



Can Electromyography and Subjective Metrics Work Better Together? Exploring Dynamic Muscle Fatigue to Promote the Design of Health and Fitness Technology

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Abstract. The assessment of local muscle fatigue during dynamic exercises is viewed as essential, since people tend to maximise effective muscle training and minimise harmful muscle injuries. This study aims to investigate how surface electromyography (sEMG) and subjective metrics together can play a role in dynamic muscle fatigue prediction during exercises to promote the design of health and fitness technology. 20 healthy male participants were recruited in the experiment, and sEMG and self-reported data were collected. Features in temporal and spatial domain were extracted from sEMG data, such as RMS (root mean square) and FI_{nsm5} (spectral parameter proposed by Dimitrov). Our results showed that some sEMG features indicated directional changes with the increase of dynamic muscle fatigue. Spearman correlation analysis indicated that Borg ratings had strong correlations with RMS and FI_{nsm5} (spectral parameter proposed by Dimitrov) slopes. Then this paper discusses how to use sEMG and Borg data to evaluate muscle fatigue during exercises. A framework is proposed based on the joint analysis of spectra and amplitudes across RMS and FI_{nsm5} slopes. This paper further discusses how to design health and fitness technology for the benefits and the limitations of the study.

Keywords: Subjective metrics · Electromyography · Muscle fatigue · Design · Fitness technology

1 Introduction

Muscle fatigue describes a decrease in the ability of a muscle to contract and exert force, and it develops gradually from the start of a contraction [1]. In muscle strength training, muscle fatigue could be beneficial in muscle growth while it can also be harmful if the fatigue level is high for too long [2]. Apart from the physiological aspect of fatigue, the psychological aspect also plays an important role. People may perceive and sense fatigue differently, and it, in turn, can affect people's physiological performance [3]. Therefore,

it is important to explore the relationships between the physiological measurements and psychological aspects of fatigue.

Currently, existing health and fitness technologies on the market are mostly limited to monitoring heart rate, counting the number of steps, and they require users to manually select specific sports for recording purposes. Very few intelligent products can monitor and evaluate muscle fatigue. Since excessive muscle fatigue can lead to muscle injuries during resistance training, a research gap, as well as a business opportunity, exists in innovating wearable devices for monitoring muscle fatigue in-situ.

Generally, there are two approaches to measure and assess individuals' degree of muscle fatigue. The first approach is to collect people's physiological data such as surface electromyography (sEMG). sEMG electrodes can be easily placed on different muscle parts on the surface of the body. Most of the research makes use of sEMG to obtain objective data that can reflect muscle fatigue. However, it is complicated to collect suitable physiological data and translate it into individuals' degree of muscle fatigue. The second approach is to collect people's subjective fatigue, where self-reported data are collected during or after each repetition of a workout. Currently, the most widely used subjective measure is the Borg scale CR10 [4].

This study aims to explore how sEMG data and subjective metrics can be combined to assess dynamic muscle fatigue during exercises. We intended to initiate discussions for the purpose of designing new health and fitness interactions to help people monitor muscle fatigue during muscle training. The objectives of this study include:

- To understand how sEMG features and subjective metrics change with the increase of muscle fatigue.
- To explore how to combine sEMG data and subjective metrics to evaluate dynamic muscle fatigue.

2 Background and Related Work

This section introduces related work in three parts: (1) muscle fatigue assessment via sEMG, (2) fatigue assessment via subjective metrics, and (3) challenges of evaluating muscle fatigue in the fitness context.

2.1 Muscle Fatigue Assessment via sEMG

sEMG is a non-invasive approach that is widely used for muscle fatigue monitoring. There are a variety of articles discussing static and dynamic muscle fatigue detection by analysing sEMG data, such as exploiting and comparing sEMG features in temporal and spatial domain methods. Strimpakos et al. [8] explored neck muscle fatigue, using two features of sEMG data: normalised median frequency (MDF) and root mean square (RMS). Al-Mulla et al. [6] required participants to perform a static biceps curl activity and sEMG signals were successfully utilised to predict muscle fatigue. However, during the dynamic muscle fatigue monitoring, some changes, such as changes in muscle force, changes in muscle length, and muscle fibre conduction velocity, may increase the non-stationarity of the sEMG signals [17]. This study intends to focus on exploring how to

evaluate dynamic muscle fatigue using sEMG, for the purposes of eliciting design ideas to promote the user experience of health and fitness technologies.

To evaluate dynamic muscle fatigue, features in the spatial domain are mostly used. Cruz-Montecinos et al. [18] asked participants to perform five sets of leg presses and found that the Dimitrov spectral index of muscle fatigue (FI_{nsm5}) was significantly relevant to local muscle fatigue during a high-loading fatiguing task. Chang et al. [13] found that the regression line of median frequency (MDF) decreased with the increase of dynamic fatigue, where their experimental tasks required participants to run on a pedalled-multifunctional elliptical trainer for approximately 30 min at different loading levels. However, Jesus et al. [14] found that when muscular loads are at a low level, mean frequency (MNF) and MDF will be less effective to measure fatigue level. As for temporal domain features, the amplitude of sEMG features is rarely used as an independent indicator to assess muscle fatigue [17]. There is a controversy among researchers regarding reproducibility [10], and amplitude might be significantly influenced by muscle force level [11]. While in assessing static muscle fatigue, temporal features are often used in combination with other indicators, such as the Joint Analysis of EMG Spectrum and Amplitude (JASA) [12]. In JASA, four different categories of muscle performance can be distinguished based on the sEMG features, such as muscle fatigue and recovery.

Classification of dynamic muscle fatigue can be approached via various methods. Different machine learning algorithms can predict muscle fatigue by utilising sEMG features, but there is not a widely agreed mechanism that can evaluate muscle fatigue effectively and efficiently across all contexts. Papakostas et al. [15] proposed a post-processing mechanism that has improved the classification accuracy combining both subjective reports and sEMG signals. For repeated isokinetic dumbbell curl exercise, Hwang et al. [5] proposed an algorithm to predict dynamic muscle force and fatigue level based on integrated values and slopes of sEMG features. For example, frequency and amplitude of certain sEMG features are influenced by both the degree of muscle force and fatigue. Yet, most studies focus on physiological data such as sEMG, while subjective reports by users are often ignored.

2.2 Fatigue Assessment via Subjective Metrics

Muscle fatigue can also be evaluated via psychological approaches. There are three types of subjective rating scales that are mostly used to evaluate fatigue [9]: (1) visual analogue scales (continuous scale); (2) Borg scale (12 points with detailed descriptions); and (3) Likert scale. Grant et al. [9] found that compared with visual analogue scales and Likert Scales, Borg scales had a higher sensitivity for general fatigue during submaximal exercises.

Borg's ratings of perceived exertion (RPE) (6–20 Borg) and Category-Ratio (CR10) scales were developed to rate the level of perceived exertion regarding cardiovascular (e.g., increased heart rate and breathing difficulty) and muscular (e.g., muscle exertion and pain) loads during physical activity [4]. The 6–20 Borg scale ranges from “6” (no exertion) to “20” (maximal exertion), while the CR10 scale ranges from “0” (no exertion) to “10” (maximal exertion) [4]. Borg ratings were coincidental with decreases in muscle's power output [8], while an increase in the RPE value using CR10 is correlated with a reduction in maximal voluntary muscle force [18]. Research has found that the

ratings of perceived fatigue are related to muscle fatigue, and the ratings can be measured physiologically. However, existing literatures lack the knowledge about how Borg ratings and physiological data can together play a role in muscle fatigue assessment.

Some studies have analysed the correlation between self-reported data and physiological data. For example, Öberg et al. [7] found that when assessing shoulder muscle fatigue, a statistically significant correlation was shown between Borg scores and mean power frequency (MPF) values of sEMG at high load level, but no significant correlation at low load level. Some studies used subjective reports as labels for fatigue assessment to train and test the machine learning algorithms. Elshafei et al. [19] mark the fatigue level as high when reported Borg values are greater than 16, using the RPE scale, for algorithm development. However, subjective data can be more than the labels in machine learning algorithms. This study intends to explore the combination of subjective fatigue and physiological data for dynamic muscle fatigue assessment.

2.3 Challenges of Evaluating Muscle Fatigue in Fitness Context

To collect sEMG signals in the fitness and exercise context, one of the obstacles is that most movements of strength training are dynamic and complex, so the sEMG signals may be interfered with because of the constant moving. Meanwhile, it is normal for people to change the parameters during a training session. The parameters include the choices of weight in dumbbell workouts, the rest time length between sets and repetitions, etc. It is important that the sEMG signals can capture these changes of choices so that further analysis can evaluate muscle fatigue accordingly.

Collecting users' subjective perceptions of the feeling of fatigue in the process of strength training is also a challenge. Firstly, people's perception of muscle fatigue varies between individuals. Similar to people's perceptions of pain, psychological factors such as situational and emotional factors can profoundly alter the strength of people's perceptions of muscle fatigue. Secondly, the timing of collecting subjective perceptions of fatigue is also very important. It is an intrusive method to assess fatigue levels, as data are collected during exercise sets or between sets. The question that whether or not the collection of subjective data would disturb the exercise process needs careful consideration.

Since the scale and sampling frequency of subjective reports are different from the scale and sampling frequency of sEMG data, it requires more work to explore how to combine these two metrics to evaluate muscle fatigue. Subjective reports can act as labels of fatigue level, but they can also be viewed as an input variable of a fatigue evaluation mechanism. Thus, one of the goals of this study is to explore how to combine subjective metrics and sEMG data in a framework to assess muscle fatigue, to further elicit design ideas for health and fitness interactions and technologies.

3 Method

3.1 Study Design and Procedure

To simulate strength training scenarios, participants were asked to complete at least five sets of seated isolated dumbbell curls, 12 repetitions in each set. A warm-up session was

required at the beginning. To suit the participants with different muscle strengths, we provided three weights of dumbbells (5 kg, 8.5 kg, or 10 kg) that allowed the participants to select freely according to their individual abilities. To include different resting settings between repetitions, two exercise patterns were designed (see Fig. 1), and half of the participants were required to follow pattern 1 and the remaining to follow pattern 2.

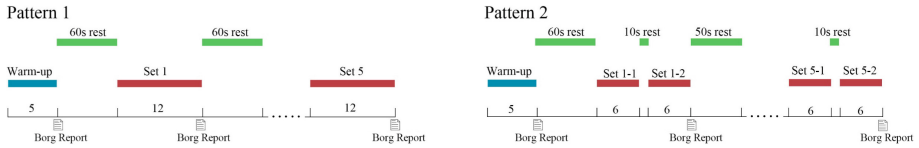


Fig. 1. Exercise pattern 1: 60 s rest between sets, Exercise pattern 2: 10 s rest in the middle of each set and 50 s rest between sets.

The procedure of the experiment included:

Step 1: After reading the information sheet and signing the consent form, participants were asked to choose a weight of the dumbbell that fit their ability best and were informed of the given exercise pattern. After a warm-up of the biceps brachii (using a 2 kg dumbbell), the participants were asked to sit down and wear the wireless sEMG device until the end of the whole procedure. Alcohol pads were used to clean the skin surface before putting the sEMG nodes on.

Step 2: The participants were required to complete the second warm-up of seated isolated dumbbell curls, using the dumbbell that they chose (5 kg, 8.5 kg, or 10 kg). Then, the participants could officially start their sets. We asked them to complete at least five sets with 12 repetitions in each set. The participants were instructed to continue the sets until they felt extreme fatigue, but they could stop at any fatigue level. The fatigue levels were also measured through subjective metrics right after each set (see Fig. 1). The participants needed to report their subjective feeling of fatigue (Borg scale). Table 1 shows the details of the subjective metrics, where Borg's CR10 was adopted and adapted. Without explanation, the participants might rate their fatigue level differently based on their own feeling of exhaustion, which would lead them to report their levels of exertion inaccurately. To address this, we provided them with a few brief explanations. For example, '3' indicates that the muscle starts to ache and '10' indicates a status of the arm that is unable to lift the dumbbell at all. Not all points from 0 to 10 were explained since it was hard to specify, and it might be sensible to give the participants some room.

Step 3: After completing the workout, the participants were asked to answer semi-structured questions about the whole experience, involving the time of rest between sets and the pattern of their daily exercises.

Table 1. Borg’s CR10 scale

To what extent do you feel tired or exhausted?			
Point	Level	Note	Explanation
0	Nothing at all		
0.5	Extremely weak	(Just noticeable)	
1	Very weak		
2	Weak	(Light)	
3	Moderate		Muscle starts to ache
4			
5	Strong	(Heavy)	
6			
7	Very strong		
8			Lifting dumbbell is very difficult
9			
10	Extremely Strong	(Almost max)	Arm is unable to lift the dumbbell at all

3.2 Participants and Data Collection

20 healthy male participants were recruited for the experiment, Table 2 shows the participant information and their choices of dumbbell weights with the given exercise patterns. Raw sEMG signals were collected through wireless 8-channel biosignals Plux HUB, a sampling rate at 1000 Hz. Body mass index (BMI) was measured (shown in Table 2) that indicates body fat based on height and weight.

Table 2. Participant information.

Number	BMI	Dumbbell weight (kg)	Exercise pattern
1	30.86	5	Pattern 1
2	20.76	5	Pattern 1
3	20.76	5	Pattern 2
4	23.66	5	Pattern 1
5	25.95	5	Pattern 2
6	23.39	5	Pattern 1
7	22.2	5	Pattern 2
8	21.97	5	Pattern 1

(continued)

Table 2. (continued)

Number	BMI	Dumbbell weight (kg)	Exercise pattern
9	23.14	5	Pattern 2
10	22.4	5	Pattern 1
11	22.49	10	Pattern 2
12	23.06	8.5	Pattern 1
13	22.86	8.5	Pattern 2
14	22.20	8.5	Pattern 2
15	23.05	8.5	Pattern 2
16	21.60	8.5	Pattern 1
17	23.12	10	Pattern 2
18	21.38	8.5	Pattern 1
19	23.14	10	Pattern 1
20	25.95	10	Pattern 2

3.3 SEMG Signal Processing

The sEMG signals were sampled at 1000 Hz and a bandpass filter was applied to cut off the frequencies between 20–500 Hz. The muscles were intermittently activated during the dumbbell curls. Teager-Kaiser Energy Operator (TKEO) was used to detect muscle activation. Then, six features were extracted in this study through python. The details of the six features are deliberated as follows:

(1) Mean absolute value (MAV)

For amplitude features, two indicators were extracted: mean absolute value (MAV) and root mean square (RMS) value. They are defined by the following equations:

$$MAV = \frac{1}{N} \sum_{i=1}^N |x_i| \quad (1)$$

where x_i is the i th sample of a signal and N is the number of samples in the epoch.

(2) Root mean square (RMS)

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N |x_i|^2} \quad (2)$$

where x_i is the i th sample of a signal and N is the number of samples in the epoch.

(3) Zero crossing rate (ZCR)

$$ZCR = \frac{1}{N-1} \sum_{n=1}^{N-1} (sig(x_n) - sig(x_{n-1})) \quad (3)$$

where $sig(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$ and N is the number of samples in the epoch.

ZCR indicates the rate of sign-changes of the signal during the duration of a particular frame.

- (4) Mean power frequency (MPF)

$$MPF = \frac{\int_{f_1}^{f_2} f \cdot P(f) df}{\int_{f_1}^{f_2} P(f) df} \quad (4)$$

where f = frequency, $P(f)$ is the power spectral density of the signal. $f_1 = 20$ Hz and $f_2 = 500$ Hz are determined for the bandwidth of the surface electromyography.

- (5) Median frequency (MDF)

$$\int_{f_1}^{f_{med}} P(f) df = \int_{f_{med}}^{f_2} P(f) df \quad (5)$$

where f_{med} is the median frequency, f_s is the sampling frequency, and $P(f)$ is the power spectral density of the signal, and $f_1 = 20$ Hz and $f_2 = 500$ Hz.

- (6) The new frequency parameter proposed by Dimitrov (FI_{nsm5}) is defined as:

$$FI_{nsm5} = \frac{\int_{f_1}^{f_2} f^{-1} \cdot P(f) df}{\int_{f_1}^{f_2} f^5 \cdot P(f) df} \quad (6)$$

where $P(f)$ is the power spectral density of the signal, and $f_1 = 20$ Hz and $f_2 = 500$ Hz.

3.4 Data Analysis

To explore how sEMG features and subjective metrics change with the increase of muscle fatigue, descriptive analysis and statistical analysis were employed via SPSS. All the sEMG features were firstly normalized. Then, the features were independently compared via a one-way analysis of variance. When a significant F-value was achieved, Sheffé post hoc procedures were performed to locate the pairwise differences between the means. At last, correlation analysis was conducted to analyse the correlation among the sEMG features and the correlation between sEMG features and subjective metrics. The results of the semi-structured interview data are not reported in this paper due to the limitation of paper length.

4 Results

4.1 Results of the Descriptive and Statistical Analysis

As shown in Fig. 2, the sEMG features in the time-domain (RMS, ZCR, MAV) and frequency-domain (MDF, FI_{nsm5} , MPF) indicate directional changes with the increase of dynamic muscle fatigue.

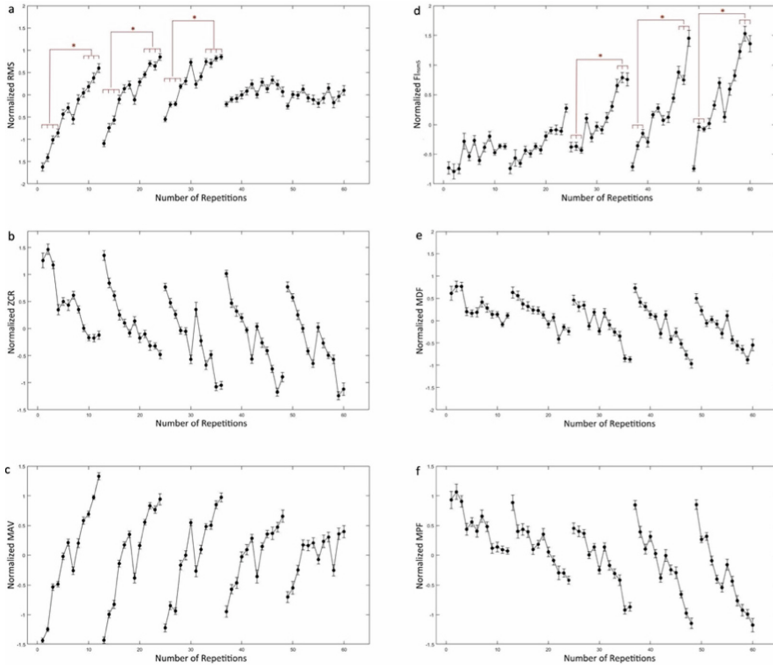


Fig. 2. Changes of sEMG features (mean \pm SD). (a) RMS, (b) ZCR, (c) MAV, (d) FI_{nsm5} , (e) MDF, (f) MPF.

ANOVA tests and post hoc procedures on RMS and FI_{nsm5} respectively showed that: (1) among the first three sets, RMS recorded during the first four repetitions was significantly lower ($p < 0.05$) than the recorded during the last four repetitions; (2) among the last three sets, FI_{nsm5} recorded during the first three repetitions was significantly higher ($p < 0.05$) than the recorded during the last three repetitions.

4.2 Results of the Correlation Analysis

Spearman correlation analysis revealed that among the six extracted sEMG features, MDF and FI_{nsm5} showed strong correlation ($r = -0.608$, $p < 0.01$), followed by RMS and MAV ($r = 0.313$, $p < 0.01$), while the others showed either weak or very weak correlation (Table 3).

Table 3. Correlation coefficients between each two of the six sEMG features

	RMS	MDF	FI _{nsm5}	MPF	ZCR	MAV
RMS		-0.059**	0.090**	-0.029	-0.091**	0.313**
MDF			-0.608**	0.025	0.165**	-0.175**
Flnsm5				-0.036	-0.206**	0.208**
MPF					0.018	-0.02
ZCR						-0.103**
MAV						

*p < 0.05, **p < 0.01

Linear regression was employed to calculate the slope of each sEMG feature within each set. Spearman correlation analysis indicated that Borg Scale ratings and RMS slope had strong correlation ($r = -0.638, p < 0.01$), followed by Borg Scale ratings and FI_{nsm5} slope ($r = 0.531, p < 0.01$), see Table 4.

Table 4. Correlation coefficients between Borg scale ratings and the slope of six sEMG features

	RMS	FI _{nsm5}	MDF	MPF	ZCR	MAV
Borg Scale ratings	-0.638**	0.531**	-0.360**	-0.415**	-0.193	-0.504**

*p < 0.05, **p < 0.01

5 Discussion

This section discusses the findings from this study, including theoretical contributions and practical implications. Theoretical contributions mainly focus on explaining a framework structured by sEMG features, proposed to assess dynamic muscle fatigue. Practical implications cover a range of design considerations that might elicit design ideas for future research and the development of health and fitness technologies.

5.1 Theoretical Contributions

Existing research showed that an increase in the sEMG amplitude is highly related to muscular force [12] and a shift in the frequency spectrum is a typical sign of muscle fatigue [16]. We found that in the first three sets, RMS significantly increased with the increase of muscular force, and there was no obvious change in the remaining two sets. On the other hand, FI_{nsm5} significantly increased in the last three sets, which is considered to be highly related to the increase of fatigue. Compared with other sEMG features, the slope of RMS and FI_{nsm5} of each set has a higher correlation with Borg scale ratings. Therefore, a joint analysis of the spectra and amplitudes across RMS and

FI_{nsm5} was applied. Three fatigue states were proposed: Muscle Activation, Transition to Fatigue, and Fatigue to Exhaustion. A framework was proposed to assess the muscle fatigue level shown in Fig. 3.

- (1) Muscle activation ($RMS\ slope > 0.1$ and $FI_{nsm5} < 0.15$), in this stage muscular force increases without fatigue.
- (2) Transition to fatigue ($RMS\ slope > 0.1$ and $FI_{nsm5} > 0.15$), in this stage muscular force increases and fatigue increases. Fatigue to exhaustion ($RMS\ slope < 0.1$ and $FI_{nsm5} > 0.15$), in this stage muscular force decreases and fatigue increases.

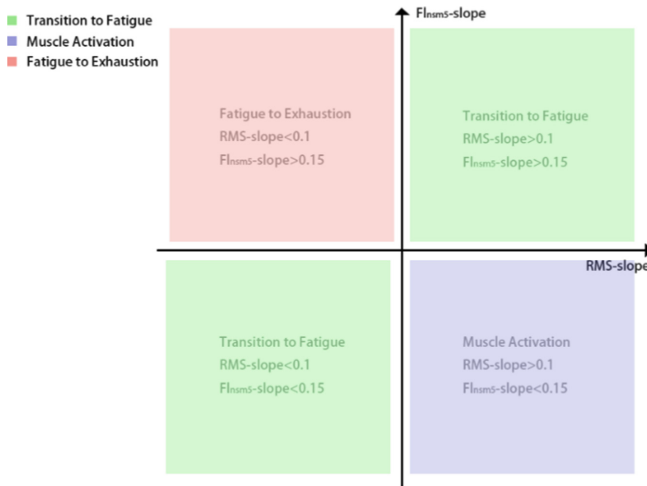


Fig. 3. Framework of fatigue assessment with RMS and FI_{nsm5} slopes

As shown in Fig. 3, the x axis represents the RMS slope of each set, and the y axis represents the FI_{nsm5} slope of each set. For example, if RMS slope is greater than 0.1 and FI_{nsm5} slope is less than 0.15, the framework would decide that the muscle state of this set is Muscle Activation.

The threshold shown in the framework is adjustable according to inter-person and intra-person performances. Based on the data we collected, we found that the sets with Borg scale ratings between 0 and 3, their RMS slopes were mostly greater than 0.1; the sets with Borg ratings greater than 7, their RMS slopes were mostly less than 0.1. Then we decided to set 0.1 as the threshold of the x axis (RMS axis). The determination of the threshold of FI_{nsm5} axis was similar. Overall, the thresholds should be able to self-adjust according to different users and different user performances. In practical scenarios, with the increase of one user using fitness product, a large amount of data will be collected about this user. Therefore, the data should be able to support self-adjustment. To test our framework, we use Borg scale ratings as labels. According to the Borg scale ratings, we defined 0–3 as Muscle Activation, 4–6 as Transition to Fatigue and 7–10 as Fatigue to Exhaustion. In Fig. 4, dots with three different colours represent different ranges of

Borg scale ratings. We took our experimental data into this framework and each dot in the axis represents the subjective fatigue level about one set. The accuracy rate is calculated by dividing the number of dots falling in the corresponding colour area by the total number of dots. The results are shown in Table 5. 64.29% of the least fatigue Borg ratings were identified as Muscle Activation; 55.56% of the medium fatigue Borg ratings were identified as Transition to Fatigue; while 61.29% of the most fatigue Borg ratings were identified as Fatigue to Exhaustion. The accuracy can be further tested with different approaches, e.g., alternative mechanisms or machine learning algorithms. On the other hand, subjective feelings (i.e., Borg ratings) can also play a role in setting the thresholds in the framework rather than labels. The next section will elaborate in detail.

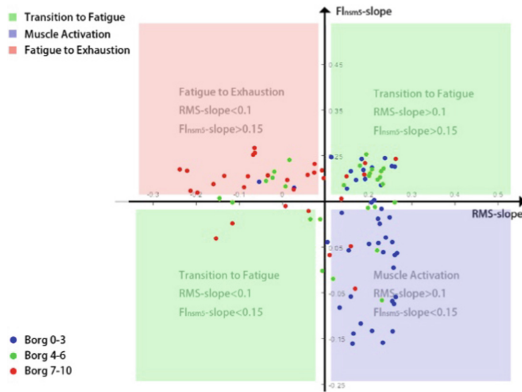


Fig. 4. Points of each set in the framework

Table 5. Accuracy of identifying three states.

	Identified as muscle activation	Identified as transition to fatigue	Identified as fatigue to exhaustion
Borg 0–3	64.29%	30.95%	4.8%
Borg 4–6	22.22%	55.56%	22.22%
Borg 7–10	9.7%	29.03%	61.29%

5.2 Practical Implications

Our framework is proposed to assess fatigue in the context of strength training. This framework can help understand people’s muscle conditions by analysing sEMG signals. The state of Muscle Activation can be used to help users understand whether the warm-up is sufficient and the state of Fatigue to Exhaustion can be used to prevent excessive fatigue. In practical applications, the thresholds can be determined by the data collected from a user’s first two to three workout repetitions. And with the increase of the user’s

muscle activation, muscular force, and fatigue level, the thresholds in the framework should be able to adjust accordingly. Furthermore, we identified different ways to utilise subjective data. Two approaches are discussed in this section in terms of how to integrate users' subjective feedback into the proposed framework:

1. Subjective reports as labels to adjust the framework and influence the fatigue assessment outcome indirectly. The thresholds that distinguish the three fatigue states are not fixed across different user segments. For example, according to a user's subjective report, when the accuracy of the mechanism is lower than a certain value, the framework will need to update its thresholds to improve the accuracy. In this case, the subjective data needs to be collected repeatedly, that the sampling frequency can be varied according to the user's degree of change in muscular force and fatigue.
2. Subjective reports as input and influence the fatigue assessment outcome directly. Feedback from subjective metrics can be used to make corrections to the results of the framework. In other words, results from subjective reports do not play a role in the adjustment of the framework for fatigue assessment, rather they adjust the outcome from the framework directly. For example, if the framework determines that a user's current state is Muscle Activation, while the user's subjective metric keeps reporting high fatigue ratings, then the result that given back to the user might be adjusted to Transition to Fatigue or even Fatigue to Exhaustion.

In real case scenarios, these two approaches can co-exist at the same time to suit different user segments. Based on the previous discussions, the requirements about designing fitness products for monitoring muscle fatigue are considered: (1) the product should be able to collect the sEMG signals of a designated muscle that is expected to be strengthened via specific workouts. sEMG sensors need to be attached to the targeted muscle, so wearable fabrics with sEMG sensors might be a good choice. (2) The product should be able to record users' subjective reports and make full use of them. A user can inform the device about his/her subjective fatigue feelings through voice or manual input, where subjective data should be collected with a certain regular pattern for him/her. (3) The product should be able to give feedback to the users about the degree of their muscle fatigue. To complete a full interaction between the users and the device, the device should be able to push the information back to the users as notifications. A portable and wearable device with a display function might be an option. The form of the notification can use voice, visual, or vibration alerts. The product could also show the users about the changes in their muscle status during strength training.

6 Conclusions, Limitations and Future Work

6.1 Conclusions

This study reveals the changes and speed of changes in which different sEMG features respond to dynamic muscle contractions in the context of strength training. Spearman correlation analysis indicated that Borg Scale ratings had strong correlations with RMS slope and FI_{nsm5} slope, which indicates that sEMG and subjective metrics could be used to predict muscle fatigue during dynamic exercises.

Practically, this study discussed two pairs of dimensions that can be put to design practices either separately or simultaneously: (1) RMS and FI_{nsm5} complement each other during the fatigue process and a framework based on RMS and FI_{nsm5} slopes is proposed. (2) sEMG data and Borg ratings can be utilised to assess muscle fatigue, and subjective metrics can either be a direct input that supports user interaction or be viewed as labels to adjust the framework structured by sEMG.

6.2 Limitations and Future Work

Firstly, this study only investigated two exercise patterns and their impacts on sEMG and subjective metrics, while there are more diverse patterns in daily fitness scenarios. Secondly, in our framework, the thresholds that distinguish the three fatigue states are determined based on the relatively small samples in this study and were classified manually. To adapt to individual users, the thresholds should be able to adjust automatically. Thirdly, in the last two sets, some participants' postures were getting poorer and improper due to fatigue, which may lead to the inaccuracy of the sEMG signals about the measured muscle. Future work could focus on exploring new mechanisms that can detect postures.

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