STABILITY, RELIABILITY AND CONSISTENCY OF THE COMPOSITIONS OF BRAIN OSCILLATIONS

Alexander A. Fingelkurts[a,*,] Andrew A. Fingelkurts[a]

Victor A. Ermolaev[b], Alexander Ya. Kaplan[b]

[a]*BM-SCIENCE – Brain & Mind Technologies Research Centre, PO Box 77, FI-02601, Espoo, Finland*
[b]*Human Brain Research Group, Biological Faculty, Moscow State University, 119899, Russian Federation*

Abstract: In the present experimental study, we examined the compositions of electroencephalographic (EEG) brain oscillations and their percent ratio in 12 subjects during resting conditions (closed and open eyes) and during the memory task (waiting, encoding and keeping-in-mind stages). The exact compositions of brain oscillations and their percent ratio were assessed by the probability-classification analysis of short-term EEG spectral patterns, which results in the probability classification profile (PCP). Within sessions the PCPs are found to be stable, as reflected by a relatively low coefficient of variability, and between sessions the PCPs are highly reproducible. Finally, test-retest reliability of subject's PCPs shows a dependency on task, being higher for the memory task, and in particular for the encoding stage. It was suggested that these findings support and strengthen the superposition principle where integrative brain functions are manifested in the superposition of distributed multiple oscillations.

Keywords: Electroencephalogram (EEG), Multiple brain oscillations, Short-term spectral patterns, Probability-classification analysis, Superposition principle.

*Corresponding author.

1. Introduction

Brain oscillations in neural networks have been intensively studied over the past years. There is common agreement that spontaneous activity at the cortical level (electroencephalogram – EEG) does reflect conditions, functional properties and global states of brain functioning (Nunez, 2000). There are numerous neuronal oscillations represented in ongoing brain activity. They are the basis of many different behavioral patterns and sensory mechanisms (Steriade, 2000) and they are closely connected to information processing, and cognitive activity (Basar et al., 2000; Nunez, 2000; Bressler and Kelso, 2001; also see review Fingelkurts and Fingelkurts, 2001).

To this day, the main analytical paradigm for EEG analysis remains spectral decomposition, where the comparison of absolute and relative changes in frequency bands of the power spectrum has revealed important information about the electrical activity of the brain and its relationship to human behavior (Muthuswamy and Thakor, 1998). Due to extensive use of EEG power spectra for research and clinical purposes it is important to know the temporal stability and reliability of EEG parameters. Virtually all studies done so far demonstrated high stability and reliability of EEG and its parameters (Gasser et al., 1985; Pollock et al., 1991; Salinsky et al., 1991; Burgess & Gruzelier, 1993; Harmony et al., 1993; Lund et al., 1995; Corsi-Cabrera et al., 1997). Thus, Burgress and Gruzelier (1993) reported average reliabilities of 0.81 and 0.86 for theta and alpha bands in resting, eyes open EEG with a test-retest interval of about 1 h. Test-retest correlation coefficients for EEG power, after a 12–16-weeks interval between measurements, are high ~0.8 for both absolute and relative power (Stassen et al., 1987; Pollock et al., 1991; Salinsky et al., 1991). For longer intervals (with an average 10 month interval), the test-retest reliability stays ~0.7 (Gasser et al., 1985). Even over a time period of 5 years the EEG parameters demonstrated high stability (Stassen et al., 1998). The inherent stability and reliability of EEG were demonstrated also with quite small segments. For example, Salinsky et al. (1991) reported that repeated 20-s segments of EEG were about 82% reliable, EEG segments of 40 s were about 90% reliable and at 60 s they were approximately 92% reliable. Thus, remarkable stability of EEG parameters suggests that the variation of EEG parameters forms a continuous phenotypic range rather than discrete phenotype classes (Stassen et al., 1998).

However, all previous studies have used averaged EEG parameters, based on extended periods of time and/or broad fixed frequency bands for a specific lead. At the same time, the

averaging of the EEG signal may not only mask the dynamics of EEG characteristics, but may also lead to ambiguous data interpretation (Fingelkurts et al., 2002, 2004). The average spectral characteristics of a broad frequency band predominantly reflect an influence of high-amplitude synchronized segments of the long EEG epochs, thereby totally obscuring the low-amplitude desynchronized ones (Lazarev, 1998). Hence, when examining the average brain electromagnetic parameters, it is not clear whether the observed phenomenon is real (not the "virtual" result of averaging procedure) and typical for the whole analyzed signal. For example, it is not clear: (1) whether temporal stability in the total power of particular brain oscillation reflect the stability in the number of its occurrence per minute rather than the stability of the average oscillation's amplitude, and (2) whether the stability of total power of particular brain oscillation typical for the whole analyzed signal or for a small portion of it. In fact, and as explored in our early work (Fingelkurts et al., 2003a, 2004) the total power spectrum does not characterize each of the individual power-spectra for each EEG segment. Moreover, total EEG power may be affected by pink noise (polyrhythmic disorganized activity) (Dumermuth and Molinari, 1987). In this case different indices and parameters of EEG may suffer from the influences of pink noise, instead of reflecting true rhythmic activity.

Additionally, in all of studies related to EEG stability and reliability the frequency bands were predefined and taken in isolation from each other. This does not permit researchers to examine temporal stability and behavior of the actual/natural composition of brain oscillations involved. At the same time, cognitive functions are represented by multiple oscillations (Basar et al., 2000). According to the superposition principle introduced by Basar et al. (1999), sensory and cognitive events induce superimposed multiple brain oscillations in many frequency bands (for the review, see Basar et al., 2004). Even though numerous evidences which support the existence of superimposed multiple brain oscillations were presented (see the same review), the stability, reliability and specificity of the actual composition of brain oscillations and their percent ratio were not yet addressed.

In connection to this, it seems reasonable to examine stability, reliability, specificity, consistency and validity of the actual composition of brain oscillations and their percent ratio during resting conditions and during cognitive tasks. To assess the exact composition of brain oscillations and their percent ratio, one can use the probability-classification analysis of short-term EEG spectral patterns (SP) which results in probability classification profile (PCP) (Kaplan et al., 1999; Fingelkurts et al., 2003a): short-term power spectra are computed from a

long EEG time series; then the individual power spectra are classified using a set of reference spectra; subsequently, the relative occurrence of each class is determined, resulting in PCP for each electrode, subject and state. It was demonstrated that PCP provides adequate and detailed description of electromagnetic brain activity (Kaplan et al., 1999; Fingelkurts et al., 2003a) and is a sensitive index of brain activity during different cognitive tasks and states (Fingelkurts et al., 2002, 2003b), reflecting drug effects on brain dynamics (Fingelkurts et al., 2004) and pathological brain conditions (Fingelkurts et al., 2000). Moreover, it was shown that distribution of spectral patterns in PCP is far from being random (Fingelkurts et al., 2003b). Another advantage to using PCP is that pink noise (polyrhythmic disorganized activity) is automatically isolated in a separate class, and thus does not affect classes with true rhythmic activity (Fingelkurts et al., 2003a). At the same time, class with polyrhythmic disorganized activity in its turn could be also subjected to analysis. This is justified since it was reported that the ratio of polyrhythmic disorganized activity and rhythmic components in EEG spectrum is strongly influenced by genetic factors (Meshkova, 1988), and as explored in our early work (Fingelkurts et al., 2003a, 2004) the amount of polyrhythmic disorganized activity in EEG is dependent on functional brain state and/or task.

In order to test individual stability and reliability of the actual composition of brain oscillations and their percent ratio, PCP can be used for the calculation of within-subjects reproducibility of upon repeat testing (test-retest reliability). Considering (1) that "multivariate EEG spectral patterns", which embodied temporal variability (Stassen, 1980, 1985), demonstrated high stability over a time period of 14 days and even 5 years (Stassen et al., 1998), and (2) that variance in individual resting EEG patterns is predominantly determined by heritable factors (Stassen et al., 1988), we hypothesize that compositions of brain oscillations and their percent ratio, indexed by PCP, would be also stable upon repeat testing.

Eight EEG electrodes (the minimum number sufficient to cover the main cortical areas) were used to test the influence of morpho-functional organization aspects on stability and reliability of PCPs. 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 PCPs stability and reliability. Hence, the aim of this study was to investigate the stability, reliability, consistency and validity of the actual composition of brain oscillations and their percent ratio during resting conditions and during cognitive task in repeated sessions using broad frequency

range: 0.5-30 Hz. Functional significance and correlates of EEG brain oscillations analyzed from the same data have already been reported (Fingelkurts et al., 2003a).

2. Materials and Methods

2.1. Subjects

Twelve healthy, right-handed adult male volunteers (aged 19-25) participated in the experiment. All subjects were students of Moscow State University and were recruited by phone call to participate. None of the subjects reported any visual defects, neurological or psychiatric disorders, or was on medication. In addition, all of them had normal autonomic (blood pressure and pulse rate) and psychometric indices.

Since alcohol influences variation of the normal EEG (Propping et al., 1980), subjects were asked to abstain from alcohol for 2 days before testing. To control variation due to food intake, participants were asked to have breakfast with two slices of toast, jelly and orange juice, and were instructed to avoid caffeine for 12 h prior to the recordings.

In order to check PCPs reliability, all of the subjects underwent the same experiment with the same instructions twice. The interval between initial testing and retesting was about 1-2 weeks. The EEG registrations began at the same time (10:00 a.m.) on both the first and second registration sessions. All the subjects were informed beforehand of the nature of the experiments and were aware that they were going to undergo the same test twice with an interval between. Written, informed consent from all subjects and institutional ethical committee approval were obtained prior to the experiment.

2.2. Stimuli and Procedure

Eight-channel 1-min EEGs were recorded during resting conditions (closed and open eyes) and the multi-stage memory task (waiting, encoding of the actual visual matrix object, and keeping in mind of the perceptual visual image). Each stage of the memory task was of 20-s duration.

The visual stimuli presented in front of the subjects to memorize were non-verbalizable matrices composed of nine square elements presented on a matrix screen. 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. Therefore, three distinct short-term (20 s) periods were tested: before, during, and after the stimulus exposure. As a control that the subjects were

memorizing the information, the subjects were 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. During the reproduction phase EEG was not recorded.

Chosen memory task was difficult because subjects were required to memorize positions of 9 square elements presented on a matrix screen, what is higher than the retention limit (7 items) for human short-term memory (Miller, 1956). At the same time, this task required subjects to attend to stimuli in order to remember the required amount of information: 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. Details of stimuli and procedure could be found in Fingelkurts et al. (2003a).

2.3. Data acquisition

Eight Ag/AgCl electrodes were placed bilaterally on the subject's scalp using the 10/20 system of electrode placement at $F_{3/4}$, $C_{3/4}$, $P_{3/4}$, $O_{1/2}$. Vertical and horizontal electro-oculograms were recorded. All electrodes were referred to linked ears. Raw EEG signals were amplified and bandpass-filtered in the 0.5-30 Hz frequency range and digitized at a sampling rate of 128 Hz by a 12-bit analog-to-digital converter. This frequency range was chosen because approximately 98% of spectral power lies within these limits (Thatcher, 2001). The impedance of the recording electrodes was always below 5 kΩ. 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 around 1 Hz, or its harmonics. Constant visual EEG monitoring allowed for selection of only those artifact-free EEG recordings for analysis.

To examine stability and reliability of PCPs a total of 144 (for the memory task – three stages) and 48 (for each closed and open eyes conditions) artifact-free one-minute EEGs were recorded for each session.

2.4. Data processing

Individual power spectra were calculated in the range of 0.5–30 Hz with 0.5-Hz resolution (61 values), using FFT with a 2-sec Hanning window shifted by 50 samples (0.39-sec) for each channel of one-minute EEG. These values proved the most effective for disclosing oscillatory patterns from the signal (according to a previous study). Sliding spectral analysis compensated for the effects of windowing and permitted us not to lose information from residual activity (bursts, oscillations, transients and other episodic events).

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

The compositions of brain oscillations (in terms of EEG SPs) during rest conditions and the memory task were estimated with the help of probability-classification analysis of the short-term EEG SPs (SCAN0.1) which was suggested by A.Ya. Kaplan (1999, Moscow State University). This analysis was performed in two stages (Fig. 1). During the first stage, sequential single EEG power spectra were adaptively classified in each EEG channel using a set of standard SPs.

The set of standard SPs was formed automatically using heuristic procedures and Pearson's correlation coefficients (CC): A pool of SPs ($n = 228\ 864$) was built from all the SPs of the entire EEG signal (all locations) for all subjects. From this pool, all identical SPs with peaks in the same frequencies were counted. The peak detection was based on normalizing the SP to within-SP relative percentages of magnitude, where acceptance is achieved when the peak exceeds a given (60%) percent-magnitude (100% corresponds to the magnitude of the highest peak within the SP). The set of identical SPs with the highest count were the most probable candidates to form the "set of standard SPs." Only those SPs with a minimum mutual correlation were selected. As a result, the standard set included 32 SPs.

The basic procedure of adaptive classification was performed in three steps (Fig. 1). During the *first step*, the initial matrix of mutual correlations between standard and current individual SPs of analyzed EEG was calculated for each channel separately. The current SPs that their CC passed the acceptance criteria of $r \geq 0.71$ were attributed to their respective standard classes. Thus the same current SPs may be included simultaneously into different standard classes. The CC acceptance criteria r was determined such as for $r \geq 0.71$ more than 50% of the SP variances were coupled/associated.
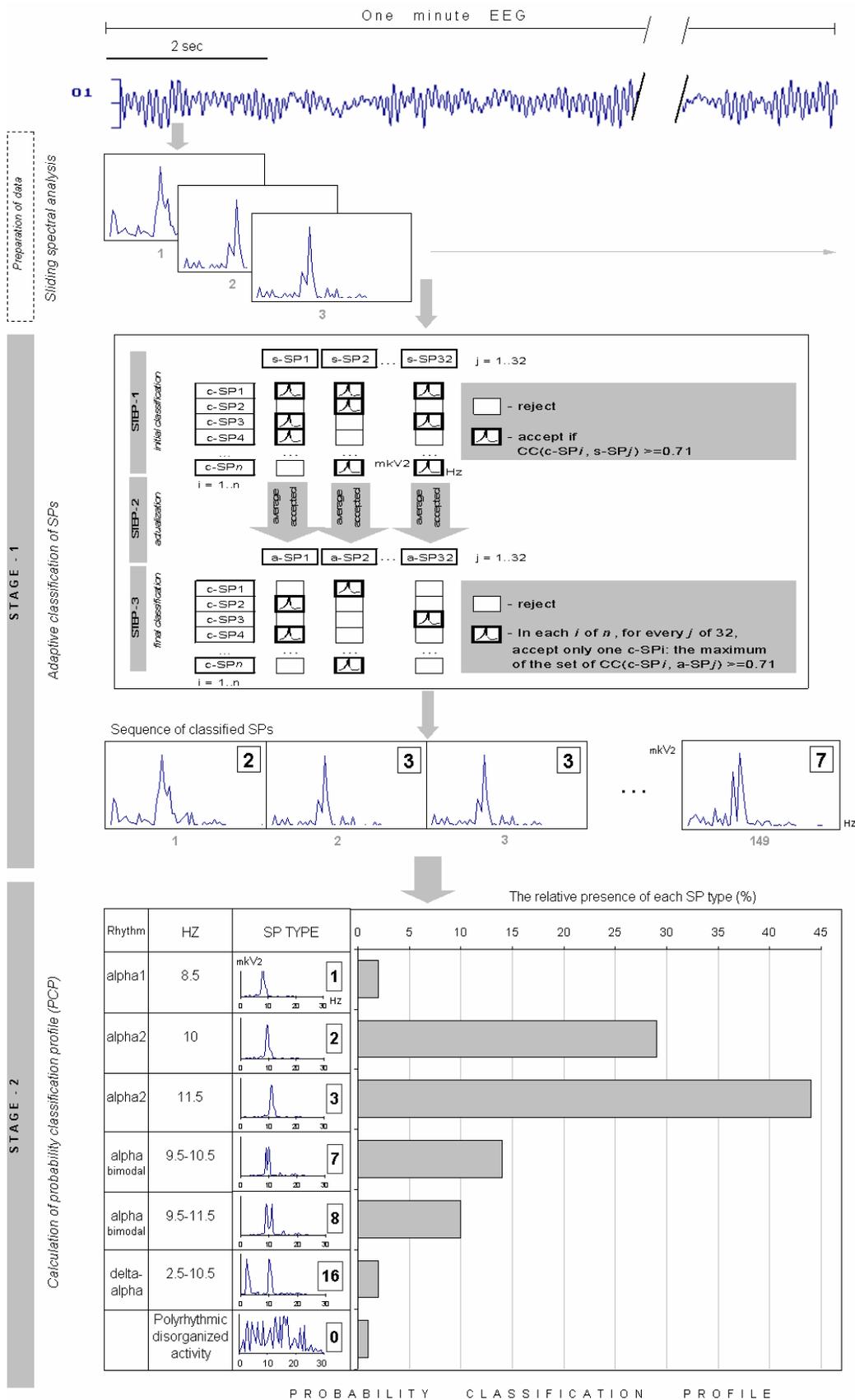
One minute EEG

2 sec

O1

Preparation of data

Sliding spectral analysis

1

2

3

STAGE - 1

Adaptive classification of SPs

s-SP1 s-SP2 ... s-SP32   j = 1..32

STEP-1 initial classification

c-SP1
c-SP2
c-SP3
c-SP4

...

c-SPn

i = 1..n

mkV2   Hz

☐ - reject

- accept if
CC(c-SPi, s-SPj) >=0.71

STEP-2 actualization

average accepted   average accepted   average accepted

a-SP1 a-SP2 ... a-SP32   j = 1..32

STEP-3 final classification

c-SP1
c-SP2
c-SP3
c-SP4

...

c-SPn

i = 1..n

☐ - reject

- In each i of n, for every j of 32,
accept only one c-SPi: the maximum
of the set of CC(c-SPi, a-SPj) >=0.71

Sequence of classified SPs

| 2 | | 3 | | 3 |

mkV2 | 7 | Hz

1   2   3   ...   149

STAGE - 2

Calculation of probability classification profile (PCP)

The relative presence of each SP type (%)

Rhythm	HZ	SP TYPE	0	5	10	15	20	25	30	35	40	45
alpha1	8.5	mkV2 ... Hz **1**										
alpha2	10	... **2**										
alpha2	11.5	... **3**										
alpha bimodal	9.5-10.5	... **7**										
alpha bimodal	9.5-11.5	... **8**										
delta-alpha	2.5-10.5	... **16**										
	Polyrhythmic disorganized activity	... **0**										

0 10 20 30

PROBABILITY CLASSIFICATION PROFILE

Figure 1. **The scheme of the data processing.** Sliding spectral analysis, adaptive classification of spectral patterns (SP) and calculation of the probability-classification profiles (PCP) were done separately for each subject and each channel of 1-min EEG. Gray small numbers under each SP represent the running numbers from 1 to 149. The numbers in the square represent the labels – types of classified SPs. Column "Hz" represents the main dominant peak(s) in particular SP. Presented PCP illustrates the composition and percent ratio of brain oscillations in O1 EEG for one subject during closed eyes condition. s-SPj – standard spectral pattern of type j, c-SPi – current spectral pattern of type i, a-SPj – actual spectral patterns of type j, CC – coefficient of correlation.

During the *second step*, the current SPs included in a particular class were averaged within this class. The same procedure was performed for all classes separately for each EEG channel. On the back of this, the standard spectra were reconstructed but this time taking into account the peculiarities of the spectral description of concrete channel of the particular EEG. In this way an "actualization" of the initial standard SP set was performed. In other words, standard SPs were converted into so-called actual spectral patterns. This actual SP set was used further for the *third step* - the final classification of the current SPs: each of current SPs was attributed to only one actual SP class for which the CC was the maximum of the set of $r \geq 0.71$. Details of probability-classification procedure can be found in Kaplan et al. (1999) and Fingelkurts et al. (2003a).

The adaptive classification technique employs several adequate correction algorithms to achieve considerable reduction in the variance of single spectral estimations and to account the relationship between neighbor frequencies in the frequency continuum (Fingelkurts et al., 2003a). This justifies the use of individual short-term SPs and increases the sensitivity of this analytical approach to EEG dynamics. This SP classification method made it possible to identify up to 100% of the individual single spectra in the initial EEG recordings due to algorithm's self-adaptivity to local signals. Considering that a single EEG spectrum illustrates the particular integral dynamics of tens and hundreds of thousands of neurons in a given cortical area at a particular point in time (Dumermuth and Molinari, 1987), it can be considered that the SPs within each class are generated by the same or similar dynamics with the same or similar driving force. SPs from different classes, however, have had in effect different driving forces and therefore have been generated by different dynamics (Manuca and Savit, 1996). In this case, one type of SP may be considered as single event in EEG phenomenology from viewpoint of its spectral characteristics (see Appendix). As the result of the adaptive

classification technique, each current SP was labeled according to the index of the class to which it belongs. Thus, a sequence of SP labels that represents the sequence of EEG oscillatory states through which the system passes was obtained. Hence, each EEG signal was reduced to a sequence of individually classified SPs (Fig. 1).

At the second stage, the probability classification profile (PCP) of spectral patterns for each EEG channel in each subject was calculated (Fig. 1). This index was calculated by taking the relative number of cases of an SP type as a percentage of the total amount of all SPs within each EEG channel – the histogram of the relative presence of each SP type (Fingelkurts et al., 2003a). PCPs were averaged across the twelve (for the memory task) and four (for the closed and open eyes) 1-min EEG signals for each subject separately for each EEG channel and session. It was expected that these PCPs would make it possible to portray (in SP description) the composition of brain oscillations and their percent ratio in detail.

2.5. Statistical analysis

In order to decide upon the trait character of the PCPs we used:

a) Calculation of coefficient of variability (CV = standard deviation / Mean) for averaged PCPs across all 1-min EEGs ($n = 4$ for resting condition, $n = 12$ for the memory task) separately for each subject, EEG channel and session. CV can be used as a first measure of pattern *stability*: CV ~1 indicates nearly random process; CV<<1 reflects very high stability;

b) Repeated assessments at 1-2 weeks interval on each of subjects so that the *within-subject reliability* of the PCPs could be determined. A measure may be called 'reliable' if it yields the same results when tested in multiple sessions over time ('test–retest reliability') (Jack and Roepstroff, 2003). Spearman rank correlations test was used.

For averaging the correlation coefficients across the subjects, the correlation coefficients were converted into so-called Fisher *Z* values. It is necessary since an average of correlation coefficients across the subjects does not represent an "average correlation" in all those subjects (because the value of the correlation coefficient is not a linear function of the magnitude of the relation between the variables). Thus, before averaging, correlation coefficients were converted into Fisher *Z* values (which are additive measures), using the following formula:

$Z = \frac{1}{2} * \log [(1 + r) / (1 - r)]$, where *r* is correlation coefficient.

In order to evaluate the correlation between variables, it is important to know the "magnitude" or "strength" as well as the significance of the correlation. To obtain the strength of the relationship the correlation coefficients were squared, resulting in the values (r^2, the *coefficient of determination*) that represent the proportion of common variation in the two variables. Multiplied by 100, this proportion of variance indicates the percentage of variance that is explained by the regression function;

c) Regular changes in PCPs in accordance with the changes of functional brain state and stages of the memory task so that *consistency* (functional relevance) could be detected. A measure may be called 'consistent' when it can be shown that the results are not due to specific features of the measurement technique (Jack and Roepstroff, 2003). Wilcoxon matched pairs test was used to compare correlations during resting conditions and during different stages of the memory task so that *validity* could be estimated. A measure is validated when it can be shown to accurately reflect the phenomenon it purports to measure (Jack and Roepstroff, 2003).

3. Results

3.1. *Stability of the probability classification profiles within subjects*

As test-retest reliability will necessarily be constrained by stability of measurement at each 1-min EEG within each subject and session, we start our analysis by evaluation of coefficient of variability (CV = standard deviation / Mean) as a first measure of stability for averaged PCPs across all 1-min EEGs separately for each subject and each EEG channel. Thus, analysis of CV revealed that PCPs were stable (CV ranged from 0.0 to 0.6 for different EEG channels and subjects) during resting conditions and during memory task for both sessions (Table.1).

3.2. *Within-subject test-retest reliability of the probability-classification profiles and its consistency*

Under constant experimental conditions PCPs for each subject demonstrated considerable test-retest reliability for resting conditions and the memory task ($P < 0.04$-$P < 9E-11$, Table 2). A coefficient of determination (r^2 x 100) of 50% or above was considered indicative of good test-retest reliability.

Table 1. Stability (indexed by coefficient of variability (CV = standard deviation / Mean)) of averaged PCPs across all 1-min EEGs separately for each subject.

	rest conditions				memory task					
	Closed eyes		Open eyes		Waiting		Encoding		Keeping in mind	
subjects	1 s	2 s	1 s	2 s	1 s	2 s	1 s	2 s	1 s	2 s
1	0.0-0.5*	0.0-0.6	0.0-0.4	0.0-0.4	0.0-0.4	0.0-0.5	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.5
2	0.0-0.1	0.0-0.6	0.0-0.5	0.0-0.6	0.0-0.4	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5
3	0.0-0.5	0.0-0.3	0.0-0.6	0.0-0.6	0.0-0.5	0.0-0.4	0.0-0.5	0.0-0.5	0.0-0.4	0.0-0.4
4	0.0-0.4	0.0-0.5	0.0-0.6	0.0-0.5	0.0-0.5	0.0-0.4	0.0-0.5	0.0-0.4	0.0-0.5	0.0-0.4
5	0.0-0.5	0.0-0.5	0.0-0.6	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.6	0.0-0.5	0.0-0.4	0.0-0.5
6	0.0-0.6	0.0-0.5	0.0-0.6	0.0-0.6	0.0-0.5	0.0-0.4	0.0-0.4	0.0-0.6	0.0-0.5	0.0-0.5
7	0.0-0.5	0.0-0.2	0.0-0.5	0.0-0.4	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5
8	0.0-0.4	0.0-0.4	0.0-0.6	0.0-0.6	0.0-0.5	0.0-0.6	0.0-0.4	0.0-0.5	0.0-0.5	0.0-0.6
9	0.0-0.5	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.5	0.0-0.5	0.0-0.6	0.0-0.4	0.0-0.5
10	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5	0.0-0.5
11	0.0-0.5	0.0-0.6	0.0-0.4	0.0-0.5	0.0-0.3	0.0-0.5	0.0-0.3	0.0-0.4	0.0-0.4	0.0-0.5
12	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.6	0.0-0.4	0.0-0.5	0.0-0.4	0.0-0.4	0.0-0.5	0.0-0.4

* Range means that coefficient of variability varies for different EEG channels within these limits.
$n = 4$ for rest condition; $n = 12$ for the memory task condition
s - session

Consistency (or functional relevance) of test-retest reliability of PCPs could be assessed by examining the regular changes in the reliability values in accordance with the changes of functional brain state and stages of the memory task. From Figure 2 it can be seen that the degree of reliability of PCPs depends on the functional brain state and stages of the memory task. In general, PCPs for the memory task revealed higher reproducibility over time (with the maximum during encoding stage) than resting conditions (with the minimum during open eyes condition) ($P < 0.01$, Fig. 2). Thus, average coefficient of determination demonstrated that about 63% of PCPs variance in 1st session was coupled/associated with PCPs variance in 2nd session for closed eyes condition. Open eyes condition was characterized by ~53% association of PCPs variances in 1st and 2nd sessions. During memory task the association of PCPs variances in 1st and 2nd sessions was above 74% (Table 2). Thus, test-retest reliability of PCPs was functionally relevant and consistent with the changes of functional brain state and stages of the memory task.

Example of high test-retest reliability for one subject during closed eyes condition is illustrated by scatter plot in which PCPs derived from recordings at 2-week interval were plotted against each other (Fig. 3). All points lying along the diagonal indicates perfect reproducibility. The shape of the point cloud in a scatter plot indicates the degree of specificity

of the underlying parameters: a "sausage"-shaped cloud along the diagonal indicates a high specificity (informativeness), whereas all points clustering in a compact "ball" is an indicator of low specificity (Stassen et al., 1998). Results presented in Figure 3 demonstrated high reproducibility and specificity of PCPs.

Table 2. Within-subject test-retest reliability (indexed by the coefficient of determination – R2) of the probability classification profiles. Values averaged across 12 subjects and presented as mean +- standard deviation.

| rest conditions				memory task					
CLOSED EYES		OPEN EYES		WAITING		ENCODING		KEEPING IN MIND	
	R2		R2		R2		R2		R2
O2	0.54+-0.26	O2	0.49+-0.12	O2	0.72+-0.11	O2	0.72+-0.13	O2	0.75+-0.11
O1	0.56+-0.18	O1	0.49+-0.18	O1	0.69+-0.11	O1	0.74+-0.18	O1	0.68+-0.11
P4	0.67+-0.14	P4	0.52+-0.17	P4	0.71+-0.15	P4	0.73+-0.18	P4	0.74+-0.12
P3	0.66+-0.12	P3	0.55+-0.21	P3	0.74+-0.12	P3	0.77+-0.07	P3	0.75+-0.09
C4	0.65+-0.16	C4	0.58+-0.18	C4	0.73+-0.15	C4	0.78+-0.09	C4	0.81+-0.06
C3	0.6+-0.18	C3	0.57+-0.19	C3	0.76+-0.13	C3	0.78+-0.08	C3	0.8+-0.08
F4	0.67+-0.15	F4	0.52+-0.21	F4	0.8+-0.09	F4	0.82+-0.09	F4	0.81+-0.09
F3	0.67+-0.1	F3	0.52+-0.21	F3	0.78+-0.1	F3	0.82+-0.06	F3	0.8+-0.11
Mean	0.63+-0.05	Mean	0.53+-0.03	Mean	0.74+-0.04	Mean	0.77+-0.04	Mean	0.77+-0.05
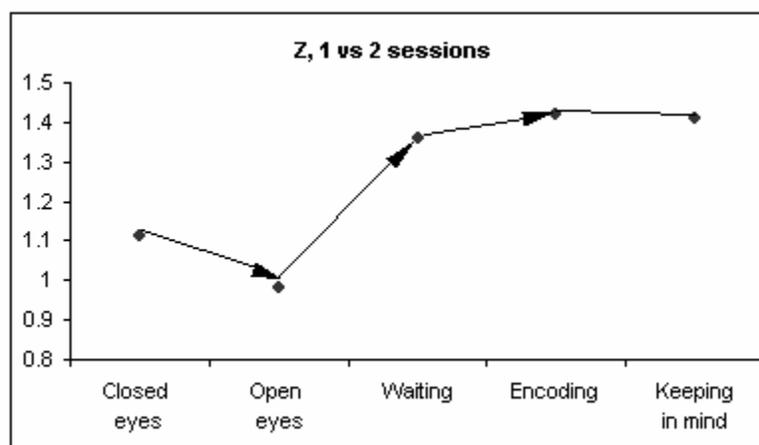
Figure 2. Within-subject test-retest reliability (indexed by Fisher Z values – converted Spearman rank correlations) of the probability-classification profiles. Values averaged across 12 subjects and all EEG channels. Arrows indicate significant ($P < 0.03$-0.01) changes.

Does within-subject test-retest reliability of PCPs differ in various brain areas? In the present study reliability values demonstrated increased trend from occipital to frontal areas: they were higher for the anterior brain areas, than for the posterior ones ($P < 0.05$) for all conditions (Table 2).
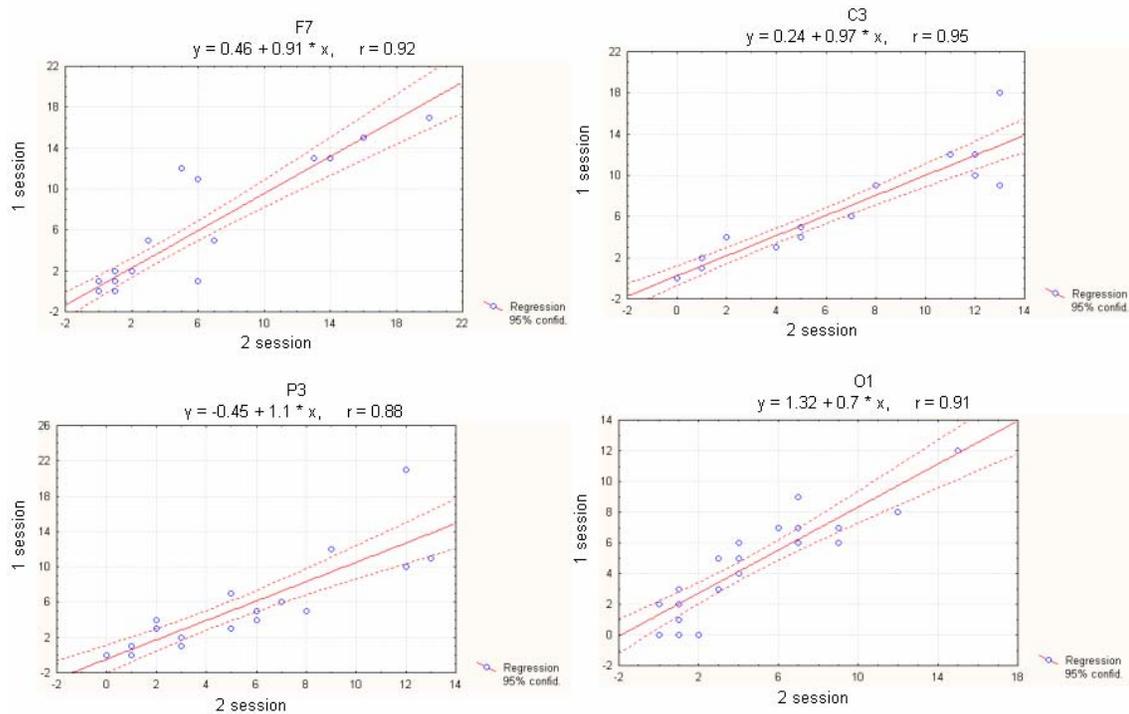

Figure 3. Reproducibility of the probability-classification profiles for different EEG channels for one subject (s12) during closed eyes condition: scatter plots show a comparison between measurements carried out at 2-week interval. O1 – occipital, P3 – parietal, C3 – central, F7 – frontal EEG channels placed on the left hemisphere of the scalp.

4. Discussion

In this paper, we report the results from a pilot study that examines for the first time stability, test-retest reliability and consistency of the compositions of brain oscillations and their percent ratio (in terms of PCPs) during resting conditions and the memory task.

4.1. Stability

It was demonstrated that PCPs were stable across all 1-min EEGs within each subject. It means that the number of EEG recordings was sufficient ($n = 4$ for rest conditions, and $n = 12$ for the memory task for each subject and session) to achieve adequate internal stability (for discussion see Allen et al., 2004; Hagemann, 2004). Such stability can be explained by the fact that diversity of spectral patterns (SPs) in PCPs is restricted and depends on the functional brain state and/or cognitive task (Fingelkurts et al., 2003a). Stable diversity of SPs in individual PCPs determines most likely low variation of the mean absolute and relative power in the frequency bands (less than 10%) and low variability in median and peak power (about 3%) (Oken and Chiappa, 1988). Thus, in addition to the known fact that averaged EEG power spectrum is stable and to a large extent is determined genetically (Stassen et al., 1987; van Beijsterveldt et al., 1996; for a review and meta-analysis, see van Beijsterveldt and van Baal, 2002), present finding suggests that brain "maintains" a particular composition of brain oscillations and their percent ratio (indexed by short-term SPs in PCPs) during particular functional state.

Finding of the present study together with the literature data can be understood in the following terms. Considering that a single EEG spectrum illustrates the particular integral dynamics of tens and hundreds of thousands of neurons in a given cortical area at a particular point in time (Dumermuth and Molinari, 1987), PCP can be viewed as a representation of the composition of different types of neuronal integral dynamics and their percent ratio. Thus, PCPs reflect the probability of the occurrence of particular neuronal dynamics which altogether constitute a dynamical repertoire of brain activity in the particular functional state.

4.2. Within-subject test-retest reliability

Reliability is particularly crucial for studies of individual differences assumed to have trait status because traits are assumed to reflect homogenous characteristics that are stable over time. In the present study, PCPs of the same individuals showed high similarity between the two test sessions and specificity for all examined conditions, signifying that there were no systematic differences between the composition of brain oscillations (indexed by short-term SPs) and their percent ratio in two sessions (Table 2, Fig. 3). The data derived from repeated assessments of the same individuals may serve us as reference values with respect to "natural" EEG fluctuations over time, thus enabling the detection of "significant" intra-individual changes at high resolution. From this point of view EEG considered as a superimposition of a

static, person-specific part with non-static and state-specific parts (Dunki et al., 2000). Test-retest results in the present study probably indicate that the influence of the common genetic/environment factors was highly stable over time and mentioned superposition was kept across the sessions. In other words this finding might be the manifestation of intra-individual stability of neurodynamics and their underlying regulatory mechanisms.

High test-retest PCP reliability when measured during resting condition is consistent with a number of studies, which demonstrated that the resting EEG is stable (Gasser et al., 1985; Pollock et al., 1991; Burgress and Gruzelier, 1993; McEvoy et al., 2000). However, results of the present study substantially extended previously known data: not only different frequency bands more or less reliable, but in fact, the whole composition of brain oscillations as a set (PCP) is highly reliable.

Whether PCP is meaningful ultimately depends on its association with the behavioral trait or cognitive activity. In the present study it was demonstrated that the degree of PCPs reliability depends on functional state of the brain and the stages of the memory task (Fig. 2). Thus, opening one's eyes results in nonspecific activation compared to the eyes closed condition. As a more activated state, open eyes condition is characterized by nonspecific variability, and trend instability when compared to eyes closed condition (Sterman et al., 1994), what was reflected in the present study in decreased test-retest PCP reliability (Fig. 2). The memory task demonstrated significantly higher test-retest reliability (with the maximum during encoding stage), than the resting conditions (with the minimum during open eyes) (Fig. 2). Thus, waiting stage of the memory task reflecting alertness, arousal and readiness to process information (Basar, 1998) was described by decreased diversity of SP types when compared with open eyes condition (see Fingelkurts et al., 2003a for the results derived from the same data). This resulted in increased test-retest reliability during waiting stage. As task demands increase (the following stages of the memory task), maintaining task performance may require higher levels of physiological activation and enhanced attention (Hockey, 1997). Most likely, these processes are reflected in the present study in increased test-retest reliability during encoding and retention stages of the memory task (Fig. 2). This finding is in line (to some extent) with the work of McEvoy et al., (2000) where authors have demonstrated greater reliability in quantitative EEG values collected during cognitive task ($r = 0.9$) than during the resting condition ($r = 0.7$). According to McEvoy et al., the greater reliability of task-related EEG than of resting EEG is likely due to smaller variations in attention and alertness levels

during task performance than in resting condition: Task performance imposes a more uniform level of alertness and mentation, and thus has a stabilizing effect on the EEG (PCP in the present study).

Taking together, these findings suggest that PCPs were typical for each of the examined conditions, reflecting a particular composition and percent ratio of brain oscillations (in SPs description) which are needed to achieve the main goal of the particular functional state. This idea is consistent with the fact that brain oscillations are typically associated with cognitive activity (Sterman et al., 1996; Klimesch et al., 1997; Basar, 1998; Basar et al., 1999, 2000) and with increases in mental workload (Gundel and Wilson, 1992; Gevins et al., 1997, 1998). Perhaps composition and percent ratio of brain oscillations (in spectral patterns description), which comprise PCP, reflect the poly-operational structure of brain activity (for discussion see Fingelkurts et al., 2003b). Thus, changes in the brain functional state were accompanied by changes in the poly-operational structure of brain activity (indexed by PCP) which describes this functional state. Perhaps the oscillatory activity of neuronal pools, reflected in composition of brain oscillations, constitutes a mechanism by which the brain can regulate state changes in selected neuronal networks that lead to a qualitative transition between modes of information processing (Lopes da Silva, 1996). Indeed, it was demonstrated that the dynamics 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 (Fingelkurts et al., 2003a). Correlations of PCPs with actual task performance, detailed description of the composition of brain oscillations (indexed by PCPs) for different experimental conditions (closed eyes, open eyes, waiting, encoding and keeping-in-mind stages of the memory task) and their functional correlates can be found in Fingelkurts et al. (2003a).

The fact that frontal brain areas had higher reliability values than the other areas during all examined conditions might be explained (1) by decrease in anterior variability of discrete frequency components across a broad frequency range (0.5-45 Hz) during working memory task (Winterer et al., 2004); and (2) by reduced diversity of SP types in frontal EEG channels when compared with others during resting condition and working memory task (Fingelkurts et el., 2003a). Additionally, compositions of brain oscillations in frontal areas predominantly contained oscillations in theta frequencies when compared with other brain areas (Fingelkurts

et el., 2003a). It is these frontal theta oscillations that revealed the best reliability when compared with other frequencies (McEvoy et al., 2000).

One may speculate that the reason for the fact that frontal areas are characterized by reduced diversity of SP types and as a consequence by higher reliability of PCPs than the other areas during all examined conditions is the following: Frontal areas are activated during self-referential judgments (Gusnard et al., 2001; Kelley et al., 2002) and are poised to serve a major role in representing self-schemas (Holyoak and Kroger, 1995). Hence, one may hypothesize that high temporal reliability of these areas reflect temporal stability and integrity of the representation of self.

Thus, obtained results suggest that the actual compositions of brain oscillations and their percent ratio (indexed by PCP) possess distinct trait-like qualities as indicated by (a) within-subject stability over EEG recordings; (b) high reliability over time; (c) high specificity for each of the examined conditions. These findings support and strengthen the superposition principle where integrative brain functions are manifested in the superposition of distributed multiple oscillations (for the review, see Basar et al., 2004).

Acknowledgements

Appendix

Methodological aspects and interpretation of short-term spectral patterns

A single short-term EEG spectral pattern illustrates the particular integral dynamics of tens and hundreds of thousands of neurons in a given cortical area at a particular point in time (Dumermuth and Molinari, 1987). However, there is no simple (one-to-one) relation between a power spectrum computed from short epochs of ongoing EEG and the actual state of the neurons in the underlying network: many different configurations of firing neurons can give rise to a particular short-term spectrum (many-to-one relation). Here, the relation is, at best,

statistical. At the same time, the same configuration of firing neurons cannot give rise to two (or more) different short-term spectra. Thus, two different short-term power spectra most likely are originated from two different configurations of firing neurons (Manuca and Savit, 1996). Consequently, short-term spectral pattern characterizes/reflects a particular class of neurons' activities, where each of the activities has something common with the others within the class (one-class–to-one relation). Moreover, two classes of neurons' activity do not overlap (otherwise the same configuration of firing neurons could give rise to two or more different short-term spectra). Thus, one short-term spectral pattern may be considered as a single event (which reflect a particular class of neurons' activity) in EEG phenomenology from viewpoint of its spectral characteristics.

Class-to-one relation, perhaps, serves to the brain as a mechanism of multivariability reduction and increases brain adaptability (Mesulam, 1998; Fingelkurts et al., 2003b): The same final result – oscillatory state (indexed by short-term spectral pattern) may be achieved by one of many different alternative neurons' activities within the class, depending on the peculiarities of the situational context (past activity, present needs, and contemplated consequences). In the functional terms, a "compromise" based on the saving of energy resources and on agreement between intrinsic goals and motivational states permits a brain to "select" only those configurations of firing neurons that are meaningful to accomplish an actual organism's goal (Fingelkurts et al., 2002). Thus, the solution to the integrative brain functioning is therefore defined as the settling of the entire system into a metastable state of best fit (for the review, see Fingelkurts and Fingelkurts, 2001, 2004; Fingelkurts et al., 2002).

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; see also recent review Fingelkurts and Fingelkurts, 2004). These discrete metastable states, in turn, must appear in the EEG in the form of piecewise stationary organization of combination of brain oscillations which can be studied by means of Sliding Short-Time Fourier Transform with subsequent adaptive probability-classification of individual short-term spectral patterns (Fingelkurts et al., 2003a).

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