Time-frequency analysis of epileptic EEG patterns by means of empirical modes and wavelets

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ABSTRACT

In this paper we perform a time-frequency analysis of epileptic EEG patterns based on two approaches for characterizing nonstationary multi-frequency signals, namely, the continuous wavelet transform (CWT) and the empirical mode decomposition (EMD). Possibilities and limitations of both these techniques are considered, and a combined approach for automatic pattern detection is proposed.

Keywords: Wavelet analysis, empirical modes, electroencephalogram, oscillatory patterns, recognition

1. INTRODUCTION

Nowadays different interdisciplinary problems are of a great interest, and special methods for analysis and diagnostics the behavior of complex oscillatory systems are widely used in many fields of natural science including medicine and physiology.[1] These methods are effective, e.g., for analysis of brain activity in different states because the brain itself is a complex oscillatory network with a huge number of elements (neurons) that demonstrates complex dynamics.[1]

A widely used source of information about the brain activity in neurophysiological studies is the electroencephalogram (EEG).[2] EEG is an averaged sum of electric currents, generated by groups of neurons nearby to the recording electrode. Several frequency ranges are traditionally considered for EEG signal such as alpha, beta, gamma rhythms, etc.). There is a strong correlation between the nature of rhythmic activity in EEG in a specific frequency range (i.e. the presence of a rhythm or an oscillatory pattern[3,4]) and the functional state of the organism.[1,2] Thus, studying of specific rhythmic components becomes important especially in the case of disorders of the central nervous system because certain EEG patterns may be treated as biological markers of the disorder.

Among the most important types of oscillatory activity in EEG signal occurring during sleep, the sleep spindles should be mentioned, i.e., short (0.5-1.5 s) episodes of oscillations with the frequencies of 10-16 Hz and characteristic spindle shape.[5] Sleep spindles are formed due to the synchronous activity of neural network that consists of cortex and thalamus neurons. The interest in studying sleep spindles is caused by their possible connection with the absence epilepsy.[6] Neural network that normally generates sleep spindles can produce seizure activity under certain conditions (i.e., spike wave discharges).[7] Spike wave discharges serve as diagnostic markers of the absence epilepsy, and their occurence in EEG is accompanied by characteristic clinical manifestations. There is a relationship between neurophysiological mechanisms of spike wave discharges and sleep spindles, however, this relationship is complex and not obvious.

The problem of studying brain activity is closely connected with analysis of complex signals. At present, many effective methods to study nonstationary signals are developed. The most advanced and perspective methods are the empirical mode decomposition[8] and the continuous wavelet transform.[9,10] In this work we perform time-frequency analysis of epileptic EEG patterns (sleep spindles and spike wave discharges) and propose an effective method for EEG analysis.

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2. METHODS

2.1 EEG Data

When studying absence epilepsy, a convenient animal model is mainly used, namely, the WAG/Rij rats. WAG/Rij is a special line of rats with genetic predisposition to absence epilepsy.[11] Evolving of absence epilepsy in WAG/Rij rats is almost guaranteed and takes a certain period of time (about 3 month) which makes these rats candidates for studying absence epilepsy and the process of its development. Studying of rat EEG instead of human EEG has few features such as easier conditions for data gathering and the possibility for implantation of recording electrodes directly into the brain structures for better EEG resolution and long term monitoring. At the same time results obtained for rat EEG can be extended to human EEG without serious problems.[11]

In the present work we studied EEG signals of five WAG/Rij rats with fully developed absence epilepsy. These recordings are long-term and include episodes with different oscillatory patterns: sleep spindles, spike wave discharges, artifacts of different nature, background activity, so such recordings can be used for studying of specific oscillatory patterns and for testing new methods for EEG analysis. Besides, these EEG recordings are multichannel and contain information about electrical activity in different areas of the rat brain. Our research is aimed at studying sleep spindles and spike wave discharges; the frontal cortex channel provides the best images of these patterns so it was chosen for all investigations in this work. All experimental work with EEG recordings was done by experienced neurophysiologists from the Moscow Institute of Higher Nervous Activity and Neurophysiology.

2.2 Empirical Mode Decomposition

As the first method for EEG analysis we considered the empirical mode decomposition (EMD)[8] being one of the current techniques for complex signal analysis that provides decomposing of a signal into a sum of simpler components being the amplitude- and the frequency-modulated zero mean modes. The main feature of EMD is that we get a set of empirical modes with proper frequency bands: the first mode has the highest frequency, and the latter becomes lower with the growing number of the mode. It is expected that different modes are associated with different oscillatory patterns in EEG signal.

EMD is effective tool for analysis of amplitude modulated (but not phase modulated) signals. Thus, for signal with a linear growth of the frequency (a linear chirp)

$$x(t) = Asin[(\omega_0 + \omega_1 t)t] \tag{1}$$

EMD shows a single empirical mode while the classical Fourier analysis detects a full set of frequencies. Since EEG is a signal with sufficient amplitude modulation (along with the phase modulation), we can expect that EMD will be useful in studying the EEG structure. We propose a new method for analysis of oscillatory patterns in EEG. The idea of the method is the possibility to detect different oscillatory patterns using different empirical modes.

Algorithm of the proposed method includes:

- applying EMD approach to a given EEG signal;
- estimation of energy for empirical mode;
- comparison of EM energy with a threshold value.

If the energy exceeds some threshold value, the method detects an oscillatory pattern at the current time moment. This method provides basic information about time-frequency structure of EEG and detects oscillatory patterns, therefore, it can be used for express-analysis of EEG. However, further modernizations of the method seems to be useful in practice.

2.3 Wavelet-based Method

Another method used in our research was the continuous wavelet transform (CWT).[9,10] CWT is one of the most effective methods for analysis of complex signals of different nature. The main feature of CWT is the possibility to investigate different frequency components in nonstationary signals unlike classical data processing tools. For example, in signal with a switching of frequency

$$x(t) = [1 - H(t)]sin(\omega_1 t) + H(t)sin(\omega_2 t)\,, \tag{2}$$

where H is the Heaviside step function, the classical Fourier spectrum shows the presence of two frequency components but it does not provide information about time moment when each component exists. CWT gives 3D spectra with high time-frequency resolution, so it is useful in studying different oscillatory patterns on EEG. Another field of use of CWT is the construction of 2D sections of initial 3D CWT surface at some time moment. These sections represent momentary distributions of the CWT energy and can be used for analysis of frequency structure of EEG oscillatory patterns.

Within the performed research we decided to improve the EMD-based method for analysis of EEG oscillatory patterns by combining it with CWT. The general idea was to perform a preliminary analysis of EEG using EMD and to choose empirical modes associated with the studied oscillatory patterns and then to investigate time-frequency structure and features of these patterns with CWT. We tested a combined EMD-CWT method for automatic EEG diagnostics and detection of sleep spindles and spike wave discharges based on the results of previous researches.[12,13]

Algorithm of this method includes the following steps:

- applying EMD to EEG signal;
- applying CWT to extracted empirical mode; estimation of distribution of the CWT instantaneous energy;
- averaging the instantaneous CWT energy through characteristic frequency range;
- averaging of the CWT energy through characteristic time interval;
- comparison of CWT energy with a threshold value.

At the first step of this algorithm, we apply EMD to a recorded EEG signal and then we choose the best empirical mode, i.e. the mode that contains main information about the studied oscillatory patterns. According to our estimations (see Sec. 3), the first empirical mode is the most appropriate for sleep spindles, while the second mode is more preferable for spike wave discharges. Thus, the first step of the algorithm provides basic filtration of EEG signal from some artifacts and from other oscillatory patterns that are not of the interest.

At the second step, we apply CWT to the selected empirical mode and estimate distribution of the instantaneous energy

$$W(s,\tau) = \int\limits_{-\infty}^{+\infty} x(t)\psi^*_{s,\tau}(t)\; dt \tag{3}$$

In our study we used CWT with the Morlet mother wavelet

$$\varphi_0(\eta) = \pi^{-1/4} e^{j\omega_0 \eta} e^{-\eta/2}. \tag{4}$$

According to works,[14,15] the Morlet-wavelet is one of the most appropriate functions in the analysis of complex experimental signals of biological nature (including EEG) because of its high time-frequency resolution.

The third step is the core step of the algorithm; it includes averaging of the instantaneous energy through specific frequency range

$$w(t) = \int\limits_F W(f_s, t)\, df_s\,, \quad F_{SS} \in (10; 16)\,, \quad F_{SWD} \in (30; 80). \tag{5}$$

This frequency range depends on the type of the considered oscillatory pattern. Here, we used the frequency range 10-16 Hz for sleep spindles and 30-80 Hz for spike wave discharges.[3,4]

The latter two steps of the algorithm provide averaged distribution of the CWT energy that can be analyzed for detection of oscillatory patterns in EEG. Since EEG is a complex experimental signal, additional steps should be considered in order to algorithm to improve the precision of pattern detection.

Due to experimental nature of EEG signal, it can be very noisy. The most interfering artifacts include sharp bursts of energy with wide frequency range that can cause errors in detection of oscillatory patterns on EEG such as false detection. These bursts are, however, quite brief, so at the step four of the algorithm we perform an additional averaging of CWT energy through specific time interval

$$\langle w(t) \rangle = \frac{1}{T} \int_T |w(t)| dt \tag{6}$$

This time interval usually corresponds to the averaged length of oscillatory pattern; it is about 1 sec for sleep spindles of WAG/Rij rats and about 5 sec for spike wave discharges.

EEG signal is a result of electrical activity of neural network with a huge number of oscillatory elements (neurons) characterized by very complex time-frequency dynamics.[16] Such dynamics may cause different errors in detection if we analyze CWT energy by simple comparing it with some threshold value.

Aiming to improve the precision of pattern detection we proposed to use a "floating" threshold. On the step five of the algorithm we sequentially compare the value of the averaged CWT energy for every time moment with a threshold value. Oscillatory pattern is detected in some time moment if the condition $w > w_{cr}$ is satisfied; after that the threshold value of CWT energy is reduced by 40% for consequent time moments in order to smooth over the influence of complex time-frequency dynamics in EEG. Detection procedure is further performed with new threshold value $w'_{cr} = 0.4w_{cr}$ while the condition $w > w'_{cr}$ is true. If the condition is false, the detection stops and the initial threshold value is restored. Threshold values for CWT energy were experimentally defined according to the value of the averaged CWT energy of sleep spindles and spike wave discharges.

3. RESULTS

In the present research, EEG analysis starts with the EMD method. We studied brief episodes of EEG with specific oscillatory patterns: sleep spindles and spike-wave discharges. Examples of such EEG episodes, the corresponding empirical modes and distributions of the CWT instantaneous energy are illustrated in Figs. 1, 2.

By analyzing empirical modes and distributions of CWT energy for sleep spindles (Fig. 1), we can see that the first empirical mode (Fig. 1b) extracts mainly frequencies in the range 10-16 Hz which corresponds to sleep spindles, while other oscillatory patterns including low-frequency spindle-like oscillations[16] are filtered. These oscillations have a spindle-like form and length but lower frequency (5-9 Hz) and often lead to errors for different methods in detecting spindles. Spindle-like patterns with other low-frequency artifacts are mainly relate to the second empirical mode associated with the frequency range of 5-10 Hz (Fig. 1c). The last two empirical modes (Fig. 1d,e) mostly consist of oscillations with the frequencies 0-5 Hz related to the background EEG activity carrying no useful information.

Analogous EMD analysis was performed for spike-wave discharges (Fig. 2). The first empirical mode (Fig. 2b) includes frequencies corresponding to the second and the third harmonics of SWD's main frequency (so-called spikes). The second empirical mode includes the first harmonic (so-called waves) (Fig. 2c). As in the case of sleep spindles, the last two empirical modes (Fig. 2d,e) consist of slow oscillations which are related to the background EEG activity. According to the obtained results we can say that EMD method allows us extracting specific oscillatory patterns with help of different empirical modes; extraction of sleep spindles on WAG/Rij EEG with the first empirical mode and spike wave discharges with the second empirical mode is especially effective. This feature was used in developing the method for automatic detection of oscillatory patterns on EEG (see Sec. 2). This method was tested for detection of sleep spindles and spike wave discharges in EEG (Fig. 3).

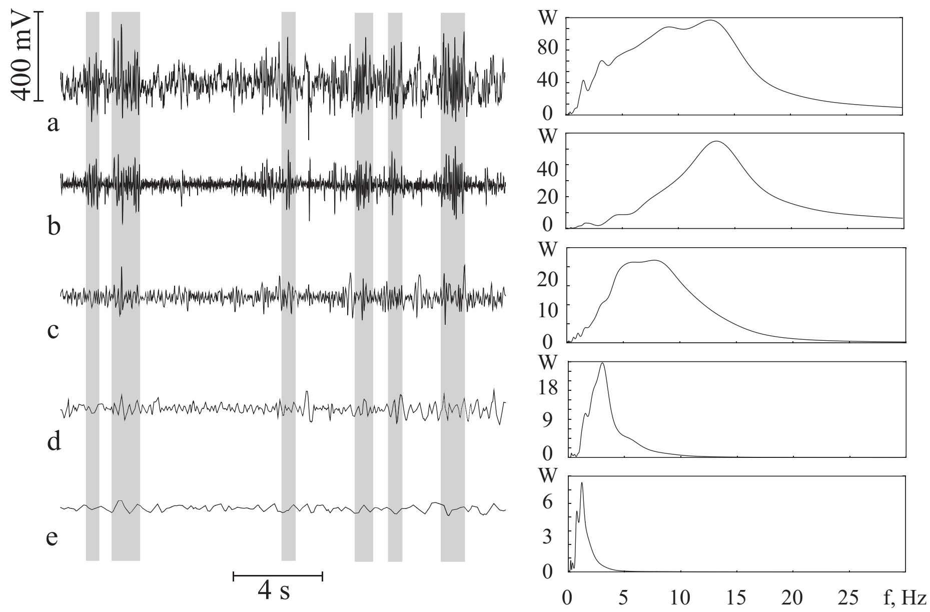

Figure 1. EMD analysis of sleep spindles. Initial EEG signal (a), and the empirical modes 1-4 (b-e)

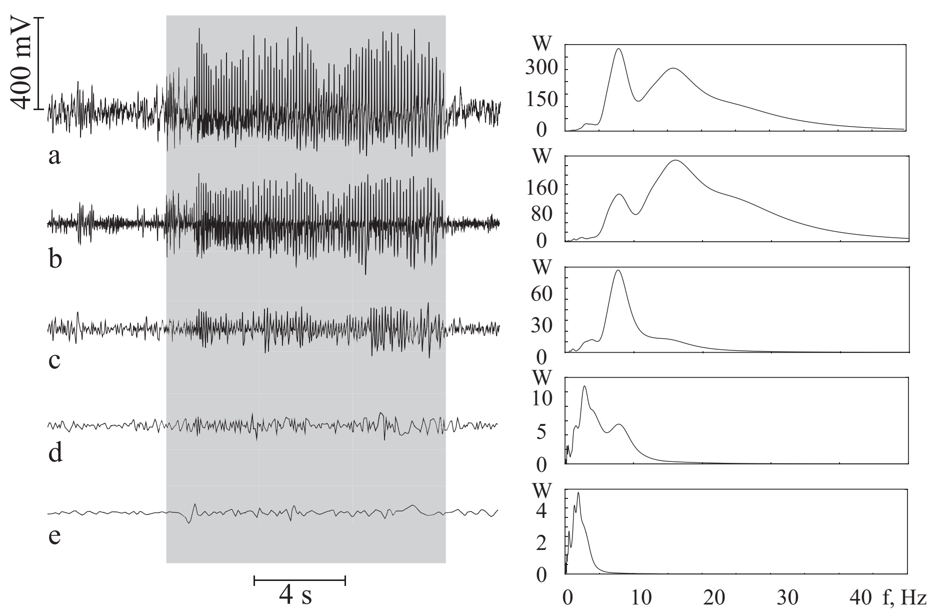

Figure 2. EMD analysis of SWD. Initial EEG signal (a), and the empirical modes 1-4 (b-e)

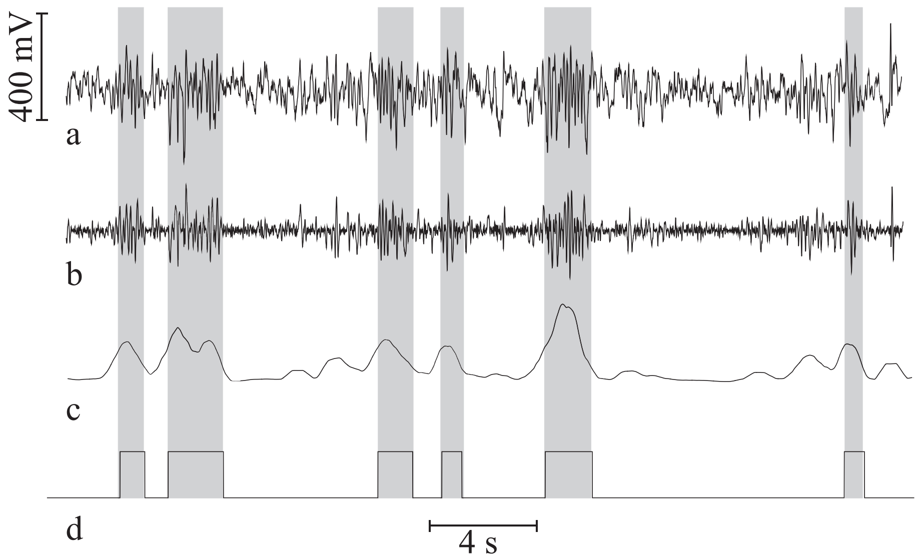

Figure 3. Method for automatic detection of sleep spindles. EEG signal (a), empirical mode (b), empirical mode energy (c), and marking of the method (d)

Fig. 3a demonstrates an example of EEG time series with sleep spindles used for analysis. Applying of EMD to initial EEG signal results in the first empirical mode illustrated in Fig. 3b. As we can see from this Figure, EMD provides a partial filtering of the signal from different non-spindle patterns. An important part of the method is estimation and analysis of empirical mode energy that is illustrated on Fig. 3c. Energy distribution seems to be quite jagged with peaks corresponding to high-energy patterns (i.e sleep spindles). This distribution is analyzed by comparing with a threshold value and fragments above this threshold are classified as sleep spindles (Fig. 3c). Thus, the method provides appropriate marking of sleep spindles in EEG (Fig. 3e). However, as we can see from Fig. 3e, some sleep spindles are missed certifying that the precision of the method should be improved. That circumstance limits the method's applicability in express-analysis. This method needs to be modified to reveal features in time-frequency structure of EEG.

CWT-analysis performed in our previous works[15,16] for detection of sleep spindles and spike wave discharges showed good precision and adaptability. At the same time it required serious computational capability for CWT energy estimations at the analysis of long-term EEG series.

Analysis performed in the given work was based on the advanced method for detecting oscillatory patterns in EEG. We applied the method to long-term EEG series in order to perform marking of sleep spindles. An example of detection of sleep spindles detection is illustrated in Fig. 4: Figure 4a includes an episode of EEG series with few sleep spindles. As within the previously described method, EMD was applied to EEG signal in order to obtain the first empirical mode and to provide a preliminary EEG filtration (Fig. 4b). A difference from the original method consists in applying of CWT to the first empirical mode. Then distribution of CWT energy was averaged through a specific frequency range and a time interval. As we can see from Fig. 4c, the averaged distribution of CWT energy has some differences from the distribution of signal energy (Fig. 3c). Distribution of CWT energy is much smoother due to consequent averaging procedures, and sleep spindles are more evident in the case of CWT energy (in other words, the difference between averaged energy levels of sleep spindles and the background activity is more significant). Both of these features essentially increase detection ability of the method. The obtained marking for sleep spindles is illustrated in Fig. 4d along with the analogous marking performed by an expert-neurophysiologist (Fig. 4e).

We analyzed EEG with different methods for detection of sleep spindles and spike wave discharges and compared some statistical characteristics of methods. The statistical characteristics used in this study were the

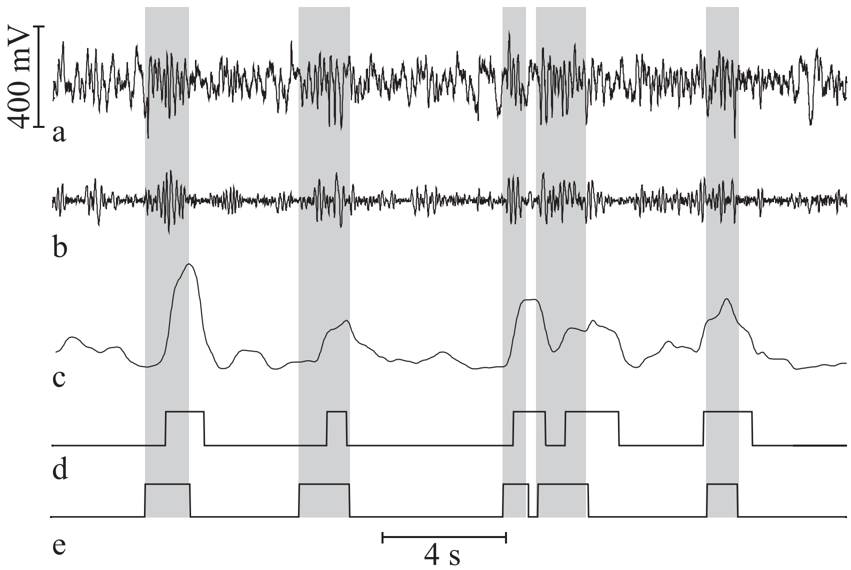

Figure 4. The combined EMD-CWT method for automatic detection of sleep spindles. EEG signal (a), empirical mode (b), CWT energy (c), marking of the method (d), and marking of an expert (e)

significance level δ and the power criterion β:

$$\delta = \frac{N_{TP}}{N_{TP} + N_{FN}} 100\%, \quad \beta = \frac{N_{TP}}{N_{TP} + N_{FP}} 100\%, \tag{7}$$

where N_{TP} is the number of correctly recognized events, N_{FP} is the number of falsely recognized events (events recognized by the method, but not recognized by an expert), N_{FN} is the number of missed events.

The significance level δ estimates the sensitivity of the method (the percentage of recognized patterns from all sleep spindles in EEG), and the power criterion β refers to the percentage of events that are correctly recognized as spindles/spike-wave discharges from all event recognized as sleep spindles/spike-wave discharges.

4. CONCLUSIONS

In the given work, EEG analysis was performed by means of the empirical mode decomposition and the continuous wavelet transform, and modifications of methods for EEG analysis were proposed.

After comparing statistical characteristics for different methods we can discuss their performances. Statistical results show that the EM-based method has lower characteristics than CWT-based method (averaged values of δ and β are 74% and 78% for EM as compared with 80% and 81% for CWT). The latter can be explained by simpler algorithm of EM-method: time-frequency analysis is represented by only decomposition of the initial signal into few empirical modes while CWT-method provides more informative 3D energy surface. However, estimation of CWT energy requires several times larger computing time (especially for long-term EEG series). EM-method with its fast performance can be treated as an appropriate instrument for express-analysis of experimental EEG signals.

Statistical results also show that the combined method has the highest precision among the discussed approaches (averaged values of δ and β are 85% and 91%). Such results are achieved by combining the EM express-analysis with a more detailed CWT analysis. EM-part of the combined algorithm is quite fast, and the CWT-part is almost the same as in the initial method. Thus, the combined approach provides a better precision with similar duration of the performed estimations. In our opinion, this approach represents a promising tool for studying features of time-frequency structure of EEG and for effective pattern detection.

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