EEG Neuro - processing for the development of neurointerfaces

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Abstract. Fast and accurate processing of electroencephalogram (EEG) signals is necessary for correct realization of neurointerfaces. Neural network is one of the ways of its processing. In this article the method of EEG processing with the help of multilayer perceptron trained by the algorithm of error backpropagation is considered. The results of modeling during training of the neural network showed the minimum value of the Mean Squared error.

Keywords: neuro-interface; electroencephalogram; neural network; backpropagation; perceptron

1. Introduction
For the first time, the idea of human communication with the machine was proposed by J. Vidal, describing the laboratory for the analysis of the electroencephalogram (EEG) signal [1]. Later, the universal architecture of brain-computer interface (BCI) was described in [2]. Classification of BCI schemes was suggested in [3]. BCI is divided by the way the user presents information into active ones, in which the user initiates a command, e.g. a hand movement, reactive ones, where the user initiates a command in response to the system, e.g. a hand movement in response to the screen signal, and passive ones, where the system reads and analyzes the user's state without initiating a command.

BCIs are classified by the way the signal is received into invasive, e.g. implanted electrodes, and non invasive, e.g. EEG, ECG, etc. BCI has found its main application as a tool for rehabilitation of patients with various motor and neurological disorders, but recently such an interface has also been used by healthy people, for example, to control cognitive condition through biofeedback, games and entertainment.

In this article we suggest using multilayer perceptron for EEG processing and will show the result of modeling such a neural network.

2. Application of EEG for neurointerfaces
A device for exchanging information between the brain and the computer is called a neuro-interface or BCI. BCIs can be invasive and partially invasive, as well as they differ in their application and area of use [2], [3].

The architecture of the BCI is shown in figure 1. It contains "Signal Acquisition", "Preprocessing", "Feature Extraction", "Translation/Classification", "Commands/Control". The points " Signal Acquisition " and " Commands/Control " are implemented by the device. Items " Preprocessing " and " Feature Extraction " implement artifact selection and motion features selection, respectively. Artefacts of EEG are conditionally divided into physical artifacts arising due to influence of various physical or technical hindrances on EEG equipment, and on physiological artifacts which are shown at various biological processes in an organism of the investigated person [4]. The item " Translation/Classification " determines which movement is performed.

EEG of the brain is a method for registering electrical signals of brain origin by placing electrodes (figure 2) on the scalp surface as a result of electrical summation and filtration of elementary processes in
neurons [5]. The EEG has the form of a graphical image, which shows the gradient oscillations of somatodendrite potentials corresponding to the excitation post-synaptic potential (ESP) and inhibitory post-synaptic potential (PSP) [5].

Electrode designations include the first letter of the Latin name of the mounting area of the electrode and a number indicating the side and location. The electrodes are placed on the scalp surface according to the standard international system "10-20%" recommended by the International Federation of Electroencephalography and Clinical Neurophysiology. According to this system, the line connecting the nose bridge (Nasion) and occipital mound (Inion) is accurately measured and divided into 10 equal segments. The first and last electrode are placed at a distance equal to 10% of the total long line from the nose bridge (Fp1/Fp2) or occipital tuber (O1/O2). The first electrode is followed by the next one at a distance equal to 20% of the total line length. The second main line, which connects the left and right ear cavities, is also divided into equal sections, followed by mounting the electrodes at a distance of 10% of the ear canals (T3/T4) and 20% of each other (C3, Cz, C4). The third line represents the arrangement of the electrodes along the head circumference from the occipital electrodes (O1/O2) to the frontal electrodes (Fp1/Fp2) at a distance of 20% from each other. Indifferent electrodes (A1/A2) are located at the earlobes. In this way, 21 electrodes are applied over the entire head surface [6].

The excitatory postsynaptic potential allows the neuron to become more excitable and thus increases the probability of generating the action potential, while the inhibitory postsynaptic potential leads to a decrease in neuron activity and decreases the probability of generating the action potential [7]. For generation of action potential by neuron to be transferred to other neurons or effectors it is necessary that the level of its excitation reaches a certain threshold value. In its turn the level of excitation is determined by the sum of excitatory and inhibitory influences which appear on the neuron by means of synapses at the moment. As soon as the sum of excitatory actions exceeds the sum of inhibitory actions by a value higher than the threshold level, the neuron generates a nerve impulse transmitted to the axon [5].

The most significant characteristics when estimating the EEG can be called average frequency of oscillations, maximum amplitude, phase of oscillations and estimation of curves difference on different channels with their dynamics in time. The frequency indicator is estimated by a fixed number of wave oscillations per second, calculated from the number of waves on the taken 4-5 sections of the record and expressed in Hertz (Hz). The amplitude gives an idea of the range of wave oscillations of eclectic potential and is measured by the distance between the wave peaks in opposite phases, expressed in microvolts (µV). The oscillation phase value estimates the current state of the process occurring in the human brain and determines its vector changes. After the end, the physical and pathological interpretation of the obtained materials is made and on its basis the EEG conclusion is formulated.
The activity of the adult brain, which can be recorded by an EEG in a waking state, is divided into the following types of rhythms. The $\alpha$-rhythm is fixed at a frequency of 8-14 Hz, present at rest with the examiner with his eyes closed, is determined at the occipital region. $\beta$-rhythm. Rhythm with wave frequency in the interval of 13-30 Hz in the active state of the brain is diagnosed in frontal lobes [8]. The $\gamma$-rhythm is fixed with frequency of fluctuations from 30 to 180 Hz, it is defined at the solution of tasks and the situations requiring a high level of concentration and attention. $\kappa$-rhythm is characterized by frequency in 8-12 Hz and is observed in a temporal lobe of a brain at mental processes. The rhythm has a low frequency of 4-5 Hz and is determined in the occipital region when the visual receptors are used. $\mu$-rhythm has a frequency of 8-13 Hz and is fixed in the occipital lobe of the brain in a calm state.

In sleep, a separate category of rhythm types is recorded [9]. $\delta$-rhythm characterizes the phase of deep sleep as well as the coma. $\theta$-rhythm has an oscillation frequency within 4-8 Hz. Waves of the given rhythm are launched by the hippocampus and appear in dreams. $\sigma$-rhythm differs in frequency from 10 to 16 Hz and is considered to be the rhythm of oscillations that occur during natural sleep in the initial stage.

By the end of XX century this method of research was applied in BCI, which allowed a person to communicate with the outside world in real time by means of changes in the activity of his own brain [10]. Today, the EEG is the leading method for studying the stages of sleep, as it allows tracking large changes in brain activity. This study also shows rhythms of brain electrical activity, consequences of brain operations, brain tumor processes and their influence on functional activity, presence or absence of foci of increased convulsive readiness and their localization, etc. [11].

The method is highly accurate, efficient, safe and painless for humans, allowing the use of EEGs to receive brain signals and their subsequent use in BCIs.

3. Application of a neural network for the analysis of EEG

The neural network can be used to decrypt the EEG. A neural network is a sequence of neurons connected to each other by synapses. The structure of a neural network is a machine interpretation of the human brain, which contains millions of neurons transmitting information in the form of electrical impulses.

Neural networks are not programmed, they are trained. The possibility of learning is the main advantage of neural networks. Learning a network is about finding the relationship coefficients between neurons. In the training process, the neural network detects complex relationships between input and output data and summarizes them. If the training is successful, the network can get the result if there is no or partial data distortion [12].

A neuron is a unit of information processing in a neural network. Figure 3 shows the biological (a) and mathematical (b) models of the neuron underlying artificial neural networks [13]. Dendrite, presented in biological neuron model, is a prototype of input signals in mathematical model $(x_1, x_2, ..., x_k)$. Axon is the prototype of the output signals, in a mathematical model it is "Activation", i.e. the result. Interaction
between neurons is realized in synapses, in the mathematical model they correspond to weight coefficients \((w_{1j}, w_{2j}, \ldots, w_{kj})\), which can take positive and negative values.

Figure 3. Neuron model. a) biological model of the neuron; b) mathematical model of the neuron

The nucleus and body of the cell in the biological model correspond to the adder and activation function of the mathematical model. The adder adds up the input signals, this operation is a linear combination. The activation function limits the amplitude of the neuron output signal. This function is also called the compression function. Normally, the neuron output amplitude range is in the range \([0, 1]\) or \([-1, 1]\) [13].

There are several models of neural network. We will consider one model of perceptron, which is the McCullock model. Its nonlinear activation function is a discrete step-type function, where the neuron output can be only two values 0 or 1 according to the rule

\[
y_k(v_k) = \begin{cases} 
1 & \text{for } v \geq 0 \\
0 & \text{for } v < 0
\end{cases}
\]

In this expression \(u_k\) the adder output signal

\[
v_k = \sum_{j=0}^{N} w_{kj} x_k
\]

Perceptron teaching implies a teacher and consists in selecting weights so that the output value is as close as possible to the specified value [14].

In our proposed method, we will use a multilayer Perceptron with at least one hidden layer. The multilayer perceptron was chosen by us as the basis for its simplicity and versatility.

The output signal of the \(j\)-type neuron of the hidden layer can be described by the function

\[
v_j = f \left( \sum_{i=0}^{K} w_{ki}^{(2)} x_i \right), \text{ provided that a single polarization signal is considered as one of the components of the } x \text{ input vector}
\]

the \(y_k = f \left( \sum_{i=0}^{K} w_{ki}^{(1)} x_i \right) = f \left( \sum_{i=0}^{K} w_{ki}^{(2)} f \left( \sum_{i=0}^{K} w_{ki}^{(1)} x_i \right) \right)\). It follows that the signals generated in the hidden layer do not depend on the weights of the output layer.

In the proposed method, an algorithm of backpropagation was used to teach the described neural network. This method of teaching a multilayer neural network is called a generalized delta rule. The method was proposed in 1986 by Rumelhart, McCleland and Williams [15]. This algorithm is the first and main practically applicable for training multilayer neural networks.

For the output layer, the correction of weights is understandable, but for hidden layers the algorithm has not been known for a long time. Weights of the hidden neuron will change directly proportional to the error of those neurons with which the given neuron is connected. Therefore, the reverse distribution allows you
to correctly adjust the weights of links between all layers. In this case the error function value is reduced and the network is trained [16].

The main relations of the method of reverse propagation of the error are obtained with the following designations - function error for the image \( p \), - desired neuron output \( j \) for the image \( p \), - active neuron output \( j \) for the image \( p \), - weighted sum of outputs of bound neurons of the previous layer on the weight of the bond (inactive state of the neuron), - weight of the bond between \( i \) and \( j \) neurons.

The main ratios of the error propagation method are obtained with the following designations. \( E_p \) is function error for image, \( t_{pj} \) is desired neuron output \( j \) for image \( p \), \( y_{pj} \) is active neuron output \( j \) for image \( p \), \( s_{pj} \) is weighted sum of yields of bound neurons of the previous layer on the weight of the bond, \( w_{pj} \) is the weight of the connection between \( i \) and \( j \) neurons.

The value of the error is determined by formula (1)

\[
E_p = \frac{1}{2} \sum_j (t_{pj} - y_{pj})^2
\]

The inactive state of each neuron \( j \) for image \( p \) is recorded as a weighted sum using formula 2

\[
s_{pj} = \sum_i w_{ij} y_{pj}
\]

The output of each neuron \( j \) is the value of the activation function \( f_j \) that switches the neuron to the activated state [5]. Any continuously differentiable monotonic function can be used as an activation function. The active state of a neuron is calculated using formula 3:

\[
y_{pj} = f_j(s_{pj})
\]

Gradient descent method is used as a method to minimize the error. To find the minimum, the movement must be in the direction of the antigradient.

The gradient of the loss function is a vector of private derivatives calculated by formula 4, where \( \nabla EW \) is the gradient of the loss function

\[
\nabla E(W) = \begin{bmatrix} \frac{dE}{dw_1}, \ldots, \frac{dE}{dw_n} \end{bmatrix}
\]

A derivative error function for a specific image can be written using formula 5

\[
\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial s_j} \frac{\partial s_j}{\partial w_{ij}}
\]

The neuron error \( \frac{\partial E}{\partial y_j} \) is usually written as an \( \delta \) (delta) symbol. Let us determine the error of the output layer [5]. To do this, let's calculate a derivative of formula 1. We will get \( t - y \) what is the difference between the desired and the obtained output.

Error \( \delta \) for the hidden layer is calculated using formula 6, where \( \delta_i \) - neuron error \( i \) of the hidden layer; \( \delta_j \) - neuron error \( j \) of the next layer

\[
\delta_i = \frac{\partial y_i}{\partial s_i} \sum_j \delta_j w_{ij}
\]

The algorithm of error propagation is reduced to the following stages: direct signal propagation through the network, neuron state calculation, error value \( \delta \) calculation for the output layer, reverse error propagation, update of network weights [12], [16].
4. Simulation of EEG processing using a neural network

The method we proposed was implemented in MATLAB R2017b. We faced the task of determining hand movement on the basis of EEG, which we solved by teaching the neural network the inverse gradient distribution of error. Figure 4 shows the first 1200 EEG signals performed using a standard 10-20% protocol with 24 sensors the first 4 sensors.

To train the neural network, vectors were created to denote hand movements. The first vector (1,0,0) denotes movement of the right hand, the second (0,1,0) - movement of the left hand, and the vector (0,0,1) - state of calm. Training is structured in such a way that some part of data is used by the neural network for self-study and the other part is used for its evaluation. In figure 5 shows the result of neural network training conducted in the mathematical environment MATLAB R2017b.

We trained the neural network with 1000 iterations and stopped training after the network made 6 consecutive errors. To evaluate the correctness of the network training, you must make sure that the root-mean-square error decreases with each iteration.
The figure 6 shows a graph of the process of training the neural network with 1000 iterations and reduction of the standard error with each iteration, which allows to draw a conclusion about correct training of the network.

5. Conclusion
The article shows the application of neural network training by the algorithm backpropagation for EEG data processing. It is shown that such training can be used for operation of BCI. A good result of the training is obtained with $MSE \approx 10^{-3}$. The BCI can be applied in human life, for example, in medicine to create the human exoskeleton or bionic prosthetics.

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