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Time–Frequency Analysis of Characteristic Patterns of the Activity of Neuron Ensembles in the Brain by Means of Continuous Wavelet Transform

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Abstract—The time–frequency characteristics of sleep spindles on EEG are studied by means of continuous wavelet transforms. Age dependence and dependence on epileptic status of animals of these characteristics was studied, the on–off intermittency in behavior of sleep spindles was found.

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INTRODUCTION

Researchers are currently interested in different interdisciplinary problems, particularly at the junction between radiophysics and physiology [1–3]. Studies of the brain's rhythmic activity, which is a consequence of the synchronous operation of the enormous numbers of neuron oscillatory elements that make up the brain's complex oscillatory network, are of special interest [1].

Electroencephalograph (EEG) signals are traditionally the main source of information on brain activity in neurophysiological studies [4]. EEGs are the averaged sum of currents generated by the group of neurons in area of recording electrode. It is common practice to delineate several ranges (e.g., alpha, beta, gamma) in an EEG signal. It has been shown that in a certain range, there is a precise correlation between the character of rhythmic activity in an EEG (i.e., a certain rhythm or oscillatory pattern [5]) and the functional state of an organism [1, 4]. The study of certain oscillatory patterns, their time–frequency structure, and the patterns of their emergence on EEGs in the different states of a living organism is thus an important task. This is especially relevant in studying the different pathologies of nervous systems, since some oscillatory patterns can in this case act as diagnostic signs of one illness or another.

Sleep spindles are one type of oscillatory EEG activity that interest researchers. Sleep spindles are short (duration, 0.5–1.3 s) oscillatory episodes of 10–16 Hz frequency that arise in the deep sleep phase in characteristic spindle-like shapes [6]. The interest in studying sleep spindles is motivated by their possible link with absence epilepsy [7]. It is known that under certain conditions, the neuron network that normally generates sleep spindles can trigger epileptic activity (spike-wave discharges) [8]. Spike-wave discharges are diagnostic signs of absence epilepsy, and their presence on EEGs is accompanied by characteristic clinical manifestations. There is a link between the neurophysiological mechanisms of spike-wave discharges and sleep spindles, though at present it appears to be complicated and is far from clear.

The aim of this work was to study the time–frequency characteristics of specific oscillatory patterns (sleep spindles) on EEGs. In studies of absence epilepsy, an effective animal model exists: the special WAG/Rij line of rats with hereditary predisposition to absence seizures. Epilepsy develops in the overwhelming majority of animals from this line; in addition, epilepsy develops in a certain age range (from 5 to 9 months), making WAG/Rij rats appropriate objects for studying absence seizures and their progress. The study of rat instead of human EEGs offers a number of advantages: among these are simpler conditions for experimental control and long-term data collection, and the possibility of implanting recording electrodes directly into brain structures to improve the quality of EEG recording. At the same time, the results obtained in studying rat EEGs can be extrapolated to human EEGs quite easily.

ANALYTICAL APPROACH

In this study, the EEGs of six WAG/Rij rats at three different ages were used: without developed epilepsy (5 months), with developing epilepsy (7 months), and with fully developed epilepsy (9 months). All EEG records were of 24 h duration and contained different oscillatory patterns: sleep spindles, spike-wave discharges, artifacts of different origin, and background activity, making these records appropriate objects of study. The EEG signals were preliminarily filtered in the range of 0.5–100 Hz, since it contains all of the main informative patterns. All of the experimental work on recording EEGs was done by expert neurophysiologists from the Institute of Higher Nervous Activity and Physiology, Russian Academy of Sciences (Moscow).

It should be noted that EEGs are complex experimental signals with such features as nonstationarity, the presence of different oscillatory patterns, the need to analyze short temporal series, and high levels of noise. These limitations do not allow us to use classical methods for analyzing EEGs (e.g., Fourier analysis); instead, other methods are required that are suited for the analysis and filtration of nonstationary signals under conditions with short temporal series.

The problem of studying brain activity is thus closely associated with the analysis of complex signals, a traditional part of the field of radio physics and nonlinear dynamics. Many effective radiophysical methods for analyzing the behavior of complex oscillatory systems have now been developed. Continuous wavelet analysis in particular is one of the most advanced and promising methods [9].

The continuous wavelet transform (CWT) was used for the initial study of EEG signals [9]. In this application, it is a convolution of an EEG signal $x(t)$ and a set of basis functions $\varphi_{s,\tau}$:

$$W(s,\tau) = \int_{-\infty}^{\infty} x(t)\varphi^{*}_{s,\tau}(t)dt. \quad (1)$$

Any basis function $\varphi_{s,\tau}$ can be obtained from its so-called parent wavelet using the transform

$$\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\varphi_0\left(\frac{t-\tau}{s}\right), \quad (2)$$

where s is the temporal scale that determines expansion and compression of the parent function; τ is the temporal shift of the wavelet transform; and $\varphi_0(\eta)$ is the parent wavelet.

In practice, many types of parent wavelets can be used, depending on the given task. In this work, we used the Morlet parent wavelet,

$$\Psi_0(\eta) = \pi^{-1/4}e^{j\omega_0\eta}e^{-\eta^2/2}, \quad (3)$$

since it is the best basis for a time–frequency representation of an EEG signal, as was shown in [10,11].

At the first stage of our research, short (~10–20 s) fragments of EEGs containing sleep spindles were subjected to CWT. In the course of our study, we constructed the surfaces of wavelet energy and instant distributions of the energy of wavelet transform for different moments of time in a sleep spindle. The construction of so-called skeletons is, however, the most intuitive method: the instant distribution of CWT must be constructed for each moment in time; the one point corresponding to the most powerful frequency at

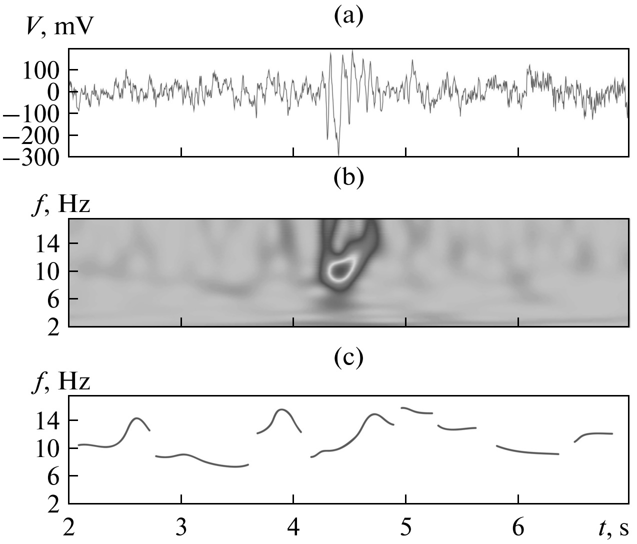

Fig. 1. Analysis of the time–frequency structure of EEGs: (a) fragment of an EEG with a sleep spindle, (b) surface of wavelet energy, (c) skeleton of wavelet surface.

a given moment in time is selected from the distribution. As a result, a two-dimensional distribution is obtained that gives us a clear idea of the duration of the sleep spindle and the composition of its frequency. An example of such analysis is presented in Fig. 1, where a short segment of an EEG with (a) a sleep spindle, (b) its wavelet spectrum $|W(t,f)|$, and (c) its skeleton are shown.

We analyzed 30 sleep spindles with continuous wavelet transform for every examined animal to estimate the main parameters of the spindles. As a result of our analysis, we obtained the main averaged characteristics for changes in the frequency composition of the sleep spindles for each experimental animal: average duration, initial and final base frequencies of oscillations, average frequency (the most powerful one in a wavelet's spectrum), and changes in the frequency of oscillations.

The average duration of a sleep spindle varied from 0.4 to 1.2 s, depending on the animal subject. The average frequencies laid within the range of 8 to 14 Hz, allowing us to determine the range of frequencies for sleep spindles more accurately. It was also noticed that the initial, final, and average oscillation frequencies for a certain sleep spindle generally fell into three large subranges: 810, 1012, and 1214 Hz. On the basis of this observation, sleep spindles were divided into three types: slow (810 Hz), rapid (1214 Hz), and transitional (1012 Hz). In addition, we managed to reveal the complex behavior of frequency during a sleep spindle, despite its brief duration (see Fig. 1b). The average change in frequency was around +1.5 Hz for all of the experimental animals. A rise in frequency by the end of the pattern in sleep spindles is thus a common tendency that distinguishes them from most other oscilla-

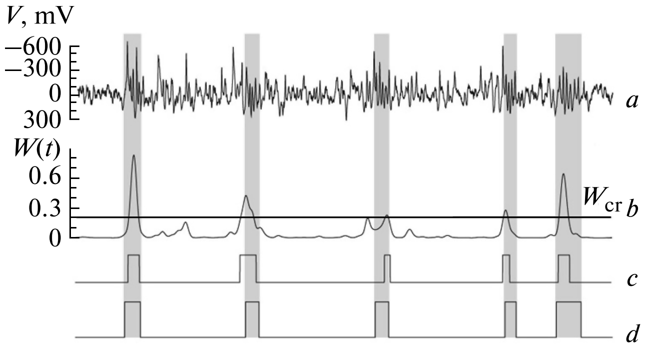

Fig. 2. Automatic isolation of sleep spindles on EEGs: (*a*) EEG fragment, (*b*) averaged energy $W(t)$ of CWT in the range of 8–14 Hz. Results from automatic marking: (*c*) marking of sleep spindles, and (*d*) comparison to expert marking. Moments at which sleep spindles appear in the EEG signals are shown in grey.

tory patterns on EEGs, in which the frequency falls by the end of a pattern (e.g., in spike-wave discharges).

In the next stage of our study, EEG records for rats of different ages (5,7, and 9 months) and different stages of the development of absence epilepsy (the so-called epileptic status, estimated from the number of epileptic seizures per a certain characteristic time interval) were studied. As a result of our analysis, the main characteristics from which structural changes in sleep spindles can be estimated were obtained for every age and epileptic status of the animals: the share of each type of spindle in the total number of spindles, the average duration of a spindle, the average frequency of oscillation, and the changes in frequency during a sleep spindle. The resulting data allowed us to detect the structural changes that appear in sleep spindles with the aging of an animal and the development of the disease.

RESULTS AND DISCUSSION

It was found that the duration of all types of spindles diminished with age and the development of epilepsy: from 0.6 to 0.4 s for rapid spindles; from 0.4 to 0.3 s for slow spindles; and from 0.5 to 0.3 s for transitional spindles. The shares of rapid and slow spindles were around 50% and 30%, respectively; with age and the development of epilepsy, these values remained virtually the same. In contrast, the share of transitional spindles fell from 25% to 17% with age and the development of epilepsy. In addition, it should be noted that the tendency toward an increase in frequency by the end of spindle remains in rapid and slow sleep spindles. Transitional spindles start to exhibit an tendency toward a drop in frequency by the end of a pattern, which is atypical of sleep spindles. The rise in frequency is thus around +2.3 Hz at the age of 5 months; it then becomes less intense but is still positive (+2 Hz) at the age of 7 months. By the age of 9 months, the rise in frequency is replaced by a drop in frequency (–0.7 Hz). Such behavior with a drop in frequency by the end of a pattern is also characteristic of spike-wave discharges. The results from this analysis allow us to suggest there is a deep relationship between sleep spindles and absence epilepsy.

The resulting data on the time–frequency composition of sleep spindles allowed us to develop an effective method for the automatic detection of sleep spindles on EEG records that was based on the continuous wavelet transform. The method, which was based on the results in [11,12], was as follows: CWT was performed for a number of EEGs, and energies $W(t)$, averaged over characteristic range of frequencies F_s, was calculated:

$$W(s,\tau) = \int_{F_s} |W(f_s,t)|^2 df_s. \qquad (4)$$

Sleep spindles were isolated in the frequency range of 8–14 Hz. We concluded a sleep spindle was present in a segment when experimentally determined threshold W_{cr} was exceeded by energy $W(t)$ at a specific moment in time.

Figure 2 illustrates how the method works. It shows (*a*) a short EEG segment with several typical sleep spindles; (*b*) the averaged CWT energy $W(t)$, calculated in following the method's algorithm; (*c*) the results from using the method (the marking of sleep spindles); and (*d*) a comparison of our markings and ones made by an expert neurophysiologist and taken as our standard. As we can see from Figs. 2*c* and 2*d*, the method is highly accurate and can be used for the automatic marking of continuous EEG records.

The above method was used to devise the automatic marking of sleep spindles on 24 h EEG recordings of all 6 experimental animals, and this marking was used as source material for studying the behavior of the emergence of oscillatory patterns on EEGs. To accomplish this, we performed a statistical analysis of time intervals L between successive sleep spindles on the EEGs and obtained the statistical distributions of time intervals according to duration $N(L)$ [13].

The obtained distributions were checked against power law $N(L) = \beta L^{\alpha}$. In the present case, the value of power α played an important role, since $\alpha = -1.5$ corresponded to a system with on–off intermittency [14]. In the course of our research, we calculated mean square error ε between experimentally obtained distributions $N(L)$ with different values of spacing ΔL and the theoretical power law. We sought the value of power α for every animal subject by enumerating ΔL to minimize mean square error ε.

It was found that the error was minimal for time spacing $\Delta L \approx 5$ s with the corresponding power $\alpha = -1.5$. Figure 3 shows the experimental distributions $N(L)$ for all six of the studied animals (dots). The theoretical distribution $N(L) = \beta L^{-3/2}$ is also constructed for the sake of comparison. As can be seen from Fig. 3, the

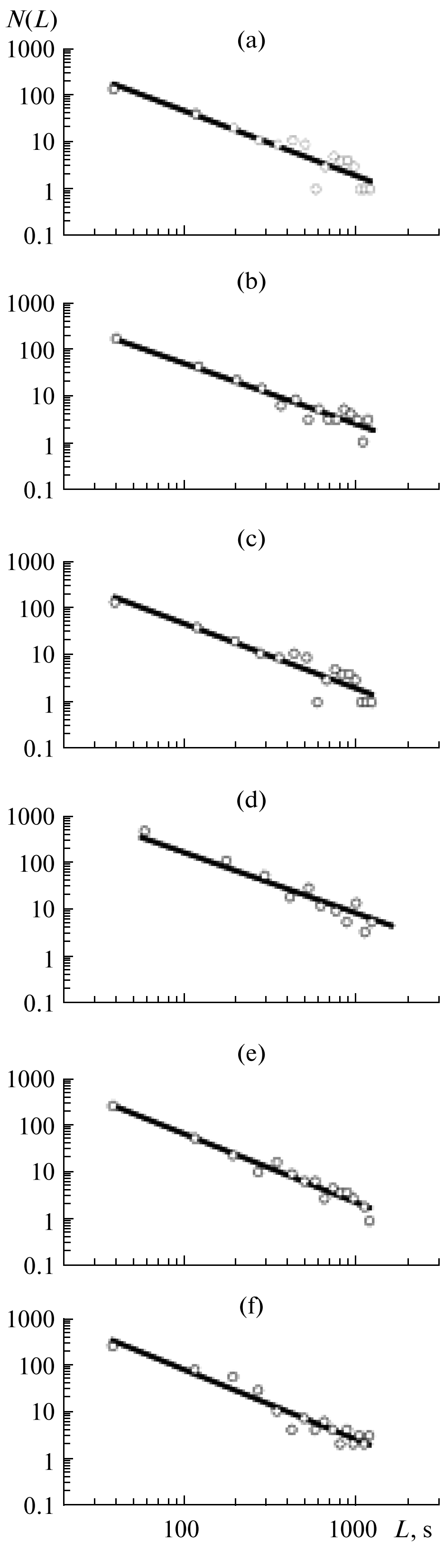

Fig. 3. Emergence of oscillatory patterns on EEGs: statistical duration distributions of time intervals $N(L)$ for sleep spindles in six experimental animals (EA).

experimental distribution conforms to the theoretical one with a fairly high degree of accuracy when $L \approx 5$ s.

A similar result was obtained in [13] for spike-wave discharges, allowing us to conclude that the temporal behavior of spike-wave discharges and sleep spindles conforms to common patterns and is described by on–off intermittency theory, confirming the link between them.

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