls the functioning of entire body. Any damage to the brain can lead to neurological, psychological or neuro-psychological disorder, that effects functioning of entire body. According to the statistics provided by the World Health Organization, around 50 million people are suffering from one of the most common neurological disorder known as epilepsy [1]. Epilepsy is a chronic neurological disorder characterized by recurrent seizure. Factors responsible for this disorder include brain injury, injury to the central nervous system, genetic abnormalities and brain tumor. Seizures in epileptic patients are caused due to the synchronous neural firing in the cerebral cortex. These seizures are highly unpredictable, as for some people they occur a several times a day whereas for some it occurs once in every few years. The process of transition from the non-seizure (interictal state) to seizure (ictal state) is called ictogenesis.

During seizures, abnormal electrical discharges generated in a small brain region is referred as partial epileptic seizure; but if the abnormal electrical discharges is observed in both the cerebral hemisphere it is referred to as generalized epileptic seizure. Though epilepsy may not appear to be critical, it can be life threatening if not treated appropriately. It can be extremely dangerous if the seizures occur when the patient is crossing a busy street, cooking, driving or staying alone. Even though there are anti-epileptic drugs used to treat epilepsy, about 30% of epileptic patients are unaffected by it which accounts to be approximately 15 million people. In these patients, physicians recommend continuous monitoring of the seizure. However, documentation of the seizure by visual inspection can often lead to inter and intra observer variability. In addition, prolonged used of these drugs can lead to various other cognitive and neurological disorders. Moreover, these drugs are more effective in the early stage of epilepsy. Hence, it is important design a system that can detect epilepsy at an early stage, monitor and document the seizure accurately.

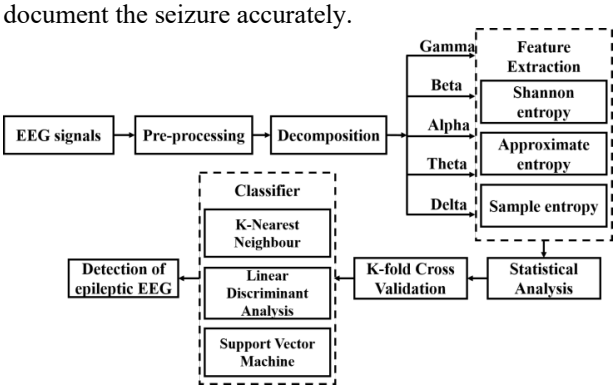

Figure 1. Proposed computer aided diagnostic system.

Various researchers such as Maiwald *et al.* [2], Lehnertz *et al.* [3], Aschenbrenner-Scheibe *et al.* [4] have designed systems that make use of Electroencephalography (EEG) to detects the onset of the seizure. These researchers have used various dimensionality analysis and entropy methods to analyze the EEG signals. They found the EEG signals to be less complex and chaotic in epileptic patients compared to that in healthy person. There has been lot of work on early detection of epilepsy lately; however, these researches do not focus on the reduced complexity measure in different EEG rhythms, which are gamma, beta, alpha, theta and delta. In this work, we have discussed on the EEG rhythms that are highly effected from the abnormal actives caused due to epilepsy. Fig. 1

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shows the proposed computer aided diagnostic system designed to determine the sensitivity of the EEG towards epilepsy.

II. Methodology

To perform this experiment we have considered 100 pairs of interictal and ictal signals obtained from Bonn university database [5]. These interictal and ictal signals were 23.6 s in duration and have sampling frequency of 173.6 Hz. These signals are low pass filtered to obtain the signals with the bandwidth of 0-60 Hz because frequency bands greater than 60 Hz mainly consists of noise. These signals are decomposed using discrete wavelet transform.

A. Signal Decomposition

Discrete wavelet transform consists of a low pass and high pass filters to decompose the signals into approximate coefficient and detail coefficient respectively. The approximate coefficient of subsequent levels are decomposed to obtain approximate coefficient and detail coefficient of next level [6]. In this work, Daubechies4 (db4) wavelet basis function is used to decompose the signals up to level four to generate wavelet coefficients: detailed coefficient 1 (60-30 Hz), detailed coefficient 2 (30-15 Hz), detailed coefficient 3 (15-7.5 Hz), detailed coefficient 4 (7.5-3.75 Hz) and approximate coefficient (less than 3.75). These wavelet coefficients represent the EEG rhythms gamma, beta, alpha, theta and delta respectively. Shannon entropy, approximate entropy and sample entropy of these EEG rhythms are determined.

B. Feature Extraction

Feature extraction is an integral part of signal analysis. It extracts subtle information commonly referred as features, which can distinguish interictal and ictal signals. Here, features such as Shannon entropy, approximate entropy and sample entropy is determined. Shannon entropy is a measure of data spread [1] and could be interpreted as measure of impurity in signal. Shannon entropy of the signal is defined as:

$$\text{Shannon entropy} = -\sum_i \mathrm{P_i} \log \mathrm{P_i} \qquad (1)$$

here, P_i represents normalized probability density function (PDF) of signal estimated over the signal; this PDF is determined by histogram method.

Approximate entropy (ApEn) of the signal quantifies the complexity of the time series signal. It measures the regularity of the signal. Two parameters *m* and *r* has to be chosen to determine the approximation entropy. Here *m* denotes the length of the compared runs and *r* is an effective filter. In this work, we have chosen *m* value to be 2 and the 'filter factor' *r* to be 0.2 times the standard deviation [1]. Vector space *x*(1) through *x*(*N*-*m*+1) is considered. Here, *x*(*i*) consists of samples *u*(*i*)…*u*(*i*+*m*-1);{ *u*(*i*)} represents *N* data points of the time series signals. Then ApEn can be calculated as

$$ApEn = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} log\, C_i^m(r) - \frac{1}{N-m}\sum_{i=1}^{N-m} log\, C_i^{m+1}(r) \qquad (2)$$

where $C_i^m(r)$ = (number of $j \le N-m+1$ such that $d[x(i), x(j)] \le r$) /$(N-m+1)$.

$C_i^m(r)$ is measured within the tolerance *r*. ApEn value calculated for the EEG helps to analyse the presence of the abnormalities. Lower ApEn values indicate reduced complexity and increased regularity, which is mainly observed in epileptic EEG signals.

Sample entropy [1] is a modified version of ApEn that also measures the regularity of the EEG. However, unlike ApEn, sample entropy is relatively consistent. It is determined by estimating negative logarithm of the conditional probability having pattern length *m* and tolerance *r*. In this work, we considered tolerance *r* to be 0.2 times the standard deviation of the signal. Sample entropy is expressed as

$$\text{Sample entropy} = lim_{n\to\infty} - ln\frac{A^m(r)}{B^m(r)} \qquad (3)$$

where parameters $A^m(r)$ and $B^m(r)$ are defined as

$$A^m(r) = \frac{1}{(N-m)}\sum_{i=1}^{N-m} C_i^{m+1}(r) \qquad (4)$$

$$B^m(r) = \frac{1}{(N-m)}\sum_{i=1}^{N-m} C_i^{m}(r) \qquad (5)$$

where $C_i^m(r)$ = (number of $j \le N-m$ such that $d[x(i), x(j)] \le r$) /$(N-m)$.

Lower value of sample entropy denotes increased regularity; hence, a reduced sample entropy value will be obtained for an epileptic signal.

C. Statistical Analysis and k-Fold Cross Validation

Features extracted are statistically analysed to remove the insignificant features. This helps to speed up the classification process. In this work, we used student *t*-test with a significance level of 95%. The *p*-Value of the feature is estimated and features with the *p*-Value less than 0.05 are considered as insignificant and does not contribute in classification process [6].

K-fold cross-validation generates training and testing data that will be used to train the classifiers. *K*-fold cross validation divides the datasets into *k* subsets, referred as folds. In the first iteration, first fold will be testing data and remaining k-1 will be training data. The process is repeated k times such that every fold is considered to be testing data. In this work, we have used 10-fold cross validation [7].

D. Classification

In this study, we have used k-Nearest Neighbour (KNN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) to classify interictal and ictal signals. K-nearest neighbour classifies the unknown sample by calculating the Euclidean distance between k-nearest neighboring samples. Unknown sample is classified into the class that is most common with respect to its neighbor. In this work, we have used 10 nearest neighbors in order to classify the unknown samples [8]. Further, we have used Support Vector Machine (SVM). Using the training data, SVM generates a hyperplane that classifies the signal. With respect to the distance between hyperplane margin of the classifier is determined. Training data that falls in the margin are support vectors.

By comparing the support vectors of both the classes, margin is maximized. Though several hyperplanes are generated, only the one that can separate the classes efficiently is chosen [9]. The features that are classified can be linear or nonlinear in nature. To perform classification of nonlinear data SVM uses kernel function such as radial basis function. Finally, we used Linear Discriminant Analysis (LDA) [10]; here the LDA computes the mean for the samples of different class. The classifier separates the classes using boundary. The best boundary is chosen by maximizing the mean of the classes and minimizing the variance. Here, classifier is tested to obtain maximum classification accuracy.

III. Results and Discussions

In this work, we have considered 100 pairs of interictal and ictal signals of sampling frequency 173.1 Hz. Since the signals greater than 60Hz is corrupted by noise, we have used low-pass filter to obtain the signals less than 60 Hz. In this work, we try to determine the sensitivity of the rhythms: gamma, beta, alpha, theta and delta present in EEG signals. These rhythms are extracted by decomposing the EEG signals. In this work, we have used discrete wavelet transform to decompose the signals up to four level. We obtained detailed coefficients of frequency ranges: 60-30 Hz (Gamma), 30-15 Hz (Beta), 15-7.5 Hz (Alpha), 7.5-3.75 Hz (Beta) and approximate coefficient of less than 3.75 Hz (Delta). Detailed coefficients: cD1, cD2, cD3, cD4 and approximate coefficient: cA for interictal and ictal signals was obtained after decomposition. Subha *et al.* [11] in their survey, stated that the presence of high theta activity is an indication of underlying abnormal and pathological condition. Shannon entropy, approximate entropy and sample entropy of different EEG rhythms are computed for both interictal and ictal signals, and compared.

Fig. 2 provides the comparison of mean Shannon entropy, approximation entropy and sample entropy value for interictal and ictal signals at different frequency ranges. We obtained higher Shannon entropy, approximate entropy and sample entropy for interictal compared to ictal signals. For higher frequency rhythms: 60-30 Hz (gamma), 30-15 Hz (beta) and 15-7.5 Hz (alpha) larger difference between interictal and ictal signals was observed. Various researchers such as Kannathal *et al.* [12], Mirzaei *et al.* [6], Song *et al.* [13] have also obtained lower entropy values for reduced ictal signals. Entropy values quantifies the complexity and self-similarity of the signal. These characteristics are lower in ictal signals. Though we obtained lower entropy values for gamma, beta and alpha rhythms of ictal signals, we were unable to observe a substantial reduction in the entropy values for theta and delta rhythms of ictal signals. This is due to the dominance of the high frequency signals in the EEG of the subjects in their awakened state. During ictal state, these high frequency signals lose their complexity and chaoticity which results in reduced entropy values.

Significance of the entropy values is determined by performing statistical analysis. Using student t-test, p-value of the Shannon entropy, approximate entropy and sample entropy values of EEG rhythms is determined for both interictal and ictal signals. Only the entropies with the *p*-value less than the 0.05 are significant and is used in the classification process. The main objective of this work is to determine sensitivity of the EEG rhythm towards epilepsy. Fig. 3 shows the p-values determined for Shannon entropy, approximate entropy and sample entropy. We found that the high frequency rhythms: gamma, beta and alpha are highly significant and contributes the maximum in the classification of the interictal and ictal signals. This is mainly because the high frequency rhythms are dominant in the normal awake person. Therefore, during seizure the large spikes and sharp waves generated reduces the complexity and chaoticity of the EEG signals there by effecting the high frequency rhythms. By comparing these high frequency rhythms, we were able to observe significant difference between the interictal and ictal signals.

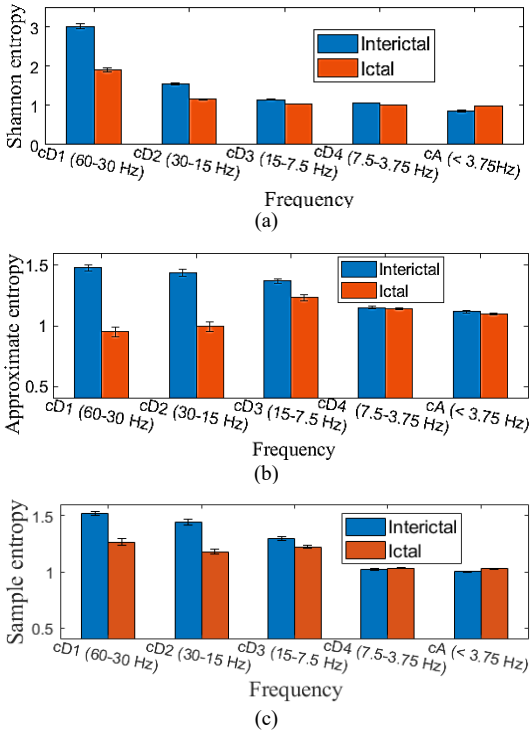

Figure 2. Mean and standard error of (a) Shannon entropy (b) approximate entropy (c) Sample entropy for decomposed signals.

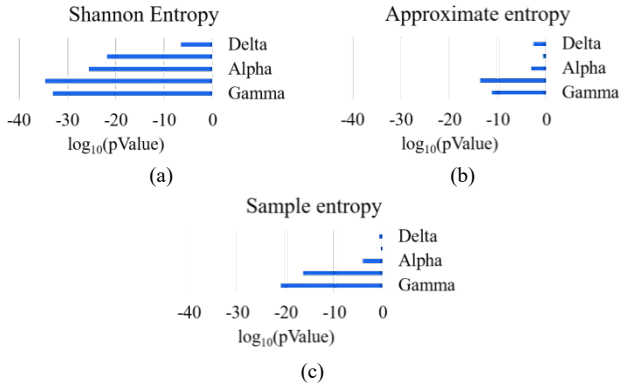

Figure 3. Comparing the pValues of features.

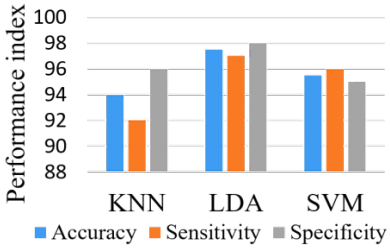

Figure 4. Performance of classifiers.

Significant features obtained from student *t*-test are further classified using k-Nearest Neighbour (KNN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA), a classification accuracy of 94%, 95.5% and 97.5% respectively was obtained. The performance of the classifier is illustrated in Fig. 4. Using LDA maximum classification accuracy of 97.5%, sensitivity of 97.9% and specificity of 98%. Several computer aided diagnostic systems have been designed to classify interictal and ictal signals. Yuan *et al* [14] have used approximate entropy, Hurst exponent and detrended fluctuation analysis to study the interictal and ictal signals. Using classifier, extreme learning machine they classified the signals with an accuracy of 96.5%. Nicolaou *et al.* [15] calculated the permutation entropy of these signals and classified them with an accuracy of 79.9% using support vector machine. Later, Tawfik *et al.* [16] modified this research by determining the weighted permutation entropy, using support vector machine they obtained an accuracy of 93.2%. Swami *et al.* [17] used Energy, root mean square values, mean values, Shannon entropy, standard deviation and maximum peaks; using general regression neural network classifier, they classified interictal and ictal signals with an accuracy of 93.3%. Harshavarthini *et al.* [18] have designed a seizure detection model that uses probabilistic neural network to detect epileptic seizure. Here, the researchers have used discrete wavelet transform and gray level co-occurrence matrix (GLCM) to extract features. Using probabilistic neural network epileptic seizures were classified with an accuracy of 85%. Ray *et al.* [19] have designed a detection model using discrete wavelet transform and genetic algorithm. Here, researchers determined the energy, entropy, mean and standard deviation. Relevant features were selected using genetic algorithm. Using support vector machine for the classification maximum classification accuracy of 86.71% was obtained. Mahmoodian *et al.* [20] have used cross-bispectrum and support vector machine to detect epileptic seizure with the classification accuracy of 96.8%. Raghu *et al.* [21] derived sigmoidal entropy from discrete wavelet transform. Using support vector machine seizure detection rate of 96.34% was obtained. Even though there are several feature extraction and classification methods present, it is very important to choose the appropriate methods to obtain maximum accuracy. Many researcher have suggested that by choosing the best classifier, maximum classification accuracy can be attained. However, in our research we found that along with the best classifier it is equally important to choose appropriate feature extraction methods to obtain better results. In our research, we used entropy methods to analyze the epileptic seizure. Compared to the other methods, entropy methods provided better information of complexity loss during the onset of seizure. The proposed system calculates approximate entropy, Shannon entropy and sample entropy; using linear discriminant analysis, we distinguished interictal and ictal signals with a higher classification accuracy of 97.5%. Moreover, using these entropy methods we were able to study how the onset of seizure effect various brain rhythms.

IV. Conclusion

Epilepsy is a most common neurological disorder caused due to unpredicted seizure and is commonly diagnosed using EEG. EEG in a healthy person is highly complex, nonlinear and chaotic; however, these features reduce in an epileptic patient. In this work, we have analysed the decrease in the complexity measure of EEG rhythms for ictal signals. Using discrete wavelet decomposition EEG rhythms namely: gamma, beta, alpha, theta and delta for both ictal and interictal signals was extracted from the EEG signals. Shannon entropy, approximation entropy and sample entropy was determined for the EEG rhythms. We found that at higher frequency rhythms: gamma, beta and alpha are highly sensitive to epileptic seizure. Entropy values were found to be lower for ictal signals, thus indicating reduced complexity measure. Using linear discriminant analysis, interictal and ictal signals were classified with an accuracy of 97.5%. In our work, we found that high frequency signals exhibit greater difference between interictal and ictal signals. Lower entropy values for ictal signals was obtained in high frequency rhythms. On contrary, for low frequency rhythms difference between entropies in interictal and ictal is very low. Hence, in our experiment we found that higher frequency rhythms contribute maximum in the classification process. The following analysis method can be used for studying and understanding various other neurological and psychological disorders.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Both the authors, Prajna Upadhyaya and Tohru Yagi planned the experiment. Prajna Upadhyaya conducted the experiment. Both Prajna Upadhyaya and Tohru Yagi wrote the paper.

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