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EVALUATION OF THE EFFICIENCY AND ACCURACY OF THE SYSTEM FOR COLLECTING AND PROCESSING EMG SIGNALS OBTAINED USING A BRACELET

The object of research is a bracelet that uses the electromyography (EMG) method to control a bionic prosthesis. In the conditions of the development of modern biomedical technologies and robotics, such a system becomes key to improving the quality of life of people with disabilities, providing efficient and accurate control of prostheses. The problem addressed in the research is the development and analysis of a bionic prosthesis control system using a bracelet using the EMG method. The main focus is on the optimization of data collection and processing processes, as well as the development of machine learning algorithms for gesture recognition in order to improve the accuracy and efficiency of prosthetic control.

The essence of the obtained results is the development and testing of a new bionic prosthesis control system that uses EMG signals obtained with the help of a bracelet. The study showed that the classifier based on the support vector method outperforms other algorithms such as neural networks and decision trees, achieving an average accuracy of 90 %. The obtained data were successfully filtered and subjected to feature extraction, which allowed to create effective gesture recognition algorithms. The system was tested in real time, which confirmed its high accuracy and efficiency.

The proposed system includes an innovative bracelet for collecting EMG data, which are then processed and analyzed using modern machine learning algorithms. The innovativeness of the proposed approach lies not only in the high accuracy of gesture recognition, but also in the possibility of adapting the system to different types of bionic prostheses and operating conditions. This is achieved by using a classifier based on the support vector method, which demonstrates significantly higher accuracy compared to other algorithms such as neural networks and decision trees. The test results show an average accuracy of 92.5 %, which confirms the high efficiency of the system.

The use of this system involves the intensive use of EMG sensors, which allows more accurate determination of the user's intentions regarding the control of the prosthesis. This, in turn, contributes to the improvement of the quality of life of users, providing them with greater functionality and convenience in the use of bionic prostheses.

Keywords: *bracelet, electromyography, bionic prosthesis, data acquisition system, signal processing, machine learning algorithms.*

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1. Introduction

The utilization of synthetic bionic hands offers extensive potential, spanning across medical and industrial domains. These hands can execute assignments within perilous or constrained settings while upholding the user's adeptness and innate response time. In such scenarios, employing vision-centric gesture recognition setups incorporating image detection [1–7] can effectively ensure the desired degree of hand maneuverability.

In [8] introduced a system for recognizing hand gestures utilizing EIT. This method involves assessing the internal electrical impedance and deducing the internal structure through surface electrodes and high-frequency AC. Despite its high accuracy, the system requires direct skin contact to function effectively. In [9] presented a control system based on gestures that utilized sEMG signals from the forearm. The proposed systems effectively simulated joystick movements for virtual devices. In [2] introduced a novel method for controlling hand prostheses using neural signals. This method employs pattern recognition applied to the envelope of neural signals. In this approach, simultaneous recordings of sEMG signals were obtained from a single human amputee, and the envelope of these signals was computed. Subsequently, a Support Vector Machine (SVM) algorithm was utilized to interpret the user's intentions.

The findings of this research demonstrated that established techniques of sEMG pattern recognition are applicable for neural signal processing, thus opening avenues for the implementation of neural gesture decoding in upper limb prosthetics. In [10] introduced a bionic hand controlled through hand gestures, with gesture recognition relying on surface EMG signals. The proposed method involved extracting various features, including mean absolute value, zero crossing, slope sign change, and waveform length. A basic k-nearest-neighbors (KNN) algorithm served as the classifier for hand posture recognition. The outcomes demonstrate the KNN classifier's capability to distinguish four distinct hand postures.

The experience presented by the authors in the mentioned studies can be useful for Ukrainian facilities in a number of aspects. The method that uses electrical impedance and surface electrodes to recognize hand movements is promising for use in creating new control systems. A gesture-based control system that effectively simulates joystick movements for virtual devices is an important step in the development of control interfaces.

Some aspects of research may be less suitable for Ukrainian facilities. For example, some methods may require high-tech equipment or have technical limitations that may be difficult to provide in Ukrainian conditions.

The perspective of research lies in the possibility of their adaptation and improvement for use in Ukrainian conditions. For example, the developed classification methods can be adapted for implementation in domestic medical practice or industry. In addition, some algorithms and approaches may be useful for the further development and improvement of Ukrainian technologies in the field of medicine, robotics and other fields.

The aim of this research is to examine the utilization of an EMG-powered wristband design for data acquisition and control functionalities in the context of a bionic limb. The research is focused on creating an effective system for collecting and processing EMG signals to ensure precise control of the bionic prosthesis.

2. Materials and Methods

The control system comprises eight MyoWare EMG modules and an Arduino board. This particular design allows for convenient placement on a limited area of the forearm situated beneath the elbow. MyoWare is a biomedical sensor designed to measure muscle electrical activity (EMG) by capturing and recording signals generated by muscle contractions. Arduino is a microcontroller platform widely used in various electronics and automation projects. It offers a convenient interface for programming various devices. The combination of Arduino and MyoWare allows for the easy and effective development of various control and monitoring systems, including EMG signal-based bionic prosthesis control systems. Each MyoWare module measures muscle electrical activity and generates an analog signal, which is fed into the analog ports of the Arduino board. The Arduino processes the received signals and transmits data to the computer using the built-in USB port. This port enables communication between Arduino and the computer via a software interface (COM port).

The scheme of the control system is presented in Fig. 1.

The diagram shows the main components and stages of the bionic prosthesis control system. The diagram shows the process of transmitting EMG data from EMG modules for their initial processing and filtering to remove noise and artifacts, and to transmit the processed signals for display on the screen.

Fig. 1. Sketch of the control system diagram [3]

Data processing, storage, and display are performed programmatically. The program relies on Arduino libraries, such as the library for working with analog inputs to read signals from MyoWare modules, the library for data transmission via the USB port, and the library for data storage and display. These libraries are necessary for working with hardware resources. Gesture recognition algorithm is implemented based on TensorFlow libraries. TensorFlow represents an open-source framework dedicated to machine learning. It offers a user-friendly interface and a diverse range of functionalities for constructing, training, refining, and implementing different categories of neural networks, encompassing Artificial neural networks (ANNs), support vector machines (SVMs), and decision tree methodologies (DTs). Using a TensorFlow-based model allows for efficiently utilizing deep learning to solve complex classification tasks of different gestures on EMG data [1, 2].

3. Results and Discussion

3.1. Data collection. Data collection was performed using a control system. Data were collected from a single subject. The band was attached around the forearm. Gestures were performed with a 90° angle at the elbow joint during data collection. Data were recorded for four hand gestures: clenched fist, extended spread fingers, extended index finger, with all others flexed; index and thumb in a pinch grip, with all others flexed. The subject performed tasks from a resting position to execute one of the proposed gestures and then return to a resting position for approximately four seconds. The procedure was repeated more than 10 times for each individual gesture. A consistent methodology was employed for all four gestures, yielding a dataset comprising 2000 files, with each file containing signals from multiple gestures. The data were processed and corrected to simplify the feature extraction phase. Arduino libraries were used for signal processing. This procedure streamlined the data collection process and allowed for data visualization during recording [4]. The received signal values are shown in Fig. 2.

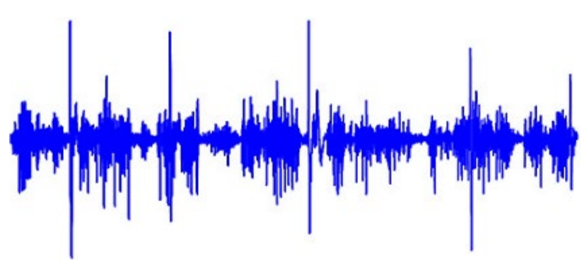

Fig. 2. Diagram of the measured signal [5]

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The diagram illustrates the recorded signal's waveform over a specific duration. Each peak and fall in the waveform represents a distinct event or activity captured by the sensor. The amplitude of the signal indicates the intensity or magnitude of the measured phenomenon. The x-axis represents time, while the y-axis represents the signal strength or voltage.

3.2. Data processing. The obtained EMG signals were processed through filtration, removal of distortions, and non-EMG effects from the recorded signal. Typically, unprocessed EMG signals have a frequency range from 6 to 500 Hz. However, there might be instances of abrupt fluctuations due to undesirable electrical interference occurring within the signal's frequency spectrum. Moreover, slow oscillations caused by either motion artifacts or electrical networks can introduce distortions in EMG signals. These undesired signals can be eliminated from the initial EMG signal by employing a filter with cutoff frequencies spanning from 20 to 450 Hz. Subsequently, the processed data's dimensionality was decreased to extract features. Typically, EMG data may contain relevant and irrelevant information. Irrelevant information can be discarded by representing EMG data on a reduced scale, ultimately simplifying the classification process [6–8]. The values of the processed EMG signals are presented in Fig. 3.

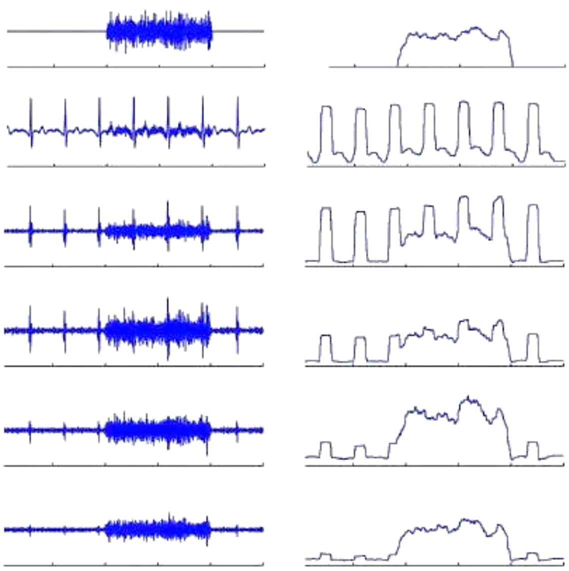


Fig. 3. Diagram of the processed signal [11]

The diagram illustrates the processed signal after passing through various methods of filtering and analysis. Comparison with the raw signal or baseline measurements provides insight into the effectiveness of the applied processing methods. A diagram helps visualize the transformation of a signal from its raw form to a more sophisticated representation, making interpretation and decision making easier.

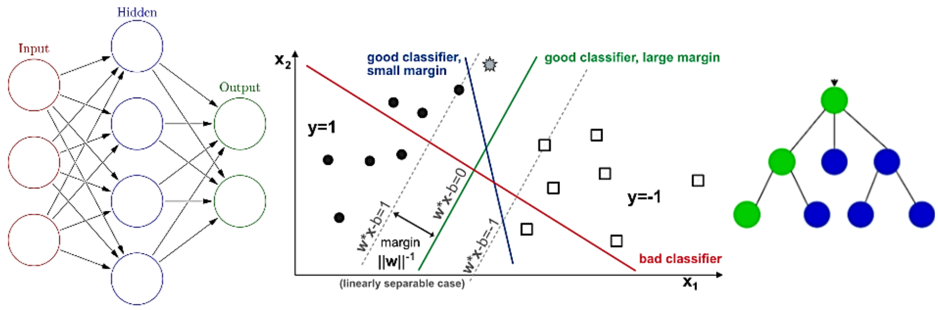
3.3. Recognition algorithms. Neural networks, support vector machines, and decision trees were employed as recognition techniques.

Artificial neural networks, also known as multilayer perceptrons, represent one of the primary methods for pattern recognition. They consist of a large number of neurons interconnected in layers. Training an optimization can readily achieve neural network functionality unknown weight coefficients to minimize a pre-selected fitness function. In general, the architecture of a neuron can be summarized as follows: the neuron (or node) receives input data, and then corresponding weights are applied to these inputs. A bias is then added to the linear combination of weighted input signals. The resulting combination is passed through an activation function. Generally, artificial neural networks comprise input and output layers, along with hidden layers, facilitating the network in acquiring knowledge of intricate functions.

Support Vector Machines (SVM) are a multiclass classifier that has been successfully applied in various disciplines. The SVM algorithm has achieved success due to its outstanding empirical performance in scenarios characterized by relatively high-dimensional feature spaces. In this algorithm, the training process involves determining weight coefficients and bias values using provided labeled training data. This is accomplished by optimizing weight coefficients and biases to maximize the margin, a concept known as hinge loss. Originally designed for binary classification, SVM has been expanded to handle multiclass classification. This is achieved either through the creation of multiple «one vs. All» classifiers, where the algorithm solves K binary problems by classifying one class against the remaining classes, or by formulating the SVM problem as a one-vs-one classification problem. In the latter approach, K(K-1)/2 binary classification problems are addressed by considering all classes pairwise.

Decision tree algorithms are transparent and easy to understand, as the classification process can be visualized as a tree-like path to obtaining the classification answer. The decision tree algorithm can be described as follows: classification is segmented into a series of decisions, with each decision corresponding to a particular feature. Then, the algorithm starts from the root of the tree and proceeds to the leaves to obtain an optimized classification result. Trees are generally straightforward to comprehend and can be converted into a collection of «if-then» rules, which are useful for streamlining the training process of machine learning applications. Typically, decision trees employ heuristic methods for search and optimization. These algorithms assess their potential choices at the current training phase and opt for the solution that seems most advantageous at that juncture [9, 12, 13].

ANN, SVM, and DT classifiers were trained with half of the data and tested with the other half. Structural diagrams of classifiers are presented in Fig. 4.



a b c

Fig. 4. Architecture of recognition algorithms [14]: *a* – ANN; *b* – SVM; *c* – DT

The structure of the architecture depicts the components and stages of the algorithmic process, demonstrating the flow of data and operations. Each block represents a specific task or operation within the recognition process, such as feature extraction, classification, or decision making. The connections between the components illustrate the sequence of operations and the flow of data between the different stages of the algorithm. The architecture diagram serves as a visual guide to understanding the overall design and operation of the recognition algorithms implemented in the study.

3.4. Recognition tests. The parameter values for each of the three classifiers were chosen following a cross-validation procedure tailored to each classifier. Each classifier underwent training and testing on identical datasets, albeit with distinct parameter configurations.

The ANN classifier has two hidden layers, with 116 and 48 neurons used in each layer, respectively. The hyperbolic tangent function (tanh) serves as the activation function for ANN. The training process utilizes an optimization technique known as the Limited-memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) algorithm.

To obtain an accurate SVM classifier, the correct value of the regularization parameter should be selected, which in our case is 80, and the kernel parameter is set to 0.04.

For the decision tree classifier, the Gini impurity index was used, with two samples for splitting at an internal node and two samples for each node.

Initially, each classifier was run for thirty trials. The SVM classifier achieved the highest classification accuracy with a mean training accuracy of 90.21 % and a standard deviation of 2.92 %. Furthermore, the SVM classifier demonstrated a testing accuracy of 88.93 %, with a standard deviation of 2.75 %. The decision tree algorithm exhibited a training accuracy of 72.46 %, with a standard deviation of 4.87 %, and testing accuracy of 69.5 %, with a standard deviation of 3.5 %. Lastly, the ANN classifiers achieved a training accuracy of 83.78 %, with a standard deviation of 5.11 %. The testing accuracy of the ANN approach was 82.91 %, with a standard deviation of 3.3 %. These findings are outlined in Table 1.

Table 1

Training and testing results for three classifiers

Method	Teaching	Testing
SVM	90.21±2.92 %	88.93±2.75 %
ANN	83.78±5.11 %	82.91±3.30 %
DT	72.46±5.87 %	69.51±3.51 %

From the provided test results, it can be concluded that the SVM classifier yields the highest accuracy. The confusion matrices for both the training and testing phases of the SVM classifier are depicted in Table 2 and Table 3, respectively. In these tables, the numerical labels correspond to specific gestures: 1 signifies a fist, 2 indicates an open palm, 3 denotes pointing with a finger, and 4 represents finger gripping. As observed, there is a slight discrepancy in accuracy between the training and testing procedures. Furthermore, the results indicate that misclassification between gestures is relatively low and mainly occurs between open and closed gestures.

Table 2

Confusion matrix for SVM classifier

No.	1	2	3	4
1	91.23 %	5.26 %	0 %	3.51 %
2	3.34 %	95 %	0 %	1.66 %
3	0 %	3.64 %	96.36 %	0 %
4	4.41 %	0 %	2.94 %	92.65 %

Table 3

Error matrix for SVM classifier

No.	1	2	3	4
1	94.64 %	0 %	3.57 %	1.79 %
2	6.35 %	88.89 %	0 %	4.76 %
3	3.75 %	0 %	96.30 %	0 %
4	8.45 %	0 %	0 %	91.55 %

3.5. Control system tests. The testing was conducted by placing the EMG electrode sleeve on the forearm and performing one of four gestures 20 times consecutively, followed by performing two different gestures consecutively for 20 times.

The testing results showed that the maximum level of gesture recognition accuracy is 100 %, while the minimum is 85 %. The sequence of executing the gesture has an average accuracy of 96.25 %, performing different gestures has an average accuracy of 90 %, and the overall average accuracy is 92.5 %, as depicted in Fig. 5.

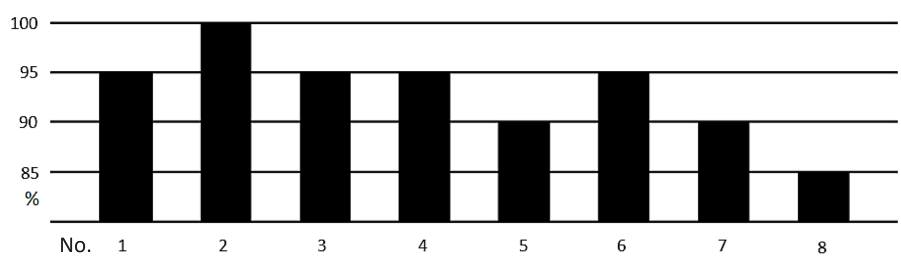


Fig. 5. Graph of gesture recognition efficiency: 1 – fist; 2 – palm; 3 – pointing with a finger; 4 – holding with fingers; 5 – fist, palm; 6 – fist, pointing with a finger; 7 – fist, holding with fingers

3.6. Discussions. The results of this study show that the SVM classifier demonstrates the highest accuracy among the three considered methods. This can be explained by its ability to efficiently process large amounts of data and work with high dimensionality of features. The correct choice of regularization and kernel parameters also contributes to the improvement of the classification accuracy. The ANN classifier, although it shows slightly lower accuracy, remained effective due to the use of two hidden layers and the tanh activation function, which allows it to better adapt to complex patterns. The classifier based on decision trees turns out to be the least accurate, but provided fast training and low computational costs. Compared to literature data, our results show higher accuracy, which can be explained by the optimization of parameters for a specific set of gestures and experimental conditions.

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The obtained results can be widely used in various fields. Gesture recognition systems can be used in medical devices for the rehabilitation of patients with limited hand mobility, in particular in bionic prostheses. In industrial settings, such systems can be used to control robots and automated systems in hazardous or restricted environments while maintaining a high level of agility and speed of response. In addition, these technologies can be implemented in virtual reality systems to increase interactivity and control accuracy, as well as in consumer devices to improve usability.

One of the main limitations is the need for a large amount of data to train classifiers, especially for ANNs. In addition, the accuracy of the classification may decrease when the environmental conditions change or when different electrodes are used to pick up the signals. To implement the obtained results in practice, it is necessary to conduct additional research on the optimization of algorithms for working in different conditions and with different types of gestures. It is also necessary to improve the stability and reliability of the system for long-term use.

The conditions of martial law in Ukraine significantly influenced the conduct of this study. There were difficulties with access to laboratories and equipment due to evacuation and damage. The transition to distance learning also limited access to some resources, which slowed down the learning process for students. In addition, legislative changes and general instability have created additional challenges for conducting scientific research. All these factors could affect the results of the study, in particular, the accuracy and stability of the obtained data.

Future research can be aimed at improving the classification algorithms for working in real conditions, in particular, taking into account changes in the environment and the use of different types of gestures. A promising direction is the integration of gesture recognition systems with other sensors to increase accuracy and reliability. It is also important to develop new signal processing techniques to reduce the reliance on large amounts of training data, and to conduct additional tests to validate the results under different conditions.

4. Conclusions

As a result of this study, a control system for a bionic prosthesis was developed, assembled, and tested. To streamline the overall operation of the bionic hand, EMG data was gathered for a series of four gestures (fist, open palm, pointing, gripping) from a single participant. The collected data were filtered and subjected to feature extraction for classifier training purposes. The findings indicated that the support vector machine classifier surpassed neural networks and decision tree classifiers, attaining an average accuracy of 90 %. The control system was tested in real-time mode, yielding an overall average accuracy level of 92.5 %, confirming its effectiveness and readiness for practical use. The obtained results could be valuable for further advancement of bionic prosthesis control technologies.

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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