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Vadim V. Grubov, Nikita S. Frolov

Vadim V. Grubov, Nikita S. Frolov, "Detection of EEG oscillatory patterns corresponding to human concentration of attention with help of perceptron type artificial neural network," Proc. SPIE 11067, Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, 1106703 (3 June 2019); doi: 10.1117/12.2527702

Event: International Symposium on Optics and Biophotonics VI: Saratov Fall Meeting 2018, 2018, Saratov, Russian Federation

Detection of EEG oscillatory patterns corresponding to human concentration of attention with help of perceptron type artificial neural network

Vadim V. Grubov, Nikita S. Frolov

Innopolis University, 1, Universitetskaya Str., Innopolis, 420500, Russia;;

ABSTRACT

In this paper we analyzed possibility for detection of EEG oscillatory patterns related to states of low and high levels of human concentration during perception of visual stimuli with help of artificial neural network. We analyzed different variation of EEG signals conmbination in order to find optimal one. We performed classification of brain states with perceptron-type artificial neural network and analyzed quality of classification.

Keywords: Electroencephalogram, oscillatory patterns, human attention, artificial neural network, perceptron

1. INTRODUCTION

It is well-known that artificial neural network (ANN) is a powerful tool for processing and classification of big poor-structured data.[1,2] In neurophysiology such data is mostly represented by long recordings of electrical and magnetic activity of subject's brain. Such data is acquired through electroencephalografic (EEG) and magnetoencephalografic experiments.[3–5]

In this context mathematical instrument of ANN is used for detection of various types of well-pronounced and/or well-reproducible activity. For example, ANN is actively used for identification of different types of motor activity and for detection of focuses of brain disorders.[6,7]

At the same time using of ANN for classification of different psychophysiological states in human brain is still very rare. There several reasons that limit research in this field:

1. patterns of cognitive activity are nor always well-reproducible even in terms of one experimental session;
2. need for specific criteria for classification of such states since even multichannel experimental data may not include all information, sufficient for proper classification .

In this paper we implemented AAN for analysis and classification of differents states on multichannel EEG signals obtained from human subjects. EEG signals were recorded during experiments aimed for studying of concentration of human attention. We used perceptron-type ANN for analysis of these EEG signals. We also tested different combination of EEG channels in order to find combination, optimal for classification of brain states related to low and high levels of concentration.

Further author information: (Send correspondence to V.V. Grubov)
V.V. Grubov: E-mail: vvgrubov@gmail.com, Telephone: +7 8452 99 88 32

Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions,
edited by Dmitry E. Postnov, Proc. of SPIE Vol. 11067, 1106703 · © 2019 SPIE
CCC code: 0277-786X/19/$18 · doi: 10.1117/12.2527702

2. METHODS

In our work we used multichannel EEG data obtained in experiments for studuing of concentration of human attention. This experimental work was held for 30 healthy subjects (males and females) in the age of 20-43 with normal or corrected-to-normal visual acuity. All participants provided informed written consent before the experiment.

During the experiment subjects observed consequent visual stimuli such as bistable images. The task of participant was to perceive large number of sequentially displayed images and to make decision on each image. These actions were used to test concentration of subject's attention and to monitorchanges in level of attention.

In the experiment the subjects were comfortably sitting at a 7080 cm distance from a 24 LCD monitor with an approximately 0.25 rad visual angle. Consequent bistable images were displayed on a white background in the middle of the monitor with a spatial resolution of 1920 1080 pixels and a 60-Hz refresh rate.

To register the EEG data, we used electroehcephalograph "Encephalan-EEGR-19/26" by Medicom MTD (Taganrog, Russia) with 19 EEG channels. For EEG signal recording the cup adhesive Ag/AgCl electrodes (one for each channel) were placed on the scalp with the help of "Tien20" paste. Before the experiment, we put the abrasive "NuPre" gel on the scalp to increase the skin conductivity. After the electrodes were placed, we monitored the impedance to get best possible quality of EEG recordings. The ground electrode N was located above the forehead, and the reference electrodes A1 and A2 were attached to the mastoids. For filtering the EEG signals, we used a band-pass filter with cutoff points at 0.016 Hz and 70 Hz, as well as a 50-Hz Notch filter.

In order to classify different states on EEG recordings we introduced special criteria based on results of our previous work.[8–10] Acquired results showed, that perception of visual stimulus-based task cab be divided into three segments: before perception of stimulus, during perception and after perception correspondingly. We found significant differencies in spectral structure of EEG signal during these segments: in the first segment alpha rhytm (8-14 Hz) is dominant and beta rhythm (15-25 Hz) is far less pronounced, in the second segment beta activity becomes dominant while alpha activity significantly decreases, in the third segment alpha rhythm regains its dominant role and beta rhythm returns to previous low level.

According to these features of perception we supposed, that the best results in classification of different brain states can be acquired if we use special ANN input with information about spectral structure of EEG. So instead of the initial EEG signals we used their Fourier spectra-based properties as input for our ANN. We examined short (2 s long) episodes of EEG signals – 1 s before visual stimulus demonstration and 1 s after. These episodes were processed with fast Fourier transform and for each EEG channel we obtained signal energy in alpha frequency range. As ANN input we used ratio between energy after and energy before demonstration of each stimulus.

Multilayered perceptron was chosen as architecture of ANN.[11] Developed ANN consisted of two hidden layers with 10 neurons on the first layer and 30 neurons on the second one. Number of ANN inputs corresponded to the number of EEG channels used in experiment (19 channels in the given case). Output layer of ANN consisted of 1 neuron due to the need of classification of only two classes: "high concentration" and "low concentration" (see Fig. 1). All experimental data was divided into 400 fragments, 60 of which were used for learning, 20 for testing, 20 for validation and remaining 300 for accuracy evaluation.

3. RESULTS

Analysis of EEG data and detection of oscillatory patterns related to high and low levels of concentration was performed for two cases: all 19 channels and 5 channels of occipital area (O1, O2, P3, P4, Pz) so we could study dependence of classification accuracy from chose combination of channels.

In search of optimal ANN parameters we considered learning of 100 ANNs for both cases – with all EEG channels and with only occipital channels. We used learning algorithm based on conjugated gradients, which provides fast convergence during optimization process of artificial neurons biases. Results as classification accuracy distributions for 19 and 5 EEG channels are illustrated on Fig. 2. It can be seen from Fig. 2b,d that classification accuracy is significantly higher if we analyze only occipital EEG channels. Average accuracy is 93%

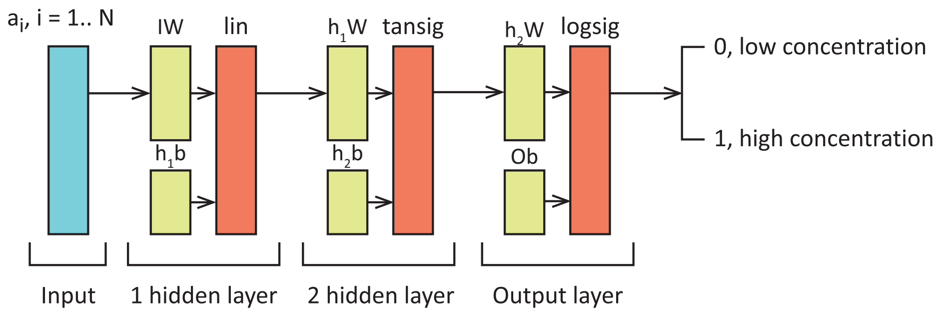

Figure 1. Scheme of ANN as multilayer perceptron, that was used for classification of states with low and high concentration level. Here N = 19 in case of all EEG channels and N = 5 in case of occipital area. IW, h1W, h2W – weight matrices, h1b, h2b, Ob – vectors of biases.

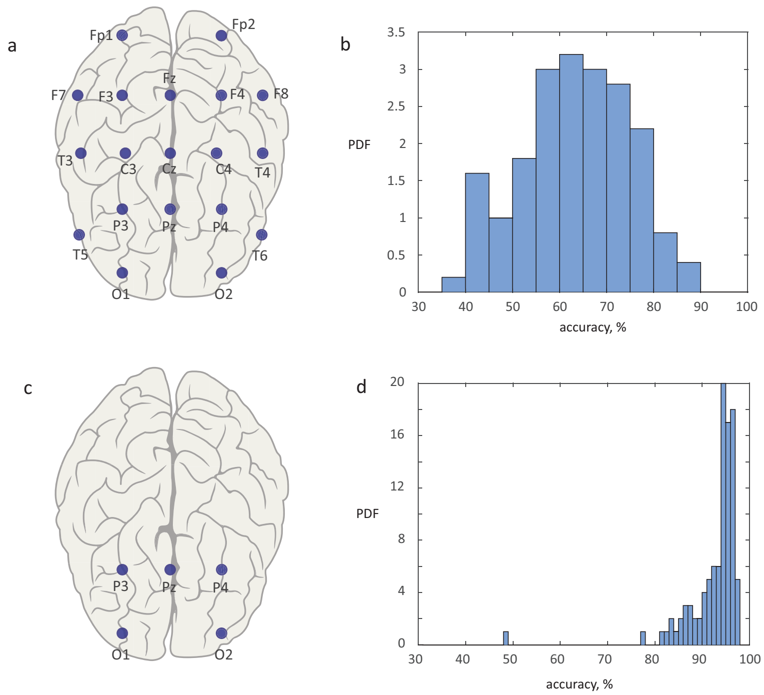

Figure 2. Schemes of electrodes placement for all EEG channels (a) and for occipital channels (c) and corresponding accuracy distributions for 19 channels (b) and for 5 channels (d).

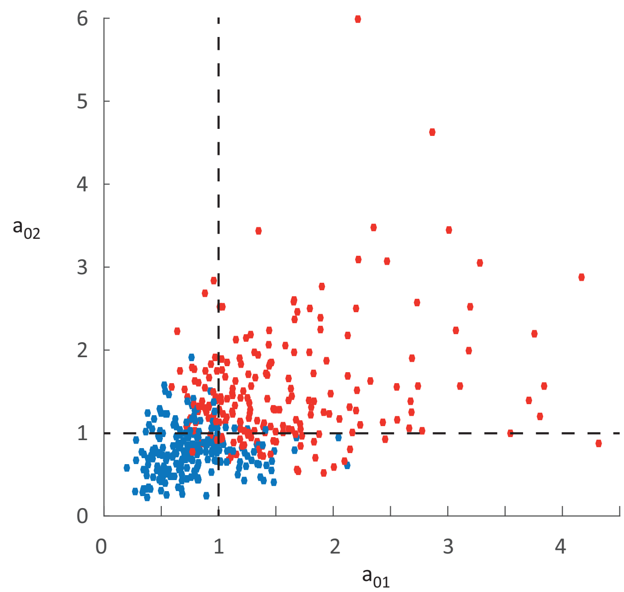

Figure 3. Illustration of classification results: states of low attention concentration (blue dots) and states of high attention concentration (red dots). These two states are divided by lines $a_{O1} = 1$ and $a_{O2} = 1$.

for occipital channels against 63% for all channels. At the same time maximum accuracies are 97% and 85% correspondingly.

Fig. 3 illustrates classification of brain states on surface $a_{O1} - a_{O2}$. Here a_{O1} and a_{O2} correspond to changes in alpha activity in left and right hemispheres. Fig. 3 shows low concentration state with blue and high concentration state with red. One can see, that states classified as low concentration, appear in area $0 < a_{O1} < 1$, $0 < a_{O2} < 1$. This fact proves, that ANN correctly classifies different brain states according to chosen criteria.

4. CONCLUSION

In this paper we implemented AAN for analysis and classification of differents states on multichannel EEG signals obtained from human subjects. EEG signals were recorded during experiments aimed for studying of concentration of human attention. We used perceptron-type ANN for analysis of these EEG signals. We also tested different combination of EEG channels in order to find combination, optimal for classification of brain states related to low and high levels of concentration. We found, that use of just occipital EEG channels greatly increases classification accuracy – 93% accuracy for occipital channels against 63% accuracy for all channels.

Obtained results can be helpful for further fundamental studies of processes related to visual perception and concentration of human attention. Knowledge of such mechanisms can be used in development of "brain-computer" interfaces.

5. ACKNOWLEDGMENTS

This work has been supported by Russian Science Foundation (grant 17-72-10183).

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