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SPIE.

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

Recognition of neural brain activity patterns correlated with complex motor activity

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ABSTRACT

In this paper, based on the apparatus of artificial neural networks, a technique for recognizing and classifying patterns corresponding to imaginary movements on electroencephalograms (EEGs) obtained from a group of untrained subjects was developed. The works on the selection of the optimal type, topology, training algorithms and neural network parameters were carried out from the point of view of the most accurate and fast recognition and classification of patterns on multi-channel EEGs associated with the imagination of movements. The influence of the number and choice of the analyzed channels of a multichannel EEG on the quality of recognition of imaginary movements was also studied, and optimal configurations of electrode arrangements were obtained. The effect of pre-processing of EEG signals is analyzed from the point of view of improving the accuracy of recognition of imaginary movements.

Keywords: Neural networks, brain-computer interface, electroencephalograms, EEG signals analysis, brain activity, multilayer perceptron, radial basis function

1. INTRODUCTION

The development of methods for recognizing human brain activity associated with exercise and with the imagination of movements is fundamentally necessary for the development of brain-computer interfaces that are in demand in many areas of science and technology, particularly in medicine, industry, high-tech, etc.[1–3] The most vivid examples of the possible application of brain-computer interfaces are: rehabilitation of patients with limited motor functions, improving the quality of life of people with disabilities, "mental" control of exoskeletons, manipulators, robots and other complex technical devices,[4,5] improving the quality of the learning process by using the brain-computer interface with biological feedback, etc.[6,7]

A number of recent studies conducted with trained subjects show that the problem of identifying patterns of brain activity associated with movements can be solved by analyzing multichannel electroencephalograms (EEGs),[8,9] less often – magnetoencephalograms (MEGs), using various mathematical methods. At present, the following approaches are used most often for this purpose: methods based on the allocation of the time-frequency structure of the signals,[10–12] methods of reconstructing connections between different regions of the brain based on multichannel data,[13] methods of nonlinear dynamics,[14–16] methods of machine learning and artificial intelligence.[17,18] Among the latter, the most promising are methods based on the use of artificial neural networks (ANNs). Indeed, ANNs are currently a very effective tool for analyzing a variety of data and therefore are widely used in various fields of science and technology.[19] However, for their successful use, it is important to select the optimal neural network parameters from the point of view of the most accurate and fast recognition and classification of data.[20,21]

It is important to note that the solution to the above problem of the classification of brain activity patterns during imaginary movements in the case of working with *untrained* subjects is much more complex, important

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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, 107171J · © 2018 SPIE · CCC code: 1605-7422/18/$18 · doi: 10.1117/12.2315161

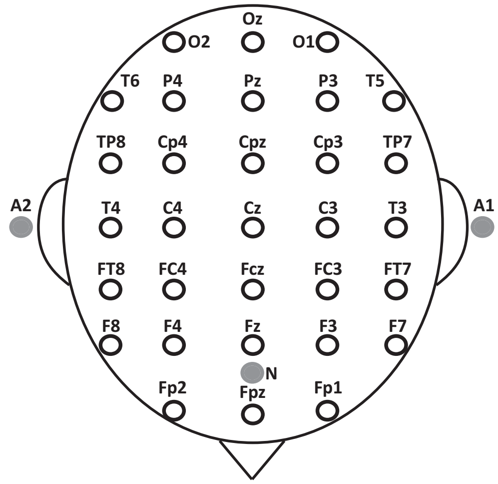

Figure 1. Scheme of electrodes arrangement "10-10" with notations

and little-studied issue.[22] The use of existing algorithms for untrained subjects is usually ineffective due to noise, EEG nonstationarity, and strong variability of characteristics among a group of subjects.[23]

In the present paper, based on the apparatus of artificial neural networks, a technique for recognizing and classifying patterns corresponding to imaginary movements on electroencephalograms obtained from a group of untrained subjects consisting of 12 people was developed. For this purpose, the works on the selection of the optimal type, topology, training algorithms and neural network parameters were carried out from the point of view of the most accurate and fast recognition and classification of patterns on multi-channel EEGs associated with the imagination of movements. The following most popular types of ANNs[19, 24–27] were considered: a linear network (LN), a multilayer perceptron (MP), and a radial basis function (RBF).

Note, it is important to separate the imaginary movements of the left and right arms and legs for the organization of the brain-computer interface to control the elements of the exoskeleton. This work is devoted to solving the problem of classification of legs imaginary movements. In the case of controlling an exoskeleton or an anthropomorphic robot, this channel is of great interest.

The influence of the number and choice of the analyzed channels of the multichannel EEG (used recording electrodes) on the quality of recognition of imaginary movements was also studied and optimum configurations of the electrode arrangements were obtained. The relevance of such a problem is due to the practical significance of finding such a configuration of the arrangements with a minimum number of electrodes that would provide the required recognition accuracy.

The effect of pre-processing of EEG signals (filtration, change of the used interval) from the point of view of improving the accuracy of recognition of imaginary movements is analyzed.

The studies carried out in this work are important not only from the applied, but also from the fundamental point of view. They will allow to advance in understanding complex mechanisms of brain functioning and processes occurring in it.

2. DESCRIPTION OF THE EXPERIMENT

Twelve healthy volunteers (men and women) aged 20 to 43 participated in the experiment. During the experiments, multichannel EEGs from 31 electrodes were taken with the help of the Encephalan-EEGR-19/26 electroencephalograph (Taganrog, Russia) and recorded at a sampling frequency of 250 Hz. Electrodes were placed according to the international scheme "10-10" (Fig. 1).

Each subject participated in one experiment lasting approximately 30 minutes, during which he performed two types of tasks: I – imaginary movement with the left leg (raising the leg in the thigh) or II – imaginary

Name of the zone (group)	**Channels**
Full	Fpz, Fp_1, Fp_2, Fz, F_3, F_4, F_7, F_8, FCz, FC_3, FC_4, FT_7, FT_8, T_3, T_4, T_5, T_6, CPz, CP_3, CP_4, TP_7, TP_8, Pz, P_3, P_4, Cz, C_3, C_4, Oz, O_1, O_2
Forehead (Fp+F)	Fpz, Fp_1, Fp_2, Fz, F_3, F_4, F_7, F_8
T	T_3, T_4, T_5, T_6
C	Cz, C_3, C_4
C+T	T_3, T_4, T_5, T_6, Cz, C_3, C_4
P	Pz, P_3, P_4
P+C	Pz, P_3, P_4, Cz, C_3, C_4
P+O	Pz, P_3, P_4, Oz, O_1, O_2
P+C+O	Pz, P_3, P_4, Cz, C_3, C_4, Oz, O_1, O_2
Right Brain (RB)	Fp_2, F_4, F_8, FC_4, FT_8, T_4, T_6, CP_4, TP_8, P_4, C_4, O_2
Left Brain (LB)	Fp_1, F_3, F_7, FC_3, FT_7, T_3, T_5, CP_3, TP_7, P_3, C_3, O_1
Middle	Fpz, Fz, FCz, Cz, CPz, Pz, Oz
Fp+F+T	Fpz, Fp_1, Fp_2, Fz, F_3, F_4, F_7, F_8, T_3, T_4, T_5, T_6

Table 1. The zones on the electrode arrangement “10-10” with the details of the used channels (electrodes) in each zone.

movement with the right leg. The experiment consisted of 10 sessions, in half of which the subject performed tasks I, and in the other half - tasks II (20 repetitions of the task per session). Session II followed after each session I. Execution of each task in the sessions preceded by the sound signal, after which the subject had to perform the task within 4 seconds. Between the sessions there were small breaks (about 2 minutes), during which time quiet music played. The experiments took place in the first half of the day in a specially equipped laboratory, in which the influence of external stimuli was minimized.

Further analysis based on the apparatus of ANNs was carried out on a personal computer in the Matlab package with respect to the recorded signals of multi-channel EEGs, using either all channels at once (31 channels) or channels corresponding to different zones on the head. All the zones considered in the work with the details of the channels (electrodes) used in each zone are given in Table 1.

3. COMPUTATIONAL EXPERIMENT AND RESULTS

A series of computational experiments on the classification of imaginary movements of the left and right legs by the EEG signals corresponding to these movements was carried out on the PC. To this end, continuously recorded during one experiment realizations from the selected EEG channels (for one subject) were “cut” into segments (fragments) of a given duration $T_f = 2.5\,\mathrm{s}$ or $T_f = 3\,\mathrm{s}$, each containing one movement event. Classification was performed using ANNs with direct signal propagation, trained with the teacher on algorithms with back propagation of error. In the process of classification, the quality of recognition of ANNs of different architectures and types was compared: LN, MP and RBF.

The choice of data plays an important role in the training and use of neural networks. In this study, we used for training and testing of ANNs data sets containing 6000 points (24 seconds of recorded data), one of which corresponded to imaginary movements with the left leg, and the other — to imaginary movements with the right leg. Data sets consisted of pre-prepared 3- or 2.5-second fragments of EEG signals corresponding to one kind of imaginary movement. Half of the data set, chosen at random, was used to train the ANNs; the remaining half — for the control and test samples (in the ratio of 50% to 50%).

Studies on optimization of ANNs structures and parameters from the point of view of the most accurate and fast recognition and classification of EEG patterns corresponding to imaginary movements have shown that the best results can be achieved by using:

- RBF network with 251 neurons in the intermediate layer, 31 input and 1 output linear neurons;
- MP with one hidden layer of 15 neurons with the activation function in the form of a hyperbolic tangent, an input linear layer of 31 neurons and 1 output neuron with a logistic activation function;

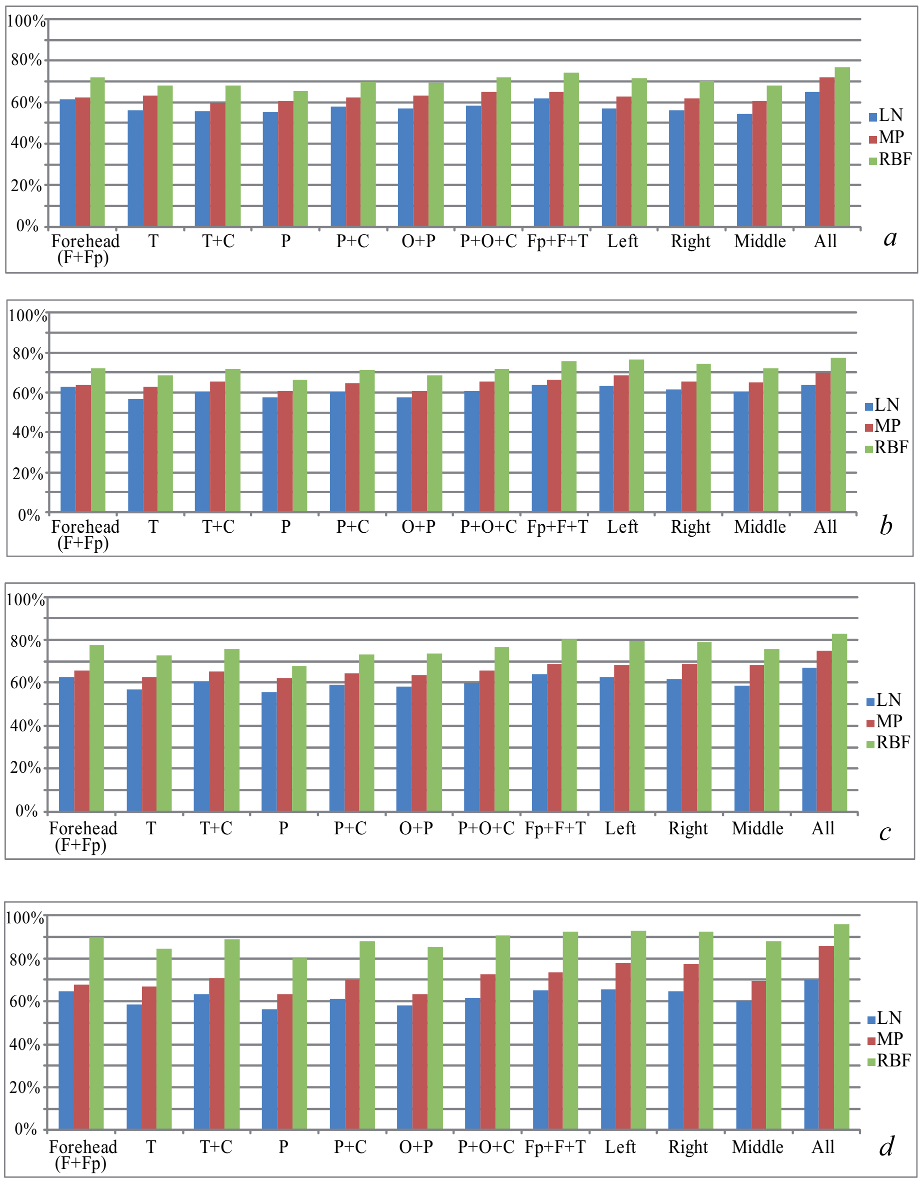

Figure 2. Averaged over all subjects accuracy (quality) of recognizing imaginary leg movements for different electrode groups (see Table 1), which are marked on the horizontal axis. Different colors correspond to different ANNs (as shown in the pictures on the right). Figure a corresponds to the case of the duration of the used fragments $T_f = 3\,\mathrm{s}$ and the absence of pre-filtering of the input data; figure b – $T_f = 2.5\,\mathrm{s}$; figure c – $T_f = 3\,\mathrm{s}$, a low-pass filter with $f_c = 15\,\mathrm{Hz}$ is applied to the input data; figure d – $T_f = 3\,\mathrm{s}$, a low-pass filter with $f_c = 4\,\mathrm{Hz}$ is applied to the input data

Now consider the results of pattern recognition on the EEG corresponding to imaginary movements of the left and right legs, using the selected trained ANNs (see Fig. 2). In the figures, averaged over all subjects accuracy of recognizing the imaginary movements of the legs is shown for different electrode groups from Table 1. It can be seen that the best results of the classification demonstrates RBF network: in cases without pre-filtering (Figs. 2*a* and *b*) – about 80% at the maximum (with the use of signals from all the electrodes) and 70% on average. MP is on the second place: about 70% at the maximum and 65% on average (see Figs. 2*a* and *b*). LN shows an uncertain recognition with an average accuracy of 58%. Comparison of Figs. 2*a* and *b* corresponding to different values of the duration T_f of the used fragments shows that this parameter does not significantly affect the recognition accuracy.

We investigated the effect of pre-filtering of EEG signals using a low-pass filter (LPF) with a cutoff frequency $f_c = 15\,\mathrm{Hz}$ or $f_c = 4\,\mathrm{Hz}$. Figs. 2*c* and *d* show that pre-filtering of the input data using a LPF significantly increases the recognition accuracy (on average by 10-20%), while the LPF with $f_c = 4\,\mathrm{Hz}$ shows the best results and allows to obtain a recognition accuracy up to 95%. From a physical point of view, the last result means that cleaning with a LPF the useful low-frequency signal from the high-frequency noise that appears when recording EEG signals allows to improve the quality of recognition.

It is important to note that it is possible to achieve the necessary recognition accuracy without the use of signals from all electrodes. For example, when using signals from electrodes from groups Fp+F+T (12 electrodes), P+O+C (9 electrodes), P+C (6 electrodes), T+C (7 electrodes) or Forehead (F+Fp, 8 electrodes) (see Fig. 2*d*), the recognition accuracy reaches 90%. Thus, the use of only 6-12 electrodes from certain zones makes it possible to achieve almost the same classification accuracy as with all (31) electrodes.

4. CONCLUSION

We have shown that the developed technique based on the apparatus of artificial neural networks for recognizing and classifying patterns on EEGs corresponding to imaginary movements demonstrated high efficiency for untrained subjects: recognition accuracy up to 95%. The RBF network shows the best recognition results. Pre-filtering of the input EEG data using the low-pass filter significantly increases the recognition accuracy (on average by 10–20%), while the low-pass filter with a cutoff frequency $f_c = 4\,\mathrm{Hz}$ shows better results than the low-pass filter with $f_c = 15\,\mathrm{Hz}$. We have demonstrated that when using signals from certain groups of electrodes (Fp+F+T, P+O+C, P+C, T+C or F+Fp) consisting of 6-12 channels, the classification accuracy reaches a value close to the maximum. The last result is important from a practical point of view, because it shows the possibility of using more compact systems for EEG signals registration (with fewer electrodes) while maintaining the required recognition accuracy.

5. ACKNOWLEDGMENTS

This work has been supported by the Ministry of Education and Science of Russia (Project 3.861.2017/4.6) in the part of experimental studies and by the Council of the President of the Russian Federation for Support of Young Scientists and Leading Scientific Schools (Grant NSh-2737.2018.2) in the part of theoretical investigations.

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