Biomedical Signal Processing Using Wavelet-Based Neural Networks

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Abstract. Electroencephalography measures the electrical activity of the brain and represents a summation of post-synaptic potentials from a number of neurons. Electroencephalograms (EEG) are widely used in medicine for diagnostic and analysis of several conditions. In this work, we propose the construction of a system based on recurrent neural networks and wavelet analysis, able to analyze, detect and classify abnormalities in the brain such as Epileptic seizure using EEG as inputs. This work aims to develop novel algorithms to enhance the classification of the EEG signals and to improve the medical diagnosis. Self Recurrent Wavelet Neural Network (SRWNN) may be considered to classify the EEG signal and to improve the percentages of recognition in the classification between normal EEG and seizure EEG.

Key words: Electroencephalogram (EEG), Epileptic seizure detection, DWT, MODWT, Self Recurrent Wavelet Neural Networks (SRWNN).

1 Introduction

The transient and unexpected electrical disturbances of the brain result in a acute disease called Epileptic seizures. 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 [1]. Epilepsy is a neurological disorder affecting around 1% of the world population, where 25% of such patients cannot be treated properly by any available therapy [2]. The Electroencephalogram (EEG) signal has been a valuable clinical tool to assess human brain activities. In the last couple of years, the EEG analysis has been mostly focused on epilepsy seizure detection diagnosis [1], [3], [4]. The seizure detection problem is basically a classification between normal and seizure EEG signals. In recent years several models of artificial neural networks have been proposed, among these the Wavelet Neural Networks (WNN) that implement the wavelet processing as part of its operation through of the change of traditional transfer

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functions as the sigmoid by wavelet functions. 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. In this work, we propose the design of a classifier, based on the use of Wavelet Transforms (WT) and WNN to detect and classify abnormalities in the human brain such as epilepsy. SRWNN may be also considered to detect these abnormalities [5].

1.1 Motivation

The human brain is obviously a complex system and exhibits rich spatio-temporal dynamics. Among the noninvasive techniques for probing human brain dynamics, electroencephalography provides a direct measure of cortical activity with millisecond temporal resolution. EEG signals involve a great deal of information about the function of the brain. Traditional methods rely on experts to visually inspect the entire length EEG recordings of up to one week, which is tedious and time-consuming [6]. The identification of right information extracted from an EEG of epilepsy patients that should be for the classification of seizures has recently attracted much attention. A classifier based on Recurrent Neural Networks can be an option to improve the classification of EEG signals due to its speed of convergence and less computational calculus.

2 Previous Work

In the last years, the EEG analysis was mostly focused on epilepsy seizure detection diagnosis. Most of the reported models are based on integration of computing technologies and problem solving paradigms, for example, neural networks [7], wavelets [8], logistical regression [6], histogram analysis [8], and chaos theory [9]. There are several approaches that have been proposed for the classification or detection of disorders of brain based on EEG signals. Next, we briefly describe some recent or relevant work where neural networks (NN) and wavelet analysis are the involved paradigms.

Tzallas et al. [4] demonstrate the suitability of the time- frequency *(t-f)* analysis to classify EEG segments for epileptic seizures and they compare several methods for *t-f* analysis of EEGs. Short-time Fourier transform and several *t-f* distributions are used to calculate the power spectrum density (PSD) of each segment. This analysis is performed in three stages: 1) *t-f* analysis and calculation of the PSD of each EEG segment; 2) feature extraction, measuring the signal segment fractional energy on specific *t-f* windows; and 3) classification of the EEG segment (existence of epileptic seizure or not), using Feed Forward Artificial Neural Network (FF-ANN). The method is evaluated using a benchmark EEG dataset of the University of Bonn [10] obtaining 89% of classification accuracy.

Gosh et al. [9] present a novel wavelet-chaos-neural network methodology for classification of EEGs of healthy (normal), ictal (seizure), and interictal patients. Wavelet analysis is used to decompose the EEG into delta (δ), theta

(θ), alpha (α), beta (β), and gamma (γ) sub-bands. This sub-bands are components of an EEG signal. Three parameters are employed for each segment of the EEG representation: standard deviation, correlation dimension, and largest Lyapunov exponent. The classification accuracies of the following techniques are compared: 1) unsupervised k-means clustering; 2) linear and quadratic discriminant analysis; 3) radial basis function neural network; 4) Levenberg-Marquardt backpropagation neural network (LMBPNN). A particular mixed-band feature space consisting of nine parameters and LMBPNN result in the highest classification accuracy of 96.7%. The EEG data used in this work are from of University of Bonn [10].

Anusha K. et al. [7] propose a NN based automated epileptic EEG detection system that uses FF-ANN incorporating a sliding window technique for pattern recognition. This work uses the database of University of Bonn, Germany [10]. The algorithm was trained with 50 segments of EEG, 25 cases of healthy patients and 25 of epileptic patients. The classification accuracy was 93.37% for distinguishing signals of normal patients and 95.5% for epileptic patients.

Shaik and Srinivasa [11] propose a classification system for epilepsy based on FF-ANN. A wavelet-based feature extraction technique is used to extract of features Energy, Covariance Inter-quartile range (IQR) and Median Absolute Deviation (MAD). Using the database of University of Bonn, Germany [10], a classification accuracy of 98% is reported.

Subasi et al. [6] present a method of analysis of EEG signals using WT and compare the classification obtained using Multilayer Perceptron Neural Network (MLPNN) and logistic regression (LR). They used lifting-based discrete wavelet transform (LBDWT) as a preprocessing method. A LR and a MLPNN classifiers were compared using EEG data owned by the authors. The result obtained of the classification accuracy of EEG signals by logistic regression was 89% and by MLPNN with Levenberg-Marquardt was of 92%.

3 Research Objective

This research project is focused on a study of a connectionist models to analyze, detect and classify abnormalities in the brain such an Epileptic seizure using EEG. Processing techniques such as Wavelet Transforms (WT) are used to analyze and detect Epileptic seizure. This work aims to develop a new algorithm based on recurrent wavelet networks to enhance the classification of the EEG signals and then improve the medical diagnosis. Our hypothesis is that a Self Recurrent Wavelet Neural Network (SRWNN)[12] may be considered to classify an EEG signal improving the classification accuracy compared with state of the art algorithms in the classification between normal and seizure EEG.

4 Research Methodology

We are taking the following steps to reach our research goal:

1. *Review the state of the art regarding classification of EEG.* This part consists of analyzing and understanding the work that have been proposed in the state of the art about classification of EEG. Also it is important to understand the characteristics and behavior of the EEG to select the databases of EEG that will be used to validate our proposal.
2. *Determine preprocessing strategies of EEG.* It is necessary to know the different methods to remove noise or artifacts from EEG signal and later to propose a suitable method to preprocess the EEG signals.
3. *Study the different techniques for processing of EEG.* This step consists on analyzing different techniques for processing and feature extraction of EEG and therefore propose the technique that will be used in this work.
4. *Modify the algorithm based on SRWNN to classify EEG signals.* Study the SRWNN and modify this algorithm to improve the classification accuracy of epilepsy on EEG signals. Notice that this step is part of our future work, therefore it is not reported here.
5. *Test the performance of the proposed algorithm.* Design representative experiments to test the performance of the new algorithm based on SRWNN in order to compare the results obtained with previous reported works and determine its advantages and disadvantages.

Fig. 1 shows the general block diagram of the proposed approach.

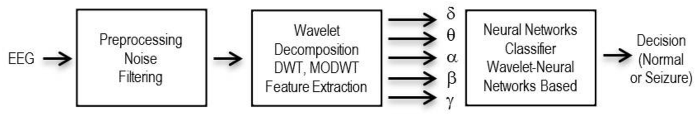

Fig. 1. General block diagram of research project

4.1 Originality and Main Contribution

In this research, the main contribution is a novel algorithm to enhance the classification accuracy of epilepsy on EEG signals by the implementation of a system using Wavelet-Based Neural Networks. The main characteristic of Wavelet-Based Neural Networks is that the activation function is changed by derivative functions of mother wavelet. Therefore, it is important to propose a suitable mother wavelet to enhance the classification of EEG signals. The selection of the wavelet must be related to the common features of the events found in real signals. In other words, the wavelet should be well adapted to the events to be analyzed [14]. This work also will consist on investigating others learning algorithms for SRWNN such as Metropoli Monte Carlo, genetic algorithms or optimization algorithms to obtain better results than previous works. Another contribution of this research consists in a suitable selection of the features extraction of each subbands of EEG signals providing the best information to enhance the classification between normal and seizure EEG. EEG signals, like most biological signals, are inherently difficult to quantify and they may be characterized as non stationary signals. Therefore, it is necessary to select the appropriate characteristics that represent these non-stationary signals.

5 Preliminary Results

At this point, we have analyzed the state of the art regarding classification of EEG and we have studied the different techniques for preprocessing and feature extraction of EEG (steps 1, 2 and 3 of the research methodology). We are cu-rrently working on an analysis of classical processing of an EEG signal. Next we present the results obtained from a simple experiment related to the use of NN for classification of seizures. The objective of this experiment was to understand the whole process of EEG classification using a FF-ANN as classifier, instead of SRWNN, that it will be designed and analyzed later. This experiment is divided into three modules: preprocessing, feature extraction and classifier.

Experimental Data EEG. A database provided by the University of Bonn [10] is used in this experiment. These EEG data contain three different cases: 1)healthy, 2)epileptic subjects during seizure-free interval (interictal), 3)epileptic subjects during seizure interval (ictal) [10]. This database contains five datasets named: O, Z, F, N, and S. Sets O and Z are obtained from healthy subjects with eyes open and closed respectively. Sets F and N are obtained from interictal subjects in different zones of the brain; set S is gotten from an ictal subject [4]. Only the sets Z and S were used for the analysis reported here. This experiment was executed using Matlab 2010a and the Neural Network Toolbox Version 6.0.3.

Preprocessing. The aim of this block is to remove noise from EEG signal added to EEG signal during its recording. Since the sampling frequency of EEG records is 173.61 Hz, according to Nyquist sampling theorem [13], the maximum frequency of EEG should be in the range 0-86.81 Hz. Based on physiological research, frequencies above 60 Hz in EEG signal are considered as noise and can be neglected [8]. A Digital Butterworth low-pass filter of order 10 and cut off frequency of 64 Hz was used to eliminate these undesired frequencies. This filter was designed to meet with the following characteristics: 3 dB of ripple in the pass-band from 0 to 64 Hz, and at least 40 dB of attenuation in the stop-band [13].

Feature extraction. Two types of Wavelet Transforms were used for de-composition of the EEG signal: the DWT and the Maximal Overlap Discrete Wavelet Transform (MODWT)[14] using a second order Daubechies (Db2) and a fourth order Daubechies (Db4). Other wavelets may also be considered. WT is capable of "zooming-in" on short-lived high frequency phenomena and "zooming-out" on long-lived low frequency phenomena [14]. DWT is a WT for which the wavelets are discretely sampled. The DWT has some limitations it requires the sample size N to be an integer multiple of 2^J and the number N_j of scaling and wavelet coefficients at each level of resolution j decreases by a factor of two, due to the decimation process that needs to be applied at the output of the corresponding filters. This limitations may introduce ambiguities in the time domain. The down-sampling process can be avoided by using the MODWT. The MODWT may be computed for an arbitrary length time series. Note, however, that the MODWT requires $O(Nlog_2N)$ multiplications, whereas the DWT can be computed in *O(N)* multiplications. There is, thus, an increase in computational complexity when using the MODWT. However, its computational burden is the same as the widely used fast Fourier transform algorithm and hence quite acceptable [14]. A key advantage of MODWT over Fourier transforms is its temporal resolution: it captures both frequency and location information (location in time). Fig. 2 illustrates the decomposition of EEG sequence with four level MODWT extracting five physiological sub-bands (shown in yellow boxes).

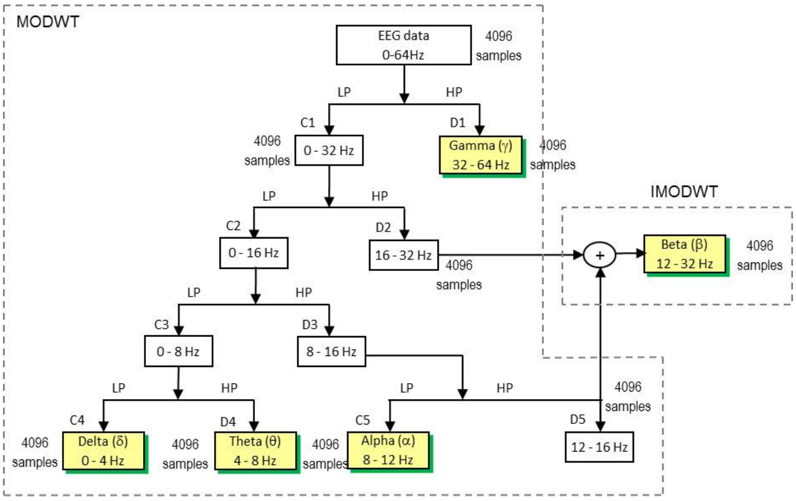

Fig. 2. Decomposition of EEG in physiological sub-bands by MODWT (yellow boxes). It shows the name of sub-bands and its respective frequency ranges.

Classification. According to Ravish [15], and Sunhaya [1] the delta and alpha sub-bands provided useful information to localize the seizure. Therefore in this experiment only these sub-bands of the EEG signal were used. Three statistical features (mean, absolute median and variance) of these sub-bands have been computed and input to a classifier based on a FF-ANN with 6 inputs, one hidden layer and one output. The classifier reported in [17] was used in this experiment. For training, 15 EEG segments from each set Z and S are used. For testing, 5 EEG segments from the same sets are used. Experiments were executed using 6 and 12 hidden nodes. The stopping criterion was specified to 0.01 Mean Square Error (MSE) and the learning rate was fixed at 0.5. The number of training epochs was fixed at 1000 and the activation function was a sigmoid. These values were experimentally chosen [17]. Fig. 3 a) and b) show a filtered EEG signal from a typical healthy and epileptic subject with its spectrum of frequency (where it can be noticed the differences among the range of frequency of each EEG signal), respectively. Upper plots of Fig. 3 a) and b) represent the 4096 samples from an EEG segment of a healthy and epileptic subject (ictal), respectively. Notice that in both plots frequency components above to 64 Hz have been eliminated due to the Butterworth low-pass filtering. Fig. 4 and Fig. 5 show the decomposition by MODWT (Db2) of a segment of an EEG signal and its frequency spectrum of each sub-band from a typical healthy and epileptic subject, respectively. The graphs on the left side of Fig. 4 and Fig. 5 correspond to the Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-32 Hz) and Gamma (32-64 Hz) frequency sub-bands obtained by the MODWT (Db2) decomposition of a healthy and epileptic subject, respectively. The graphs on right side of Fig. 4 and Fig. 5 show the frequency components of each sub-band of a healthy and epileptic subject, respectively. A similar process is done using MODWT (Db4) and DWT (Db2 and Db4).

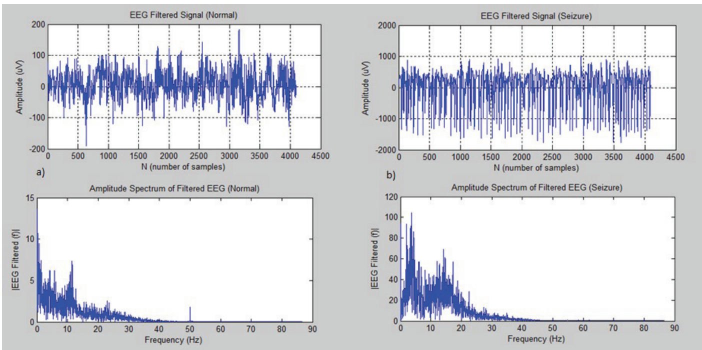

Fig. 3. Filtered signals EEG and its frequency spectrum of: a) Healthy subject, b) Ictal subject. Upper plots are samples from EEG signals and the lower plots show the frequency components of these EEG signals.

The results showed here are evaluated in terms of classification accuracy, sensitivity and specificity. Sensitivity (also called *the recall rate* in some fields) measures the proportion of actual positives which are correctly identified as such. Specificity measures the proportion of negatives which are correctly identified as such [12]. Sensitivity and specificity are calculated as:

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

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

where, TP (True positive) = correctly identified; FP (False positive) = incorrectly identified; TN (True negative) = correctly rejected and FN (False negative) = incorrectly rejected [12]. The results are compared with three published

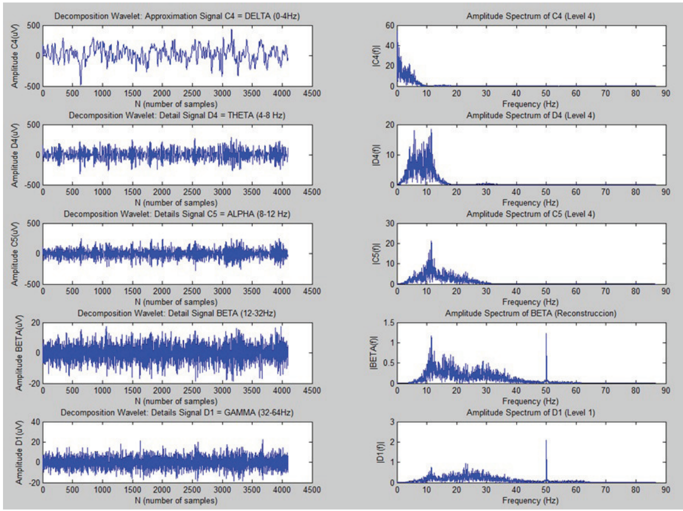

Fig. 4. Decomposition EEG signals by MODWT (Db2) of a healthy subject (normal). The graphs on the left side show the sub-bands obtained and the graphs on the right side show its corresponding frequency spectrum.

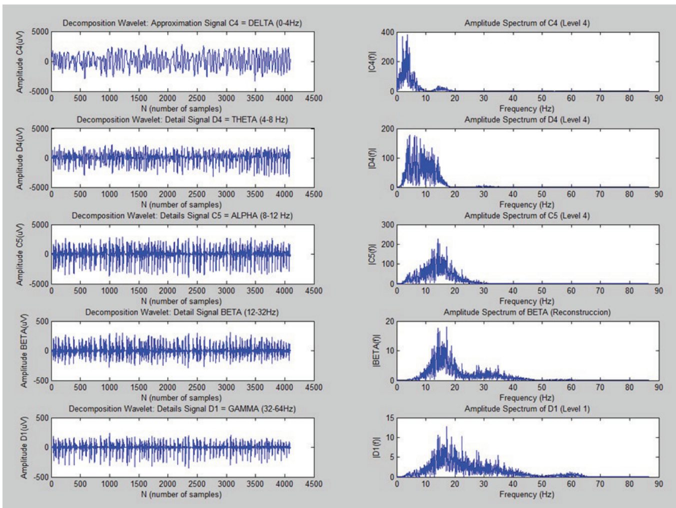

Fig. 5. Decomposition EEG signals by MODWT (Db2) of an ictal subject (seizure). The graphs on the left side show the sub-bands obtained and the graphs on the right side show its corresponding frequency spectrum.

works using the same databases, these are shown in Table 1. The best result obtained in this work was 90% of accuracy, using features calculated by MODWT (Db2) with 12 nodes in the hidden layer of the FF-ANN. The result reported in [11] was 98% of accuracy, which could be due to the fact that Shaik and collaborators used other characteristics better suited for the problem, or that they used more samples for training. They divided each segment of the database into 23 sub-segments (1 second). In this work we used the whole segment to calculate the characteristics.

Table 1. Result of the classifier of EEG signals

Authors	Parameters	Accuracy	Sensitivity	Specificity
Shaik et al. [11]	DWT Db4	**98.3**%	97.6%	98.5%
Gosh et al. [9]	DWT Db4	96.7%	—	—
Subasi et al. [6]	LBDWT Db4	92%	91.6%	91.4%
Proposed approach (6 hidden nodes)	DWT Db2	70%	100%	62.5%
	MODWT Db2	70%	75%	66.6%
	DWT Db4	70%	100%	62.5%
	MODWT Db4	80%	100%	71.4%
Proposed approach (12 hidden nodes)	DWT Db2	80%	100%	71.4%
	MODWT Db2	**90%**	**100%**	**83.3%**
	DWT Db4	80%	100%	71.4%
	MODWT Db4	90%	96.6%	83.3%

6 Conclusions

Diagnosing epilepsy is a difficult task requiring observation of the patient, an EEG, and gathering of additional clinical information. An artificial neural network that classifies subjects suffering an epileptic seizure provides a valuable diagnostic decision support tool for neurologists treating potential epilepsy. In this work, we propose the design of a new classifier based on wavelets and neural networks for identification of seizures events of epilepsy. It is expected that SRWNN classifier may obtain better results than previous reported works. The proposed classifier will use wavelet analysis as a tool for feature extraction. Here we presented the results by using two types of wavelets transforms to obtain features of EEG, and classified them using a FF-ANN. The features are extracted using the DWT and the MODWT in a whole segment of an EEG. Three features were extracted from delta and alpha sub-bands: mean, absolute median and variance. These six features are used to train a FF-ANN, which was able to discriminate among healthy and seizures EEG's in 90% of the samples in the testing set. Currently we are studying the specific characteristics of the SRWNN in order to adjust its design to this problem. We expect that SRWNN will obtain better results than FF-ANN. Future work also will be focused on investigating other possible training algorithms and a better feature selection.

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