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Wavelet multiresolution analysis and dyadic scalogram for detection of epileptiform paroxysms in electroencephalographic signals

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Abstract **Introduction**: Early detection of epilepsy by the review of large electroencephalographic (EEG) recordings is very stressful, time-consuming, and subjective for neurologists. Several automatic seizure detection systems have been proposed in the literature to solve this problem. **Methods**: This study proposes two complementary wavelet-based approaches for detecting epileptiform paroxysms in EEG signals. First methodology applied the wavelet multiresolution analysis (MRA) to filter non-epileptiform activity in long-term EEG. Second methodology used the wavelet dyadic scalogram to analyze which scales were related to the epileptiform paroxysms. For tests, 65 wavelet functions were selected between daubechies, biorthogonal, symlets, reverse biorthogonal and coiflet wavelet families in order to evaluate their performance. **Results**: For MRA, it was noted a better performance by using the *db4* function, by reaching 48.30% of energy with 8 wavelet coefficients, 0.717658 of correlation and 36.799 of root mean square error (RMSE). For wavelet dyadic scalograms, were chosen *bior3.9* and *rbio1.5* functions, by reaching 77.98% of sensitivity, 94.08% of specificity, 87.87% of efficiency and 0.9613 of area under the curve (AUC value) by using *bior3.9*. **Conclusion**: The presented approaches are highly complementary for a whole automatic seizure detection system by using the MRA as pre-processing stage to filter non-epileptiform activity, and wavelet dyadic scalogram for extracting desired features from filtered EEG signals.

Keywords Epilepsy, EEG signal, Wavelet multiresolution analysis, Wavelet dyadic scalogram, Artificial neural network.

Introduction

Epilepsy is the most common neurological disorder that affects 50 million people worldwide, being around 25% uncontrolled patients despite treatment and prevalence around 1-2%. Epilepsy is characterized by recurrent, involuntary, and paroxysmal seizure activity resulting from excessive synchronization and temporary electrical discharges of cortical neural networks in the human brain. Despite the use of new antiepileptic drugs, one-third still have seizures. The electrical discharges related to epilepsy are called epileptiform paroxysms, appearing in a single, rhythmic or periodic form, and classified into spikes (lasting from 20 to 70ms), sharp waves (70 to 200ms), and several types of epileptiform complexes like spike-wave (Figure 1) (Arunkumar et al., 2012; Fergus et al., 2015; Stevanovic, 2012; Tatum IV et al., 2009).

The daily life of the patient suffers significant impacts such as temporary impairments of perception, speech, motor control, memory or consciousness. Thereby, early detection of epilepsy could be decisive in the promotion of therapies to treat or abort epileptic seizures. Electroencephalographic signal (EEG) is an important tool widely used for epilepsy detection. EEG signal is a recording of the electrical activity of the brain measured at the scalp used in the diagnosis of many brain disorders. EEG recordings have large amount of complex cerebral information. However, EEG interpretation becomes tedious due to variability in amplitude, phase, frequency, and non-periodic features. Neurologists analyze the recordings by the review of large datasets, being a time-consuming, stressful and subjective diagnostic process (Arunkumar et al., 2012; Fergus et al., 2015; Peker et al., 2016; Ramgopal et al., 2014; Wang et al., 2014).

In order to reduce the workload of neurologists by supporting visual inspection of EEG, automatic seizure detection systems were developed since a pioneering study (Gotman and Gloor, 1976). Several techniques were explored in order to improve the performance of

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Figure 1. Most common epileptiform paroxysms in EEG signals. (a) Spike; (b) sharp-wave; (c) spike-wave complex.

automated systems (Arunkumar et al., 2012; Fergus et al., 2015; Gotman and Gloor, 1976; Hunyadi et al., 2011; Olejarczyk et al., 2009; Peker et al., 2016; Petersen et al., 2013; Ramgopal et al., 2014; Wang et al., 2014). In the last decades, a very powerful tool called wavelet transform was applied to solve this problem (Adeli et al., 2007; Ayoubian et al., 2013; Haydari et al., 2011). In (Hramov et al., 2015) are presented several studies in rats by applying time-frequency analysis (such as the continuous wavelet transform) to characterize non-stationary events in EEG signals. In Medical Informatics Laboratory at Biomedical Engineering Institute (IEB-UFSC), the wavelet transform was focused in two complementary approaches. The first one proposes to apply wavelet multiresolution analysis (MRA) composed by decomposition and reconstruction of the epileptiform activity in order to analyze each frequency band (Scolaro et al., 2012; 2013; Scolaro and Azevedo, 2010). The second one proposes the time-scale analysis by mapping the wavelet scalogram, generating a two-dimensional representation of the energy of epileptiform activity (Lobato et al., 2015).

This study aims to compare these wavelet-based approaches for detection of epileptiform paroxysms using wavelet multiresolution analysis and wavelet scalograms in order to demonstrate their usefulness in solving this issue.

Methods

EEG database

The database was collected in (Scolaro and Azevedo, 2010) and also used by the Medical Informatics Laboratory at IEB-FSC in several works such as (Lobato et al., 2015; Scolaro et al., 2012; 2013). The database is composed by scalp EEG recordings with 16 hours of total duration obtained from 11 patients truly epileptic at Governador Celso Ramos Hospital in Florianopolis, Brazil. A referential montage in Pz was used with 32 channels, sampling frequency of 512Hz and limited band from 0.3 to 70Hz filtered by a notch filter at 60Hz to attenuate power line effects (electrical noise).

Wavelet transform

Wavelet transform (WT) analyzes non-stationary signals in time and frequency domain. The wavelet functions are defined by (1), where ψ is the mother function scaled and shifted by a and b parameters, respectively.

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

The continuous wavelet transform (CWT) maps the function $f(t)$ on the time-scale space by (2) using (1). Depending on the scale parameter, the Wavelet function $\psi(t)$ dilates or contracts in time causing the opposite effect in frequency.

$$W(a,b) = \int_{-\infty}^{\infty} \psi_{a,b}(\mathrm{t}) f(t)\,dt = \psi_{a,b}, f \tag{2}$$

However, the CWT is redundant and impractical due to the continuous variation of a, b parameters. This drawback can be solved by sampling a and b, resulting the discrete parameters m and n, used to compute the discrete wavelet transform (DWT). The DWT is obtained by using the wavelet discrete function $\psi_{m,n}(t)$given by (3), where $a = a_0^m$ and $b = nb_0a_0^m$ (Akansu and Haddad, 2001).

$$\psi_{m,n}(t) = a_0^{-m/2}\psi\left(a_0^{-m}t - nb_0\right) \tag{3}$$

Wavelet multiresolution analysis (MRA)

Wavelet multiresolution analysis is composed by decomposition and reconstruction processes (Figure 2a). The analyzed signal is first split into low and high-frequency bands (approximation and details coefficients, respectively) in the first level. Then, the low-frequency subband is again decomposed and so on until complete the k desired levels of decomposition. This wavelet-based approach allows us to analyze each band of information obtained by extracting some features. After that, the inverse process is performed to recover the original signal without loss information. These processes are performed through decomposition and reconstruction filters (Akansu and Haddad, 2001; Burrus et al., 1998).

Wavelet dyadic scalogram

The wavelet scalogram illustrates how transient activity varies in time-scale plane (Figure 2b), which is constructed by evaluating the correlation between the signal and wavelet functions at different scales using (4). This equation computes the percentage of energy of wavelet coefficients. However, the discrete scale still contains much redundancy information. In this way, dyadic scales (power of two) are used to represent each band without loss of information (Shoeb and Clifford, 2006).

$$S(a) := \|Wf(a,b)\| = \sqrt{\int_{-\infty}^{+\infty} |Wf(a,b)|^2 \, db} \tag{4}$$

Artificial neural network

Artificial neural networks are computational models which attempt to simulate the nerve cells networks of the biological central nervous system. The most important characteristic of artificial neural networks is the learning process using natural mechanisms of generalization. Furthermore, other useful properties like massive parallelism, adaptability, fault tolerance and low energy consumption. Artificial neural networks are crucial to solve classical topics like signal processing, speech recognition, visual perception, control and robotics (David and Rajasekaran, 2009; Graupe, 2007; Jain et al., 1996; Livingstone, 2008).

Methodologies

Selection of events

The first methodology used 600 epileptiform events (between spikes and sharp waves) with different durations in order to test wavelet multiresolution analysis and denoising method. The second methodology used a set of 477 epileptiform events, and 657 non-epileptiform events between background activity, eye blinks, and noise in order to test wavelet scalograms and artificial neural networks.

Wavelet functions

Both methodologies were applied to 65 wavelet functions selected for this study. These functions were obtained from *daubechies*, *biorthogonal*, *symlets*, *reverse biorthogonal* and *coiflet* wavelet families, listed in Table 1.

Wavelet multiresolution analysis and denoising method

All the selected events were decomposed and reconstructed by applying wavelet multiresolution analysis (Figure 3a), generating an approximation level A6 and six levels of detail: D6, D5, D4, D3, D2, D1, which were analyzed independently. A repeated pattern was observed from D4 to D6 detail levels (4-32Hz), also low frequencies were retained in A6 approximation level. In addition, D1 to D3 levels had not relevant information, and D4 to D6 levels were retained, corresponding to

Table 1. Wavelet functions used in both methodologies.

Family	Wavelet Functions
Daubechies	'db1', 'db2', …, 'db15'.
Biorthogonal	'bior1.1', 'bior1.3', 'bior1.5', 'bior2.2', 'bior2.4', 'bior2.6', 'bior2.8', 'bior3.1', 'bior3.3', 'bior3.5', 'bior3.7', 'bior3.9', 'bior4.4', 'bior5.5', 'bior6.8'.
Symlets	'sym1', 'sym2', …, 'sym15'.
Reverse Biothogonal	'rbio1.1', 'rbio1.3', 'rbio1.5', 'rbio2.2', 'rbio2.4', 'rbio2.6', 'rbio2.8', 'rbio3.1', 'rbio3.3', 'rbio3.5', 'rbio3.7', 'rbio3.9', 'rbio4.4', 'rbio5.5', 'rbio6.8'.
iCoiflet	'coif1', 'coif2', …, 'coif5'.

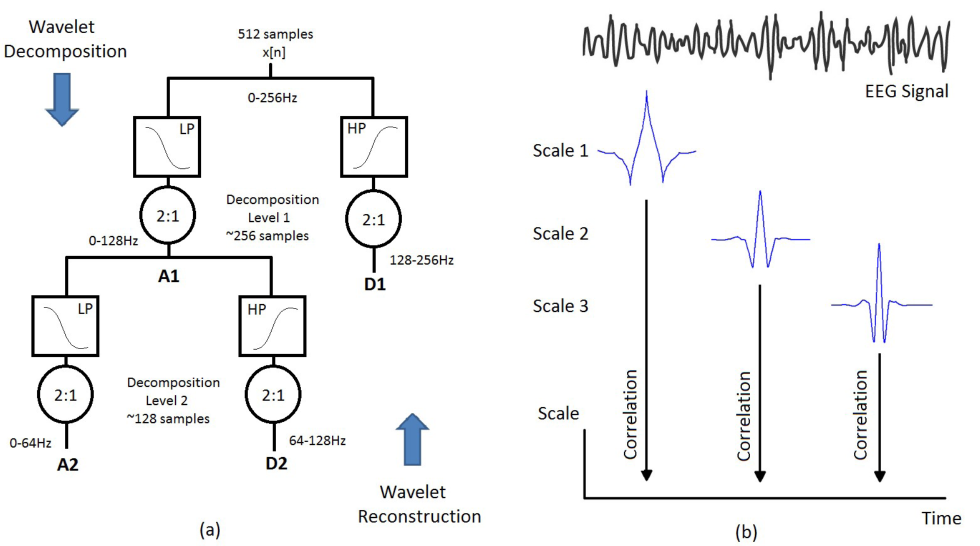

Figure 2. Two different wavelet-based approaches presented in this work: (a) Wavelet multiresolution analysis is composed by wavelet decomposition and reconstruction through low-pass (LP) and high-pass (HP) filter banks (adapted from Scolaro et al., 2012); (b) How to map the wavelet scalogram (adapted from Shoeb and Clifford, 2006).

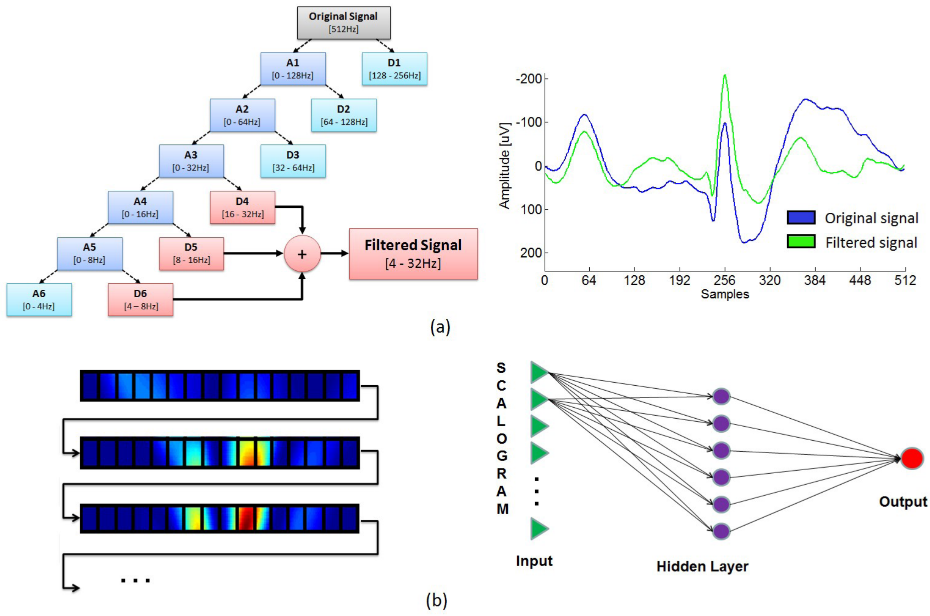

Figure 3. Block diagram of both wavelet-based methodologies: (a) Wavelet multiresolution analysis (MRA) and denoising method; (b) wavelet dyadic scalogram and artificial neural network.

the frequency band related to the epileptiform activity without noise (from 5 to 25Hz).

To determine which is the most suitable wavelet function to attenuate non-epileptiform activity, two criterions were considered: 1) the highest average of accumulated energy; and 2) the smaller number of wavelet coefficients. Experiments consisted of testing the selected events to calculate the correlation and RMSE (Root Mean Square Error) between: a) individual peaks of the original and filtered events; b) original and filtered events; c) original and filtered epochs of one-second duration.

Wavelet dyadic scalogram and artificial neural network

Wavelet scalogram was constructed by calculating the correlation between the wavelet function and the set of selected events by using (4). These correlation values were normalized from 0 to 1, and then represented by a RGB colormap with red and blue colors for minimum and maximum values, respectively (Figure 3b). It was considered only 4 dyadic scales that correspond to 0-16Hz. Scales 1 to 4 contain the most relevant features related to epileptiform activity. In counterpart, scales 4 to 8 have no relevant activity on the scalogram. In this way, the wavelet dyadic scalogram has 2,048 pixels (512 samples per 4 dyadic scales). The 2-D wavelet scalogram was converted to a single 1-D vector that was located as input layer of the artificial neural network in order to classify the selected.

The artificial neural network has 10 neurons in the hidden layer and a single neuron in the output layer (binary ANN). All layers used the sigmoid activation function for training phase. This stage includes cross-validation method to avoid under- and overfitting effects. After training stage, a mixed set for tests was created by using a portion of the database (30%) and all the events marked on other database available used in (Boos et al., 2011). This method allows to increase the reliability of this methodology. Finally, the following indicators of performance were calculated: sensitivity, specificity, positive and negative predictive values, system efficiency and the area under the ROC curve (AUC value).

Results

All the experiments were performed and arranged in Table 2. The objective was to determine which is the most suitable wavelet function for detecting the epileptiform activity. First methodology obtained that *db4* had the highest correlation and the minimum RMSE, demonstrating to be the most suitable wavelet function to maintain the epileptiform events reaching 0.717658 of correlation and RMSE value of 36.799 (see Table 2-left). These values were obtained between the epochs of original and filtered event. Other important criterion was to choose the wavelet function with the fewest coefficients and the lowest energy required to compute the wavelet filter. It was obtained that *db4* has fewest coefficients and the lowest energy (48.30%).

Table 2. Left - 10 best wavelet functions for first methodology by calculating the correlation and RMSE (Scolaro et al., 2012); Right - 10 best wavelet functions for second methodology by calculating the efficiency and AUC value.

Wavelet	Results obtained				Wavelet	Results obtained			
	Coeffs	*Energy (%)*	*Correlation*	*RMSE*		*Sensitivity (%)*	*Specificity (%)*	*Efficiency (%)*	*AUC Value*
db4	**8**	**48.30**	**0.717658**	**36.799603**	***bior3.9***	**77.98**	**94.08**	**87.87**	**0.9613**
coif5	30	76.53	0.693210	37.957277	*bior3.7*	78.44	93.51	87.69	0.9605
sym7	14	67.69	0.692088	38.061023	***rbio1.5***	**79.82**	**93.51**	**88.22**	**0.9540**
coif4	24	74.03	0.690788	38.034667	*bior3.5*	73.85	95.53	87.16	0.9578
rbio1.3	6	55.36	0.690375	38.243990	*rbio1.3*	72.48	97.26	87.69	0.9518
db8	16	59.38	0.690320	38.129404	*sym7*	76.61	93.36	86.89	0.9455
sym4	8	59.07	0.682411	38.353757	*bior2.2*	76.83	92.93	86.71	0.9457
coif3	18	70.16	0.679416	38.511218	*coif1*	78.21	92.64	87.07	0.9413
db12	24	65.23	0.675012	*	*sym4*	75.69	94.37	87.16	0.9370
db15	30	67.40	0.673080	38.828296	*bior3.3*	69.72	95.53	85.56	0.9515

*No data.

In counterpart, experiments for testing the second methodology using wavelet dyadic scalograms and artificial neural network are shown in Table 2-right. It was considered both the system efficiency and the AUC as the most important indicators of performance. For this reason, it was calculated the efficiency-AUC product, being chosen *bior3.9* and *rbio1.5* wavelet functions for this methodology, generating 77.98% of sensitivity, 94.08% of specificity, 87.87% of efficiency and AUC value of 0.9613 by using *bior3.9*.

Discussion

Two different but complementary wavelet-based methodologies were described and applied in this work. The wavelet-based techniques have had a great impact in the last decades for solving several problems on analysis of non-stationary signals due to its multiresolution analysis on the frequency or scale variables. First methodology applied a digital filter (wavelet multiresolution analysis) to attenuate non-epileptiform activity such as eye blinks, background activity, and noise in long-term 32 EEG channels. In this way, this filtering process reduces the number of false positives generated by undesired information, improving the performance of system. On the other hand, the second methodology has applied the wavelet transform as feature extraction technique (wavelet scalogram) for further pattern classification (artificial neural networks). The wavelet scalogram allows us to observe more closely the differences between the epileptiform and non-epileptiform activity through the wavelet-based colored maps. Epileptiform activity has a high percentage of energy (in red color) and short-time response which clearly differentiates it from other types of activity. These strong differences between clusters facilitates the identification of patterns by the neural classifier. Furthermore, the use of dyadic scales reduces the data dimensionality, which offers a high simplicity for further hardware implementation.

This work is not intended to compare the results obtained due to the different number of selected events, the evaluated indicators and the way the tests were performed. However, it is possible to demonstrate that, despite using the same set of wavelet functions and EEG database, the choice of the most suitable wavelet function requires a different criterion for each methodology. As demonstrated in the previous section, *daub4* was selected for the first methodology and *bior3.9*, and *rbio1.5* for the second one. In the first methodology, the difference in the indicators obtained is remarkable; however, in the second methodology it was observed that all functions reached very high indicators of performance, which means that all functions listed are capable to detect the electrophysiological triggered paroxysms that appear in epileptic patients.

Most automatic epilepsy detection systems in the literature are focused on epileptic seizures during inter-ictal stages. In (Adeli et al., 2007) was proposed a wavelet-chaos methodology in order to analyze the EEG signal by separating delta, theta, alpha, beta and gamma bands similarly to our first methodology but by evaluating other indicators as the correlation dimension, the largest Lyapunov exponent and its statistical significance for differencing data groups or filtering undesired events. On the other hand, the second methodology can be compared with current classification expert systems as (Liu et al., 2012) that proposed a wavelet-based expert system for intracranial EEG recordings achieving a sensitivity of 94.46%, higher than obtained in this work. However, the intracranial EEG is a very expensive, invasive and impractical method to record the encephalographic activity. In (Haydari et al., 2011) was proposed the combination of genetic algorithms and wavelet transform reaching more than 90% of sensitivity but using very few spikes events for classification which decrease its reliability. Other wavelet-based systems in (Aarabi et al., 2009), (Chua et al., 2011) and (Ayoubian et al., 2013) achieved a sensitivity of 68.9%, 78%, and 72%, respectively, closed to our results (77.98%). Hence, the wavelet dyadic scalogram and artificial neural network proposed here have obtained competitive results in comparison with current expert systems for epilepsy detection.

Both methodologies presented may be highly complementary, unifying their properties into a single system for detecting epileptiform paroxysms. MRA approach would be used as pre-processing stage in order to filter non-epileptiform activity, and then the wavelet dyadic scalogram would be responsible for extracting the desired features like percentages of energy. After that, several pattern classifiers would be explored like artificial neural networks, bayesian classifiers, fuzzy logic and neuro-fuzzy systems, etc. Finally, it would be interesting to test the integrated system in long-term continuous 32 EEG channels as performed in (Scolaro et al., 2012), re-evaluate and compare the new results obtained.

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Erratum

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Where it reads:
"Malaver WJL"

It should be read:
"Lobato WJ"