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ORIGINAL

Application of Model-Based Design for Filtering sEMG Signals Using Wavelet Transform

Aplicación del diseño basado en modelos para el filtrado de señales sEMG utilizando la Transformada Wavelet

Vladimir Bonilla Venegas[1], Guillermo Mosquera Canchingre[1], Miguel Sánchez Muyulema[2], Nelson Gutiérrez Suquillo[2], Jonnathan Ismael Chamba Cruz[2]

[1]Universidad Internacional del Ecuador - UIDE, Mecatrónica. Quito, Ecuador.
[2]Universidad UTE, Mecatrónica. Quito, Ecuador.

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Corresponding author: Vladimir Bonilla Venegas

ABSTRACT

The aim of this study was the integration of model-based design and Wavelet transform techniques for filtering surface electromyography (sEMG) signals. In the first stage the noises and interferences that disturb sEMG signals were analyzed to implement a digital filter in a low-cost embedded system that filters these signals. It was shown that the noises and interferences are caused by various sources. Sources of interference and noise can be divided into internal and external. Internal noise is caused by the electrodes, EMG signals of other muscles, and noise associated with the functioning of other organs such as the heart or stomach. The external noises are due to the electrical environment, the most prominent of which is the direct interference of the power hum, produced by the incorrect grounding of other devices and electromotors. For the analysis of the digital filter, sEMG signals from the biceps muscle were used when the elbow joint was at rest and during flexion and extension movements. Signals from 10 participants who did not have any atrophies or pathologies in the muscle were considered for this stage. Denoising of sEMG signals was performed using different wavelets; the smallest error was observed when using the biorthogonal wavelet 3/5 of level 6 with the soft thresholding method. The wavelet filter was implemented using the V-model, and the Processor in The Loop (PIL) tests helped to determine the characteristics of the embedded system where the digital filter was implemented. The digital filter code was implemented on an ESP32 board due to its processing speed of 328 ms.

Keywords: sEMG Signals; Wavelet Real Time Filter; Model Based Design.

RESUMEN

El objetivo de este estudio fue la integración del diseño basado en modelos y la transformada wavelet para el filtrado de señales electromiográficas de superficie (sEMG). En la primera etapa, se analizó el ruido e interferencia que afectan las señales sEMG con el fin de implementar un filtro digital en un sistema embebido de bajo costo. Se demostró que los ruidos e interferencias son causados por diversas fuentes. Las fuentes de interferencia y ruido se pueden dividir en internas y externas. El ruido interno es causado por los electrodos, las señales EMG de otros músculos, y el ruido asociado con el funcionamiento de otros órganos como el corazón o el estómago. Los ruidos externos se deben al entorno eléctrico, siendo la interferencia directa de la red eléctrica producida por la incorrecta conexión a tierra de diferentes dispositivos y electromotores. Para el análisis del filtro digital, se utilizaron señales sEMG del músculo bíceps cuando la articulación del codo estaba en reposo y durante los movimientos de flexión y extensión. En esta etapa se consideraron señales de 10 participantes que no presentaban atrofias ni patologías en el músculo. La eliminación de ruido de las señales sEMG se realizó utilizando diferentes wavelets; el menor error se observó al usar la wavelet biortogonal 3/5 de nivel 6 con el método de umbral suave. El filtro wavelet se implementó utilizando el modelo en V, y las pruebas de Processor in The Loop (PIL) permitieron determinar las características del hardware del sistema embebido en donde se implementó el filtro digital. El código del filtro digital fue implementado en una tarjeta ESP32 debido a su velocidad de procesamiento de 328 ms.

Palabras clave: Señales sEMG; Filtro Wavelet De Tiempo Real; Diseño Basado En Modelos.

INTRODUCTION

Surface electromyography (sEMG) is a widely utilized technique for measuring the electrical activity produced by skeletal muscles, finding applications in areas such as biomedical engineering, rehabilitation, sports science, and human-machine interfaces.[1,2] However, sEMG signals are often contaminated by noise and interference, making real-time analysis and processing challenging. For reliable signal acquisition and processing, effective filtering methods are essential to enhance the clarity of the signals and preserve their diagnostic value. [3]

Noise and interference affecting sEMG signals can be broadly categorized into internal and external sources and are shown in the Figure 1. Internal noise typically originates from physiological factors, including cross-talk between muscles, electrode movement, and noise from other organs, such as the heart or stomach.[4] External interference, on the other hand, arises from the surrounding electrical environment, with the most significant source being the 50/60 Hz power line interference. This interference is often amplified by improper grounding or nearby electromotors.[5,6]

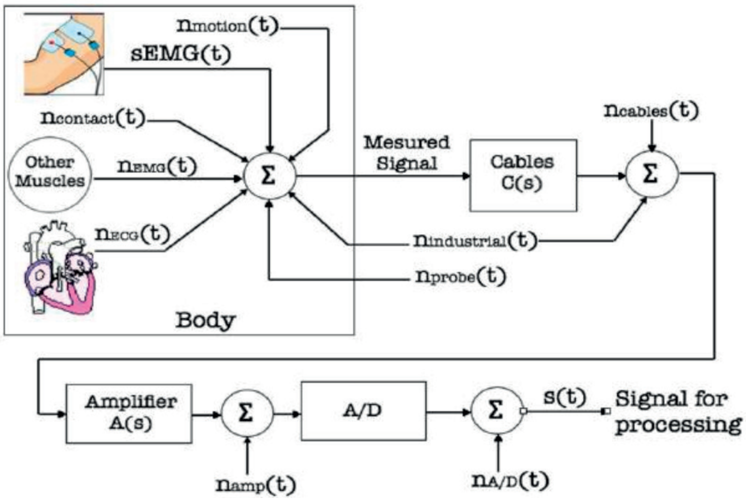

Figure 1. Block Diagram of Noise and Interference Formation in sEMG Signals

Traditional filtering techniques, such as band-pass and notch filters, are commonly used to remove noise from sEMG signals. However, these filters often result in signal distortion, reducing the reliability of the signal for further análisis.[1] To overcome these limitations, wavelet transform techniques have gained prominence in recent years. The wavelet transform allows for multi-resolution signal analysis, enabling the selective filtering of noise while maintaining essential characteristics of the original sEMG signal.[7]

In recent years, the integration of digital wavelet filters into embedded systems has gained attention due to their ability to efficiently process signals in real time. Low-cost embedded platforms, such as the Arduino Due, ESP32, and STM32microcontrollers, offer a viable solution for real-time wavelet-based filtering of sEMG signals.[8] These systems provide a balance between affordability, processing power, and flexibility, making them attractive for biomedical applications where cost and power efficiency are critical.[9]

The objective of this study is to implement a wavelet-based digital filter in a low-cost embedded system, utilizing the Model-Based Design (MBD) approach to ensure that the system meets the real-time requirements of sEMG signal processing. By leveraging the MBD methodology, specifically the V-model framework, this work provides a structured methodology for developing, validating, and implementing the wavelet filter on embedded platforms. The study evaluates the performance and feasibility of different microcontrollers (Arduino Due, ESP32, STM32) to determine their suitability for biomedical applications involving real-time filtering of sEMG signals.

METHOD

The design of the digital wavelet filter for real-time surface electromyography (sEMG) signal processing will follow by Model-Based Design (MBD) approach using the V-model. The embedded system must meet specific requirements to ensure effective real-time filtering in biomedical applications.

The response time must be less than 500 ms to ensure real-time processing of sEMG signals. This ensures that signal processing is performed without perceptible delays, which is essential for applications such as prosthetic control and rehabilitation devices.[1]

The system must be low-cost to facilitate accessibility in medical devices. Platforms such as Arduino Due (32-bit ARM Cortex-M3, 84 MHz) and ESP32 (dual-core Xtensa LX6, up to 240 MHz) are considered, as they offer the necessary balance between cost and performance.[10] The selected microcontrollers must provide sufficient memory for real-time wavelet filtering, in this case ESP32 offers 520 KB of SRAM, which supports complex signal decomposition and reconstruction.[9]

These requirements will guide the design and implementation of the wavelet filter, ensuring suitability for biomedical applications without exceeding hardware constraints.

DEVELOPMENT

In the second stage of the V-model, the focus is on the design of the filter to address potential noise and interferences that may exist in the recording of surface electromyographic (sEMG) signals in muscles. To achieve this, sEMG signals were recorded from the right biceps of 10 healthy individuals without any muscle atrophy or pathology. The signal was recorded over 10 seconds with a sampling frequency of 1000 Hz and a signal amplifier with a gain of 100.[11] During the recording, participants were instructed not to move their right arm but were asked to move their waist and left arm. The results of the signal acquisition are shown in the Figure 2 in the upper-left panel of the image, and the corresponding power-frequency spectrum is displayed in the upper-right panel.

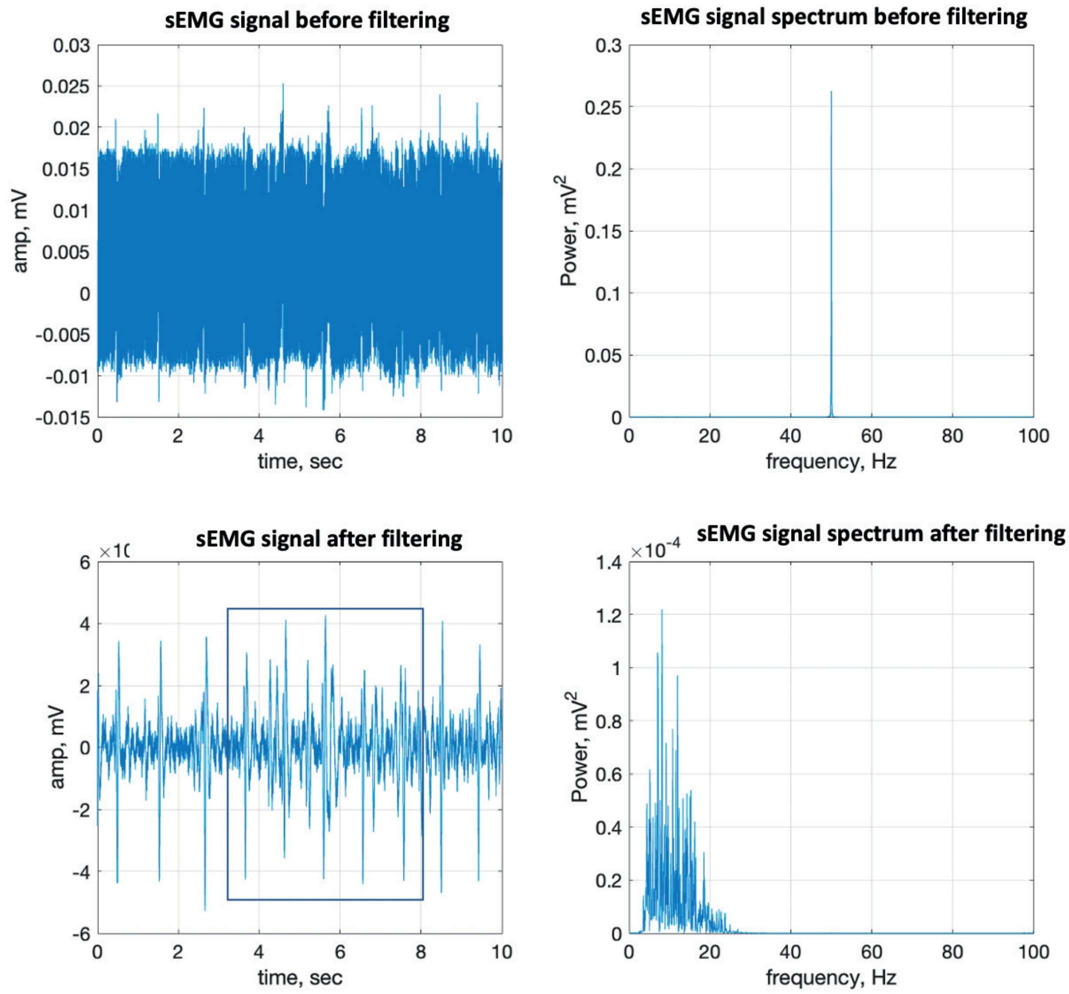

Figure 2. Analysis of the components and sources of noise of the sEMG signals

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From the spectrum, it is evident that the primary source of noise in the recorded signal is the interference caused by the power line, as the experiment was conducted in an environment with several electric actuators and their respective controllers connected, simulating an industrial setting. This interference is reflected by the significant peak at 50 Hz, corresponding to the electrical grid in Europe.[12]

To eliminate this noise, a stop-band filter at 50 Hz was implemented. Once the filter was applied, the signal was further analyzed, revealing the presence of the electrocardiogram (ECG) signal and electromyographic signals from surrounding muscles. This is particularly evident in the bottom-left panel of the image, where the filtered sEMG signal is shown. At the 4-second mark, participants were instructed to move their left arm and waist from right to left, which is noticeable in the recorded signal. The bottom-right panel displays the power-frequency spectrum after filtering, highlighting the presence of ECG components as well as electromyographic signals from the surrounding muscles.

As this project aims to study sEMG signals from the right biceps, all signals present in the recordings must be effectively filtered. However, traditional filtering methods could lead to the loss of important electromyographic components 0-500 Hz. This is a critical issue, as preserving the integrity of these components is essential for accurate analysis. To overcome this challenge, the implementation of a dynamic digital filter using the Wavelet Transform is required.[13]

In the design of the wavelet filter, the selection of the appropriate mother wavelet and the level of decomposition are the factors that directly influence the effectiveness of the denoising process. Based on the comparative analysis presented, several wavelets were evaluated for their ability to reduce noise in surface electromyography (sEMG) signals, specifically focusing on the interference from power lines and signals from surrounding muscles. After testing various mother wavelets, the biorthogonal wavelet 3/5 was identified as the most suitable option for filtering sEMG signals.[14] The biorthogonal wavelet 3/5 provided superior performance in preserving the integrity of the muscle signals while effectively reducing the interference from external noise sources, including the 50/60 Hz power line hum. This wavelet was selected due to its ability to balance between signal preservation and noise reduction, minimizing the error rate in the reconstructed signal compared to other wavelets such as Daubechies or Symlet. In this implementation, the wavelet decomposition was carried out to a level of six because it reduced both high-frequency noise from electrical interference and low-frequency noise from other muscles in the body, leaving primarily the target signal from the biceps muscle. A higher level of decomposition would increase the computational load without significantly improving noise reduction, while a lower level might leave more residual noise in the signal.

The wavelet-based denoising process was implemented in Simulink in three stages (figure 3): decomposition using the biorthogonal 3/5 wavelet, soft thresholding, and reconstruction that means that the inverse wavelet transform was applied to reconstruct the denoised signal.

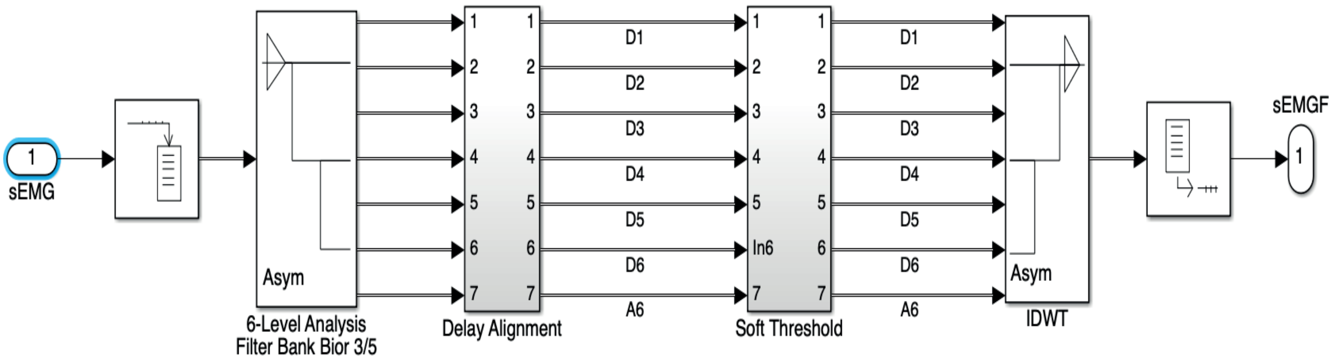

Figure 3. Wavelet-based denoising process

This process ensured that the signal preserved its original characteristics, while the noise components were significantly reduced.

The implementation of the wavelet filter was further extended using Simulink, which provided an efficient platform for designing, simulating, and validating the model-based design of the wavelet filter. One of the key advantages of using Simulink is its ability to automatically generate C/C++ code from the developed models. This feature enables direct deployment of the designed wavelet filter on low-cost embedded platforms, such as Arduino Due and ESP32, without the need for manual coding, thus accelerating the development process and minimizing coding errors.

RESULTS AND DISCUSSION

The results of the wavelet filter implementation on the embedded systems were evaluated using Processor-in-the-Loop (PIL) testing (figure 4), a critical step in the validation process following the V-model. The objective was to assess the real-time performance of the wavelet filter, ensuring that the embedded system meets the required response time of less than 500 ms for biomedical applications. The system was tested using sEMG signals obtained from the biceps muscle of a participant during a flexion and extension movement.

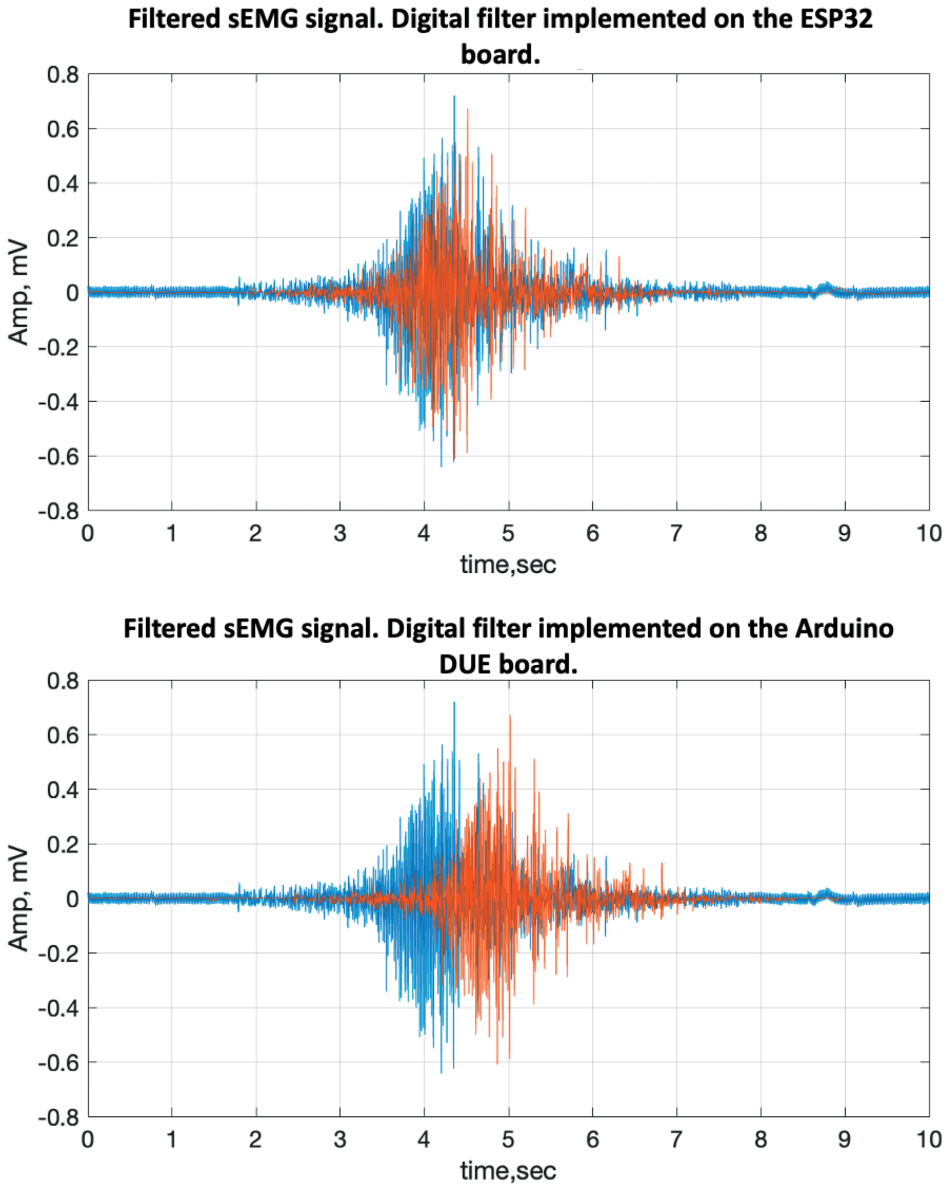

Figure 4. Results of wavelet-based denoising process on embedded hardware

In the upper graph (figure 4), the blue line represents the raw sEMG signal, while the red line shows the filtered signal processed by the ESP32 microcontroller. The observed delay in the filtered signal was 200 ms, attributed to the processing time of the ESP32. Additionally, a buffering delay of 128 ms was introduced due to the system architecture. Therefore, the total delay observed was 328 ms (200 ms processing + 128 ms buffering), which is well within the required system response time of less than 500 ms. This result demonstrates that the ESP32 platform can perform real-time sEMG signal processing, adhering to the timing constraints required for biomedical applications, such as prosthetic control or rehabilitation devices. To determine the energy consumption during the PIL test, the base load of the microcontroller (ESP32) with the implementation of the digital filter was measured at 240 mA (clock frequency: 240 MHz), along with the load from serial communication at 15 mA (57600 baud/s), resulting in a total current consumption of 255 mA. The board operates at 3,3 V, yielding an energy consumption of 0,825 Wh.

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The lower graph (figure 4) shows the same sEMG signal (blue: unfiltered, red: filtered) processed by the Arduino Due. In this case, the processing delay was significantly higher, at 522 ms, due to the more limited computational capabilities of the Arduino Due compared to the ESP32. Additionally, the system incurred a buffering delay of 128 ms, resulting in a total delay of 650 ms (522 ms processing + 128 ms buffering). This exceeds the acceptable response time of 500 ms, making the Arduino Due unsuitable for real-time biomedical applications where immediate signal processing is critical. The energy consumption for this board was 0,512 Wh, considering that the microcontroller load was 140 mA (clock frequency: 84 MHz) and the serial communication load was 15 mA.

Table 1 presents a comparison of the criteria for the ESP32 and Arduino DUE boards considered for the selection of low-cost hardware, where a digital wavelet filter was implemented.

Table 1. Comparison between the ESP32 and Arduino DUE boards

Microcontroller	Time delay (ms)	Energy consumption (Wh)
ESP32	328	0,825
Arduino DUE	650	0,512

The most important factor is the real-time constraint for biomedical engineering applications (less than 500 ms). For this reason, the ESP32 board was selected; however, due to its processing speed, it also has the highest energy consumption.

CONCLUSIONS

The application of model-based design facilitated the successful development and implementation of a digital wavelet filter employing the biorthogonal 3/5 wavelet function, a sixth-level decomposition, and the soft-thresholding method. The ESP32 met the system requirements for real-time sEMG signal filtering, with a total delay of 328 ms. Arduino Due failed to meet the required response time, with a total delay of 650 ms, making it unsuitable for time-sensitive applications. These results emphasize the importance of selecting appropriate embedded hardware based on both computational power and system architecture when designing real-time signal processing systems for biomedical applications.

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AUTHORSHIP CONTRIBUTION
Conceptualization: Vladimir Bonilla, Guillermo Mosquera.
Data curation: Vladimir Bonilla, Miguel Sánchez.
Formal analysis: Vladimir Bonilla, Guillermo Mosquera, Miguel Sánchez, Nelson Gutiérrez, Jonnathan Chamba.
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Methodology: Vladimir Bonilla, Guillermo Mosquera.
Project administration: Vladimir Bonilla.
Resources: Vladimir Bonilla, Guillermo Mosquera, Miguel Sánchez, Nelson Gutiérrez.
Software: Vladimir Bonilla, Guillermo Mosquera.
Supervision: Vladimir Bonilla.
Validation: Guillermo Mosquera, Nelson Gutiérrez, Jonnathan Chamba.
Visualization: Guillermo Mosquera, Miguel Sánchez, Jonnathan Chamba.
Writing – original draft: Vladimir Bonilla, Guillermo Mosquera, Miguel Sánchez.
Writing – review and editing: Vladimir Bonilla, Guillermo Mosquera, Miguel Sánchez, Nelson Gutiérrez, Jonnathan Chamba.