Processing and Analysis of EMG Signals from MYO Armband for Upper-Limb Prosthesis Control

Yoto Yotov[1,*], Emil Petrov[1,2], Velislava Lyubenova[1]

[1]*Institute of Robotics "St. Ap. and Gospeller Matthew"*
Bulgarian Academy of Sciences
Acad. G. Bonchev Str., bl. 2, 1113 Sofia Bulgaria
Emails: jottov@abv.bg, epetroff@abv.bg, v_lyubenova@ir.bas.bg

[2]*Institute of Biophysics and Biomedical Engineering*
Bulgarian Academy of Sciences
Acad. G. Bonchev Str., bl. 105, 1113 Sofia Bulgaria

[*]*Corresponding author*

Received: April 16, 2025 **Accepted: November 24, 2025**

Published: December 31, 2025

Abstract: *This paper presents the development of an electromyographic (EMG) signal processing system for controlling upper limb prostheses using data from the MYO Armband, which includes eight EMG sensors. The system processes raw EMG signals through filtering, frequency analysis, and other enhancement techniques to improve signal quality. An interactive MATLAB interface, built on the Myo SDK MATLAB MEX Wrapper, enables real-time visualization and application of various filters. A comprehensive comparison of filtering methods assesses their influence on signal reliability and performance. Quantitative results indicate that the Power Grip gesture produces the highest EMG activation, while the Extended Index Finger shows lower muscle engagement, highlighting distinct activation patterns. Heat map visualizations reveal spatial activation differences across sensors, essential for designing effective gesture classifiers. The developed platform enhances noise robustness and improves accuracy in interpreting motor commands. Despite hardware limitations, the system demonstrates the feasibility of adaptive prosthesis control and suggests integration with hybrid methods, such as voice control, to further enhance functionality and user experience.*

Keywords: *Myoelectric signals, Signal filtering, Surface electromyography, MATLAB interface, MYO Armband.*

Introduction

Surface electromyography (sEMG) has become a key enabling technology for intuitive control of upper-limb prostheses. By capturing the bioelectrical activity of muscles through non-invasive sensors, sEMG allows for the translation of muscle contractions into control commands for assistive and robotic systems [3, 4]. Recent developments in wearable sensor technologies and embedded processing platforms have significantly improved the accessibility of such systems, enabling real-time experimentation and user-oriented designs. Comprehensive reviews on proportional myoelectric control have been presented by Fougner et al. [8] and Patel et al. [14]. The technical documentation of the MYO Armband [21, 22] describes its sensing architecture and embedded filtering.

Despite its advantages, sEMG signal processing still faces several challenges, including susceptibility to motion artifacts, power-line interference, and inter-subject variability [9].

These factors often reduce classification accuracy and limit the robustness of prosthetic control in real-world scenarios.

The MYO Armband, developed by Thalmic Labs, represents a compact and cost-effective platform for acquiring EMG signals through eight evenly distributed dry electrodes. However, its built-in hardware filtering and relatively low sampling rate require the implementation of optimized processing algorithms to achieve reliable gesture recognition and control accuracy.

Despite the progress in sEMG control, a significant gap exists between high-performance research systems and affordable, practical solutions for everyday users. Many studies focus on maximizing classification accuracy using expensive hardware, often overlooking the need for accessible tools for signal analysis and user training. Moreover, a detailed analysis of the spatial information provided by low-channel devices such as the MYO Armband is available in a limited number of publications. Therefore, the primary objective of this study is to develop and validate a real-time MATLAB-based platform for acquiring, processing, and visualizing EMG signals from the MYO Armband. The specific aims are: (1) to incorporate a sequence of digital filters (Table 1) – bandpass, notch, rectification, and Root Mean Square (RMS) smoothing – to enhance signal quality and suppress noise; (2) to quantify the separability of six prosthesis-relevant gestures based on processed RMS values; (3) to analyze and visualize the spatial activation patterns of these gestures across the eight sensors; and (4) to assess the stability and limitations of this approach, with a view to designing future hybrid control systems.

An interactive graphical interface has been developed to monitor multiple EMG channels simultaneously and to calculate characteristic parameters such as RMS and average activation levels. The experimental setup includes six predefined gestures performed by five healthy subjects, providing a quantitative basis for assessing repeatability and signal separability.

The main EMG signal conditioning steps and their specific purposes are summarized in Table 1, which outlines the order of application, main functions, and effects of the implemented filters and processing methods. This structured approach provides a clear understanding of how raw EMG signals are transformed into stable, interpretable features suitable for prosthetic control.

The findings of this work demonstrate the feasibility of using a low-cost, commercially available EMG device for effective discrimination of muscle gestures applicable to upper-limb prosthesis control. Furthermore, the modular structure of the developed system allows its future expansion toward hybrid multimodal control integrating voice or inertial data inputs, thereby improving the functionality and adaptability of prosthetic devices. This design promotes flexibility and facilitates the rapid integration of new control strategies, enabling researchers and developers to adapt the system to various experimental conditions, prosthetic configurations, and individual user requirements, while maintaining real-time performance and signal reliability.

Materials and methods

Experimental setup and hardware specifications

In this study, an experimental setup was implemented to analyze the reliability of sEMG signals recorded by the MYO Armband when performing controlled muscle gestures aimed at controlling an upper limb prosthesis.

Table 1. Filters and EMG signal processing methods [4, 7, 12, 15-17, 19, 20]

No	Filter / method	Purpose and function	Main effect / action	Typical order of application
1	**Bandpass filter (20-90 Hz)**	Isolates useful muscle activity and suppresses noise and artefacts	Removes low and high frequency interference, preserves EMG range	First stage – applied to the raw signal
2	**Rectification**	Converts bipolar EMG to unipolar for quantitative analysis	Makes all signal values positive, preparing for amplitude evaluation	After the bandpass filter
3	**Moving average smoothing**	Reduces high-frequency fluctuations and forms the EMG envelope	Acts as a low-pass filter; stabilizes the signal for control or visualization	After rectification
4	**RMS filter**	Evaluates signal energy and activation strength	Squares, averages, and roots data - more sensitive than movement	After rectification (alternative to movement)
5	**Notch filter (50 Hz)**	Removes power line interference (50 Hz)	Cuts a narrow frequency band around 50 Hz	After the bandpass filter
6	**Zero-phase filter**	Eliminates phase distortion and time delay	Double-pass filtering (forward and backward)	For offline analysis only
7	**Channel averaging**	Reduces local variability and increases stability	Averages signals from all channels; global muscle activation estimate	After the RMS or movement
8	**PWM output (pulse width modulation)**	Translates EMG amplitude into a motor control signal	Analogue control via pulse width modulation	Final stage – after normalized RMS
9	**EMG heatmap visualization**	Displays spatial distribution of muscle activity	Shows RMS/amplitude per channel in 2D grid	After RMS and channel averaging

The device is a wearable, inertial and electromyography control armband. The key hardware specifications relevant to this study are:

Sensors: 8 medical-grade, stainless-steel dry EMG sensors, spaced evenly around the forearm.

Sampling Rate: A fixed sampling rate of approximately 200 Hz for all EMG channels, capturing raw samples directly from the MYO Armband sensors. This rate is sufficient for recording the primary frequency range of muscle activity (20-90 Hz) but limits the analysis of higher-frequency components.

In standard EMG acquisition systems, a wider bandwidth (typically 20-450 Hz) is often used to capture fine-grained spectral features, some of which are relevant for clinical diagnostics or detection of neuromuscular disorders. However, for prosthetic control and gesture recognition applications, most of the useful signal energy lies within the 20-90 Hz range, which the current setup adequately covers. Thus, although the MYO Armband's 200 Hz sampling rate restricts access to high-frequency components, it is sufficient to capture the essential activity patterns required for upper-limb movement control.

Data transmission: Data is transmitted wirelessly via Bluetooth Low Energy (BLE) to the host computer.

Five healthy volunteers (male and female) aged between 30 and 55 years, with no established neuromuscular or orthopaedic disorders, participated in the experiment. Each participant used their dominant hand to perform six predefined muscle gestures: open palm, power grip, extended thumb, thumb and index finger (pistol), fine pinch, and extended index finger Table 2.

Five repetitions were performed for each gesture, with data recorded in real time via the eight sensors of the MYO Armband positioned around the midforearm. The duration of each repetition was approximately 6 seconds, with a short recovery interval in between. The resulting RAW signals from MYO Armband are subjected to sequential processing including Bandpass filtering (20-90 Hz), Notch filtering (50 Hz) to suppress mains interference, conversion to absolute value (rectify) and averaging over a moving window (smoothing). RMS value is then calculated for each individual channel, from which an aggregated average is derived for all channels (avg. ch). The averaged RMS value is used as an indicator of overall muscle activation and serves as the main parameter for quantitative analysis.

The RMS value reported in this study corresponds to a smoothed RMS envelope, calculated using a moving-average window applied over the squared EMG signal. This approach provides a stable yet responsive estimate of muscle activation suitable for real-time analysis and visualization.

During all experiments, the RMS filter checkbox was activated to ensure that the averaged-channel (avg. ch) signal represented the RMS envelope of all eight EMG channels.

Table 2. Gestures used in the study

No	Gesture	Illustration	Description
1	Open palm		Full extension of fingers and relaxed palm
2	Power grip		Fingers flex towards palm with increased muscle strength
3	Thumb extended		Thumb extended, with remaining fingers relaxed
4	Thumb and index finger (pistol)		Thumb and index finger extended, remaining fingers flexed
5	Fine pinch		Thumb and forefinger close, rest relaxed
6	Index finger extended		Only index finger is extended

MATLAB interface [1] was developed for visualization and monitoring of the signal to provide real-time monitoring, calculation of characteristic values, and output of graphical representations of the results. The resulting data create a reliable basis for statistical analysis of the variability and recognizability of muscle gestures.

Data collection and processing

Data collection was performed using an experimental interface developed in MATLAB environment communicating in real time with the MYO Armband, which recorded surface EMG signals from eight dry sensors spaced evenly around the circumference of the forearm. The interface simultaneously displays the signals from all eight channels as well as an avg. ch calculated as the RMS average of all channels. This aggregated value is used as the main parameter to estimate muscle activation at each gesture.

During the experiment, Open Broadcaster Software (OBS) Studio was used simultaneously with MATLAB to record video with the webcam turned on. A synchronized clip was loaded into OBS to visually demonstrate the six gestures changing automatically every 6 seconds, with the participant playing them back in real time. This provides a clear mapping between the videotaped movement and the EMG activation.

Once the recording is complete, the video is reviewed frame by frame to determine the moment of peak muscle activation for each gesture. When a visual maximum is reached in the black line on the graph (avg. ch/RMS), the operator reports the Y-axis value (in %) and the moment in time (X), which are automatically output by MATLAB. The data is recorded in a spreadsheet for subsequent analysis.

The EMG [%] values shown in the plots represent normalized amplitude levels scaled between 0 and 1, derived from the 8-bit digital output range (−128 to +127) of the MYO Armband sensors. These are dimensionless relative values rather than absolute voltages or percentage of Maximum Voluntary Contraction (MVC).

It was established that in some cases, despite viewing frame by frame, the interface did not display the absolute peak of activation. This is likely due to rolling window averaging, refresh rate, or temporal latency, which may result in a partial loss of amplitude resolution. A possible solution would be to implement an automatic maximum value logging function or post-process the signal outside the real-time interface.

Results and data analysis

The data obtained from the experimental setup were summarized by a combination of statistical and visual means, which allowed the assessment of the strength and variability of muscle activation in each of the six gestures studied.

In all experiments, the same real-time filtering configuration was activated: Bandpass (20-90 Hz), Rectify, Smoothing (average window), RMS, and Notch (50 Hz).

The quantitative data presented below represent averaged RMS envelopes (avg. ch) calculated from the eight EMG sensors of the MYO Armband. This unified processing chain ensures that all results are directly comparable and reflect global muscle activation rather than isolated channel fluctuations.

To provide a robust quantitative basis for our analysis, the average RMS value, standard deviation (SD), minimum, and maximum RMS values for the avg. ch were calculated across all five participants and five repetitions for each gesture. The results are summarized in Table 3.

Table 3. Quantitative summary of average RMS values (% EMG) for each gesture

Gesture (No)	Average RMS value	SD	Min value	Max value
1. Open palm	0.089	0.014	0.065	0.112
2. Power grip	0.106	0.015	0.082	0.135
3. Thumb extended	0.075	0.011	0.058	0.094
4. Thumb & index finger	0.082	0.018	0.051	0.110
5. Fine pinch	0.071	0.016	0.045	0.098
6. Index finger extended	0.066	0.012	0.048	0.087

The data confirms that Gesture 2 (Power Grip) elicits the highest average muscle activation (RMS = 0.106, SD = 0.015), which is statistically distinct from the lowest activation gesture, Gesture 6 (Extended Index Finger) (0.066, 0.012). The relatively low standard deviations for these two gestures indicate good repeatability across participants. Conversely, Gesture 4 (Thumb and Index Finger) and Gesture 5 (Fine Pinch) exhibit higher standard deviations (0.018 and 0.016, respectively), suggesting greater inter-subject variability and potentially making them more challenging to classify reliably without user-specific training.

Fig. 1 presents the averaged-channel RMS envelopes expressed as normalized EMG [%] values across five participants. The highest overall muscle activation was recorded for Gesture 2 (Power Grip) (0.106 EMG [%]), corresponding to the strong contraction of the forearm flexors. In contrast, Gesture 6 (Extended index finger) showed the lowest activation level (0.066 EMG [%]), typical of a more subtle and localized movement.

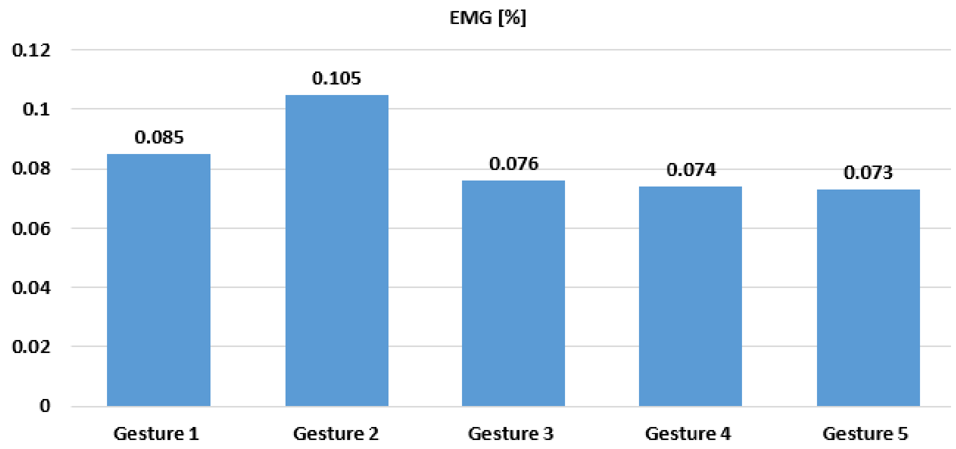

Fig. 1 Averaged-channel RMS envelopes expressed as normalized EMG [%] values for six gestures, averaged across eight sensors and five participants

Fig. 2 shows a boxplot of averaged-channel RMS envelopes expressed as normalized EMG [%] values for all gestures and participants. The results demonstrate clearly distinguishable activation levels between several gestures, with the highest median amplitude and widest dispersion again observed for Power Grip. In contrast, gestures such as Fine Pinch and Thumb and Index Finger exhibited greater inter-subject variability, likely reflecting individual differences in execution technique and muscle tone.

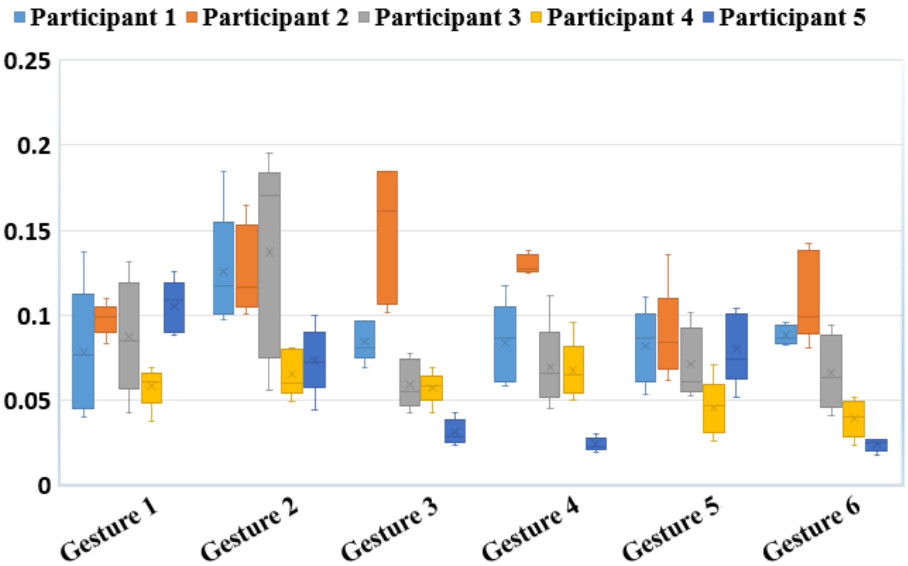

Fig. 2 Boxplot of averaged-channel RMS envelopes for all gestures and participants (5 participants × 6 gestures × 5 repetitions), illustrating inter-subject variability and gesture separability

Fig. 3 presents a heatmap showing the mean RMS-based EMG activation for each of the eight MYO Armband channels, averaged across all repetitions for every gesture. The color scale represents relative activation intensity. The highest overall activation is observed for Gesture 2 (Power Grip), which engages all channels with values around 0.2 EMG [%]. In contrast, Gestures 4 (Pistol) and 6 (Extended Index Finger) exhibit the most localized activity, mainly concentrated in channels 1, 4, 7 and 8.

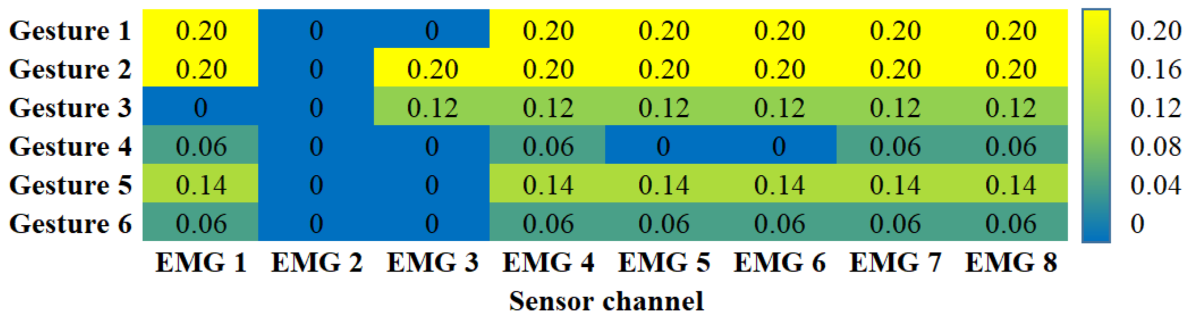

Fig. 3 Heatmap visualization of mean RMS activation per EMG channel and gesture, showing spatial distribution patterns across the eight MYO Armband sensors

Fig. 4 shows an example frame from the real-time MATLAB interface during the execution of Gesture 2 (Force Grip). There is a distinct peak in the averaged plot (avg. ch/RMS), accompanied by increased activity in all EMG channels (EMG 1-8). The measured value from the plot was Y = 0.164738 EMG [%] at time X = -0.315 s (relative to the beginning of the recording). These data were manually entered into the summary table for analysis.

 doi: 10.7546/ijba.2025.29.4.001113

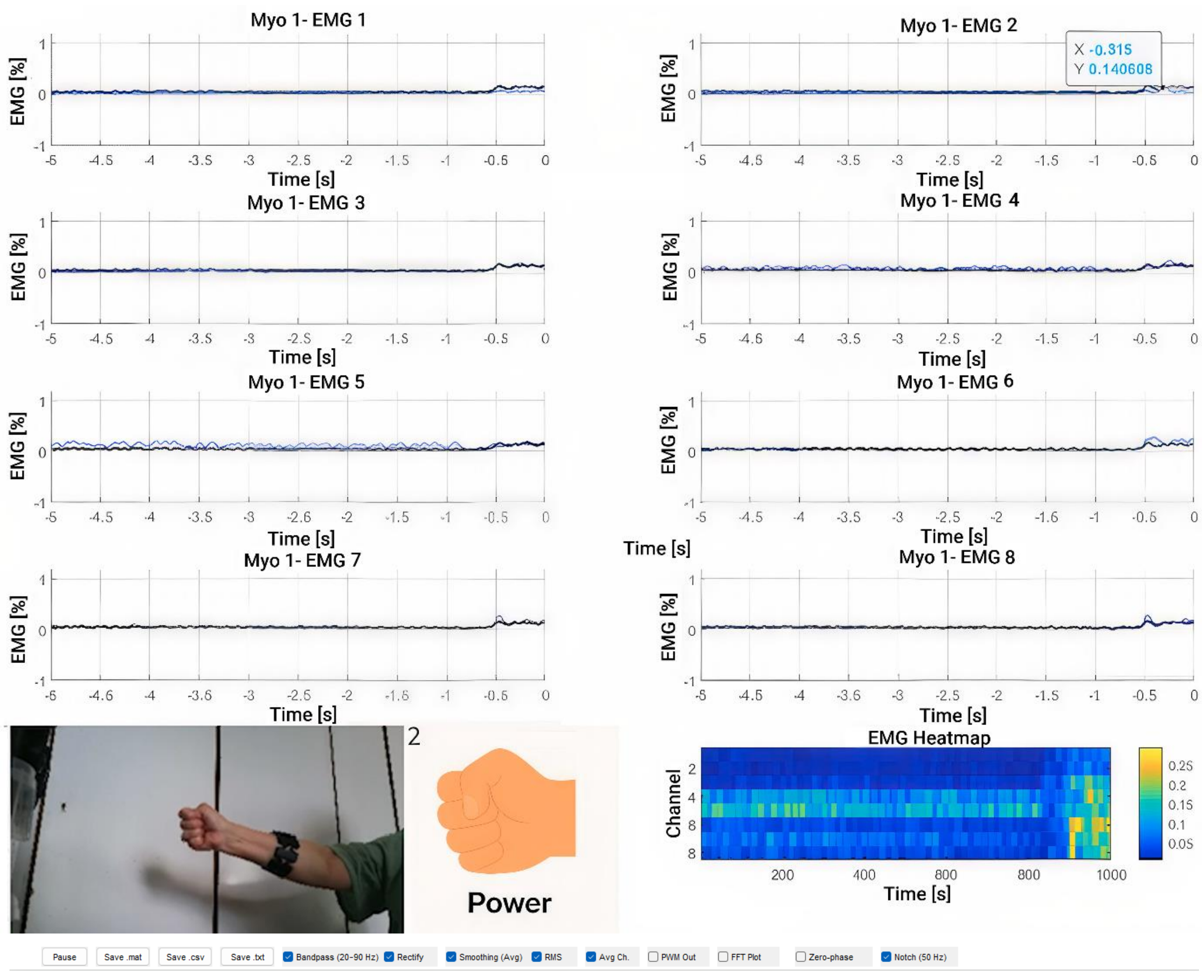

Fig. 4 Real-time MATLAB interface showing raw EMG channels (1-8) and the averaged RMS envelope during execution of the Power Grip gesture

Fig. 5 shows a QR code providing access to a video recording of the experiments with five participants. The video contains the performance of all six gestures synchronized with the graphical visualization from the MATLAB interface and footage of the participants' actual movement.

Fig. 5 QR code linking to the synchronized video recording of all six gestures performed by five participants, aligned with real-time MATLAB EMG visualization

Discussion

The results of this study confirm that six specific muscle gestures applicable to controlling an upper limb prosthesis can be reliably distinguished using sEMG recorded by the low-cost MYO Armband. The quantitative analysis Table 3 provides a solid foundation for this claim, showing significant differences in mean activation between gestures like Power Grip (0.106) and Extended Index Finger (0.066).

The results of our research are consistent with the broader literature on sEMG-based control, while also highlighting the specific context of using accessible hardware. The distinct activation patterns we observed are consistent with foundational biomechanical principles [6]. However, unlike high-performance studies that use high-density sEMG arrays (16+ channels) and report classification accuracies above 90% [2], this work demonstrates that meaningful separability is achievable with just 8 channels. The heatmap visualization (Fig. 3) provides a spatial map of muscle activation often absent in studies focused solely on classification metrics [18]. This spatial insight is crucial for understanding gesture biomechanics and can inform the design of more efficient, channel-specific classifiers, an approach [5]. The observed inter-subject variability, especially for low-amplitude gestures, underscores the need for user-specific calibration [9].

Despite the promising results, several limitations must be acknowledged:

- The MYO Armband's low sampling rate (~200 Hz) and fixed pre-filtering restrict the analysis of higher-frequency EMG components, which are important for advanced feature extraction [11]. Furthermore, the placement of dry electrodes can shift during movement, introducing variability [3].
- Methodological Scope: The study was conducted with healthy participants. sEMG signals from the residual limb of an amputee can be weaker and more spatially displaced, meaning that our results may not directly translate to the target user population [13].
- Our analysis relied primarily on the RMS feature. While robust, more advanced feature sets (time-domain, frequency-domain) have been shown to improve classification accuracy [10]. This will be a subject for future research.
- The manual identification of peak activation values introduces observer bias and is not scalable. An automated peak detection algorithm would be more reliable.

Conclusion and future work

The present study demonstrated that the use of surface sEMG signals recorded by the MYO Armband allows effective discrimination of six basic muscle gestures applicable to upper limb prosthesis control. By analyzing (avg. ch), it was possible to assess the level of muscle activation at each gesture and to identify repeatable patterns of activity between participants.

The obtained results confirm that the system is robust and suitable to build a control interface based on electromyographic signals. The boxplot and heatmap visualizations show distinct differences between gestures as well as localization of activity by sensors, which can serve as a basis for future machine learning and automatic classification.

The averaging of signals across all eight EMG channels (avg. ch) proved particularly useful for identifying global activation thresholds of the forearm muscles. This approach provides a stable reference for distinguishing between active and inactive muscle states, enabling the extraction of robust features suitable for machine-learning algorithms. However, the boxplot analysis revealed notable inter-subject variability, indicating that individual calibration or adaptive retraining will be essential in future implementations. These findings highlight the importance of personalization, as activation profiles may vary significantly between healthy participants and amputee users.

At the same time, it was noted that the stand-alone use of EMG control has limitations related to individual variability, possible errors in bracelet positioning, and sensitivity to external factors. In view of this, it is recommended to extend the system by including an additional voice control channel. Combining muscle signals with voice commands would provide a more reliable, intuitive and adaptive multimodal control suitable for different usage scenarios and different user types.

One of the future applications of the Myo Armband-based system is in the field of rehabilitation diagnostics for objective assessment of muscle activity and motor functions in patients. Analysis of electromyographic signals and movement patterns would provide reliable information on the progress of therapy and the effectiveness of the methods used. This would help personalize rehabilitation programs and optimize the clinical process.

References

1. Amin M. (2016). Myo SDK MATLAB MEX Wrapper, MATLAB Central File Exchange, https://se.mathworks.com/matlabcentral/fileexchange/55817-myo-sdk-matlab-mex-wrapper
2. Atzori M., H. Müller (2015). Control Capabilities of Myoelectric Robotic Prostheses by Hand Amputees: A Review, Frontiers in Neurorobotics, 9, 27.
3. Benatti S., F. Casamassima, B. Milosevic, E. Farella, et al. (2015). A Versatile Embedded Platform for EMG Acquisition and Gesture Recognition, IEEE Transactions on Biomedical Circuits and Systems, 9(5), 620-630.
4. Brigham E. O. (1988). The Fast Fourier Transform and Its Applications, Prentice Hall.
5. Cipriani C., C. Antfolk, M. Controzzi, G. Lundborg, et al. (2011). Online Myoelectric Control of a Dexterous Hand Prosthesis by Transradial Amputees, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 19(3), 260-270.
6. De Luca C. J. (1997). The Use of Surface Electromyography in Biomechanics, Journal of Applied Biomechanics, 13(2), 135-163.
7. De Luca C. J. (2002). Surface Electromyography: Detection and Recording, Delsys Inc.
8. Fougner A., E. J. Scheme, A. D. Chan, K. Englehart, et al. (2012). Control of Upper Limb Prostheses: Terminology and Proportional Myoelectric Control – A Review, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 20(5), 663-677.
9. Hargrove L. J., A. M. Simon, A. J. Young, R. D. Lipschutz, et al. (2013). Robotic Leg Control with EMG Decoding in an Amputee with Nerve Transfers, New England Journal of Medicine, 369(13), 1237-1242.
10. Khushaba R. N., A. Al-Timemy, A. Al-Ani, A. Al-Jumaily (2012). Toward Improved Control of Prosthetic Fingers Using Surface EMG Signals, Expert Systems with Applications, 41(9), 3955-3964.
11. Merletti R., P. A. Parker (2015). Surface Electromyography: Physiology, Engineering, and Applications, Hoboken, NJ: Wiley-IEEE Press.
12. Ogata K. (2010). Modern Control Engineering (5th Ed.), Prentice Hall.
13. Parker P. A., K. Englehart, B. Hudgins (2006). Myoelectric Signal Processing for Control of Powered Limb Prostheses, Journal of Electromyography and Kinesiology, 16(6), 541-548.
14. Patel S., H. Park, P. Bonato, L. Chan, et al. (2012). A Review of Wearable Sensors and Systems with Application in Rehabilitation, Journal of Neuroengineering and Rehabilitation, 9(1), 21.
15. Phinyomark A., P. Phukpattaranont, C. Limsakul (2012). Feature Reduction and Selection for EMG Signal Classification, Expert Systems with Applications, 39(8), 7420-7431.

16. Phinyomark A., C. Limsakul, P. Phukpattaranont (2012). A Novel Feature Extraction for Robust EMG Pattern Recognition, Journal of Computing, 1(1), 71-80.
17. Smith S. W. (1997). The Scientist and Engineer's Guide to Digital Signal Processing, California Technical Publishing.
18. Waichal S. V. (2020). Comparison of Solutions for Efficient Implementation of Sensor-based Hand Prosthesis Control on a Microcontroller Using Regression-based Machine Learning and Neural Networks, M.Sc. Thesis, Technical University of Munich.
19. Widrow B., J. R. Glover, J. M. Mccool, J. Kaunitz, et al. (1975). Adaptive Noise Cancelling: Principles and Applications, Proceedings of IEEE, 63(12), 1692-1716.
20. Mathworks (2023). Filtfilt – Zero-phase Digital Filtering, https://www.mathworks.com/help/signal/ref/filtfilt.html (Access day 24 November 2025).
21. Thalmic Labs, N. D. Thalmic Labs Myo User Manual, https://www.manualslib.com/manual/1267879/thalmic-labs-myo.html (Access day 24 November 2025).
22. Visconti P., F. Gaetani (2018). Technical Features and Functionalities of Myo Armband, https://reference-global.com/article/10.21307/ijssis-2018-005 (Access day 24 November 2025).

Assist. Prof. Yoto Yotov, Ph.D. Student
E-mail: jottov@abv.bg

Yoto Yotov is a Mechanical Engineer and a Ph.D. Student at the Institute of Robotics (IR), Bulgarian Academy of Sciences (BAS). He graduated from the Technical University of Sofia with a B.Sc. Degree in Mechanical and Instrument Engineering (2011) and with a M.Sc. Degree in Computer-aided Design and Mechanical Engineering Technology (2014). His research focuses on mechatronic biotechnological systems and the development of myoelectric upper-limb prostheses with voice control. He has over ten years of professional experience and more than 40 completed engineering projects in CAD/CAM design, CNC technologies, and prototyping of intelligent mechanical and electronic systems.

Assoc. Prof. Emil Petrov, Ph.D.
E-mail: epetroff@abv.bg

Emil Petrov graduated Technical University in 1979. In 1982 he finished the "Manipulators and Robots Control Systems" specialized course. In 2014 he defended his Ph.D. thesis. He works at the IR – BAS and the Institute of Biophysics and Biomedical Engineering – BAS as an Associate Professor. He has scientific specializations in AEG AG, Festo GmBH, CERN, etc. His interests are in the field of applied investigation in mechatronics and instrumentation – programmable controllers, embedded systems, human machine interface, field buses, etc. He has over 100 articles in specialized journals and over 2 000 citations.

Prof. Velislava Lyubenova, D.Sc.
E-mail: v_lyubenova@ir.bas.bg

Velislava Lyubenova is a full Professor at the IR, BAS. In 2016 she defended her D.Sc. Degree in the field of Monitoring of Biotechnological Processes. Currently, she is a Head of the Department "Mechatronic Bio/Technological Systems" at IR, BAS. She has more than 90 published articles in peer reviewed journals with more than 300 citations. She has been a supervisor of 7 international and 5 national projects. Prof. Lyubenova has a few long-term specializations in prestigious scientific institutions in Italy, Portugal and Germany. Her research interests are in modelling, monitoring, and control of bioprocesses.