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PAPER

Biofeedback-Based Method for Real-Time Fatigue Monitoring of Knee

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ABSTRACT

This paper introduces and implements a method to monitor muscle fatigue in real-time using a wearable biofeedback system to improve muscle rehabilitation treatments. The biofeedback system consists of an electromyography (EMG) sensor to capture muscle activity and two motion sensors to track knee angles. The proposed method for monitoring muscle fatigue involves three steps: (1) recognition of the movement phases during the knee extension exercise; (2) clipping of the EMG signal and calculation of fatigue-related metrics; and (3) normalization of metrics through a calibration process. An experimental session was performed with 10 healthy subjects performing 50 repetitions of the knee extension exercise. Processed data revealed changes in fatigue-related metrics, which align with existing literature. A comparison was also made between real-time and computer processing using raw data. While minor differences were noted between the two processing methods, the mobile app closely mirrored the trajectory of processed data in the cloud, ensuring reliability and consistency. This study advances remote muscle rehabilitation by quantifying muscle fatigue during treatment sessions. Thus, health professionals can tailor treatment plans based on individual patient characteristics, optimizing treatment duration, and reducing injury risk.

KEYWORDS

muscle fatigue, biofeedback, remote rehabilitation, real-time monitoring

1 INTRODUCTION

Over the past few decades, life expectancy has increased significantly in many parts of the world, including Europe and particularly in Portugal. This increase in life expectancy can be attributed to advances in health, technology, living conditions, and better access to education. As a result, the elderly population has also grown, significantly impacting society and health systems [1].

As the proportion of older adults increases, the demand for primary and long-term health services grows, especially those related to chronic conditions and age-related diseases. For example, the gradual decline in functional capacity due

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to aging is a natural progress common to all living beings, requiring constant care to preserve an active and dignified life [2]. Thus, rehabilitation treatments face a critical accessibility problem that tends to get worse.

A study [3] was carried out in 2019 to assess the demand for rehabilitation services globally and their impact on the health system. The estimates reveal that one in every three people in the world, approximately 2.4 billion individuals, needs such services. The authors highlight that this result counters the common view that just a few people need rehabilitation.

The concern about the delay in finding the necessary treatment is addressed by the World Health Organization (WHO) in their report on healthy aging for the decade between 2021 and 2030 [2]. The report highlights the significance of improving functional capacity to promote more independent aging and suggests data-driven solutions to achieve scalable and accessible answers.

Remote rehabilitation is a concept that has gained significant attention in recent years. It involves delivering rehabilitation services to patients in their homes using technology such as videoconferencing, mobile apps, and wearable devices. The main advantage of remote rehabilitation is the potential to support changes in patient behavior, improving active participation and living independently with less need to travel for face-to-face sessions. It can improve the quality of health service delivery, especially for patients with difficulty accessing traditional rehabilitation services [4].

The NanoStim project (https://nanostim.pt) aims to develop a remote rehabilitation solution. The project proposes a set of technologies that allow patients to perform electrostimulation treatment at home. The goal is to provide a personalized rehabilitation plan that adapts to each patient's individual needs. The Nano Stim project desires to improve access to rehabilitation services, reduce waiting lists and costs, and increase patient engagement.

Over the past three years, the project has achieved significant progress. Starting with developing a system architecture with a strategy to handle sensitive data, ensuring data protection, and mapping out how systems communicate to guarantee successful treatment at home [5]. One of the main developments is creating a wearable device capable of collecting data from an electromyography (EMG) sensor and performing electrostimulation simultaneously [6]. This wearable device communicates with a mobile app that serves as a technological interface to guide patients through the treatment session steps, storing data, and communicating with the cloud [7]. In addition, two inertial measurement units (IMU), also known as motion sensors, have been implemented into the wearable device, allowing recognize the knee angle movement during the treatment session [8].

Monitoring muscle fatigue is crucial for muscle rehabilitation treatments, allowing healthcare professionals to adjust treatment protocols and prevent overexertion or injury. Muscle fatigue is the inability of a muscle to generate or sustain a given level of force, leading to decreased performance, increased risk of injury, and delayed recovery [9]. By monitoring muscle fatigue, healthcare professionals can assess patient progress, determine if the current treatment plan is effective, and adjust treatment intensity and frequency according to the patient's muscle response.

In muscle rehabilitation treatments, patients usually perform exercises targeting specific muscles, such as the knee extension exercise, which focuses on recovering quadriceps muscle, especially the vastus medialis and vastus lateralis. These exercises are usually repeated several times, and the intensity and duration can gradually increase over time, leading to muscle fatigue [10]. In traditional clinical settings, healthcare professionals closely monitor patients and adjust exercises as needed. However, in remote rehabilitation, this level of interaction is more difficult, despite advances in remote rehabilitation, making it crucial to have a system that can monitor muscle fatigue in real-time during a treatment session.

This paper proposes and implements a method to monitor muscle fatigue in real-time using biofeedback, which can contribute to the remote rehabilitation field and align with the goals of the Nano Stim project. A method is presented to extract the EMG signal from biofeedback sensors to estimate muscle fatigue more accurately. This method includes three steps: (1) recognition of the movement performed during the knee extension exercise through the IMUs sensors, (2) clipping of the EMG signal concerning the most relevant movement phases to calculate fatigue metrics, and (3) normalize metrics through a calibration process.

A test was conducted with 10 healthy subjects using the wearable Nano Stim to validate the fatigue monitoring method. The test simulated a treatment session for muscle rehabilitation with the knee extension exercise, with the movement performed 50 times to cause minimal fatigue. The collected data were processed in real-time in the mobile application and compared with a later analysis of the raw data in Python.

This paper is organized into five more sections. Section 2 describes related works that build systems using EMG and IMU sensors in conjunction with muscle rehabilitation purposes. Section 3 describes the biofeedback system, including the flow from data collection to cloud recording. Section 4 describes the method to extract real-time muscle fatigue metrics. Section 5 explores the data generated in the tests and describes the comparative analysis of mobile app processing vs. cloud processing. Section 6 reports the main conclusions and future work.

2 RELATED WORKS

The use of wearable technologies in muscle rehabilitation has been increasingly explored in recent years [11]. Several studies have focused on developing systems that use EMG and IMU sensors to monitor muscle activity and movement patterns during rehabilitation exercises. This section will discuss three studies that successfully built wearable systems that can provide biofeedback about the patients, improving their performance and motivation during rehabilitation.

The authors in [12] developed a wearable for EMG acquisition to detect muscle fatigue in real-time while pedaling a bicycle. The wearable system comprises a microcontroller (MCU) and an EMG signal acquisition circuit. The wearable system sends the collected data to a mobile application that displays information about the exercise and the level of muscle fatigue. The raw and processed data are sent to the cloud when the exercise ends.

The authors use the median frequency (*MedFreq*) value to stimulate muscle fatigue, a metric commonly used in sports. The *MedFreq* correlates with muscle fatigue when the measured values show lower frequencies during the exercise. The study involved 20 participants who pedaled an exercise bike at different speeds to validate the developed system. With the data collected, the mobile app's performance was compared with the computer for estimating fatigue. The results showed similar performance between the two systems, with root mean square (RMS) values between 2.86 ± 0.47 Hz. The article [12] has a methodology similar to that used in the present article, especially in comparing systems to evaluate fatigue.

In [13], the authors used four wearable devices to test a methodology that remotely evaluates the quality of rehabilitation exercises. The wearable device set consisted of two EMG signal acquisition systems and two motion acquisition systems. The study involved 17 participants who performed two movements commonly prescribed in physical therapy programs while wearing the devices in different body positions.

The methodology demonstrated involves two data segmentation and preparation approaches: manual segmentation by an expert and machine learning algorithms. The resulting dataset comprised clipped EMG and IMU data and a label indicating whether the exercise was performed correctly or incorrectly. Using machine learning algorithms, the authors could evaluate exercise quality with an average accuracy of 96%. These results demonstrate the practicality of using motion and EMG sensors to provide valuable information for remote physiotherapy.

The article [14] discusses a real-time knee extension monitoring and rehabilitation system. The monitoring system consists of a wearable with two EMG sensors, an angle sensor, and a processor capable of transmitting data via Wi-Fi to a computer on the network. The software that receives the data can display the participant's muscle response and knee angle in real-time. In addition, the software can save the collected data and organize it into sessions.

After the sessions are saved, the software analyzes the performed exercises and calculates the mean absolute value (MAV) and RMS from the EMG signal and the maximum angle reached. Raw data and calculated metrics are available in the cloud for an expert to analyze. Although the software does not provide real-time data analysis, the system improves the tracking of muscle recovery progress and enables the specialist to intervene to improve rehabilitation.

In summary, the related works presented in this section have similarities and differences with the proposed fatigue monitoring system. The authors in [12] presented a real-time fatigue monitoring system that did not use an IMU sensor focusing on cycling. The authors in [13] developed a wearable with EMG and IMU sensors to verify the quality of rehabilitation exercises, while the proposed system focuses on monitoring fatigue. The authors in [14] presented a fatigue monitoring system similar to the one proposed. However, they use the computer as an interface and do not use the information processed in real-time to help the treatment session. Finally, related works showed the potential of using wearable devices in remote rehabilitation and served as a reference in the development of the present study.

3 BIOFEEDBACK SYSTEM

Creating a treatment scenario and system architecture for remote rehabilitation is a challenging task involving designing processes that ensure a simple and user-friendly experience for the patient and the healthcare professional. Furthermore, as the system will collect and process clinical data, it is crucial to ensure the security and privacy of patient information. This section describes how the proposed remote rehabilitation treatment session is conducted, focusing on where biofeedback is collected, processed, and stored at the end of each treatment session.

The biofeedback system that will be presented consists of a wearable system and a mobile app, which are part of a system architecture developed by the Nano Stim project. The complete architecture has two more essential components: a website for managing patients and treatments online and a cloud infrastructure. Figure 1 illustrates a simplified version of the system architecture used in this paper.

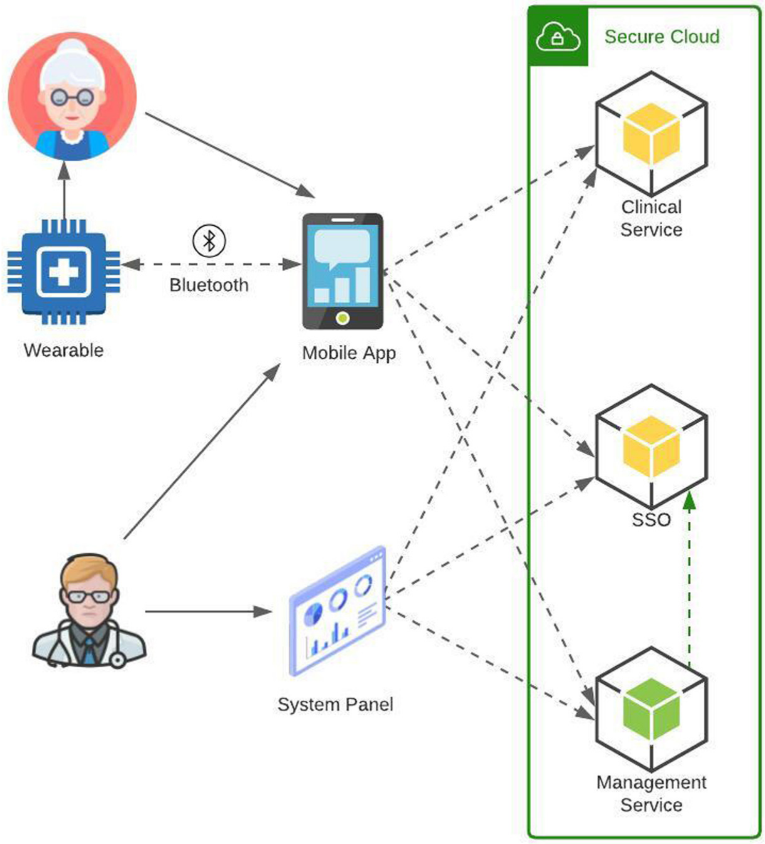

Fig. 1. System architecture (adapted [5])

Briefly, the cloud infrastructure is comprised of three APIs: (1) a single-sign-on (SSO) authentication service; (2) a clinical service that manages health-related data such as biofeedback data; and (3) a management service that stores personal information such as names and addresses. The article [5] describes the other particularities of the systems architecture, especially communications between systems, databases, and data protection strategies.

The wearable system comprises four main components that work simultaneously during the muscle rehabilitation session. The first component is the functional electrical stimulation (FES) circuit. The FES component creates electrical impulses to stimulate the nerves that control the muscles, causing muscle contractions and movement. FES aims to restore or improve the function of muscles that have been damaged or weakened due to injury or illness. This component is the only one of the wearable systems that will not be used in this study and has no influence on the tests performed.

The second component is a signal acquisition system and the EMG electrodes. This system can measure the electrical activity of a muscle with electrodes under its surface. The result is an analog signal at a frequency of 1000 Hz measured in mV. The wearable system sends every 200 ms a packet with EMG raw data to the mobile app. The EMG signal is the main data that will be used to calculate the metrics related to fatigue.

The third component of the wearable system contains two IMU motion sensors that use accelerometers and gyroscopes to detect movement and orientation at 100 Hz. In our scenario, one sensor is placed on the patient's thigh and the other on the shin. With this, the system calculates the knee angle and sends a data packet every 10 ms.

The last component is the ESP32 microcontroller, which can operate all other components and communicate via Bluetooth low energy (BLE) with the mobile app. All these components are integrated into a printed circuit board (PCB) developed by the Nano Stim project. This PCB has a protective case made in a 3D printer that attaches a battery. This wearable system can be charged via a USB cable and easily transported. Articles [6] [8] can supplement the content on the wearable system.

The positioning of the biofeedback system components on the vastus medialis muscle in the human leg model is demonstrated in Figure 2. One of the EMG electrodes is placed on the knee bone to function as a reference, while the other two EMG electrodes and FES electrodes are positioned on the top of the targeted muscle. The motion sensors, on the other hand, can be positioned at any height on the thigh and shin while facing the front of the body.

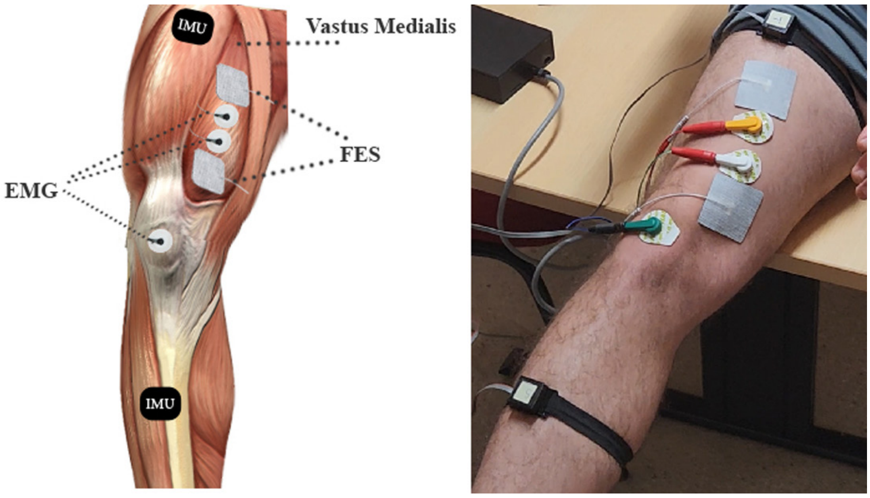

Fig. 2. Sensors of wearable system

The mobile application used in this article was developed for Android and can be used by patients and health professionals to perform rehabilitation treatment. The application was developed to manage the sessions, including operating the wearable system via BLE and storing the data received from the sensors. An article about this mobile app has been published [7], describing the steps required to perform a session and how the raw data is saved and transmitted.

The access profile that will be addressed is the health professional, in which it is possible to operate all the functionalities of the wearable system during the treatment session. Thus, this study assumes that the mobile app has the following capabilities already implemented:

1. Pair via BLE with the wearable system
2. Start and end data collection through the interface
3. Receive and store raw data from the EMG signal
4. Receive and store data from IMU sensors (knee angle)
5. Send collected data to the cloud

With this, the data considered in real-time used in this study are the data received by the mobile app according to the frequencies previously described, and then data processing is started. All collected raw data is stored in files in the app and uploaded to the cloud when a collection is complete. Thus, the data considered in the cloud are the raw data processed in Python using the Jupyter Notebook tool.

4 FATIGUE MONITORING METHOD

The fatigue monitoring method comprises three essential steps to evaluate muscle fatigue in patients submitted to knee extension exercises. The first step involves recognizing the movements performed during the exercise through the knee angle. For the movement to be considered correct, it is necessary to go through a set of phases determined by thresholds in the correct order.

In step 2, the acquired EMG signal is processed. Initially, the data are clipped according to the relevant phases detected in step 1. After that, a high- and low-pass filter is applied, and the signal is converted to mV. With the resulting signal, a series of procedures are applied to extract three metrics related to muscle fatigue: average frequency (*avgFreq*), *MedFreq*, and root mean square.

The last step is normalization, which involves a calibration process to ensure consistency between patients. This calibration process is performed at the beginning of the treatment session, where the patient must perform three knee extension movements. The values obtained are used as a reference to normalize the metrics in percentage.

4.1 Knee extension movement

The knee extension exercise is fundamental in muscle rehabilitation treatment, specifically for the quadriceps muscle group. This exercise involves extending the knee joint and activating the quadriceps femoris, the largest muscle group in the thigh. Reinforcing the quadriceps is crucial to maintain knee joint stability and promote gait patterns [15].

To perform the knee extension exercise, the subject sits in a chair or on a knee extension machine with the knees bent at a 90-degree angle and the feet flat on the floor or footrests. The exercise is started by straightening the knees and raising the legs until they are parallel to the floor or fully extended. The movement is considered complete when the subject's leg returns to the ground again. Figure 3 shows the data collected by the biofeedback system of a subject performing the knee extension exercise.

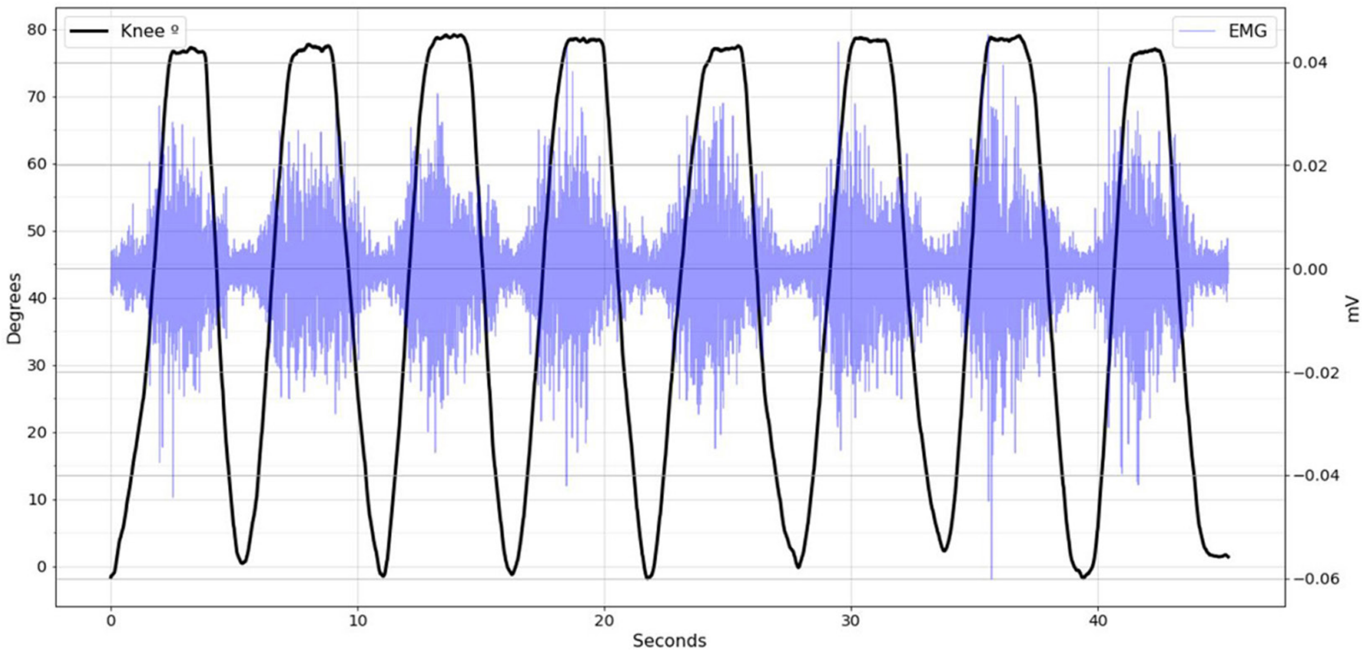

Fig. 3. Data collected during knee extension exercise

The knee angle illustrated in Figure 3 passes through several parabolas with the concavity facing upwards, representing each time the knee extension movement was performed. It is also possible to visualize the EMG signal synchronized with the movement, with an increase in the signal amplitude when the leg begins to rise and a decline in amplitude when the leg begins to descend, representing the muscle activation required by the vastus medialis muscle to perform the movement.

In this method, the knee extension movement was segmented into four distinct phases, systematically defined by two threshold lines. The first threshold line determines the minimum angle the knee angle must go through to be considered the start of the leg rise. The value for the first threshold was determined from experiments as 20°. The second threshold line represents the minimum angle the knee angle must go through for the knee extension movement to be considered sufficient. The physiotherapist should adjust this value for each patient since the full knee extension range can be reduced in a muscle rehabilitation context. However, in this study, it was defined as 60º.

From the threshold lines, the four phases are determined from the following intervals: The first phase represents the upward movement, starting with values above the first threshold and ending at the second threshold; for example, the leg left 20º and reached 60º. The second phase is when the movement is already considered sufficient. It can be categorized when the knee angle is above the value of the second threshold, that is, values above 60º. The third phase represents the downward movement of the leg, which can only happen if phase 1 and 2 have occurred previously. It can be categorized as descending when the values are between the first and second threshold, equal to phase 1. Finally, phase 4 represents the leg at rest, classified when the knee angle values are below the first threshold, for example, values below 20º.

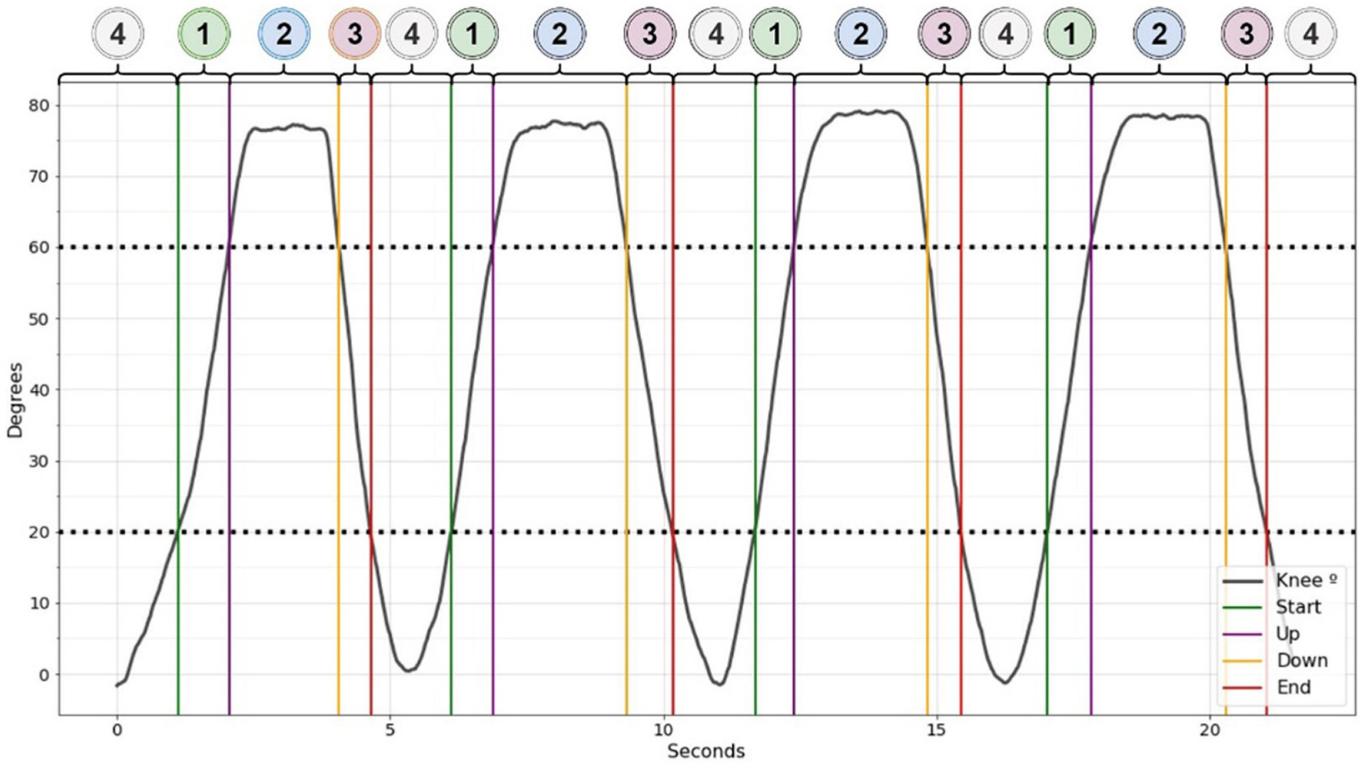

Fig. 4. Classification of movement between the four phases

In this way, as the mobile application receives the knee angle data, the current state of movement is classified based on this system of rules, as illustrated in Figure 4. Similar to a state machine, it is considered that the subject managed to perform the knee extension movement correctly once when the four phases were performed in sequence. When the sequence is complete and the movement is considered correct, it is considered in this study that the subject performed a contraction. Thus, it is possible to visualize four recognized contractions in Figure 4.

The EMG signal used to analyze each contraction in this system is obtained by cutting the corresponding EMG signal between phases 1, 2, and 3 of the knee extension movement, excluding phase 4. This cutting method focuses on capturing only the most significant part movement, omitting the rest time between contractions. The decision to exclude phase 4 is based on the understanding that this phase, characterized by leg rest, contains less representative information for analysis. Additionally, it is likely to introduce positioning noise and prolonged periods with minimal muscle activity, which can impair the accuracy of the analysis.

When the knee extension movement fails to go through all four phases, it is classified as an incorrect contraction. For example, the subject started to lift the leg, failed to reach the second threshold, and returned to the resting position, keeping phases 2 and 3 missing. In these cases, the corresponding EMG signal is disregarded for analysis.

In order to provide a user-friendly interface, a screen in the mobile application was developed to supply real-time visualization of knee angle movement. This dynamic design represents the subject's knee movement, allowing users to monitor knee extension in real-time.

The interface also displays the current phase of contractions, the description of the current angle, and the total number of contractions recognized. In addition, the physiotherapist can adjust the second limit, described as "Min Angle," using intuitive buttons on the interface, as illustrated in Figure 5.

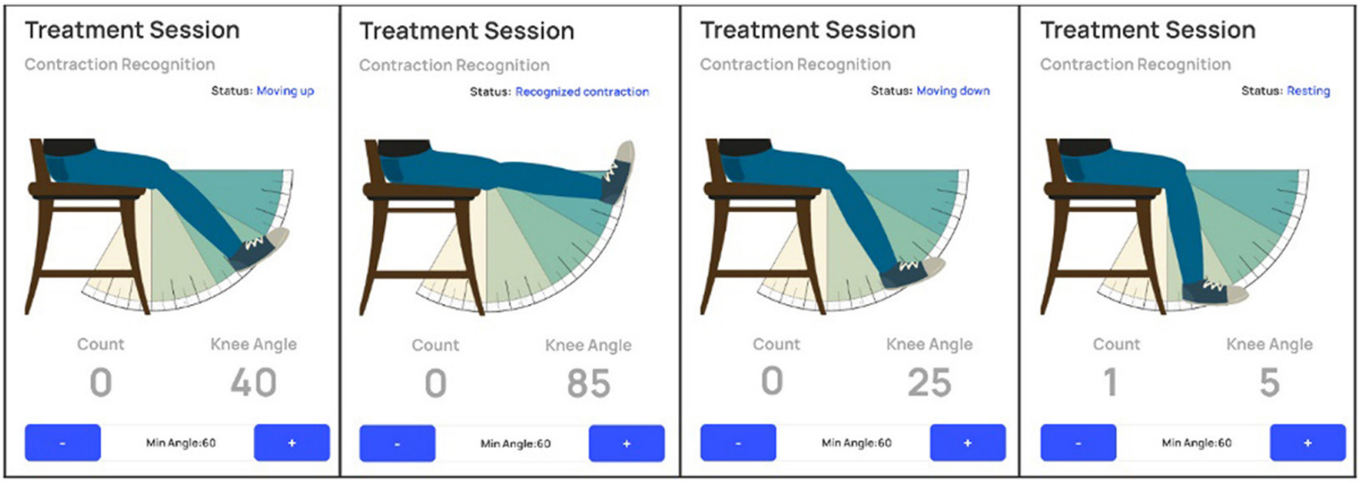

Fig. 5. Phases of contraction recognition interfaces

4.2 Fatigue metrics

This section describes the operations performed on the EMG signal clipped to calculate three relevant metrics in the context of muscle fatigue. Two metrics are related to the signal spectrum: the average and median frequencies. These metrics provide information about the frequency characteristics of the EMG signal and can indicate changes in muscle fiber activation. Specifically, a shift in activation from fast-twitch (type 2) fibers to slow-twitch (type 1) fibers indicate muscle fatigue. This shift is reflected in the signal spectrum by a leftward skew of the mean and median frequencies, resulting in lower frequency values [16].

In addition, RMS is calculated to quantify the amplitude of the EMG signal. The RMS value indicates the level of muscle activation. Higher RMS values correspond to greater muscle activation, while lower values indicate less muscle activation. Monitoring RMS over time makes it possible to assess changes in muscle activation levels, which can help evaluate muscle fatigue [16].

The EMG surface electrodes analogically capture the difference in electrical potential generated by the motor units activated at that moment. This analog signal is then transformed into a digital signal with 12 bits of resolution, producing an integer vector that discretely represents the sum of the motor unit electrical activity recorded. Since the frequency is set at 1 KHz, the size vector corresponds to the duration of the contraction in 1 ms.

To restrict the signal frequency between the most relevant ranges, a low-pass filter and a high-pass filter are applied. The low-pass filter will attenuate frequencies above a cutoff frequency of 500 Hz, allowing only the lowest frequency components to pass through. On the other hand, the high-pass filter will attenuate frequencies below a cutoff frequency of 20 Hz, allowing only the highest-frequency components to pass through [17].

In this study, Welch's method [18] was applied to estimate the power spectral density (PSD) of the EMG signal, which is required for calculating the *avgFreq* and *MedFreq*. This method divides the signal into overlapping segments with a hop size determined by the overlap factor, which must be between 0 and 1. The periodogram of each segment is computed using the Fast Fourier Transform (FFT) algorithm. Thus, the PSD estimate using the Welch method is obtained by averaging the periodograms from all segments.

Transform the signal to millivolts. The EMG signal is transformed from raw to millivolts (*mV*) using Formula 1.

$$signalEMG_t = \frac{signalRAW_t - 2048}{4096} \tag{1}$$

Where $signalRAW_t$ represents the raw EMG signal at time t, and 2048 and 4096 correspond to the values that scale the signal to the 12-bit resolution.

Compute the segments. The window size M for each segment was determined as 1024 elements. This choice ensures an appropriate balance between frequency resolution and computational efficiency. Given an EMG signal sampling frequency of 1000 Hz, the resulting frequency resolution is approximately 0.97 Hz.

An overlap factor parameter α was defined as 0.1 to minimize potential spectral leakage. Each segment will overlap the previous segment by 10% of its length. The overlap helps capture transient information and improves the overall accuracy of the PSD estimate. The number of segments L was computed based on Formula 2.

$$L = \left| \frac{N - M}{M * (1 - \alpha)} + 1 \right| \tag{2}$$

where N is the length of the *signalEMG*.

The vector S of size L can be defined as a collection of segments from the *signalEMG*, denoted as $S_i = signalEMG[a_i : b_i]$ where a_i and b_i represent the initial and final indices used to extract the segment from *signalEMG*.

The vector S can be constructed using Formula 3 as follows:

$$\begin{aligned} a_i &= (i-1) * (M - \alpha * M) \\ b_i &= a_i + M - 1 \end{aligned} \tag{3}$$

Apply Hanning window. This study employs a Hanning window in signal processing to mitigate the effects of spectral leakage and reduce aliasing [19]. The equation used to create the Hanning window is defined in Formula 4.

$$W_n = 0.5 - 0.5 * \cos\left(\frac{2\pi n}{M-1}\right), n = 0,1,2,\ldots,M-1 \tag{4}$$

where n represents the index and M is the length of the window.

The windowed signal E is a vector of segments obtained by element-wise multiplication of the vector S with the Hanning window as W. The definition of each segment is expressed by Formula 5.

$$E_{ij} = W_{ij} * S_{ij} \quad \begin{aligned} i &= 0,1,2,\ldots,L-1 \\ j &= 0,1,2,\ldots,M-1 \end{aligned} \tag{5}$$

where i represents the segment window index and j is the segment window index.

Compute the power spectral density estimated. The FFT algorithm is applied to each signal segment to compute the PSD estimate. The result of the FFT algorithm is a complex-valued spectrum that includes both positive and negative frequencies.

In this way, only the positive frequencies are considered in the subsequent analysis to extract meaningful information and avoid redundancy. Thus, the frequency vector is constructed by taking the positive frequencies from the FFT result.

The frequency vector consists of evenly spaced frequency values ranging from 0 Hz to the Nyquist frequency, which is half the sampling frequency. Thus, to match the response of the FFT algorithm applied to E, the length of the frequency vector is equal to half the window size, defined as V.

Each point in the frequency vector represents a specific frequency component of the signal. The frequency values in the vector can be computed using Formula 6:

$$F_k = \frac{k}{M} * f_s \quad k = 0,1,2,\ldots,V-1 \tag{6}$$

where k represents the index of the frequency vector F, and f_s represents the sampling frequency.

The periodogram of the segments is computed using the FFT algorithm according to Formula 7.

$$\begin{aligned} X_i &= FFT(E_i) \quad i = 0,1,2,\ldots,L-1 \\ P_{ik} &= \frac{\left|X_{ik}\right|^2}{M} \quad k = 0,1,2,\ldots,V-1 \end{aligned} \tag{7}$$

where X_i represents the result obtained from each segment E_i using the FFT algorithm, and k denotes the index of the corresponding frequency.

The averaged PSD estimate of the entire *signalEMG* defined as T, is then computed using Formula 8:

$$T_k = \frac{1}{L} * \sum_{i=0}^{L-1} P_{ik} \tag{8}$$

Average frequency computation. The *AvgFreq* is computed by weighting the frequency values by their corresponding PSD values and calculating their average. Thus, the formula required to obtain this value is described below:

$$AvgFreq = \frac{\sum_{k=0}^{V-1} F_k * T_k}{\sum_{k=0}^{V-1} T_k} \tag{9}$$

Median frequency computation. In order to calculate *MedFreq*, it is necessary to create the cumulative power vector of the estimated PSD. These values are obtained by summing the values of T cumulatively. The cumulative potency C_k and the total potency CT are obtained from Formulas 10 and 11.

$$C_k = \sum_{i=0}^{K-1} T_i \quad k = 0, 1, 2, \ldots, V-1. \tag{10}$$

$$CT = \sum_{k=0}^{V-1} C_k \tag{11}$$

The *MedFreq* is the frequency value at which the cumulative power equals half of CT. It is determined by finding the frequency bin F_k that satisfies the conditions in Formula 12:

$$C_k \geq \frac{CT}{2} \quad and \quad C_{k+1} < \frac{CT}{2} \tag{12}$$

where C_k represents the cumulative power at frequency bin F_k.

Root mean square computation. The RMS value is calculated by taking the square root of the mean of the squared values of the signal samples. Let *signalEMG* represent the signal obtained in step 1. The RMS value is calculated by:

$$RMS = \sqrt{\frac{1}{N} * \sum_{n=1}^{N} signalEMG(n)^2} \tag{13}$$

where N represents the length of the *signalEMG*.

By following these steps, it becomes feasible to calculate the three metrics (*AvgFreq*, *MedFreq*, *RMS*) employed in this system to evaluate muscle fatigue. All steps were developed from scratch within the mobile app except for the FFT algorithm. The FFT algorithm utilized in the app was imported from the Apache Math3 library in the Kotlin language. The library SciPy signal of the Python language was used for the data processed in the cloud.

4.3 Normalization and calibration

This section emphasizes the importance of normalizing the EMG data within the context of fatigue monitoring. Ensuring reliable and consistent measurements is crucial for accurately assessing muscle fatigue levels. The EMG signal exhibits inherent variability in signal amplitude due to factors such as electrode positioning and individual physiological characteristics. Consequently, comparing EMG data between sessions and subjects becomes challenging without appropriate normalization [20].

In order to address this challenge, a calibration method composed of a sequence of steps has been developed to establish a baseline reference for subsequent measurements. The reference values obtained in calibration will be used to transform the fatigue metrics into a percentage scale relative to each individual's initial state. This normalization approach establishes a standardized metric for evaluating muscle fatigue, enabling meaningful comparisons and accurate monitoring of fatigue.

The most usual method in comparative EMG signal studies is to apply normalization based on the maximum contraction volume. This method involves determining the greatest amplitude of the EMG signal generated during the performance of contractions by applying all possible forces [21]. However, this approach often requires assistance from a physiotherapist or specialized equipment, making it impractical for implementation in home settings, as the Nano Stim project aims to achieve.

Instead, an alternative method will be utilized, involving the average of three contractions performed without any associated weight. These contractions represent the baseline level of electrical muscle activity considered natural or normal during the knee extension movement. The sequence of steps for calibration comprises six intuitive screens within the mobile app, divided into three main processing steps. The terminology "Initial Evaluation" is used instead of "Calibration" to improve the user experience, as illustrated in Figure 6.

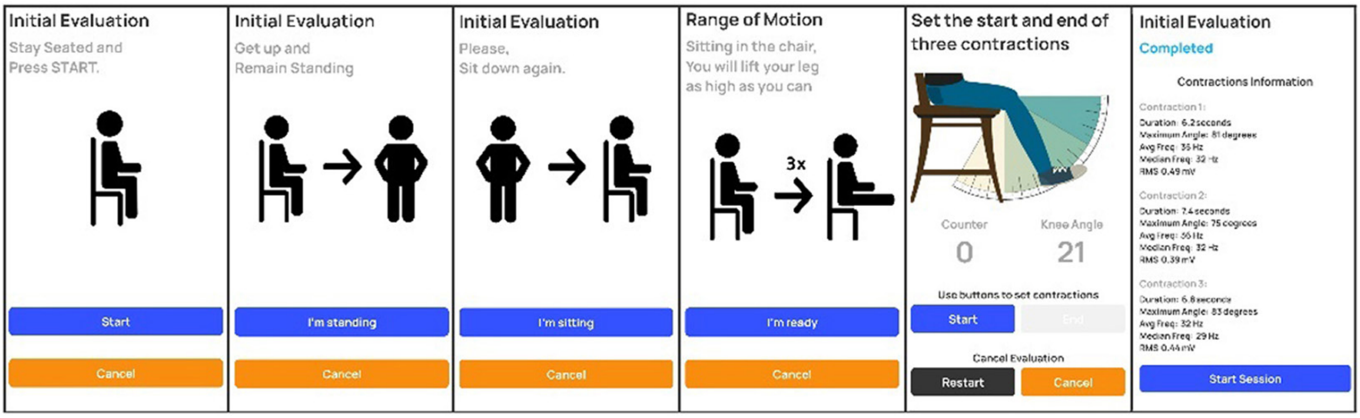

Fig. 6. Screens of the calibration process

1. **Standing evaluation:** The first screen of instructions directs the patient to sit comfortably in a chair, establishing the starting point for the calibration process. The second instruction screen guides the patient to stand up and remain standing. In the first calibration step, the app records the thigh and shin angle to minimize the positioning error of the IMU sensors and saves one second of raw EMG data.
2. **Seated evaluation:** The third screen of instructions asks the patient to sit down again, moving on to the second calibration step. During this step, the mobile app saves the thigh and shin angles from the IMU sensors and records one second of

raw EMG data again. With this, it is possible to understand the knee angle's initial position, which is not usually perpendicular.

3. **Contractions:** The fourth screen of instructions provides information on performing a contraction and knee extension movement. The fifth screen features an interface designed for physiotherapists. It includes intuitive buttons for the physiotherapist to indicate the start and end of each patient's contraction. This information allows the physiotherapist to better understand the patient's full knee extension range. This interface can be adapted without buttons for patient profiles. The unique parameter required is the minimum angle to recognize a contraction, a value that the physiotherapist can predefine. In the final calibration step, the app saves the data for all three contractions, including the duration of each contraction, calculated fatigue metrics, maximum angle reached, and the entire raw data.

Finally, the sixth screen presents the values obtained to the physiotherapist, providing an overview of the calibration results. This screen allows the physiotherapist to assess whether the calibration has been performed correctly and ensures the accuracy of the measurements for the fatigue monitoring system. After each session, processed values and raw calibration data are saved to the cloud. This data can help us to improve the system later and allows for a reassessment of the raw data.

5 EXPERIMENTAL VALIDATION

This section aims to evaluate the performance and effectiveness of the implemented fatigue monitoring method. An experiment with ten healthy subjects was conducted, employing a biofeedback system under the guidance of a physiotherapist to accurately place electrodes on the vastus medialis muscle, ensuring a 2 cm separation between electrodes. This experiment evaluated the system's ability to monitor muscle fatigue during an exercise protocol.

In addition, a comparison will be made between the values obtained in the mobile application and the raw values processed in the cloud. This comparison provides information about the accuracy, reliability, and difficulties of real-time processing.

The exercise protocol consisted of performing the knee extension exercise with 50 contractions. In order to ensure the standardization of the exercise, the subjects were asked to spend two seconds in each phase of the contraction, being two seconds to lift, two seconds sustaining the raised leg, and ending with a downward movement of two seconds, aiming to result in an average duration of six seconds.

The experimental session was conducted under the supervision of a physiotherapist and was approved by the Ethics Committee of the Instituto Politécnico de Bragança (IPB), Portugal (No 504143). The test included the participation of five men and five women researchers from IPB. Only one man did not participate in regular physical activities; all others reported visiting the gym at least four times a week and engaging in leg exercises at least once a week. Table 1 shows the average and standard deviation of participants' anthropometric data.

Table 1. Anthropometric data of the subjects

Sex	Age	IMC	Gym
M	27.0 ± 3.3	24.0 ± 2.7	4x ± 2.3
F	27.4 ± 2.2	24.8 ± 3.6	5x ± 0.4

Generally, the testing sessions lasted around 10 to 15 minutes, with half of this time spent on positioning the equipment on the subject and the other half actually performing the 50 contractions. No subject reported difficulty in performing the exercise, and overall, no significant fatigue was reported.

The graph in Figure 7 displays the subject's knee angle during each of the contractions that were recognized by the developed system. As can be seen, there was variation in the duration of contractions between subjects, with an average of five seconds for each contraction, with an average of two seconds to raise the leg, one second remaining at the top, and two seconds on the way down.

The maximum angle reached was 77° on average across all subjects. It was also noted that the majority of subjects increased the maximum angle reached with each contraction, resulting in the maximum peak between contractions 30 and 40.

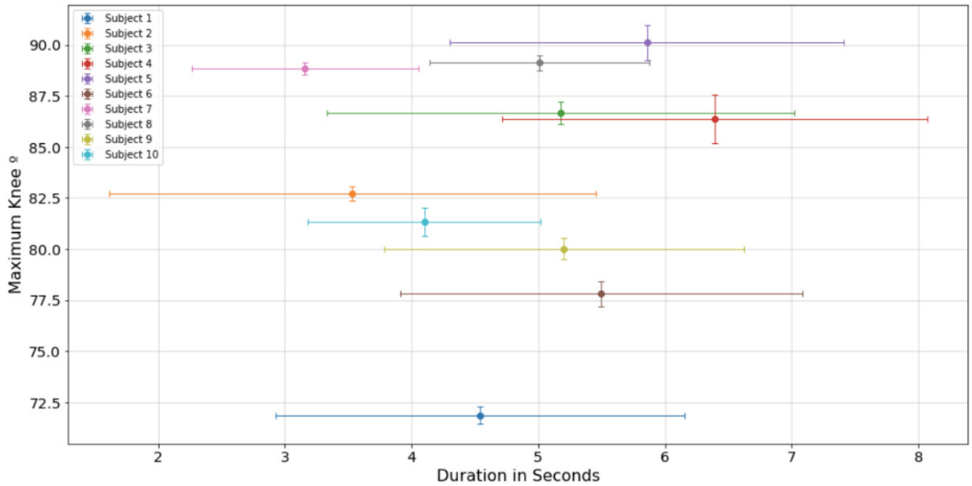

Fig. 7. Knee angle variations between recognized contractions

5.1 Fatigue metrics evaluation

This section presents a statistical analysis of three metrics related to muscle fatigue: *AvgFreq*, *MedFreq*, and *RMS*. These metrics were obtained from the EMG signal derived from the segment identified by recognizing contractions based on knee angle and subsequently calculated as described in section 4.2.

The calibration process described converts these metrics into percentages relative to the initial state of the test, which is crucial for monitoring the session's progression. However, to compare across multiple subjects, the data still needs to be standardized due to variations in EMG signal strength. Thus, the data were normalized as standard deviations from the mean.

Additionally, due to some failures in reading the EMG signal from the wearable system, it was necessary to remove up to 3 contractions from some subjects. Consequently, the reported values represent a moving average with a window size of five across 45 contractions. For subjects without signal discrepancies, the initial 5 data points were excluded. This methodology offers insights into the trend of metric values throughout the session.

Figures 8 and 9 illustrate the trends of metrics related to signal frequency, *AvgFreq* and *MedFreq* for each subject, and the average trend among the entire group. The average trend decreases as contractions progress. Eight out of 10 subjects ended the session with values for these metrics below what they started with.

This decline in frequency indicates a decrease in muscle fiber conduction velocity, which is consistent with the expected physiological response to fatigue. As the participant becomes fatigued, the muscle's ability to generate force decreases, resulting in a slower conduction velocity of the muscle fiber, shifting the signal power spectrum to lower frequencies [16].

In some cases, there was a constancy or even an increase in the *AvgFreq* and *MedFreq* metrics until the half of the session. This can be understood as a period of adaptation to the movement that the subject went through. These results demonstrate similarities with those presented in [12], where *MedFreq* went through several waves with a negative slope until the end of the exercise.

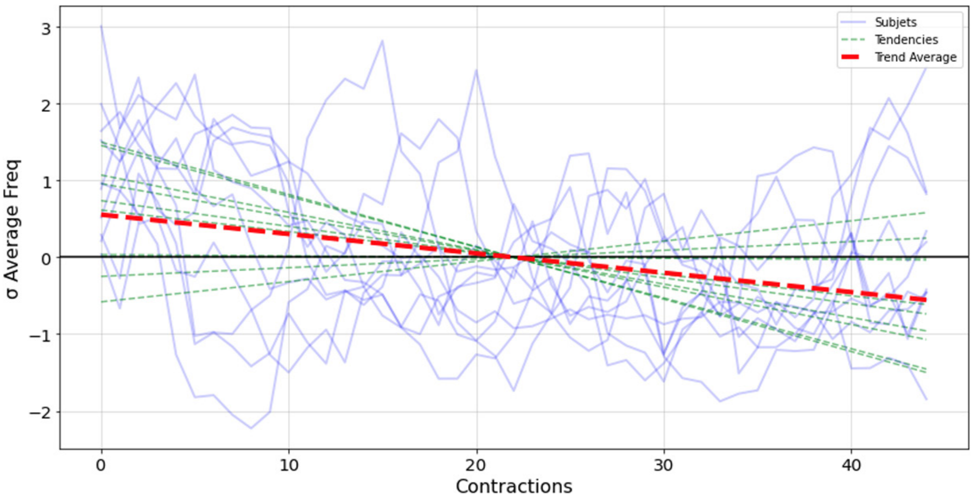

Fig. 8. Trend of the *AvgFreq* metric during the session

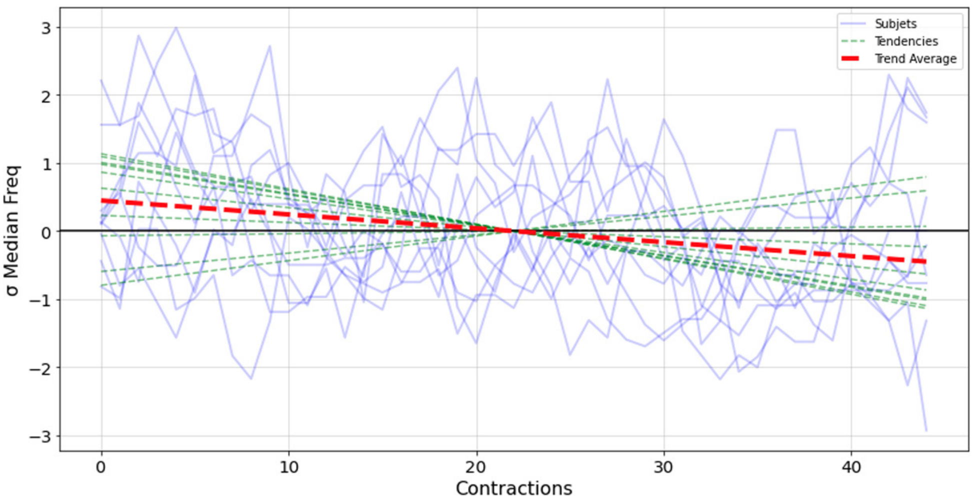

Fig. 9. Trend of the *MedFreq* metric during the session

In contrast to the frequency metrics, the average trend of the *RMS* metric illustrated in Figure 10 does not exhibit a sharp decrease. In general, the predominant behavior was an increase until halfway through the session and then a decrease. This observation suggests that the subject added strength until halfway through the session, potentially adapting to the movement and compensating for the onset of fatigue. Afterward, there are two most likely possibilities. The first is that the *RMS* decreases, indicating fatigue with a lack of ability to generate more force to sustain the movement, as demonstrated by the authors in [22]. The second option is when *RMS* stabilizes or increases, indicating that the subject calmly endured the exercise until the end.

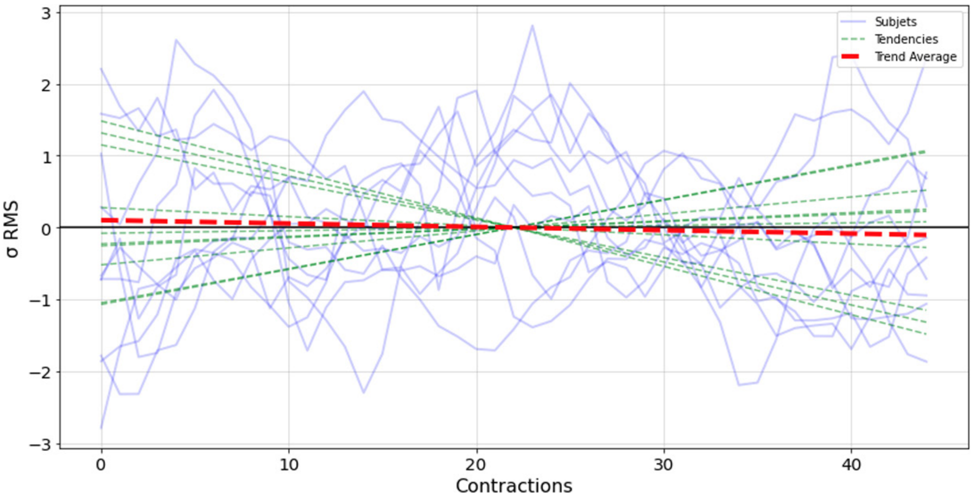

Fig. 10. Trend of the *RMS* metric during the session

The joint analysis of spectrum and amplitude (JASA) is a method that seeks to understand muscular responses by simultaneously considering the *MedFreq* and *RMS* metrics in a Cartesian plane. The JASA method aims to distinguish the changes observed in the EMG signal between the effects of muscle fatigue and variations in muscle force that occurred during exercise [16].

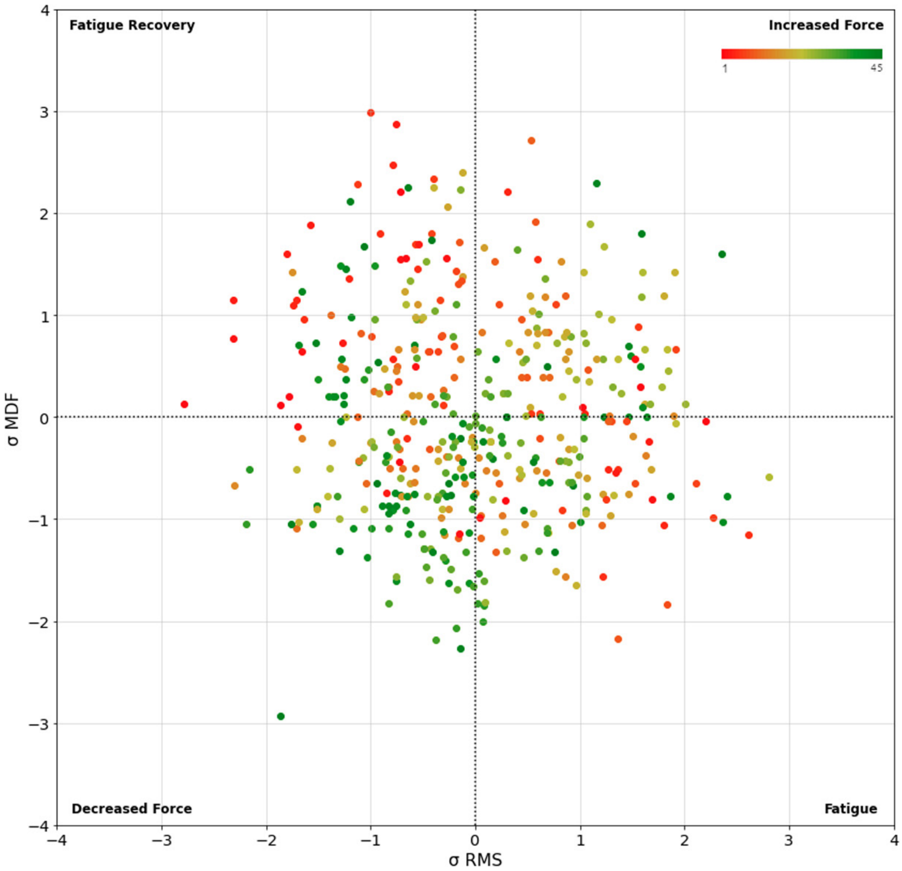

Fig. 11. JASA method apply to experimental test

These quadrants of the Cartesian plane represent different physiological scenarios: the increase in *RMS* and the displacement of *MedFreq* to the right indicate a possible increase in muscular force (Q1); the decrease in *RMS* and the displacement of *MedFreq* to the left suggests a probable reduction in muscular force (Q3); the increase in *RMS* and the shift of *MedFreq* to the left indicate muscle fatigue (Q4); the decrease in *RMS* and the shift of *MedFreq* to the right indicate recovery from previous fatigue (Q2).

Figure 11 illustrates the application of the JASA method to the contractions recognized by the entire group. The dots were colored in a gradient from red to green, indicating the first contractions as redder to the last ones as greener. Thus, it is possible to see that despite the varied start, the average progression of the muscular response during the session was a decrease in force and some cases of fatigue.

This is an expected muscular response for healthy subjects who practice physical activity regularly. Contributing again to an interpretation that there was some challenge at the beginning of the session to adapt to the movement, and then there was a control of force until the end of the session.

Using the chosen fatigue metrics allows a comprehensive assessment of muscle fatigue. While frequency metrics reflect physiological changes associated with fatigue, *RMS* provides information about participant exertion levels. The integration of these metrics improves the understanding of the progression of fatigue and facilitates the identification of different stages of muscle fatigue, as exemplified using the JASA method. Furthermore, other parameters related to muscle fatigue extracted from the EMG sensor can be used, as described in [16], once the data has been properly cut and processed with motion recognition by the inertial measurement units.

It is essential to emphasize that the interpretation of these findings must be the responsibility of the physiotherapist, who has the necessary knowledge about the patient's pathology. It is essential to recognize that different pathologies may present different fatigue behaviors compared to healthy individuals. Therefore, the physiotherapist plays a crucial role in analyzing these metrics and making informed decisions based on understanding the patient's condition.

5.2 Mobile data vs. cloud data

In order to evaluate the consistency and accuracy of the fatigue monitoring method in real-time, this session compares the data processed in the mobile app with the data processed on the computer from the raw data. With this, it is possible to obtain information about the performance and reliability of data processing algorithms.

Two metrics were used to perform the comparative analysis between the systems, namely, mean absolute error (*MAE*) and root mean square error (*RMSE*). These metrics seek to parameterize the difference between the data obtained in each system, interpreted as our error.

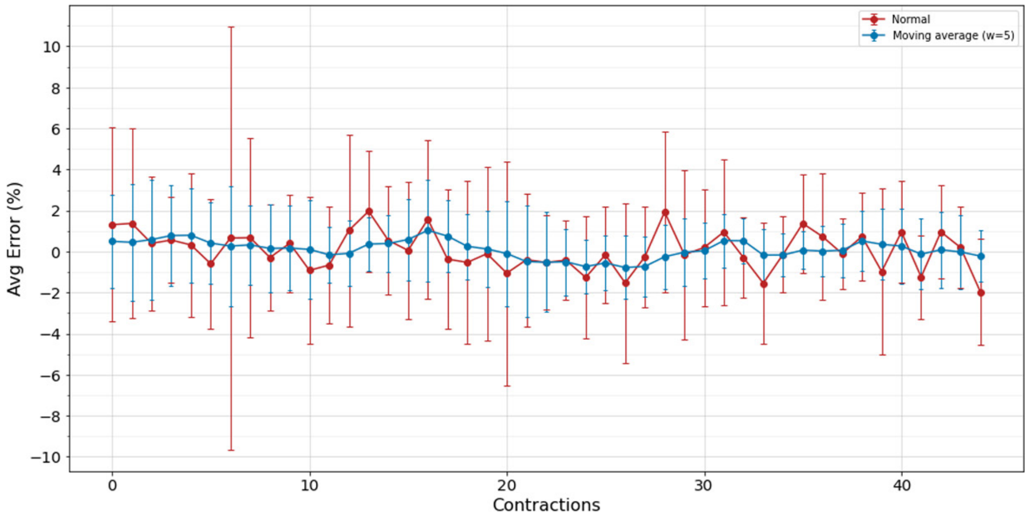

Fig. 12. Comparison between systems of the *AvgFreq* metric

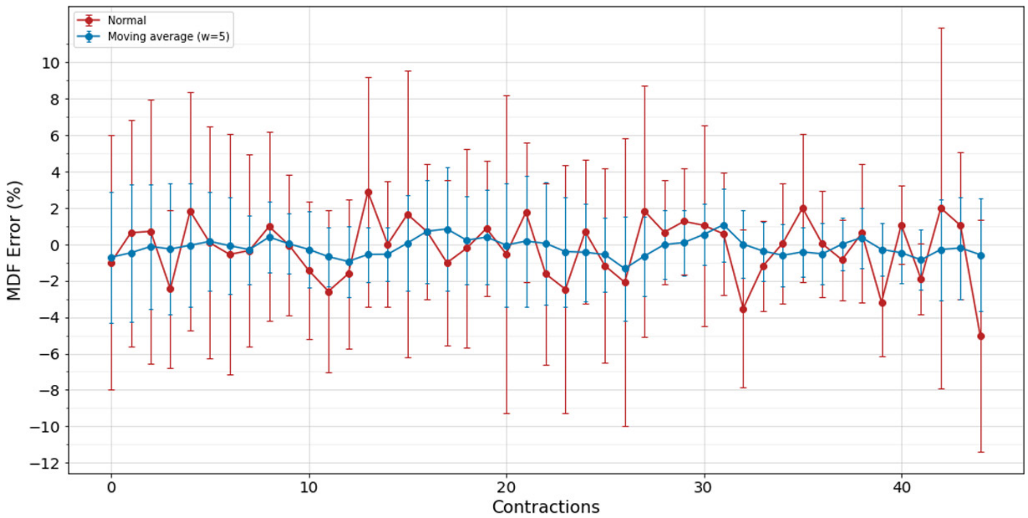

Fig. 13. Comparison between systems of the *MedFreq* metric

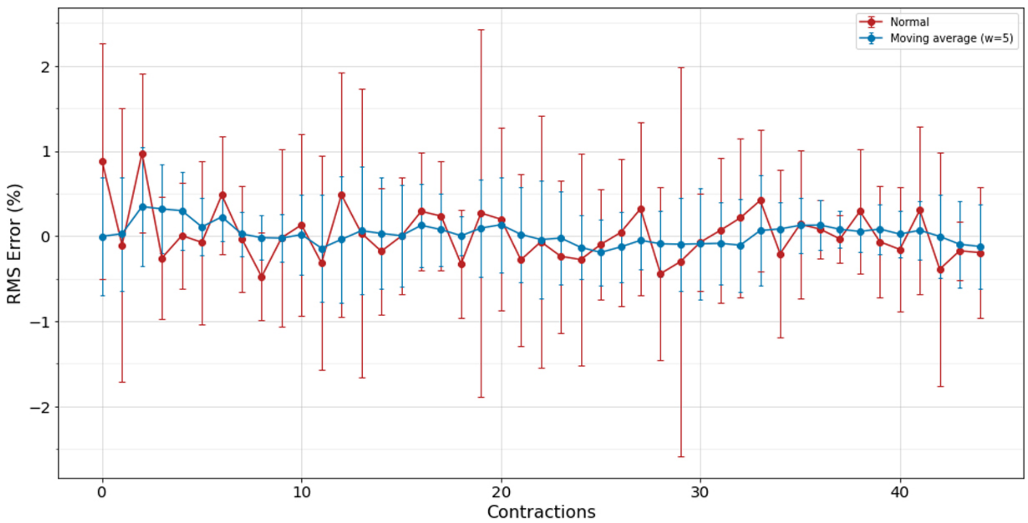

Fig. 14. Comparison between systems of the *RMS* metric

Figures 12, 13, and 14 present comparative charts showing the average error between real-time processing performed by the mobile application and cloud processing for calculating fatigue metrics for all subjects. These charts also provide insights into the average post-application error resulting from the implementation of a moving average with a window size of 5, as previously discussed. The vertical lines associated with each data point in the charts represent the standard deviation calculated across all subjects, allowing a deeper understanding of the data distribution.

From these charts, it is evident that the metrics related to frequency (*AvgFreq* and *MedFreq*) had more errors than the *RMS* metric. The most plausible explanation for the divergence between the systems lies in the calculations related to the transformation of the signal in the frequency spectrum and not in how the sensor data is cut and synchronized. Otherwise, the *RMS* metric would also present average errors similar to *AvgFreq* and *MedFreq*. Also, these calculations were one of the few parts within the mobile system that was not programmed from scratch, especially the Fourier transform algorithm. Given the use of different programming languages in implementing the method, variations such as differing variable precision may contribute to this effect.

While the standard deviation may appear relatively high in some instances, the application of the moving average substantially reduces the values. This demonstrates that there are some points with significant errors that can be suppressed by neighboring data, making the average error low. Furthermore, the emphasis of this system lies in monitoring the oscillation trajectories of metrics associated with muscle fatigue, thereby introducing linearity through aggregated values by the moving average.

Table 2 illustrates the assessment metrics on the fatigue metrics.

Table 2. Assessment metrics on fatigue metrics

Metric	Max	MAE	RMSE
AvgFreq	10.36 ± 6.35	2.61 ± 0.95	3.41 ± 1.38
AvgFreq MA	4.15 ± 1.34	1.46 ± 0.63	1.78 ± 0.71
MedFreq	16.67 ± 4.58	3.5 ± 0.77	5.35 ± 1.16
MedFreq MA	5.9 ± 1.53	1.96 ± 0.33	2.48 ± 0.45
RMS	2.72 ± 1.8	0.69 ± 0.4	0.93 ± 0.55
RMS MA	1 ± 0.54	0.34 ± 0.2	0.43 ± 0.25

Table 2 puts into numbers through the assessment metrics the difference in the application of the moving average with a window of size 5. The values of the frequency metrics *AvgFreq* and *MedFreq* have similar mean errors and standard deviations to each other, with the *AvgFreq* metric having the best precision. The *RMS* metric has a *MAE* of less than 1%; this indicates that the mobile system could execute the proposed method in real-time, similar to the late processing of the raw data in Python.

The application of the moving average managed to improve the *MAE* metric, reducing the average error by more than 40% and the standard deviation by 50%. The *RMSE* metric also has similar improvements to the *MAE* metric. However, in particular, the maximum has the most significant error reduction when applying the moving average, approximately 60% improvement.

In summary, the mobile application has successfully implemented the real-time fatigue monitoring method with some variations. The metric with the highest accuracy in real-time processing was *RMS*, while the metric with the highest deviation was *MedFreq*. Applying the moving average provided considerably smaller errors and could make the system more efficient in monitoring muscle fatigue during knee extension exercises. The mobile app could closely track the trajectory of data processed in the cloud, providing similar insights to the physiotherapist in real-time via the app.

6 CONCLUSION

This article presented a three-step method to monitor fatigue in real-time using a wearable biofeedback system. This method was implemented in a muscle rehabilitation mobile application built to deliver a treatment session remotely. In order to validate the implemented method, an experimental session was carried out with ten healthy subjects and with the help of a physiotherapist. The results show that the mobile app could recognize the movement performed and consistently calculate metrics related to muscle fatigue with similar results presented in the literature.

The collected fatigue metrics can provide valuable information about muscle activity and fatigue during the treatment session, allowing physiotherapists to evaluate and adapt treatment according to individual patient characteristics. The development of the method in the mobile app was important to bring intuitive and simple interfaces to the user. Despite requiring many processes to carry out a session, there was no difficulty on the part of the physiotherapists in using the application, facilitating the realization of the experimental session.

The knee extension exercise was chosen because it is a traditional exercise in the treatment of muscle rehabilitation using electrostimulation. However, it is possible to expand the interpretation of the method to other muscles and any movement. For this, it will be necessary to know the limits to classify the phases of the chosen movement to cut and normalize the EMG signal precisely.

Despite the fact that real-time processing presents some discrepancies in the calculation of fatigue metrics, the mobile app could closely follow the trajectory of the data processed in the cloud. Overall, this fatigue monitoring system demonstrates potential in muscle rehabilitation, offering valuable real-time muscle fatigue information and supporting personalized training and rehabilitation programs. With continued advances and refinements, this technology can significantly contribute to enabling remote rehabilitation treatment, promoting greater well-being, and increasing accessibility.

In future work, the focus is on developing a robust strategy to classify muscle fatigue into distinct levels. One proposed approach involves integrating user-friendly forms into the app, allowing patients to report their subjective levels of fatigue. This integration will facilitate a direct link between the patient's self-reported sensations and the corresponding muscular responses measured by the system, promoting a more comprehensive understanding of the patient's physiological condition.

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