DEVELOPMENT OF INTELLIGENT SYSTEM FOR CLASSIFICATION OF MULTIPLE HUMAN BRAIN STATES CORRESPONDING TO DIFFERENT REAL AND IMAGINARY MOVEMENTS

Vadim Grubov, Vyacheslav Musatov, Vladimir Maksimenko
Department of
Automation, Control, Mechatronics,
Saratov State Technical University,
Russia
vvgrubov@gmail.com, vmusatov@mail.ru, maximenkovl@gmail.com

Alexander Pisarchik
Center for
Biomedical Technology
Technical University of Madrid
Spain
alexander.pisarchik@ctb.upm.es

Anastasiya Runnova, Alexander Hramov
Department of
Automation, Control, Mechatronics,
Saratov State Technical University,
Russia
anefila@gmail.com, hramovae@gmail.com

Abstract
In this paper we considered the technique for classification of different types of electroencephalogram activity corresponded to different types of real and imaginary movement. We developed experimental design and performed series of experiments on volunteers for real and imaginary movements of hands and legs. We proposed a system based on artificial neural networks for classification of multiple human brain states corresponding to different real and imaginary movements. We provided testing and found optimal for this task size of input signal and structure of artificial neural network.

Key words
Motor action, motor imaginary, EEG, classification, artificial neural network.

1 Introduction

Interdisciplinary tasks such as studying of human brain activity are of a great relevance nowadays. This task lies in the field of combined neuroscience, physics, mathematics and nonlinear dynamics. Brain itself is commonly considered as a network with complex structure and huge number of oscillatory elements — neurons [Betzel, Medaglia, Pasqualetti, and Bassett, 2016; Hermundstad, Bassett, Brown et al., 2013; Atasoy, Donnelly, and Pearson, 2016]. Most ways for obtaining information about brain activity involve various experimental methods and data including electroencephalogram (EEG).

EEG is an experimental signal that originates from sum of electric currents generated by a small group of neurons in recording area. Since brain is a complex oscillatory network, the signal that it generates, namely EEG, also has complex structure. EEG signal is characterized by complex time-frequency structure with number of specific frequency ranges, oscillatory patterns, heavy nonstationarity, significant noise component and intermittent behavior [Sitnikova, Hramov, Grubov et al., 2012; Koronovskii, Hramov, Grubov, Moskalenko, Sitnikova, and Pavlov, 2016].

It is well-known that EEG dynamics in some frequency ranges and forming of specific rhythms and patterns are in strong correlation with functional state of brain and body. Thus, studying of EEG structure along with recognition and classification of EEG patterns is an important task for understanding fundamental mechanisms of brain. It also has quite prospective applications in technics and medicine. One of possible applications is brain-computer interface (BCI) [Kawase et al., 2017; Spuler, 2017; Bowsher et al., 2016; Chen et al., 2015; O'Doherty et al., 2011;

Stacey et al., 2008].

The BCI is based on real-time recognition of characteristic forms of activity in brain electrical (or magnetic) signals with their subsequent transformation into computer commands for programs, devices, etc. At present, the developed BCIs are used for 2D movement control of a cursor [Wolpaw and McFarland, 2004], partially speech synthesis [Birbaumer et al., 2000], simple movement control [Ma et al., 2017], rehabilitation [Daly, 2008], exoskeletons and robots control [Peternel et al., 2016]. The BCI operation is mostly determined by the operators possibility to generate and reproduce stable patterns of cognitive activity, which then can be transformed into control commands. Movement activity produces one of the most specific and stable patterns on brain activity signals, but it can be problematic for BCI-prosthesis operators with motor dysfunctions to perform some particular moves. In this context, combining of motor execution with imagination of motor activity is promising approach for BCI [Vasilyev et al., 2017].

The most important part of BCI is a system for classification of different types of brain activity, that can be transformed into control commands for executive device. There are plenty of techniques for analyzing neurophysiological features of real and imaginary motor activity with the aim of their transformation into controlling commands. For this purpose, one can use methods based on registration of event-related potentials [Basyul et al., 2015], techniques for isolation of time-frequency structure of the signals [Wang et al., 2013] and methods for restoring connections between different brain areas using multichannel data [Hamedi et al., 2016; Maximenko et al., 2017]. But one of the most effective methods for classification are based on use of artificial intelligence and machine learning [Ma, Li, Yang et al., 2017; Quitadamo et al., 2017]. This approach allows to develop an intelligent system for classification with high sensitivity and selectivity. It is especially important in case of electrical brain activity where differences between several types of activity can be very complex and unobvious.

In this paper we performed experiment with real and imaginary movement of volunteers and developed a new intelligent system for classification of multiple human brain states corresponding to different real and imaginary movements. Our approach was based on use of artificial intelligence methods. Developed system was approved on classification of patterns corresponded to real and imaginary movements on brain electrical activity of volunteers.

2 Study Methods

2.1 Experiment

Twelve healthy volunteers including both males and females, between the ages of 20 and 45 participated in the experiments. The experimental studies were performed according to ethical standards of the World Medical Association [World medical association, 2000].

EEG signals were recorded with electroencephalographic recorder Encephalan-EEGR-19/26 (Medicom MTD, Taganrog, Russia) with multiple EEG channels. Monopolar registration method and classical "10-20" electrode system with 19 recording electrodes and 2 reference electrodes were used in experiment. The multi-channel EEG was recorded at 250 Hz sampling rate and was filtered by a band pass filter with cut-off points at 1 Hz and 100 Hz and a 50-Hz notch filter.

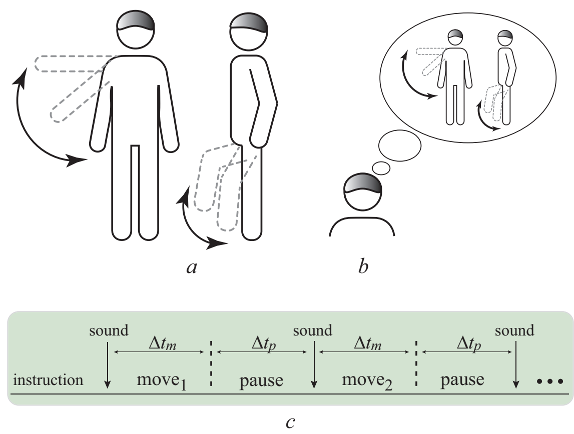

Figure 1. Design of experiment: real movements of hand and leg (a), imaginary movements of hand and leg (b), scheme of one experimental session (c).

The experiment with real and imaginary movements of volunteers had the design illustrated on Figure 1. During real movement section of experiment volunteer was instructed to perform two types of movement: to lift slowly right or left hand in the shoulder-joint and to lift right or left leg by bending knee-joint as shown on Figure 1a. During imaginary section volunteer was asked to image the same types of movement (see Figure 1b). The whole experiment was split into 24 sessions, each session included 20 iterations of real/imaginary movement for left/right hand/leg.

Structure of each session is illustrated on Figure 1c. Each session started with short instruction in form of text on monitor that told the volunteer which type of movement he is asked to perform. After the instruction sound stimulus was presented; this sound implied that volunteer should perform the asked type of movement once within a reserved time interval $\Delta t_m = 4$ s. Then a pause with length of $\Delta t_p = 2$ s took place to give the volunteer possibility to prepare for the next iteration. Then sound stimulus was presented again to start the next iteration, volunteer performed asked movement and so on.

The whole experiment included 12 sessions of real movements – 3 for left hand, 3 for right hand, 3 for left leg and 3 for right leg – and 12 analogous sessions of imaginary movements. Sessions were proceeded in random order. The experiment started with a 2-min background EEG recording and ended with a 2-min background recording. Each experiment lasted for about 52 minutes. The experiments were performed during the first half of the day in specially equipped laboratory where the volunteer was sitting comfortably and effects of external stimuli, e.g. external noise and bright light, were minimized. Each of twelve volunteers was subjected to one full experiment.

2.2 Artificial Neural Networks

Artificial neural networks (ANN) find application in wide range of tasks and are particularly effective for ill-defined problems with unknown patterns and relations between input and output [Haykin, 1998], for which the construction of models with classical methods is quite difficult. Traditionally, application of ANN requires following steps: data preparation and formation of training set, selection of correct ANN structure, ANN training, testing and simulation. Analysis of the results of ANN application is performed after the training of ANN and in order to improve the performance one may consider the change of ANN topology and/or increase its computing abilities by correcting the training set and re-training.

Solution of the classification problem is one of the most important applications of ANN and it commonly occurs in studies related to EEG analysis. Construction of classifier based on ANN suggests splitting the available data patterns, containing information about the object/system, into a number of classes that define the state of a given object/system.

In the case of brain activity studies the input data is multi-channel EEG signals recorded during real/imaginary movement experiment. To solve the problem of classification one should test different types of ANN and different types of data presentation. In present paper we created a classifier with input values as EEG oscillatory patterns [Rabinovich, Varona, Selverston, and Abarbanel, 2006] and output values as types of movement during the experiment. We tested different sizes of input EEG signals and different types of ANN structure to find optimal combination with highest classification capability.

We associated each EEG signal with class (type) of the movement, which subjects performed during experiment. The task of classifier was to successfully distinguish two classes corresponded to “left” and “right” movements, for example, real movement of left hand and real movement of right hand. The aim was to construct four classifiers: for real hand movement, real leg movement, imaginary hand movement and imaginary leg movement. The value of the class is equal to 1 if it's related to “left” movement and is equal to 0 if it's related to “right” movement. Thus, the learning set included input values (multichannel signals of set duration), and output values corresponded to the identified classes of movements. The number of channels determined the number of inputs in ANN.

3 Results

The input values were multi-channel EEG signals (oscillatory patterns). The number of channels corresponding to the scheme of recorded EEG data was 19. For each channel, we took signals of certain duration to use as input.

Choosing of size of input data may be important. In case of very short input EEG signal some significant but obscure processes may be lost which will decrease classification ability of ANN. On the other hand, in case of very long input signal it may include fragments that have nothing in common with real/imaginary movements, which also will have negative effect on classification accuracy.

As we described previously, volunteers had $\Delta t_m = 4$ s to perform the asked type of move. We assumed that all movement-related EEG activity was concentrated inside time interval of tm, so it is pointless to consider EEG input signals longer than Δt_m. On the other hand, observation during experiment showed that it took at least 2.5 s for volunteers to perform their movements, and thus input signal shorter than 2.5 s may lose some important information.

In present paper we considered ANN classifier with three different sizes of input data: 2.5, 3, 4 s. We provided learning of ANN with each size of input data and results of classification are illustrated on Figure 2.

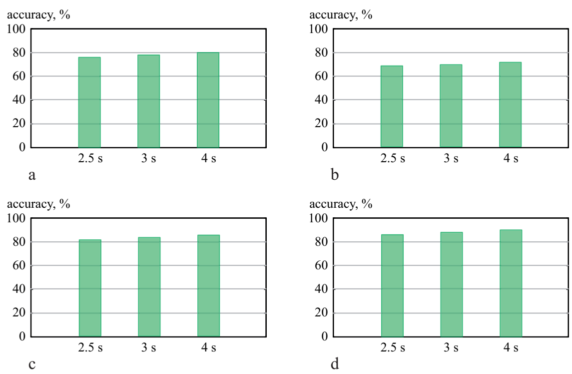

Figure 2. Dependence of classification accuracy from size of input data for: real hand movement (a), real leg movement (b), imaginary hand movement (c), imaginary leg movement (d).

As Figure 2 shows there are no significant differences in accuracy for different sizes of input data. For example, classification accuracies for imaginary movements of hands are 82% for 2.5 s input, 83% for 3 s input and

85% for 4 s input (see Figure 2c). Nevertheless, accuracy for 4 s input data are the best in all cases, so this size of input data was used in our ANN classifiers.

Another important task in construction of ANN classifier is to choose an appropriate type of ANN. In present paper we considered three popular types of ANN: linear network (LN), multi-layer perceptron (MP) and radial basis function (RBF). We tried to perform classification of "left" and "right" movement classes with each type of ANN. Results are presented on Figure 3.

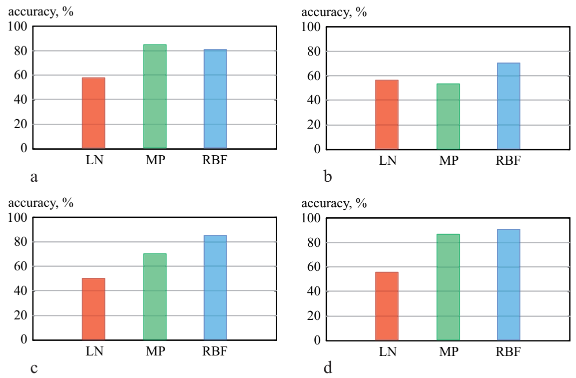

Figure 3. Dependence of classification accuracy from ANN type for: real hand movement (a), real leg movement (b), imaginary hand movement (c), imaginary leg movement (d).

As seen from Figure 3 RBF type of ANN showed best accuracy in almost all cases – up to 90% for classification of imaginary leg movement. Worst results were shown by LN – about 50-55% in all cases. MP showed good results, for example, for classification of real hand movement (90%), but in other cases accuracy is rather low (53% for real leg movement), so MP cannot be considered as a reliable option for ANN classifier. In the end, the algorithm for construction of classifier based on ANN includes the following steps:

1. Formation of the training set that includes input signals (EEG-data, oscillatory patterns) and output values of real/imaginary hand/leg movement type and segmentation of the training set for training, inspection, test.
2. Selection of size of input data segment for optimal classification accuracy.
3. Selection of ANN type and its topology, providing training and evaluation of classification accuracy.
4. Testing of ANN and classification of EEG fragments.

4 Conclusion

In this paper we considered the technique for classification of different types of EEG activity corresponded to different real and imaginary movements of hands and legs. Developed classifier was based on ANN. We provided testing and found optimal for this task size of input signal and structure of ANN.

The results of these studies appear promising for further classification of other types of activity on EEG signals. Furthermore, this approach is highly customizable to individual features of volunteers which promises its application in biofeedback systems.

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