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ABSTRACT

In this paper, we investigate the problem of identification of patterns on magnetoencephalography signals of a brain associated with human movements. The design of registration of experimental data during magnetoencephalography (MEG) is developed and described. Consecutive imaginary movements of the hands and legs of the person are chosen as the basic movements. We solve the problem of recognition and classification of patterns using artificial neural networks. For a multilayer perceptron, good results of recognition of patterns of brain activity associated with different types of motion have been obtained.

Keywords: artificial neural networks, oscillatory patterns, magnetoencephalography, classification, imaginary movements, MEG signals, brain activity

1. INTRODUCTION

Brain-computer interfaces[1–5] are one of the promising applied areas of development of neurophysiology and engineering sciences dealing with the creation of complex intelligent control systems.[6] Important aspect of the application of brain-computer interfaces is the restoration of lost human motor functions. The areas of its application are the following: the restoration of movements after a stroke, the creation of exoskeletons and "smart" prosthesis controlled by brain-computer interface.[4,5]

However, very important application of brain-computer interfaces is development of control systems using neurointerfaces for biomorphic robotics and robotic complexes. To create such systems one need to know the areas of the brain activity and the type of patterns that correspond to different human movements. Obviously, the analysis of data allowing to determine the localization of emerging patterns of brain activity during the movement (real or imaginary) of a person is the actual problem. In addition, it is important that such a system is able to recognize and classify the type of movement (both real and imaginary) that is being performed by the pattern of activity of the human brain.

Thus, the main goal of this work was to solve the problem of recognition and classification of patterns of brain activity that occur when performing imaginary movements by analysis and highlighting the most significant areas (channels) responsible for the organization of limb movements.

Electroencephalography (EEG)[7–13] as a way of registering brain activity is quite common and has a number of advantages such as ease of registration. In addition, EEG data recording technology makes it possible to record a signal using wireless systems. It allows monitoring using the portable devices, which is very important when implementing brain-computer interfaces for freely moving person.

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A fairly accurate analysis of brain activity is the registration of magnetic fields formed by the electrical activity of brain neurons, the so-called magnetoencephalography (MEG).[14,15] MEG, as EEG, allows us to evaluate patterns during the performance of various cognitive tasks.

An obvious advantage is that the MEG is more accurate from the point of view of spatial localization of sources in the cerebral cortex, and it gives an excellent temporal resolution, up to thousandths of a second. This aspect can be significant when determining the patterns of brain activity depending on the task performed by a subject. In addition, there are no interference and distortions from the scalp, the muscles of the head, or the bones of the skull with MEG, which also allows one to obtain more accurate information about the current state of the brain.

Researchers use MEG data in addition to EEG data to clarify the areas of occurrence of brain activity and obtain functional dependencies. Therefore, we plan to use the MEG data obtained during the experiments with human movements in addition to the available EEG data analysis results for the same experiments and subjects. We have assumed that the difference in the nature between MEG and EEG and the high spatial and temporal resolution of MEG will provide additional information on the emerging brain activity depending on the task being solved.

2. PROBLEM FORMULATION

Among problems of creating brain-computer interface, one of the important problem is determining the state of a person by the signals of brain activity.[16–23] In particular, the problem of recognizing imaginary human movements (of hands and legs) by MEG signal analysis can be attributed to such problems. In this paper, we solve the problem of recognition of imaginary motion type depending on the generated template and the registered multichannel MEG signal.

The idea of the experiment was to imagine the movement by each hand and leg. During the execution of the imaginary movements, we recorded the MEG data and patterns corresponding to various imaginary movements. We assumed that the generated patterns of brain activity of different movements are distinguishable and can characterize the type of movement performed by a person. Thus, the classification problem consists in determining the type of motion by the MEG data generated during the imagination of the movement. Artificial neural networks (ANNs) are used to solve the classification problem in the proposed paper.

3. EXPERIMENT DESIGN AND DATA

During the experiment, we recorded the activity of the brain when the subject consistently moved his hand and leg (right and left). When carrying out the movement by hand, a person raises a straight hand by making a turn in the shoulder joint with an amplitude of 120-140 degrees. A person raises his leg (bent at the knee) by carrying out a turn in the hip joint. During the experiment, the person was sitting, so we have excluded the influence of the brain activity associated with maintaining the person in an upright position.

The design of the experiment included real and imaginary movements. When registering MEG data, a person performs a group of real movements in advance for training before recording the activity of the brain. At the beginning of the experiment (with the eyes open) and at the end (with the eyes closed), we recorded the background activity of the brain within 5 minutes.

The group includes 4 repetitive movements: raising of the right hand, raising of the left hand, movement by the right foot and movement by the left foot. During the experiment, the commands for the movements are given randomly. Each group of movements includes 8-10 repetitions. The system beeps to a person at the beginning and end of a single movement. The time of execution of one movement varies randomly from 6 to 8 seconds. After performing a group of movements a person rested for 40 seconds. A person performs 3-4 groups of movements. The experiment lasts for about 35-40 minutes.

4. ARTIFICIAL NEURAL NETWORKS

Articial neural networks (ANNs) are used for a wide range of applications and are particularly eective for hard formalized problems with unknown patterns and dependencies between input and output variables.[24–28] For such problems the construction of models with the help of classical methods is quite difficult. Traditionally, solutions using ANNs include the following steps: preparing data of the object (the formation of the training set), the correct selection of neural network structure, neural network training, testing and simulation. Analysis of the results of problem solving is done after the training of ANN, therefore, to improve the results of the solution and/or to increase computing abilities of ANN, one may change the topology of the ANN or correct the training data set with the subsequent retraining (with a return to the stage of training).

Solution of the problem of classication is one of the most important applications of neural networks and occurs, including in relation to the tasks of MEG data analysis. Construction of classier based on ANN suggests splitting the available patterns containing information about the object / system into a number of classes that dene the states of a given system or object.

In this case, the input data is multichannel MEG signals recorded during the execution of imaginary movements, class is type of identiable movement. Dierent neural networks and various types of learning (with a teacher and without a teacher), on which the type of formed data depends, are used to solve the problem of classication. In the present paper, we have considered a multilayer perceptron to create a classier. The set of training data for learning of multilayer perceptron includes input and output (target) values. Here, the input values are oscillatory patterns, and output values are the types of imaginary movements.

Thus, the algorithm for constructing a classier based on neural networks consists of the following steps.

1. We form a training set that includes the input signals (MEG data, oscillatory patterns) and the output values - types of movements and division of the training set for training, inspection and test.

2. We select type of articial neural network, its topology, provide training and assess the eectiveness of the solution (accuracy of the solution). When determining the structure of multilayer perceptron we dene number of layers, neurons in the layers, activation function. We choose the learning algorithm and determine the accuracy of the solution. To improve the accuracy of solution, we increase number of neurons in layers, number of layers, the volume of training sample and provide retraining.

3. We test neural networks and carry out simulation.

5. CREATION OF TRAINING SET

The input values applied to the input of the multilayer perceptron are multichannel MEG signals (oscillatory patterns). MEG data in contrast to the EEG data have a high spatial resolution coupled with high temporal resolution and allow you to get more detailed information on the activity of the brain. MEG system we have used allows one to register 306-channel signals.

Neurophysiological data was acquired by using a 306 channel (102 magnetometers and 204 planar gradiometers) Vectorview MEG system (Elekta AB) placed inside a magnetically shielded room (Vacuum Shmelze GmbH, Hanau, Germany) at the Laboratory of cognitive and Computational Neuroscience of the Center for Biomedical Technology of the Technical University University of Madrid (Spain).

We used for the investigations signals from 102 main channels (Fig. 1). Also, to reduce the dimension of the neural network training task, we used the channels of the standard EEG signal registration scheme (10-20) (see Fig. 1). The number of the used channels was reduced to 19. This is the minimal number of channels that allows one to register information from the most significant areas of a brain.

The sampling frequency of MEG signals is $f = 1000\,\mathrm{Hz}$. For each MEG channel, we have formed the patterns of brain activity that characterize the person's state in the process of imaginary movement. Obviously, the time for executing an imaginary movement can be various. Therefore, to analyze the informative nature of the motion patterns, we generated signals with a duration of 2.5 s, 3 s, 4 s. To train an artificial neural network, we also used

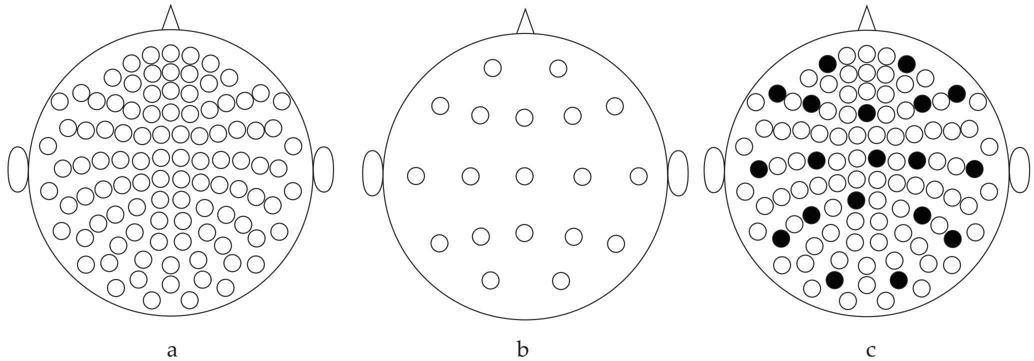

Figure 1. Electrodes positions: a – positions of 102 channels for Elekta Neuromag MEG; b – international 10/20 EEG scheme; c – 19 channels of MEG data corresponding to the 10/20 scheme

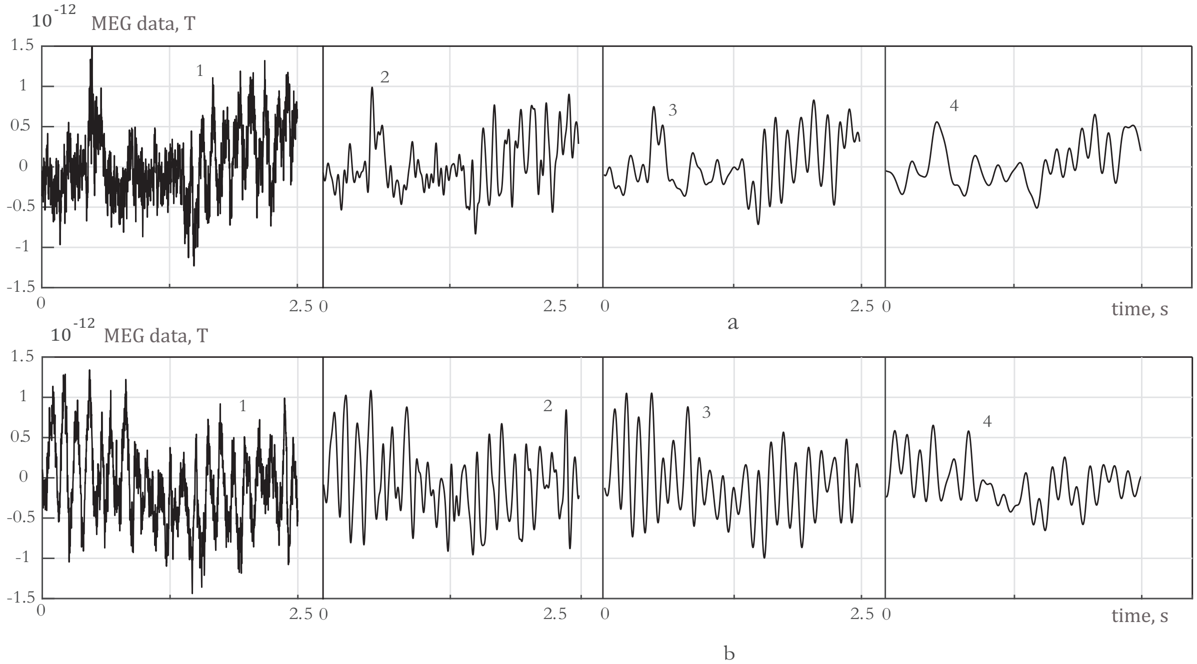

Figure 2. MEG signals (1) associated with the movement by the left (a) and right (b) hands (2.5 s). Filtered MEG signals in the frequency bands 0.5-10 Hz (2), 0.5-15 Hz (3) and 0.5-30 Hz (4)

signals processed by a bandpass filter in the frequency range of 0.5-10 Hz, 0.5-15 Hz or 0.5-30 Hz (see Fig. 2). Each such signal was associated with the certain type of movement that a person had imagined.

We have formed separately training samples to recognize the movements of the arms and legs. That is, when solving the problem of classifying the type of hand movement, the class of motion was the first if the person imagined the movement with the left hand and the class of motion was the second if the subject imagined the movement with his right hand. Training set for the classification of legs movements has been formed in the similar way.

Thus, training set includes input values — multichannel MEG signals (motion patterns) — and output values that correspond to the types of movements. The number of channels determines the number of inputs of the neural network.

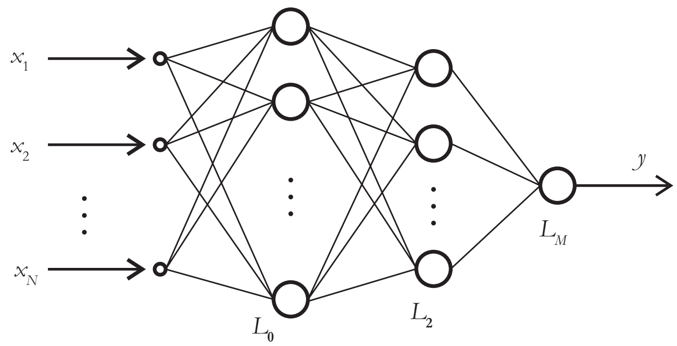

Figure 3. The structure of the multilayer perceptron: L_0 – the layer of propagation of input signals; L_1, L_2, L_M – the hidden and output layers of the ANN; $x_1 - x_N$ – MEG signals inputs

6. CHOICE OF NEURAL NETWORK STRUCTURE

To solve the classification problem, we use in our work ANNs of direct propagation. Multilayer perceptron shows good results of recognizing types of movements. Multilayer perceptron is a frequently used tool for solving a wide range of problems in many scientific fields.[29, 30] The effectiveness of solving a problem using multilayer perceptron depends not only on the representativeness of a training set, but also on the successful choice of the structure of the ANN.

There are some of problems for which we can fairly easy choose type and topology of the neural network. However, the problem of relating the complexity of the neural network topology and its computational properties (the ability to solve the problem) often requires additional analysis and selection of relevant structure. If the ANN topology is too simple, the problem will remain unsolved. However, excessive ANN structure will require larger volume of training sample and learning time.

The general structure of the used multilayer perceptron is shown in Fig. 3. The number of inputs of the ANN corresponds to the number N of channels of the input set (the maximum number of channels corresponds to the dimension of the MEG data $N_{max} = 102$). The number of neurons of the rst layer is equal to or more than the number of inputs. Multilayer perceptron contains hidden layers. Classication problem in the case of two classes can be solved by a neural network with one output, which takes one of two values.

7. LEARNING. CLASSIFICATION ACCURACY

The process of training of multilayer perceptron is the process of the determination of the synaptic weights and biases in ANN. The learning process is a solution to the problem of optimization of the error function which depends on the dierence between the output values and the target values (reference values of ANN output). In the methods used for optimization the target function (a complex function of several variables) is the error function, and the variables are the weightes and biases values of ANN. Obviously, increasing the neurons and synapses in neural network results in complication of target function (error function) and increasing of the number of local extremums. Therefore, correct choice of optimization method determines the eectiveness of training. We have used Levenberg-Marquard method, who has a good convergence and accuracy of the solution, for learning of ANN.

After learning, we tested the ANN with data that were not used in the training. To compare the ANN output values with target values of the test set, we used mean squared error function. If the error is less than 0.5, then the pattern is considered to be recognized right, at the values of the error higher or equal to 0.5 type of movement is considered to be not recognized. As a result, it is possible to determine the total number of recognized types of movements, the number of "right" and "left" movements. Recognition accuracy, ρ, of recognizing types of movements is dened as:

$$\rho = \frac{N_\rho}{N} \times 100\%, \tag{1}$$

Table 1. Accuracy of recognition of the patterns associated with movements (19-channel MEG data, signal duration 2.5 s)

Patterns associated with the movements of hands			Patterns associated with the movements of legs		
MEG data pre-processing, Hz	Accuracy of recognition, %	Structure of ANN	MEG data pre-processing	Accuracy of recognition, %	Structure of ANN
–	60	$19-11-1$	–	76	$19-10-1$
$0,5-10$	99	$19-14-1$	$0,5-10$	99	$19-14-1$
$0,5-15$	94	$19-12-1$	$0,5-15$	96	$19-12-1$
$0,5-30$	88	$19-14-1$	$0,5-30$	88	$19-15-1$

Table 2. Accuracy of recognition of the patterns associated with movements (19-channel MEG data, signal duration 3 s)

Patterns associated with the movements of hands			Patterns associated with the movements of legs		
MEG data pre-processing, Hz	Accuracy of recognition, %	Structure of ANN	MEG data pre-processing	Accuracy of recognition, %	Structure of ANN
–	67	$19-11-1$	–	76	$19-12-1$
$0,5-10$	98	$19-15-1$	$0,5-10$	99	$19-15-1$
$0,5-15$	90	$19-13-1$	$0,5-15$	94	$19-14-1$
$0,5-30$	80	$19-12-1$	$0,5-30$	83	$19-12-1$

where N_p is the number of true detected types of movements, N is the total number of movements.

Finally, the results of application of the trained multilayer perceptron for recognition of various types of movements on multichannel MEG data are given in Tables 1-3. The tables show the characteristics of the duration and the number of channels of MEG data, the structure of the neural network in the form of the $N-M-K$ scheme (N – the number of neurons in the input layer, M – the number of neurons in the hidden layer, K – the number of neurons in the output layer), the recognition accuracy and the frequency band of pre-processing filter.

Using 102-channel MEG data, the ANNs of the proposed architecture show acceptable recognition quality for both hands (78%) and legs (73%). The use of a minimal configuration of MEG electrodes (19 channels) for recognition with ANN makes it possible to obtain satisfactory results for hands ($\tilde{7}6\%$) and legs (up to 67%). Application of data filtering in the frequency bands 0.5-10 Hz, 0.5-15 Hz and 0.5-30 Hz significantly improves the quality of recognition. So, for 19 channels, filtering in the range of 0.5-30 Hz improves the quality by 12%-28%, in the range 0.5-15 Hz — by 18%-34%, and in the range 0.5-10 Hz — by 23%-39%. The use of low-frequency filtering for 102-channel MEG data allows almost complete recognition of imaginary movements of hands and legs ($\tilde{9}9\%$). Thus, the results of the studies show that the low-frequency filtering in the range up to 10 Hz allows achieving maximum improvement in the quality of recognition of imaginary movements of hands and legs.

The quality of recognition of leg movements (67%) is much lower for unfiltered data than for hands (76%). However, the use of filtration in the above ranges increases them to close values that differ in each range by 1%-4%. This suggests that the data on the movements of the legs are more noisy at higher frequencies, and the use of filtration in the range of natural frequencies of the brain makes it possible to isolate and use the useful information of the MEG for the classification of the corresponding motions. It is important to note that a serious reduction in the number of MEG channels from 102 to 19 in combination with preliminary filtering

Table 3. Accuracy of recognition of the patterns associated with movements (102-channel MEG data, signal duration 2.5 s)

Patterns associated with the movements of hands			Patterns associated with the movements of legs		
MEG data pre-processing, Hz	Accuracy of recognition, %	Structure of ANN	MEG data pre-processing	Accuracy of recognition, %	Structure of ANN
–	73	$102-29-1$	–	78	$102-24-1$
$0,5-10$	100	$102-25-1$	$0,5-10$	99	$102-12-1$

of data leads to a slight decrease in the quality of recognition, which is quite acceptable for solving practical problems. Reducing the number of channels can dramatically reduce the amount of data used in computing, increase the speed of recognition algorithms, and reduce the complexity of the brain-computer interface.

8. CONCLUSION

The researches on recognition and identification of patterns of various types of human movements using ANNs demonstrate that the use of multilayer perceptron allows to classify confidently (with an accuracy of more than 80%) imaginary movements on rather short time fragments of MEG signals. In addition, preliminary data processing, namely, filtering the signal with a bandpass filter in the frequency range of 0.5-10 Hz, demonstrates an increase in recognition accuracy to acceptable level (88-99%).

It is important to note that acceptable accuracy is achieved for a smaller number of channels of MEG data that makes it possible to reduce the volume of the training set, and, consequently, the dimension of ANN and, accordingly, the learning time.

The positive results of this study are very useful for creating brain-computer interfaces and control systems for exoskeletons and anthropomorphic devices.[31,32]

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