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Comparative Analysis of Linear and Nonlinear sEMG Methods for Detecting Muscle Fatigue During Dynamic Biceps Curls

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Abstract - Muscle fatigue, a key concern in sports science, rehabilitation, and occupational health, influences performance, injury risk, and provides insights into muscle functionality and endurance. Surface electromyography (sEMG) has emerged as a vital tool for non-invasively tracking muscle electrical activity and gauging health. As its application for muscle fatigue assessment grows, identifying the most accurate analytical methods is essential. Current sEMG analyses employ both linear and nonlinear metrics to measure fatigue onset and progression, yet research is ongoing to determine which method is most effective in the context of dynamic contractions. The study was aimed to evaluate the efficacy of established linear and nonlinear methods in measuring muscle fatigue caused by dynamic contractions through surface electromyography (sEMG) signals. A group of twelve healthy individuals completed biceps curls at a consistent pace of one repetition per four seconds, which constituted 75% of their 10-repetition maximum. Concurrently, sEMG signals were captured from the biceps brachii muscle at 1000 Hz. To assess the sEMG signals during the initial, middle, and final sets of 10 repetitions, three linear metrics—mean frequency, median frequency, and spectral moment ratio (SMR)—along with two nonlinear approaches, namely sample entropy and detrended fluctuation analysis (DFA), were utilized. The study's outcomes indicated notable shifts in the SMR values and the two DFA-derived scaling exponents across the exercise sets. These results indicated that SMR, sample entropy, and DFA are effective in gauging muscle fatigue, with sample entropy and DFA demonstrating heightened sensitivity to the fatigue levels when compared to the linear metrics.

Keywords—Muscle Fatigue, Surface Electromyography (sEMG), Dynamic Contractions, Linear and Nonlinear Metrics, Fatigue Assessment, Biceps Curl Exercise

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1. INTRODUCTION

Stroke, a cerebrovascular disease resulting from interrupted or reduced blood supply to the brain, affects approximately 2.5% of the population [1]. In many countries, stroke stands as a leading cause of death and disability

[2]. Nearly one-third of stroke survivors contend with persistent disabilities, primarily characterized by motor impairments [2]. Consequently, the rehabilitation of motor functions holds immense significance for stroke survivors.

The potential for recovering lost motor functions hinges on the brain's neuroplasticity [2]. Existing evidence supports the idea that intensive, task-specific training can significantly enhance motor function recovery among stroke patients [3]. Nevertheless, some patients may struggle to engage in such intensive training due to muscle fatigue. In these instances, patients may require assistance from a therapist or a robotic system, with an aid tailored to their specific physical condition. Therefore, it becomes essential to detect the onset and extent of muscle fatigue during rehabilitation exercises.

2. LITERATURE REVIEW

Muscle fatigue, defined as the muscle's diminished ability to sustain force generation or reduced capacity to generate force following exercise [4, 5], can be assessed using various methods. One particularly useful approach is surface electromyography (sEMG), which allows for real-time, noninvasive detection of muscle fatigue. Studies have confirmed that sEMG signals can reveal signs of muscle fatigue, often preceding its actual onset [4]. Presently, there are roughly two categories of methods for analyzing sEMG signals to assess muscle fatigue, i.e., linear methods and nonlinear methods [6].

The most commonly used linear measures in this context are mean frequency (MNF) and median frequency (MDF). The rationale is that muscle fatigue leads to a shift in sEMG signal power from high to low frequencies, which results in decreased MNF and MDF and increased spectral moment ratio (SMR) [4]. However, different techniques for estimating the power spectral density can lead to different results of frequency-domain indices. Corvini and Conforto [7] found that autoregressive model outperformed the Welch method in estimating mean and median frequency during severe muscle fatigue. Furthermore, it was found that for the Welch method, the parameters such as window size, weighting, and overlap influence the estimation of the power spectral density and that a combination of a smaller time window and a larger overlap would lead to a better result [8]. Since sEMG signals are generally nonstationary, especially for those from dynamic contraction of muscles, advanced signal processing methods such as time-frequency analysis are essential for the extraction of muscle fatigue indices. Hari et al. [9] analyzed sEMG signals from the biceps brachii (BB) muscle during dynamic contractions based on synchrosqueezed wavelet transform. They found that the proposed approach is capable of characterizing nonstationary changes in sEMG signals. Additionally, several recent studies have proposed to use topological and geometric features of sEMG signals to assess muscle fatigue and showed promising results [10, 11].

Conversely, owing to the inherent nonlinearity of myoelectric activity, nonlinear methods have been introduced to capture the intricate patterns of sEMG signals. Numerous studies have consistently demonstrated that a reduction in the complexity of sEMG signals corresponds with muscle fatigue [4]. Moreover, it appears that certain nonlinear measures exhibit greater sensitivity to muscle fatigue when compared to traditional linear measures [4, 12]. Murillo-Escobar et al. [13] utilized a nonlinear measure called permutation entropy to characterize sEMG signals during dynamic contractions and showed that this measure could distinguish different fatigue states more effectively than the classic features such as MDF. Overall, these studies suggest that nonlinear methods may provide more accurate and sensitive detection of muscle fatigue during dynamic contractions compared to linear methods.

Among a variety of nonlinear methods, sample entropy (E_s) [14] and detrended fluctuation analysis (DFA) [15]are most commonly used ones. E_s quantifies the complexity, i.e., regularity degree, of a time series and the time series can be very short [14]. Several studies showed that a decrease in E_s of sEMG signals is associated with muscle fatigue [12, 16]. DFA is used to quantify the self-similar property of time series [15]. It was found that an increase in DFA coefficient is associated with muscle fatigue [17]. However, the relevant studies mainly involved isometric contractions. Kahl and Hofmann [6] compared the performances of several linear and nonlinear methods to quantify muscle fatigue during isometric contractions. They reported that SMR showed a slightly better performance than the others. Hernandez and Camic [17] showed that E_s and scaling exponent yielded by DFA are influenced by muscle fatigue as well as contraction type. It is still unclear which measures are sensitive and robust for detecting muscle fatigue during dynamic contractions.

The present study aims to identify which measures are more suitable for assessing muscle fatigue in the case of dynamic contractions. We compared the performances of several commonly used linear and nonlinear methods. We hypothesized that E_s and DFA coefficient would be able to characterize alterations of myoelectric activity induced by muscle fatigue. We also hypothesized that nonlinear measures would be more sensitive to muscle fatigue compared to linear measures.

3. RESEARCH METHODOLOGY

3.1 Participants

This study involved twelve healthy young adults, comprising an equal number of males and females with an average age of 27.54 years (±6.35) and a mean body mass index of 22.32 (±2.61) kg/m^2. To ensure the participants' safety, those with a history of cardiovascular, pulmonary, or neuromuscular disorders, as well as those who had previously experienced negative reactions to exercise, were not included. The institutional review board granted approval for this research, and written consent was secured from each participant before his/her involvement.

3.2 Research Procedures

To construct a dataset for the comparative analysis of sEMG-based methods in detecting muscle fatigue, each participant was instructed to perform biceps curls while the sEMG signal from the BB were meticulously recorded. The experimental protocol comprised two consecutive visits, as depicted in Figure 1. During the initial visit, the primary objective was to establish the ten-repetition maximum (10RM) for each participant.

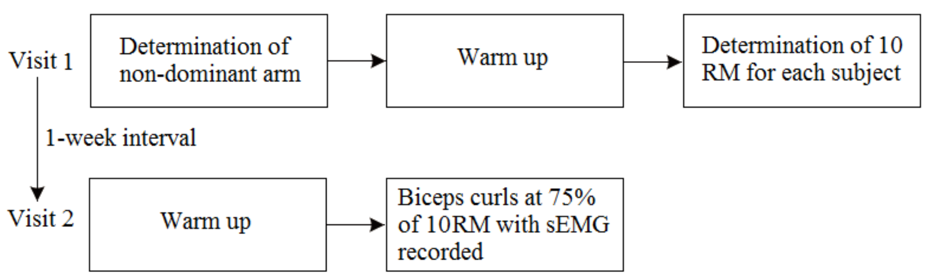

Figure 1. Experimental Procedures Of This Study- 10RM: Ten-repetition Maximum

In this regard, the subjects were seated on a bench and initiated their biceps curls without any added resistance, essentially serving as a warm-up exercise, which lasted for a duration of 5 minutes. To minimize any potential influences from daily physical activities, all subjects were specifically directed to employ their non-dominant arm for this purpose. Subsequently, the subjects were granted a 3-minute rest period. Following this interval, the subjects commenced their biceps curls, employing dumbbells of varying weights [18].

The initial weight for each subject was chosen based on the sbuject's estimation. Then, the subject tried to determine an appropriate weight according to the number of repetitions he/her was able to complete. If the number of repetitions exceeded 10, the weight would be increased. Conversely, if the number of repetitions was less than 10, the weight would be decreased. The ultimate weight that enabled the subject to perform precisely 10 repetitions was determined as his/her 10RM.

During the second visit, the subject first underwent a warmup for 5 minutes and rested for 3 minutes. Then, the suject did biceps curls at a consistent pace of one repetition per four seconds using 75% of 10RM [19, 20]. After completing every session of exercise, including 10 repetitions, the subject rested for 30 seconds and then repeated this process until task failure. During the whole process, sEMG signal from the BB was recorded at 1000 Hz using a differential amplifier through a bipolar electrode configuration (BIOPAC Systems, Inc., Santa Barbara, CA, USA). Figure 2 shows a typical sEMG signal from a subject.

3.3 Data Analysis

To compare the performances of E_s, DFA coefficient, and the commonly used linear measures for characterizing muscle fatigue, we focused on the first, second, and last sessions of exercise. Accordingly, for each sEMG signal epoch corresponding to a session of exercise, after being filtered by a 4th order Butterworth band pass filter (20-450 Hz), it was divided into 10 segments, each of which corresponded to a repetition of exercise. The linear measures, E_s, and DFA coefficients were computed for all signal segments and averaged. The relative changes of these measures for the second and last signal epochs with respective to that for the first signal epoch were defined in the same manner. For example, the relative change of E_s for the second epoch was defined as $100\% \times (E_{s,2} - E_{s,1}) / E_{s,1}$, where $E_{s,1}$ and $E_{s,2}$ are the entropy values for the first and second signal epochs, respectively.

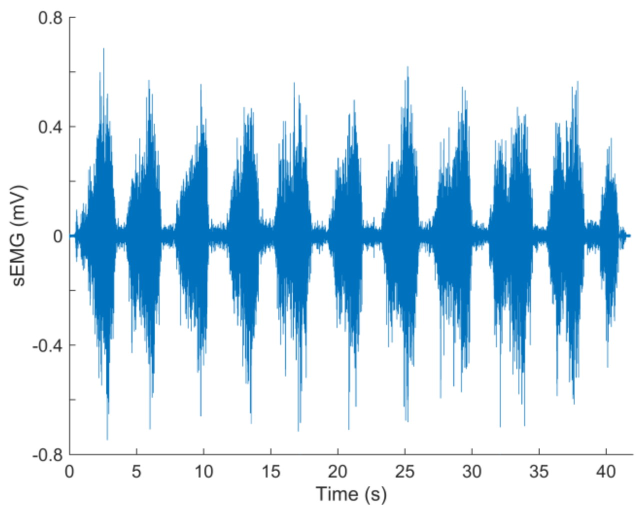

Figure 2. A Typical sEMG Signal From The BB Of A Subject When Performing Exercise

3.3.1 Linear Methods

Three linear measures, including MNF, MDF, and SMR, were computed. Given a sEMG signal segment, suppose that the power spectrum is divided into n frequency bins, MNF is defined as

$$MNF = \sum_{j=1}^{n} f_j p_j / \sum_{j=1}^{n} p_j \,, \tag{1}$$

where f_j and p_j are the frequency and power at the j th frequency bin, respectively. MDF is defined as the frequency f_m satisfying

$$\sum_{j=1}^{m} p_j = \frac{1}{2} \sum_{j=1}^{n} p_j \,. \tag{2}$$

SMR is defined as

$$SMR = \ln \frac{M_{-1}}{M_k}, M_k = \sum_{j=1}^{n} f_j^k p_j \,. \tag{3}$$

In this study, the parameter k =5 was used [6].

3.3.2 Sample Entropy (E_s)

E_s is frequently used to quantify the complexity, i.e., regularity degree, of a time series [14]. It yields a smaller (larger) value for a more regular (irregular) time series. In this study, we adopted a modified algorithm [21] to compute E_s. Given a time series $\{x(i)\}, i=1,...,N$, its sequences of length m are defined as

$$\mathbf{x}_i^m = \{x(i),...,x(i+k\tau)\},\ 1 \le k \le m-1,\ 1 \le i \le N-m\tau, \tag{4}$$

where τ is an integer. The similarity between two sequences $\mathbf{x}_i^m$ and $\mathbf{x}_j^m$ is quantified by the distance between them, defined as

$$d(\mathbf{x}_i^m, \mathbf{x}_j^m) = \max\{|x(i)-x(j)|,...,|x(i+(m-1)\tau)-x(j+(m-1)\tau)|\},$$
$$1 \le i, j \le N-m\tau,\ |i-j| > \tau. \tag{5}$$

If $d(\mathbf{x}_i^m, \mathbf{x}_j^m) < r$, where r is a predefined threshold, the two sequences are considered to be similar to each other. Suppose that given a sequence $\mathbf{x}_i^m$, there are n_i sequences $\mathbf{x}_j^m$ satisfying $|i-j|>\tau$, and n_i' of them satisfy $d(\mathbf{x}_i^m, \mathbf{x}_j^m) < r$. Hence, $p_i^m(r) = n_i'/n_i$ represents the probability that a sequence $\mathbf{x}_j^m$, $|i-j|>\tau$, is similar to the given sequence $\mathbf{x}_i^m$; and $p^m(r) = \sum_{i=1}^{N-m\tau} p_i^m/(N-m\tau)$ represents the probability that any two sequences, $\mathbf{x}_i^m$ and $\mathbf{x}_j^m$, $|i-j|>\tau$, are similar to each other. Likewise, $p^{m+1}(r)$ represents the probability that any two sequences of length $m+1$, $\mathbf{x}_i^{m+1}$ and $\mathbf{x}_j^{m+1}$, $|i-j|>\tau$, are similar to each other. In this way, E_{ms} is estimated by

$$E_{ms}(m,r,\tau,N) = -\ln\frac{p^{m+1}(r)}{p^m(r)}. \tag{6}$$

The influences of three parameters, m, r, and N, on E_s have been tested and discussed extensively in previous studies [14, 21]. Briefly, E_s almost does not depend on N and shows relative consistency when m or r changes in a wide range. In the present study, m=2, r=0.25×SD (standard deviation of the signal) were adopted according to previous studies [14]. As for the parameter τ, an approach to determine it involves computing the auto mutual information function of the signal and determining the first minimum of the function [21]. Using this approach, we obtained τ=2 for most of the sEMG signals. Thus, we adopted τ=2. A typical example is shown in Figure 3. Figure 3(A) and 3(C) show the illustration of the determination of τ on a sEMG signal segment corresponding to one repetition of the first session (s_1) of exercise and its mutual information function $MI(\tau)$, while Figure 3(B) and 3(D) show the illustration of the determination of τ on a sEMG signal segment corresponding to one repetition of the second session (s_2) of exercise and its $MI(\tau)$. In both cases, the first minimum of $MI(\tau)$ is located at τ=2.

3.3.3 Detrended Fluctuation Analysis (DFA)

DFA is a method to assess self-similar property of a time series [15]. Given a time series $\{x(i)\}, i=1,...,N$, the first step is to divided the integrated series $\{y(i)\}$ into M non-overlapping boxes of size n. Then, the trend of $\{y(i)\}$ within each box, denoted as $\{y_n(j)\}$, is extracted by fitting a regression line to $\{y(i)\}$. A fluctuation function is therefore defined as

$$F(n) = \sqrt{\frac{1}{M\times n}\sum_{j=1}^{M\times n}[y(j)-y_n(j)]^2}. \tag{7}$$

When $F(n)$ is plotted against varying box size n on a log-log scale, if $F(n)$ changes linearly with n, the slope α, called scaling exponent, indicates the presence of self-similar behaviors of the signal. Specifically, white noise, pink noise, and brown noise yield α =0.5, 1, and 1.5, respecttively. In this study, however, we found that all sEMG signals yield two distinct scaling regions (Figure 4). One scaling region is roughly n<9, and another is roughly n>16. This means that a single scaling exponent is incapable of characterizing the dynamics of the sEMG signals. Such a phenomenon was also observed in previous studies on heart rate variability [22] and skin blood flow oscillations [23]. Thus, we extracted two scaling exponents, denoted as DFA α_1 and DFA α_2, respectively.

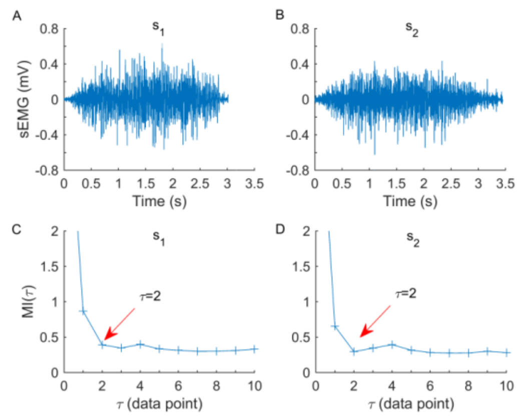

Figure 3. Illustration of the determination of τ . (A),(C) Correspond to one repetition of the first session (s_1); (B),(D) Correspond to one repetition of the second session (s_2)

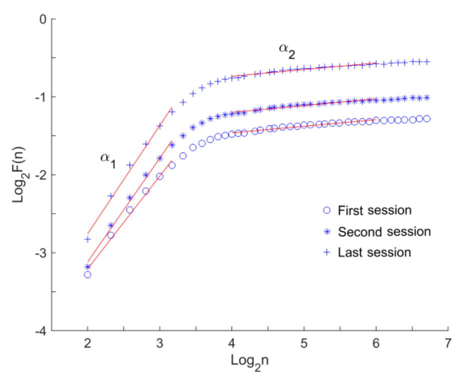

Figure 4. Examples Of DFA Of sEMG Signal Epochs Corresponding To The First, Second, And Last Sessions

3.3.4 Statistical Analysis

The differences in all measures, i.e., MNF, MDF, SMR, E_s, DFA α_1, and DFA α_2, of the sEMG signal epochs between the first, second, and last sessions were examined using one-way ANOVA with paired t-tests. For each measure, the distribution of the obtained values was tested using Shapiro–Wilk test. All tests were implemented using the SPSS software (Version 26, USA).

4. RESULTS AND DISCUSSION

4.1 Results

Figure 5 shows the statistical results of three linear measures and their relative changes. SMR for the sEMG signal epochs during the last session of exercise was significantly larger than that during the first and second sessions of exercise (Figure 5E). For MNF and MDF, no significant change was observed (Figures 5A-D). Figure 5(A) and 5(B) show the statistical results of MNF of the sEMG signal epochs corresponding to the first, second, and last sessions of exercise, Figure 5(C) and 5(D) statistical results of MDF of the same signal epochs, while Figure 5(E) and 5(F) show the statistical results of SMR of the same signal epochs. The results are presented as mean±standard error. The symbol * indicates $p<0.05$.

Figure 6 shows the statistical results of E_s and its relative change. E_s for the sEMG signal epochs during the second and last sessions of exercise was significantly lower compared to the first session, whereas it did not show significant difference between the second and last sessions. Figure 6(A) shows E_s of the sEMG signal epoachs corresponding to the first, second, and last sessions of exercise, while Figure 6(B) shows the relative change of E_s during the second and last sessions. The results are presented as mean±standard error. The symbol ** indicates $p<0.01$.

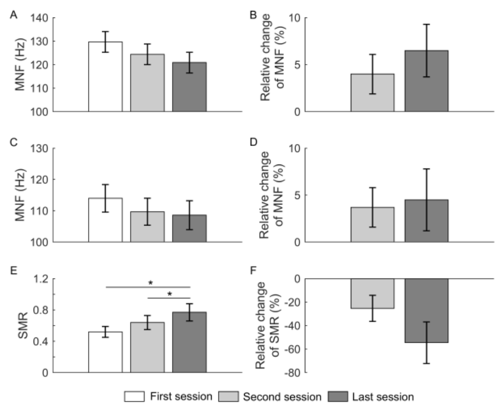

Figure 5. Statistical Results Of Three Linear Measures And Their Relative Changes

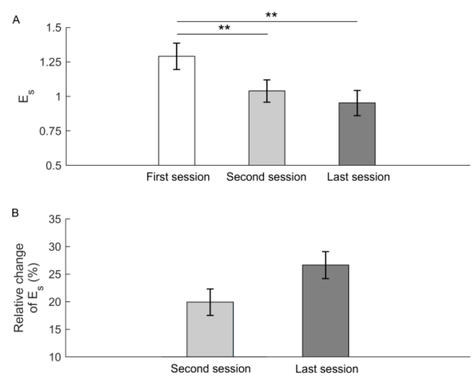

Figure 6. Statistical Results of E_s And Its Relative Change

Figure 7 shows the results of DFA α_1 and DFA α_2 and their relative changes. DFA α_1 significantly increased from the first session to second session and from the second session to last session. DFA α_2 significantly increased from the second session to last session but did not show significant difference between the first and second sessions. Figure 7. Figure 7(A) and 7(C) shows the DFA α_1 and DFA α_2 of the sEMG signal epochs corresponding to the first, second, and last sessions of exercise, Figure 7(B) shows the relative change of DFA α_1 while Figure 7(D) shows the relative change of DFA α_2. The results are presented as mean±standard error. The symbols * and ** indicate $p<0.05$ and $p<0.01$, respectively.

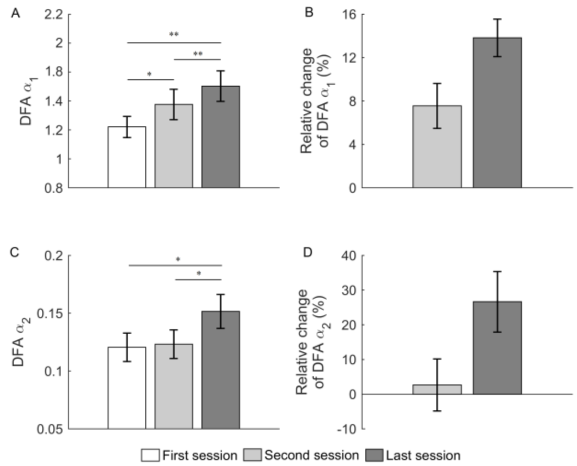

Figure 7. Statistical Results Of DFA α_1 And DFA α_2, And Their Relative Changes

4.2 Discussion

This study was aimed to compare linear and noninear methods to analyze sEMG signals for assessing muscle fatigue caused by dynamic contractions. Base on the assumption that compared to the first session of exercise, the BB was somewhat fatigued during the second session and highly fatigued during the last session, our results showed that SMR, E_s, and DFA α_1 are suitable for assessing muscle fatigue. Furthermore, E_s and DFA α_1 showed more sensitivity to alterations of sEMG signals caused by muscle fatigue.

In this study, the rationale for using E_s and DFA coefficients to reveal alterations of myoelectric activity were as folllows. First, it is considered that the generation of sEMG is a nonlinear process [24] because sEMG signals exhibit nonlinear behaviors. There is evidence that the nonlinear properties of sEMG undergo changes during muscle activation [25]. Typically, muscle fatigue leads to reduced complexity of the sEMG signal [26]. Hence, nonlinear methods may reveal certain features that cannot be captured by linear methods. Second, most nonlinear methods do not work well enough on short time series. In this study, however, the sEMG signal segments are very short. Given the exercise tempo of one repetition per four seconds, a signal segment corresponding to one repetition of exercise typically lasted 4 s. This requires that the employed nonlinear measures could be applied to short series. Fortunately, it has been demonstrated that E_s is almost independent on record length [14].

Our results indicated that with the progress of exercise-induced muscle fatigue, SMR, E_s, DFA α_1 and DFA α_2 of the sEMG signal underwent significant changes (Figures 5, 6, 7) but MNF and MDF did not. According to the literature, a decrease in MNF and MDF of sEMG signals indicates a shift in energy from high to low frequencies [4]. Such a shift is largely attributed to fatigue-induced decreases in conduction velocity of action potentials in the muscle fibres [27]. SMR has been shown to be an improved spectral index and can yield better results compared to MNF [6]. Our results also showed that SMR is more sensitive for detecting muscle fatigue compared to MNF and MDF (Figure 5).

The significant decreases in E_s from the first session to second and last sessions (Figure 6) indicate that the sEMG signal became more regular. It has been revealed that when central fatigue occurs, the pattern of recruiting motor units tend to be more synchronized [4]. Hence, the significant decreases in E_s indicated the occurrence of muscle fatigue.

Our results also indicated that DFA α_1 significantly increased from the first session of exercise to the second session and from the second session to the last session, while DFA α_2 significantly increased from the second session to the last session (Figure 7). According to the literature, when α exceeds 1, a higher value of α (closer to 1.5) indicates a lower degree of complexity [17]. Thus, the results of DFA α_1 and DFA α_2 were roughly consistent with those of E_s and SMR. However, it should be noticed that E_s and DFA α_1 seem to be more sensitive to alterations of myoelectric activity induced by muscle fatigue. Such discrepancies were likely due to that these measures characterize different features of myoelectric activity. On one hand, muscle fatigue makes the recruitment of motor units more synchronized, manifesting as more regular oscillations in the sEMG signal. On the other hand, muscle fatigue results in a shift in signal power from high to low frequencies [4].

Since sample entropy and spectral measures characterize distinctly different features of sEMG signals, they could be used complementarily for assessing muscle fatigue. Because sample entropy shows robustness in the case of short time series [4], it could be employed in situations where muscle fatigue assessment needs to be completed as quickly as possible. Such situations may be frequently encountered in practical applications such as developing exercise training programs to enhance athletes' competitive performance or for rehabilitation purpose. On the other hand, our findings may be applicable to other muscle groups, because it was reported that fatigue status of the vastus lateralis induced by concentric, eccentric, and isometric knee-extensor contractions leaded to a decrease in sample entropy of the sEMG signals [17].

This study had two limitations. First, only 12 participants were recruited. This was unfavourable for obtaining a reliable conclusion from the statistical analyses. However, our main purpose was to verify whether nonlinear methods are suitable for assessing muscle fatigue caused by dynamic contractions. Our results showed that sample entropy and DFA coefficients are more sensitive to muscle fatigue compared to linear indices. Second, the involvement of only healthy participants differed from the motivation of this study, i.e., to detect the onset and extent of muscle fatigue during rehabilitation exercises. Nevertheless, since post-stroke patients are expected to be more prone to muscle fatigue during exercises, the findings of this study could be applicable to post-stroke population. Future studies may involve more healthy participants and post-stroke patients. Further more, our future studies may utilize deep learning methods [28, 29] to detect muscle fatigue in post-stroke patients.

5. CONCLUSION

The findings of this study indicate that E_s and DFA of sEMG signals are able to reveal alterations in myoelectric activities caused by muscle fatigue. Therefore, these methods can be utilized to assess muscle fatigue caused by dynamic contractions. Furthermore, E_s and DFA α_1 are more sensitive than the commonly used linear measures in detecting muscle fatigue. These findings suggest that nonlinear measures could capture detailed features of sEMG signals that cannot be revealed by the traditional linear measures. This implies that nonlinear methods are a necessary supplement to linear methods for studying myoelectric activities using sEMG signals. However, most nonlinear methods require long time series to ensure their reliability. Hence, there is a need to develop nonlinear indices that can be meaningfully applied to short time series.

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AUTHOR CONTRIBUTIONS

Tang Ming: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
Ling Weay Ang: Project Administration, Supervision, Writing –Review & Editing;
Sellappan Palaniappan: Validation and Writing –Review and Final Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

The relevant informed consent was obtained from each subject.

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