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Analysis of bistable perception based on MEG data

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ABSTRACT

In the present research we studied the cognitive processes, associated with the perception of ambiguous images using the multichannel MEG recordings. Using the wavelet transformation, we considered the dynamics of the neural network of brain in different frequency bands, including high (up to 100 Hz) frequency gamma-waves. Along with the time-frequency analysis of single MEG traces, the interactions between remote brain regions, associated with the perception, were also taken into consideration. As the result, the new features of bistable visual perception were observed and the effect of image ambiguity was analyzed.

Keywords: Artificial neuronal networks, multilayer perceptron, radial basis functions, multichannel EEG, brain activity patterns, recognition, imaginary movements, perception.

1. INTRODUCTION

Human brain being one of the complex living systems attracts great interest of the world scientific community in various areas of modern science and technology, including neurophysiology, physics, mathematics etc.[1–4] One of the intriguing problems in the area of human brain cognitive functions research is the understanding of processes underlying visual perception and decision-making.[5,6] From the viewpoint of modern technology these tasks are of strong interest for the creation of new types of intellectual control systems in robotics and computer technologies.

It is known that features of visual perception performed by human brain are often studied by means of bistable or multistable ambiguous visual stimuli.[7] Observation of such images during an adequate time period causes switches between different interpretations that demonstrates individual features of visual perception – for example, Necker cube could be perceived as left- or right-oriented[8] or Rubin vase could be interpreted as a vase or two faces.[9] The existing theories state that such switches are caused by the stochastic nature of inter-neuron signal transfer due to random synaptic connections and spontaneous activation of separate neurons.[10–12] According to mentioned above it is clear that the analysis and classification of different brain states arising during visual perception and decision-making process open wide prospectives for deep understanding of various aspects of brain cognitive functioning.

One of the appropriate and widely used techniques for experimental study of brain dynamics is registration of brain electrical or magnetic activity with the help of electroencephalography (EEG) and magnetoencephalography (MEG) devices. The existing EEG devices are rather inexpensive, simple to maintain and carry out the experiment, while MEG registrar gives a better spatial and temporal resolution of human brain activity. To encode multichannel EEG and MEG signal there is a number of data processing techniques well-established for neurophisological data analysis: methods of time-frequency analysis, namely wavelet transformation;[3,14,15] methods based on event-related synchronization;[13] indedpendent component analysis;[16] artificial intelligence methods, namely artificial neural networks (ANNs).[17]

In this work we applied the wavelet-based transformation and ANN approch to MEG signals obtained during experimental study of visual perception of bistable Necker cube, considered the behaviour of brain corresponding to different brain rhythms and classified brain states via ANN using multichannel MEG signals. We showed that perception of highly ambiguous Necker image causes excitation of β-rhythms in the frontal lobe of brain cortex.

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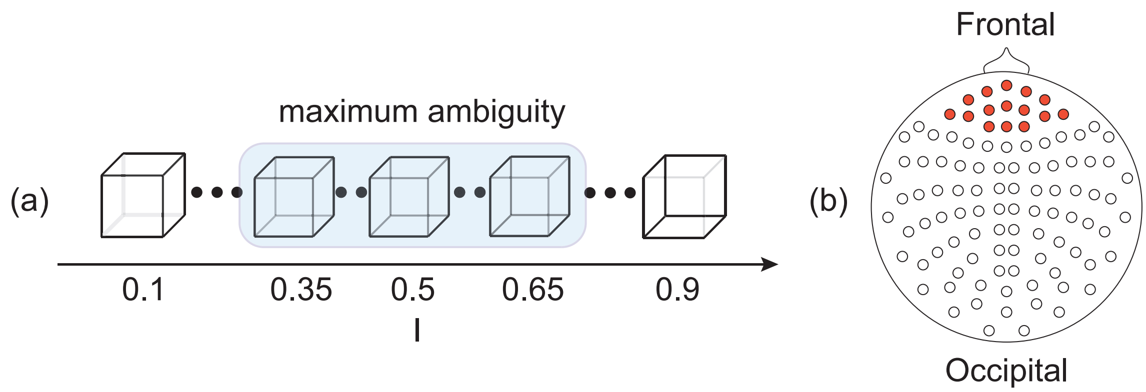

Figure 1. (a) Ambiguous images of the Necker cube with different edges intensity I, presented to subjects during the experiments. The cubes with $I < 0.5$ and $I > 0.5$ are usually interpreted as left-oriented and right-oriented, respectively. (b) Neuromag Elekta MEG system layout with highlighted frontal lobe channels.

Moreover, based on the ANN analysis we shown that perception of unambiguous image is charactrized by the stable brain state whereas spontaneous switches between brain states are inherent for highly ambiguous images perception.

2. EXPERIMENT

Five healthy unpaid subjects, males and females, between 26 and 30 years old with normal or corrected-to-normal visual acuity participated in the experiments. All of them provided written informed consent before participating in the experiment. The experimental studies were performed in accordance with the Declaration of Helsinki at the Center for Biomedical Technology of the Technical University of Madrid using magnetoencephalograph Neuromag Elekta Vectorview.

The ambiguous image was the Necker cube[18] frequently used in experimental[19–21] and theoretical studies.[19, 22, 23] This image is seen as a cube with transparent faces and visible edges; an observer without any perception abnormalities perceives the Necker cube as a 3D-object due to the specific position of the cube's edges. Bistability in the cube perception consists in the interpretation of the Necker cube as being oriented in two different ways, i.e., left-oriented or right-oriented. 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 (white) and 255 (black) pixels' luminance of the middle lines. Therefore, the contrast parameter in the 8-bit grayscale palette was defined as $I = y/255$, where y is the brightness level of the middle lines. Visual stimuli were presented with the help of Cogent (a graphics toolbox for MATLAB) and the contrast parameter of the presented stimuli was controlled by a software specially developed for this study.

Each subject took part in two experimental sessions. The structure of both sessions was the same except for one feature: in the first session the subject was instructed to press either a left or right key depending on his/her interpretation of the Necker cube in each demonstration, while in the second session the button pressing was excluded. The data obtained in the first session was analyzed after the key press to estimate the participant's uncertainty level based on the experimental results (a typical level of uncertainty can be seen in Fig. 1(b)). The aim of the second session was to collect the MEG data for a further analysis using ANN trained on the data of the first session. The MEG data recorded in the second experimental session was not associated with the motor-related brain activity and therefore suitable for the analysis of the cognitive activity involved in the decision-making process.

The structure of each session was as follows. (i) First, background MEG activity was recorded for 2 minutes while the subject was sitting comfortably with open eyes. (ii) Then, a set of Necker cubes with different wireframe contrasts were presented during approximately 20 minutes. (iii) Finally, another 2-min background MEG was recorded while the subject was sitting comfortably with closed eyes. As a result, the whole session took about 25 minutes.

In this experiment, we used 15 Necker cubes with randomly chosen contrast parameters from the set $I = (0.1, 0.15, 0.3, 0.4, 0.47, 0.48, 0.49, 0.5, 0.51, 0.52, 0.53, 0.6, 0.7, 0.85, 0.9)$. Each contrast was presented 15 times. Each image was presented to the participants for a short period of time, randomly chosen between 0.8 s and 1.2 s. It is known from literature, that the mean duration of a visual percept can vary from one second to several minutes depending on individual features of the observer and stimulus conditions, while the mean response times are rather consistent and vary only by a few hundred milliseconds. The most common experimental length for each perception of the Necker cube was found to be approximately 1 s.[24,25] Therefore, in order to fix the first impression of the person and avoid switches between two possible percepts, the image exhibition in our experiments was limited to $\nu \in [0.8, 1.2]$ s.

The short duration of stimulus presentation is also needed to reduce the stabilization effect.[26] Indeed, the probability of the configuration persisting until the subsequent presentation is known to be highly dependent on how long it was seen before the stimulus was removed.[26] Only when the perceptual configuration was consistently seen for a relatively long time before the stimulus disappeared, there was a high probability of it persisting to the next stimulus presentation. Since the required time for consistent observation of the Necker cube is about 1 s,[26] the stimulus exhibition for a shorter time diminished the "memory" effect. The random sequence of the Necker cubes with different values of the control parameter I also prevented the appearance of the perception stabilization. Lastly, to draw away the observer's attention and make the perception of the next Necker cube independent of the previous one, different abstract pictures were randomly exhibited for about $\eta \in [4.20, 5.25]$ s between demonstrations of the different Necker cube images.

3. METHODS

We carried out the time-frequency analysis by means of application of continuous wavelet transformation to the chosen channels of the entire multichannel MEG signal:[3]

$$W(f, t_0) = \sqrt{f} \int_{-\infty}^{+\infty} x(t)\psi^* \left((t - t_0) f\right) dt, \tag{1}$$

where $x(t)$ is a signal from single MEG channel, $\psi(\eta) = (1/\sqrt[4]{\pi}) \exp(j\Omega_0\eta) \exp\left(-\eta^2/2\right)$ is Morlet complex mother wavelet function, $\Omega_0 = 2\pi$ is the parameter of wavelet. We consider wavelet spectrum:

$$W(f, t_0) = |W(f, t_0)| \exp i\phi(f, t_0) \tag{2}$$

where $|W(f, t_0)|$ and $\phi(f, t_0)$ are the amplitude and phase of the wavelet spectrum, respectively. We define wavelet amplitude in the frequency range W_r as:

$$W_r(t_0) = \int_{f_{min}}^{f_{max}} |W(f, t_0)| df, \tag{3}$$

where f_{min} and f_{max} are boundary frequencies of certain range. This definition is useful if one needs to consider energy of wavelet spectrum consentrated in certain rhythmic brain activity.

To classify brain states which are induced under observation of bistable Necker cube image from experimental MEG data we used ANN in the form of multilayer perceptron (MLP) architecture (Fig.2,(a)). MLP represents a feed-forward neural network, where information signal $\mathbf{X}$ is fed to an input layer of the network and sequentially travels towards an output layer, which generates output signal Y. MLP was successfully applied for classification and pattern recognition in neuroscience and biomedical applications.[?,17] MLP was implemented through the Neural Network Toolbox of MATLAB. Here, we describe an instantaneous human brain state as an N-dimensional column vector

$$\mathbf{X}^j = \left(x_1(t_j), x_2(t_j), ..., x_N(t_j)\right)^T, \tag{4}$$

an instantaneous signal from $N = 102$ MEG sensors at time t_j. We analyze the multivariable MEG signal

$$\mathbf{X} = \left\{\mathbf{X}^j\right\}\Big|_{j=1}^{1000} \tag{5}$$

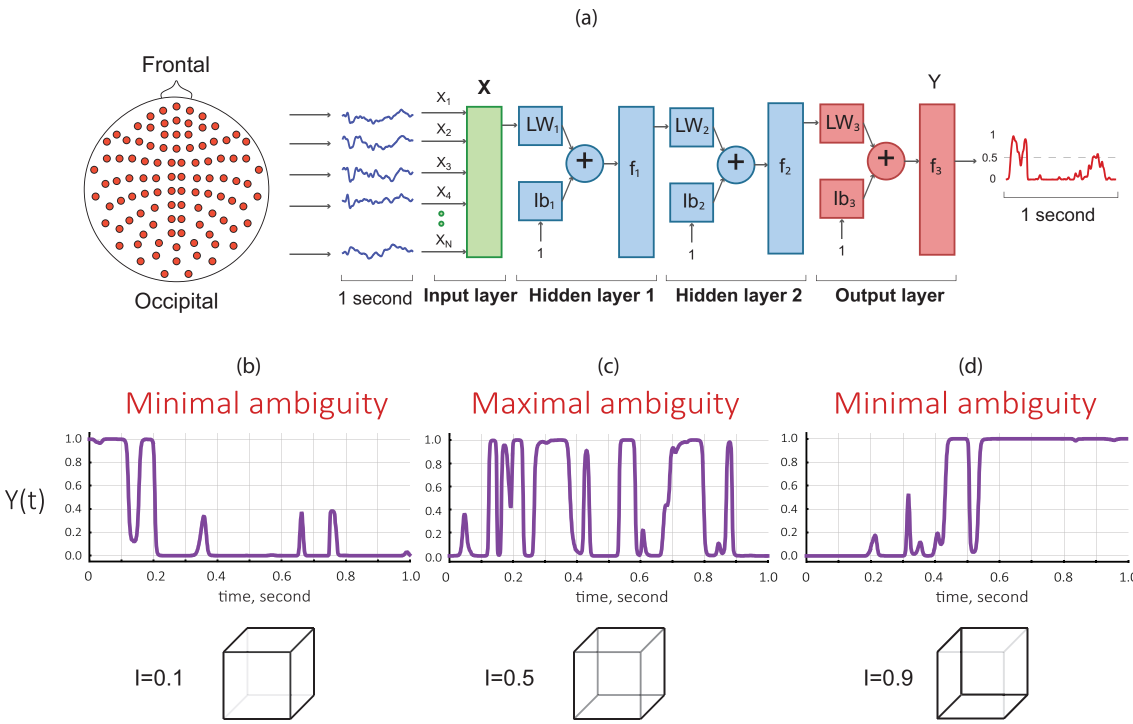

Figure 2. (a) Structure of the feed-forward multilayer perceptron (MLP) neural network. One can see typical input MEG trials X_n (*blue curves*), corresponding to brain activity after demonstration of left-oriented Necker cube and typical MLP response Y (*red curve*). The subscripts of X_n indicate the MEG channel number ($n = 1, ..., 102$). (b)-(d) Typical output MLP traces to individual MEG trials corresponding to different ambiguity and orientation of Necker cube image: (b) $I = 0.1$, (c) $I = 0.5$, (d) $I = 0.9$.

for 1 second after the Necker cube demonstration, with time discretization step $\Delta t = 1$ ms as a discrete sequence of 1000 instantaneous brain state vectors. MLP is trained to classify brain states according to Levenberg-Marquardt learning algorithm.

4. ANALYSIS AND RESULTS

The time series in Fig. 2(b-d) show typical MLP responses to individual MEG trials when cubes with different ambiguity were presented. On can see in Fig. 2(b,d), that in the case of a low-ambiguous left- or right-oriented cube, the MPL response curve, after short transient fluctuations, converges to a stable state "0" or "1", respectively. Instead, the observation of a highly-ambiguous image is characterized by multiple spontaneous switches between the two brain states, as seen in Fig. 2(c). Based on this results one can introduce the measure which is equal to the number of switches between brain states during 1 second trial indicating decision-making uncertainty – more switches show higher uncertainty about bistable image interpretation.

Besides, it was interesting to consider time-frequency properties of brain functioning associated with higher nervous activity focused on visual perception of bistable image of Necker cube. It should be noted that further time-frequency analysis was carried out using MEG trials averaged over experimental sessions to highlight the most meaningful trends of brain behavior.

It is known that this type of brain activity localized mostly in the frontal cortex of brain neural network. So, we consider wavelet surfaces of entire MEG signal, averaged over the frontal cortex channels:

$$|W|_{FC} = \frac{1}{N_{FC}} \sum_{j \in FC} |W|_j, \tag{6}$$

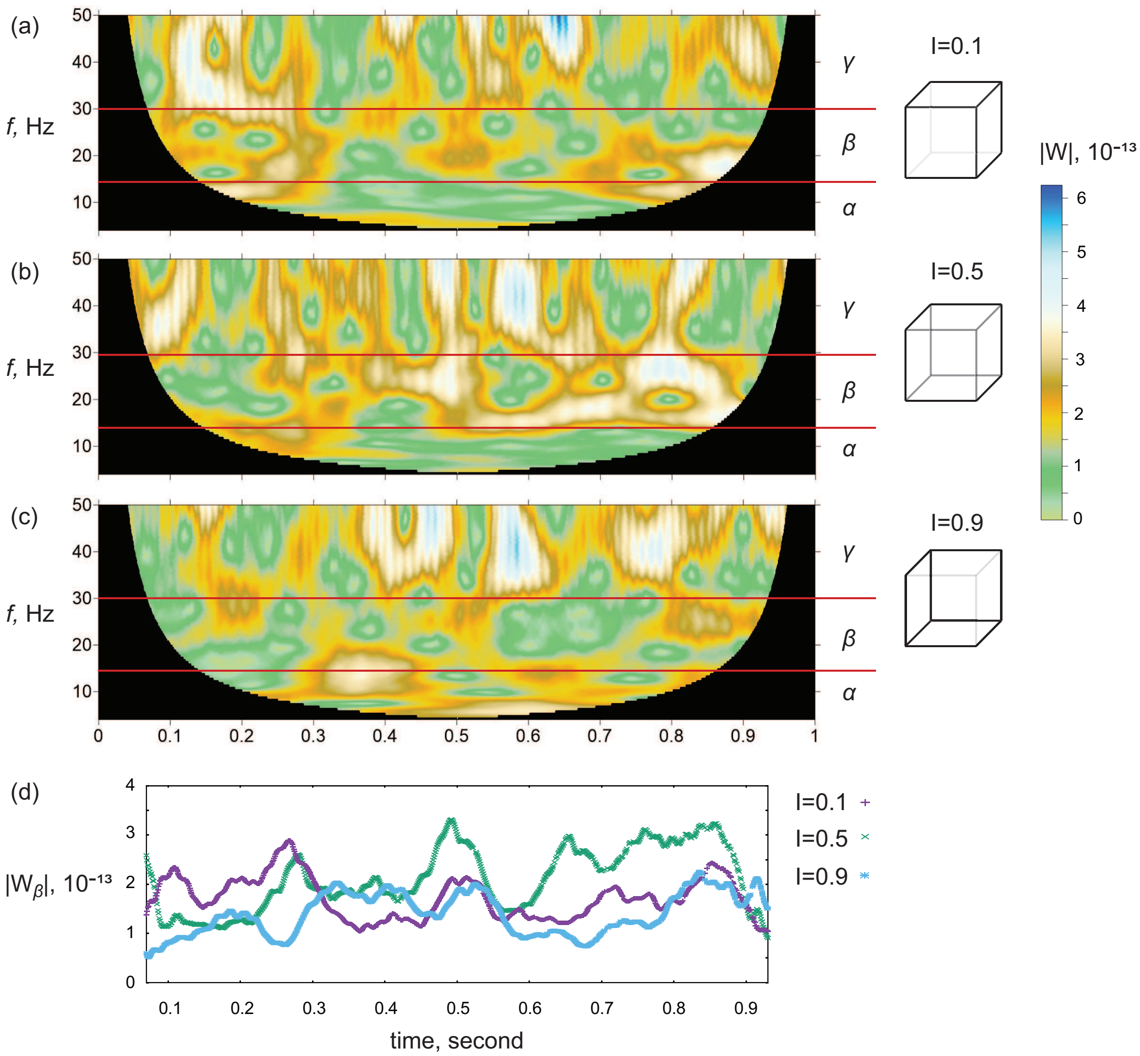

Figure 3. (a)-(c) Wavelet surfaces, averaged over frontal cortex channels, of MEG trials, averaged over experimental sessions, corresponding to different ambiguity and orientation of Necker cube image: (a) $I = 0.1$; (b) $I = 0.5$; (c) $I = 0.9$. (d) Dependence of wavelet energy of β-waves associated with different ambiguity and orientation of Necker cube image on time.

Results of wavelet transformation of $x_{FC}(t)$ signals when cube images with different ambiguity were observed are presented in Fig. 3(a-c). One can see that ambiguous images observation excites mostly high-frequency brain activity in frontal cortex while α-rhythm activity (8-12 Hz) is mostly absent – it shows that higher cognitive processes associated with maximal attention focusing, decision-making and visual perception are activated. At the same time, one can see the significant difference between perceiving low-ambiguous and highly ambiguous images. Observation of low-ambiguous images is characterized by activation of brain oscillatory activity in γ-band (over 30 Hz) responsible for conscious perception (Fig. 3,(a),(c)). It means that human brain easily interprets low-ambiguous object. On contrary, observation of highly-ambiguous image excites strong β-waves (over 13-30 Hz) associated with focusing attention and concentration along with γ-waves (Fig. 3,(b)). Excitation of β-waves means that it is hard for the participant's brain to give a stable interpretation of highly-ambiguous image and participant is highly concentrated on his visual tasks. We have calculated wavelet energy concentrated in β-band:

$$|W|_{\beta}(t) = \int_{13Hz}^{30Hz} |W|(f,t)\, df. \qquad (7)$$

Comparison of $|W|_\beta(t)$ for highly- and low-ambiguous images is presented in Fig. 3,(d). One can see the increasing of $|W|_\beta(t)$ in the case of highly-ambiguous image observation after 0.45 second after image presentation compared to observation of low-ambiguous Necker cube images.

5. CONCLUSION

In this work we applied the wavelet-based transformation and ANN approch to MEG signals obtained during experimental study of visual perception of bistable Necker cube, considered the behaviour of brain corresponding to different brain rhythms and classified brain states via ANN using multichannel MEG signals. We showed that perception of highly ambiguous Necker image causes excitation of β-rhythms in the frontal lobe of brain cortex. Moreover, based on the ANN analysis we showed that perception of unambiguous image is charactrized by the stable brain state whereas spontaneous switches between brain states are inherent for highly ambiguous images perception. The results obtained in this paper allows distinguishing between brain processes associated with low- and-highly-ambiguous visual stimuli interpretation.

Besides, it should be noted that application of multivariate data processing tools described in this paper allow accessing features of brain activity and decision-making process without the feedback from participant, i.e. it opens wide prospectives to the development of intellectual control systems and BCIs based on these methods.

6. ACKNOWLEDGMENTS

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