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Design of an EMG acquisition system oriented to the development of myoelectric prostheses

Diseño de un sistema de adquisición EMG orientado al desarrollo de prótesis mioeléctricas

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Abstract: This article describes the development and implementation of electromyography (EMG) signal acquisition and processing for the control stage of a myoelectric prosthesis. A method is established for detecting and classifying muscle activity with low computational load and high reproducibility, using a hybrid analog-digital architecture. The EMG signal passes through a passive RC low-pass filter and then to a window comparator circuit with LM393 integrated circuits, which classifies the electrical activity into three levels: rest, contraction, or partial contraction. This classification generates pulse-width modulation (PWM) signals for servomotor control. The implementation of a digital Butterworth bandpass filter results in output voltages of 0.1 V, which can be amplified to obtain a 1.9 V voltage for servomotor activation. This fulfills the objective of generating the dynamics of an actuator with low-cost components, with the possibility of increasing the number of actuators due to the use of a Raspberry Pi 4, which has input/output ports.

Keywords: rehabilitation engineering, signal conditioning, surface electromyography (sEMG), embedded systems, servomotor, Raspberry Pi.

Resumen: Este artículo describe el desarrollo e implementación de la adquisición y el procesamiento de señales de electromiografía (EMG) para la etapa de control de una prótesis mioeléctrica. Se establece un método para detectar y clasificar la actividad muscular con baja carga computacional y alta reproducibilidad, utilizando una arquitectura híbrida analógica-digital. La señal EMG pasa a través de un filtro pasivo RC de paso bajo y luego a un circuito comparador de ventana con circuitos integrados LM393, que clasifica la actividad eléctrica en tres niveles: reposo, contracción o contracción parcial. Esta clasificación genera señales de modulación por ancho de pulso (PWM) para el control del servomotor, teniendo como resultado de la implementación de filtro pasabanda Butterworth digital obteniendo valores de voltaje 0.1 V a la salida que pueden ser amplificados y obtener para la activación del servomotor un voltaje de 1.9 V, cumplido con el objetivo que es generar la dinámica de un actuador con elementos de bajo costo con posibilidad de aumentar el número de actuadores debido al uso de Raspberry Pi 4 que cuenta con puertos de entrada y salida.

Palabras clave: ingeniería de rehabilitación, acondicionamiento de señales, electromiografía de superficie (sEMG), sistemas embebidos, servomotor, Raspberry Pi.

1. INTRODUCTION

Upper limb amputation is a pathology that negatively impacts the functionality, quality of life, and autonomy of those who experience it. The most prevalent causes associated with amputation include trauma, vascular diseases, infections, tumors, and congenital malformations. In developing countries, such as Colombia, amputee patients face difficulties accessing prostheses due to a lack of rehabilitation technology and the high cost of the most advanced prostheses. In this context, myoelectric prostheses have emerged as an interesting alternative, as they are capable of collecting surface electromyographic (sEMG) signals from muscle activity to control mechanical actuators and other existing mechanisms. Several studies have demonstrated a relationship between EMG signals and muscle activation, leading to their use as an interface between the neuromuscular system and prosthetic devices [1], [2].

However, EMG signals present certain challenges due to their low amplitudes (50μV to 5mV), their high sensitivity to noise, and their variability depending on the user and measurement conditions. Therefore, they require conditioning, filtering, and processing stages to improve signal quality and facilitate interpretation [2], [3]. In recent years, various EMG signal processing and classification techniques have been proposed, including basic machine learning and deep learning methods that have demonstrated very high levels of accuracy in recognizing gestures and muscle patterns [4], [5], [6].

However, the presented architectures are often associated with high computational complexity, the need for large data volumes to carry out a proper training phase, and greater hardware requirements, which can limit their integration into low-cost embedded systems [7], [8], [9]. On the other hand, simplified architectures have been presented that use analog conditioning techniques and discrete classification strategies, reducing the computational load and/or not compromising system performance [10].

In addition to the above, the use of low-cost embedded platforms, such as the Raspberry Pi (equipped with excellent functional and processing characteristics of microcontrollers), has enabled very low-cost systems for the acquisition, control, and processing of biomedical signals under real-time conditions [11], [12]. In fact, these embedded platforms offer a flexible and scalable solution for the implementation of support systems and devices in academic and research environments.

Despite these advances, challenges persist related to signal stability, system robustness and reliable identification of muscle activation states in operating situations [13]. Moreover, the present work proposes the design/prototyping of an EMG signal acquisition and control system based on a very low-cost analog-digital hybrid architecture, which allows the discrete classification of muscle contraction states and its common use in the control of myoelectric prostheses.

2. MATERIALS AND METHODS

2.1. System Architecture

The proposed system combines analog and digital stages to acquire, classify and control surface electromyography (sEMG) signals aimed at future applications in myoelectric prostheses.

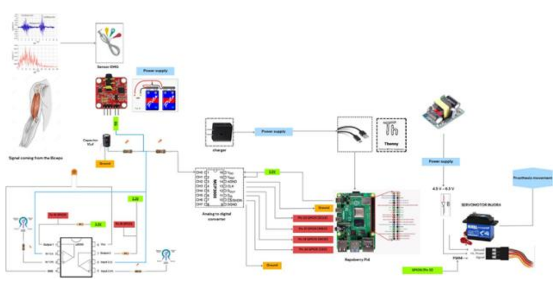

Fig. 1. *General diagram of the EMG acquisition system and myoelectric control.*
Source: *own elaboration.*

As shown in Fig 1, the architecture consists of a surface EMG sensor, an analog conditioning stage, a window comparator using the LM393, an MCP3008 analog-to-digital converter, a processing unit using Python on the Raspberry Pi 4 board, and an INJORA servomotor as the final actuator. The EMG signal used as a reference by the biceps muscle is captured by surface electrodes and conditioned to improve its stability. The signal is read by the comparator, which classifies the levels of muscle contraction. This same signal is then digitized for monitoring and storage, and the Raspberry Pi is able to identify the detected states and send control signals to the actuator.

2.2. Hardware Implementation

The EMG signal acquisition process was carried out using a commercial EGBO surface module, which is based on the Muscle Sensor v3 architecture developed by Advancer Technologies. This device employs several analog signal-conditioning stages consisting of an AD8226 instrumentation amplifier for the acquisition of low-amplitude signals, with a typical common-mode rejection ratio (CMRR) of 90 dB, a gain-bandwidth product of approximately 1 MHz, and an adjustable gain from 1 to 1,000; this is followed by an operational amplifier (op-amp) full-wave rectifier configuration based on the TL084 FET-family device; a first-order inverting low-pass filter with Fc = 1.98 Hz, responsible for reducing signal noise; and subsequently an inverting amplifier stage with an adjustable gain from 1 to 207.

The TL084, characterized by high input impedance, a typical CMRR of 86 dB, and a gain-bandwidth product of approximately 4 MHz, provides characteristics that favor the acquisition of low-amplitude biomedical signals [14].

The analog conditioning of the acquired signal was implemented using an RC low-pass filter, whose behavior was specifically designed to attenuate high-frequency noise and enhance the envelope of the EMG signal, providing sufficiently representative information to detect contraction levels in a specific muscle area [15]. The cutoff frequency of the filter was calculated using the following relationship:

$$fc = \frac{1}{2\pi RC} \quad (1)$$

where R and C represent the resistance and capacitance of the circuit, respectively. For the proposed system, values of R = 56 kΩ and C = 22 nF were selected, resulting in an approximate cutoff frequency of 129 Hz. The selection of this value allowed the analog filtering to remain within the frequency range of interest for surface electromyographic signals, whose useful spectral content is typically found between 20 Hz and 500 Hz, while simultaneously reducing high-frequency noise components prior to signal digitization. Since the EGBO module already incorporates internal amplification and analog conditioning stages, the RC filter implemented in this work acted as a complementary stage prior to the acquisition process.

Subsequently, the signal digitized by the MCP3008 analog-to-digital converter was processed on the Raspberry Pi 4. Additionally, a 100 nF decoupling capacitor was incorporated into the comparator stage in order to improve operational stability and reduce the influence of high-frequency noise [12].

The electronic design was verified through simulation in Proteus, as shown in Fig. 2.

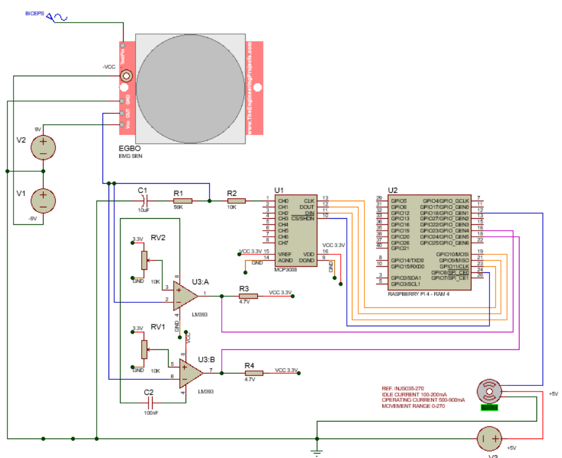

Fig. 2. *Schematic of the conditioning and classification circuit implemented in Proteus.*
Source: *own elaboration.*

A window comparator was constructed using the LM393 integrated circuit. Two reference levels were established using 10 kΩ potentiometers configured as voltage dividers between 3.3 V and ground. The variable terminals of the potentiometers were connected to the comparator reference inputs, thereby establishing the lower threshold (TH1) and the upper threshold (TH2). The unfiltered signal was simultaneously applied to both comparator inputs and evaluated with respect to the defined reference levels. This configuration allows the signal to be classified into the following muscle activation states: rest, mild contraction, and strong contraction. The threshold values were experimentally adjusted according to the amplitude of the acquired EMG signal. The typical ranges were approximately 0.4 V for rest, 0.8 V for mild contraction, and up to 1.9 V for strong contraction.

These ranges provided clear separation between the states and improved system stability in response to signal variations. Fig. 3 illustrates the physical implementation, which includes the EMG sensor,

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the breadboard conditioning stage, the MCP3008 converter, the Raspberry Pi 4, and the servomotor.

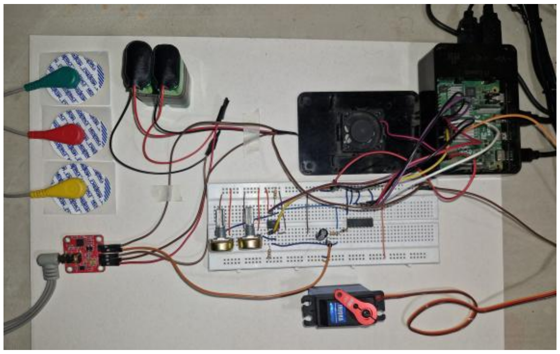

Fig. 3 *Experimental setup of the proposed system showing EMG electrodes, the sensor module, the conditioning and comparison circuit based on the LM393, the MCP3008 converter, the Raspberry Pi 4 and the servomotor used as an actuator.*
Source: *own elaboration.*

An MCP3008 analog-to-digital converter was used to digitize the signal, communicating with the Raspberry Pi 4 through the SPI protocol. It is important to note that the digitized signal was used exclusively for monitoring and data storage, while the contraction states were classified directly by the analog comparator. The actuator was controlled by an INJORA servomotor, driven by PWM signals generated by the Raspberry Pi 4. The actuator was selected based on its nominal torque capacity, which was sufficient to demonstrate the operation of the system under laboratory conditions.

2.3. Signal Acquisition and Processing

The electromyographic signal was acquired using channel 0 of the MCP3008 analog-to-digital converter, configured with a 10-bit resolution and a reference voltage of 3.3 V. This converter communicates with the Raspberry Pi 4 through the SPI protocol, allowing continuous reading of the conditioned analog signal.

Once digitized, the signal was processed using a fourth-order Butterworth band-pass filter implemented in software, with a lower cutoff frequency of 20 Hz and an upper cutoff frequency of 500 Hz. The selection of this interval was based on the fact that the useful spectral content of surface electromyographic signals is predominantly found between these frequencies. The filtering attenuated very low-frequency components associated with motion artifacts and baseline variations, as well as reduced high-frequency components related to electrical noise and interference from the acquisition system, thereby improving the signal-to-noise ratio for muscle activity analysis. It is important to note that the digitized signal was not used for decision-making by the control system; the classification of muscle contraction levels was performed using an analog comparator with an LM393 to separate control processing from signal monitoring, thereby reducing the computational load on the Raspberry Pi 4. Data acquisition was performed at an approximate sampling frequency of 50 Hz, which was sufficient to track the envelope of the EMG signal as it passed through the low-pass filter.

The system was implemented using the Python programming language, making use of the spidev libraries for SPI communication with the MCP3008, GPIO for reading the digital outputs of the LM393 comparator and controlling the servomotor through PWM, and Matplotlib for real-time representation of the acquired signal. The data were stored in CSV format for experimental data storage. The MCP3008 was configured using SPI bus 0 and device 0, with a maximum communication speed of 1.35 MHz. The conditioned signal from the EMG module was acquired through channel CH0 of the converter and converted into instantaneous voltage values using a reference voltage of 3.3 V.

Table 1: *Voltage values experimentally obtained during system calibration, together with the logic combinations generated by the LM393 comparator and their corresponding classification of muscle states.*

Voltage experimentally measured with multimeter (V)	OUT1 (LM393)	OUT2 (LM393)	Classified muscle state	Description
≤ 0.4 V (Experimentally measured with multimeter)	1	1	**Rest**	Absence of muscle activation.
0.4 V – 0.8 V (Experimentally measured with multimeter)	0	1	**Mild contraction**	Moderate muscle activation.
0.8 V – 1.9 V (Experimentally measured with multimeter)	0	0	**Strong contraction**	Maximum muscle activation.
> 0.8 V and < 1.9 V (Experimentally measured with multimeter)	1	0	**Mild contraction** (stability criterion)	Transient state due to signal fluctuations. It is classified as mild contraction to ensure system stability.

Source: *Authors' own work.*

2.4. Servomotor control

The actuator system was designed using an INJORA servomotor, which was controlled by pulse-width modulation (PWM) signals generated by a Raspberry Pi 4. The PWM signal was configured with a frequency of 50Hz, the operating frequency for this type of device.

Three angular positions were defined, corresponding to the previously defined contraction states: 0° for the rest state, 45° for medium contraction, and 90° for maximum contraction. To stabilize the control and eliminate unwanted oscillations in the actuator, a time validation algorithm was included. The system operates with a sampling frequency of approximately 50Hz (0.02s interval), continuously evaluating the comparator outputs. A state change will only be accepted if it remains constant across five consecutive samples, implying a minimum validation time of approximately 0.1s. Furthermore, minimum state dwell times were defined: 0.20s at rest, 0.30s during average contraction, and 0.80s when the maximum value is reached during muscle contraction. This strategy makes it possible to differentiate transient signal variations (noise or short spikes) from a sustained contraction and significantly reduces erratic servomotor behavior.

2.5. Data visualization and storage

A Thonny-Python application was created for the acquisition and storage of the electromyographic signal in real time. The signal, converted to digital by the MCP3008, is processed and plotted using the Matplotlib library, which allows for the graphical representation of the signal's dynamic behavior under different muscle contraction conditions. The visualization is displayed in an interactive window, where the signal is continuously updated based on the acquired samples, enabling the identification of patterns derived from resting, mid-contraction, and maximum contraction states. The data is stored in CSV files, which contain information such as acquisition time, ADC digital value, corresponding voltage, comparator outputs (OUT1 and OUT2), and the contraction state identified by the system.

3. RESULTS

The experimental setup used to validate the system is shown in Fig 3, while the circuit-level implementation is detailed in Fig 2. Both setups allowed us to verify the system's behavior under different muscle activation conditions, for the analog conditioning stage and the total integration of the classification and control system.

3.1. EMG signal conditioning

Fig. 4 presents a comparison between the EMG signal acquired before and after analog conditioning using the RC filter implemented in the system. The superposition of both signals shows that the filtering reduces rapid fluctuations and high-frequency components, resulting in a more stable envelope that facilitates the identification of different levels of muscle activation. Although the signal amplitude decreases slightly due to the smoothing process, the information required to classify the rest, mild contraction, and strong contraction states is preserved.

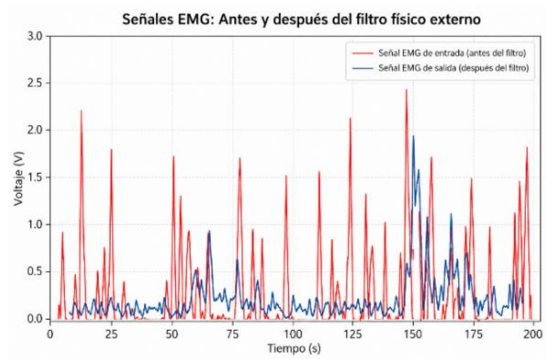

Fig. 4. *Comparison of the EMG signal acquired before and after external physical filtering using a low-pass RC filter.*
Source: *Authors' own work.*

In order to analyze the effect of conditioning in the frequency domain, Fig. 5 shows a comparison of the EMG signal spectrum before and after combined filtering, consisting of the analog RC filter and a digitally implemented Butterworth band-pass filter with cutoff frequencies of 20 Hz and 500 Hz. It can be observed that the filtering attenuates the very low-frequency components, mainly associated with baseline drift and motion artifacts, as well as the high-frequency components related to electrical noise, while preserving most of the useful spectral content of the electromyographic signal.

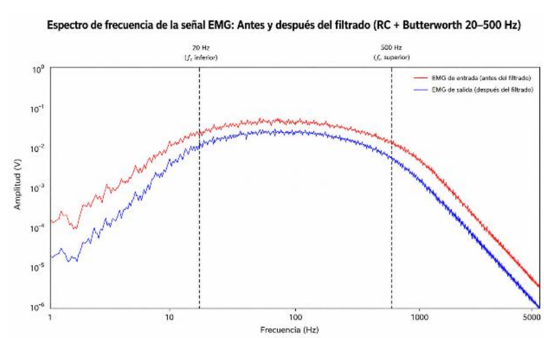

Fig. 5. *Comparison of the frequency spectrum of the EMG signal before and after the filtering process using an RC filter and a digital Butterworth band-pass filter.*
Source: *Authors' own work.*

As a result of the conditioning and filtering process, the signal used by the system exhibits a more stable response and an improved signal-to-noise ratio, enabling more reliable detection of muscle activation levels. These characteristics facilitated the experimental adjustment of the thresholds used by the LM393 comparator to discriminate among the three operating states of the system: rest, mild contraction, and strong contraction, which were subsequently used to control the servomotor.

3.2. System response with classification using LM393

Fig. 5 shows the system response after incorporating the LM393 window comparator, together with the complete control architecture, where the signal is not continuous but rather represented by discrete levels corresponding to the muscle activation states defined by the system.

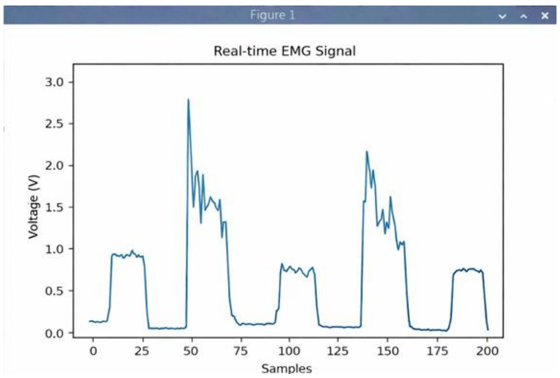

Fig. 6*. System response with contraction level classification.*
Source: *own elaboration.*

Unlike the signal obtained solely with low-pass filtering, the system output exhibits well-defined discretization into three clearly differentiated levels. These levels correspond to the rest, medium contraction, and maximum contraction states, which are identified in the signal as low-amplitude regions, stable plateaus, and high-amplitude peaks, respectively. The rest regions are characterized by low and relatively constant values, indicative of significant muscle inactivity. Medium contraction appears as plateau-like segments, indicating sustained muscle activation; maximum contraction is manifested as higher-amplitude peaks, associated with greater muscular effort.

The transitions between these states are well-defined and consistent, demonstrating the proper selection of the comparison thresholds established in the system.

3.3. Control system behavior

The behavior of the control system was evaluated based on the servomotor response to different detected muscle activation states. The system responds consistently to the signals from the LM393 comparator, with a clear correspondence between the rest, medium contraction, and maximum contraction states and the defined angular positions of the actuator.

Regarding sustained contractions, the classified signal exhibits stable plateau-like regions. This information allows the servomotor response to be properly guided without perceptible oscillations. If the EMG signal exhibits rapid variations or transient peaks, the output will not be altered. Overall, the control system demonstrates stable responses to changes in muscle activation, allowing well-defined transitions between states without undesirable fluctuations in the actuator.

4. DISCUSSION

The results obtained confirm the operability and functionality of the designed myoelectric control system. The hybrid architecture based on analog conditioning, digital filtering, and classification using discrete logic experimentally enabled the discrimination of rest, mild contraction, and strong contraction states, achieving stable servomotor actuation without significant oscillations. These findings validate the proposed system as a viable and low-cost alternative for the development of myoelectric prostheses and experimental platforms [16], [17].

In recent years, sEMG pattern recognition has shifted toward machine learning and deep learning techniques, which combine multichannel information to discriminate gestures and movements with greater accuracy [17], [18]. Various studies employ advanced feature extraction algorithms and classifiers such as support vector machines (SVMs) or artificial neural networks, achieving high accuracy rates in complex tasks [19], [20]. However, although these alternatives represent a substantial advancement, they require high computational capacity, as well as rigorous training stages using annotated databases and individualized calibration [21], [22]. This increases algorithmic complexity and limits their direct implementation in resource-constrained embedded systems [23], [24], [25].

From a design perspective, the proposed architecture offers substantial advantages over more complex approaches. The integration of accessible commercial components (EGBO EMG sensor, MCP3008 converter, and Raspberry Pi 4) resulted in a modular, reproducible, and scalable platform. By delegating primary classification to the analog comparator, digital processing was focused on signal conditioning and storage, optimizing the use of computational resources without compromising stability during testing. This strategy is particularly efficient when only a limited number of muscle states need to be discriminated.

Despite these strengths, the system presents limitations inherent to its discrete nature. Dependence on fixed thresholds implemented through adjustable potentiometers makes the classification susceptible to inter-individual physiological variations, muscle fatigue, or shifts in electrode placement. Likewise, the scope of the method is limited to three activation levels, unlike artificial intelligence-based models that recognize a broader range of gestures and adapt more effectively to dynamic conditions [17], [19].

However, the decoupled design between the acquisition, conditioning, and processing stages constitutes a solid basis for future improvements. This modular architecture allows pattern recognition algorithms or AI models to be progressively integrated without modifying the signal acquisition hardware. Thus, discrete logic classification can evolve toward machine learning schemes that increase the number of recognized degrees of freedom while preserving the same electronic infrastructure.

In summary, the combination of analog conditioning and discrete classification represents a computationally efficient, stable, and accessible solution for myoelectric control applications. Although it is not intended to replace advanced clinical systems based on artificial intelligence, it provides a flexible and scalable platform for prototyping in educational and research environments.

4. CONCLUSIONS

A low-cost sEMG signal acquisition and control system for myoelectric prostheses was designed and implemented. The platform acquires, conditions, and classifies the EMG signal into three discrete muscle contraction states using a Raspberry Pi 4 processor, which drives an actuator through PWM signals.

The combination of an RC low-pass filter with a window comparator (LM393) demonstrated that muscle activation levels can be accurately identified without resorting to complex digital processing. Likewise, the temporal validation strategy integrated into the control algorithm mitigates oscillations associated with the non-stationary nature of the sEMG signal, ensuring a stable and consistent actuator response.

The main contribution of this work lies in the hybrid (analog-digital) architecture, which significantly reduces the computational load and optimizes performance in embedded systems. This approach validates the feasibility of implementing functional, stable, and accessible myoelectric control schemes for basic rehabilitation applications.

Author Contributions: Yeison Manuel Arias Nuñez: Writing – review and editing, writing – original draft, visualization, prototyping, results analysis, conceptualization. Sandra Patricia Usaquen-Perilla: Writing – review and editing, validation, conceptualization. Mauricio Alejandro Gómez-Figueroa: Writing – review and editing, methodological advisor, prototyping, validation, conceptualization.

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