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Localized Muscle Fatigue Prediction and Detection Using Surface Electromyography: A Review Study

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A B S T R A C T

Detection of muscle fatigue is present in many fields, from the training of athletes and the aid in rehabilitation to the control of prosthetics. It can be considered ongoing research aiming to understand the human body and aid in protecting it. Fatigue itself can't be measured directly but can be detected through other means, for example, electromyography, more specifically surface electromyography (sEMG), which is considered a noninvasive and easy-to-use tool. There are various studies on sEMG and its use in detecting muscle fatigue. This study presents a closer look at the application of sEMG in muscle fatigue detection, as well as the specifications required when dealing with it, such as muscle signal preprocessing, analysis methods, and post-processing, including feature extraction. This research serves as a simple guide for individuals that are new to this topic, enabling them to have a comprehensive view about it.

1. Introduction

A central topic of interest for researchers since the beginning of mankind is the understanding of the human body and how it functions, especially internally. Fatigue, specifically muscle fatigue, can be considered one of those interests [1]. In medicine and sports, muscle fatigue is defined as the inability of the muscle to produce the force required to maintain specific tasks [2]. The detection of muscle fatigue can aid in stabilizing prosthetics [3], preventing major injuries for athletes as the leading cause of injuries is fatiguing overtraining [2], and aiding in rehabilitation protocol design [4].

Muscle fatigue detection is aligned with six of the 17 sustainable development goals (SDGs), which is another major reason for it being studied. The goals are "No Poverty," "Zero Hunger," "Good Health and Well-Being," "Quality Education, “and Reduced Inequalities." [5]. Early detection of muscle fatigue decreases injuries, which in turn maintains people's health, productivity, and jobs, resulting in increased efficiency and reduced poverty. For example, in the case of rehabilitation patients, it reduces physical injuries, resulting in a higher recovery rate. Another case for students is the addition of user-friendly fatigue detection devices and implanting them in learning facilities to teach them the importance of the human body and how to deal effectively with it, as well as encourage self-care, thereby encouraging them to stay in good health. Finally, the creation of cost-effective fatigue detection systems that are affordable and accessible to underserved communities, promoting equitable health care.

Muscle fatigue generally falls into two categories: perceived and performance [6]. Perceived fatigue is caused by one's physiological state, mode, and motivation, as well as the hypothalamus’s regulation of the central nervous system, whereas performance fatigue is caused by peripheral factors from the fatigued muscles or central factors from the nervous system [7]. The peripheral fatigue can be detected by monitoring the changes in the muscle signals. Muscle fatigue can’t be measured directly, but through the utilization of certain variables and metrics, one way to obtain these metrics is by the use of surface electromyography [8]. Surface electromyogram (sEMG) is a device that measures the electrical signal generated from body muscles as they contract; it is simply a very sensitive voltmeter put together with amplifiers, filters, and rectifiers [9].

1.1 Muscle signal generation

There are three different types of muscles in the human body; one of them is skeletal muscle, which is voluntarily controlled, and fatigue can be localized in [10]. Skeletal muscles are responsible for body movements. They are attached to the bone by tendons and consist of multiple fascicles that in turn include countless muscle fibers [11] (see Fig. 1).

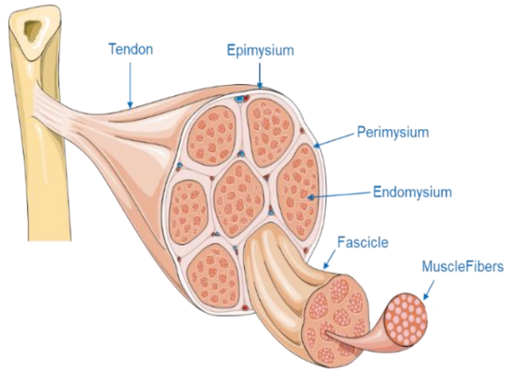

Fig. 1. Muscle anatomy [12].

The contraction of the muscle is done by electric stimuli generated from the general nervous system. The stimulus travels to the muscle fibers via a nerve called motor neurons. This motor neuron inserts into the muscle cells along with blood vessels to the fibers. Every motor neuron, along with the muscle fibers attached to it, is called a motor unit [2]. The excitation of one motor unit generates the motor unit action potential (MUAP), which is the source of the SEMG signal; a motor unit that contains more muscle fibers produces higher MUAP and vice versa [13]. The sEMG reads the summation of all the MUAPs (see Fig. 2).

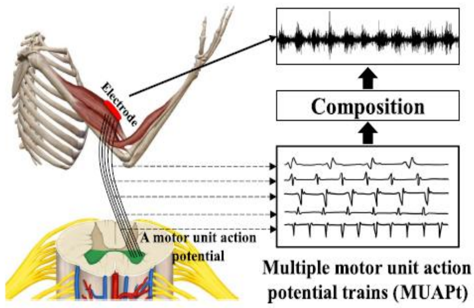

Fig. 2. sEMG signal generation [8].

1.2 sEMG signal preprocessing

The sEMG signal typically gets filtered, rectified, and segmented before its analysis. [14].

The filtration of the sEMG signal is done to get rid of noise that comes from various factors, including surrounding noise, electrocardiographic (ECG) artifacts, motion artifacts, and others [15]. Since the sEMG frequency signal ranges between 10-500 Hz and is dominant around 50-150 Hz [16], bandpass filters with a cutoff at 20-500 are usually used [14]. Rectification is done to get rid of the negative part of the signal; it is either full wave or half wave [9]. The signal segmentation is performed with a temporal window, which typically has a length of 150-200 ms [7]. The window scans the signal and split it into segments, each handled individually. There are two types of windowing methods: adjacent and overlapping [17].

1.3 Feature extraction

After the segmentation, the signal is then analyzed, and its features are extracted. There are three types of analysis: time, frequency, and time-frequency domain analysis [18]. The time domain features have lower complexity than frequency domain features as they depend on the amplitude of the signal and its relation with time, whereas frequency domain features are harder to compute as the signal needs to be transformed to the frequency domain using methods like fast Fourier transform [19]. Lastly, the time-frequency presents information about the signal using a joint analysis of time and frequency, which gives varying non-stationary details of the signal [20]. Some of the time and frequency domain features can be seen in Table 1 along with the definition for each feature. The comparison of sEMG features across individuals other than the resting baseline condition should be done with caution, as there are varying elements that can change and affect them, like muscle resting length, muscle mass, age, gender, and other conditions [21]. The solution to this problem is the normalization of the signal. There are various techniques used to normalize the signal; the most common is maximum voluntary contraction (MVC) [22]. In this method, the individuals are asked to perform contractions in their targeted muscle group with maximal effort several times with specific timings between them; the highest level is recorded as a baseline, and the others are expressed as percentages, e.g., 20% of MVC, 50% of MVC [23].

Table 1. sEMG signal features [16],[17],[19],[24],[25].

Domain	Features	Abbreviation	Definition
Time	Root Mean Square	RMS	Gives the root of the mean square of the signal for a given time window.
	Integrated EMG	iEMG	Gives the integral of the absolute value of the signal for a given time window.
	Zero Crossing	ZC	Gives how many time the signal crossed the x-axis for a given time window.
	Waveform Length	WL	Gives a measure of the signal complexity or the cumulative length for a given time window.
	Variance	VAR	Gives how much the signal points deviate from the mean for a given time window.
	Mean Absolute Value	MAV	Gives the mean absolute value of the signal for a given time window.
	Willison Amplitude	WAMP	Gives the amount of times that the signal amplitude exceeds a threshold for a given time window.
Frequency	Mean Frequency	MNF	Gives the average frequency of the frequency components of the signal for a given time window.
	Median Frequency	MDF	Gives the frequency in which the sEMG power spectrum is divided into two regions with equal amplitude for a given time window.
	Peak Frequency	PK	Refers to the highest point in the signal for a given time window.
	Median Power Frequency	MPF	Gives the average frequency based on power distribution across frequencies for a given time window.
	Normalized Spectral Moment	NSM	A measure of how many times significant spikes occur in the signal for a given time window.
	Normalized Root Mean Square	NRMS	Gives the normalized RMS value of the signal for a given time window.
	Mean Power	MP	The average power of the signal for a given time window.
Time And Frequency	Wavelet Transform	WT	Analyze the signal by splitting it down into multiple frequency components using localized time information.
	Short-Time Fourier Transform	STFT	Analyzes the signal in both time and frequency domains during short, overlapping intervals.
	Continuous Wavelet Transform	CWT	A type of wavelet transform that generates a continuous representation of the signal.

	Empirical Mode Decomposition	EMD	A method for breaking a signal into several parts called intrinsic mode functions.

1.4 Feature analyzing

After the analysis of the sEMG signal, the features are further analyzed to select the best feature suitable for research being conducted. The selection is either statistical, like the use of Analysis of Variance (ANOVA) [26] and Higher-order statistics (HOS) [19], or by the use of artificial intelligence (AI) [27]. In ANOVA, the basic idea is to compare the data variance in response to another; the result is mostly shown as a p-value, where if it is less than 0.05, then there is a significant difference between the group's means [28].In AI there are various algorithms used for multiple purposes; one of them is machine learning (ML), which includes supervised and unsupervised approaches and deep learning [27]. In ML supervised learning, there are classifiers that learn and respond based on entered data and labeled outcomes. For example, after entering the sEMG features that are labeled as fatigue, the classifiers learn it and can predict new cases that have similar features (e.g., classifying the entered features that have similar values to what they learned as fatigue to fatigue condition) [17]. The classifier prediction accuracy depends entirely on the entered data, as the accuracy might increase or decrease by deleting a specific feature or adding it [29]. On the other hand, ML unsupervised learning algorithms train on unlabeled data [27]. Another subset of ML is deep learning (DL) [30]. DL models consist of multiple layers of neurons designed to process data in its raw form, requiring only labeling (e.g., categorizing the input signal as either a fatigue signal or a non-fatigue signal). [31]. The handling of raw sEMG signals with DL is done by converting them to an image or dealing with them as a sequence [32][33].

1.5 Electrodes placement

Two types of electrodes are commonly used in sEMG acquisition: wet and dry electrodes. Dry electrodes consist mainly of fabric and are reusable, whereas wet electrodes are disposable. Wet electrodes, commonly utilized with sEMG, are composed of metal alloys such as Ag/AgCl and gold/gold chloride [34].

There are three types of electrode montages: monopolar, bipolar, and multipolar, which are generally used with sEMG signal acquisition. The monopolar measures the possible difference between a reference neutral site and a measuring site. Bipolar is mostly used in simple and repeated operations and can help to lower common mode noise. Lastly the multipolar setup is ideal for complex motions or monitoring several muscles, as it provides detailed information about the MUAP [7]. Surface Electromyography for the non-invasive evaluation of muscle activity or SENIAM, is European standard recommendations [9] in electrode placement. The chosen muscle locations for measurement have to be superficial, so their signals do not interact with those of surrounding muscles.

2. Previous Studies

There is a great number of research studies present in the literature bout muscle fatigue:

In 2015, Marri et al. employed multifractional features along with machine learning classifiers to classify sEMG signals as fatigue and non-fatigue conditions. Multifractional is a mathematical concept that describes a complex type of signal. To describe a signal by this concept, the signal must be in non-integer dimensions and have repeated characteristics like sEMG signals. In their research, they analyzed the signal of 26 volunteers after they performed a dynamic contraction dumbbell curl, which affects the biceps brachii muscle. They extracted 8 features, 4 of which are standard when using multifractional and 4 that they derived from the first 4; namely, maximum exponent (HEMAX), minimum exponent (HEMIN), Hurst exponent (HE2), degree of multifractality (DOM), the average square of extreme generalized exponents (HIX), mean sum of Hurst exponent (MHE), mean Hurst exponent order (MEX), and Hurst exponent at negative order 2 (HI2). They found that the difference in the multifractional characteristic of the sEMG signal differs in muscles in the non-fatigue and fatigue conditions, increasing the classification accuracy of the ML classifiers, as there appear to be distinct burst patterns in sEMG signal amplitude. Their research can assist in refining classification methods in terms of accuracy and applicability [35].

In 2016, Tosovic et al. investigated the effect of accumulated fatigue on muscle ability to contract in the long term. In their research, they used sEMG and mechanomyography (MMG) to record signals from 11 participants while doing weight lifting using the biceps brachii muscle for 13 days. The MMG result was taken using electrically evoked muscle contractions in both arms at the start and the end of exercise, while the EMG recordings were taken from the non-dominant arm in between as they performed dynamic contractions. Results from both devices were taken simultaneously during the same testing sessions. For analysis, they measured the MPF for the signal before and after the fatigue condition. They found that there is a decline in MPF and MVC for the participants after each session; also, the numbers of lift repetitions dropped by 59.6% from their first day. Their research showcases the importance of having a tool to measure accumulated muscle fatigue that can later on aid in the prediction and prevention of injuries in athletes and safeguard their health [36].

In 2016, Hwang et al. suggested to use integration to predict muscle fatigue from EMG signals for continuous isokinetic activity. Using isokinetic exercise dumbbell curls at 20%, 35%, 50%, and 75% MVC levels, they examined the cumulative exhaustion for biceps muscle for 15 people. In their analysis, they used iEMG and MNF; they calculated the mean iEMG by dividing the integrated iEMG by cycle time. Their result showed that when a muscle is fatigued, the MNF value approaches 60% of the initial MNF, and the mean IEMG value is saturated to a specific value regardless of MVC levels except for the overload condition (75% MVC). They used the mean IEMG value and mean frequency values to create a global EMG index map and study their correlations with muscle exhaustion and force. their result showed that, the global EMG index map can be used to predict muscle fatigue and force from EMG data by combining IEMG and MNF [37].

In 2016, Panahi et al. employed sEMG to assess muscle fatigue for surgeons as they performed surgery in which they analyzed it using the data using recurrence quantification analysis (RQA). In their research, they collected the EMG signals off four bilateral muscles from five surgeons as they performed fifteen various laparoscopic operations. They found that the fatigues appeared more obvious in the trapezius and deltoid muscles and contributed to their roles in maintaining posture and moving instruments during surgery [38].

In 2017, Lobo-Prat et al. detected the sEMG signals of a Duchenne muscular dystrophy (DMD) patient in the last stage of the disease. In their research, they took the signal from a single DMD patient as he performed maximal and submaximal isometric contraction using biceps and triceps muscles. For analysis, they used the obtained signal RMS value to compute a co-activation ratio (CAR) of both muscles and a signal-to-noise ratio (SNR). Their result showed that the DMD patient signal is 100 times lower than a healthy individual's, and it is still measurable and controllable by the individual. [39].

In 2017 Zhang et al. combined two approaches to classify limb motion using WT along with Singular Value Decomposition (SVD). SVD is a mathematical technique that factorizes matrices. They used a pre-collected dataset from the University of Technology Sydney that consists of 14 healthy untrained subjects that performed three exercise programs associated with the knee joint. For analysis, along with WT and SVD, they extracted the following time and frequency domain features: MAV, RMS, IEMG, ZC, MNF, and MDF. Their results showed that when compared to their combination with other time and frequency domain characteristics, WL and SVD by themselves provide greater precision in detecting the motion of the lower limbs [40].

In 2017, T. Nourhan et al. investigated the effectiveness of detecting upper limb fatigue using Myoware, a low-cost sEMG instrument. In their study, they examined the signal from three participants' upper limb muscles during dynamic contraction. They classified the signal into fatigue and non-fatigue states using DL algorithms, and they used RMS and MDF for analysis. Their findings suggest that Myoware is useful for detecting and categorizing fatigue [41].

In 2018, Kuthea et al. proposed a method to measure muscle strength during fatigue in both trained and untrained subjects, which they then used their findings in clinical environments in rehabilitation programs for lower limbs impairments patients. In their research, they measured the isometric contraction of biceps brachii signals from 28 trained and untrained volunteers at 50%, 75%, and 100% of their MVC. For analysis, they used RMS and MDF along with CWT. A statistical test was used to compare the changes in muscle force with RMS and MDF for two groups (trained and untrained volunteers). Then they used a slope of regression of MDF, which is a slope that represents changes in a variable in response to another, to indicate muscle fatigue. Their result shows that the trained subjects can sustain a contraction for a longer period as compared with untrained subjects and are less prone to fatigue. And there is a significant difference between them in the MDF slope. They implanted their findings clinically on total knee replacement patients as they designed rehabilitation protocols depending on their research findings. They found that the muscle strength of the patient improved significantly after performing the rehabilitation program daily. Their research contributes to the understanding of muscles with a live example of measuring a group of muscles and using the result on another group of muscles and proving its effectiveness [4].

In 2019, Jebelli et al. investigated the accuracy of wearable sEMG in detecting workers' fatigue. In their research, they recorded the sEMG signals from the bicep and shoulder muscles for 8 volunteers as they performed dynamic contraction lifting weights. For the analysis, they extracted MAV, RMS, MDF, and MNF. Their result showed that higher muscle fatigue levels lead to higher MAV and RMS values and lower MNF and MDF values [42].

In 2019, Chen et al. developed a continuous sEMG signal-monitoring DL model that records and analyzes the signals from the three-dimensional movements of the upper limb muscles. In their research, they recorded the signals from 7 participants while they performed The three tasks: shoulder abduction, shoulder forward flexion, and finger-nose. The signal was collected from 7 muscles: the brachioradialis muscle, biceps brachialis, triceps brachialis, posterior deltoid, middle deltoid, anterior deltoid, and pectoralis major. In their analysis, they employed RMS, VAR, MAV, and WL; they then compared their proposed DL model accuracy with another commonly used model. Their result indicated that their model has higher accuracy for estimating the angular motion of the upper limb. It has the potential to be applied in rehabilitation robots [43].

In 2019 Liu et al. developed a wearable, continuous, and real-time sEMG signal monitoring and analyzing patch of sEMG signal during exercises in the lower limbs. In their research, they measured the signals from lower limb muscles from 20 participants during cycling on a bike. For the analysis, they extracted MNF and MDF and used Empirical Mode Decomposition (EMD), which is a data-driven technique used to analyze non-linear and non-stationary signals. It splits a signal into a group of intrinsic mode functions, each representing different frequencies of the original signal [44].

In 2019, Papakostas et al. suggested combining subjective user feedback with physical sEMG signal monitoring to enhance machine learning's ability to classify upper limb fatigue. Ten individual upper limb signals were collected during shoulder flexion, shoulder abduction, and elbow extension during the course of their study. They employed the mean, SD, maximum, and minimum values of the time domain within a given frame for the analysis. The spectral values of MIN, MAX, SD, and MEAN were also included. Finally, they took into account variables like Willson amplitude (WAMP), energy entropy (EE), ZC, spectral entropy (SE), and spectral flux (SF). To identify fatigue, they used several types of popular ML classifiers, evaluating the accuracy of each before and after using their suggested technique. Their result showed that their proposed method can improve classification accuracy in fatigue detection [45].

In 2020, Krishnamani examined different sEMG signal frequency bands to identify fatigued muscle contractions using geometric features. In their study, 25 volunteers' signals were collected while they performed isometric biceps brachii contractions. They separated the fatigue and normal segments into three regions: low frequency (LF: 15-45 Hz), medium frequency (MF: 55-95 Hz), and high frequency (HF: 95-500 Hz). They extracted the area and perimeter for the analysis. According to their results, the geometric features in LF are more fatigue-sensitive than those in the other two regions [46].

In 2020, Na et al. introduced a method for understanding the way long muscle contraction affects the wrist movement of stroke patients. Seven patients' sEMG signals were recorded during four different wrist movements: flexion, extension, radial deviation, and ulnar deviation as they performed 20% and max MVC isometric contraction. MAV, MNF, and a joint analysis of amplitude and spectrum (JASA) were used for the analysis. They employed a DL algorithm for classification. They found that no significant difference was found in the classification accuracy and the changes of sEMG features due to long-term contractions. Their result indicates the reliability of using stroke patient wrist movement identification during sEMG-based robotic rehabilitation [47].

In 2020, Cognolato proposed a method to stabilize prosthetic control by the inclusion of multiple parameters, including gaze, visual, and inertial grasp signals of able-bodied and amputee volunteers. In their research, they asked 45 amputees and able-bodied people to perform ten static and dynamic grasp movements. For analysis, they used mean and standard deviations. Their dataset can aid in the study of eye-hand coordination and can be used in the context of psychophysics, neuroscience, and assistive robotics besides the application for upper-limb prosthetics [48].

In 2021 Liu et al. introduced a method to investigate the fatigue condition in muscular contractions by employing synchronization of MU spike train decomposed from high-density sEMG (HD-sEMG). In their research, they compared the synchronization of MU in Delta (1–4 Hz), alpha (8–12 Hz), beta (15–30 Hz), and gamma (30–60 Hz) frequency bands during the fatigue condition in the biceps brachii muscle for 21 volunteers as they performed isometric and dynamic contractions. Their results showed that MU synchronization increased significantly in all frequency bands across the two contraction tasks in fatiguing conditions. The results indicate that the microscopic fatigue mechanism of the biceps brachii muscle does not vary due to different contraction tasks [49].

In 2021, Wang et al. proposed an algorithm for determining the impact of muscle fatigue on hand grasp force and wrist movements. In their research, they measured the signal of 10 participants as they performed isometric contractions from the upper limb muscles. for analysis, the measured RMS and MNF/ARV (average rectified value). They found that the addition of muscle fatigue to ML algorithms can increase the classification accuracy of estimating hands grasp and wrist movements [50].

In 2021 Phillips et al. proposed the use of the sEMG signals of isometric handgrip to assess fatigue detection and improve exercise program outcomes. In their study, they measured the isometric squat and isometric handgrip at 30% of the MVC of 10 participants. For analysis, they measured the mean and SD. In their result, they reported a significant rise in the amplitude of the sEMG signal during fatigue and developed a practical method for exercise and coaching decisions where the handgrip fatigue was used to identify sEMG responses to fatigue; the change of sEMG signal in the squat outside the range was considered fatigue [51].

In 2021, Liao et al. searched the effect of muscle fatigue and recovery on upper limb sEMG signals. The researchers evaluated the signal from 12 volunteers who did biceps curls at 70% MVC under two conditions: immediately and 24 hours after cupping therapy. They employed RMS, MNF, MDF, and spectral moment ratio (SMR) for analysis; they also used a modified sample entropy (Ems) algorithm to assess muscle fatigue and recovery from fatigue after cupping therapy. Sample entropy (Es) quantifies the degree of irregularity in a time series and is also defined as the negative natural logarithm. Their findings demonstrated that Ems exhibit greater sensitivity to muscle fatigue than conventional linear features [52].

In 2022, Bawa et al. tested the performance of a low-cost Myoware sEMG sensor in detecting muscle fatigue and evaluated its performance against a commercial one. In their research they took the signals from seven participants as they completed four dynamic exercises: wall sit, squat, band sidewalk, Frankenstein walk. For analysis, they extracted RMS, MAV, and MNF. For analysis they used Spearman's correlation the intraclass correlation coefficient (ICC) to validate their sensor against the other device. Their findings indicated that the low cost device can indeed be used for fatigue detection [53].

In 2023, Otálora et al. combined several non-invasive sensors to assess fatigue; in their research, they took the signal from 30 participants as they performed repetitive biceps curls. The used sensors included optical fiber sensors, inertial measurement units, and sEMG. For analysis, they segmented the signal into fatigue and repetition cycles and extracted the following features per cycle: normalized duration of each cycle, mean, SD, RMS, MNF, MDF, and instantaneous mean frequency (IMNF). Five machine learning algorithms were employed, and their accuracy was evaluated using various combinations of sensors and features. Their results showed that the best accuracy came from combining the three sensors with 33 characteristics.

Table 2. Summary of the previous literature

Ref	year	Purpose	Features	Analysis Method	Contraction	Muscle	findings
[35]	2015	Classify sEMG signals to fatigue and non-fatigue conditions using multifractional characteristics.	HEMAX, HEMIN, HE2, DOM, HIX, MHE, MEX, HI2	ML	Dynamic	Biceps brachii	The multifractional characteristic of the sEMG signal increases classification accuracy.
[36]	2016	Investigate the effect of accumulated fatigue on muscle ability to contract in the long term.	MPF	ANOVA	Dynamic	Biceps brachii	There is a drop in muscle ability to contract by 59.6% after 13 days of repetitive, fatiguing exercise.
[37]	2016	Investigate the fatigue predictability possibility when using iEMG and MNF features.	MNF, iEMG	Global index map	Dynamic	Biceps brachii	There is a possibility to detect fatigue by using MNF and iEMG along with the map.
[38]	2016	To assess muscle fatigue for surgeons during work.	Moving average	RQA	Dynamic	Upper limbs muscles	RQA has high sensitivity in muscle fatigue detection during dynamic contractions.
[39]	2017	Detect sEMG signal from DMD patient.	RMS	SNR, CAR	Isometric	Upper limbs	The DMD patient could generate signals, but it was 100 times lower than a healthy individual.
[40]	2017	Evaluate WT and SVD in terms of movement	WT, SVD, MAV, RMS, IEMG, ZC, MNF, and MDF	ML	Isometric and dynamic	Vastus medialis	WT and SVD increase

		classification accuracy.					classification accuracy.
[41]	2017	Detection of muscle fatigue using the Myoware device.	RMS, MDF	DL	Dynamic	Upper limbs	Myoware can be used for fatigue detection.
[4]	2018	Designing rehabilitation protocols depending on collected muscle fatigue signals.	RMS, MDF, CWT	slop of regression for MDF	Isometric	Biceps brachii	There is a significant difference between trained and untrained subjects in the MDF slope. And the rehabilitation patient who used their designed protocol showed noticeable improvement.
[42]	2019	Detecting fatigue using wearable sEMG.	MAV, RMS, MDF, MNF	Borg Rate of Perceived Exertion	Dynamic	Upper limbs	Higher muscle fatigue levels lead to higher MAV and RMS values and lower MNF and MDF values.
[43]	2019	Designing a DL model for the Continuous monitoring of sEMG signals.	RMS, VAR, MAV, WL	DL	Dynamic	Upper limbs	Their model achieved high accuracy in estimating the movements.
[44]	2019	Designing an sEMG patch for the real-time monitoring of muscle fatigue.	MNF,MF	EMD	Dynamic	Lower limbs	Their patch is reliable for monitoring muscle fatigue.
[45]	2019	Fatigue monitoring based on physical and subjective reports.	MIN, MAX, SD mean, SE,SF, ZC, EE, WAMP	ML	Isometric	Upper limbs	Improved classification accuracy.
[46]	2020	Analyzing muscle fatigue using the sEMG signal geometric features.	area and perimeter	t-test	Isometric	Biceps brachii	Low-frequency geometric features are applicable for real-time monitoring of muscle fatigue.
[47]	2020	Study the effect of long-term contraction on patient muscle signals.	MAV,MN, JASA	DL	Isometric	Upper limbs	Long-terms contraction doesn’t affect classification accuracy
[48]	2020	Study the inclusion of eye movements along with sEMG and other signals in the control of prosthetics.	Mean, SD	ML	Isometric and dynamic	Upper limbs	Their method improved the prosthetics control.
[49]	2021	Investigate the fatigue condition using synchronization of the MU spike train.	Delta, alpha, Beta, Gamma frequency bands	ANOVA	Isometric and dynamic	Biceps brachii	Fatigue condition is the same for different contraction tasks.

[50]	2021	Evaluate the fatigue effect on wrist movements.	RMS, MNF/ARV	ML	Isometric	Upper limbs	Adding fatigue indication to models lead to higher wrist classification accuracy.
[51]	2021	Assess fatigue detection of isometric handgrip and squats.	RMS, mean, SD	t-test	Isometric	Lower limbs	Muscle fatigue lead to an increase in sEMG readings.
[52]	2021	Investigate the influence of muscle fatigue and recovery on sEMG signals	Ems, RMS, MNF, MDF, SMR	Statistical test	Dynamic	Biceps brachii	Ems is more sensitive to muscle fatigue than usual methods.
[53]	2022	Design a low-cost sEMG sensor and compare its result in detecting muscle activity and fatigue with a commercially available one.	RMS, MAV MNF	ICC	Dynamic	Lower limbs	The designed system is reliable and can be used in rehabilitation or sports.
[54]	2023	A DL model that employs multiple sensor combinations to assess muscle fatigue.	normalized duration mean, SD, RMS, MNF, MDF,IMNF.	DL	Dynamic	Upper limbs	The integration of the three sensors with 33 features yielded the highest accuracy.
[55]	2023	Design a low-cost portable sEMG sensor and compare its result in detecting muscle activity and fatigue with a commercially available one.	RMS,MNF,MDF,IMNF, IMDF, STFT	Spearman correlation analyses	Isometric and dynamic	Upper limbs	The designed system is reliable and can be used in rehabilitation or sports.
[56]	2024	Propose a system composed of sEMG and ECG to analyze muscle fatigue and detect stress for trauma rehabilitation using DL algorithms.	RMS, MDF	DL	Isometric	Upper limb	The designed system is reliable and can be used in rehabilitation or sports.
[57]	2024	Create a continuous textile-based sEMG system.	MAX, mean, MED, SD, VAR, PP, ZC, AUC, RMS,MP, MAV, EN, WL, SK, KUR, MNF, MDF,SPC	Statistical method	Dynamic	Upper and lower limbs	The proposed system can effectively measure the sEMG signal.

Their studies can be used in human-robot interactions and in workplaces to reduce fatigue during longer work shifts [54].

In 2023, Garouche et al. compared the ability of a newly designed low-cost portable sEMG system for the detection of muscle fatigue against a research-grade device. They took the signals from 34 volunteers as they performed isometric and dynamic wrist contractions. For analysis, they extracted the RMS, MDF, MNF, instantaneous mean (IMNF), instantaneous median (IMDF), and STFT. Their results show that their device is usable for fatigue detection. [55].

In 2024, Worassa et al. proposed a combination of two system signals sEMG and ECG to evaluate muscle fatigue with DL algorithms. They extracted RMS and MDF for analysis. Their result showed that their proposed DL model achieved high accuracy and can be used for monitoring the muscle condition and mental status of traumatized patients in a clinical environment and is good for effective physical rehabilitation. They extracted RMS and MDF for analysis. They also introduced an interactive website for their proposed model [56].

In 2024, Etana et al. developed a continuous textile-based sEMG system using an IoT-based approach. In their work, they used two types of electrodes, textile and gelled electrodes. They collected the signal from a single volunteer's upper and lower limbs as he performed dynamic contraction. For analysis, they extracted 15 time-domain parameters, including MAX, mean, MED, SD, VAR, peak-to-peak distance range (PP), ZC, area under the curve (AUC), RMS, mean amplitude power (MP), MAV, signal energy (EN), WL, skewness (SK), and kurtosis (KUR), as well as three frequency-domain parameters: MNF, MDF, and spectral centroid (SPC). After that, they carried out three different statistical tests to assess and pinpoint the best use of the characteristics. Their results show that the suggested approach can quantify the sEMG signal rather successfully [57].

3. Discussion

The reviewed studies (see Fig. 3) show five repeating trends: for example, researchers [28], [46], [49], and [52] utilize multiple approaches to identify fatigue. This covers similarities in the time and frequency domains as well as factors unique to every study, such as the region of the signal or the frequency bands and how fatigue alters the signal for every band. They also study how fatigue affects these features. Another similar pattern is observed in the studies [35], [40], [50], and [54], which employ various AI algorithms to classify the signal as either fatigue or non-fatigue conditions, each employing different approaches to enhance classification accuracy. Another pattern in studies such as [36], [38], [41], [4], [48], and [51] where they investigate the impact of muscle fatigue on different parts of the body and its influence on muscular mobility, its effects on prosthetic operation, and its use for practical purposes such as the development of rehabilitation protocols. Another common pattern can be seen in [43] and [45]. Which show that ongoing monitoring of fatigue is necessary and is the aim of their research. Another prevalent pattern includes using various electronic components to construct a novel sEMG sensor through diverse combinations of circuits and elements, as evidenced in [44], [53], [55], [56], and [57] (see Fig. 4).

A notable absence of research on fatigue prediction is evident; while there is a study [37], it is limited to measuring the feature's capacity to detect fatigue rather than concentrating on prediction itself. Predicting fatigue is crucial as it can prevent injuries, enhance physical performance, and optimize rehabilitation results. In turn, future research emphasizing prediction will increase, and that can be the main aim of fatigue research. Another notable area is that most of the earlier research focuses on the detection and classification of fatigue and rarely discusses continuous monitoring in ordinary settings. This is important as, often an immediate or long-term problem, fatigue calls for immediate treatment to preserve health and physical performance. Future studies in the interesting field of wearable technology for continuous muscle fatigue monitoring in real-world settings could find great success.

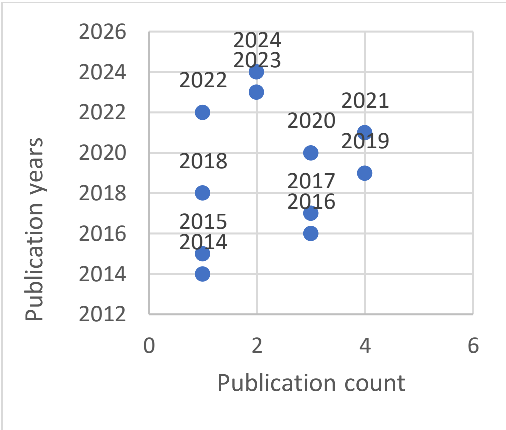

Fig. 3. Amount of reviewed research grouped by the years of publication.

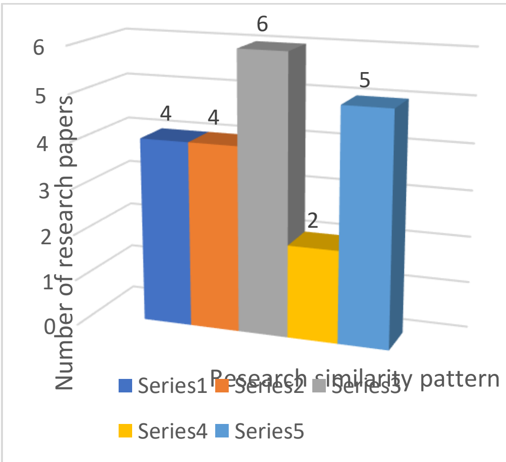

Fig. 4. The five patterns noted in the research and the corresponding number of studies exhibiting these patterns.

Another interesting finding is the contrast between statistical analysis and artificial intelligence, in which it is clear from 25 research projects that 15 use statistical techniques in their analysis and the remaining use artificial intelligence (see Fig. 5). While statistics remains basic to the scientific field, it is obvious that the AI is becoming more known for its ability to reveal patterns and insights that may escape conventional approaches. It is clear from studies of the benefits and disadvantages of both approaches that a good mix of statistical analysis and artificial intelligence could yield better outcomes.

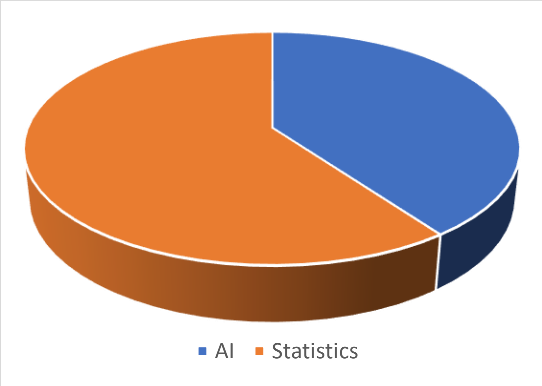

Fig. 5. The amount of research that use AI analysis compared to statistical analysis.

4. Conclusion

The detection of muscle fatigue is an important issue for individuals, whether to protect athletes from injuries or to enhance human-machine interactions, such as stabilizing prosthetics or formulating rehabilitation protocols, not to mention how it benefits progress on sustainable development goals.

We may utilize prior research findings to get clear insights on how to advance our research. For instance, employing bipolar electrodes is acceptable for simple measurements involving basic muscular actions. Low-cost EMG sensors and devices can be used for detection, allowing for the use of affordable sensors. Various combinations of features and algorithms can be implemented to achieve the best results. Both AI and statistical approaches can be utilized for fatigue detection. Following through several protocols is essential for obtaining accurate measurements. Lastly, the majority of studies on muscle fatigue focus on detection over prediction; despite some early efforts, many have not produced satisfactory outcomes, nor has there been a continuous attempt to improve this area of research. Therefore, future research should aim to bridge this gap by developing predictive models or algorithms that not only identify fatigue but also anticipate its onset.

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