Towards Improving the Usability of Muscle Sensing in Open Source Bionic Hand: Mechanomyography vs. Electromyography with Novel Electrodes

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***Abstract*—This work embraces two comparative studies: one amongst three different sensing approaches and the other using EMG with three different types of electrodes. The three sensors used in the study were: the common ElectroMyoGraphic (EMG) sensor, considered as the reference; an InfraRed (IR) sensor and a Force Sensing Resistor (FSR) as two modes of acquisition of a MechanoMyoGraphic (MMG) signal. The BITalino platform was used for the acquisition of each of these three signals, being its EMG sensor module also used for the comparison of pre-gelled Ag/AgCl electrodes, considered as the reference electrode, with two other novel and low-cost electrodes: one built from a conductive leather material, and another based on desktop 3D printing using conductive PLA (PolyLactic Acid).**

Six gestures were selected for these studies, and acquisitions were performed from 15 healthy young subjects. Signals from these six different gestures and for all sensors and electrode types were processed through Matlab routines that include onset and offset detection, as well as feature extraction. Finally, this dataset was used with a data science and machine learning platform (RapidMiner), in order to evaluate the ability to perform accurate gesture recognition from previously extracted features.

Preliminary results show a slightly improved performance in gesture recognition for the IR sensor in comparison to EMG sensor (overall accuracy of 81% vs 72%) as well as a somewhat degraded performance for the two novel electrodes in respect to Ag/AgCl reference electrodes (51% and 52% vs 65%).

Keywords— Electromyography (EMG), Mechanomyography (MMG), Biomedical Sensors, Electrodes, Feature Extraction, Machine Learning

I. Introduction

For the development of a bionic hand, ElectroMyoGraphic (EMG) sensors combined with pre-gelled Ag/AgCl electrodes are commonly the first choice. However there are different modes of sensing muscle activity that can be tested, with the goal of reducing the costs while assuring a similar ability to acquire relevant data. Additionally, the huge evolution in the sensor and microprocessor technologies, as well as in 3D (Three-Dimensional) printing, has opened many different opportunities in the development of prosthesis.

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, which are capable of executing individual motions of the fingers, subsequently having a higher functionality approaching the human hand. In the case of the more widely used, the so called myoelectric hand, it is generally able to grasp objects, through the opening and closing of the hand.

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 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 types 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].

Other modes of sensing muscle activity are under research, namely those in which the mechanical change of the muscles is measured by a method with sensitivity to the position/motion of a small area in surface of the muscle, whose are typically known as MMG (MechanoMyoGraphy). Some solutions are described in literature, as the case of the acquisition of a mechanical deformation map implemented using FSR (Force Sensitive Resistor) [2], that seems potentially interesting as the shape of the muscles changes when different sets of fingers are moved. The relationship between forearm electrical activity and forces exerted by the fingertips measured through the application of load cells had also been investigated [3].

MMG techniques can also be implemented using 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.

Under this project it had been already published a previous work with the aim of studying the effectiveness of low-cost sensors for the replacement of EMG sensors commonly used for upper-limb prosthesis [4]. The results of the application of two MMG sensors a FSR and an IR (InfraRed) reflectance sensor, and their comparison with EMG signals 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 [4].

In this paper we describe and present the results of a new application of those same two MMG sensors, improving the setup by using a more solid fixation and placement, and their comparison with EMG signals. The BITalino platform was used for the acquisition of each of these three signals but, this time, its EMG sensor module was also used for the comparison of pre-gelled Ag/AgCl electrodes, considered as the reference electrode, with two other novel and low-cost electrodes: one built from a conductive leather material, and another based on desktop 3D printing using conductive PLA (PolyLactic Acid).

II. MATERIALS AND METHODS

A. Sensors/Electrodes

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 its main specifications can be found in Table I.

One option for obtaining MMG signals is to use a force sensor in order to react to changes in the muscle volumes, for which an FSR FlexiForce A201 sensor (Tekscan, Inc., USA) was selected. It is capable of sensing forces from 0 to 100 lb (445 N) and it has a circular form factor with 9.53 mm in diameter. A summary of its main specifications can be found in Table I. Owing to the low magnitude of the forces to be measured, a calibration process has been performed in order to obtain the optimum value for the load resistor (11.8 MΩ) in the electronic circuit, used to achieve the force-to-voltage conversion, a voltage divider followed by an op-amp.

TABLE I. MAIN SPECIFICATIONS OF EACH SENSOR.

EMG Module specifications	
Gain	1000
Range	±1.65mV
Bandwidth	10-400Hz
FSR FlexiForce A201 Specifications	
Force Sensitivity Range	0 – 445 N
Force Repeatability	<±2.5%
Sensing Area (Diameter)	9.53mm
QTR-1A Reflectance Sensor Specifications	
Optimal Sensing Distance	3mm
Maximum Sensing Distance	6mm

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 output voltage decreases. Its maximum and optimal sensing distances are presented also in Table I. A practical verification of these sensing distances, particularly the optimal value, has been made due to its importance for the acquisition of a signal with a larger SNR.

Fig. 1 shows the two novel and low-cost electrodes: built from a conductive leather material (left); and based on desktop 3D printing using conductive PLA (right).

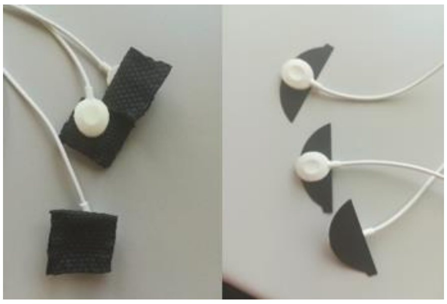

Fig. 1. Two novel electrodes. Conductive leather (left) and PLA (right).

The conductivity of a leather material may be in the range necessary to operate touch-sensitive electronic devices without relying on a conductive path to the human body. Its conductivity can be changed by the incorporation of electrically conductive metallic or nonmetallic particles, that could allow its application for EMG electrodes.

PLA is biodegradable and it is relatively cost efficient to produce. One of a vast array of applications for PLA are biodegradable medical devices. Additionally, the ease with which PLA melts allows for some interesting applications in 3D printing. As this one has been functionalized with conductive properties, we attempt its used for the replacement of traditional EMG electrodes.

B. Data Acquisition and Processing

For this study each sensor (or each set of three electrodes) was placed separately and acquisitions were carried out using similar timing parameters. The sampling data from 15 healthy young subjects is summarized in Table II.

It is possible to observe that, in average, in each acquisition the same gesture is made four times and each gesture lasts for approximately three seconds with similar rest time between them. The six gestures considered in this study (*open, close, point, pinch, flexion, extension*) are illustrated in Fig. 2. It is important to explain that for FSR sensor the acquisition of data from other gestures besides close would be expected to be achieved successfully using a sensor with a lower force sensitivity range. Also for the IR sensor further improvement is demanded on its fixation and placement in order to increase its consistency in the acquisition of signals from mscle activations. A correct fixation and placement of the sensors is an extremely important issue for the acquisition, with a fair signal-to-noise ratio and appropriate sensitivity, of signals from any of these sensors/electrodes types. Photos of the placement of each of them are shown in Fig. 3.

TABLE II. DESCRIPTION OF THE WHOLE DATA ACQUIRED: NUMBER OF ACQUISITION FILES (#ACQ) AND OF MUSCLE ACTIVATIONS (#MACT).

	Gesture	**open**		**close**		**flexion**		**extension**		**pinch**		**point**	
Sensor	**Electrodes**	**#Acq**	**#MAct**	**#Acq**	**#MAct**	**#Acq**	**#MAct**	**#Acq**	**#MAct**	**#Acq**	**#MAct**	**#Acq**	**#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
IR		1	4	6	24	3	12	2	7	4	16	1	4
FSR				3	12								

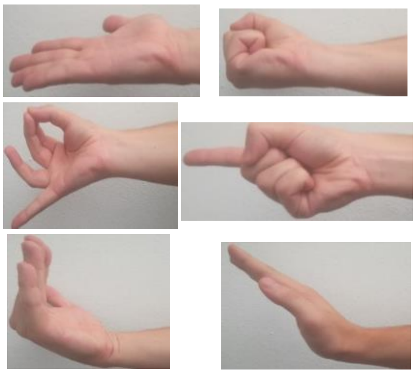

Fig. 2. Pictures of all of the gestures performed by each subject.

The description of the procedure used for signal acquisition and filtering as well as for onset/offset detection can be found in [4]. Success in gesture identification greatly depends on the correcteness in onset/offset detection. For all the sensors/electrodes types, the same method was used, for determining the time interval in which the muscle is active, which uses a double threshold with a moving average for calculating an adaptative threshold [5].

Feature extraction was the last task performed in Matlab (Mathworks Inc.). A set of six features in the signal had been considered initially [6]: *RMS, Mean; Standard deviation, Maximum, Minimum and Peak-to-Peak value*. These are calculated for each muscle activation.

Erroneous onset/offset detection had been observed in Matlab time plots of each acquisition, therefore a criteria had been empirically established in order to exclude these wrongly detected time intervals: an onset/offset shift equal or higher than 500 ms in relation to visually observed instants.

C. Gesture Recognition

The dataset, composed by the whole data of those six features, calculated for each correctly detected muscle activation, was used with a data science and machine learning platform (RapidMiner), in order to evaluate the ability to perform accurate gesture recognition from previously extracted features.

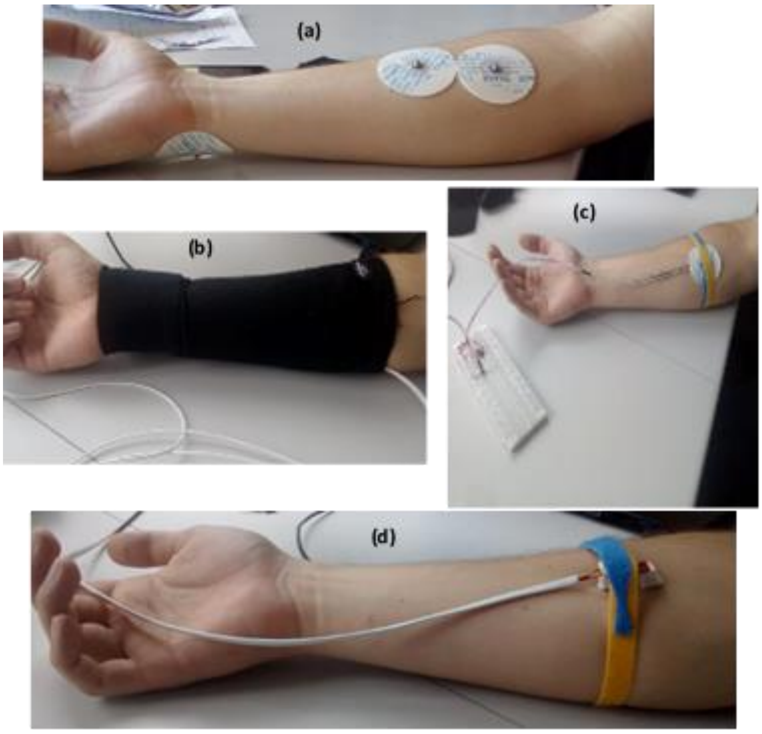

Fig. 3. Photos of the sensors/electrodes placement. Three EMG pre-gelled Ag/AgCl electrodes (a) and conductive leather material/PLA electrodes (b); FSR sensor with velcro strap for fixation and EMG electrode pin for more localized force application (c) and IR sensor mounted using several layers of of adhesive to keep at a correct distance from the skin/muscle support and velcro strap for fixation (d).

For its implementation the dataset was splitted: RapidMiner used 70% of the whole data for analysis purposes and to train and learn how to distinguish the six gestures from the values of the six features extracted. The remaining 30% of the data was used for evaluation and prediction of the different gestures. Amongst the different processing tools provided by RapidMiner two were used: Decision Tree and Neural Network. This later one achieved better results.

Ideally gesture recognition should be performed for all the six gestures. However, results were very poor, owing to the fact that only one sensor was used and in the same muscle for all the acquisitions. As such, sets of two, three and four gestures were evaluated; those sets of two and three gestures are presented in graphs of results. They were grouped using a criteria based on muscles that are activated in each gesture. On the other hand, due to its lower interest for bionic hands, flexion and extension were the gestures removed in order to have the set of four.

Running RapidMiner for each of those sets of gestures, a confusion-matrix is presented and the following parameters are computed [7]

- Precision (of each gesture recognition) – it considers only the positive outputs given by the classifier and it is defined as the raio of the correctly identified gestores (*TP*) by the whole gestures, both classified as positive (*TP*+*FP*);
- Recall or Sensitivity (of each gesture recognition) – only the positive gestures are considered (*TP*+*FN*) and it corresponds to the fraction of those gestures correctly classified as positive (*TP*);
- Accuracy (on the whole gesture recognition) – takes into account the whole data (*TP*+*FP*+*TN*+*FN*), corresponding to the overall effectiveness of the classification process as it is defined as the fraction of whole gestures that are correctly classified (*TP*+*TN*).

Additional computation had been performed using data from the different confusion matrix for a more complete assessment of comparison between sensors and electrodes types as well as for the calculation of another parameter:

- Specificity (of each gesture recognition) – in opposition to sensitivity, only the negative gestures are considered (*TN*+*FP*) and it corresponds to the fraction of those gestures correctly classified as negative (*TN*).

III. Experimental Results

A previous statement has to be made about the fact that FSR results had been discarded because signal acquisition from muscle activations was only accomplished for *close* gesture. On the other hand, even the better RapidMiner results using neural network processing tool showed its complete unability for the recognition of pinch gesture for sets of three or four gestures when conductive PLA electrodes are used. Also the conductive leather material had failed in this later case.

A. Dependence of the Precision, Recall and Specificity in Gesture Recognition on the Sets of Gestures Used

From the four graphs in Fig. 4, one for each sensor/electrode type, some important remarks arise:

- A previous one to mention that, as expected, owing to their definition, precision and recall lines have a more similar behaviour than specificity line;

1) Comparison Between Sensors

- IR sensor has a perfect gesture recognition for two pairs of gestures;
- For the third pair of gestures [pinch; point] as well as for the sets of three gestures the parameters have a similar behaviour in both IR sensor and EMG sensors combined with pre-gelled Ag/AgCl electrodes;

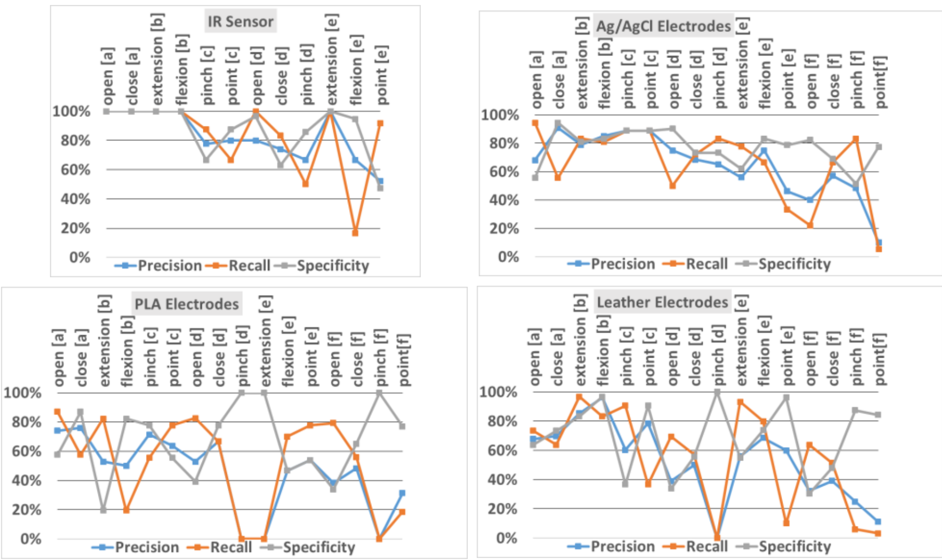

Fig. 4. Graphs showing for each gesture and for each sensor/electrode type the results for precision, recall and sensitivity across the different gesture combinations. The gesture combinations are coded as follows: [a] - [open; close]; [b] - [extension; flexion]; [c] - [pinch; poimt]; [d] - [open; close; pinch]; [e] - [extension; flexion; point]; and [f] - [open; close; pinch; point]. Note: Although there is no dependency between the points on each line, the three lines were drawn for a better view.

2) Comparison Between Electrode Types

- Despite sporadic diferences, PLA and leather electrodes have a quite similar behaviour for all the three parameters, showing both increased difficulty in pinch gesture recognition.
- PLA electrodes had shown good results in point gesture recognition, in opposition to its poor performance in extension gesture recognition.
- Besides pinch, point gesture recognition is also a weakness for leather electrodes.

B. *Comparison of the Accuracy in Gesture Recognition by Each Sensor/Electrode Type*

Accuracy is the parameter that RapidMiner computes for each set of gestures that were considered, as shown in the example presented in Fig. 5.

Using those values extracted directly from RapidMiner, as well as the overall accuracy computed for each sensor/electrode type considering the results from the whole sets of gestures, it is possible to grapically sumarize them as shown in Fig. 6. Therefore it is possible to say:

1) Comparison Between Sensors

- The IR sensor has an improved accuracy in gesture recognition comparatively to EMG sensors combined with pre-gelled Ag/AgCl electrodes;
- Amongst the total of five gesture combinations, the pair [point; pinch] is the only in which IR sensor has lower accuracy than EMG sensor combined with traditional electrodes;

2) Comparison Between Electrode Types

- Novel electrodes have a very similar accuracy in gesture recognition but somewhat lower than Ag/AgCl electrodes;
- Conductive leather materials electrodes have shown the highest accuracy in two of the six gestures combinations but the lowest in the other four;
- PLA electrodes have shown more homogeneous results throughout the whole gestures combinations (accuracy in the range of 40%-75%) comparatively to leather electrodes (range of 33%-90%).

IV. Conclusions and Future Work

EMG sensors combined with pre-gelled Ag/AgCl electrodes are commonly used for control hand prosthetics. The measurement of electical activity of the muscles have shown some limitations in respect to signal-to-noise ratio, which, together with the use of a single channel, has lead to a low accuracy for finger movement recognition, as is demanded in bionic hands.

This paper introduced two different approaches in order to improve the usability in muscle sensing: through MMG sensors, namely FSR and IR, and EMG but with two novel electrodes, one using a conductive leather material, and another using conductive PLA. Amongst these sensors/electrode types only some applications of FSR are described in literature.

accuracy: 66.67%

	true POINT	true PINCH	class precision
pred. POINT	15	6	71.43%
pred. PINCH	12	21	63.64%
class recall	55.56%	77.78%	

Fig. 5. Classification results obtained with RapidMiner for conductive PLA electrodes in the case of a set of two gestures ([pinch; point]).

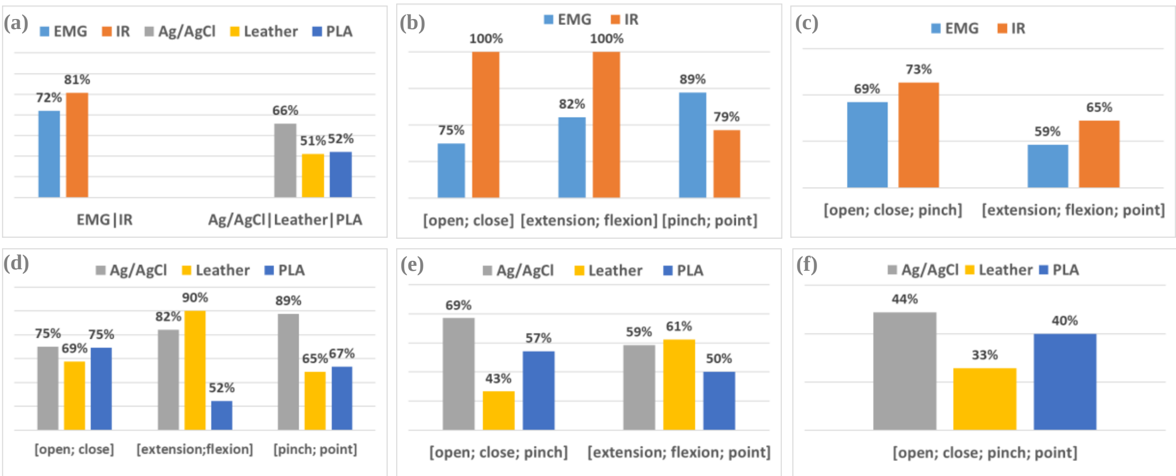

Fig. 6. Bar graphs showing a comparison of the accuracy in gesture recognition between sensors as well as between electrode types, for the whole results available (a) and for each gesture combination (b-f). Note: datasets EMG and Ag/AgCl are both refered to EMG sensor combined with pre gelled Ag/AgCl electrodes, the former used in sensors comparison, in which gestures combinations is lower, and the later in electrodes comparison.

Six gestures had been chosen and only FSR was unable to detect the correspondent MMG signals. Then MMG signals from IR sensor and EMG signals from the three electrode types sensors were used in order to compare their precision, sensitivity, specificity and accuracy in gesture recognition.

Results show that the IR sensor is very attractive for muscle sensing, as its overall accuracy is higher than EMG sensors combined with Ag/AgCl pre-gelled electrodes. A more detailed analysis of those parameters throughout the different sets of gesture combinations allows us to identify some combinations where this improvement is clearer. 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.

The operating principle of this IR sensor imposes some difficulties for its placement because its output signal depends on the intensity of light reflected by the skin, but its distance from the skin should be in the range of 1.5mm - 3mm. A solution has been adopted but, despite its promissing results, a more solid fixation and placement is needed, and its response from outliers must be studied. On the other hand the application of this FSR sensor had been a quasi-complete flop, as it was only able to detect its signal for the close gesture and even that with a low signal-to-noise ratio. However, as its force range was not the more appropriate to typical low intensity forces exerted by the muscle in these gestures, it should be replaced by another with a better sensitivity in this force range.

In spite of their lower overall accuracy in gestures recognition, in comparison to Ag/AgCl pre-gelled electrodes, the results obtained for the novel electrodes are very similar to 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 set of sensors, in order to acquire simultaneously the MMG signals from different muscles, instead of a single one, is expected to highly improve the precision, sensitivity, specificity and accuracy of the gesture recognition results. Similarly with the simultaneous acquisition of EMG signals in two or more muscles, duplication of electrodes and experimentation of alternative geometries (in the case of conductive PLA) should be tested. These are future work directions towards improving the usability of muscle sensing, i.e., achieving lower cost as well as more ecological solutions for modern hand prosthetics.

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