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DEVELOPMENT OF A GRIP FORCE RECOGNITION SYSTEM BASED ON EMG SIGNALS AND NEURAL NETWORKS

The object of research is a bionic prosthesis control system that uses EMG signals read using the MYO bracelet, as well as feedback sensors to determine the grip force. In the context of the development of modern bioengineering and neurotechnology, this system is aimed at ensuring accurate and adaptive control of the prosthetic hand, taking into account the user's intentions.

The problem considered in the research is to recognize the grip force of a bionic hand based on EMG signals and transmit feedback to the user. Special attention is paid to the use of a deep neural network for classifying force levels and developing a real-time signal processing technique. The task is to create a stable and user-friendly grip control system.

The essence of the results obtained is to create an experimental system that classifies the grip force of objects with a bionic hand with high accuracy (95%). The system is based on a neural network with a two-layer autoencoder, trained on labeled and unlabeled data. To improve the accuracy of the model, the temporal characteristics of EMG signals were used: MAV, RMS, SD and WL.

The results are explained by effective biosignal processing and machine learning. The division of force into 8 levels and the use of a fuzzy controller ensured stable control of the grip and the transfer of information to the user via vibration feedback. The system was successfully tested in real time.

The innovation lies in the integration of the MYO bracelet, force sensor and FSR with deep learning. This provides accurate force classification and natural feedback, which increases controllability and ease of use.

The use of the system provides new opportunities in prosthetics: it more accurately conveys the user's intentions, reduces errors and increases comfort. The results have the potential for clinical implementation to improve modern prostheses.

***Keywords**: electromyography, prosthetics, training, neural network, sensor, vibration, feedback, capture, control, management.*

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1. Introduction

The development of intelligent prosthetic systems has garnered increasing attention due to its significance in both clinical rehabilitation and human-machine interaction. These systems are especially useful for restoring functionality to people with limb loss. They provide improved control and sensory feedback, which increases the usability of prosthetic devices. In modern prosthetic hand control, various methods based on electromyographic (EMG) signals have been developed. These methods are often combined with machine learning algorithms to ensure fast response and adaptability in real time.

In this research, a multi-component system was proposed that integrates the MYO armband for capturing surface EMG signals from the forearm muscles, a six-axis force sensor for measuring grip intensity, and a force-sensitive resistor (FSR) mounted on the fingertip to enhance tactile feedback. Vibration-based feedback is employed to convey grip strength back to the user's arm, closing the loop for a more intuitive interaction.

The EMG signals are processed using a deep neural network (DNN) equipped with a two-layer autoencoder structure. This configuration is designed to classify grip force into eight discrete levels ranging from 0 to 40 newtons. The discretization of force enables more stable control, as continuous values tend to produce signal instability and erratic feedback responses. Feature extraction is based on time-domain characteristics such as mean absolute value (MAV), root mean square (RMS), standard deviation (SD), and waveform length (WL), which collectively capture the signal's amplitude, complexity, and dynamic behavior.

The current work extends this concept by integrating force feedback and fuzzy control to enable adaptive grip modulation. In contrast to methods relying on image processing or electric impedance tomography (EIT), the proposed system maintains non-invasiveness while delivering high classification accuracy.

The experimental setup involved collecting synchronized EMG and force data from participants performing three-finger pinch gestures across predefined force levels. Data were segmented using overlapping sliding windows, allowing for high-resolution signal processing. The DNN was trained using labeled datasets, achieving an average classification accuracy of 95% in real-time testing scenarios.

From a practical standpoint, the proposed methodology offers several advantages for adaptation in Ukrainian clinical and engineering contexts. Its reliance on commercially available hardware and efficient machine learning architecture enables feasible deployment in domestic medical facilities. Furthermore, the ability to relay tactile feedback without requiring invasive sensors or complex imaging systems makes it suitable for rehabilitation and assistive robotics applications.

However, certain challenges remain. The system's performance may depend on proper skin preparation and sensor positioning, which could affect reproducibility under less controlled conditions. Nevertheless, the flexibility of the DNN framework and the modular design of the sensing components provide strong potential for further development.

Overall, the findings underscore the viability of applying deep learning to EMG-based prosthesis control, particularly when combined with intuitive feedback mechanisms. Such systems may serve as a foundation for future efforts aimed at improving the functionality, responsiveness, and user experience of next-generation prosthetic devices in Ukraine and beyond.

The development of bionic prosthetic control systems based on electromyographic (EMG) signals has been actively studied in recent years. [1, 2] have shown the effectiveness of using deep recurrent neural networks to predict and simultaneously control joint positions and grip force. However, these models, although they demonstrate high accuracy, often require significant computational resources, which complicates their implementation in real time.

Papers [3–5] present methods for continuous estimation of grip force using various neural networks, including generalized regression networks. However, in practice, the accuracy of these methods depends on the stability and quality of the signal, which can deteriorate when the position of the sensors or the physiological parameters of the user change.

Papers [6, 7] emphasize the importance of simultaneously sensing hand posture and grip force to improve prosthetic functionality, but most systems lack haptic feedback to help the user control force more accurately. At the same time, [8, 9] consider the integration of force sensors and vibration feedback to improve the user experience, but such approaches have not yet been sufficiently explored in the context of everyday prosthetic use. There is also the problem of generalizability of models – the variability of EMG signals between different users and changes in the same user over time make it difficult to apply universal solutions. As noted by [10, 11], adaptive neural networks with the ability to learn may be the key to overcoming this problem, but the methods for their implementation have not yet received widespread practical application.

The aim of the research was to create a system for accurate recognition of the grip force level of a prosthetic hand based on surface electromyography (sEMG) signals in real time. The challenge was to develop an efficient method for classifying discrete grip force levels, which would allow for stable control of the prosthesis and tactile feedback to the user. An important task was to overcome the instability when working with continuous force values and adapt the system to the limitations of the feedback device, which works with fixed force levels.

2. Materials and Methods

The object of research is the process of controlling and estimating the grip force of a prosthetic hand based on surface electromyography (sEMG) signals.

This research employed a combination of experimental, computational, and analytical research methods:

Experimental method: A series of controlled laboratory experiments were conducted with human participants to record surface electromyography (sEMG) signals and corresponding grip force values. The experimental protocol was standardized to ensure reproducibility and to minimize the influence of external variables such as fatigue, sensor placement variance, and ambient conditions.

Empirical data collection and signal processing: sEMG signals were collected using the MYO armband, and grip force was measured using a six-axis force sensor. Time-domain features of the EMG signals were extracted using a sliding window approach (50 ms window with 25 ms overlap), which is commonly used for real-time biomedical signal processing.

Machine learning method: A supervised machine learning approach was applied using a deep neural network (DNN) with a two-layer autoencoder for classification. The model was trained in two stages: unsupervised feature extraction from unlabeled data, followed by supervised classification using labeled force data. Regularization techniques (sparsity penalty) and the backpropagation algorithm were used to improve generalization and prevent overfitting.

Comparative analysis: The performance of the proposed discrete force classification method was compared with continuous force estimation approaches described in related studies. The analysis demonstrated that the discretization method provides greater control stability and is more suitable for real-time applications with limited hardware capabilities.

Software-based simulation and testing: The system was implemented using Python and TensorFlow, and real-time testing was conducted to evaluate accuracy, responsiveness, and usability. A prototype prosthetic hand controlled by the model was used to validate real-world functionality.

These combined methods ensured that the results were not only computationally valid but also grounded in real-world user interaction, providing a comprehensive evaluation of the prosthesis control system.

The system consists of several main components that operate in real time.

The first component is the MYO armband [1], which records surface electromyographic signals from the forearm muscles. This device was chosen due to its portability, non-invasive nature, and the ability to capture multichannel sEMG data without the need for gel electrodes. Compared to traditional EMG systems with wired electrodes, the MYO offers ease of use and user comfort, which is important for prosthesis users in everyday environments.

The second component is a six-axis force sensor, which measures the actual grip force applied to an object. It was selected for its high precision and ability to capture multi-directional forces, allowing for reliable ground-truth data during the training of the model. Compared to simpler FSRs, the force sensor provides more accurate and linear force measurements, which are critical for model validation. The system block diagram is presented in Fig. 1.

To increase the user's sensitivity and precisely control the grip force, a force-sensitive resistor (FSR) [2] is installed at the fingertip. FSRs are cost-effective and compact, allowing for real-time tactile feedback implementation. While FSRs are less accurate than full-scale force sensors, their integration into the fingertip is practical for lightweight, embedded feedback applications.

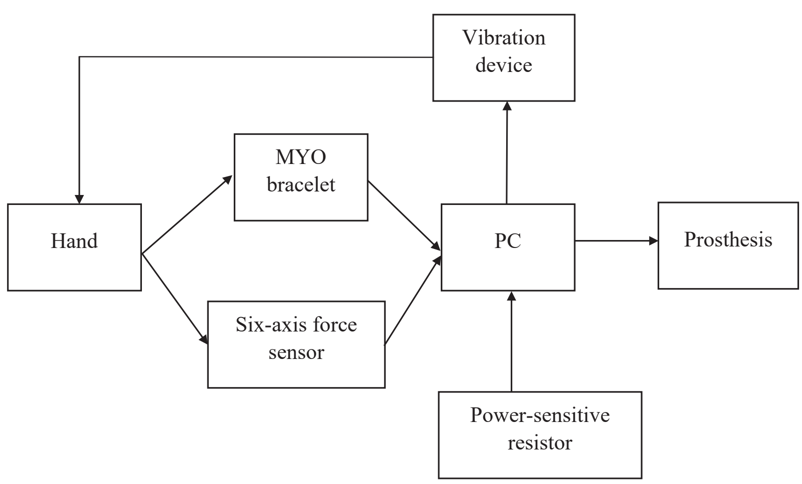

Fig. 1. System block diagram

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A vibration device is used to transmit the grip force level back to the user's hand in the form of tactile feedback. This method was chosen over visual or auditory feedback due to its intuitive nature, lower cognitive load, and suitability for real-time closed-loop control, especially in noisy environments or when vision is obstructed.

Signal processing is performed using a deep neural network (DNN) [3], which classifies the grip force into several discrete levels. DNNs were selected due to their ability to model complex, non-linear relationships between EMG features and grip force, outperforming traditional machine learning methods such as SVM or decision trees in preliminary tests. The use of a two-layer autoencoder architecture enables unsupervised pretraining, which improves feature extraction and generalization.

To improve control stability, the grip force is divided into 8 discrete levels (from 0 to 40 N). Discretization was used instead of continuous force estimation to minimize control oscillations and instability observed in real-time operation. Continuous models are sensitive to minor signal noise and often require high-quality, consistently placed sensors – conditions not always possible in practice. In contrast, force discretization ensures more robust and predictable system behavior.

The study focused on the three-finger pinch gesture with force measured along the Z axis. This gesture was chosen because it is common in daily object manipulation and suitable for demonstrating the system's ability to distinguish force levels.

The movement detection is based on the Mean Absolute Value (MAV) of the sEMG signal. MAV is a widely used, computationally efficient time-domain feature that reflects muscle activation level. It was preferred over frequency-domain methods (like FFT) due to its simplicity, low-latency calculation, and good performance in online systems.

To predict grip force, four common time-domain features were extracted from the EMG signals. The study used four most common time domain (TD) characteristics:

$$MAV_k = \frac{1}{N}\sum_{i=1}^{N}\left|x(i)\right|, \quad (1)$$

$$RMS_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x(i)^2}, \quad (2)$$

$$SD_k = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x(i)-u\right)^2}, \quad (3)$$

$$WL_k = \sum_{i=1}^{N-1}\left|x(i+1)-x(i)\right|. \quad (4)$$

These features are standard in EMG analysis and were chosen because they balance computational efficiency with information richness. They have been widely validated in the literature for classifying muscle activity patterns.

A sliding window approach (50 ms window with 25 ms overlap) was used for real-time signal segmentation. This method ensures that rapid changes in EMG signals are captured while maintaining manageable computational load.

The deep neural network uses two hidden layers of 200 neurons each with sigmoid activation. This architecture provides sufficient capacity for complex classification while remaining lightweight enough for real-time embedded processing. In contrast to larger architectures (e. g., deep CNNs or RNNs), this model was optimized for execution on mid-range embedded hardware, making it suitable for portable prosthetic applications.

The network is trained in two stages: unsupervised feature extraction with an autoencoder and supervised classification with softmax output. Regularization (sparsity penalty) and backpropagation are applied to enhance generalization and reduce overfitting.

3. Results and Discussion

Two main devices were used to collect data in the experiment: the MYO armband for reading surface electromyographic (sEMG) signals and a six-axis force sensor for measuring grip strength. Both devices operated at a sampling rate of 200 Hz, which provides 200 measurements per second for each channel. Such a high data acquisition rate allows for obtaining sufficiently accurate and detailed signals necessary for further processing and classification.

The MYO armband was chosen due to its ease of use, non-contact nature, and ability to provide reliable EMG signals from 8 channels without the need for complex skin preparation or electrode placement. This makes it ideal for experiments where it is important to combine participant comfort and signal quality. A high-precision six-axis sensor was used to accurately measure the applied force, allowing for reliable data on grip strength along the required axis (Z-axis).

The software for data collection, processing and analysis was developed based on the Python 3.8 language, as it is widely used in scientific research due to the large number of libraries for machine learning and working with hardware. The TensorFlow 2.4 library was used to build and train the neural network, which provides efficient work with deep neural networks and allows optimizing the model for real-time operation. In addition, the NumPy, SciPy and scikit-learn libraries were used for signal processing. Communication between the computer and hardware (Arduino, sensors) was carried out using the pySerial library, which provides reliable and fast data exchange.

This combination of hardware and software was chosen due to the balance between accuracy, ease of use and real-world limitations (e. g., computing resources), which allows the system to be used in everyday conditions.

Before the experiment began, participants' skin was prepared by removing hair and cleaning the area with alcohol to reduce skin resistance and improve signal quality. The MYO armband was then placed on each participant's forearm, and they were instructed to perform a three-finger pinch gesture, simulating the act of gripping an object.

The grip force was divided into 8 levels, ranging from the weakest (0–5 N) to the strongest (35–40 N). At each level, the participant applied force to the sensor for 4–6 seconds, followed by a 10-second rest period. This cycle was repeated ten times for each force level. Between each change in force level, a 20-minute break was given to prevent muscle fatigue.

For training the deep neural network (DNN), datasets containing 8 EMG features and 1 force feature were used. The eight EMG features were fed into the input of the DNN, while the single force feature served as the ground truth for comparison with the model's output. This allowed researchers to evaluate how accurately the DNN could predict grip force. The artificial neural network (ANN) was trained for 1000 epochs. During training, the model was gradually improved to achieve optimal accuracy in classifying grip strength levels. The results of training the model on EMG signal and grip force data are given in Table 1.

Table 1

Model training results on EMG signal and grip force data

Epochs	Accuracy (%)	Loss	Training time (minutes)
100	68.5	1.10	40
200	79.3	0.75	80
300	86.7	0.52	120
400	90.1	0.38	160
500	92.0	0.30	200
600	93.3	0.25	240
700	94.0	0.22	280
800	94.4	0.20	320
900	94.7	0.18	360
1000	95.0	0.17	400

For comparison, a separate artificial neural network training was conducted exclusively on surface electromyography signals, without using grip force data. The results of training the model on data of EMG signals only are given in Table 2.

Table 2

Model training results on data of EMG signals only

Epochs	Accuracy (%)	Loss	Training time (minutes)
100	72.4	0.65	40
200	79.1	0.48	80
300	83.0	0.37	120
400	86.2	0.29	160
500	87.8	0.24	200
600	88.7	0.20	240
700	89.1	0.17	280
800	89.5	0.15	320
900	89.9	0.13	360
1000	90.0	0.12	400

If to analyze the results in Table 1 and Table 2, in the first case, combined input data were used – surface electromyography (sEMG) signals together with grip strength indicators, which allowed to achieve high classification accuracy at the level of 95%. This is explained by the fact that additional information about grip strength helps the model better distinguish different levels of muscle tension and control the force of gestures, which provides more reliable and stable prediction. However, this option requires the use of additional force sensors, which complicates the hardware part of the system. In the second case, the neural network was trained exclusively on the basis of sEMG signals, and this gave a slightly lower accuracy – about 90%. Although this approach significantly simplifies the hardware configuration, reducing costs and increasing usability, it does not provide the same detailed information about the force of gestures, which can be critical for some tasks. Therefore, the choice between the two approaches depends on the specific requirements: if the priority is maximum accuracy and granularity of control, it is advisable to use combined sEMG and grip strength data; If the simplicity of the system and its portability are important, it is possible to limit yourself to only sEMG signals.

During real-time testing, the classification results demonstrated high accuracy, with an average recognition rate of 95%. Fig. 2 presents the recognition accuracy graph obtained after 100 recognition cycles, with each cycle representing a percentage accuracy result.

The developed system for controlling the grip force of a prosthetic hand is based on the processing of surface electromyography (sEMG) signals using a deep neural network (DNN) with a two-layer autoencoder that classifies the grip force into 8 discrete levels. This approach provides more stable control compared to the continuous force estimation methods observed in the works of [3–5].

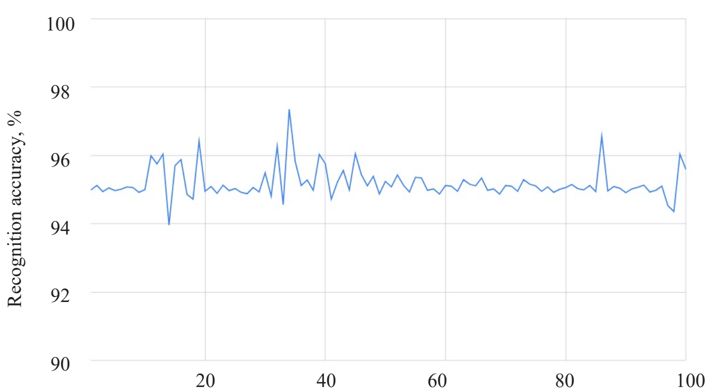

Fig. 2. Recognition accuracy graph

Although the mentioned studies show good accuracy in predicting continuous values of grip force, they require high signal quality and stable sensor placement, which complicates their application in real conditions. In comparison, our approach with force discretization and integration of haptic feedback via a vibration device allows to improve the usability of the prosthesis, which partially coincides with the approaches of [8, 9], but it is possible to develop this idea in the context of everyday use.

Other works, such as [1, 2], demonstrate the effectiveness of deep recurrent networks, but they require significant computational resources, which complicates real-world use. In contrast, our DNN has an optimized architecture for real-time operation with high accuracy (95%) without large hardware requirements.

The main limitations of the proposed system are the requirements for skin preparation and precise placement of sensors, such as the MYO armband and FSR, since the signal quality and prediction accuracy depend significantly on these factors. Misalignment or poor contact of the sensors can lead to a decrease in signal quality and, as a result, a deterioration in the system performance. In addition, the use of discrete force classification (8 levels) limits the accuracy of reproducing continuous force changes, which can be critical in some fine motor tasks. The system is also focused on a specific type of movement – a three-fingered grip with force measured along the Z axis, which reduces its versatility for other types of grips. Finally, there is a need for regular training and tuning of the network for each user, which can be a problem when trying to scale the system for different individuals or with long-term use.

Further research can be aimed at developing adaptive neural networks with the ability to learn online, which can adapt to individual user characteristics and dynamic changes in sEMG signals during operation. This will improve the stability and accuracy of the system, which is in line with the recommendations of [10, 11]. It is also promising to expand the functionality of the system to support a larger number of gestures and grip types, using multi-channel sensors and multi-dimensional signal analysis. The integration of different types of feedback – tactile, temperature, vibration – will help make the use of the prosthesis more intuitive and natural.

In addition, the implementation of a lightweight, portable hardware platform will allow for wider application of the system in medical practice and at home. An important direction is to investigate the impact of prolonged use of the prosthesis on signal stability and develop compensation methods to maintain classification accuracy in the long term [12, 13]. Multisensor approaches can also be considered, combining sEMG with other technologies, such as electrical impedancemetry or optical sensors, to improve the reliability of user intention recognition.

4. Conclusions

The developed system for predicting grip force in a prosthetic hand based on EMG signals has proven its effectiveness in real-time operation. The use of the MYO armband for acquiring muscle activity, along with the integration of a six-axis force sensor, enabled accurate tracking of grip intensity and ensured adaptive response of the prosthesis to the user's motor intentions. This real-time responsiveness is crucial for creating a more natural and intuitive user experience, especially for daily tasks that require precision and dynamic adjustment of grip strength.

Through the implementation of a deep neural network (DNN) for discrete classification of grip force levels, the system demonstrated a high average recognition rate of 95%, confirming the efficiency and reliability of the proposed approach. The model was optimized for embedded environments, enabling high performance without requiring extensive computational resources. This characteristic is particularly important for wearable devices, where energy efficiency, processing speed, and system miniaturization are critical design factors.

A crucial contribution to the system's success was the carefully designed preprocessing pipeline, which included time-domain feature extraction and the application of a sliding window method (200 ms). This approach enhanced temporal consistency and noise robustness in signal interpretation, which is often a challenge in EMG-based systems due to the inherently variable nature of biological signals. Additionally, the modular design of the signal processing and classification pipeline facilitates future improvements and easy adaptation to different sensor configurations or user-specific calibration needs.

The inclusion of a vibration-based tactile feedback module further improved user interaction by allowing the wearer to intuitively perceive changes in grip force. This sensory feedback played a significant role in enhancing motor learning and adaptation, empowering users to perform tasks with greater confidence and control. It also helped to close the sensorimotor loop, which is essential in prosthetic design for fostering a sense of embodiment and user engagement.

Thus, the proposed system not only achieves a balance between performance and practicality but also contributes to the broader advancement of intelligent prosthetic technologies. It exemplifies the potential of EMG-driven neural networks to enable intuitive, responsive, and efficient control of prosthetic limbs. By combining robust signal interpretation, adaptive force prediction, and real-time tactile feedback, the system supports real-world usability and paves the way for broader clinical integration in assistive technologies. Furthermore, its scalable architecture and energy-efficient design make it a promising candidate for future development in both research and commercial prosthetic applications.

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 research and its results presented in this paper.

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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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