# Advances in Muscle Fatigue Detection: A Comprehensive Review

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***Abstract*** – *Muscle fatigue measurement is crucial in various domains, including occupational health and safety, as muscle fatigue adversely affects cognitive and motor performance, leading to reduced productivity and increased injury risks. Wearable systems offer promising solutions for muscle fatigue monitoring, enabling continuous and long-term assessment of biomedical signals in unattended settings with comfort and non-intrusiveness. These systems facilitate performance optimization, injury prevention, training load management, individualized training programs, rehabilitation, and recovery. Surface electromyography (sEMG) signals are commonly utilized by some systems to extract features and classify muscle fatigue. Additionally, the utilization of goniometers, which are used in kinematic analysis, and other innovative approaches like tissue Doppler imaging, demonstrates promising potential for detecting localized muscle fatigue in wearable devices. This review article explores the challenges and advancements in fatigue monitoring through wearable devices and discusses the diverse applications of these technologies.*

***Keywords***— Muscle fatigue, Detection, Monitoring, Wearable, Non-invasive

## I. INTRODUCTION

Muscle fatigue is a critical aspect to consider in various domains, including sports performance, rehabilitation, and ergonomics. Monitoring and detecting muscle fatigue can provide valuable insights into an individual's physical condition, performance capabilities, and risk of injury. By understanding the dynamics of muscle fatigue, practitioners and researchers can develop effective strategies to optimize training regimens, prevent overexertion, and enhance overall performance.

However, accurately assessing muscle fatigue poses several challenges and limitations. Traditional methods, such as subjective self-reporting or reliance on perceptual cues, have limitations in terms of accuracy and objectivity. Therefore, there is a need for objective and reliable techniques that can quantitatively measure and monitor muscle fatigue. The objective of this review article is to provide a comprehensive overview of the existing research on muscle fatigue detection and highlight recent advancements in the field. By synthesizing the findings from numerous studies, this review aims to shed light on the strengths and weaknesses of different detection methods and identify potential areas for future research and development.

Through this review, we aim to contribute to the understanding of muscle fatigue detection and its implications in sports performance, rehabilitation, and ergonomics. By addressing the current challenges and summarizing the state-of-the-art approaches, this review will serve as a valuable resource for researchers, practitioners, and professionals seeking to enhance fatigue monitoring strategies and optimize performance outcomes in diverse settings. Overall, this review will provide a comprehensive and up-to-date perspective on muscle fatigue detection, offering insights into the existing methodologies, their limitations, and the potential for future advancements in the field.

In this review article, an extensive electronic database search was conducted across platforms including NCBI, ResearchGate, Cambridge Core, IEEE Xplore, Tech Science Press, and PubMed. The aim was to identify pertinent research papers concerning muscle fatigue detection and monitoring through wearable device-based systems. Inclusion criteria involved papers focusing on non-invasive fatigue quantification using wearables, while exclusion criteria encompassed those centred on mental fatigue, drowsiness, or disease-associated fatigue. The selection process involved screening titles and abstracts for relevance to the research topic, followed by a thorough review of potentially relevant full-text articles. Additionally, a snowballing approach was employed by manually examining reference lists of selected articles to uncover supplementary studies.

## II. APPROACHES

### *A. Electromyography (EMG) Approach*

*1) Ayaz et al. (2020):* implemented an Arduino-based fatigue level measurement system using the Root Mean Square (RMS) technique. The study proposes an Arduino-based system utilizing an EMG sensor to measure fatigue levels in muscular activity. The researchers focus on the relationship between BMI and muscle fatigue. They calculate the RMS value of EMG samples and establish thresholds based on BMI classes to determine fatigue levels.

The system focuses specifically on the forearm muscle, and it may be beneficial to expand the coverage to include other major muscle groups for comprehensive fatigue assessment.

BMI is a general measure of body weight and height and may not accurately reflect individual muscle strength or fatigue. Future research should explore more specific measures of muscle composition and fitness levels to enhance the accuracy of fatigue assessments. The proposed fatigue thresholds based on BMI classes may not be universally applicable and can vary among individuals. Future work could investigate personalized threshold determination methods for better accuracy. The study lacks external validation, which is crucial for establishing the reliability and generalizability of the proposed system's results. Future research should include a cost-effectiveness analysis to assess the practicality and feasibility of implementing the proposed system on a larger scale.

The system appears to provide fatigue level measurement based on recorded EMG samples (span of 30 seconds) rather than real-time monitoring. Real-time monitoring would enable continuous assessment of fatigue levels during muscular activity, offering more valuable insights for various applications.

*2) Ma et al. (2018):* They developed a muscle fatigue detection and treatment system driven by the Internet of Things (IoT). This study examines the biceps brachii muscle using EMG transducer electrodes. However, the methodology for detecting fatigue using sEMG is unclear. The study conducted interference tests in different environments to evaluate the system's anti-jamming performance. Like the previous study, the system's focus only on a specific muscle group. The absence of detailed information about the experimental setup, including procedures, experiment duration, and fatigue measurement criteria, hinders the assessment of the system's validity and reliability. The paper lacks a comprehensive analysis of the proposed system's reliability and validity, which is essential to establish its effectiveness. It is also important evaluating the cost-effectiveness of implemented system.

*3) Al-Mulla et al. (2011):* designed an autonomous wearable system for predicting and detecting localized muscle fatigue. The study presents an autonomous wearable system for predicting and detecting localized muscle fatigue. The study utilizes surface electromyography (sEMG) signals and a goniometer to extract features and classify fatigue levels. The system uses a previously developed feature, 1D Spectro, to analyse sEMG signals and classify them into fatigue classes using linear discriminant analysis (LDA). The system was tested on five individuals and showed 90.37% accuracy on average of correct classification and an error of 4.35% in predicting the time to when fatigue will onset.

Similar to previous studies, this system has limited muscle coverage, which restricts its applicability to specific muscle groups. The system may not be accurate for all individuals and may require calibration for each user. Future studies should investigate methods to improve user-specific calibration to enhance the accuracy of fatigue detection.

As in previous studies this also lack a cost-effectiveness analysis. Given the advancements in IoT technologies, future research could explore integrating IoT capabilities into the system to enable real-time data transmission, remote monitoring, and enhanced data analysis for more effective fatigue detection and prediction.

*4) Siwach et al. (2017):* proposed a wearable device for monitoring muscle fatigue. This paper describes a system for real-time monitoring of muscles using an RF module to transmit data wirelessly. The technique used involves observing the average mean between two groups: the first group consists of individuals where no muscle fatigue is observed, while the second group comprises individuals experiencing muscle fatigue. Based on the observed average mean values, a range is set with the lowest value representing muscle fatigue onset and the maximum value indicating the maximum level of fatigue.

The method of determining threshold values based on the average mean between two groups may have limitations. It does not consider individual variations in muscle fatigue onset and progression. Future research should explore alternative approaches to establish personalized threshold values, considering individual characteristics and fatigue patterns. The reliance on data obtained from different groups introduces potential uncertainties and variations. To enhance the reliability and generalizability of the findings, future studies should aim to collect data from a larger and more diverse sample, ensuring representation across different demographics and activity levels. The proposed wearable device for monitoring muscle fatigue should undergo validation against established measurement methods or clinical assessments. This validation process should involve a larger sample size and comparison with reliable fatigue assessment tools. Validating the accuracy and reliability of the device is essential for its acceptance and practical use. Like previous studies, it is important to conduct a cost-effectiveness analysis to evaluate the feasibility of implementing the wearable device on a larger scale. The paper does not specify the extent of muscle coverage provided by the wearable device.

*5) Gehlot et al. (2021):* They conducted real-time monitoring of muscle fatigue using IoT and wearable devices. The study proposes an architecture based on the Internet of Things (IoT) and a wearable device equipped with an EMG sensor for monitoring muscle fatigue. To visualize muscle activity, a LabVIEW-based data logger is implemented as an acquisition system. The rectified amplitude value of the raw EMG signal is analysed using a time-domain feature extraction technique, and the threshold level is determined by calculating the mean RMS value. The study concludes three fatigue conditions based on the threshold values: >2 V for extensive fatigue, 1–2 V for moderate fatigue, and <1 V for relaxed fatigue. Additionally, the total power consumption of the device is calculated and analysed.

Table 1. Power Consumption Analysis

| Component | Power Consumption |
|---|---|
| Arduino UNO | 40 mA*5v |
| EMG Sensor | 46 mA*9v |
| Total power consumption | 614 mW |

Source: Gehlot et al. (2021)

The study acknowledges the limitation of limited muscle coverage. It is essential to consider a broader range of muscles to obtain a comprehensive assessment of muscle fatigue. The study utilizes a cloud server for data storage and analysis. However, the reliability and stability of the cloud server are potential concerns. Future studies should address issues related to data security, server uptime, and the potential impact of server downtime on real-time monitoring and analysis. Implementing backup systems or exploring alternative data storage and analysis methods could improve the overall reliability of the system.
The cost-effectiveness and accessibility of the proposed IoT-based wearable device should be evaluated.

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*B. Goniometer Approach*

Al-Mulla et al. (2011) designed an autonomous wearable system for predicting and detecting localized muscle fatigue. The study introduces a goniometer as part of the system to enhance the prediction and detection of localized muscle fatigue. Along with surface electromyography (sEMG) signals, the goniometer measures two main kinematic criteria: elbow angle and arm oscillation. These criteria serve as inputs to a fuzzy classifier, which automates the classification process.

Table 2. Fuzzy Classification

| Rules | IF Input 1 (Elbow Angle) | IF Input 2 (Angle Oscillation) | THEN Output |
|---|---|---|---|
| 1 | Non-Fatigue | Low | Non-Fatigue |
| 2 | Non-Fatigue | High | Transition-to-Fatigue |
| 3 | Transition-to-Fatigue | Low | Transition-to-Fatigue |
| 4 | Transition-to-Fatigue | High | Transition-to-Fatigue |
| 5 | Fatigue | Low | Fatigue |
| 6 | Fatigue | High | Fatigue |

Source: Al-Mulla et al. (2011)

*C. Tissue Doppler Imaging Approach*

Majdi et al. (2022) developed a wearable monitor for detecting local muscle fatigue during electrical muscle stimulation (EMS) using tissue Doppler imaging (TDI). The study was based on two hypotheses. The first hypothesis suggests that TDI is sensitive to the mechanical indicators of muscle fatigue during EMS and has the potential to provide real-time monitoring of muscle fatigue and recovery. The second hypothesis proposes that changes in muscle tissue velocities would be associated with increases in isometric muscle torque during fatigue recovery. The study provides a comprehensive description of the experimental setup, protocol, data analysis, and static analysis, among other aspects. Statistical analyses were conducted using JASP Version 0.16 (JASP Team, Amsterdam, NL) and SPSS Version 27.0 (IBM Corp., Armonk, NY), with significance defined a priori as $p < .05$.

Supporting the first hypothesis, the study revealed significant changes in the average tissue velocity waveforms during stimulated muscle twitches after the fatiguing EMS protocol. This finding indicates that TDI can capture alterations in muscle mechanics associated with fatigue during EMS. In support of the second hypothesis, the study demonstrated that features extracted from the average muscle tissue velocity waveforms during muscle twitches could predict changes in isometric ankle torque. This suggests a relationship between muscle tissue velocities and changes in muscle strength during the recovery phase of fatigue. While the study successfully assessed muscle fatigue during Electrical Muscle Stimulation (EMS) using a 2-

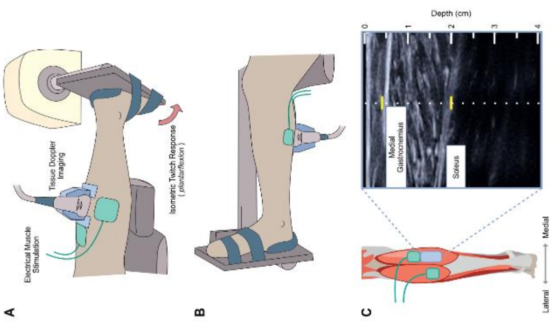


Figure 1. TDI experimental setup

Source: Majdi et al. (2022)

minute rest period with measurements taken at 20-second intervals, future research should explore shorter time windows (less than 20 seconds) and longer recovery periods (more than 2 minutes). The study focused on the net torque generated at the ankle joint by the two heads of the gastrocnemius muscle, primarily examining the medial gastrocnemius. To gain a deeper understanding of muscle fatigue mechanisms, future studies should decompose the individual contributions of multiple muscles involved in generating torque. Although the study employed analysis methods to mitigate potential positioning effects, it did not specifically analyse the impact of subject positioning (prone vs. seated) on muscle fatigue assessments. Future research should compare results from different subject positions and consider positioning as a factor in the analysis. Muscle fatigue involves various central and peripheral mechanisms, and the observed changes in ankle torque may be influenced by additional underlying factors. Future research should explore and identify these factors to gain a comprehensive understanding of muscle fatigue and its determinants.

The Tissue Doppler Imaging (TDI) method used in the study estimates the axial component of tissue velocity, while muscle shortening primarily occurs along the fibre direction. Considering the complexity introduced by changing pennation angles during muscle contraction, future research could explore advanced imaging techniques or alternative methods to estimate more accurately shortening velocity during muscle contraction. The observed relationship between axial velocity and torque during muscle fatigue was not found to be dependent on the initial pennation angle at rest. To further comprehend the underlying mechanisms, future research could investigate and quantify the relationship between velocity and torque during muscle fatigue.

*D. Comparison of results*

Ultrasound has gained attention in the field of Electrical Muscle Stimulation (EMS) due to its compatibility with EMS applications, which are not well-suited for the gold standard, surface electromyography (sEMG).

However, it is important to note that ultrasound is not limited to EMS applications alone. The velocity and anatomical information provided by ultrasound are independent of and complementary to the electrophysiology information obtained from sEMG. This versatility implies that ultrasound can be used alongside or as an alternative to sEMG. Unlike sEMG, ultrasound measurements are depth-resolved, allowing identification of specific muscles and their depths. A significant limitation of the proposed systems in the reviewed studies is the limited muscle coverage they provide. In future research, it would be beneficial to utilize methods such as multi-channel sEMG sensors that can cover crucial muscles throughout the body. Furthermore, except for Gehlot et al. (2021), none of the studies included a power consumption analysis or a cost-effectiveness analysis. Additionally, ethical consent from participants was explicitly mentioned only in two studies, and most of the research was conducted in a laboratory environment.

## III. DISCUSSION

The reviewed literature highlights the potential of Tissue Doppler Imaging (TDI) in monitoring muscle fatigue during Electrical Muscle Stimulation (EMS). This presents unique opportunities in the fields of biomechanics, rehabilitation, and sports performance. TDI provides valuable insights into the mechanical signs of muscle fatigue, offering real-time monitoring capabilities and the potential for assessing muscle fatigue and recovery dynamics.

Spectral Moments capture higher-order statistical moments of the sEMG power spectrum, offering a different perspective on muscle fatigue. Wavelet Transform and Time-Frequency Analysis techniques allow for a more detailed analysis of the time-varying frequency components associated with fatigue. Nonlinear analysis techniques delve into the complex dynamics of muscle fatigue by exploring entropy, fractal dimension, and other nonlinear features. Incorporating these alternative methods into muscle fatigue detection can lead to a more comprehensive understanding of the phenomenon.

While the reviewed studies predominantly focused on the sEMG method, it is important to recognize the strengths and weaknesses of different detection methods. Each method may have its own limitations, such as sensitivity to noise, dependency on signal quality, or the need for specific equipment and expertise. In addition, future research should aim to identify and understand additional factors that contribute to muscle fatigue. Muscle fatigue is a complex process involving various central and peripheral mechanisms. Exploring these underlying factors can contribute to a more comprehensive understanding of muscle fatigue and its determinants.

It is worth noting that the use of nano sensors and modified electrodes employing nanotechnology holds promise in

enhancing the reliability of data acquired from sensors. Future studies could explore the incorporation of advanced nano sensors and modified electrodes to improve the accuracy and reliability of muscle fatigue detection systems.

Nanotechnology-based approaches could potentially offer enhanced sensitivity, precision, higher signal-to-noise ratio, and miniaturization of sensors, allowing for more precise measurements and reducing interference from external factors. By leveraging nanotechnology, researchers can develop sensors that provide more accurate and dependable.

data, leading to more robust muscle fatigue assessments.

The integration of machine learning and artificial intelligence (AI) techniques holds significant potential in advancing muscle fatigue detection and monitoring. By training algorithms on large datasets AI models can learn complex patterns and relationships that may not be apparent through traditional analysis methods. Additionally, AI-powered systems can adapt and self-improve over time, enhancing their capabilities to recognize subtle fatigue indicators and adapt to individual variations.

The implications and applications of muscle fatigue detection extend beyond research settings and have significant relevance in sports, healthcare, and occupational domains. In sports, monitoring muscle fatigue can aid in optimizing training programs, preventing overuse injuries, and enhancing performance. By tracking muscle fatigue levels in athletes, coaches and trainers can make informed decisions regarding training load, recovery strategies, and injury prevention protocols. Additionally, real-time monitoring of muscle fatigue during sports activities can provide valuable feedback for athletes, enabling them to optimize their performance and avoid reaching a point of detrimental fatigue.

Table 3. Overview of Studies Investigating Muscle Fatigue

The rationale for favouring the TDI method over sEMG

| Study done by | Type of study | Ethical Aspect | Participants | Target Muscle type | Sensor Used | Fatiguing Task | Experimental Setup/Apparatus |
|---|---|---|---|---|---|---|---|
| Ayaz et al. (2020) | Lab | Not mentioned | 46 participants (32 of them are underweight participants and 14 of them are overweight participants.) | Forearm body muscle | sEMG | Positions of Arm in order of (a) Open hand, (b) Closed fist and (c) Closed fist inward | Not mentioned |
| Ma et al. (2018) | Both indoor and out door | Not mentioned | 10 men in each group, 100 men in total, no participants reported any musculoskeletal or neurological diseases | Biceps brachii muscle | sEMG | Holding a 1.5 kg dumbbell | Not mentioned |
| Al-Mulla et al. (2011) | Lab | Approved | five male athletics, healthy subjects (mean age 28 +/– 2.5 year), all non-smokers | Bicep muscle | sEMG + Goniometer | Static biceps curl activity | Preacher biceps curl machine, An embedded platform called SunSPOT |
| Siwach et al. (2017) | Lab | Not mentioned | Unclear | Unclear | sEMG | Not mentioned | LabView |
| Gehlot et al. (2021) | Lab | Not mentioned | 6 Participants | Biceps brachii | sEMG | Not mentioned | Matlab (Initially) LabView (Later on) |
| Majdi et al. (2022) | Lab | Approved | 13 participants (9 male, 4 female) | Gastrocnemius muscle | Ultrasound | Electrical stimulation | Biodex II dynamometer retrofitted with a Humac interface. LabView |

and Goniometer approaches in muscle fatigue measurement hinges on the utilization of numerical indices.

These indices offer quantifiable measurements that permit cross-method comparisons. However, since other approaches lack these numerical indices in their studies, asserting the dominance of the TDI approach is not conclusive. To ensure a balanced evaluation, it's essential to identify numerical indices for those other methods.

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## IV. CONCLUSION

In conclusion, the reviewed literature underscores the potential of TDI and alternative methods for muscle fatigue detection. The integration of advanced technologies, such as nano sensors and modified electrodes, holds promise for improving the accuracy and reliability of fatigue detection systems. Future research should focus on exploring shorter time windows, decomposing individual muscle contributions, analysing the impact of subject positioning, investigating additional factors influencing muscle fatigue, and exploring different stimulation patterns and protocols. These advancements will enhance our understanding of muscle fatigue dynamics and contribute to the development of more effective and practical muscle fatigue detection methods. The implications and applications of muscle fatigue detection in sports, healthcare, and occupational settings are substantial, providing opportunities for optimizing performance, rehabilitation, and occupational health and safety.

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