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Assessment of Muscle Fatigue Progression Based on Surface Electromyograph Sensor: A Pilot Study

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ABSTRACT

Surface muscle fatigue (MF) is an important area to study especially in medicine and sport. One way to detect and process muscle fatigue is by the use of surface electromyography (sEMG). This study presents a real-time sEMG signal acquisition and processing system designed to detect muscle fatigue during. The study included four participants that performed isometric contractions until muscle fatigue was reached, during which sEMG signals were continually monitored. The acquired sEMG data underwent systematic processing, including filtering, rectification, and feature extraction. Four features were extracted: Root Mean Square (RMS), Mean Absolute Value (MAV), Mean Frequency (MNF), and Median Frequency (MDF). The results show that MNF is the clearest indicator of fatigue in the suggested system. Moreover, RMS and MAV can be helpful in indicating the early signs of fatigue. The selected method is useful for real-time muscle fatigue monitoring without the need for complex algorithms. These results offer a basis for the next research focusing on enhancing real-time sEMG signal processing techniques using industrial sensors.

1. Introduction

Muscle fatigue can be defined as the inability of the muscle to perform the expected movement or exert the expected force[1]. The study of muscle fatigue is present in many fields; in medicine, the detection of muscle fatigue can aid in designing protocols for the rehabilitation of stroke that help fasten the healing process [2][3], in sport, it is important for the prevention of injuries for the athletics [4]; in the biomedical field, it is used to improve the human-machine interaction in which the stabilization of is essential, especially in critical cases [5]; not to mention that the detection of muscle fatigue satisfies many of the Sustainable Development Goals (SDGs), one of which For example, Goal 10: Reduced Inequalities; considerable researches are focused on the creation of cost-effective fatigue detection systems that are inexpensive and accessible to those with limited resources, promoting equal access to healthcare [6][7].

Muscle fatigue can't be measured directly, but it can be identified by indications [8], one of which is the muscle electric signal, that is generated by muscle fibers and controlled by brain neurons. Each neuron, when paired with its associated muscle fiber, forms a motor unit. When a neuron's signal reaches the motor unit, it creates electricity; this electricity is known as the motor unit action potential (MUAP), and the sum of all of them can be read by a surface electromyography (sEMG) [4]. sEMG is a highly sensitive voltmeter that can be used to graphically display the MUAP signal[9].

The signal in its raw condition is displayed alongside noise produced by tissue characteristics, power line noise, or motion noise, requiring several signal processing procedures: filtration, rectification, segmentation, and normalization [10][11][12]. Following signal preprocessing, different features are extracted. Because the sEMG signal can change in amplitude and frequency, reflecting muscle electric activity, three types of features are normally used in studies: time domain features, frequency domain features, and a combination of the two [13]. Some of these metrics include root mean square (RMS), mean absolute value (MAV), mean frequency (MNF), and median frequency (MDF) [14].

Most studies employ various methods to investigate muscle fatigue and the most effective means of its smooth detection. Generally, the high pass filters (HPF) are used to eliminate DC offset and movement artifacts, and low pass filters (LPF) are used to eliminate high frequency noise or for smoothing.

Some studies directly use a band pass filter (BPF) for these purposes, and some include an additional notch filter (NF) for power line interference. In 2015, Marri et al. employed a BPF ranging from 5 Hz to 1000 Hz and an NF at 50 Hz to minimize noise and improve signal quality, afterwards segmenting it into six parts that represented non-fatigue and fatigue conditions. Multifractional features were extracted, which include both time and frequency domain features [15].

In 2016, Tosovic et al. investigated the impact of cumulative fatigue on muscle signals and fatigue levels. They applied a 20 Hz HPF on the signal and extracted the Median Power Frequency (MPF) [16]. In 2017, Lobo-Prat et al. studied the EMG signal of a late-stage Duchenne muscular dystrophy patient. They also used a 20 Hz HPF and a low 1 Hz LPF. The raw sEMG signals underwent full-wave rectification. RMS was used to calculate the signal-to-noise ratio (SNR) and co-activation ratio (CAR) [17]. In 2018, Kuthea et al. proposed a method to quantify muscle strength during fatigue for both trained and untrained individuals, after which they utilized their findings in rehabilitation programs. A 1000 Hz sampling frequency and a BPF were employed, with a frequency range of 5–500 Hz. The filtered EMG signals were rectified and subsequently smoothed using an LPF with a cutoff frequency of 50 Hz. RMS values were used for normalization alongside the Continuous Wavelet Transform (CWT) [2]. In 2019, Liu et al. developed a wearable patch for continuous and real-time monitoring and analysis of sEMG signals during lower limb exercises. A sampling frequency of 1000 Hz was employed, along with a 33.9 Hz HPF and a 482.5 Hz LPF. The main features derived from the analyzed EMG signals were the MNF and MDF [18]. In 2020, Krishnamani et al. conducted a review of various frequency bands of sEMG signals to identify fatiguing muscle contractions through geometric features. The sEMG signals were collected at a sampling frequency of 10,000 Hz. A BPF with a range of 10-500 Hz was used along with a 50 Hz NF. The frequency bands were categorized as follows: low-frequency band (LFB: 15-45 Hz), medium-frequency band (MFB: 55-95 Hz), and high-frequency band (HFB: >95 Hz). Geometric features, including area and perimeter, were derived from the analytical representations of the signals produced by the application of the Hilbert transform [19].

Table 1. participant info

Participant ID	gender	age	Dominate arm
P1	Female	24	Right
P2	Male	19	Right
P3	Male	22	Right
P4	Female	20	Right

In 2021, Liao et al. examined the effects of muscle fatigue and recovery on upper-limb sEMG signals. A BPF was employed, with a frequency range of 20–450 Hz. The signal was segmented using a moving overlapping window of 0.1 seconds. RMS, MNF, MDF, and spectral moment ratio (SMR) were used for analysis [20]. In 2022, Bawa et al. compared the effectiveness of a low-cost sensor in detecting fatigue with a commercial one. The signals underwent filtering to eliminate noise. The commercial system employed a BPF filter with a frequency range of 20 to 450 Hz. The low-cost EMG sensor utilized a BPF filter with a narrow range of 45–55 Hz to address noise centered at 50 Hz. RMS, MAV, and MNF were extracted [21]. In the same year, Qassim et al. proposed the detection of muscle fatigue using a unique fatigue index. They used two BPF and analyzed the signal in both the time and frequency domains; their analysis included separating the signal into two sub-signals [22].

In 2023, Otálora et al. introduced a computational model utilizing various sensor combinations to evaluate muscle fatigue. sEMG signals were sampled at a frequency of 2000 Hz. BPF was utilized within the frequency range of 20 to 450 Hz along with a 60 Hz NF. For analysis, the following features were extracted per cycle: normalized duration, mean, standard deviation (SD), RMS, MNF, MDF, and instantaneous mean frequency (IMNF) [23]. In 2024, Worassa et al. proposed a system that integrates sEMG and ECG to assess muscle fatigue and recognize stress in upper limb trauma rehabilitation, utilizing deep learning algorithms. Two BPFs were used along with an NF. RMS and MDF were extracted for subsequent analysis [24].

The majority of existing research processes sEMG signals after they have been acquired, with only a few studies using real-time processing methods. However, the real-time processing in them is complex and difficult to implement. This study presents a method for acquiring and processing EMG signals in real time while extracting fatigue-related features. This study expands on previous research by introducing a real-time processing framework that improves fatigue detection efficiency and accessibility for applications in rehabilitation, sports science, and biomedical research.

Fig. 1. Experiment setup along with the sEMG recording system.

2. Method

2.1 Participants

The study involved five participants with no neuromuscular disorders or upper-limb musculoskeletal injuries. Each participant was asked to sign a written statement of consent for their involvement in the study. Table 1 shows the participants' characteristics. Prior starting the experiment, all participants received information about the procedure and completed a simple warm-up to familiarize themselves with the required emotions.

2.2 Experimental techniques

During the experiment, the participants performed isometric contractions while seated comfortably in a chair in front of a computer screen for visual feedback, with their arms fixed at a 90-degree angle. The sEMG signals from the biceps brachii muscle were captured continuously until fatigue (see Fig 1). Participants were asked to do three maximum voluntary contractions (MVC) of 5 seconds each, with a 5-second rest period in between; the three were then averaged to determine the 100% MVC. The measured MVC was used to normalize the signal, allowing for comparisons between people following the trial. After a brief break, participants were asked to perform an isometric contraction with their dominant arm at 100 MVC until fatigued. Fatigue was measured using both subjective and objective criteria. Participants were asked to stop the contraction when they reported a fatigue level of 2 on the Borg scale or were unable to generate any more force, suggesting fatigue.

Table 2. Time and frequency domain features [13].

Domain	Features	Equation	Equation parameters
Time	Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert E_i\rvert$ (1)	N = number of samples in the window. $\lvert E_i\rvert$ = i-th sample of the EMG signal
	Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert E_i\rvert^2}$ (2)	
Frequency	Mean Frequency (MNF)	$MNF = \frac{\sum_{i=1}^{N} f_i P_i}{\sum_{i=1}^{N} P_i}$ (3)	f_i = frequency at the i-th bin P_i = power at frequency f_i N = total number of frequency bins
	Median Frequency (MDF)	$\sum_{i=1}^{MDF}\lvert P_i\rvert = \frac{1}{2}\sum_{i=1}^{N}\lvert P_i\rvert$ (4)	

2.3 EMG recording

The sEMG electrodes placement and skin preparation comply with the European SENIAM (Surface Electromyography for the Non-Invasive Assessment of Muscles) standardization, in which the skin above the biceps brachii is cleaned before the experiment to reduce impedance between the skin and electrode arrays. The used electrodes were of the Ag/AgCl type, and they were positioned along the muscle fiber direction, at the midpoint between the muscle origin and insertion.

To assist researchers in determining the proper electrode locations, volunteers were asked to perform a simple biceps curl. The sole distinction was that the reference electrode wasn't put on a bony location, as the used sensor Myoware sEMG v2.0 has a built-in reference place. Signals from the sEMG sensor were transmitted to a host PC using Arduino mega 2560 microcontroller with a 10-bit ADV operation at a sampling frequency $f_s = 1000\ Hz$ sampling rate using 115200 bps baud rate. All data collected from the individuals were stored and processed in real time fashion.

2.4 Preprocessing and Feature Extraction.

To simplify signal reading, the signals of the sensor were converted from the raw ADC value (e.g., 0 to 1023) to millivolts (mV). Then, the signal was filtered using a 4th-order Butterworth HPF with a 10 Hz cutoff and an LPF with a 499 Hz cutoff frequency.

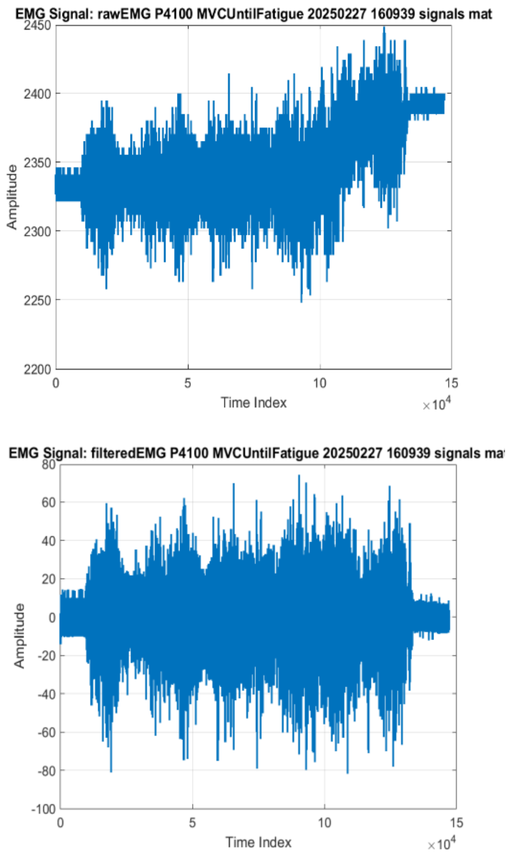


Fig. 2. Raw and filtered signals of one of the participants.

The filtration was followed by rectification, which eliminated the signal's negative components and allowed for feature extraction. This study extracted two time-domain and two frequency domain features; see Table 3.

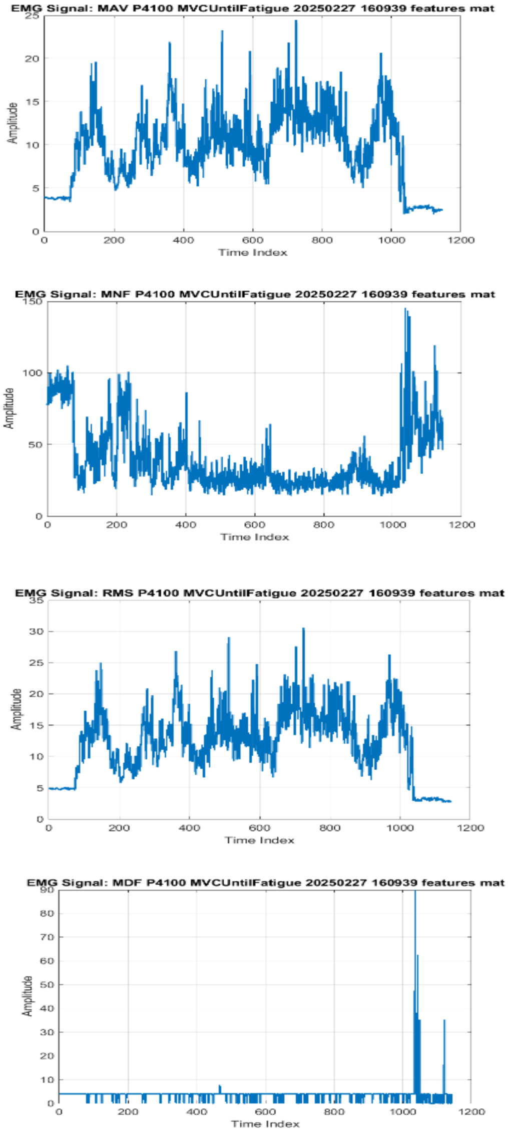


Fig. 3. Time and frequency domain features plot of one of the participants

The data was segmented using two types of windows: rectangular and Hanning. The time domain features were extracted from the rectified EMG signal using 256 ms windows with 50% overlap, whereas the frequency domain features were computed using the Power Spectral Density (PSD) obtained via Welch's method with a Hanning window with the same length. Features were retrieved from the segmented signal while constantly recorded and visualized for direct feedback.

When the process was finished, the signal and extracted features were saved in separate files, along with the viewable graph. Following the trial, the participants' signals were normalized using the MVC for each feature. The fatigue index was calculated using a statistical approach.

2.5 Statistical Analysis [25]

A simple fatigue index (FI) calculation was performed for each feature to assess muscle fatigue by analyzing changes in sEMG signals over time.

$$FI = \frac{\Delta\, Featur}{\Delta\, t} \times 100 \qquad (5)$$

Where $\Delta\, Feature$ indicate changes in feature value over time (start of contraction and the start of fatigue) and $\Delta\, t$ is the time duration of the analysis.

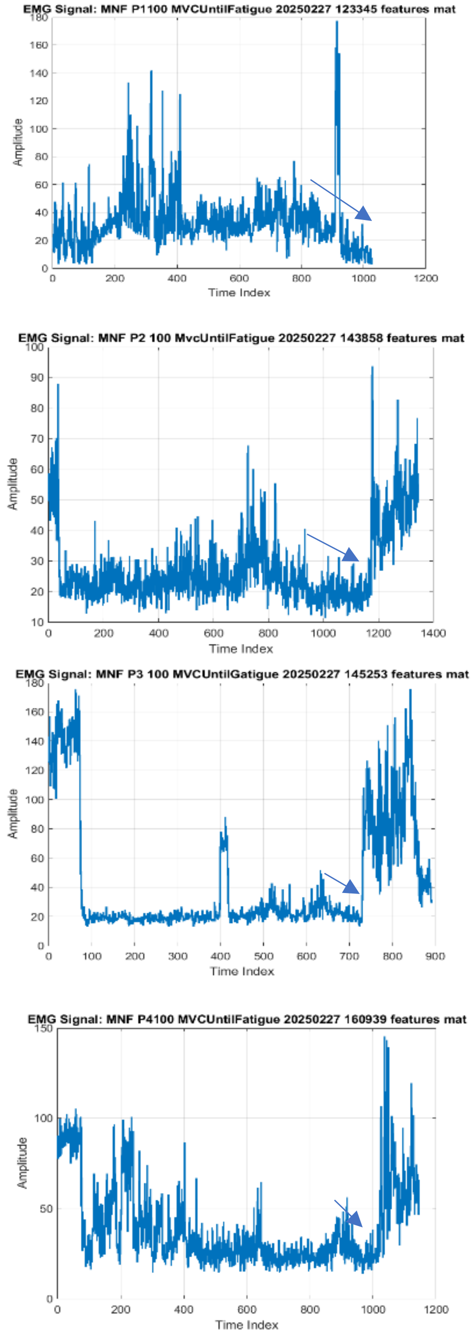


Fig. 4. MNF decreasing trend for all participants

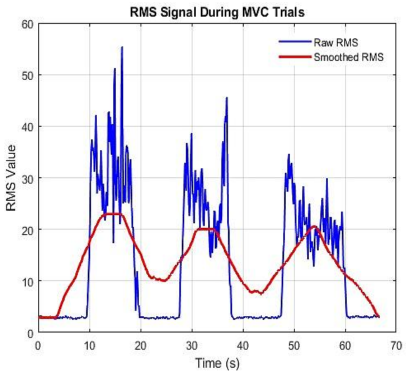
3. Result and Discussion

The sEMG signal obtained from four subjects during isometric contraction exhibits similar tendencies when fatigue sets in. The raw signals were filtered, rectified, and smoothed whenever necessary to ensure that the processed signal displayed muscle activity with minimal noise artifacts. The filtration and rectification were performed online while the signal was being acquired (see Fig.2). For the sake of a straightforward reading, the signal amplitude was changed from ADC value to mV.

Four features have been extracted from the signal as it was being recorded collected (see Fig.3). Two time-domain features, MAV and RMS, were calculated for each time window (256 ms, 50% overlap).

The other two are frequency domain features, MNF and MDF, which were computed using the Welch method, a much quicker alternative to the Fourier transform.

MAV and RMS show similar trends over time with minor variances which is their normal state. the MDF could not reveal much of a difference because it remained reasonably stable during the acquisitions until fatigue, when a sudden spark erupted, the same thing happens in the remainder participants;



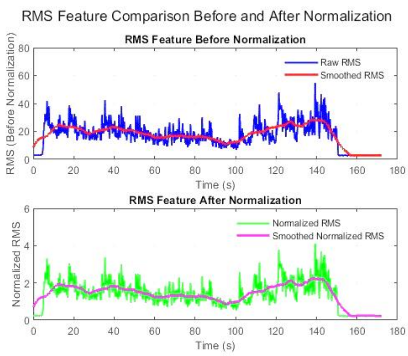


Fig. 5. normalization of one participant RMS value

however, it's might be an artifact or caused by noise. On the other hand, the MNF revealed a trending tendency among the four individuals, gradually decreasing as fatigue occurred, which can be employed in future studies (see Fig.4). The value in the start and the end of the signals are rest periods which can be ignored.

3.1 Normalization

The signal was normalized offline using the MVC taken from each individual, and the features were recreated using the normalized value for each feature, allowing for comparisons across individuals.

The normalization procedure was performed by calculating the mean of the participants' prerecorded 3 100% MVC.

This resulting mean was then used to compute the normalized form for each participant's features. An example of the RMS feature of one participant after normalization can be seen in the figure (see Fig.5).

Table 1 displays the RMS, MAV, MDF, and MNF for normalized and non-normalized signal levels at the beginning of contraction and at the fatigue occurring for each participant. from the table an observation can be seen there is minor increase in RMS and MAV at the start of fatigue, while the MDF remains reasonably consistent.

On the other hand, MNF levels have decreased significantly since the start of contraction which follow the previous observation. RMS and MAV levels increased in most subjects, indicating higher muscular activity. MDF revealed mixed results, with large increases in P1 and P2, whereas P3 decreased and P4 remained steady. MNF regularly reduced, indicating neuromuscular fatigue, especially in P1 and P3.

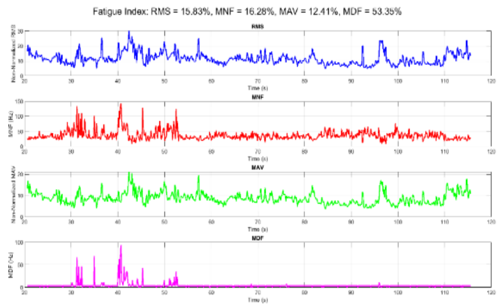


Fig. 6. fatigue index for one participant four features

Table 3. Signal features at the start of contraction and at the beginning of fatigue

Non normalized feature								
ID/features	Start of contraction				Beginning of fatigue			
	RMS (mV)	MAV (mV)	MDF (Hz)	MNF (Hz)	RMS (mV)	MAV (mV)	MDF (Hz)	MNF (Hz)
P1	16.8	12	3.9	44	23.8	17.5	11.7	39.5
P2	32.6	32.3	7.8	22.3	34.6	27.9	11.7	21.5
P3	23.1	18.3	7.8	26.9	43.3	31.5	11.7	16.5
P4	8.3	5.3	3.9	35.7	15.3	17.3	3.9	22.9
Normalized feature								
ID/features	Start of contraction				Beginning of fatigue			
	RMS (mV)	MAV (mV)	MDF (Hz)	MNF (Hz)	RMS (mV)	MAV (mV)	MDF (Hz)	MNF (Hz)
P1	2.6	2.3	0.9	0.7	3.7	3.4	0.9	0.4
P2	2.0	3.2	0.3	0.4	5.2	5.0	0.4	0.2
P3	1.2	1.4	0.2	0.3	1.5	1.6	0.7	0.2
P4	1.6	1.8	1.1	0.5	2.8	3.2	1.1	0.4

To gain a better understanding of the data, a fatigue index was calculated (see Fig 6) which included the 25% signal beginning and end (fatigue beginning). The start and end points were manually changed according to the participant's feedback at the onset of fatigue. Table 4 shows the fatigue index for all participants features. Participants with higher positive RMS and MAV values (P1, P3) may have higher fatigue metrics, implying that their signals change faster over time, possibly due to fatigue buildup. Participants with more stable or negative values (P2, P4), on the other hand, may experience less fatigue or display greater uniformity in their performance, especially in the frequency domains, where P2 and P4 frequencies are more stable or less changeable. Overall, the evidence reveals that the use of an online basic algorithm can in fact show fatigue levels for individuals and can be utilized in future works with some modifications to give the immediate feedback to the persons at the occurrence of fatigue or the forecast of it.

Table 4. Fatigue index table

ID/feature	Normalized (%)				Not normalized (%)			
	RMS (mV)	MAV (mV)	MDF (Hz)	MNF (Hz)	RMS (mV)	MAV (mV)	MDF (Hz)	MNF (Hz)
P1	16.79	13.66	53.26	15.32	15.83	12.41	53.35	12.41
P2	-10.52	-8.72	-0.98	10.7	-11.41	-9.73	-0.54	-9.73
P3	51.50	52.66	-4.25	-22.06	51.57	-25.56	-3.53	-25.56
P4	-28.50	-28.65	5.70	45.32	-34.09	-34.22	4.94	-34.22

4. Conclusion

The understanding of muscle function and fatigue needs the processing and analysis of sEMG signals. Researchers can gain important insights on muscle behavior by following a systematic set of protocols that include signal acquisition, filtering, feature extraction, and statistical analysis. Furthermore, technological improvements have made it possible to perform online fatigue detection. The ability to successfully analyze and interpret EMG data, alongside real-time monitoring abilities, makes a significant contribution to the biomedical, sports, and medical fields. Continued study and development in these areas will help us improve our understanding of muscle behavior and fatigue.

5. Recommendation

As the signal was processed and the features were acquired directly, we couldn't crop the signal as the fatigue occurred but can be improved in future research by making a separate file to save the fatigued signal alone.

A better indication of muscle strength should be used to minimize any possible error. The addition of a wearable device can be more practical for real-world use, and by exploring advanced algorithms, we can get better fatigue signal detection in real-time applications. Although the number of participants is small, in future research it should be expanded, as this is only a pilot study.

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