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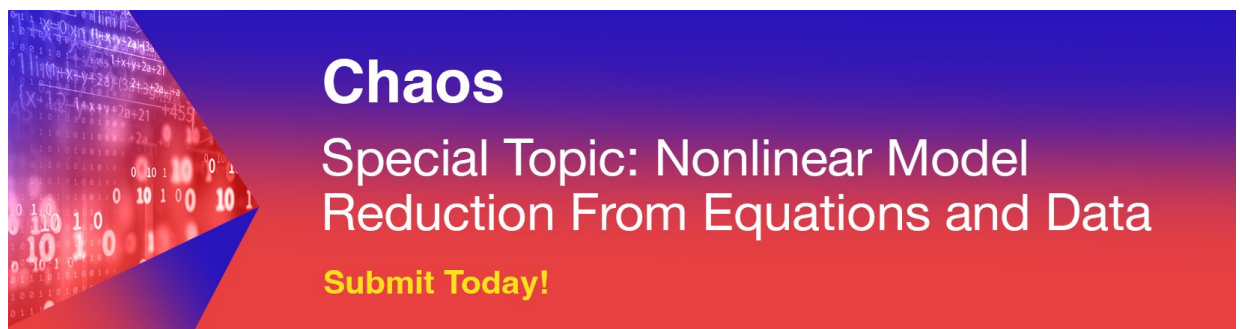
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ABSTRACT

In our work, we compare EEG time–frequency features for two types of K-complexes detected in volunteers performing the monotonous psychomotor test with their eyes closed. Type I K-complexes preceded spontaneous awakenings, while after type II K-complexes, subjects continued to sleep at least for 10 s after. The total number of K-complexes in the group of 18 volunteers was 646, of which of which type I K-complexes was 150 and type II K-complexes was 496. Time–frequency analysis was performed using continuous wavelet transform. EEG wavelet spectral power was averaged upon several brain zones for each of the classical frequency ranges (slow wave, δ , θ , α , β_1 , β_2 , γ bands). The low-frequency oscillatory activity (δ -band) preceding type I K-complexes was asymmetrical and most prominent in the left hemisphere. Statistically significant differences were obtained by averaging over the left and right hemispheres, as well as projections of the motor area of the brain, $p < 0.05$. The maximal differences between the types I and II of K-complexes were demonstrated in δ -, θ -bands in the occipital and posterior temporal regions. The high amplitude of the motor cortex projection response in β_2 -band, [20; 30] Hz, related to the sensory-motor modality of task in monotonous psychomotor test. The δ -oscillatory activity preceding type I K-complexes was asymmetrical and most prominent in the left hemisphere may be due to the important role of the left hemisphere in spontaneous awakening from sleep during monotonous work, which is an interesting issue for future research.

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This article presents the results of the study of K-complexes on the EEG activity of volunteers during episodes of microsleep and spontaneous awakenings, caused by monotonous activity. K-complexes are special single events detected in non-REM sleep, the appearance of which is presumably associated with the processes of memory reconsolidation, as well as the restoration of work instructions during episodes of microsleep. Estimates of the frequency–time picture of the energy characteristics of K-complexes were carried out on the basis of a reference tool of nonlinear dynamics and computational neuroscience, continuous

wavelet transform (CWT). Statistically significant K-complexes can be divided into two types—awakening the volunteer (type I) and not leading to immediate sleep disturbance (type II). We demonstrate that type I K-complexes show an increase in energy power for slow EEG oscillations and a significant asymmetry with activity predominating in the left hemisphere. Perhaps the ability of these K-complexes to “wake up” a person by restoring the working instruction is due to the important role of the left hemisphere in spontaneous awakening from sleep during monotonous work, which is an interesting issue for future research.

I. INTRODUCTION

Functional activity of neural systems, particularly the brain, could be assessed in two different ways. The first approach tries to model recorded brain activity, i.e., EEG, using complex stochastic non-linear models, which could be described and then predicted in terms of stationary noises or linearly correlated noises.^{1–3} This approach, sometimes referred to as “onthological,” has many limitations, because it requires many parametric characteristics of the object modeled just to start modeling. Therefore, such modeling is capable to describe only a small-time interval of the activity recorded from a living subject. Though linear models with feedback circuits can successfully describe and predict cardiovascular system dynamics under broad conditions,⁴ brain neural networks are much more complex to model, and significant results in this research area are yet to follow.

Nowadays, one can simulate several aspects of some brain areas’ activity, but it is obvious that each element of complex neural networks can only be described in terms of nonlinear models.^{5,6} Despite the simplicity of each neuron dynamics, it has much more connections and chemical feedback circuits in real life than the modeled ones. This leads to even more nonlinearity and computational complexity when one tries to model some EEG signal resulted from the complex neural network activity.^{7,8}

The second, “processing” approach is less pretentious, because it is not meant to predict the whole system activity. Instead, it focuses on the correlates of certain psychophysiological processes in the signals recorded. Within this framework, various, primarily nonlinear, methods of brain activity analysis are being developed. The “processing” approach does not explain the “cause” of a living system behavior in one way or another. However, it allows us to detect the onset of important events, for example, epileptic seizures,^{9–11} or to detect stable biomarkers accompanying neurological diseases or certain neurophysiological processes in animals and/or humans. Automatic analysis of such biomarkers’ dynamics in EEG can be used to analyze volunteers’ cognitive functions,^{12,13} features of visual and hear perception,^{14,15} during clinical studies of post-stroke rehabilitation and movement recovery using active feedback systems,¹⁶ to predict early stages of neurodegenerative diseases,^{17–19} etc. EEG analysis can be based on various modifications of time–frequency analysis,^{20,21} spatial modes,^{14,22} nonlinear correlation dimensions,^{15,23} different types of entropy,^{24,25} and Lyapunov exponents.^{26,27}

Our work was performed within the frame of the “processing” approach to biological signal analysis. We used the classical continuous wavelet transform (CWT) to refine the EEG characteristics during spontaneous manifestations of short-term single powerful disturbances, known as K-complexes, which mainly appear in the second sleep stage.

K-complexes can be described as sharp single complex pulses within EEG signal, observed over a period of 100–700 ms, as demonstrated in Figs. 1(a) and 1(b). Its amplitudes can reach up to 200 mV. The left and right columns, (a) and (b), respectively, show two K-complexes recorded in the same subject during one sleep episode. In general, the shape of K-complexes is very diverse and can be modeled by a small packet of triangular pulses of different amplitudes, which are convolutions of a significant number of rectangular pulses. It was already shown, for example, in Hramov *et al.*,²⁸

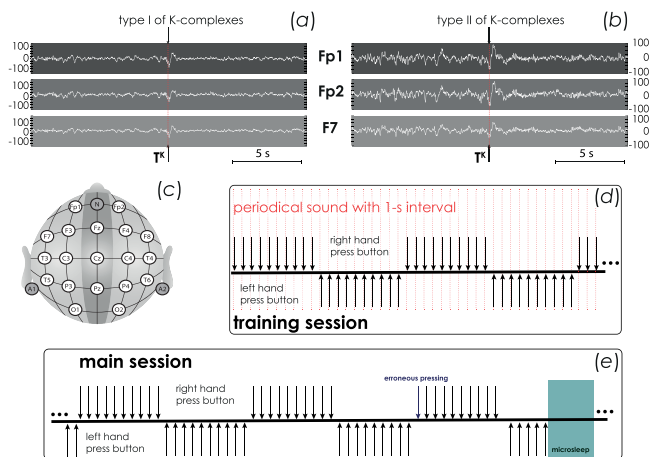


FIG. 1. (a) and (b) Fragments of K-complexes detected by the neurophysiologist during a full electroencephalography and myography analysis for participant #4, detected just before awakening (type I K-complex) and 1 min before awakening (type II K-complex). (c) Scheme of the arrangement of the electrode system according to 10–20. (d) Scheme of the first stage of the experimental work; the red vertical lines show the moments of sound signals. (e) Scheme of the main stage of the experimental work; blue color shows erroneous pressing by the subjects, and the green color shows the episode of sleep.

that CWT can be used for signals with a triangular shape, where the transmitted pulses are characterized by a constant period T and duration τ . However, it is obvious for any somnologist that K-complex period, duration, and amplitude vary widely even within one subject. To study similar impulse activity in biological signals, special modifications of CWT are used, for example, the construction of skeletons of CWT surfaces for sleep spindles analysis^{10,20} to assess changes in neuronal activity linked with an increase in the blood–brain barrier permeability. However, we demonstrate that the analysis of such complex impulses on non-stationary EEG signals is quite possible using direct CWT. Modern parallel computing technologies make classical CWT available in real time, and its results are much more interpretable from a neurophysiological point of view than the radiophysical representation of complex signals. Therefore, in this work, we tested whether CWT could be used to find biomarkers that precede or maybe even lead to spontaneous awakenings after short sleep episodes (“microsleep”) that occur during monotonous activity. In our earlier works,^{29,30} it was suggested that even when a human falls asleep during monotonous work, his working memory contains some kind of working instruction. When such instruction could be retrieved, it causes awakening and immediate return to work. K-complex, as it is well known by somnologists, often (but not necessarily) occurs just before awakenings, so we assumed that type I K-complex could mark physiological brain network activation which, in turn, makes the instruction’s implementation possible.

Modern psychophysiology considers monotony either in terms of various brain networks’ activation,^{31,32} or as a result of attention transformation that reduces subject’s ability to detect environmental changes,^{33,34} that could be revealed using evoked potentials methodology.^{35,36}

Because monotony strengthening could lead to microsleep or even sleep episode, it is quite obvious that their mechanisms should be researched together.^{37,38} Therefore, studying of sleep onset and spontaneous awakenings during monotonous work is important for all operators, including pilots and car drivers.^{39,40} However, there are also several fundamental aspects of such works, because sleep onset and awakening are strongly correlated with the higher cognitive functions and consciousness itself, and there is a strong need to understand its structure and its physiological basis.^{41–43}

In summary, it can be said that the “pragmatic” approach to brain understanding provides valuable practical results and many insights that could be used in the future to model and understand cognitive processes and even self-consciousness.

As it was mentioned before, in our previous study,²⁹ we assumed that spontaneous awakening and immediate returning to work is not really spontaneous but is initiated with the instruction retrieval from working memory. K-complexes are of particular interest, because many studies did already empathize their correlation with awakenings and external stimuli during the second sleep stage. In this work, we consider the experimental paradigm of daytime monotonous activity of test subjects, during which they occasionally spontaneously fell asleep and woke up. During the entire experiment, the test subjects had to follow a simple instruction, including a thinking counting and a real push of buttons. After the detection of all K-complexes developing during short sleep episodes in volunteers, the oscillating and spatial characteristics of these K-wave events are evaluated on the basis of continuous wavelet analysis. The results of this automatical numerical analysis show that K-complexes prior to awakening (I type) differ reliably from background complexes far from the end of the sleep episode (II type).

II. MATERIALS AND METHODS

A. Test subjects

In our work, 20 generally healthy subjects, 12 women and 8 men, recruited among university students participated. The study protocol was approved by the Ethics Committee of the Institute of Higher Nervous Activity and Neurophysiology (No. 046/19), and all experimental procedures were performed in accordance with the ethical standards laid down in the Declaration of Helsinki. All subjects were informed about the experimental procedures in detail and have signed standard consent forms.

The subjects' average age was 20.9 ± 2.4 years. All test subjects were right-handed. All participants were instructed to have partial sleep deprivation (an average of 5.1 h of nocturnal sleep before the experiment).

B. Experimental design

The study is based on our experimental model of consciousness activation during spontaneous awakening that was published earlier,^{29,30,44} and its experimental design is quite the same. All experiments were performed in day time, starting at 1–3 p.m.; the experiment duration was 1.5 h. During the experimental session, the subject lays on a bed in a dark and quiet room, with his/her eyes

closed, counting from one to ten and pressing two pneumatic buttons simultaneously. The buttons were placed between the subject's thumbs and index fingers of each hand. To prevent buttons from falling, the experimenter fixed them with adhesive plaster.

Subjects were instructed to press the buttons once a second and to keep the hand rotation (ten right hand presses, ten left hand presses, ten right hand presses, and so on). Buttons signals were recorded continuously. Therefore, several behavioral measures of the subject's psychological state were available: amplitude, or force, of each press, distance between them, and counting accuracy. Electromyogram (EMG) from both thumb fingers and monopolar EEG from 19 Ag/AgCl electrodes (10–20 system of electrode placement) were also recorded. The sampling rate for all data was equal to 500 Hz, and mastoid electrodes A1 and A2 were used as references. The ground electrode was placed above the forehead. Bandpass filter with cutoff frequencies 0.05 and 45 Hz and 50-Hz notch filter were applied to all EEG channels.

Each subject participated in two experimental sessions with 1–10 days in between. During the first training session, the periodical sound was used to teach the subject to maintain 1-s intervals, as it is shown in Fig. 1(d). This session lasts only 10–15 min. The second (main) session lasted for 55–60 min [Fig. 1(e)]. This monotonous psychomotor test causes several short episodes of sleep and spontaneous awakenings in most sleep deprived volunteers.

Periods without button presses for 3 s or longer were considered as sleep or microsleep episodes, though two sleep experts (somnologists) marked the exact sleep onset using EEG markers, such as a decrease of alpha rhythm and emerging theta waves. 18 from 20 subjects demonstrated short sleep episodes that lasted from 10 s to several minutes, and their EEG records were included in further numerical analysis. EEG patterns of second (N2) and third (N3) sleep stages were also observed in these subjects' recordings.

After the short sleep episodes, the test subjects renewed the performing of the psychomotor test. The overall statistical evaluation across 18 test subjects presented that in 71.09% the post-sleep series of button presses began with their right hand. This fact was correlated with the right hand dominance for all participants.

C. K-complex analyses

Labeling of K-complexes was made using two-step algorithm. First, each EEG signal was filtered in a 0.25–3 Hz band and thresholded in accordance with the K-complex classic definition (not less than $50 \mu\text{V}$ between minimum and maximum, since the filtering mentioned above often diminishes sharp first peak of K-complex) for each electrode. Timestamps were placed at the first peaks minima. Then, labels seen on several electrodes within 0.5 s were united as a single K-complex, and only the earliest timestamp for each of such groups was left. After that, all labels were checked by two experts using visual EEG analysis and spectrogram in accordance with the American Academy of Sleep Medicine (AASM) criteria.⁴⁵ Independent expert estimations of K-complexes coincided by $84.1 \pm 2.8\%$. For numerical calculations, we used a set of K-complexes with identical expert assessments. Within this set, only single K-complexes, with no artifacts or other K-complexes within the ($-15, \dots, +15$ s) time range, were chosen for further analysis.

TABLE I. Number of types I and II K-complexes for each test subject.

#	I type	II type	#	I type	II type
#1	5	9	#10	7	53
#2	9	44	#11	5	49
#3	15	29	#12	2	10
#4	7	26	#13	6	12
#5	11	45	#14	19	32
#6	9	5	#15	4	5
#7	1	4	#16	20	46
#8	5	27	#17	12	25
#9	4	52	#18	9	23

K-complexes for each subject were divided into subsets which were defined above as type I (less than 10 s before awakening) and type II (no less than 10 s after sleep onset and no less than 10 s before the next awakening) using button presses information. The number of type I and II K-complexes for each of the 18 test subjects is given in Table I.

Examples of types I and II are shown in Figs. 1(a) and 1(b), respectively. Finally, CWT spectra were averaged for each subset, each spectral range, and each EEG zone (see below) of each subject, and these data were used for further statistical group analysis. No statistically significant differences were found comparing types I and II K-complexes within each subject.

D. Continuous wavelet transformation

We denote the array of recorded discrete EEG signals as $E_1(t_j); \dots; E_e(t_j); \dots; E_{19}(t_j)$, where $E_e(t_j)$ is the value of the signal registered in the current EEG channel e -number at the moment of discrete time t_j , and the classical CWT using the Morlet wavelet function could be calculated as

$$W_e(f_i, t_j) = \sqrt{\frac{1}{f}} \sum_{j=1}^N \exp\left(\frac{-\left[f_i \cdot \left(t_j - \frac{1}{f_i}\right)\right]^2}{2}\right) \times E_e(t_j) \cdot \left[-\exp\left(i2\pi f_i \left(t_j - \frac{1}{f_i}\right)\right) - \exp(-\pi)\right] \cdot \Delta t. \tag{1}$$

In Eq. (1), the following notation is introduced: f_i is the signal frequency, similar to that for the usual Fourier transform, t_j is the discrete recording time, N is the number of time samples in the signal analyzed, i is the imaginary unit, $\Delta t = (t_{j+1} - t_j) = 0.002$ s is the time step of the signal sampling. We have chosen sampling along the frequency axis equal to 0.01, i.e., $\Delta f = (f_{i+1} - f_i) = 0.01$ Hz.

For each channel $E_e(t_j)$, the CWT energy $P_e(f_i, t_j)$ was calculated at each f_i frequency and t_j time moment as

$$P_e(f_i, t_j) = W_e^2(f_i, t_j). \tag{2}$$

Next, CWT energy $P_e(f_i, t_j)$ could be averaged over certain frequency bands $\Delta f_{fb} = [f_1; f_2]$ as

$$\tilde{P}_e(t_i) |_{\Delta f_{fb}} = \sum_{i=f_1}^{f_2} P_e(f_i, t_i). \tag{3}$$

The energy of oscillational activity was estimated in seven frequency ranges, $\Delta f_{SW} = [0.25; 1.00]$, $\Delta f_{\delta} = [1.0; 4.5]$, $\Delta f_{\theta} = [4.5; 8.0]$, $\Delta f_{\alpha} = [8.0; 12.0]$, $\Delta f_{\beta_1} = [12.0; 20.0]$, $\Delta f_{\beta_2} = [20.0; 30.0]$, and $\Delta f_{\gamma} = [30.0; 40.0]$ Hz, accordingly to accepted in neurophysiological analysis.⁴⁶ Such processing was performed for each of K-complexes labeled by experts in the 30-s interval surrounding each label: $\Delta T_{K_{1,2}}^K = [T^K - 15; T^K + 15]$ s. Then, averaging was made for each of two K-complexes types described above, for each subject and EEG channel,

$$\left\langle P_e(t_R) |_{\Delta f_{fb}} \right\rangle_{K^{I,II}} = \frac{\sum_{k=1}^{N_{K^{I,II}}} \tilde{P}_e(t_R) |_{\Delta f_{fb}}}{N_{K^{I,II}}}, \tag{4}$$

where $t_R \in \Delta T_{K_{1,2}}^K$, Δf_{fb} is one of our seven frequency bands Δf_{SW} , Δf_{δ} , Δf_{θ} , Δf_{α} , Δf_{β_1} , Δf_{β_2} , Δf_{γ} , and $N_{K^{I,II}}$ is the number of detected first and second types of K-complexes, K^I and K^{II} , respectively.

Thus, for each of the 19 channels $E_e(t_j)$, 14 variables, $\left\langle P_e(t_j) |_{\Delta f_{fb}} \right\rangle_{K^{I,II}}$, were calculated to describe energy variations over 30 s, 15 s before, and 15 s after labels for each K-complex type. To assess spatial dynamics of the CWT energy, EEG channels were divided into seven spatial zones: L#1—left hemisphere (EEG channels: Fp1, F3, C3, P3, O1, T5, T3, F7), L#2—right hemisphere (EEG channels: Fp2, F4, C4, P4, O2, T6, T4, F8), L#3—left part of occipital and back temporal lobes (EEG channels: O1, P3, T5), L#4—right part of occipital and back temporal lobes (EEG channels: O2, P4, T6), L#5—parietal lobe, according to the zone of the motor cortex, and the frontal temporal lobe (EEG channels: T3, C3, Cz, C4, T4), L#6—left part of the parietal lobe, according to the zone of the motor cortex, and the frontal temporal lobe (EEG channels: T3, C3), L#7—right part of the parietal lobe, according to zone of motor cortex, and the frontal temporal lobe (EEG channels: T4, C4).

For each spatial region L#1–L#7, the energy characteristics of the EEG $|_{L\#l}$ channels of the corresponding L#l brain area were averaged as

$$L\#l_{K^{I,II}}^{\Delta f_{fb}}(t_R) = \sum_{EEG \in L\#l} \left\langle P_{EEG}(t_i) |_{\Delta f_{fb}} \right\rangle_{K^{I,II}}. \tag{5}$$

Thus, for each spatial brain area, seven variables $L\#l_{K^{I,II}}^{\Delta f_{fb}}$ were estimated at time intervals of 30-s for two types of K-complexes, K^I and K^{II} .

III. RESULTS AND DISCUSSION

Figures 2 and 3 show $L\#l_{K^I}^{\Delta f}(t_R)$ and $L\#l_{K^{II}}^{\Delta f}(t_R)$ sets of energy characteristics, averaged for K^I and K^{II} K-complexes within one experiment. The panels in Figs. 2 and 3, labeled (a) through (g), correspond to the analyzing seven frequency bands of EEG from the lowest-frequency Δf_{SW} to the highest-frequency Δf_{γ} , accordingly. Each panel demonstrates oscillation activity of seven spatial zones,

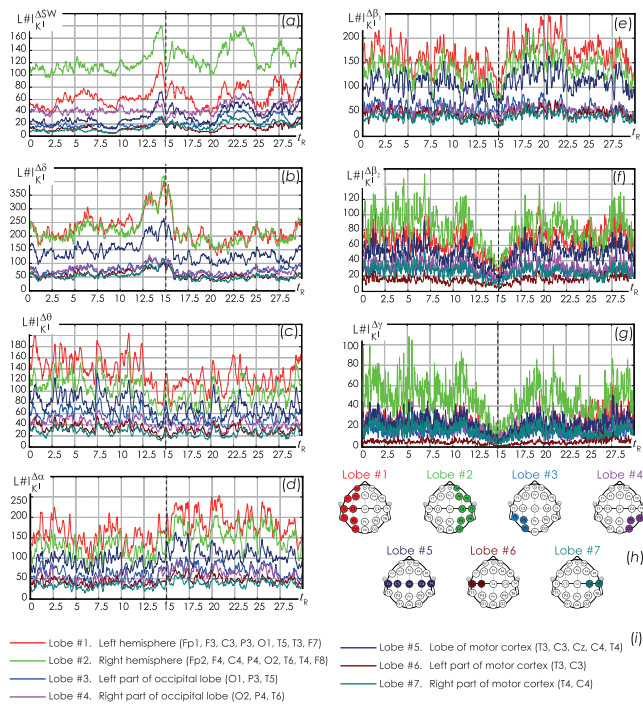


FIG. 2. (a)–(g) Time dynamics of $L\#_{Kl}^{\Delta SW}(t_R)$, $L\#_{Kl}^{\Delta \delta}(t_R)$, $L\#_{Kl}^{\Delta \theta}(t_R)$, $L\#_{Kl}^{\Delta \alpha}(t_R)$, $L\#_{Kl}^{\Delta \beta_1}(t_R)$, and $L\#_{Kl}^{\Delta \beta_2}(t_R)$, $L\#_{Kl}^{\Delta \gamma}(t_R)$, averaged for type I K-complexes of volunteer #3. The vertical dotted lines show the first peak of the observed K-complex, T^K . (h) Layout of spatial scalp areas, L#1–L#7. (i) Spatial areas L#1–L#7 are shown using different colors.

L#1–L#7, of the cerebral cortex during K-complexes. The dynamics was similar for all subjects and both K-complex types: near the K-complex label, energy increases in slow wave (SW) and δ bands due to K-complex frequencies itself, and energy in the β_2 and γ frequency ranges decreases. One can also mention the decrease in θ -band after K-complexes of both types, as well as an increase in α and β_1 ranges. The analysis of the spatial dynamics observes that the maximum amplitude of oscillatory activity is observed when averaging over the right hemisphere in bands Δf_θ , Δf_α , and Δf_{β_1} , i.e., in the frequency interval [4.5; 20.0] Hz [Figs. 2 and 3: (c)–(e)]. At the same time, the oscillatory activity of the left hemisphere dominates for the remaining bands, reaching maximum values in band $\Delta f_{SW} = [0.25; 1.00]$ Hz [Figs. 2(a) and 3(a)].

It is crucial to mention that special-frequency EEG dynamics after type II K-complexes is by definition related to the neurophysiological processes of waking up, including self-consciousness activation, and restoration of the subject’s working capacities. At the same time, K-complexes of type II do not cause awakening but still are followed by a similar decrease of θ activity and increase of α and β_1 activity. Moreover, a direct comparison in Figs. 2 and 3 of typical patterns of vibrational activity of types I and II of K-complexes displays no fundamental differences.

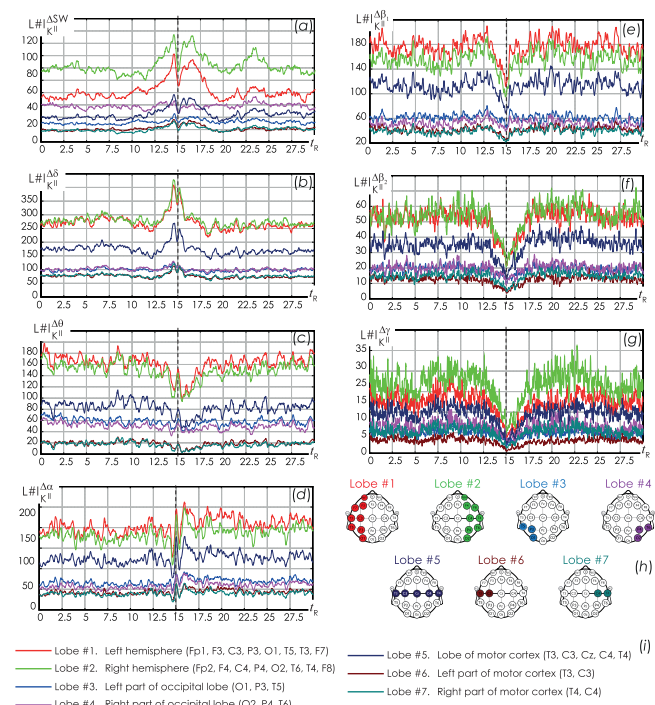


FIG. 3. (a)–(g) Time dynamics of $L\#_{Kl}^{\Delta SW}(t_R)$, $L\#_{Kl}^{\Delta \delta}(t_R)$, $L\#_{Kl}^{\Delta \theta}(t_R)$, $L\#_{Kl}^{\Delta \alpha}(t_R)$, $L\#_{Kl}^{\Delta \beta_1}(t_R)$, $L\#_{Kl}^{\Delta \beta_2}(t_R)$, and $L\#_{Kl}^{\Delta \gamma}(t_R)$ wavelet energies, averaged for type II K-complexes of volunteer #3. The vertical dotted lines show the first peak of the observed K-complex, T^K . (h) Layout of spatial scalp areas, L#1–L#7. (i) Spatial areas L#1–L#7 are shown using different colors.

A. Group statistics

To assess group differences of K-complexes of types I and II, we calculated the difference of wavelet energies before and after K-complex for each spatial zone (L#1–L#7) and band, Δf_{fb} ,

$$\Delta L\#_{Kl,II}^{\Delta f_{fb}} = \sum_{t_R=T^K-15}^{T^K} L\#_{Kl,II}^{\Delta f_{fb}}(t_R) - \sum_{t_R=T^K}^{T^K+15} L\#_{Kl,II}^{\Delta f_{fb}}(t_R). \quad (6)$$

The box plots corresponding are presented in Fig. 4. Each panel of Fig. 4 clearly demonstrates the differences (6) in oscillational EEG activity before and after the K-complex for the described seven spatial zones of the brain.

As one could see in Fig. 4, there are 49 variables to compare statistically (7 spatial regions and 7 bands for K-complexes of types I and II). There were no significant differences in the SW (slow wave) frequency band. In the δ band, a significant spectral energy difference increase for K-complex of type I compared to type II was found in the left and right hemispheres and also in the motor cortex area, but no significant differences were found compared to the left and right motor cortex areas separately. For θ , the band energy difference was increased for the type I K-complexes compared to type II

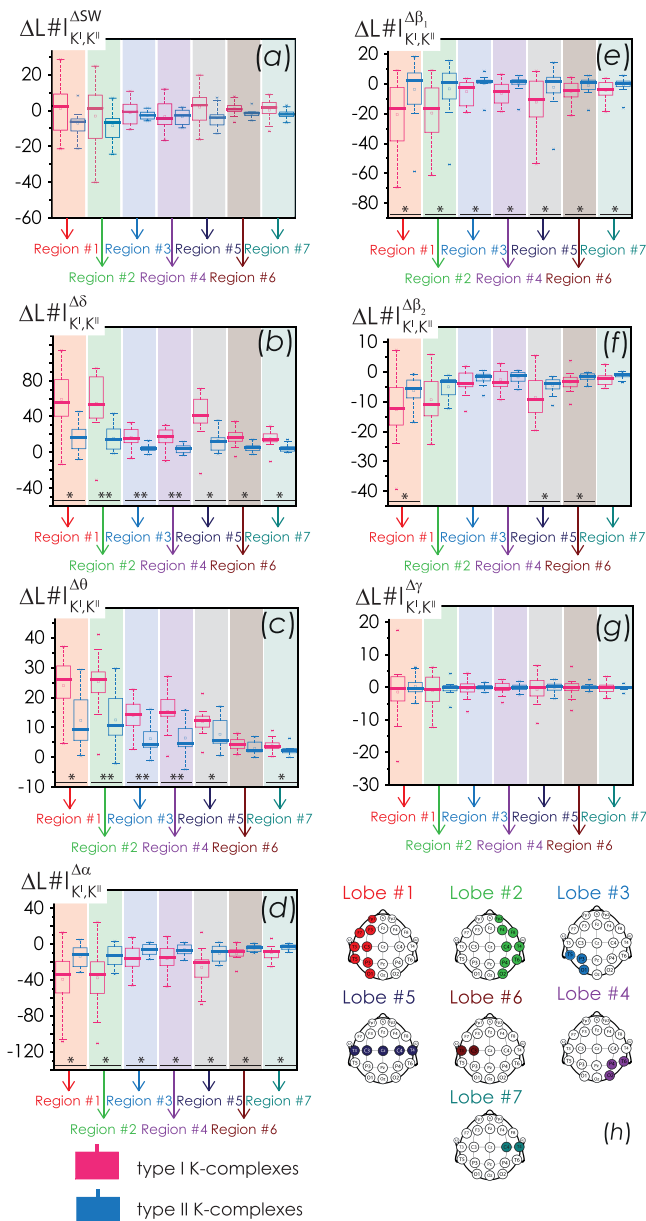


FIG. 4. (a)–(g) Box plots for $\Delta L\#1_{K',K''}^{\Delta SW}$, $\Delta L\#1_{K',K''}^{\Delta \delta}$, $\Delta L\#1_{K',K''}^{\Delta \theta}$, $\Delta L\#1_{K',K''}^{\Delta \alpha}$, $\Delta L\#1_{K',K''}^{\Delta \beta_1}$, $\Delta L\#1_{K',K''}^{\Delta \beta_2}$, and $\Delta L\#1_{K',K''}^{\Delta \gamma}$ (differences between spectral energies before and after K-complexes of each type for each spatial zone and frequency band), calculated for the group of test subjects. Diagrams for types I and II K-complexes are highlighted in red and blue colors, accordingly. Each subplot depicts the following statistical characteristics of numerical indicators: the first and the third quartiles (25%–75%, inside the box); the median and the mean (transverse line and point inside the box, respectively); 1.5 interquartile range (shown by whiskers). Outliers are represented as asterisks. (h) Layout of spatial scalp areas, L#1–L#7. Color designations are similar to those used in Figs. 2 and 3. At the bottom, underlining with one and two asterisks highlights the pairs of values meeting the Mann-Whitney test with $p < 0.05$ and $p < 0.005$, correspondingly.

ones in all spatial zones, especially for regions L#1–L#5 (both hemispheres, both occipital regions, motor cortex projection). There was no interhemispheric difference in this frequency band. For α and β_1 bands, energy difference was lower for K-complexes of type I than for the type II ones, representing awakening processes in EEG. Finally, changes in β_2 and γ bands were subtle to near-zero.

To summarize, at the Fig. 4, we compared each spatial-frequency pair for K-complexes of types I and II using Mann-Whitney U-test. It was found that I and II K-complex types could be distinguished using δ , θ , α , β_1 , and β_2 frequency ranges of the L#1 (left hemisphere) and L#5 (motor cortex) regions ($p < 0.05$). Maximal confidence level ($p < 0.005$) was quite unexpectedly observed in δ and θ ranges in L#3 (left part of occipital and back temporal regions) and L#4 (right part of occipital and back temporal regions) areas, though K-complexes are known to be most prominent in frontal and central electrodes.

The frequency profile of EEG preceding K-complexes type I (leading to the immediate awakening of the subject and his return to the execution of the work instruction) often differs quantitatively from one preceding K-complex type II that emerged within the framework of uninterrupted sleep. Thus, we could assume that the classical application of the well-known CWT tool made it possible to separate these types of K-complexes and processes linked to them. It is possible because of the high level of mathematical stability of the CWT transform and its good temporal resolution.

We observed the maximum differences between K-complexes of types I and II for δ and α frequency bands. High amplitude of the motor cortex projection response (region L#5) may be related to the task characteristics, because it requires to resume pressing the corresponding buttons, which is obviously a sensory-motor task. However, it requires further investigation to understand whether our results are task-specific or universal.

We believe that the fact that low-frequency oscillatory activity (δ -band) preceding type I K-complexes is asymmetrical and most prominent in the left hemisphere also requires further attention. One could assume that the left hemisphere plays an important role in spontaneous awakening from sleep during monotonous work. All subjects participating in the experiment were right-handed, which may be due to the observed cross-activation of the corresponding hemisphere.

The spontaneous appearance of K-complexes within the N2 stage of human sleep attracts considerable attention of neurophysiologists, since it is directly associated with the occurrence of multifactorial processes. In particular, the literature suggests a connection between these complexes both with the processes of reconsolidation of working memory and the perception of weak sensory stimuli.⁴⁷ It is suggested that these processes are not independent but are somehow connected with each other.

At the same time, the performed numerical analysis relates to studies of microsleep in monotony than the study of the processes of the full-fledged night or day sleep. The observed results indirectly suggest a relationship between the generation of K-complexes and the recovery of the ability to execute a working instruction, i.e., processes of reconsolidation of working memory and, possibly, the recovery of self-consciousness. However, the performed analysis is based on numerical processing of short periods of falling asleep from 10 s to several minutes, making it impossible to compare the

distributions and characteristics of K-complexes in such spontaneous sleep episodes with normal night and even daytime sleep.

Thus, during nocturnal sleep, K-complexes are realized during the two-stage of NREM, and their analysis is a separate topic for further research. In particular, assessing the correlations between the characteristics of micro-awakenings and the development of K-complexes in EEG during nocturnal sleep may be an interesting continuation of this study direction.

In addition, to exceed the other limitations of our study, different experimental designs should be tested, like the one with K-complexes evoked by weak sounds that lead to awakening or in front of leaving the subject asleep.^{48–50} The possible activation of different hemispheres in left-hand and ambidextrous subjects, as well as the preservation of the identified characteristics of K-complexes with increasing age of participants, is also an open question today.

IV. CONCLUSION

This paper is devoted to the study of various types of K-complexes accompanying short episodes of human microsleep sleep. As part of the experimental paradigm, the generally healthy subjects performed simple actions in the darkened room for quite a long time (about 1 h), according to the instructions, with almost no motor activity, which led to the development of monotonia and, accordingly, episodes of spontaneous sleep. During short sleep episodes, which lasted from 10 s to several minutes, almost all test subjects demonstrated the development of K-complexes both immediately before waking up (I type), and 10 s or more before waking up (II type). Numerical processing of I and II types K-complexes was carried out on the basis of continuous wavelet analysis.

The performed work demonstrates the great possibilities of using the classical continuous wavelet transform to work with short extreme events in complex multicomponent noisy EEG signals. K-complexes of type I are maximally different from similar K-complexes of II type in low-frequency bands, $\delta = [1.0; 4.5]$ and $\theta = [4.5; 8.0]$ Hz, in the left and right parts of the occipital and posterior temporal regions, $p < 0.005$. The use of CWT based on the Morlet wavelet can identify I type of K-complexes, the power of which is sufficient to awaken the subject and, possibly, activate working memory processes in the process of restoring a complex behavioral response according to a given instruction. The high amplitude of the motor cortex projection response in β_2 -band, [20; 30] Hz, may be related to the sensory-motor modality of the task in the monotonous psychomotor test.

Thus, the differences between types I and II of K-complexes are observed in the asymmetry of their parameters in different EEG ranges and different areas of the brain. It has been shown for the first time that these differences are most pronounced in the left hemisphere. The most obvious finding to emerge from this study is that performing a monotonous psychomotor activity with two hands, awakening is initiated by the left hemisphere in people with a dominant right hand.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

V. B. Dorokhov: Conceptualization (equal); Funding acquisition (equal); Supervision (equal); Writing – review & editing (equal). **A. Runnova:** Investigation (equal); Writing – original draft (equal). **O. N. Tkachenko:** Data curation (equal); Formal analysis (equal); Writing – review & editing (equal). **A. O. Taranov:** Formal analysis (equal); Project administration (equal). **G. N. Arseniev:** Supervision (equal); Validation (equal). **A. Kiselev:** Investigation (equal); Project administration (equal); Visualization (equal). **A. Selskii:** Formal analysis (equal); Methodology (equal); Resources (equal); Visualization (equal). **A. Orlova:** Formal analysis (equal); Methodology (equal). **M. Zhuravlev:** Data curation (equal); Formal analysis (equal); Methodology (equal); Software (equal).

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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