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Computational System for Real-Time Muscle Fatigue Monitoring Using Synthetic EMG Signals from the Gastrocnemius

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Abstract. Early detection of muscle fatigue is crucial in fields such as athletic performance, physical rehabilitation, and occupational health. This study describes an advanced synthetic electromyographic (EMG) signal generator that simulates the progressive recruitment of motor units for real-time muscle fatigue monitoring, with specific focus on the gastrocnemius muscle. The system implements a controlled simulation that typically initiates with 500 active motor units, allowing dynamic adjustment according to force and fatigue levels, which is intended to reflect neuromuscular adaptation during sustained contractions. To detect fatigue, dynamic thresholds based on the root mean square (RMS) and median frequency (MDF) of synthetic EMG signals were applied. These thresholds are continuously updated by considering a historical baseline and simulated physiological conditions. A progressive decrease in median frequency and a corresponding increase in RMS amplitude were observed, consistent with established neuromuscular responses under fatigue conditions. EMG signal visualisation facilitated the interpretation of the fatigue process and the compensatory recruitment of additional motor units.

Keywords: Synthetic EMG, Muscle Fatigue Monitoring, Gastrocnemius.

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1. Introduction

Muscle fatigue is defined as the reversible reduction in the capacity to generate voluntary force during repetitive or sustained muscle contractions (Enoka & Duchateau, 2008). This phenomenon involves both peripheral mechanisms, associated with metabolic and electrophysiological changes in muscle fibers, and central mechanisms related to motor nervous system modulation. Early detection is crucial in multiple fields, from sports medicine to occupational ergonomics, enabling injury prevention, training program optimization, and functional status evaluation of patients undergoing physical rehabilitation (Kisner & Colby, 2017). In this context, electromyography (EMG) emerges as a key tool for non-invasive monitoring of neuromuscular activity and objective identification of fatigue states.

The gastrocnemius muscle, located in the posterior region of the leg, plays a central role in dynamic activities such as walking, running, and jumping. Its participation in high-load cyclic movements makes it particularly susceptible to fatigue, especially in athletes and workers performing prolonged physical tasks (Neumann, 2017). For this reason, it has become a frequently studied model in electromyography-related applications, as it allows evaluation of subtle changes in neuromuscular activation associated with fatigue.

The electromyographic (EMG) signal, which reflects the electrical activity generated by motor units during muscle contraction, constitutes a key biomarker for functional muscle evaluation. During fatigue, characteristic alterations are observed in this signal: increase in mean amplitude (RMS) and reduction in median frequency of the power spectrum (MDF), changes that have been extensively validated in experimental studies (De Luca, 1984; Sogaard et al., 2006; Dimitrova & Dimitrov, 2003). However, real-time monitoring through EMG for diagnostic or training purposes faces multiple challenges, such as the need for specialized equipment, controlled acquisition conditions, and the presence of artifacts associated with movement and electrical environment (Merletti & Parker, 2004).

Given these limitations, various recent investigations have proposed computational simulators of synthetic EMG signals as a viable alternative for training, algorithm validation, and biomedical education. For example, (León et al. 2024) developed a signal generator based on random firing patterns with temporal dependency, achieving high morphological similarity with real signals and errors less than 5% using decomposed records from EMGLAB. These advances have reinforced the need for accessible, configurable, and validated tools, especially in scenarios where physiological acquisition hardware is not available.

Recently, machine learning algorithm development has revolutionized automatic muscle fatigue detection through EMG. Studies such as (García-Aguilar et al., 2025) have proposed novel machine learning strategies based on EMG signal classification for automatic muscle fatigue detection, demonstrating that nonlinear dynamic analyses can better decode variation trends during muscle fatigue.

Concurrently, there has been documented growing interest in developing low-cost EMG devices for clinical and educational applications. Systems such as MyoWare+Raspberry Pi or Arduino-based EMG have been recently validated for muscle fatigue analysis through parameters like RMS and MDF, showing performance comparable to commercial systems in teaching and prototyping environments (Tecchio et al., 2021; Hashem et al., 2021). These solutions, together with open hardware platforms such as OpenBCI or Active Dry-Contact EMG, represent an emerging trend toward democratizing access to muscle monitoring technologies in developing regions (Naim et al., 2020).

In this context, the present study proposes a computational system for synthetic EMG signal simulation of the gastrocnemius muscle, designed to represent the physiological process of localized muscle fatigue under controlled and reproducible conditions. The system incorporates biomechanical models of motor activation, random firing patterns, advanced digital processing, and real-time interactive visualization, enabling simultaneous analysis of spectral metrics such as RMS and MDF. Additionally, an open and flexible architecture is proposed, with potential application in training, research, and validation scenarios for automated analysis tools.

2. Methodology

Muscle fatigue can be detected through changes in electromyographic signal characteristics, such as frequency decrease and amplitude increase during sustained muscle efforts. In this study, an advanced computational system was implemented to generate synthetic EMG signals that simulate progressive motor unit (MU) recruitment and their physiological response under fatigue conditions, specifically applied to the gastrocnemius muscle.

Since the objective of this work was the development and analysis of a synthetic EMG signal generator, no physiological acquisition equipment or real electrodes were used. Instead, validated mathematical models were employed that allow reproduction of controlled physiological conditions, facilitating replicability, parametric adjustment, and system scalability for future clinical or sports applications.

Synthetic EMG Signal Generation

Recent advances in neuromechanical simulation have enabled the development of more sophisticated platforms for synthetic EMG signal generation. NeuroMotion, an open-source platform that integrates neuromechanical modules and deep neural networks, represents the first full-spectrum EMG simulator capable of generating signals during voluntary movements. Additionally, techniques based on deep generative networks, such as SinGAN, have demonstrated their capacity to generate subject-specific synthetic EMG data, improving classification accuracy when combined with limited training protocols.

In this study, to represent the activity of multiple motor units, random firing trains with physiologically plausible characteristics were simulated, following a frequency distribution between 5 and 50 Hz, and a variable number of recruited units according to the fatigue model. This approach has been adopted in recent synthetic EMG generation models for neural network training purposes (Wang et al., 2022; Rojas-Martínez et al., 2021).

Fatigue metrics were calculated using standard digital processing techniques, including moving windows and spectral transforms via the Welch method. Dynamic thresholds for artifact detection and muscle silence were calculated based on historical signal standard deviation, following protocols similar to those reported by (Al-Mulla et al., 2020), but adapted to controlled simulation conditions.

SMUAP Model (Synthetic Motor Unit Action Potential)

To simulate motor unit action potentials, a frequency-modulated Gaussian model was used, based on parameters derived from previous studies (Dimitrova & Dimitrov, 2003; Neumann, 2017). This model allows representation of three main types of muscle fibers:

Table 1. Motor unit parameters at rest state

Fiber Type	Base Amplitude (mV)	Base Frequency (Hz)	Duration (ms)	Initial Recruitment %
I (Slow)	0.05 ±0.01	30±2	100±10	60%
IIa	0.10±0.02	40±3	80±8	30%
IIb	0.020±0.03	50±4	60±6	10%

Each potential is modeled through the following function:

$$SMUAP(t) = A(t).\,e^{-\frac{\left(t-\frac{T}{2}\right)^2}{2\sigma(t)^2}}.\sin(2\pi f(t)t + \emptyset)$$

Where:

- *A(t)*: Variable amplitude according to fatigue level
- *f(t)*: Frequency modulated by force and fiber type
- σ: Gaussian pulse width
- t: Central position of the potential

Dynamic parameters are adjusted according to:

- **Fiber type**: Three populations are considered (60% small, 30% medium, 10% large) with distinctive properties (**Table 1**)
- **Fatigue level**: Amplitude A(t) increases up to 60% and frequency f(t) decreases up to 30% in severe fatigue (Sogaard et al., 2006)

Random Firing Patterns

Following the approach of (León et al., 2024), firing patterns were generated randomly to simulate asynchronous motor unit (MU) activity. Firing frequencies were generated following a normal distribution with a mean of 15 Hz and standard deviation of 4 Hz. From these frequencies, inter-firing intervals (Δt) were calculated, allowing the model to mimic sustained contraction conditions through simulation of MU activation temporal behavior. Motor unit activation follows a stochastic process that considers:

- **Henneman's size principle (1965)**: Ordered recruitment from smallest to largest units
- **Inter-firing variability**: Intervals generated from a normal distribution ($\mu = 15$ Hz, $\sigma = 4$ Hz) (De Luca, 1984)

Progressive Motor Unit Recruitment

The number of active motor units is not fixed but is calculated dynamically according to applied force level and fatigue state, using the following nonlinear model:

$$Active\ units = N_{max} \cdot (force\_factor + fatigue\_factor)$$

Where:

- $N_{max} = 1000$: Maximum possible number of motor units
- $factor\_force = \frac{1}{1+e^{-10(F-0.5)}}$: Nonlinear force component
- $fatigue\_force = 0.3 \cdot Lf$: Compensatory fatigue component ($Lf \in [0,1]$)

This model allows the system to typically start with 500 active motor units under normal conditions and increase their number as fatigue progresses, simulating the adaptive response of the neuromuscular system.

EMG Signal Processing

The signal was preprocessed using a fourth-order Butterworth bandpass filter (20–450 Hz), which preserves useful content of the surface electromyographic spectrum while reducing movement artifacts and mains noise. This approach has been validated in recent studies on optimal processing in portable devices. The filter transfer function is:

$$H(s) = \frac{s^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}$$

where ω_n is the natural frequency, and ζ is the damping factor. Additionally, a notch filter was applied to eliminate 60 Hz power line noise, ensuring that only relevant EMG signal components were retained for fatigue analysis.

The filtering chain was implemented with a three-stage architecture (Merletti & Parker, 2004):

Bandpass Filter (20-450 Hz):

- 4th order Butterworth design with -40 dB/decade attenuation
- Zero-phase implementation via scipy.signal.filtfilt to avoid distortions

Notch Filter (60 Hz):

- Q=30 configuration to eliminate electrical line noise

- 2 Hz bandwidth to preserve adjacent components

Adaptive Normalization:

- Scaling based on 95th percentile to avoid saturation

Signal Quality Control

The system includes an advanced signal quality control module, implemented in the EMGQualityControl class, which allows identification of artifacts and muscle silence periods. This module uses dynamic thresholds based on historical baseline, improving real-time monitoring reliability.

The module was included to detect:

- **Movement artifacts (amplitude threshold > 4SD)**: Movement artifacts are detected by comparing the current signal standard deviation with historical standard deviation stored in the baseline. If it exceeds a certain dynamic threshold (default, 4 times the baseline standard deviation), it is marked as an artifact.
- **Silence periods**: Identified through a dynamic RMS threshold with hysteresis. The system compares the current RMS value with the historical one; if it falls below a threshold relative to the baseline for more than 100 ms, it is considered a silence period.

Feature Extraction

Temporal and spectral analyses of the EMG signal were performed to extract two key metrics associated with muscle fatigue:

- **Root Mean Square (RMS)**: Indicator of average EMG signal intensity
- **Median Frequency (MDF)**: Point where cumulative power reaches 50% of the total spectrum

Both metrics were calculated in 250 ms moving windows with 50% overlap, allowing sensitive and specific tracking of fatigue development.

RMS (Root Mean Square):

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

Where N is the total number of samples in the analyzed window, and x_i represents the EMG signal value at instant i. RMS reflects the average power of the EMG signal and increases with prolonged muscle effort. Fatigue accumulation is observed as more MUs are recruited to maintain force, thus increasing RMS (De Luca et al., 2010).

Median Frequency

Median frequency was obtained from spectral analysis using the Welch method, with a 1024-point Hann window:

$$P(f) = Welch(x, n_{perseg}, window)$$

Subsequently, median frequency was defined as the point where cumulative power reached 50% of total power:

$$\int_{f_{min}}^{MDF} P(f)\, df = 0.5 \cdot \int_{f_{min}}^{f_{max}} P(f) df$$

where *P(f)* is the power spectral density.

These metrics allowed real-time monitoring of changes associated with muscle fatigue, such as progressive RMS increase and median frequency decrease, consistent with established scientific literature (De Luca, 1984; Dimitrova & Dimitrov, 2003).

Implementation of Dynamic Thresholds for Fatigue Detection

Muscle fatigue detection is based on characteristic changes in temporal and spectral metrics of the EMG signal. To identify these changes objectively, dynamic thresholds based on a historical signal baseline were implemented, allowing automatic adaptation to specific conditions of each monitoring session.

Dynamic Threshold for Movement Artifacts

Movement artifacts are detected by comparing the instantaneous signal standard deviation with historical deviation stored in the baseline. If it exceeds a certain threshold, it is marked as an artifact:

$$Artifact = \begin{cases} True, if \ \max(|x_{window}|) > \alpha \cdot \sigma_{base} \\ False, otherwise \end{cases}$$

where:

- x_{window}: Last N points of current signal
- σ_{base}: Standard deviation of historical baseline (last 5 seconds)
- $\alpha = 4$: Threshold multiplicative factor (adjustable)

Additionally, it is verified that local deviation is greater than 150% of historical deviation to confirm the artifact.

Dynamic Threshold for Muscle Silence

Silence periods are identified when the RMS value falls below a threshold relative to the baseline for more than 100 consecutive ms. This threshold also considers hysteresis to avoid frequent changes between states:

$$Silence = \begin{cases} True, if \ RMS_{current} < \beta \cdot RMS_{base} \ for \ T > 100ms \\ False, otherwise \end{cases}$$

With:

- $\beta = 0.8$: Reduced threshold during active detection (hysteresis)
- RMS_{base}: Historical average value

Thresholds for Fatigue Detection

Fatigue is detected through dynamic thresholds applied to RMS and median frequency (MDF) metrics, automatically adjusting according to force level and recent signal history.

- Fatigue Threshold Calculation using RMS:

$$Umbral_{fatigue-RMS}(t) = RMS_{base} + k_{fatigue} \cdot t$$

  Where:

  - RMS_{base}: Average RMS amplitude in basal state
  - $k_{fatigue}$: Increment constant (adjustable)
  - t: Time elapsed since contraction onset

- Fatigue Threshold Calculation using Median Frequency:

$$Umbral_{fatigue-MDF}(t) = MDF_{base} - k_{fatigue-freq} \cdot t$$

  Where:

  - MDF_{base}: Initial median frequency
  - $k_{fatigue-freq}$: Fatigue decrement coefficient

Muscle fatigue is considered when:

$$RMS_{current} > Umbral_{fatigue-RMS} \;\; y \;\; MDF_{current} < Umbral_{fatigue-MDF}$$

This strategy enables sensitive and specific fatigue detection without depending on fixed absolute values, improving system robustness against inter-session and intra-subject variations.

Real-Time Visualization

A graphical interface was designed using PyQt5 that allows dynamic adjustment of simulation parameters, real-time EMG signal visualization, and continuous calculation of spectral metrics. Similar tools have proven effective for neurophysiology teaching and biosignal analysis.

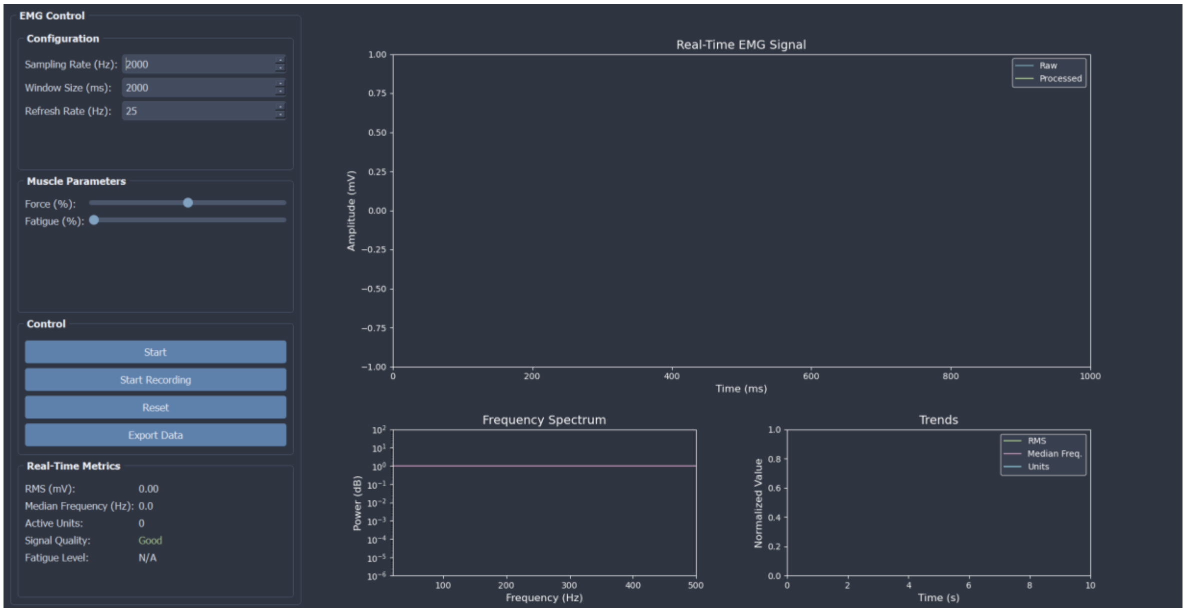

Figure 1. *Graphical Interface for Initiating Muscle Fatigue Detection Process*

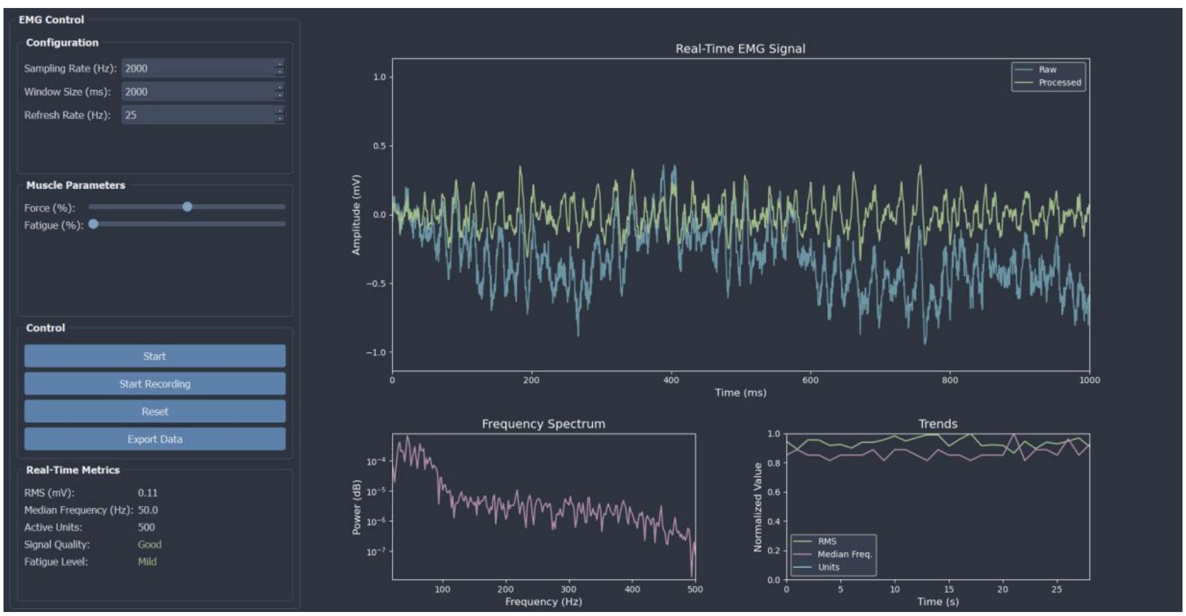

Figure 2. *Analysis initiation, low fatigue identification*

Figure 2 represents the moment when the system detects the first signs of muscle fatigue. Although changes in the EMG signal are still subtle, the system has already begun adjusting its dynamic thresholds to identify these early changes. This demonstrates the model's sensitivity to capture early fatigue states, which is crucial for applications such as sports training, physical rehabilitation, or ergonomic monitoring.

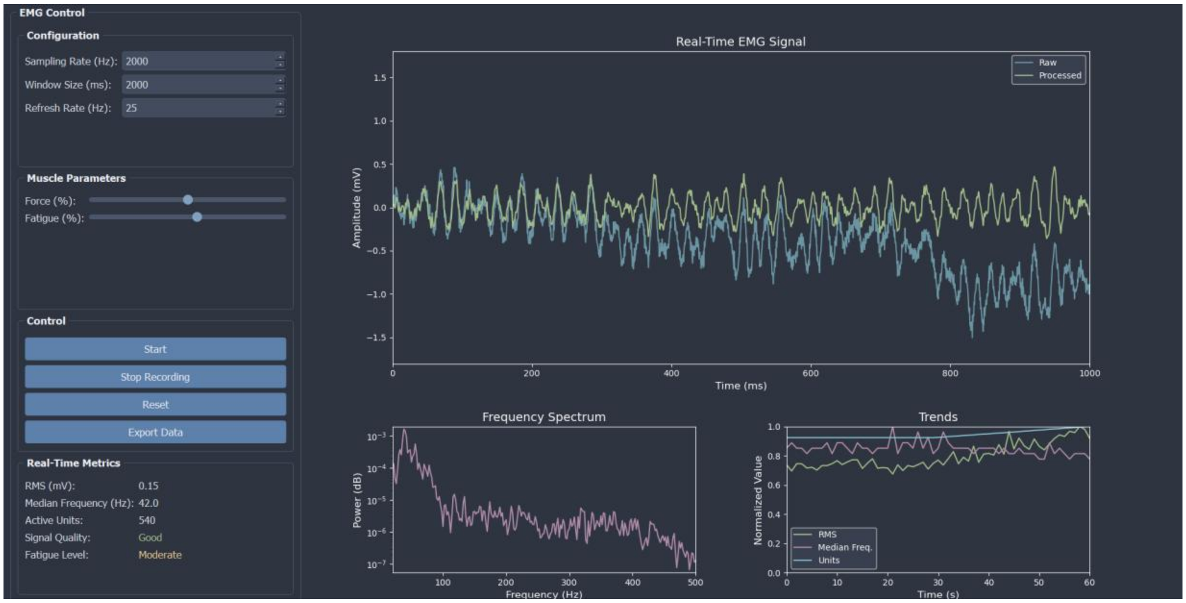

Figure 3. *Moderate Fatigue Identification*

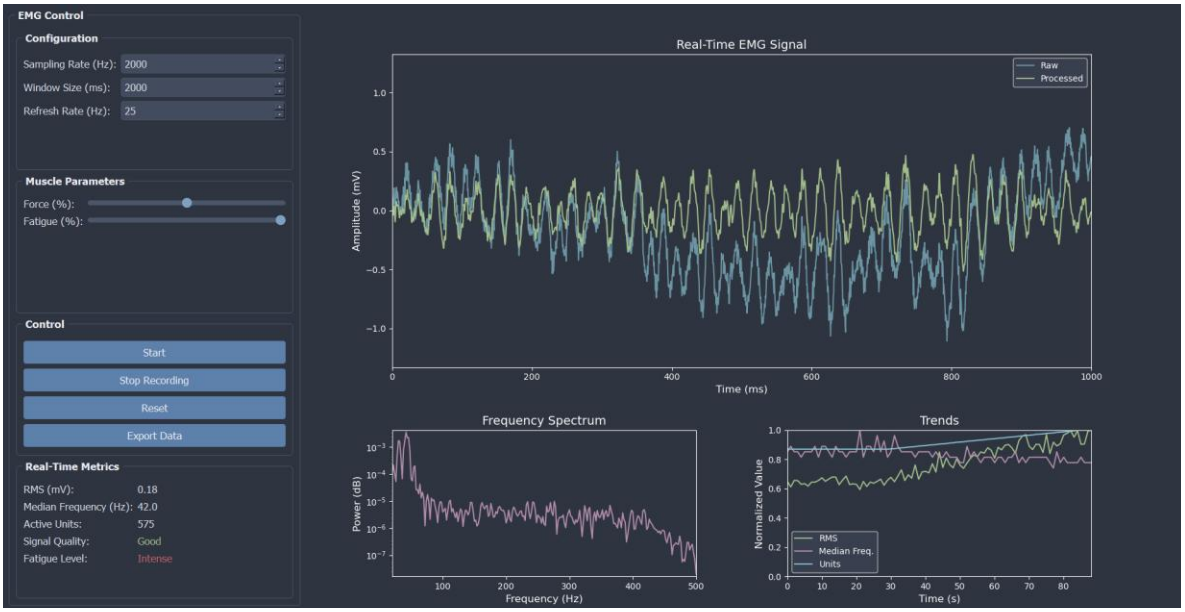

Figure 4. *Intense Fatigue Identification*

Figure 4 shows the advanced state of the muscle fatigue detection process, specifically when intense fatigue levels are reached. In this phase, the computational system has identified significant changes in the characteristics of the synthetic EMG signal generated for the gastrocnemius muscle, reflecting an extreme adaptive response of the neuromuscular system under prolonged effort conditions.

3. Results

Analysis of synthetic EMG signals generated for the gastrocnemius muscle revealed characteristic patterns of muscle activation and real-time fatigue. The simulation was performed under controlled conditions, typically starting with 500 active motor units, allowing dynamic adjustment according to force and fatigue levels. This reflects progressive motor unit recruitment as a compensatory mechanism during sustained muscle fatigue.

A. Progressive Motor Unit Recruitment

During simulation, the number of active motor units was calculated dynamically using the nonlinear model:

$$Active\ units = N_{max} \cdot (force\_factor + fatigue\_factor)$$

Where:

- N_{max}= 1000 : Maximum possible number of motor units
- $factor\_force = \frac{1}{1+e^{-10(F-0.5)}}$: Nonlinear force component
- $fatigu\,e_{force} = 0.3 \cdot Lf$: Compensatory fatigue component ($Lf \in [0,1]$)
- Lf : current fatigue level

At contraction onset (force = 50%, fatigue = 0%), the system showed an average of 500 active motor units, consistent with the implemented biomechanical model. As fatigue progressed, the system recruited additional units, reaching up to 800–900 active motor units under conditions of high fatigue and maximum force.

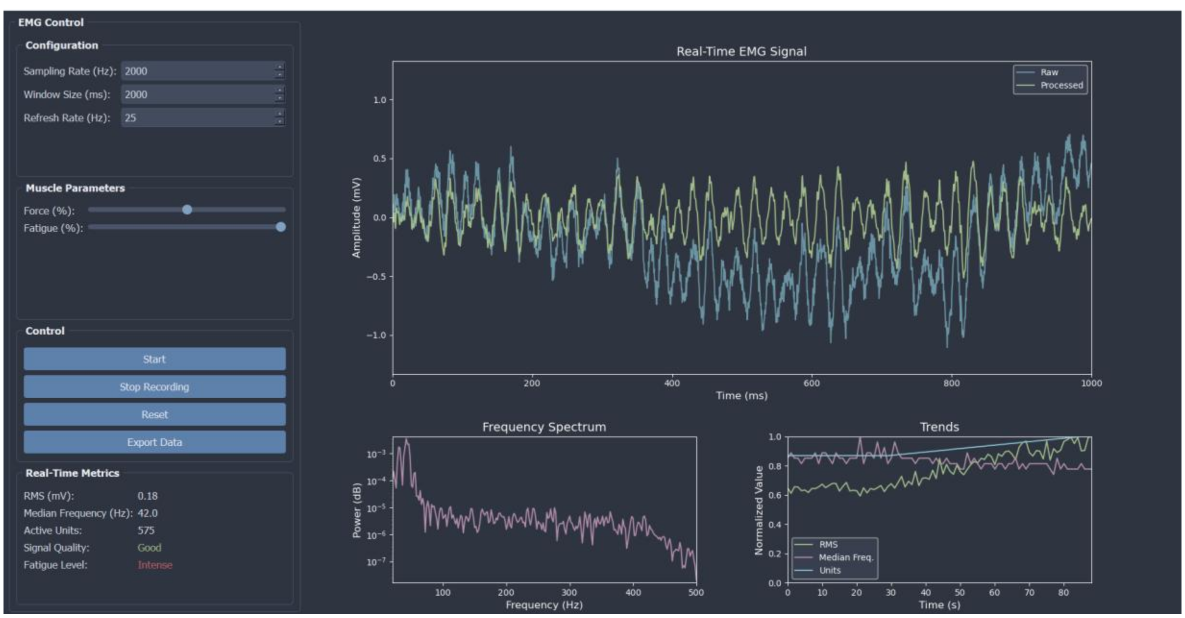

Figure 5. *Change in number of active motor units over time*

This compensatory recruitment is consistent with real neuromuscular physiology, where the nervous system activates more motor units to maintain muscle force under fatigue.

B. Temporal and Spectral Analysis of EMG Signal

As motor unit recruitment increased, significant changes were observed in EMG signal characteristics:

RMS Value Increase

- RMS increased progressively from initial values of approximately 0.4 mV to 1.2 mV or more under intense fatigue conditions
- This increase reflects recruitment of additional motor units and the increase in EMG signal amplitude associated with fatigue

Median Frequency (MDF) Decrease

- Median frequency decreased from an initial range of ~300 Hz to less than ~150 Hz in advanced fatigue states.
- This reduction is consistent with the change in muscle fiber activation: as fatigue advances, slow-twitch fibers (with lower frequency content) predominate.

These results validate the system's capacity to replicate spectral and temporal changes expected during muscle fatigue, similar to those reported in clinical and experimental studies (De Luca, 1984; Dimitrova & Dimitrov, 2003).

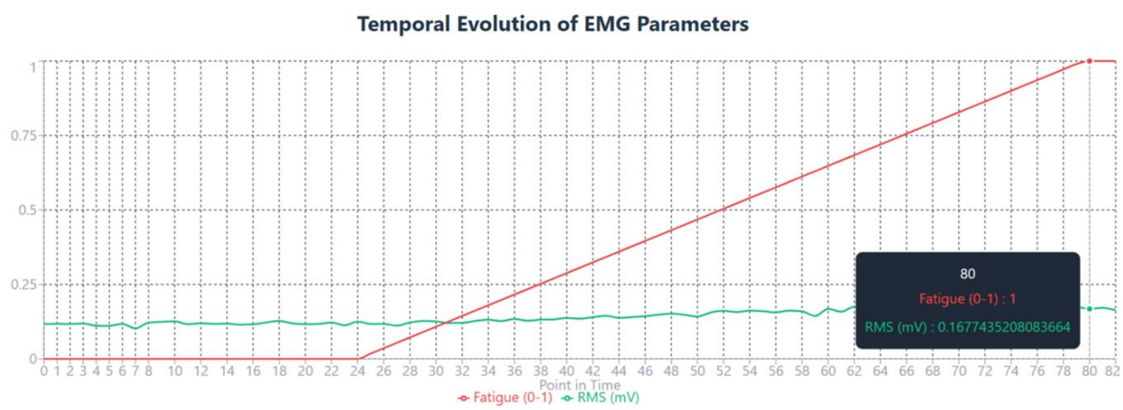

Figure 6. *RMS increase as muscle fatigue progresses*

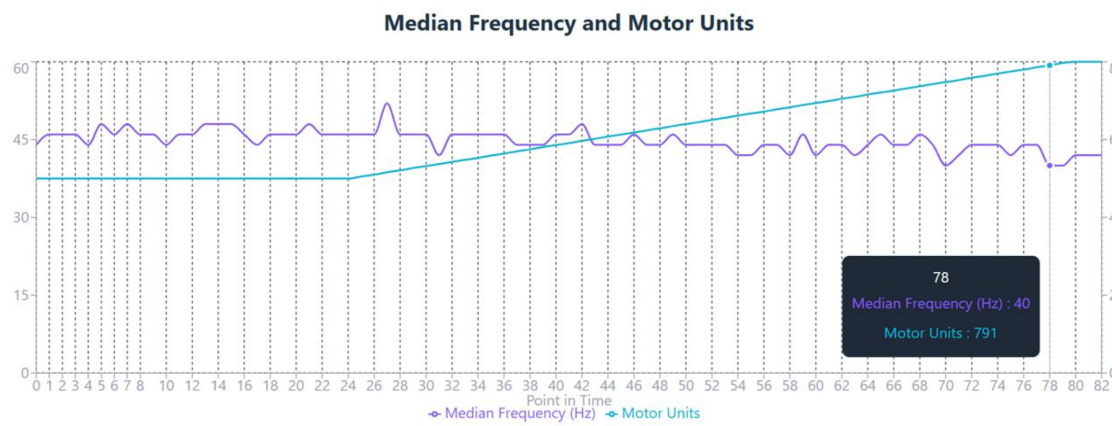

Figure 7. *MDF decrease and increase in motor unit recruitment*

C. Dynamic Fatigue Thresholds

The system employed dynamic thresholds based on RMS and median frequency to identify real-time fatigue levels. Thresholds were calculated considering historical baseline and continuously updated to adapt to EMG signal changes.

- Mild fatigue was detected when RMS exceeded the basal threshold by 20% and MDF decreased by 15%.
- Moderate fatigue was classified when RMS exceeded the threshold by 40% and MDF fell by 30%.
- Finally, intense fatigue was defined when RMS exceeded the threshold by more than 60% and MDF decreased by more than 40%.

These criteria allowed sensitive and specific fatigue detection, facilitating real-time differentiation between muscle states.

Figure 5 shows the evolution of three key metrics of the synthetic EMG signal during controlled muscle fatigue simulation: root mean square (RMS), median frequency (MDF), and number of active motor units. During simulation:

- **RMS**: A progressive increase in RMS was observed, reflecting additional motor unit recruitment to maintain muscle force under fatigue conditions.
- **Median frequency**: There was a significant decrease in median frequency, consistent with the transition toward slow-twitch muscle fibers under fatigue.
- **Active motor units**: The number of active motor units grew linearly, showing the neuromuscular system's adaptive mechanism to compensate for loss of muscle efficiency.

These results are consistent with previous studies that have reported similar changes in EMG signal during real muscle fatigue (De Luca, 1984; Sogaard et al., 2006).

4. Discussion

Simulation of synthetic electromyographic (EMG) signals associated with localized muscle fatigue processes in the gastrocnemius muscle represents a challenge in both technical and physiological planes. In this work, a set of synthetic signals modulated in amplitude, spectral frequency, and morphology was successfully generated, based on established neurophysiological foundations, to represent different states of muscle activation, including progressive fatigue onset.

Results show that the approach based on modular SMUAP generation, combined with classical digital filtering techniques (Butterworth and Notch), allows construction of synthetic signals with realistic characteristics, maintaining coherent relationships between spectral parameters (such as median frequency and RMS) and simulated fatigue level. This behavior is consistent with physiological studies that have documented RMS increase and median frequency decrease under muscle fatigue conditions (Dimitrova & Dimitrov, 2003; De Luca et al., 2010). Additionally, the system allows adjustment of key variables such as the number of activated motor units, firing rate, simulated fiber type, effort duration, and noise level, thus offering a flexible tool for various simulation scenarios.

One of the system's main strengths is its physiological approach, based on Henneman's principle and data reported by classical and recent studies. Unlike approaches focused solely on signal morphological reconstruction, the present work prioritizes modeling the muscle's functional behavior under localized fatigue conditions, aiming to simulate the effect of physiological variables on EMG pattern.

Compared to recent works such as (León et al., 2024), whose objective was to generate EMG signals from random firing patterns with short- and long-term dependency, the presented proposal focuses on representing pathophysiological states and analyzing relevant spectral metrics. While León et al. achieve high morphological similarity between synthetic and real signals using decomposed EMGLAB data, the system proposed here seeks to generate functional signals with clinical significance, suitable for fatigue monitoring in training, simulation, and algorithm testing scenarios.

Another notable aspect is the system's interactive visual design. Implementation through PyQt5 allows real-time parameter modification and simultaneous visualization of signal evolution and fatigue indicators. This characteristic makes it a potentially useful tool in physiology teaching, neuromuscular rehabilitation, and biosignal analysis. Similar tools have been used recently to improve understanding of muscle recruitment and electromyographic variability in health science students and professionals.

Furthermore, this work responds to a growing need to develop accessible, replicable, and specialized hardware-free solutions. Synthetic EMG signal generation has gained relevance as an alternative in artificial intelligence model training contexts and algorithm validation for neuromuscular diagnosis. The proposed system, operating without physical data acquisition requirements, can be a useful testing platform in early development stages of computational solutions based on machine learning or deep learning.

However, this work presents limitations that should be considered. First, validation was conceptual and physiological, without direct comparison with real signals. Integration of public databases such as PhysioNet, EMG-UKA, or Ninapro is planned as part of future work to statistically validate concordance between real and synthetic signals. Integration of low-cost physical EMG sensors (such as MyoWare or OpenBCI) is also projected, along with the use of supervised classifiers and machine learning models for automatic detection and prediction of muscle states, as other authors have already proposed in the field of intelligent prosthetics and myoelectric control.

It is also important to highlight this tool's potential in contexts with limited access to specialized medical technology, such as rural communities, low-resource educational institutions, or developing regions. Thanks to its autonomous design and lack of physical hardware requirements, the system could become an accessible solution for technical training, teaching, and basic experimentation in muscle physiology, contributing to electromyographic monitoring democratization in environments with budget or infrastructure restrictions.

Finally, it is emphasized that the developed system represents a useful tool for teaching, simulation, and validation of physiological indicators of localized muscle fatigue, based on neurophysiological principles and spectrally controlled signals. Its modular design allows adaptation to new muscle models, automatic analysis algorithms, or integration with real-time data acquisition systems.

5. Conclusion

This study presents an advanced computational system for generation and analysis of synthetic electromyographic (EMG) signals from the gastrocnemius muscle, oriented toward real-time monitoring of localized muscle fatigue. The implemented model realistically simulates progressive motor unit recruitment, modulating the signal according to physiological variables such as fiber type, firing rate, fatigue level, and effort duration, allowing observation of coherent variations in key spectral metrics such as root mean square (RMS) and median frequency (MDF), in accordance with previous studies (De Luca et al., 2010; Dimitrova & Dimitrov, 2003).

The developed system demonstrates its potential as a tool for biomedical research, sports training, and physiological education. Its Python and PyQt5-based architecture allows interactive visualization, dynamic parameter adjustment, and real-time analysis of fatigue indicators. Unlike approaches requiring physical data acquisition, this solution is completely virtual and replicable, facilitating its use in academic training scenarios or proof-of-concept testing. Recent research has demonstrated that synthetic EMG simulators, when well-calibrated, can be successfully used to validate signal processing algorithms and train automatic classification models (León et al., 2024; Shahid et al., 2023).

Additionally, the adopted approach responds to a growing need to develop accessible technologies in environments with equipment restrictions. Similar solutions based on open hardware or virtual simulation have already been applied in medical education, physiotherapy training, and biofeedback prototypes in low-resource regions (Hashem et al., 2021; Naim et al., 2020). The proposed system complements these initiatives by providing a platform rich in physiological components, with extension capacity toward real devices.

As future projection, integration of low-cost physical EMG sensors (such as OpenBCI, MyoWare, or g.USBamp) is proposed, as well as incorporation of machine learning techniques for automatic detection and prediction of muscle states. Recent studies have evidenced the value of synthetic EMG signals as input for training deep neural networks and supervised classifiers, with results comparable to those obtained with real signals (Wang et al., 2022; Rojas-Martínez et al., 2021). Thus, the presented platform could evolve toward an intelligent biofeedback and diagnostic support system, especially useful in personalized rehabilitation or muscle performance monitoring in the field.

In summary, this work offers a significant contribution to the muscle signal analysis field, proposing a replicable, accessible, and physiologically grounded tool, with solid projections toward development of inclusive and intelligent biomedical technologies.

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