Chapter 1

Introduction

One of the most important organs of the human body is the brain, this consists of some billions nerve cells that not only put together thoughts and highly coordinated physical actions but regulate our unconscious body processes, such as digestion and breathing. The nerve cells of the brain are known as neurons, which make up the so-called "gray matter" of the organ. The neurons transmit and gather electrochemical signals that are communicated via a network of millions of nerve fibers called dendrites and axons. This interaction of physiological and chemical processes gives rise to observed neuro-electrical activity in the brain controlling the processes of our body. Electroencephalography is a medical imaging technique that reads scalp electric activity generated by the brain. An electroencephalogram (EEG) is defined as electrical activity of an alternating type, which is recorded from the scalp surface after being picked up by metal electrodes and conductive media. An EEG has been used frequently in the clinical area for the evaluation and treatment of brain diseases, such as epilepsy [SHA11], [YUE11].

Epilepsy is a common chronic neurological disorder affecting around 0.1% of the world's population [SHA11], [YUE11]. In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior, or sometimes convulsions, muscle spasms and loss of consciousness. There are many possible causes of epilepsy. Anything that disturbs the normal pattern of neuron activity ranging from illness to brain damage to abnormal brain development can lead to seizures [SHA11]. The traditional method of EEG analysis is by visual inspection of the signals plotted on paper, and this inspection of the signals requires highly trained professionals. These professionals, although guided by the general definitions for epileptogenic sharp transient waveforms, use additional subjective criteria based on contextual information and other heuristics to reach a decision [ANU12]. In addition, some cases may require experts to visually inspect the entire length EEG recordings of up to one week, which is tedious and time-consuming [SUB05].

Modern computer analysis can extend electroencephalograph's capabilities by supplying information not directly available from the raw data. However, visual analysis is still a widespread technique, especially for detection of transient features of signal. In most cases, the agreement of an automatic method with visual analysis is a basic criterion for its acceptance. In recent years, several models have been proposed to classify EEG signals, some of them based on wavelet analysis and artificial neural networks. The combination of wavelet analysis and artificial neural networks 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 [YUE11], still there is a need to improve the classification accuracy obtained by the available models.

In this thesis, we look for wavelet-based neural networks architectures able to efficiently handle the classification of EEG signals with respect to epilepsy-related stages. A model called Multidimensional Radial Wavelons Feed-Forward Wavelet Neural Network (MRW-FFWNN) is proposed for classification of three classes of EEG related to epilepsy conditions: Ictal, Interictal and Healthy. The Discrete Wavelet Transform (DWT) and the Maximal Overlap Discrete Wavelet Transform (MODWT) are used to decompose the EEG signals into delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) sub-bands. Each EEG signal is represented by a feature vector of six components, built using the mean, absolute median and variance of delta (δ) and alpha (α) sub-bands. In this regard, some researches have reported that these sub-bands are suitable for the identification of epileptic episodes [RAV12], [SUN12]. We have used binary-tree and one-vs-one (OVO) decomposition strategies [GAL11] with two aggregation methods (Voting strategy and Weighted voting strategy) [GAL11] obtain the predicted class of EEG signals. Cross correlation coefficients were used to evaluate the degree of similarity between mother wavelets and EEG signals, and then the most appropriate mother wavelet was chosen. A database provided by the University of Bonn [BON16], [AND01] (see also Table 3.1) is used to assess our proposed model and to compare it with similar works proposed by Subasi & Ercelebi [SUB05], Shaik & Srinivasa [SHA12] and Ghosh et al. [GHO07]. We used a 3-fold validation to evaluate the performance of our proposed model. The best result of classification of three classes of EEG signals was of 96.67 % of accuracy using a binary-tree strategy based on our proposed model (MRW-FFWNN).

1.1 Previous works

During the past decade, the EEG analysis has been mostly focused on epilepsy seizure detection [YUE11], [SUN12], [TZA09]; EEG signals have been analyzed in time or frequency domains. The applied methods involve spectral analysis by Fourier Transform (FT)[SUB05], autoregressive (AR) parametric models [SUB05], Kalman Filters and time-scale methods (Wigner distributions [BLI06], wavelet analysis [GHO07], [MIR11], matching pursuit [BLI06], Empirical Mode Decomposition [MAR12] (EMD), Artificial Neural Networks [ANU12], [SHA12]). The most common methods used for processing EEG signals in the last years are Wavelet transforms and Artificial Neural Networks [LOT15], [SRI14], [SHA12], [SHA11].

As we stated before, an automatic EEG epilepsy diagnosis system would be very useful to improve medical diagnosis. Several techniques taken from the theory of signal analysis have been used to epilepsy seizure detection. In this research,

Table 1.1: Relevant works related to detection of epilepsy evaluated with the Bonn's database [GOM14].

Authors	Type classifier (hidden nodes)	Feature Extraction	Bonn's dataset	Accuracy %	Sensitivity %	Specificity %
Wang Y. et al. [WAN13]	SVM	Fractal features	Z, F, S	97.13	—	—
Sheng-Fu et al. [SHE10]	PCA and GAs	Power spectral	Z, F, S	98.67	—	—
Tzallas et al. [TZA09]	FF-ANN (15)	T-F Analysis	O, Z, F, N, S	89.00	89.0	89.1
Ghosh et al. [GHO07]	FF-ANN (15)	DWT Db4	Z, F, S	96.7	—	—
Martis et al. [MAR12]	C4.5 Decision tree	–	Z, F, S	95.3	98.0	97.0
Duque et al. [DUQ14]	K-NN	short-time rhythms	Z, F, S	98.12	—	—

we briefly describe some works that report results using a EEG database built by the University of Bonn, which has been acting as a benchmark for comparing these kind of classification techniques [BON16]. This database contains extra-cranial and intra-cranial recordings of several patients. A detail description of this structure can be found in [AND01]. Table 1.1 summarizes these works. In such table, column headed as "Bonn data set" refers to the type of data being used, where "Z" refers to extra-cranial EEG recording of healthy subjects with open eyes; "O" refers to extra-cranial EEG recording of healthy subjects with closed eyes; "N" refers to intra-cranial EEG recording into the hippocampal formation zone of interictal stages; "F" refers to intra-cranial EEG recording into the epileptogenic zone of interictal stages, and "S" refers to intra-cranial EEG recording of seizure stages. With respect to the way of evaluating the performance of epilepsy identifiers, it is a common practice to use 3 metrics: accuracy, sensitivity and specificity. Accuracy gives the proportion of correctly identified samples (both true positives or correctly identified and true negatives or correctly rejected) [ALA14]. Sensitivity, also known as the recall rate, measures the proportion of actual positive results which are identified as such. Specificity measures the proportion of negative results which are correctly identified as such [ALA14].

Wang Y. et al. [WAN13] extracted two nonlinear features derived from fractal geometry, known as blanket dimension and fractal intercept and used them to measure the behavior of EEG signals from the epileptic patients. The fractal theory is a branch of nonlinear dynamics theory. A fractal is a mathematical set with a typically self-similar property which means the whole is exactly or approximately similar to one or more of the parts at different scales. In fractal geometry, fractal dimension is a statistical quantity that gives an indication of how a fractal occupies space and measures the degree of complexity, roughness, irregularity [WAN13]. The vertical intercept of the fitted straight line for estimating fractal dimension is called fractal intercept. It reflects the change speed of the surface of irregular sets. In time series analysis, fractal dimension can be used to quantify the irregularity, complexity and self-similar property of a waveform. Wang et al. found that there is significant difference of the blanket dimension and fractal intercept between interictal and ictal EEGs. The difference of the fractal intercept feature between interictal and ictal EEGs is more noticeable than the blanket dimension feature. These two fractal features at multi-scales in combination with a Support Vector Machine (SVM), achieve an accuracy of 97.13% for normal, ictal and interictal EEG classification on Bonn's datasets.

Sheng-Fu L. et al. [SHE10] proposed a epilepsy detection method that obtains a balance between computational complexity analysis and detection accuracy. The authors applied Principal Component Analysis (PCA) for feature reduction and radial-basis-function SVM as classifier, combining median-filtered approximate entropy (ApEn) and multiband EEG power spectra led to average accuracies of 96.83% by linear classifying methods and 98.67% using nonlinear classifying methods for discrimination of three classes of EEG: ictal state, interictal state and healthy state.

Tzallas et al. [TZA09] compared several methods for *time-frequency* analysis of EEGs. A Feed Forward - Artificial Neural Network (FF-ANN) was used for the classification of the EEG segments to determine the existence of an epileptic seizure. This method was also evaluated using the EEG dataset of the University of Bonn [BON16], [AND01] obtaining 100% and 89% of classification accuracy over the sets, healthy (Z), interictal (F) e ictal (S); and sets, healthy (Z, O), inter-ictal (N, F), and ictal (S), respectively.

Ghosh et al. [GHO07] presented a wavelet-chaos-neural network model for classification of EEGs of healthy, ictal, and interictal subjects. Wavelet analysis was used to decompose the EEG into sub-bands. Using a mixed-band feature space consisting of nine parameters and a Levenberg-Marquardt Backpropagation Neural Network (LMBPNN), they obtained a classification accuracy of 96.7%.

A methodology is proposed to automatically classify EEG of normal, interictal and ictal subjects using Empirical Mode Decomposition (EMD) by Martis et al. [MAR12]. EEG decomposition using EMD yields few intrinsic mode functions (IMF), which are amplitude and frequency modulated (AM and FM) waves. Hilbert transform of these IMF provides AM and FM frequencies. Features as spectral peaks, spectral entropy and spectral energy in each IMF are extracted and fed to a decision tree classifier for automatic diagnosis. In that work, the authors compared the performance of classification using two types of decision trees: classification and regression tree (CART) and C4.5. The best result was achieved using C4.5, which obtained an average accuracy of 95.33%, average sensitivity of 98%, and average specificity of 97% using the database from University of Bonn [BON16], [AND01].

Duque-Munoz, et al. [DUQ14] analyzed the extraction of physiological rhythms from EEGs to find traces of interictal/ictal states of epilepsy. They based their work on the stochastic relevance analysis, which estimates the contribution of each time variant EEG rhythm, in order to discriminate between normal and ictal/interictal states. For this purpose, a subspace-based stochastic analysis of EEG rhythm dynamics was introduced. Thus, instead of a widely used scalar-valued parameter set extracted from a given EEG signal, neuronal states are detected throughout this analysis, by using a vector set of short-time rhythms. A Short Time Fourier Transform was used as an enhancing decomposition, to provide suitable temporal and spectral resolutions of extracted EEG rhythms. They have obtained the average accuracy of 98.12%.

1.2 Aim of thesis

The most common methods used for processing EEG signals in the last years are Wavelet transforms and Artificial Neural Networks [LOT15], [SRI14], [ANU12], [GAN11], [SHA11]. Wavelet transform is particularly effective for representing various aspects of non-stationary signals as trends, discontinuities and repeated patterns, whereas some signal processing approaches fail or they are not as effective as other techniques [SUB05]. On the other hand, Neural Networks (NN) are widely used for classification, approximation and control problems with different models, available for complex classification problems. NNs provides an alternative form of computing that attempts to mimic the functionality of the brain [HAR12]. However, some NN models have some drawbacks, which come from their inherent characteristics, such as slow convergence and settlement of local minima [SUN05]. Wavelet Neural Networks (WNN), which have been widely used for identification and control of nonlinear systems, have been proposed to overcome that limitations. [SUN05]. WNN is an integrated type of ANN with wavelet techniques and has been used successfully in many fields. Instead of conventional nonlinear activation functions, the activation functions of hidden layer nodes in a WNN are the wavelet bases. Because the wavelets bases are characteristic of time precision in high frequency domains and frequency precision in low frequency domains due to dilating and translating of the mother wavelet, the ability of WNN in mapping complicated nonlinear functions is highly enhanced [JIA08].

In this thesis, we look for wavelet-based neural networks architectures able to efficiently handle the classification of EEG signals with respect to epilepsy-related stages and then support the improvement the medical diagnosis. We propose the design of a structure for classification of three classes of EEG signals: Ictal, Interictal and Healthy, using a model called Multidimensional Radial Wavelon Feed-Forward Wavelet Neural Network (MRW-FFWNN). Hence, we also evaluated different Wavelet-Based Neural Networks classifiers and compare their results of classification with the proposed model. A database provided by the University of Bonn [BON16], [AND01] is used to assess our proposed model and to compare it with similar works [SUB05], [SHA12], [GHO07].

Our hypothesis is that the use of feed-forward wavelet neural networks, combined with radial wavelon is an alternative method for the classification of EEG signals. To prove it, we design a new feed-forward wavelet neural network model, comparing its performance with state-of-the-art algorithms in the classification to epilepsy-related stages.

1.2.1 Specific Objectives

In order to evaluate our hypothesis, we define the following particular objectives for this research:

- To propose preprocessing strategies in order to remove noise or artifacts from EEG signals.
- To analyze EEG signals and to propose a strategy for feature extraction of EEG.
- To propose a structure to enhance the classification accuracy of EEG signals with respect to epilepsy-related stages by the implementation of a system based on Wavelet-Based Neural Networks.
- To propose the optimal selection of mother wavelet on a classifier based on Wavelet-Based Neural Networks.

1.3 Contributions

The first contribution of this work is a novel structure to enhance the classification accuracy of epilepsy on EEG signals by the implementation of a system based on Wavelet-Based Neural Networks. The proposed model is called Multidimensional Radial Wavelon - Feed Forward Wavelet Neural Network (MRW-FFWNN). The proposed model is composed of processing nodes known as Multidimensional Radial Wavelons (MRW)[ZHA93] in a Feed Forward Wavelet Neural Network architecture. The difference between our proposal and the architectures proposed in [ZHA92], [ZHA93] is that our model uses the same dilation factor for all dimensions of each neuron. Therefore, the parameters of dilation into all the network depend only on the number of neurons, whereas in [ZHA92], [ZHA93] the parameters of dilation depend on the number of neurons and the number of inputs (dimensions). This modification reduces the number of adjusting parameters in the net.

The second contribution is an optimal selection of mother wavelet for the feature extraction to enhance the classification of several stages identified in EEG signals related to epilepsy. The involved stages are: the ictal stage, which corresponds to the occurrence of a seizure; the interictal stage, which occurs between epileptic events (seizures) and the healthy stage which related to the behavior of an EEG signal obtained from healthy patients. 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 [ALA09]. The optimal wavelet is selected using two criteria, the degree of similarity of mother wavelet with EEG signals by assessing the cross-correlation coefficient and the classification accuracy of EEG signals.

The third contribution of this research consists in a suitable selection of the features from EEG signals, providing the best information to enhance the classification accuracy of epilepsy. We have assessed several filters IIR and FIR, combining several wavelet decomposition methods, wavelet mothers and features.

The fourth contribution is the use of binary-tree and OVO decomposition strategies with two aggregation methods: *Voting strategy* and *Weighted voting strategy*, based on the proposed model Multidimensional Radial Wavelon - Feed Forward Wavelet Neural Network (MRW-FFWNN) for classification of EEG signals.

1.3.1 Publications

The results of this research have been published in several conferences and journal papers:

1. Juárez-Guerra E., Gómez-Gil P., Alarcon-Aquino V.: Biomedical Signal Processing Using Wavelet-Based Neural Networks. Special Issue: Advances in Pattern Recognition, Research in Computing Science, Vol. 61, ISSN: 1870-4069, 2013. pp. 23-32.

2. Juárez-Guerra E., Alarcon-Aquino V., Gómez-Gil P., : Epilepsy Seizure Detection in EEG Signals using Wavelet Transforms and Neural Networks. New Trends in Networking, Computing, E-learning, Systems Sciences, and Engineering, Lecture Notes in Electrical Engineering. Eds: K. Elleithy, T. Sobh. Vol 312, 2015, pp 261-269. DOI: 10.1007/978-3-319-06764-3_33

3. Goméz-Gil, Pilar, Juárez-Guerra, Ever, Alarcon-Aquino V., Ramírez-Cortés Manuel, Rangel-Magdaleno, José: Identification of Epilepsy Seizures using Multiresolution Analysis and Artificial Neural Networks; Recent Advances on Hybrid Approaches for Designing Intelligent Systems. Studies in Computational Intelligence 547, DOI: 10.1007/978-3-319-05170-3_23, Springer International Publishing Switzerland 2014.

4. Juárez-Guerra E., Alarcon-Aquino V., Gómez-Gil P., Ramírez-Cortés J. M., García-Treviño E .S.: Epilepsy Seizures Classification in EEG Signals using

Wavelet Neural Networks with Multidimensional Radial Wavelon. To be submitted 2016.

1.4 Organization of this document

The organization of this document is as follows. In **Chapter 2**, background information of Epilepsy and Electroencephalogram (EEG) and their characteristics are presented. This chapter also presents a brief description of Wavelet Transforms and Wavelet Neural Networks. **Chapter 3** presents the description of proposed model for classification of three classes of EEG signals: Ictal, Interictal and Healthy. This chapter, also explains the methodology followed for designing of the three modules that composed the proposed model: preprocessing, feature extraction and classification. **Chapter 4** presents the description of the proposed classifier called MRW-FFWNN and its learning algorithm. Architectures and characteristics of several classifiers based on neural networks, used in this thesis for comparison purposes, are also described in this chapter. **Chapter 5** reports experimental results using our proposed model and several neural network architectures. **Chapter 6** concludes this research and outlines the directions for future work. Finally, **Appendix A** and **Appendix B** present the results obtained of all the experiments made in this research.