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A Bimodal EMG/FMG System Using Machine Learning Techniques for Gesture Recognition Optimization

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Abstract: This study is part of a broader project, the Open Source Bionic Hand, which aims to develop and control, in real time, a low-cost 3D-printed bionic hand prototype using signals from the muscles of the forearm. This work is intended to implement a bimodal signal acquisition system, which uses EMG signals and Force Myography (FMG) in order to optimize the recognition of gesture intention and, consequently, the control of the bionic hand. The implementation of this bimodal EMG-FMG system will be described. It uses two different signals from BITalino EMG modules and Flexiforce™ sensors from Tekscan™. The dataset was built from thirty-six features extracted from each acquisition using two of each EMG and FMG sensors in extensor and flexor muscle groups simultaneously. The extraction of features is also depicted, as well as the subsequent use of these features to train and compare Machine Learning models in gesture recognition through MATLAB's Classification Learner tool (v2.2.5 software). Preliminary results obtained from a dataset of three healthy volunteers show the effectiveness of this bimodal EMG/FMG system in the improvement of the efficacy on gesture recognition as it is shown, for example, for the Quadratic SVM classifier that raises from 75.00% with EMG signals to 87.96% using both signals.

Keywords: bionic hand; electromyogtaphy; force myography; feature extraction; gesture recognition; classification models

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1. Introduction

Upper limb myoelectric prostheses, also called bionic hands, are electromechanical devices that are attached to the residual limb of amputees in order to replicate the functionality of the human hand and consequently improve the quality of life of these people.

Commercial bionic hand models use surface electromyographic (EMG) sensors to capture the electrical activity produced when muscle remnants are activated. However, this is a detection method whose effectiveness is susceptible to external electromagnetic noise, muscle fatigue, or impedance changes in the sensor-skin interface. So, research in the field of myoelectric prostheses is faced with the constant challenge of replicating the functionality of the human hand.

This study is part of a broader project, the Open Source Bionic Hand, which aims to develop and control, in real time, a low-cost 3D-printed bionic hand prototype using signals from the muscles of the forearm. In literature it is possible to find previous contributions from this project, focused on the implementation of a prototype of a low-cost controller of a bionic hand, namely from the application of alternative mechanomyographic sensors and novel and low-cost electrodes, built from a conductive leather material as well as based on desktop 3D printing using conductive PLA (PolyLactic Acid) [1].

The main objective of the work presented in this paper is the implementation and evaluation of the effectiveness of a bimodal EMG/FMG signal acquisition system for the control of a bionic hand. The idea is to counter the limitations of EMG sensors by integrating FMG, which shows benefits such as robustness in the face of impedance changes at the skin interface and sweating and lower sensitivity to sensor positioning. This is despite having its own challenges, such as sensitivity to unintentional movements and external noises. Thus, the simultaneous acquisition of both signals increases the system's immunity to any defect or deviation in operation that may sporadically or systematically condition success in recognizing gestures. The previously mentioned weaknesses of EMG sensors will then be mitigated by the possibility that the classification models also use characteristics of the FMG signal, which will allow learning that leads to a more robust system in the control of the bionic hand.

The term FMG, or force myography, describes the various non-invasive techniques that use force sensors to detect voluntary changes associated with the activation/deactivation of superficial muscle groups relative to a default state that usually corresponds to the limb in a relaxed position [2]. It also detects voluntary changes caused by the movement of tendons under the surface of the skin (e.g., in the wrist [3]).

The first work on the FMG technique as a modality for the control of myoelectric prostheses was published in 1999 [4], but it was only in the middle of the last decade that it gained traction among researchers, driven by the development of Machine Learning techniques.

Several scientific publications [5–7] present promising results on the possibility of using the FMG technique to predict movement intention in implementations of bionic hand prostheses. More recently, there has been a growing interest in combining sEMG and FMG in order to create more robust control systems to be used by pattern recognition models [8–10]. What makes the bimodal system interesting is the fact that it detects both electrical and volumetric phenomena associated with muscle contraction. In 2020, Jiang et al. [11] proposed a co-localized approach to acquire EMG and FMG simultaneously at the same location, achieving a 10% increase in accuracy in identifying 10 American sign language signals, relative to isolated modalities. In fact, this area of sign language recognition has many points in common with gesture recognition, and it is important to realize that there are several applications of machine learning in this area using neural and diffusion models, some of them convolutional, or even of deep learning techniques [12–14].

In general, robustness and/or accuracy increase when using multimodal acquisition systems. However, it also increases the information processing required and the complexity of integrating all sensors into the same hybrid acquisition system.

It is also expected that in unimodal FMG systems, the number of sensors will strongly influence accuracy as they enable higher spatial resolution and the extraction of a greater number of features [2]. However, there are still several shortcomings [10,15] that need to be addressed in order to be able to use FMG technology in commercial bionic prostheses.

In this paper, we will describe the implementation of a bimodal EMG/FMG system using the physiological signal acquisition platform, BITalino (Plux Wireless Biosignals S.A., Lisbon, Portugal), to make the acquisition of these two different signals from BITalino EMG modules and Flexiforce™ sensors from Tekscan™. The simultaneous acquisition of EMG and FMG data was then performed, using BITalino and OpenSignals, as well as the optimization of the MATLAB routines for signal processing and onset/offset detection of the acquired signals, implemented in previous works within the scope of this same project [16]. These steps are crucial for the extraction of features and subsequent use of these features to train and compare Machine Learning models in gesture recognition through MATLAB's Classification Learner tool. Exploring the potential of this tool, two studies were developed with on the one hand, the objective of analyzing the impact of each of the characteristics on the success in the recognition of gestures and, on the other hand, the objective of optimizing the classification models, by adjusting some parameters of these same models, for example, the number of layers in a neural network or the number of neighbors in a nearest-neighbors model. Preliminary results point to significant gains in the effectiveness of the classification of gestures, in line with the conclusions of other studies [11,17].

2. Materials and Methods

This work involved the selection of EMG and FMG sensors as well as the platform for robust data acquisition. Subsequently, it was necessary to implement the filters for signal processing, namely the EMG signal, as well as for the detection of onset/offset. Finally, the features of the EMG and FMG signals to be extracted were selected, and the entire methodology for the application of the classifiers was developed. The main objective is to analyze the improvement in efficacy achieved with this bimodal system and also to optimize the application of these classifiers.

2.1. EMG and FMG Signals

The EMG signal is a widely used tool in the detection of motion intent in commercial bionic prosthetic applications. However, the search for additional information on muscle activity has motivated the exploration of complementary techniques, such as force myography (FMG).

The EMG signal is the electrical expression of muscle activity, in this case captured by surface electrodes placed on the skin on the study muscle. The amplitude of the EMG signal, which is stochastic (random) in nature, is influenced by the strength of muscle contraction and usually ranges from 0 to 10 mV peak-to-peak, or from 0 to 1.5 mV RMS. The EMG signal is particularly useful in the 0–500 Hz frequency range, with the dominant energy in the 50–150 Hz range. This signal characteristic is illustrated in Figure 1, which shows power density spectra of EMG signals from different hand gestures.

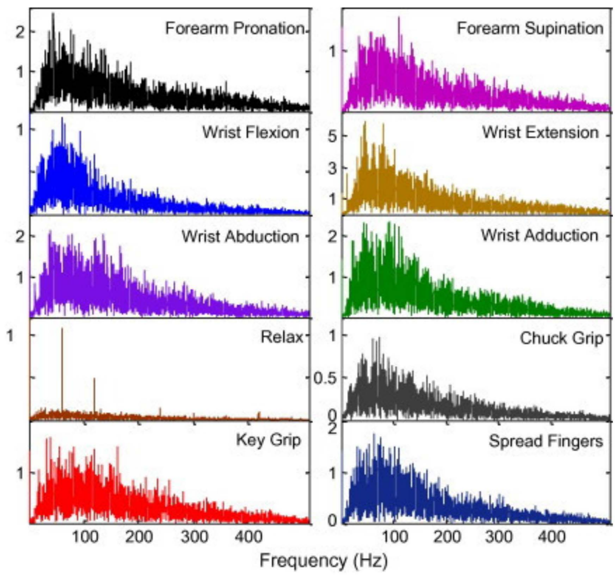


Figure 1. Power density spectra (in dB/Hz) of EMG signals in hand gestures (from [18]).

FMG is a non-invasive technique that makes use of pressure sensors placed on the skin above the muscles to capture changes in pressure and volume associated with the activation and deactivation of superficial muscle groups. Instead of measuring muscle electrical activity like EMG, FMG records mechanical changes, thus capturing distinct information, which can be valuable in the context of bionic prostheses.

Although FMG has benefits such as robustness to changes in skin impedance and sweating and less sensitivity to sensor positioning, it faces challenges such as sensitivity to unintentional movements and external interference.

For the acquisition of physiological signals, we used BITalino (r)evolution (PLUX Biosignals, Lisbon, Portugal). This platform is distinguished by its ability to integrate a wide diversity of sensors as electromyography (EMG), electrocardiography (ECG), accelerometer (ACC), and many others.

In the context of this work, the BITalino board was used to collect EMG and FMG signals. The EMG signals were obtained using two BITalino's own EMG sensors. On the other hand, the capture of FMG signals required the use of two external FSR 402 sensors (Interlink Electronics, Camarillo, CA, USA), which, after a signal conditioning circuit, were integrated into BITalino. Table 1 summarizes the main technical specifications of BITalino (r)evolution.

Table 1. BITalino (r)evolution: technical specifications.

Sampling Rate	1, 10, 100 or 1000 Hz
Analog Inputs	4 in (A1–A4, 10-bit) + 2 in (A5–A6, 6-bit) + 1 out (8-bit)
Digital Inputs	2 in (1-bit) + 2 out (1-bit)
Connectivity	Bluetooth Class II v2.0 (range till 10 m)

The transmission of data to the computer is done in real time via Bluetooth. In turn, the OpenSignals v2.2.5 software (Plux Wireless Biosignals S.A., Lisbon, Portugal), compatible with the BITalino platform, allows real-time visualization of data from multiple channels and devices (up to 24 channels and 3 devices). In addition, the software allows the export of data in .txt and .h5 formats, as well as their offline viewing. Figure 2 shows an example of visualization of offline signals in Opensignals.

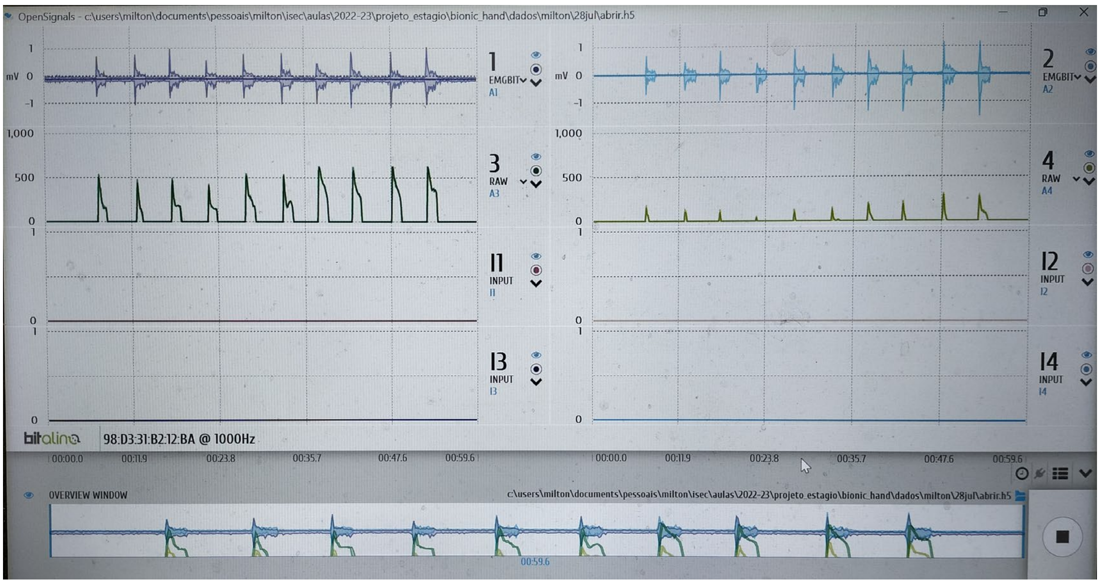


Figure 2. Previously stored data file in Opensignals, showing EMG (**top**) and FMG (**bottom**) signals for the "hand opening" gesture (channels I1 to I4 not used).

As previously mentioned, the monitoring of the electrical activity of the flexor and extensor muscle groups of the forearm was done using two BITalino EMG sensors, specially designed for sEMG acquisitions. It is compatible with gel and dry electrodes and offers high-quality data with low noise due to its bipolar configuration. The EMG sensor is responsible for analog filtering, amplification, and A/D conversion of the signal. Table 2 presents the technical specifications of BITalino's EMG module sensor.

Table 2. Technical specifications of the EMG module sensor.

Gain	1009
Range	$\pm$1.64 mV (com VCC = 3.3 V)
Bandwidth	25–480 Hz
Power Voltage	2.0–3.5 V
Input Impedance	7.5 GΩ
CMRR	86 dB

Within the scope of this project, sensors of the FSR 402 model were selected. Two of these sensors were applied, one for each muscle group under study: the flexor and extensor forearm. The choice of FSR sensors is justified by their ability to detect variations in force from an initial/resting state rather than providing an accurate measurement of the applied force. This property is essential for FMG systems in gesture recognition, where the goal is not necessarily to quantify the exact force being applied but to identify if there is any force being applied and how that force changes over time. The FSR 402, in particular, was chosen for its active area (14.7 mm diameter) and minimum actuation force (0.1 N), which were considered suitable for the application in question.

2.2. Data Acquisition

EMG and FMG signals were collected simultaneously from each participant, using the BITalino platform with four acquisition channels: two for EMG and two for FMG. One pair of EMG/FMG sensors was placed in the extensor muscle group of the forearm and the other in the flexor muscle group.

BITalino transmits the data via Bluetooth to a PC, where the data that is being acquired is visualized in real time and stored for further processing using OpenSignals software. Participants were instructed to perform five gestures: open, close, pinch, point, and thumb-up. Each collected data file contains approximately ten activations of each gesture.

The implementation of signal acquisition went through the following steps:

1. For each acquisition session, EMG sensors (in bipolar configuration) were positioned in the flexor and extensor muscle groups, with a separation of approximately 2 cm;
2. Between the two active electrodes, an FSR sensor (on a rigid PVC base) was fixed with an adhesive;
3. A velcro tape was applied to the forearm over the two FMG sensors simultaneously to stabilize the sensors in place;
4. Each participant was instructed to perform a series of activations of a specific type of gesture, with durations and rest intervals between activations ranging from 1 to 3 s to ensure the representativeness of the data collected. During data collection, the participant was asked to remain as relaxed as possible between activations and to keep the elbow joint still to minimize the influence of residual muscle strains on the collected data;
5. Each series of activations was recorded in a separate file with the name of the gesture performed, using the OpenSignals software. The sampling rate was 1000 Hz. Figure 3 shows images of signal acquisition for two different gestures. 4-Channels of BITalino

made the acquisition of the signals from two pairs of EMG and FMG sensors in flexor and extensor muscles.

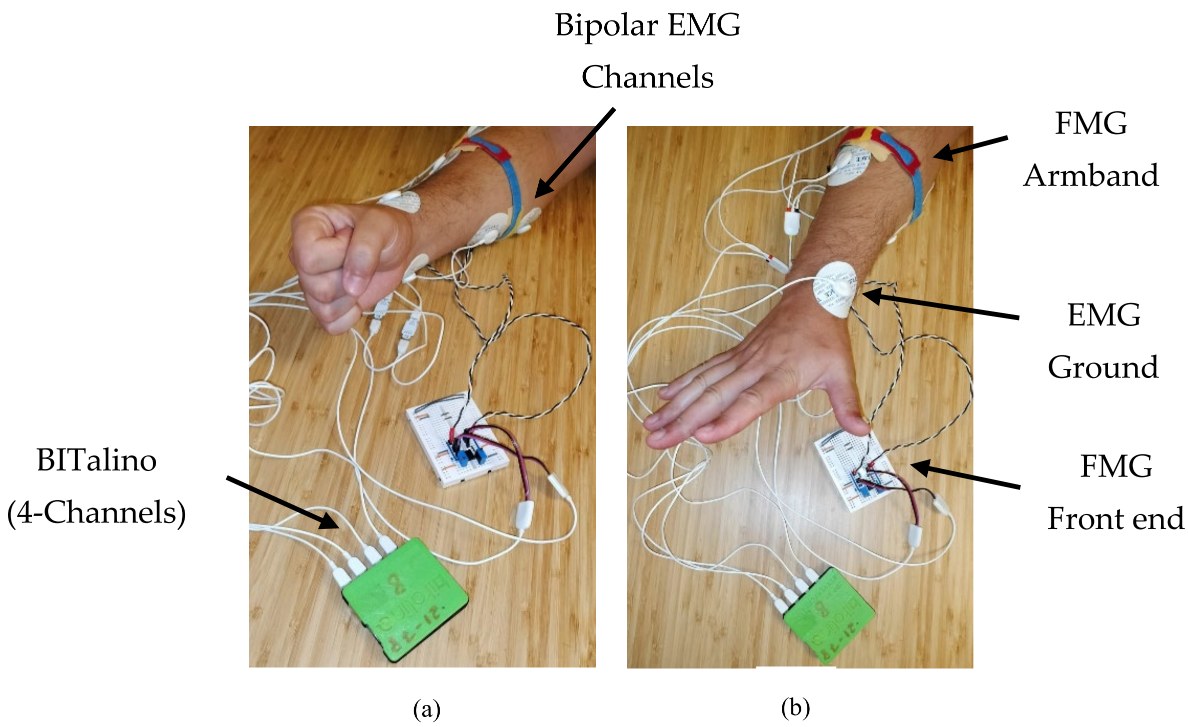


Figure 3. Acquisition of EMG and FMG signals: (**a**) On the clasp of the hand; (**b**) Opening the hand.

2.3. Data Processing

As illustrated in Figure 4, the EMG and FMG signals are then initially acquired by BITalino, where they undergo basic preprocessing, which includes amplification and initial filtering.

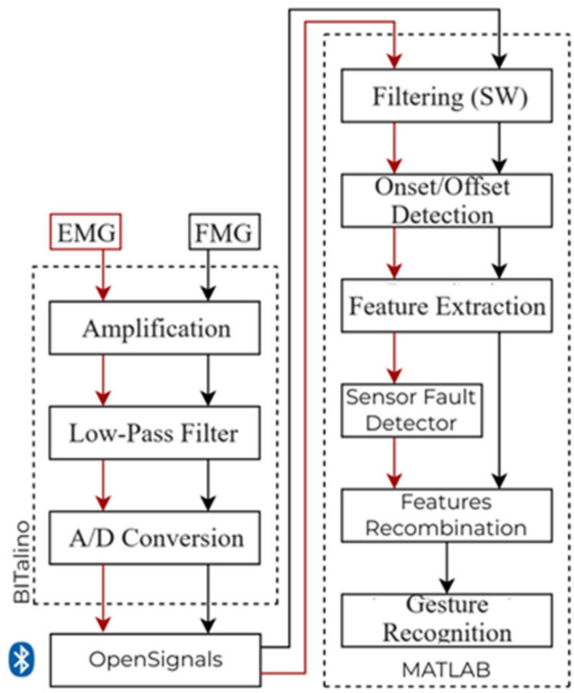


Figure 4. Steps of EMG and FMG signal processing.

After pre-processing, the data enters the phase of extracting the characteristics of the most relevant signals for the discrimination of gestures. Previously, it was necessary to detect signal onsets and offsets in order to identify the periods of muscle activation.

The signals are then forwarded for offline processing in MATLAB. Here, additional denoising and bandpass filtering operations are performed to maintain only the relevant frequencies. The signal offset is also removed.

Using the MATLAB software, the signals are processed, and their features are extracted through a set of previously developed routines [1,14]. This set comprises a main routine with the pipeline, along with auxiliary functions for onset/offset detection and feature extraction from EMG and FMG signals.

The main routine, implemented in MATLAB, performs a series of critical steps in signal processing:

1. EMG signal filtering: For each text file (with EMG and FMG data), the code applies a bandpass filter from 20 to 500 Hz to the EMG signals;
2. Wavelet Denoising: EMG signals go through a second stage of noise reduction, this time using the wdenoise function of MATLAB's Wavelet Toolbox. This technique, which acts in the time-frequency domain, eliminates random noises that could be mistaken for true muscle activity;
3. Onset and offset detection of muscle activity: This is a crucial step. The code uses the onsetting function to determine when the muscle started to contract (onset) and when it stopped (offset). The result is a time series (vectors) of onsets and offsets of muscle contraction. The onset/offset function is responsible for identifying the moments when the EMG signal demonstrates significant activity. The function does this by full-wave rectification of the signal, applying a moving average to calculate the test function, and setting a threshold for onset detection. If the signal falls below this threshold, an offset is detected. In addition, the function also ensures that the detected activity moments have a minimum duration to avoid false detections (650 ms);
4. Corresponding activations: The code looks for muscle activations that coincide between the EMG signals of the two muscle windows (extensor and flexor). The onset and offset times of the FMG signals are given by the values saved for the corresponding EMG signals. The tolerance for coincidence is given by the value of the constant tolerance_window and has been maintained at 500 ms. Figure 5 shows an example of the signals acquired with the detection of the onsets and offsets of each muscle activation;
5. Feature extraction: For each muscle activation that matches, the code extracts a set of features from both the EMG and FMG signals. Features are measures that provide a deeper understanding of the signals, which would otherwise be very difficult to interpret.

The extract_emg_features and extract_fmg_features functions were used to extract characteristics from the EMG and FMG signals, respectively. These functions compute a set of characteristics, both in the time and frequency domains (in the case of EMG), for each instance of a gesture. In total, thirty-six characteristics were extracted, twelve EMG and six FMG for each muscle group.

2.4. Selection and Application of Classification Models

Finally, each feature vector is labeled with the corresponding gesture (which appears in the data file name), and the data is prepared for classification. This data is then used to train a classification model, which identifies gestures based on the characteristics extracted from the signals [19].

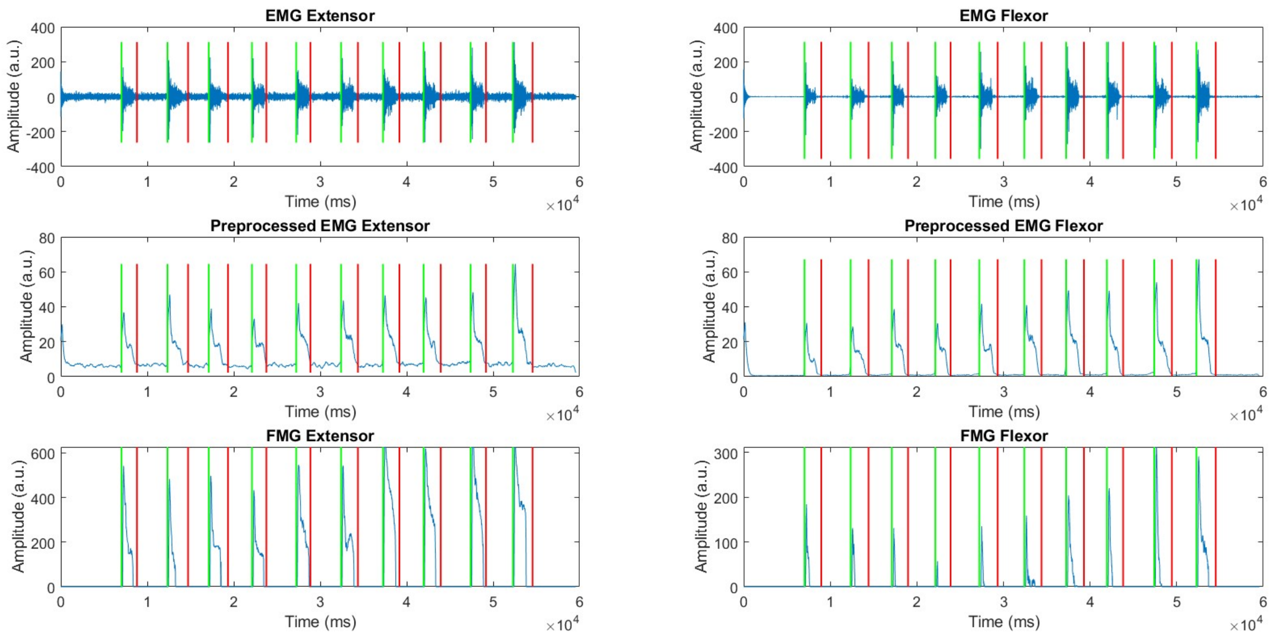


Figure 5. Example of FMG raw-signals and EMG raw and pre-processed signals. The green and red vertical lines shown are, respectively, the onset and offset time for each muscle activation.

Using MATLAB's Classification Learner app, a systematic approach was implemented for the selection and application of classifiers. A strategy from the general to the particular was followed, allowing a comprehensive evaluation of the models. It was composed of four steps:

1. Initial comparison of classifiers: In a first stage, a preliminary comparison of the thirty-three available classification models was made, using accuracy (or "effectiveness") as the main metric. At this stage, not only did accuracy continue to be considered as an evaluation metric, but additional metrics—the F-score and the area under the ROC curve (ROC-AUC)—were also introduced to obtain a more complete picture of the performance of the models;
2. Impact of features selection on the selected models: After selecting the best-performing classifiers, an in-depth study was conducted to understand the impact of feature selection on the performance of these models;
3. Hyperparameter adjustment: based on the best combinations of the classification method and percentile obtained in the previous step, the hyperparameters were optimized for these models. This step allowed us to further refine the selected models;
4. Performance comparison between the use of all data, only EMG, and only FMG: in parallel, a comparison of the performances of the models was made using all the characteristics and characteristics exclusively derived from EMG or FMG. This step is justified by the traditional practice of using only EMG signals in the control of myoelectric prostheses and by studies that evaluate the performance of systems with FMG only. The objective of this comparison was to evaluate the feasibility of each of these types of signals for the control of prostheses.

3. Results

The preliminary results of this study show significant improvement of efficacy on gesture recognition using a bimodal EMG/FMG acquisition system. This is accomplished through a detailed study of the application of different machine learning models.

3.1. Dataset

In this study, three healthy individuals participated, and the dataset was formed from the thirty-six characteristics of the EMG and FMG signals extracted from each activation in each of the files corresponding to each of the five gestures.

In total, seventy data files suitable for the following stages of the study were recorded, distributed as follows: hand opening (14), hand closing (16), pinch (11), thumbs-up (16), and pointing (15). These files were selected after discarding others due to acquisition problems, such as excessive noise and incorrect positioning and/or improper fixation of the sensors.

Figure 6a shows the dataset for each gesture, while Figure 6b shows how the total of thirty-six features extracted from each activation are distributed. In fact, the number of signal characteristics extracted from extensor and flexor muscles is equal.

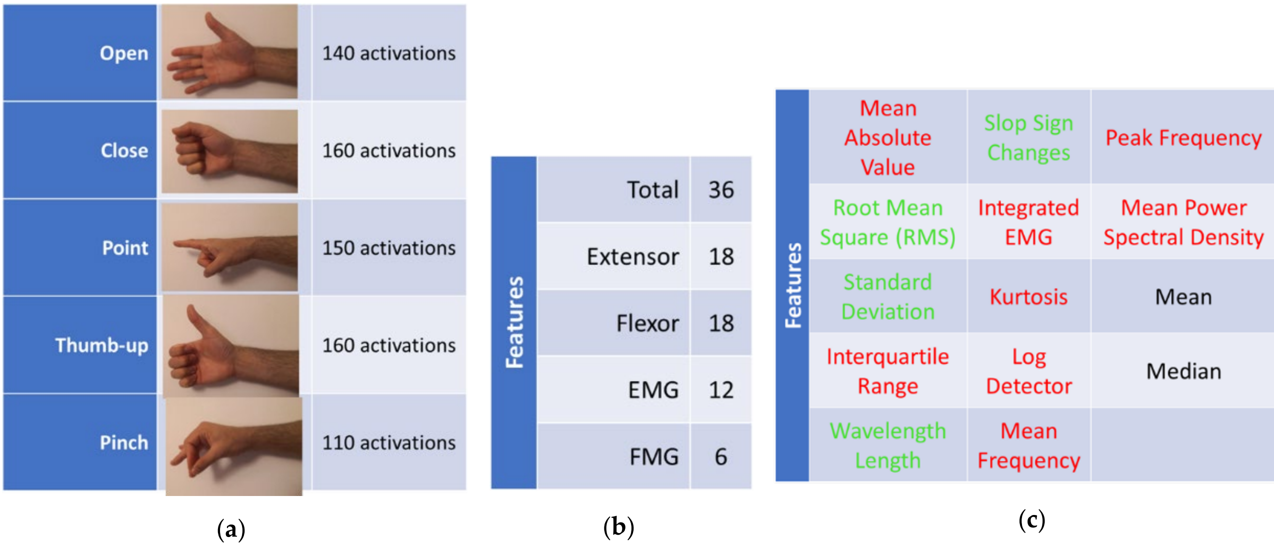


Figure 6. (**a**) Dataset for each gesture. (**b**) Distribution of the number of features extracted per muscle and per sensor type. (**c**) 4 features are extracted from FMG and EMG signals simultaneously (green), 8 features from EMG signal (red), and 2 features from FMG signal (black).

However, of these eighteen characteristics, only six are extracted from the FMG signal. Of these six characteristics, only two are different from those extracted from the EMG signal. In Figure 6c, all the characteristics are presented, showing whether they are common to both signals or from only one of the signals through the use of different colors.

The collected data from the EMG and FMG signals of each muscle group, which consists of the relevant characteristics that were extracted, is used as input for the training of the Machine Learning models, through MATLAB's Classification Learner, in order to predict the execution of each gesture.

3.2. Classifiers Comparison

A total of thirty-three classifiers were trained, and the assessment of the performance of each classification model was made using accuracy (or "effectiveness") as the main metric. However, additional metrics—the F-score and the area under the ROC curve (ROC-AUC)—were also introduced to obtain a more complete picture of the performance of the models.

The F-score combines accuracy and sensitivity (or recall) into a single metric that evaluates the accuracy and robustness of the model. ROC-AUC, on the other hand, measures the model's ability to distinguish between classes.

Table 3 summarizes the results obtained. Initially, using only the effectiveness, twelve models were selected, and with the additional metrics, the five that can be highlighted were confirmed: Quadratic SVM, Cubic SVM, Fine KNN, Weighted KNN, and Wide Neural Network.

Table 3. Results of the metrics used for the selection of the better classification models (green, darker indicates better results).

Model	Accuracy % (Validation)	Accuracy % (Test)	F-Score (Validation)	F-Score (Test)	ROC-AUC (Validation)	ROC-AUC (Test)
Quadratic Discriminant	83.68	83.80	0.8377	0.8324	0.9370	0.9405
Quadratic SVM	89.35	87.96	0.8827	0.8758	0.9823	0.9733
Cubic SVM	89.24	87.96	0.8928	0.8788	0.9811	0.9669
Medium Gaussian SVM	85.65	87.96	0.8577	0.8772	0.9750	0.9676
Fine KNN	86.69	86.57	0.8687	0.8625	0.9180	0.9155
Medium KNN	83.80	85.65	0.8382	0.8514	0.9703	0.9620
Cosine KNN	80.56	84.26	0.8058	0.8371	0.9633	0.9704
Cubic KNN	81.02	83.80	0.8119	0.8338	0.9641	0.9533
Weighted KNN	86.92	88.43	0.8684	0.8810	0.9785	0.9709
Bagged Trees	85.88	83.33	0.8586	0.8276	0.9700	0.9643
Medium Neural Network	85.07	81.02	0.8514	0.8039	0.9527	0.9182
Wide Neural Network	88.43	82.41	0.8831	0.8179	0.9684	0.9410

3.3. Feature Selection

These twelve models were trained with different feature selection methods—mRMR, Chi2, ReliefF, ANOVA e Kruskal-Wallis—in order to assess the impact of each feature and determine which were most relevant to our goal of gesture recognition. Different percentiles of features were used with each model—30, 24, or 18 of the initial 36—in order to identify the ideal balance between model complexity and gesture prediction efficacy.

The performances of the Cubic SVM and Quadratic SVM models stand out, which presented remarkable robustness, maintaining a high level of effectiveness, both in validation and in the test set, regardless of the number of characteristics or the selection method used. Specifically, the Cubic SVM model achieved 88.08% in the validation with 18 features selected by the ReliefF method and 90.28% in the test set, with the selection of 18 features using the Chi2 method. The Fine KNN and Weighted KNN models also proved to be very resilient, maintaining a remarkable effectiveness in both validation and testing, although lower than that of the SVM models.

The results indicate a variable robustness of the models in the face of the selection of features. While most models showed resilience, maintaining efficacy even with the reduction in the number of features, some models, in particular Quadratic Discriminant, demonstrated greater sensitivity to this reduction. The effectiveness of this model fell drastically by limiting the number of features selected by the ANOVA and Kruskal-Wallis methods to 18. In contrast, the Cubic SVM, Fine KNN, and Weighted KNN models stood out for their robustness, maintaining or even improving their effectiveness even with the reduction in the number of features.

The ranking of the characteristics for the five methods of selection of characteristics shows that there is a predominance of characteristics taken from the signals measured in the extensor muscle, with two methods in which in the top-10 there is no characteristic related to the flexor muscle. On the other hand, it is also observed that in the top 5, there are no characteristics taken from FMG signals in three of the five methods. It should be noted that, on the contrary, the ReliefF method has only characteristics of the FMG with the exception of #4. Table 4 presents these top 10 characteristics.

Table 4. Top 10 of the ranking of characteristics for the five feature selection methods used.

#	Features	Chi2	#	Features	mRMR	#	Features	ReliefF
1	mnf_Extensor	288	**1**	mnf_Extensor	0.354	**1**	median_fmg_Extensor	0.094
2	mnpsd_Extensor	220	**2**	median_fmg_Extensor	0.322	**2**	mnf_Extensor	0.093
3	rms_Extensor	213	**3**	ssc_fmg_Extensor	0.281	**3**	std_fmg_Extensor	0.068
4	sd_Extensor	213	**4**	wl_Flexor	0.057	**4**	rms_fmg_Extensor	0.068
5	mav_Extensor	196	**5**	kurt_Extensor	0.042	**5**	mean_fmg_Extensor	0.067
6	iqr_Extensor	173	**6**	std_fmg_Flexor	0.034	**6**	sd_Extensor	0.067
7	log_Extensor	153	**7**	mnf_Flexor	0.026	**7**	rms_Extensor	0.067
8	median_fmg_Extensor	150	**8**	rms_Extensor	0.021	**8**	mnf_Flexor	0.062
9	rms_fmg_Extensor	122	**9**	wl_fmg_Extensor	0.021	**9**	mav_Extensor	0.058
10	mean_fmg_Extensor	108	**10**	std_fmg_Extensor	0.019	**10**	median_fmg_Flexor	0.055
#	**Features**	**ANOVA**	**#**	**Features**	**Kruskal**			
1	sd_Extensor	230	**1**	mnpsd_Extensor	139			
2	rms_Extensor	230	**2**	rms_Extensor	137			
3	mnpsd_Extensor	224	**3**	sd_Extensor	137			
4	mav_Extensor	199	**4**	mav_Extensor	128			
5	iqr_Extensor	150	**5**	log_Extensor	109			
6	log_Extensor	145	**6**	iqr_Extensor	107			
7	mnf_Extensor	137	**7**	mnf_Extensor	93			
8	rms_fmg_Extensor	95	**8**	kurt_Extensor	86			
9	pkf_Extensor	94	**9**	mnf_Flexor	85			
10	median_fmg_Extensor	94	**10**	rms_fmg_Extensor	82			

3.4. Model Optimization

In this phase, we moved on to the final stage of the modeling process: the adjustment of the hyperparameters of the models that were identified as the most promising in the previous sections.

Hyperparameters are settings external to the model, which can be adjusted to control how the model will "learn". Unlike model parameters, hyperparameters are not learned from the data during training but are decided from the start. Examples of hyperparameters include the number of "neurons" or layers in a neural network, the type of kernel in an SVM model (linear, polynomial, etc.), or the number of neighbors in a KNN model.

The five most promising models were then used: Quadratic SVM, Cubic SVM, Fine KNN, Weighted KNN, and Wide Neural Network. This last model performed slightly lower than the others, but its inclusion in this is due to the fact that neural networks have the ability to capture complex and nonlinear interactions between features that other models may not be able to identify.

Each model will be optimized with the goal of finding the best combination of hyperparameters and feature selection strategies for each model. The models were evaluated with 100% of the features and subsets obtained by the selection methods, using different percentiles. The combinations with the best performance will be the ones that will now be explored. Preliminary results in Table 5 show that for some classification models, it is possible to achieve an improvement in accuracy with a subset of features, even using only 50% in one case.

Table 5. Impact of hyperparameter tuning on model performance (values of Accuracy).

Model	Selected Features (#)	Validation (Pre)	Test (Pre)	Validation (Post)	Test (Post)
Quadratic SVM	All (36)	90.05%	88.43%	90.28%	88.89%
Cubic SVM	ReliefF (30)	89.00%	90.28%	89.70%	88.89%
Fine KNN	All (36)	88.19%	86.57%	89.12%	90.74%
Weighted KNN	All (36)	87.15%	85.65%	89.47%	90.74%
Wide NN	ReliefF (18)	86.00%	86.11%	89.81%	88.89%

In the choice of these combinations, the test results were privileged, however, the validation results were also considered. This procedure was fundamental to ensure that the good results observed in the test data were not a consequence of a particularity of this subset, which could be "easier" to predict or more favorable to certain models.

In particular, for multiclass classification problems such as this, the F-score (macro) and the area under the ROC curve (ROC-AUC) are often used. Based on this, Table 6 summarizes the accuracy, F-score, and ROC-AUC metrics for these optimized models. It allows you to show the significant impact of hyperparameter optimization on improving the effectiveness of almost all models, compared to the values in Table 3.

Table 6. Performance of Optimized Models: accuracy, F-Score, and ROC-AUC.

Model	Accuracy (Validation)	Accuracy (Test)	F-Score (Validation)	F-Score (Test)	ROC-AUC (Validation)	ROC-AUC (Test)
Quadratic SVM	90.28%	88.89%	0.9030	0.8858	0.9806	0.9710
Cubic SVM	89.00%	90.28%	0.8914	0.9046	0.9798	0.9751
Fine KNN	89.12%	90.74%	0.8926	0.9012	0.9331	0.9396
Weighted KNN	89.47%	90.74%	0.8956	0.9027	0.9816	0.9764
Wide NN	89.81%	88.89%	0.8974	0.8860	0.9839	0.9683

From the results shown in Table 6, it is possible to see that all models have very close performances. Even so, if you consider the models with the best effectiveness in the test set (Fine KNN and Weighted KNN), the Weighted KNN stands out for showing greater robustness in the other metrics. In fact, it has one of the best F-Scores (a sign that it effectively balances accuracy and sensitivity across all classes) and the highest ROC-AUC, suggesting superior performance in sorting the different classes.

Confusion matrices help you understand how each model handles the different classes and provide a visual understanding of the models' performances. As an example, Figures 7 and 8 present the confusion matrix for the two models with the best performance, Weighted KNN and Cubic SVM, considering the test results and the values of the three metrics.

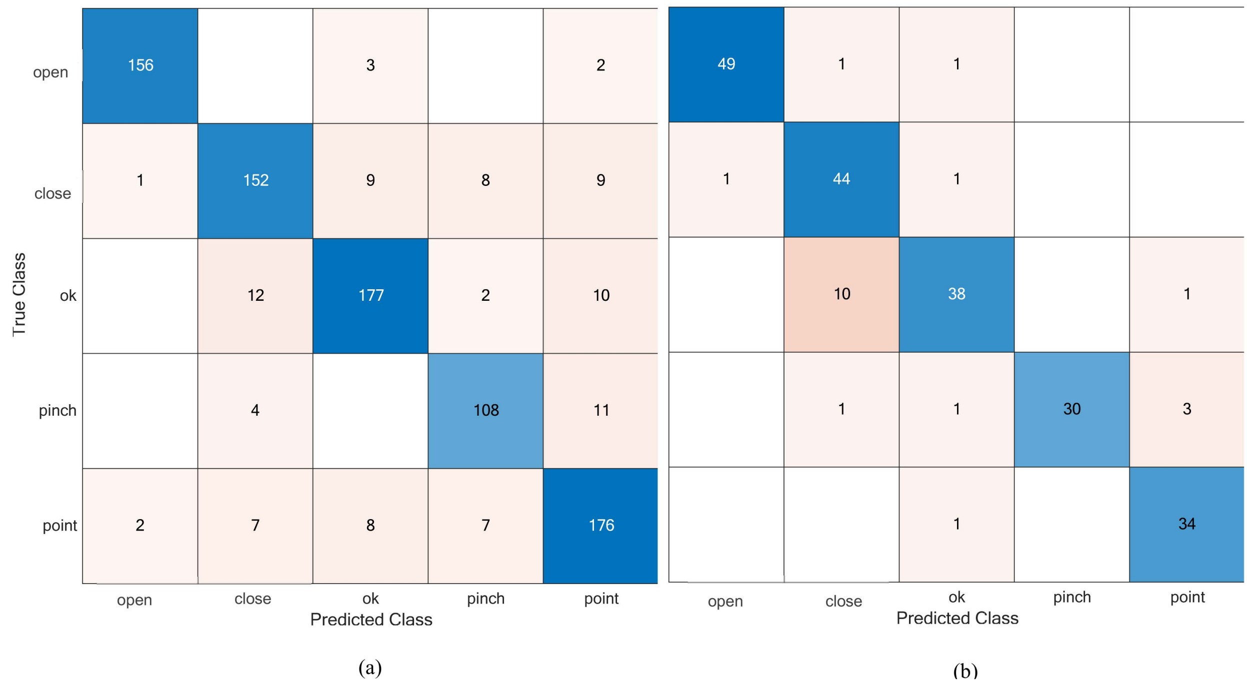
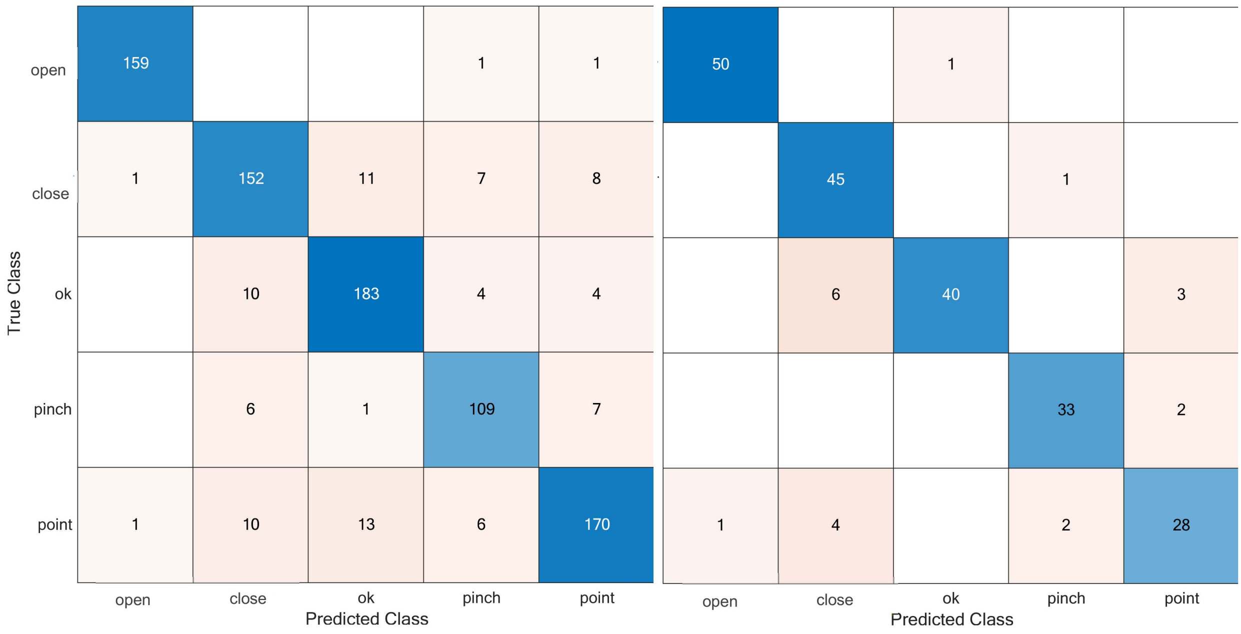


Figure 7. Confusion matrices for the Weight KNN model. (**a**) validation (**b**) test.



(a) (b)

Figure 8. Confusion matrices for the Cubic SVM model. (**a**) validation (**b**) test.

3.5. Bimodal vs. EMG vs. FMS Efficacy

In this section, we explore the impact of combining EMG and FMG characteristics on the performance of classifiers. To this end, the bimodal approach was contrasted with the more common practice that exclusively uses EMG characteristics. Table 7 details the performance of the six classifiers indicated above when they use all characteristics, only EMG characteristics, and only FMG characteristics.

Table 7. Comparison of the accuracy of the classifiers between the use of all data, EMG only, and FMG only.

Model	Validation (EMG + FMG)	Test (EMG + FMG)	Validation (EMG)	Test (EMG)	Validation (FMG)	Test (FMG)
Efficient Logistic Regression	38.77	31.02	34.72	26.85	47.92	50.93
Quadratic SVM	89.35	87.96	79.28	75	65.16	68.06
Cubic SVM	89.24	87.96	79.4	79.63	70.49	70.37
Fine Gaussian SVM	74.88	72.69	75.93	75.46	66.32	68.06
Fine KNN	86.69	86.57	74.88	80.09	65.05	63.43
Weighted KNN	86.92	88.43	75.58	77.31	67.25	64.81
Wide NN	88.43	82.41	78.47	79.17	67.25	68.06

The results are based on the initial evaluation of the classifiers, presented in Table 3, without the selection of features or tuning of hyperparameters. The results of Table 7 show that the effectiveness of most classifiers is greater when using a combination of EMG and FMG characteristics, rather than just one of them. This is true for all top 5 classifiers in which it is also found that better results are obtained using only features of EMG signals than only those of FMG. But regarding test accuracy, it is clear the benefit of using both EMG and FMG characteristics, p.i., in Weighted KNN and Cubic SVM accuracy raises from 79.63% to 87.96% and from 77.31% to 88.43%, respectively.

However, there are notable exceptions to this trend. For example, for the Fine Gaussian SVM classifier, the effectiveness obtained with the exclusive use of EMG characteristics is slightly higher than that obtained with all data. This indicates that for certain classifiers, EMG information may be sufficient to achieve good performance, eliminating the need to include FMG features. Interestingly, for the Efficient Logistic Regression classifier, the performance when using only FMG features outperforms that when using all features or only EMG. This is a peculiar case that highlights how certain classifiers may be better suited to specific sets of features. Besides the five models with the best results, these two exceptions are presented in Table 7. In any case, these two models, and in particular the last mentioned above, have a very low accuracy.

4. Discussion and Conclusions

This paper presents the preliminary results of the implementation of a bimodal system with EMG and FMG sensors in which two EMG + FMG pairs are placed in the flexor and extensor muscles. A total of thirty-six characteristics of these two acquired signals were used for three healthy individuals, and the dataset consisted of five different gestures. Even considering the sample bias that could be caused by this reduced number of participants, the main objective of this study is to evaluate the benefit, in terms of efficacy in the recognition of the gestures performed, that is obtained by the acquisition of the FMG signal simultaneously with the EMG signal, because this signal when used in isolation has some limitations that result, for example, from variations in the impedance of the skin interface.

MATLAB's Classification Learner was used, thirty-three classifiers were applied, and a study was also made on the possibility of reducing the number of characteristics, which will be an important point to reduce the processing time and consequently the response time of the bionic hand in the execution of gestures. For this, three different methods of selection of the characteristics were used, with different percentages (75%, 50%, and 25%) of the total of thirty-six characteristics.

The preliminary results presented focus on the most used metric, which is accuracy, but the results are also being analyzed with other metrics, namely, F-score and the area under the ROC curve. It is possible to verify how different classifiers have very different behaviors, with those that are more effective but more sensitive to the reduction of the number of characteristics and others that are more immune to this selection of characteristics.

Although this evaluation of the bimodal system is still ongoing, the results presented here reinforce the idea, supported by previous research, that the combination of EMG and FMG allows to improve the efficiency of machine learning models in gesture recognition. In some classification models, the results obtained using only the characteristics of the EMG sensors, or even only those of the FMG sensors, are a little better than with all the characteristics of the bimodal system. However, in these cases, the accuracy results are low, showing that these models are not suitable for this application. Thus, based on the analysis of the accuracy values obtained in this previous study, six of the thirty-three classification models initially considered were selected.

In this work, two studies were developed that we believe to be innovative. In one of them, the impact of each of the characteristics on success in the recognition of gestures was analyzed. From the five feature selection methods and with different numbers of features (36, 30, 24, or 18), it was possible to find a ranking showing the characteristics with the greatest impact for each of the five selection methods. From their analysis, it can be seen that these characteristics, being different between methods, allow us to draw the conclusion that those extracted from the extensor muscle have a greater presence in these rankings than those from the flexor muscle. It is not so evident that there is a predominance of the characteristics of one type of sensor, and it should also be remembered that a total of twenty-four EMG characteristics were used against only twelve FMG. Thus, although in three of the five selection models, the FMG characteristics appear only in the lowest places of the top 10, in the other two models, they appear in prominent positions in these rankings.

On the other hand, strategies for the optimization of the classification models were also studied through the configuration of some parameters of these models, for example, the number of layers in a neural network. These tuning of the parameters were tested simultaneously with the different methods of feature selection in order to combine computational efficiency with effectiveness in gesture recognition. These results, although still preliminary, showed that it is possible to obtain significant improvements in efficiency with the application of these optimization methods to a smaller set of characteristics.

So, as an ultimate conclusion, this study contributes to the field of myoelectric prostheses by exploring the implementation and testing the efficiency of a bimodal EMG/FMG signal acquisition system for the control of a bionic hand. It also seeks to contribute to paving the way towards optimizing the application of machine learning techniques for gesture recognition.

Finally, for the development and testing of gesture recognition techniques, in which the application of machine learning models has proven to be essential, the sharing of data in repositories has gained increasing importance in this research area. An example of a repository is NINAPRO, which promotes machine-learning research in human, robotic, and prosthetic hands [20]. In this sense, as a future work, and following the development of the project, with the consequent acquisition of data from more healthy volunteers, and including amputees, it is intended to share this data in an existing repository in this scientific area (for example Physio Net) or by creating a repository of our institution.

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