BioAmp EXG Pill Based Biosignal Acquisition System

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Abstract-*This paper presents the design and implementation of a real-time Electromyography (EMG) signal acquisition and processing system using the BioAmp EXG Pill hardware module interfaced with Arduino/ESP32 microcontrollers and MATLAB/Python-based software platforms. The proposed system acquires surface EMG signals from muscle electrodes, applies analog amplification and conditioning, performs analog-to-digital conversion, and transmits data wirelessly or via USB for real-time visualization and processing. Signal processing operations including bandpass Butterworth filtering (20–450 Hz), full-wave rectification, moving-average smoothing, and Fast Fourier Transform (FFT)-based frequency analysis are implemented to extract clinically relevant features such as Root Mean Square (RMS), Mean Absolute Value (MAV), Signal Energy, and Median Frequency. Two operational scenarios are evaluated: (i) general muscle activity analysis, and (ii) muscle strength and fatigue assessment for patient rehabilitation monitoring. Experimental results confirm effective noise removal, accurate feature extraction, and real-time signal visualization. The system demonstrates practical applicability in healthcare monitoring, physiotherapy rehabilitation, prosthetic limb control, and gesture-based gaming interfaces, establishing a scalable framework for future wearable biomedical systems.*

Keywords-EMG signal processing, BioAmp EXG Pill, wearable biomedical system, muscle fatigue analysis, gesture recognition, MATLAB, myoelectric control, real-time monitoring.

1. INTRODUCTION

Electromyography (EMG) is a biomedical technique that captures the electrical activity produced by skeletal muscles during voluntary and involuntary contractions. The resulting signals, derived from Motor Unit Action Potentials (MUAPs), encode neuromotor intent and are widely exploited in prosthetic control, human–machine interaction (HMI), rehabilitation engineering, and clinical diagnostics. Surface EMG (sEMG) offers a non-invasive alternative to intramuscular recording and has been the preferred modality in wearable biomedical devices since the 1960s. However, sEMG signals occupy a narrow amplitude range (0–10 mV) with dominant energy concentrated between 50–150 Hz, making them highly susceptible to power-line interference, motion artifacts, and electrode-skin impedance variations. Recent hardware advances, exemplified by the BioAmp EXG Pill a compact, low-cost analog front-end module have lowered the barrier for constructing wearable EMG systems suitable for both clinical and consumer applications. When coupled with commodity microcontrollers such as the Arduino Uno or ESP32 and modern scientific computing environments (MATLAB, Python), complete acquisition-to-application pipelines can be realized at minimal cost.

2. EMG SIGNAL BACKGROUND

2.1 Physiology of EMG Generation:

The fundamental excitable unit of the neuromuscular system is the motor unit, comprising a single alpha motor neuron and all skeletal muscle fibers it innervates. Upon reaching depolarization threshold (~−55 mV from a resting potential of −80 to −90 mV), a propagating action potential traverses the muscle fiber at 2–6 m/s, generating an electromagnetic dipole detectable at the skin surface. The surface-recorded superposition of Motor Unit Action Potential Trains (MUAPTs) from concurrently active motor units constitutes the EMG signal. Key signal characteristics include: amplitude 0–10 mV (peak-to-peak), useful frequency band 20–500 Hz with dominant energy at 50–150 Hz, and stochastic amplitude distribution approximated by a zero-mean Gaussian function. Signal properties are modulated by motor unit recruitment thresholds, firing rates, tissue conductivity, and electrode skin impedance.

2.2 Noise Sources and Electrode Considerations:

EMG noise sources include ambient electromagnetic interference (predominantly 50/60 Hz from AC power infrastructure), transducer noise arising at the electrode–electrolyte interface, motion artifacts, and baseline drift attributable to sweat-induced electrode–skin impedance changes. Silver–silver chloride (Ag-AgCl) wet electrodes minimize impedance and DC offset, while dry gold electrodes offer convenience at the cost of higher impedance. Bipolar differential recording with a high-quality instrumentation amplifier attenuates common-mode interference, achieving Common-Mode Rejection Ratios (CMRR) exceeding 90 dB.

2.3 Feature Extraction:

EMG features are categorized across three domains. Time-domain features including RMS, MAV, Zero-Crossing Rate (ZCR), and Waveform Length (WL) are computationally efficient for real-time implementation. Frequency-domain features such as Mean Frequency (MNF) and Median Frequency (MDF) encode spectral shift patterns characteristic of muscle fatigue. Time-frequency representations via Short-Time Fourier Transform (STFT) and Wavelet Transform provide simultaneous temporal and spectral resolution beneficial for non-stationary EMG analysis.

3. SYSTEM ARCHITECTURE AND HARDWARE DESIGN

3.1 Hardware Components:

The acquisition hardware comprises three functional blocks: (1) Electrode interface, (2) Analog signal conditioning, and (3) Microcontroller data acquisition. Disposable Ag-AgCl surface electrodes are placed over the target muscle belly following standard skin preparation (abrasion with isopropyl alcohol to reduce impedance below 10 kΩ). A bipolar electrode configuration with inter-electrode distance of 20 mm and a reference electrode over a bony landmark is employed. The BioAmp EXG Pill serves as the analog front-end, providing instrumentation-amplifier-based differential amplification, high-pass filtering to remove DC offset, and band-limiting to constrain the signal within the EMG band. Its compact form factor (< 25 mm^2) and single-supply 3.3/5 V operation render it suitable for wearable implementation.

An Arduino Uno (ATmega328P, 10-bit ADC at 10 kSPS) provides the microcontroller platform for tethered acquisition, while the ESP32 (Xtensa dual-core, 12-bit ADC at up to 2 MSPS, integrated Bluetooth 4.2 / IEEE 802.11 b/g/n) is deployed for wireless wearable scenarios. USB-UART serial communication at 115200 baud transfers digitized samples to the host computer for real-time processing.

3.2 System Architecture Overview:

The end-to-end signal flow follows the chain: Surface Electrodes → BioAmp EXG Pill (Analog Conditioning) → Arduino/ESP32 (ADC + Microcontroller) → USB/Wireless → Host Computer (MATLAB/Python Processing) → Application Layer (Visualization / Gaming / Healthcare). This modular architecture isolates hardware-dependent and algorithm-dependent components, facilitating independent development and validation of each stage.

4. SIGNAL PROCESSING METHODOLOGY

4.1 Preprocessing and Filtering:

Raw EMG data received by MATLAB undergoes a multi-stage preprocessing pipeline. A fourth-order zero-phase Butterworth bandpass filter with cutoff frequencies of 20 Hz and 450 Hz preserves clinically relevant EMG components while attenuating low-frequency motion artifacts and high-frequency electronic noise. A 50 Hz notch filter (Quality factor Q = 35) removes power-line interference. Zero-phase filtering is implemented using the MATLAB filtfilt function to eliminate phase distortion, which is critical for accurate timing analysis of muscle activation.

4.2 Signal Rectification and Envelope Detection:

Following bandpass filtering, full-wave rectification converts the bipolar EMG waveform to a unipolar representation by computing the absolute value of each sample. Linear envelope extraction via a moving-average filter with window length proportional to the desired temporal resolution (typically 100–200 ms) produces a smooth activation envelope. The resulting envelope provides an intuitive representation of muscle activation intensity directly proportional to the number and firing rate of active motor units.

4.3 Feature Extraction:

Four primary features are computed over non-overlapping analysis windows of 256 ms:

Root Mean Square (RMS): $x\_rms = sqrt((1/N) * \Sigma x^2[n])$, reflecting muscle contraction force.

Mean Absolute Value (MAV): $x\_mav = (1/N) * \Sigma |x[n]|$, a computationally efficient contraction strength estimate.

Signal Energy (E): $E = \Sigma x^2[n]$, the aggregate power of the window.

Median Frequency (MDF): the frequency that bisects the power spectral density, a sensitive fatigue indicator that decreases as conduction velocity diminishes during sustained contraction.

4.4 Frequency-Domain Analysis:

The Fast Fourier Transform (FFT) of each analysis window converts the time-domain EMG into its power spectral density (PSD) representation. Spectral analysis reveals dominant frequency components, identifies residual interference, and enables fatigue monitoring through downward shifts in MDF over sustained contractions. A

Hann window is applied prior to FFT computation to reduce spectral leakage.

4.5 Fatigue Detection Criterion:

Muscle fatigue is quantified by monitoring the temporal evolution of MDF across sequential analysis windows. A statistically significant monotonic decrease in MDF (assessed by linear regression slope < −0.5 Hz/s over a 10-second epoch) triggers a LOW/MODERATE/HIGH fatigue classification. Concurrent RMS increase followed by eventual amplitude decline provides a corroborating secondary indicator.

5. EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Scenario 1: General Muscle Activity Analysis:

EMG signals were acquired from the forearm flexor digitorum superficialis during a series of controlled grip contractions at 5-second intervals over a 5-second recording window. The raw signal exhibited peak-to-peak amplitudes of approximately ±1.2 mV with visible 50 Hz interference. Following bandpass filtering, the interference was reduced to below the noise floor, yielding a visibly cleaner waveform with preserved activation transients.

Full-wave rectification and subsequent moving-average smoothing produced a stable EMG envelope clearly delineating contraction and relaxation phases. FFT analysis identified dominant frequency components at 50 Hz (power-line residual, post-filter) and 90 Hz (primary muscle activity band). Extracted features for this scenario are summarized in Table I.

TABLE I EMG Features Scenario 1 (General Muscle Activity

Feature	Value
RMS Value	0.4192
Mean Absolute Value (MAV)	0.3380
Signal Energy	1757.65
Median Frequency (MDF)	499.45 Hz
Fatigue Classification	LOW MUSCLE FATIGUE

5.2 Scenario 2: Muscle Strength and Fatigue Assessment:

In the second scenario, a patient-simulating subject performed repeated isometric forearm contractions over a 10-second window to induce progressive muscle fatigue. The raw EMG signal over this duration was acquired, filtered, rectified, and smoothed following the same pipeline as Scenario 1. A bar graph of extracted strength features revealed high Signal Energy (1757.65) relative to normalized RMS (0.4192) and MAV (0.3380), consistent with sustained neuromuscular activity. Fatigue assessment via MDF evolution yielded a Median Frequency of 499.45 Hz (pre-fatigue dominant frequency) with the system classifying the session as LOW MUSCLE FATIGUE, indicating the contraction duration was insufficient to induce significant spectral downshift. These results validate the system's capacity to discriminate fatigue states and are summarized in Table II.

TABLE II EMG Features — Scenario 2 (Muscle Strength & Fatigue)

Feature	**Value**
RMS Value	0.5133
Mean Absolute Value (MAV)	0.4305
Variance	0.2635
Signal Energy	1317.44

5.3 Discussion:

The experimental results confirm that the proposed pipeline effectively removes noise artifacts while preserving physiologically meaningful EMG content. The bandpass Butterworth filter demonstrated a roll-off sufficient to eliminate motion artifacts below 20 Hz and high-frequency noise above 450 Hz without introducing perceptible phase distortion. Feature extraction accuracy was validated by comparing RMS values against reference contraction force levels measured qualitatively, showing proportional agreement consistent with literature.

The BioAmp EXG Pill demonstrated stable amplification across repeated trials, with minimal inter-session electrode re-application variability. The ESP32 wireless variant maintained real-time data integrity at 1 kHz sampling rate over Bluetooth with sub-5 ms latency, meeting real-time control requirements. The gesture-based gaming interface achieved successful trigger detection with a command latency of approximately 150 ms from muscle activation onset, rendering it suitable for interactive applications.

6. CONCLUSION

This project concludes complete, low-cost, real-time EMG signal acquisition and processing system built upon the BioAmp EXG Pill analog front-end, Arduino/ESP32 microcontrollers, and MATLAB-based signal analysis. The system successfully demonstrated effective bandpass filtering, full-wave rectification, envelope detection, and multi-domain feature extraction across two clinically motivated scenarios. Experimental results confirm reliable noise suppression, accurate muscle activity quantification, and fatigue classification with direct applicability to physiotherapy monitoring and gesture-based HMI applications.

The modular, open-source architecture lowers the barrier for researchers, clinicians, and developers to implement wearable EMG systems, providing a reproducible foundation for advanced neuromuscular signal analysis and biomedical application development.

7. FUTURE SCOPE

Future work will integrate machine learning classifiers including Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks to enable robust multi-gesture recognition for prosthetic limb control. IoT-enabled cloud connectivity will facilitate remote rehabilitation monitoring and longitudinal patient data analytics. Multi-modal biosignal fusion incorporating ECG and EEG alongside EMG is planned to develop comprehensive wearable

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