Epileptic Seizure Classification using Statistical Features of EEG Signal

Md. Mamun or Rashid
Department of Biomedical Engineering,
Khulna University of Engineering & Technology
Khulna-9203, Bangladesh
mamunbme@yahoo.com

Mohiuddin Ahmad
Department of Electrical and Electronic Engineering,
Khulna University of Engineering & Technology
Khulna-9203, Bangladesh
ahmad@eee.kuet.ac.bd

***Abstract*—Epilepsy detection is enough time consuming and requires thorough observation to determine epilepsy type and locate the responsible area of the cerebral cortex. This paper proposes an effortless epilepsy classification method for straightforward epilepsy detection and investigates the classification accuracy of multiclass EEG signal during epilepsy. To accomplish our research work we exploit DWT MATLAB toolbox to obtain responsible features to accumulate feature vectors. Afterwards feature vectors are given in the input layer of the NN classifiers to differentiate normal, interictal and ictal EEG periods. Accuracy rate is calculated based on the confusion matrix. Proposed method can be utilized to monitor and detect epilepsy type incorporating with alarm system.**

Keywords*—Discrete wavelet transform (DWT); artificical neural network (ANN); epileptic seizure classification; statistical features; interictal period; ictal period; epilepsy detection.

I. INTRODUCTION

Human brain is a complex structure engineered and among innumerable neurological disease, epilepsy holds the second place after stroke where 50 million people suffer globally [1]. Temporal, sudden and irregular cerebral electrical discharge characterizes epilepsy that compelled patient to shake their extremities and lose consciousness. Depending on the affected neuron cell area of the cortex, epilepsy categorized as partial and generalized epileptic seizures [2]. It is crucial to differentiate the normal EEG period, interictal EEG period and ictal EEG period signal to classify the types of epileptic seizures. Interictal period is EEG signal during a seizure-free interval of an epileptic subject and ictal period is EEG signal during a seizure of an epileptic subject.

Many researches have been accomplished. In [3] authors used DWTs for preprocessing of EEG signal and enquires the efficacy of the WNNs for the detection of epileptic seizure. The performance varies according different wavelets, features. Authors in [4] applied immune clonal algorithm (ICA) to organize feature vectors incorporating DWT and three classifiers used to differentiate epilepsy types. Researchers in [5] adopted a combined method using neural network with weighted fuzzy membership functions (NEWFM) to classify epileptic and normal EEG. Performance results in terms of accuracy, sensitivity and specificity. In [6] researchers adopted nonlinear analysis of time, frequency and time-frequency domain to collect responsible features and a quadratic classifier calculates classification accuracy. In [7], authors proposed time-frequency analysis and extracts PSD as feature for each EEG segment. Further ANN used to calculate the classification rate of epileptic seizures. In [8], researchers developed an epilepsy detection method where WT is used for feature collection and quadratic classifier classifies the three class EEG signal. In [9], authors embraced ANFIS classifier to differentiate between ictal and inter-ictal EEG signal. Authors in [10] adopted DWT and MLPNN based technique that resulted promising accuracy rate for five different experiments. In [11], authors proposed a method based on the empirical mode decomposition (EMD) and the second-order difference plot (SODP) to classify ictal and seizure-free EEG signals using the artificial neural network (ANN) classifier. Authors [12] proposed a focal and non-focal EEG signals classification method using EMD method and entropy measures. Several entropy features are used for LS-SVM classifier and outcomes average 87% classification accuracy. Authors in [13] proposed an automatic detection process using WT and ANN. Outputs average specificity of 99.19%, sensitivity of 91.29% and selectivity of 91.14% are obtained. In [14], authors proposed empirical mode decomposition (EMD) based method to classify focal and non-focal EEG signals. The average Renyi entropy and the average negentropy of IMFs for EEG signals are computed as features and set to input in ANN.

Long term monitoring of epileptic EEG signal and manual visual inspection results inaccuracy. As a result many algorithms have been exploited for efficient epilepsy detection. In our research work we adopted DWT MATLAB toolbox and ANN to classify different epileptic EEG signal in a straightforward way.

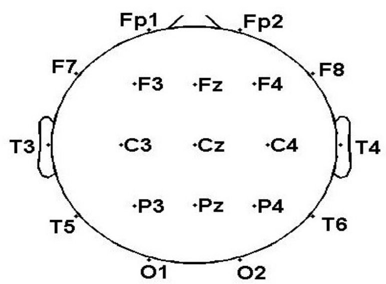

Fig. 1. Nineteen surface electrodes placement position.

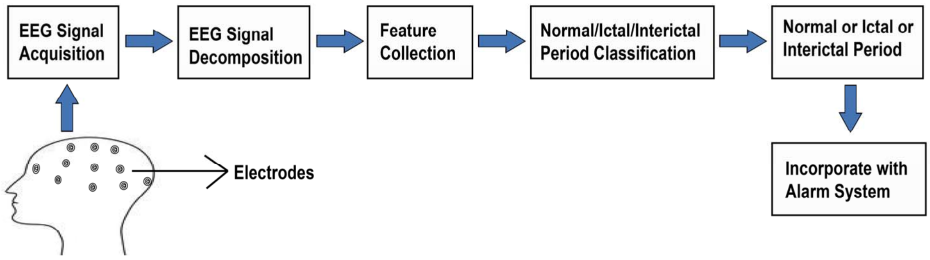

Fig. 2. Block diagram of the complete working procedure of epilepsy classification.

II. Materials and Methods

A. Data Collection and Description

In our research purpose we utilized a dataset made publicly available by Dr. Ralph Andrzejak [15]. This EEG dataset contains five subsets (A, B, C, D, E) of EEG data from both normal and epileptic subjects. Set A and B contain normal EEG data during eyes open and eyes closed respectively from 5 subjects. Data acquisition performed by using 19 surface electrodes placed according to the international 10-20 system. Set C, D and E carries data from epileptic patients. But set C and D contain interictal activity and EEG signals recorded from hippocampal formation and epileptogenic zone respectively of the brain. Only set E carries ictal activity. Set C, D and E signals recorded using implanted intracranial electrodes from five subjects. Each subset of this dataset contains 100 text file of segmented EEG signals. Each signal is 23.6 seconds long and total 4097 samples at a 173.61 Hz sampling rate. Nineteen surface electrode positions are shown in Fig. 1.

B. Experimental Flowchart

Data acquisition from the normal and epileptic is the elementary step to accomplish this study. To use an exact dataset we utilize a well-known dataset sot that we can compare the results. After dataset collection it is necessary to perform preprocessing steps for art effects removing and data segmentation. In this dataset signals are already segmented and processed. Each subset contains 100 trials for every class. We decompose all five subsets using DWT MATLAB toolbox. This toolbox after decomposition provides 10 most significant features are collected to organize the feature vectors. Consequently for each class feature vectors will be 100×10. This set of feature vectors provided to the designed NN to show the classification accuracy. It is very important to classify EEG signal during epileptic seizure, seizure free EEG signal and normal EEG signal (either eyes are open or close) to detect ictal and interictal period during seizure. So feature vectors are arranged according to interest of class. The complete working procedure is shown in block diagram in Fig. 2.

C. Feature Vectors Extraction using DWT

Each signal from all subset is decomposed using DWT. Daubechies-4 (db4) wavelet is used to decompose each signal to level 5. If the signal is X(t) then decomposition level with one approximate coefficient is A5 and 5 detail coefficients D1, D2, D3, D4, and D5 are shown in Fig. 3.

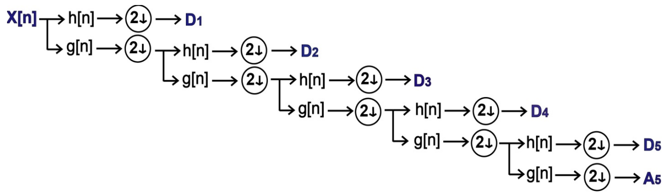

Fig. 3. Decomposition of each signal for feature extraction.

DWT MATLAB toolbox provides 12 statistical parameters of the decomposed signals. Among 12 features 10 features are arranged to make feature vectors. Those statistical parameters are mean, median, maximum, minimum, range, standard deviation, median absolute deviation, mean absolute deviation, l2 norm and max norm. The mathematical expression of the DWT of the signal say X(T) is given in (1) [7].

$$X(t)=\sum_{k}2^{j_0/2}a_{j_0}(k)\phi(2^{j_0}t-k)+\sum_{j=j_0}^{\infty}\sum_{k}2^{j/2}d_j(k)\psi(2^{j}t-k) \qquad (1)$$

Here $a_j(k)$ and $d_j(k)$ are approximation and detail coefficients of wavelet, respectively [7].

D. NN Design for Classification

Different layers of the designed NN are shown in Fig. 4. As we have 10 structure feature vectors so depending on the number of features there are 10 inputs in the input layer. Based on the number of the classifying class, number of output will be selected. Three class NN is shown in Fig. 4 with 10 hidden neurons in the hidden layer. These hidden neurons interconnected with input and output layer and mostly determine the accuracy rate of the NN.

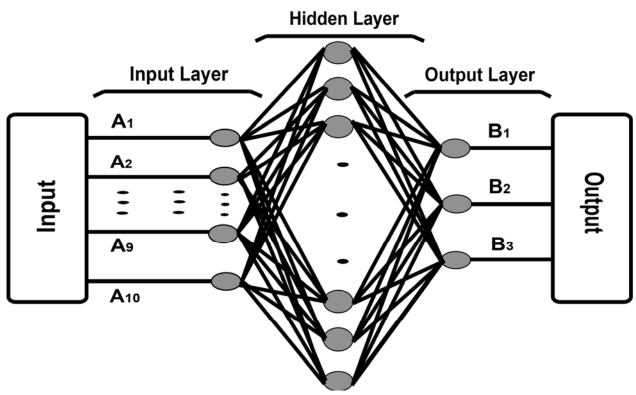

Fig. 4. Designed ANN with 10 neurons in hidden layer.

III. RESULTS

A. DWT decomposition and feature collection results

All trials from all subsets are decomposed (500 signals) and 10 features are recorded. The decomposition of an EEG signal from A, C and E subsets of normal, interictal and ictal EEG period are shown in Fig. 5, Fig. 6 and Fig. 7, respectively into different coefficients. The recorded statistical parameters are mean, median, maximum, minimum, range, standard deviation, median absolute deviation, mean absolute deviation, l2 norm and max norm. So for a 2 class feature vector structure is 200×10 and for 3 class is 300×10 according its class.

B. NN design for classification

When feature vectors are given to the NN, NN randomly divides total signals or trials as follows: 70% for training, 15% for testing and rest 15% for validation. So finally for 2 class classification, among 200 feature vectors 140, 30 and 30 feature vectors are randomly selected for training, testing and validation, respectively. For 3 class, among 300 feature vectors, 210, 45 and 45 feature vectors are randomly differentiate for classification. In Table I and Table II confusion matrix of the NN are given for 2 class and 3 class classification respectively. Table III represents the overall performance of the methodology for both classes.

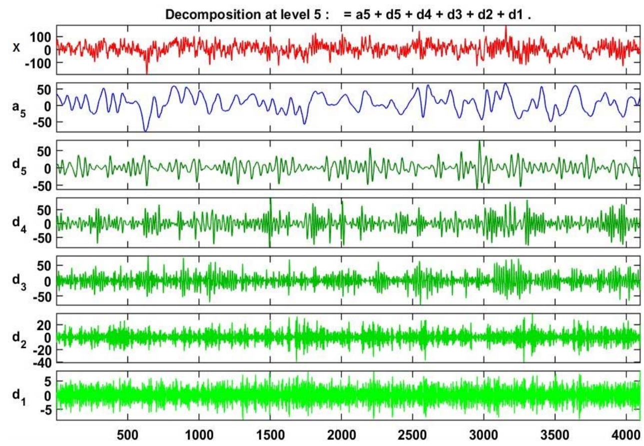

Fig. 5. EEG signals decomposition from data subset A.

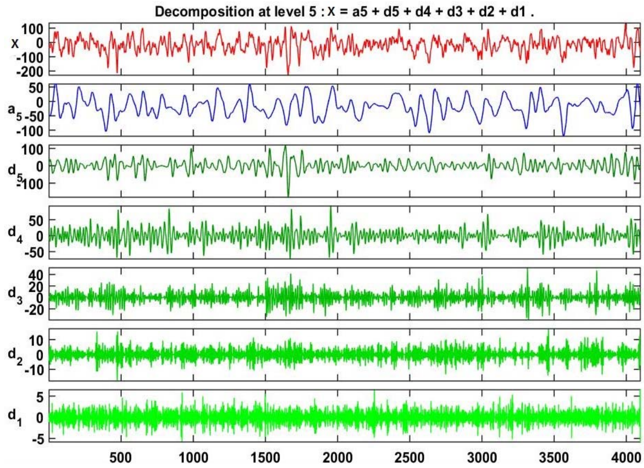

Fig. 6. EEG signals decomposition from data subset C.

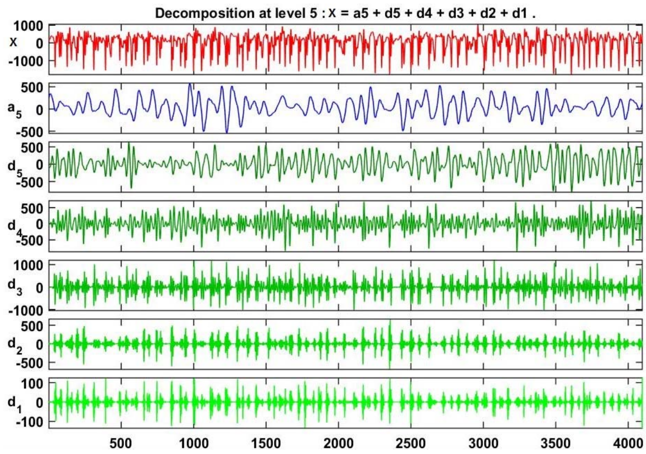

Fig. 7. EEG signals decomposition from data subset E.

From the classification results Table III shows that for 2 class classification, subset E i.e. ictal period shows best classification accuracy with normal EEG periods and interictal EEG periods (both subset C and D). For 3 class classification all subsets show less accuracy (average 79.5%) than 3 class but acceptable for epilepsy detection.

TABLE I. CONFUSION MATRIX OF 2 CLASS CLASSIFICATION OF SUBSET A, B, C, D, & E

Subset A & E		Subset B & E		Subset C & E		Subset D & E	
A	E	B	E	C	E	D	E
100 50.0%	0 0.0%	99 49.5%	0 0.0%	100 50.0%	1 0.5%	99 49.5%	1 0.5%
0 0.0%	100 50.0%	1 0.5%	100 50.0%	0 0.0%	99 49.5%	1 0.5%	99 49.5%

TABLE II. CONFUSION MATRIX OF 3 CLASS CLASSIFICATION OF SUBSET A, B, C, D, & E

Subset ACE			Subset BCE			Subset ADE			Subset BDE		
A	C	E	B	C	E	A	D	E	B	D	E
93 31.0%	50 16.7%	0 0.0%	71 23.7%	28 9.3%	5 1.7%	93 31.0%	49 16.3%	0 0.0%	81 27.0%	33 11.0%	1 0.3%
7 2.3%	47 15.7%	0 0.0%	28 9.3%	70 23.3%	0 0.0%	7 2.3%	47 15.7%	0 0.0%	17 5.7%	60 20.0%	2 0.7%
0 0.0%	3 1.0%	100 33.3%	1 0.3%	2 0.7%	95 31.7%	0 0.0%	4 1.3%	100 33.3%	2 0.7%	7 2.3%	97 32.3%

TABLE III. TWO & THREE CLASS CLASSIFICATION ACCURACY RESULTS

	2 Class Classification Accuracy				3 Class Classification Accuracy			
Data Subset	**AE**	**BE**	**CE**	**DE**	**ACE**	**BCE**	**ADE**	**BDE**
Accurately Classified	100.0%	99.5%	99.5%	99.0%	80.0%	78.7%	80.0%	79.3%
Misclassified	0.0%	0.5%	0.5%	1.0%	20.0%	21.3%	20.0%	20.7%

C. *Regression plots*

Regression plot establishes relationship between input and output of the NN. Fig. 8 and Fig. 9 illustrate the regression plot of the data subsets of the highest (AE) accuracy rate of the 2 class and lowest (BCE) accuracy rate of the 3 class classification to analyze the interconnection and distribution of the data. In Fig. 8, the solid line completely fits with the dashed line. In Fig. 9 depicts that solid line did not fully matched with dashed line. So both lines are not well fitted. The regression value R should be 1 or nearly 1 that represents good fit. In these figures R values are 1and 0.80 for best and lowest accuracy rate for AE and BCE, respectively.

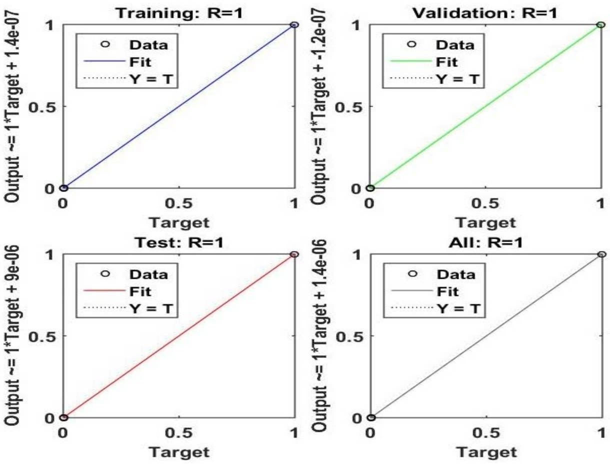

Fig. 8. Regression plot of AE subsets.

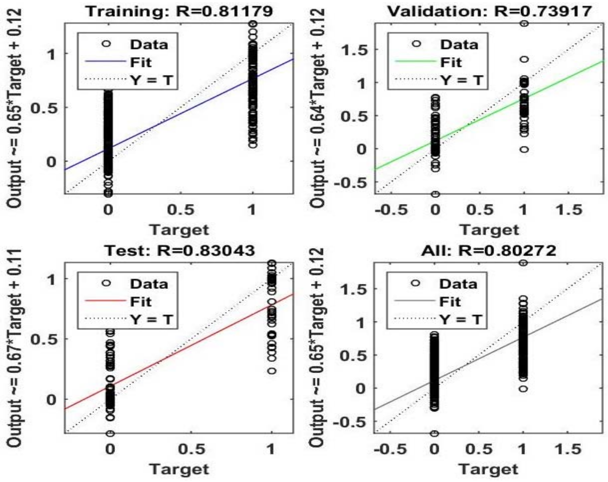

Fig. 9. Regression plot of BCE subsets.

IV. DISCUSSION

The proposed method shows 100 % (average 99.5%) classification accuracy for epileptic EEG signal (ictal period) detection corresponding to normal EEG (both eyes open and close), epileptic patient's EEG signal but seizure free (interictal periods). For 3 class classification accuracy rate is 80.0% (average 79.0%) and classifies all 5 subsets of data. This method shows constant accuracy rate for all classes.

However, In Table IV we present current research work accomplished on these same dataset for better understanding.

TABLE IV. METHODS AND PERFORMANCE OF RECENT ACCOMPLISHED RESEARCH WORK ON THE SAME DATASET

Authors	Data Subset	Methods	Performance
Z. Zainuddin [2] et. al.	-----	DWT WNN	96.56% to 98.66%
Y. Peng [3] et. al.	Seizure-free (A, C) and Seizure (E). Normal Group (A, B), Interictal Group (C, D) and Ictal Group (E).	Immune Clonal Algorithm (ICA) and SVM, KNN and LDA.	Seizure & Seizure free 97.51% Normal, Interictal & Ictal 95.04%.
S-H. Lee [4] et. al.	Normal and the Epileptic Seizure.	WT, PSR, and ED and Neural Network with Weighted Fuzzy Membership Functions (NEWFM).	98.17%.
D. Gajic [5] et. al.	Non-Epileptic & Epileptic.	DWT, Quadratic Classifier.	98.7%.
A. T. Tzallas [6] et. al.	Z,S & Z,F,S & Z,O,N,F,S.	Time–Frequency (T-F) Analysis and Artificial Neural Network (ANN).	100%, 100% & 89%.
D. Gajic [7] et. al.	Normal EEG, Interictal EEG & Ictal EEG	DWT, PCA and Quadratic Classifier.	99%.
S. A. Hosseini [8] et. al.	Normal & Inter-Ictal. Normal & Ictal, Inter-Ictal & Ictal.	Chaos-ANFIS (Adaptive Neuro-Fuzzy Inference System).	97.4%, 96.9% & 96.5%.
U. Orhan [9] et. al.	ABCD-E, A-E, AB-CDE. AB-CD-E, A-D-E.	DWT and MLPNN.	99.60%, 100%, 98.80%, 95.60% 96.67%.
M. S. Mercy [16] et. al.	Normal and Seizure Signals.	DWT & ICA, SVM & NN.	99.5%.
Proposed Method	AE, BE, CE, DE, AC and BC ACE, BCE, ADE and BDE.	DWT and ANN.	100.0% 99.5% 99.5% 99.0% & 80.0%, 78.7%, 80.0% and 79.3%.

V. CONCLUSION

Epilepsy is a severe life threatening neurological disease. Taking EEGs of the patient it can be monitored and decide whether it is a generalized or partial epilepsy. This research work using proposed method investigates the classification accuracy of every EEG subset data in a 2 class and 3 class order and shows epilepsy detection with 100% and 80% accuracy respectively which can increase the detection accuracy of epileptic seizure in comparison with normal and interictal EEG signal period, specially to detect ictal periods of an epileptic patient. This will reduce the wrong alarm and increase the long-term epilepsy monitoring ability of the hospital.

ACKNOWLEDGMENT

This work was supported by Higher Education Quality Enhancement Project (HEQEP), UGC, Bangladesh; under Subproject "Postgraduate Research in BME", CP#3472, KUET, Bangladesh.

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