Exploration and Application of a Muscle Fatigue Assessment Model Based on NMF for Multi-Muscle Synergistic Movements

Jinxu Yu, Lijie Zhang, Yihao Du, Xiaoran Wang, Jianhua Yan, Jie Chen, and Ping Xie

***Abstract*— Muscle fatigue significantly impacts coordination, stability, and speed in daily activities. Accurate assessment of muscle fatigue is vital for effective exercise programs, injury prevention, and sports performance enhancement. Current methods mostly focus on individual muscles and strength evaluation, overlooking overall fatigue in multi-muscle movements. This study introduces a comprehensive muscle fatigue model using non-negative matrix factorization (NMF) weighting. NMF is employed to analyze the duration multi-muscle weight coefficient matrix (DMWCM) during synergistic movements, and four electromyographic (EMG) signal features in time, frequency, and complexity domains are selected. Particle Swarm Optimization (PSO) optimizes feature weights. The DMWCM and weighted features combine to calculate the Comprehensive Muscle Fatigue Index (CMFI) for multi-muscle synergistic movements. Experimental results show that CMFI correlates with perceived exertion (RPE) and Speed Dynamic Score (SDS), confirming its accuracy and real-time tracking in assessing multi-muscle synergistic movements. This model offers a more comprehensive approach to muscle fatigue assessment, with potential benefits for exercise training, injury prevention, and sports medicine.**

***Index Terms*— Multi-muscle synergistic movements, NMF, MDWCM, PSO, CMFI.**

Manuscript received 22 November 2023; revised 11 March 2024 and 11 April 2024; accepted 20 April 2024. Date of publication 24 April 2024; date of current version 1 May 2024. This work was supported in part by the National Natural Science Foundation of China under Grant U20A20192 and Grant 62076216, in part by the Natural Science Foundation of Hebei Province under Grant F2022203079, in part by Hebei Innovation Capability Improvement Plan Project under Grant 22567619H, and in part by Hebei Province Science and Technology Research and Development Plan Science and Technology Support Plan Under Project 21372001D. *(Jinxu Yu and Lijie Zhang are co-first authors.) (Corresponding authors: Jie Chen; Ping Xie.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethical Committee of the Rehabilitation Hospital Affiliated to the National Rehabilitation Assistive Devices Research Center, and performed in line with the Helsinki.

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Digital Object Identifier 10.1109/TNSRE.2024.3393132

I. Introduction

MUSCLE fatigue is a key indicator for studying human movement status [1], [2], [3]. At present, most of the detection studies on muscle fatigue and muscle strength focus on single muscles or single movements [1], [4], [5], [6], [7], [8], [9]. Therefore, the existing evaluation The applicability of the indicator in multi-muscle synergistic movements remains to be confirmed.

Muscle fatigue, characterized by a reversible decline in the neuromuscular system's force or power generation ability, can be categorized as central fatigue and peripheral fatigue [10], [11]. Central fatigue induced by exercise results from the central nervous system's inability to generate and sustain impulses for muscle demands, affecting motor neurons from the brain to the spinal cord [8], [12], [13]. In contrast, exercise-induced peripheral fatigue arises from exercise-induced loss of skeletal muscle function, causing it to be unable to maintain the intended contraction intensity [14]. Electromyographic (EMG) is widely used for fatigue assessment due to its non-invasive nature and real-time monitoring capabilities [15], [16], [17], [18]. Previous studies have applied various time-domain, frequency-domain, and complexity metrics based on EMG signals for muscle fatigue assessment [19], [20], [21]. Common indicators include root mean square (RMS) and median frequency (MF), where increased RMS amplitude during movement reflects motor unit recruitment associated with fatigue [20], [21], [22], [23], and decreased MF relates to reduced motor unit discharge rate induced by fatigue [21], [23], [24], [25]. Additionally, permutation entropy (PE) measures EMG signal complexity, reflecting its randomness and regularity; as muscle fatigue increases, EMG signal complexity decreases, leading to reduced PE, which mirrors the impact of fatigue on muscle activity regulation [26], [27]. Some studies have also proposed using fractal dimension (FD) as an indicator, where fatigued muscle signals often exhibit lower FD [10], [18]. However, current fatigue assessment models predominantly focus on individual muscles, lacking a comprehensive method for evaluating overall fatigue during multi-muscle synergistic movements. Thus, the development of a comprehensive assessment method is essential to gain a more comprehensive understanding of the fatigue status of multiple muscles during synergistic movements.

In the realm of multi-muscle synergistic movements, a substantial body of research has demonstrated that as muscle fatigue deepens, the synergistic patterns of multiple muscles undergo changes to compensate for the fatigued muscles, ensuring the completion of the intended motor tasks [28], [29]. For example, research by Ciubotariu et al. suggests that when muscles experience fatigue and pain, endurance time is shortened, and some non-fatigued synergistic muscles exhibit increased compensatory activity at the end of contractions to maintain the target force [30]. Furthermore, Dul et al. have introduced a new physiological criterion for assessing muscle load sharing and found that, during synergistic movements, relatively more force demands are allocated to muscles with greater strength and a higher proportion of fatigue-resistant muscle fibers [31]. In a study investigating the effects of fatigue in the ankle dorsiflexors on multi-muscle synergistic movements, Singh and Latash observed that one of the adaptive mechanisms in a redundant multi-muscle system involves an increase in variance in the activation of non-fatigued muscles and an increase in the co-variation among muscle activations [32]. These studies collectively highlight how fatigue induces changes in the strategies of multi-muscle synergistic movements, with non-fatigued muscles compensating to maintain task execution. However, it's worth noting that these studies have primarily focused on muscle compensation based on muscle synergy and have been lacking in research on comprehensive methods for evaluating muscle fatigue during multi-muscle synergistic movements.

To gain deeper insights into the state of muscles during multi-muscle synergistic movements, this paper proposes the comprehensive muscle fatigue index (CMFI) model. It utilizes EMG signals as the foundational data, combines non-negative matrix factorization (NMF) to analyze the Duration multi-muscle weight coefficient matrix (DMWCM) during multi-muscle synergistic movements, and extracts typical time-domain, frequency-domain, and complexity-based metrics to quantitatively analyze the extent of muscle fatigue in these scenarios. This analysis is then applied to a blackboard writing activity, which demands a high degree of synergy and stability among multiple upper limb muscles. The onset of fatigue during blackboard writing activity visibly impacts the quality and speed of the writing, making it an objective indicator of fatigue. Additionally, subjective ratings from the perceived rating of perceived exertion (RPE) questionnaire are used to further validate the accuracy of CMFI. Finally, by studying the evaluation indicators of multi-muscle fusion, we can more comprehensively explore the characteristics and changes of muscle status.

II. Method

A. Research on Main Motion Pattern Based on NMF

In multi-muscle synergistic movements, there are multiple muscles involved. such as in the case of blackboard writing activity. However, assessing the state of individual muscles does not provide a holistic evaluation of overall performance. Consequently, it is crucial to dissect the primary movement patterns within the context of blackboard writing and ascertain the respective muscle involvement weights in these patterns.

Firstly, an EMG matrix, denoted as X_{mn}, is constructed. The matrix X_{mn} consists of m rows, representing the signals acquired from m different muscle groups, and n columns, representing the sampled values within each channel. Subsequently, X_{mn} undergoes a NMF decomposition, using the decomposition methods as described in [33] and [34].

$$X_{mn} \approx (WH)_{mn} = \sum_{\alpha=1}^{r} W_{ma} H_{\alpha n} = X'_{mn} \tag{1}$$

where W_{ma} represents the weight coefficient matrix, $H_{\alpha n}$ is the activation coefficient matrix, and r is the number of columns into which the base model matrix is decomposed. The column vectors of the original matrix X_{mn} can be explained as weighted combinations of all column vectors in W_{ma}, with the weighting coefficients being the elements within the corresponding column vector of $H_{\alpha n}$. The two matrices obtained through the decomposition, W_{ma} and $H_{\alpha n}$, are multiplied to reconstruct the data matrix X'_{mn}. Matrix consistency is quantified by calculating the sum of squared errors, and iterative optimization is performed to obtain the base matrix and coefficient matrix in such a way that the sum of squared errors is minimized when the number of decomposition columns is r.

In order to determine the number of motion patterns in the above decomposition process, that is, the number of columns of basis matrix decomposition, use the variability accounted for (VAF) calculation method [35], which is defined as follows.

$$\mathrm{VAF} = 1 - \frac{\mathrm{RSS}}{\mathrm{TSS}} = 1 - \frac{\sum (X_{mn} - X'_{mn})^2}{\sum X_{mn}^2} \tag{2}$$

where RSS is the residual sum of squares, and TSS is the total sum of squares. As the number of synergies increases, the VAF gradually increases, with a diminishing rate of growth. When the average VAF value reaches 90% or more, and the increase in the average VAF value with the addition of one more motion pattern is less than or equal to 2%, it is considered to have reached the optimal number of motion patterns.

With this method, we can determine the primary motor pattern at any given moment.

$$M = \begin{pmatrix} [bool(H_{11} > H_{21}), bool(H_{11} < H_{21})]^T \\ \vdots \\ [bool(H_{1n} > H_{2n}), bool(H_{1n} < H_{2n})]^T \end{pmatrix}^T \tag{3}$$

$$M_t = [bool(H_{1t} > H_{2t}), bool(H_{1t} < H_{2t})]^T \tag{4}$$

where M_t represents the primary motor pattern at time t; furthermore, we can calculate the corresponding DMWCM.

$$W = \begin{pmatrix} (W_{11}(1), W_{12}(1))M_1 & \dots & (W_{11}(n), W_{12}(n))M_n \\ \vdots & \ddots & \vdots \\ (W_{i1}(1), W_{i2}(1))M_1 & \cdots & (W_{i1}(n), W_{i2}(n))M_n \end{pmatrix} \tag{5}$$

$$W(t) = \begin{pmatrix} (W_{11}(t), W_{12}(t))(M_t) \\ \vdots \\ (W_{i1}(t), W_{i2}(t))(M_t) \end{pmatrix} \tag{6}$$

$$w_i(t) = (W_{i1}(t), W_{i2}(t))(M_t) \tag{7}$$

where $w_i(t)$ represents the muscle weight coefficient of the i-th muscle at time t.

B. Construction of CFMI

EMG signals, as a vital physiological signal, capture neural activation patterns within muscles and can be employed for the study of muscle fatigue. To enable comprehensive quantification and assessment of muscle fatigue from both the time and frequency domains, a prediction method for CMFI in multi-muscle synergistic movements was introduced based on NMF weighting. Furthermore, the PSO algorithm was utilized to optimize the weighting parameters of fatigue features in the CMFI algorithm.

1) Selection of Fatigue Features: Fatigue features refer to statistical and morphological characteristics extracted from the time series of EMG signals [36]. These features reflect information about the signal's amplitude, waveform, distribution, and other aspects, and they are of critical importance for in-depth exploration and analysis of the dynamic properties of EMG signals and understanding muscle fatigue status.

Amplitude metrics are considered the most intuitive and straightforward indicators in fatigue research. RMS is a significant parameter used to assess the intensity of EMG signal activity. It enables the analysis of muscle activation levels in different motor tasks, thereby revealing the level of muscle involvement and load conditions [37]. The formula for calculating RMS is as follows:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{8}$$

where N represents the total number of sample points, and x_i represents the amplitude of each sample point.

RMS has wide-ranging applications as it can provide information about variations in muscle activity across different motor tasks and levels of muscle fatigue. This makes RMS an important tool in the fields of muscle biomechanics and fatigue research.

MF is an important frequency-domain metric used to describe the frequency characteristics of EMG signals. It is often closely related to the level of muscle fatigue and provides essential information about the frequency distribution within EMG signals. MF is highly valuable for understanding muscle fatigue states and the field of exercise physiology.

The calculation formula of MF is as follows [38]:

$$\mathrm{MF} = \int_0^{MDF} P(\omega)d\omega = \int_{MDF}^{\infty} P(\omega)d\omega = \frac{1}{2}\int_0^{\infty} P(\omega)d\omega \tag{9}$$

where $P(\omega)$ represents the Power Spectral Density (PSD) of the signal, and ω is the frequency variable. The Median Frequency can be seen as the central position within the frequency distribution, and its calculated outcome is instrumental in evaluating the distribution of frequency components within EMG signals.

The PE of EMG signals serves as a signal analysis metric. By quantifying the probability distribution of different permutation patterns in EMG signals, it effectively reflects the irregularity of muscle activity, providing an objective method to assess muscle fatigue status [39], [40]. The calculation method for PE can be expressed as follows:

$$\mathrm{PE} = -\sum_{i=1}^{n} p_i \log(p_i) \tag{10}$$

where n represents the number of different ways of permutations and p_i denotes the probability of each permutation. PE is used to measure the uncertainty and complexity of various permutation patterns in a signal, aiding in revealing the regularity and complexity of the signal. It can be used to analyze the dynamic characteristics of EMG signals and their changes under fatigue conditions. This indicator finds wide applications in fatigue research and the analysis of biological signals.

The FD as another typical fatigue indicator, is a metric used to describe the complexity and irregularity of signals, commonly employed in analyzing biological signal features. In fatigue assessment, FD can be utilized to analyze the changing characteristics of signals during muscle fatigue processes, aiding in the identification and assessment of fatigue status [41]. As another typical fatigue indicator, we used the box-counting method to calculate the FD in our study, following the approach from previous research [10]. This method involves covering the signal with a grid of square boxes and determining the number of boxes that the EMG waveform passes through. The range of box sizes is restricted to avoid saturation of high and low values. Box sizes are fixed at 13 equally spaced steps on a logarithmic scale, with the smallest box equal to 1/128 second and the largest box equal to 1/8 second. The boxes on the vertical side are normalized to the signal's range over a period of 1 second and are divided into an equal number of boxes.

The calculation formula of FD is as follows [10]:

$$\mathrm{FD} = \frac{\lg N}{\lg \frac{1}{L}} \tag{11}$$

where N is the number of boxes needed to cover the signal, L is the box edge, and the ratio indicates the slope of the interpolation line.

As muscle fatigue increases, the EMG signal may exhibit lower FD values, resulting in a decrease in FD compared to the signal in a non-fatigued state.

2) Feature Normalization: In order to merge the various fatigue features of the CMFI algorithm onto the same scale for the calculation of a unified CMFI value, it is necessary to normalize each feature, as shown in the following equation:

$$x_{\text{Normalized}} = \frac{x - \mu_x}{\sigma_x} \tag{12}$$

where μ_x represents the mean of feature x, and σ_x represents the variance of feature x.

The normalized RMS, MF, PE, and FD are represented as: r, m, p, and f.

In summary, we have selected four typical features of EMG signals as quantitative assessment metrics for muscle fatigue. By assigning weight parameters to each feature, we obtain the Muscle Fatigue Index (MFI) for each muscle, as follows:

$$\mathrm{MFI}_i = T_R \cdot r_i + T_M \cdot m_i + T_P \cdot p_i + T_F \cdot f_i \tag{13}$$

where T_R, T_M, T_P, and T_F are the weighting coefficients corresponding to the fatigue features r, m, p, and f, respectively.

Furthermore, in combination with the DMWCM matrix obtained through NMF, we can calculate the CMFI value for multi-muscle synergistic movements as follows:

$$\mathrm{CMFI} = \sum_{i=1}^{n} w_i(t) \cdot \mathrm{MFI}_i \tag{14}$$

where i represents the i-th muscle, and $w_i(t)$ represents the weight coefficient of the i-th muscle for the main motion pattern at time t.

3) Calculation of Fatigue Contribution Rate: To explore the contribution of each muscle in multi-muscle synergistic movements, we introduce the fatigue contribution rate metric. By calculating the fatigue contribution rate metric under multi-muscle synergistic movements, we can further analyze the impact of each muscle on overall fatigue. The formula for calculating it is as follows:

$$FCRM_i = \frac{FC_i}{FC} \times 100\% \tag{15}$$

$$FC = \sum_{i=1}^{n} \sum_{t=1}^{T} w_i(t)(T_R \cdot r + T_M \cdot m + T_P \cdot p + T_F \cdot f) \tag{16}$$

$$FC_i = \sum_{t=1}^{T} w_i(t)(T_R \cdot r + T_M \cdot m + T_P \cdot p + T_F \cdot f) \tag{17}$$

where $FCRM_i$ represents the fatigue contribution rate of the i-th muscle.

4) Optimization of CMFI Feature Weight Coefficients Based on PSO: The basic idea of PSO is to simulate the behavior of groups and individuals in nature, where each individual is called a particle. These particles search in the solution space, and each particle adjusts its movement direction and velocity based on its own best-known position (local optimum) and the best-known position of the entire group (global optimum). This collaborative and information-sharing approach enables particles to quickly converge to the optimal solution or its approximate solution within the search space [42], [43].

Using the PSO algorithm to optimize the feature weight coefficients in CMFI, you first need to determine the parameters to be optimized and the objective function. The parameters to be optimized include the four feature weight parameters T_R, T_M, T_P, and T_F. The objective function is as follows:

$$goal = \sqrt{\frac{\sum_{t=1}^{T} (CMFI_t - RPE_t)^2}{N} t} \tag{18}$$

where $CMFI_t$ is the CMFI value obtained at time t based on the muscle fatigue quantification evaluation model, and RPE_t is the score obtained at time t from the RPE [43], [44] based on subjective physical sensation levels in actual experiments.

Suppose each particle is composed of a 4-dimensional vector (T_R, T_M, T_P, T_F), and the position of the i-th particle in the three-dimensional solution space is represented as follows:

$$x_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})^T \tag{19}$$

Velocity is represented as follows:

$$v_i = (v_{i1}, v_{i2}, v_{i3}, v_{i4})^T \tag{20}$$

This iteration's individual best is $pbest_i$, and the global best is $gbest$. In each iteration, particles adjust their positions and velocities for this iteration by tracking these two best values and their own previous state, following the iteration formula:

$$\begin{aligned} v_i(t+1) = wv_i(t) + c_1 r_1(pbest_i - x_i(t)) \\ + c_2 r_2(gbest - x_i(t)) \end{aligned} \tag{21}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{22}$$

where $v_i(t)$, $v_i(t+1)$, $x_i(t)$, and $x_i(t+1)$ represent the velocity and position of the i-th particle in the current and next iterations, respectively. c_1 and c_2 are learning factors, while r_1 and r_2 are random numbers between 0 and 1. w is the weight factor used to adjust the convergence speed, and it is modified through a linearly decreasing method as follows:

$$w = w_{\min} + \frac{(t_{\max} - t)}{t_{\max}}(w_{\max} - w_{\min}) \tag{23}$$

where $t_{\max}$ represents the maximum number of iterations, t is the current iteration count, and $w_{\max}, w_{\min} \in [0, 1]$ are the maximum and minimum weight factors, respectively.

III. Experimental Procedure and Data Processing

In this study, the CFMI model proposed in this paper is validated using board writing activities as an example. Such upper limb activities can engage a majority of the upper limb muscles. A total of 20 participants were recruited, including 10 males and 10 females. The participants ranged in age from 20 to 30 years, with body weights between 55 and 75 kg, and heights between 157 and 178 cm. All participants were right-handed, in good health, and had no history of musculoskeletal injuries or related medical conditions. To ensure the objectivity of the experimental results, participants were instructed to avoid vigorous physical activity 24 hours before the experiment and to wear comfortable clothing during the experiment.

The EMG signal data were collected using the Trigno Avanti surface EMG recording system produced by Delsys [45], [46], a company based in the United States, as shown in Fig. 1 (D). The muscles on the right upper arm that were monitored included the middle deltoid (MD), biceps brachii (BB), triceps brachii (TB), extensor carpi radialis (ECR), flexor carpi radialis (FCR), extensor digitorum (ED), and flexor digitorum superficialis (FDS), totaling 7 muscle groups, the electrode positions are shown in Fig. 1 (A). The study received ethical approval from the Ethics Committee of the First Hospital of Qinhuangdao City.

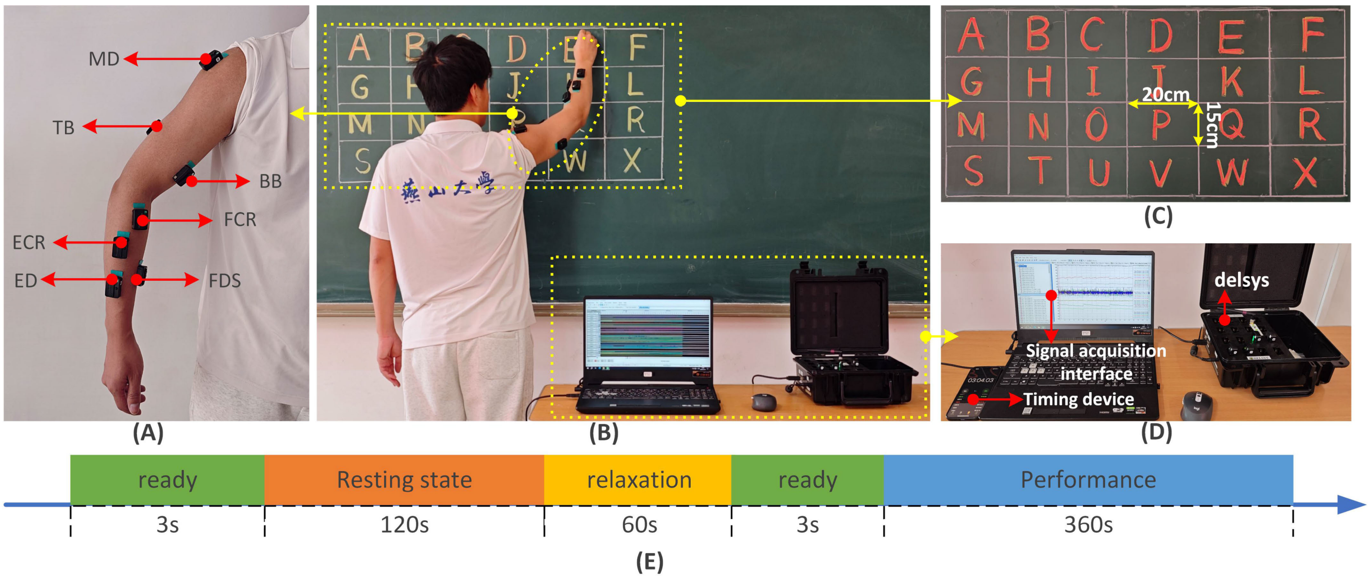

Fig. 1. (A) EMG electrode location diagram; (B) The actual experimental scene; (C) Blackboard schematic; (D) Delsys EMG acquisition equipment, signal acquisition interface and timing device; (E) Experimental flowchart.

A. Experimental Procedure

Firstly, we needed to establish the experimental duration to ensure that participants could engage in writing activities for as long as possible while maintaining writing quality. We conducted continuous writing experiments for all participants lasting 10 minutes, assessing their writing quality and fatigue status in real-time. Ultimately, we determined that the formal experimental writing duration would be 6 minutes.

Participants were instructed to maintain a standing position. The Delsys EMG collection module sites were disinfected with alcohol to remove sweat and dust from the body surface, ensuring signal quality. After alcohol disinfection, the Delsys collection modules were attached to the relevant muscle belly positions of the participants. Before the experiment started, the subjects' speed of writing each line of letters in the fatigue-free state was counted as the original writing time. Once the experiment began, the participants first underwent a resting state experiment, which included a 3-second preparation time and a 2-minute resting period. After the resting state, there was a 60-second relaxation period, followed by the experimental task of blackboard writing, which included a 3-second preparation period and 360 seconds of task execution, as shown in Fig. 1 (E).

During the experiment, participants were required to monitor their RPE in real-time to assess their overall fatigue levels at different time points. This was done using a self-reporting method, where reminders or timers were set to prompt participants to self-assess their perceived writing difficulty or fatigue level every 10 seconds. Each time they were reminded, participants used the levels on the RPE scale to evaluate their current writing difficulty or fatigue sensation and recorded it accordingly.

The experimental diagram for the blackboard writing activity is illustrated in Fig. 1 (B), with the following specific requirements: (1) Draw a 4 × 6 grid within a fixed range suitable for normal blackboard writing for all participants, with the size of each rectangular being 20 × 15 cm. Inside each rectangular, write a single English letter, in sequential order from A to X, as shown in Fig. 1 (C). (2) Instruct the participants to copy the English letters inside the grid, recording the duration of writing for each row. This duration is used to calculate the Speed Dynamic Score (SDS) and the number of rows should be increased sequentially.

The real-time assessment of participants' perceived fatigue was conducted according to the RPE questionnaire. The SDS was calculated as follows:

$$S = [s(1), s(2), \ldots, s(k)] \tag{24}$$

$$s(i) = \frac{t(i)}{t_k} \tag{25}$$

$$k = (i\%4) + 1 \tag{26}$$

where $t(i)$ represents the writing time of the i-th line recorded, t_k represents the actual original writing time of the k-th line letters, corresponding to the actual number of lines recorded by $t(i)$; and the time of $s(i)$ is recorded as the center position of the i-th line time period.

Writing speed, as an objective indicator of assessing overall fatigue, is influenced by both peripheral fatigue and central nervous system fatigue [47]. Peripheral fatigue primarily refers to fatigue in hand muscles [48]. Prolonged writing tasks lead to gradual fatigue in upper limb muscles, resulting in a gradual decrease in writing speed. Meanwhile, central nervous system fatigue is also a significant factor affecting writing speed [49], [50]. Prolonged concentration and fine motor activities can cause fatigue in the nervous system, reducing nerve conduction velocity and reaction speed, thereby affecting writing speed and accuracy. Therefore, writing speed can serve as an objective measure to evaluate the comprehensive fatigue level of individuals, reflecting the impact of peripheral fatigue on hand muscles as well as the influence of central nervous

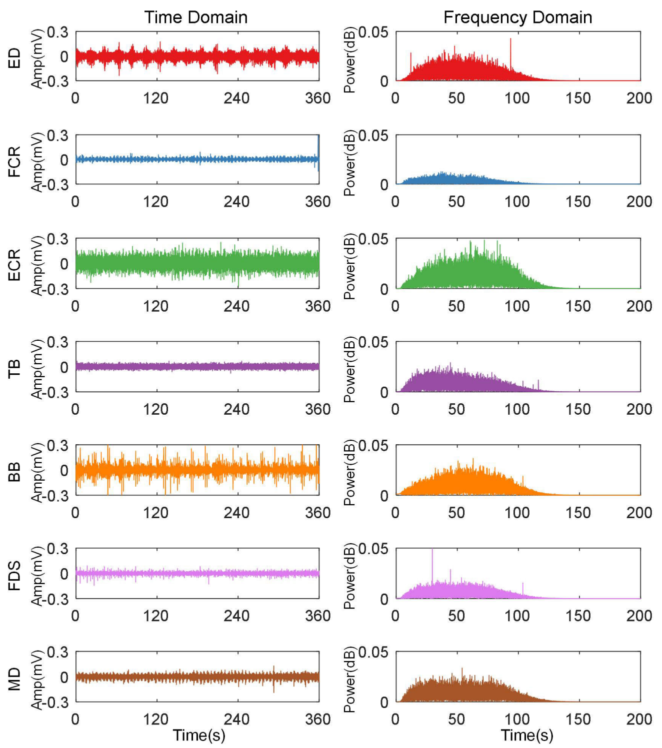

Fig. 2. Time domain diagram and spectrum diagram of EMG signal after preprocessing.

system fatigue on the neural system, thus comprehensively reflecting an individual's fatigue state during writing tasks.

B. Data Preprocessing

To optimize signal quality for muscle fatigue and strength analysis, preprocessing of the raw EMG signal is necessary. The preprocessing methods applied to the raw EMG data include removing baseline drift, eliminating powerline interference, and getting rid of motion artifacts and other noise. Specifically, the raw EMG signal was downsampled to 400Hz, baseline drift was removed, and a 50Hz notch filter was applied. As the effective components of EMG signals are primarily below 100Hz, a butterworth filter was used to eliminate high-frequency components above 100Hz and low-frequency linear drift below 10Hz [51], [52]. The preprocessed EMG signal, with both time-domain and frequency-domain representations, is shown in Fig. 2.

IV. Results

A. NMF Analyzes the Main Motion Patterns

First, the primary motion patterns and corresponding muscle weights during blackboard writing activity were analyzed using NMF. A comparative analysis between the male and female groups showed that their motion patterns were essentially consistent. As an example, Fig. 3 illustrates the NMF analysis results for the 7-channel EMG signal from the right upper limb of one of the subjects.

Fig. 3 (A) displays the three motion patterns during blackboard writing activities obtained using the NMF algorithm. These different motion patterns dominate at different times. Fig. 3 (B) represents the correspondence between the main motion patterns and time, calculated using the method proposed in Chapter 2. It can be observed that from 0 to 95 seconds, the main motion pattern is mode 2, from 95 to 260 seconds, mode 1 predominates, and after 260 seconds, mode 3 takes the lead. Based on this result, we can calculate the corresponding DMWCM.

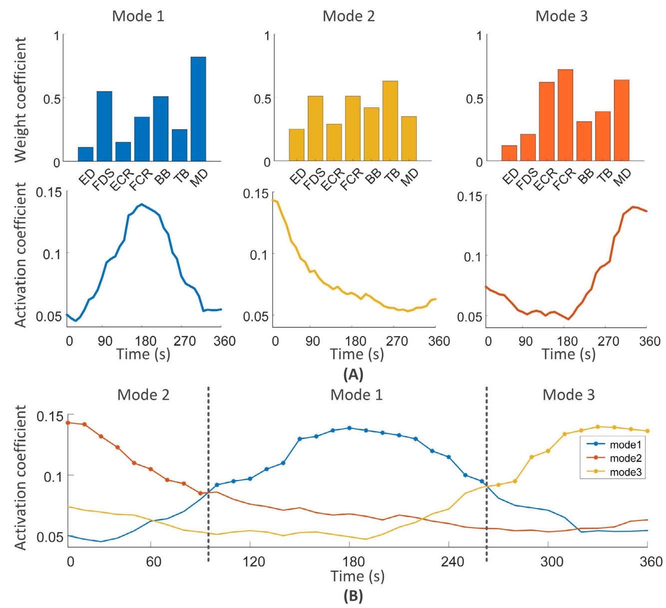

Fig. 3. (A) Three motion patterns during blackboard writing activities; (B) Main movement patterns changing over time.

B. Extraction of Fatigue Features

The fatigue features were calculated, and the results of linear fitting are shown in Fig. 4. In Fig. 4, it can be observed that during the blackboard writing activity, the RMS values gradually increase with time, possibly due to the recruitment of more motor units as fatigue sets in to produce the same level of force. In the frequency domain features, the MF of the EMG signals gradually decreases with time, indicating a reduction in the firing rate of motor units due to fatigue. The FD and PE of EMG signals in each channel all show a decreasing trend with time, suggesting the effectiveness of FD and PE indices in assessing fatigue in multi-muscle synergistic movements.

Furthermore, the rate and magnitude of fatigue in each channel vary. For example, the RMS feature exhibits a clear increase in the FDS, ECR, FCR, and MD channels, while no significant increase or decrease trend is observed in the ED and BB channels. This indicates that in multi-muscle synergistic movements, muscle fatigue does not occur synchronously. The most frequently used muscles fatigue first, while muscles with lower intensity of use during synergistic movements fatigue more slowly or not at all. And, it is worth noting that the RMS values in the ECR channel reach a certain level and then stabilize, while at the same time, the RMS values in the TB channel begin to increase. This may be due to compensatory actions after muscle fatigue.

Additionally, we conducted further correlation analysis by comparing various fatigue feature indices with the RPE curve. The results, as shown in Fig. 5, reveal that the RMS feature index in the MD channel has the highest correlation with

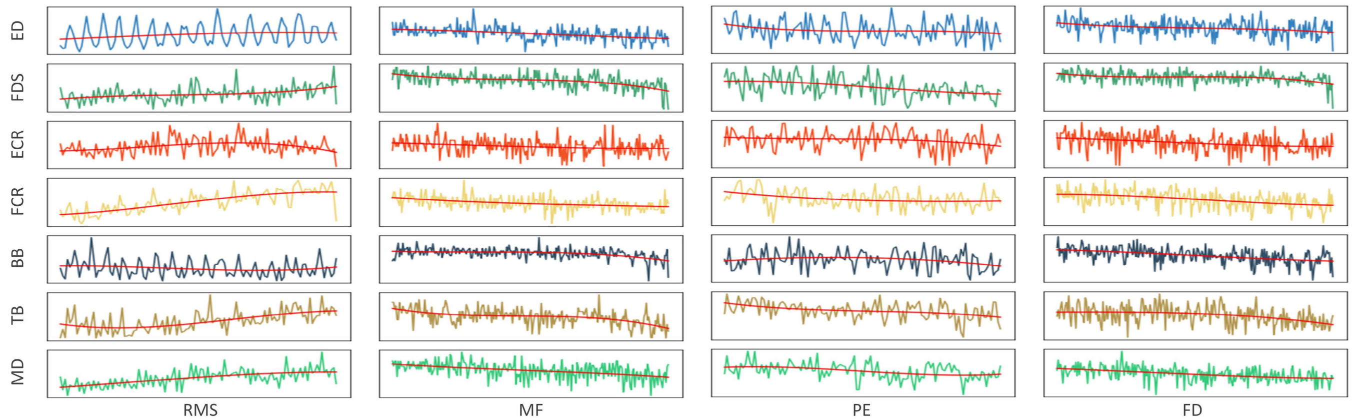

Fig. 4. Schematic of various fatigue feature indices.

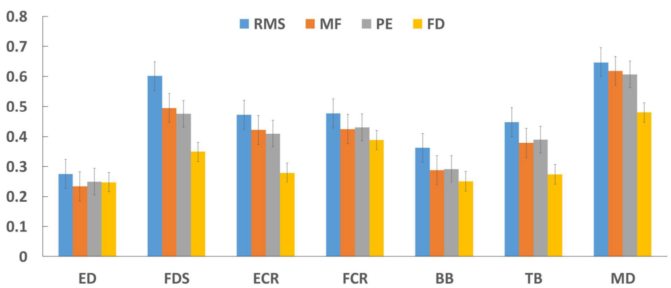

Fig. 5. Pearson correlation coefficients between different fatigue feature indices of each muscle and the RPE curve.

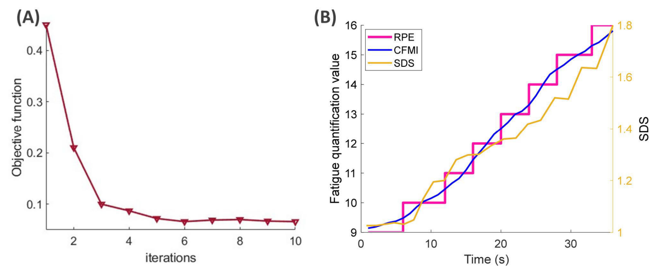

Fig. 6. (A) PSO algorithm iteration results; (B) the fitting performance of the optimized CMFI weight parameters concerning the RPE and SDS curves.

RPE (r=0.647, p<0.001), while the RMS feature index in the ED channel has the lowest correlation with RPE (r=0.275, p<0.001). This indicates that in multi-muscle synergistic movements, the fatigue feature index of a single muscle cannot adequately reflect the overall fatigue state. Furthermore, the differences in the correlations between different fatigue feature indices within the same muscle and RPE emphasize the limitations of individual fatigue features. This further underscores the need to integrate multiple feature indices for a more accurate assessment of muscle fatigue in multi-muscle synergistic movements.

Therefore, when evaluating muscle fatigue in multi-muscle synergistic movements, it is essential not to focus solely on the EMG signals from individual channels or single fatigue feature indices. Instead, the assessment should take into account the muscle's level of involvement and the motion patterns, combining various fatigue feature indices for a comprehensive evaluation.

C. Calculation and Analysis of CMFI

Due to the limitations of single-channel and single-feature fatigue assessments in evaluating overall muscle fatigue in multi-muscle synergistic movements, we calculated muscle CFMI based on the DMWCM matrix obtained through NMF.

Through PSO optimization of the fatigue feature weight parameters mentioned above, we utilized fatigue features as input data, combined them with non-negative matrix factorization to obtain the DMWCM matrix, iteratively calculated CMFI values, and used the experimentally measured RPE values as a reference to compute the objective function. The CFMI model results for one participant are depicted in Fig. 6. Fig. 6 (A) shows the iterative results of the PSO optimization algorithm, demonstrating improved outcomes after 10 iterations.

It's evident that the CFMI index, after optimization through the PSO algorithm, fits well with the participant's fatigue curve. By calculating the Pearson correlation coefficient between CFMI and RPE curves for all participants, we observed a significant correlation ($r > 0.83$, $p < 0.001$) between CFMI and the RPE curve. This implies that the relationship between CFMI and the RPE curve is statistically significant and practically meaningful. Furthermore, we fitted the CFMI and SDS curves, as displayed in Fig. 6 (B). It's apparent that CFMI fits the SDS curve quite well, and there is a strong correlation between the two ($r > 0.79$, $p < 0.001$). This underscores the effectiveness of SDS as an objective fatigue state detection index for blackboard writing activities.

Furthermore, to observe the contribution of different muscles to fatigue, we plotted the fatigue curves of various muscles for one participant based on the fatigue feature weight coefficients obtained from PSO fitting. We then calculated the Fatigue Contribution Rate of each muscle to assess its intrinsic fatigue mechanism. The results are shown in Fig. 7.

According to Fig. 7(A), it is evident that the fatigue curves of different muscles exhibit differences. The fatigue values of FDS and MD rise rapidly, which may be attributed to the fact that FDS muscles are primarily responsible for frequent finger pressing actions with chalk, while MD muscles maintain arm elevation during chalkboard activities. Conversely, the fatigue value of ED muscles increases at a slower pace, possibly due to their lesser involvement in chalkboard activities, primarily

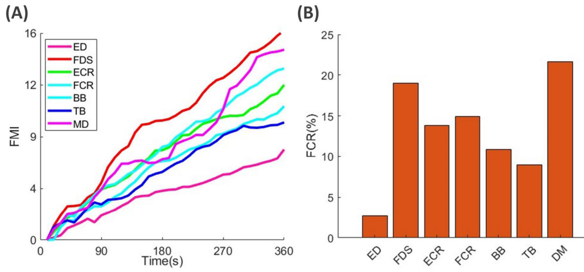

Fig. 7. (A) MFI value of each muscle; (B) Fatigue contribution rate value of each muscle.

handled by FDS muscles for pen gripping actions. Additionally, it is observed that the fatigue coefficients between ECR and FCR, as well as between BB and TB, are similar. This is because these muscles are involved in tasks with similar intensity and motion requirements. ECR and FCR mainly maintain arm posture stability during writing, in coordination with MD to keep the arm fixed in the writing position, while BB and TB primarily control chalk movement.

Similar characteristics can also be observed in Fig. 7(B). It is worth noting that a larger MFI value does not necessarily correspond to a larger fatigue contribution rate. This difference is related to the intensity of muscle use during movement and its fatigue resistance characteristics. Taking FDS and MD muscles as examples, although the MFI value of FDS muscles increases faster and reaches a higher maximum, its FCR value is smaller than that of MD muscles. This may be because MD muscles bear greater intensity during writing activities, leading to a larger muscle weighting coefficient and a higher ultimate fatigue contribution rate. However, due to the superior fatigue resistance of MD muscles, their MFI value is smaller than that of FCR muscles. As all muscles collaborate to complete writing actions, evaluating the overall fatigue status during the motion process requires a comprehensive consideration of the fatigue status of each muscle.

The above analysis reveals the fatigue characteristics of different muscles in multi-muscle coordinated movements, which are crucial for understanding the underlying mechanisms of muscle fatigue. By studying the fatigue variations of different muscles, we can gain insights into the development process of muscle fatigue and the mechanisms of mutual influence. This aids in optimizing training programs, preventing sports injuries, and providing more effective rehabilitation strategies.

V. Discussion

This study aims to investigate methods for assessing comprehensive fatigue in multi-muscle coordinated movements and proposes a CFMI model based on NMF and PSO algorithms. The DMWCM matrix under multi-muscle synergistic movements is analyzed using NMF, and then the weight coefficients of fatigue feature indicators are optimized using the PSO algorithm. Ultimately, the CFMI under multi-muscle synergistic movements is obtained to assess the overall fatigue state. To validate the effectiveness of the CFMI model, we collected 6-channel EMG signals from the right arm muscles during blackboard writing activities and applied the preprocessed signals to the CFMI model.

By collecting SDS data during the experimental process, we observed that the average writing speed of participants showed a decreasing trend. This is because as the duration of writing increased, the continuous contraction of various muscles in the human body gradually led to fatigue [53]. On the other hand, prolonged concentration and engagement in fine motor activities can also lead to fatigue in the nervous system [54], thereby reducing nerve conduction velocity and reaction speed, thus affecting writing speed and accuracy. Moreover, we also observed a high degree of similarity between the objective fatigue indicator SDS and the subjective comprehensive fatigue quantification index ($r > 0.79$, $p < 0.001$). This further confirms the rationality of choosing SDS as an objective evaluation indicator, ensuring the accuracy of the experiment.

Afterwards, we extracted four typical fatigue feature indicators from each EMG channel separately and conducted linear fits for these features, as depicted in Fig. 4 and Fig. 5. It is worth noting that different features exhibit varying rates of change and trends across different EMG channels, indicating that in multi-muscle synergistic movements, different muscles experience varying levels of usage intensity and fatigue. Moreover, we observed that the RMS values of the ECR channel reached a stabilization point after a certain threshold, while simultaneously, the RMS values of the TB channel shifted from a stable state to an upward trend. This phenomenon may be attributed to compensatory mechanisms activated after muscle fatigue. Furthermore, we computed the Pearson correlation coefficients between single-muscle fatigue indicators and the RPE curve, revealing that the correlation between the fatigue curve derived from a single indicator and the RPE curve was relatively low ($r < 0.647$, $p < 0.001$). Hence, when evaluating muscle fatigue within the context of comprehensive movement, relying solely on signals from individual EMG channels proves inadequate. Instead, we should consider the usage intensity and movement patterns of the muscles for a more comprehensive assessment.

Furthermore, we calculated the CFMI for EMG signals and fine-tuned the parameters using the PSO algorithm [42], [43]. The outcomes are presented in Fig. 6. Fig. 6 distinctly illustrates that through optimization with the PSO algorithm, the CFMI index aligns well with the participants' RPE and SDS curves. Subsequently, we calculated the Pearson correlation coefficients between the CFMI with the RPE and SDS curves. The results revealed substantial Pearson correlations between the CFMI index and the RPE curve ($r > 0.83$, $p < 0.001$) and the SDS curve ($r > 0.79$, $p < 0.001$). This underscores the practical effectiveness and feasibility of the CFMI index, underscoring its significant value in comprehensive fatigue assessment.

Simultaneously, to observe the contribution of different muscles to fatigue during multi-muscle coordinated movements, we calculated the MFI curves and fatigue contribution rate of different muscles based on the weight coefficients obtained from PSO, as shown in Fig. 7. It can be seen that due to different movement patterns, the fatigue curves of different muscles are not identical, and they correspond well with the intuitive fatigue sensations experienced during actual chalkboard activities. Additionally, we found that the fatigue contribution rate of muscles do not entirely correspond to their MFI curves. For instance, in the case of FDS and MD muscles, the MFI of FDS increases more rapidly and achieves a higher final MFI value, but its FCR value is smaller than that of MD. This is because MD experiences greater intensity during chalkboard activities, resulting in a larger muscle weighting coefficient and a higher ultimate fatigue contribution rate. However, due to its better fatigue resistance characteristics, the MFI value of MD is smaller than that of the FCR muscle. Furthermore, according to the fatigue curves in Fig. 7(A), the fatigue variation rate of FDS and MD muscles is faster. This could be attributed to the fact that FDS muscles are mainly responsible for frequent finger pressing actions with chalk, while MD muscles are involved in maintaining arm elevation during chalkboard activities, leading to a faster increase in fatigue. Conversely, the fatigue growth rate of ED muscles is slower, possibly because they are less involved in chalkboard activities, primarily handled by FDS muscles for pen gripping actions. Therefore, the significant differences in fatigue characteristics among different muscles during multi-muscle coordinated movements are crucial for understanding the intrinsic mechanisms of muscle fatigue.

However, this study still has some limitations. It primarily focuses on upper limb writing tasks as the motion pattern for discussion, without considering or introducing other patterns. This limitation results in the difficulty of applying the comprehensive fatigue model fitted to this motion pattern to other patterns. Furthermore, the fatigue indicators selected in this study are limited, lacking exploration into the fitting effects of other fatigue characteristics. Thus, there may be a need for optimization in selecting fatigue indicators for fitting.

In summary, our CMFI model has not only been theoretically validated but has also yielded satisfactory results in practical applications. This provides us with a powerful tool for gaining deeper insights into muscle status, particularly in multi-muscle coordinated movements. In future research, we plan to introduce a wider variety of motion patterns to build a more generalized CFMI fatigue model. Additionally, we will explore the strengths and weaknesses of various feature indicators in comprehensive assessments and propose more targeted optimization and solutions to achieve a more comprehensive evaluation of overall motion states. Furthermore, we will prioritize the inclusion of experiments involving patients to further validate and refine our methods. These efforts will contribute to a better understanding of the mechanisms underlying muscle fatigue and provide more effective tools and strategies for rehabilitation and prevention of occupational diseases.

VI. Conclusion

Due to the lack of a method for assessing muscle status in multi-muscle synergistic movements, this study utilizes EMG signals as the foundational data, extracts four typical fatigue-related indicators, and employs NMF to analyze the DMWCM matrix and PSO to optimize weight parameters for a comprehensive quantitative analysis of muscle fatigue levels. By investigating evaluation metrics for multi-muscle integration, we aim to explore muscle status in multi-muscle synergistic movements comprehensively. To validate the effectiveness of the evaluation method, we conducted experiments in a chalkboard writing activity scenario, collecting EMG signals from six channels of the right arm during the writing process. The results indicate that the CFMI indicator, optimized through PSO, can better fit the actual fatigue curve compared to single muscle fatigue indicators. Additionally, by calculating the feature parameters based on PSO, one can compute the MFI and fatigue contribution rate of various muscles, revealing variations in the FMI curve and fatigue contribution rate values among different muscles due to varying muscle intensities.

The methods proposed in this paper can be applied to various types of multi-muscle coordinated movements to assist in assessing the real-time changes in muscle fatigue status during such movements. In future research, we can introduce more evaluation indicators into the CFMI model and study the strengths and weaknesses of various feature indicators in comprehensive assessments, proposing targeted optimization and solutions for a more comprehensive evaluation of overall motion states. This will contribute to a better understanding of the mechanisms underlying muscle fatigue and provide more effective tools and strategies for rehabilitation and prevention of occupational diseases.

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