Approaches for the Improvement of Motor-Related Patterns Classification in EEG Signals

Semen Kurkin
Neuroscience and Cognitive Techology Lab, Center for Technologies in Robotics and Mechatronics Components
Innopolis University
Innopolis, Russia
kurkinsa@gmail.com

Vladimir Maksimenko
Neuroscience and Cognitive Techology Lab, Center for Technologies in Robotics and Mechatronics Components
Innopolis University
Innopolis, Russia
maximenkovl@gmail.com

Elena Pitsik
Neuroscience and Cognitive Techology Lab, Center for Technologies in Robotics and Mechatronics Components
Innopolis University
Innopolis, Russia
pitsikelena@gmail.com

***Abstract*—We apply artificial neural network (ANN) for recognition and classification of electroencephalographic (EEG) patterns associated with motor imagery for untrained subjects. Classification accuracy is optimized by reducing complexity of input experimental data. For multichannel EEG recorded by the set of 31 electrodes, we select an appropriate type of ANN which reaches 80±10% accuracy for single trial classification. We analyze the time-frequency structure of EEG signals and find that motor-related features associated with left- and right-leg motor imagery, are more pronounced in the mu (8-13 Hz) and delta (1-5 Hz) brainwaves. Based on the obtained results, we propose the optimization approach by pre-processing the EEG signals with a low-pass filter with different cutoffs. We demonstrate that the filtration of high-frequency spectral components significantly enhances the classification performance: up to 90±5% using 8 electrodes only.**

Keywords—EEG analysis, motor-related patterns, artificial neural network, classification accuracy

I. Introduction

EEG is a wide-spread inexpensive method for brain research which gives a deep insight into brain functionality related to various human activities. However, the treatment of multichannel EEG signals is a very sophisticated task because they are non-stationary, high-dimensional and extremely noisy. All these factors make difficult the recognition and classification of specific motor-related or percept-related patterns in a single-trial mode [1, 2] and require extensive statistical measures.

Among existing approaches for EEG data analysis, the most promising and effective tools for classification of single EEG trials are based on artificial neural networks (ANNs) [3]. The successful application of ANNs requires careful selection of their parameters which can significantly vary depending on a particular task and different subjects [4]. The optimization of EEG input data and channel selection are key problems for the development of efficient ANN-based brain-computer interfaces (BCIs). Traditional methods of dimensionality reduction include principal component analysis (PCA) and linear discriminant analysis (LDA). However, such methods are non-generic and require the input data optimization for every subject due to strong inter-subject variability [5] and a lack of association of on-going optimization with physiological processes in the brain. These problems are particularly relevant for untrained subjects [5, 6]. Indeed, many BCI studies involve specially trained subjects, since the classification of brain activity patterns during motor imagery of untrained subjects is significantly more difficult and hence poorly studied [7, 8].

A promising approach to solving the above problems 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.

Here, we propose an approach for optimization of input dataset based on the low-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.

II. Experiment and Methods

A. Design of the Experiment

The main part of experimental work involved 12 subjects, both males (8 persons) and females (4 persons). Each subject participated in one experiment lasting about 30 minutes during which he/she had to perform two types of tasks: 1) real movement of left/right leg (raising a leg in a hip); 2) imaginary movement of left/right leg. The real movements in the first task were performed in order to make the subjects clearer how exactly they should imagine the movement by performing the second task. Each task proceeded by a whistle signal and followed by pauses of random durations (5-10 seconds).

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. To register the EEG data, we used a cup with Ag/AgCl electrodes placed on the "TIEN–20" paste. The EEGs were recorded with the electroencephalograph "BE Plus LTM".

B. ANNs Application

Training and testing of the ANN were performed for every subject using two datasets containing 6000 points each for imaginary movements of the left and right feet. Each dataset consisted of the combination of eight 3-s EEG trials. Half of the datasets, chosen at random, were used to train the ANN based on backpropagation algorithm, and the remaining half – to test it. For each subject, the ANN training process was carried out anew. The number of ANN inputs was equal to the number of used EEG channels. Different combinations of used channels were considered in this research. The number of neurons in the output layer was one, because the output can only be 0 or 1. The recorded data were low-pass filtered with cut-offs at f_c^1=4 Hz or f_c^2=15 Hz.

The fastest and accurate recognition of motor imagery EEG patterns can be achieved with the following machine learning approaches: 1. radial basis function (RBF) network with 251 neurons in hidden layer, 31 input and 1 output linear neurons; 2. 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; 3. 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). A linear network (LN) was applied for more representative results.

III. Results

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. 1a, the classification accuracy of each network was calculated for all 31 EEG channel.

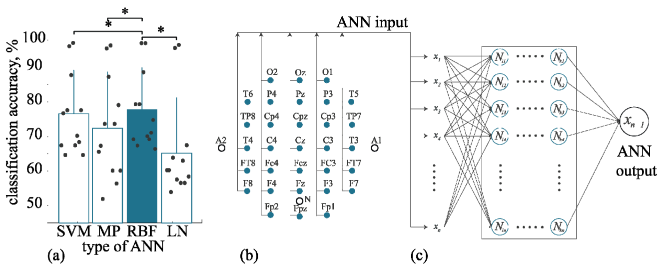

Fig. 1. (a) Classification accuracies (mean values ± SD) for SVM, MP, RBF, and LN averaged over all subjects; (b) position of electrodes according to extended 10-10 international system on human head; (c) general model of ANN, where each input neuron receives data from one of electrodes.

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). 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.

In order to reduce the number of EEG channels, we analyze the RBF-based accuracy rate obtained for different predefined sets of channels. In Fig. 2a, the values of classification accuracy are shown for 9 most representative configurations. One can see that the most accurate result is obtained using combination S_1 which corresponds to full placement (31 electrodes) (see Fig. 2a). 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. 2b). Let us consider S_5 corresponding to the combination of frontal and temporal lobes. One can see that among others channels' combinations (except for S_1), S_5 provides the best recognition quality.

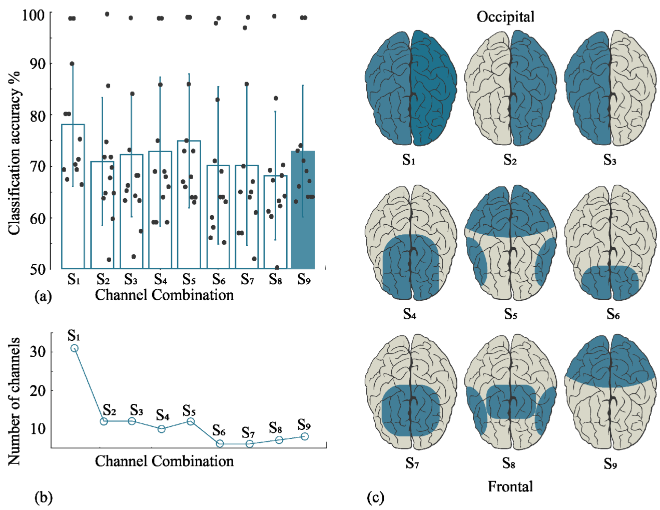

Fig. 2. (a) RBF classification performance for different brain areas, averaged over all subjects; (b) number of channels in each combination S_i (i = 1..9); (c) brain areas used for motor imagery classification.

The 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, decision-making and many others important cognitive and emotional aspects [9, 10]. This result is in agreement with the previous research [10-13], where the time-frequency analysis revealed highly pronounced arm's motor imagery events in event-related desynchronization of delta band in frontal cortex.

So, by focusing on optimization of classification accuracy, we have reduced complexity of input data [14]. In the context of optimization, we have made the optimal selection of a set of EEG channels. The obtained results can be used to increase efficiency of brain-computer interfaces designed for untrained subjects or a group of subjects.

Acknowledgment

This work was supported by the President Program (projects NSH-2737.2018.2) and Russian Foundation for Basic Research (Project 16-29-08221).

References

[1] V.A. Maksimenko, A.E. Runnova, M.O. Zhuravlev, et al. "Visual perception affected by motivation and alertness controlled by a noninvasive brain-computer interface," PLoS ONE, vol. 12, No. e0188700, 2017.

[2] A.E. Hramov, V.A. Maksimenko, S.V. Pchelintseva, et al. "Classifying the perceptual interpretations of a bistable image using EEG and artificial neural networks," Frontiers in Neuroscience, vol. 11, 674, 2017.

[3] J. Yang, H. Singh, E.L. Hines, et al. "Channel selection and classification of electroencephalogram signals: an artificial neural network and genetic algorithm-based approach," Artificial Intelligence in Medicine, vol. 55, pp. 117–126, 2012.

[4] H. Bashashati, R.K. Ward, G.E. Birch, A. Bashashati. "Comparing different classifiers in sensory motor brain computer interfaces," PLoS ONE, vol. 10, No. e0129435, 2015.

[5] M.C.B. □berg, J. Wessberg. “Evolutionary optimization of classifiers and features for single-trial EEG discrimination,” Biomed. Eng. Online, vol. 6, No. 32, 2007.

[6] S. Kurkin, E. Pitsik, N. Frolov. "Artificial intelligence systems for classifying EEG responses to imaginary and real movements of operators," In Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, vol. 11067, International Society for Optics and Photonics, 2019, p. 1106709.

[7] V.A. Maksimenko, A. Pavlov, A.E. Runnova, et al. “Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects,” Nonlinear Dynamics, vol. 91, pp. 2803–2817, 2018.

[8] C. Parth, G. Niso, V.A. Maksimenko, et al. "Visual and kinesthetic modes affect motor imagery classification in untrained subjects," Scientific reports, vol. 9, No. 1, p. 9838, 2019.

[9] P. Pressman, H.J. Rosen, “Disorders of frontal lobe function,” in Neurobiology of Brain Disorders, Academic Press, San Diego, 2015, pp. 542–557.

[10] V.A. Maksimenko, A.E. Runnova, N.S. Frolov, et al. “Multiscale neural connectivity during human sensory processing in the brain,” Physical Review E, vol. 97, No. 5, p. 052405, 2018.

[11] V.V. Grubov, V.Yu. Musatov, V.A. Maksimenko, et al. “Development of intelligent system for classification of multiple human brain states corresponding to different real and imaginary movements,” Cybernetics and Physics, vol. 6, pp. 103–107, 2017.

[12] S. A. Kurkin, A. A. Koronovskii, A. E. Hramov, "Formation and dynamics of a virtual cathode in a tubular electron beam placed in a magnetic field," Technical Physics, V. 54, no. 10, p. 1520, 2009.

[13] S. A. Kurkin, A. E. Hramov, A. A. Koronovskii, “Nonlinear dynamics and chaotization of virtual cathode oscillations in annular electron beam in uniform magnetic field,” Plasma Phys. Rep, V. 35, no. 8, pp.628-642, 2009.

[14] V.A. Maksimenko, S.A. Kurkin, E.N. Pitsik. “Artificial neural network classification of motor-related eeg: An increase in classification accuracy by reducing signal complexity,” Complexity, vol. 2018, No. 9385947, 2018.