IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 21, 2019, accepted December 19, 2019, date of publication January 3, 2020, date of current version January 15, 2020.

Digital Object Identifier 10.1109/ACCESS.2019.2963881

Myoelectric Interfaces and Related Applications: Current State of EMG Signal Processing–A Systematic Review

BERNABE RODRÍGUEZ-TAPIA [1,2], ISRAEL SOTO [2], DANIELA M. MARTÍNEZ [1], AND NORMA CANDOLFI ARBALLO [1]

[1]Facultad de Ciencias de la Ingeniería y Tecnología, Universidad Autónoma de Baja California, Tijuana 21500, Mexico
[2]Instituto de Ingeniería y Tecnología, Universidad Autónoma de Ciudad Juárez, Ciudad Juárez 32310, Mexico

Corresponding author: Bernabe Rodríguez-Tapia (rodriguez.bernabe@uabc.edu.mx)

ABSTRACT The myoelectric interfaces are being used in rehabilitation technology, assistance and as an input device. This review focuses on an insightful analysis of the data acquisition system of EMG signals from these interfaces. According to applications reported in research articles of the last five years, the properties of the sensors, the number of channels, the pre-processing of the EMG signal, as well as the software and hardware used were identified. This analysis was performed for the following applications: monitoring of muscular activation for rehabilitation, muscle activation plans, and identification of possible pathologies, exoskeletons, electric of wheelchairs, prosthetics control, myoelectric bracelets, handwriting recognition and silent speech recognition. The results presented in this review become a guide of recommendations for the myoelectric signal processing according to the application of the interface. The main developments, degrees of research and open challenges are also presented in this direction.

INDEX TERMS Emg acquisition system, emg processing, electromyography sensors, myoelectric control, myoelectric signals.

I. INTRODUCTION

Electromyography (EMG) is a technique used to measure the muscle's response to electrical stimulus of the nerves [1]. The EMG signal acquired from the skin surface around muscle and joint areas is the summation of the electrical activity of all the muscle-fibred motor unit action potentials (MUAPs) caused as a result of motion activity [2].

EMG signals have been relevant in several health fields. The periodical monitoring of EMG signals can be utilized to detect diseases like Huntington's disease, Myopathies, or Muscular dystrophies, and to timely address problems such as heart attacks or stroke occur [3], [4]. Furthermore, EMG signals could be useful to detect neuromuscular disorders that could affect motor units (Mus) and to identify the origin of such disorders [5]. Recently, in the Human-Computer Interaction (HCI) field, the use of bio signals has opened the way for the development of muscle-computer interfaces. Particularly, EMG signals collected by sensors attached to superior limbs, have been used for controlling devices by means of the electric impulses generated through the muscles [6].

Given all the possibilities for exploiting EMG signals, it is critical to ensure that the data collected is reliable and that it is a precise representation of the electrical activity of the muscles. Therefore, an important research area, is the analysis of the specific application design requirements of the acquisition system considered for obtaining the myoelectric signals. Once these requirements are identified, it will be possible to provide widespread recommendations for the design of efficient and reliable EMG signal acquisition systems.

An EMG signal acquisition system consists of four main stages: (i) signal collection (ii) signal amplification, (iii) signal filtering and (iv) analog-to-digital converting. Each stage demands specific requirements according to its operational characteristics. These requirements can be specified in terms of the design parameters necessary for the implementation of EMG signal acquisition systems and will be further discussed in the rest of this document.

The associate editor coordinating the review of this manuscript and approving it for publication was Shaohua Wan.

The method for collecting the EMG signal is by using electrodes. An electrode is a transductor that represents the level of muscle activity by recording the electrical activity in it. Invasive approaches, also known as needle electromyography (nEMG), record electrical activity through needle electrodes. Whereas, non-invasive approaches, also known as surface electromyography (sEMG), record muscle activity from the skin surface through wet or dry surface electrodes [1], [7]. The suitability of each approach depends on the feasibility of using an invasive or non-invasive approach to collect the EMG signal. Although nEMG provides more features of the muscular activity, its main disadvantage emerges from the dynamics of muscular activities. Given the inherent invasiveness of the approach, it is difficult to repeatedly reposition the needle electrode if multiple locations of the muscle need to be analyzed. Thus, only a limited number of active engine units can be measured [8]. sEMG is preferable for obtaining information regarding the duration or intensity of superficial muscle activation [9]. The majority of applications consider the non-invasive sEMG approach, as it is free of discomfort and observes extremely low risk of infection to amputees [10].

Two critical design parameters for the signal collection stage are the selection (type) and location (placement) of the electrodes. Given that the signal-to-noise ratio (SNR) depends on the place where the signal is collected, an optimal selection of the electrode placement is mandatory to achieve an adequate SNR level [11]–[13]. On the other side, the open-loop gain (output-to-input ratio) as well as the input and output impedances, are key parameters in the amplification stage [14].

Given the proximity of many other bio signals in the surroundings of the muscle and power line interference, it is expected that the collected EMG signals will contain undesired features that may obscure important information regarding the electrical activity of the muscle. Hence, the optimal design of the filtering stage is critical to exclude all the unwanted frequency components. Several variables must be considered in order to efficiently design the filtering stage: the selected muscles, the type of contraction, the configuration of the sensor and the source of the specific noise [15]. The characteristics of the amplifiers and filters will determine the quality of EMG signal.

After the EMG signal is amplified and filtered, it is fed into an analogue-to-digital converter (ADC) circuit [16]. For each specific application, EMG signals must be processed by means of advanced signal processing algorithms, which are commonly implemented in computer systems. Therefore, the analogue-to-digital conversion stage needs to be carefully designed. Three main variables must be considered during the design of the ADC stage: the open-loop gain considered during the amplification stage, the maximum output voltage at the back-end of the EMG signal acquisition system, and the additive noise. Moreover, in order to reconstruct digitized signals with minimal errors, it is necessary to determine the optimal sampling frequency, which makes it another important design parameter for the ADC stage [14].

Insightful recommendations regarding non-invasive evaluation of muscles were provided by the European project SENIAM [17], published in 2000. Sensor type selection and sensor placement were remarkable topics addressed in the recommendations. More than a decade later, the considerations draw from SENIAM for sensor placement were updated [18]. Moreover, key features as signal amplification, filtering and sampling rate were added to the previous recommendations. Recently, works have been developed to perform analysis related to filtering, thinking about obtaining minimum sampling frequency parameters to determine more favorable conditions for processing time and its implementation in portable acquisition systems [19], [20]. These contributions have been very valuable for the pre-processing of EMG signals, however, none of these previous works study the relationship among the configuration of the data acquisition system and the specific application of the EMG signal.

Therefore, this paper focuses on providing an insightful analysis of the data acquisition system requirements, from a measurement and data pre-processing point of view, as related to the myoelectric interface for a specific application of the EMG signal.

II. METHODOLOGY

A. SEARCH STRATEGY

In order to collect significant information regarding the parameters of EMG signal acquisition systems, a systematic search was conducted. The references were indexed by the following keywords: emg acquisition system, emg sensors, electromyography sensors, myoelectric control and myoelectric signals. The search was conducted in the following databases: IEEE Xplore®, SCOPUS, Springer and ScienceDirect search engine to determine the state of the art of the topic.

B. REVIEW PROCESS

Articles found after the previously described search were evaluated by analyzing the title and the abstract. The following criteria was considered for final selection of articles: (i) Articles written in English; (ii) articles published from 2014 to 2018; (iii) comprehensive initial search results that included journal articles only.

The study was conducted using the systematic review method proposed by Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA), as shown in Fig. 1.

C. INCLUSION CRITERIA

Articles found after the previously described search were evaluated by analyzing the title and the abstract. The following criteria was considered for final selection of articles: (i) Articles written in English; (ii) articles published from

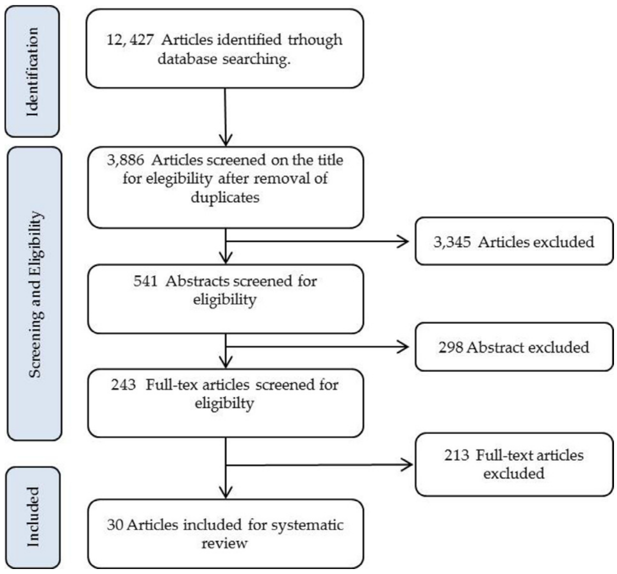


FIGURE 1. Flowchart of searching and screening strategy.

TABLE 1. Parameters considered during the reference scan process.

Parameter	Specification
General purpose information	Journal
	Publication title
	Abstract
	Research oriented to a specific application
Sensor properties	Type of sensor (invasive or non-invasive)
	Type of signal
	Number of conductive contact points for the EMG sensor
	Material, size and shape of the sensor
Pre-processing features	Gain and amplification type
	Filtering stage design
	Sampling frequency and ADC resolution
	Hardware and software for data pre-processing

2014 to 2018; (iii) comprehensive initial search results that included journal articles only.

III. RESULTS

A. STUDY SELECTION

From the 12,427 results found in the databases, only 3,886 did not duplicate. From these, 3,345 were discarded after title screening. 541 works were selected to perform abstract review, resulting in the selection of 243 papers for full-paper review. After the full-paper review process, 30 papers were selected according to the fulfillment of the specifications shown in Table 1. It is important to note that although there is a significant amount of publications in the field, only a small number of publications address the specifications regarding the design of EMG signal acquisition systems.

All the applications found during the screening process are listed below:

- Monitoring of muscular activation for rehabilitation, muscle activation plans, and identification of possible pathologies [4], [5], [21]–[24].
- Support mechanisms based on the estimation of muscular strength, known as exoskeletons [25], [26].
- Electric control of wheelchairs [27], [28].
- Prosthetics control [29]–[36].
- Command control by means of myoelectric bracelets [37]–[40].
- Handwriting recognition from EMG signals for controlling computer peripherals and identification of pathologies as Parkinson's disease and dysgraphia [41]–[45].
- Surface EMG-based sketching recognition for the development of electronic sketching systems and computer-aided sketching systems [46], [47].
- Silent speech recognition by means of myoelectric sensors interface [48]–[50].

The aforementioned applications are classified by Hakonen [18] into three categories: (1) Rehabilitative technology, that includes activation of exoskeletons and monitoring of muscle activation which is useful for the detection and prevention of health problems, as well as for activation and strengthening of muscular structures; (2) assistive technology, involving the control of prosthetics and motorized wheelchairs by means of EMG signals; and (3) technology as an input device, which includes the use of myoelectric bracelets for the identification of gestures or sign language, myoelectric interfaces for writing interpretation and sketching, and myoelectric sensors for silent speech recognition.

After the comprehensive review of the 30 selected papers, it was found that the requirements of the EMG signal acquisition system vary from one application to another. In this sense, the objective of the present review is to analyze these requirements to provide an adequate property classification and to define the recommended operational characteristics of the EMG signal acquisition systems for each of the previously listed applications.

B. STAGE ANALYSIS OF THE EMG SIGNAL ACQUISITION SYSTEM

EMG systems are characterized for acquiring, analyzing and processing complex bio signals. These bio signals are small in amplitude but very rich in information, and given that they are controlled by the nervous system, they depend on the anatomy and physiological properties of the muscles [51]. The electrical characteristics of EMG signals reported in the reviewed works are listed in Table 2. In the table, it can

TABLE 2. Electrical characteristics of the EMG signal.

Amplitude	Frequency	Author
0-6 mV	0 a 500Hz	[52]
0-10mV	NS	[51]
NS	20 to 400Hz	[53]
10uv-10mV	10 -500Hz	[54]
1-10mV	20-500Hz	[55]

Note: NS: Not specified

TABLE 3. Harmful interferers that affect the recording of the EMG signal.

Interfering	Authors
Moving artifacts Transmission line Saturation of the amplifier Physiological interference (for example ECG signals) Noise (Additive White Gaussian Noise)	[21], [56]–[58]

be identified that the amplitude in voltage of a muscular contraction can vary from 0 to 10mV and the energy is within the first 500 Hz in the frequency spectrum.

On the other hand, Table 3 presents a collection of harmful interferers that may affect the performance of the EMG system. Among the main interferences, the following were identified: moving artifacts affecting low frequencies, transmission line that can affect the frequency of 50 or 6OHz depending on the energy sub-ministered of each country, saturation of amplifier, physiological interference, specifically, the electrocardiogram and noise bio signal.

Due to the characteristics described above, EMG signals require specific treatment to take the full advantage of the information provided by them. Therefore, the design of the EMG signal acquisition system stages must be carried out in such a way that this specific treatment is effectively achieved. In general terms, an EMG signal acquisition process requires two main activities: signal sensing and signal pre-processing. Several authors agree in dividing pre-processing of EMG signals into three stages: amplification, filtering, and analog-to-digital conversion [51], [21], [57], [59], [60]. Hence, we will consider that EMG signal acquisition systems are comprised by four stages: (1) sensing, (2) amplifying, (3) filtering, and (4) analog-to-digital conversion.

As stated before, the main goal of this review is to classify the application-specific properties of each stage of the EMG signal acquisition system and to draw recommendations regarding the design requirements for the stages. In this sense, Table 4 abstracts the main properties identified for the sensing stage. The information in Table 4 was completed by identifying in each research article what type of technique was used, superficial or intramuscular, if only the EMG signal was analyzed or in conjunction with another bio signal, how many channels were used, and the characteristics of the sensors used.

While Table 5 summarizes the properties related to the amplifying, filtering, and analog-to-digital conversion stages as well as the software and hardware used, both tables were constructed from the information extracted from the 30 reviewed articles.

1) SENSING STAGE

a: PROPERTIES OF THE EMG SENSOR

In a myoelectric interface, electrodes are used to detect the biological potential that is generated due to muscle contraction [3]. EMG signals can be analyzed independently or along with other bio signals that are useful to the better understanding of the muscle's movement. The number of implemented sensors is related to the type of movement that is analyzed, and the amount of information provided by each channel needs to be considered for further processing. Properties such as construction material, configuration and size are variables that need to be considered when designing and implementing the signal acquisition system for each specific application.

In this sense, the properties of the sensors considered in the 30 papers selected for this systematic review, were thoroughly analyzed. It is worth mentioning that the selected works cover most of the applications of EMG signals discussed in the previous section. It can be observed in Table 4, that 9 out of the 30 research works correspond to applications falling into the rehabilitation technology category, 10 out of the 30 works fall into the assistive technology category, and finally, 11 out of the 30 works belong to the technology as an input device category.

b: SENSING TECHNIQUE (SUPERFICIAL OR INTRAMUSCULAR)

Bioelectrical activity inside the muscle of a human body is detected by means of EMG electrodes. There are two main types of EMG electrodes: superficial (skin surface electrodes) and intramuscular (needles and thin wires) [61].

From 30 works shown in table 4, 28 resorted to the superficial technique for gathering the EMG data, one work considered the intramuscular technique (sEMG), and one employed a fusion of both techniques (hybrid approach). Of the works that did not report using surface technique, one of the two researches used the intramuscular technique which is focused on EMG signal classification methods for identifying health problems [5]. Signal classification method proposed in [5] allows discriminating among normal, myopathy and Amyotrophic Lateral Sclerosis (ALS) patients. On the other hand, the work that considered the hybrid approach addresses the problem of prosthetics control by means of signal classification [32].

c: TYPE OF ANALYZED SIGNAL

As stated before, it is possible that the sensors collect other bio signals along with the EMG signal. These bio signals may differ according to the application considered. The analysis of the signals used in the studies proposed in each of the 30 reviewed works, highlights that 21 works consider only EMG signals, while the remaining 9 publications consider

TABLE 4. Properties of the sensors according to the application type (N=30).

#	Author	Technology	Application	Technique	Signal type	EMG channels	Sensor features
1	[4]	❶	a	S	EMG, ECG, EDA, ACC and LUX	Single channel	Ag/AgCl/NE
2	[21]	❶	a	S	EMG and ECG	Single channel	RF-ECG EK / 41mm x 44mm x 9.4mm
3	[5]	❶	a	I	EMG	Single channel	Monopolar/ 0.07mm
4	[29]	❷	d	S	EMG	16 channels	Monopolar /12 mm
5	[30]	❷	d	S	EMG	8,9 ,16 channels	Monopolar /NE
6	[31]	❷	d	S	EMG, Position tracking	8 channels	Monopolar/NE
7	[32]	❷	d	S/I	EMG, Strength	12 channels	Bipolar /NE
8	[22]	❶	a	S	EMG, PPG and BIA	4 channels	Bipolar /NE
9	[23]	❶	a	S	EMG and IMU	10 channels	Bipolar /NE
10	[24]	❶	a	S	EMG	Single channel	Bipolar /NE
11	[33]	❷	d	S	EMG and Pressure	24 channels	Ag/AgCl / 1.25cm
12	[34][38]	❷	d	S	EMG	10 channels	NE
13	[35]	❷	d	S	EMG	8 channels	Bipolar
14	[36]	❷	d	S	EMG	8 channels	Bipolar
15	[25]	❶	b	S	EMG	4 channels	Bipolar
16	[26]	❶	b	S	EMG	8 channels	Ag/AgCl /8mm
17	[41]	❸	F	S	EMG	8 channels	Ag/AgCl/NE
18	[42]	❸	f	S	EMG, elbow movement and pressure.	8 channels	Ag/AgCl / 19.8mm x 35m
19	[47]	❸	f	S	EMG	8 channels	Ag/AgCl /5.7 cm
20	[43]	❸	f	S	EMG	NE	Ag/AgCl
21	[46]	❸	f	S	EMG	4 channels	Ag/AgCl /5cm x 3.5 cm
22	[44]	❸	f	S	EMG	6 channels	Ag/AgCl/NE
23	[45]	❸	f	S	EMG	6 channels	Ag/AgCl
24	[27]	❷	c	S	EMG	4 channels	Bipolar
25	[28]	❷	c	S	EMG	4 channels	Ag/AgCl/NE
26	[37]	❸	e	S	EMG	4 channels	Ag/AgCl/NE
27	[62]	❶	b	S	EMG	8 channels	Ag/AgCl / 10mm
28	[38]	❸	e	S	EMG, acceleration, orientation in space.	8 channels	NS
29	[48]	❸	g	S	EMG	3 channels	Bipolar
30	[49]	❸	g	S	EMG	4 channels	Bipolar /10mmx20mmx3mm

Source: Own elaboration.
Notes: NS: Not specified; S: Superficial; I: Intramuscular
❶: Rehabilitative technology; ❷: Assistive technology; ❸: Input devices technology.

[a] Monitoring of muscular activation; [b]exoskeletons; [c]electric power wheelchairs; [d]prosthetics control; [e]myoelectric bracelets; [f]handwriting recognition; [g] silent speech recognition

other signals as: strength, signals acquired by IMU sensors, electrocardiogram (ECG) signals, pressure, acceleration, space orientation, electrodermal activity (EDA), adaptive cruise control (ACC), illuminance (LUX), elbow movement, photo plethysmography (PPG), bioelectrical impedance analysis (BIA) and position tracking.

In Table 4 it is remarked that the papers that involve the measurement of other bio signals in addition to the EMG signals are, in general, those that study signal classification methods for prosthetic control. This is mainly since these applications require knowledge regarding additional information as position, speed, rotation and force to improve the efficiency of parameters interpretation. The use of other sensors for monitoring different bio signals has also been reported, although they are not necessarily analyzed all together with the EMG signals.

d: NUMBER OF EMG CHANNELS

The number of channels used in an EMG signal acquisition system is related to the muscles intended to be analyzed.

TABLE 5. Pre-processing features according to the application (N=30).

#	author	Technology	Application	Amplifier gain	Filter type	Sampling frequency/ ADC resolution	Pre-processing Hardware/ Software
1	[4]	❶	a	1000	10-400 Hz Band-pass	1000 Hz	BITalino toolkit based on microcontroller ATmega238P/NS
2	[21]	❶	a	NS	NS	1000 Hz/ 12 bits	NS/Matlab
3	[5]	❶	a	4000	2-10 Hz Band-pass	23438 Hz/ 16 bits	Motorola DSP56ADC16 microcontroller/NS
4	[29]	❷	d	NS	20-250 Hz Band-pass (4th order Butterworth); 50 Hz Notch filter.	1200 Hz/ 24 bits	Computer (2.67GHz dual-core 8GB RAM)/ Matlab
5	[30]	❷	d	500 - 1000	10- 500 Hz Band-pass	2048 Hz /12 bits	NS/Matlab
6	[31]	❷	d	NS	20-500 Hz Band-pass (4th order Butterworth); 50 Hz Notch filter	1000 Hz/ NS	NS
7	[32]	❷	d	Variable	20-500 Hz Band-pass (4th order Butterworth)	10,000 Hz /16 bits	NI-DAQ USB-6259/NS
8	[22]	❶	a	Variable	500 Hz Low-pass (3rd order SALLEN-Key)	1000- 2500 times greater that Nyquist rate/ 8 bits	FPGA (Cyclone IV, Altera Corp., CA) and peripheral integrated circuits/NS
9	[23]	❶	a	600	20-500 Hz Band-pass (2nd order Butterworth)	1000 Hz /12 bits	ADS1198 (Texas Instruments, Dallas, TX, EE.UU)/ Matlab
10	[24]	❶	a	Variable	NS	1500 Hz/ 16 bits	ADS1298 for AFE, MD3880 for VHA and INA329 for LNA/NS
11	[33]	❷	d	NS	Band-pass 10-400 Hz Band-pass (3rd order Butterworth)	1000 Hz/ 24 bits	Electrophysiological signal recording system (Eegosports from ANT-Neuro, Netherlands)/ Matlab
12	[34],[38]	❷	d	NS	NS	NS	NS/Matlab
13	[35]	❷	d	NS	50 Hz Notch filter ; 20 Hz high-pass	1000 Hz/ NS	Microcontroller ARM Cortex M4/ Matlab
14	[36]	❷	d	Variable	50 Hz Notch filter	500 Hz-1000Hz/ NS	Microcontroller ARM Cortex (STM 32F407)/NS
15	[25]	❶	b	NS	30 Hz high-pass; (3 a 10 Hz) low-pass with 7 Hz.	NS	NS/Matlab
16	[26]	❶	b	Variable (2000-5000)	NS	1000 Hz/ 12 bits	A/D (Scientific Solution Lab Master)/ Matlab -Simulink
17	[41]	❸	f	1000	5-500 Hz Band-pass (2nd order Butterworth)	1000 Hz/ NS	Amplified recording system (Grass, model 15LT/15A54-2), Digitizer (Polyview/16SYS)/NS
18	[42]	❸	f	NS	20-250 Hz Band-pass (2nd order Butterworth)	1000 Hz/ NS	Recording system (Myomonitor IV Delsys Inc., Boston, MA)/Matlab
19	[47]	❸	f	NS	10-500 Hz Band-pass	1000 Hz/ NS	Digital system (ZJE-ii Studio Ltd., China)/NS
20	[43]	❸	f	1000	Cutoff frequency fc=60hz; Chebychev IIR with Fc=16 Hz and 81 dB attenuation	2000 Hz/ NS	DAC NI/ Labview TTL SYNC
21	[46]	❸	f	1000	10-500 Hz Band-pass 50 Hz Notch filter	1000 Hz/ 14 bits	12 channels EMG digital system (ZJE-II, ZJE Studio Ltd., China)/NS
22	[44]	❸	f	NS	10-200 Hz Band-pass 50 Hz Notch filter	1000 Hz/NS	Syn Amps system (Neuroscan , EE.UU.)/NS
23	[45]	❸	f	NS	NS	1000 Hz/NS	Bimetrics, EE.UU./NS
24	[27]	❷	c	NS	NS	NS	NS
25	[28]	❷	c	455	NS	1000hz/ 10 bits	AD-623 amplifier, Microcontroller ATMEGA-8/NS

TABLE 5. ***(Continued)*** **Pre-processing features according to the application (N=30).**

26	[37]	❸	e	1000	2-750 Hz Band-pass	1024 Hz/NS	NS
27	[62]	❶	b	NS	NS	NS	NS
28	[38]	❸	e	NS	NS	NS	MYO armband (Thalmic Labs)/NS
29	[48]	❸	g	NS	20-500 Hz Band-pass 50 Hz Notch filter	1000 Hz/NS	Intel Edison board/NS
30	[49]	❸	g	Conditioned for maximal input range of 11 mV	20-450 Hz Band-pass	NS	Delsys Inc, Natick MA /Matlab

Source: Own elaboration.
Notes: NS: No specified; S: Superficial; I: Intramuscular
❶: Rehabilitative technology; ❷: Assistive technology; ❸: Input devices technology.
[a]monitoring of muscular activation; [b]exoskeletons; [c]electric power wheelchairs; [d]prosthetics control; [e]myoelectric bracelets; [f]handwriting recognition ; [g]silent speech recognition

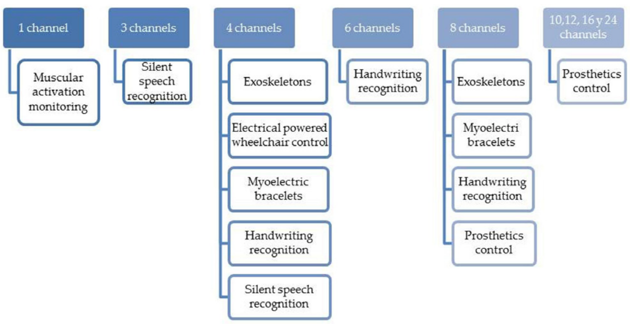


FIGURE 2. Number of channels used for each application. *1 channel* [5], [24], [21], [4]; *3 channels* [48]; *4 channels* Exoskeletons [25], Electric powered wheelchair control [27], [28], Myoelectric bracelets [37], Handwriting recognition [44], Silent speech recognition [49]; *6 channels* [42] and [43]; *8 channels* Exoskeletons [24] and [60], Myoelectric bracelets [63], Handwriting recognition [39], [40] and [45], Prosthetics control [29], [33] and [34] and *10, 12, 16 y 24 channels* [27], [28] and [30]–[32].

This design parameter will directly affect the amount of information that needs to be processed during the classification and data interpretation stage of the myoelectric system.

From the analysis shown in the Table 4 is found out that the number of channels is directly related to the specific application of the EMG signal. Fig. 2 depicts the relationship between the numbers of channels used per application addressed in the thirty reviewed papers. Articles reported having used between 1, 3, 4, 6, 8, 10, 12, 16 and 24 channels. At the bottom of the figure the reference is shown according to the channel number and its application.

According to the information provided by the reviewed papers and Fig. 2, one single channel could be enough for transmitting the muscular activity data necessary for muscular activation monitoring systems. However, if pattern recognition methods are going to be applied for identifying specific limb pathologies, then considering up to ten channels might be necessary [23].

For silent speech recognition applications, studies report that a considerable amount of words and phrases could be interpreted by using four channels [49]. On the other hand, periodic expressions as chewing, talking, gargling, and temporary expressions as sadness, surprise, happiness, pouting and anger, could be recognized by employing a minimum of three channels [48].

The number of channels documented in applications for the interpretation of command gestures is four [27], [28]. These applications are typically used in electrical powered wheelchairs to control functionalities as: moving, stopping, moving forward and reversing. Also, four channels are used in applications for simple hand gesture recognition through myoelectric bracelets [39], [64], [65]. Common uses for these applications are virtual reality gaming, computer or mobile phones control, or sign language interpretation.

Works that address applications as writing recognition and exoskeleton activation have documented the use of, at least, six and eight channels. The number of electrodes used in the prosthesis can vary from 1 to 32 electrodes. The importance of this configuration lies in its electro-accuracy control, production cost, computational load, the type and number of tasks to be achieved and degrees of freedom (DoFs) [66].

e: SENSOR FEATURES (CONFIGURATION, CONSTRUCTION MATERIAL AND SIZE)

According to the investigation reported in [17], there are three different sensor configurations: monopolar, bipolar and array/line electrodes. By analyzing the sensor configuration considered in each of the 30 reviewed works, it was observed that the bipolar configuration is the most used. Only 3 out of the 30 works consider the monopolar configuration, and none of them consider the array/line sensor configuration.

On the other hand, a desirable feature for data recording electrodes is their capability for avoiding overpotentials due to polarization. A silver chloride (Ag/AgCl) electrode complies with this feature [67]. In this regard, 13 out of the 27 works that consider bipolar sensors, reported that the sensors were constructed using Ag/AgCl, while the remaining 14, do not specify the construction material of the sensors employed.

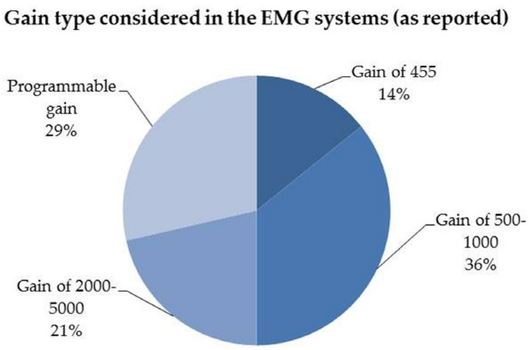


FIGURE 3. **Percentage of the works per gain type.**

Regarding the size of the sensor, only 10 out of 30 papers provided a detailed description of the sensor size and shapes. The information is summarized below:

- Rectangular: 41mm x 44mm x 9.4mm, 19.8mm x 35mm, 5cm x 3.5cm, 10mm x 20mm x 3mm
- Circular: 8mm, 10mm, 12mm y 5.7cm
- Needle electrode: 0.07mm

2) AMPLIFYING STAGE

As mentioned before, EMG signals are very weak. This characteristic is exacerbated in some specific muscles. Therefore, it is expected that the amplifier gain design must be tailored according to the application in relation to the muscles involved. 14 out of the 30 reviewed works reported the amplifier gain considered for their systems, the results are shown in Fig. 3, considering that 100% corresponds to the 14 papers that report the gain type and value used for their systems, it was identified that over the majority of the works, 36%, documented earnings between 500 and 1000 over the original signal.

The information provided in Figure 3 can be further described to classify the gain value used per specific application:

- Myoelectric bracelet: Gain of 1000 [37].
- Prosthetic control: Programmable gain amplifiers [30], [32], [36].
- Exoskeleton: Programmable gain from 2000 to 5000 [26].
- Handwriting: Gain of 1000 [41], [46] and of 2000 [43].
- Muscular activation monitoring: Gain of 600 [23], of 1000 [22], of 4000 [5], low noise and variable gain amplifier [24].
- Electric powered wheelchair control: Gain of 455 [28].

From the works that do not specify the amplifier gain, 5 of them are related to prosthetic control applications, 1 to muscular activation monitoring, 2 to exoskeleton activation, 3 to writing recognition, 1 to myoelectric bracelet, 1 to electric powered wheelchair control, and 1 to silent speech recognition.

It can be assumed that the lack of information on this matter is mainly due to the unavailability of the specific parameters of design in commercial devices. For example, in [38] the hand control application is based on the myoelectric bracelet, which is manufactured by MYO from Thalmic Labs. Thalmic Labs does not provide further information regarding the amplifier stage of the acquisition system of the bracelet.

3) FILTERING STAGE

As discussed previously, EMG signals can be affected by other intended or non-intended signals, for example other bio signals (ECG, EEG, etc.) or radiofrequency emissions (cellphones, Wi-Fi, Bluetooth, etc.). Furthermore, temperature fluctuations, compensations in amplification stage, characteristics of the sensor, etc., can also affect the waveform of the EMG signal. All these undesired signals and random variations can be modelled as noise whose frequency characteristics may vary depending of the actual noise sources [61]. In this sense, the filtering stage in a signal acquisition system is of paramount importance to reduce the detriment of the EMG signal caused by noise.

According to its frequency response, the filters reported in the reviewed works on Table 5 can be classified into three categories:

(1) Band-pass filters:

- 500 Hz, 3rd order [22]
- 5-500 Hz, 2nd order [41]
- 10-200 Hz [44]
- 10-400 Hz [4], 3rd order [33], [4]
- 10-500 Hz [30], [46], [47]
- 20-250 Hz 2nd order [42]
- 20-450 Hz [49]
- 20-500 Hz [48], 2nd order [23] and 4th order [31], [32]
- 30-300 Hz 4th order [29]
- 2-750 Hz [37]
- 13 works do not specify the characteristics of the filtering stage

(2) Notch filters: 50 Hz and 60 Hz (depending on the frequency of the electrical network in each country).

(3) Low-pass filters:

- 2 and 10 Hz [5]
- 20 Hz [35]
- 7 Hz [25]
- 16 Hz [43]

4) ANALOG-TO-DIGITAL CONVERSION

Applications as pattern recognition or device control through EMG signals take place after the EMG signal is converted to a digital format. Hence, the sampling frequency and quantization levels of the analog-to-digital converter (ADC) are important design parameters that must be thoroughly analyzed for each specific application.

Regarding the sampling frequency, 24 out of the 30 works from Table 5 presented a detailed report of the sampling frequency considered in their applications, summarized as follows: 21 papers reported sampling frequency values ranging from 1000 to 1500 samples per second; for the remaining 3 papers, the sampling frequency ranges from 2000 to 23434 samples per second. The latter are related to applications that resort to classification methods for pathology

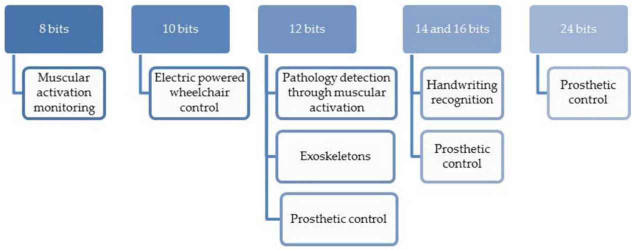


FIGURE 4. **ADC resolution reported in some EMG signals applications. 8 bits [22]; 10 bits [28]; 12 bits Pathology detection muscular activation [23], [21], Exoskeletons [26], Prosthetic control [30]; 14 and 16 bits Handwriting recognition [46], Prosthesis control [32] and 24 bits Prosthetic control [29], [33].**

detection through muscular activation, prosthetic control and writing interpretation.

On the other side, the resolution of the ADC is reported in 12 out of the 30 works from Table 5. The classification of the resolution considered in these research works is presented in Fig. 4, where it is shown that the ADC can vary between 8, 10, 12, 14, 16 and 24 bits, with ADC converters of 12, 14 and 16 bits being more used. At the bottom of the figure, the reference is shown according to the number of bits and their application.

According to the classification provided in Figure 4, it is possible to infer that applications that require simpler gestures interpretation would require lower resolution, as compared to that requiring more complex gestures interpretation, as in, for example, writing recognition or prosthetic control with higher degrees of freedom, where higher resolution, ADC is necessary.

5) SOFTWARE AND HARDWARE

According to Table 5 it can be seen that there is a diverse range of commercial systems developed for the monitoring of EMG signals, these may vary according to the number of synchronized channels and the use of these signals. Each of these systems develop the processing and visualization in closed-source hardware/software systems. However, the commercial software of these owners often have the opportunity to provide ways to export files for use on other platforms such as Matlab, Excel, Labview among other. They can be exported by ''Selected signal(s)'' or ''Raw data set''. The export of these can be done in different types of files: Bynary, CSV o Matlab files. Some suppliers offer the opportunity to access the different sensors with some adaptation to be read by Simulink, for example.

On the other hand, the works report the development of owned systems for research purposes, these systems are usually just as reliable as the commercial ones and have a degree of flexibility adequate for analysis and research purposes. The general architecture is represented in the type of sensors, the type of amplifiers, the converter card A/D, and the microcontroller that controls the process. C++, LabVIEW (National Instruments Corp., Austin, TX, EE. UU.) and MATLAB (The Mathworks Inc., Natick, EE. UU.) They are mainly used as programming languages.

Currently, there are also systems called ''open -source hardware'', based on platforms like Arduino, Raspberry Pi, Atmel, Pololu, among other whose hardware, software and mechanical design files are available online offering a solution to the high costs and slow pace of innovation of medical devices.

IV. DISCUSSION

The use of the myoelectric signals has extended in the last decades for diverse applications: in its commercial use, it is more remarkable in the medical and rehabilitation area; however, it has gained ground in mechanisms of support to the upper extremities such as the prosthetics and exoskeletons. Challenges remain and there are various applications that continue to be worked in the laboratory with the challenge of becoming new and ergonomic input peripherals on the HMI, as are the myoelectric bracelets, the handwriting and silent speech recognition. In order to add to this branch of knowledge, in this review and according to the application, the technical aspects of the main signal acquisition system were identified along with important differences in the configuration of these. The main findings found at each stage are shown below.

A. SENSING STAGE

Although there are different techniques to acquire the myoelectric signals, there are enough results in the analyzed works to consider that the superficial type technique (sEMG) is the most appropriate when you want to develop more ergonomic devices and equipment for commercial use. The most used sensors on investigations were those of biopotential configuration with silver chloride material (Ag/AgCl) since it has been shown to have the appropriate standards for the myoelectric interfaces due to its impedance characteristics.

The type of shape and measurements of the sensor have their variations, however, the most common are the round of 8mm and 10mm diameter. This information is consistent with the recommendations given in the European project SENIAM [17] published in 2000.

Regarding the relationship in the number of channels per application, it was identified that according to the number of muscles needed for a more efficient analysis, will be the number of channels to utilize. This trend, however, in research, is to decrease the number of channels. For this, the techniques of electrode location as sensors placement procedures for the sensors sEMG [68] and Crosswalk studies [69], [70], are important aspects to consider for the reduction or the correct selection of muscles and channels.

According to the analyzed investigations, works with only 3 channels, were able to recognize periodic expressions such as: chewing, speaking, gargling and transient expressions such as: sadness, surprise, happiness, pout and anger. For the gesture's recognition defined through myoelectric bracelets, electric control of wheelchairs and of silent speech recognition, 4 channels are commonly used. 8 channels for applications of prosthetics control more than 1 DoF, exoskeletons and handwriting recognition; 10, 16 and 24 are the most utilized channels for complex systems of prosthetics control for an important variety of movements.

The design of the surface electrodes can be classified as: 1) Muscle-oriented design, precise location of the muscle is necessary when using and adhering pairs of electrodes, 2) Arrangement of the low-density surface electrode (LD), it is necessary to have electrodes in certain patterns and distribute them uniformly in the skin forming ring structures or belts, what is also known as uniform electrode positioning. The number of channels can vary from 2 to 16, 3) Arrangement of high density surface electrodes (HD), which collects the EMG signals from the closely spaced electrodes, allows exploiting spatial information through the muscles, therefore, this strategy can be useful for the study of complex dynamic tasks in the free space with a greater number of DoFs. However, it remains a challenge to deal with many EMG channels to interact with a practical prosthetic hand.

B. AMPLIFICATION STAGE

From the analyzed documents, it was identified that there is not much of attention in documenting precise characteristics of amplification and filtering. This is more recurrent on the applications with a greater number of channels, as in myoelectric control; however, they documented having worked with programmable amplifiers. This makes sense because the efficiency of the classifiers focuses on patter recognition and classification algorithms about muscular regions not on a single muscle.

The Works that documented the gain value for applications such as monitoring of muscular activation, the gesture interpretation like electric control of wheelchairs, the handwriting recognition and the silent speech recognition, converge on the need to amplify the signal with a gain of 500 – 1000 unlike work [28] which proposes an amplification of 400.

Without a doubt, the gain and noise characteristics that these signals have, become complex and although the largest amplitude is desired, you have the risks of saturation in the amplifier. In [24], the need for low noise amplifier (LNA) and considering the risk of saturation on the amplifiers is mentioned. The consideration to incorporate a preamplifier is to have a high common mode rejection ratio (CMRR) and high input impedance.

C. FILTERING STAGE

The signal sEMG is inevitably contaminated, therefore, it is necessary to consider the different factors to determine the specifications of the filtering which include: the selected muscles, the type of contraction, the configuration of the sensor and the source of the specific noise and [15] adds that it's important to consider the corner frequency, the roll-off rate and the circuit topology chosen. The determination of the band-pass is important to reduce noise and the contamination by the artifacts and to preserve the desired signal, this way, the majority of the systems utilizes filters between 10 and 500 Hz. However, [71] indicates that utilizing the high-pass angle frequency of 20 Hz offers the best compromise to optimize the informational content desired of the SEMG signal, since at low frequencies of the spectrum frequency, noise sources are involved which overlap with the SEMG signal, for this reason, the determination of filtered characteristics in this region, has been a focus of attention.

The order of the reported filters can vary from first to fourth order, however, comparisons have been made between the second and fourth order Butterworth high pass, confirming that a second order can replace the high-pass filter of the fourth order [15].

Although the modern technology is substantially immune to some noises, it is not so for the reference noise, such is the case of the noise generated by the power lines. The works reported using the notch filter for frequencies of 50 or 60 according to the standards in each country.

D. ANALOG-TO-DIGITAL CONVERSION

The similarities on the works continue per the frequency sampling, most of the scanned works, documented to have used sampling frequency of 1000 Hz, as stablished by the sampling theory of Nyquist, which must be equal or less than half the speed of sampling of the signal, which it is known as the greater power (approximately 95%) of the signals, sEMG is explained by harmonics of up to 400 – 500 Hz. However, some differences were noted: [5] worked with a sampling frequency of 23428 Hz, [30] with 2048 Hz and [32] increased up to 10,000 Hz.

It is observed that those works that used a greater number of channels also increased the frequency. Although the use of a higher sampling frequency can acquire more myoelectric information that can increase the precision of the motion classification, this adds more computational complexity and analysis, as well as memory requirements. Some works such as [72] have shown that it is possible to decrease the sampling frequency up to 500 Hz were you can save approximately 50% storing memory and reduce 50% data processing time with a slight accuracy sacrifice (around 2%).

The ADC conversion was achieved with resolutions of 8, 10, 12, 14, 16 and 24 bits. In monitoring applications, a resolution sufficiency of 8 bits is shown, unlike electric control of wheelchairs and control by means of myoelectric bracelets, which are more efficient to use in a 10-bit resolution. The application that used 12, 14 and 16 bits are those that desire to interpret more complex pathologies or gestures such as prosthetics control, exoskeletons, handwriting recognition. The works that document the use of 24 bits are those that interpret complex gestures determined by the movement of upper extremities.

Although the ADC conversion varies for each application, [73] states that a 16 bit converter may be preferable for any acquisition system, since the aggregate resolution may eliminate the need for manual gain of each EMG amplifier.

E. SOFTWARE AND HARDWARE STAGE

According to the results of the documents analyzed, 3 types of systems were identified; each of them used for specific purposes due to its hardware and software characteristics.

High-end data acquisition platforms. These systems are used for medical and prosthetics applications whose main characteristics are: off-line processing, they do not focus on optimization for resource constrained platforms such as wearables, can obtain high gesture classification accuracy, the used algorithms are not documented and design of real time efficient systems is still a challenge.

Embedded data acquisition platforms: Systems used for research purposes, these systems are usually: open source platform, meet real-time requirements, are low power system. For the development of a wearable and low-power system, targeting high accuracy, the most promising approach seems to be the synergy between a low power Analog front-End (AFE) and a microcontroller, merging the system flexibility with a good signal quality and maintaining a good trade-off between power consumption and computing capabilities [36], [74].

Low cost wearable device. Used for interactive applications. Currently, the most interesting solution for wearable EMG gesture recognition is the MYO armband, from Thalmic Labs. This is a wearable and low-cost device equipped with EMG and inertial sensors. It connects to a PC or tablet via Bluetooth Low Energy (BLE) and allows both raw data streaming and the use of a proprietary library for gesture recognition. The signal processing is performed on the host platform and the used algorithms are not documented [36]. Nevertheless, the device presents low flexibility in terms of possible applications because it lacks embedded computing capabilities and cannot be used as a stand-alone system.

V. CONCLUSION

Although there are recommendations made by [17] regarding the non-invasive evaluation of muscles and those made by [18]–[20],which make references to key features such as amplifier, filter and sampling frequency. The approach proposed in this review allowed us to study the relationship between the configuration of the data acquisition system and the specific application of the signal.

The aforementioned applications can be classified into three categories: (1) Rehabilitative technology, that includes activation of exoskeletons and monitoring of muscle activation, useful for the detection and prevention of health problems, as well as for activation and strengthening of muscular structures; (2) assistive technology, involving the control of prosthetics and motorized wheelchairs by means of EMG signals; and (3) technology as an input device, which includes the use of myoelectric bracelets for the identification of gestures or sign language, myoelectric interfaces for writing interpretation and sketching, and myoelectric sensors for silent speech recognition.

The stages of the EMG data acquisition system include census, amplification, filtering and digital analog conversion. When reviewing a variety of papers documented by the researchers, it is concluded that the surface technique is preferable in its biopotential configuration for the EMG signal census, the amount of sensors used may vary according to the application of the interface, for example, interpretation applications of simple gestures such as motorized wheelchairs control or signal monitoring, use fewer sensors than the control of prosthetics or the use of exoskeletons; the majority of the works documented gains between 500 and 1000 on the original signal, the considerations to incorporate amplifiers is to have a high CMRR and a high input impedance; the most common filtering has to do with the elimination of interference from power lines, the movement of artifacts and other bio signals detected. Butterworth filters of the second or fourth order were the most reported; the most documented sampling frequency was 1000 Hz, as established by the Nyquist theorem, however, wireless systems usually use frequencies lower than 250 Hz and higher frequencies in medical platforms, the resolution of the analog-digital converter varies according to the application although, 16-bit converters are preferable.

According to the results of the documents analyzed, three types of systems were identified that allow the acquisition of High-end data acquisition platforms, Embedded data acquisition platforms and Low-cost wearable device, each using hardware and software features according to their purpose.

The results presented in this review can already be recommendation guides for the design of emg signal acquisition and processing systems according to their application, however the recommendations are based on the common practices of the researchers, in order to obtain reliable and optimal criteria, it is pending to carry out a study with the same approach, paying attention to the processing times, computation cost and the classification results for those interfaces that involve the interpretation of gestures.

REFERENCES

[1] Y. Athavale and S. Krishnan, "Biosignal monitoring using wearables: Observations and opportunities," *Biomed. Signal Process. Control*, vol. 38, pp. 22–33, Sep. 2017, doi: 10.1016/j.bspc.2017.03.011.

[2] P. Konrad, "Signal origin and acquisition," in *A Practical Introduction to Kinesiological Electromyography*. Scottsdale, AZ, USA: Noraxon, 2006, ch. 1, pp. 5–16.

[3] A. Narayan, H. Dasgupta, and H. Pal, "Instrumentation of a portable EMG sensor in a single PCB for human motion pattern detection," in *Proc. 2nd Int. Symp. Phys. Technol. Sensors, Dive Deep Into Sensors (ISPTS)*, 2015, pp. 1–5, doi: 10.1109/ISPTS.2015.7220069.

[4] H. P. Da Silva, A. Fred, and R. Martins, "Biosignals for everyone," *IEEE Pervasive Comput.*, vol. 13, no. 4, pp. 64–71, Oct. 2014, doi: 10.1109/mprv.2014.61.

[5] G. R. Naik, S. E. Selvan, and H. T. Nguyen, "Single–channel EMG classification with ensemble-empirical-mode-decomposition-based ICA for diagnosing neuromuscular disorders," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 7, pp. 734–743, Jul. 2016, doi: 10.1109/tnsre.2015.2454503.

[6] T. S. Saponas, D. S. Tan, D. Morris, and R. Balakrishnan, "Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces," in *Proc. 26th Annu. CHI Conf. Hum. Factors Comput. Syst. (CHI)*, Florence, Italy, 2008, p. 515, doi: 10.1145/1357054.1357138.

[7] G. R. Naik, K. G. Baker, and H. T. Nguyen, "Dependence independence measure for posterior and anterior EMG sensors used in simple and complex finger flexion movements: Evaluation using SDICA," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 5, pp. 1689–1696, Sep. 2015, doi: 10.1109/jbhi.2014.2340397.

[8] M. Ibitoye, E. Estigoni, N. Hamzaid, A. Wahab, and G. Davis, "The effectiveness of FES–evoked EMG potentials to assess muscle force and fatigue in individuals with spinal cord injury," *Sensors*, vol. 14, no. 7, pp. 12598–12622, Jul. 2014, doi: 10.3390/s140712598.

[9] R. Merletti and C. J. De Luca, "New techniques in surface electromyography," in *Computer Aided Electromyography and Expert Systems*, vol. 9, no. 3. Amsterdam, The Netherlands: Elsevier, 1989, pp. 115–124.

[10] R. Chowdhury, M. Reaz, M. Ali, A. Bakar, K. Chellappan, and T. Chang, "Surface electromyography signal processing and classification techniques," *Sensors*, vol. 13, no. 9, pp. 12431–12466, Sep. 2013, doi: 10.3390/s130912431.

[11] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 9, pp. 2537–2544, Sep. 2011, doi: 10.1109/tbme.2011.2159216.

[12] U. Imtiaz, L. Bartolomeo, Z. Lin, S. Sessa, H. Ishii, K. Saito, M. Zecca, and A. Takanishi, "Design of a wireless miniature low cost EMG sensor using gold plated dry electrodes for biomechanics research," in *Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA)*, Aug. 2013, pp. 957–962, doi: 10.1109/icma.2013.6618044.

[13] E. Vavrinský, M. Daříček, F. Hornek, M. Horniak, and D. Donoval, "Design of EMG wireless sensor system," in *Proc. Int. Conf. Appl. Electron.*, Pilsen, Czech Republic, 2011, pp. 1–4.

[14] C. Kitchin and L. Counts, "In-amp basics," in *A Designer's Guide to Instrumentation Amplifiers*, 3rd ed. Norwood, MA, USA: Analog Devices, 2004, pp. 1–4.

[15] J. Wang, L. Tang, and J. E Bronlund, "Surface EMG signal amplification and filtering," *Int. J. Comput. Appl.*, vol. 82, no. 1, pp. 15–22, Nov. 2013, doi: 10.5120/14079-2073.

[16] T. S. Poo and K. Sundaraj, "Design and development of a low cost EMG signal acquisition system using surface EMG electrode," in *Proc. IEEE Asia–Pacific Conf. Circuits Syst.*, Dec. 2010, pp. 24–27, doi: 10.1109/apccas.2010.5774896.

[17] H. J. Hermens, "Development of recommendations for SEMG sensors and sensor placement procedures," *J. Electromyograph. Kinesiol.*, vol. 10, no. 5, pp. 361–374, Oct. 2000, doi: 10.1016/S1050-6411(00)00027-4.

[18] M. Hakonen, H. Piitulainen, and A. Visala, "Current state of digital signal processing in myoelectric interfaces and related applications," *Biomed. Signal Process. Control*, vol. 18, pp. 334–359, Apr. 2015, doi: 10.1016/j.bspc.2015.02.009.

[19] H. Chen, Y. Zhang, Z. Zhang, Y. Fang, H. Liu, and C. Yao, "Exploring the relation between EMG sampling frequency and hand motion recognition accuracy," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Banff, AB, Canada, Oct. 2017, pp. 1139–1144, doi: 10.1109/smc.2017.8122765.

[20] A. Phinyomark, R. N. Khushaba, and E. Scheme, "Feature extraction and selection for myoelectric control based on wearable EMG sensors," *Sensors*, vol. 18, no. 5, p. 1615, May 2018, doi: 10.3390/s18051615.

[21] N. A. I. M. Rosli, M. A. A. Rahman, S. A. Mazlan, and H. Zamzuri, "Electrocardiographic (ECG) and Electromyographic (EMG) signals fusion for physiological device in rehab application," in *Proc. IEEE Student Conf. Res. Develop. (SCOReD)*, Dec. 2014, pp. 1–5, doi: 10.1109/SCORED.2014.7072965.

[22] I. Kim, Y. A. Bhagat, J. Homer, and R. Lobo, "Multimodal analog front end for wearable bio–sensors," *IEEE Sensors J.*, vol. 16, no. 24, pp. 8784–8791, Dec. 2016, doi: 10.1109/jsen.2016.2564942.

[23] Y. Li, X. Zhang, Y. Gong, Y. Cheng, X. Gao, and X. Chen, "Motor function evaluation of hemiplegic upper-extremities using data fusion from wearable inertial and surface EMG sensors," *Sensors*, vol. 17, no. 3, p. 582, 2017, doi: 10.3390/s17030582.

[24] M. Balouchestani and S. Krishnan, "Effective low–power wearable wireless surface EMG sensor design based on analog–compressed sensing," *Sensors*, vol. 14, no. 12, pp. 24305–24328, Dec. 2014, doi: 10.3390/s141224305.

[25] U. J. Naeem, C. Xiong, and A. A. Abdullah, "EMG-muscle force estimation model based on back-propagation neural network," in *Proc. IEEE Int. Conf. Virtual Environ. Hum.-Comput. Interfaces Meas. Syst. (VECIMS)*, Tianjin, China, Jul. 2012.

[26] J. Rosen, M. Brand, M. Fuchs, and M. Arcan, "A myosignal-based powered exoskeleton system," *IEEE Trans. Syst., Man, Cybern. A, Cybern.*, vol. 31, no. 3, pp. 210–222, May 2001.

[27] R. Mahendran, "EMG signal based control of an intelligent wheelchair," in *Proc. Int. Conf. Commun. Signal Process.*, Melmaruvathur, India, Apr. 2014, pp. 1267–1272.

[28] A. S. Kundu, O. Mazumder, P. K. Lenka, and S. Bhaumik, "Omnidirectional assistive wheelchair: Design and control with isometric myoelectric based intention classification," *Procedia Comput. Sci.*, vol. 105, pp. 68–74, Dec. 2017, doi: 10.1016/j.procs.2017.01.200.

[29] J. M. Hahne, S. Dahne, H.-J. Hwang, K.-R. Muller, and L. C. Parra, "Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 4, pp. 618–627, Jul. 2015, doi: 10.1109/tnsre.2015.2401134.

[30] S. Muceli, N. Jiang, and D. Farina, "Extracting signals robust to electrode number and shift for online simultaneous and proportional myoelectric control by factorization algorithms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 623–633, May 2014, doi: 10.1109/tnsre.2013.2282898.

[31] K.-H. Park, H.-I. Suk, and S.-W. Lee, "Position–independent decoding of movement intention for proportional myoelectric interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 9, pp. 928–939, Sep. 2016, doi: 10.1109/tnsre.2015.2481461.

[32] E. N. Kamavuako, J. C. Rosenvang, R. Horup, W. Jensen, D. Farina, and K. B. Englehart, "Surface versus untargeted intramuscular EMG based classification of simultaneous and dynamically changing movements," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 6, pp. 992–998, Nov. 2013, doi: 10.1109/tnsre.2013.2248750.

[33] N. Jarrasse, C. Nicol, A. Touillet, F. Richer, N. Martinet, J. Paysant, and J. B. De Graaf, "Classification of phantom finger, hand, wrist, and elbow voluntary gestures in transhumeral amputees with sEMG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 1, pp. 71–80, Jan. 2017, doi: 10.1109/tnsre.2016.2563222.

[34] S. Shin, J. H. Lee, and S. H. Son, "A survey of approaches for recognizing hand gestures using EMG signal," in *Proc. IEEE 22nd Int. Conf. Embedded Real-Time Comput. Syst. Appl. (RTCSA)*, Aug. 2016, p. 263, doi: 10.1109/RTCSA.2016.22.

[35] R. Meattini, S. Benatti, U. Scarcia, L. Benini, and C. Melchiorri, "Experimental evaluation of a sEMG-based human-robot interface for human-like grasping tasks," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2015, pp. 1030–1035, doi: 10.1109/robio.2015.7418907.

[36] S. Benatti, F. Casamassima, B. Milosevic, E. Farella, P. Schonle, S. Fateh, T. Burger, Q. Huang, and L. Benini, "A versatile embedded platform for EMG acquisition and gesture recognition," *IEEE Trans. Biomed. Circuits Syst.*, vol. 9, no. 5, pp. 620–630, Oct. 2015, doi: 10.1109/tbcas.2015.2476555.

[37] K. Xing, P. Yang, J. Huang, Y. Wang, and Q. Zhu, "A real-time EMG pattern recognition method for virtual myoelectric hand control," *Neurocomputing*, vol. 136, pp. 345–355, Jul. 2014, doi: 10.1016/j.neucom.2013.12.010.

[38] Y. Xu, C. Yang, P. Liang, L. Zhao, and Z. Li, "Development of a hybrid motion capture method using MYO armband with application to teleoperation," in *Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA)*, Aug. 2016, pp. 1179–1184, doi: 10.1109/icma.2016.7558729.

[39] M. Sathiyanarayanan and S. Rajan, "MYO armband for physiotherapy healthcare: A case study using gesture recognition application," in *Proc. 8th Int. Conf. Commun. Syst. Netw. (COMSNETS)*, Jan. 2016, pp. 1–6, doi: 10.1109/comsnets.2016.7439933.

[40] R. Lipovsky and H. A. Ferreira, "Hand therapist: A rehabilitation approach based on wearable technology and video gaming," in *Proc. IEEE 4th Portuguese Meeting Bioeng. (ENBENG)*, Feb. 2015, pp. 1–2, doi: 10.1109/enbeng.2015.7088817.

[41] M. Linderman, M. A. Lebedev, and J. S. Erlichman, "Recognition of handwriting from electromyography," *PLoS ONE*, vol. 4, no. 8, pp. 2–9, 2009, doi: 10.1371/journal.pone.0006791.

[42] C. Carmona-Duarte, R. de Torres-Peralta, M. Diaz, M. A. Ferrer, and M. Martin-Rincon, "Myoelectronic signal-based methodology for the analysis of handwritten signatures," *Hum. Movement Sci.*, vol. 55, pp. 18–30, Oct. 2017, doi: 10.1016/j.humov.2017.07.002.

[43] M. Djioua and R. Plamondon, "A new methodology to improve myoelectric signal processing using handwriting," in *Proc. Int. Conf. Frontiers Handwriting Recognit.*, Jan. 2008, pp. 112–118.

[44] G. Huang, D. Zhang, X. Zheng, and X. Zhu, "An EMG-based handwriting recognition through dynamic time warping," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2010, pp. 4902–4905, 2010, doi: 10.1109/IEMBS.2010.5627246.

[45] S. Tan, Y. An, Y. Wu, and D. Zhang, "Electromyography based handwriting recognition system using LM–BP neural network," in *Proc. 9th Int. Conf. Hum. Syst. Interact. (HSI)*, Jul. 2016, pp. 83–88, doi: 10.1109/hsi.2016.7529613.

[46] Y. Chen, Z. Yang, H. Gong, and S. Wang, "Recognition of sketching from surface electromyography," *Neural Comput. Appl.*, vol. 30, no. 9, pp. 2725–2737, Nov. 2018, doi: 10.1007/s00521-017-2857-3.

[47] Y. Chen and Z. Yang, "A novel hybrid model for drawing trace reconstruction from multichannel surface electromyographic activity," *Frontiers Neurosci.*, vol. 11, pp. 1–17, Feb. 2017, doi: 10.3389/fnins.2017.00061.

[48] Y. Cai, Y. Guo, H. Jiang, and M.-C. Huang, "Machine-learning approaches for recognizing muscle activities involved in facial expressions captured by multi-channels surface electromyogram," *Smart Health*, vols. 5–6, pp. 15–25, Jan. 2018, doi: 10.1016/j.smhl.2017.11.002.

[49] G. S. Meltzner, J. T. Heaton, Y. Deng, G. De Luca, S. H. Roy, and J. C. Kline, "Silent speech recognition as an alternative communication device for persons with laryngectomy," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 25, no. 12, pp. 2386–2398, Dec. 2017, doi: 10.1109/taslp.2017.2740000.

[50] A. D. C. Chan, K. Englehart, B. Hudgins, and D. F. Lovely, "MYO-electric signals to augment speech recognition," *Med. Biol. Eng. Comput.*, vol. 39, no. 4, pp. 500–504, Jul. 2001, doi: 10.1007/bf02345373.

[51] M. B. I. Raez, M. S. Hussain, F. Mohd-Yasin, M. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: Detection, processing, classification and applications.," *Biol. Procedures Online*, vol. 8, no. 1, pp. 11–35, 2006, doi: 10.1251/bpo115.

[52] L. Liu, P. Liu, E. A. Clancy, E. Scheme, and Englehart, "Electromyogram whitening for improved classification accuracy in upper limb prosthesis control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 5, pp. 767–774, Sep. 2013, doi: 10.1109/tnsre.2013.2243470.

[53] T. Supuk, A. Skelin, and M. Cic, "Design, development and testing of a low–cost sEMG system and its use in recording muscle activity in human gait," *Sensors*, vol. 14, no. 5, pp. 8235–8258, May 2014, doi: 10.3390/s140508235.

[54] H. Fuketa, K. Yoshioka, Y. Shinozuka, and K. Ishida, "Measurement sheet with 2 V organic transistors for prosthetic hand control," *IEEE Trans. Biomed. Eng.*, vol. 8, no. 6, pp. 824–833, 2014, doi: 10.1109/TBCAS.2014.2314135.

[55] N. Prince, S. Nadar, S. Thakare, V. Thale, and J. Desai, "Design of front end circuitry for detection of surface EMG using bipolar recording technique," in *Proc. Int. Conf. Control, Instrum., Commun. Comput. Technol. (ICCICCT)*, Dec. 2016, pp. 594–599, doi: 10.1109/iccicct.2016.7988019.

[56] P. Mccool, G. D. Fraser, A. D. C. Chan, L. Petropoulakis, and J. J. Soraghan, "Identification of contaminant type in surface electromyography (EMG) signals," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 774–783, Jul. 2014, doi: 10.1109/tnsre.2014.2299573.

[57] A. Chan and D. MacIsaac, "CleanEMG: Assessing the quality of EMG signals," in *Proc. 34th Conf. Can. Med.*, Nov. 2011, pp. 17–20.

[58] N. Nazmi, M. Abdul Rahman, S.-I. Yamamoto, S. Ahmad, H. Zamzuri, and S. Mazlan, "A review of classification techniques of EMG signals during isotonic and isometric contractions," *Sensors*, vol. 16, no. 8, p. 1304, Aug. 2016, doi: 10.3390/s16081304.

[59] J. J. A. Mendes, Jr., E. Agostini Jr., S. Okida, and S. L. Stevan, Jr., "Circuit design of amplification and filtration for surface electromyography data acquisition," *IEEE Latin Amer. Trans.*, vol. 13, no. 10, pp. 3193–3200, 2015, doi: 10.1109/TLA.2015.7387221.

[60] R. Barioul, S. F. Ghribi, and O. Kanoun, "A low cost signal acquisition board design for myopathy's EMG database construction," in *Proc. 13th Int. Multi-Conf. Syst., Signals Devices (SSD)*, Mar. 2016, pp. 274–279, doi: 10.1109/ssd.2016.7473767.

[61] M. Zahak, "Signal acquisition using surface EMG and circuit design considerations for robotic prosthesis," in *Computational Intelligence in Electromyography Analysis—A Perspective on Current Applications and Future Challenges*. London, U.K.: IntechOpen, Oct. 2012, doi: 10.5772/52556.

[62] K. Kiguchi, M. H. Rahman, M. Sasaki, and K. Teramoto, "Development of a 3DOF mobile exoskeleton robot for human upper-limb motion assist," *Robot. Auto. Syst.*, vol. 56, no. 8, pp. 678–691, Aug. 2008, doi: 10.1016/j.robot.2007.11.007.

[63] S. Pancholi and R. Agarwal, "Development of low cost EMG data acquisition system for arm activities recognition," in *Proc. Int. Conf. Adv. Comput., Commun. Informat. (ICACCI)*, Sep. 2016, pp. 2465–2469, doi: 10.1109/icacci.2016.7732427.

[64] J. G. Abreu, J. M. Teixeira, L. S. Figueiredo, and V. Teichrieb, "Evaluating sign language recognition using the MYO armband," in *Proc. 18th Symp. Virtual Augmented Reality (SVR)*, 2016, pp. 64–70, doi: 10.1109/SVR.2016.21.

[65] S. Rawat, S. Vats, and P. Kumar, "Evaluating and exploring the MYO ARMBAND," in *Proc. Int. Conf. Syst. Modeling Adv. Res. Trends (SMART)*, 2016, pp. 115–120, doi: 10.1109/sysmart.2016.7894501.

[66] Y. Fang, N. Hettiarachchi, D. Zhou, and H. Liu, "Multi–modal sensing techniques for interfacing hand prostheses: A review," *IEEE Sensors J.*, vol. 15, no. 11, pp. 6065–6076, Nov. 2015, doi: 10.1109/jsen.2015.2450211.

[67] J. L. Correa-Figueroa, E. Morales-Sánchez, J. A. Huerta-Ruelas, J. J. González-Barbosa, and C. R. Cárdenas-Pérez, "Sistema de adquisición de señales SEMG para la detección de fatiga muscular," *Revista Mexicana de Ingenieria Biomedica*, vol. 37, no. 1, pp. 17–27, 2016, doi: 10.17488/RMIB.37.1.4.

[68] L. Mesin, R. Merletti, and A. Rainoldi, "Surface EMG: The issue of electrode location," *J. Electromyograp. Kinesiol.*, vol. 19, no. 5, pp. 719–726, Oct. 2009, doi: 10.1016/j.jelekin.2008.07.006.

[69] P. Artemiadis, "EMG-based robot control interfaces: Past, present and future," *Adv. Robot. Autom.*, vol. 1, no. 2, pp. 10–12, 2012, doi: 10.4172/2168-9695.1000e107.

[70] J. P. Mogk and P. J. Keir, "Crosstalk in surface electromyography of the proximal forearm during gripping tasks," *J. Electromyograp. Kinesiol.*, vol. 13, no. 1, pp. 63–71, Feb. 2003, doi: 10.1016/s1050-6411(02)00071-8.

[71] C. J. De Luca, L. D. Gilmore, M. Kuznetsov, and S. H. Roy, "Filtering the surface EMG signal: Movement artifact and baseline noise contamination," *J. Biomech.*, vol. 43, no. 8, pp. 1573–1579, May 2010, doi: 10.1016/j.jbiomech.2010.01.027.

[72] G. Li, Y. Li, L. Yu, and Y. Geng, "Conditioning and sampling issues of EMG signals in motion recognition of multifunctional myoelectric prostheses," *Ann. Biomed. Eng.*, vol. 39, no. 6, pp. 1779–1787, Jun. 2011, doi: 10.1007/s10439-011-0265-x.

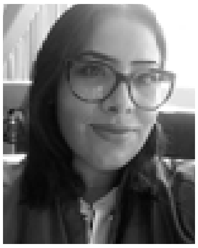
[73] E. A. Clancy, E. L. Morin, and R. Merletti, "Sampling, noise-reduction and amplitude estimation issues in surface electromyography," *J. Electromyograp. Kinesiol.*, vol. 12, pp. 1–16, Feb. 2002.

[74] N. Van Helleputte, M. Konijnenburg, J. Pettine, D.-W. Jee, H. Kim, A. Morgado, R. Van Wegberg, T. Torfs, R. Mohan, A. Breeschoten, H. De Groot, C. Van Hoof, and R. F. Yazicioglu, "A 345 μW multi–sensor biomedical SoC with bio–impedance, 3-channel ECG, motion artifact reduction, and integrated DSP," *IEEE J. Solid-State Circuits*, vol. 50, no. 1, pp. 230–244, Jan. 2015, doi: 10.1109/jssc.2014.2359962.

BERNABE RODRÍGUEZ-TAPIA received the B.S. degree in electronics engineering and the master's degree in engineering from the Universidad Autónoma de Baja California (UABC). He is currently pursuing the Ph.D. degree in technology with the Universidad Autónoma de Ciudad Juarez. He is also a Professor with the School of Engineering Sciences and Technology, UABC. His research interests include control, signal processing, and applied artificial intelligence.

ISRAEL SOTO received the M.S. and Ph.D. degrees in electrical engineering from the Instituto Tecnológico de la Laguna, Torreón, Mexico, in 2009 and 2014, respectively. He is currently a Research Professor with the Institute of Engineering and Technology, Universidad Autónoma de Ciudad Juárez. His research interests include modeling, design, and control of mechatronics systems.

DANIELA M. MARTÍNEZ received the B.S. degree in electrical engineering and the Ph.D. degree in telecommunications engineering from the Universidad Autónoma de Baja California (UABC), in 2009 and 2014, respectively. She is currently a Professor with the School of Engineering Sciences and Technology, UABC. Her research interests are within the field of statistical signal processing and cognitive radio systems.



NORMA CANDOLFI ARBALLO received the B.S. degree in computer engineering and the master's degree in engineering from the Universidad Autónoma de Baja California (UABC). She is currently pursuing the Ph.D. degree with the University of Guadalajara. She is also a Professor with the School of Engineering Sciences and Technology, UABC and a Leader of the Academic Corps of Research of Continuous Distance Education. She is also a member of the ICTC Mediated Education Quality Network, the Education Network Supported in Information, Communication and Collaboration Technologies, and the Mexican Network of Researchers in Emerging Technologies in Education.