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# ROS2 gesture classification pipeline towards gamified neuro-rehabilitation therapy

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**Resumen**

La rehabilitación es una herramienta esencial que ayuda a las personas a restaurar la movilidad en las extremidades afectadas por diversas afecciones, como enfermedades neurológicas. Las terapias convencionales, que incluyen terapia ocupacional, física y del habla, se han mejorado con nuevas tecnologías, como sistemas robóticos asistidos y juegos de realidad virtual y aumentada, para aumentar la participación y, en consecuencia, la efectividad. Esta investigación se centra en la implementación de un dispositivo portátil de sensores de electromiograma (EMG) de ocho canales, el brazalete Mindrove, para el reconocimiento de gestos. El objetivo es desarrollar un modelo clasificador utilizando el algoritmo de Máquinas de Vectores de Soporte (SVM) para distinguir ocho gestos diferentes de la mano y aplicarlo en un sistema de reconocimiento de gestos. El estudio demuestra la viabilidad de este sistema de reconocimiento y explora la aplicación potencial de esta tecnología en juegos interactivos de Unity para terapia de rehabilitación. Los resultados muestran una precisión prometedora en la clasificación del modelo y se necesita más investigación para abordar los desafíos relacionados con la especificidad del usuario y la precisión del reconocimiento de gestos. El trabajo futuro implica ampliar el repertorio de gestos reconocidos, incorporar datos adicionales del sensor y explorar técnicas de extracción de características más avanzadas para mejorar el rendimiento general del sistema de reconocimiento de gestos en terapias de rehabilitación..

*Palabras clave:* EMG, Reconocimiento de gestos, ROS2, Rehabilitación, Robotica Asistencial,,

**ROS2 gesture classification pipeline towards gamified neuro-rehabilitation therapy**

**Abstract**

Rehabilitation is an essential tool that aids individuals in restoring mobility in limbs affected by various conditions, such as neurological diseases. Conventional therapies, including occupational, physical, and speech therapy, have been improved by new technologies, such as assistive robotic systems, along with virtual and augmented reality games, to enhance engagement and, consequently, effectiveness. This research focuses on implementing an eight-channel electromyogram (EMG) wearable sensor device, Mindrove armband, for gesture recognition. The objective is to develop a classifier model using the Support Vector Machine (SVM) algorithm to distinguish eight different hand gestures and apply it in a gesture recognition system. The study demonstrates the feasibility of this recognition system and explores the potential application of this technology in interactive Unity games for rehabilitation therapy. The results show promising accuracy in model classification, and further research is needed to address challenges related to user specificity and gesture recognition accuracy. Future work involves expanding the repertoire of recognized gestures, incorporating additional sensor data, and exploring more advanced feature extraction techniques to enhance the overall performance of the gesture recognition system in rehabilitation therapies.

*Keywords:* EMG, gesture recognition, ROS2, rehabilitation, assistive robotic systems, Support Vector Machine (SVM).

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## 1. Introduction

Rehabilitation plays a vital role in assisting individuals who have experienced partial or complete loss of mobility in one of their limbs. Neurological disease, stroke, Spinal Cord Injury (SCI), Traumatic Brain Injury (TBI), birth defects and limb amputation are some of the most common conditions which often require rehabilitation therapy Londoño et al. (2017). The primary objective of rehabilitation is to help patients recover from motor capacities and improve their overall mobility. By implementing rehabilitation programs adapted to individual needs, patients can make significant progress in their recovery process ScienceDaily (2017).

Conventional therapy usually includes a combination of occupational, physical and speech therapy. However, in recent years, new technologies have been incorporated alongside these therapies, enhancing their effectiveness. One such advance is the integration of assistive robotic systems, which provides patient-specific and personalized physical trainingsBrewer et al. (2007). These systems have also shown themselves to be more economic in the long runLo et al. (2019). This will allow physical rehabilitation in reaching all the people that require of it, one of the challenges described by the WHO WHO (2023). Additionally, virtual and augmented reality games are commonly included as part of the rehabilitation process, serving to keep patients highly motivated [1]. These technologies, apart from engaging and making rehabilitation interactive, include enhanced results in rehabilitation due to specific patient needs tailoring, which maximizes their potential for recovery.

Monitoring sensors are crucial to be integrated with these systems in order to enable remote monitoring and control user data, as well as to carry out personalized therapy programs. These sensors can be categorized as invasive or non-invasive sensors. For this particular research, electromyogram (EMG) wearable non-invasive recording sensors were used.

EMG sensors are able to detect and record muscle activity via semi-dry electrodes. They capture action potentials originated in the neurons of the Central Nervous System (CNS), including both brain or spinal cord. These action potentials are propagated through a series of interconnected neurons until reaching the Peripheral Nervous System (PNS). At this stage, the axon terminal of each neuron will branch out and interact with a given set of skeletal muscle fibers at the neuromuscular junction, aiding their contraction as soon as the electric impulse reaches the muscle fibers.

These sensors have a wide range of applications, serving as valuable tools for creating gesture classification algorithms. They are able to accurately recognize and analyze a patient's movement, enabling their implementation to control and monitor other rehabilitation systems.

Recently, there have been numerous research studies focusing on gesture recognition using EMG sensors Sultana et al. (2023). However, a significant challenge that persists in this field is the lack of user specificity, which needs individualized training for optimal performance. Therefore, further extensive studies are still required to address this issue effectively. Besides, enhancing the recognition accuracy is crucial for the advancement of gesture recognition technology.

In the present study, an 8 EMG channel sensor device, Mindrove armband, will be used. The main objective is to develop a classifier model able to distinguish 8 different gestures, shown in Table 1. Subsequently, a real-time gesture recognition algorithm will be implemented to detect and identify these gestures in real-time as performed by the user wearing the EMG device. The final objective of this approach is to integrate the gesture recognition system into Gamified unity games, thereby enhancing interactivity, allowing users to control the game by the gestures captured with the EMG sensor. By achieving this, the study aims to demonstrate the feasibility and potential applications of EMG-based gesture recognition in novel rehabilitation therapies.

The paper is organized as follows: Firstly, it covers some mathematical prerequisites neccesary to the overall understanding of the applied methods, followed by the algorithm employed for generating the classification model. Subsequently, the implementation of model within a ROS2 system will be described in experiment section, for gesture recogntion. Finally, it is explained how the recognized gestures are implemented in Unity games. Lastly, the paper presents the results and conclusions obtained from the experiments.

## 2. Mathematical Prerequisites

Machine learning, a subfield of Artificial Intelligence, is based on learning from data, pattern recognition and decision-making, with the highest automatization process as possible Spiewak et al. (2018).

This project focuses on pattern recognition using machine learning techniques. It aims to automatically interpret datasets, pattern identification, and data classification. Specifically, the project has the objective to recognize hand gestures based on surface electromyography (sEMG) signals. By analyzing these signals, a model, accurately classifying and interpreting different hand gestures, will be trained.

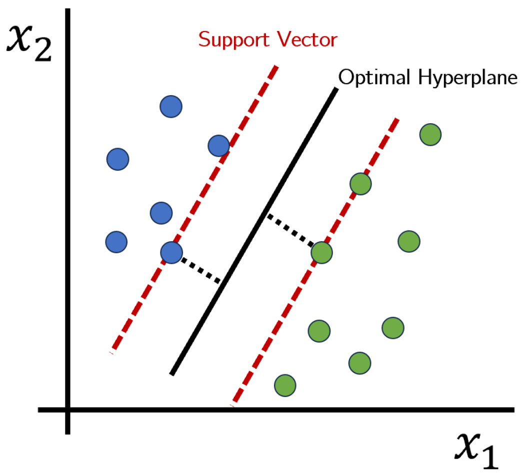


Figura 1: Support Vector Machine with linear kernel

Gesture recognition process requires a classifier model for the gesture classification. Support Vector Machine (SVM), a supervised machine learning algorithm, was employed for this particular research. SVM is a statistical approach which looks for a hyperplane accurately dividing different classes. It finds the maximum distances between different categories by figuring out the maximum margin among hyperplanes, as shown in Fig. 1. While it is true that the SVM algorithm is primarily designed for binary classification, it can be extended to handle multiclass problems by reducing to a series of binary problems.

This algorithm is based in Kernel approach, which simplifies non-linear data set into a higher dimension linear one, in order to distinguish different classes in the hyperplane, observed in Fig. 2.

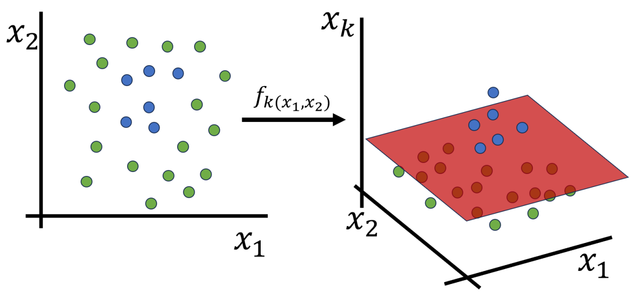


Figura 2: Non-Linear Kernel approach in SVM

The most common Kernel functions, and the ones which are tested for this project, are: linear kernel, Radial Basis Function (RBF) kernel and Polynomial kernel; which can be seen in Equation 1, 2, and 3.

$$K_{lin}(x, y) = x^{\top} y \tag{1}$$

$$K_{poly}(x, y) = (1 + x^{\top} y)^{d} \tag{2}$$

$$K_{RBF}(x, y) = e^{-\frac{(x-y)^2}{\sigma^2}} \tag{3}$$

One of the main advantages of SVM are its accuracy and high prediction speed. Nevertheless, it is quite sensitive to the type of kernel applied and loss of efficiency when dealing with overlapping classes.

## 3. Algorithm

Generally, the steps to follow for machine learning classification techniques are the following ones, acquisition of the data to be trained and tested, preprocessing of the data including normalization and noise and background reduction, feature extraction which will be the data applied for the classification model, continuing with the proper data classification making use of a machine learning algorithm. Finally, the evaluation of the classification will be carried out. A detailed overview of these steps is shown in Fig. 3.

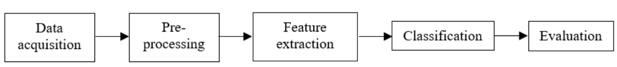


Figura 3: Steps for the classification

Datasets used for the classification of this study were acquired from Eftimiu et al. (2022). It comprised of 5 different datasets, of 5 healthy, male, right-handed volunteers within the range of 25 and 35 years old, performing 3 repetitions for each 8 different gestures, shown in Table 1. The recordings were acquired using the Mindrove armband device, which consists of 8 semidry electrode channels. Each dataset includes raw ADC (analog-to-Digital) EMG signals from these 8 channels during the execution of repetitions for all the gestures. Additionally, there is a column indicating the task number associated with the gesture being performed, in each of the samples. While there are other values present in the datasets, will not be given focus for this research. The gestures and their association to a task number can be observed in Table 1.

Tabla 1: Gestures with corresponding task number

**Gesture Classification**

| ***Task number*** | ***Gesture*** |
|---|---|
| 0 | Idle |
| 1 | Thumb flexion (TF) |
| 2 | Index finger flexion (IFF) |
| 3 | Middle finger flexion (MFF) |
| 4 | Ring finger flexion (RFF) |
| 5 | Pinky finger flexion (PFF) |
| 6 | Wrist extension (outward) (WE) |
| 7 | Wrist flexion (inward) (WF) |

For the pre-processing, data was converted to microvolts multiplying it by 0.045, as specified in the SDK manual from Mindrove. The armband device contains its own sinc low pass filter of 131 Hz for antialiasing. Besides, a filter to eliminate the power line noise of 50 Hz was applied. It must be mentioned that no other filters were implemented for the classification.

Subsequently, due to the horizontal symmetry of the EMG signals, a rectification which transforms all values in absolute values was done. The next step consisted in a mix-man normalization process for each individual channel from values from -1 to 1, in order to avoid a predominating feature which could lead to adverse results. The obtained output after this preprocessing can be observed in Fig. 4.

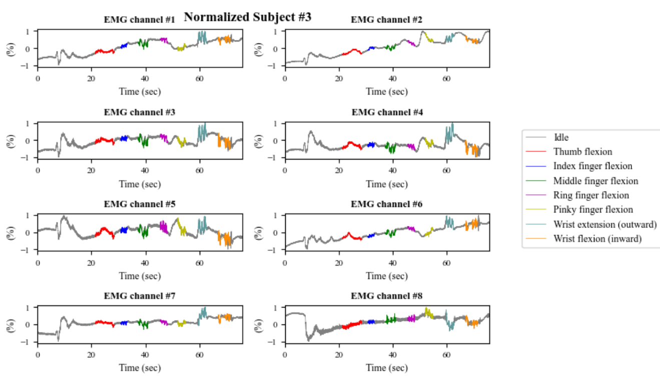


Figura 4: Results after pre-processing of one of the subjects

Before feature extraction, a rolling approach was performed, creating fragments each containing 10 samples with an advancing step of 8 values. These were fragments applied for each of the feature extraction.

This is done in order to convert the data in each of the fragments into a set of features, which will be the ones applied for the classification. For this case, two time domain features were selected, Mean Absolute Value (MAV) and Simple Square Integral (SSI).

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{4}$$

$$\mathrm{SSI} = \frac{1}{N}\sum_{i=1}^{N}|x_i|^2 \tag{5}$$

Following this, the classification took place. As mentioned, SVM was used. Linear Kernel, Polynomial Kernel and RBF kernel approach were used independently so that a comparison was done to select the best model. However, Linear Kernel showed outstanding poor outcomes, confirming the non-linearity of the dataset; and thus, it was discarded and no further used in subsequent processes.

The Python library Scikit-learn (`sk-learn`) provides its own Support Vector Machine model system, which takes as input the features previously created as and the corresponding labels with the task number. It is needed to specify the type of Kernel wanted to be used, as well as the percentage of the data to use as testing data and as training data, together with other specifications that depend on the selected Kernel approach, such as degree and C, which is a regulation parameter, for polynomial kernel; and gamma, a Kernel coefficient, for RBF approach. For this model, 80 % of the data was used for training the model, and 20 % for testing.

Finally, evaluation of the saved model was performed. Accuracy, F1 Score, Precision and Recall were compared for Polynomial and RBF Kernel approach, shown in Table 2.

Tabla 2: Results from the classification

| | **Polynomial Kernel** | ***RBF Kernel*** |
|---|---|---|
| **Accuracy** | 86.62 % | 95.57 % |
| **F1 Score** | 84.14 % | 95.49 % |
| **Precision** | 87.10 % | 95.50 % |
| **Recall** | 86.62 % | 95.57 % |

Furthermore, results of the accuracy were able to be sfveen in Confusion Matrix in 5 and 6.

It is needed to note the predominance of Task 0, which corresponds to idle position, since this is, with significant difference, the most repeated gesture throughout the recordings, consuming most of the data for training and testing. Furthermore, one must bear in mind, that this gesture is the one which can lead to greater confusion compared to the rest ones, in which evident peaks can be distinguished. For those reasons, more data belonging to idle position is applied for the classification model.

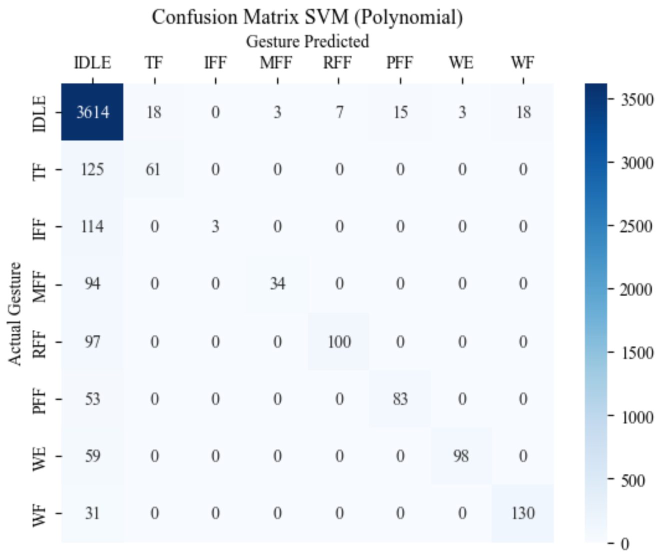


Figura 5: Confusion matrix for the SVM with Polynomial Kernel

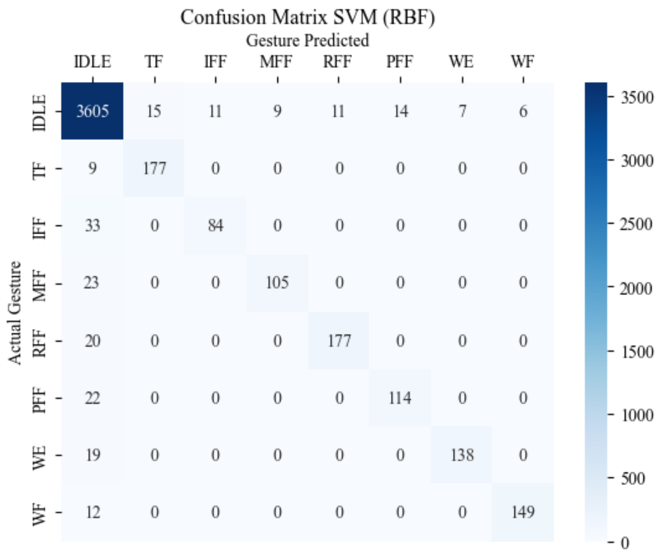


Figura 6: Confusion matrix for the SVM with Radial Basis Function Kernel

## 4. Experiment

The classification model finally saved using the RBF kernel, as it was clearly the one with better outputs.

Once the classification model was created and saved, the following approach was to implement it in a real - time signal recognition system, able to record the signals of the device and create an instantaneous response giving the corresponding gesture being performed by the user wearing it.

In order to carry this out, ROS2 and Ubuntu operating systems were used.

A publisher was created, able to record directly raw data from the 8 channels from the armband device. This data was sent to the topic, where a subscriber node was in charge of acquiring that data from the topic. In the subscriber node, the data followed the same steps used for data preparation to insert in the classification, which includes: creating fragments of 10 samples, rectification, normalization and feature extraction (MAV and SSI). Next, that data was inserted in the previously created classifier model, giving as output the task number associated with the gesture. Data flow from the recording of the signals from the device until a gesture is recognized can be clearly seen in the diagrams provided in Fig. 7 for a more specific view of ROS2 system and more detailed in Fig. 8.

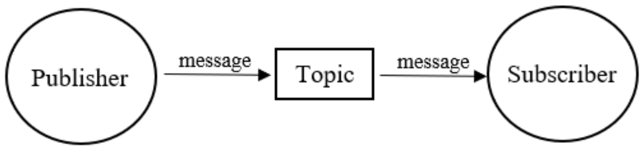


Figura 7: Simplified working diagram of ROS2

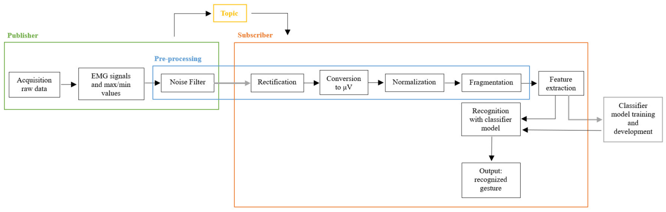


Figura 8: Diagram of data flow for classification model generation and gesture recogntion

First, the created ROS2 system was tried with the datasets used for the classifier model creation, giving an accuracy of 97 %. This was performed in order to ensure that the system was correctly set up, for other incoming data.

Afterward, it was connected to the sensor, by a subscriber node, which was adapted to receive signals from the Mindrove Armband device. Once the data is acquired, the steps provided by Fig 8 are followed, giving as output with the gesture recognized for each of the input samples.

The last aim of the project consisted in the linkage of the recognized gesture with Unity games. The subscriber node, which outputs the gesture recognized per sample, was incorporated as a publisher node sending results obtained from the gesture recognition to Unity game engine, a cross-platform game engine used for video games creation and development. Concretely, the MYO-Gesture game, Arkanoid game and MYO-Space game, were the games applied, seen in Fig. 9, 10, 11.


Figura 9: MYO-Gesture game

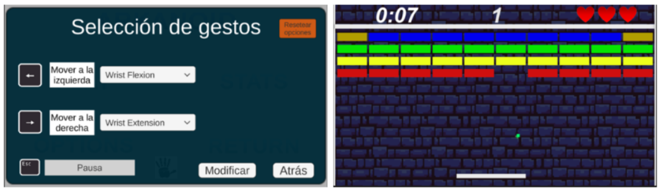


Figura 10: Arkanoid game


Figura 11: MYO-Space game

## 5. Results

The main objectives of the research, which consisted of the development of an upper limb gestures classification model together with gesture recognition system via ROS 2 and incorporation of Unity games, were successfully achieved.

The final model, saved for further applications, involves a Support Vector Machine based on Radial Basis Function Kernel approach, using as feature inputs Mean Absolute Value and Simple Square Integral.

Nevertheless, in order to achieve a more efficient gesture recognition using the actual device intended for future real-time recognition, a new model was created using the same parameters. This new model incorporated a new set of gesture recordings specifically collected for this purpose. The updated model was then integrated into the gesture recognition system developed with ROS2.

The new model demonstrated improved performance, achieving an accuracy of 92.12 %, precision of 91.72 %, F1 Score of 98.68 %, and recall of 92.12 %.

Furthermore, a Confusion Matrix was created in order to analyze the occurrence of True Positives, True Negatives, False Positives, and False Negatives among the different gestures, as shown in Fig. 12. It is noteworthy, that the pinky finger flexion gesture exhibited poor performance in the evaluation. This can be attributed to the minimal muscle movement when performing this gesture and consequently the weaker signal generated compared to the other movements, being misclassified as Idle position.

It is worth noting that in order to achieve even better results, it is recommended to perform a fine-tuning process for each individual, with a reduced set of recordings. This ensures a better fit with their specific signal values, resulting in improved accuracy and overall performance.

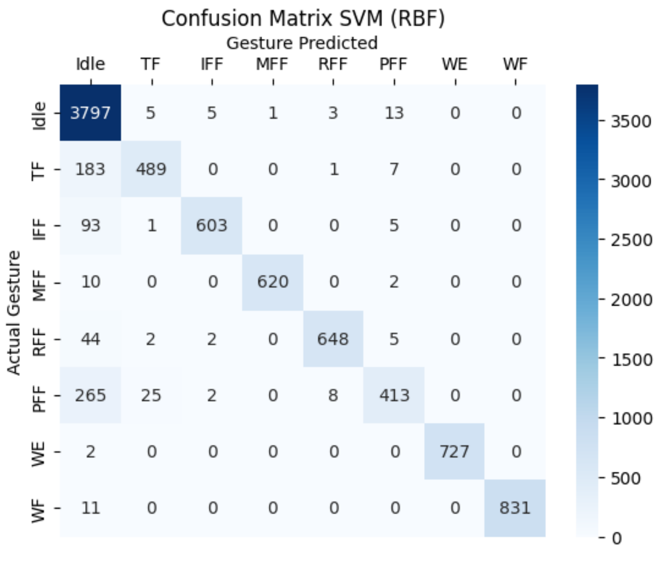


Figura 12: Confusion Matrix from the new model

## 6. Conclusion and Future Work

Rehabilitation plays a crucial role in assisting individuals with mobility loss. Recently, new technologies have enhanced conventional therapies. This research focuses on gesture recognition using surface electromyography (sEMG) signals. The study aims to develop a classifier model using the Support Vector Machine (SVM) algorithm to distinguish eight different hand gestures together with a gesture recognition system using ROS2. The integration of gesture recognition into Unity games is explored to enhance interactivity in rehabilitation therapies. The research highlights the potential of EMG-based gesture recognition in novel rehabilitation therapies and emphasizes the need for further studies to address challenges in user specificity and recognition accuracy.

After good performance reached for the model classification, gesture recognition system and association with Unity games, the subsequent step to be followed involves the expanding the repertoire of the gestures recognized, providing a broader range of movement options. This advance aims to approach and emulate the natural span of hand movements, allowing for more diverse and complex motions. As a result of increasing the number of recognized gestures, the system will become more versatile, enabling users to perform a greater variety of gestures within the gaming or interactive environment, and thus, enhancing the overall user engagement.

Mindrove armband, provides not only EMG signals, but also Inertial Measurement Units (IMU), including values for accelerometer and gyroscope in x, y and z axis. Making use of this multisensorial system, incorporating dual data acquisition, will efficiently benefit the classifier model. The incorporation of IMU data together with EMG signals enables a more comprehensive and detailed understanding of the user's movements and gestures. The combination of data will significantly improve the accuracy and precision of the model, resulting in a better recognition and classification performance. Furthermore, in this manner, the system will efficiently acquire a broader range of movements, with better results, providing a more reliable and robust gesture recognition.

Moreover, for this particular research, Support Vector Machine (SVM) making use of two time domain features was applied for gesture recognition. Nevertheless, it must be mentioned that the number of features introduced into the SVM could be amplified, incorporating features from other domains, such as features from frequency domain, or even time-frequency domain. In this way, the model could take advantage of a wider data analysis and lead to an enhanced and more accurate classifier model.

This gesture classification system developed in this research has potential applications in several rehabilitation techniques, including the control of prostheses for individuals with upper limb amputations. Besides, it could be advantageous to integrate it with the actual rehabilitation devices, facilitating the interaction between patients and robotic systems.

## Agradecimientos

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