

*Below is the unedited draft of the article that has been accepted for publication
(© Neuroscience Research, 2010, V. 66, No 3, P. 299-312.)*

Morphology and Dynamic Repertoire of EEG Short-Term Spectral Patterns in Rest: Explorative Study

Alexander A. Fingelkurts^{1*}, Andrew A. Fingelkurts¹

¹ *BM-Science – Brain and Mind Technologies Research Centre, Espoo, Finland*

Abstract

In the present explorative experimental study, we examined the diversity of electroencephalographic (EEG) short-term spectral patterns (SPs) within a broad frequency band (1.5-30 Hz) for healthy adult subjects during closed eyes and open eyes resting conditions. The types of EEG SPs were assessed by counting all identical SPs with peaks in the same frequency bins from the pools of SPs, which were built from all the SPs of the entire EEG signal (all locations) for all subjects separately for closed and open eyes conditions. This study demonstrated that independently of the resting functional state of the brain (closed eyes *vs* open eyes) (a) the diversity of short-term EEG SP types was limited, (b) the percent distribution of SP types among different categories of SPs (based on morphology of SPs) was constant and (c) the most preferred frequencies were restricted to delta-theta and alpha bands. At the same time, closed eyes and open eyes conditions differed from each other by the percent distribution of different types of SPs. The probabilities for the occurrence of particular SP types were typical for each of the examined conditions with domination of alpha-rhythmical SPs during closed eyes condition and domination of delta-theta-rhythmical SPs during open eyes condition. The findings suggest that the diversity of SPs varies as a function of functional state of the brain during resting conditions. Understanding of the diversity of short-term EEG SP types is important theoretically and practically, and is significant for advancing the interpretation of the EEG signal.

Keywords: Electroencephalogram (EEG), Multiple EEG oscillations, Short-term spectral patterns, Resting conditions.

1. Introduction

Currently there is common agreement in the field of cognitive neuroscience that ongoing spontaneous activity at the cortical level (electroencephalogram – EEG) does indeed reflect conditions, functional properties and global states of brain functioning and is closely connected to information processing and cognitive activity (Corsi-Cabrera et al., 1989; Arieli et al., 1996; Tsodyks et al., 1999; Nunez, 2000; Bressler and Keslo, 2001; Leopold et al., 2003; also see review Fingelkurts and Fingelkurts, 2001). Ongoing brain activity is

characterised by numerous neuronal oscillations. They are the basis of many different behavioural patterns and sensory mechanisms (Miller and Schreiner, 2000; Steriade, 2000).

Brain oscillations in neural networks have been intensively studied over the past years: Basar et al. (1999, 2000; 2004), Klimesch (1996, 1999a,b, 2003), Klimesch et al. (2005), Fingelkurts et al. (2002, 2003a,b, 2004, 2006a), just to mention a few. As a result of this research, it is suggested that the oscillatory activity of neuronal pools reflected in characteristic EEG rhythms constitutes a mechanism by which the brain can regulate changes of a state in selected neuronal networks to cause qualitative transitions between modes of information processing (Lopes Da Silva, 1996). Different oscillatory patterns may be indicative of different information processing states, and it has been proposed that the oscillatory patterns play an active role in these states (Bhattacharya, 2001; Lakatos et al., 2005).

Spectral decomposition, to this day, still remains the main analytical paradigm for analysis of brain oscillations. The power spectral density (power spectrum) reflects the “frequency content” of the signal or the distribution of signal power over frequencies. Additionally, power spectrum is a compact and natural representation of steady state of neural activity (Dumermuth and Molinari, 1987). 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 behaviour (Muthuswamy and Thakor, 1998).

However, conventional spectral analysis assesses 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 a “static” picture) might not only mask the original signal dynamic aspects, but also give rise to ambiguous data interpretation (Effern et al., 2000; Laskaris and Ioannides, 2001; Fingelkurts et al., 2002). In fact, and as explored in our early work (Fingelkurts et al., 2003a; Fingelkurts et al., 2004) the total power spectrum does not characterise each of the individual power spectra for each EEG segment.

Additionally, the frequency bands are predefined and taken in isolation from each other in the vast majority of EEG studies. This does not permit researchers to examine behaviour of the actual/natural composition of brain oscillations involved. At the same time, brain functioning

is represented by multiple oscillations (Basar et al, 2000). According to the superposition principle introduced by Basar et al. (1999), brain activity is accompanied by superimposed multiple brain oscillations in many frequency bands (for the review, see Basar et al., 2004).

In order to overcome the limitations of conventional spectral analysis based on averaging procedures and to reveal functionality in EEG spectral variability, short-term spectral analysis was introduced (Bodenstein and Praetorius, 1977; Priestley, 1981; Barlow, 1985; Bodunov, 1985; Jansen and Cheng, 1988; Hilfiker and Egli, 1992; for current development see Fingelkurts et al., 2003a,b, 2006a).

Assuming that the duration of the stationary segments of spontaneous EEG is not usually more than 2 sec (McEwen and Anderson, 1975; Barlow, 1985; 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. In our previous studies (Fingelkurts et al., 2003a,b) it was shown that a *limited number* (up to 14 ± 0.6) of spectral pattern (SP) *types* may describe an EEG accurately. However, only about half of all SP types are functionally active: the occurrence of these SP types changed along with alterations in the functional state of the brain (Fingelkurts et al., 2003a). Each EEG channel or small group of channels is characterised by a relatively specific set of SP types. Additionally, it was shown that SP types are of different significance: usually, 3-5 SP types were the most probable when compared with the others for particular state, condition or task. The occurrence of the most probable SP types is not occasional and may have a functional nature. For the details of the SP variability in ongoing EEG activity during resting conditions and cognitive tasks see Fingelkurts et al. (2003a,b).

All of these findings possess distinct trait-like qualities (Fingelkurts et al., 2006a) as indicated by (a) high within-subject stability over EEG recordings, (b) high reliability over time and (c) high specificity for each of the examined conditions.

However, systematic detail description of the *diversity* of EEG short-term SP types has not been examined yet. By diversity we mean a multitude of SPs where each SP type differs from another by its morphology (the number of dominant peaks and peak(s) broadness) and by position of dominant peak(s) at the frequency bins from given frequency range within a given functional state of the brain. Theoretically, within each SP the dominant peak may occupy any frequency bin from a given frequency range. Additionally, the number of dominant peaks

may vary significantly. Whether all possible types of SPs have occurred in the actual EEG or some SP types are missing within a given functional state of the brain is largely unknown. It is of further interest to study whether there is equal occurrence of each of SP type and which SP types are dominant for a given functional state. Finally, an important but unaddressed issue is whether diversity of SPs changes with the change of a functional state of the brain.

Due to extensive use of EEG (and power spectra in particular) for research and clinical purposes it is important to fill these gaps with empirical data. It appears that as a neurophysiological phenomenon EEG has its own peculiarities, regularities and rules of organization (Nunez, 2000; Fingelkurts et al., 2003a,b). Only when one knows these characteristics, it is possible to make proper use of EEG as a tool and to give adequate interpretations of the obtained data. In fact, it is impossible to design a cognitive EEG experiment not biased by assumptions (explicit or implicit) about brain dynamics. In connection to this, a much deeper understanding of brain dynamics which is reflected in EEG is essential to genuine long-term progress in psychophysiological and cognitive sciences. Therefore, the current paper is important as an explorative data-driven study that may help scientists to find new directions in research and to generate new hypotheses regarding structural aspects of the signal which is usually sparse in EEG literature.

Taking together all of the aforementioned, the *objective* of this work was to describe in detail the “morphology” of EEG short-term SPs, the diversity of SP types and to examine what the limits of this diversity are. Therefore, the concrete *aim* of the present study was to evaluate the diversity of EEG short-term SPs within a broad frequency range (1.5-30 Hz) for healthy adult subjects during resting conditions (closed and open eyes). The eyes closed and eyes open conditions are often regarded as baseline conditions with the lowest levels of arousal accessible in the laboratory. As there is data on how SP morphology depends on neurophysiological parameters and nonlinear measures (Inouye et al., 1991; Pereda et al., 1999; Tirsch et al, 2000; Quian Quiroga et al, 2001; David and Friston, 2003; Perez Velazquez and Wennberg, 2004; Zavaglia et al., 2006; Moran et al., 2007), a frequency domain approach should reveal which types of states of the underlying neurodynamical system (neuronal assembly) are characteristic for a given functional state of the brain.

2. Subjects and methods

2.1 Subjects

Twenty-seven healthy, right-handed adult male volunteers (aged 19-33) participated in the study. None of the subjects reported any history of brain traumas or concussions, neurological or psychiatric disorders, acute or chronic medical illness, or was on medication at the time of the EEG registration. In addition, all of them have normal autonomic (blood pressure and pulse rate) indices. To capture variability of EEG types (the degree of alpha domination) in general population, 16 subjects with different EEG types were selected randomly from the initial sample in proportion similar to that of the general population (Simonova et al., 1967; Stern and Engel, 2004): 19% (3 subjects) with dominant alpha, 50% (8 subjects) with subdominant alpha, 25% (4 subjects) with little alpha and 6% (1 subject) with no alpha. Such a sample is known as a stratified random sample (Kalton, 1983). The degree of alpha domination in EEG was determined in resting condition with closed eyes. These 16 selected subjects (aged 19-26) who did not differ significantly from the initial sample were taken for further analysis.

Women were excluded from the study for the following reasons: (a) there are no differences in spectral composition of EEG between males and females (Horita et al., 1995) and there are no studies which would demonstrate such differences, therefore one gender may be used for the first study of the diversity of EEG SPs; (b) female's EEG is highly affected by phases of menstrual cycle (variations of estrogen and progesterone levels) and hormonal contraceptives (Becker et al., 1982; Solis-Ortiz et al., 1994; Smith et al., 2002), therefore the diversity of EEG SPs in females (preferably for each phase of the menstrual cycle) should be examined in a separate study.

All the subjects were informed beforehand of the nature of the procedure. Written, informed consent from all subjects and institutional ethical committee approval were obtained prior to the experiment.

Since alcohol influences variation of normal EEG (Propping et al., 1980), subjects were asked to abstain from alcohol for 2 days before EEG registration. 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. The EEG registrations began at 10:00 a.m.

2.2. Procedure and data acquisition

EEG was recorded using a Mitsar 21 channel EEG system (Mitsar, Ltd). Eight Ag/AgCl electrodes were placed bilaterally on the subject's scalp using the 10/20 International System of electrode placement at O₁, O₂, P₃, P₄, C₃, C₄, F₃ and F₄ (minimum number to cover the main cortical lobes). Vertical and horizontal electro-oculograms were recorded. All electrodes were referred to linked ears (linked-ears reference was obtained digitally from two separate, impedance-checked channels). Raw EEG signals were amplified and filtered in 1.5-30 frequency range and digitized at a sampling rate of 128 Hz by a 12-bit analog-to-digital converter with resolution of 1 μ V/bit. This frequency range was chosen because approximately 98% of spectral power lies within these limits (Thatcher, 2001). Even though frequencies above 30 Hz (gamma band) have been proposed to be functionally informative, there are a number of methodological issues which lead us to exclude frequencies above 30 Hz from the present analysis: (a) it was shown, that there is little effect of volume conduction on the shape of the spectrum below about 25 Hz and spatial filtering is significant only for frequencies above 25 Hz (Robinson et al., 2001); (b) high-frequency spindles have very low signal-to-noise ratio, what results in considerable contamination of gamma band by noise; (c) dynamics of high-frequency responses may be a trivial by-product of power changes in lower frequencies (Pulvermuller et al., 1995), (d) the increased power in the gamma range may be due to harmonics of activity in lower frequency ranges, and/or due to ringing of filters by EEG spikes recurring at theta rates (Freeman, 2003), (e) gamma band may be an artifact of (un)conscious micro-constrictions of muscles of the organism and/or face muscles (Whitham et al., 2007; Yuval-Greenberg et al., 2008; Ball et al., 2008); (f) comprising only 2% of spectral power (Thatcher, 2001), contribution of high-frequency band into spectrum cannot be significant; (g) Bullock et al (2003) demonstrated many "good" rhythms in the 2-25 Hz range which were mainly sinusoidal, but did not find them in 30-50 Hz band. Considering all of these, there might be difficulties in the meaningful interpretation of effects in high-frequency band regardless of how powerful or statistically significant they are.

DC drifts were removed using high pass filters (1.5 Hz cut-off). The impedance of the recording electrodes was always below 5 k Ω . 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 was explained. To reduce muscular artefacts in the

EEG signal, the subject was instructed to assume a comfortable position and to avoid movement.

Instructions designed to minimize movement and relax jaw muscles resulted in suppression of the myogram class of artefact to the point that the high-frequency spectrum was not significantly affected. A subject was instructed also to look straight in front of him (in both closed and open eyes conditions) and to avoid unnecessary eye movements. The presence of an adequate EEG signal was determined by visual inspection of the raw signal on the computer screen. Constant visual EEG monitoring allowed for selection of only artefact-free EEG recordings for further analysis.

For each subject ten 8-channel one-minute EEGs were recorded randomly during steady resting conditions for closed and open eyes separately. Such ongoing EEG activity during resting condition reflects current functional state of neuronal masses rather than a random process (Livanov 1984; Fingelkurts et al., 2003b). To examine diversity of SPs in EEG, a total of 109 (for closed eyes) and 53 (for open eyes) artefact-free one-minute EEGs were selected in this study.

According to literature two one-min EEGs have proven to produce reliable estimates of internal consistency (Coan et al., 2001). Moreover, even the duration of 20 sec of EEG epoch is sufficient to reduce adequately the variability inherent in the EEG (Gasser et al., 1985). In the present study majority of the subjects contributed to EEGs' pool with 10 one-min EEGs (for closed eyes) and 4 one-min EEGs (for open eyes), which is well above the aforementioned limits.

2.3. Data processing

Since an EEG is widely referred to as a nonstationary signal with varying characteristics (for the review see Fingelkurts and Fingelkurts, 2001), brain oscillations are expected to be dynamic in nature. In order to capture such changing dynamics, the data series were divided into overlapping windows. Thus, individual power spectra¹ were calculated in the range of

¹Log transformation of the power spectra was not used for the following reason: Log transformation usually normalizes a power spectrum, but, at the same time, it artificially reduces the contrast of the differences between large and small power values. This leads to the increased contribution of the small-amplitude values and correspondently, the noise into a total spectrum. For the purpose of this paper "clean" power spectra without noise contamination are of great importance.

1.5–30 Hz with 0.5-Hz resolution (59 values), using Fast Fourier Transform with a 2-sec Hanning window shifted by 50 samples (0.39-sec) for each channel of one-minute EEG (Fig. 1). According to previous studies, these values have proved to be the most effective for revealing oscillatory patterns from the signal.

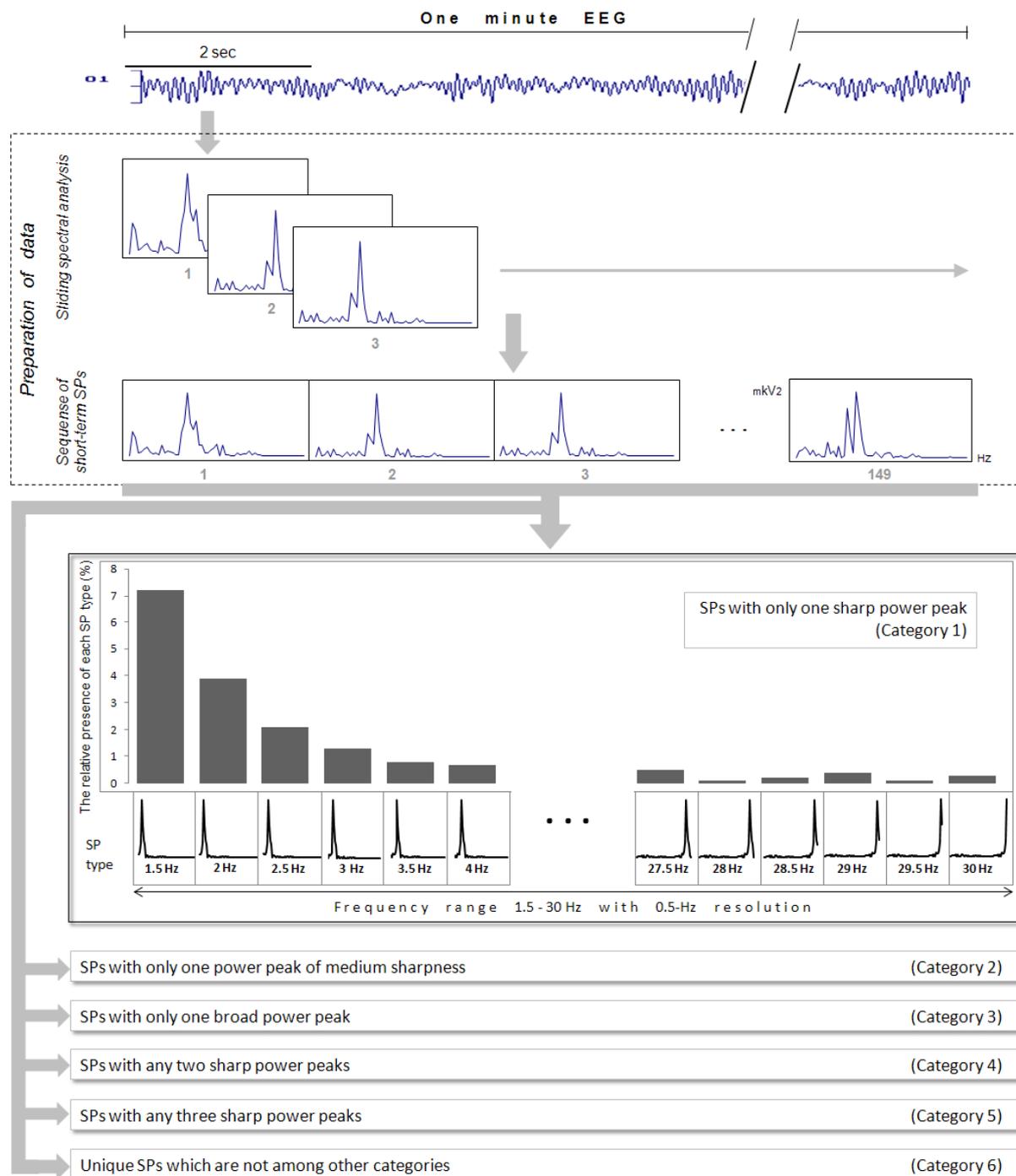


Figure 1. The scheme of the data processing. Sliding spectral analysis was done separately for each subject and each channel of one-min EEG. Gray small numbers under each spectral pattern (SP) represent the running number from 1 to 149. Distribution of SPs among SP categories was based on morphology of SPs and was performed on pools of SPs for closed and open eyes conditions separately. Distribution of the presence of each SP type for category-1 for closed eyes condition is presented.

The works which have studied the effect of epoch length on the variability of power spectrum (Levy, 1987; Kaplan, 1998) demonstrated that (a) the epoch-to-epoch variability with power spectra computed using 2-sec epochs was significantly less than the variability when power spectra were computed using longer epoch lengths, and (b) analysis using 2-sec epochs identified changes more rapidly than analysis using any longer epoch length, and (c) the obtained differences were clinically significant as well. Moreover, a 2-sec epoch is long enough to get a reliable estimation of the lowest frequency (0.5 Hz), and is short enough to be almost stationary (McEwen and Anderson, 1975; Inouye et al., 1995). Taken together these findings suggest that 2-sec epoch lengths are preferable when power spectrum analysis is used. According to the work of Kaplan (1998), in which the author studied the effect of window shift on disclosing oscillatory patterns from the signal using shifts from 1 to 256 samples, the window shift in 50 samples was the most effective.

To summarise, sliding spectral analysis with overlapping segments, previously applied to EEG signals (Keidel et al., 1987; Tirsch et al., 1988, 2004; Fingelkurts et al., 2003a,b, 2006a), (a) takes the non-stationarity of the time series into account, compensates for the effects of windowing, (b) prevents loss of information due to residual activity, (c) reduces random error of the mean, (d) increases the effective number of degrees of freedom, and (e) improves the statistical confidence in the results due to a relatively large number of SPs (Muller, 1993; Riley, 2003). Additionally, using overlapping intervals (which just means a different aggregation scheme) cannot add any artifactual information (Muller, 1993).

As a result, the total number of individual SPs for each channel of one-min EEG was 149. Pools of SPs were built from all the SPs of the entire EEG signal (all locations) for all subjects separately for closed and open eyes conditions. SPs from all locations were pooled together since we were interested in global SP diversity. In each pool ($n = 129928$ for closed eyes and $n = 63176$ for open eyes), all identical SPs with dominant power peaks (peaks that rise significantly above the general average) in the same frequency bins were counted automatically. 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, where 100% corresponds to the magnitude of the highest peak within the SP. According to the preliminary study, this value has proved to be the most effective for peak detection.

Analysis of the SP type diversity revealed that each pool of SPs can be subdivided in 6 categories based on morphology of SPs (Fig. 1): (1) SPs with only one power peak, which occupies any one frequency bin, (2) SPs with only one power peak, which occupies any two adjacent frequency bins, (3) SPs with only one power peak, which occupies any three adjacent frequency bins, (4) SPs with all possible combinations of two power peaks, (5) SPs with all possible combinations of three and more power peaks and (6) unique SPs which are not among other categories and each of them has occurred in the pool of SPs only once. As explored in our early work (Fingelkurts et al., 2003a), the category of unique SPs is comprised of SPs which reflect transitory and/or noisy/disorganised episodes in the EEG.

These categories may be functional: (a) the number of peaks in the EEG spectrum reflects complexity (the number of neuronal assemblies) of the neurodynamical system (David and Friston, 2003; Zavaglia et al., 2006) and (b) the sharpness or broadness of the peak in the EEG spectrum reflects the degree of (dis)order in the neurodynamical system (Inouye et al., 1991; Tirsch et al, 2000; Quiñero et al, 2001).

2.4. Statistics

In order to reveal any statistically significant differences in the presence of each SP type in EEG between closed eyes and open eyes conditions, the Wilcoxon matched pairs test was used. Statistical significance was assumed where $P < 0.05$. Since only the difference between pairs of states was of interest and we intended to assess each variable in its own right, no correction for multiple comparisons was necessary (for a detailed discussion, see Rothman, 1990; Perneger, 1998). Since the absolute number of SP in SP-pools within each condition was different, the percentage of the number of SP in SP-pools was calculated.

3. Results

3.1. General description of the diversity of EEG SP types

From figure 2 it can be seen that there were no statistically significant differences in the number of SP types in each category between closed and open eyes.

However, distribution of SP types amongst the six categories was uneven (Fig. 2). Thus, the vast majority (42–44%) of all short-term EEG SPs belonged to the category of SPs with only

one sharp power peak. Other categories were characterised by considerably smaller number of SPs. Both, category of SPs with all possible combinations of two power peaks and category of SPs with all possible combinations of three and more power peaks comprised about 18% each. The next was the category of SPs with only one power peak, which occupied any two adjacent frequency bins (11.20%) followed by the category of unique SPs which are not among other categories (7–9%). Finally, the minimum number of SPs belonged to the category of SPs with only one power peak, which occupies any three adjacent frequency bins (about 2%).

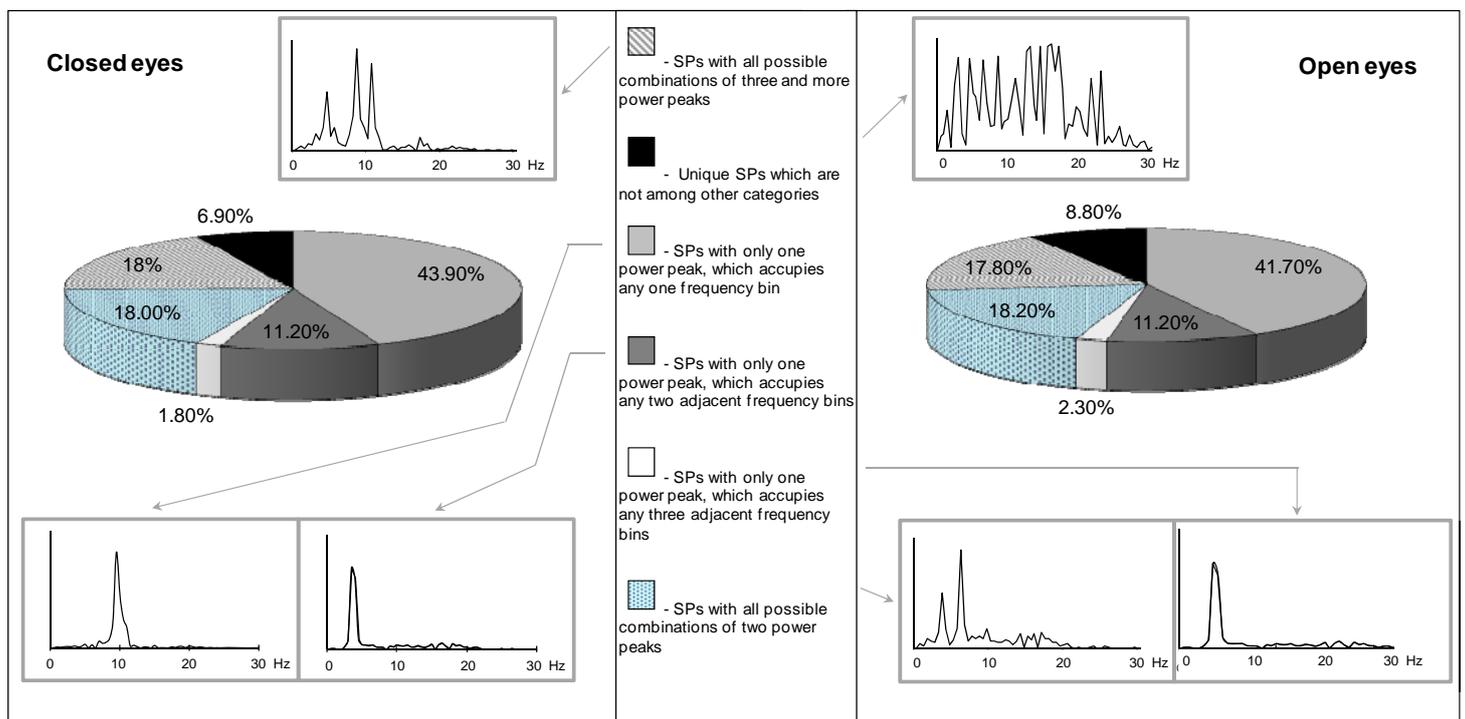


Figure 2. The pie diagrams representing percent distribution of spectral pattern (SP) types among categories of SPs based on morphology of SPs during resting conditions ($n = 129928$ for closed eyes and $n = 63176$ for open eyes). Different colours reflect the percentage of SP types. Examples of SPs for each category are presented in the insertions.

3.2. Detail description of the diversity of EEG SP types within categories of SPs

Figure 3 summarises a percentage distribution of the number of SPs with one sharp, medium-sharp, and broad power peak. As can be seen from the figure, the diversity of SP types was limited and mainly restricted to delta-theta (1.5–4 Hz) and alpha (8.5–11.5 Hz) frequency ranges within which the power peak of SP may occupy any frequency bin (Fig. 3). Notice that the closer a SP power peak is to 1.5 Hz or 10 Hz, the higher the percent of SP type in the pools of SPs.

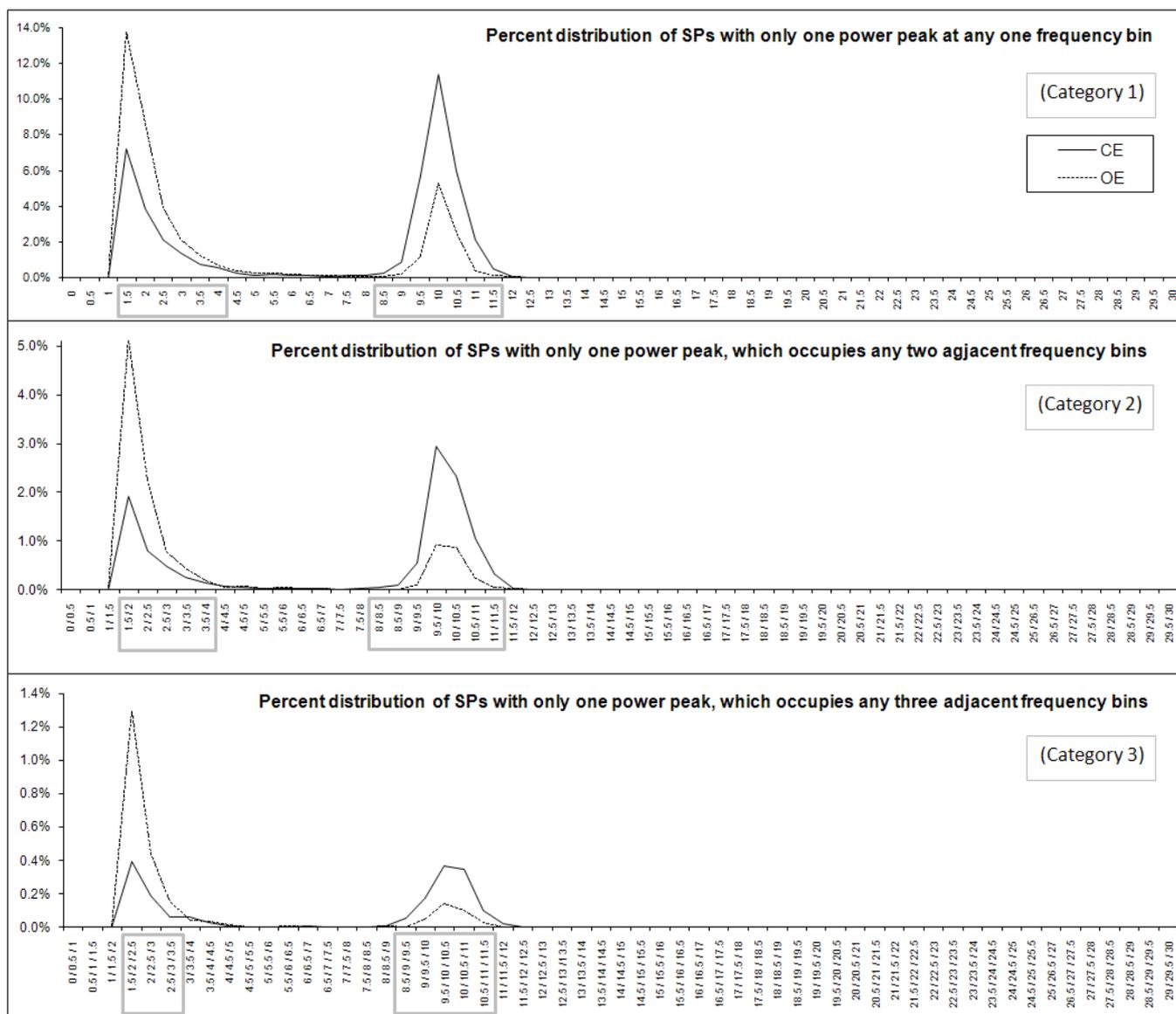


Figure 3. Percent distribution of spectral pattern (SP) types with one power peak during resting conditions. The X-axis displays SP types with one power peak at a particular frequency bin from 1.5 to 30 frequency range with 0.5 Hz resolution. The Y-axis displays the relative presence of each SP type in the percentage from the total number of SP types ($n = 129928$ for closed eyes and $n = 63176$ for open eyes). A line graphic was chosen instead of a bar for the ease of comparison. (Note that X-axis consists of discrete values, all the in-between values are meaningless). CE = closed eyes, OE = open eyes. Grey frames indicate delta-theta and alpha bands.

Additionally, there was a clear expected difference between closed and open eyes conditions (Fig. 3). Thus for all three categories of SP types, closed eyes condition was characterised by (a) significantly higher percent ($P < 0.02 - P < 0.04$) of SPs, the power peak of which occupied any frequency bin within 8.5–11.5 Hz frequency range and (b) significantly lower percent ($P < 0.03 - P < 0.04$) of SPs, the power peak of which occupied any frequency bin within 1.5–4 Hz frequency range, when compared with the open eyes condition (Fig. 3).

Figure 4 illustrates the percentage number and distribution of SPs with any two power peaks. The largest number of SPs was observed for those which have one power peak fixed at 1.5 Hz bin and another power peak that could occupy any other frequency bin (Fig. 4, A). The number of SPs decreased gradually as fixed frequency of the power peak increased. This was a common dynamic for both closed and open eyes conditions. However, for closed eyes condition this dynamic took a different direction starting from 7.5 Hz: the number of SPs increased gradually as fixed frequency of the power peak increased until 9.5 Hz and then decreased again (Fig. 4, A).

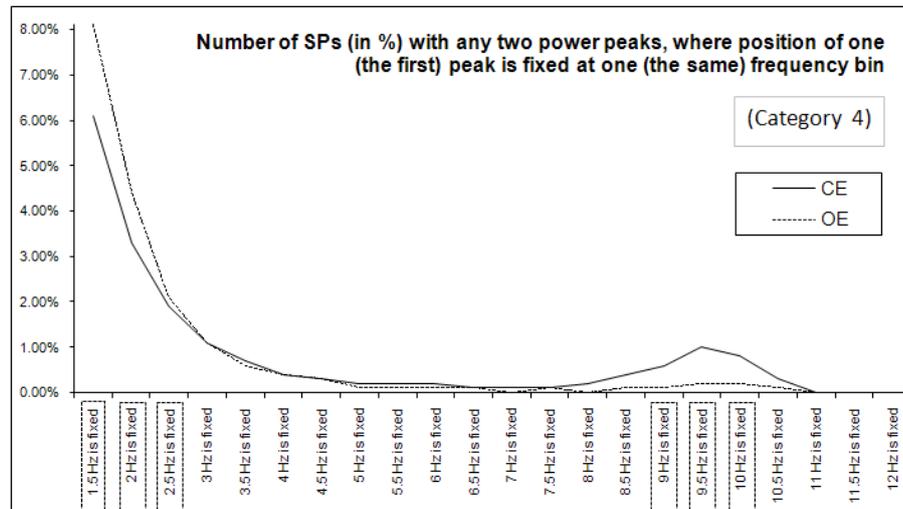
Closed eyes condition was characterised by (a) significantly smaller percent ($P<0.05$) of SP types the power peak of which was fixed at any frequency bin within 1.5-3 Hz frequency range and (b) significantly higher percent ($P<0.01$) of SP types where the power peak was fixed at any frequency bin within 5-10.5 Hz frequency range when compared with the open eyes condition (Fig. 4, A).

Analysis of the percentage distribution of the number of SPs within each class (fixed power peak at particular frequency bin) revealed a common effect (Fig. 4, B): closed eyes condition was characterised by (a) significantly smaller percent ($P<0.01$ – $P<0.005$, for different classes) of SP types, the power peak of which was fixed at particular frequency bin within 1.5–8 Hz frequency range and (b) significantly higher percent ($P<0.02$) of SP types, the power peak of which was fixed at particular frequency bin within 8.5–11 Hz frequency range when compared with the open eyes condition.

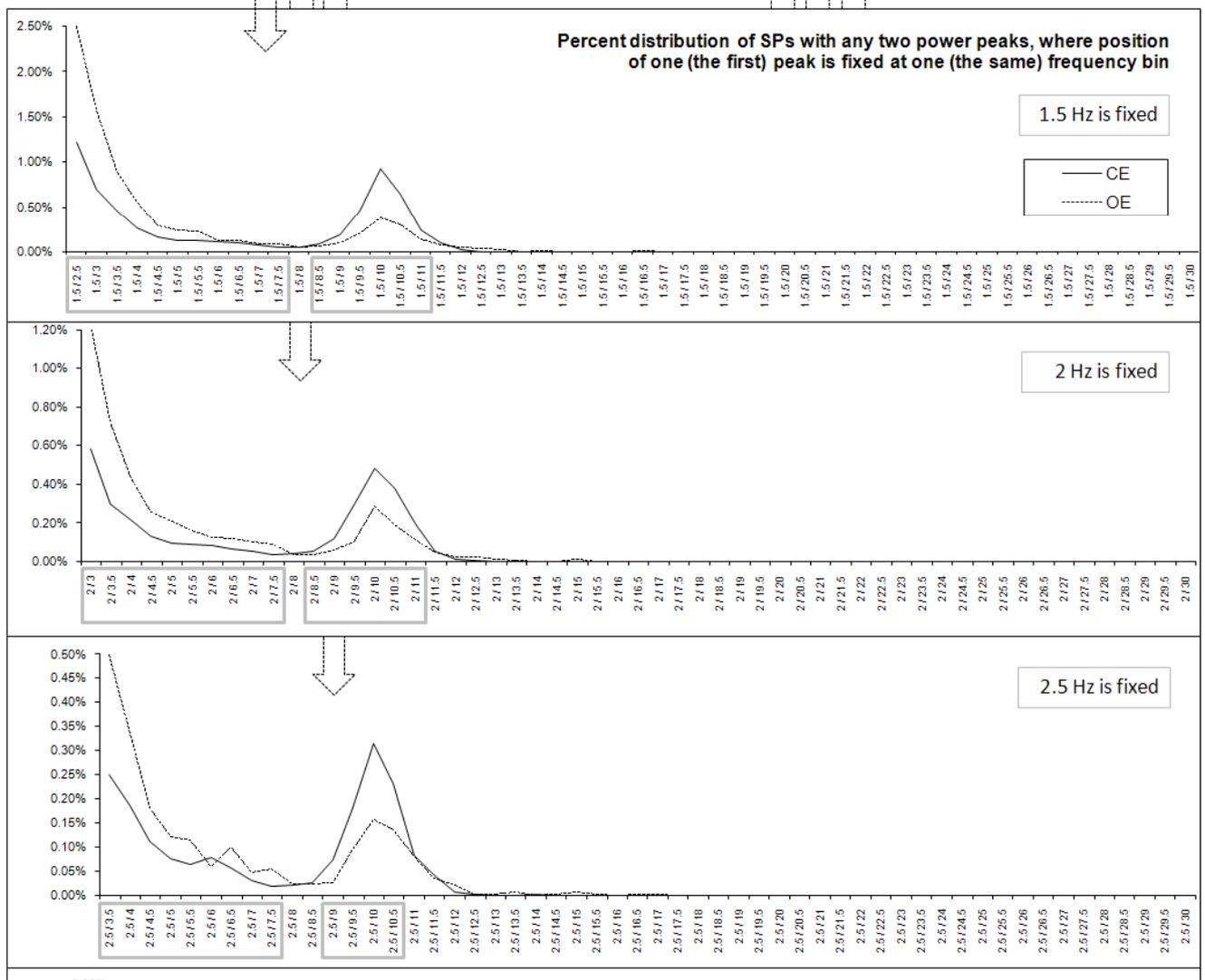
Table 1 illustrates dynamic repertoire of SP types for closed and open eyes conditions. It can be seen that around 39% of all SP types with one and/or two power peaks which described alpha band and around 27% of all SP types with one and/or two power peaks which described delta-theta band were characteristic for the repertoire of SP types during closed eyes condition. Eyes opening resulted in reorganisation of the repertoire of SP types (Table 1). The number of all SP types with one and/or two power peaks which described alpha band decreased to 13% and the number of all SP types with one and/or two power peaks which described delta-theta band increased to 53%.

Notice that there was not any SP type which described beta frequency range above 12 Hz in any SPs' category during both resting conditions.

A



B



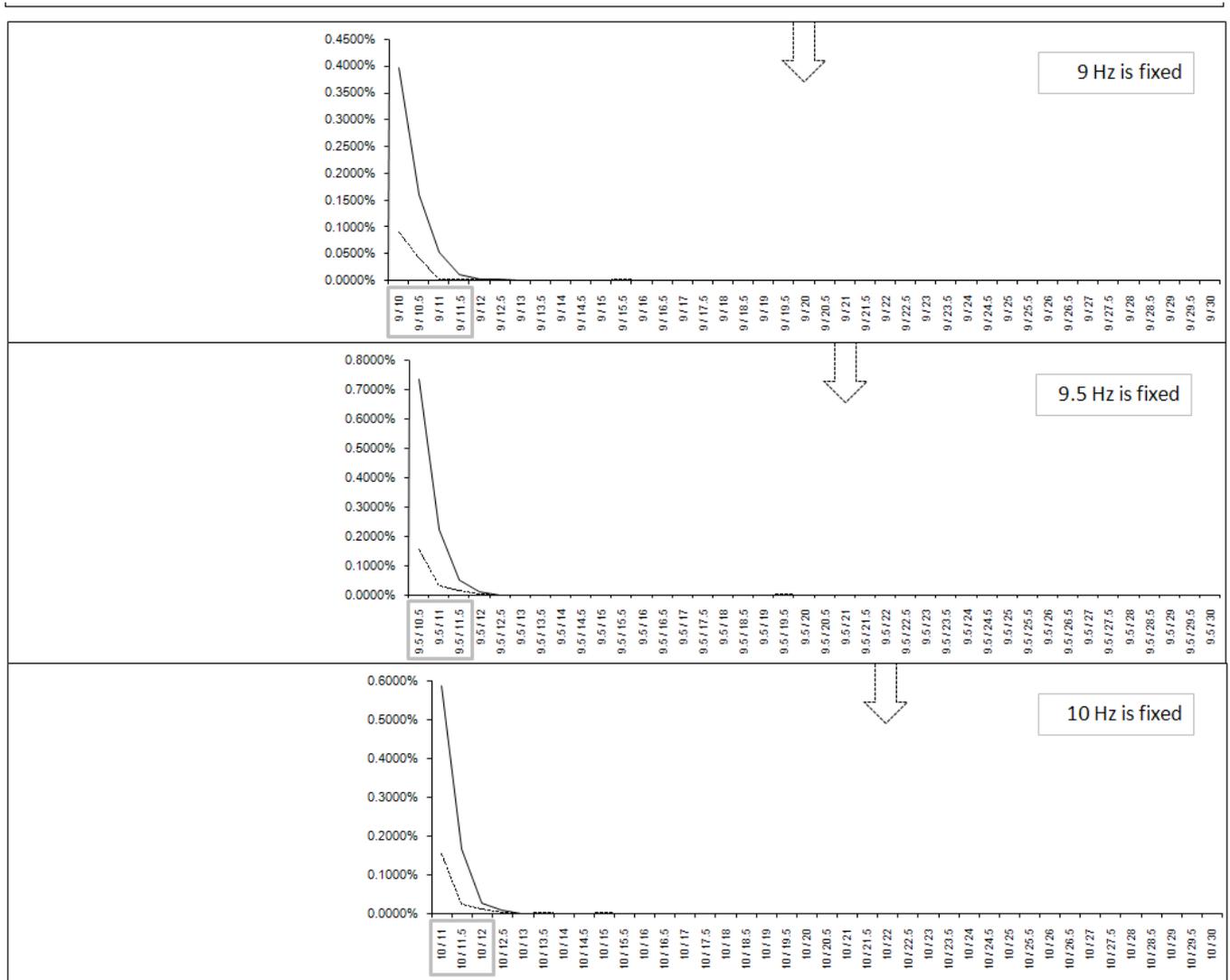


Figure 4. (A) Percent distribution of classes of spectral pattern (SP) types with two power peaks where position of one power peak is fixed at a particular frequency. The X-axis displays classes of SP types with two power peaks where position of one power peak is fixed at a particular frequency bin from 1.5 to 30 frequency range with 0.5 Hz resolution. The Y-axis displays the relative presence of each class of SP types in the percentage from the total number of SP types ($n = 129928$ for closed eyes and $n = 63176$ for open eyes). A line graphic was chosen instead of a bar for the ease of comparison. (Note that X-axis consists of discrete values, all the in-between values are meaningless). **(B) As an example, percent distribution for each SP type from particular SP classes from (A) is presented.** Only those SP types percent of the occurrence of which is reached at least 0.5% are displayed. The X-axis displays SP types with two power peaks where position of one power peak is fixed at a particular frequency bin from 1.5 to 30 frequency range with 0.5 Hz resolution. The Y-axis displays the relative presence of each SP type in the percentage from the total number of SP types ($n = 129928$ for closed eyes and $n = 63176$ for open eyes). A line graphic was chosen instead of a bar for the ease of comparison. (Note that X-axis consists of discrete values, all the in-between values are meaningless). CE = closed eyes, OE = open eyes. Grey frames indicate delta-theta and alpha bands.

Table 1. Repertoire of spectral pattern (SP) types for closed and open eyes conditions calculated as sum of all SP types with one and/or two power peaks which described alpha or delta-theta bands.

	CE	CE	OE	OE
Number of peaks	Alpha	Delta- Theta	Alpha	Delta- Theta
SPs with 1 peak (category1 + category2 + category3)	35.20%	20.30%	12.30%	41.30%
SPs with 2 peaks (category4)	3.38%	6.56%	0.79%	12.50%
Total	38.58%	26.86%	13.09%	53.80%

CE = closed eyes, OE = open eyes

4. Discussion

4.1. General characteristics of the diversity of EEG short-term SPs

Analysis of the diversity of EEG short-term SPs for closed and open eyes conditions revealed that there is (a) a limited set of categories of SPs based on SP morphology and (b) a stable number of SPs which contributes constantly to each category of SPs independently on condition (closed vs open eyes) (Fig. 2). This can be interpreted as the brain “operating” by a limited number of oscillatory states which are produced by different but limited configurations of firing neurons (for the relations between EEG SP and the actual state of the neurons in the underlying network, see appendix in Fingelkurts et al., 2006a). This is in line with our previous studies (Fingelkurts et al., 2003a,b) where it has been shown that EEG may be described accurately by a limited number of SP types, half of which is the same for different functional states.

Considering extensive data on how SP morphology depends on neurophysiological parameters and nonlinear measures (Inouye et al., 1991; Pereda et al., 1999; Tirsch et al, 2000; Quian Quiroga et al, 2001; David and Friston, 2003; Perez Velazquez and Wennberg, 2004; Zavaglia et al., 2006; Moran et al., 2007; to mention just a few), our data on SP morphology can be interpreted in terms of states of the underlying neurodynamical system i.e. neuronal assembly. Thus, the finding that more than half (up to 57%) of all short-term EEG SPs belongs to the category of SPs with only one power peak (Fig. 2) suggests that a short-term EEG signal is characterised by individual rhythm (Bullock et al., 2003) which is produced by a single neuronal ensemble (David and Friston, 2003; Zavaglia et al., 2006) in a given cortical area at a particular point in time. The fact that the majority (up to 44%) of these SPs

have sharp power peak suggests that the underlying neurodynamical system (neuronal assembly) is characterised by resonant ordered behaviour with low entropy (Inouye et al., 1991; Tirsch et al., 2000; Quian Quiroga et al., 2001) in short-term temporal scale. Our data confirmed the findings of Bullock et al. (2003) who demonstrated that most oscillations in EEG samples have quite narrow peaks.

Up to 36% of all short-term EEG SPs have two or more sharp power peaks (Fig. 2), thus reflecting the activity of two or more neuronal ensembles with resonant ordered behaviour within each individual ensemble (Inouye et al., 1991; Tirsch et al., 2000; David and Friston, 2003). This is in line with the work of Bullock et al. (2003) who demonstrated that power spectra usually have 1 to 3 dominant peaks which reflect “true” EEG rhythms.

And finally, a minority (7–9%) of all short-term EEG SPs belong to a unique category of SPs, each of which has occurred in the pool of SPs only once and reflects transitory and/or noisy/disorganised episodes in EEG (Dumermuth and Molinari, 1987; Tirsch et al., 2000; Fingelkurts et al., 2003a). The ratio of this activity in EEG is influenced by genetic factors (Meshkova, 1988) and as explored in our early work (Fingelkurts et al., 2003a, 2004) the amount of noisy/disorganized activity in EEG is dependent on functional brain state.

Notice that different types of SPs within the same or different SP categories are combined temporally in a “mosaic” way. Therefore, any of the mentioned above percentages does not mean that any single type of SP characterises an EEG continuously, rather these percentages signify that a given SP type dominates in EEG only in sum. Such “mosaic” dynamics of SP types is consistent with our previous studies (Fingelkurts et al., 2003a,b).

The described finding supports the idea that the dynamics of an EEG signals reflect a chaotic deterministic process with state transitions from “high-dimensional” or disordered to “low-dimensional” or ordered nonlinear dynamics, and vice versa (Lopes da Silva, 1991; Tirsch et al., 2000, 2004).

The observation that only up to 9% of short-term EEG reflects transitory or noisy/disorganised episodes in resting EEG, whereas most of it comprises highly organized oscillatory activity is in contradiction with the conclusion by Bullock et al. (2003). These authors used a specific tool (Period-Specific-Average) to reveal “true”, as they call it, periodicities in the EEG. They concluded that “...most of the power spectrum most of the time in most human cortex is without significant rhythms”. Such contradiction may be due

the fact that Bullock et al. analysed 4-sec non-overlapping EEG epochs, whereas in the present study 2-sec highly overlapping (80%) EEG epochs were used. According to previous studies, the values used in our study have proved to be the most effective for revealing oscillatory patterns from the signal (Levy, 1987; Kaplan, 1998). Additionally, close analysis of the Bullock et al. (2003) article revealed that in spite of their own conclusion the authors actually found that “Many EEG samples do show one or more periodicity peaks rising to >99% confidence” and that authors “...find many examples of “good” rhythms in the 2-25 Hz range, and they are chiefly pretty sinusoidal.” Exactly in this frequency range we observed the majority of organised/rhythmic SPs in our study.

Consistently with our previous work (Fingelkurts et al., 2003a,b) only a few SP types were the most probable (Fig. 3, Fig. 4,B). Thus, SP types which described delta-theta and alpha frequency bands were most probable during resting conditions. The maximums in the percent distribution of SP types were at 1.5 Hz (delta activity) and at 10 Hz (alpha activity). This means that these two frequencies are the characteristic and preferred frequencies during rest with domination around 10 Hz during closed eyes condition and domination around 1.5 Hz during open eyes condition.

Domination of 10 Hz in resting EEG is in line with the works of Stassen (1985) and Thatcher et al. (2003) where the authors demonstrated that distribution of the EEG peak frequency in the general population has a mean of around 10 Hz. Indeed, in the human brain the alpha activity dominates the EEG spectrum (Basar and Guntekin, 2006). An alpha rhythm system is expected to play a leading part in organization of conscious interactions with the environment (for the review, see Knyazev, 2007) and is associated with semantic memory which is enormously developed in humans (Klimesch, 1996, 1999a,b; Sauseng et al., 2005a).

Domination of delta frequencies (1.5 Hz) in resting EEG is not surprising: delta oscillations involved in the acquisition of biologically important goals such as physical maintenance and survival and are associated with autonomic functions, such as breathing and heartbeat (for the review see Knyazev, 2007). As can be seen from the figures 3 and 4.B delta and theta frequency bands were grouped together and “behaved” as one band. Such dependency of these two bands can be explained by the fact that sometimes theta oscillation current density fluctuated at delta frequencies. Furthermore, it was reported that the highest amplitude theta oscillations occurred at a specific phase of the delta oscillation (Lakatos et al., 2005). However, in spite of common behaviour of these two bands, short-term EEG epochs in most

cases were characterised by dominant peak(s) in only one frequency band (delta or theta) (Fig. 3 and 4). This may suggest that these two bands are functionally dependent for tested conditions (even though their physiological “origin” is different). The observed theta frequencies in this study are hypothesised to be associated with the orienting response, short-term (episodic) memory processes, attention, and emotional regulation (for the review see Knyazev, 2007), which can be spontaneously active during resting conditions. Cortical activity that is not driven by external stimuli, such as in the present study, may reflect processing of internal mental context (top down processing) (von Stein and Sarntheim, 2000).

Considering that only artefact-free one-minute EEG recordings were taken into analysis observed delta-theta activities were not related with artefacts.

Notice that there was no single SP type which would describe a beta frequency band. This means that independent beta rhythm is a less probable oscillation during resting conditions. This is consistent with the work of Simon (1977) which found beta frequencies in only 22% of normal adults. Well known beta activity visible in averaged power spectrum during rest is most likely a result of the contribution of the averaging of the unique SPs which have power peaks at beta frequency band along with other peaks at other frequency bands. Additionally, beta activity may be characterised by very broadband peak rather than a well defined narrow peak. In this case, SPs with this type of peak in the present study would be placed in the category of the unique SPs.

The existence of several morphological categories of SPs with different SP types within each category suggests that the alert resting EEG is very much an active state (Fingelkurts et al., 2003b). As it was demonstrated, during rest the SP types emerge, persist for some time and then disappear to be replaced by other SP types (Fingelkurts et al., 2003a). This suggests that ongoing brain activity occurs in discontinuous steps and confirms that the cerebral cortex is continuously active in wakefulness. This supposition is in line with the works of Thatcher and John (1977), Herscovitch (1994), Arieli et al. (1996), Tsodyks et al. (1999), Raichle et al. (2001), Raichle and Snyder, (2007) and others who demonstrated a highly organized intrinsic functional activity during a resting state i.e., activity which is not directly related to identifiable sensory or motor events. For details of the SP variability in ongoing EEG during resting conditions see (Fingelkurts et al., 2003a).

The frequency of the occurrence of each SP type reflects the probability of the occurrence of particular neuronal dynamics which altogether constitute a dynamic repertoire of brain activity in particular functional state (Fingelkurts et al., 2003b). Indeed, diversity creates a rich repertoire of brain activity, which can meet the complex computational and communicational demands of the brain. By preventing neural dynamics from getting “stuck” in so-called attractor states, neural diversity may facilitate quick responses to environmental demands in a wide variety of ways, and with less effort than a system where all states are identical.

The next section describes a dynamic repertoire of SP types during two functional states of the brain: closed eyes and open eyes conditions.

4.2. Diversity of EEG short-term SPs during changes in functional state of the brain (closed vs open eyes conditions)

Converging evidences suggest that characteristic EEG rhythms (indexed here by particular SP types) constitutes a mechanism by which the brain can regulate changes of state in selected neuronal networks to cause qualitative transitions between modes of information processing (Lopes Da Silva, 1996). Different frequency bands reflect functionally different components of information processing acting on various spatial scales (Bhattacharya, 2001) and prominent during different functional states (Michel et al., 1992). Indeed, in the present and previous studies (Fingelkurts et al., 2003a,b) it was demonstrated that SP types have different significance (their occurrence is more or less probable) depending on functional state of the brain.

Thus, in the present study, closed eyes condition was characterised by a higher percent of SP types which described 8.5–11.5 Hz frequency range (alpha band) and lower percent of SP types which described 1.5–4 Hz frequency range (delta-theta band) when compared with open eyes (Fig. 3 and 4). During closed eyes condition SP types which described alpha band dominated in the majority of categories of SPs over SP types which described delta-theta band. This is an expected finding (Table 1): resting EEG power spectra recorded with eyes closed are usually dominated by a peak in the alpha frequency range 8–12 Hz (Niedermeyer and Lopes da Silva, 1999; Nunez et al., 2001). Such increase in the power of alpha band may be due to an increase in synchronization or coupling strength (i.e., the degree of cooperation)

between various neuronal elements within cortical networks generating the EEG signals. von Stein and Sarnthein (2000) proposed that maximal alpha activity such as with eyes closed rest does not reflect an inactive brain state, but rather reflects a state with internal mental activity (top-down processing). It is maximal in situations where cortical processes are not determined by external stimuli but are driven by free floating associations, mental imagery, planning, etc. This supposition is in line with the work of Mantini et al. (2007) where the authors showed that an increase in alpha power at rest correlates positively with activity in the default and self-referential networks, and negatively with activity in the dorsal attention networks. See also the work of Cooper et al. (2003) who demonstrated that when attention is directed internally towards mental imagery, alpha power is greater than during externally directed, information-intake tasks.

Since in the present study subjective experiences during two resting conditions have not been collected, correspondence between observed SP types and subjective experiences could not be estimated. This should be planned for future research.

Eyes opening was characterised by a considerable increase in the number of SP types which described delta-theta band and considerable reduction in the number of SP types which described alpha band (Figs. 3 and 4; Table 1). Such reciprocal relationship between alpha and delta-theta oscillatory systems was summarised earlier (Klimesch, 1999a; Knyazev, 2007): alpha typically decreases whereas delta-theta increases.

Consistent with previous studies, a reduction in alpha activity is expected from eyes closed to eyes open. This reduction of alpha in the eyes open resting condition indicates an increase in nonspecific activation caused by basic sensory input. This could reflect the uncoupling of vast thalamo-cortical interactions to aid the processing of visual information (Gevins et al., 1997; Klimesch, 1999a; Klimesch et al., 2001). Alternatively, alpha “blockade” can be interpreted as an orienting reaction of the brain rather than a sensory processing (Jung, 1953). Indeed, alpha desynchronisation reflects general task demands and attentional processes (Sokolov, 1963; Klimesch, 1999a; Pfurtscheller and Lopes da Silva, 1999; Verstraeten and Cluydts, 2002; Babiloni et al., 2004; Sauseng et al., 2005b; Mantini et al., 2007).

Considering that opening one’s eyes results in nonspecific activation compared to the eyes closed condition, an increase in delta-theta activity is not surprising. Thus, activity in the theta band may be responsible for the encoding of incoming information and reflects

demands in attentional processes (Basar et al., 2001; see also Doppelmayr et al., 1998; Klimesch, 1999a).

Detailed description of SP types which are involved in closed and open eyes conditions can be found in Fingelkurts et al. (2003a).

The present findings substantially extended previously known data: (a) for the first time quantitative description of EEG signal is given in terms of the diversity of short-term SP types; this diversity describes quantitatively the portion of EEG which is characterised by a particular type of activity and (b) reorganisation of this diversity (the occurrence of particular SP types) rather than changes in EEG amplitude or power during transition from closed eyes to open eyes conditions was demonstrated.

Taken together, the presented findings suggest that the probability of the occurrence of particular SP types were typical for each of the examined conditions, reflecting a particular composition and percent ratio of EEG oscillations (in SPs description) which are needed to achieve the main goal of a given functional state or to maintain it. Perhaps composition and percent ratio of EEG oscillations (in SPs description) 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.

Before coming to the final conclusions, methodological questions regarding the influence of volume conduction and reference electrode on SP shape should be raised. Effect of volume conduction on the results in the present study was insignificant due to the following reasons: (a) It was shown, that there is little effect of volume conduction on the shape of the spectrum below about 25 Hz and spatial filtering is significant only for frequencies above 25 Hz (Robinson et al., 2001). All results in the present study were observed below 25 Hz; (b) The skin and skull are not considered to be serious frequency filters (Nunez, 1995); (c) The accuracy of topographic EEG mapping for determining local (immediately under the recording electrode) brain activity was already established by Cook et al. (1998) (see also Bullock, 1997; Kaiser, 2000; Freeman, 2003); (d) It has been shown that EEG and MEG (which is free from volume-conduction effects) offer comparable spatial resolutions on the order of several millimetres (Cohen et al., 1990; Ingber, 1991). Dipole localization accuracy of 7-8 mm for EEG and 3 mm for MEG has been demonstrated using a human skull phantom

(Leahy et al., 1998). Thus, spatial resolution of EEG might be better than widely believed. Additionally, the presented results cannot be attributed to the EEG recording with linked ear reference electrode for the following reasons: (a) in our early studies with the same reference electrode it was shown that the occipital and frontal regions clearly showed SPs with dominant peaks at different frequencies; (b) the analysis revealed, that each EEG channel or small group of channels has its own SP set; (c) the analysis in the present study revealed the existence of high diversity of SPs which consistently changed along with the change in condition (closed *vs* open eyes); (d) it was shown that frequency and amplitude in the delta, theta, alpha and beta bands did not vary significantly as a function of reference (Ferree et al., 2001).

4.3. Utilisation of the results

Understanding of the diversity of short-term EEG SP types has theoretical and practical importance:

- (1) The inherent dynamic structure of EEG activity is information-rich about the underlying cellular and intercellular processing, brain states, localization, forms of cooperativity, stages of development and of evolution (Bullock, 1997). Therefore, the information about the diversity of short-term EEG SP types may improve our understanding of underlying neurodynamics of brain states (Fingelkurts et al., 2003a,b, 2006a). Considering that the resting EEG is the most widely used experimental condition as a “baseline” of brain activity (a default mode, Raichle et al., 2001; Raichle and Snyder, 2007), information on the diversity of short-term EEG SP types adds additional description to the baseline brain activity and may help reveal some characteristics of a default mode of brain functioning. An important consequence of SP diversity is that several aspects of the brain’s activity that have traditionally been interpreted as irreducible randomness can now be explained in physiologically meaningful ways. Described diversity of short-term EEG SP types of spontaneous activity could provide a priori hypotheses about the way in which the brain would respond across a wide variety of task conditions. It can be hypothesised that EEG during increased functional loading (cognitive tasks) would be characterised by the same number of SP categories as in the rest conditions and by the different number of SPs within categories when compared with the rest. Additionally one may assume that

during neuropathology and/or psychopathology both the number of SP categories and the number of SPs within categories would be different from those of the resting conditions.

- (2) Frequency is an important feature of EEG activity – which would perhaps be expected from the fact that neuronal activation amplitudes are coded as firing frequency. However, there is lack of studies dedicated to EEG frequencies. At the same time, the conventional EEG has shown that the variation of EEG amplitude and frequency can be quite poorly correlated (Lazarev, 2006). In this context, the presented results quantitatively supplement the knowledge on EEG frequency component. A methodological advantage of the presented approach is that desynchronized fragments of an EEG epoch could be represented equally well with synchronized ones due to estimation of dominant frequency independently of the wave amplitude. Additionally, this approach allows researchers to investigate whether adjacent frequency bins show sharp discontinuities around the lower and upper frequencies of the broad bands.
- (3) It was suggested that integrative brain functions are shaped by (a) the superposition of oscillations including the delta, theta, alpha and beta bands and (b) activation of two or more selectively distributed oscillations in these bands (Basar, 2004). The approach presented here enables researches to measure exact percent of EEG where the superposition of oscillations is present. Additionally, presented results are of eminent significance in giving the interpretation of EEG signal. Described results suggested that (a) resting state networks should show EEG oscillations in multiple frequency bands, and that frequencies from different bands may be coupled or act together to mediate brain operations; (b) slow and fast rhythms may be not independent, and may underlie patterns of cooperation on a variety of temporal scales (Bruns et al., 2000; Fingelkurts and Fingelkurts, 2008). Hence, analysis of EEG data requires methods that consider the whole frequency spectrum rather than single frequency bands; (c) there is a limit in the number of accessible oscillatory states available to the cortex and many different ways that the microstate (indexed by SP type) can rearrange itself and still produce the same macrostate (tested condition).
- (4) EEG oscillations provide a rich source of potentially useful endophenotypes for psychiatric genetics (Begleiter and Porjesz , 2006) as they are highly correlated with human information processing and cognition (Basar et al., 1999, 2000; 2004;

Klimesch, 1996, 1999a,b, 2003; Klimesch et al., 2005 and others) on one hand and with brain dysfunction involved in the predisposition to some psychiatric disorders (Gevins et al., 1995; Chabot et al., 1996, 2001; Thatcher et al., 2001; Allen et al., 2004; Coan and Allen, 2004; Weisbrod et al., 2004; Lehmann et al., 2005; Prichep et al., 2006; Jalili et al., 2007; Rossini et al., 2006, 2008 and others) on the other. Additionally, EEG oscillations possess excellent heritability (Stassen et al., 1988; van Beijsterveldt and Boomsma, 1994; van Beijsterveldt et al. 1996; for the review and meta-analysis, see van Beijsterveldt and van Baal, 2002). In this context, the knowledge on the diversity of short-term EEG SP types may provide clues about cerebral function, and may shed light on pathogenic mechanisms involved in neurological and psychiatric disorders, where impairment in brain electrical activity is apparent (Fingelkurts et al., 2000, 2006b,c,d, 2007). Indeed, diversity is often used as a measure of the health of biological systems.

5. Conclusion

To summarize, the study demonstrated that during resting conditions and independently of functional state of the brain (closed eyes *vs* open eyes conditions) (a) the diversity of short-term EEG SP types was limited, (b) the percent distribution of SP types among different categories of SPs based on morphology of SPs was constant, (c) the most preferred frequencies were restricted to delta-theta and alpha bands and (d) independent beta rhythm was a less probable oscillation.

At the same time, closed eyes and open eyes conditions differed from each other by the percent distribution of different types of SPs. The probability of the occurrence of particular SP types were typical for each of the examined conditions with domination of alpha-rhythmical SPs during closed eyes condition (39% *vs* 13%) and domination of delta-theta-rhythmical SPs during open eyes condition (53% *vs* 27%).

Some of these results could be considered trivial, however, the present study substantially extended previously known data: (a) for the first time the diversity of short-term SP types was described both qualitatively and quantitatively and (b) reorganisation of this diversity rather than changes in EEG amplitude or power during transition from closed eyes to open eyes conditions was demonstrated.

As has been discussed above, joint analysis of the diversity of SPs obtained in this paper and published earlier data on how SP morphology depends on neurophysiological parameters and nonlinear measures reveals the following characteristics of resting EEG: up to 57% of short-term EEG signal during resting conditions is produced by activity of single neuronal ensemble and up to 44% of it reflects highly organized activity (ordered behaviour with low entropy) of the underlying neuronal ensemble. Up to 36% of short-term EEG during rest reflects the activity of two or more neuronal ensembles with resonant ordered behaviour within each individual ensemble. And finally, only up to 9% of short-term EEG reflects transitory or noisy/disorganised episodes in resting EEG. Notice that different types of SPs within the same and/or different SP categories are combined temporally in a “mosaic” way.

Understanding of the diversity of short-term EEG SP types is not only of a theoretical and practical importance, but also of eminent significance in giving a solid basis to the interpretation of EEG.

Further studies will be necessary to identify (a) what is the origin of SP diversity? (b) does SP diversity vary as a function of age and gender? (c) is SP diversity determined by genetic factors or environmental influences? and (d) does resting-state SP diversity predict cognitive performance, emotional reactivity or certain disorders? Data on the extent of intraindividual versus interindividual variability of SP types and stability of individual differences with respect to SP types have been published earlier (Fingelkurts et al., 2006a).

Acknowledgment

The authors thank Carlos Neves, computer science specialist for the programming, technical and IT support. Special thanks to Dmitry Skarin for skilful editing. This work has been supported by BM-Science Centre.

References

- Allen, J.J.B., Urry, H.L., Hitt, S.K., Coan, J.A., 2004. The stability of resting frontal electroencephalographic asymmetry in depression. *Psychophysiology* 41, 269–280.
- Arieli, A., Sterkin, A., Grinvald, A., Aertsen, A., 1996. Dynamics of ongoing activity: explanation of the large variability in evoked cortical responses. *Science* 273, 1868–1871.
- Babiloni, C., Miniussi, C., Babiloni, F., Carducci, F., Cincotti, F., Del Percio, C., Sirello, G., Fracassi, C., Nobre, A.C., Rossini, P.M., 2004. Sub-second "temporal attention" modulates alpha rhythms. A high-resolution EEG study. *Brain Res. Cogn. Brain. Res.* 19, 259-268.

- Ball, T., Demandt, E., Mutschler, I., Neitzel, E., Mehring, C., Vogt, K., Aertsen, A., Schulze-Bonhage, A., 2008. Movement related activity in the high gamma range of the human EEG. *NeuroImage* 41, 302–310.
- Barlow, J.S., 1985. Methods of analysis of nonstationary EEGs, with emphasis on segmentation techniques: a comparative review. *J. Clin. Neurophysiol.* 2, 267-304.
- Basar, E., 2004. *Memory and Brain Dynamics: Oscillations Integrating Attention, Perception, Learning, and Memory*. CRC Press, pp. 261.
- Basar, E., Guntekin, B., 2006. The key role of alpha activity in ‘‘creative evolution’’. *Int. J. Psychophysiol.* 61, 313-314.
- Basar, E., Basar-Eroglu, C., Karakas, S., Schurmann, M., 1999. Are cognitive processes manifested in event-related gamma, alpha, theta and delta oscillations in the EEG? *Neurosci. Lett.* 259, 165-168.
- Basar, E., Basar-Eroglu, C., Karakas, S., Schurmann, M., 2000. Brain oscillations in perception and memory. *Int. J. Psychophysiol.* 35, 95-124.
- Basar, E., Basar-Eroglu, C., Karakas, S., Schurmann, M., 2001. Gamma, alpha, delta, and theta oscillations govern cognitive processes. *Int. J. Psychophysiol.* 39, 241–248.
- Basar, E., Özgören, M., Karakas, S., Basar-Eroglu, C., 2004. Super-synergy in the brain: The grandmother percept is manifested by multiple oscillations. *Int. J. Bifurcat. Chaos* 14, 453-491.
- Becker, D., Creutzfeldt, O.D., Schwibbe, M., Wuttke, W., 1982. Changes in physiological, EEG and psychological parameters in women during the spontaneous menstrual cycle and following oral contraceptives. *Psychoneuroendocrinol.* 7, 75-90.
- Begleiter, H., and Porjesz, B., 2006. Genetics of human brain oscillations. *Int. J. Psychophysiol.* 60, 162–171.
- Bhattacharya, J., 2001. Reduced degree of long-range phase synchrony in pathological human brain. *Acta Neurobiol. Exp.* 61, 309-318.
- Bodenstein, G., Praetorius, H.M., 1977. Feature extraction from the electroencephalogram by adaptive segmentation. *Proc IEEE* 65, 642-652.
- Bodunov, M.V., 1985. Individual-typologic features of EEG structure. *Zh. Vyssh. Nerv. Deiat.* (Journal of High Nerve Activity) 35(6), 1045-1052 (in Russian).
- Bressler, S.L., Keslo, J.A.S., 2001. Cortical coordination dynamics and cognition. *Trends Cogn. Sci.*, 5(1), 26-36.
- Bruns, A., Eckhorn, R., Jokeit, H., Ebner, A., 2000. Amplitude envelope correlation detects coupling among incoherent brain signals. *NeuroReport* 11, 1509–1114.
- Bullock, T.H., 1997. Signals and signs in the nervous system: The dynamic anatomy of electrical activity. *PNAS* 94, 1-6.
- Bullock, T.H., McClune, M.C., Enright, J.T., 2003. Are the EEGs mainly rhythmic? Assessment of periodicity in wide-band time series. *Neuroscience* 121(1), 233-252.
- Chabot, R.J., Merkin, H., Wood, L.M., Davenport, T.L., Serfontein, G., 1996. Sensitivity and specificity of qEEG in children with attention deficit or specific developmental learning disorders. *Clin. Electroencephalogr.* 27(1), 26-34.
- Chabot, R.J., di Michele, F., Prichep, L., John, E.R., 2001. The Clinical Role of Computerized EEG in the Evaluation and Treatment of Learning and Attention Disorders in Children and Adolescents. *J. Neuropsychiatry. Clin. Neurosci.* 13, 171–186.
- Coan, J.A., Allen, J.J.B., 2004. Frontal EEG asymmetry as a moderator and mediator of emotion. *Biol. Psychol.* 67, 7–49.
- Coan, J.A., Allen, J.J.B., Harmon-Jones, E., 2001. Voluntary facial expression and hemispheric asymmetry over the frontal cortex. *Psychophysiol.* 38, 912–925.
- Cohen, D., Cuffin, B.N., Yunokuchi, K., Maniewski, R., Purcell, C., Cosgrove, G.R., Ives, J., Kennedy, J., Schomer, D., 1990. MEG versus EEG localization test using implanted sources in the human brain. *Ann. Neurol.* 28, 811-817.
- Cook, I.A., O’Hara, R., Uijtdehaage, S.H., Mandelkern, M., Leuchter, A.F., 1998. Assessing the accuracy of topographic EEG mapping for determining local brain function. *Electroencephalogr. Clin. Neurophysiol.* 107, 408-414.

- Cooper, N., Croft, R.J., Dominey, S.J.J., Burgess, A.P., Gruzelier, J.H., 2003. Paradox lost? Exploring the role of alpha oscillations during externally vs. internally directed attention and the implications for idling and inhibition hypotheses. *Int. J. Psychophysiol.* 47, 65–74.
- Corsi-Cabrera, M., Herrera, P., Malvido, M., 1989. Correlation between EEG and cognitive abilities: Sex differences. *Int. J. Neurosci.* 45, 133–141.
- David, O., Friston, K.J., 2003. A neural mass model for MEG/EEG: coupling and neuronal dynamics. *Neuroimage* 20, 1743–1755.
- Doppelmayr, M., Klimesch, W., Schwaiger, J., Auinger, P., Winkler, T., 1998. Theta synchronization in the human EEG and episodic retrieval. *Neurosci. Lett.* 257, 41–44.
- Dumermuth, H.G., Molinari, L., 1987. Spectral analysis of the EEG. Some fundamentals revisited and some open problems. *Neuropsychobiol.* 17, 85–99.
- Effern, A., Lehnertz, K., Fernandez, G., Grunwald, T., David, P., Elger, C.E., 2000. Single trial analysis of event related potentials: non-linear de-noising with wavelets. *Clin. Neurophysiol.* 111, 2255–2263.
- Ferree, T.C., Luu, P., Russell, G.S., Tucker, D.M., 2001. Scalp electrode impedance, infection risk, and EEG data quality. *Clin. Neurophysiol.* 112, 536–544.
- Fingelkurts, An.A., Fingelkurts, Al.A., 2001. Operational Architectonics of the human brain biopotential field: Towards solving the mind-brain problem. *Brain Mind* 2(3), 261–296.
- Fingelkurts, An.A., Fingelkurts, Al.A., 2008. Brain-mind Operational Architectonics imaging: Technical and methodological aspects. *Open Neuroimag. J.* 2, 73–93.
- Fingelkurts Al.A., Fingelkurts An.A., Grin' E.Yu. Ermolaev V.A. Kaplan A.Ya., 2000. Adaptive classification of EEG spectral patterns: The comparison between healthy subjects and patients with different brain pathology. *Vestnik Moskovskogo Universiteta (Bulletin of Moscow University). Series 16. Biology.* 4(3-11) (in Russian).
- Fingelkurts, Al.A., Fingelkurts, An.A., Krause, C.M., Sams, M., 2002. Probability interrelations between pre-/post-stimulus intervals and ERD/ERS during a memory task. *Clin. Neurophysiol.* 113, 826–843.
- Fingelkurts, Al.A., Fingelkurts, An.A., Kaplan, A.Ya., 2003a. The regularities of the discrete nature of multi-variability of EEG spectral patterns. *Int. J. Psychophysiol.* 47(1), 23–41.
- Fingelkurts, Al.A., Fingelkurts, An.A., Krause, C.M., Kaplan, A.Ya., 2003b. Systematic rules underlying spectral pattern variability: Experimental results and a review of the evidences. *Int. J. Neurosci.* 113, 1447–1473.
- Fingelkurts, Al.A., Fingelkurts, An.A., Kivisaari, R., Pekkonen, E., Ilmoniemi, R.J., Kähkönen, S., 2004. The interplay of lorazepam-induced brain oscillations: microstructural electromagnetic study. *Clin. Neurophysiol.* 115, 674–690.
- Fingelkurts, Al.A., Fingelkurts, An.A., Ermolaev, V.A., Kaplan, A.Ya., 2006a. Stability, reliability and consistency of the compositions of brain oscillations. *Int. J. Psychophysiol.* 59(2), 116–126.
- Fingelkurts, Al.A., Fingelkurts, An.A., Kaplan, A.Ya., 2006b. Interictal EEG as a physiological adaptation Part I: composition of brain oscillations in interictal EEG. *Clin. Neurophysiol.* 117(1), 208–222.
- Fingelkurts, Al.A., Fingelkurts, An.A., Kaplan, A.Ya., 2006c. Interictal EEG as a physiological adaptation. Part II. Topographic variability of composition of brain oscillations in interictal EEG. *Clin. Neurophysiol.* 117(4), 789–802.
- Fingelkurts, Al.A., Fingelkurts, An.A., Rytsala, H., Suominen, K., Isometsä, E., Kähkönen, S., 2006d. Composition of brain oscillations in ongoing EEG during major depression disorder. *Neurosci. Res.* 56(2), 133–144.
- Fingelkurts, An.A., Fingelkurts, Al.A., Rytsala, H., Suominen, K., Isometsä, E., Kähkönen, S., 2007. Impaired functional connectivity at EEG alpha and theta frequency bands in major depression. *Hum. Brain Mapp.* 28(3), 247–261.
- Freeman, W.J., 2003. The Wave Packet: An Action Potential for the 21st Century. *J. Integr. Neurosci.* 2, 3–30.
- Gasser T, Bacher P, Steinberg H., 1985. Test–retest reliability of spectral parameters of the EEG. *Electroencephalogr. Clin. Neurophysiol.* 60, 312–9.

- Gevins, A., Leong, H., Smith, M.E., Le, J., Du, R., 1995. Mapping cognitive brain function with modern high-resolution electroencephalography. *Trends Neurosci.* 18, 429-436.
- Gevins, A., Smith, M.E., McEvoy, L., Yu, D., 1997. High resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cereb. Cortex* 7, 374–385.
- Herscovitch, P., 1994. Radiotracer techniques for functional neuroimaging with positron emission tomography. In: Thatcher, R.W., Halletr, M., Zeffro, T., John, E.R., Huerta, M., (Eds.), *Functional Neuroimaging: Technical Foundations*. Academic Press, San Diego.
- Hilfiker, P., Egli, M., 1992. Detection and evolution of rhythmic components in ictal EEG using short segment spectra and discriminant analysis. *Electroencephr. Clin. Neurophysiol.* 82, 255-265.
- Horita, M., Takizawa, Y., Wada, Y., Futamata, H., Hashimoto, T., 1995. Sex differences in EEG background activity: a study with quantitative analysis in normal adults. *Rinsho Byori* 43(2), 177-180.
- Ingber, L., 1991. Statistical mechanics of neocortical interactions: A scaling paradigm applied to electroencephalography. *Physical Review A* 44(6), 4017-4060.
- Inouye, T., Shinosaki, K., Sakamoto, H., Toi, S., Ukai, S., Iyama, A., Katsuda, Y., Hirano, M., 1991. Quantification of EEG irregularity by use of the entropy of the power spectrum. *Electroencephalogr. Clin. Neurophysiol.* 79, 204-210.
- Inouye, T., Toi, S., Matsumoto, Y., 1995. A new segmentation method of electroencephalograms by use of Akaike's information criterion. *Brain Res. Cogn. Brain. Res.* 3, 33-40.
- Jalili, M., Lavoie, S., Deppen, P., Meuli, R., Do, K.Q., Cuénod, M., Hasler, M., De Feo, O., Knyazeva, M.G., 2007. Dysconnection Topography in Schizophrenia Revealed with State-Space Analysis of EEG. *PLoS ONE* 2(10):e1059. doi:10.1371/journal.pone.0001059
- Jansen, B.H., Cheng, W.-K., 1988. Structural EEG analysis: an explorative study. *Int. J. Biomed. Comput.*, 23, 221-237.
- Jung, R., 1953, *Neurophysiologische Untersuchungsmethoden*. In: von Bergmann, G., Frey, W., Schwiegg, H., (Eds.), *Handbuch der Inneren Medizin*, vol. 1. Springer, Berlin, pp. 1216-1325.
- Kalton, G., 1983. *Introduction to Survey Sampling (Quantitative Applications in the Social Sciences)*. Sage Publications, Inc.
- Kaplan, A.Ya., 1998. Nonstationary EEG: methodological and experimental analysis. *Usp. Physiol. Nayk (Success in Physiological Sciences)* 29, 35-55 (In Russian).
- Kaiser, D.A., 2000. QEEG. State of the art, or state of confusion. *Journal of Neurotherapy* 1530-017X, 4(2), 57-75.
- Keidel, M., Keidel, W.-D., Tirsch, W.S., Poppl, S.J., 1987. Studying temporal order in human CNS by means of 'runing' frequency and coherence analysis. In: Rensing, L., an der Heiden, U., Mackey, M.C., (Eds.), *Temporal disorder in human oscillatory systems*. Springer series in synergetics, vol. 36. Springer, Berlin Heidelberg New York, pp. 57-68.
- Klimesch, W., 1996. Memory processes, brain oscillations and EEG synchronization. *Int. J. Psychophysiol.* 24(1-2), 61-100.
- Klimesch, W., 1999a. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res. Rev.* 29, 169-195.
- Klimesch, W., 1999b. Event-related band power changes and memory performance. Event-related desynchronization and related oscillatory phenomena of the brain. In: Pfurtscheller, G., Lopez da Silva, F.H., (Eds.), *Handbook of electroencephalography and clinical neurophysiology*, vol. 6, revised edition, Elsevier, Amsterdam, pp. 151-178.
- Klimesch, W., 2003. Interindividual differences in oscillatory EEG activity and cognitive performance. In: Reinvang, I., Greenlee, M., Herrmann, M. (Eds.), *The Cognitive Neuroscience of Individual Differences*, BIS, Oldenburg.
- Klimesch, W., Doppelmayr, M., Wimmer, H., Gruber, W., Rohm, D., Schwaiger, J., Hutzler, F., 2001. Alpha and beta band power changes in normal and dyslexic children. *Clin. Neurophysiol.* 112, 1186–1195.
- Klimesch, W., Schack, B., Sauseng, P., 2005. The functional significance of theta and upper alpha oscillations. *Exp. Psychol.* 52(2), 99-108.

- Knyazev, G.G., 2007. Motivation, emotion, and their inhibitory control mirrored in brain oscillations. *Neurosci. Biobehav. Rev.* 31, 377–395.
- Lakatos, P., Shah, A.S., Knuth, K.H., Ulbert, I., Karmos, G., Schroeder, C.E., 2005. An Oscillatory Hierarchy Controlling Neuronal Excitability and Stimulus Processing in the Auditory Cortex. *J. Neurophysiol.* 94, 1904–1911.
- Laskaris, N.A., Ioannides, A.A., 2001. Exploratory data analysis of evoked response single trials based on minimal spanning tree. *Clin. Neurophysiol.* 112, 698-712.
- Lazarev, V.V., 2006. The relationship of theory and methodology in EEG studies of mental activity. *Int. J. Psychophysiol.* 62, 384–393.
- Leahy, R.M., Mosher, J.C., Spencer, M.E., Huang, M.X., Lewine, J.D., 1998. A study of dipole localization accuracy for MEG and EEG using a human skull phantom. *Electroencephalogr. Clin. Neurophysiol.* 107, 159-173.
- Lehmann, D., Faber, P.L., Galderisi, S., Herrmann, W.M., Kinoshita, T., Koukkou, M., Mucci, A., Pascual-Marqui, R.D., Saito, N., Wackermann, J., Winterer, G., Koenig, T., 2005. EEG microstate duration and syntax in acute, medication-naïve, first-episode schizophrenia: a multi-center study. *Psychiatry Res.: Neuroimaging* 138, 141–156.
- Leopold, D.A., Murayama, Y., Logothetis, N.K., 2003. Very slow activity fluctuations in monkey visual cortex: implications for functional imaging. *Cereb. Cortex* 13, 422–433.
- Levy, W.J., 1987. Effect of epoch length on power spectrum analysis of the EEG. *Anesthesiology* 66(4), 489-495.
- Livanov, M.N., 1984. Electroencephalogram rhythms and their functional significance. *Gurnal Vischei Nervnoi Deyatel'nosti (Journal of High Nerve Activity)* 34, 613-626 (in Russian).
- Lopes da Silva, L.M., 1991. Neural mechanism underlying brain waves: from neural membranes to networks. *Electroencephalogr. Clin. Neurophysiol.* 79, 81-93.
- Lopes Da Silva, F.H., 1996. The generation of electric and magnetic signals of the brain by local networks. In: Greger, R., Windhorst, U., (Eds.), *Comprehensive Human Physiology*, vol. 1. Springer-Verlag, pp. 509-528.
- Mantini, D., Perrucci, M.G., Del Gratta, C., Romani, G.L., Corbetta, M., 2007. Electrophysiological signatures of resting state networks in the human brain. *PNAS* 104(32), 13170–13175.
- Meshkova, T.A., 1988. Chapter III In: Ravich-Shcherbo, I.V. (Ed.), *The role of environment and heredity in formation of human individuality*. Pedagogica, Moscow, 335 pp.
- McEwen, J.A., Anderson, G.B., 1975. Modeling the stationarity and gaussianity of spontaneous electroencephalographic activity. *IEEE Trans Biomed. Engin.* 22(5), 361-369.
- Michel, C.M., Lehmann, D., Henggeler, B., Bandeis, D., 1992. Localization of the sources of EEG delta, theta, alpha, and beta frequency bands using the FFT dipole approximation. *Electroencephalogr. Clin. Neurophysiol.* 82, 38–44.
- Miller, L.M., Schreiner, C.E., 2000. Stimulus-based state control in the thalamocortical system. *J. Neurosci.* 20, 7011–7016.
- Moran, R.J., Kiebel, S.J., Stephan, K.E., Reilly, R.B., Daunizeau, J., Friston, K.J., 2007. A Neural Mass Model of spectral responses in electrophysiology. *NeuroImage* 37(3), 706-720.
- Muller, U.A., 1993. Statistics of variables observed over overlapping intervals. Working Paper from Olsen and Associates No 1993-06-18, November 30, p 10. File URL: http://www.olsen.ch/fileadmin/Publications/Working_Papers/931130-intervalOverlap.pdf
- Muthuswamy, J., Thakor, N.V., 1998. Spectral analysis methods for neurological signals. *J. Neurosci. Methods* 83, 1-14.
- Niedermeyer, E., Lopes da Silva, F.H., 1999. *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins, Philadelphia.
- Nunez, P.L., 1995. *Neocortical dynamics and human EEG rhythms*. Oxford Univ. Press, New York.
- Nunez, P.L., 2000. Toward a quantitative description of large-scale neocortical dynamic function and EEG. *Behav. Brain Sci.* 23(3), 371-437.
- Nunez, P.L., Wingeier, B.M., Silberstein, R.B., 2001. Spatial-temporal structures of human alpha rhythms: theory, microcurrent sources, multiscale measurements, and global binding of local networks. *Hum. Brain Mapp.* 13, 125–164.

- Pereda, E., Gamundi, A., Nicolau, M.C., Rial, R., Gonzalez, 1999. Interhemispheric differences in awake and sleep human EEG: a comparison between nonlinear and spectral measures. *Neurosci. Lett.* 263, 37–40.
- Perez Velazquez, J.L., Wennberg, R., 2004. Metastability of brain states and the many routes to seizures: Numerous causes, same result. In: Pandalai, S.G., (Ed.), *Recent research developments in biophysics*, vol. 3. Transworld Research Network, Kerala, pp. 25–59.
- Perneger, T.V., 1998. What is wrong with Bonferroni adjustments. *Br. Med. J.* 136, 1236-1238.
- Pfurtscheller, G., Lopes da Silva, F.H., 1999. Event-related EEG/MEG synchronisation and desynchronisation: basic principles. *Clin. Neurophysiol.* 110, 1842-1857.
- Prichep, L.S., John, E.R., Ferris, S.H., Rausch, L., Fangd, Z., 2006. Prediction of longitudinal cognitive decline in normal elderly with subjective complaints using electrophysiological imaging. *Neurobiol. Aging* 27, 471–481.
- Priestley, M.B., 1981. *Spectral Analysis and Time Series*. Academic Press.
- Propping, P., Kruger, J., Jonah, A., 1980. Effect of alcohol on genetically determined variants of the normal electroencephalogram. *Psychiatry Res.* 2, 85-98.
- Pulvermüller, F., Preissl, H., Lutzenberger, W., Birbaumer, N., 1995. Spectral responses in the gamma-band: physiological signs of higher cognitive processes? *NeuroReport* 6, 2057–2064.
- Quian Quiroga, R., Rosso, O.A., Basar, E., Schurmann, M., 2001. Wavelet entropy in event-related potentials: a new method shows ordering of EEG oscillations. *Biol. Cybern.* 84, 291-299.
- Raichle, M.E., Snyder, A.Z., 2007. A default mode of brain function: A brief history of an evolving idea. *NeuroImage* 37(4), 1083-1090.
- Raichle, M.E., MacLeod, A.M., Snyder, A.Z., Powers, W.J., Gusnard, D.A., Shulman, G.L., 2001. A default mode of brain function. *Proc. Natl. Acad. Sci. U. S. A.* 98, 676–682.
- Riley, W.J., 2003. Techniques for frequency stability analysis. *IEEE International Frequency Control Symposium*. Tampa, FL, May 4.
- Robinson, P.A., Rennie, C.J., Wright, J.J., Bahramali, H., Gordon, E., Rowe, D.L., 2001. Prediction of electroencephalographic spectra from neurophysiology. *Physical Review E* 63, 021903-1–021903-18
- Rossini, P.M., Percio, C.D., Pasqualetti, P., Cassetta, E., Binetti, G., Forno, G.D., Ferreri, F., Frisoni, G., Chioventa, P., Miniussi, C., Parisi, L., Tombini, M., Vecchio, F., Babiloni, C., 2006. Conversion from mild cognitive impairment to Alzheimer's disease is predicted by sources and coherence of brain electroencephalography rhythms. *Neuroscience* 143, 793–803.
- Rossini, P.M., Buscema, M., Capriotti, M., Grossi, E., Rodriguez, G., Percio, C.D., Babiloni, C., 2008. Is it possible to automatically distinguish resting EEG data of normal elderly vs. mild cognitive impairment subjects with high degree of accuracy? *Clin. Neurophysiol.* 119(7), 1534-1545.
- Rothman, K.J., 1990. No adjustments are needed for multiple comparisons. *Epidemiology* 1, 43-46.
- Sauseng, P., Klimesch, W., Doppelmayr, M., Pecherstorfer, T., Freunberger, R., Hanslmayr, S., 2005a. EEG alpha synchronization and functional coupling during top-down processing in a working memory task. *Hum. Brain Mapp.* 26(2), 148–155.
- Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., Doppelmayr, M., Hanslmayr, S., Gruber, W.R., Birbaumer, N., 2005b. A shift of visual spatial attention is selectively associated with human EEG alpha activity. *Eur. J. Neurosci.* 22, 2917-2926.
- Simon, O., (Simonova, O.) 1977. *Das Elektroenzephalogramm*. Urban & Schwarzenberg, Munich.
- Smith, M.J., Adams, L.F., Schmith, P.J., Rubinow, D.R., Wassermann, E.M., 2002. Effects of ovarian hormones on human cortical excitability. *Annals of Neurology* 51, 599-603.
- Sokolov, E.N., 1963. Higher nervous functions: the orienting reflex. *Annu. Rev. Physiol.* 25, 545–580.
- Solís-Ortiz, S., Ramos, J., Arce, C., Guevara, M.A., Corsi-Cabrera, M., 1994. EEG oscillations during menstrual cycle. *Int. J. Neurosci.* 76(3-4), 279-292.
- Stassen, H.H., 1985. The similarity approach to EEG analysis. *Meth. Inform. Med.* 24, 200-212.
- Stassen, H.H., Lykken, D.T., Propping, P., Bomben, G., 1988. Genetic determination of the human EEG. Survey of recent results on twins reared together and apart. *Hum. Genet.* 80, 165–176.
- Stastny, J., Sovka, P., Stancak, A., 2003. EEG Signal Classification: Introduction to the Problem. *Radioengineering* 12(3), 51-55.

- Steriade, M., 2000. Corticothalamic resonance, states of vigilance and mentation. *Neuroscience* 101, 243–276.
- Stern, J.M., Engel, J.Jr., 2004. Atlas of EEG patterns. Williams & Wilkins, Lippincott.
- Symonova, O., Roth, B., Stein, J., 1967. EEG studies of healthy population – normal rhythms of resting recording. *Act. Univ. Carol Med. (Praha)* 13, 543-551.
- Thatcher, R.W., 2001. Normative EEG databases and EEG biofeedback. *J. Neurotherapy* (2-4)3, 1-29.
- Thatcher, R.W., John, E.R., 1977. *Functional Neuroscience. Vol. 1: Foundations of Cognitive Processes.* Lawrence Erlbaum, New York.
- Thatcher, R.W., North, D.M., Curtin, R.T., Walker, R.A., Biver, C.J., Gomez, J.F., Salazar, A.M., 2001. An EEG Severity Index of Traumatic Brain Injury. *J. Neuropsychiatry Clin. Neurosci.* 13(1), 77-87.
- Thatcher, R.W., Walker, R.A., Biver, C.J., North, D.M., Curtin, R., 2003. Sensitivity and Specificity of an EEG Normative Database: Validation and Clinical Correlation. *J. Neurotherapy* 7(3/4), 87-121.
- Tirsch, W.S., Keidel, M., Poppl, S.J., 1988. Computer-aided detection of temporal patterns in human CNS dynamics. In: Willems, J.L., van Bemmelen, J.H., Michel, J. (Eds.), *Progress in computer-assisted function analysis*, Elsevier, North Holland, pp. 109-118.
- Tirsch, W.S., Keidel, M., Perz, S., Scherb, H., Sommer, G., 2000. Inverse covariation of spectral density and correlation dimension in cyclic EEG dynamics of the human brain. *Biol Cybern* 82:1-14.
- Tirsch, W.S., Stude, Ph., Scherb, H., Keidel, M., 2004. Temporal order of nonlinear dynamics in human brain. *Brain Res. Rev.* 45, 79–95.
- Tsodyks, M., Kenet, T., Grinvald, A., Arieli, A., 1999. Linking spontaneous activity of single cortical neurons and the underlying functional architecture. *Science* 286, 1943–1946.
- van Beijsterveldt, C.E., van Baal, G.C.M., 2002. Twin and family studies of the human electroencephalogram: a review and meta-analysis. *Biol. Psychol.* 61, 111-138.
- van Beijsterveldt, C.E., Boomsma, D.I., 1994. Genetics of the human electroencephalogram (EEG) and event-related brain potentials (ERPs): a review. *Hum. Genet.* 94, 319–330.
- van Beijsterveldt, C.E., Molenaar, P.C., de Geus, E.J., Boomsma, D.I., 1996. Heritability of human brain functioning as assessed by electroencephalography. *Am. J. Hum. Genet.* 58, 562–573.
- Verstraeten, E., Cluydts, R., 2002. Attentional switching-related human EEG alpha oscillations. *Neuroreport* 13, 681-684.
- von Stein, A., Sarnthein, J., 2000. Different frequencies for different scales of cortical integration: from local gamma to long range alpha-theta synchronization. *Int. J. Psychophysiol.* 38, 301-313.
- Weisbrod, M., Hill, H., Sauer, H., Niethammer, R., Guggenbuhl, S., Hell, D., Stassen, H.H., 2004. Nongenetic Pathologic Developments of Brain-Wave Patterns in Monozygotic Twins Discordant and Concordant for Schizophrenia. *Am. J. Med. Genet. Part B (Neuropsychiatric Genetics)* 125B, 1–9.
- Whitham, E.M., Pope, K.J., Fitzgibbon, S.P., Lewis, T., Clark, C.R., Loveless, S., Broberg, M., Wallace, A., De Los Angeles, D., Lillie, P., Hardy, A., Fronsko, R., Pulbrook, A., Willoughby, J.O., 2007. Scalp electrical recording during paralysis: Quantitative evidence that EEG frequencies above 20 Hz are contaminated by EMG. *Clin. Neurophysiol.* 118, 1877–1888.
- Yuval-Greenberg, S., Tomer, O., Keren, A.S., Nelken, I., Deouell, L.Y., 2008. Transient Induced Gamma-Band Response in EEG as a Manifestation of Miniature Saccades. *Neuron* 58, 429-441.
- Zavaglia, M., Astolfi, L., Babiloni, F., Ursino, M., 2006. A neural mass model for the simulation of cortical activity estimated from high resolution EEG during cognitive or motor tasks. *J. Neurosci. Methods* 157, 317–329.