Versatility of human body control through low-cost electromyographic interface

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Abstract: An increasing trend in Human-Machine Interaction is the development of a tighter connection between the human user and the device. This paper analyses the possibility of creating a low-cost system that enables a person to use a group of muscles to control a different part of his body using Electromyography (EMG). This system features an EMG reader, two processing boards and a robotic hand, and was tested in both ideal and practical conditions. Despite being possible to see satisfactory results in some subjects' first uses, it was concluded that the practicing time was a key factor on the precision of the artificial limb control.

Key–Words: Assistive Technologies, HMI, Electromyography, Sensorimotor Plasticity, Robotic Hand.

1 Introduction

An increasing trend in Human-Machine Interaction is the development of a tighter connection between the human user and the device. This approach is supported by numerous projects in human enhancement technologies to overcome a handicap [1] or to increase performance [2]. The idea is to enable a direct linkage between a physiological signal and the machine control system.

Two approaches are mainly used. The first one is based on the capture of the nervous system activity through the record of EEG [3, 4]. The main advantage of this method is the fact that even people who suffered a heavy handicap are able to control an artifact by mental imagery. On the other hand, it requires a long training and a possibly invasive recording, which may have important consequences in terms of system usability and collateral infections.

An alternative is using the activity of superficial muscles through the recording of EMG. This approach has the advantage of promoting a more intuitive and quicker control of the artifact by the user and to be less invasive than the acquisition of a nervous signal [5].Taking into account these considerations, several works have been developed involving a prosthetic hand controlled through EMG recordings [6, 7].

However these approaches are based on costly materials or on the use of the other arm [8, 9]. This is a limitation because the use of a healthy arm to control the artificial hand impedes its natural use. In particular, many of day-to-day activities need the use of both hands and an independent control of each one. Therefore, this paper proposes a solution that involves the usage of EMG recordings in a body area that is not related to the arm, such as, the abdomen muscles (*rectus abdominis*) to control a robotic hand. Moreover, the cost of the whole system is much lower than in the previous studies, since all the mechanical parts of the robotic hand were made through a 3D printer and all electronics were made as cost effective as possible.

Aside from the technological challenge, it tackles fundamental questions on the human capabilities to use a group and type of muscles that does not belong to the muscles used to control the limb in normal conditions. For instance, the human body can adapt itself to be able to associate the activity of muscle group with the control of a different body part. Historical studies on the brain's plasticity [10] for interpreting visual information in another sensorial modality (i.e., tactile) support this theory.

In the next sections of the article, it will described the hand's design (Section 2), the developed architecture (Section 3), the protocol used (Section 4) and the results obtained (Section 5).

2 Hand Design

The design objective was to create a fully functional prosthetic hand that could offer a good performance at an affordable cost. So this robotic hand was designed to be as similar as the human hand as possible, in terms of feel, functionality, size, weight and grasping speed and power; having the cost as a major concern.

The hand developed (see Figure 1) is capable of moving independently each one of its 15 joints since each joint is powered by an individual servo. This approach has the advantage of providing a greater flexibility in terms of movement, giving the possibility of a performance closer to the human hand. This increases the complexity of the design, specially, the incorporation of all joints' servos.

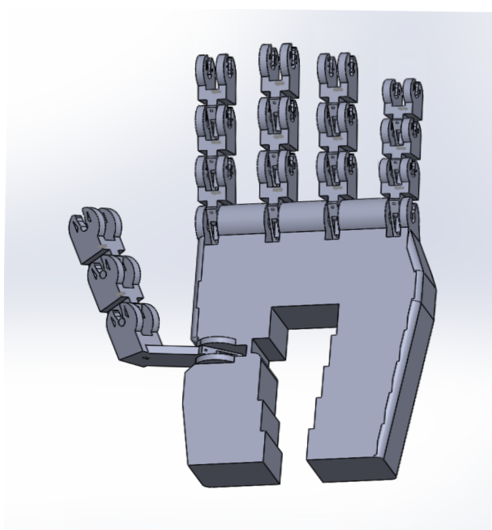

Figure 1: Hand Design View.

3 System's Architecture

Since the system needed to be as compact and energy efficient as possible, the adopted design consists of three self-adhesive passive Ag-Cl electrodes, a BITalino board to acquire the EMG signal, a robotic hand, a digital filter unit, and an EMG Classification and Servo Controller Unit (ECSCU), both implemented in two different Arduino boards. The flowchart of the architecture is depicted in Figure2.

The electrodes and the BITalino board (see the specification used in Table 1) are used together to retrieve and amplify the EMG signal.

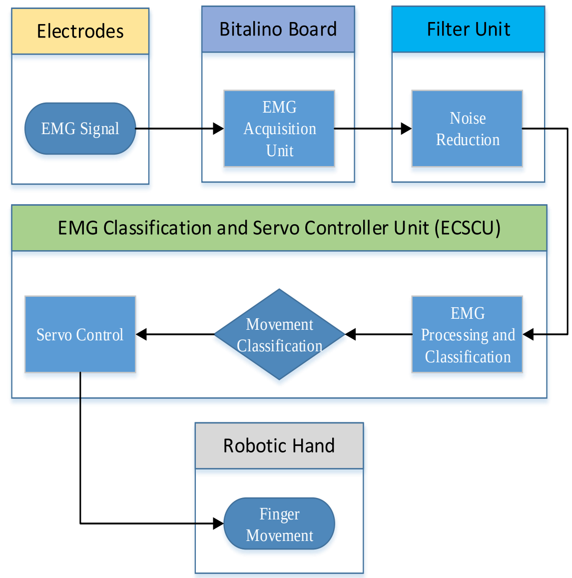

Figure 2: Flowchart of EMG recognition and servo actuation system.

Table 1: Specification used, BITalino.

Parameter	Value
Bandwidth	10 - 400 Hz
Input Impedance	100 GΩ
ADC resolution	10 bit
Signal noise ratio	$>$ 110 dB
CMRR	110 dB
Range	0 - 3.3 mV
Gain	1000

This signal is then sent to the Filter Unit via Bluetooth, using a HC-05 Bluetooth Transceiver board. The later is used to enable the communications between Arduino and BITalino boards. The Filter Unit removes some noise from the input signal, outputting the response via serial connection to the ECSCU. In this unit, a EMG processing algorithm classifies the muscles' contractions and a servo control algorithm is used to control the robotic hand.

4 Experimental protocol

Five participants took part in the long-term study and twenty in short-term study. Three male and two female subjects were asked to perform two abdominal contractions during 10 seconds. The test was repeated 5 times and all showed similar results. The differences between male and female data were taken into account during the design of the algorithms so that the ECSCU could correctly analyze both sexes' data. One of the samples was selected and analyzed in this paper.

All participants were made aware of the objective of this study and gave their consent before participating in it. The participants in this study were male between 170-180 cm height and weighted between 70-80kg. Female subjects were between 160-165 cm height and weighted between 51-58 kg. All aged between 20-25 years. No subject had any history of muscular diseases or had an estimated body fat percentage higher than 24% as determined by skinfold measurements. This value was chosen due to the risk of increased impedance during the EMG signal acquisition in subjects with body fat composition above that threshold [11].

Male and female subjects' data were studied separately, because of the variation in the amount and distribution of subcutaneous tissue between the sexes.

4.1 Data acquisition procedure

Skin of the subjects was carefully prepared before the beginning of these experiments. Since the EMG signals were acquired from abdominal area, dead skin was removed, using alcoholic solution. In order to improve the quality of the readings a gel solution was applied on all the subjects before the placement of the electrodes. One EMG channel was used with self-adhesive passive Ag-Cl electrodes. The elbow was used as reference point for the placement of electrodes because it is electrically unrelated to the abdominal muscles.

The EMG signal was sampled rate of 1KHz using the BITalino's EMG module 10 bit ADC. The data was analyzed with Biosignal Igniter Toolkit [12] and converted into a mat file in order to test algorithms in Matlab. With the information acquired, it was developed the low-cost architecture described in Section 3.

4.2 Signal processing

The EMG signal acquired and amplified in the BITalino board has a low Signal to Noise Ratio (SNR), partially due to cardiac artifacts located in the 50-80 Hz frequency region (see Figure 3) and electrical noise, located in the 50 Hz frequency region. This signal could be then processed directly (without the Filter Unit) by the ECSCU, however the performance of this unit wasn't satisfying as the analysis success varied between 50-60%.

To reduce noise from the readings and improve the performance of the ECSCU, the implementation of the Filter Unit featuring a high-pass filter was

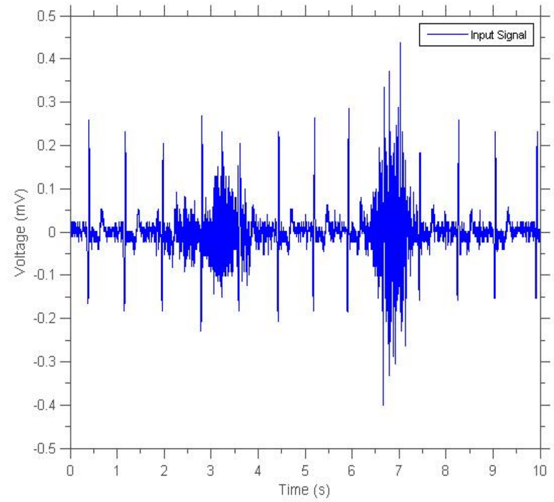

Figure 3: EMG signal acquisition. Cardiac artifacts must be taken into consideration.

tested. In particular, several high-pass Butterworth filters with different orders were designed and tested, to assess the minimum acceptable filter's order that could be implemented in the Filter Unit.

Figure 4 shows how three different orders of the high-pass Butterworth filter affected the input signal.

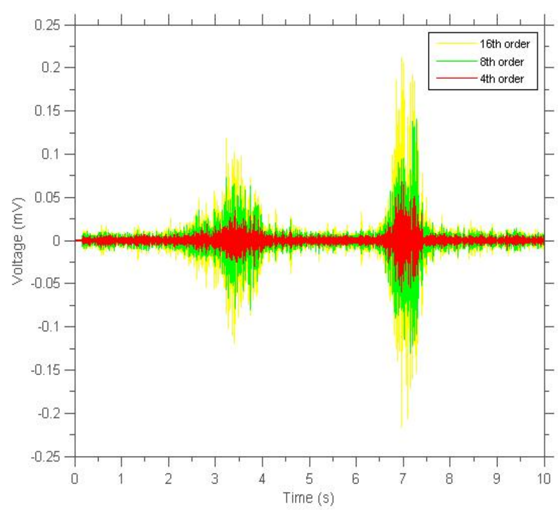

Figure 4: Resulting filtered signals.

In Figure 4 it can be seen the resulting signal after applying a 16th order, 8th and 4th order (respectively: yellow, green and red signals). It can be concluded that as the order of the filter increases, the SNR decreases. Therefore, a fourth order Butterworth filter was the minimum acceptable, as the ECSCU wasn't able to analyze resulting signals, with a good accuracy (above 90%), with filter's orders below that.

It was also tested whether a low-pass Butterworth filter could be incorporated in this unit, in order to reduce the high frequency noise. However, the final design didn't incorporate this filter because the marginal increase in the ECSCU analysis performance came with a significantly increase in the system's response time.

The ECSCU has three main algorithms (processing, calibration and classification). Its' processing algorithm incorporates features such as Zero Crossing Count and Root Mean Square (see Equations 1 and 2), in order to qualify when a contraction is developed.

Zero Crossing Count (ZOC):

$$ZOC = \sum_{n-1}^{N+1}[signal(x_n)! = signal(x_{n+1})]$$ (1);

Root Mean Square (RMS):

$$RMS = \sqrt{\frac{1}{N+1-n-1}\sum_{n-1}^{N+1} x_n^2}$$ (2);

While both features quantify muscle activity, the ZOC relies on counting the number of times that the amplitude of the signal crosses the zero value and the RMS on calculations directly related with the amplitude of the signal.

4.3 Calibration

The ECSCU also features a calibration algorithm (see Figure 5) that measures the muscles' EMG activity while at rest (minimum value) and during a contraction (maximum value). After this step, the system is able to linearly interpolate a muscle contraction. With this algorithm the system is capable of adjusting itself to different subjects.

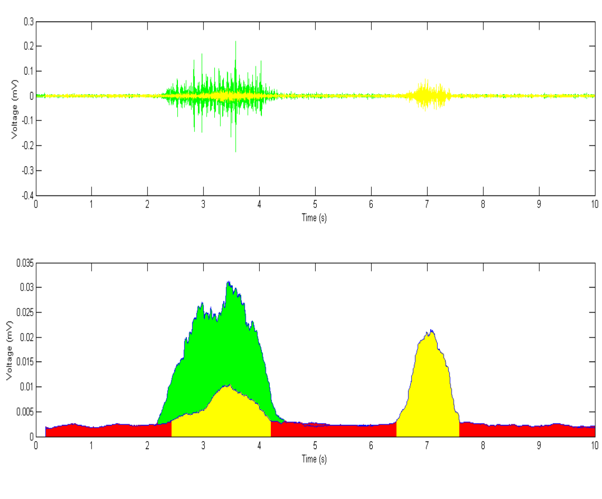

Figure 5: ECSCU calibration stage. Top graph: input signals. Bottom graph: output signals.

In Figure 6 it can be seen the output of the calibration algorithm displayed in green and the output of the processing algorithm displayed in red. It is also displayed the Filter Unit output signal in blue.

The classification algorithm takes into account information from the processing and calibration phases and classifies the muscle active area, the results are used with the interpolation equation and output to the servo control module which is responsible for controlling each finger of the robotic hand.

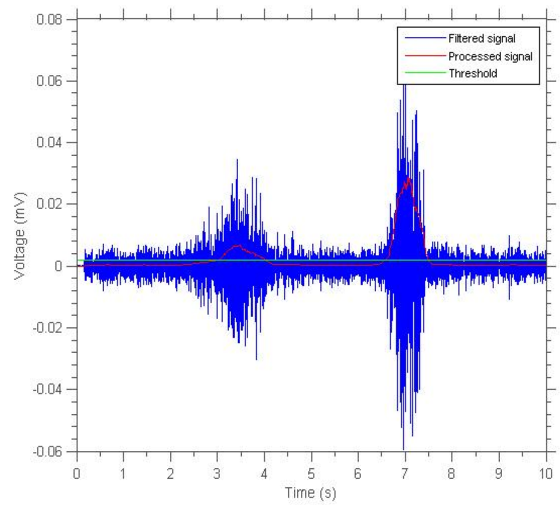

Figure 6: Filtered signal and processed signal. Green: threshold output by the calibration phase. Red: signal output by the processing phase. Blue: signal output by the Filter Unit.

All algorithms in the ECSCU were developed in order to require as little processing power as possible so that the Arduino boards were able to process the input in a reasonable time. The trade off was that some accuracy was reduced while attaining acceptable.

5 Results

To evaluate the success of this system, each subject was asked to perform an abdominal contraction and maintaining it for a short period of time, so that the robotic hand grabbed a solid object (see Figure 7 and 8). The success of this implementation was evaluated by checking whether the long and short time participants managed or not to grab the solid object.

The results of the test aren't very conclusive since the population studied is quite small. However, it can be concluded that with training and time, the participant's ability to control the robotic hand increased dramatically (see Figure 9). Since every long time participant could execute this test successfully with

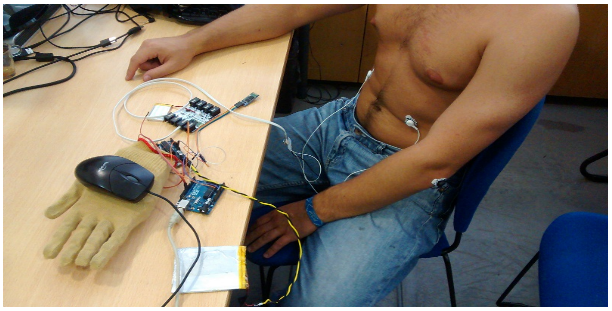

Figure 7: Subject with his abdominal muscles relaxed during the Robotic Hand Control Evaluation (RHCE).

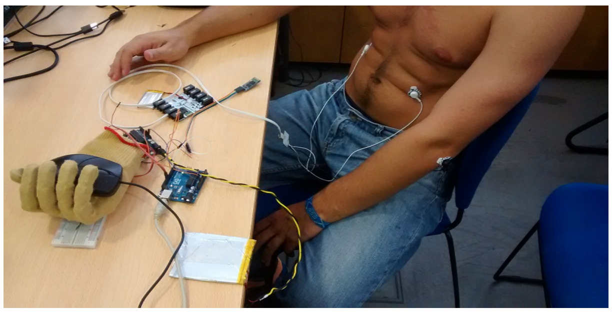

Figure 8: Subject with his abdominal muscles contracted during the RHCE.

small effort (see Table 2) while the long short participants struggled to complete it (see Tables 3 and 4). It's worth mentioning that some short time participants showed good results in the first contact with the system, this was due in part to the developed calibration algorithm.

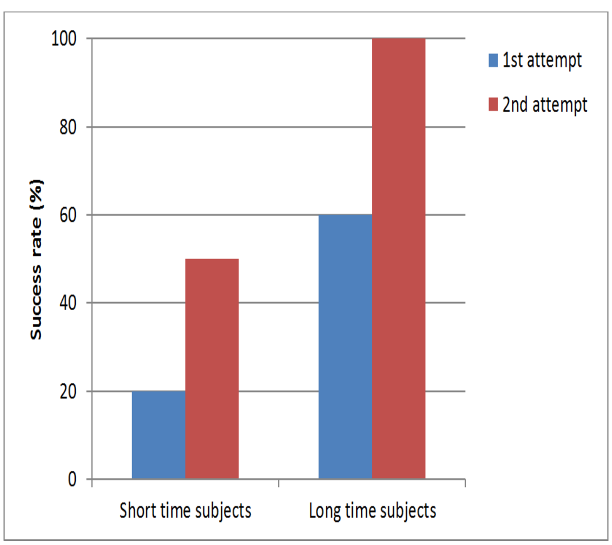

Figure 9: Short and long time participants' RHCE.

Table 2: Long time participants' RHCE.

	Age	BMI (kg/m^2)	1st test	2nd test
1.	21	22	Failed	Success
2.	22	24	Success	Success
3.	22	20	Success	Success
4.	20	21	Failed	Success
5.	25	23	Success	Success

Table 3: Short time participants' RHCE (Female).

	Age	BMI (kg/m^2)	1st test	2nd test
1.	24	21	Failed	Failed
2.	21	23	Failed	Success
3.	20	20	Failed	Failed
4.	20	24	Success	Success
5.	23	20	Failed	Failed
6.	20	22	Failed	Failed
7.	21	21	Failed	Success
8.	21	24	Failed	Failed
9.	24	22	Failed	Failed
10.	22	23	Success	Success

Table 4: Short time participants' RHCE (Male).

	Age	BMI (kg/m^2)	1st test	2nd test
1.	21	21	Failed	Success
2.	20	22	Success	Failed
3.	22	24	Failed	Failed
4.	25	20	Failed	Success
5.	21	23	Failed	Success
6.	24	21	Failed	Failed
7.	21	23	Failed	Success
8.	20	20	Failed	Failed
9.	20	23	Failed	Success
10.	22	21	Success	Failed

6 Conclusion

This system core goal is to provide the disabled people the possibility of controlling a robotic hand by using muscles that are not located on the limbs. Additionally, the low costs involved represent a major asset.

It was possible to see good results in some participants' first contact with the system. However, the best results came from the long time participants. So it was concluded that the practicing time is a key factor on the precision of the artificial limb control. Therefore, in order to use this system flawlessly,it takes some time for the person to get adjusted to it.

Further research could be done in order to combine the Filter Unit with the ECSCU and to see whether it is possible to lower the system costs even more.

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