A Low-Cost Open-Source Bionic Hand Controller: Preliminary Results and Perspectives

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Abstract. This paper presents the current state of an ongoing project for the implementation of a low-cost bionic hand controller. Research had been conducted to evaluate the possibility of using MechanoMyoGraphic signals (MMG) as an alternative to ElectroMyoGraphic signals (EMG) that are usually acquired. Moreover the application of two novel and low-cost electrodes, one built from a conductive leather material, and another based on desktop 3D printing using conductive PLA (PolyLactic Acid), as an alternative to traditional pre-gelled Ag/AgCl electrodes was also evaluated. In addition to the search for the optimization of the quality of acquired signals, a solution for the control of the bionic hand had also been implemented using a very low-cost microcontroller (Arduino UNO). Results will be briefly presented from these works already carried out. A particular emphasis should be given to the success rate attained of 100% on detecting three out of four gestures selected, when using this very low-cost hardware platform. However false activations were a weakness of this solution. In order to optimize bionic hand control, the simultaneous application of three types of sensors (EMG, force and accelerometer) is ongoing. A description of this implementation as well as a presentation of its preliminary results will also be made.

Keywords: Electromyography (EMG) · Mechanomyography (MMG) · Bionic hand · Biomedical sensors · Feature extraction

1 Introduction

The field of hand prostheses is under continuous evolution because of huge research constantly being developed in order to improve the quality in the way they reproduce the functionalities of the human hand, but also in the search for more economical solutions. It is a typical area of biomedical engineering since, in addition to the knowledge of the anatomy of the forearm and hand muscles as well as of the electromyographic signals involved, it also encompasses the knowledge of physics, mathematics and engineering

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areas, which are demanded for the acquisition of signals and their processing. The advancement of 3D printing technologies this will also be an important area for the production of the low-cost prostheses itself.

Unlike myoelectric prostheses in which the opening and closing of the hand is made without individualized control of each finger, the bionic hands have a controller that, by collecting the myoelectric signal in one or more muscles, discriminates gestures through feature extraction and with the help of machine learning techniques.

This work aims to address only one of the strands that contributes to the success of bionic hands and that is the improvement of the quality of the acquired signal, with a view to the implementation of a low-cost bionic hand.

In spite of the typical approach of using EMG signals, there are some drawbacks that have led to the attempts of extracting other type of information, namely to predict muscle forces from EMG signals using the wavelet transform [1]. One of these drawbacks is the fact that EMG signals are often degraded due to electromagnetic interference and implies a large amount of processing time for features extraction [2].

In contrast, the mechanical change of the muscles can be measured by a method with sensitivity to the position / motion of a small area in surface of the muscle, and is typically known as MMG (MechanoMyography). Different type of sensors had been used in several studies reported in literature, since the application of microphones and/or accelerometers [3–6] through force sensors [2] or even light detectors, namely IR (InfraRed) sensors [7, 8], in an individual manner or some of them together even with also EMG sensors [9–12].

In this work, preliminary results of the application of MMG sensors, such as FSR (Force Sensitive Resistor) and IR sensors with the BITalino (Plux Biosignals) platform have already been obtained [13]. It has also been studied the possibility of applying of its EMG sensor module with two novel and low-cost electrodes: one built from a conductive leather material, and another based on desktop 3D printing using conductive PLA (PolyLactic Acid), by comparison with pre-gelled Ag/AgCl electrodes, considered as the reference electrode [14].

This paper will summarize these studies and their preliminary results. Firstly it is presented the evaluation of the application of MMG sensors as an alternative to traditional EMG and then the evaluation of the application of new electrodes more economical and reusable as an alternative to traditional pre-gelled Ag/AgCl. It will also feature the low-cost platform based on Arduino Uno which was developed for bionic hand control, using only EMG signals. For this implementation, an onset/offset design algorithm was developed to meet the requirements of real-time control and the limitations of memory space and processing speed of this low-cost microcontroller [15]. Finally, the platform that is currently being implemented will be described. It is based on the integration of MMG (FSR and accelerometer) and EMG sensors with the aim of optimizing the quality of the acquired signal and thus the success rate of the bionic hand controller.

2 Study of Mechanomyographic Alternatives to EMG Sensors

A comparative study was made of the application of a FSR and a IR sensor with the reference signal in the scope of this work, the EMG signal [13]. A summary of the main specifications of these three sensors can be found in Table 1.

Table 1. Main specifications of each sensor.

EMG Module specifications	
Gain	1000
Range	± 1.65 mV
Bandwidth	10-400 Hz
FSR 400 Specifications	
Force Sensitivity Range	0.110.0 N
Force Repeatability	± 2%
Number of actuations (life time)	10 million
QTR-1A Reflectance Sensor Specifications	
Optimal Sensing Distance	3 mm
Maximum Sensing Distance	6 mm

The acquisition of the signals from each sensor is performed through the hardware platform BITalino Plugged; its OpenSignals software enables real-time data acquisition and recording in a CSV (Comma-Separated Values) format. These data is subsequently used in MATLAB (MathWorks ®) for data processing and analysis.

Besides the BITalino EMG sensor it was then used a force sensor in order to react to changes in the muscle volumes, for which an FSR 400 sensor (Interlink Electronics, USA) was selected. A third sensor was used in this study to extract features related with the variations in light reflected at the skin surface, as a result of the changes in muscle volume due to the contraction. For the acquisition of this data, a QTR-1A reflectance sensor (Pololu Corporation, USA) was used. It includes an IR LED (Light Emitting Diode) and a phototransistor, and the output varies proportionally to the amount of light reflected on a surface.

An extremely important issue for the acquisition of signals from any of these three sensors, with a fair signal-to-noise ratio and appropriate sensitivity, is a correct placement of the sensors. Photos of the placement of each of the three sensors are shown in Fig. 1.

For FSR and IR sensors, raw-data was used in spite of a variable baseline that eventually could be corrected through the use of the derivative of these signals. The EMG sensor is used in a bipolar differential front-end for a higher signal- to-noise ratio. Firstly a bandpass filter was applied to raw-data with a frequency range of 20 to 500 Hz [16]. It is important to cancel the powerline noise, so a bandreject filter is used for the 50–60 Hz range. Figure 2 shows an example of raw-data for each sensor.

For a more objective comparison between those signals, signal-to noise ratio (SNR) which is a quite well established parameter, it was calculated through the ratio of peak-to-peak values of signals from muscle activation periods and of noise from rest period.

Table 2 shows a summary of these SNR results as well as those achieved for onset/offset detection rates and in Table 3 is presented the success rate in gesture identification.

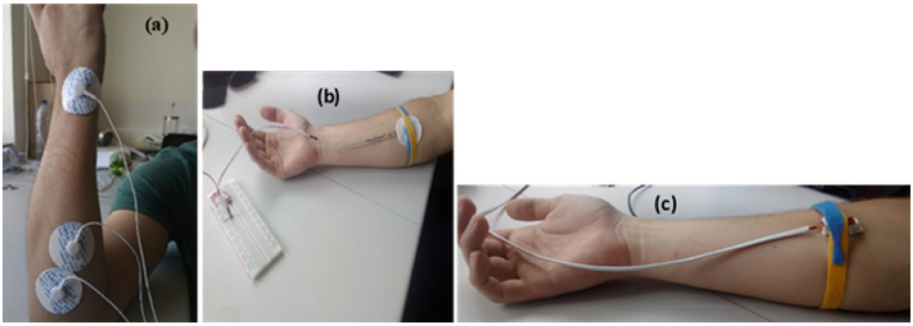

Fig. 1. Photos of the sensors placement. Three EMG pre-gelled electrodes (a), FSR sensor with velcro strap for fixation (b), and IR sensor mounted inside a 3D printed fixation support and velcro strap for fixation (c).

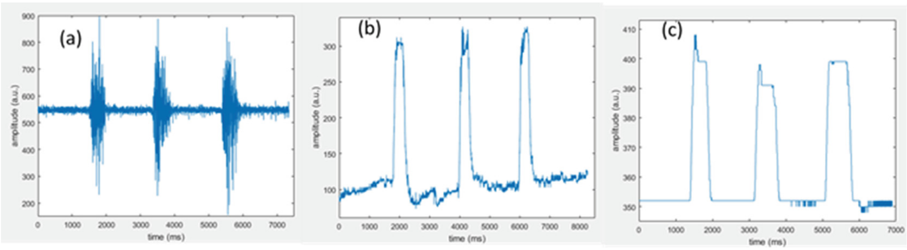

Fig. 2. Example of raw data of each sensor in case of a gesture of close. EMG (a), FSR (b) and IR sensor (c).

Table 2. Summary of SNR analysis and Onset/Offset recognition rates for each of three sensors.

Sensor	Gesture	SNR (dB)	Onset/Offset Detection	
			Detected/Total	(%)
EMG	Open	4.5	54/54	100/
	Close	2.1	70/72	97%
	Point	2.2	23/39	59%
FSR	Open	10.0	39/42	93%
	Close	9.6	87/96	91%
IR	Open	9.1	46/48	96%
	Close	14.0	59/60	98%

For this study each sensor was placed individually and acquisitions were carried out using similar timing parameters. The sampling data was collected from four healthy subjects (2 men, 2 women). In each acquisition, the same gesture was made three times. Each gesture lasts for approximately three seconds with similar rest time between them.

Table 3. Percentage of success in gesture identification for each of three sensors.

Sensor	Gesture	Gesture Identification	
		False/True	(%)
EMG	Open	6/48	89%
	Close	22/48	69%
	Point	2/21	91%
FSR	Open	0/39	100%
	Close	13/74	85%
IR	Open	0/46	100%
	Close	0/59	100%

3 Electromyography with Novel Electrodes

A study was also made regarding the applicability of novel electrodes with the purpose of reducing its cost [14]. So a conductive leather material was used to build a low-cost electrode as well as conductive PolyLactic Acid (PLA) taking advantage of 3D printing. These two electrodes are shown in Fig. 3.

The conductivity of a leather material may be in a range that is demanded for the operation of touch-sensitive electronic devices without depending on a conductive path to the human body. To change its conductivity electrically conductive metallic particles can be incorporated which could allow its application for EMG electrodes.

PLA can be considered cost efficient to produce and it is biodegradable. Amongst a wide set of PLA applications it is already well established its use for biodegradable medical devices. PLA has also the property of melting easily so it is an obvious choice for some interesting applications in 3D printing. In this case it is intended to replace traditional EMG electrodes through its function with conductive properties.

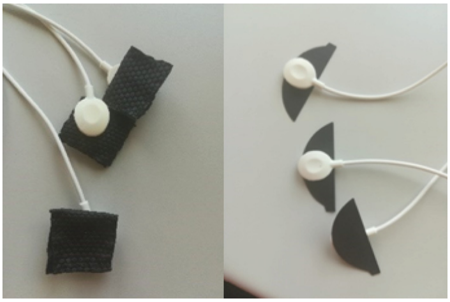

Fig. 3. Two novel electrodes. Conductive leather (left) and PLA (right).

The acquisitions from 15 healthy young subjects were carried out using similar timing parameters. The sampling data is summarized in Table 4. Each acquisition contains in average a set of four same gestures executed for around three seconds each and separated by a resting time of similar magnitude. For this study the first choice was to use six different gestures (Open, Close, Point, Pinch, Flexion, Extension).

MATLAB tools were used to perform feature extraction. Amongst others that were initially also considered, a set of six features were selected in order to be evaluated in each muscle activation [17]: Maximum, Minimum, RMS, Mean; Standard deviation, and Peak-to-Peak value. For gesture recognition it was necessary to find an appropriate data science and machine learning platform that should use a dataset that comprises the extracted features i.e. the values of those six features, calculated for each correctly detected muscle activation. These whole data was evaluated in RapidMiner.

Table 4. Description of the whole data acquired: Number of acquisition files (AcqF) and of muscle activations (MAct).

Sensor	Gesture	open		close		flexion[1]		extension[1]		pinch		point	
	Electrodes	AcqF	MAct	AcqF	MAct	AcqF	MAct	AcqF	MAct	AcqF	MAct	AcqF	MAct
EMG	Ag/AgCl	9	37	5	19	6	21	5	18	7	29	9	37
	Leather	12	47	12	59	11	46	8	30	8	32	12	47
	PLA	11	46	8	33	8	34	6	24	8	33	11	46

[1] Entire hand flexion/extension

In order to optimize the success of RapidMiner on gesture recognition it was important to define the ratio of data used for training and data used for evaluating gesture recognition. After some tests the dataset was splitted so that 70% of the whole data was for that training with the purpose of learning how to use the combination of six extracted features to achieve an higher success on the recognition of the six gestures. Consequently the remaining 30% of the data was effectively applied on the prediction of the different gestures. Also the different processing tools provided by RapidMiner were tested from which two (Decision Tree and Neural Network) were used.

As mentioned the initial goal was to perform the gesture recognition for all the six gestures. Unfortunately it was concluded that this amount of data collected from just one sensor and always in the same muscle for all acquisitions was insufficient to succeed. A less ambitious goal was then established that consisted on evaluating the accuracy on the recognition of sets of two, three and four gestures.

Amongst several parameters that RapidMiner computes, accuracy was chosen for this analysis. In fact accuracy is defined as the fraction of whole gestures that are correctly classified (TP + TN). In this manner it describes the overall effectiveness of the classification process. In a more complete way it is given by the ratio of those whole gestures that are correctly classified to the whole data (TP + FP + TN + FN). Figure 4 summarizes graphically those values of accuracy computed in RapidMiner, in order to compare the overall accuracy computed for each sensor/electrode type as well as to compare that accuracy for some gesture combinations.

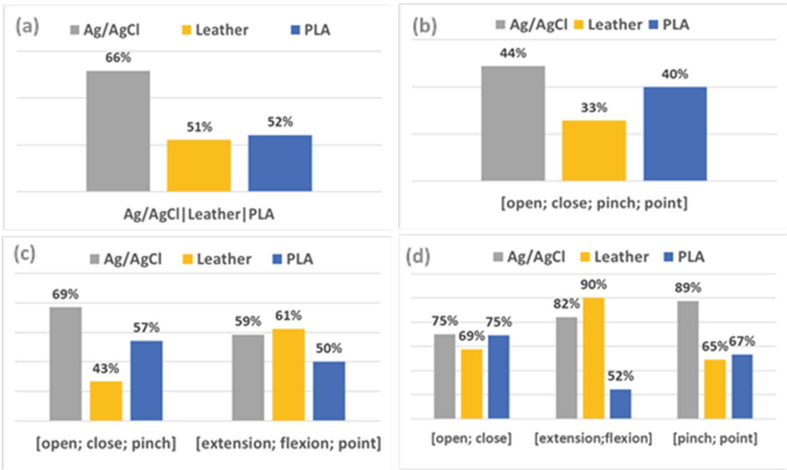

Fig. 4. Bar graphs showing a comparison of the accuracy in gesture recognition between electrode types, for the whole results available (a) and for each gesture combination (b-d).

4 Bionic Hand Controller

The success on the control of a bionic hand depends heavily on success on the identification of gestures. It is then essential to optimize onset/offset detection so that feature extraction is also improved. On the other hand this control requires that, in real time, onset/offset detection is made, as well as feature extraction and consequent identification of gestures. To implement all these features in a microcontroller ATmega328 microprocessor with 16 MHz clock speed and 32 kBytes of memory, an onset/offset detection algorithm was adapted [15]. This controller uses only the EMG signal acquired with pre-gelled Ag/AgCl electrodes. The BITalino EMG sensor was used to acquire these signals. This BITalino platform was used for the simultaneous acquisition and visualization of data in OpenSignals with the purpose of providing a mean for support on the debug of the algorithm running in the Arduino UNO.

The evaluation of the success was carried out using a servo-driven bionic-hand controller prototype, as shown in Fig. 5. Four different gestures were executed: Open, Close, Point and Pinch. Each finger is controlled by a dedicated Micro Servo SG90 (TowerPro). Each gesture is accomplished by an adequate combination of finger activation.

Additional factors were identified that may reduce detection success such as the noise in the EMG signals coming from electromagnetic interference, namely that the different rotation of the servomotors to carry out each finger generates different noise. Noise was also noted as a result of forearm movement artifacts. Due care was taken with regard to noise reduction by reducing the length of cables and winding them up. Even with the conditions presented, the results obtained for different gestures were satisfactory, as shown in Table 5.

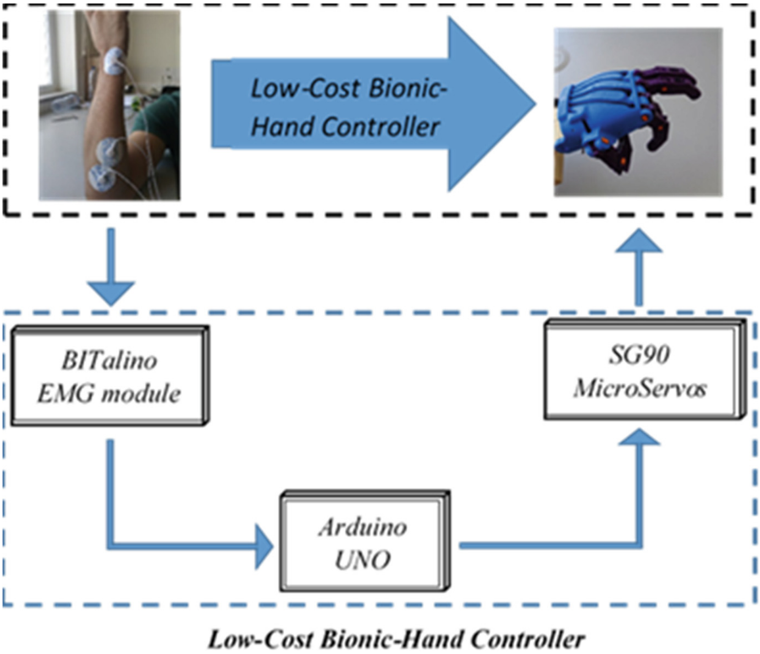

Fig. 5. Scheme of the prototype of the bionic-hand controller.

Table 5. Results of success on detection of muscle activation for the execution of different gestures.

Gesture	close	open	point	pinch
# performed	20	20	20	10
# detected	20	14	20	10
# not detected	0	6	0	0
# false activations	1	4	2	0
Success rate	100%	70%	100%	100%
Error rate	5%	50%	10%	0%

5 Platform with Integration of EMG and MMG Signals

In order to optimize hand control it is essential to improve the quality of the information acquired, as this will enhance the identification of the different gestures. As already mentioned there are numerous studies described in the literature, which have in common the search for sensors that can be used alternatively or in addition to the EMG signal [2–12]. Although the preliminary results presented here show that the IR sensor has a good SNR ratio, similar to or even higher than that of the FSR, it was verified that it has a more limited applicability with regard to the diversity of gestures detected. On the other hand, it is possible to improve the quality of the signal acquired with the FSR, provided that the most appropriate and properly sized front-end circuit is used, as well as with greater care in fixing and ensuring the application of force in the sensitive area of the sensor. Another type of sensor with positive results described in the literature in this type of application is the accelerometer [5, 6]. The decision was then to add the accelerometer ADXL335 (Analog Devices). Which is a 3-axis accelerometer, that allows to measure accelerations up to 3g. For this purpose we will apply a module that allows direct integration with Arduino /BITalino as well as a easier placement in muscle. This module also has the possibility of configuring a bandwidth up to 200 Hz, which will allow to cover the frequencies present in muscle activity.

Also with the purpose of improving the quality of the acquired signal, there is a plenty of works described in literature that use only the EMG signal but with multiple channels. This approach allows to collect information separately from the various muscles activated in the different gestures [2].

Analyzing the different options both in terms of type of sensors or use of multiple acquisition channels, seeking to maintain their low cost, we opted for the integration of seven signals/acquisition channels from three types of sensors: EMG, FSR and accelerometer. Two of them (EMG and FSR) are duplicated, placed in the flexor and extensor muscles, while the accelerometer, which uses three acquisition channels, one for each axis, is placed only in the flexor. Figure 6 illustrates the placement of these sensors/electrodes.

Seven BITalino acquisition channels will then be used, and the data is acquired from a group of volunteers and according to a previously defined protocol. Data processing and feature extraction will be performed on MATLAB. The identification of the different gestures will then be attained from the introduction of the datasets with the characteristics of the seven acquired signals, using one selected data science and machine learning tool.

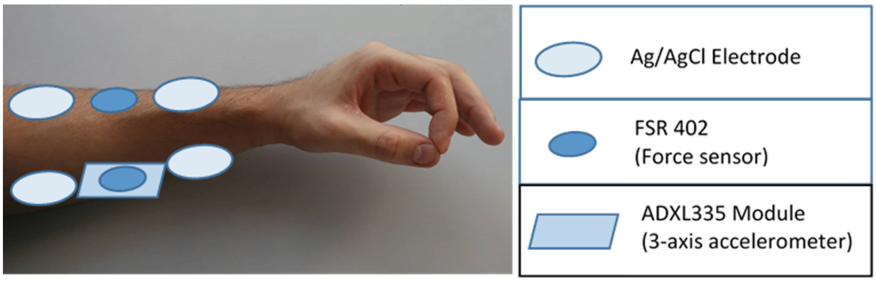

Fig. 6. Scheme of the integration of three type of sensors (EMG, FSR and accelerometer) showing the placement of Ag/AgCl electrodes and FSR in both flexion and extension muscles and accelerometer only in the flexion muscle.

5.1 Preliminary Tests

A first approach to the implementation of these different types of sensors was made using the two force sensors and two EMG sensors, in a total of four acquisition channels. Data were acquired from one ordinary healthy subject that performed five different gestures (*Open*, *Close*, *Pinch*, *Point* and *Thumb-up*). In each acquisition it was always executed the same gesture for ten times with a duration and interval approximately constants.

The data was acquired through four BITalino channels with a 10-bit ADC each. This data was viewed in real-time in Opensignals and later stored in a file for further processing in MATLAB ®. In these preliminary tests, no processing was carried out to the EMG signal and the onset/offset detection of each muscle activation was accomplished from the acquired FSR signal. This was performed separately for the FSR and EMG signals acquired from the flexor muscles and extensor muscles.

This first approach to the integration of these sensors had as main objective to evaluate their advantages over the platform initially used with only one channel of acquisition of an EMG signal. This analysis should be made according to three complementary perspectives:

1. Four signals are acquired through four channels, simultaneously;
2. The signals are of two different types: EMG and MMG;
3. Sensors are placed in two different locations: flexor and extensor muscles.

Using a simple criterion for the validation of onset/offset detection that has had a minimum duration of 0.5 s, the success rate was high, as shown in Table 6.

Table 6. Results of success on detection of muscle activation for the execution of different gestures. Flex and Ext mean Flexor and Extensor muscles, respectively.

Gesture	close		open		point		pinch		thumb-up	
	Flex	Ext	Flex	Ext	Flex	Ext	Flex	Ext	Flex	Ext
# performed	10	10	10	10	10	10	10	10	10	10
# detected	10	10	8	10	10	6	10	7	10	10
# not detected	0	0	2	0	0	4	0	3	0	0
# false activations	0	0	0	0	0	0	0	0	0	0
Success rate	100%	100%	80%	100%	100%	60%	100%	70%	100%	100%
Error rate	0%	0%	20%	0%	0%	40%	0%	30%	0%	0%

Figures 7, 8, 9 show a sample with a period of 20 s relative to the four signals acquired for each of three different gestures chosen amongst the five executed. Figure 7 shows that for the *Open* while the EMG signals acquired in the flexor and extensor muscles are very similar the FSR signal obtained from the extensor muscles has an amplitude that stands out from that relative to flexors.

In opposition to the previous case, Fig. 8 shows that for *Pinch* the amplitude of the acquired FSR signal for the flexor and extensor muscles are very similar. But the complementarity between FSR and EMG signals, associated with different behaviors

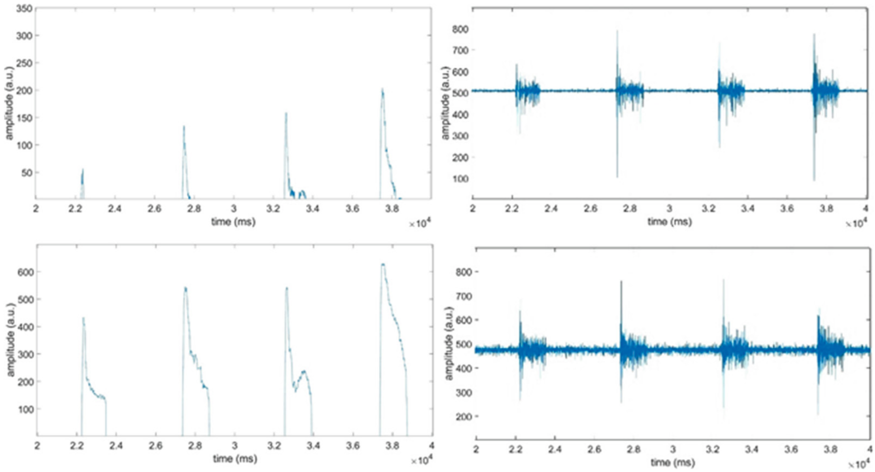

Fig. 7. Four signals acquired from flexor muscles (top) and extensor muscles (bottom) for *Open*. (Left) FSR and (Right) EMG signals.

for different gestures, is a result that meets our expectations and is very useful for the success in gesture recognition.

Finally, and unlike the two previous gestures, in *Thumb-up* the success rate in detecting their activations was 100%. In Fig. 9 it can be observed that the amplitude of the two FSR signals is superior to that of the other two gestures, with a greater amplitude in the case of flexor muscles, in which it is also shown to have a less fluctuating amplitude during activation.

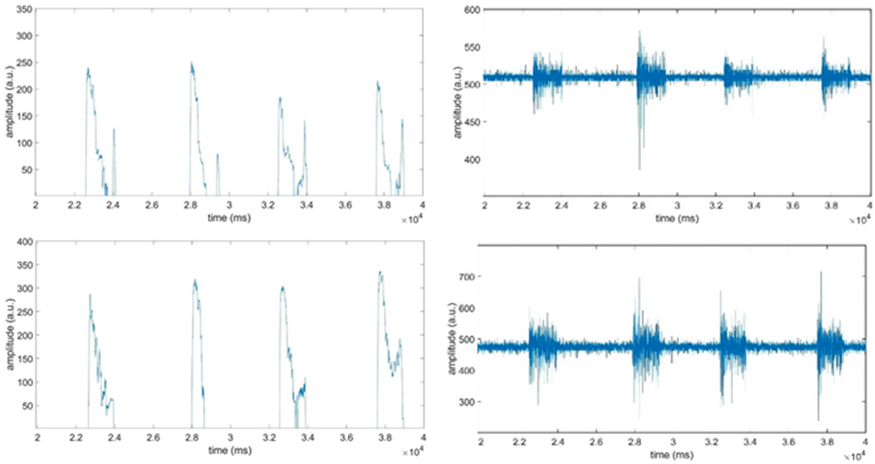

Fig. 8. Four signals acquired from flexor muscles (top) and extensor muscles (bottom) for *Pinch*. (Left) FSR and (Right) EMG signals.

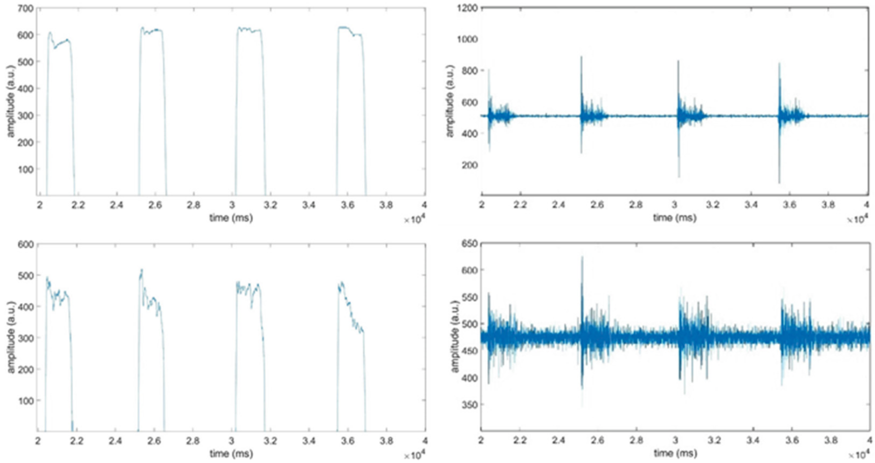

Fig. 9. Four signals acquired from flexor muscles (top) and extensor muscles (bottom) for *Thumb-up*. (Left) FSR and (Right) EMG signals

The mere observation of the signals acquired by these four channels confirms that the amount of information that is available with the consequent characteristics that can be extracted will be an added value for success in gesture recognition. Moreover, with the FSR signals the onset/offset detection becomes easier. In the case of EMG signals, one should look for the characteristics that will contribute the most to this success and which at the same time imply a shorter processing time with a view to its application in a low-cost bionic-hand controller.

6 Discussion and Conclusions

Results of the application of two MMG sensors, a FSR and an IR reflectance sensor, and their comparison with EMG signals have shown successful results in gesture recognition and a high SNR (Signal-to-Noise Ratio). It was also shown a slightly better ability of EMG sensor to detect different gestures, but simultaneously it had a lower success in gesture identification. IR sensors have shown similar results comparatively to FSR in the ability to detect different gestures but an even better success in gesture identification. Also IR and FSR signals had shown higher SNR than traditional EMG signals, for the two gestures that those two sensors were able to detect.

On the other hand the comparison between electrodes types had shown a slightly lower accuracy of the conductive leather and PLA in relation to the common electrodes. Nevertheless the conductive leather material electrodes have shown an improved accuracy in two of the total of six gesture combinations considered.

In spite of their lower overall accuracy in gestures recognition, in comparison to pre-gelled Ag/AgCl electrodes, the results obtained for the novel electrodes are very similar to those traditional EMG electrodes in, at least, half of the six gestures. The exceptions are the point and pinch gestures for conductive leather material, and those plus extension gesture for conductive PLA electrodes. Electrodes with a larger area and/or more appropriate shape, as well as a more efficient process for their fixation, should improve the signal-to-noise ratio.

The application of a low-cost bionic hand controller based on Arduino UNO with the proper requirements of real-time control has forced the development and testing of algorithms appropriate to the requirements imposed by a limitation in terms of the amount of available memory and processing speed. The test setup with the simultaneous acquisition and visualization of the EMG signals used for hand control, by Arduino and BITalino, allowed the implementation of an algorithm with a sampling rate of 1 kHz.

Although no type of processing of the acquired EMG signals was performed, it was possible to obtain very promising results regarding the success rate on performing the four different gestures considered. There have been some false activations that, in addition to using the raw EMG signal, will also be associated with some noise resulting from the micro servo SG90 option, which was motivated by its low cost, for the individual activation of the fingers of the hand. In fact, it was possible to identify that they constituted an additional source of noise, which affected the breadth of the fluctuations in the base level of the signal, with the muscle relaxed, depending on the gesture associated with the previous muscle activation.

Based on these preliminary results and those of other studies described in the literature, we opted for the implementation of a platform that complements EMG signals with two other MMG signals collected by a force sensor and an accelerometer. A next phase of this work is then underway in which these three types of sensors (EMG, FSR and accelerometer) will be integrated, and signals from the flexor and extensor muscles will be collected at the same time, in a total of seven acquisition channels. With this approach it will be possible to minimize the limitations resulting from the interferences to which the EMG signal is subject, maintaining the future possibility of implementing a low-cost controller, even with greater requirements in terms of memory space and processing capacity than the Arduino UNO, used in the preliminary version of the controller. It will be necessary to develop the more demanding algorithm in terms of the acquisition of the different acquisition channels, as well as in their processing, with possible implementation also of EMG signal filtering.

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