NEURAL CLASSIFIER FOR DETECTION AND CLASSIFICATION OF SPIKES AND SHARP WAVES

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Abstract: In this article is discussed the application of a hybrid approach that uses the Wavelet Transform and Artificial Neural Networks in detection and recognition of epileptiform events in EEG signals. It is presented the methodology used to develop a Neural Classifier as well as the experiments and its results through the Neural Networks and Wavelet Transform. The developed Neural Classifier showed good results in the classification of Epileptiform events with and without pre-processing achieving sensitive of 97.14%, specificity of 94.55% and accuracy of 96.14%, suggesting the high sample rate of the EEG signals contributed to achieve these values.

1 INTRODUCTION

Epilepsy is a chronic condition or a group of diseases with high prevalence, however, still poorly explained by science. Epileptic seizures are crises that reflect a temporary dysfunction of a small part of the brain (focal seizures) or a more extensive area involving the two hemispheres (generalized seizures).

The electrographical elements frequently found in EEG records of epileptic patients are the Spikes (20-70 ms) and Sharp Waves (70-200 ms). These events are significative for the epilepsy diagnosis, which are known as Epileptiform events (Argoud et al., 2006), (Sörnmo and Laguna, 2005), (Pillai and Sperling, 2006). In neurological practice spikes found in the records of electroencephalography (EEG) are used to confirm a diagnosis of epilepsy (Pillai and Sperling, 2006) and help identify the type of syndrome that affects the patient (Niedermeyer and Silva, 2004).

Automatic detection of Epileptiform events is an important aspect of long-term epilepsy monitoring and it is important highlights that the visual analysis is a slow and exhaustive process being extensively used as support for the diagnosis of epilepsy (Pillai and Sperling, 2006). Experts verify screens of signal composed by 24 or 32 channels in continuous EEG records with durations up to 15s (Argoud et al., 2006).

Wilson and Emerson (2002) conducted a study where algorithms to detect Epileptiform events are compared. It can be observed that few systems have practical application, because many of these don't prove to have reached an acceptable rate of false positives per minute (fp/min), resulting in little or none effective saving of time.

This work contributed to the automating process of the epilepsy diagnosis, checking the feasibility of using the Wavelet Transform as a way to processing the EEG signals as well as the capability of Neural Network works as a Neural Classifier in the classification of Epileptiform and Non-Epileptiform events. It was used this sampling rate of 512 Hz in attempt to obtain better results in the process of classification of events in relation to other studies using lower sampling rate between 100 and 256 Hz (Argoud et al., 2006), (Sovierzoski, 2008), (Khan and Gotman, 2003), (Pillai and Sperling, 2006) (Indiradevi et al., 2008), (Adeli et al., 2002) (Pang et al. 2003), (Xu et al. 2007).

The results were evaluated using performance indicators applied to the diagnostic tests. The algorithms were implemented in C++ Builder 6.

2 MATERIAL AND METHODS

2.1 Bank of EEG Signals

The bank of EEG signals is composed by records of 11 patients truly epileptic. The used signals present

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the following settings: referential montage, 32 channels, 512 Hz of sample rate, band limited 0.5-40 Hz and notch filter of 60 Hz to eliminate interference caused by the power line. They were selected 685 events between spikes, sharp waves, blinking, background activity and noise.

2.2 Wavelet Multiresolution Analysis

The analysis in time-frequency domain by Wavelet Transform is performed by taking a Wavelet prototype function called mother-wavelet. This mother-wavelet suffers escalations and translations, forming the daughter-wavelets (1) (Mallat, 1999).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \cdot \psi\left(\frac{t-b}{a}\right) \quad (1)$$

where $\psi(t)$ is the mother-wavelet and $\psi_{a,b}$ is the daughter-wavelet, $a^{-1/2}$ is the constant of energy normalization, b is the translation factor and a is the dilation factor.

The Continuous Wavelet Transform uses parameters of time and scales continuous. Using discrete parameters to a and b ($a \geq 1$, $b \geq 1$) determines the Discrete Wavelet Transform (2).

$$DWT(a,b) = \frac{1}{\sqrt{a_0^i}} \int_{-\infty}^{\infty} x(t) \cdot \psi^*\left(\frac{t - kb_0 a_0^i}{a_0^i}\right) dt \quad (2)$$

where k and i are integers, b_0 and a_0 are the parameters of translation and dilation, respectively.

The Wavelet Multiresolution Analysis is based in the computational implementation of the Discrete Wavelet Transform. The algorithm decomposes a discrete signal using filter banks (Argoud et al., 2006), (Mallat, 1999), (Indiradevi et al., 2008).

The set of filters *H[n]* extract the average characteristics, defined as approximations of the signal *x* and added to a set of filters *G[n]* extract the features of high-frequency defined as details of the signal *x* (Figure 1).

The idea to use the Wavelet Transform is extract the signal features that somehow can be used as way of separation between the classes of events before a selected epoch of signal be analyzed by the neural classifier.

In this work it was used Wavelet Function Coiflet1 because this function showed better results at the detection of Epileptiform Events as seen in studies conducted by Argoud et al. (1999), Argoud et al. (2006) and only the details of the decomposition levels were used to process the signals.

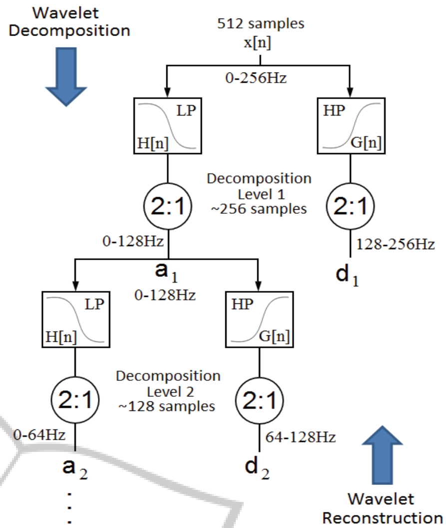

Figure 1: Representation of the Wavelet Multiresolution analysis.

2.3 Neural Networks

A Neural Network Multilayer Perceptron has multiple layers of neurons fully connected (Eberhart and Dobbins, 1990). The first layer or input layer receive the patterns, intermediate layers perform the processing and feature extraction and the output layer presents the final result. In the last layer the neurons can have an output function in order to discretize the results transforming the Neural Network in a classifier (Haykin, 2001), (Eberhart and Dobbins, 1990).

If there is only one output neuron the network becomes a binary neural classifier, as implemented in this work.

Some events were selected to generated three sets of patterns: training, validation and test showed in the Table 1.

Table 1: Description of the pattern sets.

Pattern Set	Spikes	Sharp Waves	Blinking	Normal Activity	Noise	**Total of Events**
Training	29	71	31	40	29	**200**
Validation	13	87	41	49	10	**200**
Test	28	148	36	56	17	**285**
Total	70	306	108	145	56	**685**

2.4 Indexes of Sensitivity and Specificity

In the evaluation of the neural classifier the result of classification and appointment of the expert are compared. This comparison is also known as diagnostic test widely used in medical sciences. The indicators True Positive (TP) and True Negative (TN) represent the agreement in the classification of the correct decisions. The False Positive (FP) and False Negative (FN) rates represent the disagreement in the classification (Jekel, 2001). Totaling the indicators described above can be calculated the *sensitivity*, *specificity* and *accuracy*.

Sensitivity (3) is the ability of the classifier to identify the positive events among the truly positive.

$$sensibility = \frac{TP}{TP + FN} \tag{3}$$

Specificity (4) is the ability of the classifier to identify the negative between the truly negative and both indexes are used in the ROC Analysis.

$$specificity = \frac{TN}{TN + FP} \tag{4}$$

Accuracy (5) is the global concordance of the true positive and negative results in subjects with and without the sickness (Jekel, 2001).

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

2.5 ROC Analysis

The use of ROC curve (Figure 2) as a performance measure for classifier systems and diagnostic systems regardless of their application and it is employed in expert systems and Artificial Neural Networks. To measure the performance of the ROC curve is used the AUC (*Area Under the ROC Curve*) index, which present values between 0.5 (no discrimination) and 1.0 (total discrimination) (Sovierzoski, 2008), (Jekell, 2001), (Braga, 2000).

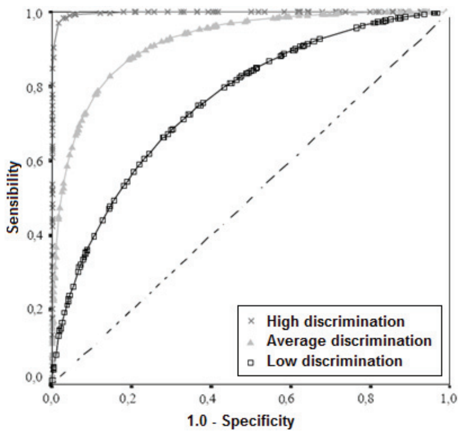

Figure 2: ROC Curves.

3 METHODOLOGY

From each EEG channel the selected epochs of signal has 512 samples. This epoch is submitted to the Coiflet1 function where is decomposed in 10 detail levels. Each decomposed level presents a particular signal with some extracted features about the selected epoch, which highlight the high frequencies of the signal. These decomposed signals are compared with a threshold composed by the mean in addition with the standard deviation of the EEG signal. If the decomposed signal exceeds the threshold the analyzed epoch is characterized as an Epileptiform Event and then presented to the Neural Network inputs. The neural classifier will classify this epoch as Epileptiform Event or not. All this process is showed in the Figure 3.

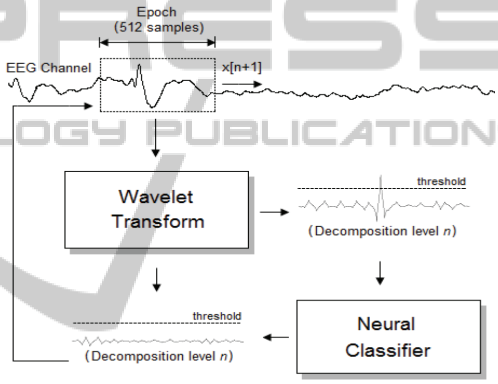

Figure 3: Overview of the work.

Some experiments were performed extracting features of the EEG signals with the objective to identify the better decomposition level to implement the neural classifier. It was plotted one chart for each detail level of decomposition with the dispersion of all the 685 selected events. In the process of decomposition each detail level presents a signal with positive and negative amplitudes (Figure 3), which characterize the high frequencies of the original signal. It was calculated the absolute value of the decomposed signal for each detail level to represent the high frequencies only in one domain.

The absolute values were plotted in the charts. It was verified that the 5th and 6th levels of decomposition (Figure 4) were the levels that more highlighted Spikes and Sharp Waves. Other events are also highlighted with lower amplitudes. Some of them showed amplitudes next to the amplitudes of the Spikes and Sharp Waves.

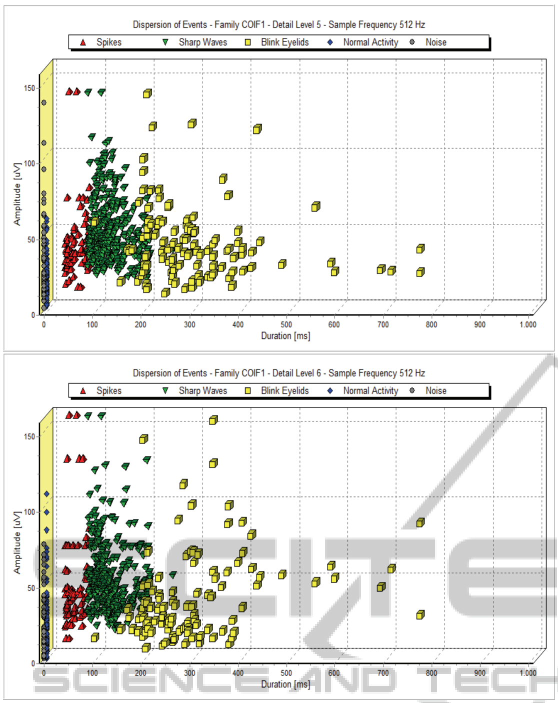

Figure 4: Groups of Spikes and Sharp Waves at the 5th and 6th levels of decomposition.

For this reason other experiments were performed only using the Neural Networks just to check its performance with signals without processing.

The topology used to implement the Neural Network was a Feedforward three-layer, with 512 neurons in the input layer, 10 neurons in the inner layer and 1 neuron to the output layer, and for all neurons was used the logistic activation function.

The convention used was the high output (1) represents the Epileptiform events and the low output (0) represents the Non-Epileptiform events. In supervised training procedure of Neural Network was used the Backpropagation.

For the training it was used the following settings: random initialization of synaptic weights with values between ± 0.01, learning rate of 0.002 and momentum of 0.7. The evaluation of the Neural Network training was performed using the method of Cross-validation with Early Stopping. In this method the evaluation of the training and validation errors are calculated when all the patterns of the training set and validation set are presented to the network. The mean square error of training is calculated from the equation (6).

$$\varepsilon_T(n) = \frac{1}{2N_t}\sum_{n=1}^{Nt}(d_t(n) - y_t(n))^2 \qquad (6)$$

Similarly, the validation error of the network is calculated by (7).

$$\varepsilon_V(n) = \frac{1}{2N_v}\sum_{n=1}^{Nv}(d_v(n) - y_v(n))^2 \qquad (7)$$

In the process of performance evaluation of the neural classifier was used the AUC index. The evaluation of the classifier starts when the set of validation patterns is presented to the network, where the indicators (TP, TN, FP, FN) were totalized. From these indicators the sensitivity and specificity curves are calculated as well as the ROC curve for each epoch of training allowing identifying epochs that presented the highest AUC.

4 RESULTS

4.1 Wavelet Transform

It was verified that the 5th and 6th levels of decomposition (Figure 4) were the levels that more highlighted Spikes and Sharp Waves. Other events are also highlighted with lower amplitudes. Some of them showed amplitudes next to the amplitudes of the Spikes and Sharp Waves. In a practical application would not be possible to define a threshold decision to perform the separation of these events using only the amplitudes of the decomposed signals.

4.2 Neural Classifier

During the training process (Figure 5) can be observed that the mean square error of the training curve showed a continuous decay, indicating the training convergence. The validation curve shows a decay of the mean square error up to the epoch 530, reaching the minimum value (**$MSE_{Vmín}$=0.05180**), characterizing the early stopping. From the epoch 531 there was an increasing in the error, indicating the specialization of the training.

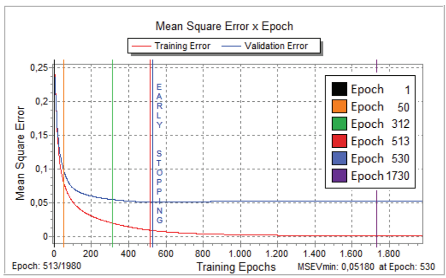

Figure 5: Curves of the mean square error of training and validation for different epochs of training.

Table 2 shows the performance indexes obtained with the neural classifier and the Figure 6 shows the ROC curves of different epochs of training.

The epoch 513 had the highest value for sensitivity and specificity, therefore, also showed the highest rates of performance demonstrating that the best results are obtained next to the epoch 530, which was the occurrence point of early stopping.

Table 2: Obtained results between the epochs of training.

Epoch	MSE_{train}	MSE_{vald}	Sens. [%]	Spec. [%]	Acc. [%]	Threshold	AUC Máx.
1	0,24992	0,24581	81,08	45,02	54,39	0,54	0,62150
50	0,08106	0,09933	91,76	82,61	88,07	0,56	0,99500
312	0,02028	0,05528	96,02	93,58	95,09	0,34	0,99790
513	**0,00973**	**0,05180**	**97,14**	**94,55**	**96,14**	**0,38**	**0,99910**
530	0,00918	0,05180	97,14	94,55	96,14	0,38	0,99850
1730	0,00123	0,05324	96,05	94,44	95,44	0,24	0,99630

After the evaluation of the neural classifier a final test was performed by selecting the epoch 513, which represents the highest AUC (**$AUC_{Máx}$= 0.99910**).

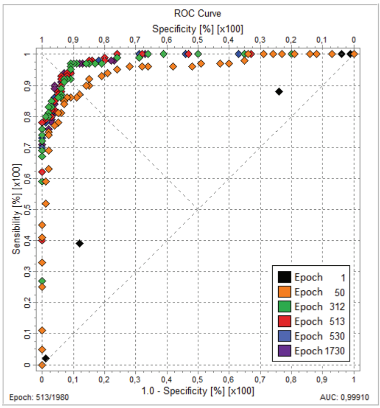

Figure 6: ROC curves for some epochs of training. It can be observed the epoch 513 had the higher AUC index.

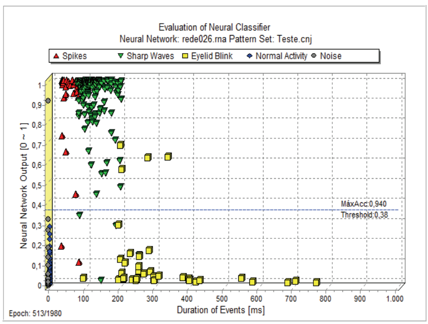

Figure 7: Representation of the classification performed with the test pattern set selecting the epoch 513 (Highest AUC Index).

It was used a set of test with 285 events. Figure 7 shows the classification made by the neural classifier, based in the epoch 513 of training reaching values of sensitivity of 97.14%, specificity of 94.55% and accuracy of 96.14%

5 CONCLUSIONS

In the obtained results using the Wavelet Transform was observed that only the amplitude of decomposed signals cannot separate Epileptiform and Non-Epileptiform events reaching values of sensitivity of 96.43%, specificity of 88.03% and accuracy of 92.98%. Further studies are being made with the Wavelet Multiresolution Analysis to signals with 512 Hz of sample rate.

The neural classifier evaluation was performed using the performance indexes (AUC index and accuracy index). These indexes could be an efficient way to verify the performance of the classifier. The best results of the classifier training were at the epochs that the indexes obtained are located near to the epoch indicated by the early stopping. The experiments with the neural classifier using signals without processing reached better results than signals processed by the Wavelet Transform: sensitivity of 97.14%, specificity of 94.55% and accuracy of 96.14%.

It can be concluded that the high sample rate of the EEG signals influence directly in the recognition process. With a high sample rate more pattern details are passed to the Neural Network inputs, improving distinction between the events, which allowed achieve better results without the need to pre-process the EEG signals. However, the high sample rate means more details about the signal, and fast variations present in the signal that characterized high frequency are highlighted too. This implied in an increase of false positives due to the fact that the Wavelet Transform confuse fast variations with spikes. This fact explains the difference between the rates of sensitivity and specificity among the use or not of the Wavelet Transform as pre-processing the inputs of neural classifier.

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