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ABSTRACT

The design of visual decision-making task with uncertainty was proposed. Set of experiments was conducted in accordance with this design and obtained EEG dataset was analyzed. Analysis of EEG characteristics in time, frequency and space domains allowed to introduce certain features that can be used to separate right and wrong outcomes in the task prior actual subject's response.

Keywords: electroencephalogram, time-frequency analysis, statistical analysis, visual task, decision-making

1. INTRODUCTION

The brain is a very complex nonlinear network with massive numbers of elements – neurons – and connections between them.[1,2] While direct study on neural network structure can be complicated, its dynamics is commonly studied by analyzing various experimental signals – for example, electroencephalogram (EEG)[3] or functional near-infrared spectroscopy.[4] EEG provides multichannel data with signals recorded from different parts of brain cortex, and the signal in each channel has complex time-frequency structure with specific frequency ranges (alpha, beta, delta, etc) and characteristic oscillatory patterns.[5–8] There is a strong correlation between electrical brain activity and functional state of organism,[3] so research on EEG features in time, frequency and space domains can provide knowledge about brain functioning.[9–12]

The interest in studying brain activity using EEG is not limited to fundamental knowledge, but also caused by important applications – such as in brain-computer interfaces (BCI).[13] The BCI transforms characteristic features of brain activity recorded via EEG, for example, machine commands for real-time control of software and/or hardware. This technology finds application in various applied fields and is often used to increase quality of life[14–19] For example, BCIs can be used for rehabilitation of patients with physical or mental injuries.[7,10,20] However, similar approach can be implemented to enhance the performance of healthy subjects – passive or reactive BCIs can be used to monitor operator's state and affect his/her performance through the feedback.[21,22]

For example, in prolong monotonous task that require high concentration of attention the outcome can be predicted based on EEG estimates.[23] In such task BCI can assess operator's status and decide whether his/her answers are trustworthy. This is especially important for jobs with high price of mistakes – such as pilots of military or civil aircraft[24] or operators of power plants.[25] When the BCI doesn't trust the decision of the operator it can implement feedback to mark questionable decisions or redistribute the workload among several operators to choose the most trustworthy one. However, in this approach BCI aims to precisely estimate right and wrong outcomes in the task, which requires monitoring of specific EEG characteristics, and to define them is a challenging task itself.

In this paper, we study EEG activity during decision-making task with uncertainty in time, frequency and space domains. We aim to find features that separate right and wrong outcomes in the task prior actual subject's response. We suggest that these features can be used in the development of assistive BCI.

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2. METHODS

Twenty six volunteers between the ages of 18 and 40, both men and women, participated in the experiment. All subjects were conditionally healthy, non-smokers, amateur practitioners of physical exercises, with normal or corrected-to-normal visual acuity and no history of neurological diseases or prescription for medications. The participants were asked to maintain a healthy life regime prior the experiment, which included 8-hour night rest, limited consumption of alcohol and caffeine, moderate physical activity. All volunteers were informed about the design of experiment, its methods and possible inconveniences, and were able to ask any related questions. The participants provided informed written consent before the beginning of the experiment. The design of experimental study was developed in accordance with the Declaration of Helsinki 1964 and was approved by the local Research Ethics Committee of the Innopolis University.

In the experiment the participants were subjected to visual decision-making task with uncertainty consisted in classification of biistable images. For a model of bistable visual stimulus we chose the Necker cube,[26] as it's often used in tasks of perceptual decision-making.[27,28] The Necker cube is a 2D image, but it represents a projection of 3D cube with visible edges and transparent faces. A regular observer with normal acuity perceives the Necker cube as a 3D object thank to specific position of cube edges. However, the cube position can be interpreted in two different ways: as either left- or right-oriented. This is the core of the Necker cube's bistability. Additionally, the contrast of certain cube edges can change the bias of perception, so we introduced contrast parameter $g \in [0, 1]$ that can be interpreted as control parameter here. The contrast parameter g can also be seen as the degree of complexity of cube's classification: cubes with g close to 1 or 0 can be easily classified as a left- or right-oriented while cubes with $g \sim 0.5$ possess the highest complexity of classification.

According to the design during the experiment the subject was sitting in a chair with hands on a table and feet flat on the ground. The task fro the subject was to look at the Necker cubes with different values of g and to classify them as left- or right-oriented. The screen before the subject was used to demonstrate visual stimuli and the input device with two buttons (left and right) was used to record the subject's answers. Each experiment lasted for ~ 40 minutes and consisted of 400 cube presentations.

In the experiment we recorded brain activity of the subject in the form of EEG. EEG represents a sum of electrical currents generated by neurons in a small part of brain network near recording electrode.[29] To record EEG signals we used electroencephalograph "actiCHamp" with "actiCAP" electrode system (Brain Products, Germany). Prior the experiment active Ag/AgCl electrodes were mounted in the sockets in special cap and placed on the subject's scalp. To increase the skin conductivity we treated scalp skin with abrasive "NuPrep" gel and added conductive "SuperVisc" gel during electrode mounting. EEG electrodes were arranged according to the "10-10" international electrode placement system – for this experiment we used 32 EEG electrodes with ground electrode N on the forehead in the "Fpz" spot and reference electrode A on the right mastoid in the "TP10" spot. During the experiment we monitored the impedances of EEG channels with common values being < 15 kΩ to ensure high signal-to-noise ratio and thus high quality of the recorded EEG data. EEG signals were recorded with sampling rate of 1000 Hz.

It is well-known that EEG signals are highly susceptible to noises, both external and internal.[30] Most noise components or artifacts possess high amplitude and interfere with frequency domain used for EEG time-frequency analysis.[31] To address this issue we filtered EEG signals by band-pass filter (cutoff frequencies at 1 Hz and 100 Hz) and 50-Hz notch filter. Band-pass filter was used to remove low frequency components such as breathing artifacts or stray effects and high frequency components caused by poor EEG electrode contact or external mechanical impact. Notch filter was applied to remove power grid interference at 50 Hz. Additionally, EEG signals were treated with Independent Component Analysis (ICA)[32] to remove artifacts with overlapping frequency ranges. We used ICA to decompose EEG data into a number of independent components, then we found components with certain types of artifacts such as eye-blink or cardiac, removed these components and reconstructed EEG signals with the rest of the components. As the last step we used visual search to find data trials with residual artifacts. Usually it concerns artifacts that cannot be removed by other methods such as highly pronounced muscle activity or data gaps due to recording errors. In this research we removed such trials and didn't use them in further time-frequency analysis of EEG.

EEG signals were analyzed with the help of continuous wavelet transform (CWT).[33,34] The CWT is computed as convolution of EEG signal $x(t)$ with wavelet basis $\varphi_{s,\tau}$:

$$W_n(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x_n(t)\varphi^*_{s,\tau}(t)dt, \qquad (1)$$

where $n = 1, 2...N$ is the number of EEG channel and "*" stands for complex conjugation.

Here we used complex Morlet mother wavelet since it is widely used in EEG studies:[35,36]

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

where parameter $\omega_0 = 2\pi$ is the central frequency of Morlet wavelet, $\eta = \frac{t-\tau}{s}$, τ – time shift, s – wavelet time scale, that can be transitioned to more common frequency f as $f = 1/s$.

To interpret CWT results we considered wavelet energy:

$$E(f,\tau) = |W(f,\tau)|^2 \qquad (3)$$

We also conducted statistical analysis of wavelet energy – we performed nonparametric statistical test by calculating Monte-Carlo estimates of the significance probabilities and critical values from the permutation distribution.

Preprocessing, time-frequency and statistical analysis were performed via FieldTrip – MATLAB software toolbox for MEG, EEG and iEEG analysis.[37]

3. RESULTS

At first we analyzed correctness of task completion for all subjects. We divided all presented visual stimuli into two groups: Necker cubes with incorrectly and correctly interpreted orientation, thus we formed two distinctive EEG datasets. In each dataset we chose two types of intervals (trials) for data analysis: 1) 2 seconds before plus 2 seconds after the cube's presentation; 2) 2 seconds before plus 2 seconds after the button press. We applied CWT to these trials and computed wavelet energy E in frequency range $1 - 40$ Hz. All trials were baseline corrected to prestimulus condition ($-1.5 - -0.5$ s before stimulus presentation).

Then we performed statistical test and compared datasets with incorrect and correct interpretation of visual stimuli in two different time intervals (experimental conditions): 1) 0.5 seconds after stimulus presentation; 2) 0.5 seconds before subject's response. Threshold for T-statistics was chosen as 0.02, number of permutations was set to 1000, minimal number of neighboring elements required to form a cluster was 0.

Statistical analysis of poststimulus EEG activity revealed positive cluster in time, frequency and space domain. This cluster is tied to time interval $0.118 - 0.5$ s after visual stimulus presentation and to frequency range of $4.75 - 8.75$ Hz. Significance value for the found cluster is $p = 0.044$. The cluster is mostly located in frontal and central area of the cortex as can be seen from topogram on Fig. 1.

Fig. 2 demonstrates time dependence of wavelet energy averaged over the frequency range of positive cluster for two experimental conditions. Time point "0" marks the moment of visual stimulus presentation. From Fig. 2 it can be seen that general dynamics of wavelet energy is the same for incorrect (shown as blue) and correct (shown as red) interpretations, however, wavelet energy for incorrectly interpreted stimuli is higher both before and after cube's presentation.

Statistical analysis of preresponse EEG activity resulted in two negative clusters in time, frequency and space domain. The first cluster is located in time interval $0.08 - 0.19$ s before the press of the button and in frequency range of $1.25 - 2.5$ Hz. P-value for this cluster is $p = 0.002$. The second cluster with $p = 0.017$ appears $0.354 - 0.5$ s in preresponse and in $21.5 - 23.75$ Hz frequency range. Topograms on Fig. 3 provide information on spatial location of the first (a) and the second (b) cluster. It can be seen from Fig. 3a that the first cluster is primarily situated in parietal and occipital cortex areas. In a similar manner Fig. 3b illustrates position of the second cluster in the middle of the frontal area.

Fig. 4 shows frequency-averaged wavelet energy distribution in preresponse time interval for the first (a) and the second (b) clusters. Here time point "0" marks the moment of the button press. From Fig. 4b it can be seen

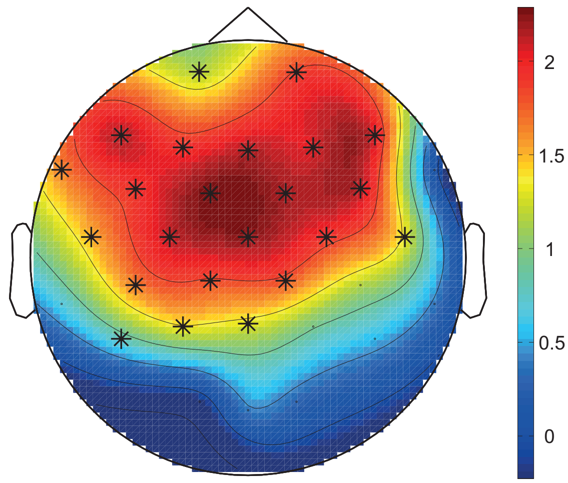

Figure 1. Topogram for the positive cluster of wavelet energy found in poststimulus; “*” denotes EEG channels that form the cluster.

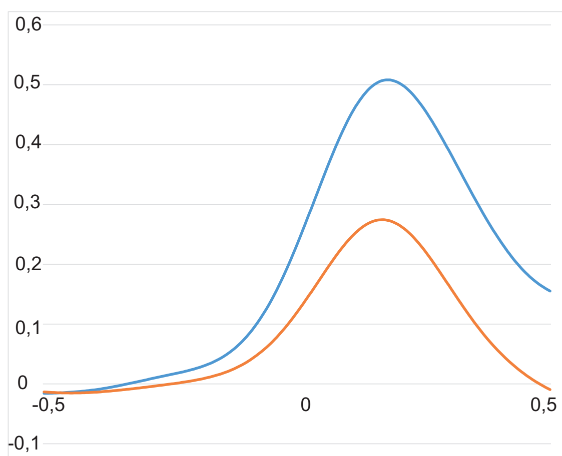

Figure 2. Time dependence of wavelet energy averaged over the frequency range of positive cluster in poststimulus for two experimental conditions: incorrectly (blue) and correctly (red) interpreted Necker cubes.

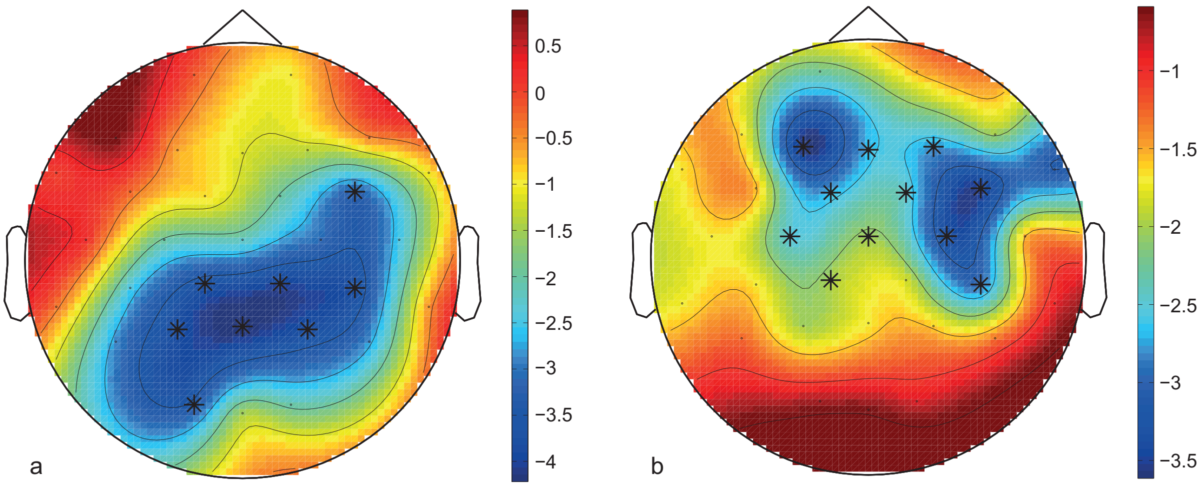

Figure 3. Topograms for the first (a) and the second (b) negative clusters of wavelet energy found in preresponse; "*" denotes EEG channels that form the cluster.

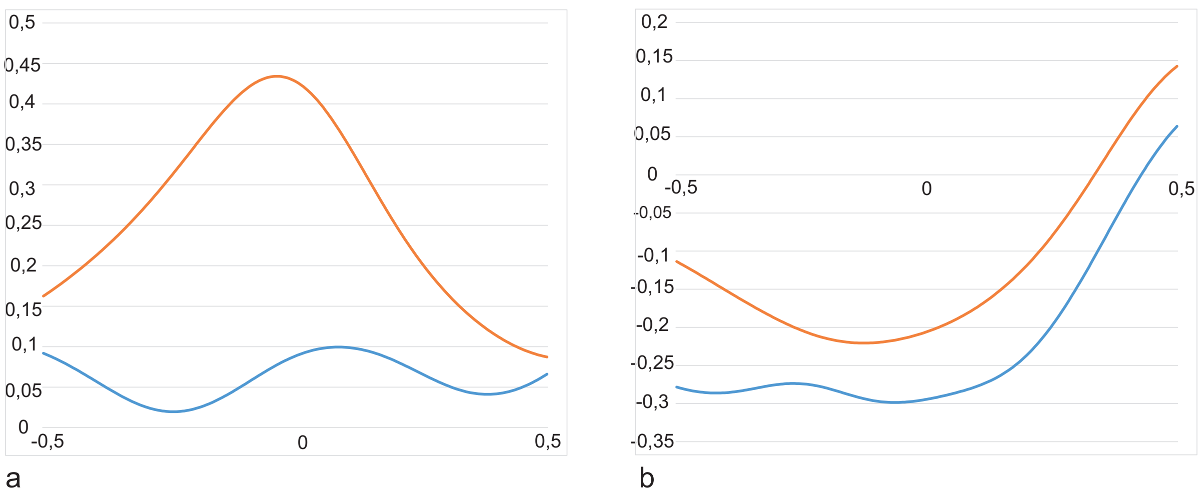

Figure 4. Time dependence of wavelet energy averaged over the frequency range of the first (a) and the second (b) negative clusters in preresponse for two experimental conditions: incorrectly (blue) and correctly (red) interpreted Necker cubes.

that general dynamics of wavelet energy is the same for incorrect (shown as blue) and correct (shown as red) interpretations – much like in situation on Fig. 2 – however, this time wavelet energy for incorrectly interpreted stimuli is lower both before and after cube's presentation. Fig. 4a shows that wavelet energy dynamics is different for incorrect and correct cube's interpretations, yet wavelet energy for incorrectly interpreted stimuli is lower.

4. CONCLUSION

In this paper we performed analysis of EEG data acquired during visual decision-making task with uncertainty. We performed analysis of EEG signals with help of CWT and statistics. We found certain differences between EEG activity of incorrectly and correctly interpreted visual stimuli. We showed that these features appear as clusters of wavelet energy in time, frequency and space domains. Obtained results can be helpful for further fundamental studies on human decision-making. Additionally, we suppose that found features can be used in development of assistive BCI.

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