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Non-Invasive Quantitative Muscle Fatigue Estimation Based on Correlation Between sEMG Signal and Muscle Mass

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ABSTRACT Muscle fatigue is required to be assessed in real-time to maintain the best physical condition, especially for sports and rehabilitation areas. In recent years, numerous studies proposed muscle fatigue estimation methods with non-invasive surface electromyography (sEMG). However, the previous approaches were limited to discerning whether muscle fatigue occurs and were unable to quantify the fatigue level due to individual differences in muscle characteristics. In this study, we propose a novel method for quantitative muscle fatigue estimation that is applicable for various people without individual calibration. Because muscle mass is closely related to muscular endurance, it is utilized as a standard parameter in our assessment process. We introduce a new concept of muscle fatigue score (MFS), based on the cosine similarity between muscle mass and representative fatigue indicators. The MFS exhibits a high correlation coefficient ($|R| = 0.7398$) with key muscle characteristics compared to previous representative muscle fatigue indicators calculated from sEMG: mean frequency ($|R| = 0.2848$), median frequency ($|R| = 0.1972$), and low-frequency ratio ($|R| = 0.0346$).

INDEX TERMS Muscle fatigue estimation, surface electromyography, muscle mass, spectrum analysis.

I. INTRODUCTION

Quantitative muscle fatigue estimation is necessary across various fields, such as fitness, sports, and rehabilitation [1]–[3]. For example, balancing training intensity and muscle condition is crucial for athletes, especially for substantial events such as the Olympics [4]. Therefore, quantitative muscle fatigue estimation can be of great help in achieving efficient training while maintaining muscle health. In addition, muscle fatigue estimation has been used to aid in rehabilitation of various musculoskeletal disorders, such as spinal cord injury, temporomandibular disorder, and cerebral palsy [5]–[7]. Previously, muscle fatigue was estimated by measuring lactic acid concentration in the blood; however, this cannot be measured in real time due to exsanguination [8]. Therefore, recent studies have focused on more the convenient non-invasive surface electromyography (sEMG) technique to estimate muscle fatigue [9]–[11]. It is known that the low-frequency components of sEMG signal increase as the muscle becomes tired [12]–[17]. Several representative muscle fatigue indicators were extracted from sEMG in previous studies: mean frequency (MNF), median frequency (MDF), and low-frequency ratio (LFR) [15]–[17]. Muscle fatigue can be estimated by observing the change in each indicator before and after a workout. Although previous studies reported a distinct increase in the low-frequency components of sEMG after a certain amount of exercising, a large standard deviation of the results indicates that the accuracy and reliability are still insufficient for practical applications. Several other studies have utilized advanced machine-learning algorithms to improve the accuracy of muscle fatigue estimation [18]–[21]. However, individual differences in muscle characteristics required additional calibration process to quantify muscle fatigue in each subject.

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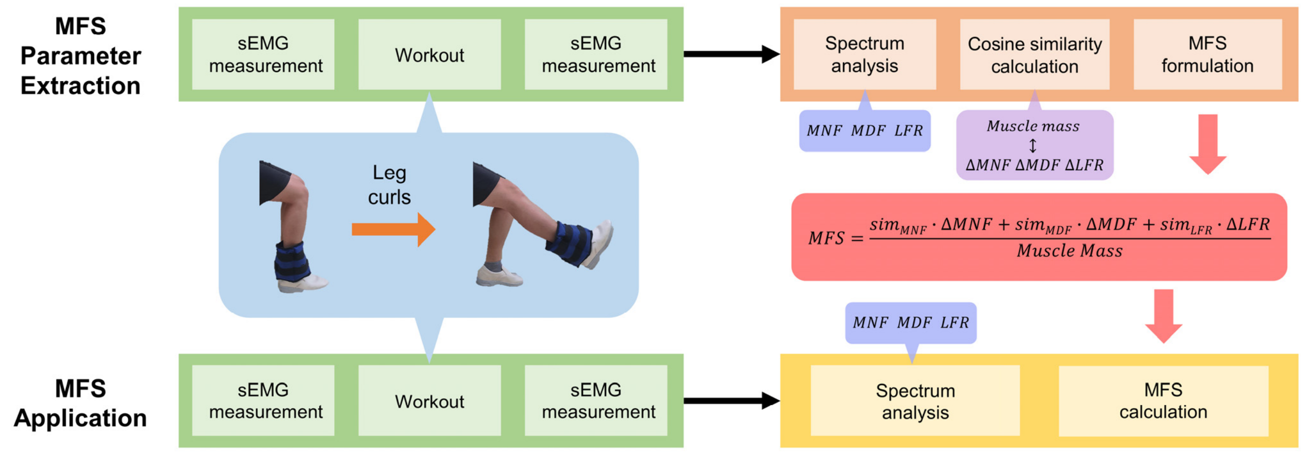

FIGURE 1. Overall flowchart of muscle fatigue score (MFS) parameter extraction and its application. During parameter extraction, surface electromyography (sEMG) of each subject is measured before and after a certain workout. Representative muscle fatigue indicators are then extracted from the spectrum analysis of measured sEMG: mean frequency (MNF), median frequency (MDF), and low-frequency ratio (LFR). The cosine similarities between muscle mass and each frequency indicator are calculated, and the MFS is formulated. In the MFS application step, sEMGs from other subjects are measured before and after a workout, and the MNF, MDF, and LFR are obtained through spectrum analysis. Finally, the muscle fatigue of each subject is estimated using the MFS formula.

In this work, we propose a novel muscle fatigue estimation approach applicable for various people without individual calibration. Our estimation process comprises two steps, as shown in Figure 1. We first extracted the muscle fatigue score (MFS) parameters and then applied the MFS formula for muscle condition assessment [22]. In the MFS parameter extraction step, the sEMG signal was measured for eight subjects before and after a workout. In each workout, subjects performed repetitive leg curls with a 5-kg sandbag until they could no longer continue. Then, we extracted the representative muscle fatigue indicators, ΔMNF, ΔMDF, and ΔLFR, from the measured sEMG. We calculated the cosine similarities between the muscle mass and the extracted muscle fatigue indicators. Finally, we formulated the MFS equation, which can be applied with a subject's sEMG and muscle mass, as shown in Figure 1. In the MFS application step, we measured the sEMG from the other eight subjects and obtained their MFS after a workout. Then, we compared our MFS with the previous muscle fatigue estimation methods in terms of quantification characteristics. As there is still no method to quantitatively measure muscle fatigue in real-time, we compared the correlation between the individual muscle characteristics and estimated muscle fatigue after the participants completed the same workout as a quantification index. If a method quantifies muscle fatigue with a high degree of accuracy, people with more muscle mass would be assessed to have less fatigue than those with lower muscle mass after the same workout [23], [24]. When we measured the muscle fatigue of subjects after they performed 40 repeats of leg curls wearing a 5-kg sandbag, previous methods showed irregular muscle fatigue, regardless of muscle mass. However, our MFS clearly showed a negative correlation between muscle mass and muscle fatigue. Because our MFS exhibits superior quantification characteristics considering individual muscle conditions, it is easy to compare fatigue levels of multiple people without complex individual calibration process.

II. MATERIALS AND METHODS

A. PARTICIPANTS

Muscle fatigue is affected by various physiological variables, such as age, gender, ethnic group, muscle mass, and red/white muscle ratio [25]–[27]; in particular, muscle mass is known to have a significant effect on muscular endurance [23], [24]. Therefore, we focused on the correlation between muscle mass and muscle fatigue. Experiments were conducted with sixteen subjects, and of whom were males aged 21–27 years, as shown in Table 1. First, the MFS parameters were extracted from eight subjects (S1–S8), and we applied the MFS formula to the other eight subjects (S9–S16) to estimate muscle fatigue. This study was approved by the Institutional Review Board of Pohang University of Science and Technology (PIRB-2019-E030).

B. EXPERIMENTAL SETUP

The muscle mass of each subject was measured using a body composition analyzer (ACCUNIQ, IOI 353). We used commercial Ag/AgCl electrodes (3M, 2223H) to measure the sEMG signals. Two electrodes were placed on the thigh at a distance of 6 cm, and one ground electrode was attached to the ankle of the opposite leg. The sEMG was measured using a high-resolution semiconductor analyzer (Keysight, B1500A) with a sampling frequency of 250 Hz. The DC offset and baseline wander were removed by a second-order Butterworth high-pass filter with a cutoff frequency of 33.9 Hz, and a notch filter was used to remove 60-Hz noise [28]. All filters used in signal processing were implemented

TABLE 1. Physical information of sixteen subjects in this work.

Subject	Age (years)	Height (cm)	Weight (kg)	Muscle mass of leg (kg)
S1	25	170.0	64.9	8.73
S2	26	180.0	88.5	9.90
S3	21	178.0	78.8	10.30
S4	23	182.7	84.1	10.72
S5	25	177.0	75.0	10.14
S6	27	181.0	75.1	10.38
S7	27	170.4	110.0	12.83
S8	26	175.0	74.3	9.68
S9	26	171.0	63.1	9.12
S10	25	187.0	91.5	11.39
S11	26	174.0	76.4	9.23
S12	26	174.1	74.8	9.94
S13	24	181.0	73.5	10.03
S14	26	171.0	63.1	8.92
S15	23	181.5	82.8	10.46
S16	26	175.0	73.5	9.21

TABLE 2. Rating of perceived exertion scale for reliable exercise intensity monitoring [29].

Score	Descriptor
0	Rest
1	Very easy
2	Easy
3	Moderate
4	Somewhat hard
5	Hard
6	
7	Very hard
8	
9	
10	Maximal

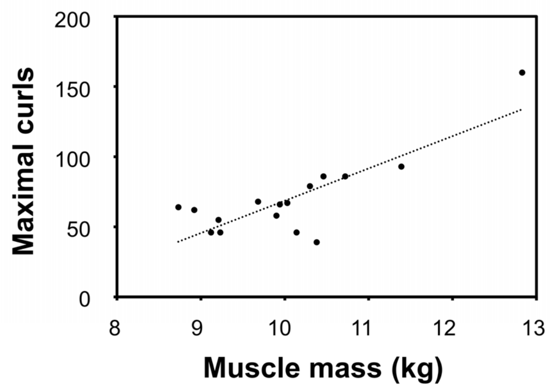

FIGURE 2. Number of maximum leg curls with 5-kg sandbag as a function of leg muscle mass. The strong correlation between muscle mass and maximum curls indicates that people with more muscle mass have better muscular endurance.

through MATLAB. To increase the muscle fatigue level, leg curls were performed with a 5-kg sandbag. The participants evaluated their subjective muscle fatigue after leg curls based on the perceived exertion scale defined in Table 2 [29], which is a well-known and reliable indicator for exercise intensity monitoring.

C. SIGNIFICANCE OF MUSCLE MASS

It is generally known that muscle mass and muscle fatigue are closely related. Previous studies have demonstrated that people with larger muscle mass perceive less fatigue after exercising with the same intensity [27], [28]. Therefore, we utilized muscle mass as a key variable to calculate the MFS from sEMG signal. As shown in Figure 2, we measured the maximum number of leg curls (5-kg sandbag) for all subjects and organized the data as a function of leg muscle mass. It is clearly shown that the maximum number of curls increases as the leg muscle mass increases. The Pearson correlation coefficient (R) between the leg muscle mass and the number of maximal leg curls is 0.8205, which indicates that the relation between muscle mass and muscular endurance is strongly positive [30]. This trend can be interpreted to indicate that a person with considerable muscle mass will experience less muscle fatigue when working out at a certain intensity. Therefore, if the muscle fatigue estimation method is accurate, it should evaluate that people with a large amount of muscle mass feel less muscle fatigue than those with less muscle mass after the same workout.

III. DATA ANALYSIS

A. PREVIOUS MUSCLE FATIGUE INDICATORS

Previous studies on muscle fatigue estimation have shown that the low-frequency component of the sEMG signal increases as the muscle becomes fatigued [13]. The representative indicators that quantify the portion of low-frequency components are the MNF [15], MDF [16], and LFR [17].

Each indicator is defined as

$$MNF = \frac{\int_0^{f_s/2} f \cdot P(f)df}{\int_0^{f_s/2} P(f)df}, \tag{1}$$

$$\int_0^{MDF} P(f)df = \frac{1}{2}\int_0^{f_s/2} P(f)df, \tag{2}$$

$$LFR = \frac{\int_0^{45} P(f)df}{\int_0^{f_s/2} P(f)df}, \tag{3}$$

where f_s denotes the sampling frequency and $P(f)$ is the power spectral density of sEMG signal. Previously, muscle fatigue was assessed by the change in the indicator after a workout. The change in each indicator (ΔMNF, ΔMDF, and ΔLFR) is defined as

$$\Delta MNF = MNF_{after} - MNF_{before}, \tag{4}$$

$$\Delta MDF = MDF_{after} - MDF_{before}, \tag{5}$$

$$\Delta LFR = LFR_{after} - LFR_{before}. \tag{6}$$

The subscript "after" refers to the indicator extracted after a workout, and the subscript "before" refers to the indicator extracted before a workout. It was clearly shown in previous muscle fatigue analysis using sEMG that the MNF and MDF shift negatively and the LFR shifts positively after a workout [12]–[17]. However, the reliability of the estimation is insufficient, owing to the large variation of the result. In addition, these methods cannot quantify muscle fatigue because of the individual differences in muscle characteristics. The value only shows the tendency, not a quantitative fatigue level. In other words, the estimated muscle fatigue value of one person does not have any meaning to another person because they have different muscular properties. However, we proposed a quantitative method to evaluate muscle fatigue by introducing muscle mass, which is closely related to muscle fatigue, into the sEMG analysis.

B. MUSCLE FATIGUE SCORE

Our muscle fatigue estimation approach, named MFS, is based on a comprehensive quantification using the previous indicators and their correlation with muscle mass. A detailed flowchart of our MFS method is depicted in Figure 3. The MFS comprises three steps: 1) sEMG signal measurement; 2) MFS parameter extraction; and 3) MFS application. In step 1, each subject's sEMG signal is measured before a specified workout; subsequently, the MNF, MDF, and LFR are obtained through spectrum analysis of the measured sEMG. An example sEMG signal and its power spectral density are shown in Figure 4a. Subjects perform leg curls up to the maximum number they could; then, sEMG is measured again from each subject, and the low-frequency components are increased, as shown in Figure 4b. The dotted lines in the power spectral density graph in Figure 4 indicate the MDF, which is shifted negatively after workout. The change in MNF, MDF, and LFR is calculated for each participant. In step 2, the cosine similarities between the muscle mass and ΔMNF/ΔMDF/ΔLFR are obtained. The calculated

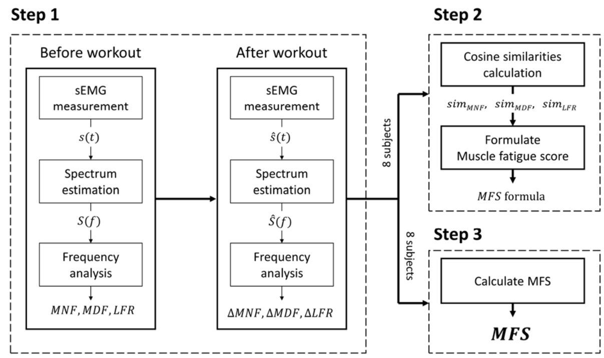

FIGURE 3. Block diagram of MFS analysis process. sEMG is measured before and after the workout, and the change in MNF, MDF, and LFR is extracted by spectrum analysis of the sEMG signal. The cosine similarities between muscle mass and each muscle fatigue indicators (ΔMNF, ΔMDF, and ΔLFR) are calculated from eight subjects, and then the MFS formula is derived. The formula is used to estimate the muscle fatigue of the other eight subjects.

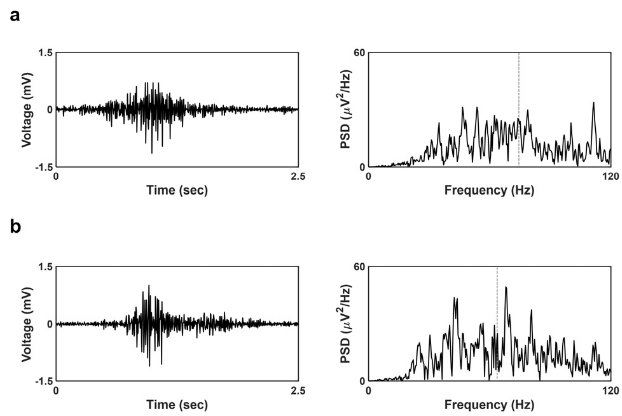

FIGURE 4. Measured sEMG signal of subject S8 (left) and its spectral data (right) a) before and b) after 60 leg curls. As shown in the spectral data, the low-frequency components of the sEMG are increased after the workout. The dotted vertical line represents the median frequency (MDF), and a clear negative shift is observed after the workout.

TABLE 3. Calculated cosine similarities between each muscle fatigue indicator and muscle mass.

	Mean frequency (ΔMNF)	Median frequency (ΔMDF)	Low-frequency ratio (ΔLFR)
Cosine similarity	−0.9161	−0.8585	0.8873

cosine similarities in our experiments are shown in Table 3. We propose the MFS formula as follows:

$$MFS = \frac{sim_{MNF} \cdot \Delta MNF + sim_{MDF} \cdot \Delta MDF + sim_{LFR} \cdot \Delta LFR}{Muscle\ Mass}, \tag{7}$$

where sim_{MNF}, sim_{MDF}, and sim_{LFR} are the cosine similarity between muscle mass and ΔMNF, ΔMDF, and ΔLFR, respectively. We utilized sEMG data from eight participants

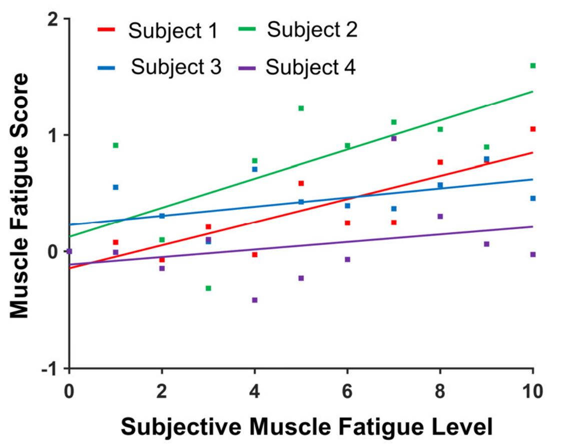

FIGURE 5. Results of muscle fatigue score (MFS) as a function of muscle fatigue level. The MFS increases as the subjective muscle fatigue level increases in all subjects.

to derive these cosine similarities. In step 3, we applied the MFS formula to the other eight subjects to estimate their muscle fatigue.

IV. RESULTS AND DISCUSSION

A. MUSCLE FATIGUE ASSESSMENT

We attached skin electrodes onto the subjects' thigh and instructed them to perform leg curls at 4-sec intervals. Then, we measured the sEMG during the leg curls and simultaneously surveyed the subjective muscle fatigue using a standard perceived exertion scale in Table 2 for each subject. In Figure 5, the calculated MFS data from four participants is plotted as a function of subjective muscle fatigue. As the subjective muscle fatigue increases, the MFS increases, which indicates that the MFS clearly quantifies the fatigue level. The MFS not only shows explicit muscle fatigue estimation, but also exhibits outstanding reliability, compared to the previous muscle fatigue indicators: ΔMNF, ΔMDF, and ΔLFR. We conducted additional experiments to numerically compare the reliability of each muscle fatigue indicator. As shown in Figure 6A, the subjects performed 40 times of leg curls, and sEMG was measured for the fatigue analyses. We repeated this process 3 times with a sufficient rest period of more than 3 days and calculated the relative variance of muscle fatigue indicators [30]. Relative variance (RV) is defined as:

$$RV = \frac{V(x)}{\{E(x)\}^2}, \tag{8}$$

where V(x) is the variance and E(x) is the mean value of muscle fatigue estimation. As shown in Figure 6B, our MFS shows lower variance compared to the previous muscle fatigue indicators, which implies that the MFS exhibits the highest reliability [31]. Because MFS is calculated based on various indicators from sEMG signal and correction by individual muscle mass, it exhibits higher reliability than the other muscle fatigue estimation methods that utilize a single indicator.

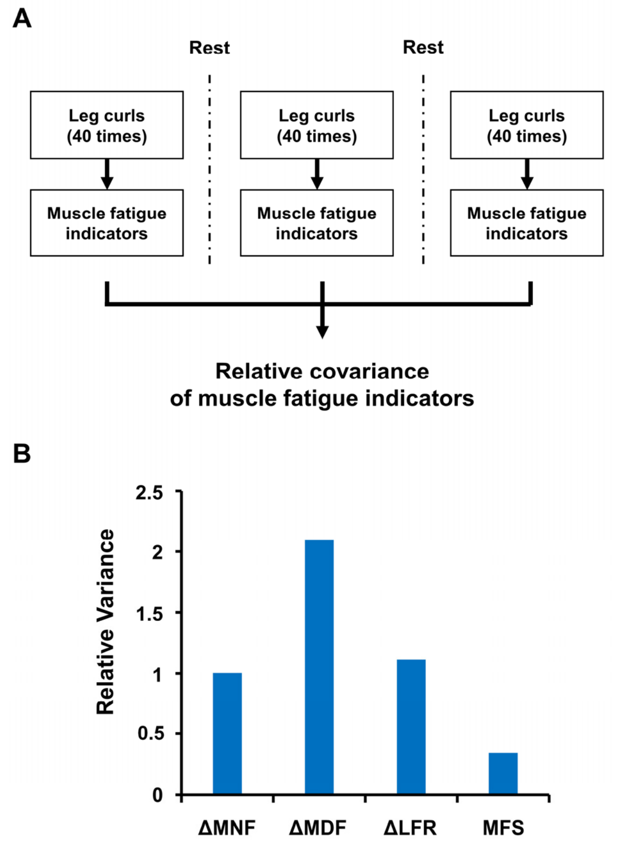

FIGURE 6. Relative variance of muscle fatigue indicators. A) The block diagram of relative covariance calculation. The subjects' muscle fatigue indicators after 40 leg curls are extracted three times with a sufficient rest period. B) Average relative covariance of eight subjects for each muscle fatigue indicator. The MFS exhibits the lowest relative variance, compared to the others.

B. MUSCLE MASS CORRESPONDENCE

Muscle mass is one of the most important indicators of muscular ability. It is well known that a person with considerable muscle mass feels less muscle fatigue, compared to a person with lower muscle mass, after the same workout [23], [24]. To confirm the reliability of the MFS with previous estimation approaches, we calculated the MFS for eight subjects after performing 40 leg curls and compared it to ΔMNF, ΔMDF, and ΔLFR. If a muscle fatigue indicator can standardize fatigue level with high reliability, the result value would be less for people with more muscle mass. As shown in Figure 7, |ΔMNF| exhibits a positive correlation with muscle mass, and |ΔLFR| shows no correlation with muscle mass. Even though |ΔMDF| has a negative correlation, its R value is only −0.1972, indicating that the MDF is weakly correlated with muscle mass [32]. This low correlations of the previous muscle fatigue indicators are caused by several abnormal data, which is usually observed when the reliability is low [33], [34]. The MFS exhibits an R value of −0.7398,

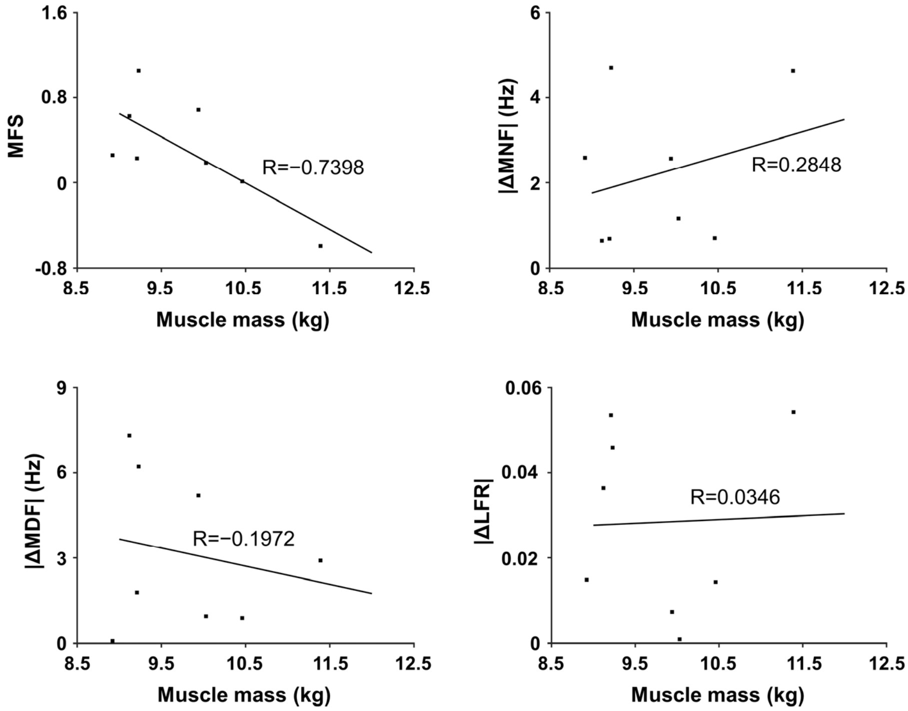

FIGURE 7. Results of muscle fatigue estimation as a function of muscle mass of each subject using our muscle fatigue score (MFS) and other conventional fatigue indicators, ΔMNF, ΔMDF, and ΔLFR, after 40 leg curls. As shown in Figure 2, people with more muscle mass have better muscular endurance and less muscle fatigue after the same workload. The MFS exhibits the most negative Pearson correlation coefficient ($R = -0.7398$), which indicates that the reliability of MFS is superior to the other methods.

which represents an outstanding high correspondence with muscle mass. We note that the muscle fatigue level can be affected by other variables, such as age, gender, and ethnic group; however, the experiment was conducted in a group of similar characteristics. The accuracy of MFS can be further improved with more diverse data sets.

V. CONCLUSION

In this article, we present a new muscle fatigue estimation method based on non-invasive sEMG measurement. As previous muscle fatigue estimation approaches were based only on sEMG signal analysis, they cannot incorporate individual characteristics in muscle conditions. We utilized muscle mass as a key parameter in fatigue estimation and calculated the cosine similarity between muscle fatigue indicators and muscle mass. Our MFS method can be applied to various people without an individual calibration process, and its reliability is better than that of previous approaches. We believe our algorithm will play an important role in sports and healthcare sectors by providing quantitative muscle conditioning with a wearable sensor platform.

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