Study of EEG with Epileptic Activity Using Spectral Analysis and Wavelet Transform

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Abstract: - In this paper we apply some signal processing methods to detect and classify specific patterns present in EEG signal, which give information about the inset of brain disorders, in particular epileptic activity. We analyze EEG signals using spectral analysis methods, namely Short-Time Fourier Transform and Discrete Wavelet Transform, applied to several sets of EEG recordings. The spectrograms and wavelet decompositions and spectra are shown for a few EEG sequences with typical pathological patterns, to prove the possibility of classification based on EEG spectrum.

Key-Words: - EEG analysis, epileptic activity, wavelet transform, spectrogram

1 Introduction

The electroencephalographic (EEG) signal obtained from scalp surface electrodes results as the sum of a large number of potentials originating from neurons located in various regions of the brain. EEG has been intensely studied due to valuable information it provides about normal brain and in the diagnosis of some brain disorders as for instance epileptic activity, seizures and even encephalopathies, dementia and Alzheimer disease [1]. Normally, surface EEG amplitudes are in the range $10-100\mu\text{V}$, while in seizure they can reach even $1000\mu\text{V}$. EEG signals can be analyzed with various signal processing methods, both in time and frequency domains [2]. Brain waves are usually classified into four basic groups: beta (14–30 Hz) is associated with active thinking and attention, alpha (8–13 Hz) is induced by a relaxed state and lack of attention, theta (4–7 Hz) indicates emotional stress, delta (0.1–4 Hz) appears mainly in deep sleep. Although EEG signal is always a superposition of brain waves, one wave will be dominant at a given moment. Morphologically, various shapes of patterns appear in normal EEG or various brain disorders. We can identify waveforms with typical event-type patterns like K complex, V waves, λ-waves, μ- rhythm, spike-wave complex [3]. An efficient analysis tool is the spectrogram, which can be successfully used in EEG pattern classification systems [4]. In recent years, the wavelet transform [5] has also been widely used for EEG analysis, due to its multi-resolution properties [6]-[8]. Some recent and relevant papers approaching the issue of epileptic seizure prediction or detection using various signal processing and machine learning methods are [9]-[12]. A time-domain approach to detect frequencies, frequency couplings, and phases using nonlinear correlation functions for short and sparse time series like EEG was given in [13]. The EEG energy distribution was studied in [14].

The aim of this paper is to make a comparative analysis of these spectral methods applied to epileptic EEG signals, to investigate and compare their feature extraction capabilities, useful in classification systems.

2 Signal Processing Methods for the Analysis of Epileptic Brain Activity

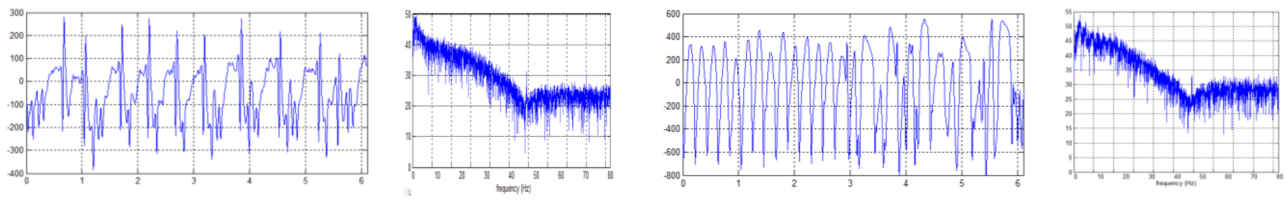
Next we will apply to a set of EEG recordings two efficient signal processing methods, namely Short-Time Fourier Transform (STFT) and Discrete Wavelet Transform (DWT) with multi-resolution signal decomposition and we make a comparative analysis of results from the signal classification point of view. These analyses were performed on a set of EEG signals with various rhythms indicating seizures or epileptiform brain activity, from a publicly available database [15].

2.1 Short Time Fourier Transform. Spectrogram.

For highly non-stationary signals like EEG, a suitable analysis technique is Short-Time Fourier Transform (STFT), which shows the variation of spectral components over time. In the discrete-time version implemented in computer programs, the signal is divided into frames, with a specified degree of overlapping to reduce boundary effects. For each signal frame the discrete Fourier transform is calculated. Mathematically, the discrete-time STFT is formulated as:

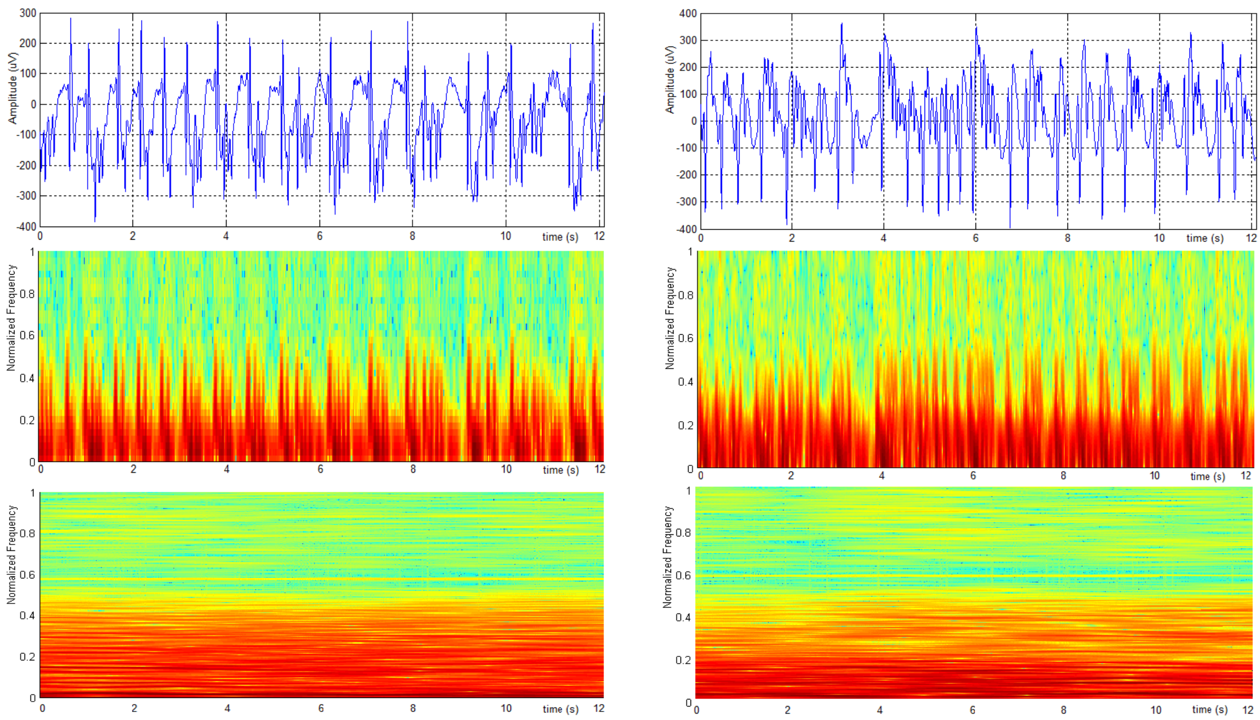
$$\mathrm{STFT}\{s[n]\}(m,\omega) \equiv S(m,\omega) = \sum_{n=-\infty}^{\infty} s[n]\, w[n-m]\, e^{-j\omega n} \qquad (1)$$

where $w[n]$ is the window function, usually a discrete Hann or Gaussian window centered around zero, and $s[n]$ is the sampled signal to be transformed. The squared magnitude $|S(m,\omega)|^2$ of the STFT yields the spectrogram of the signal, which is a surface representation of the frequency spectrum as it varies in time. The spectrogram gives comprehensive information about non-stationary signals like voice, biomedical signals etc., although it has a fixed resolution, unlike the wavelet transform. The analysis window is essential in STFT. If it has a longer duration in time, it corresponds to a narrow band-pass filter in the frequency domain, so it performs a fine sampling on frequency axis; the STFT plot has high resolution details, retaining fine variations in the frequency content of the signal, while rapid changes in time are smoothed away due to averaging. On the contrary, a shorter window preserves rapid variations in time, but fails to detect quick frequency variations. This time-frequency trade-off is known in signal theory as the uncertainty principle. The spectrogram shows time and frequency localization simultaneously, especially for sudden changes of rhythms or shapes occurring in EEG. In Fig.1 two typical epileptiform EEG rhythms, namely spike-wave and μ- rhythm are shown, with their logarithmic power spectrum. As is well known for highly non-stationary signals like EEG, the Fourier Transform (FFT) does not give relevant information about frequency



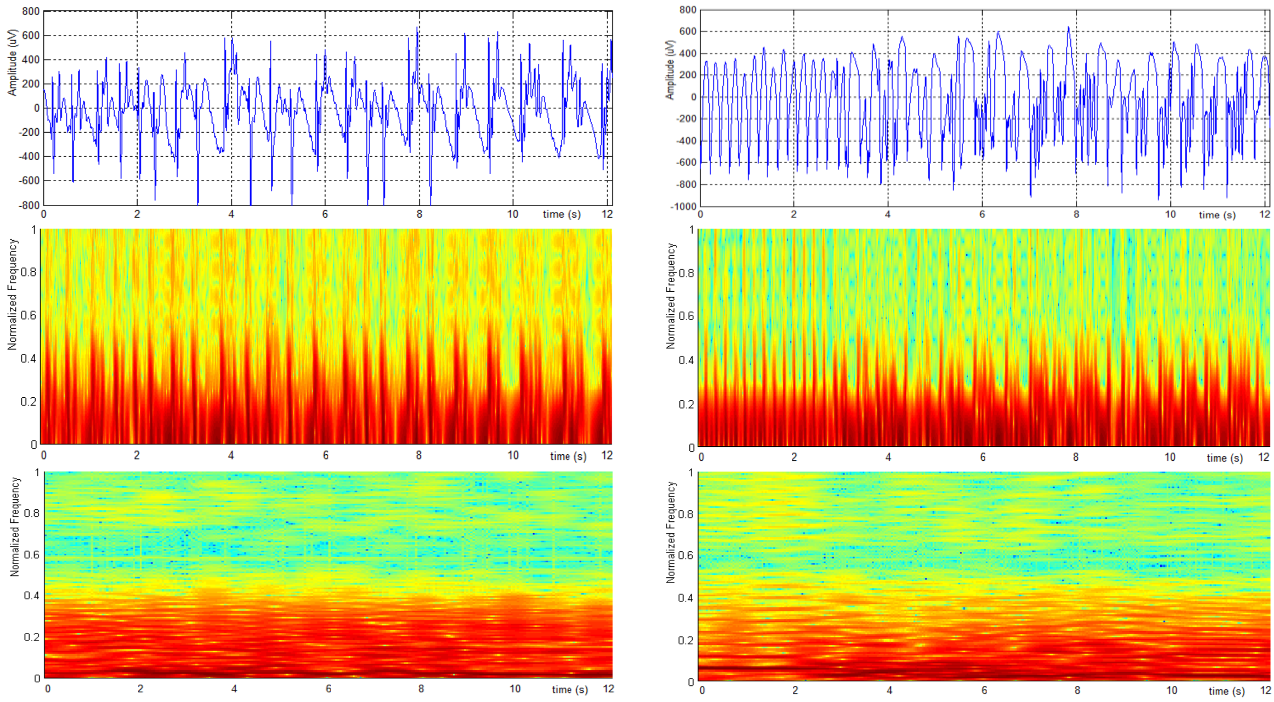
(a) (b)

Fig. 1. Signal sequences and power spectra for EEG with: (a) spike-and-wave complex; (b) μ -wave.



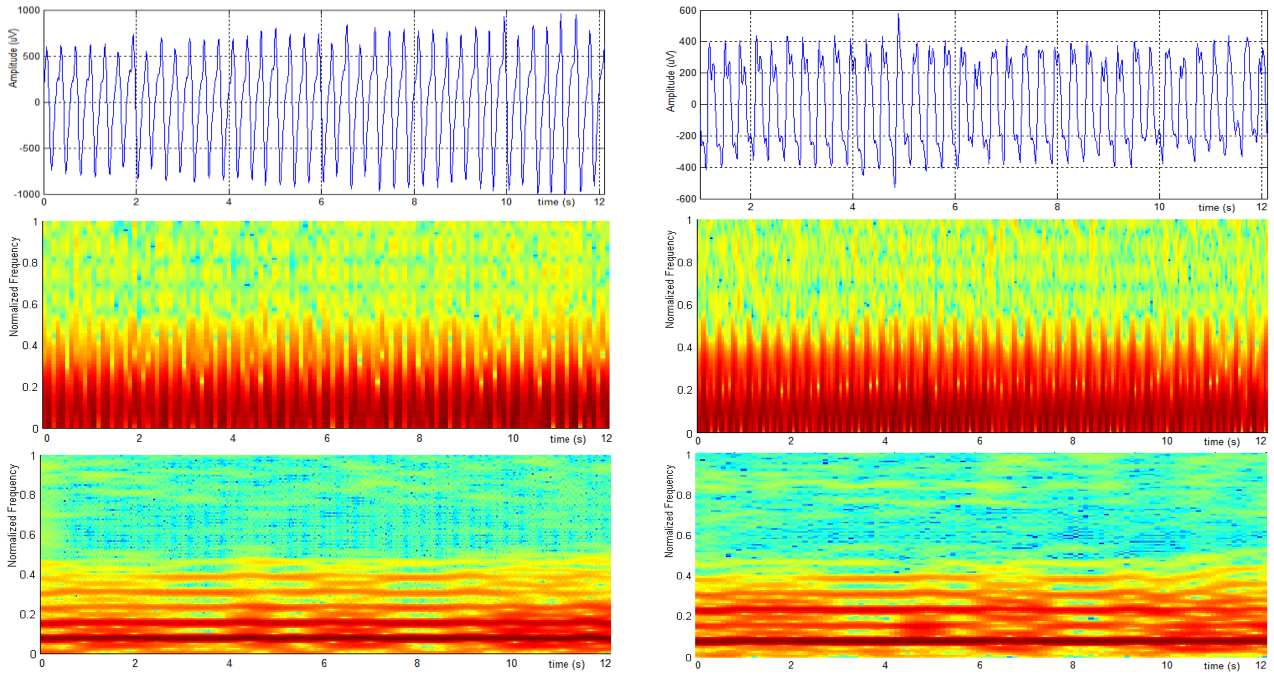
(a) (b)

Fig. 2. Waveforms and spectrograms for EEG with multiple spikes, spike-and-wave complex etc.



(a) (b)

Fig. 3. Waveforms and spectrograms for EEG with spike-and-wave complex, μ - rhythm etc.



(a) (b)

Fig. 4. Waveforms and spectrograms for EEG with simple wave rhythm

localization. Although the two rhythms are visually very distinct, the spectra look practically similar, therefore FFT does not yield any relevant information regarding the brainwave shape.

An EEG spectrogram can be fed as input data into a pattern recognition system [4] and therefore the EEG patterns can be classified based on their spectrograms, interpreted as images.

For each typical epileptic EEG waveform in Fig.2, Fig.3 and Fig.4, two spectrograms are calculated, one with narrow window (16 samples, with a duration of 100 ms), and another one with wide window (256 samples corresponding to a duration of 1.5 s). The spectrograms are displayed synchronized with waveforms, in order to highlight the time localization capability of STFT. When using a narrow window, the spikes or other quick variations in the EEG sequence appear also in the spectrogram at the exact moments of time, while the spectral components are not steady in time.

For instance, in the case of the simple brain wave shown in Fig.4(a), the narrow-window spectrogram resembles the signal itself, whereas the wide-window spectrogram shows steady frequency components (fundamental and 4 harmonics). For the EEG wave in Fig.3(b), with μ-rhythm, the wide-window spectrogram shows in the first 3 seconds a pronounced fundamental and 6-7 harmonics, more or less steady in time. For the rest of the sequence, the μ- rhythm alternates with burst discharges, so spectral lines mix up, becoming indistinguishable. For a relatively regular wave with double peaks as the one shown in Fig.4 (b), the wide-window spectrogram shows a steady fundamental and the third harmonic, while other harmonics are blurred or interrupted. For the sequences in Fig.2 (a), (b) containing successive spike-and-wave complexes, the wide-window spectrogram shows an almost continuous spectrum at lower frequencies with intervals of visible separate lines. There is a steady frequency component at about 0.6 (in normalized values), corresponding to the burst discharge.

2.2 Multi-Resolution Signal Decomposition Using Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is a very useful tool in EEG analysis, as it captures transient features and localizes them accurately both in time and frequency. The continuous wavelet transform of a signal $x(t)$ is given by the following integral, where a and b are the translation and scale parameters, respectively:

$$\mathrm{W}_{\mathrm{x}}^{\psi}(a,b) = a^{-1/2} \cdot \int_{-\infty}^{\infty} x(t)\, \bar{\psi}\left(\frac{t-b}{a}\right) \mathrm{d}t \qquad (2)$$

while $\psi(t)$ is the mother wavelet and $\psi_{a,b}(t)$ is a wavelet basis function. Using MATLAB, we can perform a multilevel decomposition of a given signal and obtain its approximation and details. Fig. 5(a) shows a 3-level wavelet decomposition pyramid, performing multi-resolution analysis. The signal $x[n]$ passes through two complementary (low-pass and high-pass) filters and is decomposed successively, at each level, into a set of approximations (high-scale, low-frequency components) and details (low-scale, high frequency components). The Daubechies orthogonal wavelets [5] are very suitable for EEG analysis. Here we have chosen the Daubechies wavelet of order 8 (db8) as it is smoother and gives sharper frequency resolution. The Daubechies scaling functions and wavelets of order 4 and 8 (db4, db8) are plotted for comparison in Fig.5 (b) and (c). In the 5-level decomposition, the signal S is reconstructed by adding all components (approximation and details), $\mathrm{S} = \mathrm{A}_5 + \mathrm{D}_5 + \mathrm{D}_4 + \mathrm{D}_3 + \mathrm{D}_2 + \mathrm{D}_1$. In Fig. 6, two EEG sequences, simple wave and spike-wave (each of duration 6 sec.), and their 5-level decompositions are shown, using the Daubechies db8 wavelet. The coarse approximation A5 (lowest frequencies) and details D5, D4, D3 (with higher frequencies), along with their spectra (limited to 40 Hz) are given.

The spectra of A5, D5, D4, D3 have their energy concentrated roughly within the frequency bands of main brain rhythms [14]. Thus, components of A5 are within δ- range (1-4 Hz), D5 within θ - range (4-8 Hz), D4 within α - range (8-13 Hz) while D3 falls within β range (14-30 Hz). As can be seen

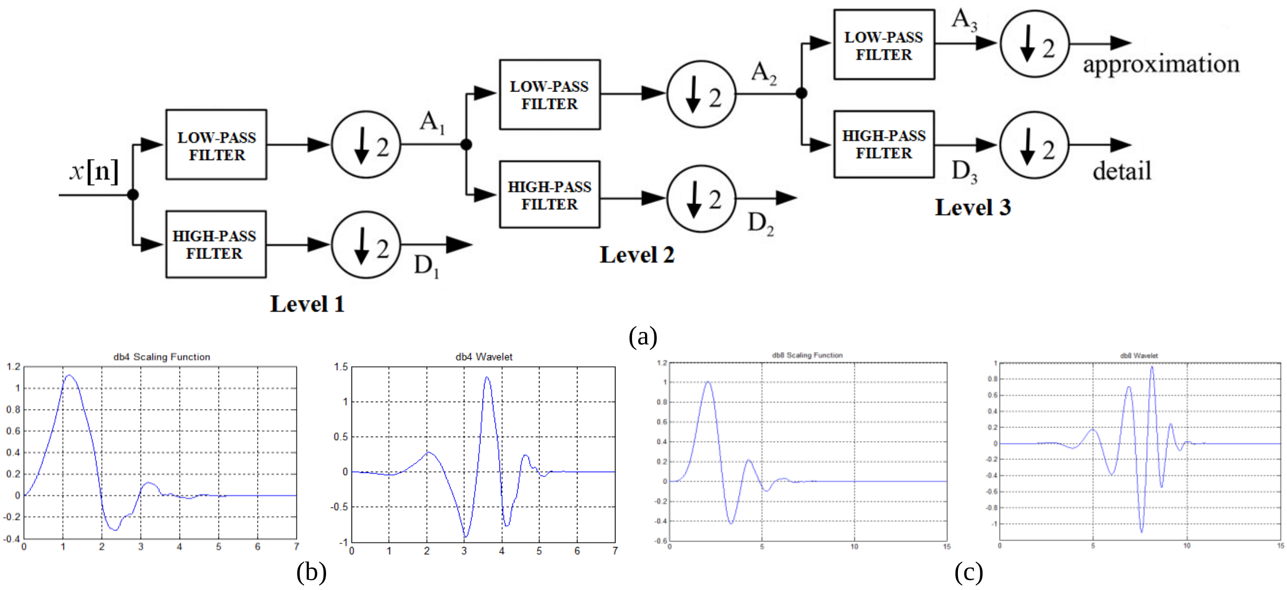


Fig. 5. (a) 3-level decomposition scheme using multiresolution analysis; (b), (c) plots of continuous scaling function and wavelet for Daubechies wavelets db4 and db8

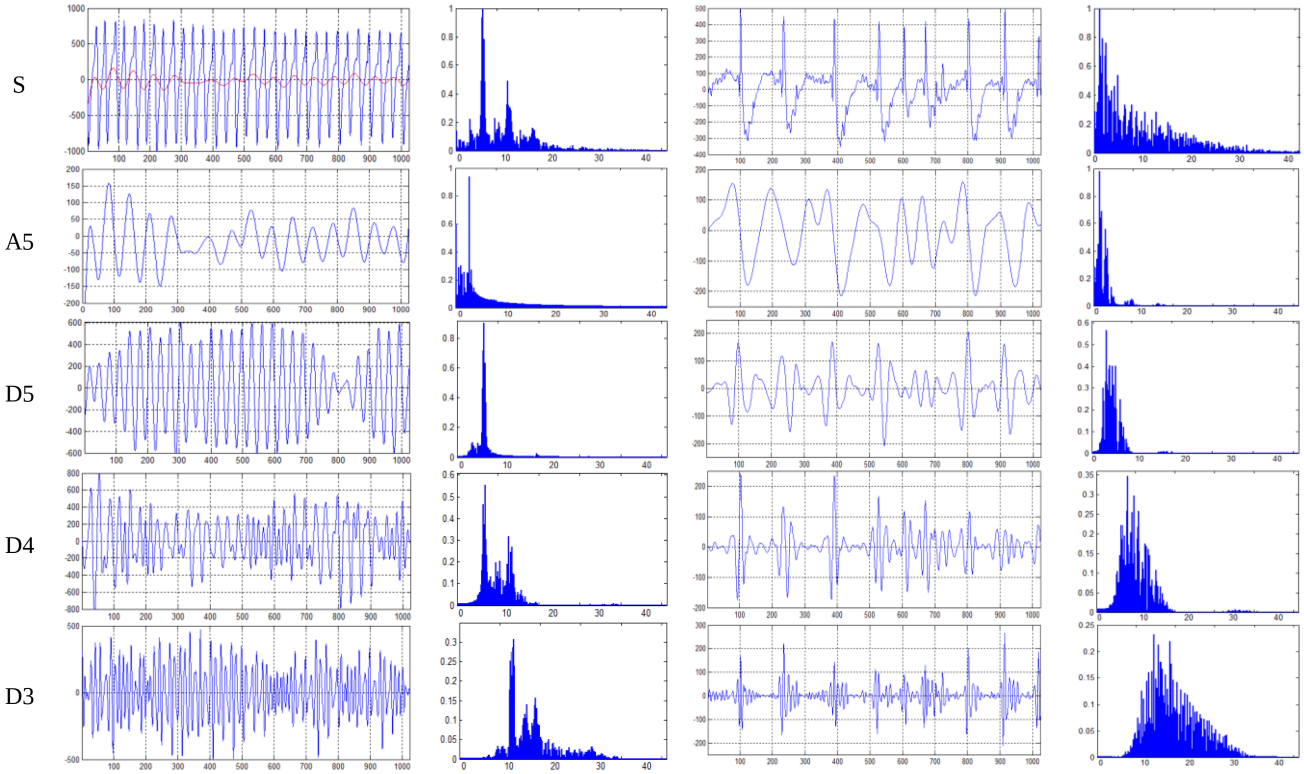


Fig. 6. 5-level decomposition of two epileptic signals: simple wave (left) and spike-wave (right); the amplitude is in μV and time in number of samples; the spectrum horizontal axis is in Hz.

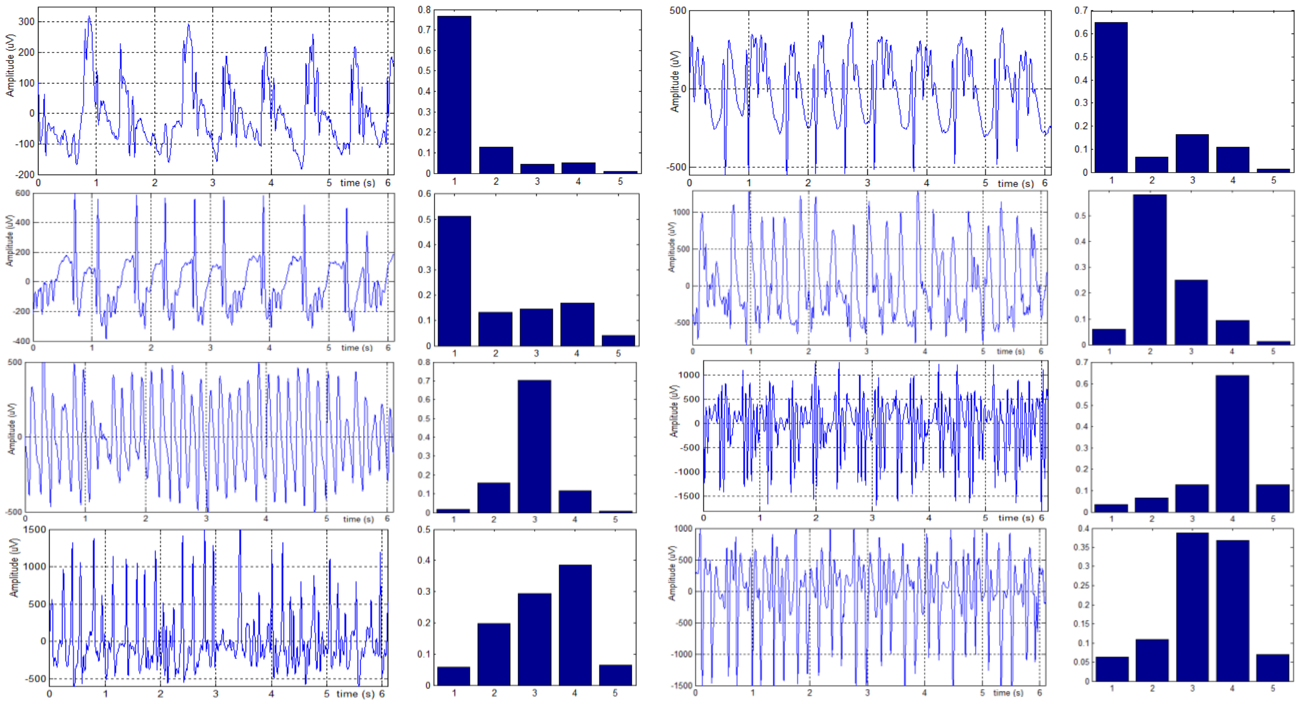


Fig. 7. Typical EEG rhythms and the corresponding relative band energy ratios

from Fig.6, the spectra shapes vary with the particular sequence of EEG signal, but essentially their supports correspond to bandwidths of the main brain waves. The lower level details D2, D1 with higher frequencies are less relevant and are treated as noise, having negligible amplitudes.

For a quantitative analysis, the relative power of a frequency band with respect to the whole spectrum can be computed. In order to evaluate the relative energy of a frequency band we use the Parseval theorem which states that the energy of frequency components in the spectrum is equal to the energy contained in a waveform summed over time; in the discrete case this is expressed as:

$$\sum_{n=1}^{N}|x[n]|^2 = \frac{1}{N}\cdot\sum_{k=1}^{N}|X[k]|^2 \qquad (3)$$

We define the relative energy E_{Bi} of band i with respect to the energy of the whole spectrum E_{SP} as the ratio $R_{SP} = E_{Bi}/E_{SP}$ and is equal according to (3) to the ratio $R_{AN/S} = EA_N/ES$, where $EA_N = \sum_{j=1}^{N}|A_{Nj}|^2$ is the energy of the coefficients of approximation of order N, and $ES = \sum_{j=1}^{N}|S_{Nj}|^2$ is the signal energy (sum of squared samples). We also define the ratio $R_{DN/S} = ED_N/ES$, where $ED_N = \sum_{j=1}^{N}|D_{Nj}|^2$ is the energy of N-order details.

Table 1. Classification of EEG rhythms by the dominant relative energy band

Type of EEG rhythm	Dominant component	$R_{A5/S}$ (%)	$R_{D5/S}$ (%)	$R_{D4/S}$ (%)	$R_{D3/S}$ (%)	$R_{D2/S}$ (%)
Spike-wave complex	A5	**54.7 ± 11.4**	16.5 ± 6.7	15.1 ± 6.7	14.2 ± 4.9	3.3 ± 2.9
μ - rhythm, spikes	D5	14.5 ± 8.7	**42.2 ± 7.2**	29.7 ± 5.6	12.2 ± 5.1	1.4 ± 0.7
Simple wave	D4	7.4 ± 6.9	21.3 ± 7.5	**51.6 ± 9.1**	18.4 ± 7.7	2.1 ± 1.4
High-frequency bursts	D3	9.4 ± 4.2	18.9 ± 6.9	21.3 ± 8.3	**43.4 ± 9.4**	6.7 ± 2.4

Using a function written in MATLAB we have calculated these relative band energy ratios for the set of EEG signals. This analysis shows statistically that a given EEG pattern can be characterized by certain values of the relative band energy ratios, which sum up to 1. Such an energy measure was used in [14] to train a neural network for EEG recognition. Typical EEG epileptical rhythms are shown in Fig.7, with their relative band energy ratios given as bar plots. In the first 3 examples the energy corresponding to approximation A5 is predominant (50-75%), while for the others, the details D5, D4 and D3 may be predominant, indicating more rapid rhythms. On the set of analyzed EEG sequences, it results that the predominant energy corresponds to components as follows: A5 (24%), D5 (15%), D4 (42%) and D3 (19%). These classes roughly contain signals with main rhythms shown in Fig.7. Therefore, energy band plots as those displayed in Fig.7 can be used in classification tasks with pattern recognition systems. Table 1 contains a classification of typical EEG rhythms based on the dominant relative energy band (of the approximation A5 and details D3-D5). The mean and standard deviation of values $R_{A5/S}$ and $R_{Dj/S}$ (j=3, 4, 5) are calculated for each class of EEG rhythms in which one component is dominant (A5, D5, D4 or D3). The values from Table 1 indicate a significantly higher energy band ratio for each dominant component compared to the others.

3 Conclusion

Both the spectrogram and multi-resolution analysis are efficient methods for detecting patterns in epileptic brain activity. The spectrogram contains comprehensive information that can be treated as an image, with image processing techniques. The choice of appropriate window is essential in STFT as it finely tunes the time-frequency trade-off. The spectra of multi-resolution components and their relative band energies can be also used in EEG pattern classification. Two analysis methods were applied to a set of EEG signals with epileptiform patterns, and the typical spectrograms and spectra of multi-level components were highlighted. There is a visible relationship between the EEG rhythm and relative band energy distribution. Both methods approached are valuable analysis tools and can be used in EEG classification, as a very useful complementary aid in clinical diagnosis.

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