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Artificial intelligence systems for classifying EEG responses to imaginary and real movements of operators

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ABSTRACT

Here, we introduce the method based on artificial neural networks (ANNs) for recognition and classification of patterns in electroencephalograms (EEGs) associated with imaginary and real movements of untrained volunteers. In order to get the fastest and the most accurate classification performance of multichannel motor imagery EEG-patterns, we propose our approach to selection of appropriate type, topology, learning algorithm and other parameters of neural network. We considered linear neural network, multilayer perceptron, radial basis function network (RBFN) and support vector machine. We revealed that appropriate quality of recognition can be obtained by using particular groups of electrodes according to extended international 10−10 system. Besides, pre-processing of EEGs by low-pass filter can significantly increase the classification performance. We developed mathematical model based on ANN for classification of EEG-patterns corresponding to imaginary or real movements, which demonstrated high efficiency for untrained subjects. Achieved recognition accuracy of movements was up to 90−95% for group of subjects. RBFN demonstrated more accurate classification performance in both cases. Pre-filtering of input data using low-pass filter significantly increases recognition accuracy on 10−20% in average, and the low-pass filter with cutoff frequency 4 Hz shows the best results. It was revealed that using different sets of electrodes placed on different brain areas and consisted of 6-12 channels, one can achieve close to maximal classification accuracy. It is convenient to use electrodes on frontal and temporal lobes for real movements, and several sets containing 6-9 electrodes — in case with imagery movements.

Keywords: artificial neural network, electroencephalographic patterns, EEG analysis, motor imagery, brainwaves, patterns recognition, brain-computer interfaces

1. INTRODUCTION

Among existing approaches for EEG data analysis (e.g., time-frequency analysis [1], methods of nonlinear dynamics [2], etc.), the most promising and effective tools for classification of single EEG trials are based on artificial neural networks (ANNs) [3,4,5]. The successful application of ANNs requires careful selection of their parameters, which can significantly vary depending on a task and different subjects [6]. Therefore, the optimization of EEG input data (dimensionality reduction, filtering, etc.) and channel selection is one of the key problems for the development of efficient ANN-based BCIs. Traditional methods of dimensionality reduction include principal component analysis (PCA) and linear discriminant analysis (LDA), where the original features are mathematically projected onto a lower-dimensional space. However, such methods are non-generic and require the input data optimization for every subject due to strong inter-subject variability [7] and a lack of association of on-going optimization with physiological processes in the brain. These problems are particularly relevant for untrained subjects [7] and create difficulties for the development of a universal BCI.

Currently, one of the most important tasks in neuroscience and neurotechnology is the development of effective and universal methods for optimizing input data, in particular, by reducing signal complexity, for further processing with ANNs. A promising approach to solving this problem is the optimization of the input data set based on the knowledge of the laws of the processes occurring in the brain when making some action, such as motor imagery. The simplest and intuitively clear method for the feature space reduction is a decrease of the number of EEG channels, basing on the time-frequency analysis. In general, the analysis of the time-frequency structure of multichannel EEG allows the brain areas detection, where a significant increase or a decrease in the energy of particular brain rhythms reflects motor activity or motor imagery (event-related synchronization/ desynchronization) [8].

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Thus, in this paper we focus on the development of an efficient classification algorithm. It should be noted, that in the case of supervised learning algorithms, the classification performance strongly depends on the dataset used for training. The training dataset must be balanced and representative to provide a good generalization ability of ANN. Here, we propose an approach for optimization of input dataset based on the high-pass filtration of input EEG data with different cut-off values and the selection of particular EEG channels, with the aim to detect the most effective spatial EEG configuration to obtain maximum classification accuracy. At the same time, it is known that different types of human activity cause responses in different cortical areas. Therefore, the second aim is to study the influence of the number of analyzed EEG channels (or electrodes) on the quality of leg motor imagery recognition and the optimization of the electrodes selection.

It should be noted, that the considering development of the methods for EEG patterns recognition associated with imaginary leg movements is of crucial importance for creation of BCIs which would help in therapy of patients with various motor disorders after trauma or stroke by using prostheses, exoskeletons or anthropomorphic robots.

2. MATERIALS AND METHODS

The main part of experimental work involved 12 subjects, both males (8 persons) and females (4 persons). The volunteers were informed about the importance of a full night rest for good experimental data and results quality. Our studies were organized until 2 p.m. with natural lighting. The experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local research Ethics Committee.

The posture of all subjects was verified and remained almost unchanged during all work. They sat on a comfortable special armchair, with both legs without shoes lying straight on stand and arms lying on the armrests. At the first experiment stage, the EEG of a passive wakefulness state was recorded. It consisted of 3-min EEG recording with open eyes, 3 minutes with closed eyes, and 4 minutes in a convenient state for the test condition. During this 10-min recording time, we recommended, if possible, to abstain from all conscious motor activity. At the second experimental stage, the subjects performed tasks according to text commands appeared on the screen. Each subject participated in one experiment lasting about 30 minutes during which he/she had to perform two types of tasks:

i. Real movement of left/right leg (raising a leg in a hip);

ii. Imaginary movement of left/right leg.

Each task proceeded by a whistle signal and followed by pauses of random durations (5-10 seconds). Thus, the second stage included two types of real and two types of imaginary movements, in particular, real movements of legs, both left and right, and imaginary movements of the same limbs. After the tasks were completed, the EEG of the passive wakefulness state was recorded during 5 minutes.

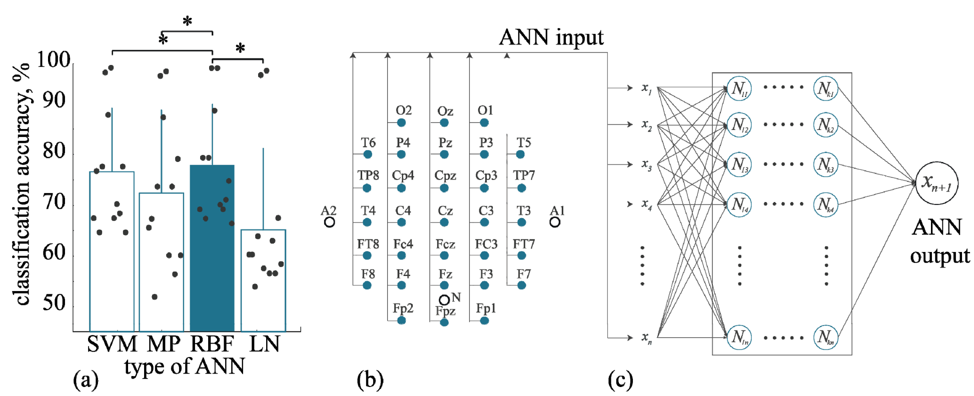

Figure 1. (a) Classification accuracies for support vector machines (SVM), multilayer perceptron (MP), radial basis function (RBF), and linear network (LN) averaged over all subjects; (b) position of electrodes according to extended 10-10 international system on human head; (c) general model of ANN, where each input neuron x_i ($i = 1,2,\dots,n$) receives data from one of $n = 31$ electrodes, N_{li}, N_{ki} are neurons of hidden layers, and x_{n+1} is output neuron.

The multichannel EEG were recorded at a 250-Hz sampling rate from P = 31 electrodes with two reference electrodes placed at the standard ears positions of the extended 10–10 international system (see Fig. 1 (b)) [9]. To register the EEG data, we used a cup with Ag/AgCl electrodes placed on the "TIEN–20" paste. Immediately before placing the electrodes, the head skin was rubbed with abrasive gel "NuPrep" for increasing skip conductivity. The EEGs were recorded with the electroencephalograph "BE Plus LTM" (EB Neuro SPA).

Training and testing of the ANN were performed for every subject using two datasets containing 6000 points each (24 seconds of recorded EEG) for movements of the left and right feet. Each dataset consisted of the combination of eight 3-s EEG trials corresponding to a particular movement for every subject. Half of the datasets, chosen at random, were used to train the ANN, and the remaining half to test it. The classification was carried out with the help of ANN trained on back propagation algorithms. For each subject, the ANN training process was carried out anew.

The ANN initial parameters were chosen taking into account the following considerations. The number of ANN inputs was equal to the number of EEG channels. The number of neurons in the output layer was one, because the output can only be 0 or 1. Initially, the minimum number of neurons in the hidden layer was chosen to be 5. Further training of such a network was conducted by monitoring the control error and verifying the classification result to reduce the error. If the control error decreased as compared with the previous step, the number of neurons in the hidden layer was increased, and the above procedure was repeated. This was done until both the training and the control errors saturated at low enough values, which barely decreased when more neurons were added to the hidden layer.

The recorded data were low-pass filtered with cut-offs at f_c^1 = 4 Hz and f_c^2 = 15 Hz. Table 1 contains detailed information about each channel combination according to the channels' position on the human head (see also Fig. 1 (b)).

Table 1. Channels configuration in 10-10 international electrode scheme with corresponding brain areas.

Brain area	**Used channels**	**Designation**
Full placement (*FP*)	Fp_z, 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	S_1
Right hemisphere (RH)	Pz, P_3, P_4, Cz, C_3, C_4, Oz, O_1, O_2	S_2
Left hemisphere (LH)	Fp_2, F_4, F_8, FC_4, FT_8, T_4, T_6, CP_4, TP_8, P_4, C_4, O_2	S_3
Parietal, occipital and central lobes (*P+O+C*)	Pz, P_3, P_4, Cz, C_3, C_4, Oz, O_1, O_2	S_4
Frontal and temporal lobes (F_P+*F*+*T*)	Fp_z, Fp_1, Fp_2, Fz, F_3, F_4, F_7, F_8, T_3, T_4, T_5, T_6	S_5
Parietal and occipital lobes (*P+O*)	Pz, P_3, P_4, Oz, O_1, O_2	S_6
Parietal and central lobes (*P+C*)	Pz, P_3, P_4, Cz, C_3, C_4	S_7
Central and temporal lobes (*C+T*)	Cz, C_3, C_4, T_3, T_4, T_5, T_6	S_8
Frontal lobe (*F*+F_P)	Fpz, Fp_1, Fp_2, Fz, F_3, F_4, F_7, F_8	S_9
Temporal lobe (*T*)	T_3, T_4, T_5, T_6	S_{10}
Central lobe (*C*)	Cz, C_3, C_4	S_{11}
Parietal lobe (*P*)	Pz, P_3, P_4	S_{13}
Middle	Fp_1, F_3, F_7, FC_3, FT_7, T_3, T_5, CP_3, TP_7, P_3, C_3, O_1	S_{14}

In the present paper, we analyze different types of ANNs in order to reveal most convenient configurations. Here, we implement machine learning algorithms for the analysis of multichannel EEG signals, designed on the base of the Matlab package containing ANN methods.

The conducted analysis revealed that the fastest and accurate recognition of motor EEG patterns can be achieved with the following ANN configurations:

- Radial basis function (RBF) network with 251 neurons in hidden layer, 31 input and 1 output linear neurons.
- Multilayer perceptron (MLP) with one hidden layer consisted of 15 neurons with hyperbolic tangent as an activation function, 31 input linear neurons and one output neuron with logistic activation function.

• Support vector machine (SVM-RBF) with nonlinear kernel based on radial basis function with values $0.01 < \gamma < 0.1$ and 2000 support vectors in summary (1000 for each class).

We also used a linear network (LN) for more representative results which demonstrated how the ANN operated with complex nonlinear data. The LN is the simplest model which consists of one input layer and one output layer with a linear activation function.

3. RESULTS

In our study, EEG signals were obtained from 12 subjects via the set of 31 recording electrodes. At the first stage, the ANN input was presented in a vector form of N = 31 dimension ($x_1,\ldots,x_N$) (see Fig. 1 (c)). The EEG trials were classified into two groups (left-leg imagery and right-leg imagery) with the help of ANNs with different configurations: SVM, MP, RBF, LN.

In Fig. 1 (a), the classification accuracy of each network was calculated for all 31 EEG channel. The data were averaged over all subjects and shown as mean ± SD. One can see that network of linear neurons did not exhibit significant performance with accuracy less than 65% for most subjects. At the same time, the results obtained for SVM, RBF and MLP demonstrated averaged classification accuracy of 76.5%, 77.9% and 72.4%, respectively. Having compared these ANN architectures, one can find RBF to be the most optimal architecture, which classification accuracy significantly exceeded the accuracy rates of both SVM and MLP ($n = 12$, $*p > 0.05$ via paired-sample t-test).

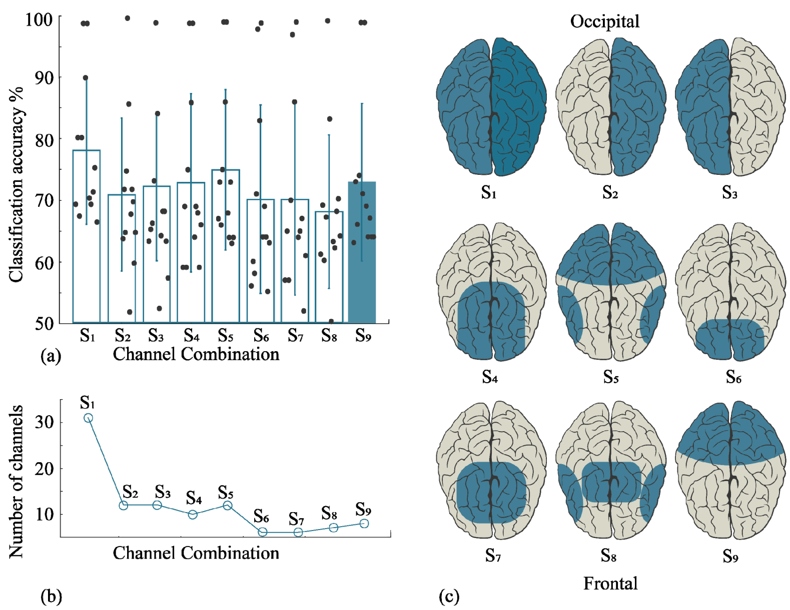

Figure 2. (a) Radial basis function (RBF) classification performance for different brain areas, averaged over all subjects; (b) number of channels in each combination S_i ($i = 1..9$). For detailed information about combinations, see Table 1; (c) brain areas used for motor imagery classification.

The demonstrated accuracy score of 77.9% was achieved for a non-optimized input, i.e., for the whole set of EEG channels containing oscillations in a wide frequency range. However, previous studies show that if one takes into account all possible features of a multichannel EEG for the classification task, the results have an extremely high-dimensional feature space that significantly increases input complexity and decreases the accuracy rate. According to this observation, here we propose to decrease the input feature space basing on spatial and frequency representations of the motor-related EEG. In order to reduce the number of EEG channels, we analyze the RBF-based accuracy rate obtained for different predefined sets of channels (see Table 1). Having compared the results of such classification, we optimize the channels' combination to obtain satisfactory classification accuracy using a small number of electrodes.

In Fig. 2 (a), the values of classification accuracy are shown for 9 most representative configurations (see Table 1 for the description of all considered configurations). Figure 2 (b) shows the number of the channels belonging to each configuration. In Fig. 2 (c), the marked brain areas show the regions where the recording electrodes are located. One can see that the most accurate result is obtained using combination S_1 which corresponds to full placement (31 electrodes) (see Fig. 2 (a)). At the same time, despite the best recognition performance, we cannot consider this combination as optimal due to a large number of channels (see Fig. 2 (b)).

The recognition in right and left hemispheres (S_2 and S_3, respectively) does not show significant results. The reason of poor performance of RBF in these areas can be the fact that motor imagery causes the response in remote brain areas, thus the best recognition score can be obtained using the combination of the electrodes which location is capable to catch this interaction. With this aim, we consider S_5 corresponding to the combination of frontal and temporal lobes (F+Fp+T). One can see that among other channels' combinations (except for S_1), S_5 provides the best recognition quality.

One can see that frontal lobe covers the largest brain area, and its combination with temporal lobes still contains too many electrodes. Considering these areas separately, we can note S_9 as the most appropriate choice due to a smaller number of channels (8 electrodes versus 12 in S_5) and about the same level of the classification score. It should be noted that frontal lobe is strongly associated with motor activity (e.g., walking), decision-making and many others important cognitive and emotional aspects [10,11]. This result is in agreement with the previous research [8,12], where the time-frequency analysis revealed highly pronounced arm's motor imagery events in event-related desynchronization of delta band in frontal cortex.

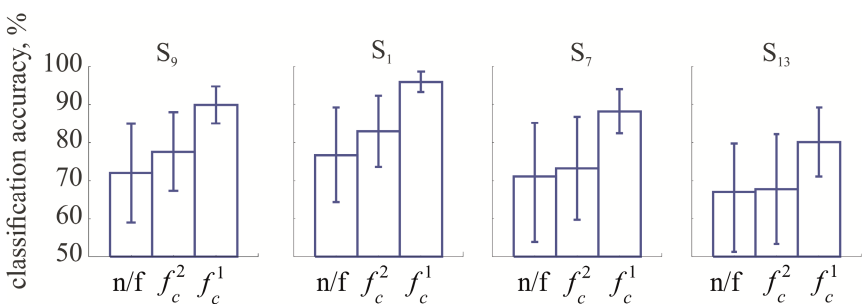

Figure 3. RBF network classification performance for different brain areas and different filtrations applied to input EEG (n/f – without filtration, f_c^2 – spectral components above 15 Hz are removed, f_c^1 – spectral components above 4 Hz are removed). The data are averaged over all subjects.

Such features of the time-frequency EEG structure affect the ANN performance. In Fig. 3, the histograms show classification accuracy (mean ± SD) achieved via the RBF network for different types of input EEG: (nonfiltered EEG, filtered with cutoffs at f_c^1 = 4 Hz and f_c^1= 15 Hz). One can see that in the case of 31 EEG channels (S_1), the exclusion of spectral components above 15 Hz leads to an increase of classification accuracy (from 76% to 82%). Instead, in the case of smaller number of channels, an increase of classification accuracy for 15-Hz filtration becomes smaller (from 73% to 77% for frontal EEG (S_9) and from 70% to 73% for parietal and central EEG (S_7)). For the case of parietal EEG, where the analysis of wavelet energy averaged over 8-12 Hz does not reflect changes between left- and right-hand movements, the f_c^1 filtration does not lead to an increase of classification accuracy. Having considered the classification accuracy obtained for EEG filtered with cut-offs at f_c^1 = 4 Hz (i.e., spectral components above 4 Hz are excluded), one can see a further increase of classification accuracy for all channel combinations.

The obtained results evidence the correlation between the performance of ANN-based classification and features of EEG signals in both spatial and frequency domains. The extraction of such features by analyzing EEG in group of participants and its use for pre-processing input data allow a significant increase (from 72% to 90% for frontal EEG) (n = 12, *p < 0.01 via paired-sample t-test) the classification accuracy of single EEG trials in all subjects in the group.

4. CONCLUSIONS

We have applied artificial neural networks for recognition and classification of single EEG-trials associated with right- and left-leg motor imagery in untrained volunteers. By focusing on optimization of classification accuracy, we have reduced complexity of input data. In the context of optimization, we have made the optimal selection of both a set of EEG channels and a frequency band with the help of preliminary analysis of spatio-temporal and time-frequency EEG features that allowed us to reach up to 90±5% classification accuracy using 8 electrodes only. We have compared our results with the results recently obtained using other optimization algorithms (e.g., genetic algorithm, common spatial pattern optimization, and filtering method) and shown that our approach (i) yields higher accuracy than other methods and (ii) is valid for all subjects and, therefore, the accuracy is not affected by individual features variability. The developed method is universal because its accuracy is almost independent of the subject's personality. We believe that our approach can be used to increase efficiency of brain-computer interfaces (BCIs) designed for untrained subjects or a group of subjects.

5. ACKNOWLEDGMENTS

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