Problem of Recognition of Patterns of Signals of an Electroencephalography in Systems of Physical Activity

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***Abstract*—An important stage in the development of biomechanical systems is the interpretation of pulses obtained by EEG and EMG methods. The main difficulties are in the classification of signals and the determination of patterns of nerve impulses that actuate the limbs of the human body. If these problems are successfully solved, the classified patterns can be used to control biomechanical systems, for example, such as bionic prostheses. Modern methods of artificial neural networks open up the prospect for realizing an effective classification of the received impulses. However, the effectiveness depends on the chosen model of the artificial neuron and its computational complexity. This article will consider the most popular hybrid neural networks, and it will be shown that they have such advantages as resource intensity, energy efficiency and high level of accuracy of calculations and at the same time are biorealistically enough.**

Keywords*— *electroencephalography; hybrid neural networks; bionic prostheses; automatic control system

I. INTRODUCTION

Electroencephalography is one of the most practical methods of studying brain activity. Based on the registration of currents generated by nerve elements, this method proves to be practically non-inertial, since it reflects the activity of brain formations without the slightest delay.

Relative simplicity of the technical implementation of the method, allowed to create one of the types of non-invasive brain-computer interfaces (BCI), demonstrating high performance.

In such interfaces, the user controls an external device, for example, the prosthesis, with the help of a mental representation of a particular movement [1-3].

When performing or imagining the movements of various parts of the body, activation of the corresponding motor sites of the cerebral cortex takes place and in the EEG leads located above these areas, desynchronization of μ- and β - rhythms is observed. At the same time, at rest, sensorimotor rhythms have a high amplitude (that is, synchronization of rhythms is observed).

When recording EEG, the system "10-20%" is usually used the standard system for placing electrodes on the head surface, which is recommended by the International Federation of Electroencephalography and Clinical Neurophysiology. In total, according to this scheme, 21 electrodes are applied to the head surface (Fig. 1).

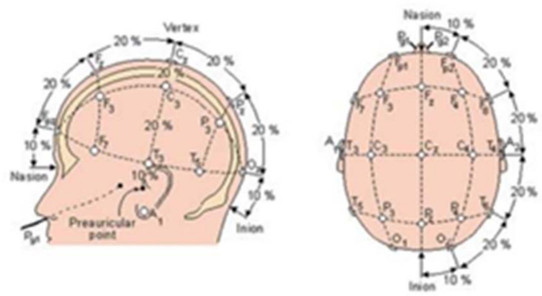

Fig. 1. The layout of the electrodes according to the "10-20%" system

However, for the management of the prosthesis, the interpretation of the impulses obtained by these methods is necessary [2-5]. The main difficulties are in the classification of signals and the determination of models of nerve impulses that activate the limbs of the human body. To classify effectively use the methods of artificial neural networks.

II. ELECTROENCEPHALOGRAM

The electroencephalogram is a curve of recording the total potential of the constantly changing bioelectrical activity of a significant group of nerve cells. This amount includes synaptic potentials and, in part, the potentials of action of neurons and nerve fibers. The total bioelectrical activity is recorded in the range from 1 to 50 Hz from the electrodes located on the scalp. The same activity from the electrodes, but on the surface of the cortex of the brain is called an electrocorticogram. When analyzing the EEG, the frequency, amplitude, shape of individual waves and the frequency of certain groups of waves are taken into account [6-8]. The amplitude is measured as the distance from the baseline to the peak of the wave. In practice, because of the difficulty in determining the baseline, amplitude measurement is used from peak to peak. By frequency is meant the number of complete cycles performed by a wave in 1 second. This indicator is measured in hertz. The inverse of the frequency is called the period of the wave. On the EEG, 4 main physiological rhythms are recorded: ά -, β -, θ -. and δ - rhythms.

In addition, there are special waves on the EEG that differ from the background ones. These include: K-complex, λ-waves, μ-rhythm, spike, acute wave. But we will mainly be interested in the μ-rhythm.

III. Signal Preprocessing

Detection by recording EEG states of synchronization and desynchronization of sensomotor rhythms is complicated by the fact that the signal recorded from the electrodes contains besides the actual potentials generated by the brain, various kinds of artifacts [9].

Artifacts by their origin can be divided into two groups: physical and physiological.

Physical artefacts include, for example, interference from electric fields, created by devices for the transmission and operation of industrial electrical current. This kind of artifacts look like oscillations of a sinusoidal shape with a frequency of 50Hz, superimposed on the current EEG.

Physiological artifacts are associated with manifestations of the body's vital activity and can have the following origin: potentials due to muscle activity (electromyogram, EMG); potentials arising from eye movement (electro-oculogram).

When analyzing the EEG, suppression of artifacts is carried out using the following methods.

a) Application of high and low frequency filters (removal of interference from electric fields).

b) Recalculation of the EEG signal values of the relative new reference potential (electrode). The method allows for spatial filtering of the EEG signal.

c) Methods based on the linear expansion of the EEG signal into its components, isolation of an artifact and EEG restoration without components of the artifact. Methods of this type include analysis of the main components and analysis of independent components.

IV. Electrode Geometry

Based on the characteristics of the EEG, we can talk about the need use methods developed in the field of artificial intelligence, such as artificial neural networks [10].

Artificial neural networks - mathematical model, as well as its a software or hardware implementation built on the principle of organization and functioning of biological neural networks – networks nerve cells of a living organism.

Distinctive features of artificial neural networks is the possibility of learning, during which neural networks are capable of allocate rules for presenting the final result, which is necessary for an adaptive selection of rules from the EEG.

There are 2 types of artificial neural networks shared by nature of training [11]:

a) Neural networks that use training with the teacher - when learning from teacher for each teaching input example requires knowledge the correct answer or the function of assessing the quality of the answer. Such training called controlled. Neural network values of input and output signals, and it adjusts the weight according to a certain algorithm synaptic connections. During the training, we adjust the weights network by comparing the actual output values with the input, known in advance.

b) The neural networks using training without a teacher - in training without the teacher, the internal structure of the data or the correlation between samples in the dataset. Outputs of the neural network are formed independently, and weights change according to an algorithm that takes into account only input and derived signals from them. This training is also called uncontrollable. As a result of such training, objects or examples categories, and the number of categories can be not known in advance.

To date, neural networks are able to solve the following range of tasks [12]:

a) Recognition of images and classification - the task is to associations of classes and images.

b) Decision-making and management - the input image is represented as the vector of features of a particular situation, the output of a neural network is a certain decision that she took.

c)Clustering - A task is a partitioning of a set input signals to classes, while the number of classes and number of symptoms. The result of learning the neural network is, the ability of a neural network to determine to which class the input form. The neural network is able to identify new, unknown classes.

d)Forecasting - based on several previous values and / or some existing factors at the moment, a neural network can make an assumption, on the basis of the ability to generalize and the allocation of hidden dependencies between input data, the future meaning.

e) Approximation - neural networks have the ability approximate continuous functions. Using linear operations and cascade connection, it is possible, from an arbitrary nonlinear element, get a device that calculates any continuous function, with some given accuracy.

f) Data compression and associative memory-the neural network is capable of to express data of large dimension, more compact.

To solve the problem of analyzing and classifying EEG signals on evoked potentials, it is necessary to use neural networks trained without the teacher because of the possibility of clustering the received data and Discover new phenomena in EEG data.

Among the existing algorithms of neural networks trained without teachers can be identified: self-organizing map of Kohonen and growing neural gas, as the most promising algorithms for solving the problem analysis and classification of EEG data.

V. SELF-ORGANIZING MAP OF KOHONEN

Self-organizing map of "Kohonen" - is a two-layer neural network that divides the input n-dimensional space into m areas (clusters), each region corresponds to one neural winner. As a training procedure, the method competitive learning. An example of the Kohonen map is shown in Figure 1 [13].

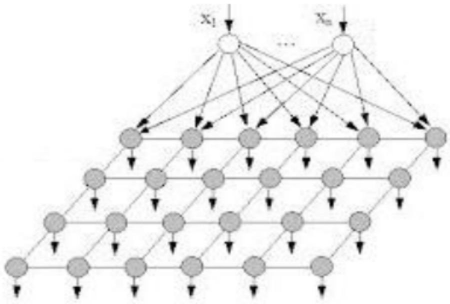

Fig. 2. Visual representation of the self-organizing Kohonen map

Competitive training is a method of teaching used in self-organizing maps of Kohonen. In competitive learning, neurons compete with each other so that the vector of their weights is as close as possible to the vector of characteristics of the object presented. Competitive learning is an iterative process in which, at each iteration 3 actions are performed: competition, consolidation and adjustment of weights.

The goal, a self-organizing neural network, is ordering input images in such a way that they correspond to neighboring neural elements of the computational layer [14].

Arrangement of input images is possible using the function attraction, in most cases the Gaussian function has the form:

$$h(t,k,p) = e^{\frac{-|u_k - u_p|^2}{2\sigma^2(\tau)}} = e^{\frac{-(i_k - i_p)^2 + (j_k - j_p)^2}{2\sigma^2(\tau)}}$$

where u_k – the neuron winner with the number and coordinates in the matrix output layer; u_p – the current neuron with the number and coordinates in the matrix output layer; $u_k - u_p$ – the distance between the winner neuron k and the current neuron p; $\sigma(t)$ – characterizes the radius of the region of attraction and is decreasing function of time.

The learning algorithm for self-organizing networks is next, let *n* be the dimension of the input images, and we want divide all *L* input images into *M* clusters.

The procedure for learning the self-organizing map of Kohonen looks like in the following way:

- randomly initialized weighting factors - w;
- the iteration number (time) is set to t = 1, I set the function σ(t) and determine the initial value of the radius of attraction - σ(1);
- for all input images l=1..L, operations are performed;
-the vector is calculated by the formula:

$$D_{ij} = \left(X^1 - W_{ij}\right)$$

where $i = 1 \ldots m_1, j = 1 \ldots m_2$.

changing weight coefficients.

VI. GROWING NEURAL GAS

A growing neural gas is an algorithm that allows adaptive clustering of input data, that is, not only to divide space on clusters, but also to determine the required number of them based on from the characteristics of the data itself. This is a new class of computing mechanisms.

Number and location of artificial neurons in the space of signs it is not specified in advance, but is calculated in the process of learning the models in accordance with the characteristics of the input data, independently adjusting to them [15]. Example of clustering data using growing neural gas is shown in Figure 3.

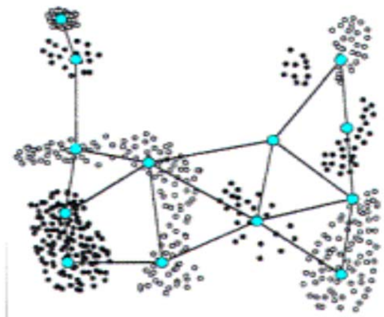

Fig. 3. Example of clustering data using growing neural gas

The neural gas algorithm looks like in the following way:

1. Initialize 2 neuron nodes network (from the source data) and connect them with an age of 0. As weighting coefficients of these nodes are taken the coordinates of the corresponding points.

2. Submit to the input of the algorithm arbitrary vector

3. Find the 2 neurons s and t closest to $\bar{x}$. Usually as a measure distance is chosen Euclidean metric, however, as a measure distance can also be used measure Jacquard, cosine coefficient, etc. Further description of the algorithm will be given for Euclidean measure.

4. Update the error of the winner neuron (neuron, for which the distance to the input vector x is minimal.

5. Displace the neuron s and all its neighbors. In the classical neural gas algorithm, they remain constant throughout the learning process.

6. Increase by 1 the age of arcs emanating from *s*.

7. If the neurons *s* and *t* are connected, then the age of their connection is reset; if the connection no, then create a new one.

8. Delete all arcs with an age greater than parameter algorithm.

9. If the iteration number is a multiple, then insert the new node.

10. Reduce the errors of all neurons.

11. If the stop criterion is not met, go to step 2.

For EEG analysis it is preferable to use growing neural gas, because of the possibility of adaptive clustering of the input data. The use of growing neural gas, shows the best results for solving the problem of data clustering, than the self-organizing map of Kohonen.

Based on the characteristics of the EEG, the use of a set of neural networks united in a cascade, for analysis of the information received from each sensor, and attempt interpreting the results using the group numbers.

Level 1 – Solution of the problem of signal clustering caused by different potentials, for each of the EEG sensors.

Level 2 – Training ensemble of neural networks, including in yourself:

– Expanding neural gas - to highlight the regularity in clusters of evoked potential and subsequent interpretation of the final result;

– Neural network tracing error trainee with teacher , for training management teams on the temporary set received signals in the form of cluster numbers.

Thus, the cascade structure of the neural network will allow at level 1 cascade to find patterns in each EEG sensor and form clusters activity, extracted from the EEG, at level 2 of the cascade using Formed clusters of activity, isolated from EEG possibly interpret the final result. The proposed approach is one of the possible for the interpretation of EEG results [16].

VII. CONCLUSIONS

EEG analysis is a difficult task, since the nature of the rhythmic activity of the EEG is specific for each individual, the classifier of vectors of characteristic EEG characteristics must adaptively adapt to the subject. The use of neural networks is advisable since they can provide a high level of accuracy of calculations and at the same time are sufficiently bio-realistic.

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