Neural network model in the exoscelete verticalization control system

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Abstract. The aim of the study is to develop a biotechnical system of the rehabilitation type, designed to restore the motor activity of the patient’s muscles through biotechnical and biological feedback. The obtained classification models of surface signals of electromyograms can be used to create intelligent rehabilitation systems for patients with neurological diseases and will allow the development of diagnostic test stimulation programs that can be used to create artificial biological feedback. This will provide new predictors of the risk of socially significant diseases.

1. Introduction
Devices called exoskeletons have become more widespread in recent years [1]. Biotechnical system exoskeleton-patient must function in a combined mode for the implementation of post-stroke rehabilitation. At a certain point in time, the patient takes an active position and performs a given movement on his own. At another point in time, the patient takes a passive position and the exoskeleton performs a given programmed motion or movement, determined by decoding an electromyogram (EMG). In this case, the patient makes the specified movements using the exoskeleton, and the biotechnological system determines the moment and amount of help. Therefore, the EMG decoder must determine not only the type of movement and the coordinates of the limb, but also the force (moment) that is transmitted to the corresponding executive body.

The main requirement for the code is its ease of reception and its decoding (or classification) speed. The following values in the time domain, measured as a function of time, are used as signs: integral EMG; the average; average cost of the module; final differences; sum of elementary areas; dispersion; standard deviation; signal length; the maximum value of the EMG signal. More detailed information on the selection of characteristics for classification is given in [2].

Thus, the adaptation of a rehabilitating exoskeleton to the functional state of the patient through analysis and decoding of surface EMG signals is an actual task.

2. Methods
Many technical solutions allow controlling of the exoskeleton through biotechnical feedback [3]. Decision modules with interpretation of surface EMG are needed to control the rehabilitation process.
Trained classifiers are used as such decision-making modules. They are built on the basis of neural network models, fuzzy inference models, or hybrid (heterogeneous) models [4, 5]. At the same time, training samples for training these classifiers are formed from a database obtained as a result of search analysis.

The block diagram of an exoskeleton control device by EMG signals is shown in figure 1. The device consists of a block of electrodes 1, an EMG processing block 2; the onboard processor 3, and the controller of the servomotors 4. A distinctive feature of this device is the lack of biotechnological feedbacks. Feedback is carried out only through the sensor channel of the operator (patient).

**Figure 1.** Block diagram of an exoskeleton control device using an EMG signal.

The essence of the proposed exoskeleton control method is that when decoding EMG we use not only amplitude indicators, but also frequency characteristics. It is known that an increase in motor activity leads to an increase in the amplitude of the EMG signal, to an increase in the number of motor units involved. That is, for encoding EMG, the hypothesis of amplitude and frequency modulation of EMG is used [6].

The exoskeleton control process begins with the segmentation of the current EMG signal into nonoverlapped windows of width TW with the subsequent formation of the informative sign FD from the samples of each window. To this end, we make the transition from the current discrete EMG sample \( x_\tau \) to the sample \( y_\tau \), obtained by comparing the current sample with threshold \( \Theta \) and calculated according to the expression

\[
y_\tau = \begin{cases} 
1, & \text{if } |x_\tau| \geq \Theta; \\
0, & \text{if } |x_\tau| < \Theta.
\end{cases}
\]  

(1)

Based on samples (1), the informative feature in the TW window is calculated as

\[
FD = \frac{1}{TW} \sum_{i=1}^{TW} y_\tau.
\]  

(2)

Figure 2 shows how the signal \( y(t) \) of figure 2b is obtained from the EMG signal \( x(t) \) in figure 2a for one threshold \( \Theta \). At the width of the window, we use many thresholds \( \Theta \) and as a result, we get many informative signs FD.

Thus, on the aperture of the TW window, we form many informative features (2). Based on their recognition, we form the corresponding command for servomotors 4 figure 1. Having asked for the EMG aperture, on which the decision is made to turn on the corresponding servomotor, we can select many windows on it. Given that the temporal aperture of decoding the EMG signal is 250 ms, and the minimum information quantum, that is, the minimum length of the EMG signal that carries the relevant information, is 25 ms, the decision aggregator operates at the aperture of 250 ms. Since the decision made by analyzing one window is a private decision, an aggregator of these decisions is necessary. Thus, we conclude that two stages of EMG decryption are necessary.

We use trained neural networks of direct signal propagation for decoding EMG at two stages. The first neural network (NET1) operates with the space of informative features (2) formed in the Tw
window. As an aggregator, we also use a trained direct distribution neural network that operates on the aperture MW=int(250/W) or, if windows with overlap are used, on the aperture MW=int((250-TW)/W), where W is step of moving the window on the EMG aperture. Figure 3 illustrates the process of determining the number of non-overlapping windows.

The exoskeleton control algorithm through EMG analysis is presented in figure 4.

Figure 2. Illustration of the transition from the EMG signal x(t) (a) to the signal y(t) (b).

Figure 3. Illustration of the process of forming windows on the EMG aperture.
Figure 4. Scheme of exoskeleton control algorithm.

Blocks 2-5 of the algorithm analyze EMG windows at a given signal aperture. The results of this analysis are accumulated in memory unit 5. After EMG analysis at a given aperture, the transition is made to the NET 2 aggregator. In this aggregator, the final decision on the command to the servomotors is made.

Since the outputs of NET1 are spaced in time, the storage device is necessary for making decisions on the totality of the results of these outputs. The results of the classification of windows in NET1 are accumulated in block 5 of figure 4. After analyzing the corresponding number of windows, the results of this analysis are sent to the trained neural network NET2 (block 6), the outputs of which are connected
to the controller of servomotors 4 (figure 1). The number of analysis windows, that is, NET2 inputs, depends on the decryption time of the command encrypted in the EMG signal and on the minimum quantum of information carried by the EMG signal.

Figure 5. Structural diagram of a classic EMG using duplicate channels.

3. **Results**

The process of patient verticalization with a support for the hands, which acts as the simplest rehabilitation product, was chosen as the basis of the rehabilitation process [1]. To control the exoskeleton servomotors during verticalization, we use five EMG channels that read the EMG signal from the gluteus maximus muscle, biceps femoris muscle, semimembranous muscle, hemispinus muscle, and psoas major muscle.

The verticalization process is controlled by decoding the EMG in the channels and the rate of verticalization depends on the intensity of the EMG signals in the channels. With certain combinations of EMG intensities in the channels, the servomotors can stop in any phase of verticalization. If the patient feels that he "does not have enough strength to stand up," then he can sit down. In this case, it is possible to generate the corresponding EMG signals, which can be used to reverse the servomotors. To implement the "sit down" mode, EMG channels from the iliopsoas muscle are used. Thus, for the verticalizer, as an decoder of EMG signals, we use at least six channels of EMG and another neural network structure used as an aggregator of decoders of channel EMG. The block diagram of such a decoder is shown in figure 5. NET3 neural network is a fuzzy neural network. Its output is calculated by defusing six membership functions [5].

The second servomotor is controlled by a servo motor controller based on the exoskeleton motion model in the “stand up-sit down” mode. The parameters of the model are adapted to the physical condition of the patient, which eliminates the main disadvantage of the known rehabilitation exoskeletons.

4. **Conclusions**

To control the exoskeleton during the rehabilitation process, we used a multi-channel EMG signal. The decryption of this signal in each channel was carried out by stepwise segmentation into overlapping or non-overlapping windows. EMG decoder is based on a two-level neural network structure. The formation of the vector of informative features for a neural network of the first level was carried out by
means of a multilevel comparator, the number of levels of which is determined by the dimension of the vector of informative features. The components of the vector of informative features were determined through the clipping procedure of the EMG signal at various levels of comparation.

Based on the base classifier models, exoskeleton movement control in the “stand up - sit down” mode has been implemented. The location of the electrodes on the muscle group is determined for the implementation of the verticalization mode with combined control. We showed that a simplified kinematic model of the verticalization mode allows, together with a two-level neural network model of an electromyosignal decoder, to adapt the rehabilitation process to the functional state of the patient.

The obtained models of classifiers of surface signals of electromyograms can be used in the construction of intelligent rehabilitation systems for patients with neurological diseases and will allow the development of adaptive stimulating programs. Testing the results of these programs will allow us to develop new methods and tools for the rehabilitation of patients with neurological diseases.

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