Gesture Recognition Through the Implementation of a Bimodal Acquisition System Using EMG and FMG Signals

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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. In this work, it 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. 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.

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) (Marques, 2020) (Silva, 2019).

The main objective of the work presented in this paper it 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

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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.

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 (Grushko, 2020). It also detects voluntary changes caused by the movement of tendons under the surface of the skin (e.g. in the wrist) (McIntosh, 2016).

The first work on the FMG technique as a modality for the control of myoelectric prostheses was published in 1999 (Abboudi, 1999) 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 present promising results on the possibility of using the FMG technique to predict movement intention in implementations of bionic hand prostheses (Citi, 2016) (Kadkhodayan, 2016) (Radmand, 2016). More recently, there is a growing interest in combining sEMG and FMG in order to create more robust control systems to be used by pattern recognition models (Jaquier, 2017) (Nowak, 2017) (Xiao,2017). 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., 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 (Jiang, 2020).

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 (Grushko, 2020). However, there are still several shortcomings that need to be addressed in order to be able to use FMG technology in commercial bionic prostheses (Xiao,2017) (Jiang, 2020) (Xiao, 2019).

In this paper, we will describe the implementation of a bimodal EMG/FMG system using the physiological signal acquisition platform, BITalino (Plux Biosignals), 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 (Rodrigues, 2022) (Rodrigues, 2023). 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. So our main differentiating mark is the choice of low-cost hardware, in order to obtain a similar or even greater efficacy with a smaller number of sensors than that described in the literature, based on an in-depth study that allows the selection of a smaller set of the best characteristics and supported by an optimized classification method. Preliminary results point to significant gains in the effectiveness of the classification of gestures, in line with the conclusions of other studies (Esposito, 2018) (Rafiee, 2011). These results, although still very preliminary, are also better than those reported in the literature for commercial systems with EMG sensors, with an accuracy of 87.96% vs 84.60% for these systems (Jiang, 2017).

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 but 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.

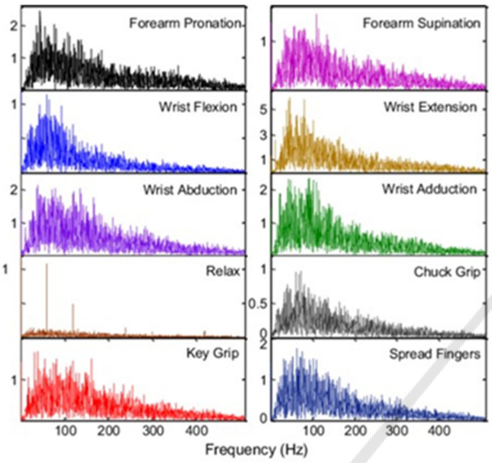

Figure 1: Power density spectra of EMG signals in hand gestures (from (Xiao, 2019)).

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. These limitations could be addressed through the project of a novel 3D printed adapter that achieves a more solid fixation of the sensor as well as the study of filtering techniques that would be able to cancel the noise induced by these sources.

For the acquisition of physiological signals, we used BITalino (r)evolution. 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, 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 ou 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)

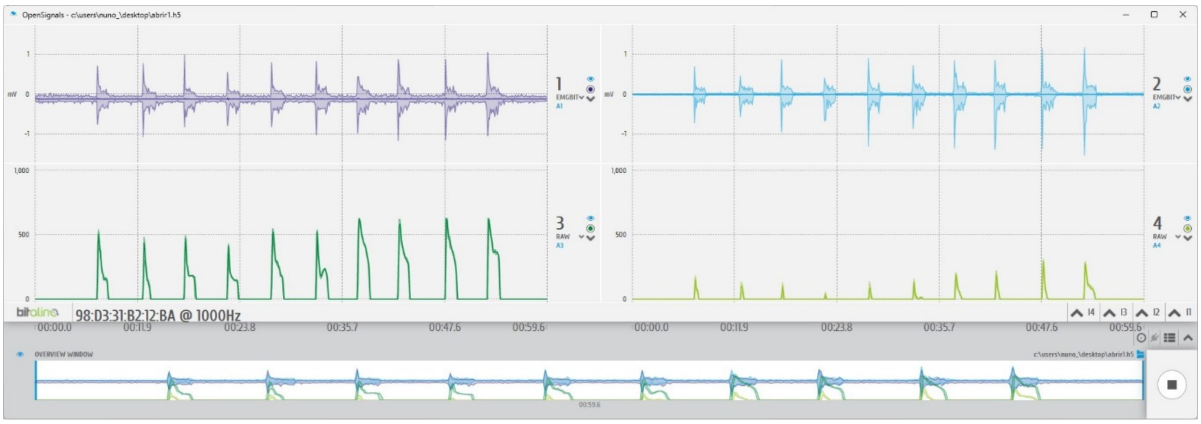

Figure 2: Previously stored data file in Opensignals, showing EMG (top) and FMG (bottom) signals for the "hand opening" gesture.

Table 2: Technical specifications of the EMG sensor.

Gain	1009
Range	±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

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 sensor.

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. Data acquisition from these four channels is commanded by the microcontroller unit of BITalino according to the previously defined acquisition rate. 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 it 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 seconds, 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.

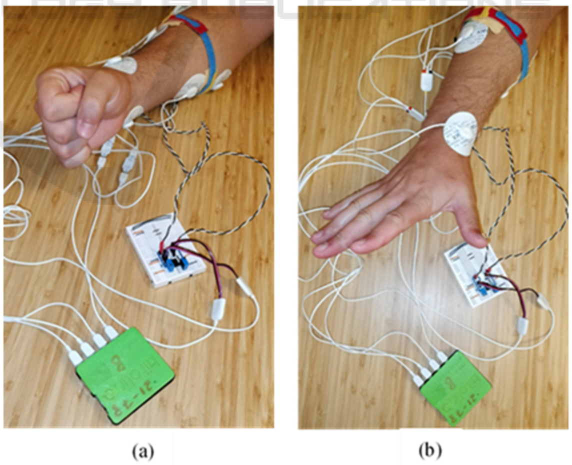

Figure 3: Acquisition of EMG and FMG signals: a) On the clasp of the hand; b) Opening the hand.

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 analog filtering as it is the case of a low-pass filter to cancel high-frequency noise (>500 Hz).

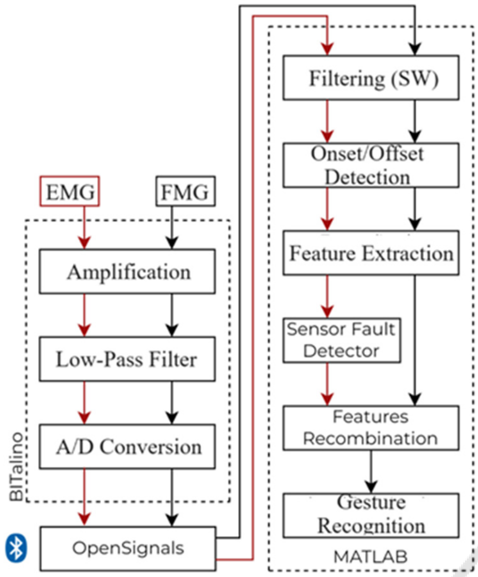

Figure 4: Steps of EMG and FMG signal processing.

After preprocessing, the data enters the phase of extracting the characteristics of the most relevant signals for the discrimination of gestures. Previously, it is 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 actually started to contract (onset) and when it stopped (offset). The result is 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 calcu-late the test function, and setting a threshold for onset detection. If the signal falls be-low 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 coin-cide 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.

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 (Pires, 2023).

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 from a detailed study of the application of different machine learning models.

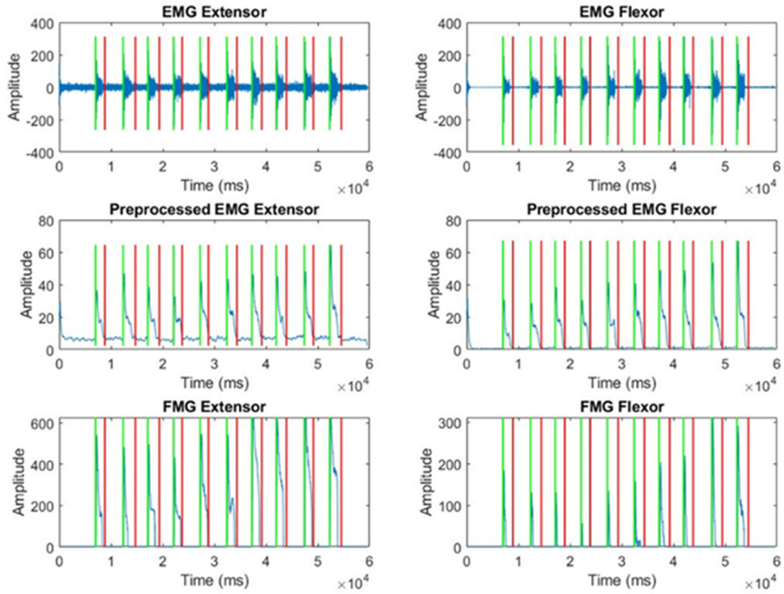

Figure 5: Example of FMG raw-signals and EMG raw and pre-processed signals. Green and red vertical lines shown are, respectively, the onset and offset time for each muscle activation.

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

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 6.(c) 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.

It is also possible to observe that there are only three characteristics (Mean Frequency, Peak Frequency and Mean Power Spectral Frequency), and only from EMG signal, that are frequency domain being all the rest time domain, which are usually preferred in sEMG based pattern recognition as they are easy and quick to calculate since they are based on the amplitude of the EMG signal (Christopher et al., 2018)

The collected data from the EMG and FMG signals of each muscle group, that consists on 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 Feature Selection

The preliminary results of this study show significant advances in the development of the gesture recognition system. In a first phase, a preliminary comparison of the thirty-three available classification models was made, using accuracy (or "effectiveness") as the main metric. In this study, these thirty-three classification models were trained and evaluated, using the built-in algorithms of the MATLAB Classification Learner tool. The techniques applied ranged from more linear approaches, such as Quadratic Discriminant, to more sophisticated methods, including SVMs and Neural Network architectures. From these study six classification models can be highlighted: Linear Discriminant, Quadratic SVM, Cubic SVM and three Neural Network architectures (Narrow, Medium and Wide). These models were trained with different

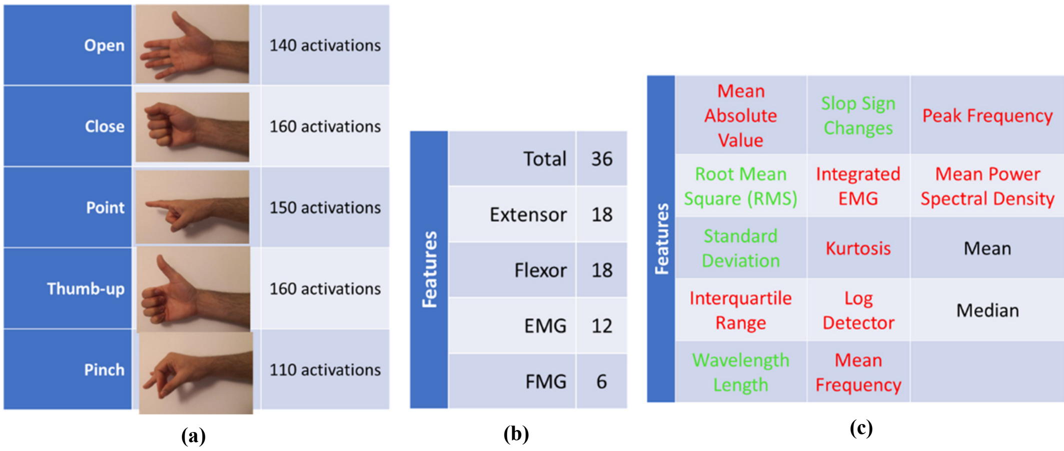

Figure 6: (a) Dataset for each gesture. (b) Distribution of the amount of features extracted per muscle and per sensor type. (c) 4 features are extracted from FMG and EMG signals simultaneously (green), 8 features from EMG signal (red) and 2 features from FMG signal (black).

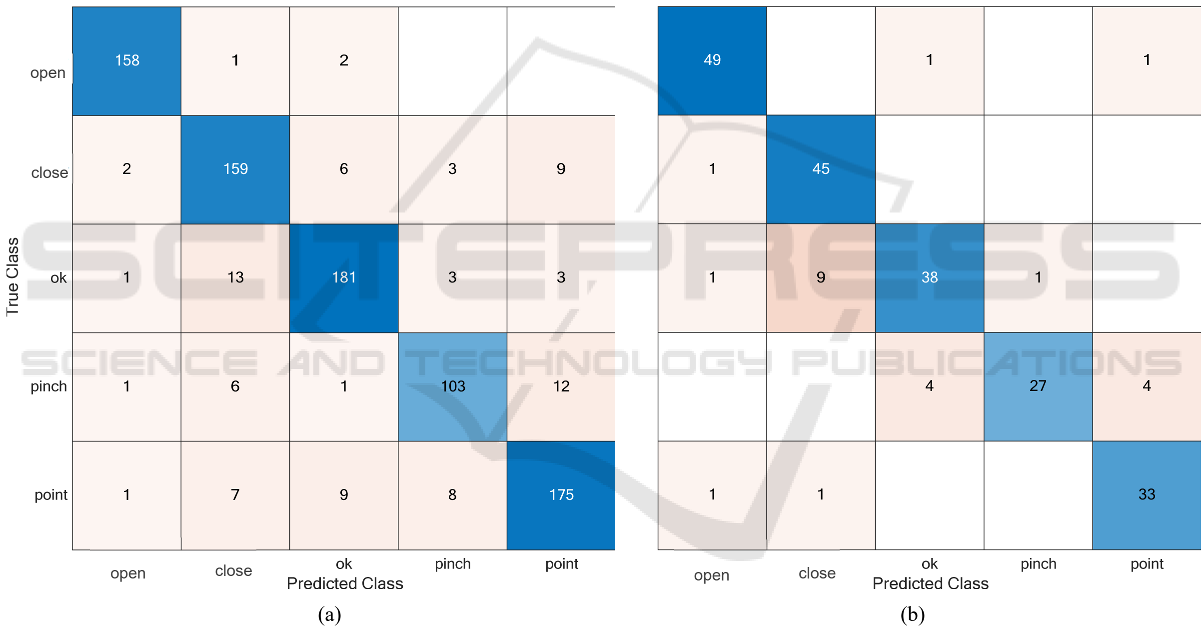

Figure 7: Confusion matrices for the Wide Neural Network model. (a) validation (b) test.

feature selection methods - ANOVA, ReliefF and Kruskal Wallis - and varying the percentage of selected features (75, 50 or 25%). standing out with 100% of the features, achieving validation and test accuracies of 91.7% and 93.8%, respectively. On the other hand, the classifiers based on neural networks showed a greater variability in their results, indicating a sensitivity to the selection of features. In particular, the wide neural network showed excellent performance without feature selection, achieving validation and testing accuracies of 95.1% and 93.8%, respectively.

Figure 7 shows the confusion matrices for an example of the trained models (Wide Neural Network), to show that these matrices help to understand how each model handles the different classes and provide a visual understanding of the models' performances.

Table 3: Comparison of the accuracy of the classifiers between the use of all data, EMG only and FMG only.

Classifier Model	Validation (EMG +FMG)	Test (EMG +FMG)	Validation (EMG)	Test (EMG)	Validation (FMG)	Test (FMG)
Linear Discriminant	74,07	75,46	62,96	64,35	50,69	53,24
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
Narrow NN	79,51	78,7	73,96	74,54	63,19	68,52
Medium NN	85,07	81,02	74,54	75	59,49	60,19
Wide NN	88,43	82,41	78,47	79,17	67,25	68,06

3.3 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 uses exclusively EMG characteristics. Table 3 details the performance of the six classifiers indicated above, when they use all characteristics, only EMG characteristics and only FMG characteristics.

4 DISCUSSION

This paper presents preliminary results of the implementation of a bimodal sys-tem 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. 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-one 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. So, as 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.

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