Recognition and classification of oscillatory patterns of electric brain activity using artificial neural network approach

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ABSTRACT

In the paper we study the problem of recognition type of the observed object, depending on the generated pattern and the registered EEG data. EEG recorded at the time of displaying cube Necker characterizes appropriate state of brain activity. As an image we use bistable image Necker cube. Subject selects the type of cube and interpret it either as aleft cube or as the right cube. To solve the problem of recognition, we use artificial neural networks. In our paper to create a classifier we have considered a multilayer perceptron. We examine the structure of the artificial neural network and define cubes recognition accuracy.

Keywords: artificial neural networks, oscillatory patterns, Necker cube, classification, bistable image

1. INTRODUCTION

The solution of problems related to the data processing and analysis of neuronal activity of the brain is still relevant and has attracted the attention of researchers and scientific groups. Traditionally, brain activity analysis uses in the diagnosis of neurophysiological deceases. However, a wide range of scientific applications is associated with neurobiological brain research.

One of the promising fields in the contemporary neuroscience is the development of control systems based on the brain-computer interfaces[1] which are included the analysis of typical oscillatory patterns by means of brain activity processing. Nowadays, brain-computer interfaces can be considered as perspective technology provided control of complex technical systems such as intelligent robotics, wheelchairs, exoskeletons by means of specific neurointerfaces. These techniques and devices restore or augment some human functions (sight, hearing, cognition, movement/motor abilities).

The modern neurointerfaces are used usually for recording brain activity such technologies as electroencephalography (EEG)[2] and magnetoencephalography (MEG).[3] Electroencephalography (EEG) is a method for recording bioelectric signals of brain activity. The electrical activity of the brain reflects the functional state of the cortex and subcortical structures. Actually, the EEG signals are the sum of electric field potentials of neurons. There are different methods and EEG schemes for analyzing various areas brain activity and localization of process.

Magnetoencephalography (MEG) registers super-weak magnetic fields of brain activity. MEG in contrast to EEG records (registers) brain activity of the deep parts with a high signal / noise ratio. Despite the seeming advantages MEG is considered as an additional method to the EEG registration which also has disadvantages. In particular, equipment for recording MEG is highly expensive. MEG is very sensitive to the displacement of the sensor relative to the head and to external magnetic fields. However, shielding the external magnetic field is

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Dynamics and Fluctuations in Biomedical Photonics XIV, edited by Valery V. Tuchin, Kirill V. Larin, Martin J. Leahy, Ruikang K. Wang, Proc. of SPIE Vol. 10063, 1006317 · © 2017 SPIE
CCC code: 1605-7422/17/$18 · doi: 10.1117/12.2250001

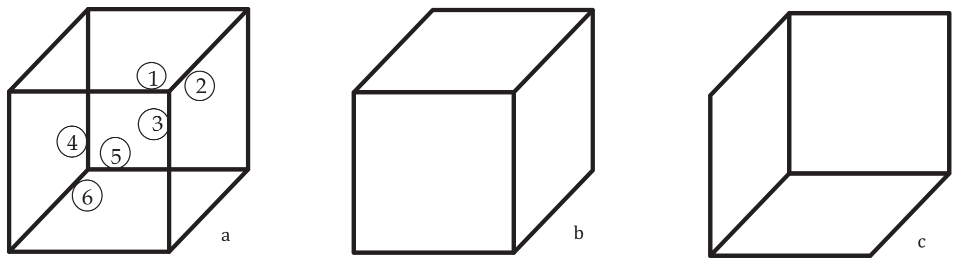

Figure 1. Necker cube: a - Necker cube face defining the possible interpretation of the type cube (1, 2, 3 - left cube, 4, 5, 6 - right cube); b - left (observed bottom and left); c - right cube (observed top and right)

a difficult technical problem. MEG is mainly registers the neuronal activity located in the sulci. Whereas, EEG registers mostly cortical neuronal activity in the grooves and on the surface of the brain gyri.

In addition, EEG data recording technology makes it possible to record a signal using wireless devices. It allows us to monitore neuronal activity of the freely moving persons using the portable devices. It opens up broad prospects for their use in many different applications for a variety of technical devices.

2. PROBLEM FORMULATION

Among tasks of creating a brain-computer interface is one of the important problem of determining the state of a person by the signals of brain activity. For such problems can be attributed, and the problem of classifying the images perceived by human on the EEG signal analysis.

In this paper, we solve the problem of recognition type (class) of the observed object, depending on the generated pattern and the registered multi-channel EEG signal. A tool for the implementation of the classifier is artificial neural networks.

Test image in the experiments was chosen one of the typical ambiguous image the so-called Necker cube.[5] The Necker cube relates to a simple bistable image, often used in different experiments to study the human perception models .[6–9] Human perception system does not allow for ambiguity object identification. Therefore, the subject, looking at the Necker cube, selects the type of cube and interpret it either as a left cube (the observed bottom, left, fig. 2b), or as the right cube (observed top and right, fig. 2c).

EEG recorded at the time of displaying cube Necker characterizes appropriate state of brain activity. Thus, assuming that the model of the human perception of the Necker cube has two stable states,[4] EEG at the time of observation and identification of the test cube can be associated with the type / class of the selected cube. The classification problem thus consists in determining the class cube depending on EEG data cube formed at perception. To solve the problem of classification in the article proposed and investigated the use of artificial neural networks (ANN).

3. EXPERIMENT DESIGN. DATA

The purpose of the experiment was to EEG recording the subject at a consistent demonstration Necker ube. In this case a variable parameter Necker cube is an intensive edges that impact on interpretations of the cube as "right" or as "left. Fig. 2 shows examples of cube faces with different intensity. The intensity of the faces defining the type of possible interpretations of the cube (1-6, Fig. 1a), varied from 15% to 85%. Cube edges with different intensities were presented to the subject in random sequence. presentation time varied from 2 to 2.5 s. The subject in the showing determined the type observed cube by pressing the appropriate button, which was reflected in the marks recorded EEG. Presentment cube alternated with the presentation of a static background neutral image without marked attention grabbing points, the show which varied from 1-3 s. For the studies were selected conditionally healthy subjects without any vision problems or correction of existing restrictions.

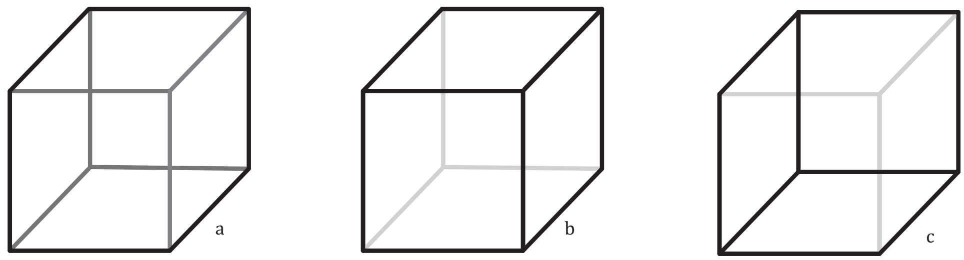

Figure 2. Necker cube with the intensity of edges 1, 2, 3 - 80%, 4, 5, 6 - 20% (a); 1, 2, 3 - 20%, 4, 5, 6 - 80% , (b); 1-6 50% (c)

The experiment lasted about 30-35 minutes. And includes a demonstration of a series of cubes, including entire set of intensities. In all the experiments performed background recording of brain activity of the subject in a free state with eyes open immediately before and after the experiment. Electroencephalographic equipment "Encephalan-EEGR-19/26" (Medicom MTD) was used to record the electrical activity that allows you to record multi-channel EEG with high temporal resolution for a long time. The standard international system "10-20" monopolar electrodes placement registration method was used for EEG recordings.

4. SOLUTION TO THE PROBLEM OF ANN

Artificial neural networks (ANN) is used for a wide range of applications and are particularly effective for hard formalized with unknown patterns and dependencies between input and output variables.[10] For such problems the construction of models of classical methods is quite difficult. Unlike traditional methods involving construction of a mathematical model of the system or object, knowledge of the object or system presented experimental data and central to solving the problem is getting ANN training. Traditionally, solutions using ANN task includes the steps of: preparing data of the object - the formation of the training set, the correct selection of a neural network structure, neural network training, testing and simulation. Analysis of the result of problem solving is done after the training of ANN, therefore, to improve the results of the decision may change the topology of the ANN and / or increase its computing abilities correction the training set data with the re-training (with a return to the stage of training). Solution of the problem of classification is one of the most important applications of neural networks, and occurs, including in relation to the tasks of EEG analysis. Construction of classifier based on ANN suggests splitting the available patterns, containing information about the object / system into a number of classes that define the state of a given system or object. In this case, the input data is a multi-channel EEG signals recorded at the time of the demonstration Necker cube, a class is a type of identifiable cube. To solve the problem of classification is used as different neural networks, and various types of learning (with a teacher, without a teacher), on which depends the type of data formed. In our paper to create a classifier we have considered a multilayer perceptron. The set of training data for learning multilayer perceptron includes input and output (target) values. Here, the input value is oscillatory patterns, and output values are the types of cubes. Thus the algorithm for constructing a classifier based on neural networks consists of the following steps.

Thus the algorithm for constructing a classifier based on neural networks consists of the following steps. 1. We form of a training set that includes the input signals (EEG-data, otsillyatornye patterns) and the output values of type Necker cubes and divide of the training set for training, inspection, test. 2. We select the type of artificial neural network, its topology, provide training and assess the effectiveness of the solution of (accuracy of the solution). When determining the structure of a multilayer perceptron we define layers number, neurons number in the layers, activation function. We choose the learning algorithm and determine the accuracy of the solution. To improve the accuracy of the solution, we increase neurons number of in layers, layers number, the volume of training sample and provide retraining. 3. We test neural networks and provide simulation. After testing, we choose the structure of the neural network, which gives the best ability to classification.

Table 1. Learning and test sets

Learning data			Test data		
Intensity of cube edges	Number of EEG signals	Cube class	Intensity of cube edges	Number of EEG signals	Cube class
15	1	9	15	1	12
15	2	3	15	2	0
50	1	4	50	1	3
50	2	8	50	2	8
85	1	0	85	1	0
85	2	11	85	2	12
Number of "right" cubes		22	Number of "right" cubes		20
Number of "left" cubes		13	Number of "left" cubes		15
Number cubes		35	Number cubes		35

5. CREATION A TRAINING SET

The input values applied to the input of the multi-layer perceptron are multi-channel EEG signals (oscillatory patterns).[11–13] The number of channels corresponding to the scheme of recorded EEG data is 20. For each channel, we generate signals of duration 1 s (250-dot patterns). For the pattern that characterizes the human condition in the process of identifying the Necker cube, we choose the interval from the time the EEG demonstration cube. The pattern formed in this interval of time is supposedly most informative. Each such signal we associated the class (type) of the cube, which subjects chose during the demonstration. The value of the class is equal to 1 if the cube was identified as "left", and is equal to 2 if the subject sees the "right". Thus, the learning set includes input values (multichannel signals with a duration 1 s which corresponds 250 samples), and output values that correspond to the identified classes Necker cubes. The number of channels determines the number of inputs of the neural network.

6. CHOICE OF A NEURAL NETWORK STRUCTURE

Multilayer perceptron ANN is universal, which is used for a wide range of tasks. Multilayer perceptron for solving classification problems shows good recognition result Necker cubes and acceptable time training the neural network. There are some of problems for which we can fairly easy choose the 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 topology of the neural network is too simple, the problem will remain unsolved. However, excessive structure of the neural network will require larger volume of training sample and learning time. Therefore, we conducted a study of the neural network topology and accuracy of the solution to the number of layers and neurons in them is sufficient to solve the problem. We used a neural network, the structure of which is shown in Fig. 2. The number of inputs of artificial neural network corresponds to the number N of channels of recorded EEG (maximum number of channels $N_{max} = 20$). The number of neurons of the first layer is equal to or more than the number of inputs. Multilayer perceptron contains a hidden layer. classification problem in the case of two classes can be solved by a neural network with one output, which is to take one of two values (1 or 2). The activation functions of the first and the hidden layer is a sigmoid logic function. Output layer activation function comprising one neuron is linear activation function.

7. LEARNING. CLASSIFICATION ACCURACY

The process of training a multilayer perceptron is the process the determination of the synaptic weights and bias ANN. The learning process is a solution to the problem of optimization of the error function, which depends on the difference between the output values and the target values (reference values ANN output). The methods used optimization target function (a complex function of several variables) is a function of the error, and the variables are the weight and bias values of ANN. Obviously, increasing the neurons and synapses in the neural

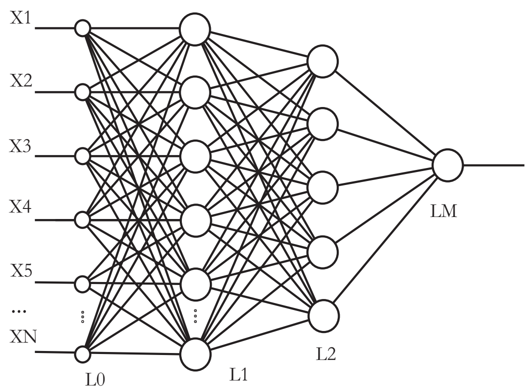

Figure 3. Structure of the Multilayer Perceptron, where L_0 is the layer propagation of input signals; L_1, L_2, L_M are the input, hidden and output layers of the ANN respectively; $X_1 \div X_{N_{max}}$ are the EEG signal inputs ($N_{max} = 20$)

Table 2. The recognition accuracy depending on the number of hidden layer

The number of neurons in the hidden layer	6	9	11	13	16	18	21
Recognition accuracy, cubes	27	28	28	29	29	30	30
Recognition accuracy, %	77.14	82.9	82.9	83	83	85.7	85.7

network results in complication of target function (error function) and increased the number of local extremums. Therefore, the correct choice of optimization method determines the effectiveness of the training. In teaching ANN we used Levenberg-Marquard method, who has a good convergence and accuracy of the solution. When training a multilayer perceptron we use the local optimization when the resulting local extremum at a better value the target function is an approximate solution. If we do one learning cycle there is a possibility to reach a local minimum and find the less fortunate of the possible solutions of the problem. So we conducted many times training (200) and choose the best ANN depending on the classification accuracy. After the learning, we tested the INS 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 the recognized right, at a value higher or equal to 0.5 cube was considered not a recognized. As a result, it was possible to determine the total number of recognized cubes, the number of "right" and "left" cubes.

Recognition accuracy, ρ, of recognizing cubes is defined as

$$\rho = \frac{N_p}{N} \times 100\%,$$

where N_p is the number of true detected cubes, N is the total number of cubes. Recognition accuracy was determined for all 200 neural networks.

8. CONCLUSION

When testing the neural network performance evaluation solutions classification tasks performed on the data, which are not used for teaching. We got the result for 12 individuals. Recognition accuracy ranges from 75—85%, for some individuals up to 95%. We analyzed the classification accuracy, depending on the number of neurons of the hidden layer of a multilayer perceptron. The percentage of recognition shown in Table 2. If you change the number of neurons in the hidden layer of 6-21 recognitions, classification accuracy increases from 77.14 to 86%.

9. ACKNOWLEDGMENTS

This experimental study of brain activity during perception of bistable images has been supported by the Russian Science Foundation (Grant No. 16-12-10100). The development of artificial neuronal network has been supported by the Ministry of Education and Science of Russian Federation in the framework of the implementation of state assignment 3.861.2017/PCh.

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