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PERCEPTION OF MULTISTABLE IMAGES: EEG STUDIES

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Abstract
In the paper we studied the dynamics of the complex patterns in human EEG data during a psychophysiological experiment by stimulating cognitive activity with the perception of ambiguous object. A new method based on the calculation of the maximum energy component for the continuous wavelet transform (skeletons) was proposed. The paper presented the processing results of experimental data for 20 male volunteers. Skeleton analysis allowed us to identify specific patterns in the EEG data set, appearing during the perception of ambiguous objects. Thus, it became possible to diagnose some associated cognitive processes. We found complex dynamics in delta, alpha and beta frequency ranges on EEG during the bistable image perception. We believe that this dynamics could be associated with processes of concentration of attention and recognition of complex visual objects.

Key words
Multistability, bistable image, perception, electroencephalogram, continuous wavelet transform, frequency ranges

1 Introduction

At the present time interdisciplinary tasks are of a great interest for investigators from different fields of science. One of the most relevant problem from prospect of fundamental research and application in technics is studying of human brain activity. At the end of XX century studies of human brain were mainly limited to its physiological and psychological aspects, while at present time brain investigation moves to the field of combined neuroscience, physics, mathematics and nonlinear dynamics.

Brain itself is commonly considered as a complex network structure that consist of huge number of oscillatory elements – neurons [Betzel, Medaglia, Pasqualetti, and Bassett, 2016; Hermundstad, Bassett, Brown et al., 2013; Atasoy, Donnelly, and Pearson, 2016]. Main source of information about brain activity are various experimental methods including electroencephalogram (EEG). EEG is a sum of electric currents generated by a group of neurons near recording electrode. Complex nature of brain neuronal network results in complex structure of EEG signal, which commonly has number of specific rhythms, oscillatory patterns and different types of intermittent behavio [Sitnikova, Hramov, Grubov et al., 2012; Koronovskii, Hramov, Grubov, Moskalenko, Sitnikova, and Pavlov, 2016]. It is well-known that time-frequency structure of EEG signal correlates with functional state of body and brain. Thus, studying of specific features and processes on EEG is important for understanding fundamental mechanisms of brain.

Cooperative neuronal dynamics causes different states of brain, including various types of cognitive activity, e.g., formation of memory traces [Buzsaki, 1989; Haenschel, Vernon, Dwivedi, Gruzelier, and Baldeweg, 2005], information processing [Cichy, Khosla,Pantazis, Torralba, and Oliva, 2016; Palmeri and Gauthier, 2004], spatial orientation [Sargolini, Fyhn, Hafting et al., 2006; Kjelstrup, Solstad, Brun et al., 2008], intelligence [Colom, Karama, Jung, and Haier, 2010; Van den Heuvel, Stam, Kahn, and Hulshoff Pol, 2009], etc. The information processing in the brain includes the following steps: acquisition of external data (perception), their analysis, and the brain response (reaction). Therefore, perception plays an important role in further data analysis and cognitive activity, especially visual perception and image recognition, since human brain acquires about 90% of information through eyes.

Visual perception and corresponding cognitive processes were often studied using ambiguous (bistable) images [Leopold and Logothetis, 1999; Sterzer, Kleinschmidt, and Rees, 2009; Pisarchik, Jaimes-Reategui, Magallon-Garcia et al., 2014; Runnova, Hramov, Grubov et al., 2016]. The perception of bistable images is one of important tasks allowing to understand various different aspects of visual perception and objects recognition. The mechanism of image recognition is not well understood yet, but it is known that the perception is the result of processes in distributed neuronal network of occipital, parietal and frontal cortex areas [Tong, Meng, and Blake, 2006]. This problem also requires the consideration of the brain activity simultaneously in different frequency ranges associated with different rhythms of brain (delta, alpha, beta) [Tewarie, 2016; Blanco, 2013]. According to recent papers [Stam, 2000; Elgendi, Vialatte, Cichocki, Latchoumane, Jeong, and Dauwels, 2011], this approach would allow simultaneous observation of different states of the neural network, that, in turn, is very useful for understanding not only perception, but also other types of cognitive brain activity.

In this paper we studied features of brain cognitive activity associated with visual perception of ambiguous images among groups of participants. Our approach was based on the analysis of spectral properties of multichannel EEG signals, the powerful tool for studying brain activity at the macroscopic level. The features were associated with different ratio between delta, alpha, and betta rhythms before, during and after perception.

2 Study Methods

2.1 Experiment

The experimental studies were performed according to ethical standards of the World Medical Association [World medical association, 2000]. Twenty healthy subjects from a group of unpaid male volunteers in the age of 19-30 with normal visual acuity participated in the experiments. The purpose of this experiment was to obtain multichannel EEG data during the unconscious decision on ambiguous image interpretation. In our physiological experiment with EEG activity registration we used a set of images based on a well-known bistable object, the Necker cube [Necker, 1832], as a visual stimulus. This is a projection of cube with transparent faces and visible ribs; an observer without any perception abnormalities treats the Necker cube as a 3D-object thanks to the specific position of the ribs. Bistability in perception consists in the interpretation of this 3D-object as to be oriented in two different ways, in particular, if the different ribs of the Necker cube are drawn with different intensity.

In our experimental work the contrast of the three middle lines centered in the left middle corner, $I \in [0, 1]$, was used as a control parameter. The values $I = 1$ and $I = 0$ correspond, respectively, to 0 (black) and 255 (white) pixels' luminance of the middle lines. Therefore, we can define a contrast parameter as $I = y/255$, where y is the brightness level of the middle lines using the 8-bit grayscale palette.

Figure 1 demonstrates two Necker cubes with different values of parameter I: $I = 0.15$ (A) and $I = 0.75$ (B) correspondingly. Necker cube with $I = 0.15$ is more likely to be perceived as a projection of 3D-cube with its frontal face looking to the left. This way of cube's orientation and perception was conditionally called "left-oriented", while another way of perception (like cube with $I = 0.75$) was called "right-oriented". Also Figure 1 depicts examples of multichannel EEG signals during perception of "left-" and "right-oriented" cubes. EEG channels for investigation were chosen from International "10-20" scheme of EEG electrode placement [Jasper, 1958]. Chosen electrodes (O2, O1, P4, P3, C4, C3, Pz, Cz) are mostly located in occipital area since that part of brain is known to be responsible for visual perception.

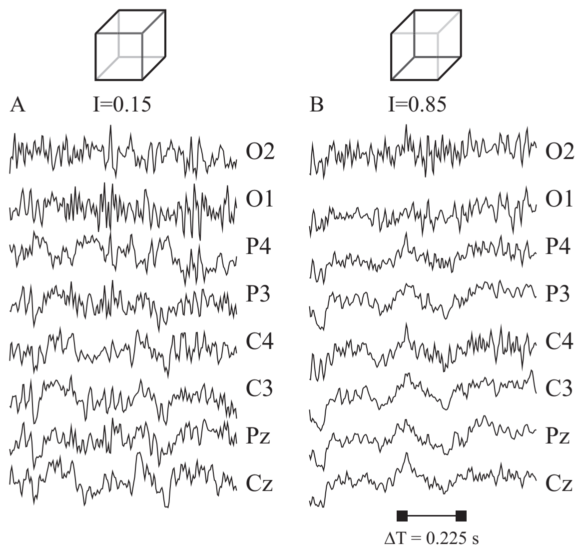

Figure 1. Examples of "left-" and "right-oriented" Necker cube images with different values of control parameter I: $I = 0.15$ (A) and $I = 0.75$ (B) and fragments of corresponding EEG data from O2, O1, P4, P3, C4, C3, Pz, Cz channels of "10-20" scheme.

The Necker cube images with different values of I ($I = 0.15, 0.4, 0.5, 0.6, 0.85$) were demonstrated for a short time, each lasting between 1.0 and 1.5 seconds, interrupted by a background abstract picture for 5.0 – 5.5 seconds. The subject was instructed to press either left or right key on special input device depending on his interpretation of the Necker cube projection observed during each demonstration. The background abstract images were used for neutralization of possible negative secondary effect of the previous Necker cube image demonstrations [Leopold, Wilke, Maier, and Logothetis, 2002]. The whole experiment lasted for about 45–50 min for each participant, including short recording of EEG background activity without cognitive stimuli. During the experimental session the cubes of different configuration were presented randomly (each configuration for about 100 times) and the electrical brain activity was recorded as multichannel EEG.

EEG signals were recorded with electroencephalographic recorder Encephalan-EEGR-19/26 (Medicom MTD, Russia) with multiple EEG channels and two-button input device. Monopolar registration method and classical “10-20” electrode system were used for EEG recording.

2.2 Wavelet-Based Method

In our work we used continuous wavelet transform (CWT) [Hramov, Koronovskii, Makarov et al., 2015; Koronovskii, Ponomarenko, Prokhorov et al., 2007; Hramov, Koronovskii, Ponomarenko et al., 2007; Pavlov, Hramov, Koronovskii et al., 2012] for time-frequency analysis of oscillatory patterns in EEG. CWT is a convolution of investigated signal $x(t)$ (EEG signal in our case) and a set of basic functions $\varphi_{s,\tau}$:

$$W(x,\tau) = \int_{-\infty}^{\infty} x(t){\varphi^*}_{s,\tau}(t)dt \qquad (1)$$

In equation (1) “ * ” marks cojugation of complex number. Each basic function from this set can be obtained from one function φ_0, the so-called mother wavelet, by following transform:

$$\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\varphi_0\left(\frac{t-\tau}{s}\right) \qquad (2)$$

In equation (2) φ_0 — mother wavelet, s — time scale, which determines extension or compression of initial mother function, τ — time shift of wavelet transform.

There are a lot of different mother wavelets that find a use according to the problems of the current study. In present work we used CWT with Morlet mother wavelet with parameter $\omega_0 = 2\pi$ [Ovchinnikov, Luttjohann, Hramov et al., 2010; Ovchinnikov, Hramov, Luttjohann et al., 2011]:

$$\varphi_0(\eta) = \pi^{-\frac{1}{4}} e^{j\omega_0\eta} e^{-\frac{\eta^2}{2}} \qquad (3)$$

According to papers [Sitnikova, Hramov, Koronovskii et al., 2009; Luijtelaar, Hramov, Sitnikova et al., 2011; Sitnikova, Hramov, Grubov et al., 2014] the Morlet wavelet is one of the most effective in analysis of complex experimental signals of biological nature (including EEG data) because of its optimal time-frequency resolution.

In present work intrinsic frequency dynamics was investigated using “skeletons” of wavelet surfaces [Sitnikova, Grubov, Hramov et al., 2011; Hramov, Kharchenko, Makarov et al., 2016]. The “skeletons” of wavelet surfaces are constructed to extract dominant EEG frequencies and determine the evolution of oscillatory patterns in EEG data. In this paper, we focused on the processing of EEG data recorded in the occipital region (see Fig. 1). First, the momentary wavelet energy distribution $E_i(f_s,t_0)$ was constructed for some time moment t_0.

$$E_i(f_s,t_0) = |W(f_s,t_0)|^2 \qquad (4)$$

Then the function $E_i(f_s,t_0)$ was examined for the presence of local maximum E_{max}. If several local maxima $E_{max,k}$ were detected in $E_i(f_s,t_0)$, then the highest maximum was selected and its frequency was considered as dominant frequency of oscillatory pattern at given time moment t_0. In order to construct full “skeleton” of wavelet surface the procedure described above was repeated consequently for all points in time series of given EEG signal.

3 Results

In present paper we directly focused on the processes that take place during perception of Necker cube. We proposed a method for estimation of level and nature of beta–activity in occipital region of the human brain since this type of activity is commonly associated with visual perception. For this we consider the main characteristic of the frequency range of 2030 Hz, well traced through the processes associated with the recognition of ambiguous images for the majority of volunteers.

We introduced a numerical criterion for the presence of beta-rhythm in every time moment of EEG signal: the values of first two “skeletons” lie in range of 20–30 Hz in this time moment. In other words, if the condition is satisfied for a particular channel of the occipital region, the beta-criterion β is equivalent to the constant, “1”, and otherwise β is “0”, then β – criterion:

$$\beta_i = \begin{cases} 1 \text{ if } 20 < f_{1,2}^i 30 \\ 0 \text{ in other cases} \end{cases} \qquad (5)$$

Figure 2A demonstrates the example of calculation of the proposed beta-criterion β for the channel Pz. This

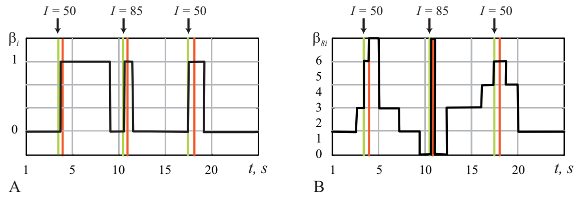

Figure 2. Dependence of the betacriterion β_i over time for Pz channel (A) and betacriterion $\beta_8 i$ for brain occipital region (B).

EEG-signal is related to the electrical activity of the interhemispheric slot in human brain. The distribution of beta-criterion β is shown in black, green marks on Figure 2 correspond to the moments of each Necker cube demonstration while red marks show the moments of humans response (pressing the button). Figure 2A shows that in all presented cases the beta-criterion β is "0" before bistable stimulus, then it changes to "1" after stimulus demonstration and keeps "1" during response, few moments later it lowers to "0" again till the next stimulus demonstration.

However, consideration of the signal for each EEG channel is not convenient and leads to the accumulation of errors. Thus we decided to average characteristics of excitable beta–activity for the whole occipital region. Note that in this case we consider the spatial and temporal dynamics of occurring beta–pattern correlated with the cognitive process of recognition of a complex ambiguous object. In this case the presence of the beta–rhythm criterion β_8 for each channel, it can simple sum the "0" and "1" for eight channels occipital EEG channels.

$$\beta_{8i} = \sum \begin{cases} 1 \text{ if } 20 < f_{1,2}^{O2} < 30 \text{ else } 0 \\ 1 \text{ if } 20 < f_{1,2}^{O1} < 30 \text{ else } 0 \\ \qquad\qquad \dots \\ 1 \text{ if } 20 < f_{1,2}^{Cz} < 30 \text{ else } 0 \end{cases} \tag{6}$$

Figure 2B demonstrates the results of calculation of beta–criterion β_8. The results are similar to the ones shown on Figure 2A, but with more accurate demonstration of gradual increase and decrease of beta–criterion β_8.

The results obtained with beta–criteria β and β_8 were promising so we decided perform additional analysis for another two significant frequency ranges on EEG signal: delta (1-4 Hz) and alpha (8-12 Hz). We introduced delta-criterion δ_8 and alpha-criterion α_8 similar to beta–criterion β_8:

$$\delta_{8i} = \sum \begin{cases} 1 \text{ if } 1 < f_{1,2}^{O2} < 4 \text{ else } 0 \\ 1 \text{ if } 1 < f_{1,2}^{O1} < 4 \text{ else } 0 \\ \qquad\qquad \dots \\ 1 \text{ if } 1 < f_{1,2}^{Cz} < 4 \text{ else } 0 \end{cases} \tag{7}$$

$$\alpha_{8i} = \sum \begin{cases} 1 \text{ if } 8 < f_{1,2}^{O2} < 12 \text{ else } 0 \\ 1 \text{ if } 8 < f_{1,2}^{O1} < 12 \text{ else } 0 \\ \qquad\qquad \dots \\ 1 \text{ if } 8 < f_{1,2}^{Cz} < 12 \text{ else } 0 \end{cases} \tag{8}$$

Also we divided the process of perception of bistable image into three phases: before perception, during perception, after perception. We calculated criteria δ_8, α_8, β_8 for each phase separately and averaged them through multiple cases of bistable stimulus demonstration to obtain averaged criteria $\langle\delta_8\rangle$, $\langle\alpha_8\rangle$, $\langle\beta_8\rangle$.

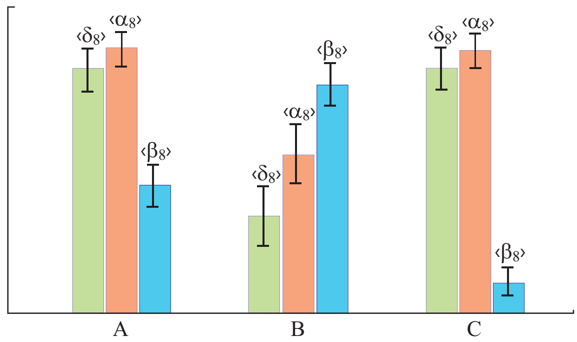

Figure 3. Averaged criteria $\langle\delta_8\rangle$, $\langle\alpha_8\rangle$, $\langle\beta_8\rangle$ during different phases of bistable stimulus perception: before perception (A), during perception (B), after perception (C).

Figure 3 shows the results of analysis of averaged criteria $\langle\delta_8\rangle$, $\langle\alpha_8\rangle$, $\langle\beta_8\rangle$, where green bar corresponds to averaged delta-criterion $\langle\delta_8\rangle$, red – to alpha-criterion $\langle\alpha_8\rangle$, blue – to beta-criterion $\langle\beta_8\rangle$, different stages of perception are marked as following: before perception (A), during perception (B), after perception (C). Figure 3 demonstrates that frequency EEG dynamics during bistable image perception is more complex, than was shown on Figure 2. There is a significant decrease in delta and alpha activity during the phase of perception (Fig. 2B) along with comparable increase in beta range.

4 Conclusion

In this paper we considered the technique for studying evolution of the complex patterns in human EEG data during a psychophysiological experiment by stimulation of cognitive activity with the perception of bistable object. The new method based on continuous wavelet transform allows to estimate the energy contribution of various components in the general and partial dynamics of the electrical activity for the projections of various areas of the brain.

The results of these studies appear promising for further research of dynamics and activity of the cerebral cortex in various cognitive processes. The technique is based on the calculation of the wavelet "skeleton", it is universal for studying of processes of different nature. Furthermore, this approach is highly customizable to individual features of volunteers which promises its application in biofeedback systems.

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