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ANALYTICAL REVIEW OF METHODS FOR RECORDING AND CLASSIFYING MOVEMENTS BASED ON ELECTROMYOGRAPHY

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Abstract. This paper provides a comprehensive overview of optimal methods and processes for recording, processing, and classifying electromyography (EMG) signals in the context of human movement rehabilitation. It begins by exploring advanced techniques for accurate and noise-free EMG signal acquisition, emphasizing the importance of electrode placement, signal amplification, and filtering strategies. The paper then delves into modern signal processing methods, such as feature extraction and dimensionality reduction, which enhance the interpretability of EMG data. Furthermore, the study highlights cutting-edge machine learning and deep learning approaches for classifying movements based on EMG signals, offering insights into their practical applications in rehabilitation systems.

Keywords: electromyography, sensor, electrode, artificial intelligence, data set, muscles, non-invasive, classification.

1 INTRODUCTION

With the introduction of modern technologies into medicine, the diagnosis of the disease, and rehabilitation of patients with disabilities began.

It also began to be widely used in controlling artificial body organs through biosignals with the help of muscle activity, isolating signal interactions in human and Computer Communication, brain-computer interface systems, and studying human behavior based on exoskeletons.

Currently, people who have lost the limbs of the hands or feet (congenital or increased organ failure) are the majority. They may have been born so or they may have lost their functioning organs due to diabetes, infections of different types, trauma, cancer, or complications of blood vessels. For this reason, several disabled people with circulation in members of the movement is increasing year by year. The use of prosthetics around the world is limited for a while. According to the World Health Organization's reports, 30 million people on Earth need prosthetics [1].

There are several types of prostheses: wooden or iron prostheses, prostheses that work through the body, myoelectric prostheses, and biological prostheses. Currently, myoelectric-robotic prostheses are developing rapidly. The main principles of these prostheses, that is, myoelectric control systems (MCS), consist of the classification and transmission of EMG signals emitted by muscles.

When a person wants to immobilize body organs, such as hands, feet, or neck, a motor contact signal that is part of the brain is produced (Fig.1).

Raw signal comes to certain skeletal muscles through the spine. Motor neurons are the functional unit of the nerve network. They are connected by muscle. Motor neurons or motor blocks are attached to myofibers.

The strength of muscle contraction depends on the number of motor blocks involved [2]. For example, to raise a sheet from the table, several motor blocks are required, but to raise a book with a hardcover, you will need more motor unit (MU). The volume of the MU population depends on the volume of muscles [3].

In some small muscles, the MU indicator is equal to 1:1. To perform harmonious and delicate movements that require less control, you need large muscles. When increasing strength and strength, these fibers will have to gather [4].

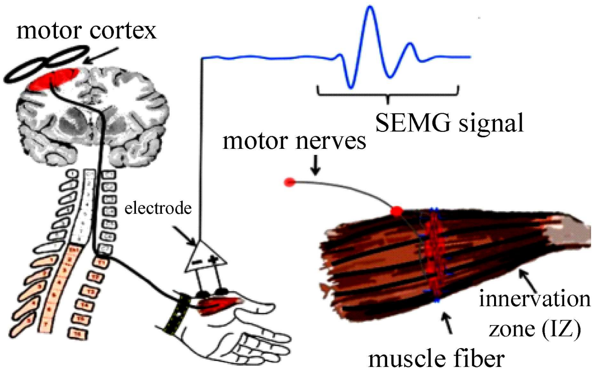

Figure 1. Control of the muscle through the nervous system.

All muscle fibers relax, shrinking at approximately the same time. Furthermore, if the muscle fibers are faxed to the MU muscle contraction, the fibers will be in a state of maximum contraction. MU is a functional unit of myofibers, which releases muscle contraction [5, 6].

2 ANALYSIS AND DISCUSSION

Nowadays sucks a large number of people with disabilities, amputates with impaired arm or leg movement functions. Rehabilitation of their movement functions as much as possible, and their inclusion in society is one of the essential manners. Amputants are people who have a member of the hand or foot, that is, a member of the movement whose function is impaired, a member of the movement is cut off due to unpleasant phenomena (road traffic officer, diseases, etc.) without a landing.

It is known that as a result of muscle contraction, movement occurs, and the muscle is reduced as a result of the influence of impulses from the brain on muscle fibers. This means that the muscle, which shrinks in amputation, will be damaged, and it will not be able to perform certain movements. However, there will be impulses coming from the brain to the affected muscles that induce it to act, but the impulses will not be able to act, since a certain part of the hand does not exist.

The idea behind this is that if I have an impact on the muscles as a result of the impulses, we will be able to record the signals coming from those muscles and turn them into digital computer commands that trigger the movement in the body. One problem here is that we will have to figure out how many hand movements the residual muscles that are present in the amputee can release. While we know that the movements of the hands are mainly the muscles of the forearm, we need to dress the table of attachment to the forearm muscles or their combination hand movements (table 1).

On the human wrist, six basic muscles provide movement (Fig.2). They are flexor carpi radialis, palmaris longus, pronator teres, flexor digitorum superficial, flexor carpi ulnaris, and flexor policis longus. They are involved in some movements alone, but sometimes several muscle combinations participate in some complex movements. It should be noted that if we correctly determine the connection of the movement to the muscles, and record the signal, we will avoid the fact that the signal data will increase, and as a result, the process of cheating will be more difficult.

Table 1: table of the muscles of the forearm and the movements that they can cause on the surface

	Elbow : bending	Palm movement: (palm turn 180 degrees)	Wrist: Bend the palm forward	Wrist: Bend the palm back	Palm movement: making a fist	Palm movement:	The movement	2-5 fingers	Palm Movement:
flexor carpi radials	X	X	X		X	X			X
Palmaris longus	X	X	X						
Pronator trees	X	X							
Flexor digitorum superficial			X				X		
Flexor carpi ulnaris			X	X					
Flexor pollicis longus								X	

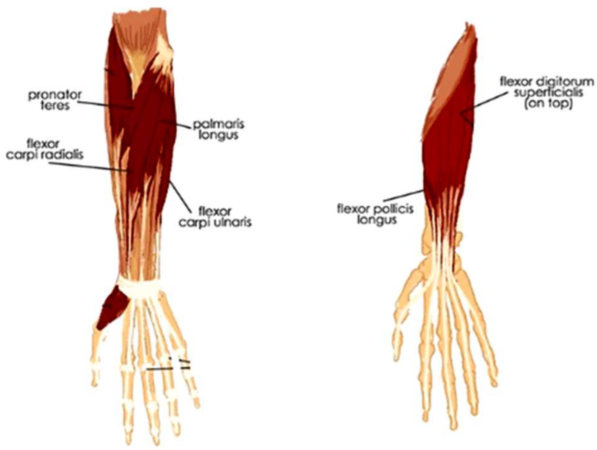

Figure 2. The structure of the forearm muscles.

Recording an EMG signal is easy, but interpreting it is a difficult process. The analysis of this signal allows you to understand the movements that occur in the body through the strength, and muscles that are characteristic of the muscles. It should be noted that getting the above information correctly will depend on the method of receiving the signal. The traditional method of EMG signal capture consists mainly of three stages: signal capture, signal mining, and signal processing.

Since muscle contraction leads to the appearance of an electric field on the surface of the skin, it is enough to place the electrodes on the surface of the skin.

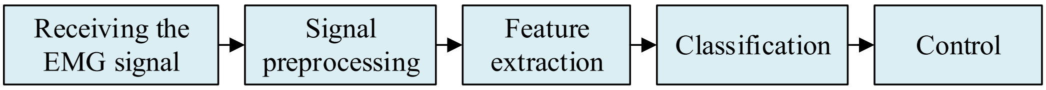

Figure 3. Signal processing process in EMG signal-based control systems.

It should be noted that, although this is not the case, it may be because it can lead to a deterioration in health. EMG signals that the time spent on trips can be stopped due to the merger (Fig. 3).

The collection and analysis of generalized data, which will be presented below, were carried out in the sequence of processes shown in Fig 3.

The EMG signal recognition will consist of four stages.

1st stage. At the stage of receiving an EMG signal, the process of recording the EMG signal from the human body is the study of the anatomy of the muscles present in the hand, determining the structure, location, and shape of the muscles, analyzing the possibilities of performing what movements of the hand in the process of studying the muscles, based on recording the signal, the procedures for the correct selection of the location of the electrodes are performed.

2nd stage. After receiving the signals from the human body as a result of the necessary actions, the preliminary processing of this signal is carried out. In this case, procedures such as selecting the desired filter, segmentation, and processing of signals in the window, are performed to clean the signal from unnecessary artifacts and noise.

3rd stage. At this stage, the separation of the necessary parameters from the cleaned signal is carried out. It will be necessary to determine the most optimal variant of the parameters or the effectiveness of their combinations through certain operations. In subsequent processes, these parameters are obtained and used as a benchmark.

4th stage. The tutorial, dressed through Signal parameters, is taught based on selective algorithms, and the signal is classified based on certain hand movements.

A. Receiving the EMG signal

There are various hardware supplies to get the SEMG signal. One of them is the Bitalino device (table 2).

This device is characterized by mobility and productivity. The device can record multiple biosignals at the same time. To get a kind of biosignal, the Har allocated one channel on the device. Currently, BTS FreeEMG analyzers are being used for receiving SEMG signals (table 3). This device is 10-channel, which is used only in obtaining potential from muscles.

B. Signal preprocessing

Processing an unprocessed initial signal (Raw signal) is a necessary step to minimize internal noise and ensure proper analysis of signals. Different types of noise are detected in the recordings of EMG signals. These interactions include noise in data collection equipment, environmental noise caused by electromagnetic radiation, movement artifacts caused by electrode interaction or cable movement, and signal instability caused by changes in the response speed of motor units.

Table 2: bitalino device physical parameters

Specification	
Sample size	1, 10, 100 bath 1000 Hz
Analog ports	4 incomings (10-bit) + 2 incoming (6-bit)
Digital ports	4 incomings (1-bit) + 4 outgoing (1-bit)
Contact information	Class II Bluetooth v2 .0 (up to 10 meters of coverage)
Actuators	LED

Specification	
Sensors	ECG; EMG; EDA;
Battery	3.7 V LiPo
Weight	30 g
Size	100 × 60 mm

Table 3: technical parameters of the bts freeemg device

Weight	13 gr
Frequency of use	2.4 GHz (standard IEEE802.15. 4)
Frequency of Information Retrieval	1GHz (16-bit)
Sensitivity	1µV
Connection	USB
USB size	82x44x22, 5mm

The use of low-level conductive filters often eliminates the initial shrinkage on notes that are worn due to movement. In the literature, it has been concluded that the EMG signal is located in the range of 20-500 Hz with the main data [7]. The sliding window method is suitable for myocontrol because it seeks to make a reliable classification decision and reduces the maximum delay time. The choice of the window length is one of the factors that lead to a change in the delay time, and the accounting time. In the studies, 150ms, 250 MS, 50ms, and 100 MS size windows were proposed [7].

C. Feature extraction

Feature extraction - it is understood to obtain the necessary informative parameters from the signal data. Three main categories of features are relevant for EMG signal-based management systems: time (time-domain features - TD), frequency (frequency domain features - FD), and time-frequency domain (time-frequency domain features - TFD) features. Separation of characteristics plays a decisive role in signal processing and classification. This process is carried out by constructing a vector of properties through certain signs of the initial signal. TD properties are distinguished by the signal amplitude. The signal amplitude varies depending on the strength, condition, and types of muscles. Such features do not require changing the signal when allocating. FD is done through the power spectral density of the signal. TFD will be able to accomplish this through a combination of time and frequency fields. The application of the combined form of these features increases a plurality of also precision [8-12]: mean absolute value slope, slope sign changes (SSC), zero crossing (ZC), and waveform length (WL). Although the ZC and SSC features display FD data the signal does not convert to FD. In several studies conducted in the field of manual behavior detection, EMG alarm features such as MAV, ZC, SSC, root mean square (RMS), variance (VAR), and standard deviation (SD) were used. Later, a feature called MAX was introduced, this feature represents the maximum point in WL. Studies have shown that RMS, MAX, and SD feature vectors were the best combinations [8]. Other studies have begun to use features such as Kurtosis (Kurt) skewness (Skew), and approximate entropy (moving ApEn) [9]. These features can classify the EMG signal contraction phases (for example, the beginning, end, and middle of the movement). Studies have shown that the use of ApEn for distinguishing features in clinical processes is effective [10]. The Integrated EMG (IEMG) feature, is used [11]. The FD characteristics of the EMG signal are realized through the properties of its spectrum and frequency fields (Figure 10). Bunda assesses the nature of muscle fatigue [8-12]. The change of signal in FD is due to the median power frequency (MPF), which changes as a result of a relative decrease in the signal strength of the high frequency, and a small increase in the signal strength of the low frequency. In clinical practice, EMG provides data on the mean power frequency (MPF) of signals in the muscle and nervous system changes [12]. This means that EMG signals are reduced as long as they are used as the PSD, MNF, and MNP index on the FD SoC. Scientists have modified mean frequency (MMNF) and modified median frequency (MMDF) to monitor muscle fatigue. They used robust properties of MNF, average frequency (median frequency - MDF), bandwidth (BW), and normalized spectral moments (Normalized spectral moments - NSM) [11].

The third type of SEMG signal characteristic is the characteristics of the signal in the time-frequency field. It should be noted that the Muhim factors in the classification of EMG signal should be high in this accuracy and that the calculations should not be complicated.

D. Classification

There are several artificial intelligence (AI) algorithms based mostly on neural networks to process and differentiate EMG signals (TABLE 4). Below is an analysis of the neural networks used in classifying the EMG signal. In the use of artificial neural networks in the classification of hand movements based on EMG signal, 95% accuracy was achieved when using the AR (autoregressive coefficient) coefficient vector of the signal [13,14,15], but to improve this network, the neural network requires multilayer [16]. This leads to an increase in time consumption in the calculation of signal characteristics and decision-making [17]. The system of computer mouse movement was created through familiar hand movements, and BPNN - (Backpropagation Neural Network) was used in this issue [18]. The mouse cursor worked with 70% accuracy. In such a neural network, hand movements will be limited and you will not be able to use the network in the long term. As an incoming parameter in this neural network, mainly RMS parameters of the signal are used [19]. The Log-Linearized Gaussian Mixture Network (LLGMN) network was used to recognize both EMG signals. Compared to other neural networks, high indicators of discrimination can be achieved, but the accuracy indicator is lower [20]. Not only EMG alarms in space fields can be used in familiar processes but also in such a process, more and more Hidden Markov models (HMM) are used. This network avoids incorrect classification [21], which takes the name of more difficult-to-do accounts than the MLP method.

Table 4: Comparative analysis of classifiers used in EMG signal classification

Classifier	Accuracy	EMG signal parameters	Positive aspects	Negative aspects
ANN [13, 14, 15, 16]	95%	Autoregressive coefficient (AR)	-	A more robust classifier is needed for the disabled. Further improvements require more sophisticated neural networks and better training methods.
	98%	Both the time and frequency domains.	MLP-based model RBF Compared to LVQ, it gave a better result	The computation time was doubled, Features are difficult to

				differentiate and identify.
	78%	4-level AR	-	There were problems with classification.
BPNN [17, 18, 19]	70%	-	A new type of EMG-controlled mouse has been developed.	Not suitable for long-term use Movement is limited to four directions
	97%	RMS values of the signal	-	Hand movements are limited to 3-6.
LLGMN [20, 22]	86%	-	Higher rates of discrimination can be achieved.	-
Recurrent LLGMN [23]	92%	Time domain parameters	The existing errors in recognition have been significantly improved.	Integration into the device is complex and difficult
PNN [23]	97,9	-	FPGA integration is easy	Out of memory for hardware language. Processing speed needs to be improved.
FMMNN [24]	97%	Difference Absolute Mean Value (DAMV) features	It was possible to classify six wrist movements well	Using more channels when receiving a signal
RBFNN [25]	-	-	RBFNN network, interpolation/extrapolation is performed for real-time recognition of hand movements.	Some parameterization errors were found due to the stochastic nature of the EMG signals.
HMM [21, 22]	95%	-	Averaging signal parameters increases efficiency.	The adaptation and calibration phase require certain adjustments in the model

Bayesian Network [26]	94%	Both the time and frequency domains.	Using an accelerometer together with EMG signal recognition increases the accuracy by 5-10%.	Even the slightest wrong movement can lead to negative results in EMG signal classification, so a special environment is needed for signal acquisition.
RF [27]	99%	Time domain features	Very short reaction time (223ms). The process of integration into the device is easy.	-

Because this requires a phase of flexibility and calibration in the implementation of the process, it requires the implementation of certain corrections in the model [22]. Based on LLGMN, the process of integration with the device in the recognition of a Probabilistic Neural Network (PNN) based EMG signal is improved. However, they experienced a lack of memory for hardware language manners [23]. Here the processing speed is low. EMG uses stochastic parameters of the signal to recognize the signal. Therefore, the use of the Fuzzy Mean Max Neural Network (FMMNN) network makes it possible to increase accuracy, but increasing accuracy requires the selection of the stochastic parameters of the signal with extreme accuracy [24]. In real-time EMG signal recognition, both interpolation/extrapolation methods are used. In this process, the Radial Basis Function Artificial Neural Network (RBFNN) network is often used. However, increasing the familiar accuracy requires an increase in the quantification of the signal and the implementation of the Halda using more sensors [25]. This leads to the fact that as a result of the increase in signal data, the training time of the network increases. Based on the Bayes Network method, it is possible to achieve an accuracy of up to 94% in the signal recognition process, however, a little incorrect behavior can lead to negative results in the signal classification of both EMG, to avoid this, a separate correspondent will be needed when receiving the signal [26].

In recent scientific studies in this field, the use of neural networks in EMG signal classification has been reduced for some time. The main reason for this is that the EMG signal is a low-frequency and amplitude signal, and the signal values obtained as a result of each motion of the hand are very close to each other. Therefore, in the classification of such value signals, the use of machine learning (ML) algorithms will be sufficient. Since the delay time in myocontrol systems is one of the most important factors, our classification algorithm should be fast. Such a feature is found in Random Forest method (RF) algorithms [27, 28].

When classifying an EMG signal, it will be necessary to pay great attention to the following factors:

- Correct selection of window size and character phase when EMG signal analysis.
- Selection of classification algorithms that are quick and accurate is great.
- Due to the following advantages of RF algorithms, they are being used in the classification of EMG signals and myocontrol systems.
- High training speed compared with neural networks, as well as low training parameters, high integration with the device in the myocontrol systems, and flexibility.
- Superiority of visual recognition. It is easy to classify the previously obtained characters (such as in time or frequency fields) by the classification algorithms of RF.
- Ability to easily classify large amounts of signal values through existing, accurate previously issued signal markers.

3 CONCLUSION

From the views expressed in this analytical article, one can draw the following conclusions. The EMG signal, being a stochastic and highly variable signal, requires meticulous attention during recording to ensure its quality and reliability. Proper signal acquisition begins with creating a controlled environment to minimize noise and external interferences. Additionally, the correct placement of electrodes, specifically in the innervation zone, is critical to accurately capture the muscle activity related to specific movements. Identifying which movements muscles respond to and selecting the appropriate signal parameters, such as sampling frequency, filtering, and gain, based on principles of signal engineering, are essential for effective analysis.

Furthermore, the RF method proves to be highly effective for classifying EMG signals and integrating these classifications into rehabilitation or assistive devices. This method offers several advantages over alternative approaches, including reduced reaction time, enhanced classification accuracy, and the ability to handle a wide range of classification tasks with fewer channels. These features make the RF method particularly suitable for real-time applications where efficiency, precision, and resource optimization are paramount. By leveraging these insights, the integration of EMG signals into advanced rehabilitation technologies can be significantly improved, paving the way for more effective and adaptive solutions in human movement restoration.

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АНАЛИТИЧЕСКИЙ ОБЗОР МЕТОДОВ РЕГИСТРАЦИИ И КЛАССИФИКАЦИИ ДВИЖЕНИЙ НА ОСНОВЕ ЭЛЕКТРОМИОГРАФИИ

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Аннотация. В этой статье представлен всесторонний обзор оптимальных методов и процессов для записи, обработки и классификации сигналов электромиографии (ЭМГ) в контексте реабилитации движений человека. Она начинается с изучения передовых методов для точного и бесшумного получения сигналов ЭМГ, подчеркивая важность размещения электродов, усиления сигнала и стратегий фильтрации. Затем в статье рассматриваются современные методы обработки сигналов, такие как извлечение признаков и уменьшение размерности, которые повышают интерпретируемость данных ЭМГ. Кроме того, в исследовании освещаются передовые подходы машинного обучения и глубокого обучения для классификации движений на основе сигналов ЭМГ, предлагая понимание их практического применения в системах реабилитации.

Ключевые слова: электромиография, датчик, электрод, искусственный интеллект, набор данных, мышцы, неинвазивный, классификация.