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The regularities of the discrete nature of multi-variability of EEG spectral patterns

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Abstract

The short-term structure of electroencephalogram (EEG) spectral transformations during different brain functional states (closed/opened eyes and memory task) was studied. It was shown that approximately 50% of spectral pattern (SP) types occur not more than 2–3 times per 149 analysis epochs in a 1-min EEG. The remaining 50% of SP types were the same for the different EEG channels, in all subjects and various brain functional states. Additionally, a high incidence of the neighboring SP types in strongly overlapping (by 80%) 2-s analysis epochs of the EEG was shown. The SP identified in a given epoch has only a limited predictive value on the SPs identified in the subsequent epochs. The incidence effect was restricted by the limited SP set and by a 50% reduction in the functionally active SPs, which resulted in a temporary stabilization of SPs in sequential combinations. The parameters of temporary stabilization of SPs were significantly different from ‘random’ EEG which provides evidence of the non-occasional character of stabilization of the main dynamic parameters of neuronal activity. Thus, the findings suggest that the multi-variability of neuronal nets is discrete in time, and limited by the dynamics of the short quasi-stable brain states.

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1. Introduction

Cognitive neuroscience now leaves no or little doubt that electroencephalogram (EEG) is closely connected to brain dynamics, information processing, and cognitive activity (Nunez, 2000; Bressler and Keslo, 2001 also see review Fingelkurts and

Fingelkurts, 2001). Neural oscillations, which comprise EEG, exhibit large variability in both amplitude and frequency and this variability has quasi-stationary quantity (Stassen, 1980). However, the dynamic nature of the fluctuations of brain oscillations has remained unclear.

It was found that the power variability of the main EEG spectral components for successive short (5–10 s) EEG segments was in the range of 50–100% (Oken and Chiappa, 1988). It was also

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shown (see the review, Kaplan, 1998) that in the phenomenon of the EEG spectral variability it is not only the stochastic fluctuations of the EEG parameters, but also the temporal structure of the signal that is reflected. This may indicate that the EEG spectral variability may be *functional* (see reviews Kaplan, 1998; Kaplan and Shishkin, 2000).

The most common approach for quantifying brain oscillations is through a spectral analysis (Florian and Pfurtscheller, 1995; Muthuswamy and Thakor, 1998). However, conventional methods assess the mean characteristics of the EEG power spectra averaged out over extended periods of time and/or broad frequency bands in order to obtain statistically reliable characteristics. In that case, averaging procedures resulting in ‘static’ picture might not only mask the signal dynamic aspects, but also give rise to ambiguous data interpretation (Efferen et al., 2000; Laskaris and Ioannides, 2001; Fingelkurts et al., 2002).

In order to overcome the limitations of conventional spectral analysis based on averaging procedures and to reveal functional EEG spectral variability the short-term spectral analysis was introduced (Barlow, 1985; Jansen and Cheng, 1988).

Assuming that the duration of the minimal stationary segment of an EEG is not usually more than 2 s (Inouye et al., 1995) it is possible to get a whole set of individual short-term spectra of various types in accordance with the number of stationary EEG segments. The parameters of the relative presence of the individual EEG segments of each type and the peculiarities of its alternation in the analyzed EEG may provide more adequate characteristics of the operational brain activity (see the review Kaplan and Shishkin, 2000; Fingelkurts et al., 2002).

In connection to this, for studying functional variability of individual short-term spectral patterns (SP) an adaptive classification technique was developed. This technique was presented in abstract form in Fingelkurts et al. (1998) and published in Kaplan et al. (1999) (details of the technique see in Appendix A). This technique uses a universal standard SP set, which adapts to the specifics of any given EEG.

The frame hypothesis of this paper is that the regularities of short-term spectral transformations reflect additional information on the fast functional dynamics of brain information processing. It was supposed that by using the adaptive classification technique, it might be possible to detect the short-term structure of the dynamics involved in processing information within the brain. Eight EEG electrodes (the number sufficient to cover the main cortical areas) were used to test the influence of morpho-functional organization aspects on the short-term structure of brain dynamics. A multi-stage memory task made of gradually increasing cognitive load (rest-condition-closed-eyes, rest-condition-open-eyes, waiting-stimulus, stimulus-memorizing, keeping-stimulus-image-in-mind) was chosen to study the functional variability of short-term SPs. Hence, the aim of this paper was to investigate the regularities and structure of the variability of the short-term EEG spectra and their temporal group-sequencing during the different brain functional states.

2. Methods

2.1. Subjects

Seventeen healthy, right-handed adult volunteers (males, aged 19–26) participated in the experiment. None of the subjects reported any visual defects, neurological disorders, or was on medication. In addition, all of them have normal autonomic (blood pressure and pulse rate) and psychometric (Eysenck’s, Spielberg-Khanin’s and Doskin’s scales) indices. All the subjects were informed beforehand of the nature of the experiments.

All of the subjects underwent the same experiment with the same instructions twice. The interval between initial testing and retesting was approximately 1–2 weeks. The EEG registrations began at the same time (10:00 h) on both the first and second registration sessions. All of the subjects were aware that they were going to undergo the same test twice with an interval between. Consent was obtained from all subjects prior to the experiment.

2.2. Stimuli

The visual stimuli presented in front of the subjects to memorize were non-verbalizable matrices composed of nine square elements (1.5–1.5 cm²) presented on a matrix screen 6×6 squares in size, which was positioned 60–70 cm away from the subject's eyes. The combination of the squares was selected quasi-randomly and presented on the screen for 20 s by lighting with bottom-mounted red light diodes. During the course of the experiment, illumination within the laboratory box was constant at such a level that allowed the subject to reliably distinguish the matrix squares without lighting.

2.3. Procedure

After the electrodes were placed on the subject's head and the instrument calibrated, the subject was seated in a comfortable chair in a registration room and the procedure of the experiment was explained. To reduce muscular artifacts in the EEG signal, the subject was instructed to assume a comfortable position and to avoid movement. The subject was asked to look at the screen and to avoid unnecessary eye movements. The behavior of the subject was observed on a TV monitor throughout the experiment.

The protocol of the experiment was as follows: immediately preceding the EEG recording, the subject was given a command 'Attention to the screen' with the instruction to remember the matrix pattern to be presented. Between 30 and 50 s after the command was given, a random combination of 9 matrix elements was exposed for 20 s. For the following 20 s with the lighting switched off, the subject was required to sit motionless with open eyes trying to keep in mind the image of the square composition presented in that matrix. The subject was then asked to reproduce the pattern by touching squares in the matrix with a special pencil. Each touch switched on the lighting of the corresponding square element.

Two minutes after the reproduction was finished, a completely new combination of squares was presented. A total of 12 matrix compositions were presented to each subject. Between the signal

presentations, four control trials were randomly introduced. In the control trials, the EEG was also recorded, but the command 'Attention to the screen' was not followed by the expected matrix presentation.

Therefore, three distinct short-term (20 s) periods were tested: waiting, memorizing of the actual matrix object, and retention of the perceptual visual image. In addition, four EEG registrations were made for eyes closed and eyes opened (rest conditions) for each subject.

EEGs were recorded for 12 subjects during the memory task, control condition, and rest conditions (eyes closed/open). For 5 more subjects EEGs were registered during special task where the subjects observed visual objects without being required to memorize them (Section 3).

2.4. Recording

Eight Ag/AgCl electrodes (Siemens–Elema) were placed bilaterally on the subject's scalp using the 10/20 system of electrode placement at F3, F4, C3, C4, P3, P4, O1, O2. Additionally, two EOG electrodes were put on the outer side of the eyes. All electrodes were referred to linked ears, which also served as the ground electrodes.

Raw EEG signals were amplified and filtered (0.5–30 Hz) using the Medicor EEG and digitized at a sampling rate of 128 Hz by a 12-bit analog-to-digital converter. The impedance of recording electrodes was monitored for each subject and it was always below 5 k Ω . The presence of an adequate EEG signal was determined by visual inspection of the raw signal on the computer screen.

Instructions designed to minimize movement and relax jaw muscles resulted in suppressing the myogram class of artifact to the point that the high-frequency spectrum was not significantly affected. Cardiac interference at low frequencies was also found to be minimal, with no spectral peak detection at the heartbeat frequency of approximately 1 Hz, or its harmonics. Constant visual EEG monitoring allowed for selection of only those artifact-free EEG recordings for analysis.

To estimate the effects of various brain states 646 artifact-free 1-min EEGs were recorded for two sessions in rest conditions (eyes closed/opened), control conditions, and during the memory task (before, during, and after the stimulus exposure—three periods, 20 s each).

2.5. Data processing

The EEG spectral analysis conducted by means of Fast Fourier Transform with Hanning's window used a sliding 2 s analysis window that was shifting by 50 sample points (390 ms) between adjacent windows. These values revealed the best results in disclosing temporal patterns from the signal (according to a special study). Each individual short-term power spectrum was calculated with a frequency resolution of 0.5 Hz. Thus, each individual power spectrum had 61 values for a 0.5–30 frequency range.

As a result, 50 individual power spectra with a 0.5 Hz step were calculated for three consecutive 20-s fragments of the 1-min EEG recordings. The total number of individual SPs for each channel of 1-min EEG was 149. These SPs formed the multitude of the objects for further classification procedure.

The parameters of variability within the EEG SPs during rest conditions and the memory task were estimated at two stages. At the first stage, the adaptive classification of sequential single EEG spectra was performed in each EEG channel separately by reference to a set of 32 standard SPs. Details of this procedure, published firstly in Russian (Kaplan et al., 1999), are contained in Appendix A. It is worth noting here however, that this way of SP classification makes it possible to identify up to 96% of individual single spectra in the initial EEG. Thus, each channel of each EEG was reduced to the sequences of classified individual SPs.

At the second stage, the classification profiles of SPs for each channel of each EEG from each subject and for the group of subjects as a whole were calculated. An index was calculated as the number of cases of SP type as a percentage of the total amount of all SPs in any given EEG channel.

Firstly, the classification profiles were averaged for each subject separately for each EEG channel and condition. After this, the data for each condition was averaged across all subjects separately for the first and second sessions. Since there were no significant differences in the results from first and second sessions (see example at Fig. 3) the entire data were combined for further analysis.

The analysis of variance for repeated measurements was conducted to test the following interaction: the variability of the number of non-classified spectra and the factor experimental condition (eyes closed, eyes open, memory task). In order to reveal statistically significant transformations of classification profiles and for testing condition-specific effects, paired *t*-test was used. *t*-Test analysis was performed separately for each type of SPs presented in classification profiles. Correlation analysis was used to assess the test–retest reliability per se (session 1 vs. session 2). Only statistically significant *P*-values are displayed.

As control for the neural origin of temporal dynamics of SPs, the so-called surrogate data were used which is commonly applied as probing a signal for a non-random temporal structure (Ivanov et al., 1996). Surrogate signals have identical parameters with the original signals but do not have temporal correlations (see Section 3, 'random EEG').

3. Results

3.1. General characteristic of SPs distribution in local EEGs

By using adaptive classification technology, approximately 90–96% of EEG SPs (for different subjects and EEG channels) were successfully classified. The number of non-classified spectra was less than 10% for all types of EEG (with alpha rhythm, or without), for all EEG channels and for all examined types of brain functional states (rest conditions: closed/opened eyes, memory task and task without memorizing). Analysis of the non-classified spectra showed that they were characterized by polyrhythmically disorganized and/or 'noisy' spectra (the peak is on 1 Hz with

further asymptotic decrease of the power). This means that the percentage of non-classified spectra in the EEG recorded in the specified conditions may be viewed as an index of the polyrhythmically disorganized and/or 'noisy' activity. This percentage (not more than 10%) was dependent on the EEG type, EEG channel and brain functional state. Thus, variance analysis of the variability of the number of non-classified spectra showed that this parameter was significantly influenced by the factor of functional loading with the decrease in the number of non-classified spectra during the memory task ($F(1, 287) = 7.98$; $P < 0.001$).

At the same time, distribution of the classified SPs within the classification profiles demonstrated particular peculiarities. It was shown that even within the limits of 20 s EEG fragments, there is a considerable transformation of the EEG segmental structure when compared across separate brain functional states: eyes closed, eyes opening and different stages of the memory task. This microdynamics was expressed in percentage changes ($P < 0.05$ – 0.001 for different cases and EEG channels) of the particular combinations of individual SPs (Fig. 1).

Thus, while eyes were closed, only about half of the segments of the EEG were characterized by the dominant monomodal (41%—SP types 2, 3) or bimodal (10%—SP types 7, 8) peak in alpha band. In most of the other cases, either the alpha peak was expressed at the same extent as the peaks of other frequency bands (8%—SP types 16, 28, 29, 31), or the spectral peaks in the band of Δ – θ frequency (15%—SP types 21–25 and others) were the most noticeable (Fig. 1a). The opening of the eyes resulted in more than a twofold decrease in the number of EEG segments with high-amplitude alpha peak ($P < 0.001$) and in the increase of about the same number of segments with dominant but less expressed in spectral power Δ – θ activity ($P < 0.005$ – 0.001 for different EEG channels) (Fig. 1a). The same effect continues to develop from this later state to the 'waiting' stage, and from this one to the 'memorizing' stage of the memory task (Fig. 1a,b, compare closed eyes with open eyes, then open eyes with the 'waiting' stage of the memory task, and then 'waiting' with the 'memorizing' stages of the memory task). In con-

trast, the comparison of the three 20 s periods of the EEG for the control condition where visual object was expected but not presented (Section 2.3) showed no statistically significant differences.

Some topological specifics of the transformations in the EEG classification profiles were detected. The effects described above were first of all typical for the occipital and parietal EEG channels, less pronounced in the central EEG channels, whereas there were no statistically significant changes in EEG classification profiles for frontal channels (Table 1). At the same time, the number of Δ -rhythmical SPs in the frontal channels decreased ($P < 0.01$) during 'memorizing' and 'keeping-in-mind' of the visual image when compared with the 'waiting' stage of the memory task (Table 1).

How specific were the transformations described above of the EEG classification profiles regarding the task of visual object memorizing? Maybe these effects are determined by alpha blockade when focusing attention on the structural peculiarities of the visual field. To test out this supposition, a special test was carried out. The subject observed visual objects without being required to memorize them. The temporal diagram and all conditions of visual presentation were identical to the main test, the only exception being that the instruction for the subject was different. He was asked to watch the changes in the lighting brightness of the matrix elements for 20 s and report the number of changes 20 s after the lighting was switched off. This task required considerable attention from the subject, since the brightness of the squares did not in fact change during the whole course of the experiment (the subject was not made aware of this). Transformations of the EEG classification profiles while the subject's attention was directed to visual objects 'with memorizing' and 'without memorizing' differed considerably (Tables 1 and 2). In the second case, the general number of EEG classification profile transformations during transition from the 'waiting' stage to 'observation' of the visual object decreased mainly at the expense of alpha-rhythmical types of SPs (Table 2) when compared with transition from 'waiting' to 'memorizing' stage (Table 1).

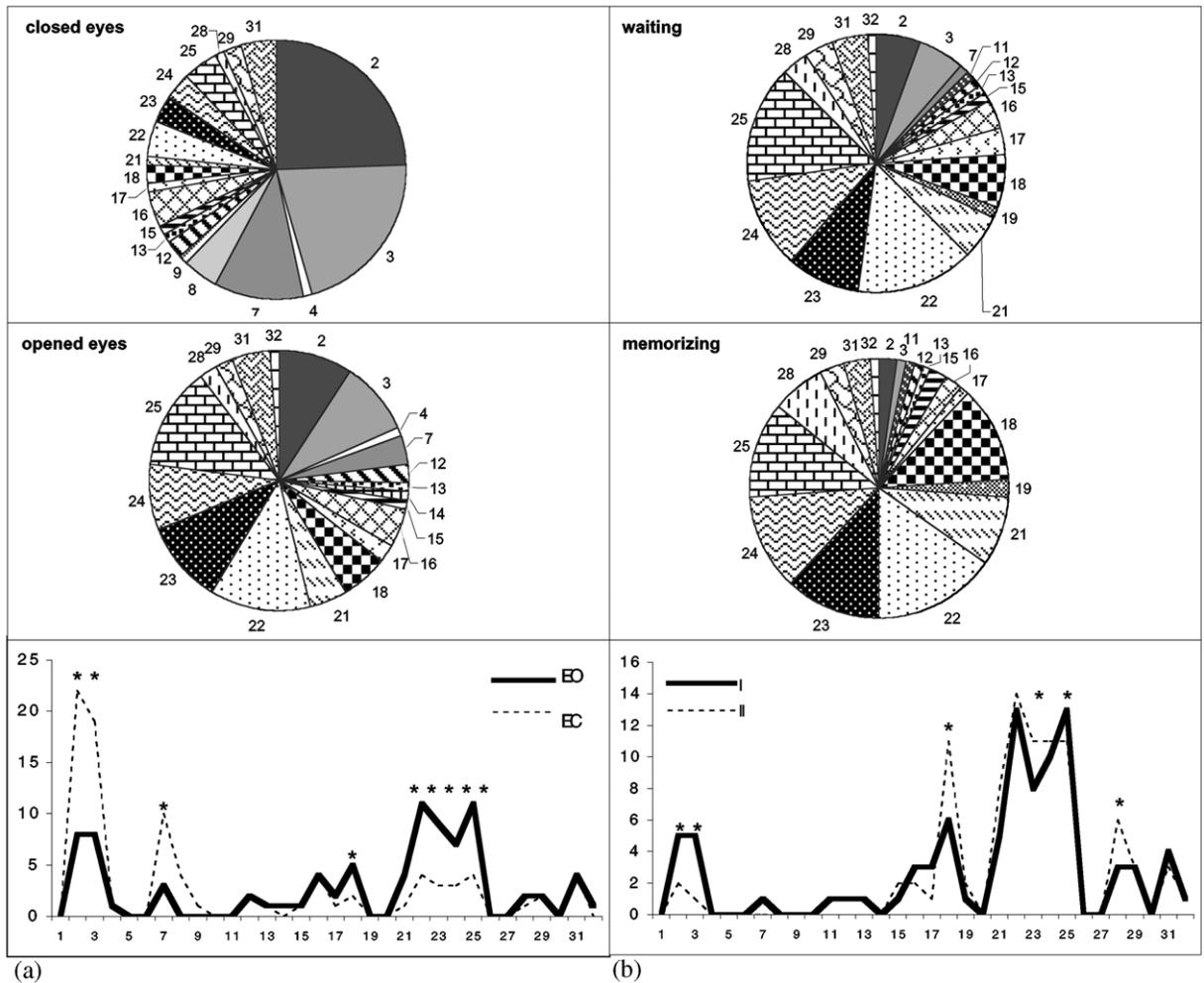


Fig. 1. Example of the pie diagrams and corresponding classification profiles (averaged for 12 subjects) during resting conditions with opened/closed eyes ($n=96$) (a) and the memory task ($n=288$) (b) for O2 EEG channel. At the pie diagrams the different colors reflect the percentage of the different EEG SPs in classification profiles. The numbers indicate the labels of the standard SP. The X-axis displays the labels (numbers) of the standard SPs from 1 to 32. The main frequency peaks for each SP are: 1—8.5 Hz, 2—10 Hz, 3—11.5 Hz, 4—13 Hz, 5—14.5 Hz, 6—8–9 Hz, 7—9.5–10.5 Hz, 8—9.5–11.5 Hz, 9—8.5–11.5 Hz, 10—12.5–20.5 Hz, 11—4–8.5 Hz, 12—4–10.5 Hz, 13—5.5–10.5 Hz, 14—6.5–12.5 Hz, 15—2.5–8.5 Hz, 16—2.5–10.5 Hz, 17—2.5–12.5 Hz, 18—4 Hz, 19—5.5 Hz, 20—7 Hz, 21—3–6.5 Hz, 22—2.5–4 Hz, 23—2.5–3.5–5.5–9.5 Hz, 24—2.5–5.5 Hz, 25—2.5 Hz, 26—2.5–20.5 Hz, 27—20.5 Hz, 28—2.5–4.5–8.5 Hz, 29—2.5–4.5–10.5 Hz, 30—2.5–10.5–16.5 Hz, 31—3–6.5–11 Hz, 32—2–6.5–8.5–12.5 Hz. The Y-axis displays the share of the corresponding SPs in the percentage from the total number of the classified SPs. A line graphic was chosen instead of a bar for the ease of comparison. (Note that X-axis consists of 32 discrete values, all the in-between values are meaningless.) EO—eyes opened; EC—eyes closed; I—the stage of the ‘waiting’ of the matrix visual object, II—the stage of the ‘memorizing’ of the matrix visual object. *— $P < 0.01$ –0.001 (for different SPs).

Analysis of the individual classification profiles of SPs for each subject showed that there is considerable similarity of the SP sets as presented in different classification profiles. However, the

individual classification profiles differed from each other by the percentage of particular SPs presented within them. The most noticeable difference was for ‘pure’ alpha-rhythmic SPs. According to this

Table 1

Changes of the SP presentation (in the percentage from the total number of the classified SPs during 20 s ($n=50$)) in the classification profiles for comparison of the three stages of memory task (averaged for 12 subjects, $n=288$)

SP type	25	18	2, 3	7 ^a	22	24	16	17	12 ^a	28	23
Hz	2.5	4	10, 11.5	9.5–10.5	2.5–4	2.5–5.5	2.5–10.5	2.5–12.5	4–10.5	2.5–4.5–8.5	3–4–6–10
Rhythms	Δ	θ	α	α	Δ-θ	Δ-θ	Δ-α	Δ-α	θ-α	Δ-θ-α	Δ-θ-θ-α
Stages	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC
O1	↓--	↑↑-	↓↓-		---	---	↓↓-	↓↓-		↑-↓	↑↑-
O2	---	↑↑-	↓↓-		↑↑-	↑↑-	↓↓↑	↓↓-		↑-↓	↑↑-
P3	---	↑↑-	↓↓-		-↑-	---	↓↓↑	↓↓-		↑-↓	↑↑-
P4	---	↑↑-	↓↓-		↑--	↑-↓	↓↓↑	↓↓-		↑-↓	↑↑-
C3	---	↑↑-	↓↓-		---	---	↓↓-	---		↑--	↑↑-
C4	↓↓-	↑↑-	↓↓-		↑↑-	---	↓↓-	---		↑--	↑↑-
F3	↓↓-	---	↑↓↓		---	---↓	---	---		---	↑↑-
F4	↓↓↓	---	-↑↑		---	---	---	---		---	---

↑—Statistically significant ($P<0.05$ – $P<0.001$ for different channels) increase of SP presentation; ↓—statistically significant ($P<0.05$ – $P<0.001$ for different channels) decrease of SP presentation; ‘-’—absence of statistically significant changes; A—comparison of the ‘waiting’ and ‘memorizing’ stages of the memory task; B—comparison of the ‘waiting’ and ‘keeping-in-mind’ stages of the memory task; C—comparison of the ‘memorizing’ and ‘keeping-in-mind’ stages of the memory task.

^a Absence of the particular SPs.

parameter of individual classification profiles the subjects were assigned to two analysis subgroups: subjects ($n=8$) with dominant alpha-rhythmical SPs in their classification profiles and subjects ($n=4$) without or with a minimal occurrence of alpha-rhythmical SPs in their classification profiles. A visual inspection of the EEGs and a mean spectral power analysis, calculated for the resting period for these two subgroups confirmed this

division. Thus, classification profiles of the subjects with high alpha-index were characterized by a higher number of the ‘pure’ alpha-rhythmical SPs and/or SPs, which mostly contain alpha components ($P<0.05$ – 0.001 for different EEG channels) when compared with the subjects with low alpha-index. Whereas classification profiles of the subjects with low alpha-index were characterized by more number of the ‘pure’ Δ-, θ-rhythmical

Table 2

Changes of the SP presentation (in the percentage from the total number of the classified SPs during 20 s ($n=50$)) in the classification profiles for comparison of the three stages for the task ‘attention without memorizing’ (averaged for 5 subjects, $n=70$)

SP type	25	18	2, 3	7	22	24	16	17 ^a	12	28	23
Hz	2.5	4	10, 11.5	9.5–10.5	2.5–4	2.5–5.5	2.5–10.5	2.5–12.5	4–10.5	2.5–4.5–8.5	2.5–3.5–5.5–9.5
Rhythms	Δ	θ	α	α	Δ-θ	Δ-θ	Δ-α	Δ-α	θ-α	Δ-θ-α	Δ-θ-θ-α
Stages	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC	ABC
O1	-↑-	↑--	---	-↓-	↑↑-	↑↑-	---		---	-↑-	↑↑-
O2	-↑-	-↑-	-↓-	↓↓-	↑↑-	-↑↑	---		---	-↑-	↑↑-
P3	---	↑--	---	---	---	-↑-	---		---	---	---
P4	↑↑-	↑--	-↓-	---	---	-↑-	---		---	↑↑-	---
C3	---	---	-↓-	---	---	---	↓--		---	---	-↑-
C4	-↑-	---	-↓-	---	-↑-	---	-↓-		---	---	---
F3	-↑↑	↑--	↓↓-	-↓-	↑--	-↑↑	-↓-		↓--	---	-↑-
F4	---	↑--	-↓-	---	---	---	---		---	---	-↑-

↑—Statistically significant ($P<0.05$ – $P<0.001$ for different channels) increase of SP presentation; ↓—statistically significant ($P<0.05$ – $P<0.001$ for different channels) decrease of SP presentation; ‘-’—absence of statistically significant changes; A—comparison of the ‘waiting’ and ‘observation’ stages of the task; B—comparison of the ‘waiting’ and ‘rest-opened eyes’ stages of the task; C—comparison of the ‘observation’ and ‘rest-opened eyes’ stages of the task.

^a Absence of the particular SPs.

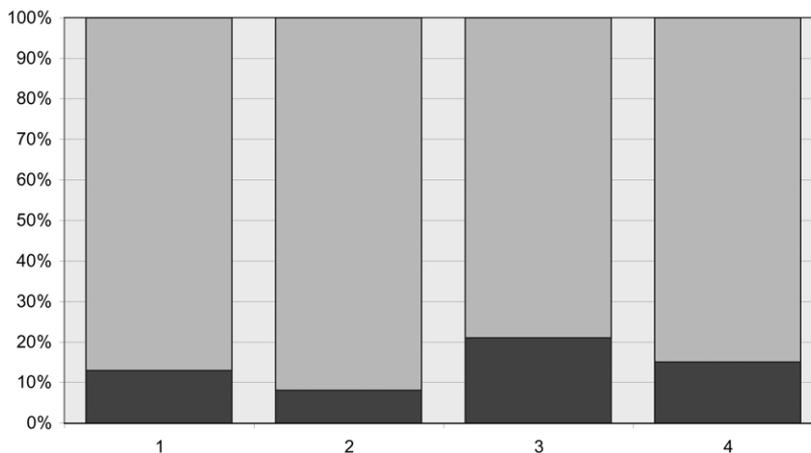


Fig. 2. 100% stacked columns for the SP relative percentage, which was changed (black colour) during the comparison of the averaged classification profiles for different functional states. 1—The comparison of the state ‘eyes closed’ with the state ‘eyes opened’ ($n=96$); 2—the comparison of the state ‘eyes opened’ ($n=96$) with the ‘waiting’ period of the memory task ($n=288$); 3—the comparison of the ‘waiting’ period with the ‘memorising’ period of the memory task ($n=288$); 4—the comparison of the ‘memorising’ period with the ‘keeping-in-mind’ period of the memory task ($n=288$).

SPs and/or SPs, which mostly contain theta components ($P<0.05$ – 0.001 for different EEG channels), when compared with the subjects with high alpha-index.

Comparison of classification profiles for the ‘waiting’ and the ‘memorizing’ stages of the memory task revealed opposite behavior of the classification profile transformations for those subjects with a high and low alpha-index. Thus, memorizing the visual matrix object resulted in an increased number of ‘pure’ Δ - and Δ - θ -rhythmical SPs ($P<0.05$ – 0.001 for different EEG channels) for the subjects with high alpha-index, when compared with the ‘waiting’ stage of the memory task. For the subjects with low alpha-index, memorizing the visual matrix object resulted in a decreased number of the same SPs ($P<0.05$ – 0.001 for different EEG channels) when compared with the ‘waiting’ stage of the memory task.

The ‘mosaic’ dynamics of all the transformations described above was unexpected: they affected only 8–21% of EEG individual segments in different brain functional states (Fig. 2)! Hence, dominant types of SPs determine the total picture of EEG spectral transformations only due to its energetic predomination in total spectrum, but during this, they do not absolutely characterize the

greater part of the individual segments of analyzed EEG. The main part of EEG individual segments, as has been shown, contributes constantly to the EEG classification profile during changes in cognitive loading.

What are the main peculiarities of the dynamic variability of SP types?

It was shown that functional loading such as the opening of eyes and a memory task caused an increase ($P<0.001$) of the relative incidence of the SP type change in the transition between neighboring EEG epochs of the same EEG (Table 3). This means that the increased functional loading leads to a more frequent changes in the type of SPs. This is proved by the fact that the decrease in functional loading (see the task ‘attention without memorizing’) resulted in less frequent changes in the type of SPs ($P<0.001$) when compared with the memory task (Table 3). In addition, the data for those subjects with high and low alpha-index also demonstrate the same dependent relationship between the functional loading and the incidence index ($P<0.01$) (Table 3, see the memory task for $\alpha+$ and $\alpha-$). The incidence index was largest ($P<0.01$) for subjects with a low alpha-index.

Table 3

The relative incidence of the SP type change for various EEG channels and different brain functional states (averaged for all subjects)

EEG channels	Eyes closed (<i>n</i> =96)	Eyes opened (<i>n</i> =96)	Memory task (<i>n</i> =288)	Memory task for $\alpha+$ (<i>n</i> =192)	Memory task for $\alpha-$ (<i>n</i> =96)	'Attention without memorizing' (<i>n</i> =70)
O1	0.52±0.02	0.56±0.02	0.59±0.05	0.58±0.06	0.62±0.08	0.51±0.02
O2	0.49±0.02	0.55±0.02	0.59±0.05	0.59±0.07	0.61±0.09	0.51±0.02
P3	0.54±0.02	0.58±0.02	0.60±0.05	0.59±0.07	0.62±0.08	0.52±0.02
P4	0.54±0.02	0.58±0.02	0.60±0.05	0.60±0.07	0.62±0.09	0.53±0.02
C3	0.56±0.02	0.59±0.02	0.60±0.05	0.60±0.06	0.62±0.07	0.56±0.01
C4	0.56±0.02	0.58±0.02	0.60±0.05	0.60±0.06	0.62±0.08	0.56±0.01
F3	0.56±0.02	0.58±0.02	0.60±0.05	0.60±0.06	0.62±0.08	0.56±0.01
F4	0.56±0.02	0.57±0.02	0.60±0.05	0.60±0.07	0.61±0.09	0.56±0.01
Mean	0.54±0.02	0.57±0.02	0.60±0.05	0.59±0.07	0.62±0.08	0.54±0.02

$\alpha+$ —Subjects with high alpha-index; $\alpha-$ —subjects with low alpha-index; '±'—mean error.

The diversity of the type of SPs was estimated as a ratio of the number of SP types detected in a given EEG to the total number in the standard set (32 standard SPs—100%). Diversity for the different EEG channels varied in the range of 31–50% (for different cases) (Table 4).

The SP type displaying the lowest diversity ($P<0.001$) was during the memory task (subjects with low alpha-index), while the SP type displaying the maximum diversity was during the task

called 'attention without memorizing' ($P<0.001$) (Table 4). It was interesting to note that there is a specific set of SPs for each EEG channel or small group of channels, since the diversity in SP types in all EEG channels taken together was substantially greater (for different cases the range was $48\pm 0.8\%$ – $68\pm 1.3\%$) than in each individual EEG derivation ($P<0.001$). Moreover, if SP types that occurred in less than 2% of the cases were not taken into account, then this value decreased

Table 4

The EEG SP types diversity for various EEG channels and different brain functional states (averaged for all subjects)

EEG channels	Eyes closed	Eyes opened	Memory task	Memory task for $\alpha+$	Memory task for $\alpha-$	'Attention without memorizing'
O1	34±1.4	39±1.5	38±0.5	40±0.7	34±0.6	41±2.2
O2	34±1.6	39±1.5	38±0.5	41±0.7	33±0.7	41±1.8
P3	38±1.2	39±1.5	37±0.5	39±0.7	32±0.6	44±2.3
P4	38±1.1	37±1.6	36±0.5	39±0.7	31±0.6	43±2.0
C3	39±1.3	36±1.3	36±0.4	38±0.6	32±0.5	49±1.3
C4	39±1.2	36±1.3	36±0.4	37±0.6	32±0.6	49±1.3
F3	38±1.3	35±1.2	35±0.4	37±0.7	31±0.6	50±1.3
F4	38±1.3	36±1.2	35±0.4	37±0.7	32±0.5	47±1.4
Mean	37.3±1.3	37.0±1.4	36.4±0.5	38.5±0.7	32.1±0.6	45.5±1.7
Ns	63±1.5	60±2.0	56±1.5	60±0.7	48±0.8	68±1.3
Ns(>2)	36±1.1	33±1.0	34±0.4	35±0.6	31±0.4	38±1.6

Ns—SP type diversity for all EEG channels taken together; Ns (>2)—the same like Ns, but without SP types, which were presented in classification profiles less than in 2% cases; $\alpha+$ —subjects with high alpha-index; $\alpha-$ —subjects with low alpha-index; '±'—mean error.

Table 5

Mean values of the estimation of the SP type change in the neighboring epochs at different time shifts between them

Shift	50	100	150	200	250	300	350	400	450	500	550
Eyes closed	0.54	0.69	0.76	0.79	0.81	0.82	0.82	0.82	0.82	0.82	0.82
Eyes opened	0.58	0.72	0.79	0.83	0.85	0.85	0.86	0.86	0.86	0.86	0.86
Memory task	0.61	0.75	0.82	0.86	0.88	0.88	0.88	0.88	0.88	0.89	0.89
Memory task for $\alpha+$	0.60	0.75	0.82	0.86	0.88	0.89	0.89	0.89	0.89	0.89	0.89
Memory task for $\alpha-$	0.62	0.75	0.82	0.86	0.87	0.87	0.87	0.87	0.88	0.88	0.88
'Attention without memorizing'	0.54	0.70	0.77	0.82	0.84	0.85	0.85	0.86	0.86	0.86	0.86
'Random' EEG	0.83	0.82	0.82	0.82	0.83	0.83	0.83	0.83	0.83	0.83	0.83

Averaged over all EEG channels and subjects. Shift—The number of the points of a digitized EEG signal between the initial moments of the neighboring analysis epochs. $\alpha+$ —Subjects with high alpha-index; $\alpha-$ —subjects with low alpha-index. Italic indicates the critical shift.

($P < 0.001$) to $31 \pm 0.4\%$ – $38 \pm 1.6\%$ (for different cases) (Table 4). This indicates that approximately 50% of the SP types have a very low occurrence; i.e. not more than 2–3 times per 149 analysis epochs in a 1-min EEG!

The data presented above refers to the level of variability of SPs in the neighboring epochs which overlapped by 80%. It would be expected that where the epochs overlap to a lesser extent (until they converge completely in time) the variability in type of SPs should increase to a certain value which is characterized by a stochastic level of the SP type change incidence. At the equiprobable occurrence of each of the 33 SP types (including non-classified spectra) in the EEG, the relative rate of their random alternation should be $1 - (1/33) = 0.97$. The actual EEG recordings showed that some of SP' types occur very frequently and others are almost entirely absent. Consequently, the levels of SP stochastic alternation in the actual EEG should be substantially lower than 0.97.

In order to find the value of the relative rate of SP stochastic alternation in the actual EEG, it was subjected to a randomized mixing of SPs. In such a way, the natural dynamics of SP sequence within each EEG channel were completely destroyed, but the percentage ratio between different types of SP remained the same. This modified EEG was described as 'random'. Using the procedure of randomly mixing SPs, the relative rate of the SP type alternation from the first and to the last interepoch shifts was 0.825 ± 0.007 (Table 5). This value presents an estimation of the maximum possible rate of relative alteration in the type of

SPs for a given EEG. Approaching this estimation testifies to the attenuation of mutual SPs determination between the neighboring EEG analysis epochs.

The average values of the relative SP alternation rate in the actual EEG for different shifts between the initial moments of the analyzed epochs (256 points) are given in Table 5 for different brain functional states. The maximum rate of change in the SP type, equal to 0.82, was reached at the shift in 300 points with closed eyes. This rate remains constant when the time interval between the epochs is increased. The shift at which the maximum rate of change in the SP type approach the value 0.82 was described as critical. It was shown that an increase in the functional loading resulted in a decrease of the critical shift to 200 points with eyes open and to 150 points during the memory task. On the other hand, a decrease in the functional loading resulted in an increase of the critical shift to 200 points during the task 'attention without memorizing' (compare with the 'memorizing' stage, Table 5). Thus, the SPs of the neighboring analysis epochs within a single EEG only have a significant deterministic influence on each other where the overlap in epochs is no longer than 50 points (Table 5). At greater shifts between the epochs, the estimations of the SP type alternation decrease practically to a stochastic level.

3.2. The dynamics of temporal stabilization of SPs in local EEGs.

A single EEG spectrum illustrates the particular integral dynamics of tens and hundreds of

Table 6

The mean number of the individual EEG epochs (averaged for all EEG channels), which follow like blocks by 'n elements' in succession without SP type change (including non-classified spectra—the type '0'), where n—is an integer from 1 to 149

The block length	Eyes closed	Eyes opened	Memory task	Memory task for $\alpha +$	Memory task for $\alpha -$	'Attention without memorizing'	'Random' EEG
1	34	37	39	38	41	32	72
2	22	24	25	25	25	23	17
3	15	15	15	16	15	16	6
4	10	9	10	10	9	11	3
5	6	7	6	6	5	8	1
6	4	3	3	3	2	5	1
7	2	2	1	1	1	2	–
8	2	1	1	1	–	2	–
9	1	1	–	–	–	1	–
10	1	1	–	–	–	1	–
11	1	–	–	–	–	1	–
12	1	–	–	–	–	–	–

The values are presented in the percentage from the total number of the individual epochs in all EEG recordings. '–'—The absence of the blocks with given length. $\alpha +$ —Subjects with high alpha-index; $\alpha -$ —subjects with low alpha-index.

thousands of neurons in a given cortical area at a particular point in time (Dumermuth and Molinari, 1987). Therefore, the absence of variance of a single spectrum during several analyzed epochs proves that in a given cortical area the same macro-regimen of neuronal pool activity is maintained during that period. This phenomenon of a temporary stabilization may be explained by a stabilization in the brain oscillatory patterns.

It was interesting to consider the mean number of individual EEG epochs averaged across all EEG channels, which follow like blocks by 'n elements' in succession without a change in SP type (including non-classified spectra—the type '0'), where n is an integer from 1 to 149 (Table 6).

The effect of the temporary stabilization of SPs in the individual EEG was almost identical for all functional states and took on a common characteristic: this index decreased as the length of block increased. At the same time, functional loading such as opening eyes and further—memory task, led to a reduction in the maximum length of block from 12 (eyes closed) to 8 (the memory task) because of the increase in the number of blocks of length 1 (Table 6). This effect is supported by the increased relative incidence of change in type of SPs with eyes opened and during the memory task (Table 3). At the same time, the decreased

functional loading resulted in an increase in the maximum block length from 8 (the memory task) to 11 ('attention without memorizing' task). Moreover, the actual EEGs (Table 6) substantially differed from the 'random' EEG (see above). An excessive increase in the number of blocks of length 1 for 'random' EEG may indicate a stochastic process. It was also shown that the majority of the blocks with the length equal to 1 consist of the SP type '0' (disorganized and/or 'noisy' activity) for all functional states observed.

An analysis of the maximum period of stabilization for various SP types showed that the brain 'maintains' the stabilization period of neuron' activity for between 3.5 s (for the memory task) and 4.7 s (when eyes are closed) depending on the functional state and the type of rhythmical activity generated (SP type). It was shown that even in the absence of any correlation between the EEG SPs there is a temporary stochastic stabilization of the SPs, which may reflect merely occasional combinations of SP types. The duration of such periods (an EEG with a random mix of different SP types) was substantially lower than in the actual EEG and reached up to 2.3–2.6 s (for different SP types).

The test–retest reliabilities of the classification profiles parameters between the two sessions

(obtained through 1–2 weeks) were very high which confirmed the validity of the findings (for example see Fig. 3).

4. Discussion

Analysis of various classification profiles of EEG for subjects in different functional states have shown that the whole palette of SPs of the individual EEG may be described by a limited and steady set of SP types. It should be noted that in this study only a 0.5–30 Hz frequency range was examined (Section 2). Thus, it was shown, that the number of different SP types that describe EEG independently of the EEG channel, brain functional state and individual peculiarities of the EEG was always below 50% of the standard set ($n=32$). This finding is in agreement with data collected by other researchers (Barlow, 1985; Creutzfeldt et al., 1985). It may be assumed that the standard set consists of EEG SP types, which reflect universal micro-temporal quasi-stationary elements (Bodunov, 1988). These elements form the EEG 'portrait' during macro-temporal transformations of the functional state (Kaplan and Shishkin, 2000).

As can be seen from the data obtained, approximately 50% of SP types occur not more than 2–3 times per 149 epochs analyzed in a 1-min EEG. It is the rarely occurring SPs which characterize the individuality of different EEG channels and/or a subject's EEG. The remaining 50% of SP types were the present in all EEG channels, all subjects and the various brain functional states studied. Perhaps, this part of SP types may be general for the brain (Bodunov, 1988). This hold is supported by the fact that all significant transformations, detected in EEGs during changes in the brain's activity, affected only this group of general SPs (Table 7). This means that the main part of the individual EEG segments, which has individual connotation, remains at a constant level whilst changes in the functional state of the brain occur (e.g. the opening of eyes, different stages of the memory task).

What characterizes the changes in these 50% of general SPs? It was found that an increased functional loading such as the opening of eyes and

then the performance of a memory task leads to a significant decrease in the percentage of non-classified spectra without changes in the number of classified SP types. This means that the number of some SPs that already exist in classification profile was increased. Thus, during the 'memorizing' stage of the memory task, the number of 'pure' theta-rhythmical SPs and SPs with Δ - θ components increased when compared with the 'waiting' stage of the task. The activity in the theta band may be responsible for the encoding of new information and retrieval from short-term memory (Klimesch, 1999). The delta response is related to signal detection (Basar-Eroglu et al., 1992). Moreover, short-term memory processes have been associated with oscillations within the 4–7 Hz (theta rhythm) (Klimesch et al., 1994). These findings suggest that the increased number of theta-rhythmical SPs and SPs with Δ - θ components for the 'memorizing' stage when compared with the 'waiting' period may indicate that the signal detection and encoding in short-term memory processing is playing a role.

At the same time, the decrease in the alpha-rhythmical SPs and SPs mostly with alpha components during the 'memorizing' and 'keeping-in-mind' stages of the memory task when compared with the 'waiting' stage may be due to the activation of cognitive and, perceptual processes and stimulus encoding as was shown for alpha rhythm desynchronization by Klimesch (1997).

The different behavior of α - and θ -activity during the memory task was also revealed by Klimesch et al. (1994). The reciprocal relationships between α - and θ -activity as with alpha desynchronization and theta synchronization in similar conditions suggest the existence of different neuronal generators associated with the production of alpha and theta rhythms (Klimesch, 1996). The opposite results for the subjects with high and low alpha-index during the 'memorizing' stage of the memory task suggest that the neurodynamic processes of the brain differ for these groups of subjects.

However, all EEG transformations mentioned above affected only 8–21% of the individual segments at the EEG. Thus, an important conclu-

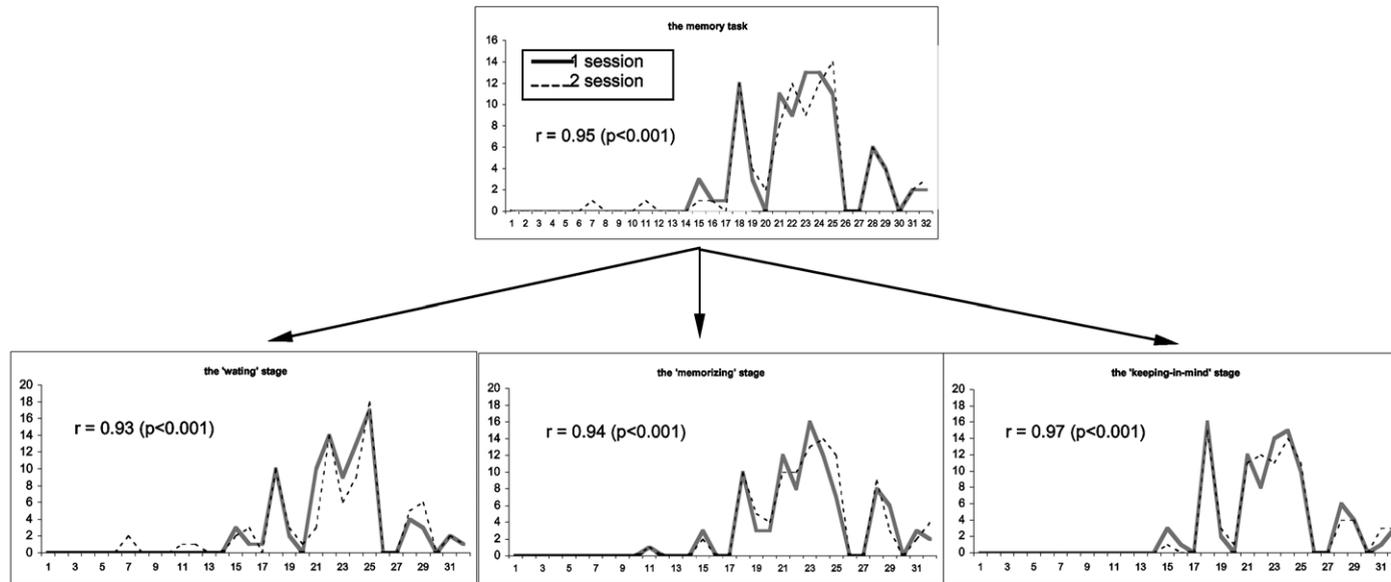


Fig. 3. Example of the EEG classification profiles calculated for 1st and 2nd sessions for the memory task and for the three stages of the memory task separately. Individual data for subject 03 (O2 EEG channel) are presented. The X-axis displays the labels (numbers) of the standard SP from 1 to 32. The Y-axis displays the share of the corresponding SPs in the percentage from the total number of the classified SPs. A line graphic was chosen instead of a bar for the ease of comparison. (Note that X-axis consists of 32 discrete values, all the in-between values are meaningless.) r —coefficient of correlation.

Table 7

General SP types, which occur in the EEG more than 2% of the cases for different brain functional states (*italics*)

Eyes open				Eyes closed				Memory task				'Attention without memorizing'			
1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
5	6	7	8	5	6	7	8	5	6	7	8	5	6	7	8
9	10	11	12	9	10	11	12	9	10	11	12	9	10	11	12
13	14	15	<i>16</i>	13	14	15	<i>16</i>	13	14	15	<i>16</i>	13	14	15	<i>16</i>
17	18	19	20	17	<i>18</i>	19	20	17	<i>18</i>	19	20	17	<i>18</i>	19	20
21	22	23	<i>24</i>	21	22	23	<i>24</i>	21	22	23	<i>24</i>	21	22	23	<i>24</i>
25	26	27	28	25	26	27	28	25	26	27	28	25	26	27	28
29	30	<i>31</i>	32	29	30	<i>31</i>	32	29	30	<i>31</i>	32	29	30	<i>31</i>	32

Other cells indicate that given SPs did not occur in the EEG for the particular brain functional state. The numbers in the cells indicate the labels of the corresponding SPs from standard set.

sion from this observation is that the limited number of SP types may successfully describe the EEG, but only about the half of them are functionally active. It is these functionally active SPs of a general nature that provide the changes of the steady SP combinations during the changes in the brain's functional state. Evidently, the dynamic of the brain's informational processes may manifests itself in the transformations of the small number of packages of relatively stable patterns of the cortex oscillatory activity (Basar et al., 2001).

At the same time, in the present work it was found that concrete parameters in the lifetime and the relative frequency of the occurrence of each of the SPs are specifically related to a particular brain functional state. So, it is interesting that even during rest conditions when the eyes are closed, the relative incidence of the SP type change during the transition between neighboring EEG epochs was more than 0.50. And this is in strongly overlapping (by 80%) 2-s analysis epochs! This apparent 'switching' from one dynamic to another is characterized as multi-variability, with new patterns being continually created, destroyed, and subsequently recreated (Keslo, 1995). This finding relates to the discrete (but not independent) work of the different morphological brain systems (Dierks et al., 1997; Strik et al., 1997) and cognitive activity (for reviews see John, 2001; Fingelkurts and Fingelkurts, 2001). Moreover, the SP types changed more frequently during an increase in the functional loading (eyes opening, the memory task) (Table 3). The decrease of the

shift of the mutual SPs determination (Table 5) and the reduction in the maximum block length during the increase in the functional loading (Table 6) testifies to the same idea. It is important to note that all these estimations did not approach the possible characteristics of the EEG whose natural sequence of SP type has been completely removed in each individual channel ('random' EEG; Tables 5 and 6).

Furthermore, the maximum period of SP temporary stabilization depended on the type of dominant frequency and also decreased when the functional loading was increased. However at the same time, this parameter differed significantly in the 'random' EEG, which may demonstrate that the temporary stabilization of the main dynamic parameters of neuronal activity had the non-occasional character. Perhaps, the decrease in the stabilization periods of SP type indicates that the brain's operations completed more dynamically and that there exists a transition to a more differential organization of spectral relations, where nerve elements become more independent and able to function as separate informational channels (Lindsley, 1961).

Before coming to the final conclusions, alternative explanations for the phenomena observed must be considered. It could be suggested that some of the results presented in this study could be attributed to the EEG recording with a linked ear reference electrode or volume conduction. This explanation seems unlikely for the following reasons: (a) the occipital and frontal regions clearly

showed different accentuations in their EEG effects (Section 3); (b) the analysis revealed, that each EEG channel or small group of channels has its own specific SP set (Table 4); (c) a high incidence of the SP type changing during the transition between neighboring EEG epochs was observed and where this index was dependent on functional loading (Table 3); (d) SP sets that were presented in classification profiles were limited, but not minimal: 50% from the standard one.

In another of our studies the same analysis for 102 locations of MEG-measurements was used. It is well known that MEG-measurements have perfect spatial resolution, there are no reference electrodes, and influence of the volume conduction is minimal. In spite of these differences, the main effects of discrete variability of SPs were almost the same (paper in submission).

When taken together, analysis of the different indices presented in this study show various (but converging) aspects of the discrete dynamics of multi-variability in SP types. Nevertheless, the parameters of the occurrence of SPs in any given EEG rather characterize the most general structure of the segmental organization of an EEG.

The internal logic of this organization is evidently hidden in the regulation of the sequential combinations of the separate EEG patterns. It is suggested that particular sequences of several EEG patterns appeared in consistent groupings (steady bundle with each other) and comprise more integral blocks of EEG structural organization. The idea that there may exist stable 'over-segments' in the individual EEG (the steady combinations of the particular segment types) was first demonstrated by Jansen and Cheng (1988). Other researchers have also found steady combinations of individual patterns in EEG (Sanderson et al., 1980; Lopes da Silva, 1981).

So, when taken together, these findings lead to the conclusion that stabilization processes influence not only the parameters of the analyzed EEG (the reduction of the functionally active segments), but also the sequence peculiarities of the EEG quasi-stationary segments (the temporary stabilization of SP types). Here, we are faced with an interesting phenomenon: the co-existence of a high multi-variability of the EEG parameters with a

simultaneous stabilization of these parameters in time. Perhaps, the high multi-variability of SPs indicates a wide range of the possible variations in current brain state or activity. On the other hand, a temporary stabilization in the SPs reflects the maintaining of the relative stability in the neuro-dynamics within that particular time interval on both a micro- and macro-level. The brain dynamics may be viewed here as balancing between multi-variability and metastability (Bressler and Keslo, 2001). So, a high incidence of the neighboring SP types where a strong overlapping (of 80%) of 2-s analysis epochs of the EEG was restricted by the limited SP set and by a 50% reduction in the functionally active SPs. This resulted in a relative temporary stabilization of the SPs sequential combinations.

Thus, the multi-variability of neuronal nets is evidently discrete in time and limited by the dynamics of the short quasi-stable brain states. This supports the idea that it is the limitation of degree of freedom of the neuron's ensemble variables which allows these ensembles to perform a finite number of operations (Kaplan, 1998).

5. Psychophysiological framework of the results

The brain keeps on surprising us with its unimaginable potential for multi-variability. It is evident, however, that to control effectively the functioning of the organism, a strict constraining is required on the degree of freedom that is given at all levels of the brain structural and functional hierarchy (for the discussion see Kaplan, 1998). This problem of constraining the number of degrees of freedom is, most probably, very difficult to solve in a framework of brain states continuum. The abrupt reduction of the number of degrees of freedom during cognitive operations could be easily achieved if the dynamical organization of the system is constrained by a finite number of metastable states (Kaplan, 1998). The findings obtained in present study support this view.

Taking also into account the hypothesis about the hierarchy of the segmental description of the EEG in different time scales, it could be suggested that the discrete structure of brain activity depicted in the EEG piecewise stationary structure is the

framework in which a variety of rapid ‘microscopic’ variables of a large system can obey the ‘macroscopic’ operational structure of brain activity (Kaplan, 1998). For peculiarities of the dynamics of macroscopic operational structure of brain activity, see the recent review (Fingelkurts and Fingelkurts, 2001).

Thus, the spatial and temporal hierarchy of discrete metastable states of neuronal assemblies can serve as a basis of functioning of such a potentially multivariable system like the brain (Kaplan, 1998). These discrete metastable states, in their turn, must appear in the EEG in the form of its piecewise stationary organization which can be studied by means of Sliding Short-Time Fourier Transform with subsequent Adaptive Classification of individual SPs.

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Appendix A: Adaptive classification of EEG SPs (SCAN-M, was developed and tested at Moscow State University)—published firstly in Russian (Kaplan et al., 1999)

Main idea of EEG SP classification

Firstly, it was necessary to create a standard SP set that covers the diversity of current individual SPs taken within normative EEGs. This standard SP set was then used to calculate the matrix of Pearson’s correlation coefficients (CC) between the standard and the current SPs of analyzed EEGs. Each current SP was labeled with the number of those standard SP for which the maximum CC exceeded a certain threshold was achieved. Where the specified threshold was not achieved, the corresponding current SP was given the category ‘non-classified SPs’ and was labeled as ‘0’. Thus, each individual EEG SP was given a classification

number, which corresponds to the label (number) of the standard SP most similar to it. Each channel of the whole EEG was characterized further by a classification profile.

Standard SP set creation

Firstly, 48 8- and 16-channel EEGs were recorded for subjects with strong- and weak-pronounced alpha activity during rest conditions (closed and opened eyes) and a memory task. Then, each EEG channel was reduced to the sequence of short-term power SPs. After that, all individual SPs ($n=3000$) obtained from EEGs registered for various subjects during different conditions were mixed into one SP pool.

Secondly, three independent highly qualitative experts selected by means of visual inspection the most representative SPs for 3000 short-term SPs. In the final version the standard SP set included 32 SPs (only those SPs which had minimum mutual correlation, were selected).

During the adjusting of the classification procedure it was possible to use either amplitude or power values of EEG spectrum and, also to change the values of the CC threshold level. In order to decrease the effects of individual spectra variability it was decided to employ two procedures: either spectrum glide smoothing, or choosing the maximum CC out of the three values of the correlation function, which was calculated between the standard SP and the current SP on zero shift and on double-side shift by one point (± 0.5 Hz). According to tests and modeling calculations, the latter procedure was chosen.

Basic procedure of adaptive classification

This procedure was performed in two stages. During the first stage, the initial matrix of mutual correlations between standard and current individual SPs of analyzed EEG was calculated (for each channel separately). According to the maximum CC from this matrix each current SP had the same label (number) as in the corresponding standard SP.

Attempts to decrease the number of non-classified SPs invariably resulted in a considerable increase in the number of the standard SPs in the SP set. Moreover, it was necessary to create

specific sets of the standard SPs for each of EEG derivations. It is the absence of a standard set' adaptability for particular EEG that prevents scientists from devising SP classification procedures on the basis of a simple correlation comparison of standard and current SPs. For this reason this study was conducted on a modified SP classification using a second stage—the creation of the actual SP set.

The creation of the actual SP set

On the basis of CC which were obtained at the first stage, the current short-term SPs were sorted: all current SPs for which the CCs were equal or exceeded the value 0.71 were attributed to the corresponding standard classes. According to this algorithm the same current SPs may be included simultaneously into different standard classes. It creates a unique palette of spectral variety in each class. The features of standard SP which form this particular class, limit the variability within this class. Then, the current SPs which were included in a particular class, were averaged within this class. This procedure was performed for all classes separately for each EEG channel. On the back of this, the standard spectra were reconstructed but taking into account the peculiarities of spectral description of concrete channel of the particular EEG. Thereby an 'actualization' of the initial standard SP set was performed. In other words, they were converted into the so-called actual SPs.

Thus, by using the common standard SP set for every given EEG the new set of spectra which adapted exactly to the particular EEG appeared. Each of these actual SPs resembled its standard predecessor however it differed from it in that it showed more similarity with the current SPs of particular EEG. This actual SP set was used further for the final classification of the SPs.

The final optimization of standard SP set

The adaptive classification of the current SPs using actual SP set produced two new problems. (1) Some actual SPs may be differ so greatly from the standard SPs which 'generate' them, that they almost resemble another standard SP—the effect of renumbering; (2) Some actual SPs may not bear resemblance to any other standard SPs accord-

ing to the established threshold of CC—the effect of declassification. In both cases a one-to-one correspondence between the labels (numbers) of standard and actual SP classes was lost. This might complicate the comparison of the results of SP classification for different EEGs. These problems were solved by 'manually' editing some standard SPs with subsequent repeated tests of the new standard SP sets. Editing of standard SPs involved moving apart ($D=1.5$ Hz) those main frequency peaks, which during choosing the maximum CC out of the three values of correlation function calculated for zero shift and double-side shift by one point (± 0.5 Hz), may occupy the same frequency. As the result of such correction of standard SPs the number of cases of actual SP 'renumbering' and 'declassification' were decreased to 0.2 and 0.6% correspondingly which does not prevent the comparison of different SP classifications for different EEGs.

General remarks

In each classification technique the most essential criterion to optimize the procedure is the degree of classification of the current set of segments by means of the compact standard SP set. The suggested adaptive classification of SPs is based on 32 standard SPs, 27 patterns of which correspond to not less than 96% of classified EEG segments. The number of non-classified SPs does not usually exceed 10%. According to the testing of the classification procedure, the small variations of the standard SP set did not result in changes in the final result due to adaptation stage (actualization of SPs).

When considered briefly, the simplicity, the universality of the standard SP set, the adaptability to the signal and classification accuracy, the adaptive classification technique compares favorably to other classification methods. Also, adaptive classification technique presented in this paper designed to handle a temporal data what is missing in other classification methods. Besides this, by using this approach it is possible not only to distinguish two or more different states, but also to capture 'why they are different'.

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