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Automatic Extraction and Analysis of Oscillatory Patterns on Nonstationary EEG Signals by Means of Wavelet Transform and the Empirical Modes Method

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Abstract—The time-frequency structure and dynamics of oscillatory patterns in electroencephalograms of rats is studied by means of continuous wavelet transform and the decomposition of the signal by empirical modes. A method for the automatic selection of patterns using the empirical modes is developed. The method is applied to the study of sleep spindles, and it is shown that their dynamics depends on the regularities of on—off intermittency.

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INTRODUCTION

There are a great number of effective radiophysical methods for analyzing and diagnosing the behavior of complex oscillatory systems. These are widely used in different fields of natural science in studying and diagnosing many systems, including those found in medicine and physiology [1–3]. The application of these methods in analyzing the rhythmic activity of the brain is particularly relevant. This activity is a result of the synchronized operation of a large number of neurons that make up the complex oscillating network of the brain [1].

Electroencephalograms (EEGs) are traditionally used in neurophysiological studies to analyze brain activities [4]. An EEG is the average sum of the currents generated by the group of neurons in the area of the recording electrode. Several frequency bands (alpha, beta, gamma, etc.) are can usually be distinguished in an EEG signal. It has been proven that there is a clear correlation between the nature of the rhythmic activity in an EEG in a specific frequency range (due to the presence of a rhythm or oscillatory pattern) and the functional state of the body [1, 4]. An important aspect of investigating the nervous system is thus the study of certain oscillatory patterns, along with the regularities of their appearance in EEGs in different states of the organism.

One type of oscillatory activity in an EEG, which manifests itself during sleep, is sleep spindles, i.e., short (0.5–1.5 s) episodes of oscillations with frequencies of 10–16 Hz and a characteristic spindle shape [5]. It is known that sleep spindles are formed due to the synchronous operation of the neural network that consists of the cortex and the thalamus neurons.

The interest in studying sleep spindles is due to their possible connection with epilepsy. [6] It is known that the neural network that normally generates sleep spindles can, under certain conditions, produce seizure activity (i.e., spike wave discharges) [7]. Spike wave discharges serve as a diagnostic sign of absence epilepsy, and their presence in an EEG is accompanied by characteristic clinical manifestations. There is a relationship between the neurophysiological mechanisms of spike-wave discharges and sleep spindles, but it is complex and far from obvious.

The aim of this work was to study the time-frequency dynamics of sleep spindles (oscillatory patterns) in the EEGs of rats with a genetic predisposition to absence epilepsy (the WAG/Rij line). Both traditional wavelet analysis [8] and a new method for decomposing signals into empirical modes (the Hilbert—Huang transform) [9, 10] were used in our analysis of EEGs.

EXPERIMENTAL DATA AND TIME-FREQUENCY EEG ANALYSIS

We used EEG records for the cortex and thalamus of six adult WAG/Rij rats. Recording was continuous over 24 hours and thus contains fragments of sleep with strong sleepy spindles and fragments of wakefulness. EEG signals were prefiltered in the range of 0.5–100 Hz. Our experimental work was performed at the Institute of Higher Nervous Activity and Neurophysiology of the Russian Academy of Sciences.

Continuous wavelet transform (CWT) [8] was used for the initial study of EEG signals. As applied to our

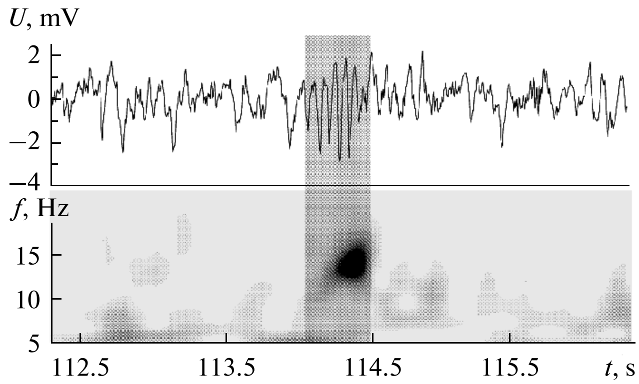

Fig. 1. Typical example of an EEG signal $U(t)$ and the wavelet spectrum for a sleep spindle (shown in gray) with the characteristic frequency increase.

problem, CWT involves convolution of the EEG signal, $x(t)$, and the set of basic functions $\varphi_{s,\tau}$,

$$W(s,\tau) = \int_{-\infty}^{\infty} x(t)\varphi^*_{s,\tau}(t)dt, \quad \varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\varphi_0\left(\frac{t-\tau}{s}\right), \quad (1)$$

where s is the time scale that determines the expansion or contraction of the parent function, τ is the time shift of the wavelet transform, and $\varphi_0(\eta)$ is the mother wavelet. The Morlet mother wavelet was used in this work,

$$\psi_0(\eta) = \pi^{-1/4}e^{j\omega_0\eta}e^{-\eta^2/2}, \quad (2)$$

since, as was shown in [11, 12], it is the optimum basis for the time-frequency representation of EEG signals.

The short (~10–20 s) intervals of EEGs containing the investigated patterns (sleep spindles) were subjected to CWT. A typical example of the wavelet spectrum of a sleep spindle on an EEG is shown in Fig. 1. Table 1 summarizes the average characteristics that reflect changes in the frequency content of sleep spindles, i.e., the average duration, the start and end base oscillation frequencies, the medium frequency (the most powerful in the wavelet spectrum), and the change in the oscillation frequency. Data are shown for all six experimental animals. The results presented in Table 1 and Fig. 1 reveal the complex dynamics of frequency during a sleep spindle despite its short duration (3–4 periods of oscillations). The general tendency is a rise in oscillation frequency by the end of the oscillatory pattern.

Another method for the time-frequency analysis of nonstationary signals is decomposition in empirical modes (EMs), which presents the signal as a sum of amplitude-modulated components (modes) with a zero mean [9].

Let us consider in detail the procedure for the decomposition of EM signals. In the signal interval $x(t)$ between two consecutive extremes (e.g., between two minima in the signal at time t_- and t_+) a local high frequency (HF) component $\{d(t),\ t_- \le t \le t_+\}$ can be formally introduced. In a similar fashion, we can formally introduce the low-frequency (LF) component $m(t)$ as $m(t) = x(t) - d(t)$. Signal $x(t)$ in the interval $t_- \le t \le t_+$ is thus the sum of HF $d(t)$ and LF $m(t)$ components. Repeating the procedure n times for the low-frequency component, the signal can be decomposed into a set of modes.

The EM method involves the following procedure for the decomposition of LF and HF components (empirical modes) from a signal

(1) Finding all the extrema of the signal $x(t)$.

(2) Interpolation of the signal between minima (maxima) and the plotting of the envelope $e_{min}(t)$ ($e_{max}(t)$).

(3) Calculating the average LF component $m(t) = (e_{min}(t) + e_{max}(t))/2$.

(4) Extracting of the HF component $d(t) = x(t) - m(t)$.

(5) Repeating steps 1– 4 for the LF part of the signal $m(t)$. In step 1, the signal $x(t)$ must be used together with $m(t)$.

Features of the time-frequency dynamics of EEG oscillations of WAG/Rij line rats during sleep spindle patterns determined by continuous wavelet transform

Rat Number	Duration of sleep spindle, s	Frequency, Hz			
		at the start of the spindle	at the end of the spindle	average	change in frequency
1	1.17 ± 0.65	8.81 ± 1.78	10.78 ± 2.49	9.78 ± 2.14	1.96 ± 2.31
2	0.51 ± 0.14	10.86 ± 1.86	12.01 ± 2.40	11.44 ± 2.13	1.15 ± 1.70
3	0.58 ± 0.19	9.32 ± 1.92	10.21 ± 1.96	9.77 ± 1.94	0.88 ± 1.01
4	0.44 ± 0.26	11.15 ± 2.07	11.40 ± 2.01	11.28 ± 2.04	0.25 ± 1.97
5	0.44 ± 0.11	11.26 ± 2.88	12.03 ± 2.60	11.65 ± 2.74	0.76 ± 1.95
6	0.38 ± 0.08	10.26 ± 1.63	11.12 ± 2.11	10.69 ± 1.87	0.86 ± 2.11

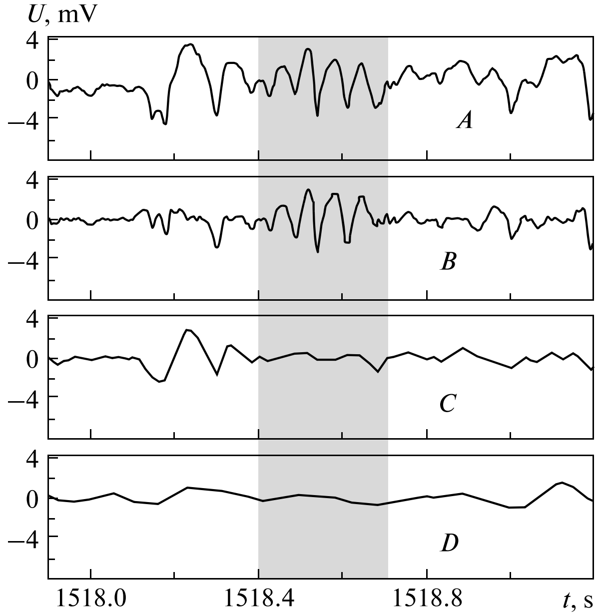

Fig. 2. (*A*) EEG segment with a sleep spindle and (*B–D*) its first three empirical modes.

The first empirical mode $d_1(t)$ will obviously be the one with the highest frequency, and the frequency increases along with the number of the mode, so the highest empirical modes $d_n(t)$ $(n > 1)$ will be low frequency. The average value of each of the empirical modes is zero.

In this paper, the EM method was applied to the EEG. EGG intervals containing sleep spindles were analyzed. These sleep spindles were used previously in the CWT procedure. Figure 2 shows a typical result from analyzing of a segment of an EEG with a sleep spindle (shown in gray) by means of EM. Analysis of the figure shows clearly that the first empirical mode contains a pattern of sleep spindles, while the areas of the background EEG in the signal $d_1(t)$ have a much lower amplitude that is close to zero. Analysis shows that the spectrum of the first mode is almost identical to the spectrum of the sleep spindle. The second, third, and subsequent modes describe LF components that are always present in the EEG signal. The EM method thus provides an opportunity to conduct the local decomposition of the signal by dividing it into separate components (modes) with characteristic frequencies that are located in descending order of the base frequency.

AUTOMATIC EXTRACTION OF SLEEP SPINDLES BASED ON THE EMPIRICAL MODE METHOD

The problem of the automatic marking of oscillatory patterns in the EEG is very real and attracts the attention of researchers [12–14]. Decomposing an EEG signal into EMs enables us to effectively extract

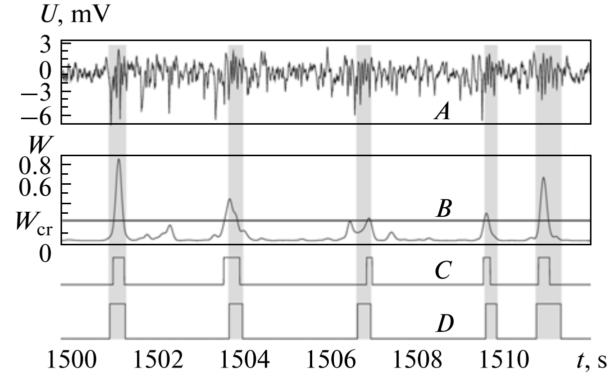

Fig. 3. (*A*) EEG segment, (*B*) average energy $|W(t, f)$ of WCT in the frequency range of 9–16 Hz, and (*C*) the results from automatic marking, i.e., the marking of sleep spindles, along with (*D*) a comparison with expert markings. The time of the occurrence of sleep spindles in the EEG signal is shown in gray.

sleep spindles in the first empirical mode. This property was used to develop a system for the automatic extraction of sleep spindles.

The heart of the method, which is based on results of [12, 15], is as follows. Instead of an EEG, we analyzed the first empirical mode, for which the CWT procedure was performed and the average values were calculated from the typical frequency range F_s of the energy values $W(t)$

$$W(t) = \int_{F_s} |W(f_s, t)|^2 df_s. \tag{3}$$

The extraction of sleep spindles was conducted in the frequency range of 10–16 Hz. If the average energy of $W(t)$ exceeded the experimentally determined threshold W_{cr} (see [8]), it was concluded that there was a sleep spindle in the signal at the given time.

The method was applied to 24-hour EEGs (an example of the method is shown in Fig. 3). The resulting printout was compared to the expert markings made by a neurophysiologist. It was shown that the proposed method has a high degree of accuracy exceeding that of the method based solely on CWT [12].

The automatic marking data obtained by the above method served as our source material for studying the dynamics of the emergence of oscillatory patterns in the EEG. For this a statistical analysis of the time intervals L between successive sleep spindles in the EEG was performed and statistical distributions of time intervals by the duration of $N(L)$ were obtained [16].

The obtained distributions were tested for conformity to the power law $N(L) = \beta L^{\alpha}$. In this case, an important role was played by the value of the parameter α, since $\alpha = -1.5$ corresponds to a system with on-off intermittency [17]. In the course of our study, standard error ε between the experimentally obtained distributions $N(L)$ was calculated with different step values ΔL and theoretical power laws. The value of α was exhaustively sought for each experimental animal by ΔL in order to minimize the mean square error ε. It was found that the error was minimal for $\Delta L \approx 5$ s, for which $\alpha = -1.5$.

A similar result was obtained for spike wave discharges in [16], suggesting that the temporal dynamics of spike-wave discharges and sleep spindles obeys the same laws and can be described by the on–off intermittency theory, confirming the existence of a connection between them.

CONCLUSIONS

We performed a time–frequency analysis of oscillatory patterns (sleep spindles) in EEGs by means of continuous wavelet analysis and the method of empirical modes. A method for the automatic identification of the investigated patterns in an EEG was developed on the basis of decomposing a signal into empirical modes, its subsequent wavelet transform, and analyzing the energy in its characteristic frequency bands. Analysis of the results obtained via the automatic extraction of sleep spindles from an EEG confirmed that the temporal dynamics of sleep spindles is subject to the laws on–off intermittency.

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