Diagnosis of Epilepsy from EEG Signals Using Global Wavelet Power Spectrum

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Abstract— **Epilepsy diagnosis using EEG signals represents important segment in general clinical practice. However, EEG signal features such as amplitude, are not helpful in order to visually distinguish between healthy and epileptic patients; and therefore additional signal processing and results analysis is needed. In this paper, the analyses and the results of the properties of EEG signals of healthy subjects and patients with an epileptic syndrome without seizure, using global wavelet power spectrum (GWS) are presented. The results of the analysis of the 200 EEG signals confirm that this approach can enable a simple recognition of epileptic EEG signals in a standard clinical practice. The results indicate that the magnitudes of the EEG signal components for the patients with an epileptic syndrome are considerably different to the EEG signal components of the healthy subjects. Also, the GWS dominant values for selected signals of patients with an epileptic syndrome are found in the delta and theta frequency bands.**

Keywords— **EEG, Epilepsy, Wavelet transform, Global Wavelet Spectrum.**

I. INTRODUCTION

Epilepsy is one of the most common neurological diseases or disorders, and due to epilepsy characteristics it presents a serious medical and social problem. Epilepsy is a chronic disorder of cortex with varying symptoms and causes [1-2]. Electroencephalographic (EEG) brain observation represents one of the most significant approaches in studying epilepsy, since EEG signals contains huge amount of useful information. However, EEG interpreting is not a simple task, and visual EEG analysis often do not provide for quality conclusions. In the last several years large number of multidisciplinary research teams suggested different methods and approaches addressing: disease development identification [3], fast and accurate EEG signal classification in the context of precise diagnosis [2], [4-9], etc. Number of different algorithms development were facilitated with innovation in mathematical techniques for signal processing as: wavelet transform (WT) [2], [4-9] and Hilbert Huang transform [10-11], and some applications in the context of EEG signal processing can be found in the work of Shayan et al [12].

In this paper, continuous WT (CWT) is applied using the Morlet wavelet function and the Global Wavelet Spectrum (GWS) for analyses of 200 EEG signals: 100 EEG signals of healthy subjects and 100 EEG signals of subjects with an epileptic syndrome without seizure. Generally, the CWT and the wavelet power spectrum provide large number of information at different time-frequency bands. With the aim to determine the temporal variability for individual periodic components, the power spectrum of the WT can be summarized within an interval scale, and summing over the entire analysis period the GWS is obtained, making the use of the GWS very practical and with results providing a lot of useful information [13].

The results presented in this study clearly indicate that the magnitudes or energy values of the EEG signal components of healthy subjects and patients with an epileptic syndrome in different frequency bands are significantly different and that the GWS has a capacity to produce parameters to classify EEG as either healthy or epileptic.

Described work is a continuation of the research presented in the previous papers [14] where power spectrum values of the EEG components were explored using the Discrete WT, and the results confirm conclusions published in 2012 [14]. It is important to note that this study does not include the classification of EEG signals or improvements in so far suggested classifiers available in the literature, which represents an important chapter in the automatic classification of EEG signals in the clinical practice. Also, this paper does not discuss the causes or identification of epilepsy development, which is today perhaps the most important issue in this area.

II. DATA AND APPLIED APPROACH

The data used in this study come from the EEG signal database from the Epilepsy Center in Bonn, Germany, collected by Dr. Ralph Andrzejak (http://epileptologie-bonn.de/) [15]. The database set consists of five 100 single-channels EEG groups of 23.6-second duration at a sampling rate of Fs=173.61 Hz. In the research described in this paper sets A and C were used. Set A presents five healthy subjects with open eyes, while set C presents EEG signals of patients with an epileptic syndrome without seizure. Examples of two EEG signals from the database, Z001 from A set and N001 from C set, are shown in Fig. 1.

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Methodology used in this paper is presented by Torrence and Compo [13]. Following [13], the Morlet wavelet function $\psi_0(\eta)$ is defined as $\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2}$, where ω_0 presents dimensionless frequency and η is dimensionless time.

The CWT of the EEG signal $EEG = \{EEG_n, n = 0, \dots, N-1\}$, which has equal time intervals δ_t, with defined wavelet function $\psi_0(\eta)$ will be calculated as [13]:

$$W(s) = \frac{\delta_t}{\sqrt{s}} \sum_{n=0}^{N-1} EEG_n \, \psi * \left[\frac{(n-m)\delta_t}{s}\right] \quad (1)$$

$m = 0, 1, \dots \quad , N-1.$

where operator '*' represents conjugate complex value, N is the number of points in the time series, and ψ is the wavelet function at scale s and translated in time by m [13].

The local wavelet power spectrum or the squared absolute value of the wavelet transform coefficients is defined as $|W(s)|^2$, while the GWS (time-averaged wavelet spectrum) is defined as [13]:

$$\overline{W}^2(s) = \frac{1}{N} \sum_{n=0}^{N} |W(s)|^2 \quad (2)$$

Practical application and illustration of the methodology described above, using a software tool available at: http://paos.colorado.edu/research/wavelets/ are shown in Fig. 2 where the wavelet power spectrum and the GWS of EEG signal of a healthy subject (Z001 from A set) and the wavelet power spectrum and the GWS of EEG signal of a patient with an epileptic syndrome without seizure (N001 from C set) can be compared.

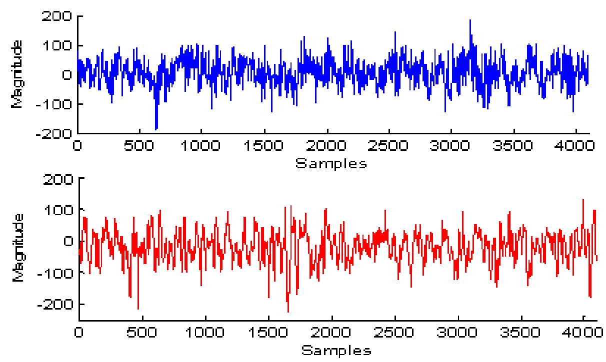

Fig. 1 EEG signal of a healthy subject (Z001 from A set) and EEG signal of a patient with an epileptic syndrome without seizure (N001 from C set)

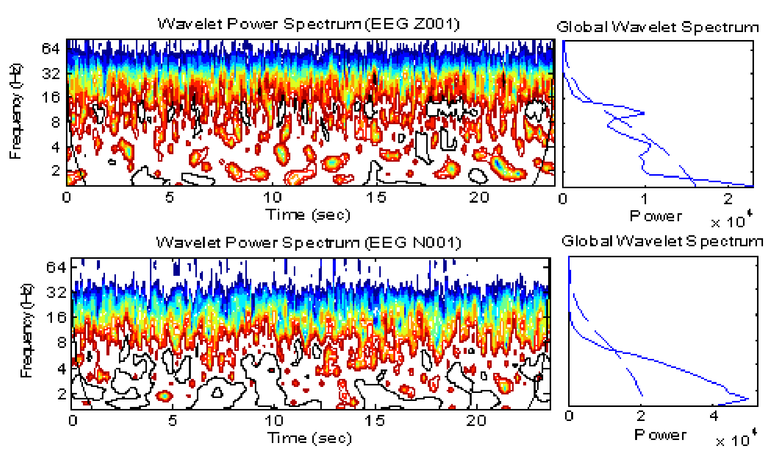

Fig. 2 WPS and GWS of a healthy subject (Z001 from A set) and WPS and GWS of a patient with an epileptic syndrome without seizure (N001 from C set)

The color code in Fig. 2 indicates different Morlet wavelet power spectrum ranges, ranging from blue (low power) to red (high power), adding to the significance of the regions of the analyzed EEG signals. Power presented in the Fig. 2 is in μV^2.

For detailed elaboration of the results from Fig. 2 it is necessary to consider the frequency bands corresponding EEG signal rhythms: *delta* (0–4 Hz), *theta* (4–8 Hz), *alpha* (8–12 Hz), *beta* (13–30 Hz), and *gamma* (30–60 Hz). Insight into the characteristics of EEG rhythms can give a more information about the neuronal activities and thus provide additional valuable information [9]. It is evident from Fig. 2 that the difference in the magnitude of the EEG signal N001 component in the frequency range up to 6 Hz is quite significant compared to the same component of the EEG signal Z001. Also, for the signal Z001 it can be concluded that a component of the EEG signal in the frequency range between 8-16 Hz is quite distinct compared to the same frequency range for the signal N001, which represents the area including alpha waves.

III. RESULTS AND DISCUSSION

This section presents the main results and findings of the analyses performed for the selected EEG data sets, using the previously described methodological approaches. The GWS of healthy and epileptic EEG signals are presented in the Fig. 3. The first 100 GWS results in the Fig. 3 (0-100) are related to the set A or EEG signals of healthy subjects, while second 100 GWS results (100-200) belong to the set C or EEG signals of patients with an epileptic syndrome without seizure.

It is obvious that the GWS results for these two groups are significantly different when comparing the activities of different EEG signals components. For the first 100 EEG signals, one dominant component can be identified around 10Hz, what represents the alpha rhythm. On the other hand, the values of the GWS in the area up to 4 Hz (delta rhythm) are not so dominantly expressed.

However, the GWS results for the EEG signals 100-200 in the Fig. 3, vary significantly compared to the GWS results for the signals 0-100 in the Fig. 3. The GWS values in the alpha frequency range are negligibly small compared to the values in the range of frequencies up to 8 Hz, which is the frequency range of the delta and theta rhythm.

To quantify the difference between the epileptic and healthy EEG signals, the following statistical features have been calculated: mean and mode, for representative frequency bands and the results are presented in Table 1. It is visible from Table 1 that for the epileptic EEG the GWS magnitudes, in delta and theta frequency bands, are high compared to normal EEG.

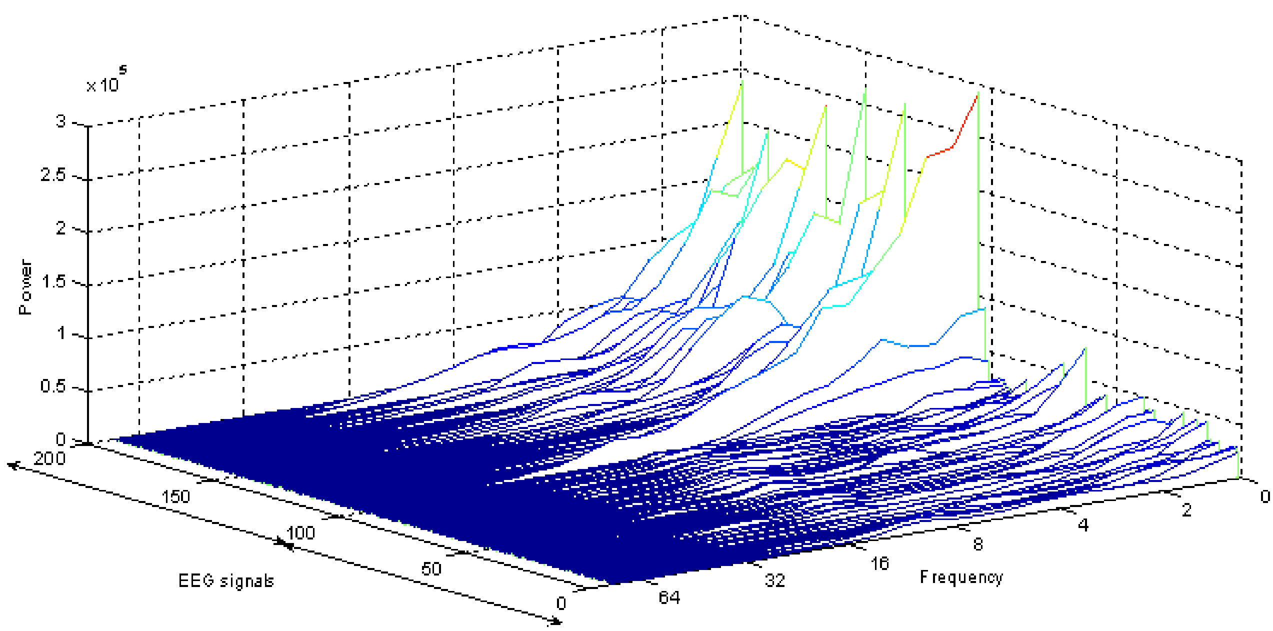

Fig. 3 GWS of 100 signals of healthy subjects and GWS of signals of patients with epileptic syndrome without seizure

It has been shown that the GWS magnitude observed in delta and theta frequency bands has a capacity to indicate the differences between healthy and epileptic EEG.

Table 1 Extracted statistical features for the GWS magnitude

Frequency band	Feature	Set A	Set C
0-4Hz	Mean	16365,55	56530,27
	Mode	9087,43	37182,33
4-8 Hz	Mean	8820,22	31836,87
	Mode	8190,48	9846,57
8-16 Hz	Mean	5923,26	11586,24
	Mode	10609,07	2496,92

Comparing the results for two analyzed sets, it is clear that the GWS provides a clear differentiation between EEG signals of healthy subjects and patients with epilepsy syndrome, and that in clinical practice can facilitate more accurate interpretation of EEG records and diagnosis of epilepsy. Also, as GWS presents a set of values for the specific component of the EEG signal at different frequency ranges, it is quite clear that the GWS values can serve as input data for the automatic classifiers such as neural-network (NN), support vector machines (SVM), etc. The usage of a GWS-NN EEG classifier authors reserve for their future research in this area.

IV. CONCLUSIONS

In this paper the CWT and the GWS approach is applied to 200 EEG signals of healthy subjects (100 EEG signals) and of epilepsy patients (100 EEG signals). Results presented demonstrate different activities in the specific EEG signal components for these two different groups. The GWS presentation of the EEG signal enables excellent observation of activities within the specific components, and clear distinction between the analyzed groups. Additionally, the proposed approach needs relatively small data set, and when combined with a classification algorithm, is suitable for development of a simple EEG classifier.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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