Study of Mechanomyographic Alternatives to EMG Sensors for a Low-Cost Open Source Bionic Hand

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1 Introduction

Owing to the huge evolution in the sensor and microprocessor technologies, as well as in 3D (Three-Dimensional) printing, the development of prosthesis has undergone a great transformation. Particularly for the hand, the myoelectric solution is still the choice of the majority of amputees, although limited by the prohibitive price of bionic hands. Differences are in the versatility of each solution, because in the myoelectric case the hand is opened and closed being able to grasp objects. In opposition, bionic hands are capable of executing individual motions of the fingers, subsequently having a higher functionality approaching the human hand. There is a plethora of commercial hands with a wide range of costs; two of them are shown in Fig. 1. Its cost greatly varies from 5 to 50 k euros, for Open Bionics and Michelangelo hands.

The aim of this work is to study the effectiveness of low-cost sensors for the replacement of EMG (ElectroMyography) sensors commonly used for upper-limb prosthesis. Any movement/gesture executed by a human hand is triggered by command signals sent by the brain, and it implies the ability of nervous cells

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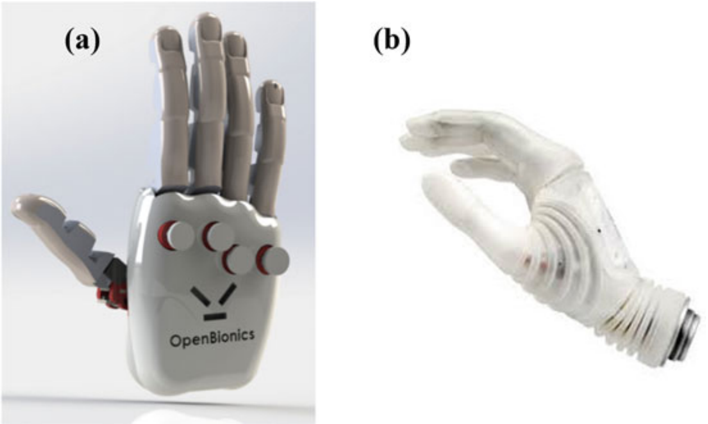

Fig. 1 Examples of commercial hands. Open Bionics (**a**) and Michelangelo (**b**)

to transmit electrical signals. In the typical approach, EMG sensors acquire these myoelectric signals through electrodes placed in appropriate locations, taking into consideration the muscles involved in each movement.

Surface-mounted electrodes are preferably used in case muscles provide signals with enough intensity to be detected. These electrodes, placed on the skin surface, capture the aggregated activity within the area of detection. Three electrodes are used with their locations being chosen depending on the muscles activated in a certain gesture. One of the electrodes is the ground electrode, typically placed in a bone region (electrical neutral) and the other two are active electrodes that collect a signal whose amplitude is proportional to the electrical activity differential between them, and also to the electrode area.

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 those drawbacks is the often degradation of EMG signals due to electromagnetic interference which implies a large 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). The possibility of acquiring a mechanical deformation map seems potentially interesting as the shape of the muscles changes when different sets of fingers are moved. It has already been implemented using FSR (Force Sensitive Resistor) [2]. Also the application of load cells is described in literature [3].

Another obvious choice to detect mechanical changes is light instrumentation. Amongst the vast offer in these types of sensors, affordable options are available that integrate, in a single package, a light source and detector that could be easily linked to a biosignals acquisition hardware platform.

In this paper we describe and present the results of the application of two MMG sensors and their comparison with EMG signals. Those MMG sensors, an FSR and an IR (InfraRed) reflectance sensor, have shown successful results in gesture recognition and a high SNR (Signal-to-Noise Ratio) in spite of a lower ability to detect different gestures.

2 Materials and Methods

2.1 Sensors

As already mentioned, the reference signal in the scope of this work is the EMG signal. A BITalino EMG sensor was used, which is capable of measuring signals with maximum amplitude of ±1.65 mV and frequencies in the range of 10–400 Hz. A summary of the main specifications can be found in Table 1.

One option for obtaining MMG signal is to use a force sensor in order to react to changes in the muscle volumes, for which an FSR 400 sensor (Interlink Electronics, USA) was selected. It is capable of sensing forces from 0.1 to 10 N (Newton) and it has a circular form factor with 7.62 mm in diameter. A summary of the main specifications can be found in Table 1. The force sensitivity is dependent on the electronic circuit used to achieve the force-to-voltage conversion, which can be realized using a voltage divider followed by an op-amp.

Finally, 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 (InfraRed Light Emitting Diode) and a phototransistor, and the output varies proportionally to the amount of light reflected on a surface. As the light intensity increases (i.e., greater reflection occurs), the lower is the output voltage. It is able to measure a maximum distance of 6 mm, with an optimal sensing distance of 3 mm.

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	0.1–10.0 N
Force repeatability	±2%
Number of actuations (life time)	Ten million
QTR-1A reflectance sensor specifications	
Optimal sensing distance	3 mm
Maximum sensing distance	6 mm

2.2 Data Acquisition

For this study each sensor was placed individually and acquisitions were carried out using similar timing parameters. The sampling data from four healthy subjects (two men, two women) is summarized in Table 2, from which it is possible to observe that, in each acquisition, the same gesture is made three times. Each gesture lasts for approximately 3 s with similar rest time between them. It is also important to explain that for FSR and IR sensors the acquisition of data from other gestures besides open and close would require the design of a new holder for its fixation and placement that can adapt two or more sensor units.

The acquisition of the signals from each sensor is performed through the hardware platform BITalino Plugged[1]; its OpenSignals software enables real-time data acquisition and recording in a CSV (Comma-Separated Values) format. These data is subsequently used in Matlab[2] (MathWorks, Inc.) for data processing and analysis.

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. 2.

From preliminary signal acquisition different strategies were implemented for each sensor, taking into account their sensing parameters. EMG signals were acquired using three pre-gelled electrodes, whose correct placements were chosen taking into consideration the data available in literature [4].

In the case of FSR signals, initially two different positions were tested for open and close gestures, but no features could be extracted. Because of its operation, the IR (reflectance) sensor has different requirements for its placement. It was found that the placement in the two different positions shown in Fig. 2 is suitable to detect open and close gestures.

Table 2 Summary of sampling data

Sensor	Gesture	#Acquisitions	#Muscle activations
EMG	Open	18	54
	Close	24	72
	Point	13	39
FSR	Open	18	42
	Close	32	96
IR	Open	16	48
	Close	20	60

[1] http://bitalino.com/datasheets/BITalino_Plugged_Datasheet.pdf.

[2] https://www.mathworks.com/products/matlab.html.

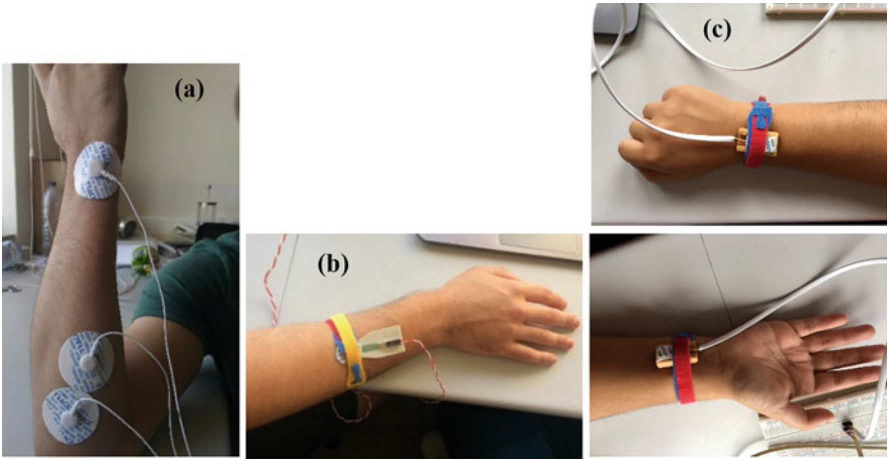

Fig. 2 Photos of the sensors placement. Three EMG pre-gelled electrodes (**a**), FSR sensor with velcro strap for fixation (**b**), and IR sensor mounted inside a 3D printed fixation support and velcro strap for fixation (**c**)

2.3 Data Processing

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 20–500 Hz [5]. It is important to cancel the powerline noise, so a band-reject filter is used for the 50–60 Hz range. Figure 3 shows an example of raw data for each sensor.

The visualization of the signals acquired from each sensor was important in an initial stage but a more objective comparison between those signals should be attempted. Signal-to noise ratio (SNR) is a quite well-established parameter; hence, it was calculated through the ratio of peak-to-peak values of signals from muscle activation periods and of noise from rest period.

Table 3 shows the SNR values in dB for each of the three sensors and each of the gestures [6]. As it was predictable from the signals shown in Fig. 3, FSR and IR signals have a higher SNR than EMG signals.

2.4 Onset/Offset Detection

A crucial step for success in gestures identification is the onset/offset detection. The correct feature extraction from the signal requires a high precision in the determination of the time interval in which the muscle is active. Several methods

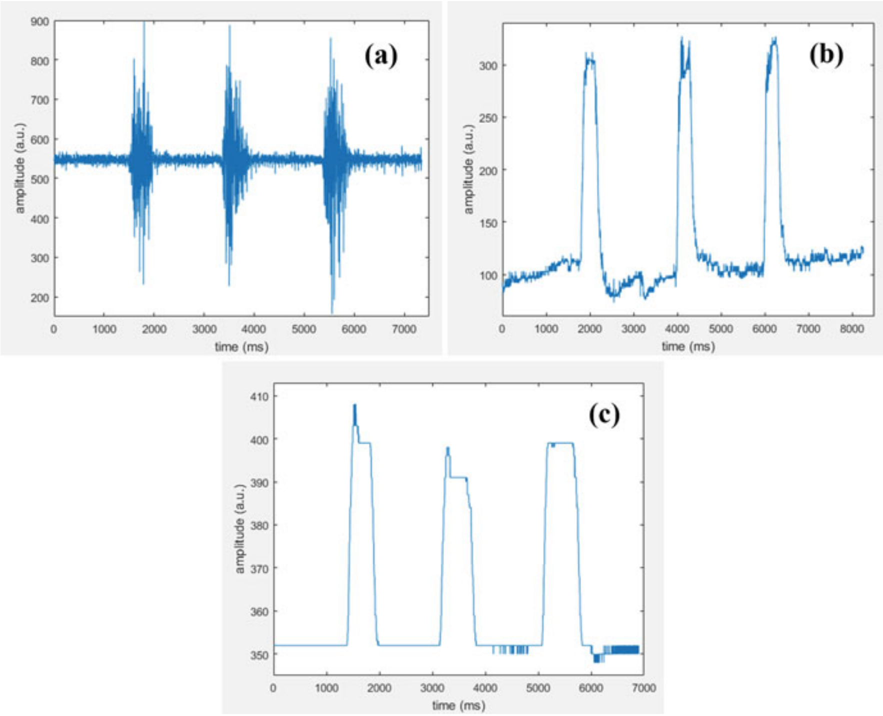

Fig. 3 Example of raw data of each sensor in case of a gesture of close. EMG (**a**), FSR (**b**), and IR sensor (**c**)

Table 3 Summary of SNR analysis

Sensor	Gesture	SNR (dB)
EMG	Open	4.5
	Close	2.1
	Point	2.2
FSR	Open	10.0
	Close	9.6
IR	Open	9.1
	Close	14.0

are available in literature [7–9], using different definitions of thresholds to find the beginning and end of a muscle activation, considering a single threshold of signal amplitude based on a deviation from the baseline of three times the standard deviation [7], or using a double threshold [8, 9]. Other method available in literature detects the muscle activity onset, using the energy of the signal, as it increases with the start of the activation [10]. In this work, the method selected for onset detection it is based on one proposed in literature [9].

The method used in this work for onset detection is based on one also described in literature [9]. It uses a double threshold with a moving average for calculating

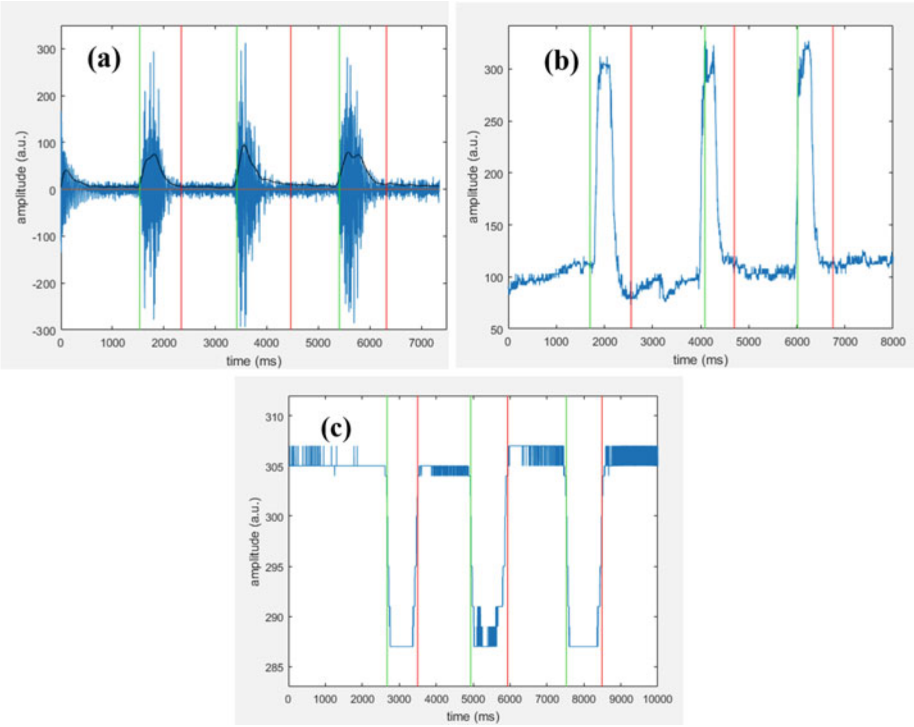

Fig. 4 Example of application of onset/offset detection in signals from each sensor, in case of a gesture of close for EMG and FSR, and open for IR sensor. EMG with envelope curve (**a**), FSR (**b**), and IR sensor (**c**)

an adaptive threshold. Besides EMG filtered signals, this method was also used for onset/offset detection of FSR and IR sensor signals; an example of its application in the three signals is presented in Fig. 4. Examples are the same as shown previously in Fig. 3 for EMG and FSR, and for the IR sensor it is an example of the gesture of open to show how it is distinguishable from the gesture of close.

3 Experimental Results

3.1 Onset/Offset Detection

The experimental data available from signal acquisition is different, depending on sensor and gestures as shown in Table 2. The main reason is the difficulty to maintain the correct placement of the sensor for every acquisition. These data files were discarded since it is not related to the sensor itself. Table 4 summarizes the onset/offset recognition rates for each sensor and gesture.

Table 4 Onset/offset recognition rates

Sensor	Gesture	#Muscle activations	#Activations detected	Onset/offset detection (%)
EMG	Open	54	54	100
	Close	72	70	97
	Point	39	23	59
FSR	Open	42	39	93
	Close	96	87	91
IR	Open	48	46	96
	Close	60	59	98

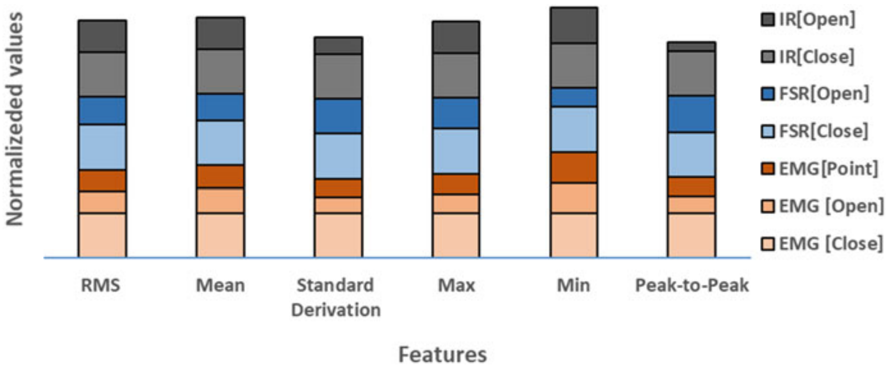

Fig. 5 Graphs comparing the average values measured for the six features in each gesture: EMG [Open; Close; Point]; FSR [Open; Close]; IR sensor [Open; Close]

3.2 Features Extraction

A set of features in the signal had been considered initially [11]. From the extraction of these six features in all of the data acquired in this work, it was found that just one or two depending on the sensor signals could be used for gesture recognition. This is illustrated in the graph presented in Fig. 5. The average values measured for the six features were previously normalized separately for each sensor and for each of the gestures considered; two or three gestures depending on the sensor.

3.3 Comparison of the Success in Gesture Recognition by Each Sensor

With the EMG sensor it is possible to detect signals of three different gestures, while with the FSR and IR sensor only two of those three gestures can be detected. From the average values of the features already shown in Fig. 5, different criteria had been

Table 5 Features and criteria adopted and percentage of success in gesture identification for each of three sensors

Sensor	Gesture	Criteria	Gesture identification	
			False/true	(%)
EMG[1]	Open	[$11<\mu<18$; $\sigma^2 < 6$]	6/48	89
	Close	[$\mu > 18$; $\sigma^2 > 15.5$]	22/48	69
	Point	[$\mu < 11$; $6 < \sigma^2 < 15.5$]	2/21	91
EMG[2]	Open	Other	9/45	83
	Close	[$\mu > 15$; RMS >16]	4/66	94
FSR	Open	[70 < RMS < 140; min < 40]	0/39	100
	Close	Other	13/74	85
IR	Open	Other	0/46	100
	Close	[RMS > 360]	0/59	100

established for the identification of those gestures. Table 5 shows the features used for each sensor and presents the criteria adopted. For the EMG sensor two sets of criteria were chosen: one for the recognition of the three gestures and the other for comparison purposes, with the other two sensors only the same two gestures were considered.

The results of the application of those criteria are also presented in Table 5 in terms of percentage of success, i.e., accounting the true and false events of gesture recognition for each sensor.

With these results a confusion matrix was built for each pair sensor/gesture and the analysis of these results had been based on the application of the well-known equations of generalized Precision, Recall (or Sensitivity), and Specificity [12].

As, in opposition to the other two sensors, EMG had shown capability for the recognition of three gestures, Fig. 6 shows solely its results with the purpose of evidencing the differences between the successful in recognition of each of the three gestures. Results are mostly between 85% and 95% with the only two exceptions of Recall or Sensitivity for close gesture (69%) and Precision for point gesture (54%).

On the other hand in Fig. 7, a comparison of success in gesture recognition for each sensor is presented; therefore, in this case, EMG results are reported to the recognition of the same two gestures as FSR and IR sensors. A very distinctive behavior is found for the IR sensor as it reaches the absolute success for the recognition of the two gestures, consequently achieving the maximum value on any of the three parameters. FSR and EMG sensors have very similar overall values of these three parameters but FSR with great discrepancy between the two gestures, excellent for open gesture but very deficient for the close gesture. EMG has a more balanced performance that is translated in also quite similar values of the three parameters for each gesture.

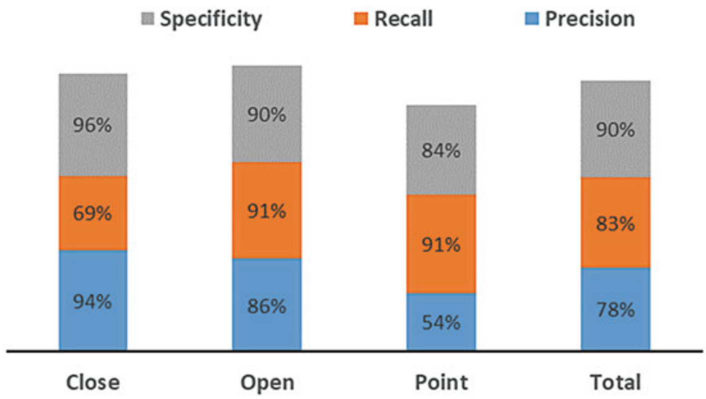

Fig. 6 Graph comparing the Specificity, Recall, and Precision for each gesture recognition using the EMG sensor

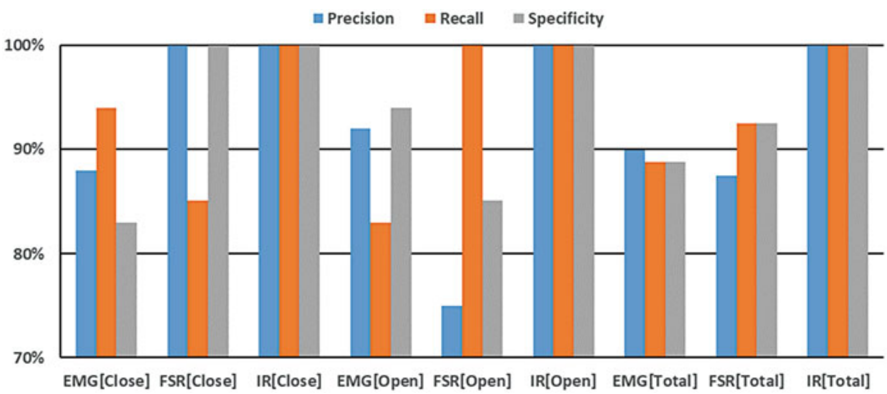

Fig. 7 Graph comparing the Specificity, Recall, and Precision for each of the two gestures recognition of the three sensors [EMG; FSR; IR]

4 Discussion and Conclusion

EMG sensors measure electrical activity of the muscles and are the more obvious choice for control hand prosthetics. However signals are often impaired by noise imposed by electromagnetic radiation and have low accuracy for finger movement recognition, as is demanded in bionic hands. A different sensing method may be more convenient, e.g., the use of force sensors to build a pressure distribution map of the muscle. But other types of sensors should be also investigated trying to measure any parameter that changes when different gestures are made.

This paper describes a comparison study embracing the application of an IR sensor besides the traditional EMG sensor and an FSR sensor, which has some results already documented in literature. IR sensors are able to detect movements in a muscle surface as its output signal depends on the intensity of light reflected by the skin with maximum distance of 6 mm.

Results from signal acquisitions of these three sensors had shown a slightly better ability of EMG sensor to detect different gestures, but simultaneously it has 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 signal-to-noise ratios than traditional EMG signals, for the two gestures that those two sensors were able to detect.

There is plenty of space to improve these results from FSR and IR sensors, namely by the development of holders for a more solid fixation and placement. The application of a set of sensors instead of a single one is expected to highly improve the detectability as well as the specificity of finger motion recognition for both FSR and IR sensors. Also, some signal processing techniques can be applied, namely to reduce the effects on the signal derived from the poorly fixation. Further research should be carried out in order to find other type of sensors or combinations of sensors suitable for a more accurate gesture identification or finger motion recognition in modern hand prosthetics based on MMG signals/sensors.

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