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Epilepsy Seizure Detection in EEG Signals Using Wavelet Transforms and Neural Networks

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***Abstract*—An electroencephalogram (EEG) is a record of the electric signal generated by the cooperative action of brain cells, that is, the time course of extracellular field potentials generated by their synchronous action. EEG are widely used in medicine for diagnostic and analysis of several conditions. In this paper, we present a system based on neural networks and wavelet analysis, able to identify epilepsy seizures using EEG as inputs. This work is part of a research looking for novel models able to obtain classification rates better that the state-of-the-art, for the identification of normal and epileptic patients using EEG. Here we present results using a Discrete Wavelet Transform (DWT) and the Maximal Overlap Discrete Wavelet Transform (MODWT) for feature extraction and Feed-Forward Artificial Neural Networks (FF-ANN) for classification. By using the benchmark database provided by the University of Bonn, our approach obtains an average accuracy of 99.26 % tested using three-fold cross-validation, which is better than other works using similar strategies.**

***Index Terms*—Electroencephalogram (EEG), Epileptic seizure detection, DWT, MODWT, Self Recurrent Wavelet Neural Networks (SRWNN).**

I. Introduction

THE human brain is a complex system that exhibits rich spatio-temporal dynamics. Epilepsy is a common brain disorder that affects about 1% of the world population, where 25% of such patients cannot be treated properly by any available therapy [1]. Epileptic seizures are manifestations of epilepsy; these seizures are seen as a sudden abnormal function of the body, often with loss of consciousness, an increase in muscular activity or an abnormal sensation [2]. Among the noninvasive techniques for probing human brain dynamics, electroencephalography provides a direct measure of cortical activity with a millisecond temporal resolution. EEG signal can provide valuable insight and improved understanding of the mechanism causing epileptics disorders. Since in the human brain there are millions of neurons interconnected in a very complex manner, the resultant EEG signal is complex, nonlinear and nonstationary in nature. A non-stationary signal is one whose basic statistical properties, such as the mean and variance do not remain constant over time [3].

Analysis, detection and classification are required in many applications where signals are nonstationary and/or multicomponent [4]. Lately, the EEG analysis has been mostly focused on epilepsy seizure detection diagnosis [2], [5], [6], which consists of normal and seizure EEG signals using methods such as Empirical Mode Decomposition (EMD), Wavelet Transforms and Artificial Neural Networks. EMD is a spontaneous multi resolution method that represents nonlinear and non stationary data as a sum of oscillatory modes inherent in the data, called Intrinsic Mode Functions (IMFs) [7]. Wavelet transform is one subclass of time-scale transforms. It has been used for representing various aspects of nonstationary signals [8].Traditional methods rely on experts to visually inspect the entire length EEG recordings of up to one week, which is tedious and time-consuming [9]. Therefore, in recent years several models have been proposed, some of them based on wavelet analysis and artificial neural networks. The combination of both theories seeks to exploit the features of analysis and decomposition of wavelet processing along with the properties of learning, adaptation and generalization of neural networks. Despite of all works recently published, still there is a need to improve the classification accuracy obtained by the available models, as well as the generalization capabilities of such classifiers. As a result we are looking for novel models based on neural networks and wavelet analysis [10]. In this paper, we present the results obtained by a classifier based on Infinite Impulse Response (IIR) and Finite Impulse Response (FIR) filters, Wavelet Transforms (WT) and Feed-Forward Artificial Neural Networks (FF-ANN). The database provided by the University of Bonn [11], [12] was used to assess this model and to compare it with similar works. Our model, tested using three-fold cross-validation, was able to obtain an accuracy of 99.26 %, which is better than the the results obtained by similar works using the same database [9], [13], [14].

The rest of this paper is organized as follows. Section II presents an overview of recent works related to epileptic classification, using wavelet analysis and neural networks; the EEG database, pre-processing, feature extraction and classification method proposed in this work are described in Section III; Section IV provides the experimental results and Section V summarizes the conclusions drawn from previous sections.

II. Related Work

An electroencephalographer, although guided by the general definitions for epileptogenic sharp transient waveforms, uses additional subjective criteria based on contextual information and others heuristics to reach a decision [15]. Visual screening of EEG records requires highly trained professionals. An automated EEG epilepsy diagnostic system would be very useful to improve this medical diagnosis. Several approaches have been proposed for this task. We briefly describe some works that report results using the Bonn database, which is used in our research. Performance metrics such as accuracy, sensitivity and specificity are described in Section IV.

A method of analysis of EEG signals based on WT and classification of EEG signals using FF-ANN and logistic regression (LR) are presented by Subasi and Ercelebi [9]. They used lifting-based discrete wavelet transform (LBDWT) as a preprocessing method. A LR and a FF-ANN classifiers were compared using EEG data owned by the authors. This database consists in 500 segments of EEG signals. A classification accuracy of 89% of EEG signals was obtained by logistic regression and a classification accuracy of 92 % by FF-ANN trained using Levenberg-Marquardt algorithm.

Tzallas et al. [6] demonstrated the suitability of the time-frequency *(t-f)* analysis to classify EEG segments for epileptic seizures and they compared several methods for *t-f* analysis of EEGs. Short-time Fourier transform and several *t-f* distributions were used to calculate the power spectrum density (PSD) of each segment. A FF-ANN was used for the classification of the EEG segments (that is, determine the existence of an epileptic seizure). The method is evaluated using a benchmark EEG dataset of the University of Bonn [11], [12] obtaining 89% of classification accuracy.

Another proposal based on FF-ANN incorporating a sliding window technique for pattern recognition is presented by Anusha K. et al. [15] for detection of epilepsy based on EEG signals. This work used 50 segments of EEG, 25 cases of healthy patients and 25 of epileptic patients of the database of University of Bonn (it uses two data sets, Z and S) [11], [12]. The classification accuracy obtained was 93.37% for signals of normal patients and 95.5% for epileptic patients.

A wavelet-chaos-neural network model for classification of EEGs of healthy (normal), ictal (seizure-active), and interictal patients is presented by Gosh et al. [14]. Interictal refers to the period between seizures. Wavelet analysis is used to decompose the EEG into delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) sub-bands (see Section III-C for the meaning of each sub-band). Three parameters are employed to represent each segment of the EEG: standard deviation, correlation dimension, and largest Lyapunov exponent. A mixed-band feature space consisting of nine parameters and a Levenberg-Marquardt Backpropagation Neural Network (LMBPNN) obtained a classification accuracy of 96.7%, using the EEG database of the University of Bonn [11], [12]. Experiments were performed using the data sets named Z, F and S.

A classification system for epilepsy based on FF-ANN and features extraction from EEG, based on wavelet is presented by Shaik and Srinivasa [13]. They used features of Energy, Covariance Inter-quartile range (IQR) and Median Absolute Deviation (MAD) from each sub-band of EEG as input to a classifier based on FF-ANN. The authors divided all segment of EEG signal of the database into 23 sub-segments (1 second each) generating 2300 samples from each set of the database from University of Bonn [11], [12]. This work obtained 98% of classification accuracy.

TABLE I
Comparison of several published works related to detection of epilepsy.

Authors	Type classifier (hidden nodes)	Feature Extraction	Dataset	Accuracy %	Sensitivity %	Specificity %
Subasi et al. [9]	FF-ANN (21)	LBDWT Db4	Own data	92	91.6	91.4
Tzallas et al. [6]	FF-ANN (15)	T-F Analysis	Bonn (O,Z,F,N,S)	89	89.0	89.1
Anusha et al. [15]	FF-ANN (20)	T-F Analysis	Bonn (Z, S)	93.3	—	—
Shaik et al. [13]	FF-ANN (-)	DWT Db4	Bonn (O,Z,F,N,S)	**98.3**	97.6	98.5
Gosh et al. [14]	FF-ANN (15)	DWT Db4	Bonn (Z,F,S)	96.7	—	—
Juárez et al. [10]	FF-ANN (12)	MODWT Db2	Bonn (Z,S)	90.0	100	83.3

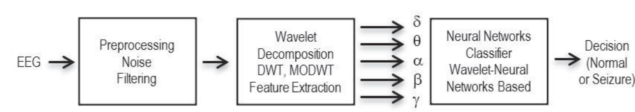

Fig. 1. General block diagram for seizure classification [10]

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In a previous work we reported the use a FF-ANN for classification of ictal/normal states [10]. An accuracy of 90% was obtained using a Maximal Overlap Discrete Wavelet Transform (MODWT) [19] based on a second order Daubechies (Db2) for characterizing the signal and a FF-ANN with 12 hidden nodes for classification. The MODWT was applied on segments of 23.6 seconds taken from the subset Z and S of the database provided by the University of Bonn [11], [12]. The EEG signals were filtered using a digital Butterworth low-pass filter of order 10 and cut off frequency of 64 Hz.

Table I summarizes these works in terms of classification accuracy, sensitivity and specificity. Notice that the highest accuracy is 98%.

III. Materials and methods

In this work, Wavelet Transforms (WT) are used to extract features of EEG signal and ANN are used to classify Epileptic seizure. The results of two experiments each using different filters, wavelets and size of samples of the database are described. Fig. 1 shows the general block diagram of the proposed approach, which is divided in three modules: preprocessing, feature extraction and classification. In what follows, we explain each module.

A. Experimental Data

The EEG database used in the experiments showed here was provided by the University of Bonn [11], [12]. This collection contains EEG data coming from three different events, namely, healthy subjects, epileptic subjects during seizure-free intervals (known as interictal states) and epileptic subjects during a seizure (ictal states) [11], [12]. The collection contains five datasets identified as: O, Z, F, N and S; each set holds 100 segments of EEG signals of 23.6 seconds. The sampling frequency of these signals was 173.6 Hz, so each segment contains 4,096 samples. Sets O and Z were obtained from healthy subjects with eyes open and closed respectively; sets F and N were obtained during interictal states in different zones of the brain and set S was gotten from an subject during ictal state [6]. In order to make a fair comparison with some of the works described in Section II, sets Z and S were used only for the results reported here.

B. Preprocessing

A filtering of the EEG signals was performed in order to remove noise added during recording. Some physiological researchers consider that EEG frequencies above 60 Hz are noise and can be neglected [17]. Considering this value, the cut-off frequency of the low-pass filters used here was set to 64 Hz. The value 64, which is an exact power of two, was used instead of 60 Hz, in order to obtain more easily the frequency sub-bands of the EEG during the wavelet analysis. Two approaches for filtering were tested: Finite Impulse Response (FIR) and Infinite Impulse response (IIR). A FIR filter is one whose impulse response (or response to any finite-length input) is of finite duration, because it settles to zero in finite time. An IIR filter may has internal feedback and responds indefinitely, usually decaying [16]. Low-pass filters were designed with 3 dB of ripple in the pass-band from 0 to 64 Hz and at least 60 dB of attenuation in the stop-band [16]. An IIR Chebyshev type II filter of order 24, an Elliptic filter of order 9, a FIR filter Equiripple of order 343 and a Least Squares filter of order 350 [16] were implemented using Matlab 2010a and the Signal Processing Toolbox Version 6.19.

Figure 2 shows a segment of 4,096 samples of a filtered EEG from a healthy subject(part a) and an ictal subject (part b) with their corresponding frequency spectrum. Notice the differences in the frequency range of each subject. Upper plots of Figure 2 correspond to EEG segments and lower plots are the corresponding frequencies. Notice that frequency components above to 64 Hz have been eliminated due to the low-pass filtering.

C. Feature extraction

In this work wavelet analysis was used to decompose the EEG signals into delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) sub-bands. Delta (δ) waves are between 0-4Hz, shown during deep sleep, infancy and serious organic brain disease [18]. Theta (θ) waves have frequencies between 4-8 Hz, shown mainly in parietal and temporal regions in children and during emotional stress in some adults [18]. Alpha (α) waves have frequencies between 8-12 Hz; they are found in EEGs of almost all normal subjects when they are awake but in quiet, resting and relaxed condition [18]. Beta (β) waves normally occur in frequencies from 12 to 30 Hz. A beta wave is normally associated with active thinking, active attention or problem solving, that is, during intense mental activity [18]. Gamma (γ) waves show frequencies above 30 Hz, related to information processing and the onset of voluntary movements

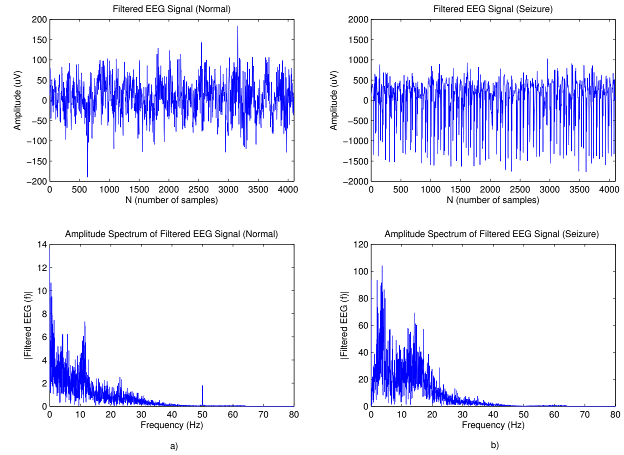

Fig. 2. Filtered signals EEG by an Least Squares FIR filter and its frequency spectrum of: a) Healthy subject, b) Ictal subject. Upper plots are samples from EEG signals and the lower plots show the frequency components of these EEG signals.

[18]. According to Ravish [18] and Sunhaya [2], the delta and alpha sub-bands provide useful information to localize a seizure. Therefore, only these sub-bands of the EEG signal were used in this work. The wavelet analysis was carried out using both a Discrete Wavelet Transform (DWT) and the Maximal Overlap Discrete Wavelet Transform (MODWT) [19]. In both cases a Haar wavelet, a second order Daubechies (Db2) wavelet and a fourth order Daubechies (Db4) wavelet were used. The selection of the wavelet must be related to the common features of the events present in real signals. That is, the wavelet should be well adapted to the events to be analyzed. Different wavelet families have a trade-off between the degree of symmetry (i.e., linear phase characteristics of wavelet) and the degree to which ideal high-pass filters are approximated (i.e., frequency response functions). The degree of symmetry in a wavelet is important in reducing the phase shift of features during the wavelet decomposition. If the phase shift is large, it can lead to distortions in the location of features in the transform coefficients [19].

Figure 3 illustrates the decomposition of a EEG time series using a four-level MODWT extracting five physiological sub-bands [10]. Figure 4 shows the delta (0-4 Hz) and alpha (8-12 Hz)sub-bands of a EEG segment of a healthy subject, obtained using MODWT (Db2). Plots on the left side of the figure correspond to sub-bands and plots on the right side correspond their frequency components. Figure 5 shows the same for a epileptic subject. Each segment of EEG was represented by a feature vector of six components, built using the mean, absolute median and variance of both delta and alpha sub-bands. These features were also used in the work reported in [13].

D. Classification

A FF-ANN with one hidden layer was used to build the classifier. The network has 6 input nodes (one for each feature) and 2 output nodes (one for each class). The experiments reported here were executed using the code provided by [20],

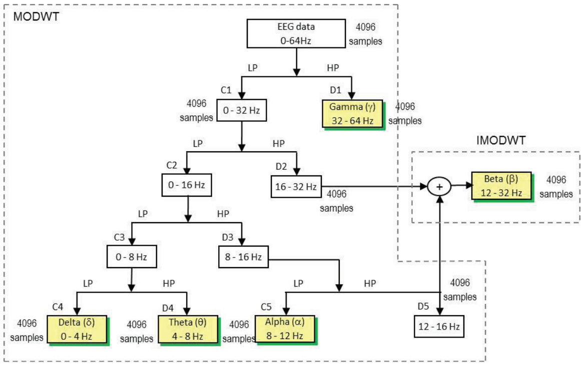

Fig. 3. Decomposition of EEG in physiological sub-bands by MODWT. The figure shows the name of sub-bands and its respective frequency ranges [10].

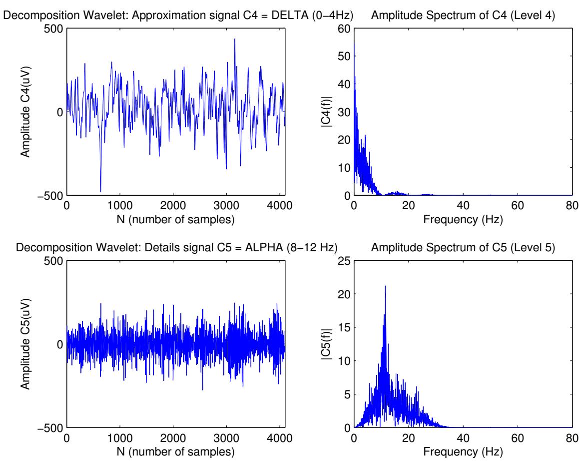

Fig. 4. Delta and Alpha sub-bands of an EEG signal obtained by MODWT (Db2) of a healthy subject (normal). The graphs on the left side show the obtained sub-bands and the graphs on the right side show its corresponding frequency spectrum.

which is implemented in Matlab 2010a using the Neural Network Toolbox Version 6.0.3 The stopping criterion for learning algorithm was set to a value of 0.01 in the Mean Square Error (MSE); the learning rate was fixed at 0.5. The number of training epochs was fixed at 1,000 and the activation function for all nodes was a sigmoid. These values were experimentally chosen and similar to the ones reported by [20]. In order to find the best number of hidden nodes for the network, several tests were done using 6, 9, 12, 15, 16, 18, 21 and 24 nodes in the hidden layer of the FF-ANN. The network was trained using 200 segments of EEG signals of the database of University of Bonn [11], [12].

IV. Results

Two experiments were carried out. In the first experiment, feature vectors to train the network were obtained using the whole segments coming from sets Z and S in the database (see Section II-A). Note that in order to use a training set with a total number of elements divisible by three, the last two segments were eliminated. A total of 198 samples were generated; 132 samples were used for training and 66 patterns were used for testing the FF-ANN. For the second experiment,

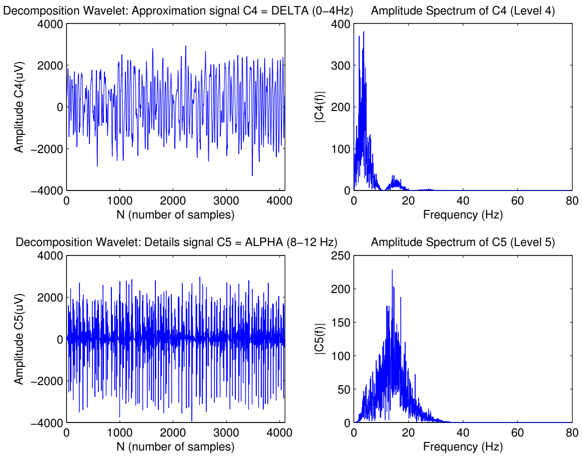

Fig. 5. Delta and Alpha sub-bands of an EEG signal by MODWT (Db2) of an ictal subject (seizure). The graphs on the left side show the obtained sub-bands and the graphs on the right side show its corresponding frequency spectrum.

features are obtained using portions of EEGs available in the database. We divided each EEG segment into 23 sub-segments (1 second) for decomposition by DWT, whereas that for decomposition by MODWT each segment was divided into 32 sub-segments (0.7375 seconds). This is done in order to provide the classifiers with more data to be learned. A total of 4,599 patterns (3,066 for training and 1,533 for testing) are used for the classification when DWT is used, and 6,399 patterns (4,266 for training and 2,133 for testing) when MODWT is applied.

Each experiment was tested using 3-fold cross validation. Besides, in order to avoid bias generated by the randomness of initial weights in the networks, each case was executed five times, and an average of the performance is reported. The results are evaluated in terms of classification accuracy, sensitivity and specificity. Sensitivity (also called *the recall rate*) measures the proportion of actual positive results which are correctly identified as such. Specificity measures the proportion of negative results which are correctly identified as such [21]. Sensitivity and specificity are calculated as follows:

$$sensitivity = \frac{TP}{TP + FN} \times 100\% \quad (1)$$

$$specificity = \frac{TN}{TN + FP} \times 100\% \quad (2)$$

where TP (True positive) = correctly identified; FP (False positive) = incorrectly identified; TN (True negative) = correctly rejected and FN (False negative) = incorrectly rejected [21].

A. Experiment I

As explained previously, during this experiment FF-ANN classifiers were trained using patterns coming from whole segments of EEG. The EEG were filtered using [16]: low-pass IIR Chebyshev type II and Elliptic; low-pass FIR Equiripple and Least Squares. Table II shows the results obtained in each case using the FF-ANN classifier with different number

TABLE II
EXPERIMENT I: RESULTS OF THE FF-ANN CLASSIFIER USING WHOLE SEGMENTS

Filter	Wavelet	Hidden nodes	Accuracy %	Standard deviation	Sensitivity %	Specificity %
Chebyshev II	DWT - Haar	9	82.82	21.10	82.79	74.64
Chebyshev II	DWT - Db2	15	83.73	21.52	82.56	82.04
Chebyshev II	DWT - Db4	6	91.11	14.59	91.72	88.37
Chebyshev II	MODWT - Haar	9	53.83	15.58	37.92	48.44
Chebyshev II	MODWT - Db2	6	85.85	22.14	82.76	88.67
Chebyshev II	MODWT - Db4	18	84.44	21.33	86.44	85.74
Elliptic	DWT - Haar	21	88.38	16.76	86.46	91.58
Elliptic	DWT - Db2	6	80.30	21.73	79.87	76.85
Elliptic	DWT - Db4	9	82.82	20.20	80.19	87.61
Elliptic	MODWT - Haar	21	59.09	21.31	30.05	56.12
Elliptic	MODWT - Db2	6	90.00	12.91	88.17	96.32
Elliptic	MODWT - Db4	24	87.17	14.85	87.22	85.61
Equiripple	DWT - Haar	18	87.17	19.09	85.47	90.96
Equiripple	DWT - Db2	12	83.03	20.57	81.48	85.36
Equiripple	DWT - Db4	18	86.56	17.05	85.90	91.14
Equiripple	MODWT - Haar	6	87.07	17.66	84.83	92.02
Equiripple	MODWT - Db2	6	88.88	18.52	89.17	82.80
Equiripple	MODWT - Db4	6	85.52	19.04	83.71	84.74
Least Squares	DWT - Haar	6	84.44	21.32	80.00	82.82
Least Squares	**DWT - Db2**	**6**	**93.23**	**14.85**	**93.87**	**90.07**
Least Squares	DWT - Db4	18	82.72	20.13	91.24	81.42
Least Squares	MODWT - Haar	9	83.73	18.32	82.71	90.97
Least Squares	MODWT - Db2	21	84.14	15.96	82.76	87.16
Least Squares	MODWT - Db4	21	87.37	15.82	85.88	90.89

TABLE III
EXPERIMENT II: RESULTS OF THE FF-ANN CLASSIFIER USING SUB-SEGMENTS

Filter	Wavelet	Hidden nodes	Accuracy %	Standard deviation	Sensitivity %	Specificity %
Chebyshev II	**DWT - Haar**	**18**	**99.26**	**0.26**	**98.93**	**99.59**
Chebyshev II	DWT - Db2	18	99.03	0.27	98.75	99.32
Chebyshev II	DWT - Db4	15	96.57	5.87	95.38	98.91
Chebyshev II	MODWT - Haar	24	99.24	0.32	98.86	99.64
Chebyshev II	MODWT - Db2	24	95.80	12.84	94.77	96.19
Chebyshev II	MODWT - Db4	24	97.72	4.55	96.76	99.13
Elliptic	DWT - Haar	21	95.49	11.10	97.48	95.30
Elliptic	DWT - Db2	21	95.96	12.33	96.65	96.23
Elliptic	DWT - Db4	9	98.44	1.26	97.91	99.06
Elliptic	MODWT - Haar	18	95.98	12.52	95.49	99.74
Elliptic	MODWT - Db2	6	99.12	0.40	98.73	99.51
Elliptic	MODWT - Db4	24	95.34	12.62	91.27	96.14

of hidden nodes. The best result obtained in this experiment was 93.23 % of accuracy using features calculated by a Least Squares FIR filter and by DWT (Db2) with 6 hidden nodes in the FF-ANN.

B. Experiment II

For this experiment low-pass filters Digital Chebyshev type II and digital Elliptic were used [16]. Table III shows the best results obtained in each case using the FF-ANN classifier for different filters and number of hidden nodes. The best result obtained in this experiment was 99.26 % of accuracy using features calculated by a Chebyshev II filter and by DWT (Haar) with 18 nodes in the hidden layer of the FF-ANN. The fact that Haar wavelet has compact support and only one vanishing moment compared with others wavelets that have more vanishing moments may be a reason for obtaining the best result using this type of wavelet. That is, the resulting wavelet basis functions are unsuitable as basis functions for classes of smoother functions and the EEG signals are not smooth signals. Notice that the second and third best results were 99.24 % and 99.12 % of accuracy, respectively. These results were obtained with features calculated by MODWT. The values about standard deviation, sensitivity and specificity are similar to the best result of this experiment.

V. CONCLUSION

In this work, we present the results of a model based on wavelet analysis and neural networks for identification of seizures events of epilepsy. Inspired from previous results reported in [10], and [13], and in order to find a suitable combination to improve the results reported for this problem we tested several filters, wavelets and wavelet transformations. In addition, we tested the use of segments and sub-segments for training the classifier. Two types of wavelets transforms (DWT and MODWT) with Haar, Db2 and Db4 were used for decomposition of EEG segment and sub-segments. Six features were used to train a FF-ANN: mean, absolute median and variance of Delta and alpha sub-bands. When using whole segments for training, 93.23 % of accuracy was achieved. Whereas when using sub-segments for training, 99.26 % of accuracy was achieved. The result of this experiment improved the 98% obtained in [13]. As future work we will analyze the use of a classifier based on a Self Recurrent Wavelet Neural Network (SRWNN) [21],[22] for classification and EMD for feature extraction. Furthermore, other training algorithms and features will be explored.

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