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Detection of rapid eye movement sleep period in EEG signals using wavelet modifications

© M.O. Zhuravlev, A.E. Runnova, A.P. Kiselev, A.A. Orlova, M.V. Agaltsov, O.M. Drapkina

National Medical Research Center for Therapy and Preventive Medicine, Moscow, Russia
E-mail: zhuravlevmo@gmail.com

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The aim of the present research was to examine the electrical activity of the brain on polysomnographic recordings using a new approach of oscillatory wavelet patterns. This study has shown that EEG signals recorded in the REM stage of sleep have specific oscillatory characteristics in the band 20−40 Hz, which make it possible to statistically reliably distinguish this stage of sleep both from other stages of sleep and from wakefulness.

Keywords: continuous wavelet analysis, polysomnography, sleep stages.

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Biomedicine is one of the key areas of application of novel nonlinear dynamics techniques. Specifically, automation and avoidance of subjectivity of the clinical assessment of sleep of patients are currently regarded among the long-range goals of application of such methods. A complete scientific understanding of the role of sleep in normal functioning of a human organism and preservation of cognitive abilities is still lacking. The fundamental and clinical study of sleep is made difficult by the complexity of staging and analysis of polysomnographic recordings (PSGRs; in essence, overnight recordings of a complex of biomedical signals). Somnologists still routinely perform visual analysis of PSGRs in accordance with official standards [1–3]. This analysis takes quite some time and makes such studies rather costly. In addition, the PSGR interpretation becomes subjective and strongly dependent on the proficiency of the expert. The introduction of new analysis techniques should help automate the process of sleep staging and thus make the analysis more ergonomic, reduce the expenditure of human labor, and make the results of somnology studies less subjective.

A considerable number of papers focused on the construction of automated PSGR staging systems have already been published. Various fractal methods and their modifications for electroencephalogram (EEG) analysis [4,5], nonlinear dynamics techniques [6,7], and artificial neural networks (including multilayer ones with simultaneous use of EEGs, electromyograms (EMGs), and electrooculograms (EOGs) [8]) serve as the mathematical basis for such studies. However, expert reviews of the obtained results of automated staging in routine clinical testing still reveal them to be largely incorrect [9,10].

The detection and identification of clear EEG markers differentiating between stage 1 of non-rapid eye movement sleep (N1), rapid eye movement sleep (REM), and wakefulness is one of the subproblems that need to be solved in order to create a versatile automated marking system for polysomnographic recordings [11,12]. Additional EOG and EMG signals are currently used to differentiate between these stages [13]. This complicates the process of PSGR analysis and makes it infeasible to construct portable devices for sleep structure monitoring based on EEG signals only.

In the present study, we examine the possibility of application of a new method for analysis of frequency patterns [14] for identification of clear distinctions between stage N1, REM sleep, and wakefulness on EEG recordings made in overnight monitoring. The frequency pattern method, which is based on the continuous wavelet transform, is distinct in its capacity to reveal fine distinctions between bioelectric signals that are impossible to identify using classical methods (see [14–16]).

The continuous wavelet transform is the mathematical basis of the developed technique [17,18]:

$$W(s, t_0) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t - t_0}{s}\right)dt, \qquad (1)$$

where $x(t)$ is the signal under analysis, s is the time scale that sets the wavelet width, complex conjugation is denoted by an asterisk, and $\psi_{t_0,s}(t)$ is the wavelet transform basis in the form of a complex function. The Morlet wavelet is commonly used as a basis function in the analysis of biological signals [17]:

$$\psi_{t_0,s}(t) = \sqrt{f}\pi^{1/4} e^{j\omega_0 f(t-t_0)} e^{f(t-t_0)^2/2}. \qquad (2)$$

Here, ω_0 is the wavelet scaling parameter that relates the time scale of the wavelet transform (s) to the Fourier transform frequency (f), where $f = 1/s$. The instantaneous energy distribution of the continuous wavelet transform is given by

$$E(f, t_n) = |W(f, t_n)|^2. \qquad (3)$$

Let us give a brief description of the algorithm for identification of frequency patterns proposed in [15]. We compile

a set of frequencies f_j $(j = 1, 2, \ldots, m)$ corresponding to local maxima $E(f_j, t_n)$ of the instantaneous energy for each time point t_n. A set of frequencies f_j^n, where n is the experimental signal duration (i.e., the number of signal samples), is produced in analysis of the complete duration of the studied signal. We then introduce the condition of existence of a pattern of activity with frequency f_j within time interval $[t_n; t_{n+1}]$:

$$|f_j^n - f_s^{n+1}| < \delta, \tag{4}$$

where f_j^n is every frequency for which local maxima $E(f_j, t_n)$ are observed at time step t_n, f_s^{n+1} are frequencies with local maxima $E(f_s, t_{n+1})$ at the next time step t_{n+1}, and δ is a numerical constant chosen according to the specifics of experimental signals. If condition (4) is satisfied for certain frequencies f_{a1}^n and f_{a2}^{n+1}, one needs to check the fulfillment of this condition at each subsequent time step for f_{a2}^{n+1}, stopping at the moment when condition (4) gets violated (in other words, when the activity of a given oscillatory pattern ceases). Each oscillatory pattern P may be characterized by a certain frequency at each moment of its existence; i.e., $P(f, t) = \{\{a_1, t_n\}, \{a_2, t_{n+1}\}, \ldots, \{a_m, t_{n+m}\}\}$, where m characterizes the discrete duration of pattern existence. The „lifetime“ of pattern P is then written as

$$T = t_{n+m} - t_n. \tag{5}$$

In addition, we may introduce mean frequency f_{md} for each frequency pattern P:

$$f_{md} = \frac{\Sigma_{i=1}^m a_i}{m}. \tag{6}$$

If time duration T of oscillatory pattern P does not exceed the oscillation period of its mean frequency f_{md} (i.e., $T < (f_{md})^{-1}$), this pattern is regarded as random noise interference and is neglected in further analysis. However, we propose to calculate mean energy E in addition to these known pattern parameters:

$$E = \frac{\Sigma_{i=1}^m E_i}{m}. \tag{7}$$

This method was applied to PSGRs of five apparently healthy patients studied at the clinical site (National Medical Research Center for Therapy and Preventive Medicine). Standard signals (EEG, EMG, EOG, ECG tracing, breathing pattern) were recorded during polysomnographic testing. An experienced somnologist processed the obtained data and plotted a hypnogram (i.e., a graph that represents the stages of sleep as a function of time). EEGs were recorded for each patient in six channels (O1, O2, C3, C4, Fp1, Fp2) in accordance with the standard international „10-20“ system.

Pattern characteristics (5)–(7) were calculated for each EEG recording in eight frequency ranges: $\Delta f_1 \in [1; 2.5]$ Hz, $\Delta f_2 \in [2.5; 4.5]$ Hz, $\Delta f_3 \in [4.5; 6.5]$ Hz, $\Delta f_4 \in [5; 9]$ Hz, $\Delta f_5 \in [9; 12]$ Hz, $\Delta f_6 \in [12; 14]$ Hz, $\Delta f_7 \in [14; 20]$ Hz, $\Delta f_8 \in [20; 40]$ Hz. Number N of patterns emerging in a given window and averaged characteristics of „lifetime“ T and normalized energy E for these patterns were calculated within each interval Δf_i in sliding time window $\Delta t = 30$ s. The statistical estimates of these characteristics for each sleep stage were also determined based on hypnograms prepared by the expert. Figure 1 presents the distributions of pattern number N, mean „lifetime“ of patterns T, and mean pattern energy E for all EEG channels in frequency range Δf_8 for one of the patients. Compared to all the other stages for EEGs recorded in channels O1, O2, C3, and C4, the REM sleep stage features statistically significant differences in mean pattern „lifetime.“ Statistically significant differences in pattern number N and energy E are also seen between the REM stage and N1 and AW (wakefulness) stages in all EEG channels.

Let us now introduce parameters characterizing the difference between mean numbers N, mean „lifetimes“ T, and mean energies E in frequency range Δf_8 to compare each stage with the REM sleep one:

$$\Delta\tau_{N_{\mathrm{N1,N2,N3,AW}}}^{\mathrm{O1,O2,C3,C4}} = \langle N_{\mathrm{N1,N2,N3,AW}}^{\mathrm{O1,O2,C3,C4}} \rangle - \langle N_{\mathrm{REM}}^{\mathrm{O1,O2,C3,C4}} \rangle, \tag{8}$$

$$\Delta\tau_{T_{\mathrm{N1,N2,N3,AW}}}^{\mathrm{O1,O2,C3,C4}} = \langle T_{\mathrm{N1,N2,N3,AW}}^{\mathrm{O1,O2,C3,C4}} \rangle - \langle T_{\mathrm{REM}}^{\mathrm{O1,O2,C3,C4}} \rangle, \tag{9}$$

$$\Delta\tau_{E_{\mathrm{N1,N2,N3,AW}}}^{\mathrm{O1,O2,C3,C4}} = \langle E_{\mathrm{N1,N2,N3,AW}}^{\mathrm{O1,O2,C3,C4}} \rangle - \langle E_{\mathrm{REM}}^{\mathrm{O1,O2,C3,C4}} \rangle. \tag{10}$$

The results of estimation of relations (8)–(10) are presented in Fig. 2. The pattern „lifetime“ in frequency range Δf_8 for the REM sleep stage tends to decrease in all EEG channels (except for frontal ones). In addition, the REM sleep stage differs significantly from wakefulness in that the patterns in it are fewer in number and have a lower energy. At the same time, N1 and REM stages differ significantly in the number of patterns only in channels C3 and C4.

Thus, the method of frequency wavelet patterns solves one of the problems of staging of sleep: relying exclusively on the analysis of EEG recordings, it introduces clear criteria for isolation of REM stages against the background of N1 and wakefulness stages. The obtained result opens further opportunities for development of automated PSG marking systems with the application of wavelet patterns.

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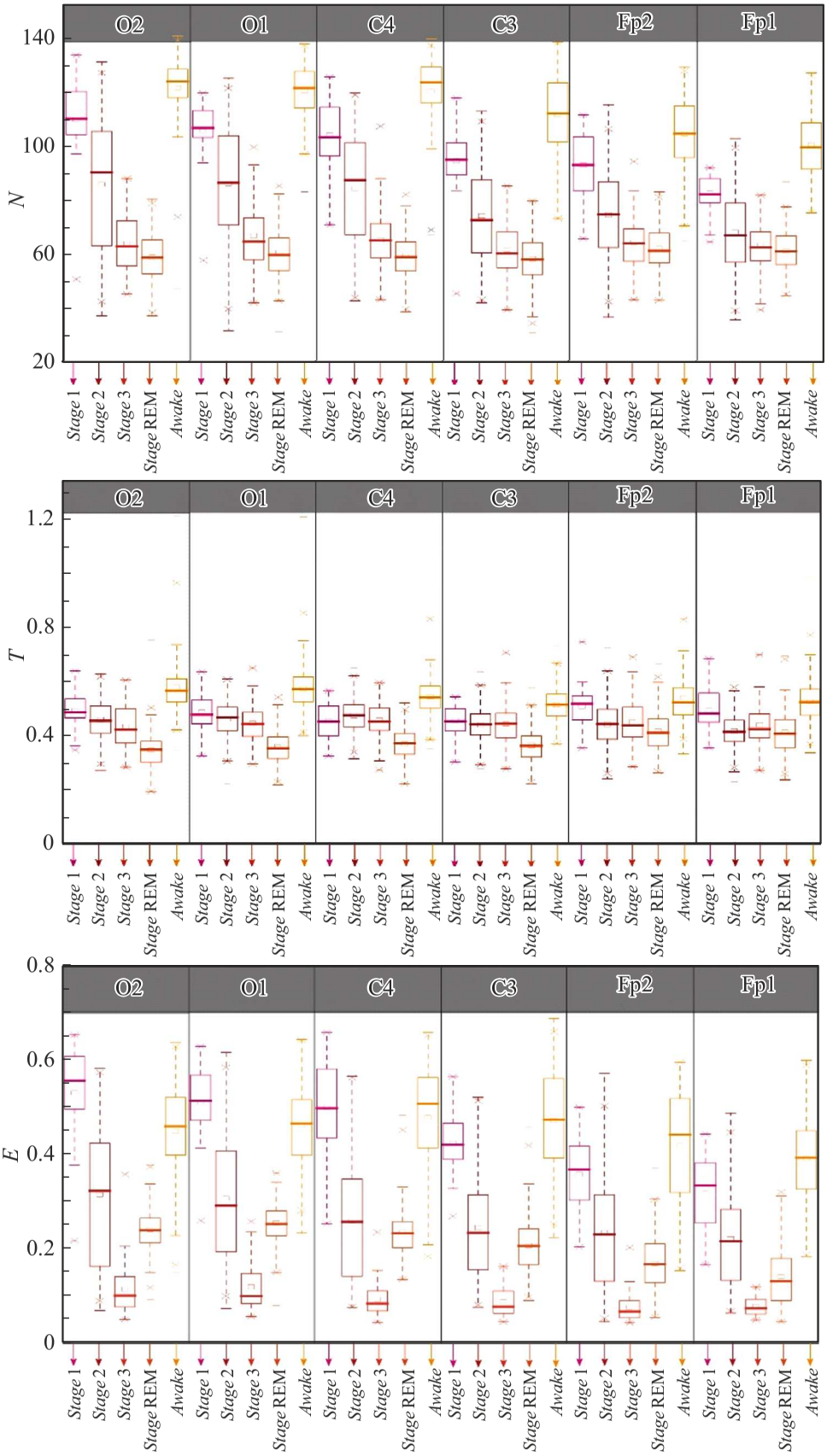

Figure 1. Distribution of pattern number N, mean „lifetime“ of patterns T, and mean normalized pattern energy E over sleep stages of one of the patients for frequency range Δf_8.

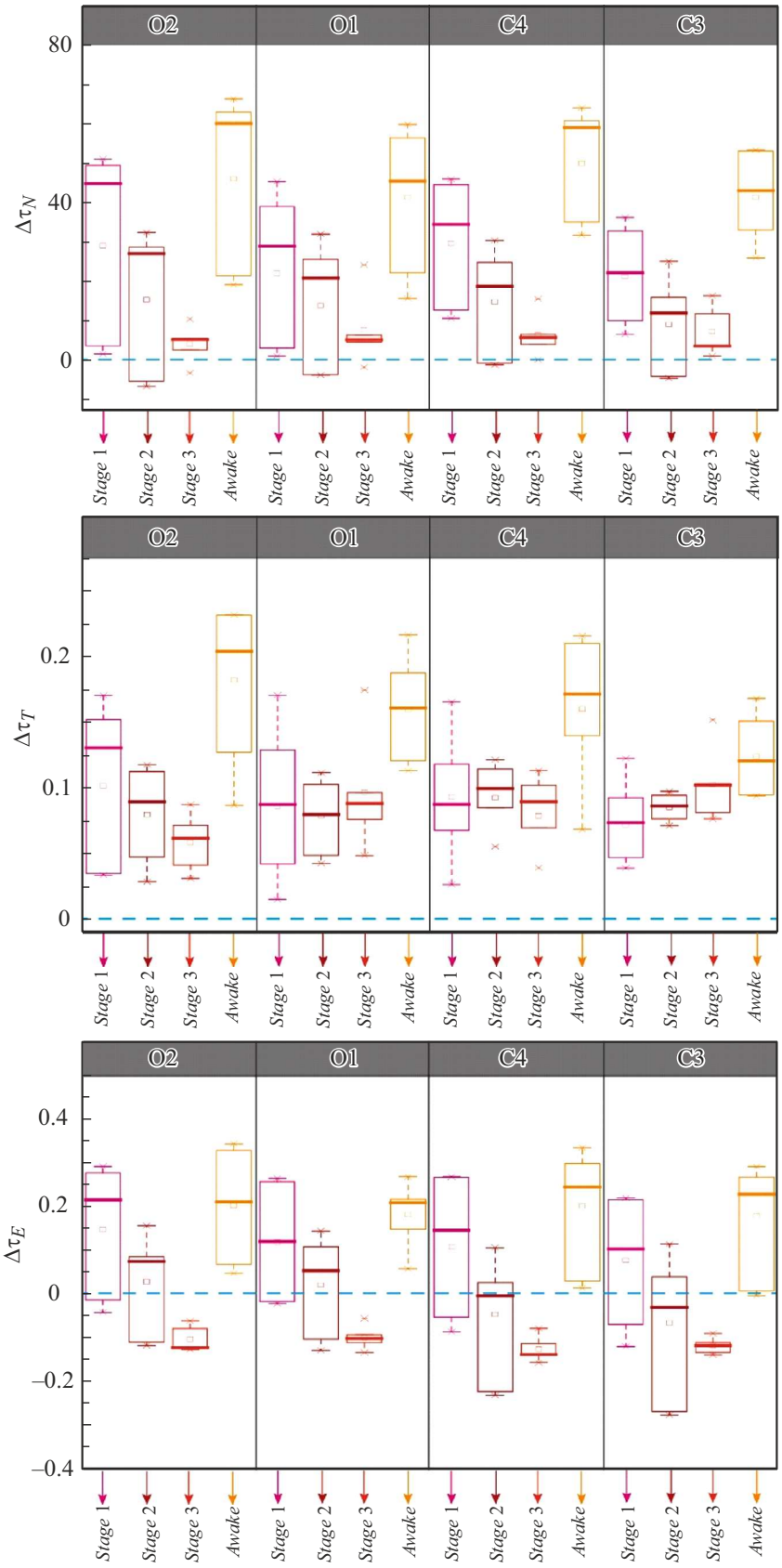

Figure 2. Distribution of parameters (8)–(10), which characterize the difference between mean pattern numbers N, mean „lifetimes“ of patterns T, and mean pattern energies E in frequency range Δf_8 in all sleep stages and the REM sleep stage for all patients.

Compliance with ethical standards

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed voluntary consent was obtained from each study participant.

Conflict of interest

The authors declare that they have no conflict of interest.

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