**1.1 Background and Motivation**

Muscle fatigue, characterized by a decline in muscle performance during sustained activity, significantly impacts athletic performance, rehabilitation outcomes, and daily functional tasks. Accurate monitoring and assessment of muscle fatigue are crucial for optimizing training regimens, preventing injuries, and enhancing recovery processes.

Surface electromyography (sEMG) has emerged as a non-invasive and effective method for evaluating muscle activity and fatigue. By detecting electrical signals generated during muscle contractions, sEMG provides real-time insights into muscle function and fatigue levels. Changes in sEMG signal characteristics, such as shifts in frequency and amplitude, are indicative of muscle fatigue. The analysis of sEMG signals enables the identification of specific patterns associated with fatigue, facilitating timely interventions and personalized training adjustments.

The integration of Wireless Sensor Networks (WSNs) into sports and rehabilitation domains has further revolutionized the monitoring of physiological parameters. Wearable IoT devices equipped with sEMG sensors allow for continuous, real-time data collection and analysis, providing immediate feedback to users and practitioners. This advancement enhances the ability to track muscle performance, detect early signs of fatigue, and implement preventive measures effectively.

Despite these technological advancements, challenges persist in accurately quantifying muscle fatigue due to individual variability and the complex nature of muscle dynamics. The development of robust, personalized fatigue indices that adapt to individual differences and provide reliable assessments across various contexts would offer invaluable insights.

**1.2 Related Work**

Recent advancements in surface electromyography (sEMG) technology have led to significant progress in real-time muscle fatigue detection systems, with increasing emphasis on wearable, wireless, and low-power solutions. Early work in this field has focused on real-time monitoring using wearable sEMG systems, which are increasingly used to track muscle performance during exercise. Systems such as those developed by Liu et al. (2019) and Xu (2020) have laid the foundation for understanding how sEMG signal features -particularly in the frequency domain- can be linked to fatigue. Median Frequency (MDF) and Mean Power Spectrum Frequency (MNF) are widely recognized as key indicators of muscle fatigue, as these features tend to decrease with sustained muscle activity. However, the lack of wireless capabilities in earlier systems limited their practical applications, especially in dynamic or real-world settings. Wireless communication, particularly via Bluetooth Low Energy (BLE), has since been integrated into sEMG systems, enabling long-duration monitoring with minimal power consumption.

The importance of low-power wireless communication has been underscored in recent studies, such as Wu et al. (2021), which proposed an ultra-low power sEMG sensor optimized for wearable biometric applications. Their system, using BLE, achieved significant improvements in energy efficiency, making it suitable for continuous, real-time monitoring of muscle fatigue. The Multiple Feedback Filter (MFB) used in their design further enhanced signal quality by effectively removing noise, thus improving the reliability of fatigue detection.

Furthermore, machine learning (ML) techniques have begun to play a crucial role in enhancing the performance of sEMG-based fatigue monitoring systems. Traditional methods of fatigue detection relied heavily on signal processing techniques, but the advent of ML has allowed for more accurate and personalized predictions. Sun et al. (2022) and Yousif et al. (2022) provide comprehensive reviews of the role of ML in analyzing sEMG signals. ML methods, including support vector machines (SVM), random forests, and k-nearest neighbors (k-NN), have demonstrated superior accuracy in classifying muscle fatigue patterns compared to conventional methods. These techniques are particularly useful in handling the complex, non-linear relationships inherent in sEMG data, which are challenging for traditional signal processing alone.

The combination of signal processing and ML approaches has also led to the development of more sophisticated fatigue indices, such as the two-step classification algorithm proposed by Qassim et al. (2022). By combining time-domain features like Integrated EMG with frequency-domain analysis to distinguish between high-frequency components (HFC) and low-frequency components (LFC), their system was able to achieve a high level of accuracy (95%) in detecting fatigue during isometric exercises. This innovative approach reflects a growing trend toward integrating more advanced classification algorithms into wearable devices to improve the reliability and real-time applicability of fatigue detection.

The recent work by Kinugasa and Kubo (2023) further exemplifies the growing trend of affordable, consumer-friendly systems for muscle fatigue detection. Their low-cost wireless system, which uses commercially available components, shows that it is possible to design a system that is both economical and effective for real-time monitoring of muscle fatigue. The use of basic time-domain metrics such as Root Mean Square (RMS) and Mean Power Frequency (MPF) demonstrated that low-cost, wearable sEMG systems can provide insights into muscle fatigue comparable to more expensive commercial systems. This work highlights the potential for widespread adoption of wearable sEMG devices in both sports and rehabilitation settings, where cost and accessibility have traditionally been barriers to entry.

Overall, the integration of wireless, low-power devices, coupled with advanced signal processing and machine learning algorithms, is revolutionizing the way we monitor muscle fatigue in real time. These systems, through improved accuracy, personalization, and affordability, are opening up new possibilities for applications in sports, healthcare, and rehabilitation. However, challenges remain in achieving robust and scalable solutions that can adapt to the diverse needs of users and exercise conditions. Continued innovation in both the hardware and algorithmic domains will be essential to overcoming these challenges and realizing the full potential of wearablefatigue detection systems.

**1.3 Contribution of This Work**

This study presents a wearable, IoT-enabled sEMG system designed for real-time muscle fatigue monitoring. By integrating Bluetooth Low Energy (BLE) technology, the system enables wireless, low-power data transmission, overcoming the mobility constraints of traditional wired sEMG setups. A comprehensive signal processing pipeline was implemented, analyzing time-domain, frequency-domain, and combined-domain features to enhance fatigue detection. The study also evaluated the fatigue-related metrics, incorporating advanced analysis to determine optimal window sizes, baseline calibration, and feature stability, ensuring accurate and reliable fatigue assessment.

To improve fatigue estimation, machine learning regression models were employed, creating a novel fatigue index that tracks fatigue progression across individuals and sessions. A structured methodology for sEMG dataset creation ensures high-quality data collection, supporting future research in wearable muscle monitoring. By combining advanced signal analysis, machine learning, and IoT technologies, this work provides a scalable, real-time solution for athletes, clinicians, and researchers, aiming to enhance performance, prevent injuries, and optimize rehabilitation strategies.

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**2.1 System Design**

The proposed muscle fatigue monitoring system is designed as a wearable, low-power, wireless surface electromyography (sEMG) acquisition setup, ensuring real-time signal processing and data transmission. The system consists of sEMG sensors, a microcontroller unit (MCU), and a Bluetooth Low Energy (BLE) communication module, all working together to provide an efficient and mobile monitoring solution.

The core processing unit selected for this study is the Arduino UNO R4 WiFi, which integrates a dual-core microcontroller with BLE 5.0 capabilities. This platform was chosen due to its high-resolution ADC, low-latency data processing, and extended BLE range, making it well-suited for continuous physiological monitoring applications. The system captures sEMG signals using pre-gelled Ag/AgCl electrodes placed on the desired muscle, ensuring optimal signal acquisition. A fourth-order Butterworth IIR filter is applied to preprocess the signals before transmission, eliminating unwanted noise and improving the accuracy of fatigue detection. BLE 5.0 is employed for data transmission, offering an energy-efficient communication protocol that ensures stable connectivity during movement. This approach enables real-time fatigue monitoring without the constraints of wired systems, making it particularly suitable for sports and rehabilitation applications.

Two commercially available sEMG sensors, the BioAmp EXG Pill and MyoWare 2.0, were evaluated for their suitability in the system. The BioAmp EXG Pill, a compact analog front-end module, provides high signal fidelity due to its configurable gain settings (up to 1000x) and built-in noise rejection. It supports biopotential measurements beyond EMG, including EEG, ECG, and EOG, making it a versatile solution for wearable monitoring. Compared to other sensors, BioAmp EXG Pill exhibited superior signal clarity, particularly in environments with electrical interference. In contrast, the MyoWare 2.0 sensor is a self-contained sEMG module that features built-in signal rectification and envelope detection. While it offers ease of integration with microcontrollers and rapid deployment capabilities, its fixed gain settings and increased exposure to motion artifacts made it less suitable for precise fatigue analysis.

Given these observations, BioAmp EXG Pill was selected as the primary sensor for the study due to its enhanced signal quality and flexibility in gain adjustment. MyoWare 2.0 was initially used in pilot testing, providing valuable insights into signal acquisition but proving less effective in applications requiring high signal fidelity. The integration of the selected sensor into the Arduino-based system enables robust real-time muscle activity tracking, forming the foundation for subsequent signal processing and feature extraction analyses.

**2.2 Data Collection**

The experimental protocol was designed to assess muscle fatigue through surface electromyography (sEMG) signals recorded from the Vastus Medialis during an isometric leg-extension exercise. This exercise was selected due to its ability to maintain a controlled contraction while minimizing movement artifacts. A total of eleven participants, consisting of ten males and one female, with an average age of 29.73 ± 7.98 years, completed three sessions each. Participants performed the exercise on a leg-extension machine, holding a static contraction at a predetermined knee angle for a sustained duration ranging between 60 and 80 seconds. The relevant weight was chosen based on the athlete's frequency of exercise and preferences, ranging between 11 kg, 18 kg, and 25 kg to simulate realistic training conditions. To establish a baseline for muscle activity, a 5-7 second resting phase was included at the beginning of each trial, ensuring accurate calibration before the onset of fatigue-related changes. Between trials, participants were given a 1 to 2-minute rest period to allow partial recovery while maintaining fatigue accumulation over multiple sessions. While most participants maintained a consistent exercise execution, minor variations in muscle activation effort were observed, which were taken into account during data analysis. A representative image of the experimental setup is shown in **Figure 1**.

**Figure 1:** **Experimental setup** (photo of a participant performing the **isometric leg-extension exercise**, showcasing knee angle and electrode placement).

Electrode placement followed the SENIAM guidelines, ensuring high-quality signal acquisition. Electrodes were positioned parallel to the muscle fibers to maximize signal amplitude and reduce phase cancellation effects. The primary electrodes were placed at 80% of the distance between the anterior superior iliac spine and the patella, while the reference electrode was positioned over a neutral bony site above the patella. A detailed illustration of the electrode placement is presented in **Figure 2**. This configuration was chosen to align with the natural anatomical orientation of the muscle fibers, reducing variability in signal acquisition and improving reproducibility. Alternative electrode placements were briefly explored but exhibited higher vulnerability to cross-talk from adjacent muscles and inconsistent amplitude variations.

**Figure 2:** **Electrode placement diagram** (illustrating placement on **Vastus Medialis**, following SENIAM guidelines).

To mitigate cross-talk and external noise sources, several measures were implemented. The differential recording technique was employed, using closely spaced electrodes to enhance signal specificity while canceling out common noise. Additionally, proper skin preparation, including shaving, cleansing with alcohol, and drying, was performed to reduce impedance and improve electrode contact. Motion artifacts were minimized by ensuring a tight but non-restrictive electrode attachment, preventing displacement during contractions. Environmental noise, particularly 50 Hz powerline interference, was suppressed using a notch filter, and the system operated on a battery-powered supply to eliminate ground loops.

sEMG signals were sampled at 1000 Hz, a frequency sufficient to capture relevant muscle activation characteristics while preventing aliasing. The acquired signals underwent preprocessing with a 4th-order Butterworth bandpass filter (25–480 Hz) to isolate the physiological sEMG frequency range while eliminating low-frequency motion artifacts and high-frequency electrical noise. The filter order was implemented as two cascaded second-order sections, reducing numerical errors and improving stability. These frequency values were selected to avoid interference near 20 Hz and 500 Hz, ensuring a clean and informative sEMG signal. The signal acquisition and processing pipeline is depicted in **Figure 3**.

**Figure 3:** **Signal acquisition flowchart** (depicting data collection steps: **sEMG capture → preprocessing → BLE transmission → data storage**).

For real-time data transmission, Bluetooth Low Energy (BLE) 5.0 was implemented, ensuring efficient wireless communication between the acquisition system and the processing unit. The BLE protocol was structured to maintain low latency while transmitting sEMG data continuously. The BLE central device, such as a computer or mobile application, requested data from the BLE peripheral device (Arduino-based system), ensuring synchronized data flow. The microcontroller unit acquired sEMG signals and buffered them locally before transmitting packets in 236-byte frames, each containing 59 floating-point values. This communication process is detailed in **Figure 4**.

By integrating high-fidelity signal acquisition, optimized electrode placement, and wireless data transmission, this methodology enables real-time muscle fatigue monitoring with minimal artifacts, making it applicable for both sports performance and rehabilitation settings.

**Figure 4:** **BLE communication structure** (diagram showing **peripheral (Arduino) → central device (computer/mobile) → data packet structure**).

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