PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Brain states recognition during visual perception by means of artificial neural network in the different EEG frequency ranges

V. Yu. Musatov, A. E. Runnova, A. V. Andreev, M. O. Zhuravlev

V. Yu. Musatov, A. E. Runnova, A. V. Andreev, M. O. Zhuravlev, "Brain states recognition during visual perception by means of artificial neural network in the different EEG frequency ranges ," Proc. SPIE 10717, Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV, 107171O (26 April 2018); doi: 10.1117/12.2314829

SPIE.

Event: Saratov Fall Meeting 2017, 2017, Saratov, Russian Federation

Brain states recognition during visual perception by means of artificial neural network in the different EEG frequency ranges

V. Yu. Musatov, A. E. Runnova, A. V. Andreev, M. O. Zhuravlev

REC “Artificial Intelligence Systems and Neurotechnology”, Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov, 410056, Russia

ABSTRACT

In the present paper, the possibility of classification by artificial neural networks of a certain architecture of ambiguous images is investigated using the example of the Necker cube from the experimentally obtained EEG recording data of several operators. The possibilities of artificial neural network classification of ambiguous images are investigated in the different frequency ranges of EEG recording signals.

Keywords: Electroencephalogram, data filtering, frequency ranges, ambiguous images, neurophysiological experiment, artificial neural network, pattern recognition, artificial intelligence.

1. INTRODUCTION

At present, the dynamics of neuronal networks of human brain is attracted the attention of researchers of natural sciences and humanities.[1,2] The multidisciplinary approach will come closer to understanding the brain mysteries and a better understanding of the neural mechanisms underlying its dynamics, open prospects in the field of medicine and neuroscience in the near future. The study of various aspects of the functioning of the human brain is usually based on objective data acquired in the course of psycho-physiological and cognitive experimental work[3,5–7] The most convenient and low-cost method of recording brain signals in cognitive research today remains EEG. A study of nonlinear processes in the brain neural network during perception of “ambiguous” (also known as bi- or multistable) images is very important for the understanding of both the visual recognition of objects and the decision-making process in human brain.[8,9] Despite the considerable efforts of many researchers, the basic mechanisms underlying the interpretation of such the images are not yet clear enough. At present, we only know that perception is the result of nonlinear processes which take place in the distributed neural network of the occipital, parietal and frontal cortical areas of the brain.[10,11] However, the question remains how the interpretation of the image affects the human EEG. Earlier we demonstrate the efficiency of artificial neural network method in the classification of EEG oscillations.[12,13] It is well-known that using the different frequency bands of EEG signals leads to find additional information on brain dynamics.[14–17] This article shows the results of using bandpass filtering of experimental EEG data to improve their classification based on the artificial neural networks.

2. EXPERIMENTAL SETUP

In our physiological experiment with EEG activity registration we used a set of images based on the well known bistable object, the Necker cube,[18] as a visual stimulus. The cube with transparent faces and all visible ribs is treated a three-dimensional object due to a specific position of the cube ribs. Bistability in perception consists in interpretation of this 3D-object as being oriented in two different sides, either left or right oriented cube, depending on the ribs intensities. Figure 1, a shows various examples of the Necker cube image with different parameter I, being the brightness of the cube wires converging in the right upper inner corner. The brightness of the wires converging in the left lower inner corner is defined as $(1 - I)$. The values $I = 1$ and $I = 0$ correspond, respectively, to 0 (black) and 255 (white) pixels' luminance of the middle lines, using the 8-bit grayscale palette

Further author information: (Send correspondence to A. E. Runnova)
A. E. Runnovav: E-mail: anefila@mail.ru, Telephone: +7 8452 99 88 31

Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV, edited by Vladimir L. Derbov, Dmitry E. Postnov, Proc. of SPIE Vol. 10717, 107171O · © 2018 SPIE · CCC code: 1605-7422/18/$18 · doi: 10.1117/12.2314829

for visual stimulus presentation. Therefore, we can define parameter as $I = g/255$ where g is the the brightness level of the middle lines in used 8-bit grayscale palette. It should be noted that the contrast of the six visible outer cube edges was fixed to 1. The experimental studies were performed in accordance with the ethical standards[19] and approved by the local research ethics committee of Yuri Gagarin State Technical University of Saratov.

Forty healthy subjects from a group of unpaid volunteers, male and female, between the ages of 18 and 45 with normal or corrected-to-normal visual acuity participated in the experiments. All persons have provided informed consent before participating in the experiment. The purpose of these experiments is a study of unconscious decision on ambiguous image interpretation.

The experimental procedure was performed as follows. The Necker cube images with different wireframe contrasts were demonstrated for a short time, each lasting between 0.2 and 0.7 seconds, interrupted by a background abstract picture for 2.5—3.5 seconds. The subject was instructed to press either a left or a right key depending on his/her interpretation of the cube orientation at each demonstration. The use of the background images allowed neutralization of possible negative secondary effects which may arise from the previous Necker cube image. The whole experiment lasted about 40 min for each subject.

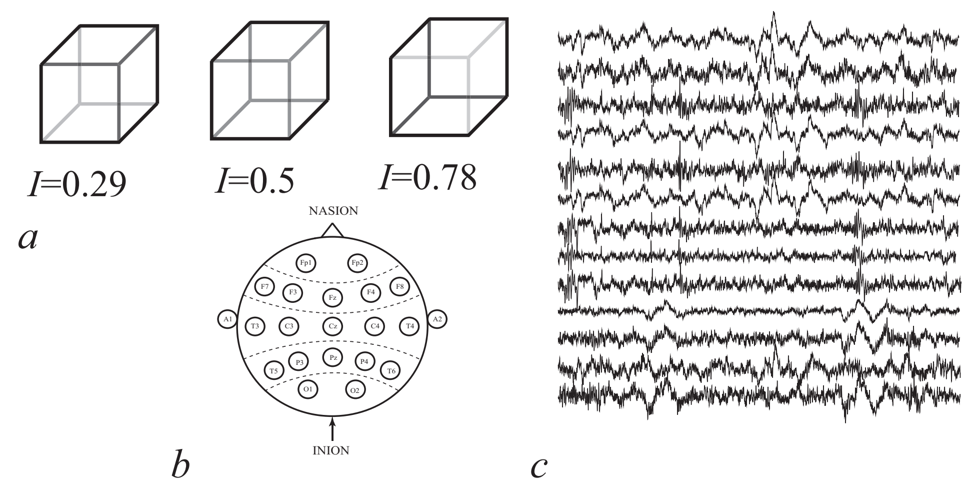

Figure 1. (a) Examples of Necker cube images with different rib contrast I. (b) International EEG electrode placement scheme "10 – 20". (c) Typical EEG recordings from electroencephalograph Encephalan-EEGR-19/26 during recognition of visual stimulus — Necker cubes.

During the experiment, the Necker cube images with different frame contrasts were randomly exhibited, each for about 100 times, with simultaneous recording of multi-channel EEGs using the electroencephalograph-recorder Encephalan-EEGR-19/26 (Russia) with a two-button input device. The monopolar registration method and classical ten-twenty electrode system were used (Fig. 1, b). Figure 1, c shows an example of typical EEG data set during the Necker cube images exhibition.

3. METHODS

It is known that artificial neural networks are often used to solve non-linear problems when an analytical solution is difficult to obtain.[20]In our work we focus on the method of supervised learning, is traditionally chosen to solve this type of problems of pattern recognition and classification. In the work, the classification of EEG images is carried out with the help of feedforward artificial neural network with error back propagation (Figure 2 a) of two types: (i) radial basis function (Figure 2 b) and (ii) multilayer perceptron (Figure 2 c), which showed the best results in the previous studies.[12,13] The differences of these artificial neural networks are in the different functions of activation of neurons and the number of hidden layers.[20] Thus, in the case of using radial basis function it is always one hidden layer of radial elements, each of which reproduces the Gaussian response surface, and the multilayer perceptron can have several hidden layers with activation functions such as hyperbolic tangent, sigmoid, etc.

The band-pass filtering of the initial data was carried out using a Butterworth filter implemented with Matlab functions:

$$H(\omega) = \frac{1}{1 + \sqrt{(\omega/\omega_c)^{2n}}} \tag{1}$$

where ω_c is the boundary frequency, n is the filter order.

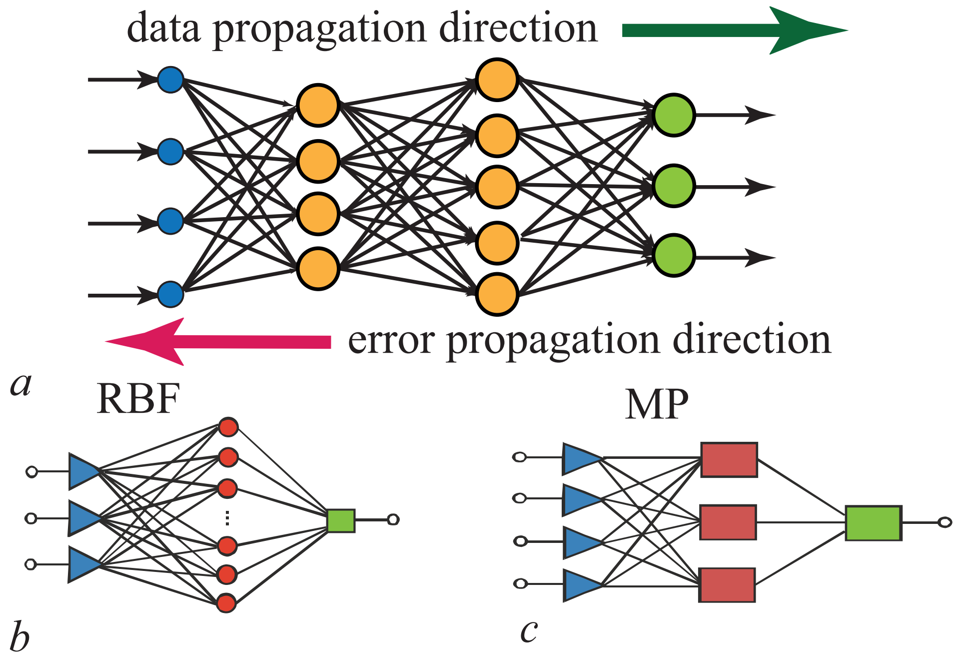

Figure 2. Scheme of feedforward artificial neuronal network with error back propagation (a), radial basis function ANN (b) and myltilayer perceptron (c).

4. RESULTS

In our experimental studies we separated all Necker cube images on the "left" and "right" in accordance with the apparent position of the front face of the cube. EEG data corresponding to Necker cubes of various intensities are represented in the form of images that are recorded at a frequency of 250 Hz, corresponding to the decision time of the operator about the cube class (1 second). Samples of data with a capacity of 24 images. The band-pass filtering of the initial data in the bands 1–4 Hz, 8–12 Hz, 15–20 Hz and 25–45 Hz was carried out and saved in files corresponding to each frequency band.

Half of the data, chosen randomly, was used for training. The remaining half part — for the control and test samples. Using the data of the entire set of EEG signals (31 channels), the best results of classification were shown by radial basis function networks with linear neurons in the input and output layers, radial synaptic functions and exponential activation functions of 251 middle layer neurons and multilayer perceptron networks with 15 neurons in the hidden layer with the activation function hyperbolic tangent with an input layer with linear and output layer with logistic activation functions.

Recognition results of EEG data filtered in different bands for two types of neural networks with radial basis function (a) and multilayer perceptron (b) are presented on Figure 3.

Artificial neural networks with the radial basis function type show the best recognition quality for all frequency ranges of filtration in comparison with multilayer perceptrons. For the data studied, better recognition occurs when information filtered at low frequencies is used. As the filtering frequency increases, the recognition becomes

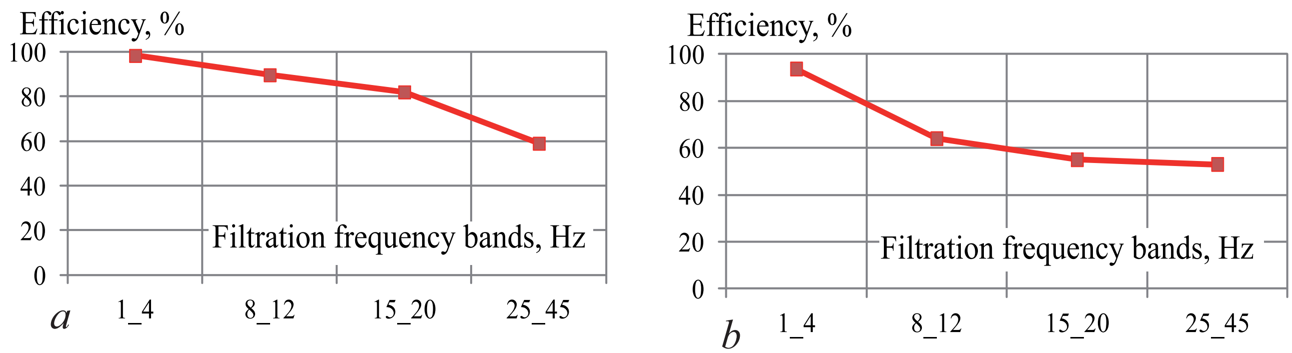

Figure 3. Artificial neuronal network classification efficiency of filtered EEG data (a) for case of perception of the left cube and (b) for case of perception of the right cube in the different frequency bands.

noticeably worse. Visual comparison of the type of EEG signals filtered in the range of 1–4 Hz. (Figure 4) allows to reveal their significant differences for cubes of different classes (left (a) and right (b)).

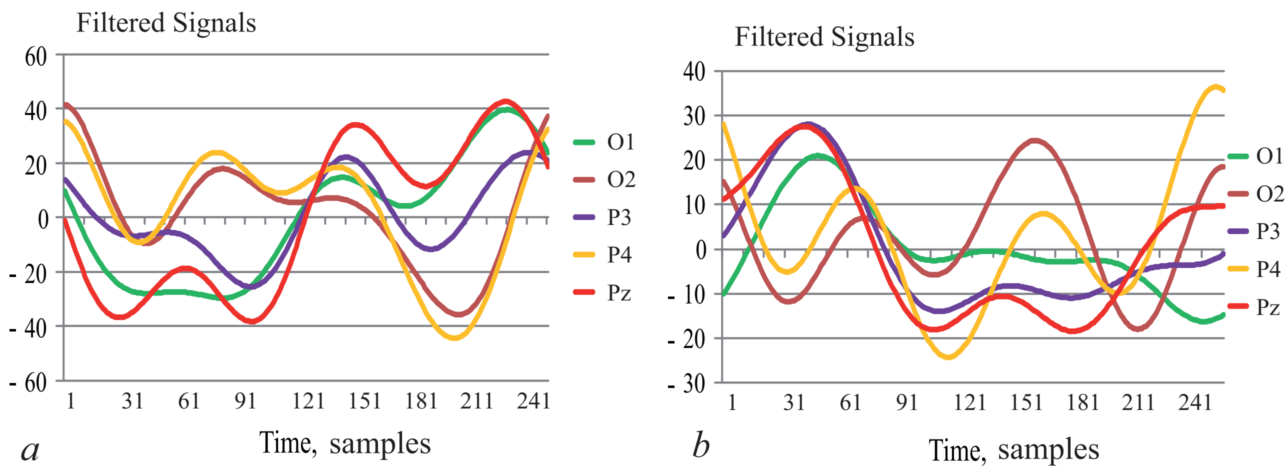

Figure 4. The averaged values of EEG data filtered for the 1–4 Hz range for occipital EEG channels (O1, O2, P3, P4 and Pz) (a) for case of perception of the left cube and (b) for case of perception of the right cube.

5. CONCLUSION

In this work, the features of the classification of various states in the human brain related to the perception of ambiguous images were studied. For this, artificial neuronal networks were used which previously showed a good quality of classification of multichannel EEG data (at the level of 80-90%), in this study, the initial data was filtered in the ranges 1–4 Hz, 8–12 Hz, 15–20 Hz and 25–45 Hz. The obtained results show that for the investigated data the best recognition occurs when using the information filtered at frequencies of 1–4 Hz, approximately corresponding to the gamma - rhythm of the brain (95-98%). With the increase in the filtering frequency, the recognition significantly deteriorates: up to 65-90% in the range corresponding to the alfa-rhythm, and up to 53–80% in the beta-rhythm range. Visual comparison of the type of EEG signals filtered in the range of 1-4 Hz. allows to reveal their significant differences for cubes of different classes. The best results are shown by the artificial neuronal network with radial basis functions. In general, it can be concluded that low-frequency filtering of multi-channel EEG data is necessary to improve the quality of their classification when analyzing processes in neural network of the brain, associated with the perception of ambiguous images. Moreover, we believe that the value of our results is not limited to studies of brain activity during the perception of ambiguous images. The application of data filtering will be useful for analyzing a wide range of processes in the human and animal brain using multichannel EEG and MEG data, for example to create on-line recognition systems for brain-computer interfaces.[21–24]

6. ACKNOWLEDGMENTS

This work has been supported by Russian Science Foundation (Grant 16-12-10100).

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., Paradiso, M. A., [*Neuroscience. Exploring the brain*], Woters Kluwer, (2015).

[3] 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).

[4] Pisarchik, A. N., Bashkirtseva, I. A., and Ryashko, L. B., "Controlling bistability in a stochastic perception model," *Eur. Phys. J. Special Topics* **224**(8), 1477–1484 (2015).

[5] Grubov, V. V., Runnova, A. E., Kurovskaa, M. K., Pavlov, A. N., Koronovskii, A. A., Hramov, A. E., "Demonstration of brain noise on human EEG signals in perception of bistable images," *Proc. SPIE* **9707**, 970702 (2016).

[6] Hramov, A. E., Kurovskaa, M. K., Runnova, A. E., Zhuravlev, M. O., Grubov, V. V., Koronovskii, A. A., Pavlov, A. N., Pisarchik, A. N., "Intermittent behavior in the brain neuronal network in the perception of ambiguous images," *Proc. SPIE* **10063**, 1006314 (2017).

[7] Runnova, A. E., Hramov, A. E., Grubov, V. V., Koronovskii, A. A., Kurovskaya, M. K., and Pisarchik, N. A., "Theoretical background and experimental measurements of human brain noise intensity in perception of ambiguous images," *Chaos, Solitons and Fractals* **93**, 201–206 (2016).

[8] Leopold, D. A. and Logothetis, N. K., "Multistable phenomena: changing views in perception," *Trends in Cognitive Sciences* **3**(7), 254–264 (1999).

[9] Blake, R., Logothetis, N. K., "Visual competition, Nature Reviews," *Neuroscience* **3**, 13–21 (2002).

[10] Tong, F., Meng, M., and Blake, R., "Neural bases of binocular rivalry," *Trends in Cognitive Sciences* **10**(11), 502–511 (2006).

[11] Sterzer, P., Kleinschmidt, A., and Rees, G., "The neural bases of multistable perception," *Trends in Cognitive Sciences* **13**(7), 310–318 (2009).

[12] Musatov, V. Yu., Pchelintseva, S. V., Runnova, A. E., Hramov, A. E., "Patterns recognition of electric brain activity using artificial neural networks," *Proc. SPIE* **10337**, 1033714-1 (2017).

[13] Pchelintseva, S. V., Runnova, A. E., Musatov, V. Yu., Hramov, A. E., "Recognition and classification of oscillatory patterns of electric brain activity using artificial neural network approach" *Proc. SPIE* **10063**, 1006317-1 (2017).

[14] Pavlov, A. N., Hramov, A. E., Koronovskii, A. A., Sitnikova, Y. E., Makarov, V. A., and Ovchinnikov, A. A. "Wavelet analysis in neurodynamics," *Physics-Uspekhi* **55**(9), 845–875 (2012).

[15] 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., Boccaletti, S., "Macroscopic and microscopic spectral properties of brain networks during local and global synchronization," *Phys. Rev. E.* **96** 012316, (2017).

[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] van Luijtelaar, E. L. M., Hramov, A. E., Sitnikova, E., and Koronovskii, A. A., "Spikewave discharges in WAG/Rij rats are preceded by delta and theta precursor activity in cortex and thalamus," *Clinical Neurophysiology* **122**, 687–695 (2011).

[18] 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).

[19] "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).

[20] Haykin, S., [*Neural Networks: A Comprehensive Foundation*], Prentice Hall PTR Upper Saddle River, NJ, USA (1998).

[21] Lin, C.-t., Ko, L.-w., Chung, I.-f., Huang, T.-y., Chen, Yu-c., Jung, T.-p., Liang, Sh.-f., "Adaptive EEG-based alertness estimation system by using ICA-based fuzzy neural networks," *IEEE Transactions on Circuits and Systems I: Regular Papers* **53**, 2469–2476 (Nov 2006).

[22] Hill, N. J. and Schlkopf, B., "An online braincomputer interface based on shifting attention to concurrent streams of auditory stimuli," *Journal of Neural Engineering* **9**(2), 026011 (2012).

[23] 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).

[24] Luijtelaar, van Gilles, Lttjohann, A., Makarov, V. V., Maksimenko, V. A., Koronovskii, A. A., 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).