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A Proof of Concept for an IoT-Based Architecture to Monitor Hamstring Muscle Activity

Filipe Costa Pereira
Mackenzie Presbyterian University, Computing and Informatics Department,
São Paulo, Brazil, 01302907
costapfilipe@gmail.com

and

Bruno da Silva Rodrigues
Mackenzie Presbyterian University, Computing and Informatics Department,
São Paulo, Brazil, 01302907
bruno.rodrigues@mackenzie.br

Abstract

Hamstring strain injuries (HSI) represent a high prevalence in sports, with literature indicating that multifactorial elements, such as neuromuscular fatigue, significantly contribute to injury onset. In this context, IoT-based wearable technologies have emerged as robust tools for monitoring myoelectric activity, enabling the early detection of fatigue and supporting injury prevention strategies. Similarly, these devices facilitate the acquisition of physiological data essential for characterizing muscle exhaustion.

This study presents a proof of concept (PoC) developed to validate an architecture for real-time data acquisition and analysis. The proposed system demonstrates the feasibility of integrating wearable sensors, a smartband, and a data processing platform for muscle activity monitoring. The prototype captures electromyographic (sEMG) signals and performs fatigue detection through frequency domain analysis, where a downward shift in median frequency relative to the baseline indicates fatigue onset. Experimental evaluations during hip lift exercises were conducted to identify fatigue patterns. Designed for scalability, the system architecture allows simultaneous monitoring of multiple users, making it suitable for both professional athletes and recreational users.

Keywords: IoT; wearable device; hamstrings; muscle activity; muscle fatigue; injury prevention.

1 Introduction

Muscular tissues are composed of specialized cells that undergo contraction and relaxation cycles in response to various stimuli, functions that are essential for the Musculoskeletal support, locomotion, and postural maintenance [1]. Within this scope, muscular injuries represent a critical concern, as they are highly prevalent in sports, leading to significant downtime for athletes during training and competitive cycles [2], as well as impacting recreational practitioners.

Among the various musculoskeletal injuries that affect both amateur practitioners and professional athletes, it is evident that HSI is one of the most prevalent in sports [3]. Trauma to this muscle group is frequently documented in Association Football (FA) but also occurs commonly in high-intensity sports such as American football, Australian football, track and field, and water skiing. It is noteworthy that this injury presents the highest clinical recurrence rate when compared to other types of soft tissue injuries [4].

Amid the various factors that can trigger HSI, neuromuscular fatigue stands out [5], which is characterized by a reduction in the force-generating capacity during muscle contractions, limiting individual performance [6]. At the conclusion of European soccer matches, a high incidence of hamstring injuries is observed, suggesting muscle fatigue as a significant risk factor for these clinical outcomes [7].

In this regard, the development of non-conventional interaction interfaces that facilitate the acquisition and processing of myoelectric signals, coupled with data interpretation frameworks for real-time decision support, offers significant advantages. For elite athletes, such systems enable the quantification of muscular workload and fatigue, facilitating training optimization and injury mitigation. Similarly, recreational users benefit from these technologies through enhanced recovery protocols and the optimization and dosing of training load in training.

The identification and assessment of muscular/neuromuscular fatigue is of paramount importance and can be performed through myoelectric signal acquisition using electromyography (EMG) during physical activities [8]. Electromyography may be implemented non-invasively through surface electromyography (sEMG), a technique that employs transcutaneous electrodes to quantify the electrical activity of underlying musculature [9]. Consequently, sEMG represents a important modality for the acquisition and continuous monitoring of physiological data within wearable architectures.

In conjunction with electromyography, the analysis of physiological metrics is essential in elucidating the mechanisms underlying neuromuscular fatigue. In this context, among several variables, sleep architecture and heart rate (HR) are prominent; sleep deprivation can induce deleterious effects on cognitive load, alertness, and fatigue thresholds [10], while heart rate variability and heart alterations serve as autonomic markers directly correlated with muscular exhaustion [11]. In view of this, the multimodal correlation between electromyographic signals and physiological datasets may enhance the predictive analysis of fatigue progression.

Therefore, this study is framed as a PoC primarily aimed at validating a proposed architecture for data acquisition and processing physiological data. The objective is to develop a system that leverages wearable technology for the real-time monitoring of hamstring myoelectric activity via sEMG, integrates multimodal physiological metrics, and evaluates fatigue kinetics to support injury mitigation strategies. Rather than presenting a production-ready deployment, this PoC focuses on demonstrating the technical feasibility and modular integration of the system's core components, including wearable sensors, smartbands, and the data processing platform thereby providing the foundation for advanced analytics and future large-scale validation.

The remainder of this article is organized as follows: Section 2 presents the theoretical background, establishing the background necessary to contextualize the subsequent sections; Section 3 delineates the materials and methods, including a detailed overview of the proposed system architecture; Section 4 specifies the prototype implementation, detailing each architectural component; Section 5 presents the experimental results and discussion regarding system performance; and Section 6 provides the concluding remarks and future directions of this research.

2 Theoretical Background

2.1 Muscles

The human muscular system comprises three distinct histological classifications of tissue: skeletal, cardiac, and smooth. Skeletal muscles are primarily anchored to the skeletal framework of the body enabling them to play a fundamental role in the control and execution of voluntary movements [12].

A skeletal muscle system is composed of group of muscle cells, also referred to as muscle fibers [12]. These specialized cells undergo contraction and relaxation cycles in response to neural stimuli, functions that are indispensable for structural support, locomotion, and the maintenance of postural morphology [1].

The motor unit is fundamental functional component responsible for skeletal muscle contraction, consisting of a group of muscle fibers innervated by a motor neuron. Upon activation, all associated muscle fibers undergo synchronized recruitment [12].

Muscles are capable of executing different types of contractions. Isometric contraction occurs when the tension generated by the muscle equals the external load, resulting in no joint displacement or change in fascicle length. In concentric contraction, the force generated exceeds the resistance, leading to muscle shortening. Conversely, eccentric contraction involves resistance that exceeds the muscular force, resulting in controlled muscle lengthening [13].

2.2 Hamstring Muscles

Among the human musculoskeletal system is the hamstring complex, which comprises three distinct muscles: semitendinosus, semimembranosus, and biceps femoris [4]. The biceps femoris is further characterized by two distinct heads: the long head and the short head [14].

The hamstring muscles primarily insert into the tibia; however, the biceps femoris additionally inserts into the fibula. Innervation is predominantly provided by the tibial nerve, except for the short head of the biceps femoris, which is innervated by the common fibular nerve. Vascular supply to the hamstring muscles is provided by perforating branches of the deep femoral artery [15]. Figure 1 illustrates the anatomy of the posterior thigh region, where the hamstring muscles are located.

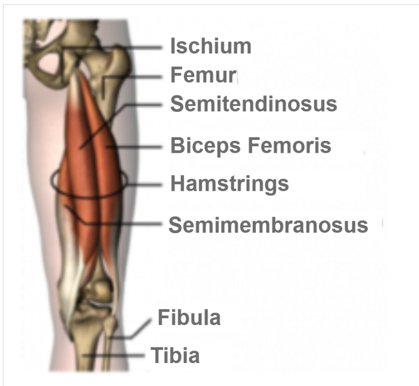


Figure 1: Anatomy of the posterior thigh region.

The hamstring complex functions as a primary driver for knee flexion, medial rotation, and hip extension movement [4]. The biceps femoris, through its short and long heads, is responsible for knee flexion and lateral rotation of the tibia. The long head also contributes to hip extension. The semitendinosus and semimembranosus exhibit overlapping functional roles, performing knee flexion and hip extension, as well as medial tibial rotation when the knee is in a flexed position [12].

2.3 Muscle Injury

Muscle injuries are common in sports [2] and can be caused by bruising, stretching or laceration [16]. The majority of sports related muscle injuries consist of bruising, stretching, with bruising resulting from external compressive forces and strains resulting from excessive internal tensile forces [17].

Various characteristics are utilized for the clinical classification of these injuries, including chronicity, severity, and mechanism of injury. Regarding chronicity, an injury is defined as acute if its evolution occurs within a period of less than three weeks, or chronic otherwise. In terms of structural severity, injuries are categorized by the degree of tissue disruption: stretching, partial rupture, or total rupture of the muscle fibers. Furthermore, injuries may occur from extrinsic or intrinsic factors, with extrinsic injuries resulting from external mechanisms and intrinsic ones by problems in the muscle structure [13].

The physiological process from injury to full recovery is divided into three distinct phases: destruction, repair, and remodeling. The destruction phase is characterized by the rupture and necrosis of myofibrils, the formation of a hematoma, and an inflammatory response. The repair phase involves myofibril regeneration, and the synthesis of fibrotic scar tissue, accompanied by angiogenesis and neural reinnervation. Finally, the remodeling phase entails the maturation of regenerated myofibrils and the functional reorganization of connective tissue. These phases are interdependent and exhibit temporal overlap during the healing process [18].

2.4 Hamstring Strain Injuries

HSI is among the most prevalent musculoskeletal pathologies in sports [3] and has the highest clinical recurrence rate when compared to other injuries. For the athletic population, the reinjury to this muscle group after returning to sports remains the main complication [4].

Regarding the biomechanical mechanism of injury the “Muscle strain occurs when the hamstrings contract eccentrically while simultaneously lengthening at high speed, followed by a concentric contraction” [19]. Consequently, during maximal sprinting activities, there is a heightened susceptibility to structural failure within this muscle complex [20].

A critical risk factor for HSI is muscular fatigue, which degrades an athlete’s biomechanical efficiency, impairs neuromuscular control, and reduces force-production capacity [5]. This phenomenon is evidenced in the final stages of professional soccer matches, where a significant spike in HSI incidence is observed [7]. Notably, muscle fatigue is considered a key contributing factor in the onset of musculoskeletal injuries [21].

2.5 Electromyography

EMG is a diagnostic and analytical technique utilized for measuring myoelectric signals generated by motor neuron activity within the central nervous system. EMG signals have a wide range of applications, including the diagnosis of muscle injuries [22] and the identification and assessment of muscle fatigue [8].

EMG may be applied non-invasively, through sEMG, which involves the strategic placement of transcutaneous sensors on the skin layer [9]. These electrodes, which utilize electrolytic gels or dry-contact interfaces, facilitate the detection of a current changes via an electrolytic conduction process at the skin-electrode interface [22].

This technique enables the analysis of muscle activation during movement and allows for the estimation of the muscular effort or energy expenditure associated with specific muscle contractions [23].

2.6 Wearable Devices

Wearable devices can be incorporated into the human body, facilitating ubiquitous constant monitoring of an individual's activities and ensuring free movement of the user [24]. In general, these devices have a reduced size and enable real-time data acquisition and monitoring [25].

A significant application of wearable technology is in identifying abnormalities in an individual the health status, providing critical alerts that may clinical intervention [26]. In this context, the development of biosensors plays a crucial role, as it provides real-time health monitoring with a focus on prevention and personalized medicine approaches [27].

In recent years, wearable devices have been widely adopted for monitoring and preventing sports injuries [25]. With the advancement of wearable technologies, various opportunities for data collection arise, enabling the monitoring of multiple athletes simultaneously, without requiring invasive techniques [28].

3 Related Works

Zadeh et al. [29] conducted a longitudinal study involving United States military cadets, evaluating the use of wearable technologies as tools for predicting and preventing injuries during sports training activities. The results demonstrated that these devices allowed instructors to collect important information to personalize exercises according to the physical characteristics of each participant, exhibit significant potential for predicting sports injuries.

Liu et al. [25] conducted study in which wearable devices were used to monitor myoelectric muscle activation in a group of 20 cyclists, seeking to identify precursors of fatigue during physical exertion. The researchers employed EMG to extract amplitude-based features for quantifying muscles groups, while simultaneously implementing spectral signal analysis to evaluate the state of the musculature. The findings demonstrated that the developed system exhibited high empirical efficacy in monitoring muscular fatigue thresholds throughout the exercise protocols.

Bona et al. [30] investigated the correlation between physiological variables, such as oxygen consumption, and electromyographic data in patients with chronic heart failure, heart transplant recipients, and healthy individuals. In this context, the study emphasized that the integration and correlation of these variables may contribute to understanding gait in individuals, thereby supporting physical rehabilitation strategies. Overall, the authors concluded that a relationship exists between metabolic transport cost and the electromyographic cost across all evaluated groups, indicating that muscle coactivation direct influence on impacts oxygen consumption.

Costa et al. [31] conducted a comparative analysis of muscle fatigue indices between professional cyclists and non-cyclists, using spectral analysis of EMG signals based on Fourier transform (FT) and wavelet transform (WT) techniques. During an incremental maximum power test, parameters such as median frequency (MDF) and muscle fatigue rates were evaluated. The findings indicated that while WT may be suitable for dynamic tasks and that both methods (FFT and WT) produced similar MDF values and fatigue metrics with no statistically significant divergence was observed between the two analytical approaches.

Previous studies have demonstrated the potential of wearable technologies for monitoring and injury prevention, primarily focusing on the analysis of physiological data to detect fatigue or mitigate injury risk. Building upon the findings of these studies, the present work proposes a modular and integrated IoT-based architecture for real-time muscle monitoring and data analysis aimed at supporting the prevention of hamstring injuries. The proposed architecture integrates multiple data sources and establishes a real-time connection between data acquisition, processing, and visualization layers, thereby ensuring scalability and the integration of heterogeneous sensors.

4 Methodology

Regarding the methodology framework employed in this work, systematic exploratory research was initialy executed across specialized databases, include PubMed and IEEE via Periódico Capes, with the objective of identifying scientific articles and publications aiming to understand hamstring muscle injuries, to identify techniques with the potential to assist in injury prevention, and to analyze the state of the art in this research area. Through this analysis, it was established that surface electromyography (sEMG) serves as a primary modality for detecting muscular fatigue progression, thus acting as a critical tool for injury mitigation. Furthermore, it was determined that spectral decomposition of the EMG signal, utilizing Fast Fourier Transform (FFT) and Wavelet Transform (WT) algorithms, enables a quantitative assessment of fatigue-related frequency shifts.

Building upon these requirements, a cost-effective multi-modal architecture was designed, comprising a proprietary wearable node equipped with sEMG instrumentation for muscle activity monitoring, a commercial smartband for biometric telemetry, a low-latency processing engine for real-time analysis of the myoelectric streams, and a centralized dashboard for data management and longitudinal analytics. The system architecture developed in this study are delineated in Figure 2.

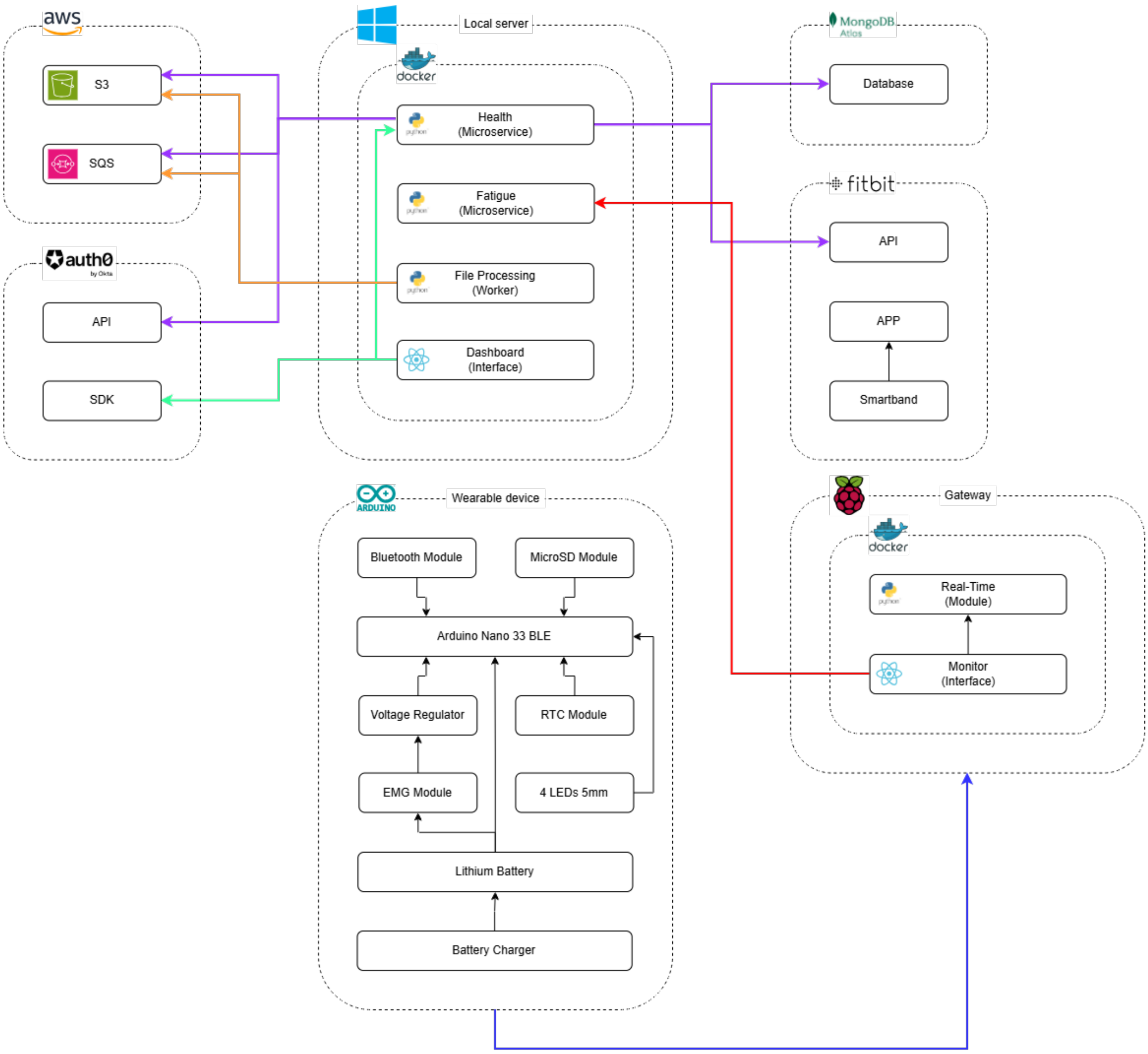


Figure 2: System architecture.

As illustrated in Figure 2, the proposed architecture incorporates, beyond the sEMG wearable node (device), a gateway designed and configured to ingest and orchestrate data streams and display then in real time through an interface. The gateway, implemented on a Raspberry Pi 4 plataform, hosts a data visualization interface implemented with a JavaScript/React frontend and a Python/Flask microservices backend. The entire software was containerized using Docker to ensure isolation and customization of the execution environments.

In addition to facilitating real-time monitoring of myoelectric activity, the gateway serves as the bridge between the wearable node and a centralized local server. The server infrastructure host the following microservices: a data persistence and management service for handling ingested telemetry; a computational engine for muscular fatigue assessment; a background worker for the asynchronous execution of signal processing tasks; and a dashboard for multi-modal data visualization

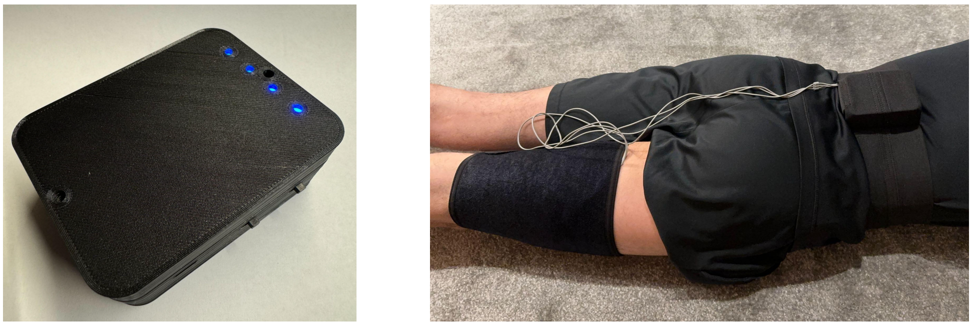
Similarly, a Fitbit smartband was integrated into the ecosystem to acquisition of physiological data. These data are retrieved from the Fitbit cloud platform through a REST API and incorporated into the system via the data management microservice hosted on the local server.

It is worth noting that the system leverages a hybrid cloud architecture by integrating several third-party managed services, including: identity and access management (IAM) via Auth0; object storage and message queuing through Amazon Web Services (AWS); biometric data ingestion from the Fitbit API; and cloud-native NoSQL data persistence using MongoDB Atlas.

5 Results and Discussion

5.1 Wearable Device

As presented in Figure 2, the development of the low-cost wearable device utilized the open-source Arduino prototyping platform and built around the Arduino Nano 33 BLE (Bluetooth Low Energy) board. In addition to this board, the hardware architecture comprises: a BLE module whose model is the JDY-24; a micro SD (Secure Digital) memory card module; an RTC (Real Time Clock) module; a module with EMG sensor; a voltage regulator from 5V to 3.3V; 4 LEDs of 5mm; an 8.4V and 3000mAh lithium battery; and an 8.4V battery charger. The developed wearable device was fitted with a case modeled and printed using a 3D printer to protect the circuit during testing. Figure 3 presents the final prototype of the wearable device.



(A) (B)

Figure 3: Prototype of the wearable device case turned on (A) and device worn by system user (B).

In order to facilitate user-device interaction, four diagnostic LEDs were integrated into the custom chassis. As shown in Figure 3 (A), sequenced from left to right, these indicators monitor the following system states: power status, data acquisition, micro SD card initialization/activity, and BLE connectivity. Table 1 details the operational logic and visual feedback protocols of the LEDs within the wearable device.

Table 1: Operation of LEDs in the wearable device.

LED Function	***Action***	***Meaning***
Power LED	On	Device turned on
	Off	Device turned off
Data LED	Flashing intermittently	Data set being collected
Memory card LED	Flashes once	Data set is persisted
	Flashing intermittently	Signaling a problem with the SD card
Bluetooth LED	Flashes once	Data set is sent to the gateway
	Flashing intermittently	Signaling a connection problem

Regarding the logical operation of the circuit, the data acquisition process is triggered when the wearable device receives a control packet (START command) from the gateway via BLE. Upon initialization, a file in CSV format is generated on the local storage (micro-SD card in wearable device), where the EMG stream is synchronized with temporal metadata obtained through the RTC module. On the Arduino board, these samples are formatted and pushed to a memory buffer with a predefined capacity of 1,000 samples. When the buffer reaches its threshold, the payload is transmitted by the BLE module, persisted to the CSV file, and the buffer is flushed. This iterative cycle persists until the wearable device receives a control packet (STOP command) from the gateway, triggering a final buffer flush to prevent data loss before concluding the session. Figure 4 presents a flowchart detailing the firmware's execution logic.

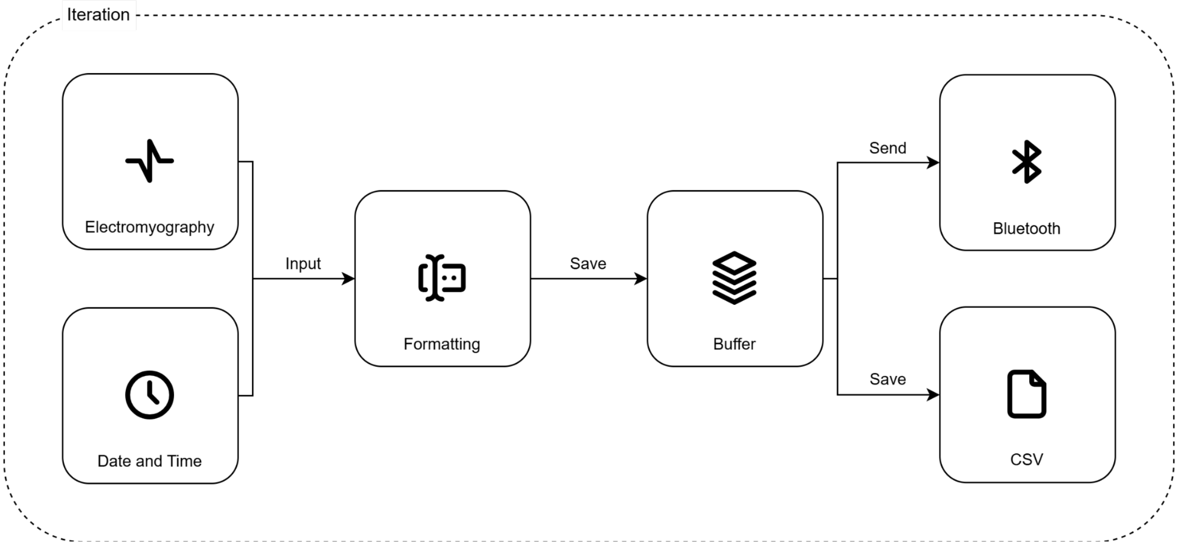


Figure 4: Data processing steps in the wearable device.

5.2 Gateway Application

The gateway facilitates real-time monitoring of muscle activity by receiving data packets transmitted via BLE communication from the wearable device. To optimize user experience (UX), the application interface is structured into functional modules, including: the Monitoring tab and the Devices tab.

The Devices tab (Fig. 5) enables the user to perform device discovery and establish paired connections with the gateway. Within this interface, a 'Scan' function was implemented to perform a broadcast inquiry, identifying and listing nearby Bluetooth-enabled peripherals. Furthermore, a toggle mechanism for connection management facilitates the pairing handshake between the wearable device and the central application. Figure 5 presents the device management interface of the gateway.

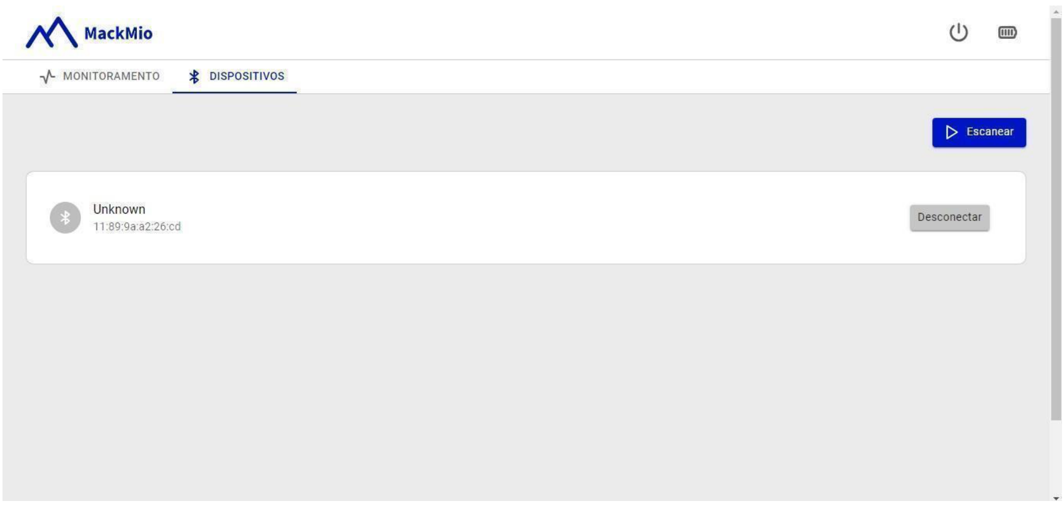


Figure 5: Interface of the devices tab of the application gateway.

The Monitoring tab within the user interface was designed to provide dynamic tracking of myoelectric activity through a real-time temporal waveform representing the sEMG signal as a function of time. This visualization engine ensures high-fidelity representation of the acquired physiological streams. Additionally, the interface incorporates a control trigger to initiate monitoring, allowing the user to activate the transduction of muscle signals, alongside a dedicated visual indicator for fatigue-threshold alerts. Figure 6 presents the graphical user interface optimized for real-time monitoring of muscle activity.

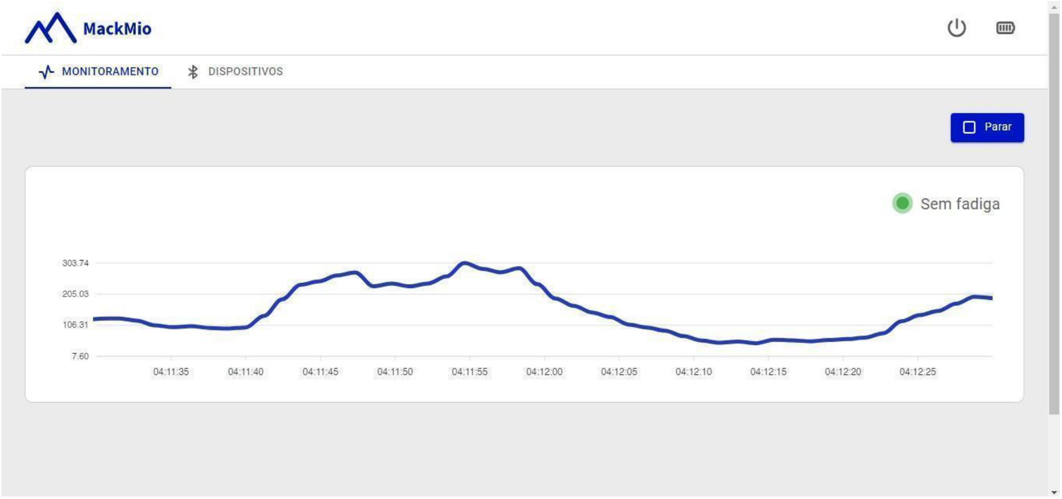


Figure 6: Interface of the monitoring tab of the application gateway.

5.3 Smartband

In addition to the developed hardware devices, the system was engineered to ingestion data from commercial wearable devices in order to support data analysis, making it possible to correlate physiological variables with electromyographic signals. For this purpose, a smartband, model Inspire 2 by Fitbit, was incorporated into the system. This device collects physiological data from the individual both before physical activity and during exercise, serving as a complement to the analysis of muscle activity data. Figure 2 presents the integration workflow for the Fitbit ecosystem, and Figure 7 shows the commercial biometric peripheral used.

Figure 7: Smartband.

Regarding operational workflow, the smartband captures data and transmits it via BLE to a mobile device running with the Fitbit application. Following session termination, these data are synchronized and made available through the API, allowing for subsequent integration into the system during the synchronization phase executed on the local server (Figure 2). Among the data integrated into the system are sleep architecture and heart rate. It is noteworthy that, for sleep analytics, a seven-day retrospective window preceding the physical activity is captured.

Although the smartband integration is functionally implemented in this system iteration, the empirical validation of this component is currently pending. The proposed architecture, however, supports the end-to-end collection, synchronization, and persistence of physiological data from the smartband. The systematic validation and analysis of this multi-source integration will be addressed in future studies, aiming to evaluate its predictive power for fatigue analysis and injury prevention.

5.4 Local Server

The local server delineated in the system architecture (Fig. 2) was designed using a microservices architecture, comprising two discrete two microservices, a background worker and a dashboard.

The "Health" microservice provides a HTTP API to facilitate data orchestration, including asynchronous file (CSV file) uploads and resource management. Upon the ingestion of a new data file, the microservice persists it to AWS and processing is performed by the worker asynchronously. Through the API, it is possible to insert, view, update, or remove activity data.

The worker module continuously monitors a message queue of files to be processed. During the execution phase, the worker parses the raw file to extract activity timestamps and applies pre-processing heuristics to the sEMG time-series data. Subsequently, the worker synchronizes with the 'Health' microservice via API to instantiate a new session and populate the database with the structured time-series data.

The dashboard communicates with the "Health" microservice API for data visualization and management, structured into three primary pages: home, activities, and integration. Figure 8 presents the dashboard's home page.

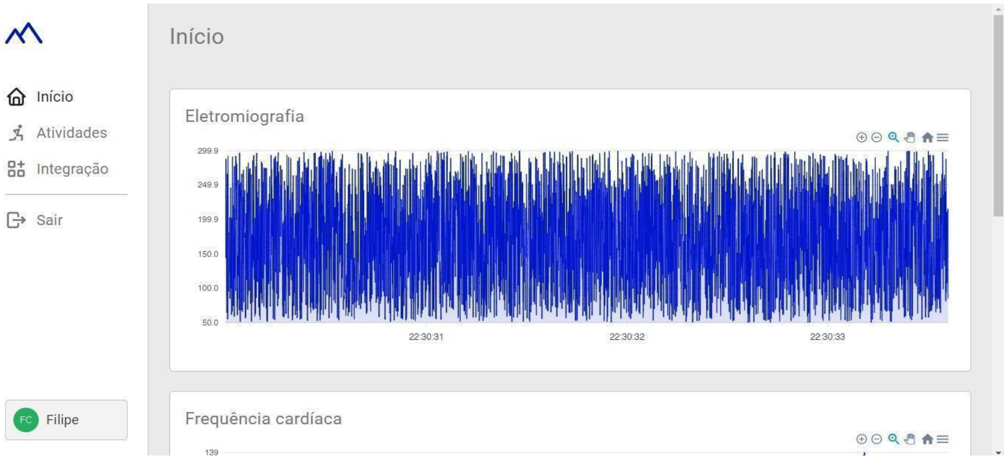


Figure 8: Dashboard home page with electromyography graph.

On the integration page, the user can authorize the system to link to their Fitbit account to synchronize physiological data. Figure 9 illustrates the integration page of the dashboard. authorize

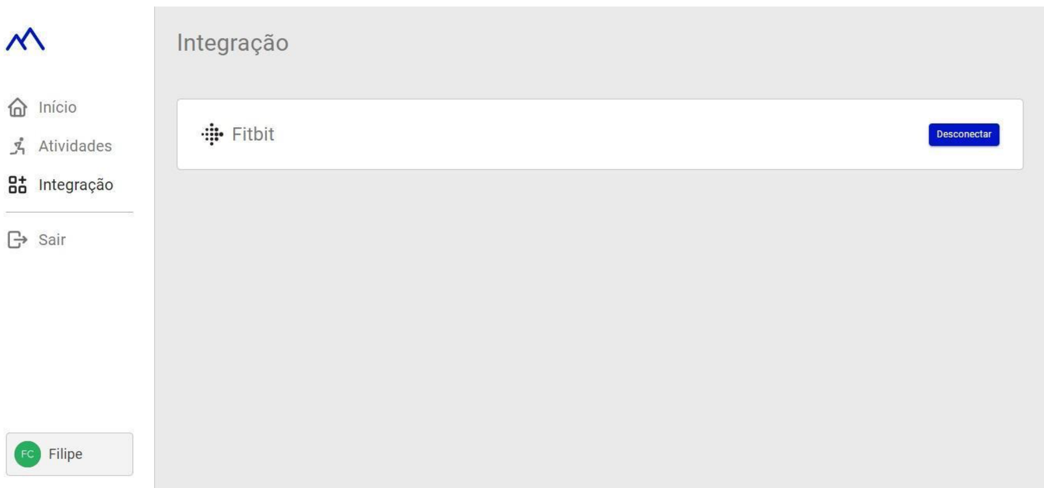
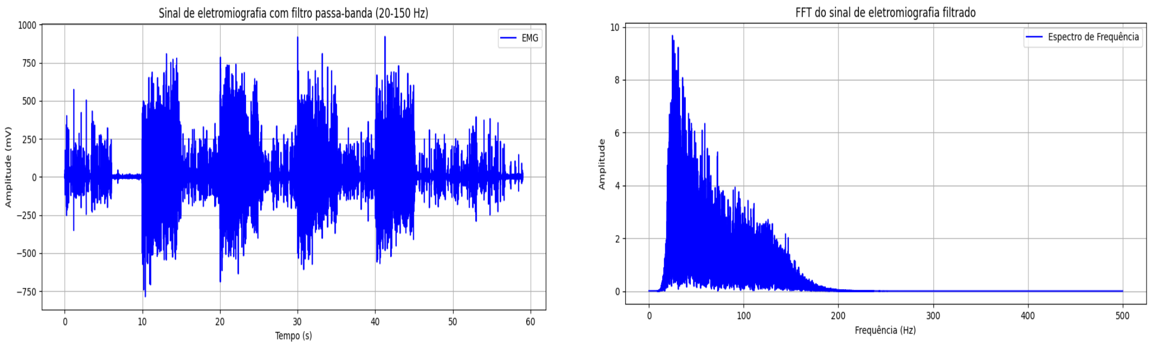


Figure 9: Dashboard integration page.

The microservice dedicated to fatigue analysis exposes an HTTP API for inter-service communication and establishes a WebSocket connection with the gateway to receive real-time EMG data streams. The incoming data are stored in a circular buffer to support continuous processing. Regarding the analytical procedure, a window-based segmentation approach is employed, using windows of 1024 samples with an overlap of 512 samples. Consequently, the processing is initiated only when the buffer contains at least 1024 data points. Upon the arrival of new data, the oldest 512 samples are discarded, and the windowed analysis is iteratively repeated. For each new data segment, a pre-processing stage is applied, consisting of a Butterworth bandpass filter with a lower cutoff frequency of 20 Hz and an upper cutoff frequency of 150 Hz. This frequency range was selected because it encompasses the region with the highest concentration of relevant electromyographic information [32]. Figure 10(a) illustrates a filtered EMG signal acquired from the hamstring muscles during the hip lift exercise, in which four repetitions with isometric contraction were performed.



(a) (b)

Figure 10: Electromyography signal with bandpass filter (20-150 Hz) (a) and Fast Fourier Transform of the filtered electromyography signal (b).

Following signal pre-processing, the Fast Fourier Transform (FFT) is applied to extract the frequency spectrum of the signal (Fig. 10 (b)). Subsequently, the Power Spectral Density (PSD) is obtained, which represents the distribution of signal power among frequencies. From the PSD, the MDF is derived [33], storing the result of this calculation in an array of MDF. When this array contains at least 2 datas, then: the most recent MDF value is compared with the first recorded data and, if there is a relative decrease of at least 10% or great is detected [34], the system triggers a positive neuromuscular fatigue state. Additionally, a linear regression is applied to calculate the slope coefficient [25], representing the MDF's rate of decay over time. A negative shift in the slope serves as a quantitative indicator of progressive muscle fatigue. Finally, the microservice exposes both the slope coefficients and fatigue status via the API for real-time visualization. Figure 11 presents the longitudinal trend of the MDF and its corresponding slope over time.

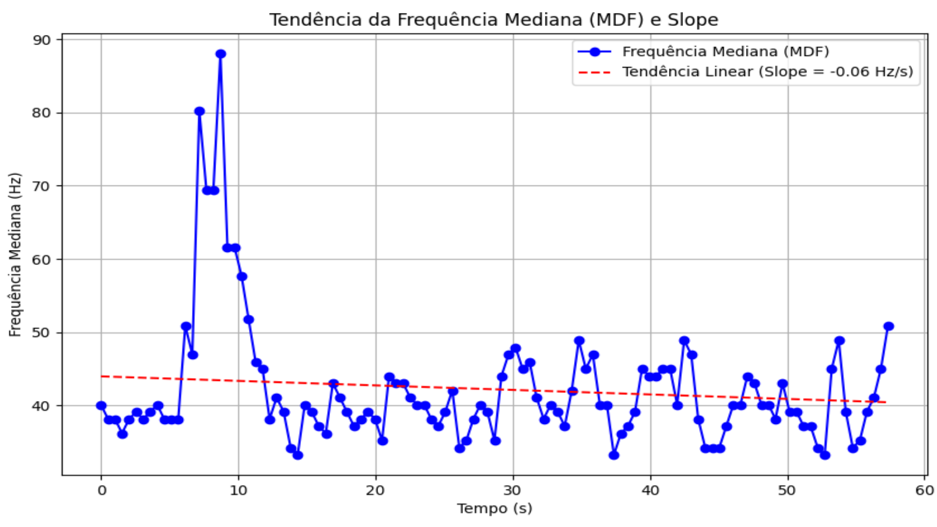


Figure 11: Median frequency and slope over time.

6 Conclusion

Hamstring strain injuries are among the most recurrent musculoskeletal injuries in sports, with muscle fatigue recognized as a critical factor in their etiology. In this study, a proof of concept (PoC) was presented to demonstrate the technical feasibility of an IoT-based architecture for real-time muscle monitoring and data analysis aimed at supporting the prevention of hamstring injuries. The results indicate that the proposed system can effectively integrate wearable sensors, multimodal physiological data, and real-time processing mechanisms. Overall, the architecture shows potential to support both professional and recreational practitioners, providing a foundation for future large-scale validation and advanced analytical approaches.

The system was conceived and implemented based on established scientific research on muscle injuries, with a particular focus on the hamstrings. In this context, EMG emerges as a relevant technique for assessing muscle activity, supported by validated methods for identifying muscle fatigue. In addition, the integration of multiple technologies within the proposed architecture contributes to effective data acquisition, processing, and visualization, while improving the overall user experience.

It is worth highlighting several characteristics of this PoC: scalability, as it supports the integration of data from multiple users; methodological flexibility, allowing adaptation to injury prevention in muscle groups beyond the hamstrings; and architectural extensibility, which enables the incorporation of additional sensors for the acquisition of heterogeneous data types.

As this study represents a PoC, some limitations were inherent to its scope. The experiments were conducted under controlled conditions, which allowed testing the integration of sensing, processing, and visualization modules. As a preliminary stage, the results should be viewed as indicative of system potential rather than a validated performance assessment.

As future work, experimental trials involving athletes will be conducted to collect a larger volume of data and evaluate the system's performance in real-world sports environments, enabling statistical validation of the obtained results. In addition, an artificial intelligence model will be incorporated to identify patterns within the collected data, working in conjunction with the existing algorithms. Furthermore, new functionalities will be explored, including the integration of the system with services provided by healthcare-sector organizations.

Therefore, it is expected that the project will progress to a new development stage, focused on system refinement and maturation, with the objective of eventual deployment to end users. This evolution aims to enhance safety during physical activity while providing advanced data analysis capabilities to support improvements in physical conditioning.

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