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Alexander Hramov[ab], Vyacheslav Yu. Musatov[a], Anastasija E. Runnova[a], Tatiana Yu. Efremova[a], Alexey A. Koronovskii[ba], Alexander N. Pisarchik[ca]

[a]Research and Education Center "Artificial Intelligence Systems and Neurotechnology", Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov, 410056, Russia

[b]Saratov State University, Astrakhanskaya Str. 83, Saratov, 410028, Russia

[c]Center for Biomedical Technology, Technical University of Madrid, Madrid, Spain

ABSTRACT

In the paper we propose an approach based on artificial neural networks for recognition of different human brain states associated with distinct visual stimulus. Based on the developed numerical technique and the analysis of obtained experimental multichannel EEG data, we optimize the spatiotemporal representation of multichannel EEG to provide close to 97% accuracy in recognition of the EEG brain states during visual perception. Different interpretations of an ambiguous image produce different oscillatory patterns in the human EEG with similar features for every interpretation. Since these features are inherent to all subjects, a single artificial network can classify with high quality the associated brain states of other subjects.

Keywords: artificial neuronal network, neuronal network, neurotechnology, brain state

1. INTRODUCTION

The brain is likely to be the most convoluted object attracting the burning interest of the broad scientific community.[1–5] Nowadays, the brain is the subject of intensive research of diverse areas of science and technology. Among the different approaches the multidisciplinary studies providing insight into the mysteries of the brain and a deeper understanding of mechanisms underlying its dynamics open promising opportunities for humanity in education, neuroscience and neurotechnology in the near future.

One of the enigmatic features of the brain is the abilities to recognize objects and make decisions. Having simulated by the principles of operation of the interacting elementary cells of the brain, *the neurons*, the scientists have developed the artificial neural network (ANN) approach. The artificial neural networks,[6,7] based on nonlinear models of neural units (artificial neurons) have widely used in various studies in computer science, biophysics, deep learning, econometrics, etc.[8,9] where some kind of decision making is required.

It should be noted that different linear and nonlinear techniques have been proposed for the classification of observed patterns in EEG data.[10,11] Among various approaches, we should mention discriminant analysis methods, very popular in the 1960s,[12] independent component analysis,[13] often used for finding and eliminating the biased artifacts in EEG signals,[14] short-time Fourier transform,[15] and wavelet-based methods[1,16] including techniques with adaptive mother wavelets.[17,18] Nowadays, a classification technique known as ANN is widely used in computer science, biophysics, deep learning, econometrics, etc.[9] This method, based on nonlinear models of neural units (artificial neurons), claims to be inspired by biological interconnected neurons.

Although the ANN performance, obviously, are inferior to the real brain productivity, the use the ANNs to solve the problems being the subjects of the real brain seems to be the very enticing task. In this context we have analyzed multichannel EEG for recognition of brain states associated with distinct visual stimulus. Here

Further author information: (Send correspondence to A.E. Hramov)
A.E. Hramov: E-mail: hramovae@gmail.com, Telephone: +7 8452 51 42 94

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we have considered the process of visual perception of bistable images by subject as simple cognitive task. The perception of bistable images[19] is one of the interesting problems of the brain studies being connected with an objects recognition, alertness, and decision-making processes in human brain. Recently, ambiguous images awoke interest of mathematicians and experimental neurophysiologists.[20,21]

To apply the artificial neural networks for recognition of different states of brain neuronal network related to the visual perception we have used such the traditional and powerful method of the registration of human brain behaviour as recording the electrical activity generated by the cerebral cortex nerve cells from multiple electrodes placed on the scalp (EEG technique).[22] The spontaneous electrical activity of the human brain was first observed by German neurologist Hans Berger who reported in 1929 the electroencephalogram recorded on the human scalp. On the base of his studies, clinical and experimental studies of the EEG have been carried out between 1929 and 1938. Multichannel EEG signals have been used to discover different brain states,[23–25] the direct indication of cooperative neural activity. In clinical practice, EEG is often used to diagnose different types of epilepsy, sleep disorders, coma, encephalopathies, and other brain diseases.[26–29]

In this paper, we have shown that the ANN may be used effectively for multichannel EEG recognition of the different brain states. As simple bistable image, we have used the Necker cube.[30] Remarkably, the proposed ANN technique gives the strong possibility to extract the core features from the multichannel EEG trials.

2. MATERIALS AND METHODS

Twenty five subjects participated in the experiment (seventeen males and eight females, mean age 24 years, standard deviation 5 years). All subjects were students and stuff members of the Yurij Gagarin State Technical University of Saratov, without any previous training in the task. All subjects had normal or corrected to normal vision, with no neurological problems, and were free of psychoactive medications at the time of the experiment. Subjects were unpaid volunteers. All participants have provided informed consent before participating in the experiment. The experimental study was performed in accordance to ethical standards[31] and approved by the local ethics committee at the Yurij Gagarin State Technical University of Saratov.

Subjects were facing a display screen on which ambiguous images were displayed as visual stimulus. As an ambiguous image, we used the Necker cube,[20] a simple cube with transparent faces and visible ribs. A person with normal perception treats the Necker cube as a 3D-object thanks to a specific position of the cube's ribs. Visual bistability consists in the fact that this 3D-object can be treated as oriented in two different ways, especially if different ribs of the Necker cube are drawn with different intensity. Specifically, the contrast of the three middle lines centered in the left middle corner, $g \in [0, 1]$, was used as a control parameter of displayed images. The values $g = 1$ and $g = 0$ correspond, respectively, to 0 (black) and 254 (white) pixels luminance of the middle lines, using the 8-bit grayscale palette for visual stimulus presentation. Therefore, we can define a contrast parameter as $g = b/254$, where b is the brightness level of the middle lines in the used 8-bit grayscale palette. The contrast of the three middle lines centered in the right middle corner was set to $(1 - g)$, and the normalized contrast of the six visible outer cube edges was fixed to 1.

The multi-channel EEG was recorded at 250-Hz sampling rate from $P = 19$ electrodes with two reference electrodes placed at standard positions of the 10–20 international system.[22] The EEG signals were filtered by a band-pass filter with cut-off points at 1 (HP) and 100 (LP) and a 50-Hz Notch filter. The electroencephalograph-recorder "Encephalan–EEGR–19/26" (Taganrog, Russian Federation) with multiple EEG channels and two-button input device (joystick) was used for amplification and analog-to-digital conversion of the EEG signals. Preliminary signal processing was provided by the original software for EEG registration artifact suppression. Machine learning algorithms were implemented with MATLAB. To demonstrate a grayscale stimulus we used a 24" BenQ LCD monitor with spatial resolution of 1080 pixels and refresh rate of 60 Hz.

All participants were instructed to press either the left or the right key on the control panel (two-button keypad) according to their first visual impression of the cube (left-/right-oriented one). While observing the Necker cube, the mean duration of a visual percept is known to vary from one second to several minutes depending on subjects and stimulus conditions,[32] while the mean response time is rather consistent and varies only by a few hundred ms among subjects and stimulus conditions.[33] At the same time, the experimentally measured typical duration of one of the percepts of the Necker cube was found to be approximately 1 s.[34] Therefore, to fix the first impression of the person and avoid switches between two possible percepts the image exhibition was limited to $\tau = 1.0 \div 1.4\,\mathrm{s}$. In addition, to divert attention and make the perception of the next Necker cube image independent of the previous one, abstract pictures were exhibited for about $\eta = 2.0 \div 4.0\,\mathrm{s}$ in the time intervals between subsequent demonstrations of different Necker cube images. It should be noted that the length of stimuli presentations, τ_i, as well as durations of intervals between stimuli, η_i, have been chosen randomly from defined above temporal intervals. When one and the same stimulus is subsequently presented to the subject, the effect of stabilization of visual perception can take place.[35,36] This effect consists in persistent visual perception between subsequent presentations of ambiguous images. Although some model-based approaches[37] were proposed to explain this phenomenon, the underlying mechanism of the visual perception stabilization effect is not yet well understood. To decrease the influence of this effect on the results, the Necker cubes with the different parameter values g we presented in the random sequence as well as the values of η_i were chosen to be sufficiently large.

After presentation of abstract picture the screen with mentioned above questions (1) or (2) is presented, and the subject pressed a corresponding button on the keypad to indicate his/her first visual impression of interpretation of the Necker cube as left- or right-oriented. After click the next Necker cube image with a randomly selected parameter g is shown. The following protocol was used in each of the runs. Each trial stage consisted of 3 steps, which were repeated $N = 400$ times. (1) The visual stimulus (the Necker cube with randomly chosen contrast parameter g_j) was displayed on the screen during a randomly chosen time interval τ_i between 0.8 s and 1.3 s. (2) After observing the stimulus on the screen, the subject analyzed their first visual impression and pressed a button on the joystick to indicate his/her interpretation of the Necker cube as left- or right-oriented. (3) Between subsequent demonstrations of the stimulus (Necker cube), abstract pictures (AP) were exhibited during a randomly chosen time γ_i in the interval $2.0 \div 3.0$ s) to divert attention and make the perception of the next image independent of the previous one.

The ANN consists of a three layers of artificial neurons interconnected with each other by synaptic weights to form multilayer perceptron (MLP).[6] MLP is the universal and popular class of ANN widely used for a broad range of applications including the classification problem.[10,38] In our case we have considered the recognition of two different multistable brain states corresponding to the perception of the ambiguous Necker cube image as left- or right-oriented. We have introduced another characteristic for estimation of recognition precision, called *recognition accuracy* ρ of visual stimules defined as

$$\rho = \frac{N_p}{N} \times 100\%, \tag{1}$$

where N_p is the number of true recognized cubes and N is the total number of analyzed images.

3. RESULTS

The recognition accuracy of the brain states recognition during visual perception (left-/right-oriented cube perception) for group of 12 subjects are shown in Fig. 1a. To analyze the recognition accuracy we took the remaining part of the EEG that was not used for training, i.e. about 280 EEG trials of the registered brain states after image demonstrations. We started the analysis of our classification algorithm from the training ANN for each subject under study. The training data set was formed individually for each subject and the optimal set of ANN parameters was obtained for classification of the brain states of subject. In this case the mean accuracy for all 12 subjects was close to $83 \pm 5\%$ (mean $\pm$ S.D.). The recognition accuracy for every subject vary between 68 and 98%.

It should be noted that one subject demonstrated recognition accuracy of classification of perception type close to 98%. When we used ANNs trained on these subjects for other subjects, we obtained much higher accuracy than if using their own ANNs. These results are shown in the right black columns in Fig. 1. Using ANN evaluated for this subject the accuracy of classification was close to 98% for almost all subjects. Thus, we can conclude that features of EEG oscillatory patterns corresponding to perception of the left- or right-oriented cubes are typical for all subjects and a single ANN trained on the EEG data set of one person can classify with high accuracy the corresponding brain states of a large group of people.

The recognition accuracy essentially depends on the choice of EEG channels that are used for detection of brain states. As noted above, the average accuracy with all EEG channels is equal to $83 \pm 5\%$ Using only EEG

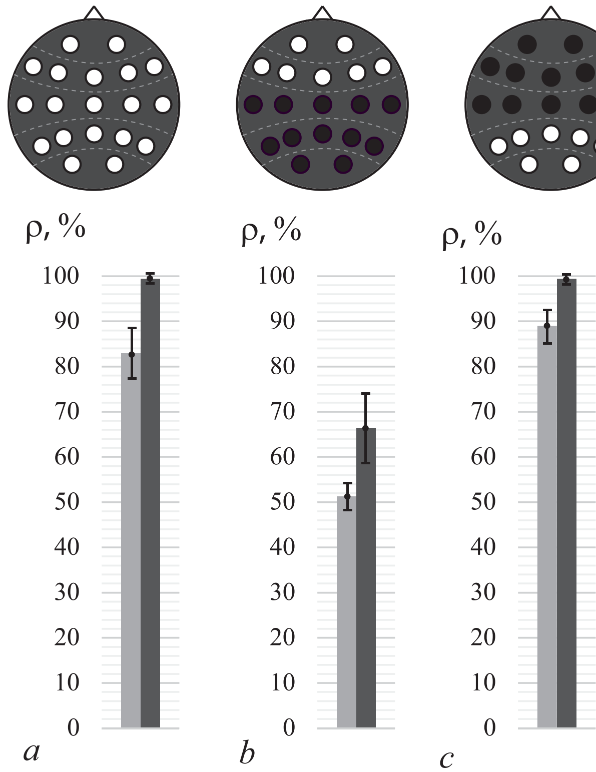

Figure 1. Recognition accuracy averaged for all 12 subjects for different spatial EEG representations shown on top of figure. Left grey columns represent accuracy averaged for each subject using ANN trained on own EEG, while right black columns show averaged accuracy using ANN trained for one subject.

channels from the frontal cortex demonstrates the significant decrease in the recognition accuracy as shown in Fig. 1b. A similar situation is observed when we use EEG channels from the somatosensory cortex. In this case recognition accuracy is equal to $51 \pm 4\%$

An another situation is observed if we include in the used EEG data set channels only from the occipital region (see Fig. 1c). The use of all occipital EEG channels leads to an increase of accuracy close to 90%, and for some subjects — close to 98%.

4. CONCLUSION

We have proposed to use an artificial neuronal network for the classification and recognition of human brain states associated with visual perception. We have optimized the spatiotemporal representation of multichannel EEG using obtained experimental data and have shown that it is possible to achieve close to 100% accuracy in the classification of the EEG patterns during perception of bistable images. We have found particular features of the EEG oscillatory patterns corresponding to different brain states, typical for all subjects.

We firmly believe that the significance of our results is not limited to visual perception. We are sure that the proposed experimental approach and developed computational technique for recognition will be useful for classifying different brain states and can stimulate future research in the field of cognitive brain activity. The developed approach provides a solid experimentally approved basis for further understanding brain functionality. The obtained results can be used in neurotechnology, e.g., for the brain-computer interface task and control of robotics equipment. We expect that our work will be interesting for scientists carrying out interdisciplinary research at the cutting edge of physics, mathematics, neurophysiology and engineering.

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REFERENCES

1. Hramov, A. E., Koronovskii, A. A., Makarov, V. A., Pavlov, A. N., and Sitnikova, E., [*Wavelets in Neuroscience*], Springer Series in Synergetics, Springer, Heidelberg, New York, Dordrecht, London (2015).
2. Bear, M. F., Connors, B. W., and Paradiso, M. A., [*Neuroscience. Exploring the brain*], Woters Kluwer (2015).
3. Chavez, M., Valencia, M., Navarro, V., Latora, V., and Martinerie, J., "Functional modularity of background activities in normal and epileptic brain networks," *Physical Review Letters* **104**, 118701 (2010).
4. Wolf, F., "Symmetry, multistability, and long-range interactions in brain development," *Physical Review Letters* **95**, 208701 (2005).
5. van Luijtelaar, E. L. M., Hramov, A. E., Sitnikova, E., and Koronovskii, A. A., "Spike-wave discharges in WAG/Rij rats are preceded by delta and theta precursor activity in cortex and thalamus," *Clinical Neurophysiology* **122**, 687–695 (2011).
6. Haykin, S., [*Neural Networks: A Comprehensive Foundation*], Pearson; 3d edition (2008).
7. Bishop, C. M., [*Pattern Recognition and Machine Learning*], Springer (2007).
8. Goodfellow, I., Bengio, Y., and Courville, A., [*Deep Learning*], MIT Press (2016).
9. Zhou, S. K., Greenspan, H., and Shen, D., [*Deep Learning for Medical Image Analysis*], Academic Press (2017).
10. Dias, N. S., Kamrunnahar, M., Mendes, P. M., Schiff, S. J., and Correia, J. H., "Comparison of eeg pattern classification methods for brain-computer interfaces," *Conf Proc IEEE Eng Med Biol Soc* **1**, 2540 (2007).
11. Siuly, S., Zhang, Y., and Li, Y., [*EEG Signal Analysis and Classification: Techniques and Applications*], Springer (2016).
12. Niedermeyer, E. and Lopes da Silva, F. H., eds., [*Electroencephalography. Basic Principles, Clinical Applications, and Related Fields, 5th ed.*], Lippincott, Williams & Wilkins (2005).
13. Ungureanu, M., Bigan, C., Strungaru, R., and Lazarescu, V., "Independent component analysis applied in biomedical signal processing," *Measurment Sscience Review* **4**(2), 1–8 (2004).
14. Jung, T., Humphries, C., Lee, T., McKeown, M., Iragui, V., and Makeig, S., "Removing electroencephalographic artifacts by blind source separation," *Psychophysiology* **37**, 163–178 (2000).
15. Gotman, J., Skuce, D. R., Thompson, C. J., Gloor, P., Ives, J. R., and Ray, W. F., "Clinical applications of spectral analysis and extraction of features from electroencephalograms with slow waves in adult patients," *Electroencephalography and Clinical Neurophysiology* **35**(3), 225–235 (1973).
16. Sitnikova, E., Hramov, A. E., Grubov, V., and Koronovsky, A. A., "Time-frequency characteristics and dynamics of sleep spindles in wag/rij rats with absence epilepsy," *Brain Research* **1543**, 290–299 (2014).
17. Sitnikova, E., Hramov, A. E., Koronovskii, A. A., and Luijtelaar, E. L., "Sleep spindles and spikewave discharges in eeg: Their generic features, similarities and distinctions disclosed with fourier transform and continuous wavelet analysis," *Journal of Neuroscience Methods* **180**, 304–316 (2009).
18. Nazimov, A. I., Pavlov, A. N., Nazimova, A. A., Grubov, V. V., Koronovskii, A. A., Sitnikova, E., and Hramov, A. E., "Serial identification of eeg patterns using adaptive wavelet-based analysis," *EJP-ST* **222**, 2713–2722 (2013).
19. Cao, R., Braun, J., and Mattia, M., "Stochastic accumulation by cortical columns may explain the scalar property of multistable perception," *Physical Review Letters* **113**, 098103 (2014).
20. Pisarchik, A. N., Jaimes-Reategui, R., Magallón-Garcia, C. D. A., and Castillo-Morales, C. O., "Critical slowing down and noise-induced intermittency in bistable perception: bifurcation analysis," *Biological Cybernetics* **108**(4), 397–404 (2014).
21. Runnova, A. E., Hramov, A. E., Grubov, V., Koronovsky, A. A., Kurovskaya, M. K., and Pisarchik, A. N., "Theoretical background and experimental measurements of human brain noise intensity in perception of ambiguous images," *Chaos, Solitons & Fractals* **93**, 201–206 (2016).

22. Niedermeyer, E. and da Silva, F. L., [*Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*], Lippincot Williams & Wilkins (2004).
23. Tatum, W., [*Handbook of EEG interpretation.*], Demos Medical Publishing. (2014).
24. Cooper, R., Osselton, J., and Shaw, J., [*EEG Technology*], Butterworth-Heinemann Ltd; 3rd edition (1980).
25. Luijtelaar van, G., Luttjohann, A., Makarov, V. V., Maksimenko, V. A., Koronovskii, A. A., and Hramov, A. E., "Methods of automated absence seizure detection, interference by stimulation, and possibilities for prediction in genetic absence models," *Journal of Neuroscience Methods* **260**, 144–158 (2016).
26. Walker, M. C. and Eriksson, S. H., "Epilepsy and sleep disorders," *European Neurological Review* **6**(1), 60–63 (2011).
27. Hofmeijer, J. and Putten van, M. J. M., "{EEG} in postanoxic coma: Prognostic and diagnostic value," *Clinical Neurophysiology* **127**(4), 2047–2055 (2016).
28. Maksimenko, V. A., Heukelum van, S., Makarov, V. V., Kelderhuis, J., Luttjohann, A., Koronovskii, A. A., Hramov, A. E., and Luijtelaar van, G., "Absence seizure control by a brain computer interface," *Scientific Reports* **7**, 2487 (2017).
29. Maksimenko, V. A., Luttjohann, A., Makarov, V. V., Goremyko, M. V., Koronovskii, A. A., Nedaivozov, V. O., Runnova, A. E., Van Luijtelaar, G., Hramov, A. E., and Boccaletti, S., "Macroscopic and microscopic spectral properties of brain networks during local and global synchronization," *Phys. Rev. E* **96**, 012316 (2017).
30. Necker, L. A., "Observations on some remarkable phenomena seen in switzerland; and an optical phenomenon which occurs on viewing of a crystal or geometrical solid," *Philos. Mag.* **3**, 329–343 (1832).
31. "World medical association (2000) declaration of helsinki: ethical principles for medical research involving human subjects," *The Journal of the American Medical Association* **284**(23), 3043–3045 (2000).
32. Pastukhov, A., Garcia-Rodriguez, P. E., Haenicke, J., Guillamon, A., Deco, G., and Braun, J., "Multi-stable perception balances stability and sensitivity," *Frontiers in Computational Neuroscience* **7**, 17 (2013).
33. Carpenter, R. H. S., "Analysing the detail of saccadic reaction time distributions," *Biocybernetics and Biomedical Engineering* **32**(2), 49–63 (2012).
34. Merk, I. and Schnakenberg, J., "A stochastic model of multistable visual perception," *Biological Cybernetics* **86**, 111–116 (2002).
35. Leopold, D. A., Wilke, M., Maier, A., and Logothetis, N. K., "Stable perception of visually ambiguous patterns," *Nature Neuroscience* **5**, 605–609 (June 2002).
36. Kornmeier, J., Ehn, W., Bigalke, H., and Bach, M., "Discontinuous presentation of ambiguous figures: How interstimulus-interval durations affect reversal dynamics and erps," *Psychophysiology* **44**(552-560) (2007).
37. Wilson, H. R., "Minimal physiological conditions for binocular rivalry and rivalry memory," *Vision research* **47**, 2741 (September 2007).
38. Hasan, M. R., Ibrahimy, M. I., Motakabber, S. M., and Shahid, S., [*Classification of Multichannel EEG Signal by Linear Discriminant Analysis*], ch. 0, 279–282, Springer International Publishing (2015).