Patterns recognition of electric brain activity using artificial neural networks

V. Yu. Musatov[a], S. V. Pchelintseva[ab], A. E. Runnova[ab], A.E. Hramov[a]

[a]Department of Automatization, Control and Mechatronics, Saratov State Technical University, Politechnicheskaya Str. 77, Saratov, 410056, Russia;
[b]REC "Nonlinear Dynamics of Complex Systems", Saratov State Technical University, Politechnicheskaya Str. 77, Saratov, 410056, Russia;

ABSTRACT

An approach for the recognition of various cognitive processes in the brain activity in the perception of ambiguous images. On the basis of developed theoretical background and the experimental data, we propose a new classification of oscillating patterns in the human EEG by using an artificial neural network approach. After learning of the artificial neural network reliably identified cube recognition processes, for example, left-handed or right-oriented Necker cube with different intensity of their edges, construct an artificial neural network based on Perceptron architecture and demonstrate its effectiveness in the pattern recognition of the EEG in the experimental.

Keywords: Electroencephalogram, ambiguous images, neurophysiological experiment, artificial neural network, pattern recognition, artificial intelligence.

1. INTRODUCTION

Currently, the dynamics of neuronal network of the brain attracted the attention of researchers in diverse areas of science, including psychology, neurophysiology, medicine, physics, mathematics, and nonlinear dynamics.[1–7] The multidisciplinary approach will come closer to understanding the brain mysteries and a better understanding of the neural mechanisms underlying its dynamics, and will open prospects in the field of medicine and neuroscience in the near future.[?, ?, 8–13] The well example of such multidisciplinary investigation is the observation of intermittent behavior in epileptic brain that gives new possibility to discover mechanisms of epileptic states formation in the brain.[?, 14–16]

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[17–22] and cognitive experimental work[?, 23–25] 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- and multistable) images is very important for the understanding of both the visual recognition of objects and the decision-making process.[19, 20] In spite of considerable efforts of many researchers, the main mechanisms underlying the interpretation of such images are not yet well understood. At present, we only know that perception is the result of nonlinear processes which take place in the distributed neural network of occipital, parietal and frontal regions of the brain cortex.[26, 27] However, the open question still remains of how the image interpretation affects the human EEG. In this paper, we propose an approach based on the artificial neural network (ANN), which allows us to answer this question. We demonstrate the efficiency of our method in the classification of EEG oscillatory patterns corresponding to the different interpretation of bistable images.

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

Saratov Fall Meeting 2016: Laser Physics and Photonics XVII; and Computational Biophysics and Analysis of Biomedical Data III, edited by Vladimir L. Derbov, Dmitry E. Postnov, Proc. of SPIE Vol. 10337, 1033714 · © 2017 SPIE · CCC code: 1605-7422/17/$18 · doi: 10.1117/12.2267701

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,[28] 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 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[29] and approved by the local research ethics committee of Saratov State Technical University. 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.

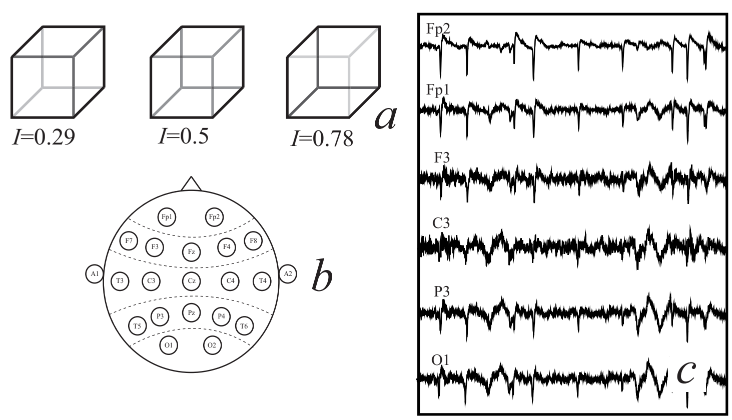

Figure 1. (a) Examples of a data set from a typical EEG recording from electroencephalograph Encephalan-EEGR-19/26. The solid black lines show the moments of time when the Necker cubes with different parameter I were presented, and the gray areas show the time intervals between moments of pressing and squeezing of buttons on the remote control.(b) International EEG electrode placement scheme "10–20". (c) Examples of Necker cube images with different rib contrast I

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 (Russian Federation) 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 the typical EEG data set during the Necker cube images exibition.

3. MATHEMATICAL METHODS

The present work is devoted to research capacities of such methods clustering complex data as the principal component analysis (PCA) and methods based on artificial neural networks to classify the brain states of EEG data.

The principal component analysis idea is the input data vector with dimension $D = n$ transformation to a new vector consisting of mutually orthogonal component and has a lower dimension $D_1 = n - k$.[?] In this case to simplify the data structure by reducing the dimension and the further allocation of the component with the highest "significance" carried out on the basis of linear transformation and orthogonalization procedures. Conversion in some cases leads to a significant reduction in the dimensions and separation of only a few components relevant maximum initial data analysis which is used for further identification and classification of the various states in the investigated system dynamics. In other words, the method is directed to a linear reduction of the number of components required for the data classification. Maximum simplification of the high dimension raw data results in final data set of only a few variables, the so-called "principal components". So, the principal component analysis method is based on the search and subsequent exclusion of linearly correlated component in a multidimensional vector of raw experimental data.[?]

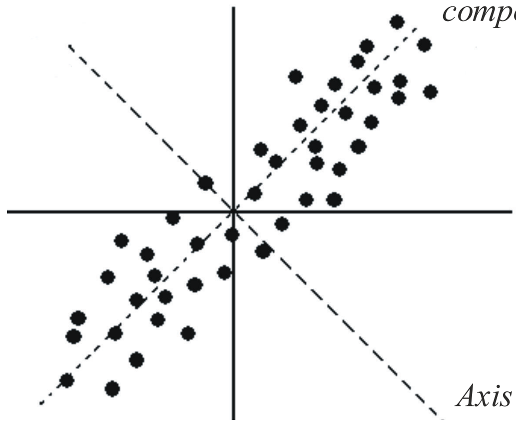

Figure 2. Principal component analysis scheme illustrated the allocation of the first principal component (PC1)

For the principal component analysis method the first principal component (PC1) is characterized the direction of maximum data changes, and the second direction (PC2) is perpendicular to the first one to describe the remaining change in the data set (Fig. 2).

The artificial neural network approach is frequently applied for the solving nonlinear problems, when an analytical solution is difficult to obtain.[?] 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. We have considered several types of neural networks (see Fig. 3, I) with direct data propagation and back error propagation architecture (see Fig. 3, II). As a part of the numerical experiments we considered such variants of the artificial neural network architecture as linear artificial neural network (LN), a neural network of radial basis function (RBF), and multilayer perceptron (MP).[?] The considered types of the artificial neural network architecture are shown in Figs. 3, III, a, b, 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. We used ten different images of the Necker cube with different intensities of several key edges. Obviously, the intensity I of the ribs provided on the impact of the perception of the observer. In particular, an image with a small parameter I is usually interpreted as "left" one, respectively, with a large parameter I – as right. All images that are close to symmetrical distribution of the intensity of the edges are perceived as left- or right-handle cube with a probability determined by the personal characteristics of the observer (e.g., the level of cognitive noise).[?,23,24,30]

Thus, the set of experimental multi-channel EEG data was divided into two classes, united by common events. For each subject, we analyzed the type of the presented stimuli (Necker cubes) and the perception of an object

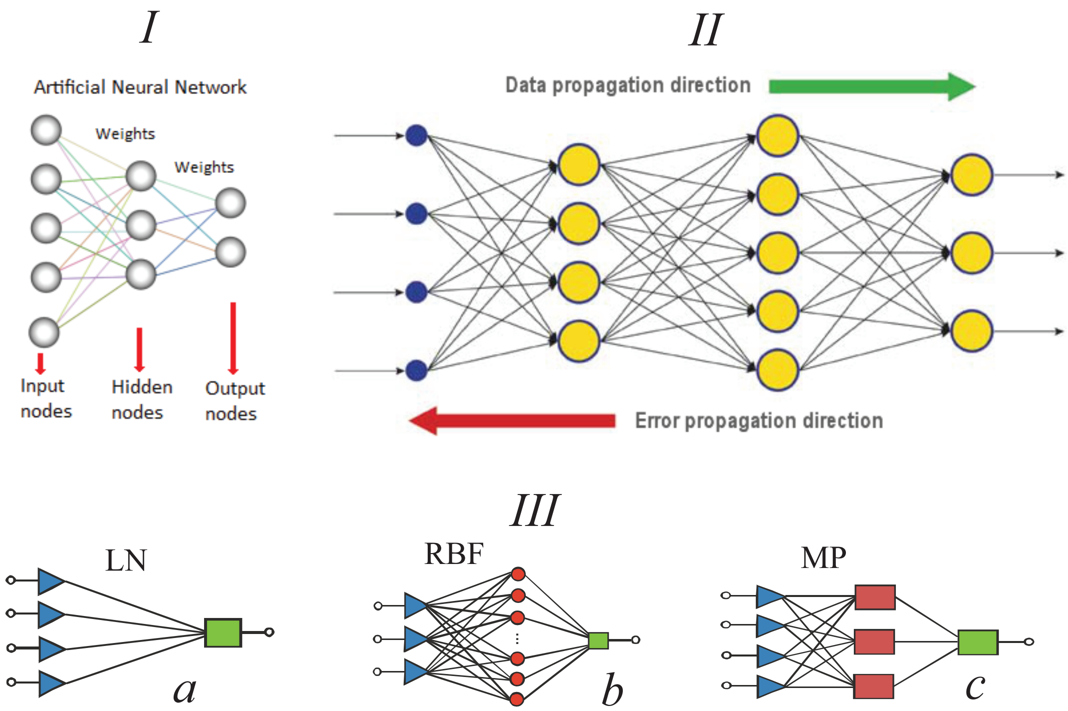

Figure 3. Artificial neural networks architectures used for the classification of EEG oscillatory patterns corresponding to the different interpretation of ambiguous image

("left" or "right" cube). Thus, for each the Necker cube image with intensity parameter I we can distinguish two classes of events corresponding to the perception of the "left" and "right" cube orientations. For automatic classification of the experimental EEG data for each of the Necker cube on perceived "left" and "right" ones was used the principal component analysis method. The projections of the two components were built on the basis of three data operators and analyzed the possibility of separating two different clusters.

The results of computational experiments implemented in MATLAB Software Package are shown in Figure 4 which shows the first and second principal components for clarity, the use of principal component analysis does not allow the required classification of the experimental data.

Next, we studied the possibility of using the artificial neural network to classify experimental EEG data. On the basis of the STATISTICA Software Package the problem of classification of the different artificial neural network architectures (LN, RBF, MP)[?] was successfully solved (Fig. 5).

A part of the EEG fragments of data corresponding to each of the two possible perceptions the Necker cube was used to supervise the learning artificial neural network using the experimental EEGs of three different volunteers. Then, the trained artificial neural network was explored to classify all available experimental data.

The theoretical and experimental analysis showed that the artificial neural network approach quite successfully cope with the task of EEG data classification. Figure 5 demonstrates a high efficiency in classification of the EEG patterns based on different types of artificial neural network architecture. As the calculation of efficiency of the neural network we mean the percentage of correctly identified situations of operator choice in EEG data. In other words, if the artificial neural network correctly identifies the operator choice in 90 times of 100 Necker cube presentations, then the efficiency E is equal to 90%. So, during the experiments we found that the best results were achieved on the basis of multi-layer perceptron (95–97%), and the linear artificial neural network showed the worst productivity of the classification of human perception processes (50–55%). The artificial neural network of the radial basis function showed the effectiveness at the level of 80—85%.

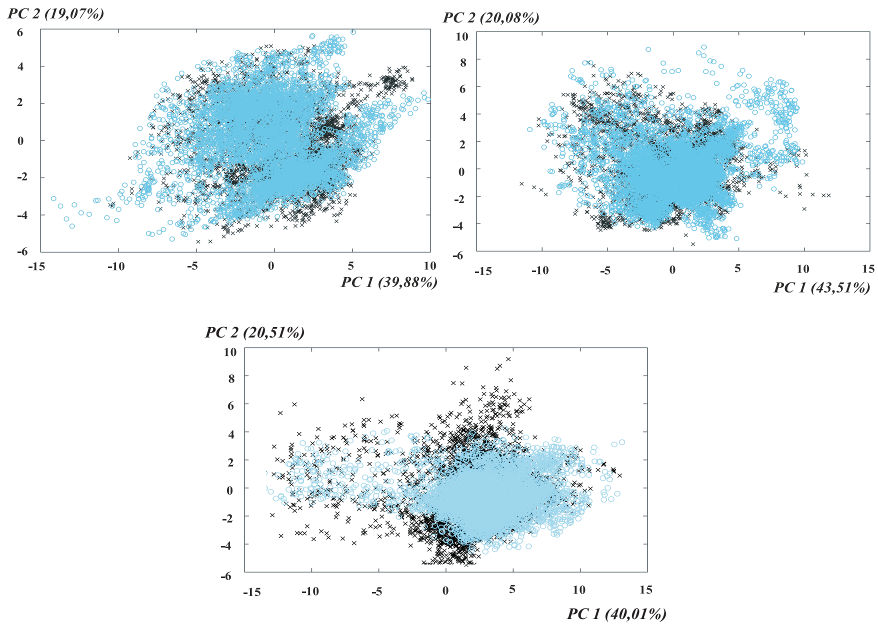

Figure 4. Results of principal component analysis application for EEG data classification: show the geometrical interpretation of the principal components for the three different operators. The array of black dots corresponds to the choice of the operator as the “left” cube and the blue dots – “right”

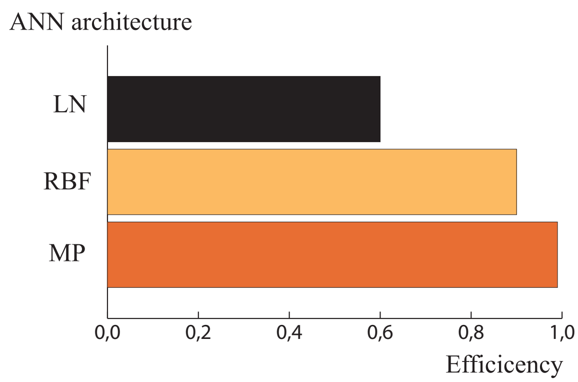

Figure 5. Artificial neural network classification efficiency of experimental EEG data

5. CONCLUSION

In this paper we supposed method for the classification of various states of in the human brain related to the perception of ambiguous images. We have considered different classification approaches based on the construction and learning linear and nonlinear artificial neuronal networks. First-of-all, we have shown that principal component analysis linear method and linear artificial neuronal network does not provide classification of various states by means of the multi-channel EEG. At the same time, the nonlinear artificial neuronal network architectures demonstrate high efficiency of classification of two states of the perception of ambiguous image (Necker cube). Our numerical results have been shown that the use of multilayer perceptron architecture of artificial neuronal network demonstrates the best result of multi-channel EEG signals classification. This artificial neuronal network is selected for further optimization of the mathematical model for processing and classification of different patterns in the EEG signals. In general, our results indicate the necessity of nonlinear mathematical models for analysis of processes in the brain neuronal network related to the ambiguous images perception. Moreover, we that the value of our results are not limited to studies of brain activity during the perception of ambiguous images. We that the developed method will be useful for the study and classification lasting a wide variety of processes in the human brain network recorded multi-channel EEG and MEG recordings. Moreover, we assume that the significance of our results are not limited only by the ambiguous images perception brain activity studies. We believe that the developed technique will be useful for studying and classification of the wide spectrum of different processes in the human brain network registered by the multi-channel EEG and MEG records.

6. ACKNOWLEDGMENTS

This work has been supported by the Russian Science Foundation (Grant No. 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., 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] Bick, C. and Rabinovich, M. I., "Dynamical origin of the effective storage capacity in the brains working memory," *Physical Review Letters* **103**, 218101 (2009).

[5] 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).

[6] 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).

[7] 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).

[8] Prusseit, J. and Lehnertz, K., "Stochastic qualifiers of epileptic brain dynamics," *Physical Review Letters* **98**, 138103 (2007).

[9] Smith, P. L. and Ratcliff, R., "Psychology and neurobiology of simple decisions," *Trends in Neurosciences* **27**(3), 161–168 (2004).

[10] Wang, X.-J., "Decision making in recurrent neuronal circuits," *Neuron* **60**(2), 215–234 (2008).

[11] Ratcliff, R. and Smith, P. L., "A comparison of sequential sampling models for two-choice reaction time," *Psychological Review* **111**(2), 333–367 (2004).

[12] Heekeren, H. R., Marrett, S., and Ungerleider, L. G., "The neural systems that mediate human perceptual decision making," *Nature Reviews Neuroscience* **9**, 467–479 (2008).

[13] 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).

[14] Hramov, A. E., Koronovskii, A. A., Midzyanovskaya, I. S., Sitnikova, E., and Rijn, C. M., "On-off intermittency in time series of spontaneous paroxysmal activity in rats with genetic absence epilepsy," *Chaos* **16**, 043111 (2006).

[15] Hramov, A. E., Koronovskii, A. A., Kurovskaya, M. K., Ovchinnikov, A. A., and Boccaletti, S., "Length distribution of laminar phases for type-I intermittency in the presence of noise," *Phys. Rev. E* **76**(2), 026206 (2007).

[16] Sitnikova, E., Hramov, A. E., Grubov, V. V., Ovchinnkov, A. A., and Koronovsky, A. A., "Onoff intermittency of thalamo-cortical oscillations in the electroencephalogram of rats with genetic predisposition to absence epilepsy," *Brain Research* **1436**, 147–156 (2012).

[17] Schwartz, J.-L., Grimault, N., Hupé, J.-M., Moore, B. C. J., and Pressnitzer, D., "Multistability in perception: binding sensory modalities, an overview," *Physophical Transactions of the Royal Society B* **367**, 896–905 (2012).

[18] 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).

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

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

[21] Moore, B. C. J. and Gockel, H. E., "Properties of auditory stream formation," *Philosopical transactions of the Royal Society B* **367**, 919–931 (2012).

[22] Carter, O., Konkle, T., Wang, Q., Hayward, V., and Moore, C., "Tactile rivalry demonstrated with an ambiguous apparent-motion quartet," *Current Biology* **18**, 1050–1054 (2008).

[23] 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).

[24] 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).

[25] Etcoff, N. L. and Magee, J. J., "Categorical perception of facial expressions," *Cognition* **44**(3), 227–240 (1992).

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

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

[28] 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).

[29] "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).

[30] 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).