Algorithm for Onset/Offset Detection of EMG Signals for Real-time Control of a Low-cost Open-source Bionic-hand

Sandra Rodrigues[1] and Milton P. Macedo[1,2,a]
[1]Instituto Politécnico de Coimbra, ISEC, DFM, Rua Pedro Nunes, Quinta da Nora, 3030-199 Coimbra, Portugal
[2]LIBPhys, Department of Physics, University of Coimbra, Rua Larga, 3004-516 Coimbra, Portugal

Keywords: Electromyography (EMG), Onset/Offset Detection, Algorithm, Real-time Control.

Abstract: This work was carried out as part of a project to develop a low-cost open source bionic hand using electromyographic (EMG) signals. Probably the most important task for the success of this bionic hand is to achieve a correct determination of muscle activation intervals. In this paper it is presented an algorithm for the detection of Onset/Offset to be executed in an Arduino UNO. The aim of this algorithm is to be executed in this ATmega328 microprocessor with a 16 MHz clock speed and 32 kBytes of memory in order to accomplish with effectiveness the real-time control of the bionic hand. The tests performed up to its application in real-time detection of muscle activation will also be described. The preliminary results presented show a 100% success rate in most gestures performed by the bionic hand but with the occurrence of a few false activations.

1 INTRODUCTION

With the purpose of using EMG signals for the control of a bionic hand there is an absolute need of an algorithm that is able to make a correct identification of time windows in which the muscle activation occurs. The hardware platform is continuously acquiring a EMG signal and it is demanded that in real-time, i.e., as soon as possible, following the muscle deactivation, it is detected. Additionally it has to save the data regarding the whole time interval of muscle activation in some way in order to afterwards complete the execution of the correct action. This work is focused on the implementation of one algorithm for onset/offset detection but facing these constraints, with the aim of using a low-cost microcontroller, Arduino Uno, as a standalone controller of a bionic hand. Regarding this real-time application, in a certain sense, the requisites for the algorithm are more demanding, as well as limitations in memory space and processing speed of the hardware platform, has to be considered.

Several methods are available in literature for onset/offset detection, i.e., for the determination of time intervals in which the muscle is active, 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 (Di Fabio, 1987), or using a double threshold (Bonato, 1998). It is also described in literature a method that detects muscle activity onset using the energy of the signal which increases with the start of the contraction (Rasool, 2012).

However these methods are general purpose in the sense that the acquisition of EMG data is performed previously. The need to carry out real-time control of the bionic hand imposes a number of additional requirements also on algorithms for data acquisition, particularly in respect to onset/offset detection. In the literature there are examples of algorithms developed for similar applications, but in some cases it is required that the processed signal is known a priori. To implement an algorithm independent of the a priori knowledge one option was to focus onto the Teager-Kaiser Energy Operator (TKEO), which puts in evidence the instantaneous increase of the action potential and reduces the baseline noise (Li, 2007) (Gentile, 2017). A threshold algorithm was then implemented in TKEO's domain for detecting muscle activity, taking into consideration the minimum period of muscular activity, the minimum period of muscle inactivity and the margin of accuracy in the

[a] https://orcid.org/0000-0003-0595-5298

Rodrigues, S. and Macedo, M.
Algorithm for Onset/Offset Detection of EMG Signals for Real-time Control of a Low-cost Open-source Bionic-hand.
DOI: 10.5220/0010976500003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 872-878
ISBN: 978-989-758-552-4; ISSN: 2184-4305

estimation of such measures (Konrad, 2006) (De Luca, 1997).

Another paper concerns with the acquisition and analysis of EMG signals for multiple active hand movements based on wrist-hand mobility for control of prosthesis robotic hand (Raurale, 2014). An EMG hardware module had been developed but the classifier based on Linear Discriminant Analysis (LDA) with threshold detection approach, resulted in a very low processing time for the pattern recognition.

In spite of the documented success of some of these methods, the algorithm presented in this paper is based on a previous work in which a smoothing filter is applied to EMG signal (Russo, 2019). These filtering is achieved through a derivative component that evidences the largest variations discarding the signal noise. These enables the more efficient application of a single threshold as higher frequencies of the signal were suppressed.

2 METHODS

The algorithm was initially tested in Matlab using previously acquired data from EMG signals. Later, the code had to be adapted in order to be executed in an ongoing data acquisition. To face the difficulty in carrying out its debug, there was an intermediate step of executing the algorithm in Arduino Uno through the Arduino IDE platform with visualization of the acquired signals in Opensignals. At this stage, for the sake of ease in debugging, signals were acquired from the accelerometer module of BITalino, whose shape it was possible to adjust in a simple way. Through Arduino's serial monitor, it was possible to follow the values of some flags used for debugging, which were complemented by the visualization of signals in Opensignals. At this stage, the accelerometer signals were acquired in parallel by Arduino UNO and a BITalino. Through these, it was possible to improve the code, identifying and correcting errors in the algorithm and debugging the code until the conditions for the independent execution of the code in Arduino UNOo were created.

3 ALGORITHM

The initial code of the algorithm was developed in Matlab, based on data smoothing previously described in the literature (Russo, 2019). Three parameters were defined that must be previously adjusted in order to optimize the efficiency of onset/offset detection. These parameters together with auxiliary flags allow to control the flow of execution of the different routines.

Figure 1 shows the data of an EMG signal acquisition in which three muscle activations are identified. Green and red markers corresponding to onset and offset detection, respectively, are also represented. These markers are obtained from each raw-data from EMG sensor, which is computed in order to calculate the difference from the previous value. The average of an amount of these values defined by the parameter *arraySize* is the key value for the application of a threshold, defined by a second parameter, *activation*, from which it is compared in order to detect firstly the onset in upward direction and offset in downward direction.

These markers do not delimit muscle activation, and it is necessary to establish the time when activation starts, with the help of *First_onset_flag*, as well as the time when muscle activation ends. In this case, *Last_offset_flag* is used, defining a period of time that must elapse since the previous offset, using the third parameter, *DesactDelay*. The description of the various flags used for this flow control is presented in table 1.

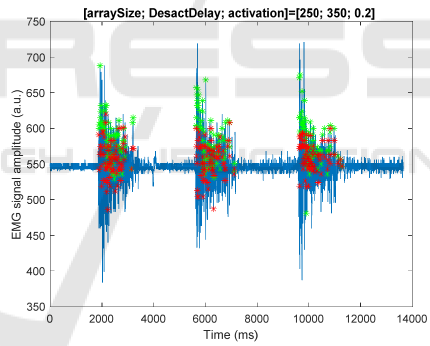

Figure 1: EMG signal acquisition with onset and offset markers, green and red, respectively.

The parameter *arraySize* imposes the degree of smoothness as it raises when the average is calculated over a larger amount of values of EMG signals. Consequently it also influences the sensitivity of the algorithm in onset/offset detection as a greater smoothing of the signal reduces its fluctuations and the number of times it crosses the threshold value.

The *activation* parameter, on the other hand, has a direct action in the detection of the onset/offset, as a lower threshold value implies a more frequent recognition of a variation as an onset, that is, it increases the sensitivity of the algorithm. It is important to be clear that this threshold is applied to the smoothed signal instead of raw EMG signal. In

Table 1: Description of the flags used for flow control.

Flag	*Description*
Init_flag	To avoid onset detection for the first data acquisition owing to a large difference to previous value
State_sign	Identification that an onset is already active
First_onset_flag	Signals the occurrence of a first onset and starts time counting
Last_offset_flag	Activated when the defined time interval has elapsed from the last offset with no onset between

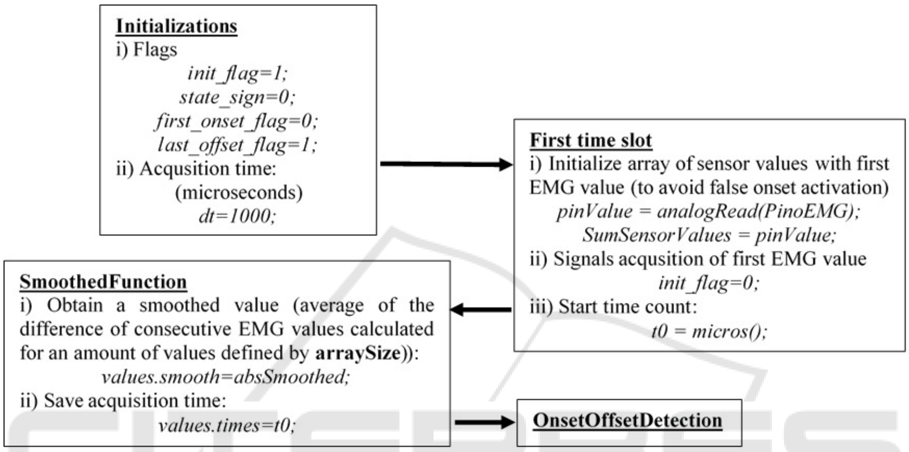

Figure 2: Overall schematic of the algorithm.

short, these two parameters act to detect the onset/offset that occurs multiple times during a muscle activation. On the other hand, the DesactDelay parameter will only act to identify the end of muscle activation, as it sets the time that will have to elapse after an offset, without the following onset, so that it is considered as the end of muscle activation. Therefore, it also influences the determined instant for muscle relaxation.

Figure 2 illustrates the overall schematics of the algorithm from the initializations of the flags listed in Table 1 through the specific code in the first time slot in order to avoid false activation and the function to calculate the smoothed values to the function for onset/offset detection that is described in detail in Figure 3.

Figure 4 shows the muscle activation intervals obtained with this algorithm for the acquisition of EMG signals shown in Figure 1.

As can be seen, the values of the three parameters are shown in the figures. To illustrate the effect of the *DesactDelay* parameter, through the observation of figure 5, it can be seen that decreasing its value by 100 milliseconds (250 instead of 350), the instant of time obtained for muscle relaxation then shifts to the left. In this case, it has no other effect, namely in determining the moment of muscle activation and sensitivity in detecting onset/offset.

But with smaller values of this parameter, several false activations can be identified within a single muscle activation. It is important to adjust this value, taking into account the type of signal that is acquired, namely the frequencies present in that signal.

So, for example, when an application is made for the acquisition of accelerometer signals, this parameter must be the used with a different value than from EMG signals.

Figure 6 is intended to illustrate the effect of the other two parameters. In (a) and (b) the *arraySize* parameter has been reduced by 100 units, that is, the signal smoothing is weaker, since the average value of the differences between consecutive values of the EMG signal is calculated for a smaller amount of values.

As a consequence, fluctuations in this mean value increase, making the algorithm more sensitive to fluctuations in the EMG signal. This fact is responsible for the identification of a false muscle activation.

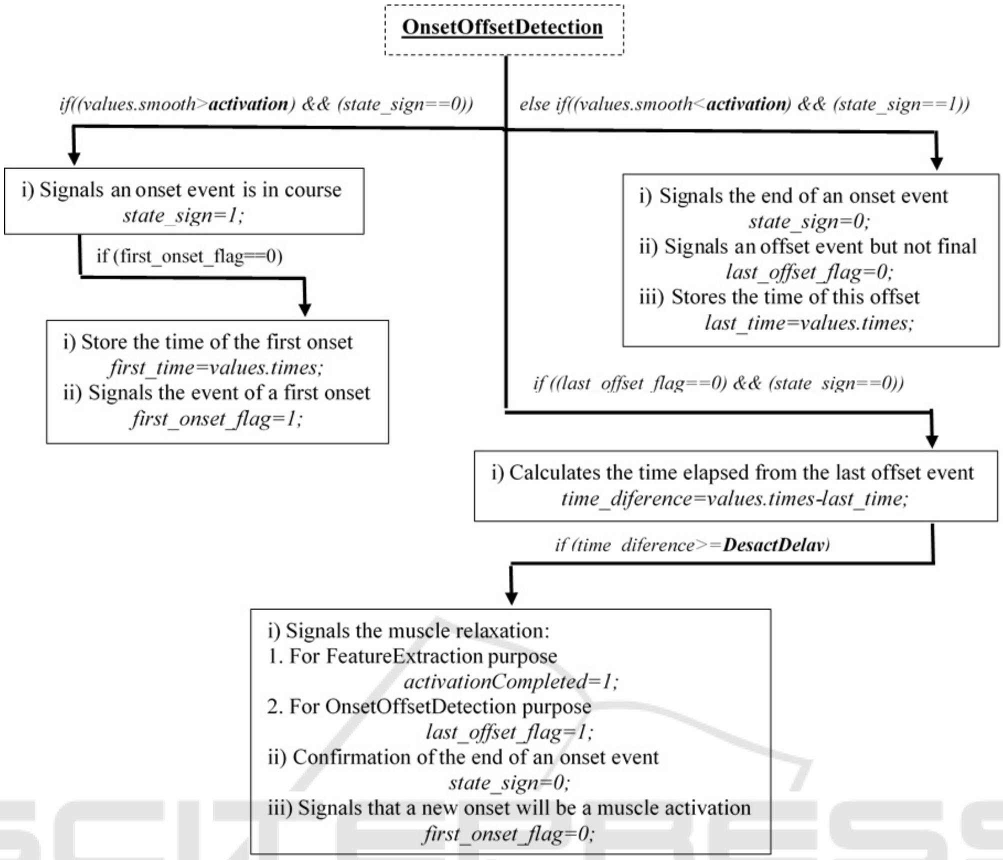

Figure 3: Schematic of the function OnsetOffsetDetection of the algorithm.

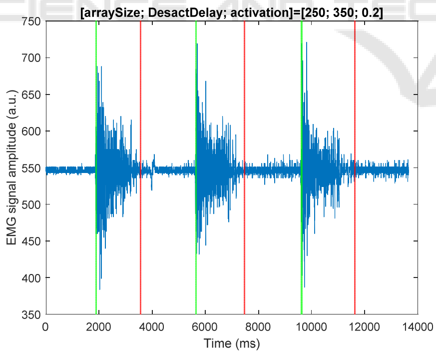

Figure 4: EMG signal acquisition with lines showing the start and end of muscle activation, green and red, respectively.

In (c) and (d) it is possible to observe the effect of reducing the *activation* parameter value, which is the threshold value, i.e., the minimum value of the smoothed EMG signal to be considered as an onset. The time interval of muscle activation has no variation, but there are several false activations, as this threshold value was not adjusted in accordance with the amplitude of the oscillations that occur in the baseline of the signal. It is important that this adjustment is made taking into account the noise present in the acquired signals.

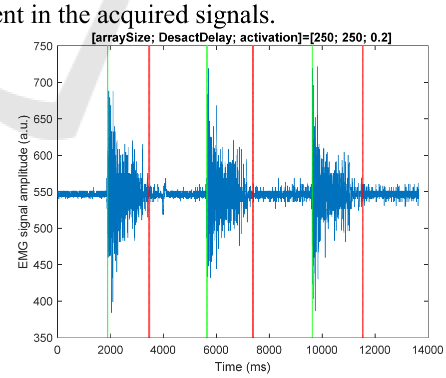

Figure 5: Same EMG signal acquisition using a lower value of *DesactDelay* parameter (250 instead of 350).

Finally, looking at (a) and (c), and comparing with figure 1, it can be seen that, as expected, the amount of onset/offset detections during the three muscle activations has suffered an significant increase as the two parameters, *arraySize* and *activation*, were reduced.

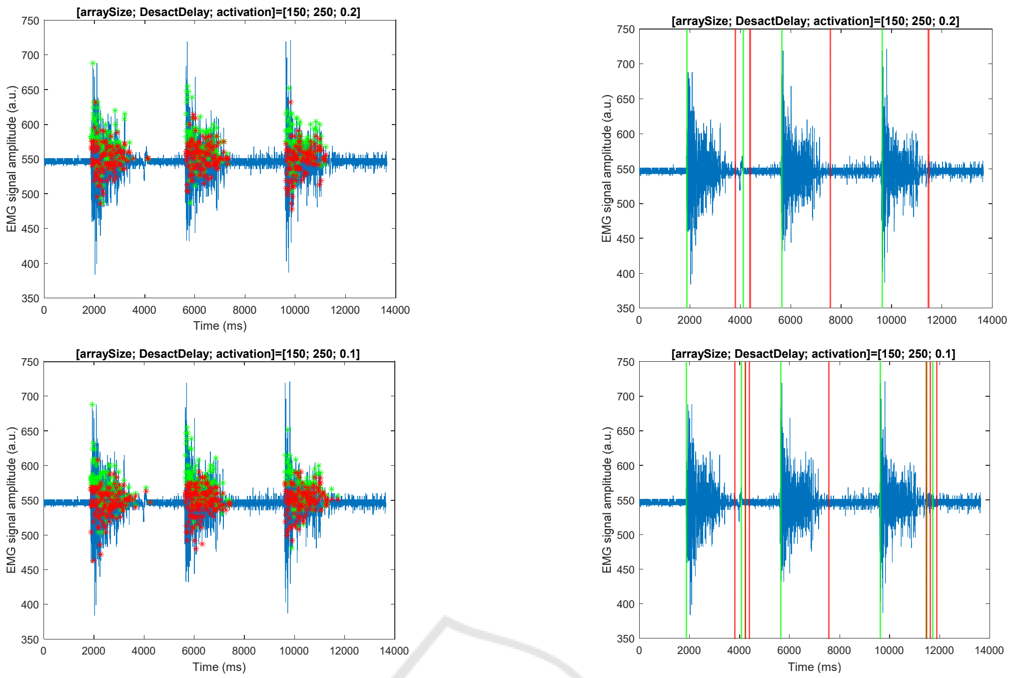

Figure 6: Same EMG signal acquisition using a lower value of: (a) and (b) *arraySize* parameter (150 instead of 250); (c) and (d) also of *activation* parameter (0.1 instead of 0.2).

4 REAL-TIME APPLICATION

After testing the algorithm offline in Matlab, it was necessary to find a platform capable of providing a correct environment for its transition to the application of the algorithm in real-time control of a bionic hand, executed by a standalone Arduino Uno. As shown in figure 7, previous tests were performed with the accelerometer module of BITalino, due to its greater ease in data analysis. These data were acquired in parallel by Arduino and BITalino, enabling the simultaneous visualization of the acquired data, using the Serial Monitor and Serial Plotter, in the first case, and Opensignals, in the second case.

Through the correct use of the flags, already presented in table 1, for the control of the algorithm's flow, it was possible to obtain a satisfactory success in the detection of the onset/offset of activations with the accelerometer sensor.

Subsequently, the necessary adaptations were made to the code for the acquisition of data from the EMG sensor, namely in determining the values of the three parameters described above. Furthermore, although the sampling rate is adjustable, in these tests a cycle time of one millisecond had been used. Both in the selection of this value and in the arraySize depth, there are constraints imposed by Arduino Uno's limitations, which were met, but did not prevent the successful application of this algorithm, as shown in table 2, for the detection of muscle activation when random gestures are performed for the control of a bionic hand.

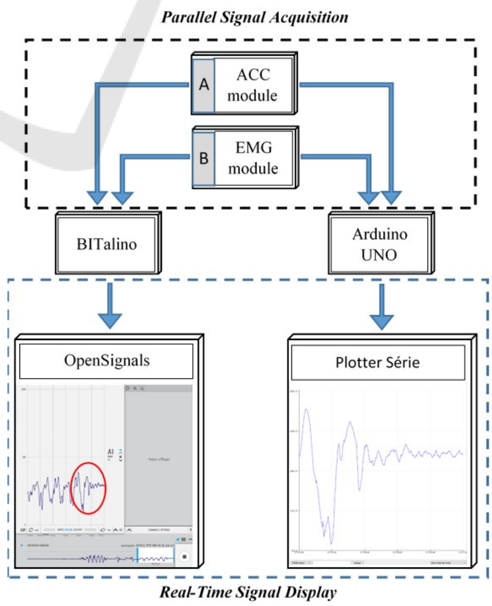

Figure 7: Schematic of previous tests setup. First with accelerometer (A) and afterwards with EMG module (B).

Table 2: Results of success on detection of muscle activation from random gestures.

Muscle activation	random
# performed	18
# detected	18
# not detected	0
# false activations	0
Success rate	100%
Error rate	0%

This evaluation of the success of this algorithm in real-time muscle activation detection was carried out using a servo-driven bionic one-hand controller prototype, as shown in Figure 8.

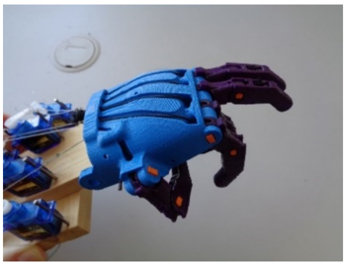

Figure 8: Photo of the prototype of the bionic-hand controller.

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 person 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 3.

5 DISCUSSION AND CONCLUSIONS

Preliminary results from the application of this algorithm in real-time detection of muscle activations are promising. The method based on smoothing the acquired signal from the EMG sensor, using flags in order to identify for each acquisition the global state of muscle activation, proved to be adequate for the proposed objective. It is now necessary to broaden and deepen this assessment in order to validate these results. This will allow an optimization of the three parameters defined in the algorithm, through a better characterization of the factors with an impact on that decision. In fact, the analysis performed did not address the precision in determining the time interval for muscle activation, which will be an important factor in the evaluation of the proposed algorithm. This will be a next objective, as this initial work focused on demonstrating the applicability of this algorithm, regarding the detection of muscle activation in a real environment.

This work also aimed to evaluate the real-time application of the algorithm, using a hardware platform based on Arduino UNO, a cheap microcontroller, as it is part of a project to develop a very low-cost bionic hand. Thus, the level of requirement raises, as the limitations in terms of microcontroller performance, both in terms of processing and memory, significantly reduce the options in terms of algorithm. Even so, it was possible to implement this algorithm with a sampling rate of 1 kHz, without an evaluation of the response time for the control of the bionic hand, as this is not the objective of this work.

The option for Micro Servo SG90 servomotors also contributed to the low cost of the platform used. However, it was possible to identify that they constituted an additional source of noise, which affected the amplitude of the fluctuations in the base level of the signal, with the muscle relaxed, depending on the gesture associated with the anterior muscle activation. It is also worth remembering that, contrary to what happens in the algorithms described in the literature, for this real-time application of the algorithm, the pre-processing with the use of filters was not carried out, using the raw EMG signal instead.

Table 3: Results of success on detection of muscle activation for the execution of different gestures.

Muscle activation	Close	Open	Point	Pinch
# performed	20	20	20	10
# detecteds	20	14	20	10
# not detected	0	2	0	0
# false activations	1	4	2	0
Success rate	100%	70%	100%	100%
Error rate	5%	30%	10%	0%

Thus, given all these constraints, it will be difficult for any algorithm to be able to determine with high precision the time interval of each muscle activation. Despite this, future work will be focused on optimizing the algorithm presented in this paper, and subsequent integration into the bionic hand control software, in order to characterize it in terms of the success rate in performing the different gestures and in its response time.

REFERENCES

Bonato P., D'Alessio T., Knaflitz M. (1998). A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait. *IEEE Transactions on Biomedical Engineering*, 45, 287–299.

De Luca, C.J. (1997). The Use of Surface Electromyography in Biomechanics. J. Appl. Biomech. 1997, 13, 135–163.

Di Fabio, R.P. (1987). Reliability of computerized surface electromyography for determining the onset of muscle activity, *Physical Therapy*, 67, 43–48.

Gentile, P., Pessione, M., Suppa, A., Zampogna, A., & Irrera, F. (2017). Embedded wearable integrating real-time processing of electromyography signals. In Multidisciplinary Digital Publishing Institute Proceedings (Vol. 1, No. 4, p. 600).

Konrad, P (2006). The ABC of EMG, A Practical Introduction to Kinesiology Electromyography, Version 1.4; Noraxon Inc.: Scottsdale, AZ, USA.

Li, X.; Zhou, P.; Aruin, A.S. (2007). Teager–Kaiser Energy Operation of Surface EMG Improves Muscle Activity Onset Detection. Ann. Biomed. Eng., 35, 1532–1538.

Rasool, G., Iqbal, K. (2012). Muscle activity onset detection using energy detectors. In: Proc. of the IEEE Engineering in Medicine and Biology Society Annual Int'l Conf. (EMBC) (pp. 3094- 3097). IEEE Publisher, San Diego.

Raurale, S. A. (2014). Acquisition and processing real-time EMG signals for prosthesis active hand movements, 2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE), 2014, pp. 1-6-

Russo, P (2019). Desenvolvimento e Teste de Algoritmos para a Extração de Características em Tempo Real a partir de Biosinais. [Unpublished Biomed. Tech BSc, thesis]. Polytechnic Institute of Setubal.