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RESEARCH ARTICLE

Robust neural network filtering in the tasks of building intelligent interfaces

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Abstract
Objectives. In recent years, there has been growing scientific interest in the creation of intelligent interfaces for computer control based on biometric data, such as electromyography signals (EMGs), which can be used to classify human hand gestures to form the basis for organizing an intuitive human-computer interface. However, problems arising when using EMG signals for this purpose include the presence of nonlinear noise in the signal and the significant influence of individual human characteristics. The aim of the present study is to investigate the possibility of using neural networks to filter individual components of the EMG signal.
Methods. Mathematical signal processing techniques are used along with machine learning methods.
Results. The overview of the literature on the topic of EMG signal processing is carried out. The concept of intelligent processing of biological signals is proposed. The signal filtering model using a convolutional neural network structure based on Python 3, TensorFlow and Keras technologies was developed. Results of an experiment carried out on an EMG data set to filter individual signal components are presented and discussed.
Conclusions. The possibility of using artificial neural networks to identify and suppress individual human characteristics in biological signals is demonstrated. When training the network, the main emphasis was placed on individual features by testing the network on data received from subjects not involved in the learning process. The achieved average 5% reduction in individual noise will help to avoid retraining of the network when classifying EMG signals, as well as improving the accuracy of gesture classification for new users.

Keywords: digital signal processing, frequency filtering, electromyography, machine learning, neural networks, interfaces, gesture manipulation

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НАУЧНАЯ СТАТЬЯ

Применение робастной нейросетевой фильтрации в задачах построения интеллектуальных интерфейсов

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Резюме
Цели. В последние годы возрос научный интерес к построению интеллектуальных интерфейсов для управления компьютером на основе биометрических данных. Одним из источников таких данных служит сигнал электромиографии (ЭМГ). Сигнал ЭМГ можно использовать для классификации жестов рук человека. Это позволяет организовать интуитивно понятный интерфейс «человек – компьютер». Основными проблемами при использовании сигналов ЭМГ являются наличие нелинейных шумов в сигнале и значительное влияние индивидуальных особенностей человека. Цель работы – исследование возможностей применения нейронных сетей для фильтрации индивидуальных компонент сигнала ЭМГ.
Методы. Использованы математические методы обработки сигналов и методы машинного обучения.
Результаты. Проведен анализ исследований по теме обработки ЭМГ-сигналов. Предложена концепция интеллектуальной обработки биологических сигналов. Разработана модель фильтрации сигнала, построена структура сверточной нейронной сети на основе технологий Python 3, TensorFlow и Keras. Проведен эксперимент на наборе данных ЭМГ по фильтрации индивидуальных компонент сигнала.
Выводы. Продемонстрирована возможность применения искусственных нейронных сетей для выявления и подавления индивидуальных особенностей человека в биологических сигналах. При обучении сети основной упор делался на индивидуальные особенности, тестируя сеть на данных, полученных от субъектов, не участвующих в процессе обучения. Достигнуто уменьшение индивидуального шума в среднем на 5%. Для решения задачи классификации сигнала ЭМГ данный результат поможет избежать переобучения сети и повысить точность классификации жестов для новых пользователей.

Ключевые слова: цифровая обработка сигнала, частотная фильтрация, электромиография, машинное обучение, нейронные сети, интерфейсы, управление жестами

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INTRODUCTION

One of the key steps in software design is the choice of a method to communicate with an individual. For this, unified structural, hardware, and software tools are used, which are necessary for the interaction of various functional elements of the system. A set of such elements is referred to as an “interface”. The interface between an individual and software is especially important since this is what standardizes the interaction and determines the boundaries of the functionality of working with the software. Thus, interface concept is closely related to the usability of software systems. First of all, the usability is associated with a graphical user interface. The interface is considered usable if the user needs the least amount of time to use the information system. The second parameter that affects the usability is, of course, the simplicity and time needed to train a new user to work with the information system. A good interface should be intuitive and have as few hidden dependencies as possible, as well as a minimal learning curve. In addition to the graphical interface, an information system may also have some command-program interface, which is a set of messages (commands) that can be perceived by the software system and processed using the application programming interface (API). The usability of this type of interface is evaluated by the number of commands that need to be used to perform the targeted action on the system. At the same time, it is desirable that commands for different target actions not be repeated (duplicated). These requirements impose a serious responsibility on interface developers when designing interfaces for software products and systems.

In the modern digital space, a human (user) is transformed into an interactive system possessing a rapidly expanding set of its capabilities. However, the range of interactivity varies from system to system. For example, in the aviation or aerospace industry, where the working conditions of a user operating with an information system are constrained by physical conditions, interactivity can be described as limited. On the other hand, everyday interactive systems, such as multimedia devices and gaming complexes, do not impose significant physical restrictions on the set of interactions of an individual (user) with an information system.

In order to improve the efficiency and usability of information systems, researchers are constantly looking for new ways to organize interfaces. Among the factors that reduce the usability of information systems, we can distinguish between technical, physical, and informational varieties. Technical factors refer to the quality of technologies applied both in software development (network speed, amount of memory) and in hardware (for example, the quality of a computer monitor or camera). Physical factors mean the physical environmental conditions during the use of the software system, such as humidity, light, visibility, the possibility of physical movements, etc. Information factors are understood as the development of the interface of the software system that ensures ease of use in general, for example, the size of buttons in the graphical interface, the ability to enter text, the ability to save data, etc.

Interfaces can be divided into several categories: text, graphic, voice, video and hybrid. To improve usability, each of these approaches should be considered. Currently, interfaces based on audio and video information received from various external sensors are being actively developed. Among the difficulties of using video, the following factors can be distinguished: extraneous noise, poor visibility, physical obstacles between the camera and the subject, the lack of the appropriate angle for shooting, or a lack of verbal communication (silence mode). Nevertheless, interfaces based on audio or video can greatly expand the scope of software systems. Moreover, while a text-based or graphical interface necessarily requires an input console or a screen plus input devices (keyboard), an audio- or video-based interface requires only a microphone and a video camera. This allows a user to free his or her hands and improve the quality of the user experience when working with the system, using hands as an additional control channel. In order to overcome the discussed limitations of interfaces based on video information and preserve their advantages, it is required to use a new type of interface either hybrid or biological. Biological interfaces are widespread in medicine. It should be noted, however, that in medicine, an individual interacts with information systems mostly passively, allowing the device to retrieve and process the information received through the interface. At the same time, the potential of using biological interfaces is much wider. They can be used to build complete information systems with a high level of usability.

Measurements of biological signals, such as electromyography (EMG), electroencephalography (EEG), etc., can be used as additional information exchange channels. In recent years, innovative research has been carried out on the development and use of clothes containing various sensors and transducers [1, 2], which allow a person's physiological activities to be recorded. Such studies commonly use items of clothing that contain sensors for recording EMG signals [3, 4]. EMG allows you to record the electrical activity that occurs when the muscle fibers are excited. Clothes containing EMG sensors are in demand in many areas: from any physically active activity (e.g., construction work and sporting activities) to the calmest (e.g., office work).

EMG signals are used to diagnose neuromuscular diseases, in psychophysiology, in the study of motor activity, in studies of higher nervous activity, to evaluate the results of prosthetics and orthopedics, and in engineering psychology. Among other things, research into the possibility of organizing a silent interface, that is, an interface that does not require voice input and allows controlling the information system through articulation, has recently gained popularity.

The present work is focused on the use of EMG signals as a basis for a human-computer interface. Much research is aimed at analyzing the EMG signal for developing smart prosthetics systems [5, 6] and systems controlled by gestures [7]. Besides the EMG signal, ultrasonic scanners can be used to solve the problems of gesture classification [8]. A particular problem identified by researchers involves the difficulty of recovering specific control units in the EMG signal, along with a high dependence of classification accuracy on the specific person with whom the experiment is carried out [9, 10]. To solve such problems, methods of decomposition [11] and clustering of EMG signals are used in order to identify the muscle groups involved in a particular hand gesture [3]. Signal conversion methods used to minimize noise include the method of principle components, auto-encoders, etc. [12, 13].

1. LITERATURE OVERVIEW

In a number of studies devoted to the classification of the EMG signal, the problem of its filtering is raised. In most of the publications only frequency filtering is used, but other approaches are researched as well. The most effective method is the preliminary clustering of EMG signals in order to isolate motor units. However, this approach leads to irreversible signal distortion and does not apply to filtering.

In [14], the authors developed a system for identifying muscles using needle EMG for prosthetics. The main characteristics of this model are the following: the use of needle EMG (16 sensors) and kinematic gloves, signal preprocessing with low (10 Hz) and high (100 Hz) frequency filters, and the use of artificial neural networks. The data set consists of 5 movements with 10 repetitions of each movement. The input data for the neural network are correlation matrices. The advantage of the model is the compactness of a fully connected neural network (3 hidden layers). The disadvantages of the model include relatively low accuracy (90.1% for the test set) and the need to use kinematic gloves. The negative impact in model evaluation is due to the low accuracy of signal recognition from a number of muscles for the data set. The authors note that classification errors may be due to insufficiently accurate labeling of reference data.

In [15], the authors conducted an experiment to compare statistical approaches to classify an EMG signal with machine learning models. The task of the researchers was the binary classification of the EMG signal. The goal was to recognize meal intervals in a person's daily activities. The comparison was made between SVM [16], RandomForest [17], LogisticRegression [18], XGBoost [19], LightGBM [20], LSTM [21], and Conv-LSTM models [22]. The advantages of the work include an extensive comparison of statistical methods and machine learning methods. An accuracy of 94.76% was achieved for the balanced dataset for statistical methods and 95.35% for the unbalanced dataset. XGBoost turned out to be the most effective statistical method for classifying the EMG signal. The use of LSTM-type neural networks has improved the classification accuracy up to 97%, however, the researchers note the problem associated with the need for a large amount of data to train this type of networks, as well as insufficient data for machine learning methods, data pollution by cumulative actions, poor Bluetooth connectivity, features of right-handers and left-handers.

In [3], the authors developed a device for reading an EMG signal powered by solar energy. The main characteristics of the developed model are ultra-low power consumption and an intelligent EMF sensor localization system on a user's wrist. Data for the experiment were collected from 20 people and included 15 unique hand movements. Accuracy of 95.3% was achieved when classifying 15 gestures. The position of sensors on a person's wrist is one of the problems for this kind of tasks. EMG signal analysis methods are highly sensitive to the position of sensors. Therefore, the model needs to be retrained every time the position of the sensors changes. This problem can be solved by locating sensors on the wrist using intelligent data processing from capacitive sensors. In order to analyze EMG signals, clustering of all wrist muscles into 8 groups was performed. To adjust the position of the bracelet on the wrist, calibration based on data from 15 sensors using convolution was used. To classify gestures, a convolutional neural network with two convolution layers with the rectified linear unit (ReLU) activation function was used. It is noted that it is such small number of layers allows solving the problem of retraining. The disadvantage of the method is a significant drop in the accuracy of the classification of movements in a static position (a decrease in accuracy by 3%). Also, gestures describing fine motor skills of fingers were not included in the work.

In [23], a model for classifying gestures based on ultrasound was developed. An ultrasound representation of the muscles of the forearm was used to classify gestures.

2. NATURE OF THE EMG SIGNAL

EMG is a method for studying the bioelectric potentials that arise in the skeletal muscles of humans and animals during excitation of muscle fibers.

There are three types of EMG:

1) EMG using needle electrodes that are inserted into the muscle;
2) stimulation EMG;
3) EMG using skin electrodes.

Needle EMG provides the most accurate representation of the electrical activity that occurs during muscle stimulation but requires physical penetration into human muscle tissue. The invasive nature of the method is a limitation for use as a basis for an information system interface.

Stimulation EMG is a type of non-invasive EMG that uses skin surface electrodes to assess the conduction of an impulse along peripheral nerves in response to stimulation with a low-intensity electrical current. This

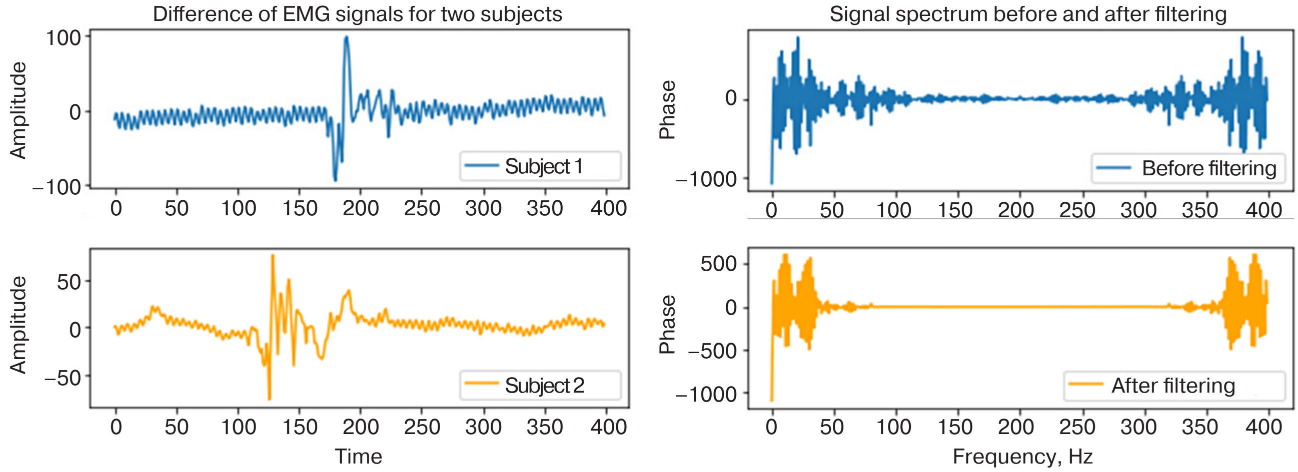


Fig. 1. EMG signals in the time and frequency domains

type of EMG is used, in particular, to diagnose diseases of the peripheral nervous system.

Surface EMG is a type of EMG in which skin surface electrodes are used. Unlike stimulation EMG, this type does not involve stimulation of the nervous system but, on the contrary, consists only in recording electrical activity during active excitation and relaxation of muscle tissues.

With weak muscle contraction, either the potential of a single motor unit or the potential of many motor units is recorded. With an average strength and strong muscle contraction, interference EMG is observed, in which it is almost impossible to identify the potentials of individual motor units. For people at rest, who do not have problems in the area of the nervous system, usually either no electrical potential activity is detected or electrical potentials of individual muscle fibers are recorded.

In a simple case, we will consider the following scenario: a muscle reacts to a single action with a single contraction. In this case, three phases can be distinguished:

- latent period (from 2–3 to 10 ms), lasting from the moment of applying irritation to the start of contraction;
- shortening or contraction phase (40–50 ms);
- relaxation phase (about 50 ms).

The device for recording an EMG signal includes electrodes that pick up muscle potentials, an amplifier of these potentials, and a recording device.

The main parameters of the EMG signal are:

- amplitude (1 μV – 50 mV),
- frequency (0.5–500 Hz).

To analyze the EMG signal in more detail, it is presented as a decomposition of frequencies and amplitudes obtained using the Fourier transform.

Any part of a muscle can contain muscle fibers belonging to 20–50 motor cells. As a result of movement, many motor units are excited. The cumulative action potential can be recorded using EMG equipment and will be presented in the time domain in the following form:

$$S(t)=\sum_j \mathrm{SAPMC}_j(t)+n(t)=\sum_j\sum_i k_j\, f\left(\frac{t-\theta_{ij}}{a_j}\right)+n(t)$$

where SAPMC_j is the sequence of the action potential of the motor cell; k_j is the amplitude factor for the muscle of the jth motor cell; f is the shape of the action potential; θ_{ij} is the time of occurrence of SAPMC; a_j is the scale change; $n(t)$ is the additional noise.

In this work, we use the signal obtained with a single-channel surface EMG. The use of a single-channel system makes it possible to simplify signal registration by ignoring the time synchronization of data from parallel EMG channels.

The main problem when using EMG signals as a control interface is their variability and instability, primarily due to external interference, electrode displacement, skin sweating, and muscle fatigue.

Attempts to eliminate the influence of muscle fatigue consist in the use of switching devices when the signal changes, or the use of static methods such as filtering.

The success of the implementation of the device control interface is determined by the degree of reliability of the decoding of muscle biopotentials in the registered EMG signal during the planned movement. An accurate determination of the motion type is hindered by the low signal-to-noise ratio in the measuring system.

Signal distortions can occur due to the side effect of the signals of the electrical activity of the heart, shifts of the electrodes relative to the designated position, changes in muscle biopotentials, noise from electronic devices, ambient electromagnetic radiation, and similar factors.

To date, a common method for determining the types of movement is the use of various classifiers.

3. PROBLEM STATEMENT

To build an efficient interface based on EMG signals, it is necessary to solve a number of problems. First, it is necessary to clean the signal from noise, which is recorded during excitation of human muscles. Secondly, the signal must be classified in some way so that the received actions or patterns can be used to create control actions by the information system. In this work, we will solve the problem of cleaning the signal from noise. The main problem is the non-linear nature of the noise. By noise, we mean some non-linear component of the signal, which depends on the parameters of recording the EMG signal from a biological object. The amount of noise depends on such parameters as the level of voltage in the laptop electrical network, the parameters of the signal amplifier, the quality of the electrodes, the quality of the preparation of the skin surface for installing EMG electrodes, etc.

A signal $\mathbf{X}$ is a sequence of samples x_i ($i = \overline{1, N}$). It is assumed that this signal may contain non-linear noise $\mathbf{Z}$, which can be suppressed using a filter:

$$\mathbf{I} = \mathbf{X} \times \mathbf{h},$$

where $\mathbf{I}$ is a useful signal, $\mathbf{X}$ is a noisy signal, $\mathbf{h}$ is a neural network filter.

We compared data for one type of gesture from two subjects (Fig. 2). As can be seen from the figure, these signals differ from each other not only in the phase of the signal, but also in the shape. Neural network filtering is used to minimize these differences.

The purpose of neural network filtering is to get rid of the individual component of the signal, which varies from person to person. This type of distortion is called individual noise. Individual noise is understood as a non-linear component of the signal, which can be defined as follows:

$$\mathbf{Z} = \mathbf{X} - \mathbf{I},$$

where $\mathbf{Z}$ is individual noise.

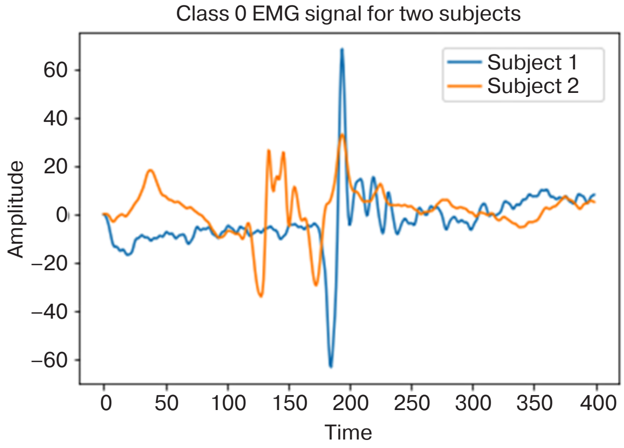


Fig. 2. EMG signal for one gesture received from two different subjects

The task is to find the filter parameters $\mathbf{h}$, which will minimize the difference in signals describing the same gesture class, but received from different subjects. Such a task can be described as:

$$(\mathbf{X}_{i,k} \times \mathbf{h} - \mathbf{X}_{j,k} \times \mathbf{h}) \rightarrow \min,$$

where i is the subject index, k is the gesture class number.

3.1. Signal processing block-diagram

After receiving the EMG signal from the sensors, filtering is carried out in two stages. At the first stage, a low-bandpass filter (up to 50 Hz) and a high-bandpass filter (more than 1.5 MHz) are used. These filters allow you to get rid of the noise generated by electronic equipment and external static electric field. The signal processing block-diagram is shown in Fig. 3.

3.2. Datasets

When planning the experiment, two databases containing EMG data were considered suitable for building an information system with gesture-based control. The experiment required a data set containing EMG signals received from the forearm region when

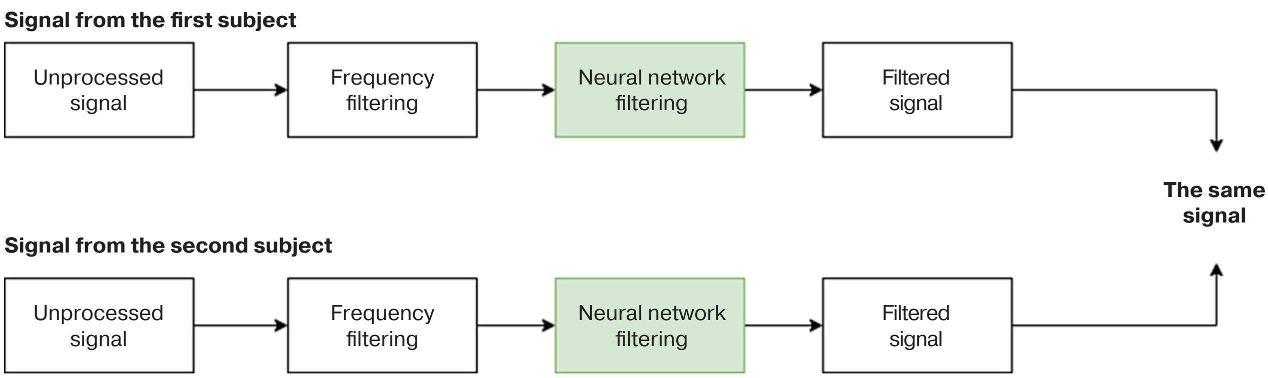


Fig. 3. Block-diagram of neural network filtering

making a set of hand gestures. When working with the information system, each of the gestures can be used as a control action when.

3.2.1. Ninapro Data

This database is available for academic purposes on a dedicated website[1] [24]. The goal of the project is to develop a family of algorithms that can significantly increase dexterity and reduce learning time for a controlled sEMG prosthesis. The project's challenge is how to provide patients with a cheap, easy to use prosthesis that can be controlled in a natural way.

The data set consists of bioelectrical muscle activities collected under special conditions using differential sEMG electrodes. Currently, data are available for 67 healthy subjects and 11 amputees.

The Ninapro data collection process was designed to be easily repeated for obtaining new data from different research groups.

3.2.2. RF-Lab. Digital Signal Processing Laboratory (DSP) RTU MIREA

The project database contains EMG signals sampled from the forearm area. Six subjects participated in data collection. Each subject consistently repeated one of the 9 hand movements (gesture) 79 times. The signals recorded for each gesture were written into a 400-sample vector. The total number of signals is 2820 [9]. The data set includes gestures of the following classes:

- wrist up (class 0);
- wrist down (class 1);
- clenching all fingers (class 2);
- clenching the index finger (class 3);
- clenching the middle finger (class 4);
- clenching the ring finger (class 5);
- clicking the thumb with the middle finger (class 6);
- unclenching all fingers (class 7);
- turning the hand to the left (class 8).

The following components were used to register the signals: Arduino Leonardo (Arduino AG, China), ECG-EMG Arduino Shield (OLIMEX LTD, Bulgaria), single-channel surface electrodes and USB Type-A / USB Micro-B.

As a result, 79 vectors of 400 units in length were used for each gesture which provided a window in which the action potential was captured. Thus, it includes only the most important data that are needed for the classification task, thereby reducing the consumed computing resources and increasing the accuracy.

As part of this work, the RF-Lab[2] dataset was used as it is focused on building a human-machine interface with gesture control.

[1] http://ninapro.hevs.ch/. Accessed June 15, 2022.
[2] https://rf-lab.org/. Accessed June 01, 2022.

3.3. Filtration quality assessment

To assess the quality of the signal, the standard deviation of the EMG signals is analyzed. For each type of movement, the value of the standard deviation of the signal for all subjects is calculated (Fig. 4).

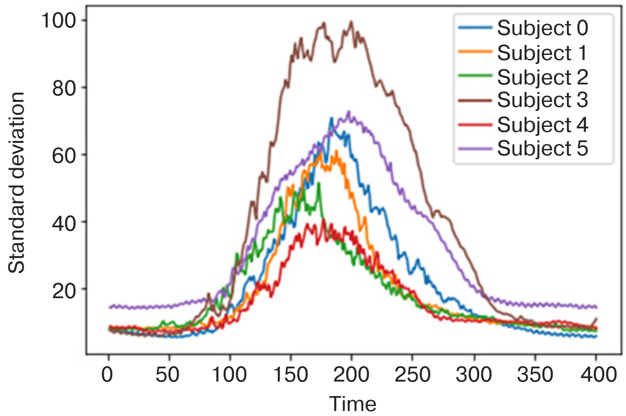


Fig. 4. Standard deviation for gesture classes for each subject

When filtering the signal, it is necessary to reduce the standard deviation of the EMG signal within each gesture class. As an example, the standard deviation was calculated for a class 0 gesture before and after filtering using a frequency filter (Fig. 5).

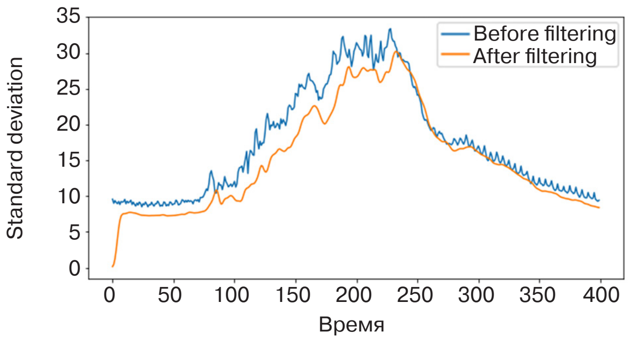


Fig. 5. Comparison of the standard deviation of the EMG signal amplitude before and after frequency filtering

It can be seen from the figure that frequency filtering reduces the standard deviation of the signal over the entire segment; therefore, this method is used to evaluate the efficiency of signal filtering in our experiment.

4. DEVELOPED MODEL OF A NEURAL NETWORK

Digital filters are widely used today in various areas of signal processing, both technical and biological, which include the EMG signal. Mathematical models of digital filters can be described using vectors and numerical matrices. For a binary signal, the numbers in the matrices can be binary. There are two types of filters: finite pulse

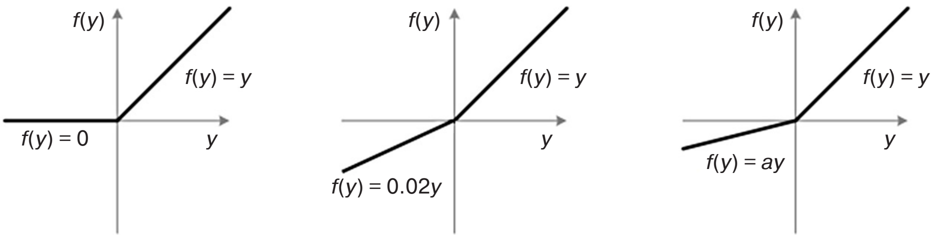


Fig. 6. Comparison of the activation function of ReLU (left), LeakyReLU (center), and PReLU (right). *a* is a parameter of the PReLU activation function; *y* is an input signal

response and infinite pulse response. The filter must suppress the harmonic components of the original signal in one frequency band (stop band) and pass them in another frequency band (pass band). In most cases, in extremely complex problems of signal analysis, classical techniques based on the Fourier transform and wavelet transform are used to construct the feature space. Due to the complexity of understanding the nature of the signal, the features of one task may be completely unsuitable for another task, and it is required to construct a feature space from scratch. The EMG signal falls into the category of signals with a complex nature, for which standard filters are not suitable for processing. It can be represented as a time series [25]. Therefore, to build a filter for the EMG signal, it may be appropriate to use intelligent models. One of the most effective intellectual models at the moment is neural networks.

To solve the problem, we will use a neural network type that includes convolution layers. Such networks are called convolutional networks. As an activation function, it is proposed to use parameterized ReLU (PReLU). The use of this activation function is an achievement in machine vision that has allowed for surpassing the human level in ImageNet[3] image recognition tasks. The error back propagation and update process for PReLUs is simple and similar to traditional ReLUs. The main difference between PReLU and ReLU is that this function does not zero out negative input signals. Instead, negative input signals are multiplied by some non-zero factor, which allows negative values to be taken into account in network training and signal processing. A comparison of the PReLU activation function with a regular ReLU is shown in Fig. 6.

As part of the National Data Science Bowl (NDSB) Kaggle competition, the PReLU activation function made it possible to reduce overtraining due to the element of randomness in the work. When comparing the classification accuracy of two convolutional artificial neural networks with different activation functions on data sets (images used to test the quality of pattern recognition algorithms) CIFAR-10, CIFAR-100[4], and NDSB[5], results were obtained that indicate that for all sets the modified functions ReLU family activations have surpassed traditional functions. RReLU is significantly superior to other activation functions on the NDSB dataset because on this dataset, the activation function avoids overtraining as this dataset contains less training data. To train machine learning models, modern cloud infrastructure tools such as Docker[6] and Amazon Azure[7] were used [26].

In the experiment, the Python 3.8 programming language and the Keras 2.9.0[8] library were used when building a neural network model. The architecture of the neural network developed for filtering the EMG signal is shown in Fig. 7.

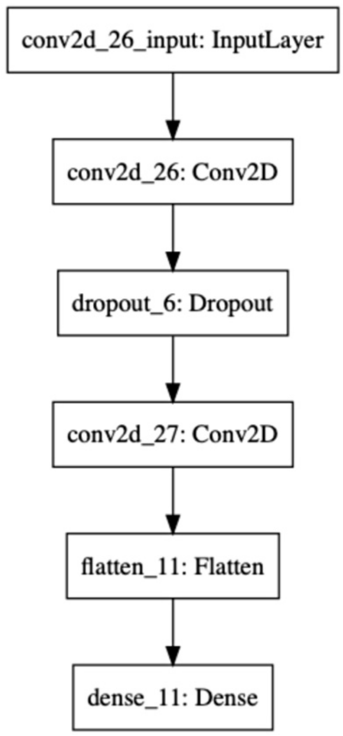


Fig. 7. Convolutional neural network architecture

The developed model contains two convolutional layers. A matrix of 20 × 20 serves as input data for the network, which is a raw EMG signal consisting of

[3] https://www.image-net.org/. Accessed June 09, 2022.
[4] https://www.cs.toronto.edu/~kriz/cifar.html. Accessed June 10, 2022.
[5] https://www.kaggle.com/competitions/datasciencebowl/overview/about-the-ndsb. Accessed June 10, 2022.
[6] https://www.docker.com/. Accessed June 10, 2022.
[7] https://azure.microsoft.com/en-us. Accessed June 10, 2022.
[8] https://github.com/keras-team/keras/releases/tag/v2.9.0. Accessed June 10, 2022.

400 samples. The first layer contains 64 feature maps of size 5 × 5 and the PReLU activation function (with parameter $a = 0.02$). The second convolutional layer contains 32 feature maps of size 3 × 3. Then there is a rectification layer and a fully connected output layer with a dimension of 400, which corresponds to the dimension of the input signal. Such a dimension at the output of the network allows the output signal to be used on a par with the input signal, expecting that the output signal will retain useful information about the subject's wrist movement pattern. The model was trained using Microsoft Azure[9] cloud computing power [26].

5. IMPLEMENTATION OF THE MODEL AND ASSESSMENT OF THE OBTAINED RESULTS

In the experiment, a data set was used collected by the team of the DSP Laboratory (RF-Lab) [9], containing the data of one channel of the EMG signal received from 6 subjects. Each subject performed 9 different hand gestures.

5.1. Experiment structure

To train the neural network, the dataset was transformed as follows. First, it was divided into 3 parts: training, validation and test sets. The training set comprised 60% of the total data and included data from four of the six subjects. The validation set contained 20% of the data, including data from the same four subjects. The test sample contained the remaining 20% of the total data and included data from two subjects not participating in training. This approach was used to demonstrate the validity of the resulting model on data from subjects that the model did not see during training. Each training example consisted of the original signal as input and the paired signal as the target value. The paired (target) signal was selected in such a way that it belonged to another subject. The neural network was trained using the Adam optimization algorithm [27], the number of training epochs was 25. The mean squared error [28] was used as the error function.

[9] https://azure.microsoft.com/en-us. Accessed June 01, 2022.

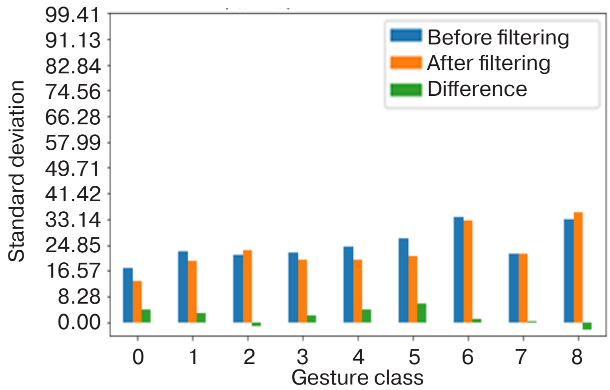


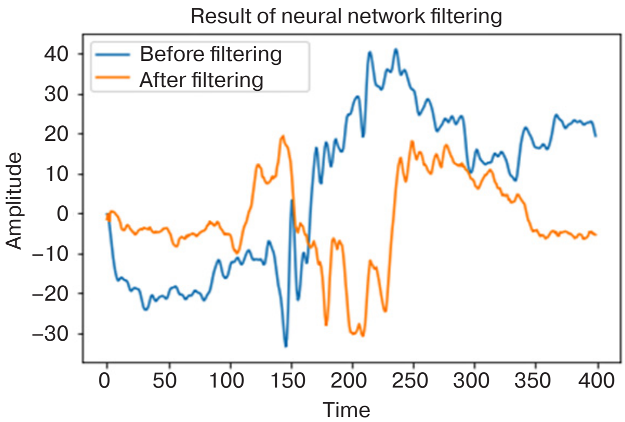
Fig. 8. Comparison of the standard deviation before and after neural network filtering for each signal class

5.2. Results

After training, the resulting model was evaluated on the remaining two subjects from the data set. Comparisons were made for each signal class separately (such as wrist movement). As an indicator of the effectiveness of the developed model, the standard deviation of the signal before and after filtering was measured. Its values before and after filtering are shown in Fig. 8. The measurements were carried out for signals of each class separately. As can be seen from the figure, the signals for gestures with class 6 (clenching the ring finger) and 8 (unclenching all fingers) have the greatest deviation.

As can be seen, on average, the reduction in the standard deviation is 5% for the signals received during the movement of the hand. The best result was obtained for movements with classes 4 and 5. An increase in the standard deviation was recorded for signals with classes 2 and 8. A decrease in the standard deviation was achieved for signals belonging to classes 0, 1, 3, 4, 5, 6, and 7.

The results obtained allow us to speak about the possibility of using neural network filtering in the tasks of cleaning individual signals. The filtering result for the class 0 gesture is shown in Fig. 9.



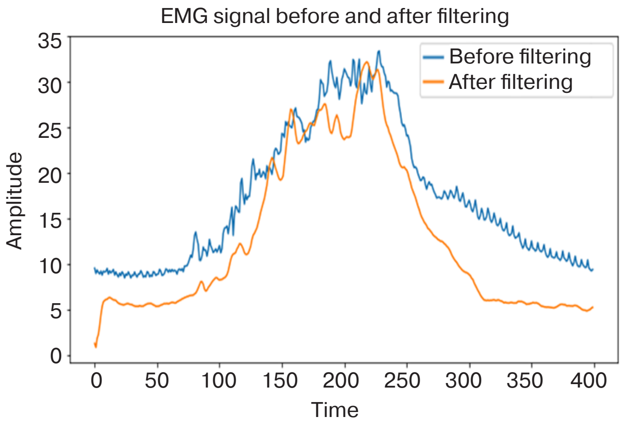


Fig. 9. Signal standard deviation before and after neural network filtering

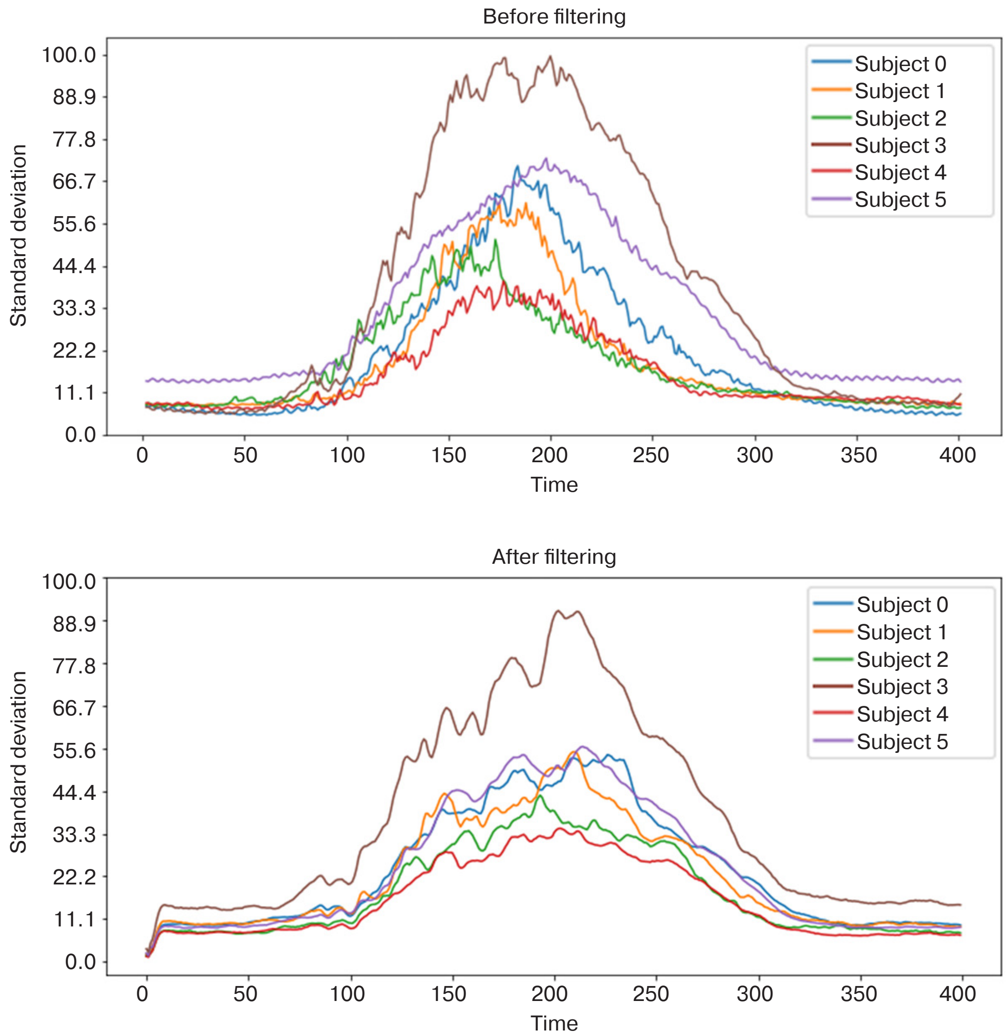


Fig. 10. Standard deviation for different gestures for each subject from the sample

Table 1. Comparison of the filtering result for different signal classes

Signal class	0	1	2	3	4	5	6	7	8
Change in the value of standard deviation after filtering	3.93	3.1	−1.33	2.16	3.95	6.03	0.99	0.07	−2.41

We also compared the standard deviation between different gestures for the same subject before and after filtering. The data obtained show that the difference between gestures remained almost at the same level (Fig. 10).

As can be seen from the results, the developed neural network filtering model is able to compensate for individual components in the EMG signal. The obtained indicators of signal quality improvement are shown in Table 1.

CONCLUSIONS

In this work, a study of approaches and methods for the development of neural network filters for biological signals was carried out. The proposed scheme for filtering biological signals takes the presence of individual signal components into account. A model was developed and a convolutional neural network for intelligent filtering was trained. Over the course of the study, an efficient convolutional neural network architecture for filtering the EMG signal was identified.

An experiment on filtering a single-channel EMG signal showed the effectiveness of the proposed model. By using neural network filtering, the influence of individual noise in the EMG signal can be reduced by an average of 5%.

In further studies, it is planned to evaluate the effect of neural network filtering on the accuracy of gesture classification using an EMG signal.

Authors' contributions

A.V. Vasiliev—preparing algorithms, data collection, conducting research, and writing the text of the article.

A.O. Melnikov—the research idea, developing objectives and aims, and formulating conclusions.

S.A. Lesko—consultations on research issues, scientific editing of the article.

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