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Effect of filtration of signals of brain activity on quality of recognition of brain activity patterns using artificial intelligence methods

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ABSTRACT

In present work we studied features of the human brain states classification, corresponding to the real movements of hands and legs. For this purpose we used supervised learning algorithm based on feed-forward artificial neural networks (ANNs) with error back-propagation along with the support vector machine (SVM) method. We compared the quality of operator movements classification by means of EEG signals obtained experimentally in the absence of preliminary processing and after filtration in different ranges up to 25 Hz. It was shown that low-frequency filtering of multichannel EEG data significantly improved accuracy of operator movements classification.

Keywords: Artificial neuronal networks, multilayer perceptron, radial basis functions, multichannel EEG, brain activity patterns, recognition, imaginary movements, perception.

1. INTRODUCTION

Human brain represents the subject of intensive research in various areas of modern science, including psychology, neurophysiology, medicine, physics, mathematics and nonlinear dynamics[1–7] due to its great importance and complexity. An interdisciplinary approach that provides understanding of brain puzzles and mechanisms of brain neural networks functioning opens up a promising prospects in medicine, neurotechnology and intellectual robotics in the nearest future. The study of various aspects of brain functioning is usually based on objective data obtained during the psychophysiological and cognitive experimental work.[8–11] High scientific and practical interest in using brain capabilities for the remote prostheses, exoskeletons and robotic devices control is associated with the development of brain-computer interfaces (BCIs).[12–14] The electroencephalography (EEG) is the most convenient and inexpensive method for brain signals recording in these neurointerfaces.[15,16] However, it is necessary to provide reliable and correct interpretation of EEG signals obtained from the operator's brain to implement the control functions of the above technical devices. For example, in case of controlling exoskeleton it is highly important to distinguish between brain states corresponding to the hands and legs movements and and correctly classify them via EEG signals. Previous studies showed the effectiveness of the machine learning method - artificial neural networks (ANNs) - to classify different brain states which appear during recognition of ambiguous images using EEG signals.[10,17,18] However, the classification accuracy of such algorithms can often be improved by data preprocessing, in particular by digital filtering. In this paper we present the results of the study of the experimental EEG data bandpass filtering effect on the accuracy of operator's movements classification by machine learning methods.

2. EXPERIMENT

Five healthy volunteers (men and women) aged from 20 to 43 participated in the EEG recording experiment. During the experiment we carried out the registration of participants brain activity via recording of multichannel EEGs using the electroencephalograph-recorder Encephalan-EEGR-19/26 (Russia) (Fig. 1, a) along with a two-button input device, when the operator performs a sequence of hand and feet movements (Fig. 1, b) . To obtain

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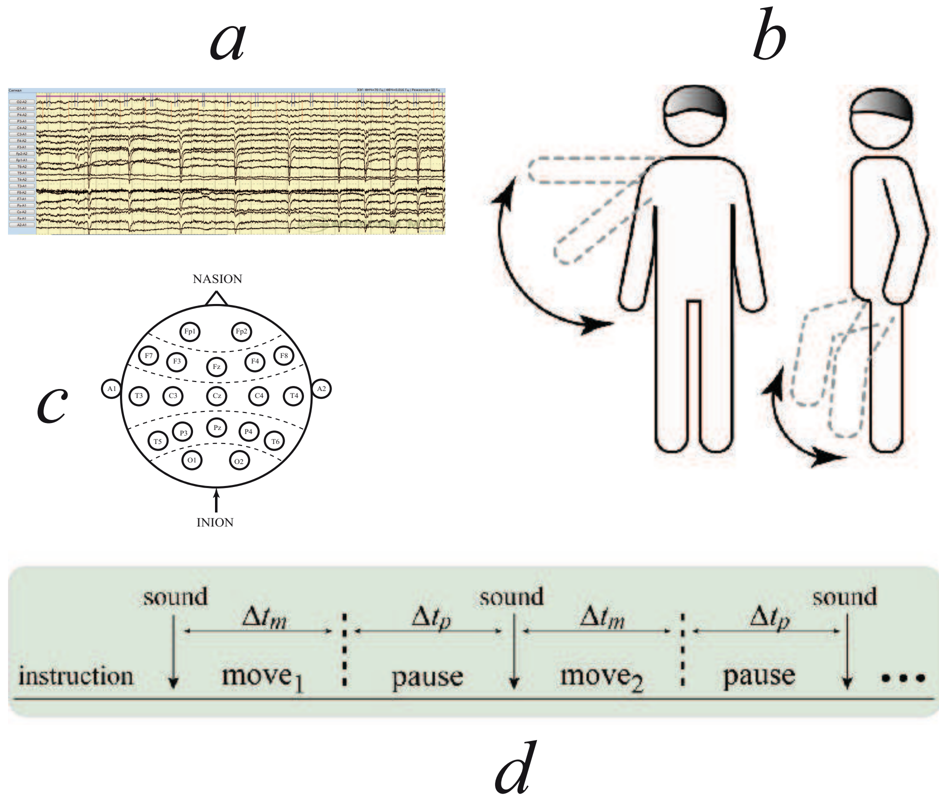

Figure 1. (a) Example of a a typical EEG recording from electroencephalograph Encephalan-EEGR-19/26. (b) The scheme of the operator's movements in the experiment. (c) International system "10 - 20" illustration. (d) Time sequence of movements.

EEG signals, the monopolar registration method and the classical "10-20" system were used (Fig. 1, c). EEG signals were recorded using 250 Hz sampling rate during the entire experiment.

The participants executed motions with their hands and legs (right and left) (Fig.1, b). Each operator raised his hand straightened at the elbow turning in the shoulder joint at 120-140 degrees. The leg bent at the knee was raised by the operator performing a turn in the hip joint.

To exclude the influence of brain activity associated with maintaining a person in a vertical position each operator performed the described actions while sitting in a chair. While registering EEG data, a person performed following motions: raising his right hand, raising his left hand, moving his right leg and moving his left leg. The commands for performing each type of motions were randomly assigned and alternated with pauses Δt_p of duration. The performance of each task was preceded by a sound signal, after which the subject had to perform the task for $\Delta t_m = 4$ s. The experiments took place in the first half of the day in a specially equipped laboratory, where the influence of external stimuli was minimized. Total duration of experimental session with participation of one subject was about 40 min.

3. METHODS

It is known that ANNs are commonly used to solve nonlinear problems when the analytical solution is difficult to obtain or is absent.[19] In our work we focused on the method of supervised learning, which is traditionally chosen to solve this type of problems related with pattern recognition and classification. To classify EEG images we used two types of supervised learning feedforward ANNs with back propagation of error (Fig. 2) – multilayer

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perceptron (MP) and radial basis function (RBF), which showed the best results in the previous studies.[10,17,18] These ANNs differ from each other by activation functions of artificial neurons and the number of hidden layers.[19] Thus, in our study RBF always had one hidden layer of radial elements and each of them reproduced the Gaussian response surface. At the same time MP could have several hidden layers with different types of activation function such as hyperbolic tangent, sigmoid, etc.

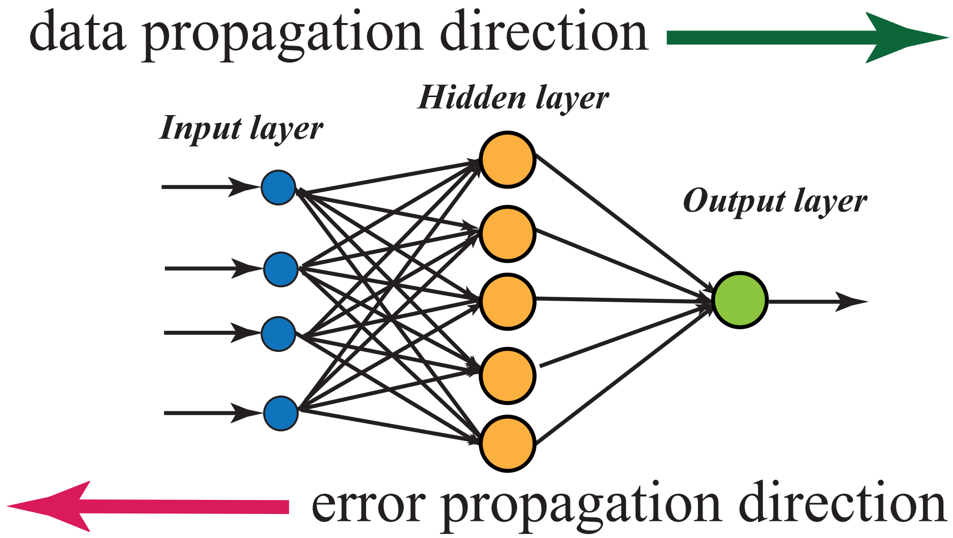

Figure 2. Schematic representation of feedforward ANN with error backpropagation.

Together with MP trained according to the error backpropagation algorithm and ANNs based on RBFs, support vector machines (SVM) are also a promising type of universal approximators that can be used to solve classification problems.[20] SVM can provide a good generalization quality in a classification problem without having prior knowledge of the subject area of a particular task. In the framework of this method, a point in space is considered as a vector of dimension p. The classifier is a hyperplane of dimension $(p-1)$ separating these points. The classifier is described by the following relations:

$$h(x) = sign(u(x)), \tag{1}$$

$$u(x) = \sum_{i=1}^{N} \lambda_i y_i K(x_i, x) - w_0, \tag{2}$$

where w_0 – is the threshold (free term); λ_i – is a coefficient; x_i, y_i – is a pair from the training set; $K(x_i, x)$ – is a kernel function.

Initially, the SVM is a linear classifier, i.e. it can solve only linearly separable problems. Applying a nonlinear kernel, one can map the original data to a space of greater dimension, where an optimal separating hyperplane can exist. As a kernel function, a radial basis function is usually used:

$$K(x_i, x) = e^{-\gamma||x_i - x||^2}, \gamma > 0. \tag{3}$$

The bandpass filtering of the initial multivariate EEG data was carried out using a Butterworth filter (4) implemented in MATLAB.

$$H(\omega) = \frac{1}{1 + \sqrt{(\omega/\omega_c)^{2n}}} \tag{4}$$

where ω_c is a cutoff frequency and n is an order of the filter.

4. COMPUTER EXPERIMENT AND RESULTS

Series of computational experiments were carried out using the PC to classify motions of of the left and right hands and legs via the analysis of EEG signals corresponding to these motions. At first, signals from selected EEG channels continuously recorded during the whole experimental session (for one subject) were "cut" into trials of a given duration of 3 seconds, each corresponding to one type of motion. Classification was carried out with the help of supervised learning feedforward ANNs with backpropagation of error (MP and RBF) and also SVM. The choice of data plays crucial role in the training and use of artificial neural networks. For training and testing, we used data sets containing 6000 samples (24 seconds of recorded data) corresponding to the hands and legs motions (left and right). Arrays are composed from samples of prepared 3-second fragments of EEG signals corresponding to one kind of motion. Half of the data of each array, chosen randomly, was used for training. The remaining half was used for the test and validation samples (in a ratio of 50% to 50%).

We used unfiltered data, as well as preliminarily filtered by means of the Butterworth bandpass filter (4) in the ranges 1-4 Hz, 8-12 Hz and 15-25 Hz for the classification process.

In case of consideration of entire set of EEG signals (31 channels) without filtration, the best results of classification were shown by RBF networks with linear artificial neurons in the input and output layers, radial synaptic functions and exponential activation functions of 251 middle layer artificial neurons and MP networks with 15 artificial neurons in the hidden layer with the hyperbolic tangent activation function with an input layer with linear and output layer with logistic activation functions, and SVM with a nonlinear kernel in the form of a RBF (3), where $0,003 < \gamma < 0,01$. Classification results of EEG data unfiltered and filtered in different bands for ANNs (MP and RBF) and SVM for legs (a) and hands (b) motions are presented on Fig. 3.

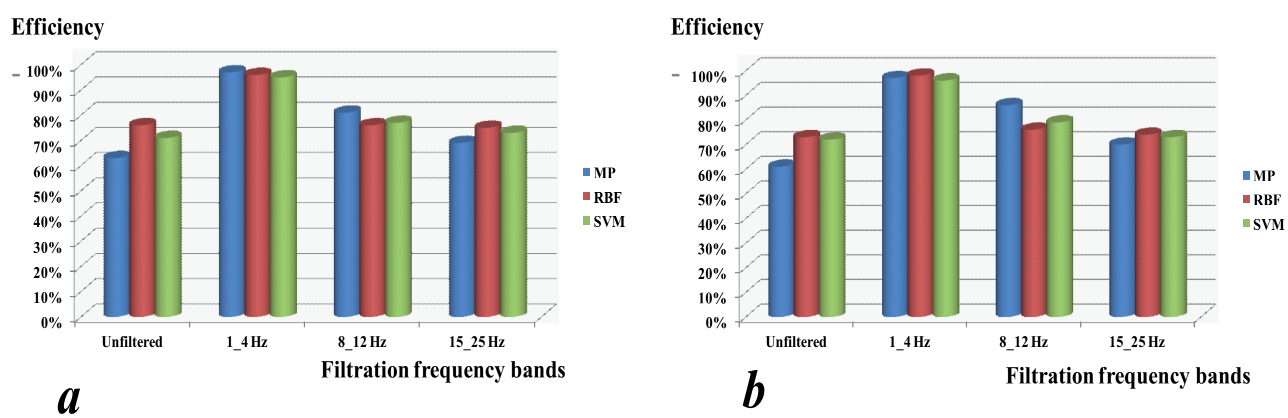

Figure 3. Classification efficiency of EEG data. (a) For legs movements. (b) For hands movements.

The results of the experiment show a qualitatively identical picture of hand and leg motions classification for all types of machine learning algorithms used – one can see that low-frequency (1-4 Hz) data filtering significantly (by 20% -36%) improves the quality of classification. Using filtering in the band 8-12 Hz improves the quality of classification by 3% - 25%, and data filtering in the 15-25 Hz band practically does not improve the quality of the classification.

5. CONCLUSION

In this paper, we studied the features of the human brain states classification, which correspond to hands and legs motions. For this purpose, ANN was used, which previously showed a good quality of classification of multichannel EEG data (at the level of 80-90%) while percieving ambiguous images and the SVM method.

In this study, the accuracy of operator's motions classification using EEG signals, obtained experimentally without preliminary processing and after filtration in the ranges 1-4 Hz, 8-12 Hz and 15-25 Hz, were compared. The obtained results showed that the best recognition occurs when EEG trials were filtered in frequency range of 1-4 Hz corresponding to the δ-rhythm of the brain activity (95-98%). With an increase in the filtering frequency range, the recognition accuracy decreases: up to 76-86% in the range corresponding to the alfa-rhythm (8-12 Hz) and up to 69-75% in the beta-rhythm range (15-25 Hz), which is very similar to the classification accuracy of the unfiltered data.

In general, it should be concluded that low-frequency filtering of multichannel EEG data is necessary if one wants to improve the classification accuracy when analyzing processes in the human brain neural network associated with motor activity. The application of data filtration is useful for analyzing a wide range of processes in the human brain using multi-channel EEG data and their use in the implementation of neurointerfaces for a wide range of neurotechnology and intellectual robotics tasks.

6. ACKNOWLEDGMENTS

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