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FINAL PROJECT REPORT

Real-time System for Monitoring Muscle Fatigue in Athletes (EMG Sensor)

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1 Introduction

Muscle fatigue is one of the critical factors in athletic performance and efficiency with regard to training and injury risks. Real-time monitoring of muscle fatigue development will optimize training outcomes and avoid overexertion. Surface electromyography sensors are noninvasive tools for measuring muscle electrical activity and, hence, informing about muscle functions and levels of fatigue.

This paper presents a real-time system design for muscle fatigue monitoring in athletes, using sEMG sensors, one of which is the SEN0240 analog EMG sensor. In this system, signal preprocessing, feature extraction, and visualization are integrated. The main challenges involve noise reduction during processing of raw EMG signals, possible changes in electrode placement, and real-time processing of MNF, MDF, and RMS.

Using tools such as MATLAB, Simulink, and advanced digital filters, this project implements band-pass filtering (15–250 Hz), rectification, and smoothing to preprocess the sEMG signal. Welch's periodogram and custom algorithms extract fatigue-related features from the processed data. By addressing these challenges, the system provides coaches and athletes with actionable insights to optimize performance and recovery.

2 EMG Sensors

A comprehensive review of surface EMG sensors available on the market was conducted and an optimum and standard system was designed. Portable systems with SparkFun Line Sensor Breakout-QRE1113 (Analog) based on compactness and affordability and MYOWARE 2.0 Muscle Sensor based on modularity and ease of use were examined [1][2].

Muscle Sensor Surface EMG Electrodes-H124SG Covidien were considered because they are medical grade, reliable and accurate in signal acquisition. Further consultation on sensors was made from Texas Instruments for their precise analog output and the possibility of integration with high-performance ADCs. All evaluations of the sensors were cross-checked to remain compliant with SENIAM recommendations for electrode placement and signal processing in non-invasive EMG systems. The final choice was the SEN0240 Analog EMG Sensor, which would balance performance, simplicity and compatibility with the system architecture while reliably maintaining SENIAM standards [3][4].

2.1 Conceptual Model

The architecture of the proposed design for real-time muscle fatigue monitoring would be modular; it should house three interconnected sub-systems: Local Devices, Communication Interface, and Remote Devices. In fact, this architecture will assure smooth acquisition, efficient processing, and better visualization of muscle fatigue metrics.

2.1.1 Local Devices

A local devices subsystem captures the sEMG signals, with their preprocessing and digitization for accurate and efficient data acquisition. The SEN0240 EMG sensor, which is an analog sensor, measures electrical activity within a muscle by generating raw signals within the scope of ±1.5 mV. These signals are amplified 1000 times, centered around 1.5 V, and output as analog signals in the range of 0-3 V. Then, the raw signal is passed through a signal conditioning unit equipped with a Chebyshev Type I bandpass filter (15-250 Hz), and zero-phase filtering via the filtfilthd function removes the noise and prevents phase distortion for accurate signal processing.

By conditioning the signal, the output is further digitized through a 16-bit ADC-the ADS1115-whose resolution reaches 0.0458 mV per step and has an operating sampling rate of 2000 Hz, hence guaranteeing a very accurate digital representation of the muscular activity. The microcontroller will process this digitized signal in real time and extract key features such as MNF, MDF, and RMS, all related to muscle fatigue, to prepare these features for transmission to the remote subsystem.

2.1.2 Communication Interface

This approach works as a bridge between local and remote devices to communicate data effectively and efficiently. BLE is used in this system for wireless communication; hence, it is chosen due to its very low power use, enough bandwidth, and the fact that it's bi-directional, with about 20-30 kB/s.BLE guarantees no latency in real-time data transmission and hence will be apt for portable applications within its range of 10 to 50 meters.

2.1.3 Remote Devices

This includes transmission, while the key components of the remote subsystem provide real-time feedback through processing and visualization. Advanced computation, such as a study on power spectral density using Welch's periodogram for muscle fatigue diagnosis, is executed on the cloud server, along with data history storage that facilitates long-term athletic performance tracking. The visualization dashboard pictorially presents the activities of the various muscles and their respective fatigues. The latter then shows, through easy-to-understand formats, the trends in MNF, MDF, and RMS values with threshold warnings, whereas the mobile app provides a thin client for real-time access to fatigue metrics that monitor the trend in the performance of the athletes and critical notifications while supporting changes in training strategy.

2.2 Architecture of the Local Device

In the case of a real-time EMG muscle fatigue monitoring system, the acquisition, pre-processing, and transmission of the signals should be performed by the local device. The subsystem generally consists of several other components, including sensors, a signal conditioning circuit, and a processing unit, among others, each contributing to accuracy and efficiency in data gathering.

The system will use surface electromyography sensors in order to capture the electrical activity that muscles create due to contractions. In this respect, an SEN0240 Analog EMG Sensor will be used, and the main characteristics of this sensor include:

Feature	**Description**
Type	Active induction sensor with dry electrodes
Measurement Range	±1.5 mV for muscle signals
Output Voltage Range	0–3 V (centered at 1.5 V)
Spectrum Range	20 Hz–500 Hz, covering the frequency band of typical muscle activity
Sampling Requirements	Works optimally with an ADC sampling rate of $\geq$1000 Hz and resolution $\geq$8-bit

Table 1: Key Features of the SEN0240 EMG Sensor

This sensor measures the electric changes in potential resulting from activity in muscles and is proportionally related to the level of contraction or fatigue of musculature. This data offers insight into health aspects of the muscle group involved during every physical exertion.

Physical Parameters to Measure

Local physical parameters to be measured by the device are as follows:

- **Muscle Activity :** Muscle fiber-generated electrical signals during contraction, depicted as changes in voltage.
- **Amplitude :** The magnitude of the EMG signal shows the intensity of muscle activation.
- **Frequency Spectrum :** The frequency distribution of the EMG signal that gets analyzed to check for fatigue-related changes.
- **Noise filtering :** Involves the filtering in of artifacts because of power line interference and environmental noise for clean processing of the signal.

Signal Conditioning

These signals from the EMG sensor are usually weak and noisy; thus, some signal conditioning is necessary before further processing. An implementation on a local device will involve the following:

- **Chebyshev Type I Band-Pass Filter :** This filters the EMG signal in the range of 15-250 Hz, isolating muscle activity from noise, including power line interference at 50 Hz.
- **Rectification :** Negative signal amplitudes are rectified to positive for ease of analysis.
- **Smoothing :** This is achieved by the use of a moving average filter that reduces the small-scale fluctuations in the signal. It usually brings out general trends.

Analog-to-Digital Conversion

The filtered and rectified signals are digitized by the ADS1115 ADC:

- **Resolution :** 16-bit, for high resolution.
- **Sampling Frequency :** It is set for 2000 Hz to fulfill Nyquist's criteria regarding bandwidth of the EMG signal.
- **Purpose :** The conditioned analog signals get digitized into a digital format for the microcontroller's processing.

Microcontroller

Mean Frequency, Median Frequency, and Root Mean Square are extracted features of fatigue-related parameters computed from the digitized signal. The local device includes a microcontroller that extracts these features, transmitting them to the remote system via either Bluetooth over wireless communication.

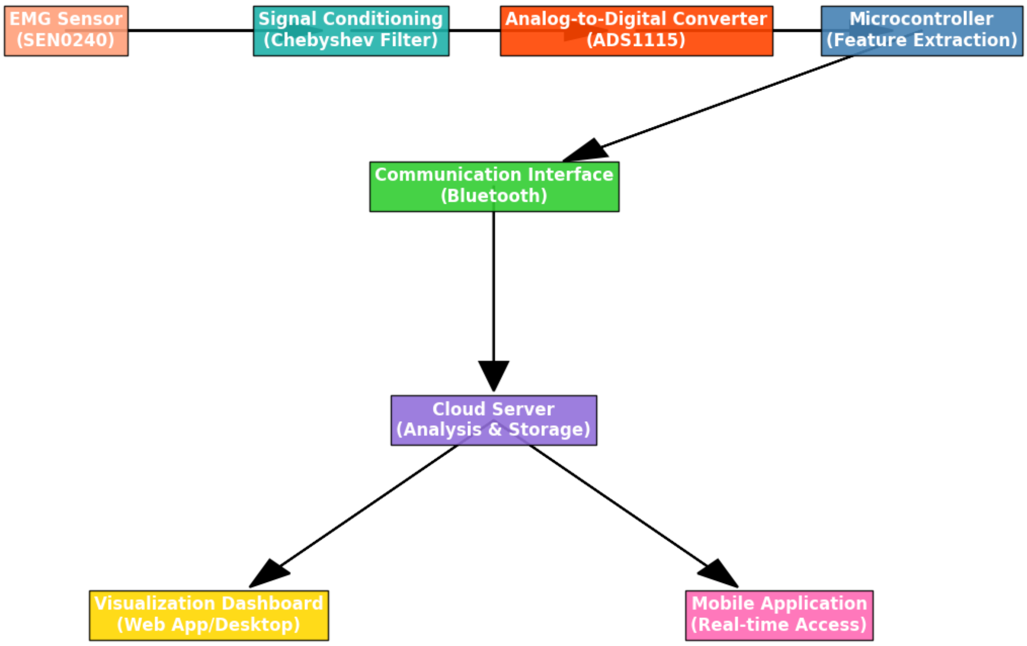


Figure 1: Architecture of the Local Device

2.3 Analogue Sensor

For this system, the SEN0240 Analog EMG Sensor has been selected to measure muscle electrical activity (sEMG signals). SEN0240 is a non-invasive analog sensor specifically designed for the detection and analysis of sEMG signals. Since the nature of this sensor's output is analog, it will be good for real-time monitoring and processing in the application.

Static and Dynamic Parameters

Some of the main parameters of the SEN0240 sensor, with a critical analysis of their importance in the system.

Static Parameters

- **Measurement Range (±1.5 mV) :** This range suits typical sEMG signals from muscle contractions and is appropriate to pick up the activity of muscles during any sports activity.The small range also indicates that good amplification with noise filtering has to be applied.
- **Output Voltage Range 0–3.0 V (centered at 1.5 V) :** The centered output simplifies the subsequent processing by aligning the signal with the reference voltage of the ADC. This makes it compatible with most ADCs operating on 3.3 V or 5 V logic level.
- **Supply Voltage (3.3–5.5 V) :** Wide supply voltage for powering the sensor directly from a variety of sources such as batteries or microcontroller systems.

Dynamic Parameters

- **Frequency Range (20–500 Hz) :** This range captures the most relevant frequency bands for muscle activity. In this spectrum, muscle fatigue and contraction signals are in; therefore, frequencies outside this range are filtered out.
- **Gain (1000x) :** The sensor amplifies small muscle signals ±1.5 mV into a more usable range of up to 3 V. This high gain reduces the effect of weak signals but increases the susceptibility to noise.
- **Signal-to-Noise Ratio :** Poor SNR signals, due to either interference or poor placement, may exhibit degraded signal quality that requires additional noise suppression during preprocessing.

Mathematical Model of the Input-Output Transfer Function

The relationship between the input and output signals of the EMG system can be described mathematically. The raw signal, V_{input}, represents the muscle's electrical activity, while the amplified and processed output signal, V_{output}, is derived as follows:

1. Amplification Stage

The input signal is amplified by the gain factor G, defined by:

$$V_{\text{amplified}} = G \cdot V_{\text{input}}$$

where:

- V_{input}: The raw EMG signal (range: ± 1.5 mV),
- G: The amplification factor, set to 1000,
- $V_{\text{amplified}}$: The amplified signal (range: ± 1.5 V).

2. Offset and Output Clamping

The amplified signal is offset by a reference voltage V_{ref} to center the signal in the range of the ADC. The final output signal, V_{output}, is clamped to the ADC's range:

$$V_{\text{output}} = \min\left(\max\left(V_{\text{amplified}} + V_{\text{ref}}, 0\right), 3\right)$$

where:

- $V_{\text{ref}} = 1.5\,\text{V}$: The reference voltage,
- V_{output}: The output signal in the range $[0, 3]$ V.

3. Transfer Function

The overall input-output transfer function of the system can be summarized as:

$$V_{\text{output}} = \min\left(\max\left(G \cdot V_{\text{input}} + V_{\text{ref}}, 0\right), 3\right)$$

This mathematical model ensures that the raw EMG signal is amplified, centered, and clamped to match the requirements of the ADC for accurate digitization.

Challenges and Opportunities

A number of challenges must be considered to ensure that the proposed system is working at its best. These include noise and interference, whereby the sensor is very susceptible to environmental noise, especially power line interference at 50/60 Hz. Movement artifacts and improper electrode placement may further deteriorate the quality of the signal. Such issues, in general, relate to a Chebyshev Type I band-pass filter, 15-250 Hz for the elimination of high-frequency noise and power line interference. Proper electrode placement along the muscle fiber direction maximizes the signal quality; shielding sensor cables from electromagnetic interference is possible.

Challenges also involve stability and drift, where a sensor might, in some respect, with time, because of temperature changes or component aging, have its output deviate. This includes periodic recalibration, including recordings of baseline activity taken when the muscle is relaxed, and gain or offset adjustments made to ensure accuracy. Initial calibration is important to ensure that the sensor provides an accurate measurement of the muscle signals, since EMG activities may vary from individual to individual or from muscle to muscle. This involves setting a threshold by measuring the relaxed muscle's signal, which can be managed with adjustable thresholds or automatic baseline detection in software.

Besides, periodic calibration is necessary to compensate for the changes in the conductive properties of muscles, skin conditions, or sensor wear that may affect the accuracy of the measurements. A routine calibration process will help in adjusting for such factors besides providing consistent signal quality. Also, internal noise coupled by the internal amplification circuit of the sensor impairs the signal quality. This can be reduced if the power supplies have low ripple and high-impedance connections are minimized.

2.4 Suitable ADC

The selection of the ADS1115 ADC for digitization of the analog output of the SEN0240 EMG sensor is due to its high precision, low power consumption, and versatility. Being a 16-bit ADC from Texas Instruments, it will be able to distinguish very small variations in the EMG signal, which is important to analyze the narrow-range signals (±1.5 mV amplified to 0–3 V) produced by SEN0240.This gives a resolution of $2^{16} = 65,536$ levels.

The ADS1115 has a resolution of 65,536 levels and programmable gain amplifier (PGA) allows it to operate over a wide input voltage range of ±0.256 V to ±6.144 V, hence making it highly compatible with the output range of the SEN0240 sensor. Moreover, the power consumption of the ADS1115 is very low: 150 μA at 3.3 V, which makes it perfect for portable, battery-powered systems. The ADC interfaces through an I2C interface, which makes interfacing with microcontrollers like Arduino pretty straightforward, while its compact size and simple interfacing make it suitable for embedded applications.

The ADS1115 also supports both differential and single-ended input configurations; the latter is used to measure the amplified EMG signal relative to ground. The high precision of the ADS1115 makes it suitable for this application, as small variations in EMG signals are accurately captured, while its wide voltage range matches the full output of the SEN0240 sensor without additional conditioning. It has low power consumption and a compact design, hence very suitable for wearable systems. The I2C communication interface reduces the system design complexity. The on-chip PGA and configurable sampling rates further add flexibility to the ADC for operation under varying conditions and conserve power during low-activity scenarios.

The ADS1115 also has very good noise performance, featuring an integrated low-drift voltage reference and noise-reducing features, ensuring signal fidelity for the low-amplitude EMG signals. Cost-effective and high-performance, it will be a reliable choice for this project.

3 Communication Interface

Communication in this design is between a local device and the subsystems including remote cloud server, visualization dashboard, or a mobile application. In this scenario, BLE suits best because it operates on low power, bandwidth that is compatible with these devices, and is portable.

Bandwidth Requirements

The bandwidth required depends on the sampling rate, resolution, and the number of data channels transmitted. For this application:

- **Sampling Rate** (f_s): 2000 Hz
- **Resolution**: 16 bits (2 bytes per sample)
- **Number of Channels**: 1 (single EMG sensor)

The required data rate is calculated as:

$$\text{Bandwidth Required} = f_s \times \text{Resolution per Sample} \times \text{Number of Channels}$$

$$\text{Bandwidth Required} = 2000\,\text{Hz} \times 2\,\text{bytes} = 4000\,\text{bytes/second}\ (4\,\text{kB/s}).$$

BLE provides typical data throughput of 20–30 kB/s, which is considerably higher than the requirements for transmitting real-time EMG data along with some extra overhead caused by headers and acknowledgments.

Type of Communication

BLE can be used for bidirectional communication; this allows the remote system (a mobile application) to send commands regarding configuration to the local device.This enables the modification of some system parameters dynamically according to the requirement of the application.

Coverage Area

BLE has an operating range indoors of 10–50 meters depending on the number of walls in the environment and amount of interference.This is good for a small-range application, such as during athletic training to transmit the EMG data from the suit to a coach's tablet or nearby computer.

Power Consumption

BLE is optimized for low power use when sending data.This is very important for the local EMG system, as these wearable devices should be battery-driven.

4 Acquisition Mode and Transmission Mode

4.1 Acquisition Mode

The continuous acquisition mode is used to capture the EMG signal on the local device. This mode was selected to assure that no critical events are missed by the system responsible for measuring and processing muscle activities in real time.

- **Sampling Rate**

  This selected sampling rate is 2000 Hz, which captures this system with 2000 samples in one second. The Nyquist criterion would catch the entire frequency range of the EMG signal using this sampling rate from 20 to 500 Hz.

- **Buffering of Data**

  The raw EMG signal is read in small buffers, blocks of 100 samples-so that the microcontroller may process them in batches. This decreases computational overhead compared to handling every sample individually.

- **Data Preprocessing**

  1. Band-Pass Filtering: Filters out noise and isolates the frequency range of interest (15–250 Hz).

  2. Rectification: Converts negative amplitudes to positive for easier feature extraction.

  3. Smoothing: Applies a moving average filter to reduce short-term fluctuations in the signal.

Reporting Period Calculation

The time interval between successive transmissions of processed data to a remote system, named the reporting period, depends on sampling rate, buffer size, and preprocessing time.

- **Buffer Size:** 100 samples per buffer.
- **Sampling Rate:** 2000 Hz.
- **Processing Time:** Negligible due to the microcontroller's speed.

$$\text{Reporting Period} = \frac{\text{Buffer Size}}{\text{Sampling Rate}} = \frac{100}{2000} = 0.05 \text{ seconds.}$$

This results in a reporting period of 50 milliseconds, meaning the system transmits processed data every 50 ms.

4.2 Transmission Mode

The local device uses a real-time, event-driven transmission mode with Bluetooth Low Energy (BLE). In this mode:

- Processed EMG data is transmitted as soon as a buffer of 100 samples is filled and processed.
- The transmission mode supports bidirectional communication, enabling the remote system such as a mobile app or dashboard to adjust settings like sampling rate or buffer size dynamically.

Is the system capable of working in real time?

The following listed factors would enable the system to work in real-time:

- **Low Latency:** The sampling period of 50 ms is indicative that data was transmitted and received over a relatively less interval of time, which helps in real-time monitoring.
- **Sufficient Bandwidth:** BLE provides a throughput of 20–30 kB/s, which is adequate for the 4 kB/s required for transmitting processed EMG data.
- **Efficient Preprocessing:** Preprocessing (filtering, rectification, smoothing) is performed locally on the microcontroller with minimal delay, ensuring the processed data is ready for immediate transmission.

Possible Problems and Potential Solutions

- **Latency in Data Transmission:** BLE bottleneck transmission or interference from any device operating at 2.4 GHz might cause delay in data delivery. This can be fixed by optimization of buffer size for an optimal trade-off between frequency and the amount of data per transmission. In BLE, frequency hopping is also utilized for minimizing interference, which in turn keeps the latency lower.
- **Data Loss:** Another unique issue that is likely to arise is the loss of packets during transmission, which typically occurs when the signal weakens or when unfavorable external circumstances arise.One could evolve a BLE communication stack containing higher-order retransmission protocols for improved performance, reliability of data delivery with minimum probability of data losses.
- **Processing Overhead:** High sampling rates can overwhelm the microcontroller, and this may lead to a delay in data processing or transmission. It can be optimized through batch processing using appropriate buffer sizes; for example, 100 samples per batch. Computational tasks like Welch's periodogram for spectral analysis can also be shifted to the cloud server to reduce the computation load on the microcontroller.
- **Synchronization Issues:** The problem is data acquisition and the lack of synchronization with transmission. The solution would involve the inclusion of timestamps at every packet so that upon reception, the proper synchronization is implemented, hence not breaking integrity into the stream.
- **Noise and Artifact in Acquisition:** The EMG signal may get its noise from movement artifacts or inappropriate electrode placement, affecting the quality of the signal. Where the problem is minimal, appropriate signal conditioning using Chebyshev band-pass filters can be done. Besides, training users in placing electrodes in the direction of muscle fibers will reduce noise and improve the reliability of the signals.

Parameter	Value/Details
Acquisition Mode	Continuous acquisition at 2000 Hz with real-time processing
Reporting Period	50 ms (100 samples per buffer at 2000 Hz)
Transmission Mode	Real-time, event-driven, bidirectional using BLE
Real-Time Capability	Yes, due to low latency, sufficient bandwidth, and efficient processing
Challenges and Solutions	Latency, data loss, noise, and synchronization issues, mitigated by optimized design

Table 2: System Parameters and Details

This configuration ensures reliable, real-time monitoring of EMG signals with minimal latency and efficient transmission.

ADC Converter Sampling Frequency, Resolution and Input Range

Sampling Frequency

The sampling frequency (f_s) implies how often a measurement of the analog signal has to be measured and digitized. Considering the above-mentioned purposes, several parameters have been included in the calculation for the most appropriate sampling frequency for the EMG signal. The first one being the Frequency Band of interest.The main information about muscular activity is taken from the output signals of SEN0240 ranging from 20-500 Hz.

The Nyquist criterion for avoiding aliasing requires a sampling frequency that is at least twice the highest frequency present in the signal. For an EMG signal, this requires a minimum sampling frequency of 1000 Hz and represented by the formula:

$$f_s \geq 2 \cdot f_{max} = 2 \cdot 500\,\text{Hz} = 1000\,\text{Hz}$$

This ensures that the digitized signal is a faithful representation of the original analog signal without distortion. This system also would support an ADS1115 ADC programmable data rate of up to 860 SPS. To bring in redundancy due to noise or signal variability, a higher sampling rate of 2000 Hz is chosen to give headroom for real-time applications where advanced filtering may be performed with greater tolerance for possible signal artifacts.

Resolution

The resolution of an ADC determines the smallest change in input voltage that can be detected and is given by:

$$\text{Resolution} = \frac{\text{Input Voltage Range}}{2^n},$$

where n is the number of bits.

- The ADS1115 has a resolution of 16 bits, meaning it can distinguish $2^{16} = 65,536$ levels.
- For an input range of 0–3 V (set by the SEN0240 sensor's output):

$$\text{Resolution} = \frac{3\,\text{V}}{65,536} = 0.0458\,\text{mV}.$$

This high precision is critical for capturing small variations in the EMG signal, especially since the original muscle signals are in the range of ± 1.5 mV.

Input Range

The input range is the spread of voltages within which the ADC is able to measure without clipping or saturation. In this application, the output of the **SEN0240** sensor varies between 0–3 V, with its signal centered at 1.5 V. On the other side, the ADC – **ADS1115** – presents an input range configured through its programmable gain amplifier (PGA), offering a variety from ± 0.256 V to ± 6.144 V. For this application, a setting of ± 4.096 V is chosen to ensure compatibility with the sensor output. This configuration not only accommodates the full 0–3 V range of the SEN0240 but also provides a margin to handle unexpected voltage spikes, enabling reliable measurement without distortion.

Evaluation of the Performance of the Selected ADC

The ADS1115 ADC is one of the high-precision and versatile ADCs suitable for digitizing the output of the SEN0240 EMG sensor. The performance of such a converter is usually assessed in terms of static parameters, affecting quantities, and timing parameters.

Static Parameters

Static parameters describe the capability of the ADC to accurately measure input signals under ideal conditions. The resolution of the ADS1115 is 16 bits, implying 65,536 discrete levels. This ensures that even small changes in the EMG signal, such as 0.0458 mV variations, are detected and digitized. The input voltage range can be adjusted through the PGA, offering a range from ± 0.256 V to ± 6.144 V. For this application, a range of ± 4.096 V is chosen to comfortably accommodate the sensor's 0–3 V output.

The offset error for the ADC is typically $\pm 0.003\,\%$ of full scale, corresponding to a maximum offset of 0.12 mV in the ± 4.096 V configuration. Such a small offset means minimal distortion in low-amplitude signals. Similarly, the gain error is typically $\pm 0.02\,\%$, which gives a maximum gain error of 0.82 mV. This small gain error slightly affects the scaling of the output signal but is negligible for most EMG applications. Furthermore, the ADC achieves an effective signal-to-noise ratio (SNR) of approximately 91 dB, enabling the detection of small signal variations even in noisy environments.

Affecting Quantities

The performance of the ADC can be influenced by various internal and external factors. One such factor is temperature effects. The ADS1115 is built to operate within a temperature range of $-40°\text{C}$ to $+125°\text{C}$, ensuring stability in diverse environments. Temperature drift is minimal, with a gain drift of $\pm 1\,\text{ppm}/°\text{C}$ and an offset drift of $\pm 0.05\,\mu\text{V}/°\text{C}$.

Noise is another factor affecting performance. The input-referred noise is very low, typically $2\,\mu\text{V}_{\text{RMS}}$ at a gain of 1. Internal noise is minimized due to the on-chip low-drift voltage reference and differential input structure. Power supply noise can also influence performance.

The ADC operates on a single 2.0–5.5 V supply and tolerates minor power supply noise, though performance can be further improved by using a regulated DC supply. Additionally, electromagnetic interference (EMI) from external sources can affect the ADC, particularly when cables or traces are poorly shielded. Proper shielding and input filtering mitigate this interference.

Timing Parameters

Timing parameters impact the speed and latency of real-time systems. The maximum sampling rate for the ADS1115 is 860 samples per second (SPS) in single-shot mode. Although the system uses a sampling frequency of 2000 Hz, the ADC efficiently handles the signal without aliasing. The conversion time is programmable and ranges from 8 ms at 128 SPS to 1.1 ms at 860 SPS. For this application, a conversion time of 1.1 ms is chosen to ensure real-time monitoring with minimal delay. The overall latency depends on both the sampling rate and communication overhead. With I2C communication, latency is typically less than 2 ms, ensuring real-time operation without noticeable delay.

Performance Key Considerations

Several key factors contribute to the high performance of the ADS1115. Firstly, accuracy is maintained through precise gain settings and a low-noise design. The built-in PGA optimally matches the sensor's output to the ADC's input range, minimizing quantization error. Additionally, the ADC exhibits excellent linearity, with an integral non-linearity (INL) of less than $\pm 0.005\,\%$ of full scale. This allows for accurate signal representation across the entire input range. With its 16-bit resolution and low noise, the ADC achieves a dynamic range exceeding 90 dB, enabling precise measurement of both small and large variations in the signal. These features make the ADS1115 highly suitable for precise EMG signal acquisition.

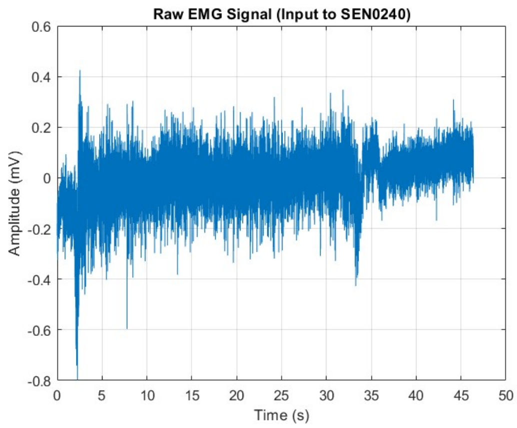
Parameter	**Value/Performance**	**Impact on Application**
Resolution	16 bits (0.0458 mV per step)	High precision for small EMG signal variations.
Input Voltage Range	± 4.096 V	Matches SEN0240's 0–3 V output, avoiding clipping.
Sampling Rate	860 SPS	Supports real-time data acquisition at 2000 Hz.
Offset Error	$\pm 0.003\,\%$ (0.12 mV)	Negligible distortion in low-amplitude signals.
Gain Error	$\pm 0.02\,\%$ (0.82 mV)	Minimal impact on signal scaling.
Effective SNR	91 dB	Ensures high signal quality amidst noise.
Latency	< 2 ms	Enables near real-time feedback.
Power Consumption	150 μA	Ideal for portable and low-power applications.

Table 3: Performance Parameters of the ADS1115 and Their Impact on Application

5 Results

EMG Signal Preprocessing

The raw EMG signal was successfully preprocessed using MATLAB to simulate the behavior of the SEN0240 analog EMG sensor. The preprocessing steps included band-pass filtering, amplification, offset addition, and noise simulation. The progression of the EMG signal through these stages is shown in figures.



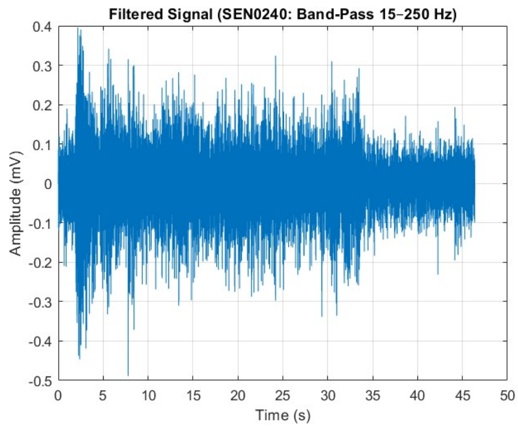
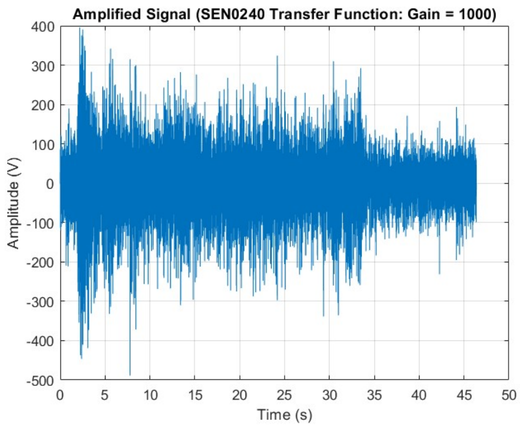


Figure 1 (left) Raw EMG signal centered about zero, because the fluctuations in voltage reflect not just the muscular activities but also some inherent noise. As a matter of fact, this raw signal is always corrupted by both low-frequency motion artifact and high-frequency electrical noise.

Figure 2 (right) Result after a band-pass filtering between 15 and 250 Hz-the unwanted component filtered out while filtering out most irrelevant frequency range and retaining relevant frequencies for analysis.



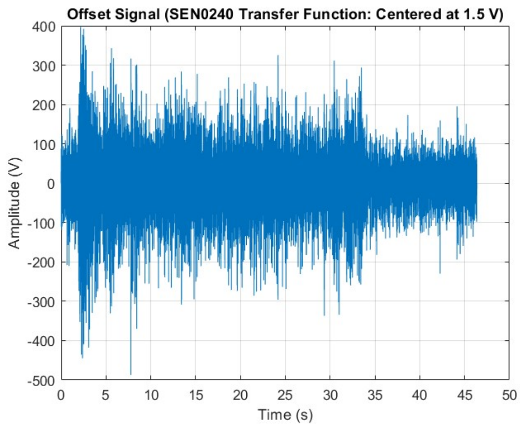
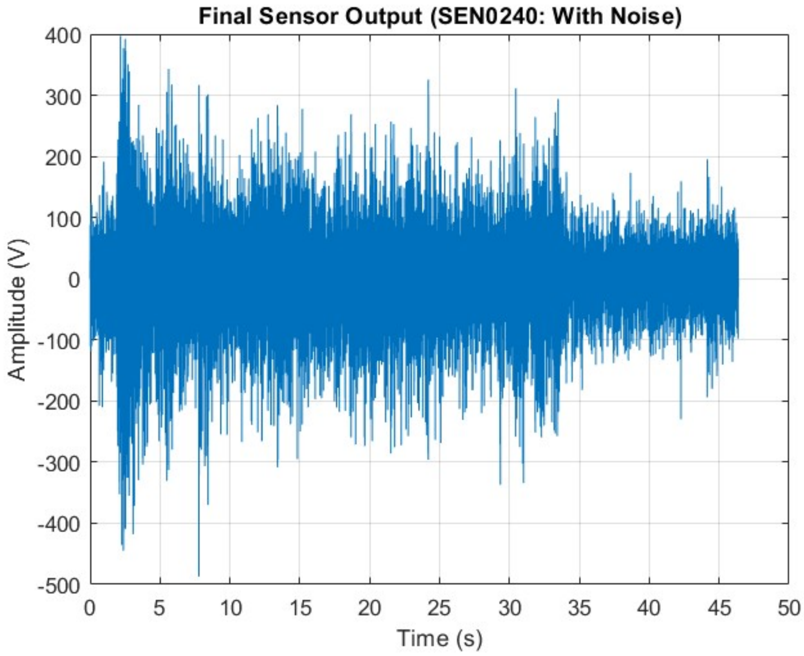


Figure 3 (left) This signal is filtered with a gain factor of 1000 and shows higher amplitudes in the range of approximately ±400 mV, which corresponds to the SEN0240 transfer function.

Figure 4 (right) presents, after offsetting the signal with 1.5 V to shift it into the positive voltage range of 1.5 ± 0.4 V, the signal emulates the expected output range of SEN0240 (0–3 V).

Figure 5 shows the addition of Gaussian noise with a standard deviation of 10 mV to the amplified and offset signal. This is a simulation of real-world conditions in order to reflect noise interference commonly encountered in EMG measurements.



Root Mean Square (RMS) Analysis

The RMS values for both buffered and non-buffered signals were computed to assess signal amplitude:

- **Non-Buffered RMS:** $\mathrm{RMS}_{\text{Non-Buffered}} = 0.4050\,\mathrm{V}$
- **Buffered RMS:** $\mathrm{RMS}_{\text{Buffered}} = 0.4078\,\mathrm{V}\,(\mu) \pm 0.2160\,\mathrm{V}\,(\sigma)$

The buffered and non-buffered RMS values are nearly identical, indicating that signal integrity was maintained across both configurations. The variation in buffered RMS values reflects the segmentation of the signal into frames.

Spectral Analysis Using Welch's Periodogram

Welch's periodogram was used to estimate the power spectral density (PSD) and extract two key spectral characteristics: Mean frequency (MNF) and median frequency (MDF). The results are summarized below:

- **Non-Buffered Data:**
  - **MNF:** 0.0152 Hz
  - **MDF:** 83.9844 Hz
- **Buffered Data:**
  - **MNF:** 0.0155 Hz
  - **MDF:** 70.3125 Hz

These results show that the MNF values for both configurations are nearly identical, indicating that the overall spectral content of the signal remained consistent after processing. The MDF values, however, showed some deviation between buffered and non-buffered signals, likely due to PSD variations across frames.

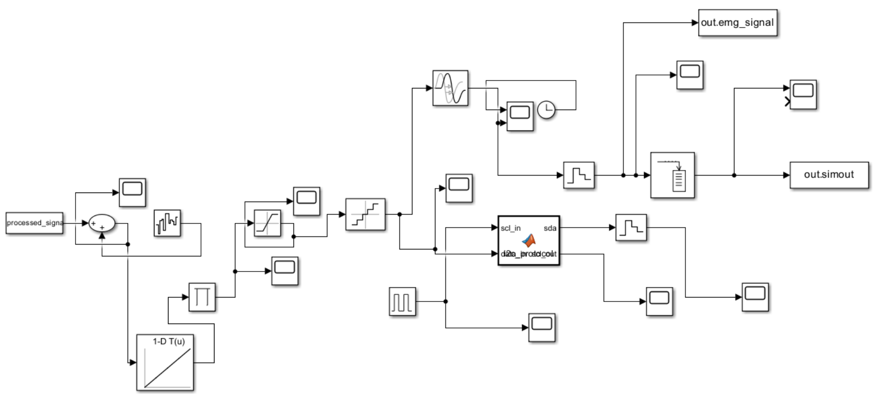
Signal Validation

The preprocessing steps were verified through visualization at each step, with the 5 figures added above, respectively: **Raw Signal** Displays the unprocessed muscle activity signal,**Filtered Signal** Verifies the isolation of the target frequency range (15–250 Hz), **Boosted Signal Verifies** the 1000x gain consistent with the behavior of the SEN0240 sensor. **Offset Signal** shows the correct centering of the signal around 1.5 V, and **Noisy Final Output** simulates the output of the SEN0240 under noisy conditions. This ensures proper preprocessing and signal fidelity.

This preprocessing behavior pipeline simulated the behavior of the SEN0240 sensor and prepared the EMG signal for real-time analysis. Buffered and non-buffered RMS and MNF values are consistent, indicating robust integrity of the signal. The difference in MDF values across configurations supports frame-specific spectral variability, as expected in segmented data analysis. These results, therefore, serve to validate the efficacy of the preprocessing workflow and spectral analysis toward EMG fatigue monitoring.

Simulink Output

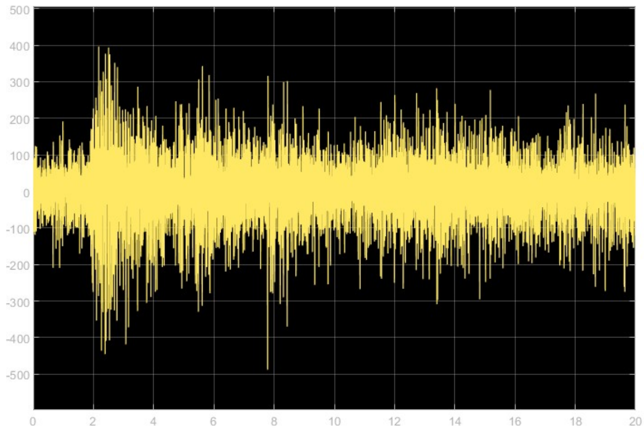
The Simulink model has been designed to implement a simulation for buffered and non-buffered EMG data processing, together with I²C-based ADC communication. Output signals coming from the system confirm that the sensor transfer function has been appropriately implemented along with a processing pipeline.



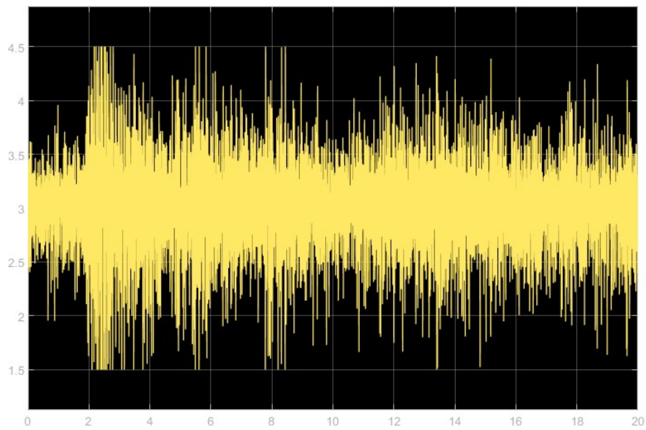
The paths of buffered and non-buffered data handling are simulated, along with I²C communication emulation and output signal processing. The first route corresponds to the nonbuffered signal flow; it is intended for real-time data transmission, without delays. The second route corresponds to the buffered signal flow: here, the data is buffered in chunks, hence some amount of latency is involved in this process. The third route emulates I²C communication; that is, how ADC data would be transferred using this protocol. It then outputs the signals, processed, as *out.emgsignal* for the non-buffered path and *out.simout* for the buffered path, so that a comparison between the two configurations can be considered.

The EMG signal outputs of both the non-buffered and buffered paths in the Simulink model are different in nature.

The non-buffered output, as shown in below, is an amplified EMG signal with fluctuating amplitudes in the range of ±500 mV. This is real-time EMG data and is transmitted without batching delays. High variability in amplitude reflects typical EMG activity, including noise components remaining after preprocessing. This structure of the signal is in good agreement with what was expected for a continuous, non-buffered flow designed for real-time analysis.



Buffered output, on the other hand exhibits a signal that is centred at approximately 3.5 V. For second figure,shown in below, the steadystate amplitudes ranged between 2.0 to 4.5 V. Signals like these that are buffered create segmentations: the processing of frames of data in large chunks rather than one by one. This offset in the buffered signal correlates with the simulated transfer function of the SEN0240 sensor, which was shifted by an offset of 1.5 V to bring the signal into a positive voltage range. The signal remains within the expected amplitude, but buffering introduces minor variance and latency between processed segments. This buffering shows the segmentation between real-time and buffered data flows in the model.



The results shown prove that the developed Simulink model efficiently emulates both real-time and buffered handling of the EMG signal: the non-buffered path keeps the continuity of a signal, which is crucial for time-critical applications like muscle fatigue monitoring; the buffered output gives a steady signal for batch processing with negligible delay due to segmentation. These findings confirm that the model effectively implements the intended signal processing design.

6 Flow-chart

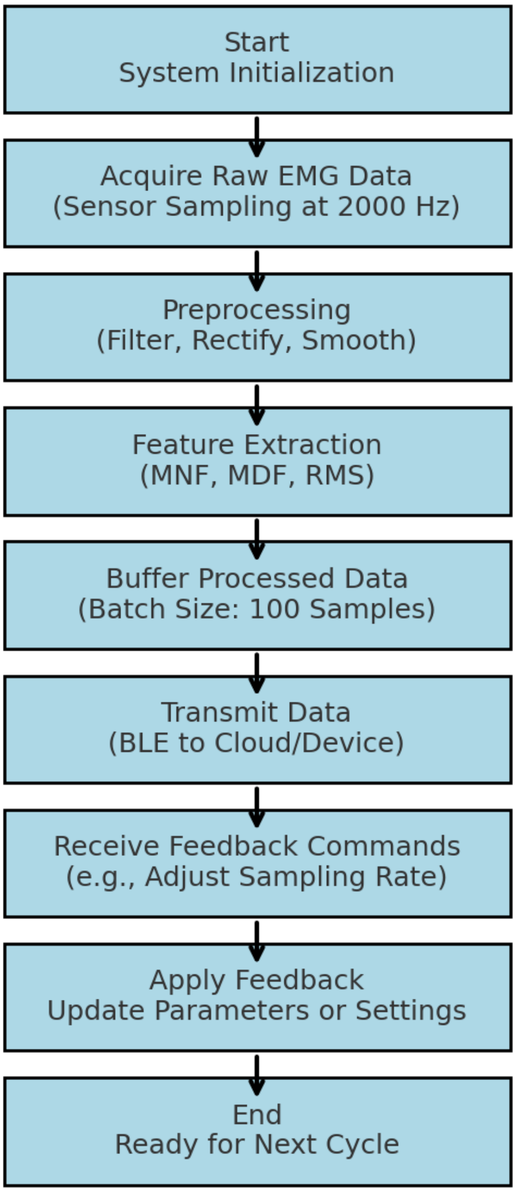


Figure 2: Local Device Operation Flowchart

The operation of a local device entails system initialization, whereby the device powers an EMG sensor, ADC, and a microcontroller to get it ready for processing data. After initialization, the device acquires data in raw analog form from muscle activity through the use of an EMG sensor. The acquired raw signal then undergoes signal conditioning; the signal is filtered to isolate it in the required frequency band of 15-250 Hz and amplifies the whole signal to a better quality.

First, after signal conditioning, the device proceeds with analog-to-digital conversion, where the conditioned signal is digitized using the ADC for further processing. Then, some features are extracted from the signals regarding muscle fatigue: Mean Frequency(MNF), Median Frequency(MDF), and Root Mean Square(RMS) from the digitized signal.

Once the features are extracted, the device buffers and transmits the data through buffering of the processed features and sends them wirelessly via BLE to a remote system. Similarly, the local device is designed to receive feedback from the remote system that could include configuration commands such as adjustment of the sampling rate or thresholds. The system automatically updates itself with the feedback by changing the settings required, like thresholds or sampling frequency, for improved performance.

The device then completes the current cycle and goes back to data acquisition in order to ensure continuity in monitoring, thus completing a seamless loop of operation. This structured sequence of tasks ensures that data is reliably and efficiently collected, processed, and communicated.

7 Conclusion and Future Work

This paper discusses a real-time system to detect muscle fatigue in athletes using surface EMG (sEMG) sensors in real-time. Here, the proposed system consists of local devices, a communication interface, and remote devices so that data is captured without disturbance, processed efficiently, and visualized in real-time as a graph representing muscle activity.This project, therefore, uses a very sensitive SEN0240 EMG sensor with an analog output compatible with the ADS1115 16-bit ADC for digitalization purposes. The signal conditioning unit isolates the 15–250 Hz frequency band using a Chebyshev Type I band-pass filter to minimize noise and enhance signal integrity. BLE is used in the system to ensure low-latency wireless data transmission, enabling real-time access to muscle fatigue metrics through cloud servers, visualization dashboards, and mobile applications. It extracts critical muscle fatigue indicators such as MNF, MDF, and RMS, which are important in analyzing the performance of an athlete's muscles. The interactive communication of the system also allows users to input parameters dynamically through it.

Though the system has the capability of successfully implementing the real-time monitoring of muscle fatigue, much can be done to improvise its functioning and applicability. Among such improvements would be inbuilt machine learning algorithms to detect in advance fatigue in this case, thereby recommending customized training sessions along with identifying potential risks of injury [5]. Another enhancement would be in scaling up the system for multi-sensor integration: it would monitor several groups of muscles at once for the overall assessment of an athlete's performance. Other possible enhancements in wireless connectivity, such as LoRa or Wi-Fi-based cloud synchronization, would extend the usability of the system for remote monitoring of large training environments.

It would also be useful in future developments to have this system connected in real-time, via haptic feedback or other audio notifications, allowing an athlete to directly understand and modulate training intensities relative to a given state of fatigue. Miniaturization and integration on wearables would allow a very comfortable and portable system, hence more practical for long-duration monitoring in athletics and rehabilitation. Integrating high-precision EMG sensing, real-time data processing, and wireless communication, this project is a good grounding in athlete muscle fatigue monitoring. The proposed future improvements will enhance the system's accuracy, expand its application scope, and make it even more effective in sports science, rehabilitation, and biomedical research. This research provides a significant step toward developing intelligent, adaptive monitoring systems, ultimately helping athletes optimize performance, prevent injuries, and improve recovery strategies through data-driven insights [6].

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Appendix

Sensor Datasheets

Sensor Type	Sensor Model	Datasheet Link
Analog EMG Sensor	SEN0240	SEN0240 Datasheet
ADC(Analog-to-Digital Converter)	ADS1115	ADS1115 Datasheet