https://doi.org/10.47734/regrasp.v10.03.p18-31

INSTITUTO FEDERAL
São Paulo
Campus São Paulo
REGRASP

IDENTIFICATION OF ELECTROMYOGRAPHIC SIGNALS USING MACHINE LEARNING TECHNIQUES AND LOW-COST TECHNOLOGIES

IDENTIFICAÇÃO DE SINAIS ELETROMIOGRÁFICOS COM TÉCNICAS DE APRENDIZADO DE MÁQUINA E TECNOLOGIAS DE BAIXO CUSTO

Jhenifer July Sousa De Almeida
Undergraduate Student in Production Engineering
IFSP/Campus São Paulo
jheniferjuly23@gmail.com

Caio Igor Gonçalves Chinelato
Ph.D. in Electrical Engineering /POLI-USP
Professor and Researcher at CECS (Center for Engineering, Modeling and Applied Social Sciences)/UFABC
caio.chinelato@ufabc.edu.br; caio.chinelato@gmail.com

ARTIGO INFO. Recebido: 16.04.2025 Aprovado: 02.07.2025 Disponibilizado: 28.08.2025

ABSTRACT
The human-robot interface (HRI) has recently become a widely studied research topic. This topic addresses the acquisition, processing and interpretation of electrobiological signals from different parts of the human body and the application of these signals for the control of robotic systems. The HRI is essential for applications involving people with disabilities, professionals working in hazardous environments, and even robotic surgery. The focus of this work is the identification of electromyographic (EMG) signals. EMG sensors were placed on specific regions of a person's arm, and gesture recognition was performed. Initially, the EMG sensors and microcontroller were determined using low-cost technologies. Posteriorly, machine learning techniques were applied for gesture recognition. The main contributions of the work were the use of an EMG sensor commercially available in Brazil and in several countries, easily accessible and little explored in the literature, besides the use of feature extraction and machine learning techniques applications from the Matlab software, which are practical and efficient tools, and also little explored in the literature. The resulting machine learning model was quite accurate and can be applied in the future for the control of robotic systems.
Keywords: Electromyographic Signals; Gesture Recognition; Machine Learning; Human-Robot Interface.

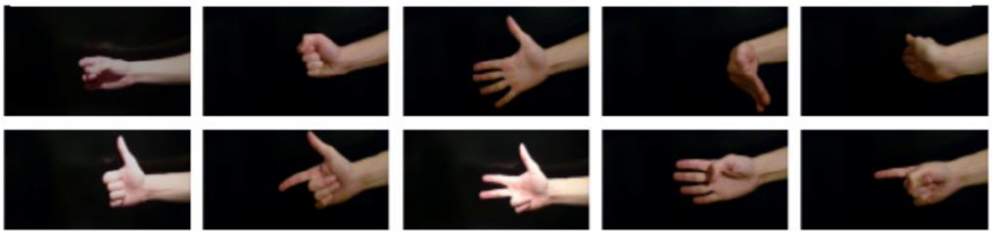
RESUMO
A interface humano-robô (IHR) é um tópico de pesquisa muito estudado recentemente. Este tópico se trata da aquisição, processamento e interpretação de sinais eletrobiológicos provenientes de diferentes partes do corpo humano e aplicação desses sinais para o controle de sistemas robóticos. A IHR torna-se necessária em aplicações para pessoas com deficiências, profissionais que trabalham em ambientes perigosos ou até mesmo na cirurgia robótica. O enfoque deste trabalho é a identificação de sinais eletromiográficos (EMGs). Sensores EMGs foram colocados em regiões específicas do braço de uma pessoa e a identificação gestual foi realizada. Inicialmente, foram determinados os sensores EMGs e o microcontrolador utilizando tecnologias de baixo custo. Posteriormente, foram aplicadas técnicas de aprendizado de máquina para identificação gestual. As principais contribuições do trabalho foram a utilização de um sensor EMG disponível comercialmente no Brasil e em diversos países, de fácil acessibilidade e pouco explorado na literatura, além da utilização dos aplicativos de extração de características (*features*) e técnicas de aprendizado de máquina do *software Matlab*, que são ferramentas práticas, eficientes, e também pouco exploradas na literatura. O modelo de aprendizado de máquina obtido foi bastante preciso e pode ser aplicado futuramente para o controle de sistemas robóticos.
Palavras-chave: Sinais Eletromiográficos; Reconhecimento Gestual; Aprendizado de Máquina; Interface Humano-Robô.

Introduction

The human–robot interface (HRI) address the acquisition, processing, and interpretation of electrobiological signals from different parts of the human body and the use of these signals to control several robotic systems. This interface can be achieved through gesture, visual, or even speech commands. Several scientific works have recently been published in this field. Among the main applications, we can highlight assistance to people with disabilities through prostheses and exoskeletons, professionals working in hazardous environments, rescue missions, and robotic surgery. Several electrobiological signals can be employed. Some of the most common are electromyographic (EMG) signals, obtained from muscle activity; electrooculographic (EOG) signals, obtained from eyes; and electroencephalographic (EEG) signals, obtained from brain activity (Ferreira et al., 2008). The focus of this work is on EMG signals.

EMG signals are electrobiological signals produced by the electrical activity of a muscle during its contraction and can be detected by electrodes or EMG sensors placed on the skin of a person (Morais et al., 2016). These signals usually require a process of amplification and filtering before being analyzed. Although muscle activation information can be extracted from analytical EMG models, these models are highly complex. Therefore, machine learning and artificial intelligence techniques, or statistical analysis methods, are usually applied to analyze, decode, and identify these signals. Then, hand gestures, as shown in Figure 1, can be more easily identified (Godoy et al., 2022b). Several works address the processing and identification of these hand gestures, as shown in Marcheix et al. (2019), Chen et al. (2021), Fu et al. (2018), Barsotti et al. (2019), and Godoy et al. (2022b).

Figure 1. Set of typical hand gestures for EMG applications.



Source: Marcheix et al., (2019).

Several recent works in the literature address the control of robotic systems through EMG signals. Basically, hand gestures, as shown in Figure 1, are acquired through EMG sensors, processed and identified by computational algorithms, and robotic systems are controlled based on these signals. Some works address the control of robotic hands, as shown in Meattini et al. (2018) and Montoya et al. (2022), and also robotic manipulators, as shown in Liao et al. (2018) and Godoy et al. (2022a). These applications can be used both to assist people with disabilities and in robotic teleoperation for industrial, commercial, or medical tasks. Other studies deal with wheelchair control using EMG signals, as shown in Maeda and Ishibashi (2017) and Abayasiri et al. (2021). Some studies also explore the control of mobile robots using EMG signals. The works Bisi et al. (2018) and Luo et al. (2020) demonstrate the control of wheeled mobile robots with EMG signals, while Ali et al. (2020) and Jun et al. (2021) show the control of quadcopters or drones through EMG signals.

Given the relevance and numerous application possibilities, the focus of this work is the identification of EMG signals. EMG sensors were placed on specific regions of a person's arm, and gesture recognition was performed. Initially, the EMG sensors and microcontroller were determined using low-cost technologies. Posteriorly, machine learning techniques were applied for gesture recognition. It is important to highlight that low-cost sensors present additional difficulties, such as lower EMG signal quality and greater susceptibility to noise; therefore, the application of machine learning techniques is essential for identifying EMG signals from low-cost sensors.

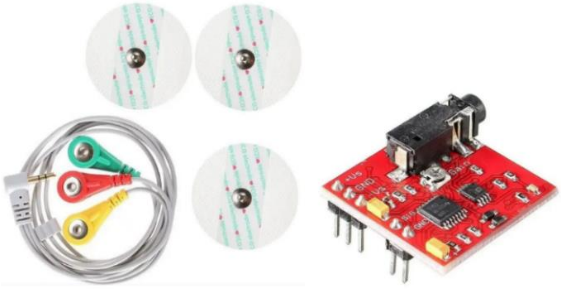
One of the contributions of this work was the use of an EMG sensor commercially available in Brazil and several other countries, easily accessible and little explored in the literature. Many works apply more expensive and less accessible technologies, especially in Brazil, such as Myo armband, which is no longer commercially available (Marcheix et al., 2019; Jun et al., 2021), and Myoware 2.0 from Sparkfun Electronics (Myoware, 2025). Other works develop their own EMG sensor (Yánez et al., 2020), which was not considered a viable or convenient suggestion for the proposal of this work. Furthermore, the entire process of EMG data sensors acquisition and processing, feature extraction, and application of machine learning techniques were performed in the Matlab software. In many studies reported in the literature, Matlab is primarily used for EMG data sensors acquisition and processing, while feature extraction and application of machine learning techniques are typically performed using Python. However, in this work, we apply the Matlab's feature extraction and machine learning techniques applications, which are practical and efficient tools, and also little explored in the literature. The resulting machine learning model was quite accurate and can be applied in the future for the control of robotic systems. Here it is also important to highlight that another advantage of using Matlab is the availability of specific tools for working with several robotic systems and simulators, which facilitates future applications of the obtained machine learning model.

The following sections present the activities realized for the development of the work, the results, and the conclusions. It is important to emphasize that the focus of the work is gesture recognition using EMG sensors and machine learning, however, some experimental and computational options for low-cost robotic systems that can be controlled by the identified EMG signals will also be discussed, which could generate promising future work.

Electronic Components – EMG Sensors and Microcontroller

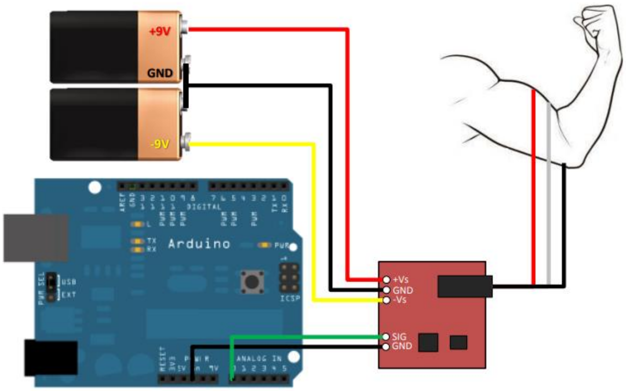
The first activity in the methodology of this work was the determination of the electronic components required to acquire and process the EMG signals. After studying several commercially available options, the EMG sensor shown in Figure 2 was obtained (Eletrogate, 2025). An Arduino Uno was used for the acquisition and processing of the EMG signals. The schematic diagram of the connection between the Arduino Uno and the EMG sensor is presented in Figure 3. The sensor is powered by a ±9 V symmetrical power supply and uses three electrodes to transmit the analog EMG signal. Two electrodes are positioned on the target muscle, and one electrode is positioned on a stationary region of the body and serves as a reference. The EMG signal is connected to the Arduino Uno's analog input. It is important to highlight that the sensor already includes a signal conditioning circuit that amplifies, rectifies, and filters the raw EMG signal. Technical details of this sensor are provided in Pololu (2025).

Figure 2. EMG sensor.



Source: Eletrogate, (2025).

Figure 3. Schematic diagram of the connection between the EMG sensor and the Arduino Uno. In the experimental tests, a power supply was used instead of batteries, which discharge over time and can cause inaccuracies in the measurements.



Source: Pololu, (2025).

It is important to highlight that three EMG sensors were applied to achieve more accurate gesture recognition of the person's arm. Each sensor was placed in different regions of the arm. The setup shown in Figure 3 was implemented, and the first tests were performed to understand the sensor's operation and to gain familiarity with practical and constructive details. Posteriorly, a computational algorithm was developed in the Arduino Uno IDE with C++ language, which employs the serial communication via the USB port to perform sampling and data acquisition from the EMG sensors through the Arduino Uno's analog inputs at a sampling rate of 20 ms.

The data are displayed on the Arduino Uno IDE's serial monitor in the format (time, sensor EMG1 magnitude, sensor EMG2 magnitude, sensor EMG3 magnitude). The time in milliseconds is obtained by the millis() function, and the EMG sensor magnitudes are obtained by the analogRead() function, which reads the Arduino Uno's analog inputs. Here it is important to note that the Arduino Uno has a 10-bit, 6-channel analog-to-digital converter that maps voltages between 0 and 5 V; Therefore, the EMG sensor magnitudes displayed in the serial monitor are given as integer values ranging from 0 to 1023.

To perform the identification of the person's hand gestures (as shown in Figure 1), computational algorithms were developed, and machine learning tools and applications available in Matlab were applied.

Training Phase

Initially, the training phase was performed. Six different hand gestures (HG1, HG2, HG3, HG4, HG5, HG6) obtained from a single person were considered. The hand gestures are shown in Figure 4. The computational algorithm was developed so that the person presses a computer key and starts the sampling process of the EMG sensor data. This was done to avoid tiredness and fatigue during the sampling process. For each hand gesture, 30 samples or repetitions of the EMG sensor data were collected, divided into training intervals of 5 s, with a sampling rate of 20 ms. Figure 5 shows the EMG sensor electrodes placed on the person’s arm.

Figure 4. Hand gestures considered in the training phase.

(a) Hand Gesture 1 (HG1). (b) Hand Gesture 2 (HG2). (c) Hand Gesture 3 (HG3).

(d) Hand Gesture 4 (HG4). (e) Hand Gesture 5 (HG5). (f) Hand Gesture 6 (HG6).

Source: Authors.

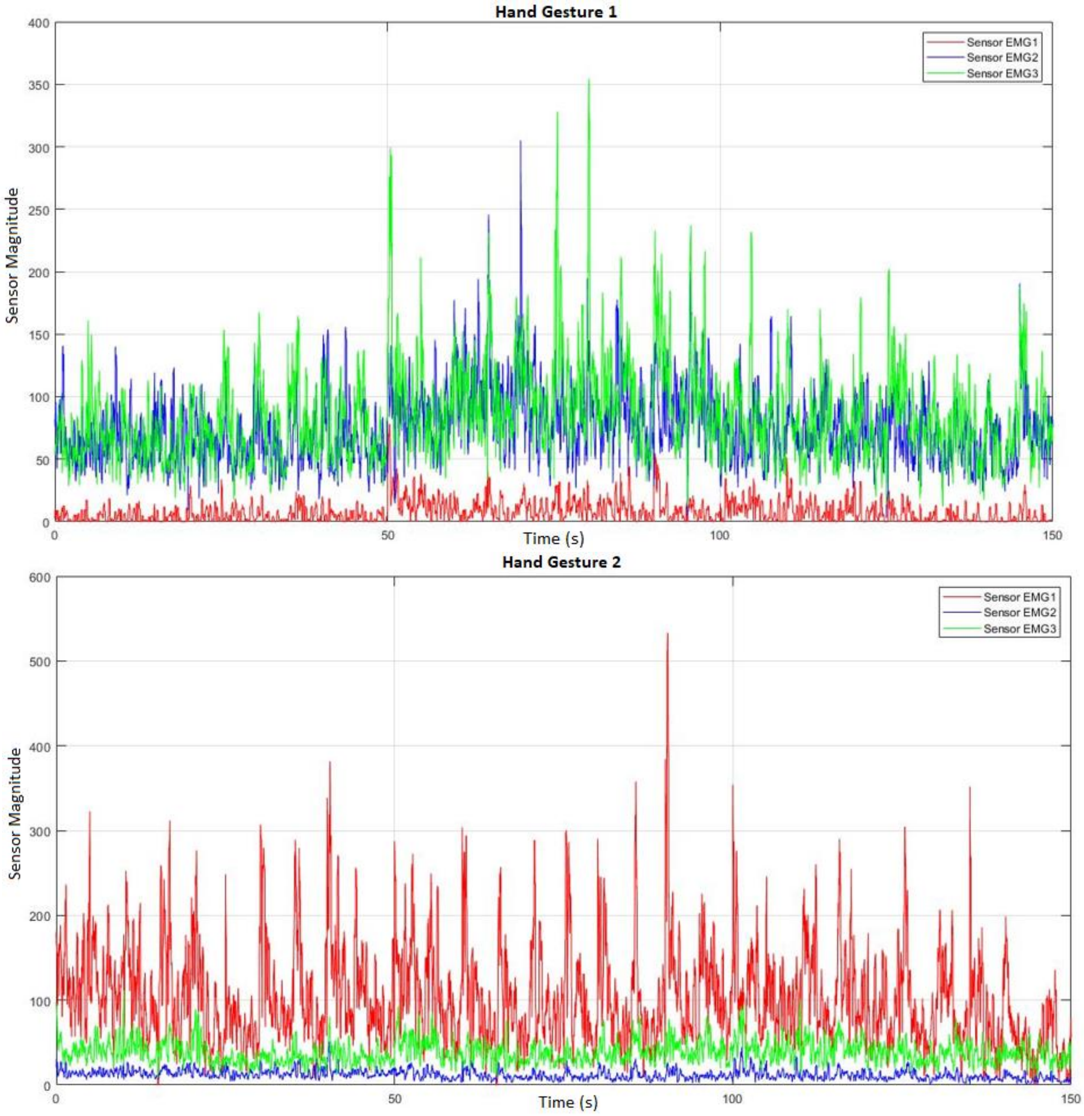
Figure 5. EMG sensor electrodes placed on the person's arm.

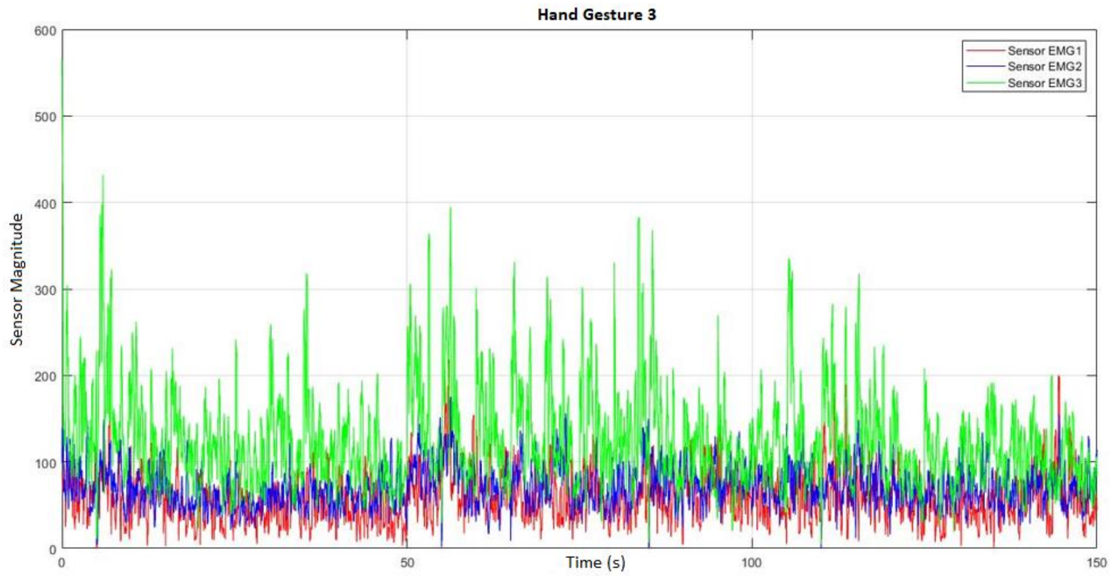
Source: Authors.

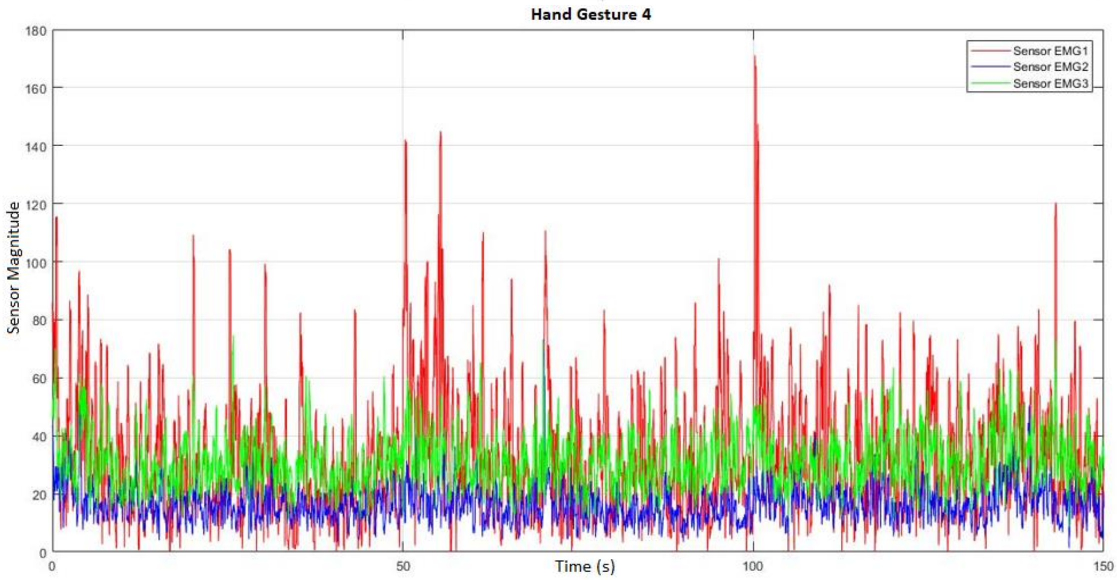
To obtain the training phase data, a computational algorithm was developed in Matlab that runs parallel to the Arduino Uno algorithm and stores the EMG sensor data at a sampling rate of 20 ms, obtained via serial communication with the Arduino Uno, in a database within Matlab for later processing and analysis. The objective of this computational algorithm is to store the data from the three EMG sensors for each hand gesture.

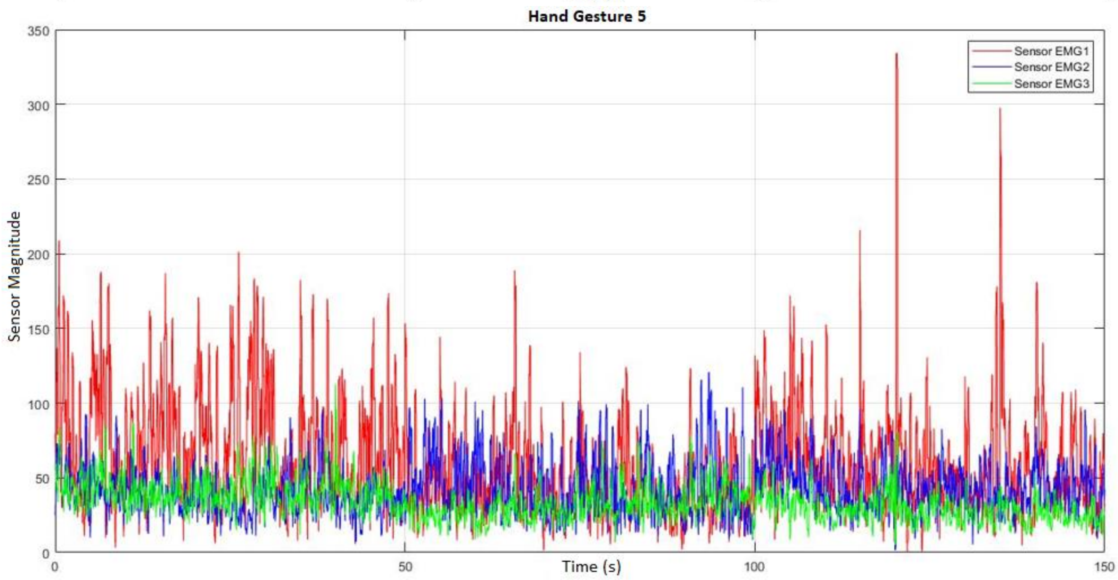
Figure 6 presents the magnitudes of the three EMG sensors for each hand gesture during the training phase. It is important to highlight that the envelopes of the sensor magnitudes were obtained in order to smooth the waveforms, since the signals present significant variations and susceptibility to noise. As 30 samples or repetitions were collected with training intervals of 5 s, the time ranges from 0 to 150 s. The sampling rate of the EMG sensors is 20 ms, as previously mentioned.

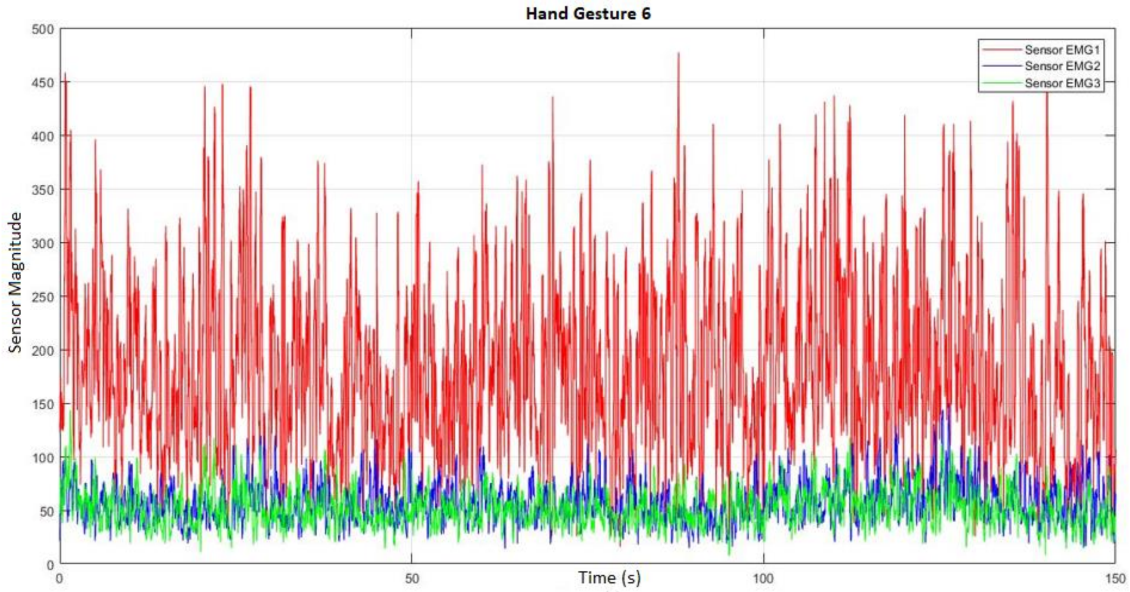
Figure 6. Magnitudes of the three EMG sensors for each hand gesture during the training phase.




Hand Gesture 3
Sensor EMG1
Sensor EMG2
Sensor EMG3
Sensor Magnitude
Time (s)
600
500
400
300
200
100
0
0
50
100
150


Hand Gesture 4
Sensor EMG1
Sensor EMG2
Sensor EMG3
Sensor Magnitude
Time (s)
180
160
140
120
100
80
60
40
20
0
0
50
100
150

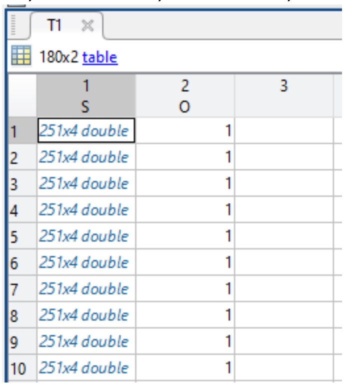

Hand Gesture 5
Sensor EMG1
Sensor EMG2
Sensor EMG3
Sensor Magnitude
Time (s)
350
300
250
200
150
100
50
0
0
50
100
150



Source: Authors.

Subsequently, the magnitudes from the three EMG sensors for the 30 samples of each hand gesture, with a training interval of 5 s, were stored in a table variable in Matlab, as shown in Figure 7. This table has 180 rows and 2 columns. Since 30 samples were collected for each of the six hand gestures during the training phase, we have 180 rows. Each row in the column S is represented by a matrix with 251 rows and 4 columns. The 4 columns represent the time in milliseconds and the magnitudes of the three EMG sensors for each sample of the hand gestures, and the 251 rows represent the sampled data, given the sampling rate of 20 ms and training interval of 5 s. The column O represents the outputs, i.e., for each hand gesture, we have a corresponding integer value.

Figure 7. Matlab table with the EMG sensor magnitudes during the training phase (HG1: O = 1, HG2: O = 2, HG3: O = 3, HG4: O = 4, HG5: O = 5, HG6: O = 6).


T1
180x2 table

	1 S	2 O	3
1	251x4 double	1	
2	251x4 double	1	
3	251x4 double	1	
4	251x4 double	1	
5	251x4 double	1	
6	251x4 double	1	
7	251x4 double	1	
8	251x4 double	1	
9	251x4 double	1	
10	251x4 double	1	

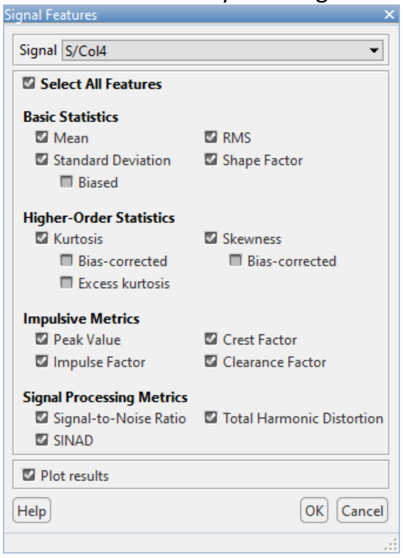
Source: Authors.

Feature Extraction for the EMG Signals

Then, we conclude the training phase and start the feature extraction phase for the EMG signals, or the magnitudes of the three EMG sensors. These features are a set of parameters related to the EMG signals (mainly in the time and frequency domains) and will later be used by machine learning techniques to classify the hand gestures. There are several types of features, as can be seen in Yánez et al. (2020). These features can be extracted using specific computational algorithms; however, Matlab provides the Diagnostic Feature Designer application, which automatically extracts a series of features. The procedure for extract these features is shown below.

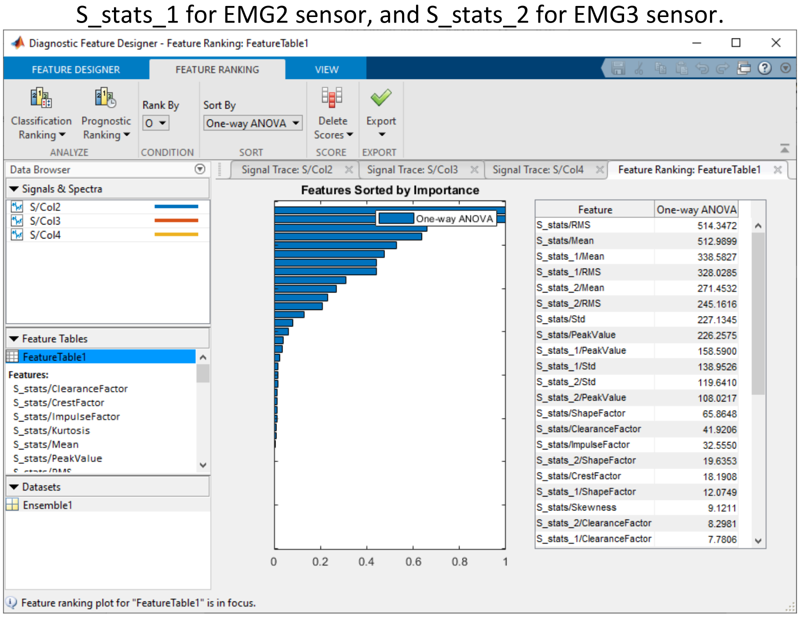
Initially, the magnitudes of the three EMG sensors, with the 30 samples of the six hand gestures obtained during the training phase, are imported to the Diagnostic Feature Designer application. Posteriorly, the features are extracted using the Time-Domain Features command. Figure 8 shows the set of time-domain features extracted by the application. Finally, Figure 9 shows the feature values for each EMG sensor. The one-way ANOVA value is a variance analysis parameter for each feature. The higher this value, the lower the variability of a feature during the training phase. Therefore, during the application of machine learning techniques, which will be showed later, it is important to use the features with the highest values of this parameter.

Figure 8. Set of time-domain features extracted by the Diagnostic Feature Designer application.



Source: Authors.

Figure 9. Features extracted for each EMG sensor. S_stats are the features obtained for EMG1 sensor, S_stats_1 for EMG2 sensor, and S_stats_2 for EMG3 sensor.



Source: Authors.

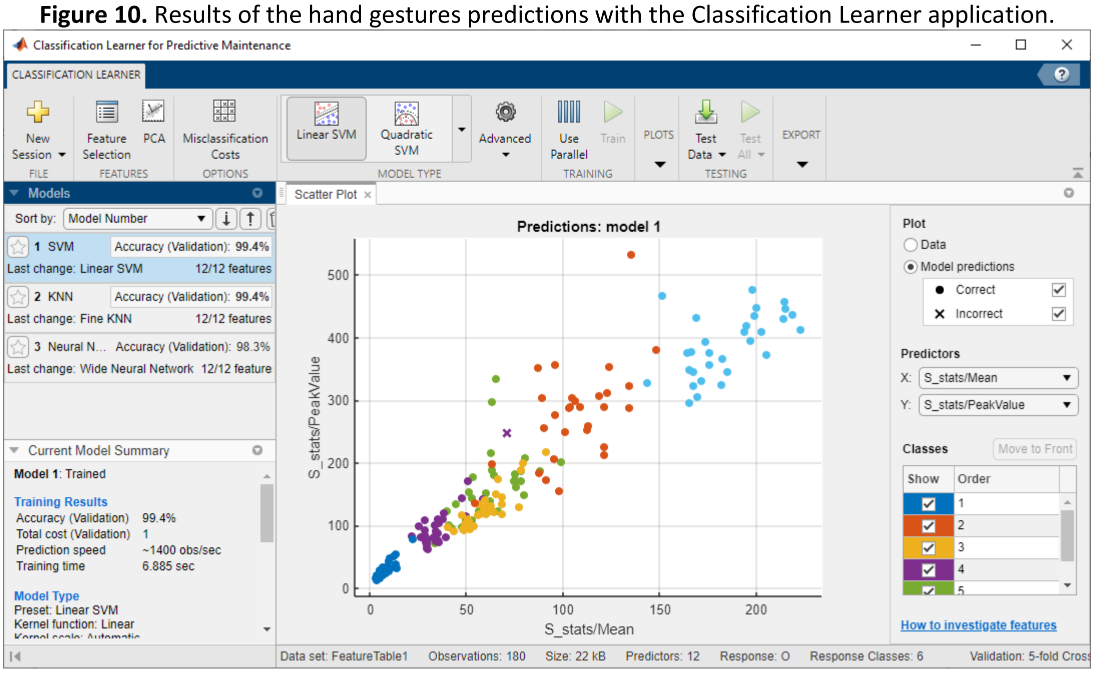
Observing Figure 9, it can be seen that the best features for each EMG sensor in terms of the one-way ANOVA value are RMS, Mean, Standard Deviation (Std), and Peak Value. Then, these features will be exported to Matlab in a table format. Therefore, for each of the 30 samples of each hand gesture, we have four features (RMS, Mean, Standard Deviation, and Peak

Value). The work of Yánez et al. (2020) presents a systematic literature review with several studies and demonstrates that, among the features selected in this work, RMS and Mean are more commonly used than Standard Deviation and Peak Value for EMG signal identification. However, the use of Standard Deviation and Peak Value is justifiable since their one-way ANOVA values are high. It is also import to note that some studies deal with fewer than four features.

Results and Discussions - Application of Machine Learning Techniques

Finally, we can apply the machine learning techniques with the selected features aiming to classify the hand gestures obtained in the training phase. For this purpose, we use Matlab's Classification Learner application. Initially, we must determine the dataset that will be used by the application. We use the table described in the previous section, which presents all the selected features. The Classification Learner application implements several machine learning techniques, such as decision tree, support vector machine, neural networks, among others.
Figure 10 presents some results of hand gesture prediction using the machine learning techniques Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Neural Network (NN). The prediction accuracy was high in all cases. Figure 11 presents the confusion matrices for the three machine learning techniques, considering the 30 samples of the six hand gestures. It can be observed that the results demonstrate good accuracy, as the predicted outputs of the hand gestures are very close to the true values. According to the systematic literature review by Yánez et al. (2020), the most commonly applied machine learning techniques for EMG signal identification are SVM and NN. The most accurate results were obtained with SVM, while the least accurate were obtained with NN and KNN. The results with NN and KNN could be improved by adjusting the models and parameters of these machine learning techniques available in Matlab's Classification Learner application.

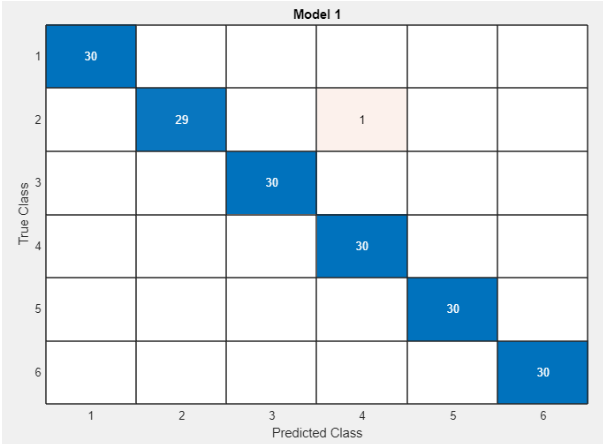
Figure 10. Results of the hand gestures predictions with the Classification Learner application.



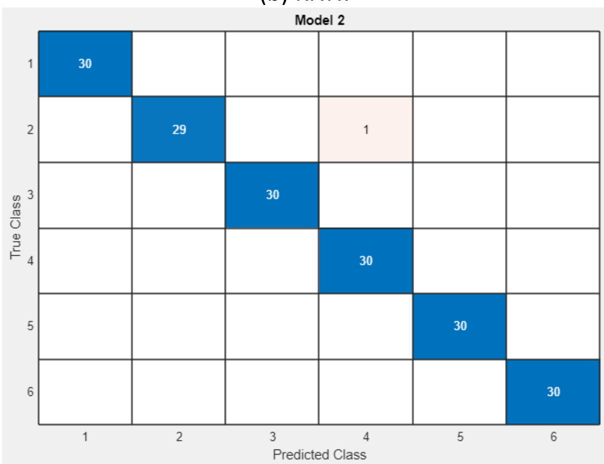
Source: Authors.

Figure 11. Confusion matrices for the three machine learning techniques.

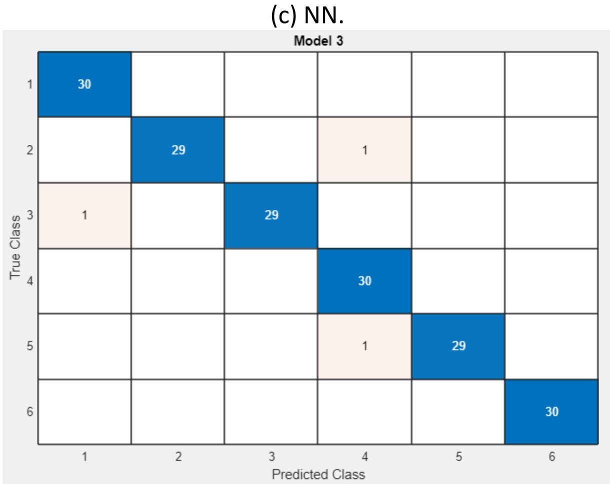
(a) SVM.



(b) KNN.



(c) NN.



Source: Authors.

After applying a specific machine learning technique, the Classification Learner application generates a trained model that is exported to the Matlab workspace and can be used to perform real-time predictions of the hand gestures readings from the EMG sensors. This model can be applied in the future for the control of robotic systems.

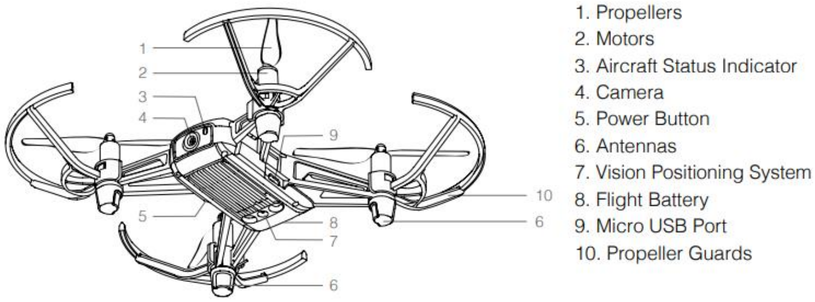
Here it is very important to highlight that, due to practical limitations, the hand gestures were obtained from a single person. For greater robustness and generalization of the trained model, it would be important to collect EMG signals from multiple individuals. However, the focus of this work was on the development of the hardware and software required for EMG signal identification. Since good results were obtained with the machine learning model generated

for a single person, good results can certainly be achieved when data from multiple individuals are used in the training phase.
It is also important to emphasize that the focus of this work is gesture recognition using EMG sensors and machine learning; however, we can mention some experimental and computational options of low-cost robotic systems that can be controlled by the identified EMG signals and can generate promising future work. We can apply, for example, the Tello quadcopter, marketed by Ryze Technology (Tello, 2025). This is a small quadcopter developed for educational and research purposes, featuring a vision-based positioning system with an integrated camera and infrared sensor, allowing precise navigation in various environments. Furthermore, it also captures photographs, transmits real-time videos, and has its own application with pre-programmed functions. The quadcopter and its basic components are shown in the figures below.

Figure 12. Tello quadcopter.

Source: Tello, (2025).

Figure 13. Basic components of the quadcopter.



Source: Tello, (2025).

It is an accessible and low-cost robotic system, which can be easily controlled by the identified EMG signals, since it can be programmed with libraries available in Matlab or Python.
Some results can also be obtained with several robotic systems, such as robotic manipulators and mobile robots, using simulators like CoppeliaSim, for example (Coppeliasim, 2025).

Conclusion

This work proposes the identification of EMG signals using machine learning techniques and low-cost technologies. EMG sensors were placed on specific regions of a person's arm, and gesture recognition was performed.
The electronic components demonstrated accurate results and good processing capability. The signal conditioning circuits of the EMG sensors are quite effective in data acquisition, and the Arduino Uno board showed good processing capacity and ease of programming and communication. The use of three sensors, although making the process more expensive and invasive, certainly improves the accuracy of the results. It is important to highlight that low-cost sensors, despite having signal conditioning circuits, present additional difficulties such as

lower EMG signal quality and greater susceptibility to noise; therefore, the application of machine learning techniques is essential for identifying EMG signals from low-cost sensors. Furthermore, the selected EMG sensor is commercially available in Brazil and several other countries, is easily accessible, and little explored in the literature.

The communication between the Arduino Uno and Matlab for the training phase was performed successfully, and the data were stored in Matlab. Matlab's Diagnostic Feature Designer application proved to be a very useful and practical resource for extracting and obtaining features from the EMG sensor signals. Finally, Matlab's Classification Learner application generated a quite accurate machine learning model that can be easily adapted for robotic systems applications. These Matlab applications are practical, efficient tools, and also little explored in the literature. Here it is also important to highlight that another advantage of using Matlab is its specific tools for working with several robotic systems and robotic simulators, facilitating future applications of the obtained machine learning model.

The first suggestion for future work is to collect hand gestures from multiple individuals so that the generated machine learning model becomes more robust and generalized. Furthermore, new training data, new features, and new machine learning techniques can be applied for comparison with the results already obtained. We also suggest applying the machine learning model to experimental robotic systems, such as the Tello quadcopter, as well as simulated robotic systems using softwares such as CoppeliaSim.

References

Abayasiri, R. A. M., Jayasekara, A. G. B. P., Gopura, R. A. R. C., & Kiguchi, K (2021). EMG based controller for a wheelchair with robotic manipulator. *Proceedings of the 3rd International Conference on Electrical Engineering (EECon)*, Colombo, Sri Lanka, 125-130. https://doi.org/10.1109/EECon52960.2021.9580949

Ali, M., Riaz, A., Usmani, W. U., & Naseer, N. EMG based control of a quadcopter (2020). *Proceedings of the International Conference on Mechanical, Electronics, Computer, and Industrial Technology (MECnIT)*, Medan, Indonesia, 250-253. https://doi.org/10.1109/MECnIT48290.2020.9166603

Barsotti, M., Dupan, S., Vujaklija, I., Dosen, S., Frisoli, A., & Farina, D (2019). Online finger control using high-density EMG and minimal training data for robotic applications. *IEEE Robotics and Automation Letters*, *4*(2), 217-223. https://doi.org/10.1109/LRA.2018.2885753

Bisi, S., De Luca, L., Shrestha, B., Yang, Z., & Ghandi, V (2018). Development of an EMG-controlled mobile robot. *Robotics*, *7*(3), 1-13. https://doi.org/10.3390/robotics7030036

Chen, X., Li, Y., Hu, R., Zhang, X., & Chen, X (2021). Hand gesture recognition based on surface electromyography using convolution neural network with transfer learning method. *IEEE Journal of Biomedical and Health Informatics*, *25*(4), 1292-1304. https://doi.org/10.1109/JBHI.2020.3009383

Coppeliasim (2025, August 28). *CoppeliaSim Simulator*. https://www.coppeliarobotics.com

Eletrogate (2025, August 28). *EMG sensor*. https://www.eletrogate.com/modulo-sensor-eletromiografico-de-sinal-muscular-emg

Ferreira, A., Celeste, W. C., Cheein, F. A., Bastos-Filho, T. F., Sarcinelli-Filho, M., & Carelli, R (2008). Human-Machine interfaces based on EMG and EEG applied to robotic systems. *Journal of Neuroengineering and Rehabilitation*, *5*(10), 1-15. https://doi.org/10.1186/1743-0003-5-10

Fu, M., Xue, J., Huang, P., Chen, Z., Wei, W., Li, G., & Chen, S (2018). Research on recognition of forearm sEMG signal based on different motion modes. *Proceedings of the IEEE International Conference on Cyborg and Bionic Systems (CBS)*, Shenzhen, China, 581-584. https://doi.org/10.1109/CBS.2018.8612195

Godoy, R. V., Dwivedi, A., Guan, B., Turner, A., Shieff, D., & Liarokapis, M (2022). On EMG based dexterous robotic telemanipulation: assessing machine learning techniques, feature extraction methods, and shared control schemes. *IEEE Access*, *10*, 99661-99674. https://doi.org/10.1109/ACCESS.2022.3206436

Godoy, R. V., Lahr, G. J. G., Dwivedi, A., Reis, T. J. S., Polegato, P. H., Becker, M., Caurin, G. A. P., & Liarokapis, M (2022). Electromyography-Based, robust hand motion classification employing temporal multi-channel vision transformers. *IEEE Robotics and Automation Letters*, *7*(4), 10200-10207. https://doi.org/10.1109/LRA.2022.3192623

Jun, J., Zhao, B., Zhang, P., Guo, W., & Fang, P (2021). UAV formation flight control by using the surface electromyography signals. *Proceedings of the 33rd Chinese Control and Decision Conference (CCDC)*, Kunming, China, 3287-3291. https://doi.org/10.1109/CCDC52312.2021.9602378

Liao, L. Z., Tseng, Y. L., Chiang, H. H., & Wang, W. Y (2018). EMG-Based control scheme with SVM classifier for assistive robot arm. *Proceedings of the International Automatic Control Conference (CACS)*, Taoyuan, Taiwan. https://doi.org/10.1109/CACS.2018.8606762

Luo, J., Lin, Z., Li, Y., & Yang, C (2020). A teleoperation framework for mobile robots based on shared control. *IEEE Robotics and Automation Letters*, *5*(2), 377-384. https://doi.org/10.1109/LRA.2019.2959442

Maeda, Y., & Ishibashi, S (2017). Operating instruction method based on EMG for omnidirectional wheelchair robot. *Proceedings of the 17th World Congress of International Fuzzy Systems Association and International Conference on Soft Computing and Intelligent Systems (IFSA - SCIS)*, Otsu, Japan. https://doi.org/10.1109/IFSA-SCIS.2017.8023339

Marcheix, B., Gardiner, B., & Coleman, S (2019). Adaptive gesture recognition system for robotic control using surface EMG sensors. *Proceedings of the IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, Ajman, United Arab Emirates. https://doi.org/10.1109/ISSPIT47144.2019.9001765

Meattini, R., Benatti, S., Scarcia, U., De Gregorio, D., Benini, L., & Melchiori, C (2018). An SEMG-based human-robot interface for robotic hands using machine learning and synergies. *IEEE Transactions on Components, Packaging and Manufacturing Technology*, *8*(7), 1149-1158. https://doi.org/10.1109/TCPMT.2018.2799987

Montoya, B. N., Añazco, M. V., Avila, A. S., Loayza, F. R., Añazco, E. V., & Teran, E (2022). Supervised machine learning applied to non-invasive EMG signal classification for an anthropomorphic robotic hand. *Proceedings of the IEEE Andean Conference (ANDESCON)*, Barranquilla, Colombia. https://doi.org/10.1109/ANDESCON56260.2022.9989874

Morais, G. D., Neves, L. C., Masiero, A. A., & Castro, M. C. F (2016). Application of Myo Armband system to control a robot interface. *Proceedings of the 9th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC)*, Rome, Italy, 227-231. https://doi.org/10.5220/0005706302270231

Myoware (2025, August 28). *Myoware 2.0*. https://www.sparkfun.com/myoware

Pololu (2025, August 28). *Muscle sensor V3*. https://www.pololu.com/file/0J745/Muscle_Sensor_v3_users_manual.pdf

Tello (2025, August 28). *Tello quadcopter*. https://www.ryzerobotics.com/tello

Yánez, A. J., Benalcázar, M. E., & Maldonado, E. M (2020). Real-Time hand gesture recognition using surface electromyography and machine learning: a systematic literature review. *Sensors*, *20*(9), 1-36. https://doi.org/10.3390/s20092467