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DEVELOPMENT OF A HARDWARE-SOFTWARE SYSTEM FOR GESTURE RECOGNITION BASED ON ELECTRO-IMPEDANCE, ELECTROMYOGRAPHIC, AND FORCE-MYOGRAPHIC SIGNALS

The object of the research is the process of gesture recognition and proportional assessment of muscle activity using electromyographic (EMG), electroimpedance (EI), and force myographic (FMG) signals. The subject of the research is methods and means of collecting and analyzing these signals to increase the accuracy of gesture recognition and assessment of muscle activity in real time.

The research is aimed at developing an integrated hardware and software system for collecting and analyzing EMG, EI, and FMG signals for gesture recognition and proportional assessment of muscle activity.

The problem that needs to be solved is the lack of reliable multimodal platforms capable of providing simultaneous acquisition, filtering, and digital processing of biosignals of various natures in real time. Existing solutions are limited to one or two modalities, are characterized by low noise immunity, and require complex equipment, which complicates practical use.

The proposed solution is based on the use of Ag/AgCl surface electrodes, piezoelectric and capacitive sensors in combination with multi-channel ADCs. Optimized filtering and amplification, digital processing and synchronization of signals, as well as data transfer via USB or UART to a personal computer, are implemented. The software performs frequency analysis based on the fast Fourier transform, visualization, and export of results.

Experimental studies have confirmed that the obtained signals correlate with motor activity: an increase in grip strength is accompanied by an increase in the amplitudes of FMG and EI, which allows for proportional control. The choice of optimal filtering frequencies, gain coefficients, and methods of sensor mounting made it possible to minimize noise and distortion, and the use of multi-channel ADCs ensured the processing of large volumes of data online.

The innovation of the development lies in the integration of bioelectrical and mechanical channels into a single multi-channel platform with support for up to 8 channels, high spatial and temporal resolution, and flexible architecture. This ensures high reliability and practical applicability of the system in rehabilitation, diagnostics, and control of bionic devices.

Keywords: *bionic manipulators, control, electrical impedance, electromyography, force myography, signals, analysis, proportional, anthropomorphic.*

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1. Introduction

In modern biomedical engineering, the development of systems for comprehensive monitoring of physiological processes, particularly muscle activity, remains highly relevant. The study of bioelectrical signals, such as electromyography (EMG) and electrical impedance (EI), in combination with mechanical signals, such as force myography (FMG), allows a more complete assessment of human muscular function. Such multimodal data are crucial for rehabilitation, medical diagnostics, sports medicine, and the development of adaptive human-machine interfaces. Traditional approaches that focus on a single modality often limit both the volume and accuracy of information obtained. Integrated systems capable of simultaneously processing multiple types of signals with high speed and reliability are therefore of particular importance [1–3].

Recent studies have highlighted the growing role of intelligent control systems in collaborative and wearable robotics. Paper [1] presents an approach to developing intelligent mechatronic "Cobot"-type systems using machine learning technologies, underlining the need for adaptive algorithms capable of reacting in real time. However, this study lacks integration of multimodal biosignals such as EMG and FMG, which are essential for fine-grained motion recognition. Similarly, the foundational analysis of collaborative robots in [2] reviews system architecture, design challenges, and safety principles, but does not include bio-signal-based control, which would enhance the intuitiveness of user interfaces. Clinical applications, such as robot-assisted pediatric surgery in Ukraine [3], demonstrate safety and precision but do not address wearable or biosignal-driven rehabilitation systems. Paper [1] proposes a software-hardware platform for gesture-based mechatronic control using contactless sensors, yet it lacks consideration of signal quality under motion artifacts or muscle fatigue – factors critical for long-term performance.

Several international studies address EMG, FMG, and EI in wearable devices. For instance, [4] reviews upper limb prosthetics and stresses the importance of user-centered design and signal reliability in rehabilitation, while [5] proposes a hand orthosis using EMG and force sensors for stroke patients, demonstrating the benefits of integrating electrical and mechanical signals. Paper [6] combines bioimpedance and EMG to improve detection of muscle contraction, showing enhanced noise immunity, yet integration with mechanical signals remains absent. In [7], simultaneous estimation of finger forces using EMG and accelerometry highlights EMG as the dominant signal for precise force estimation, but accelerometry alone cannot fully represent mechanical muscle response.

High-density EMG (HD-EMG) approaches [8, 9] improve classification accuracy by exploiting spatial patterns of motor unit activity, enabling proportional control. Nevertheless, these systems require complex and bulky hardware unsuitable for portable applications. The papers [10, 11] provide methodological foundations for HD-EMG decomposition and EI-based vein detection, forming the basis for reliable signal interpretation in noisy environments. FMG has emerged as a promising complementary modality [12–14], offering stable signal acquisition that is less sensitive to electromagnetic interference, but it is rarely integrated with other bio-signals into a single platform. Paper [15] introduces higher-order tensor methods for proportional myoelectric control, enabling robust feature extraction from EMG, yet multimodal real-time integration is not addressed.

Thus, the unresolved problem is the absence of a reliable, multimodal hardware-software platform capable of synchronously acquiring, filtering, and processing EMG, EI, and FMG signals in real time. Existing systems either lack noise robustness, do not support proportional control, or require bulky equipment unsuitable for practical use. Overcoming these limitations necessitates the integration of bioelectrical and mechanical channels into a single multi-channel system with optimized amplification, filtering, and digital processing, allowing proportional gesture recognition and enhanced stability under dynamic conditions.

The aim of this research is to develop and experimentally validate a multi-channel system for collecting and processing EMG, EI, and FMG signals, with the capability of proportional control for bionic and rehabilitation devices in real time.

2. Materials and Methods

The object of the research is the process of gesture recognition and proportional assessment of muscle activity using electromyographic, electroimpedance, and force myographic signals. *The subject of the research* is methods and means of collecting and analyzing these signals to increase the accuracy of gesture recognition and assessment of muscle activity in real time.

The study was carried out in several stages, focused on designing an integrated hardware-software system for synchronized acquisition and processing of EMG, EI, and FMG signals.

In the initial stage, a subsystem for acquiring bioelectrical signals was designed.

The signal acquisition unit employs surface electrodes for EMG signal detection.

To extract relevant signal components, a band-pass filter with a passband of 50–400 Hz is employed [3].

The transfer function of the EMG band-pass filter is described as follows [1]:

$$H(s)=\frac{w_2 s}{\left(s^2+w_1 s+w_1^2\right)\left(s+w_2\right)}, \quad (1)$$

$$s=j2\pi f, \quad (2)$$

where w_1 – the lower limit frequency, $2\pi \cdot 50$ rad/s; w_2 – the upper limit frequency, $2\pi \cdot 400$ rad/s; s is a complex frequency variable; j – an imaginary unit; f – the frequency.

To perform signal filtering, a second-order active RC filter is employed, offering a roll-off rate of 40 dB per decade [4].

The transfer function of a second-order active RC filter is given by [5]

$$H(s)=\frac{1}{\left(\frac{s}{w_c}\right)^2+1}, \quad (3)$$

where w_c – the average transmission frequency, $2\pi \cdot 200$ Hz.

The second stage involved the development of a system for force myography (FMG) signal acquisition. Mechanical signals are captured using either piezoelectric sensors [7] with a sensitivity of 10 mV/N (millivolts per newton) or capacitive sensors capable of measuring tissue deformation. These sensors are mounted on the skin surface or directly above the targeted muscles. FMG signals are recorded within the frequency range of 0.1–20 Hz, which corresponds to the slow biomechanical changes in muscles during contraction. A low-pass filter with a cutoff frequency of 20 Hz and a roll-off rate of 20 dB per decade is utilized to extract these low-frequency components.

The transfer function of the FMG low-pass filter is given by [8]

$$H(s)=\frac{1}{\frac{s}{w_c}+1}, \quad (4)$$

where w_c – the limiting frequency, $2\pi \cdot 20$ rad/s.

The third stage involved the development of a sensory system capable of integrating EMG, EI (electrical impedance), and FMG signals.

The frequency response function of the filter describes how the filter passes signals of different frequencies [10]

$$H(w)=\begin{pmatrix} 1 & \text{if } w_1<w<w_1 \\ 0 & \text{otherwise} \end{pmatrix}, \quad (5)$$

where $H(w)$ – the filter characteristic that determines which frequencies are passed or cut; w_1, w_2 – are the minimum and maximum frequencies passed by the filter; w – a variable that denotes the angular frequency of the signal.

The discrete Fourier transform (DFT) is applied for signal analysis across multiple channels and is defined by the following expression [11]

$$F[k]=\sum_{n=0}^{N-1} f[n] e^{-j\frac{2\pi}{N}kn}, \; k=0,1,\ldots,N-1, \quad (6)$$

where $f[n]$ – the signal value at discrete points in time; $F[k]$ – the spectral component for each frequency; k – the index that identifies a specific frequency in the frequency domain; N – the number of points in the sampled signal.

Data transmission is carried out via a USB 2.0 interface with a bandwidth of 480 Mbit/s, enabling rapid real-time synchronization of signals.

The final stage involved the development of software for processing and analyzing the collected signals.

3. Results and Discussion

As described in the previous section, following filtration, the EMG signal is amplified using an operational amplifier [6] with a gain factor of 1000. This results in an output signal amplitude ranging between 0.5 and 3 V, which is optimal for subsequent analog-to-digital conversion. The analog-to-digital converter (ADC) operates with a 12-bit resolution and a sampling rate of 1000 Hz, which complies with the standards for high-precision EMG acquisition.

The output FMG signal from the sensor is amplified to an amplitude range of 0.5–2 V using an amplifier with a gain of 500. The analog-to-digital converter (ADC) operates with a resolution of 16 bits and a sampling rate of 200 Hz, enabling accurate detection of

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slow mechanical variations. Data transmission to the computer is carried out via a UART or USB interface.

FMG signals have low amplitudes; therefore, a higher-resolution ADC is required to accurately measure small variations in muscle force. EMG signals typically have higher amplitudes, so a 12-bit ADC provides sufficient accuracy without loss of detail. EMG signals are high-frequency (50–500 Hz), so the main challenge is achieving a fast sampling rate (1000 Hz) rather than high resolution. FMG signals are low-frequency (0.1–20 Hz), allowing for lower sampling rates while increasing ADC resolution to improve measurement precision.

During the integration phase, the system combines EMG, EI, and FMG signals into a unified data stream. This is achieved using multichannel analog-to-digital converters [9] operating at a sampling rate of 1000 Hz for EMG and EI signals, and 200 Hz for FMG signals. Digital filters with distinct characteristics are applied to separate the different types of signals acquired from the same channels. A band-pass filter with a passband of 50–400 Hz is used for EMG signals. A low-pass filter with a cutoff frequency of 50 Hz is used for EI signals. The system supports simultaneous operation of up to eight data acquisition channels, with a total data transmission rate of up to 10 Mbit/s.

The digitized signals are transmitted to a personal computer, where they are processed using dedicated software. Filtering and analysis algorithms are implemented based on the Fast Fourier Transform (FFT) [12] to extract frequency components. The software performs frequency analysis of EMG signals by constructing amplitude-frequency spectra within the range of 10–500 Hz with a resolution of 1 Hz, and analyzes the amplitude and rate of change of FMG signals within the range of 0.1–20 Hz, providing a temporal resolution of 1 ms for EMG and 5 ms for FMG.

Analysis results are presented as interactive graphs and tables. For user convenience, data export is supported in CSV [13] and MATLAB [14] formats. Additionally, the software allows for data storage in cloud repositories for further analysis.

Fig. 1 illustrates the structural schematic of the developed system, while Table 1 summarizes the technical specifications of the prototype.

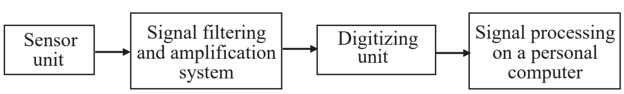

Fig. 1. Structural diagram of the development for obtaining EI, EMG, and FMG signals

Table 1

Technical parameters of the developed system

Parameter	Value
Number of channels	2
Sampling frequency	1 kHz
Types of received signals	EI, FMG, EMG
Maximum EI amplitude	300 Ohm
Maximum FMG amplitude	10 daN
Maximum EMG amplitude	3 V
EI measurement error	10 mOhm
FMG measurement error	0.01 daN
EMG measurement error	10 μV
EI signal frequency range	0–40 Hz
FMG signal frequency range	0–10 Hz
EMG signal frequency range	50–500 Hz
EI sensing current amplitude	5 mA
FMG sensing current amplitude	1 mA
EMG sensing current frequency	0.5 mA
EI sensing current frequency	75 kHz
FMG sensing current frequency	5 kHz
EMG sensing current frequency	1 kHz

The above parameters demonstrate the technical capabilities of the developed system. They cover both electrical and mechanical characteristics of the measuring channels. High accuracy and a wide frequency range ensure the possibility of operation in various experimental and clinical conditions. The combination of three types of signals (EI, FMG, and EMG) within one platform allows for a comprehensive analysis of muscle activity and increases the informativeness of the studies.

A functional prototype of the system was assembled using commercially available modules. Fig. 2 shows the experimental setup for synchronized acquisition of EMG, FMG, and EI signals.

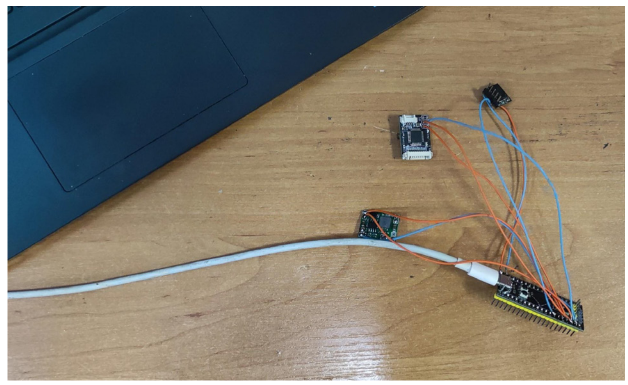

Fig. 2. Experimental setup for synchronized acquisition of EMG, FMG, and EI signals

For EMG signal acquisition, the ADS1299 analog front-end was used; for FMG signal interfacing, the HX711 module was employed. An STM32-based microcontroller managed data acquisition, processing, and communication. The prototype enabled synchronized recording of EMG, FMG, and EI signals for further analysis.

Prior to the experiment, electrodes were affixed to the participant's forearm, with a standard electrode area of 10 mm², fabricated from silver/silver chloride (Ag/AgCl) [1], to ensure high conductivity and minimize electrical noise. The inter-electrode distance is set at 20 mm, conforming to the recommendations for electromyographic (EMG) recordings. The electrical signals generated during muscle contractions typically fall within the frequency range of 10–500 Hz [2]. They were secured with a gentle compressive force, regulated using medical tourniquets to ensure stable contact. To enhance signal acquisition quality, the skin at the electrode placement sites was treated with a conductive gel and a high-conductivity spray. The electrodes were positioned on the upper forearm, aligned with the projections of antagonist muscles. The electrodes located superiorly were placed over the extensor muscles, while the lower electrode was positioned on the flexor muscles, as illustrated in Fig. 3.

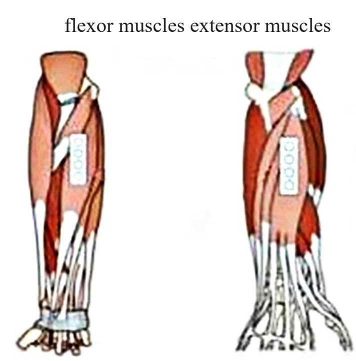

Fig. 3. Location of electrodes in the muscle projection [15]

For signal acquisition, the participant was seated comfortably in a chair with their elbow supported. Measurements commenced once the impedance (EI) signal stabilized during complete wrist relaxation. Upon verbal instruction, the participant performed a movement by clenching the hand into a fist, maintaining the contraction for a specified duration, then relaxing the hand to a resting state. This measurement cycle was repeated multiple times.

Fig. 4 presents the recorded signal graphs obtained during the gesture execution with varying force intensities. The graphs indicate that the EI and EMG signals generated during movement exhibit no phase shift. It is hypothesized that any observed phase displacement in the EI signal may result not only from morphological changes but also from physiological factors, including increased pressure of the electrodes against the forearm.

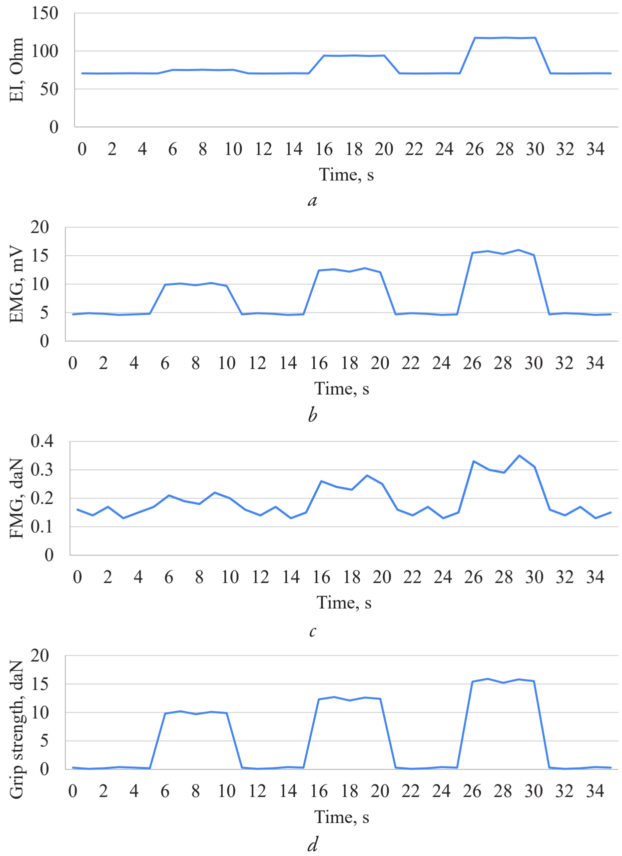

Fig. 3. EI (*a*), EMG (*b*), and FMG (*c*) signals during gesture execution with varying grip force (*d*)

The presented graphs demonstrate that the amplitudes of the EI and FMG signals increase proportionally with the applied grip force. This finding supports the feasibility of utilizing these signals for implementing proportional control mechanisms.

A neural network model was employed for signal classification and gesture recognition. For this purpose, a pre-existing architecture, 1D Convolutional Neural Network (1D-CNN), was adapted and trained on the dataset obtained from the prototype measurements. The network consisted of three convolutional layers with ReLU activation, followed by max pooling and a fully connected dense layer. Input features included normalized EMG, FMG, and EI signals segmented into 250 ms windows with 50% overlap.

The dataset used for training the neural network was constructed based on experimental recordings obtained with the developed modular prototype. Data acquisition involved synchronized sampling of EMG, FMG, and EI signals. The sampling rate was 1000 Hz for EMG and EI, and 200 Hz for FMG. Each recording session included several repetitions of predefined motor gestures. These gestures were rest, weak grip, medium grip, and strong grip. Each gesture was held for 3–5 seconds, followed by a rest period to ensure signal separation and minimize overlap between classes.

The raw signals were initially filtered using digital filters appropriate for each modality (band-pass for EMG: 50–400 Hz; low-pass for FMG: 0.1–20 Hz; and low-pass for EI: 0–40 Hz). After preprocessing, the signals were segmented into fixed-length time windows of 250 milliseconds with a 50% overlap to increase data density and improve generalization during training. Each segment was labeled according to the corresponding gesture intensity.

The final dataset consisted of approximately 12,000 labeled samples, evenly distributed across four classes (rest, low, medium, high grip force). To ensure class balance, data augmentation techniques such as Gaussian noise addition and minor temporal warping were applied to underrepresented segments. Each segment included three input channels corresponding to EMG, FMG, and EI, and was normalized using z-score standardization.

The dataset was randomly split into training (80%), validation (10%), and testing (10%) subsets, ensuring that samples from each class were equally represented across all splits.

The trained model achieved an accuracy of 84.2% on the test set.

During practical tests with users, the model achieved an accuracy of 91.8% in real-time. The comparative analysis is presented in Table 2.

Table 2

Comparative analysis

Source	Signal Types	Accuracy
[5]	EMG + FMG	91%
[6]	EMG + EI	90%
This study	EMG + FMG + EI	91.8%

The classified signals obtained from the CNN can be used as control commands for external devices. For example, each recognized gesture can be linked to a specific position of a servo motor or similar actuator.

The proposed system provides high accuracy of gesture recognition for gesture-based control of collaborative mechatronic systems. This approach confirms the findings of [12, 13], which emphasize the advantages of combining multiple biosignal modalities. In addition, the modular nature of the prototype allows for rapid deployment for applications in prosthetics, human-robot collaboration, or rehabilitation exoskeletons.

The developed system can be applied in prosthetics, rehabilitation devices, and collaborative robotic systems for intuitive human-machine interaction. The integration of EMG, FMG, and EI signals enables proportional and simultaneous control of actuators, which is important for tasks requiring fine motor control. In clinical environments, the system can assist in rehabilitation progress monitoring and patient-specific therapy adjustment. In sports medicine, it can provide detailed biomechanical feedback for training optimization.

The current prototype has been tested on a limited number of participants under controlled laboratory conditions. Variations in electrode placement, skin properties, and muscle fatigue may significantly affect signal stability. Long-term operation in mobile or outdoor environments has not yet been fully validated. Before practical deployment, it is necessary to improve sensor fixation methods, ensure robustness against motion artifacts, and expand testing to a broader demographic.

Future work will focus on miniaturization of the hardware for wearable applications, integration with wireless communication modules, and the development of adaptive filtering algorithms to improve signal quality in dynamic conditions. In addition, testing with larger participant groups and in real-world scenarios will be carried out. Extending the neural network to recognize a wider range of gestures and to adapt to individual physiological characteristics is also planned.

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4. Conclusions

As part of the research, a prototype of a sensor system for recording bioelectrical and mechanical signals was developed and tested, which combines EI, EMG, and FMG methods into a single integrated platform. The proposed architecture provides highly accurate and synchronized acquisition of signals from different sources in real time using multi-channel ADCs, optimized filtering schemes, and efficient digital processing.

The use of standard Ag/AgCl electrodes and second-order active RC filters made it possible to achieve stable EMG recording in the frequency range of 50–400 Hz with high resolution. Low-pass filtering and amplification were applied to FMG signals, which ensured the capture of slow changes in muscle tone with sufficient accuracy. Data transfer via the USB 2.0 interface guarantees the bandwidth necessary for the analysis of multi-channel signals in real time.

Experimental verification confirmed the system's ability to register and differentiate signals related to muscle activity. It was found that EI and FMG signals correlate with contraction force, which opens up prospects for creating adaptive proportional control mechanisms. The system demonstrates potential for use in medical, rehabilitation, and human-machine interfaces due to its compactness, accuracy, and scalability.

Conflict of interest

The author declares that he has no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was conducted without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The author confirms he did not use artificial intelligence technologies when creating the presented work.

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