Automatic Seizure Detection Based on Wavelet-Chaos Methodology from EEG and its Sub-bands

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Abstract: *EEG is the most important tool to detect abnormalities of the brain, e.g. epileptic seizures. In this paper we have applied a method based on wavelet-chaos methodology and evaluating four different classifiers for automatic seizure detection in EEG (Electroencephalogram). Achieving this, we have used nonlinear feature of Hurst exponent and other features based on chaotic theory i.e. Correlation Dimension, Fractal Dimension, Largest Lyapunov Exponent and Approximate Entropy. As well, EEG has been decomposed into its frequency sub bands using Discrete Wavelet Transform and three of these nonlinear features i.e. Fractal Dimension, Approximate Entropy and Hurst exponent were extracted from EEG and EEG sub- bands as combined with statistical features from EEG sub bands. EEG sub bands: Delta (<4Hz), theta (4-8Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz) were provided through Discrete Wavelet Transform (DWT). Finally they were applied to classify EEG signals of 21 different epileptic patients to three classes: pre-ictal (before the seizure), ictal (during seizure) and inter-ictal (seizure free interval). Calculating descriptive statistics using ANOVA (Analysis Of Variance), the features that were statistically significant and separated three states from each other were given to four classifiers. Also EEG Channel Selection based on Mutual Information was used for improving classification accuracy, Four classifiers were evaluated and compared for our purpose, including Artificial Neural Network (ANN), Radial Basis Function (RBF), Adaptive Neuro-Fuzzy Inference System (ANFIS) and K Nearest Neighborhood (KNN) that eventually resulted in maximum classification accuracy of %88 by using best set of features containing totally 35 features.*

Keywords: automatic detection, classification, EEG sub-bands, mutual information, wavelet-chaos.

1. Introduction

Epilepsy, as about 50 million people in the world suffer from it, is a sudden occurrence of a simultaneous activity in a vast neuronal network that makes disorder in regular function of brain. Seizure is a clinical sign of excessive discharging of neurons. Electroencephalography (EEG) is the recording of electrical activities of a group of neuronal cells. According to where these signals are taken from, EEG has been divided into two types: Scalp and Intracranial (which we are focused on here). EEG is the most important tool to detect abnormalities of the brain, e.g. epileptic seizures.

In the last few years, investigators were focused on seizure detection through EEG. Visual analysis of EEG for seizure detection can be a hard and time-consuming work, because of long-term EEG recording that is required for the diagnosis of seizure by visual inspection. Overcoming these challenges by automatic seizure detection can cause improvement in treatment and diagnosis of epilepsy [1].

A large number of investigations in EEG classification and seizure detection only classify EEG into two classes: Epileptic and non-Epileptic. Amongst, You D. S. et al [2] have examined an epilepsy detection method using feature extraction algorithms based on entropy and ELM (Extreme Learning Machine) to discriminate patients without epileptic seizures from epileptic ones.

More complete classifications have been done via different methods on different number of patients: Gulera et al [3] has applied lyapunov exponent and RNN (Recurrent Neural Network) to classify EEG into healthy, inter-ictal and ictal segments for five patients.

In recent years, Different algorithms have been used for seizure detection including frequency domain analysis [4], wavelet analysis [5], and non linear analysis [6]. Among linear and nonlinear methods for seizure detection and prediction, linear methods for EEG analysis in time and frequency domain involve many limitations. Since epileptic seizure from onset to post-ictal has a changing structure, it couldn't be deal with as a uniform object [7]. Nonlinear methods in contrast, can be appropriate for describing such a structure. Iasemedis and Sackellares [8] were first to deal with nonlinear dynamics of EEG.

Recent works have been focused on feature extraction from EEG sub-bands. Decomposition of EEG into its frequency sub-bands and considering each sub-band separately may offer some changes in EEG that are not obvious when only EEG is considered. EEG is decomposed into five sub-bands using wavelet transform: Delta (<4Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz).

Hojat Adeli et al [9] presented wavelet-chaos methodology that extract nonlinear features of CD (Correlation Dimension) and LLE (Largest Lyapunov Exponent) from EEG and its sub bands. Adeli et al [10] also offered a wavelet-chaos-neural network methodology for seizure detection that classifies EEG into 3 classes: ictal, healthy and inter-ictal segments. And also Hamed Vavadi et al [11] employed a wavelet-approximate entropy method for seizure detection.

In this study, EEG signals from 21 epileptic patients were employed for classification purposes into three classes: pre-ictal (before the seizure), ictal (during seizure) and inter-ictal (seizure free interval). There are different parts in seizure detection schemes including feature extraction and classifiers. For feature extraction, we have employed both wavelet analysis and nonlinear features based on chaos theory. These features were extracted in a fixed length 10s sliding window.

Brain signals have chaotic characteristic in normal state and as the seizure begins, because of synchronization of neuronal cells, this chaotic behavior reduces and so, feature extraction method based on chaos theory could be appropriate for describing such a structure. Brain signals have positive values of lyapunov exponent in normal state and this value reduces near a seizure occurrence. And also correlation dimension, fractal dimension and approximate entropy have been used for evaluating chaotic behavior of brain. In this paper these chaotic features i.e. correlation dimension (CD), Largest Lyapunov Exponent (LLE), Fractal dimension (FD), Approximate Entropy (ApEn) and also a nonlinear feature of Hurst exponent (H) has been used.

As well EEG has been decomposed into its frequency sub-bands: Delta (<4Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz) using discrete wavelet transform. First, three of these nonlinear features i.e. Fractal dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H) were extracted from EEG sub bands. Meanwhile some statistical features were extracted in each sub band.

Moreover, in this study Mutual Information was used for EEG Channel Selection that improved classification accuracy by selecting optimal channel. Also we have tried to achieve better classification results by improving feature vectors given to four classifiers. These classifiers are MLP trained with Levenberg-Marquardt algorithms, Radial Basis Function (RBF), Adaptive Neuro-Fuzzy Inference System (ANFIS) and K nearest neighborhood (KNN). The outputs are three classes of pre-ictal, ictal and inter-ictal.

2. Material

The database contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy [12]. The data were recorded during invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany. The EEG data were acquired using digital video EEG system with 256 Hz sampling rate.

3. Channel Selection Based On Mutual Information

In patients with Generalized Epilepsy, EEG results may show epileptic discharges affecting the entire brain, so the EEG channels receive similar signals and they don’t have independent information. Thus in this patients channel selection is not important. But in patients with partial seizures that affect only a part of brain, channel selection can be helpful.

Selecting an optimal channel of EEG instead of using all of them is being done because elimination of irrelevant channels improves classification accuracy.

In this paper EEG channel selection using Mutual Information (MI) is applied. This method selects the EEG channel such that the MI between selected feature and class label is maximized. Calculating mutual information and selecting optimal channel is done by Mutual Information Computation Package in MATLAB [13].

4. Feature Extraction

4.1 Fractal Dimension

Fractal Dimension is one of the methods of quantifying chaos that focuses on the geometric aspects of the attractors. The method that is used for calculating Fractal Dimension in this paper is based on Higuchi’s Algorithm [7]. This algorithm proceeds as follows:

Consider a limited time series:

$$X(1), X(2), \dots, X(N) \qquad (1)$$

Now from this time series, new time series, X_k^m are constructed as follows:

$$X_k^m : X(m), X(m+k), X(m+2k), \dots, X(m+[\frac{N-m}{k}], k)$$

$$(m = 1, 2, \dots, k) \qquad (2)$$

So there are k new time series. $L_m(k)$, the length of X_k^m curves, is now defined as:

$$L_m(k) = \frac{\left\{\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} | X(m+ik) - X(m+(i-1)k) |\right) \frac{N-1}{\left[\frac{N-m}{k}\right].k}\right\}}{k} \qquad (3)$$

And for each k, the length of curves is defined as $< L(k) >$, that is the mean of $L_m(k)$ values for $m = 1, 2, \dots, k$.

If $L(k)$ is proportional to k^{-D} then the time series is a fractal with the dimension of D.

4.2 Correlation Dimension

Grassberger and Procaccia introduced a dimension called correlation dimension, based on the behavior of a so-called Correlation Sum (or Correlation Integral) [14]. Correlation Sum, C(r), is the probability that two points in a set of N points are closer together than r. this probability is then calculated using the distance between each pair of points in this set. C(r) is calculated as follows:

$$C(r) \approx \frac{\sum_{i=1, j>i}^{N} \Theta(r - |\vec{x_i} - \vec{x_j}|)}{\frac{1}{2} N(N-1)} \quad (4)$$

Heaviside step function Θ is defined as:

$$\Theta(S) = \begin{cases} 1 & \text{if } s \geq 0 \\ 0 & \text{if } s < 0 \end{cases} \quad (5)$$

Then C(r) is calculated for different small values of r, and log(C) is plotted as a function of log(r). Then slope of straight line in the plot, gives the Correlation Dimension, CD.

$$CD = \lim_{r \to 0} \left(\frac{\log(C(r))}{\log(r)} \right) \quad (6)$$

4.3 Hurst Exponent

Hurst Exponent is directly related to fractal dimension:

$$H = E + 1 - D \quad (7)$$

(E is the Euclidean dimension, H is the Hurst Exponent and D is the Fractal Dimension.)

Hurst Exponent, in addition to be used as Fractal Dimension of time series, is also the measure of smoothness of signal [14], Hurst Exponent H, is defined as:

$$H = \frac{\log(\frac{R}{S})}{\log(T)} \quad (8)$$

T is the window length of signal and (R/S) is the corresponding value of rescaled range.

4.4 Largest Lyapunov Exponent

Lyapunov Exponent is a way of measuring chaos, that provide a quantitative value for the rate of divergence of nearby Trajectories that are very close together in initial conditions [14].

A system behavior is chaotic if its Lyapunov Exponent is a positive number for all initial conditions. It means that nearby trajectories separate from each other exponentially.

This is called sensitive dependence on the initial condition.

Considering two different trajectories that are very close together in initial time and their distance is $\| \overrightarrow{\Delta x(0)} \|$.

Over a time, t, their distance became $\| \overrightarrow{\Delta x(t)} \|$ and this distance increased exponentially.

$$\| \Delta \vec{x}(t) \| \approx \| \Delta \vec{x}(0) \| e^{\lambda t} \quad (9)$$

A dynamical system has m values for lyapunov exponent.

$$\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m \quad (10)$$

The largest lyapunov exponent is calculating by:

$$\lambda(\vec{x_0}) - \lim_{t \to \infty} \lim_{\|\Delta \vec{x}(0)\| \to \infty} \frac{1}{t} \log \frac{\| \Delta \vec{x}(t) \|}{\| \Delta \vec{x}(0) \|} \quad (11)$$

According to the algorithm introduced by Kantz [15] for calculating largest lyapunov exponent, S (t) function is defined as:

$$S(t) = \frac{1}{N} \sum_{i=1}^{N} \ln \left(\frac{1}{|U_i|} \sum_{x_j \in U_i} dist(xi, xj, t) \right) \quad (12)$$

That dist (xi, xj and t) is the distance between two nearby trajectories.

Here, TISEAN software package is used for calculating S (t).

4.5 Approximate Entropy

Approximate Entropy is a measure of regularity in data, as smaller values of Approximate Entropy represents more regular behavior of signals.

The algorithm is presented by Pincus et al [16]. Consider data as $X(1), X(2), \ldots, X(N)$. At first two values, m, the embedding dimension and r, that is the threshold value for noise elimination should be defined. $r = 0.2\sigma_s$ and σ_s is the standard deviation of original data. The algorithm is as below:

First $X(1), \ldots, X(N-m+1)$ vectors are constructed:

$$X(i) = [x(i), x(i+1), \ldots, x(i+m-1)], i = 1, \ldots, N-m+1 \quad (13)$$

Then consider:

$$d[X(i), X(j)] = \max_{k=0,m=1} [|x(i+k) - x(j+k)|] \quad (14)$$

Where d[X (i), X (j)] is the distance between two vectors X (i), X (j).

For a vector x (i):

$Let\ N^m(i) = no.of$ x(j) that d[X(i),X(j)] $\leq$ r,

$$Then\ C_i^m(r) = \frac{N^m(i)}{N-m+1} \quad (15)$$

Now:

$$\phi^m m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_i^m(r) \quad (16)$$

Finally, the approximate entropy is:

$$ApEn(m, r) = \lim_{n \to \infty} [\phi^m(r) - \phi^{m+1}(r)] \quad (17)$$

4.6 Feature extraction using Discrete Wavelet Transform (DWT)

EEG decomposition into its five frequency sub-bands is done using wavelet transform. Wavelet transform has many advantages over Fourier transform such as: time frequency localization and scale-space analysis [5].

In this work, Discrete Wavelet Transform (DWT) was used. Using second-order daubechies wavelet transform, five level of decomposition was done, that gives six EEG sub- bands.

Table 1 shows frequencies corresponding to different levels of decomposition for sampling frequency of 256Hz. As the table show, the components A_5 decomposition are within the Delta (<4Hz) range and D_5, D_4, D_3, D_2, D_1 are within theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz) respectively.

Three features of Fractal dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H) were extracted from EEG sub-bands: gamma, beta, alpha, theta and delta.

Also statistics over wavelet coefficients were used [17]. These statistical features are:

1. Mean of the absolute values of the coefficients in each sub band.
2. Average power of the wavelet coefficients in each sub band.
3. Standard deviation of the coefficients in each sub band.

TABLE I: Frequencies Correspond to Differrent Level of Decomposition

Decomposed signal	*Frequency range*
D_1	64-128
D_2	32-64
D_3	16-32
D_4	8-16
D_5	4-8
A_5	0-4

5. Classification

This work involves a three class classification problem to classify EEG signals from 21 epileptic patients. The three classes are: Pre-ictal (before the seizure), ictal (during the seizure) and inter-ictal (seizure free interval). Four classifiers: artificial neural network (ANN), Radial Basis Function (RBF), Adaptive Neuro-Fuzzy Inference System (ANFIS) and K-nearest neighborhood (KNN) were trained and tested for this purpose.

The applied Artificial Neural Network is a Multi-Layer Perceptron (MLP) trained with Levenberg-Marquardt Algorithm. The results are obtained with two layers of 16 neurons in the first layer and 14 neurons in the second layer. The employed Radial Basis Function is a two layer Probabilistic Neural Network. The Adaptive Neuro-Fuzzy Inference System is applied with Gaussian membership function and the fuzzy rules are formed using subtractive clustering method. K-Nearest neighbor classifier is a supervised learning algorithm and its accuracy changes with different values of K (neighborhood).

6. Simulation Results

First nonlinear features of Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Fractal Dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H) were used. As well, EEG has been decomposed into its frequency sub-bands and three of these nonlinear features i.e. Fractal Dimension, Approximate Entropy and Hurst exponent were extracted from EEG and EEG sub-bands. After calculating mean and standard deviation of each feature using ANOVA (Analysis Of Variance), some of them were eliminated as they were not significant enough. Finally 17 features that were statistically significant (p-value<0.05) and separated three states from each other were given as inputs to four classifiers (ANN, KNN, RBF, and ANFIS). The results were shown in tables 2, 3, 4, 5 and 6.

TABLE II: Accuracy of Four Classifiers

measure	**classifier**			
	ANN	***KNN***	***RBF***	***ANFIS***
Accuracy	%86	%85	%85	%81

TABLE III: Confusion Matrix of ANN

Output class	**Target class**		
	1	***2***	***3***
1	137	12	2
2	9	21	3
3	10	0	58

TABLE IV: Confusion Matrix of KNN

Output class	**Target class**		
	1	***2***	***3***
1	211	2	6
2	25	17	1
3	16	0	57

TABLE V: Confusion Matrix of RBF

Output class	**Target class**		
	1	***2***	***3***
1	200	6	2
2	14	16	2
3	26	0	69

TABLE VI: Confusion Matrix of ANFIS

Output class	**Target class**		
	1	***2***	***3***
1	205	23	28
2	2	16	0
3	10	1	50

We have achieved another set of features that improved the classification accuracy by adding statistical features extracted from EEG sub-bands to the previous features described above.

These new set of features are: Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Fractal Dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H) that three of these features i.e. Fractal Dimension, Approximate Entropy and Hurst exponent were extracted from EEG and EEG sub-bands as combined with statistical features from EEG sub-bands, totally 35 features were given as inputs to four classifiers: Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Adaptive Neuro-Fuzzy Inference System (ANFIS) and K-nearest neighborhood (KNN). The results were shown in tables 7, 8,9,10 and 11. As table 7 indicates, the classification accuracies have improved.

TABLE VII: Accuracy of Four Classifiers

measure	classifier			
	ANN	*KNN*	*RBF*	*ANFIS*
Accuracy	%88	%88	%87	%85

TABLE VIII: Confusion Matrix of ANN

Output class	Target class		
	1	*2*	*3*
1	141	2	9
2	11	23	2
3	6	0	58

TABLE IX: Confusion Matrix of KNN

Output class	Target class		
	1	*2*	*3*
1	211	3	2
2	16	24	2
3	17	0	60

TABLE X: Confusion Matrix of RBF

Output class	Target class		
	1	*2*	*3*
1	194	9	8
2	13	25	1
3	11	1	73

TABLE XI: Confusion Matrix of ANFIS

Output class	Target class		
	1	*2*	*3*
1	194	27	10
2	4	20	0
3	6	1	73

Also when only Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Fractal Dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H) as combined with statistical features from EEG sub-bands (without extracting chaotic features from EEG sub-bands) were given to four classifiers, the results are as shown in table 12:

TABLE XII: Accuracy of Four Classifiers

Measure	classifier			
	ANN	*KNN*	*RBF*	*ANFIS*
accuracy	%84	%85	%80	%80

Eventually among these three set of features that were given separately to four classifiers, the best results were belong to 35 features containing Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Fractal Dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H) that three of these features i.e. Fractal Dimension, Approximate Entropy and Hurst exponent were extracted from EEG and EEG sub-bands as combined with statistical features from EEG sub-bands. Also the entire classification accuracies have improved, especially classification results of ANFIS (Adaptive Neuro-Fuzzy Inference System).

7. Conclusion

In this study EEG signals from 21 epileptic patients were employed for classification purposes into three classes: pre-ictal (before the seizure), ictal (during seizure) and inter-ictal (seizure free interval).

For achieving this, evaluating and comparing of three set of features and four classifiers were investigated. Using best set of features containing totally 35 features resulted in maximum classification accuracy of %88. These features were nonlinear features of Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Fractal Dimension (FD), Approximate Entropy (ApEn) and Hurst exponent (H). As well, EEG has been decomposed into its frequency sub-bands using Discrete Wavelet Transform. EEG sub-bands are Delta (<4Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz).Three of these nonlinear features i.e. Fractal Dimension, Approximate Entropy and Hurst exponent were extracted from EEG and EEG sub-bands and also statistical features were extracted from EEG sub-bands.

Some descriptive statistics contain mean and standard deviation of each feature were calculated using ANOVA (Analysis Of Variance), So Features that were statistically significant (p-value<0.05) and separated three states from each other were given as inputs to four classifiers.

For improving classification accuracies, irrelevant channels were set aside by mutual information and optimal channel of EEG for each patient has been used.

Finally Accuracy and also Confusion Matrix of four classifiers: Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Adaptive Neuro-Fuzzy Inference System (ANFIS) and K-nearest neighborhood (KNN) were presented.

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