Research Inventy: International Journal of Engineering And Science
Vol.15, Issue 5 (May 2025), PP 47-54
Issn (e): 2278-4721, Issn (p):2319-6483, www.researchinventy.com

Development of an sEMG-Driven Control Architecture for a Robotic Leg Prosthesis

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Abstract:*Presented herein is the design and implementation of an sEMG-based control system for a robotic leg, utilizing surface electromyographic signals recorded from the quadriceps muscles. The developed system integrates four key functional components: (1) acquisition and preprocessing of sEMG data; (2) extraction of the root mean square (RMS) as a measure of muscle contraction intensity; (3) transformation of signal features into actuator control signals; and (4) the mechanical design of a biomimetic robotic leg. The knee joint actuator is controlled based on the RMS value, enabling the reproduction of natural and accurate lower limb flexion and extension. Initial experimental findings indicate the system's capacity for prompt and stable response to user neuromuscular input, suggesting its applicability in areas such as rehabilitation robotics, assistive devices, and human-computer interaction.*

Keywords:*sEMG signals, robotic leg, control, RMS, prosthetic systems.*

Date of Submission: 10-05-2025 Date of Acceptance: 20-05-2025

I. Introduction

The domain of biomedical engineering has witnessed the escalating significance of assistive mobility technologies in recent years, particularly in addressing the needs of individuals with motor impairments and those undergoing rehabilitation. Among the diverse biological signals employed in assistive systems, surface electromyography (sEMG) has emerged as a modality of considerable promise. sEMG, a bioelectrical signal resulting from the activation of motor units within skeletal muscles, facilitates non-invasive recording via surface electrodes applied to the skin [O. Phinyomark, P. Phukpattaranont, C. Limsakul, 2012; R. Merletti, D. Farina, 2016; M. Kim, H. Jo, K. Kong, 2019]. This technique enables real-time monitoring of muscular activity and the inference of user movement intentions, rendering it applicable to rehabilitation, intelligent prosthetics, exoskeletons, and human-machine interfaces (HMIs) [P. Zhou, B. Lock, X. Zhang, 2018; P. Konrad, 2006].

The integration of sEMG signals for the control of robotic and assistive devices has inaugurated novel pathways for the development of systems capable of supporting individuals with disabilities during rehabilitation and augmenting daily mobility. These applications are predicated on the capacity of sEMG signals to precisely reflect muscle contractions, thereby allowing mechanical systems to emulate corresponding human movements [J. Xie, Q. Wu, M. Wei, 2018]. This advancement holds particular importance for intelligent prosthetic limbs, wherein users can exert control over artificial appendages utilizing their own bio-signals, leading to a more natural and intuitive interaction compared to traditional control paradigms [J. C. P. de Azevedo, G. F. Teixeira, 2014; J. Park, J. S. Lee, D. H. Lee, 2013]

However, integrating sEMG signals into robotic control systems presents several major challenges, primarily due to the signal's low amplitude (ranging from μV to mV), susceptibility to noise, and variations caused by physiological conditions, electrode placement, and mechanical states of the body (R. L. S. S. J. R. D. Ali, 2014). These issues complicate the development of accurate and efficient control systems. A key requirement is the implementation of robust signal processing algorithms capable of reliably extracting relevant features from sEMG signals (T. V. B. Nguyen, 2017).

Within the human musculoskeletal system, the knee joint plays a critical role in supporting body weight, maintaining balance, and enabling locomotion. Major muscle groups involved in knee flexion and extension include the rectus femoris, vastus lateralis, and biceps femoris (M. D. Legrand, 2013) (M. J. Keeler, 2019). Consequently, sEMG signals obtained from the thigh region can provide accurate insights into user movement intent, serving as a valuable data source for actuating robotic mechanisms. Analyzing these signals not only improves motion classification accuracy but also facilitates the development of biologically inspired control systems that directly interface with the human body.

Within this framework, the present study introduces a robotic leg control system engineered to replicate the flexion-extension kinematics of the knee joint, employing the sEMG as the principal control modality. The system architecture comprises several fundamental modules: an sEMG signal acquisition and preprocessing unit, a root mean square (RMS) feature extraction module, a feature-to-control signal mapping unit, and a robotic leg structure designed with biomimetic principles. The primary objective of this research is the development of an integrated bio-control system with potential applications in rehabilitation, assistive mobility, and human-robot interaction. This endeavor aims to yield practical solutions for aiding individuals with disabilities while concurrently enhancing real-world human-machine synergy (T. V. B. Nguyen, 2017) (Y. Liu, W. Gao, Z. Li, 2017).

II. Materials And Method

The objective of this research is to develop and optimize a control system for a robotic leg that emulates the flexion–extension movement of the human knee joint, using sEMG signals as the primary control input. The experimental workflow includes the following stages: acquisition of sEMG signals, signal processing, feature extraction, control signal conversion, mechanical design, and system testing and evaluation. Each stage is carefully designed and executed to ensure the precision and effectiveness of the control system.

2.1. sEMG Signal Acquisition

In this study, sEMG signals are recorded from the quadriceps femoris muscle group, which plays a primary role in knee flexion and extension. This group comprises three major muscles: rectus femoris, vastus lateralis, and vastus medialis (Rahmani-Nia, F., Farzaneh, E., Damirchi, A., Majlan, A. S., & Tadibi, V., 2013). The selection of this muscle group was based on two key criteria: (1) their substantial contribution to controlling the amplitude and speed of knee joint motion, and (2) the feasibility of non-invasive sEMG recording from the skin surface due to their accessible anatomical location. The rectus femoris is the only muscle in the quadriceps group that spans both the hip and knee joints, contributing to hip flexion and knee extension. Meanwhile, the vastus lateralis and vastus medialis are primarily responsible for knee extension. The coordinated activation of these three muscles provides comprehensive insight into muscular dynamics during knee joint flexion and extension. This choice is further supported by previous studies that have demonstrated a strong correlation between quadriceps muscle activity and both knee joint torque and angle.

To optimize sEMG signal acquisition, wet surface electrodes are employed. These electrodes offer a stable electrical interface between the skin and recording device, minimizing impedance and enhancing signal quality. Electrodes were placed in accordance with standardized electromyographic and anatomical guidelines, aligned along the longitudinal axis of the muscle belly. The inter-electrode distance (IED) was standardized to optimize detection of motor unit action potentials (MUAPs) while minimizing crosstalk from adjacent muscles. Prior to electrode placement, skin preparation—including shaving and cleaning with alcohol—was rigorously performed to ensure reliable and high-quality signal acquisition.

The sEMG data were collected while subjects performed knee flexion and extension tasks at three distinct levels of muscle force: light, moderate, and strong. These levels were designed to generate sEMG signals with varying amplitudes, thereby reflecting the muscle activation levels of the quadriceps under different motor demands. The recorded sEMG signals had amplitudes ranging from 10 μV to 5 mV and a frequency bandwidth of 10 Hz to 500 Hz, which are consistent with the physiological characteristics of skeletal muscle activity.

The sEMG acquisition system was designed to accurately capture low-amplitude muscle signals. A signal amplification circuit utilizing the AD620 instrumentation amplifier was implemented, providing a gain of approximately 2000 to 3000 times to enhance signal amplitude and suppress environmental electromagnetic noise. The sampling frequency was set at 1 kHz to ensure adequate temporal resolution for signal analysis. Electrodes were firmly secured to the skin surface, and sufficient moisture was maintained to ensure stable contact, further minimizing environmental interference that could degrade signal quality.

2.2. sEMG Signal Processing

The sEMG signals collected from skin-mounted electrodes are typically of very low amplitude, ranging from a few microvolts (μV) to a few millivolts (mV), and are highly susceptible to various forms of noise, including motion artifacts, electromagnetic interference, and crosstalk from nearby muscles. To ensure that the signal is sufficiently accurate and stable for control applications, signal processing is a crucial step that enhances the signal-to-noise ratio (SNR) and eliminates unwanted components. The proposed signal processing system in this study consists of three main functional blocks: differential amplification, band-pass filtering, and rectification.

2.2.1. Signal Amplification

The initial stage of sEMG signal processing utilizes a differential amplifier circuit based on the AD620 integrated circuit—an instrumentation amplifier known for its high performance, low noise, stability, and excellent common-mode rejection ratio (CMRR). The AD620, as shown in Figure 1,is selected specifically for its capability to reject common-mode noise, particularly power line interference (50/60 Hz), which is essential when dealing with low-amplitude physiological signals.

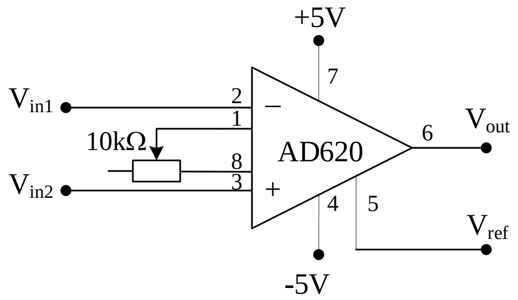

Figure 1: Signal Amplification Circuit using AD620

The amplification gain was set between 2000 and 3000, calculated based on the spectral and kinematic characteristics of sEMG signals. This level of gain ensures the signal reaches an optimal amplitude for subsequent processing stages without introducing distortion. The gain of the AD620 circuit is determined by the following formula:

$$A = \frac{49.4\ [k\Omega]}{R_g} + 1 \qquad (1)$$

Where:
- A is the amplification gain
- R_g is the gain-setting resistor

This formula enables precise gain adjustment by selecting appropriate resistor values for feedback and gain control, ensuring that the amplified signal amplitude is suitable without compromising signal integrity.

In addition, the use of a differential amplifier enhances the output signal's SNR by effectively suppressing unwanted noise sources, such as motion artifacts and electromagnetic interference, while maximizing sensitivity to weak EMG signals. Design considerations such as proper impedance matching, PCB layout optimization to reduce ground loop interference, and electromagnetic shielding were also implemented to further improve signal quality.Given these characteristics, the AD620 amplifier is well-suited for sEMG amplification in physiological applications, providing robust signal enhancement while maintaining high accuracy and reliability throughout the signal processing pipeline.

2.2.2. Band-Pass Filter

The band-pass filter circuit designed in this study aims to eliminate unwanted noise from the sEMG signal while retaining only the frequency components within the critical range of 2 Hz to 480 Hz—where the essential information of the sEMG signal resides. sEMG signals, which are typically low in amplitude and highly susceptible to interference from various sources, must be filtered to enhance signal quality and ensure accuracy in subsequent stages such as rectification and feature extraction.

The cutoff frequencies for the filter are selected based on the spectral characteristics of the sEMG signal. Since the majority of relevant sEMG information lies within the 2 Hz to 480 Hz range, the lower cutoff frequency is set at 2 Hz to eliminate low-frequency noise such as motion artifacts. The upper cutoff frequency is set at 480 Hz to suppress high-frequency noise from sources such as AC power interference (50/60 Hz) and electromagnetic disturbances. These frequency limits are crucial for preserving the signal's informative components while minimizing environmental noise.

To implement this band-pass filter, the circuit utilizes resistors (R), capacitors (C), and operational amplifier (op-amp) integrated circuits. The values of the resistors and capacitors are determined using standard formulas for high-pass and low-pass RC filters. The cutoff frequency fcf_cfc is calculated using the formula:

$$f_c = \frac{1}{2\pi RC} \qquad (2)$$

Where:
- f_c is the cutoff frequency
- R is the resistance
- C is the capacitance

Using this formula, appropriate R and C values can be selected to design a filter with desired cutoff frequencies. Specifically, the lower cutoff frequency is set at f_{c1}=2 Hz, and the upper cutoff frequency is set at f_{c2}=480 Hz, ensuring that the sEMG signal remains within the necessary frequency band.

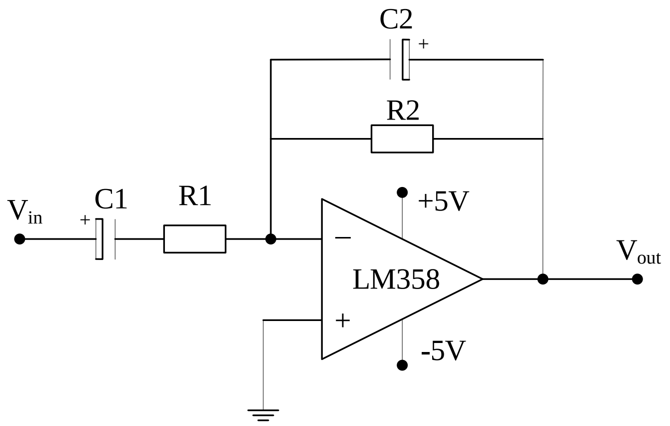

Figure 2: Band-pass filter circuit

To design a high-pass filter with a 2 Hz cutoff and a low-pass filter with a 480 Hz cutoff, suitable R and C values must be selected. For example, using R=100kΩ for the low-pass filter C=0.8 μF for the high-pass filter, the resulting cutoff frequencies can be accurately achieved.

$$f_c = \frac{1}{2\pi RC} = \frac{1}{2\pi.100000.0,8.10^{-6}} \approx 2\ \text{Hz} \quad (3)$$

Careful selection of these component values is essential to ensure precise cutoff frequencies and avoid loss of important sEMG signal components.

The operational amplifier (IC) used in the band-pass filter must have high stability, low noise, and operate effectively across the 2 Hz to 480 Hz range. In this study, the LM358 op-amp is chosen for its reliable performance and suitability for low-amplitude bioelectrical signals. The LM358 maintains signal integrity in physiological applications, where high accuracy and reliability are critical.

2.2.3. Rectifier

The half-wave rectifier circuit employs the 1N4148 diode to convert the AC sEMG signal into a DC signal by preserving only the positive half-cycles and eliminating the negative ones. The 1N4148 diode is selected for its fast switching speed and low forward voltage drop (approximately 0.7V), which is ideal for handling low-amplitude sEMG signals (see Figure 3).

In this rectifier circuit, the 1N4148 diode is connected in series with the sEMG signal. When the input signal is positive, the diode conducts, allowing the signal to pass. When the signal is negative, the diode blocks it, effectively removing the negative half of the waveform. This results in a unidirectional signal suitable for further processing, such as feature extraction.

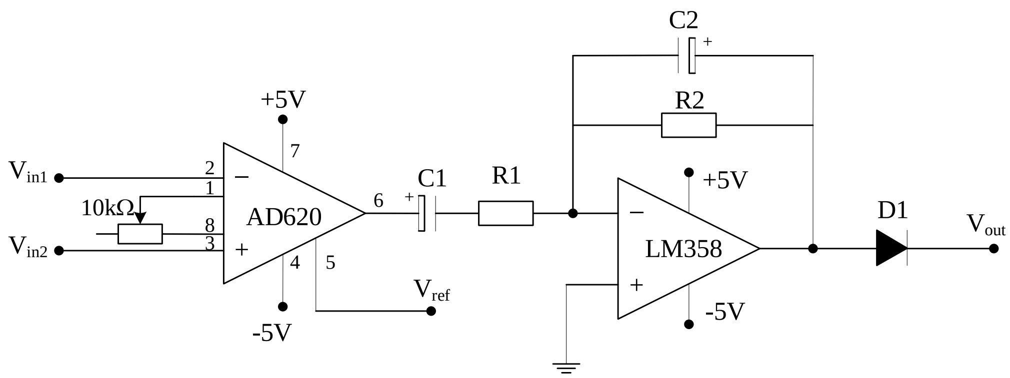

Figure 3: sEMG signal processing circuit

2.3. Feature Extraction from sEMG Signals

In this study, the Root Mean Square (RMS) feature extraction method is employed to evaluate the intensity of the sEMG signal, providing insights into muscle activity levels during robotic leg control. The Sliding Window Segmentation technique is used to divide the sEMG signal into short time windows, enabling continuous RMS calculation for each segment. This approach allows for tracking signal variations over time and minimizes the effect of noise.

2.3.1. RMS Computation Principle

The RMS value of the signal x(t) is computed using the following equation:

$$RMS(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x^2(i)} \quad (4)$$

Where:

- x(i) is the signal value at sample i
- N is the number of samples within the window

The RMS value represents the signal's amplitude at a given time and allows monitoring of intensity variations over time. This helps assess the user's muscle activity level. RMS smoothing also reduces insignificant fluctuations, creating a more reliable feature for further analysis or control algorithms.

2.3.2. Sliding Window Segmentation Technique

Sliding Window Segmentation divides the sEMG signal into fixed-length windows of size W, each containing N signal samples. The window moves through the signal with a step size S, selected to ensure adequate temporal resolution.

1) **Signal segmentation:** The sEMG signal is split into fixed-length time windows, each containing a subset of NNN data samples. RMS is computed for each window
2) **Window shifting:** The window slides along the signal by step size SSS, generating a sequence of RMS values reflecting temporal signal changes
3) **RMS feature extraction:** The RMS values of each window provide insight into muscle activity over time, capturing changes in contraction levels or muscle engagement relevant to robotic control

2.3.3. Advantages of Sliding Window Segmentation

Sliding Window Segmentation offers several benefits in sEMG signal analysis:

- Real-time signal tracking: It enables continuous monitoring of signal variations over time, helping detect changes in muscle activity.
- Noise reduction: Segmenting the signal into short windows limits the impact of transient noise within each segment.
- Adaptability to rapidly changing signals: Well-suited for sEMG's fast-varying nature in both amplitude and frequency, enhancing analytical accuracy.

2.3.4. Application in Robotic Control

The RMS feature extraction method combined with the Sliding Window Segmentation technique can be effectively applied in robotic control systems. RMS values derived from segmented sEMG signals serve as input parameters for control algorithms—such as those used to modulate robotic leg movement based on the user's muscle activity level.

2.4.Signal Features to Control Signals

In this study, control signals are generated from the RMS features of surface EMG (sEMG) signals through a linear mapping process. The objective of this process is to convert the muscle activation intensity-represented by the RMS value-into a corresponding motor rotation angle, thereby producing motion that reflects the user's muscle effort.
The linear mapping formula is described as follows:

$\theta = a * RMS + b$ (5)

Where:

- θ [degree]is the motor rotation angle
- RMS is the root mean square value of the sEMG signal
- aand b are calibration coefficients determined such that the motor's rotation accurately reflects the user’s level of muscular activity.

This mapping enables a linear relationship between muscle activation levels and motor movement, ensuring that the robotic leg performs smooth and precise motions that correspond to the user's muscle contractions. The resulting control signal is then used to drive the motor, actuating the robotic leg in accordance with the user's intended movement.

2.5. Mechanical Design of the Robotic Leg and Functional Evaluation

In this research, the mechanical design of the robotic leg was developed with the goal of replicating the natural movement of a human leg, while meeting requirements for accuracy and flexibility in control via sEMG signals. The robotic leg comprises key components such as the knee joint, ankle joint, and connecting segments. All components are designed to withstand the forces and torques generated during operation (see Figure 4).

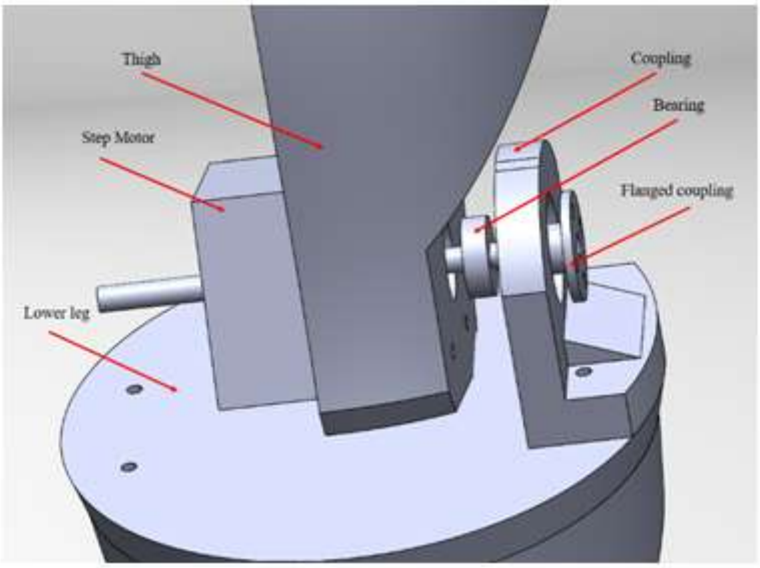

Figure 4: Actuation mechanism of the robotic leg

The knee joint is actuated by either a stepper motor or a servo motor, depending on application needs. This motor produces angular movements of the joint in response to control signals derived from processed sEMG data, allowing for rhythmic and natural joint motion. To enhance adaptability to users and reduce mechanical stress, the joints are designed with adjustable parameters tailored to individual users.

The ankle joint is incorporated to facilitate dorsiflexion and plantarflexion, supporting standing and walking while reducing user fatigue. To improve structural stability, components such as the foot base are constructed from high-durability, wear-resistant materials, enabling the leg to operate reliably over extended periods.

Moreover, optimization of weight and portability is a crucial factor in the mechanical design. It minimizes stress on moving parts and enhances the system's performance. Joint and linkage designs are calculated to ensure flexibility, ease of control, and maintainability.

All mechanical parts are designed based on mechanical engineering principles and specific technical criteria, ensuring effective, safe, and synchronized operation with control signals from the sEMG processing system.

III. Results And Discussions

This section presents experimental results and performance analyses of the sEMG signal acquisition and processing system, aiming to verify its feasibility in controlling a robotic leg that mimics flexion–extension movements. The system was tested using signals collected from human thigh muscles under various movement conditions.

3.1. Evaluation of the Signal Processing Circuit

Upon acquisition from surface electrodes, sEMG signals typically exhibit very low amplitude (0.1–5 mV) and are often contaminated by motion artifacts, power-line interference (50/60 Hz), and other electromagnetic noise. A band-pass filter circuit (2–480 Hz) was designed to effectively remove unwanted noise components. The low-cut frequency of 2 Hz eliminates low-frequency motion artifacts, while the high-cut of 480 Hz suppresses high-frequency noise. Frequency spectrum analysis before and after filtering showed that out-of-band noise was reduced by more than 20 dB, thereby improving the signal-to-noise ratio (SNR) before further processing. Figure 5 illustrates the sEMG signal wave forms after retifiying process. As shown, the half-wave rectifier circuit using a 1N4148 diode performed reliably, converting the AC sEMG signal into a unipolar signal suitable for RMS feature extraction. The rectified signal exhibited minimal distortion and accurately reflected muscle activation over time.

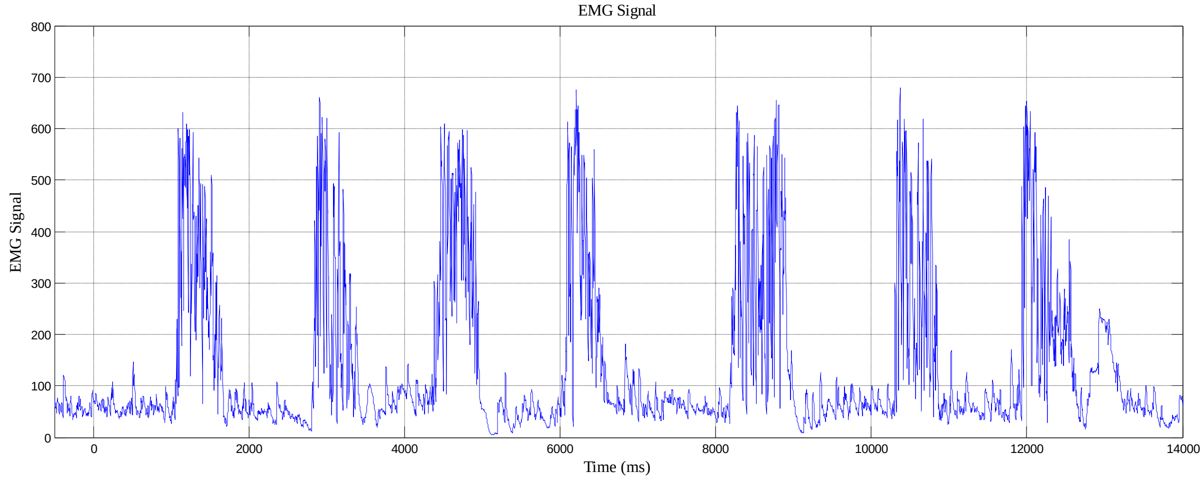

Figure 5: Processed sEMG Signal

3.2. RMS Feature Analysis and Correlation with Muscle Activity

The RMS feature extraction algorithm expressed in (4) employed a sliding window segmentation method to ensure real-time responsiveness. A window length of 200 ms with a 50 ms step was used to balance time resolution and signal stability.

3.3. Mapping RMS Features to Control Signals

The computed RMS values were linearly mapped into control signals for the stepper motor's rotation angle, simulating the knee joint's flexion-extension motion. The relationship is defined in (5). Experiments with varying muscle contractions showed that the knee joint's angular range shifted from approximately 10^0 (minimal contraction) to 75^0 (maximum contraction), closely mimicking natural knee flexion–extension.

3.4. System-Level Evaluation on Robotic Leg Model

The complete system was integrated and tested on a robotic leg prototype with a stepper-motor-driven knee joint. Trials involving three voluntary participants under varying contraction conditions demonstrated rapid system response (<150 ms latency) and high angular accuracy. The average angular deviation between desired and actual positions was 4.2^0, with a standard deviation of less than 3^0, confirming the system's sensitivity to muscle activity levels and suitability for rehabilitation control applications.

IV. Conclusions And Future Works

This study detailed the design, implementation, and experimental validation of a comprehensive system for the acquisition, processing, and utilization of surface EMG (sEMG) signals to govern the motion of a robotic leg. The system architecture incorporates critical functional modules including: signal amplification, band-pass filtering, rectification, root mean square (RMS) feature extraction, and linear mapping to stepper motor control signals.Experimental findings corroborated the system's capacity for stable sEMG signal acquisition, effective attenuation of extraneous noise, and accurate representation of muscle activation intensity through the RMS feature. The implementation of sliding window segmentation ensured rapid, low-latency responses suitable for real-time control applications.The robotic leg platform, integrated with the sEMG-based control system, successfully executed knee flexion-extension movements congruent with the user's muscular activity. Motion accuracy remained consistent with minimal deviation, highlighting the system's potential for applications in functional rehabilitation, exoskeleton robotics, and human-machine interfaces.

Future research directions may involve the expansion of the system's control capabilities to encompass multiple degrees of freedom, the application of machine learning algorithms to improve motion classification precision, and the integration of wireless communication to enhance device portability.

ACKNOWLEDGEMENT

The authors would like to sincerely thank the School of Electrical and Electronic Engineering – Hanoi University of Industry for providing the facilities and support throughout the research.

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