Epileptic Seizure Classification Using Neural Networks with 14 Features

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Abstract. Epilepsy is one of the most frequent neurological disorders. The main method used in epilepsy diagnosis is electroencephalogram (EEG) signal analysis. However this method requires a time-consuming analysis when made manually by an expert due to the length of EEG recordings. This paper proposes an automatic classification system for epilepsy based on neural networks and EEG signals. The neural networks use 14 features (extracted from EEG) in order to classify the brain state into one of four possible epileptic behaviors: inter-ictal, pre-ictal, ictal and pos-ictal. Experiments were made in a (i) single patient (ii) different patients and (ii) multiple patients, using two datasets. The classification accuracies of 6 types of neural networks architectures are compared. We concluded that with the 14 features and using the data of a single patient results in a classification accuracy of 99%, while using a network trained for multiple patients an accuracy of 98% is achieved.

Keywords: Neural Networks, Epilepsy, Seizure Prediction, Data Mining, Classification, EEG processing.

1 Introduction

Epilepsy is a common disorder that has been with us ever since ancient times, affecting about 50 million people in the world (according to the International League Against Epilepsy). Epilepsy targets the brain, a temporal change in the brains electrical activity that expresses itself in motor, psychic, sensorial and sensitive manifestations most commonly associated with spasms. Trough a visual analysis of an EEG chart a trained specialist can identify the several states of a seizure, where it begins, where it manifests onto observable characteristics and when it ends. To conduct such monitoring in real time or in a way that does not prevent the patient from performing every day tasks is a technological challenge that has the potential to minimize the impact of this illness and improve quality of life.

Techniques normally used in seizure prediction include methods based on the analysis of the EEG signal. This area of investigation generally includes,

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among others, the analysis of nonlinear dynamics, wavelet transform and signal quantification. In epileptic seizures prediction and detection, one of the most interesting methods is the development of computational methods described as classifiers (e.g. neural networks). The main goal of these studies is to accurately determine the epileptic EEG states through the processing of extracted EEG features. In [1] Approximated Entropy was used as feature, achieving an accuracy of 100%. However the classification was made only between two classes (normal and epileptic), this approach is not the best choice if the goal is the prediction of seizures. Another study [2] used some of the features applied in our work and obtained a classification accuracy of 96.7%. Although the dataset used were captured from a single brain region (temporal epilepsy, epileptogenic focus: hippocampal formation).

Other computational tools such as neuro-fuzzy computing techniques were recently demonstrated as highly promising in the identification of seizure patterns [3]. These efforts represent the increase variety of methods and techniques used in the processing of epileptic EEG. An extensive analysis of recent published works can be found in [4].

The number of patients analyzed in each study has a direct influence in the values of sensitivity. Usually, when the studies are based on EEG data of a small number of patients the sensitivity results tend to increase. On the other hand, when the studies reunite several patients, the sensitivity of the methods tends to decrease. This can be explained by several factors such as unique brain dynamics of each patient. Another important information is the absence in several studies of false positive rate information (specificity). The increased sensitivity cannot be obtained based in a large number of false positives. This would invalidate the development of any closed-loop seizure prevention system.

We propose several neural networks capable of classifying the different states of an epileptic seizure, using as evaluation metrics: accuracy, sensitivity and specificity. In order to build in the near future a prediction system our classification focus is on the pre-ictal state. By training different types of neural networks and testing them in different ways we attempt to identify wining characteristics that could get an accurate classification in different datasets. The classifier proposed distinguishes among four classes: inter-ictal (normal brain state), pre-ictal (just before the seizure), ictal (during seizure) and pos-ictal (after a seizure and before the normal brain state).

The organization of the paper is as follows. The next section describes the EEG Data and features extraction methods. Section 3 presents the neural networks studied including a brief description of each one. In section 4 the experiments made are described and finally in section 5 the conclusions are presented.

2 EEG Data

The data used in this study was collected from two patients. Both records are from the database of Freiburg Center for Data Analysis and Modeling [5]. The first one is a temporal epilepsy (with three seizures in a total of 2049 entries separated by 5 seconds) and the second a frontal epilepsy (with two seizures in a total of 1365 entries separated by 5 seconds).

The intracranial recordings utilized were acquired using Neurofile NT digital video system with 128 channels, 256 Hz sampling rate, and a 16 bit analogue-to-digital converter. Applying energy concepts, wavelet transform, nonlinear systems theory, a total of 14 features were extracted from intracranial EEG signal.

2.1 Features Extraction

The features extracted are listed in table 1. In [6,7] you can found a deeper explanation about these features and their extraction.

Table 1. Features

Concept	Features
Signal Energy	Accumulated energy
	Energy level
	Energy variation (short term energy (STE))
	Energy variation (long term energy (LTE))
Wavelet Transform	Energy STE 1 (0Hz − 12.5Hz)
	Energy STE 2 (12.5Hz − 25Hz)
	Energy STE 3 (25Hz − 50Hz)
	Energy STE 4 (50Hz − 100Hz)
	Energy LTE 1 (0Hz − 12.5Hz)
	Energy LTE 2 (12.5Hz − 25Hz)
	Energy LTE 3 (25Hz − 50Hz)
	Energy LTE 4 (50Hz − 100Hz)
Nonlinear system dynamics	Correlation dimension
	Max Lyapunov Exponent

Signal energy (accumulated energy and energy variation). Based on the algorithm presented in [8], the authors relate the EEG study with accumulated energy concept. Accumulated energy is determined by the sum of the successive values of signal energy. Then the derivative of the function is determined and analyzed, allowing the pattern evaluation; according to several authors, pre-seizure activity is related to the increase of EEG signal energy.

Accumulated energy was approximated by using moving averages of signal energy (using a short-term energy observation window vs. a long-term energy observation window).

Wavelet transform (decomposition coefficients analysis). The signal is decomposed in different frequency bands, and the extracted coefficients represent new functions (versions of the same original signal). The coefficients obtained by wavelet decomposition with four levels are processed and accumulated energy of these series is determined. Accumulated energy was approximated by using moving averages of coefficients energy (using a short-term energy observation window vs. a long-term energy observation window).

Nonlinear dynamics. Several approaches, based on the chaos theory, were used successfully in EEG analysis; due to the aperiodic and instable behavior of the epileptic brain, the structure is suitable to nonlinear techniques. Functions designed for this purpose (TSTOOL[9] matlab toolbox) were used to process EEG signal and determine the Lyapunov exponents (quantification of the exponential growth of the average distance between two nearby trajectories through error approximation) and correlation dimension (estimator method) of signal short segments.

2.2 Feature Preparation

The datasets were normalized by feature in the interval [0 1]. This normalization gives an identical influence of each feature for the calculation of neural network weights.

3 Neural Networks Applied

After some preliminary tests, we chose six neural network variants to our study. These neural networks cover a wide spectrum of the available neural network approaches, allowing us to gather a good knowledge about the use of neural networks in the Epileptic Seizure Detection problem. For a more comprehensive explanation about the neural networks described in the next subsections see [10].

3.1 Radial Basis Function (RBF)

In our study we used Exact Fit variant [11], where the number of neurons in the 1st layer is equal to the number of prototypes in the input (in our case, 14). The spread constant used, i.e. the area of input space to which each neuron responds, was 1.5.

3.2 Feed-Forward BackPropagation (FFBP) and Layer-Recurrent Networks (LRN)

FFBP [12] and LRN [13] have been used. LRN are composed by an arbitrary number of layers, with a feedback loop around each layer, except for the output layer. This feedback loop provides a single delay to the network. Our networks were configured using 2 layers, being the hidden layer composed by 10 tansig neurons and the output layer by 4 linear neurons. Both networks were trained with the Levenberg-Marquardt algorithm.

3.3 Elman and Distributed Time Delay (DTD) Networks

We used Elman Networks [13] with one hidden layer, composed by 10 tansig neurons, followed by a linear output layer, with Lvenberg-Marquardt backpropagation function. Distributed Time Delay networks [14] are dynamic neural networks, where the output of the various layers also depends on the past output of these layers. This capability is achieved by using tapped delay line memories, which record the past outputs of each layer. Our network was designed with a hidden layer of 10 tansig neurons, with a boolean output layer. The training function was the Levenberg-Marquardt backpropagation function, and we used a one step time-delay.

3.4 Feed-Forward Input Time-Delay BackPropagation (FFTD)

Input Time-Delay networks [14] are very similar to Feed-Forward Networks trained with the backpropagation algorithm. The only difference is that they take as inputs not only the training data, but also a predefined time-delay from the data. Therefore, they can deal with temporal and spatial data. Our configuration is very similar to Feed-Forward BackPropagation (one hidden layer with 10 tansig neurons, and Levenberg-Marquardt backpropagation training function). The Input Time-Delay used was one time unit.

4 Experiments

In order to apply the neural networks previously presented we used Matlab R2007b with Neural Networks Toolbox. Within this platform we implemented several scripts that allowed us to run the experiments. The developed code and the data files for training and testing are available[1].

4.1 Evaluation Metrics

To evaluate our results we used three different metrics: *sensitivity* (1), i.e. the capacity of correctly identify positive cases (pre-ictal), *specificity* (2), i.e. the capacity of correctly identify negative cases (non pre-ictal), and *accuracy* (3), i.e. the proportion of correct classified instances. The use of four brain states is useful in order to better evaluate the accuracy of the classifiers built. These metrics are largely used in this domain, making easier to compare our results with other works. In order to implement these metrics each entry of the datasets were previously classified by a medical expert as: inter-ictal, pre-ictal, ictal or pos-ictal.

$$Specificity(\%) = \frac{True\ \ Negatives}{True\ \ Negatives + False\ \ Positives} \times 100 \tag{1}$$

$$Sensitivity(\%) = \frac{True\ \ Positives}{True\ \ Positives + False\ \ Negatives} \times 100 \tag{2}$$

$$Accuracy(\%) = \frac{Correct\ \ cases}{Total} \times 100 \tag{3}$$

[1] http://student.dei.uc.pt/~racosta/epilepsy

Table 2. Results of the several experiments SP - Specificity, SS - Sensitivity, AC - Accuracy

	RBF			FFBP			Elman			Recurrent			FFTD			DTD		
	SP	SS	AC	SP	SS	AC	SP	SS	AC	SP	SS	AC	SP	SS	AC	SP	SS	AC
Single(1)	96	98	93	**99**	**98**	**98**	**99**	**93**	**98**	**99**	**97**	**97**	**99**	**97**	**98**	**99**	**97**	**98**
Single(2)	97	97	91	**100**	**100**	**99**	**99**	**100**	**98**	**100**	**100**	**98**	**99**	**100**	**98**	**99**	**97**	**98**
Different(1:2)	89	2	63	66	26	54	85	0	8	32	94	28	74	60	64	81	0	22
Different(2:1)	93	0	2	77	3	44	99	0	48	59	53	18	96	0	68	85	34	42
Multiple(1+2:1)	**100**	**97**	**100**	99	99	98	**99**	**92**	**98**	98	76	95	99	65	96	**99**	**96**	**98**
Multiple(1+2:2)	**100**	**100**	**99**	99	82	97	**98**	**96**	**97**	100	41	91	96	92	93	**99**	**90**	**97**

4.2 Single Patient

In this test, we used the data extracted from a single patient to test and train the neural networks. Were used 70% of the patient data to train the network, while the others 30% were used to test it. From each set of 3 entries were taken 2 entries to the training set and the other one to the testing set. The results obtained using the neural networks in two different patients are shown in Table 2 (row 1 for patient A and row 2 for patient B).

We can see some interesting results for the three performance criteria (1),(2) and (3). FFBP, Elman, Recurrent, FFTD and DTD show very good results in both patients.

4.3 Different Patients

In this test, we trained the network with the data from one patient and tested it with the other patient. The results obtained are shown in Table 2 (rows 3 and 4).

There is an evident degradation of performance. This is probably because the patients have different kinds of epilepsy and the networks do not have sufficient generalization capability. This seems to indicate that seizure prediction with neural networks needs a personalized network, specific for each patient.

4.4 Multiple Patients

In this test, we trained the network with the data from both patients, and tested with one of them. This was done by concatenating both datasets into one. The results obtained are shown in Table 2 (rows 5 and 6).

In this case there are still good results, with Elman and DTD networks, both with memory. This is an interesting indication that the memory may improve the generalization capability of the network. The RBF neural network obtained very good results, however the networks had more than 3000 neurons. This can lead to the impossibility of training these networks due to their excessive memory needs, at the same time this seems to show that they are strongly addicted to the training datasets (almost one neuron for each data entry). In the future the use of more than two datasets to train the neural networks should be studied.

5 Conclusions and Discussion

In this paper we propose the classification of epileptic EEG data into four states (inter-ictal, pre-ictal, ictal and pos-ictal) applying several neural networks architectures.

From the EEG data were extracted 14 features: accumulated energy, level, lyapunov exponents, correlation dimension, five variants of energy STE and five variants of energy LTE.

The classification accuracies of the following neural networks are compared: 1) Radial basis function, 2) Feed-Forward BackPropagation, 3) Layer-Recurrent, 4) Elman, 5) Feed-Forward Input Time-Delay BackPropagation, 6) Distributed Time Delay.

The results show that it is possible to find a good classifier to the four brain states based on neural networks (with an accuracy of 99%). However the classifier of one patient cannot be used for another patient. The variability of physiological systems can only be overcome personalizing the architecture and the training of the network. The performance of the classifier, if it is intended to be used for example to give the patient an alarm of an approaching seizure (classifying correctly the pre-ictal state), must be checked by both sensitivity and specificity. If one limits to only one of them, no practical usefulness can be given to the results.

Considering the brain as a nonlinear complex dynamic system, memory in the networks seems to be a natural element. Further research is needed to find more elaborated memory architectures and its appropriate training algorithms. Neural networks as classifiers have here a high potential because they can compute in real time with a high number of features. This characteristic enable the development and construction of transportable devices, improving substantially the quality of life of epileptic patients intractable by medication and that must learn to live with seizures.

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