Epilepsy Prediction based on PCA of Non Linear Features of DWT of Epileptic EEG

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**Abstract**— In the perspective of Epileptic seizures, the study documents the attempts to analyze Electro Encephalo Graph (EEG) signals during conditions as normal, between and during epileptic seizures using Principal Component Analysis (PCA). After transformation to wavelet domain, nonlinear features are extracted from the principal components and are classified using a kNN Classifier.

**Index Terms**— Electro Encephalo Graph (EEG), k Nearest Neighbour (kNN), non linear features, epileptic seizure, Principal Component Analysis (PCA).

I. INTRODUCTION

A scheme for predicting the occurrence of seizures of epilepsy patients is basically taken from [1], [2]. Relevant literatures from over six decades of exhaustive works on epilepsy detection suggest that the characteristic features of the EEG predictive of an impending seizure are seldom tapped at. Proper diagnosis for epilepsy via gold standards necessitate the use of imaging techniques as functional Magnetic Resonance Imaging (fMRI) to pinpoint the focii of epilepsy – an expensive procedure. With advances in computing speeds and power, judging patient condition objectively and automating diagnostical decisions has become possible. Having said that it may be noted that most researches in the field of seizure prediction center around anticipating the occurrence of seizure(s) in a patient with a known history of epilepsy, not with assessing the prognostic or diagnostic value of pathological EEG findings. The key focus of the study has been reducing the overheads and yet arriving at better segregation of an interictal state indicative of impending seizure(s).

A. Epileptiform EEG

Most often time series analysis of the signals are relied upon and key features that may be captured in a different domain aren’t tapped on. Identifying the Pre-ictal or interictal phase occurring before the onset of seizures (also called as the aura) correctly indicates an impending seizure[3]. Clinical findings in support of the existence of a pre-seizure state include an increase in cerebral blood flow, oxygen availability, and Blood Oxygen Level Dependent (BOLD) signal as well as changes in heart rate prior to seizure occurrence [4]. Schemes for epilepsy detection are briefly discussed:

**Spectral analysis**: Periodic like fluctuations, characterized by a peak in the power spectrum at a specific frequency may be used to identify epileptic seizures. Non parametric analysis often uses the Fourier transform of the estimate of the autocorrelation [5] while parametric analysis is based on Models to estimate the power spectrum [6]. Fig.1 shows Power Spectral

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Density (PSD) plots of Normal, Intercital and Ictal EEG of 5 seconds duration.

**Local variance**: Variance in each segment of the windowed signal is compared with a common threshold. Larger variance indicates a segment with seizure record [7],[8].

**Transform domain Analysis**: Any orthogonal transform can be used but in recent times wavelets are gaining faster and newer grounds with good results reported. In Ref. [8] EEG was analysed with 5 level decomposition using Daubechies 4 wavelet filter and classified using Neural Networks with the energy of details and approximations being the input features, while Ref[9] documents a study based on variances in conjunction with Daubechies and Haar wavelets.

**Nonlinear measures**: Correlation Dimensions (CD), Largest Lyapunov exponents (LLE) and entropies termed as Nonlinear measures or features of EEG indicate and to a large extent help in understanding the EEG dynamics [10]. The study documented in Ref. [11], discusses how CD characterizes the inter-ictal EEG for seizure prediction. Nonlinear measures fare better than most other schemes for epilepsy detection/prediction. Seizure detection performance of various entropy measures tested in [12] and entropy values computed for the epileptic EEG were found to be lower compared to the values computed for the normal EEG. The paper documents that epileptiform EEG is more predictable than the seizure free intervals that resemble Gaussian linear stochastic processes, despite its significant non linearity.

II. PROPOSED METHOD

PCA is applied on the data set that is transformed to the wavelet domain from which non linear features are extracted and given to a k nearest neighbour classifier.

![Figure 1](image1.png)

**Figure 1** PSD of Normal Background and seizure

A. Data

The approach is as illustrated in Fig. 2. The EEG data used in this research has been recorded by Dr. Ralph Andrzejak of the Epilepsy Center - University of Bonn, Germany, made available at site with details in [11].

![Figure 2](image2.png)

**Figure 2** Block Diagram of the method adopted
The database consists of five sets of 100 files, with each having 4096 samples of one EEG epoch, encoded in ASCII.

**B. Principal Component Analysis (PCA)**

PCA is a linear dimensionality reduction technique that provides projection of the data in the directions of highest variance. The PCA algorithm involves computation of covariance matrix from the ensemble of EEG beats, Eigen value and Eigenvector decomposition of covariance matrix, sorting Eigenvectors in the descending order of Eigen values and finally projecting the original ECG data in the directions of sorted Eigenvectors. The first few components will represent the most of the variability present in the data. In this work the first 395 components from the projected matrix got after performing the PCA have been used.

**Choosing of principal components:**

To select the number of principal components to be taken one needs to estimate energy contained in Eigen values. Comparing the magnitude of the two sets of cumulative sum of Eigenvalues and sum of Eigen values, yields a scree plot as shown in Figure 3. we see the two curves cross at an index around 55, suggesting that much many data could be projected into three dimensions without loss of information regarding the second order statistics of the data, as they contain 95% of the energy.

![Selection of number of principle components](image)

**C. Discrete Wavelet Transform DWT**

The multi-scale feature of the wavelet transform allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The continuous wavelet transform,$W_\psi f(b, a)$, of a signal, $f(t)$, requires that the analysing wavelet, be convolved with the signal as given as

$$W_\psi f(b, a) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t - b}{a}\right)$$  \hspace{1cm} (1)

$\psi(t)$ is the mother wavelet basis function, $a$ the scale coefficient, $b$ the shift coefficient and $a, b \in R, a \neq 0$

For large values of $a$. The wavelet transform consists of translates and dilates of a basis function - the mother wavelet, at scale $a$ and translation. When the scale and translation variables are sampled on a dyadic grid, it results in DWT, whose wavelet equation is given by:

$$\left( T f \right)_{n,k} = \left( f, \psi_{n,k} \right) = \int_{R} f(x) \psi_{n,k}(x) dx$$ \hspace{1cm} (2)

Where $\psi_{n,k}(x) = a^{-\frac{n}{2}}(a^{-n}x - k \cdot b)$  \hspace{1cm} (3)

$\psi$ - the mother wavelet satisfies $\int_{R} \psi(x) dx = 0$

For DWT we choose $a = 1, \psi = 2$. Among the numerous wavelets available, 54 wavelets from 7 families used for the study were Coiflets (1-7), Symlets (1-7), Biorthogonal (15), Reverse Biorthogonal (15), Discrete approximation of Meyer Wavelet, Haar and Daubechies (2-10) Wavelets.
D. Non Linear Feature Extraction NLFE

Epileptic EEG exhibit a high rate of quasi periodicity, decreasing the randomness factor – hence the measure of information or entropy during epilepsy[12]. The entropy Estimators used are as follows

**Approximate Entropy Estimator:**

\[ ApEn(m, r, N) = \phi^m(r) - \phi^{m+1}(r) \]  
\[ \phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} \ln(C^m_i(m)) \text{ where } C^m_i = \frac{N^m(i)}{N - m + 1} \]  

**Sample entropy Estimator:**

\[ SampEn(m, r, N) = -\ln \left[ \frac{A^m(r)}{B^m(r)} \right] \]  
\[ A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A^m_i(r) \text{ & } B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B^m_i(r) \]

**Renyi Entropy Estimator:**

Renyi entropy of the order \( \alpha \) given \( \alpha \geq 0 \) and \( \alpha \neq 1 \), for a discrete random variable \( X = x_1, x_2, \ldots, x_N \) with \( p_i \) the probability of occurrence of the event \( X = x_i \), is got from [1] and [2] as:

\[ H_{\alpha}(X_N) = \frac{1}{1 - \alpha} \sum_{i=1}^{N} \log(p_i^\alpha) \]  

Renyi Entropy of 200 samples of Normal, Interictal Ictal EEG are plotted in Fig.6 clearly indicating lower ictal values (crosses in red) as compared to the normal ones (crosses in blue).

**Higher Order Spectrum (HOS) Entropy estimators:**

These are normalised entropy estimators from polyspectra and are representations of higher-order moments or cumulants of a signal. The bispectrum of a signal is the Fourier transform of the third-order correlation of the signal. It can be estimated using the averaged biperiodogram

\[ \tilde{B}(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)] \]

Where \( X(f) \) is the Fourier transform of the signal \( x(nT) \). * denotes complex conjugation and \( E[\cdot] \) denotes the expectation operation. As the Fourier transform of a real-valued signal shows conjugate symmetry, the power spectrum is redundant in the negative frequency region. Likewise the bispectrum being a product of three Fourier coefficients, exhibits symmetry and is computed in the non-redundant region \( \Omega \), as indicated in Fig.3.

Formulae for these bispectral entropy estimators taken from [6] are given: Normalized bispectral entropy1 \( P_1 \)

\[ P_1 = \sum_n p_n \log(p_n) \text{ & } p_1 = \frac{|\tilde{B}(f_1, f_2)|}{\sum|\tilde{B}(f_1, f_2)|} \]  

Similarly Normalised Bispectral entropy 2, \( P_2 \) is given by:

\[ P_2 = \sum_n p_n \log(p_n) \text{ & } p_n = \frac{|\tilde{B}(f_1, f_2)|^2}{\sum|\tilde{B}(f_1, f_2)|^2} \]

The normalization in the equations above ensures that entropy is calculated for a parameter that lies between 0 and 1, as required of a probability, hence the Entropy estimators P and P computed are also between 0 and 1. HOS analysis helps detect non-linearity and phase relationships between harmonic components and characterises regularity of physiological signals much better than its peers [6].

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Figure 4 Approximation entropy values plotted for 100 ictal, 200 Interictal and 200 Normal EEG readings

Figure 5 Sample entropy values plotted for 100 ictal, 200 Interictal and 200 Normal EEG readings

Figure 6 Renyi entropy values plotted for 100 ictal, 200 Interictal and 200 Normal EEG readings
E. Classifier

A routine that takes in a set of labelled data and tries to affix the said labels called classes based on some decision rule that considers some key features of the data sets, onto a new similar data set is termed as a classifier. k Nearest Neighbor (kNN) algorithm being chosen for classification works on the principle of assigning the dominant class to the test object by finding a cluster of k datapoints in the training vector closest to the test object (class of the majority of the neighbours).

III. RESULTS

The entropies of the Normal signals were much higher than the Inter Ictal which were again much higher than the epileptic data as was expected by the results of all 5 entropy estimators. The Renyi entropy estimator yielded the highest entropies among the five estimators with HOS Entropy 2 being the least in value. The following table shows the values used for m and .

<table>
<thead>
<tr>
<th>Table I. VALUES USED FOR VARIOUS ENTROPY CALCULATIONS</th>
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<tbody>
<tr>
<td>Approximate Entropy</td>
</tr>
<tr>
<td>Embedding Factor m = 5, Tolerance parameter r = 0.2</td>
</tr>
</tbody>
</table>

Test Vector Generation and Cross validation

420 samples were used for training and 360 samples for testing using three fold validation. The scheme was tested on Matlab® 2012a with four metrics for performance measurement – Accuracy, sensitivity, specificity and Positive Predictive Value of which Accuracy was selected as a true indicator of performance. Accuracy is a performance metric defined as the percentage of correct predictions, given by:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

True positives (TP) are seizures identified by the classifier and EEG experts and False positives (FP) are seizures identified by the classifier but not experts. False negatives (FN): Seizures missed by the classifier system. True Negatives (TN): Non Seizures identified by both parties.

Among all the wavelet families it was observed that Symlet 7 gave the best accuracy for PCA followed by NLFE of DWT, whereas Reverse Biorthogonal 2.4 wavelets yielded the best result when the Non Linear features extracted from its components were given to a kNN Classifier.

<table>
<thead>
<tr>
<th>Table II: PERFORMANCE COMPARISON</th>
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<tbody>
<tr>
<td>Accuracy with non DWT features only [1]</td>
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<tr>
<td>90.83</td>
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</table>

* The studies in [1],[2] tabulate a result of 99.4 percent accuracy for data segmented to 5 seconds. The data used here and compared with the aforementioned studies is unsegmented.

IV. CONCLUSION

Presented was the use of kNN classifiers to test the efficiency of nonlinear features of EEG samples in epileptic seizure detection and prediction, that seems to work very well.

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REFERENCES