Artificial Neural Networks as a Tool for Recognition of Movements by Electroencephalograms

Semen A. Kurkin, Elena N. Pitsik, Vyacheslav Yu. Musatov,
Anastasia E. Runnova and Alexander E. Hramov
Research and Education Center "Artificial Intelligence Systems and Neurotechnology", Yuri Gagarin State Technical University of Saratov, 77 Politechnicheskaya str., Saratov, Russia
kurkinsa@gmail.com

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Abstract: Recognition of human brain activity associated with imaginary or real movements is a complex task that requires an accurate and conscious choice of analysis approach. Recent researches revealed the great potential of machine learning algorithms for electroencephalography data analysis due to the ability of these methods to establish nonlinear and nonstationary correlations, and the most attention is focused on artificial neural networks (ANNs). Here, we introduce the ANN-based method 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 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. Obtained results provide better insight on neural networks potential for integration in brain-computer interfaces that are based on EEG patterns recognition.

1 INTRODUCTION

Development of the recognition methods of human brain activity associated with imaginary or real movements is essential for brain-computer interfaces (BCIs), which are highly demanded in many fields of science and technology including medicine, high-tech and industry (Kawase et al., 2017; Spuler, 2017; Stacey and Litt, 2008). The most striking examples of possible application of BCIs are rehabilitation of patients with cognitive and motor disabilities, mental control of exoskeletons, manipulators, robots and other complex technical devices (Peternel et al., 2016), improving the education quality using BCI with biological feedback, etc.

Modern BCI systems require effective processing tools for EEG-patterns as a part of feedback mechanism. Here, we introduce the approach based on artificial neural networks. Indeed, application of neural networks for BCIs is actively studied issue in context of EEG-data recognition (Hamedi et al., 2014; Manor and Geva, 2015) due to a high efficiency and good recognition performance provided by these methods. In particular, we consider classification of real and imaginary movements of limbs by EEGs using different types of neural networks and various methods of training data representation (various channels selections and using of low-pass filter). Obtained results can be successfully used for development of BCI-based control systems for exoskeletons or anthropomorphic robots for therapy of patients with various motor disorders after trauma or stroke (Nam et al., 2018; Peternel et al., 2016).

2 METHODS

2.1 Experimental Setup

31-channel EEG was extracted during several sessions of carefully planned experiments with 12 volunteered participants, both male and female. All subjects were healthy and were not participating in any experimental work before, i.e. subjects were not trained for execution of imagery movements. Two types of experiments were carried out: the first corresponded to real movements, and the second — to the imagery. Each experiment was 30 minutes long and included two types of tasks: movement of left or right leg.

Two EEG-datasets corresponding, respectively, to right and left leg imagery movements were formed, each one containing 6000 samples. For ANN training, we used fragments of 3 or 2.5 seconds length. Each fragment was corresponding to one type of event. Whole dataset was divided into training and test parts in the ratio of 50% on 50% (Haykin, 2008).

Note, we collected also EEGs of real movements of the limbs to perform four-class recognition. Our goal was to obtain clear and stable classification that is appropriate for BCIs.

It is important to note that there are certain difficulties associated with EEG-data analysis extracted during experiments with untrained subjects. Recent studies revealed various advantages of BCI-training for analysis of activity associated with motor imagery: for example, evoked motor responses were larger for BCI-trained subjects (Mokienko et al., 2013; Dijkerman et al., 2004). Despite that, development of new methods of EEG-patterns recognition and classification of untrained subjects is essential for BCI-based neurologic rehabilitation therapy because of inability of patients to perform training (Jackson et al., 2001). So, current study is dedicated to development of ANN-based method that is able to perform accurate classification of imaginary and real movements by EEG of untrained subjects.

2.2 Machine Learning Methods

In present study, we used four types of neural network architectures, namely linear neural network, multilayer perceptron (MP), radial basis function (RBF) network and support vector machine. This subsection contains a short review of mathematical basis of these algorithms.

Neural networks are biologically inspired models that process input signal in the way the real neural network of the brain does. Classical neural network model consists of one input and one output layers and one or more hidden layers (see Fig. 1)

This model, in particular, corresponds to multilayer perceptron (Bishop, 1995; Carling, 1992; Fausett, 1994; Haykin, 2008). Elements with sigmoidal activation functions are organized in layered topology with forward signal transmission. This type

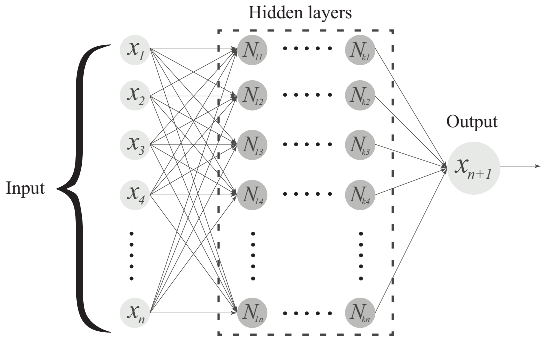

Figure 1: General model of artificial neural network.

of network can be interpreted as input–output model, where the weights and biases are free parameters. Such network can model the function of connection between inputs and outputs of almost any degree of complexity, and the number of layers and elements in each layer defines the complexity of the function.

The second network model that we considered was radial basis function network (RBFN). RBFN has a number of advantages over multilayer perceptron. First, RBFN models a random nonlinear function of connection between inputs and outputs, using only one hidden layer, which makes unnecessary the selection of number of layers. Second, parameters of linear combination in input layer can be completely optimized, using methods of linear modelling, which work fast and have no difficulties with local minima that interfere during multilayer perceptron training. Thus, RBFN trains much faster than multilayer perceptron.

On the other side, practical use of neural networks shows that RBFN requires more number of elements for correct modelling of functions, which means that RBF-based model will work slower and require more memory than corresponding MP. RBFN cannot extrapolate the conclusions beyond the area of known data. When the data is remote from the training set, the value of response function drops to zero quickly. On the contrary, MP provides more specific solutions for processing highly deviant data (Patterson, 1996; Ripley, 1996).

Along with the multilayer perceptron and RBFN, support vector machines (SVMs) are universal approximators used to solve classification problems. The idea of SVM is constructing a hyperplane that acts as the surface of solutions that maximally separates the different classes. SVM can provide good quality of generalization in classification task without a priori knowledge about subject area of particular issue. This feature is unique for SVM. According to this method, the point in space is considered as a vector of dimension p, and classifier is a hyperplane of dimension $p-1$, that divides points. The data can be classified using different hyperplanes, but the best one provides the best division between two classes.

Initially, SVM is a linear classifier, i.e. it can solve only linearly separable tasks. Applying nonlinear kernel, one can map initial data into the space of greater dimension, where an optimal separating hyperplane can exist. The following functions are often used as the kernel ones:

- Linear function: $K(x_i,x) = {x_i}^t x$
- Sigmoid: $K(x_i,x) = tanh(k(x_i,x)+c), k>0, c<0$
- Radial basis function: $K(x_i,x) = e^{-\gamma\|x_i-x\|^2}, \gamma>0$

During the analysis, we determined that the best results in accuracy and speed of recognition of EEG-patterns associated with motor or real imagery were achieved with next configurations:

- RBFN with 251 neurons in hidden layer with Gaussian activation function, 31 input and 1 output linear neurons;
- Multilayer perceptron 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;
- SVM with nonlinear kernel based on radial basis function with value $0.01<\gamma<0.1$.

All results describing below were obtained using presented configurations of neural networks. For greater representativeness we also used linear model, that consists only of the input and output layer and does not have any hidden layer. Such model is effective for establishing simple linear dependencies, but we studied it additionally in order to increase understanding of how neural networks work with such nonlinear and nonstationary data as EEG.

The described ANNs were implemented using the Matlab package. The method of error backpropagation was used to train the ANNs.

2.3 Dataset Optimization

Before training ANN, we performed dataset optimization in order to improve classification quality. The idea was to reduce number of EEG channels and use different channel sets for classification until the combination of both parameters, i.e. channels number and classification accuracy, is optimal. Channel sets associate with brain areas where corresponding electrodes were placed, namely, with frontal, central, parietal, temporal and occipital lobes. During classification, we used 13 different channel sets including full placement consisted of 31 channels. We also calculated the results of classification averaged on one electrode.

Besides the channel selection, we also performed low-pass filtering with cutoffs $f_c = 4\,\mathrm{Hz}$ or $f_c = 15\,\mathrm{Hz}$. Pre-filtering of EEG data is necessary for reducing intrinsic noise and artifacts, such as eye movements and blinks. It is known that appropriate filter provides better classification performance due to reducing signal redundancy. However, the selection of filter type, as well as development new ones, often becomes the study objective (Kumar et al., 2017; Gaur et al., 2015). Here, we shortly describe the effect of pre-filtering on neural network classification performance.

3 RESULTS

The session of numerical experiments was conducted. The full dataset that contained data from whole experiment was splitting into the sets of duration 2.5 seconds and 3 seconds, each one contained one real or imaginary movement event. The qualities of classification of different ANN architectures and types were compared.

3.1 Imaginary Movements

The Fig. 2 presents averaged over all subjects values of recognition accuracy of imaginary movements of legs using different groups of electrodes. One can see, that the best results of classification correspond to RBFN: in the case without pre-filtering (Fig. 2a and 2b) accuracy reaches 80% when using all electrodes and 70% — in average. Then goes multilayer perceptron with 70% recognition accuracy maximum and 65% in average. The linear network shows unstable recognition on the level of 58%. Comparison of Fig. 2a and 2b corresponding to different dataset lengths shows that this value does not affect significantly on recognition accuracy. Thus, we used 3-second fragments in the following analysis.

Then we investigated the influence of pre-filtering of initial EEGs with low-pass filter with $f_c = 4\,\mathrm{Hz}$ or $f_c = 15\,\mathrm{Hz}$. Fig. 2c and Fig. 2d show that pre-filtering of input data with low-pass filter allows to significantly increase the recognition accuracy ($10-20\%$ on average), and the low-pass filter with $f_c = 4\,\mathrm{Hz}$ demonstrates the best results and allows to achieve the classification accuracy up to 95%. From physical point of view, the last result means that significant increase of recognition accuracy due to low-pass filter appears on account of cleaning the use-

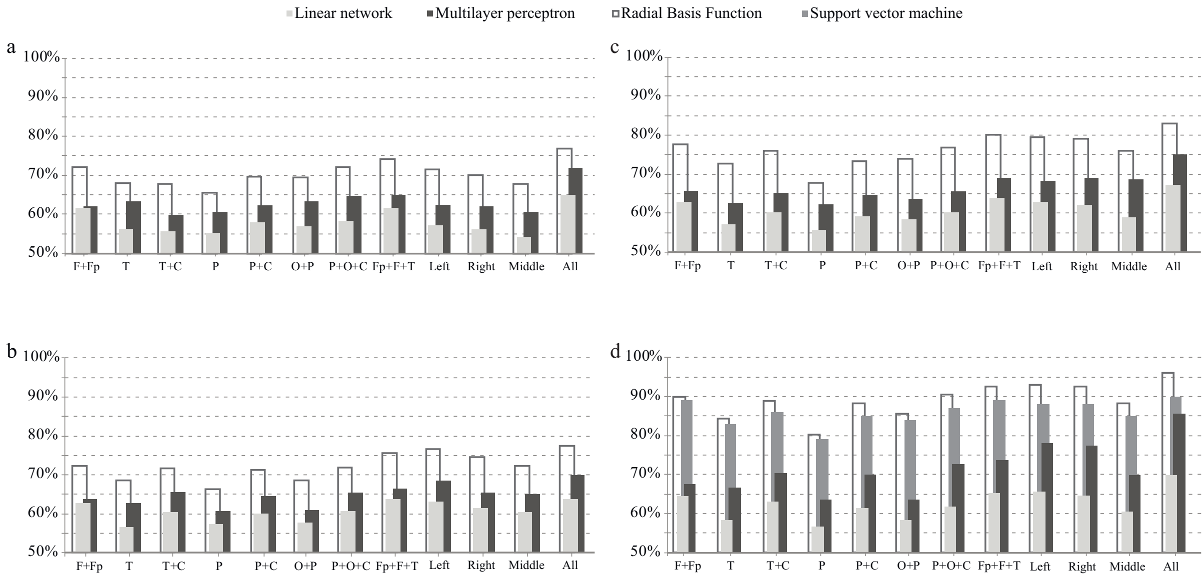

Figure 2: Recognition accuracy of legs motor imagery averaged over all subjects using different groups of electrodes (X-axis) corresponding to different EEG channel sets: (a) without pre-filtering, 3 seconds fragment length; (b) without pre-filtering, 2.5 seconds fragment length; (c) with pre-filtering with $f_c = 15$ Hz; (d) with pre-filtering with $f_c = 4$ Hz. Four types of ANNs were used (see the caption in the figure). We used next channel sets: full placement (All, 31 electrodes), right hemisphere (9 electrodes), left hemisphere (12 electrodes), parietal, occipital and central lobes ($P+O+C$, 9 electrodes), frontal and temporal ($Fp+F+T$, 12 electrodes), parietal and occipital ($P+O$, 6 electrodes), parietal and central ($P+C$, 6 electrodes), central and temporal lobes ($C+T$, 7 electrodes), frontal ($Fp+F$, 8 electrodes), middle (12 electrodes), temporal (T, 4 electrodes), parietal (P, 3 electrodes).

ful low-frequency signal from high-frequency noise, which appears during EEG recording. Note, that SVM shows $2-7\%$ lower recognition accuracy than RBFN.

It is obvious that the full placement (31 EEG electrode) provides the best classification result, despite the high dimensionality of dataset and redundant number of channels. However, it is possible to use less electrodes without significant loss in classification accuracy: one can see that electrodes placed on frontal and temporal lobes (12 electrodes, $Fp+F+T$) and several other sets (6–9 electrodes, $P+O+C, P+C, T+C, F+Fp$) provide $\sim 90\%$ accuracy. Thus, the selection of channel set depends on particular goal. If the channel set used in BCI is more important than classification quality, then one can choose one of proposed sets. However, it should be noted that using channel sets above does not affect accuracy significantly.

We also calculated the "quality per channel" characteristic, which is defined as the ratio of the classification accuracy for the given channel set to the number of channels in the set (see Fig. 3).

One can see, that frontal channel set selected above as optimal configuration shows one of the best quality of recognition per electrode. Despite the fact that middle lobe, that includes 7 electrodes from frontal, central, parietal and occipital lobes ($Fpz, Fz, FCz, Cz, Cpz, Pz, Oz$), shows the best result in Fig. 3, its integral classification performance is worse than for frontal channel set. This can be associated with complex nature of EEGs corresponding to imaginary movements, i.e. imagination of leg movement can find a response in electrical activity of remote brain areas that are not not localized near the middle.

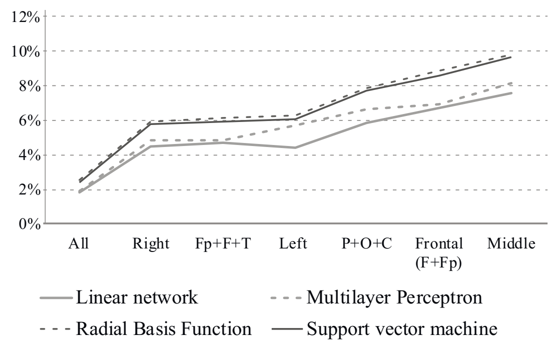

Figure 3: The results of calculating "quality per channel" characteristic.

3.2 Real Movements

In the previous section, we examined the optimal approaches to the choice of input data and channel set,

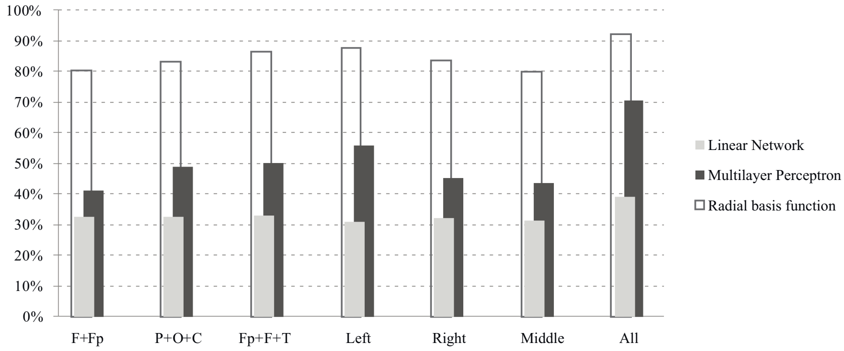

Figure 4: Recognition accuracy of legs real movements averaged over all subjects using different groups of electrodes (X-axis) corresponding to different EEG channel sets. Four types of ANNs were used (see the caption in the figure). All data is filtered with low-pass filter with $f_c = 4$ Hz.

which provide the best quality of recognition and classification of imaginary movements when using ANNs. Here, we consider the effectiveness of the proposed approaches in the recognition of real motions by EEGs. We represent the results of recognition accuracy of real movements of legs using different ANNs (see Fig. 4). Analogously, numerical experiments revealed that pre-filtering with low-pass filter with $f_c = 4$ Hz increases significantly classification performance over all channel sets.

In this case, one of the most important results is high classification performance when using different channel sets. In particular, electrodes placed on frontal lobe $(Fp + F + T)$ provide 87% classification accuracy using RBFN, which can be considered as good result.

4 CONCLUSIONS

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. In particular, it is convenient to use electrodes on frontal and temporal lobes $(Fp + F + T)$ for real movements, and several sets containing 6-9 electrodes — in case with imaginary movements $(P + O + C, P + C, T + C, F + Fp)$. This result is important from practical point of view since it allows to use more compact systems of registration of EEGs keeping required recognition accuracy.

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