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Epileptic State Detection: Pre-ictal, Inter-ictal, Ictal

Apdullah Yayik[1*], Esen Yildirim[2], Yakup Kutlu[2], Serdar Yildirim[2]

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***Abstract*:** Epileptic seizure detection and prediction from electroencephalography (EEG) is a vital area of research. In this study, Second-Order Difference Plot (SODP) is used to extract features based on consecutive difference of time domain values from three states of EEG (pre-ictal, ictal and inter-ictal), and Multi-Layer Neural Network classifier is used to classify these three classes. The proposed technique is tested on a publicly available EEG database and classified with Naive Bayes and *k*-nearest neighbor classifiers. As a result, it is shown that overall accuracy of 98.70% can be achieved by using the proposed system with Neural Network classifier.

Keywords: *Epileptic State Detection, Second-Order Difference Plot, Neural Network*

1. Introduction

Epilepsy is a chronic disease comprised by repetitive seizures. Approximately 1% of people in the world suffer from epilepsy, and 85% of them live in growing countries [1]. Seizures are resulted from sudden excessive electrical discharge in a group of brain cells. Epilepsy is explained by recurring instant seizures due to the instantaneous development of synchronous firing in the cerebral cortex caused by lasting cerebral abnormality [2]. The electroencephalogram (EEG) signals act vital role in detection of epilepsy and detection and prediction of epileptic seizures [3,4].

Detection of epilepsy is important for diagnosis of epilepsy. Besides, for an epileptic patient, recognizing the period when a seizure is occurring is necessary for the caregiver to prevent serious injuries due to the seizures. Various approaches have been applied in this field in the last decade. Vukkadala and Vijayapriya [1] discussed an automated Neural epilepsy detection system on two classes (awake healthy and pathologic) with features extracted from EEG using Approximate Entropy (ApEn). They have reached 93.3% overall accuracy. In 2011, Shen et al. [5] presented comparison of different kernels (RBF, Linear, Sigmoid and Grid) of SVM classifier on three classes (normal, inter-ictal and ictal) with ApEn features extracted from multichannel EEG signals. Grid SVM kernel resulted in the highest overall classification accuracy of 98.9%. Zainuddin et al. [6] proposed a seizure detection system using statistical features obtained from the discrete wavelet transform and an improved wavelet neural network (WNN). The performance of the classifier is reported as %98.87. Vollala and Gulla [7] presented comparison of Elman and Probabilistic Neural Network classifiers on two classes (epileptic and normal patients) using ApEn features extracted from EEG signals and reached 93.43% overall accuracy with Elman Neural Network classifier. Mercy [8] classified two classes (normal and epileptic) with both SVM and Neural Networks using DWT and Fast Independent Component Analysis and obtained an accuracy of 99.5%. Bayram [9] achieved an 98% overall accuracy in seizure detection with Wavelet Entropy features classified by using SVM.

Epilepsy is a disease which affects the patient only during the seizure and about 70% of the patients can control the seizures with medication. There are numerous studies which show that EEG recordings carry important information prior to the seizure onset [3,4]. A detailed review can be found in [4].

The goal of this study is discrimination of three states of an epileptic patient: pre-ictal, ictal and inter-ictal. For this purpose, EEG database obtained from Children's Hospital Boston (CHB) [10] is used.

Different linear and non-linear classifiers are employed for classification; Naive Bayes, *k*-nearest neighbor and Neural Network. Region parameters of Second-order difference plot are used as features to distribute classes to different data spaces without losing the pattern properties. The results are evaluated with 10-fold cross validation. This paper is organized as follows, in section 2, data used in this study is presented, and then the feature extraction based on second order difference plot is explained. The implementation of Neural Network, Naive Bayes and *k*-nearest neighbor classifiers are next described in section 3. In section 4, effectiveness of the proposed classification and performance analyses are presented, and finally conclusions are discussed in section 5.

2. Proposed Methodology

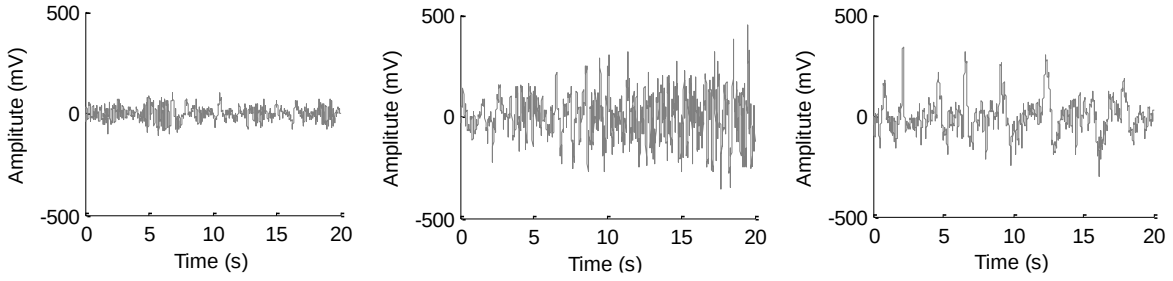
2.1. Data Description

The EEG Database used in this study is CHB-MIT Scalp EEG Database [10]. The database is collected from 5 males aged between 3 and 22, and 17 females between ages 1.5 and 19.

2.2. Data Processing

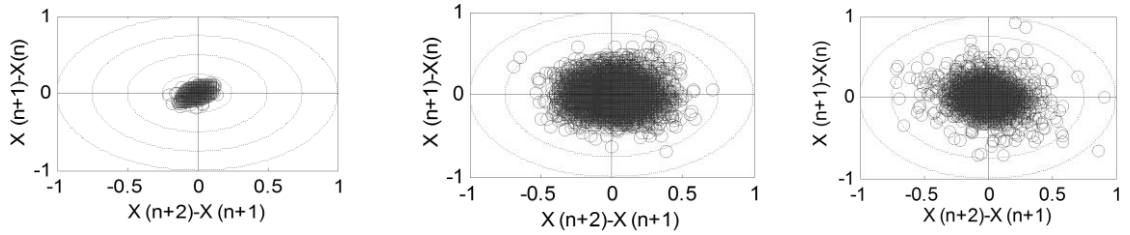
Database is divided into three sets: set A, B and C. Each of these sets consists of 20 s long 256 Hz sampled EEG segments from 18 channels. Sets A, B and C are recorded before seizure, during seizure and between seizures respectively (sample recordings are shown in Figure 1).

[1] *Turkish Army Forces, Turkey*
[2] *Department of Computer Engineering Mustafa Kemal University, Turkey*
** Corresponding Author: Email: ayayik@kkk.tsk.tr; ayayik@mku.edu.tr*
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(a) (b) (c)

Figure 1. 20 s FP1-F7channel EEG recordings belong to 11 years old female; (a) before seizure (pre-ictal), (b) during (ictal), (c) between seizures (Inter-ictal).



(a) (b) (c)

Figure 2. Second Order Different Plot of Multi-Channel EEG (a) before seizure (pre-ictal), (b) during (ictal), (c) between seizures (Inter-ictal).

2.3 Feature Extraction

Second Order Difference Plot (SODP) is a feature extraction method which is formed employing time domain information. The method of SODP can be used as an independent feature extraction tool as well as a supplemental technique to confirm the frequency domain results [11]. If X(t) is the EEG signal, SODP is formed by $X(n+1)-X(n)$ and $X(n+2)-X(n+1)$ points on the plot (Figure 2). In other words, SODP includes scattering of consecutive difference values of points in EEG signal. Thus, the statistical condition of consecutive differences can be observed. Figure 2 shows a sample of the Second-order difference plot of EEG signals before, during and between seizures. The features are extracted from second-order difference plot of the sets A, B and C Region parameters. The SODP is a figure of two-dimensional Cartesian system. The axes of a two-dimensional Cartesian system divide the quadrants, which are four infinite regions numbered from the first to the fourth each bounded by two half-axes. The region numbers and signs of two coordinates are I (+ , +), II (− , +), III (− , −) and IV (+ , −). SODPs are generally divided into different radius of circle regions in order to extract features [12]. Regions of a quadrant in a SODP are shown in Figure 3.

There are four quadrants of a Cartesian coordinate system. Each quadrant has four regions. Therefore, there are sixteen different regions. Each region shows the number of points in SODP. The numbers of points are calculated for each region and used as a feature vector.

3. Classification

3.1 Multi-Layer Neural Network Classifier

ANNs are inspired by biological neural networks. They are generated neuron-like units which are connected together with adjustable weights [13]. Each unit generates an output signal. Among different structures utilized in ANNs, the mostly used one is the multi-layer perceptron (MLP). MLP consists of successive layers each having different number of processing units. The layers are input layer, hidden layer and output layer. The units in each layer are fully connected to units in the next layer. The output of the MLP is the set of units in the output layer. In order to generate a correct output for a given input, the values of weights should be adjusted. The convenient weights are determined under

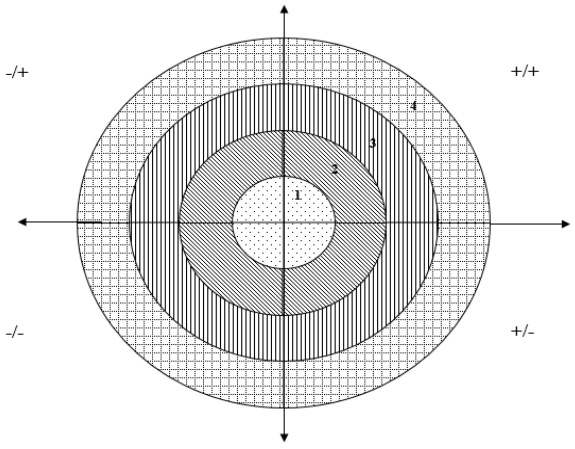


Figure 3. Regions of SODP of EEG

the control of a training algorithm. A variety of training algorithms can be utilized in the network [14]. The main goal of training a network is not to force it to learn the training set perfectly but to generate correct outputs for inputs that are not seen during the training process. In this study; neural network that has 3 layers (input layer 16 that has neurons, one hidden layer that has 9 neurons and output layer that has 3 layers) as shown in Figure 4, sigmoid transfer functions and backpropagation algorithm is used.

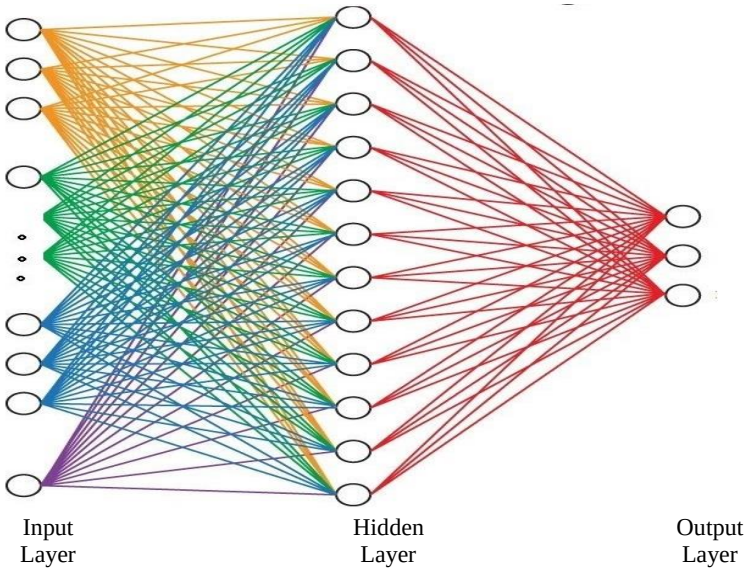


Figure 4. Proposed Multi-Layer NN Classifiers' Topology

3.2 Naive Bayes Classifier

The Naive Bayes classifier is a Bayesian network where the class has no parents and each feature has the class as its only parent. Naive Bayes models have been widely used for clustering and classification in machine learning. It is the simplest form of Bayesian theorem. The Naive Bayes algorithm is based on conditional probabilities. The conditional independence is an assumption in Bayesian theorem [15].

3.3 *k*-Nearest Neighbor (*k*-NN) Classifier

In pattern classification, the *k*-nearest neighbor algorithm (*k*-NN) is a non-parametric technique for classifying classes according to nearest training examples in all extracted features. It is a type of sample-based learning. In the machine learning algorithms, the *k*-NN algorithm is the simplest one; an object is classified by a plurality vote of its neighbors, with the features being assigned to the class most common amongst its *k* nearest neighbors [13], [14]. In this study *k* value is preferred as 3.

4. Performance Analysis

4.1 *k*-Fold Cross Validation

Cross-validation is also known as rotation estimation. It is a method to determine how the results of a statistical analysis will generalize to a new data set. In this method, the whole data set is randomly separated into k equal size subsets. One subset is used for testing and all other subsets are used in training. This step is repeated for k times leaving one fold for evaluation each time (Figure 5). This validation method is performed for better approximation error [14].

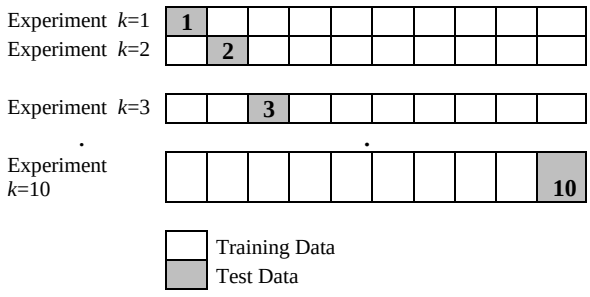


Figure 5. *k*-fold Cross Validation

4.2 Performance Measure

For classification tasks, the terms true positives, true negatives, false positives, and false negatives are used to compare the results of the classifiers. The terms positive and negative refer to the classifier's prediction, and the terms true and false refer to whether that prediction corresponds to the external judgment (sometimes known as the observation). Accuracy is the overall correctness of the model and is calculated as the total number of instances that are correctly classified over the total number of instances. Precision is calculated as the correctly classified positives over total instances predicted as positive. Recall is also known as sensitivity and is calculated as the proportion of true positives (correctly predicted as positive) to the total number of instances belongs to that class. Overall Accuracy, Recall, and Precision are formulated in Table 1.

Table 1. Performance Measurements of Classifiers

$$\textbf{Accuracy} = \frac{TP_b + TP_e + TP_a}{TP_b + TP_e + TP_a + E_{be} + E_{ba} + E_{db} + E_{da} + E_{ab} + E_{ae}}$$

$\textbf{Recall}_b = \frac{TP_b}{TP_b + E_{be} + E_{ba}}$	$\textbf{Precision}_b = \frac{TP_b}{TP_b + E_{db} + E_{ab}}$
$\textbf{Recall}_d = \frac{TP_d}{TP_d + E_{db} + E_{da}}$	$\textbf{Precision}_d = \frac{TP_d}{TP_d + E_{be} + E_{ae}}$
$\textbf{Recall}_a = \frac{TP_a}{TP_a + E_{ab} + E_{ae}}$	$\textbf{Precision}_a = \frac{TP_a}{TP_a + E_{ba} + E_{da}}$

ROC curve is a 2 dimensional graphical plot which demonstrates the performance of a binary classifier by plotting the true positive rate against the false positive rate [15]. Performances of two classifiers are compared by the areas under the ROC curves (AUC). An AUC value of 1 represents a perfect test result where as an AUC value lower than 0.5 is accepted to be worse than random prediction. The Kappa Statistic measures the agreement of prediction with the true class. A value of 1 implies complete agreement [16]. The Mean Absolute Error (MAE) measures the mean magnitude of the errors in a set. The other performance measure is The Root Mean Absolute Error (RMAE) which is a

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quadratic scoring rule which measures the average magnitude of the error [17].

5. Experimental Results and Conclusions

A method for analyzing multi-channel EEG for detecting pre-ictal, ictal and inter-ictal states using Second Order Difference Plot features are presented here. Recordings that have not common channel information are eliminated. Several classifiers' performances are compared by Precision, Recall, area under the ROC curve, Kappa Statistic, MAE, RMAE and Overall Accuracy metrics. The results are shown in Table 2. One can see that performance parameters of Neural Network classifier are higher than others. The prediction accuracy of EEG signals are 98.70%, 94.71% 95.14% using Neural Network, k-NN and Naive Bayes classifiers, respectively. Table 2 shows details of performance measures of classifiers. In order to validate classifiers performances 10 different test and training datasets, derived by 10-fold cross validation are used and mean values of performance parameters are calculated.

These results are difficult to compare with previous studies. Because previous studies are focused on binary classifications; ictal/normal (non-epileptic) EEG [6–9,19] normal/inter-ictal/ictal [5] or pre-ictal/inter-ictal [20] on different datasets. This study is focused on discriminating three states of epileptic patients; before seizure (pre-ictal state), during seizure (ictal state) or non-seizure. Details of previous studies are described in Table 3. Pachoris and Patidar [21] classified normal and seizure EEG using empirical mode decomposition (EMD) and second-order difference plot (SODP) features with ANN model on Andrzejak Dataset. Their study combines EMD and SODP methods for feature extraction. Our study aims to determine; if a seizure is expected in a near future, if the patient is having a seizure in that moment or the patient is neither in a seizure state nor a seizure is expected soon. For that purpose SODP features of raw signals are used for building a model. This study shows that the state of an epileptic patent can be classified as before, during and between seizures (pre-ictal, ictal and inter-ictal) using SODP features and machine learning algorithms.

The proposed methodology can be very helpful for medical practice. Presented system's accuracy might be improved by applying various feature extraction methods and feature selection algorithms to find the best features that characterize the seizure state.

Acknowledgments

The authors would like to thank Children's Hospital Boston for kindly sharing database freely on internet.

Table 2. Evaluated Performances for All Classifiers

Classifier	*Class*	*Precision*	*Recall*	*ROC Area*	*Kappa Statistic*	*Mean Absolute Error*	*Root Mean Squared Error*	*Overall Accuracy (%)*
Multi-Layer Neural Network	*pre-seizure*	99.00%	99.00%	0.99	0.98	0.01	0.07	**98.70**
	Ictal	97.00%	97.60%	0.99				
	Inter-Ictal	**100.00%**	100.00%	0.99				
***k*-Nearest Neighbor**	*pre-seizure*	94.10%	94.10%	0.95	0.92	0.03	0.18	**94.71**
	Ictal	92.10%	92.10%	0.93				
	Inter-Ictal	98.00%	98.00%	0.99				
Naive Bayes	*pre-seizure*	98.10%	100.00%	0.91	0.95	0.02	0.11	**95.14**
	Ictal	97.30%	94.10%	0.83				
	Inter-Ictal	96.10%	97.00%	0.96				

Table 3. Comparisons with Previous Studies

Study	*Year*	*Database*	*Features*	*Classification Problem (Epileptic States)*	*Classifier*	*Classification Accuracy (%)*
[20]	2009	Freiburg dataset [19]	Wavelet Transform	pre-ictal and inter-ictal	Convolutional NN	71,00
[1]	2009	Individual	Approximate Entropy	normal and ictal	Elman NN	93,33
[5]	2011	National Taiwan University Hospital	Approximate Entropy	normal and inter-ictal and ictal	SVM	98.1
[6]	2012	Andrzejak Dataset [22]	Discrete Wavelet Transform	normal and ictal	ANN	98,87
[7]	2012	Andrzejak Dataset [22]	Approximate Entropy	normal and ictal	ANN	93,43
[8]	2012	Andrzejak Dataset [22]	Fast Independent Component Analysis	normal and ictal	ANN	99,50
[9]	2013	Andrzejak Dataset [22]	Discrete Wavelet Transform	normal and ictal	SVM	98,00
[21]	2014	Andrzejak Dataset [22]	Empirical Mode Decomposition Second-Order Difference	normal and ictal	ANN	95,00
This Study	2014	CHB Dataset [10]	Second Order Difference	pre-ictal, ictal and inter-ictal	ANN	98,70

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