

## HIGH ACCURACY RECOGNITION OF MUSCLE FATIGUE BASED ON SEMG MULTIFRACTAL AND LSTM

XIA ZHANG, ZHONGLI GU

*College of Mechatronics and Automobile Engineering, Chongqing Jiaotong University, Nanan District, Chongqing, China*  
corresponding author Xia Zhang, w-mail: zhangx82@cqjtu.edu.cn

A muscle fatigue identification method that integrates the multifractal of sEMG with LSTM is proposed. The MFDMA method was introduced to analyze and extract non-linear properties of sEMG. The significance of differences between the fatigue and non-fatigue states in terms of spectral width, Hurst index variation difference, and peak singularity index was determined using the *t*-test. A LSTM networks under the combined feature set comprising multiple fractals was built, and its recognition accuracy was 98.91%. The LSTM network model was found to be more accurate than other classification methods in identifying muscle fatigue under the same feature set.

Keywords: multifractal, muscle fatigue, LSTM, sEMG, MFDMA

### 1. Introduction

Dynamic muscular fatigue is a physiological condition in which engaging in physical activity temporarily lowers the maximum force or power output that can be generated by the participating muscles (cao *et al.*, 2018). Continuous and repeated muscle contractions during exercise or rehabilitation training can easily cause muscle fatigue and a rapid loss of muscle strength, which can seriously cause muscle damage. A prompt adjustment of rehabilitation training modalities can effectively stop muscle damage and prevent secondary injury. Therefore, accurate measurement of the level of muscle tiredness is crucial in the fields of neuromuscular research and rehabilitation medicine.

In recent years, there has been a lot of interest (Zhang *et al.*, 2021a) in a method for measuring muscle fatigue that combines the surface electromyography (sEMG) signal denoising technology with the artificial intelligence. However, muscle fatigue estimation using sEMG frequently heavily relies on preprocessing techniques like signal filtering, noise reduction, and feature extraction because of the highly nonstationary, nonlinear, and complex nature of sEMG signals caused by irregular muscle contractions during the exercise (Na and Kim, 2016). Both time-domain and frequency-domain analysis approaches are now employed to extract features (Liu et al., 2021a,b; Boyer *et al.*, 2021). There are restrictions when analyzing complicated transient nonlinear dynamic characteristics in sEMG signals since this method of linear analysis makes the assumption that sEMG signals are smooth.

Because of this, some researchers have created a technique for examining nonlinear dynamical properties of sEMG signals that revolves around self-similarity, inhomogeneity, complexity, and other nonlinear dynamic properties of sEMG signals (Xiong *et al.*, 2013). For instance, Katz's technique was applied in the literature (Xu *et al.*, 2022; Biancardi *et al.*, 2021; Beretta-Piccoli *et al.*, 2023) to extract the multiscale entropy, which has a fractal dimension of sEMG signals. However, the complicated nonlinear dynamic development that takes place during dynamic muscle exhaustion cannot be adequately described using a single fractal dimension. As a result,

more research into changes in the local features of various levels of sEMG signals is necessary using the multifractal technology.

A spectrum that depicts a subset and the appropriate fractal dimension is typically used to define multifractals (Wang and Zhou, 2000). The major algorithms are multifractal detrended fluctuation analysis (MFDFA) (Kantelhaedt *et al.*, 2002) and a multifractal detrended moving average (MFDMA) (Gu and Zhou, 2010). The program using the MFDMA technique is faster than that using the MFDFA method when there are fewer data points in a one-dimensional signal sequence, the computational cost is smaller, and the algorithm performs better (Xi *et al.*, 2015). Several researchers, including França, have examined the nonlinear properties of ECG and EEG signals based on multiple fractals. Electroencephalography (EEG) and simulated data were used by França *et al.* (2018) to examine the sensitivity of monofractal and multifractal approaches to signal variance. In order to quantitatively compare the complexity of rhythm sequences in healthy and congestive heart failure, Li (2020) and Mahananto *et al.* (2019) used the MFDFA method to extract multiple fractal features. Mahananto *et al.* (2019) also used the MFDFA method to find out how well heart rate variability parameters could predict a short-term prognosis in sepsis patients. However, research on the use of various fractal approaches to characterize dynamic muscle exhaustion is scarce.

Regarding muscle fatigue recognition models, Zhang *et al.* (2021b) proposed a dual-sensor fusion of sEMG signals and A-type ultrasound and investigated the efficacy of the dual-sensor mode for static muscle fatigue detection. Liu *et al.* (2021a) conducted a study on static muscle fatigue recognition using a combination of kernel principle component analysis (KPCA) and support vector machines (SVM). Using high-resolution time-frequency approaches, Karthick and Ramakrishnan (2016) suggested a method for analyzing muscular tiredness by comparing classification abilities of simple Bayesian, SVM, and random forest classifiers. Long short-term memory networks (LSTM) and enhanced threshold wavelet denoising were used in Wang *et al.* (2022) who suggested a muscular fatigue identification model, and the findings showed that the denoising helped one to increase recognition rates. In 1997, Hochreiter and Schmidhuber introduced the concept of gated units in standard Recurrent Neural Networks (RNNs), addressing the issue of gradient vanishing that was present in standard RNNs (Hochreiter and Schmidhuber, 1997). Due to the design of LSTM, which allows the network to selectively retain or forget information, it has achieved a significant success in tasks involving long-term dependency (Skrobek *et al.*, 2022). LSTM methods are widely used in various applications, including energy and medicine (Skrobek *et al.*, 2020). In conclusion, the problem of low accuracy of muscle fatigue recognition models that utilize the time and frequency domain features results from the difficulty of describing the nonlinear and complex characteristics of sEMG signals in detail and comprehensively using the time and frequency domain analysis techniques based on the assumption of a linear muscle system.

This work intends to introduce a nonlinear signals analysis technique and conduct research on the nonlinear feature analysis and extraction method of sEMG signals in light of the aforementioned issues. An accurate evaluation of muscle fatigue in physical training, rehabilitation medicine, and other domains is made possible by a novel approach and research idea based on merging of multifractal data and conventional features.

## 2. Acquisition and pre-processing of the sEMG signal

### 2.1. Acquisition equipment and subjects

A wearable wireless sEMG signal collection device from OT Bioelettronica s.n.c., Italy, was used in this investigation to collect sEMG signals. This device can simultaneously collect sEMG signals from 14 muscles at a sample frequency of 2048 Hz. Ten subjects were chosen for the

examination. Ten young male participants were recruited, with an age range of  $23 \pm 2$  years, height of  $171 \pm 10$  cm, and weight of  $60 \pm 8$  kg. To ensure the scientific rigor of the experiment, necessary health information was provided to the participants prior to the experiment, including guidance, training, and risk warnings. The participants were instructed to rest adequately and refrain from vigorous exercise in the 24 hours leading up to the experiment. Myoelectric data gear included an AMD Ryzen 7 4800H 2.90 GHz CPU, 16 GB of memory, and the MATLAB R2022b software for doing numerical calculations.

## 2.2. Signal collecting technique

The vastus medialis, vastus lateralis, and rectus femoris sEMG signals were recorded while the patients were seated and performing reciprocal knee flexion and extension motions. A 3-kg sandbag was linked to the subject's ankle joint in order to hasten the development of muscular exhaustion. The experimental scenario is schematically depicted in Fig. 1. The range of motion of the knee joint was  $5^\circ$  to  $80^\circ$ . After 20 minutes of rest, the experiment was restarted when the individual felt subjectively exhausted or had significant leg muscular tremors. Data from the minutes before the start and end of the measurement were utilized for the data analysis of fatigue and non-fatigue comparison groups. A maximum of five sets of data were collected per individual each day. Additionally, before the experiment, sEMG signals were collected for each subject's muscle during maximal voluntary contraction (MVC) for normalization reasons (Tomohiro *et al.*, 2006).

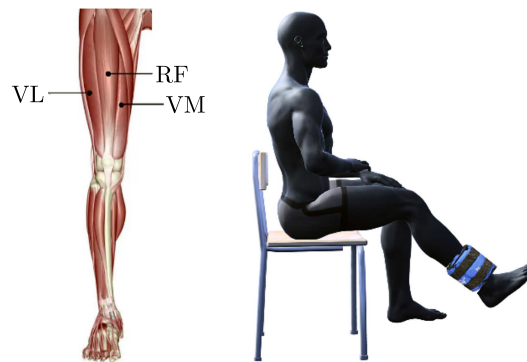


Fig. 1. A diagram of the distribution of the muscles and experimental scenarios

## 2.3. Data preprocessing

The effective signal range of sEMG signals is 0 Hz to 500 Hz, and the main energy concentration occurs between 20 Hz and 350 Hz. A 50 Hz trap is used to remove industrial frequency interference from the collected data before a fourth-order Butterworth band-pass filter is used to filter the data between 20 Hz and 350 Hz. Empirical mode decomposition (EMD) (Ye *et al.*, 2023) is also used to reduce the impact of baseline drift on the signal. In order to decrease computational redundancy and maintain motor physiological information, which is useful for further feature extraction and analysis, the envelope thresholding (Chen *et al.*, 2023) approach was employed to determine the active segments that indicate the aim of human action execution. Figure 2 illustrates the continuous sEMG signals of a particular subject's rectus femoris muscle throughout the transition from non-fatigue to fatigue states, along with their corresponding envelopes and segmented activity segments. In this study, the first activity segment is labeled as the non-fatigue state, and the last activity segment is labeled as the fatigue state. This paper sets the muscle state in the experimental dataset to 1 for rows corresponding to the feature data extracted from the sEMG data based on muscle fatigue status, and sets the muscle state to 0 for other rows.

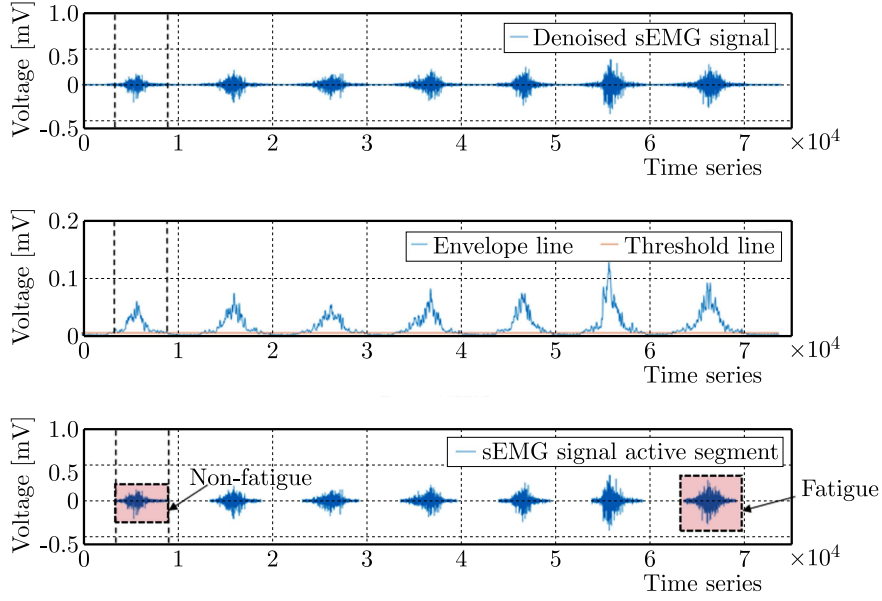


Fig. 2. The continuous sEMG signals of a subject's rectus femoris muscle throughout the transition from non-fatigue to fatigue states, along with their corresponding envelopes and segmented activity segments

### 3. Extraction of multifractal features from sEMG signals

#### 3.1. MFDMA method

One of the most popular techniques for estimating multifractal measures is the MFDMA algorithm. The steps of computation are as follows:

**Step 1:** Create a new sequence from the specified time series  $x(t)$ ,  $t = 1, 2, \dots, N$

$$y(t) = \sum_{t=1}^N x(t) \quad t = 1, 2, \dots, N \quad (3.1)$$

**Step2:** Calculate the moving average over a time window with a scale value of  $s$

$$\tilde{y}(t) = \frac{1}{s} \sum_{k=\lceil (s-1)\theta \rceil}^{\lceil (s-1)(1-\theta) \rceil} y(t-k) \quad (3.2)$$

The greatest non-negative integer less than or equal to  $x$  is represented by  $\lfloor x \rfloor$ , while the smallest non-negative integer larger than or equal to  $x$  is represented by  $\lceil x \rceil$ ,  $\theta \in [0, 1]$  denotes the location of the moving average. When  $\theta = 0$ , the moving average function is defined as

$$\tilde{y}(t) = \frac{1}{s} \sum_{k=0}^{s-1} y(t-k) \quad (3.3)$$

**Step 3:** Calculate the residual time series of the signal

$$e(i) = y(t) - \tilde{y}(t) \quad (3.4)$$

Take  $n$  data points from each interval segment by dividing the residual sequence  $e(i)$  into  $N_n$  disjoint interval segments of equal size, namely:  $N_n = \lceil (N - n + 1)/n \rceil$ ,  $3 \leq n \leq (N + 1)/11$ .

**Step 4:** Determine the value of the local root mean square

$$F(s) = \sqrt{\frac{1}{s} \sum_{i=1}^s e^2[(v-1)s + i]} \quad v = 1, 2, 3, \dots, N_m \quad (3.5)$$

**Step 5:** Determine the global order  $q$  root mean square value. The wave function is defined as

$$F_q(s) = \begin{cases} \left( \frac{1}{2N_n} \sum_{v=1}^{2N_n} [F_v(s)]^q \right)^{\frac{1}{q}} & \text{for } q \neq 0 \\ \exp \left( \frac{1}{2N_n} \sum_{v=1}^{2N_n} \ln[F_v(s)] \right) & \text{for } q = 0 \end{cases} \quad (3.6)$$

**Step 6:** By altering the scale  $s$ , the following techniques may be used to determine the power-law connection between  $F_q(s)$  and the scale  $s$

$$F_q(s) \sim s^{H(q)} \quad (3.7)$$

where  $H(q)$  stands for the Hurst index of the order  $q$ , and the multifractal mass exponent  $\tau(q)$  is characterized by

$$\tau(q) = qH(q) - D_f \quad (3.8)$$

The surface EMG signal examined in this study is a one-dimensional time series signal, hence  $D_f = 1$ .  $D_f$  is the topological dimension of the multifractal signal. The Legendre transformation may be used to produce the multifractal spectrum  $f(\alpha)$  and the singularity strength  $\alpha(q)$ , as shown below

$$\alpha(q) = \frac{d\tau(q)}{dq} \quad f(\alpha) = q\alpha(q) - \tau(q) \quad (3.9)$$

The span of the multifractal singularity intensity function may be used to determine the strength of multifractality (SOM)

$$\text{SOM} = \alpha_{max} - \alpha_{min} \quad (3.10)$$

$H_{max}$  and  $H_{min}$  differ in terms of the degree of multifractality (DOM)

$$\text{DOM} = H_{max} - H_{min} \quad (3.11)$$

The subsequent nonlinear characterization also attempted to incorporate two nonlinear indicators, the difference of the multifractal spectrum and the peak singularity index, in order to more thoroughly define the muscular fatigue condition (Ye *et al.*, 2023; Marri and Swaminathan, 2016). The multifractal spectrum difference (DFS) can be represented as

$$\text{DFS} = |f(\alpha_{max}) - f(\alpha_{min})| \quad (3.12)$$

The PSE, or peak singularity exponents, can be written as

$$\text{PSE} = \alpha(q = -5) \quad (3.13)$$

### 3.2. Non-fatigue and fatigue comparison group multifractal feature extraction study

This Section employs the aforementioned multifractal algorithm for feature extraction of the labeled segments and a statistical approach to investigate the differences in multifractal features between non-fatigued and fatigued controls in order to examine the changes in multifractal properties of the surface EMG signals during muscle fatigue. The initial and last active segments of the signal, which were labeled as non-tired and fatigued phases, respectively, should be noted.

Figures 3a and 3b, which were generated using equations (3.7) and (3.9)<sub>1</sub>, respectively, display the Hurst index and multiple fractal spectra, where the multifractal features of the

fatigue state and non-fatigue state are represented by the red and blue curves, respectively. Figure 3 demonstrates that the multifractal breadth of the spectrum is about SOM. For non-exhausted and fatigued muscles, respectively, the peak singularity index PSE is roughly 0.405 and 0.727. The difference in change of the Hurst curve DOM is approximately 0.402 and 0.621, and the measure DFS difference is approximately 0.082 and 0.421. According to the aforementioned findings, the SOM, DOM, DFS and PSE widths of the multifractal spectra were wider during fatigue than when they were during non-fatigue. The multifractal spectra are symmetrical along the approximate axis in the non-fatigued condition, but with muscular fatigue, this symmetry tendency is greatly diminished. The motor unit discharge rate fluctuates more during dynamic contraction of the muscle as tiredness rises, leading to an increase in the DOM feature parameter, which is one of the factors affecting the change in features. A higher level of multifractality and enhanced chaos are also caused by the increased recruitment of motor units and the intricacy of their spatio-temporal nonlinear connection with muscle exhaustion.

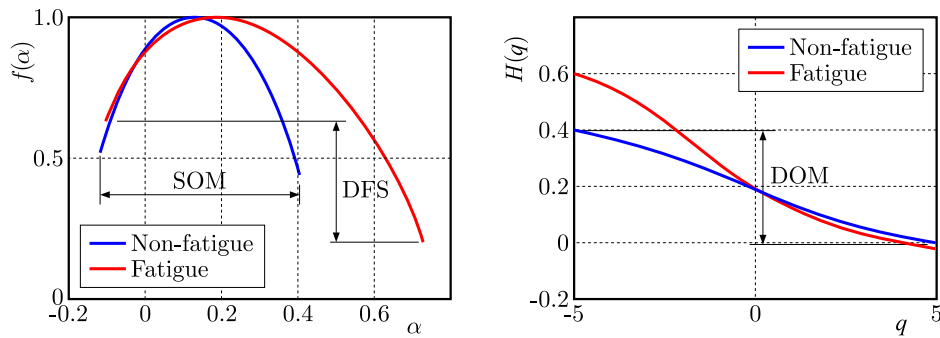


Fig. 3. Extraction of multifractal features from the comparison group of subjects with and without muscle fatigue

The scatter plots for the four multiple fractal characteristics of SOM, DOM, DFS and PSE are shown in Figs. 4a,b,c and 4d, respectively. The SOM, DOM and PSE features that correspond to Figs. 4a,b and 4d have clear feature distinctions between the non-fatigue and fatigue states, and the feature overlap rate of the two states is low, whereas the DFS features that correspond to Fig. 4c have a greater overlap, and the distinction is less clear. This can be seen more intuitively.

The difference between the aforementioned mean values of the properties of the myoelectric signals of 10 subjects under the fatigue and non-fatigue scenarios was observed using the *t*-test method in order to further determine whether the SOM, DOM, DFS and PSE extracted by the MFDMA algorithm have statistically significant differences under such scenarios. Table 1 displays the mean of each feature and *P*-value in the control condition. According to the findings, the three characteristics (SOM, DOM and PSE) that were derived from the multiple fractal spectrum using the MFDMA method were statistically significant (*P*-value 0.01) in determining whether or not the muscles were exhausted. Comparatively, the difference in DFS variability is relatively small. The findings could offer a fresh feature reference for deep learning and machine learning models that recognize muscle exhaustion.

**Table 1.** Statistical variations of attributes in the comparative groups

Features	Non-fatigue	Fatigue	P-value
	mean	mean	
SOM	0.9034	1.2414	0.0000
DOM	0.5343	0.8741	0.0000
DFS	-0.4172	-0.4960	0.0647
PSE	0.3393	0.5714	0.0000

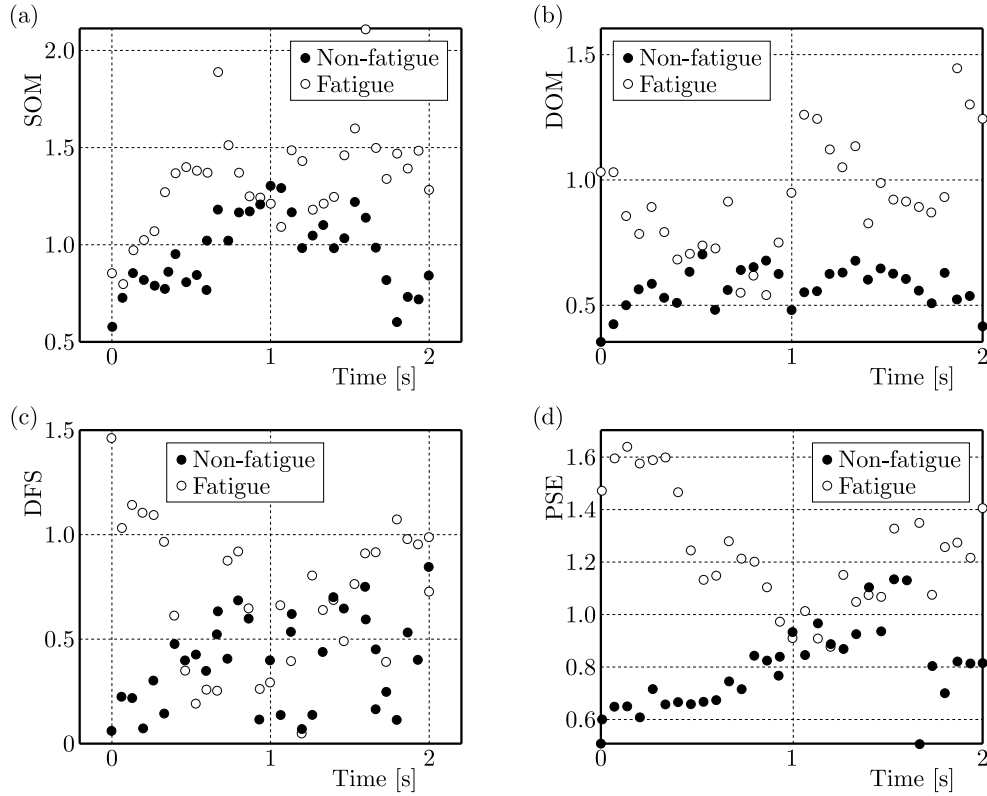


Fig. 4. Comparison of the fatigue group with the non-fatigue group using multifractal features

#### 4. Model for recognizing muscle tiredness

Long Short Term Memory (LSTM) is a widely used recurrent neural network that effectively alleviates the problems of gradient disappearance, gradient explosion, and long-term dependence in sequence data by adding cell states and updating them through forgetting gates and memory gates (Ghislieri *et al.*, 2021). LSTM units consist of input gates, output gates, and forgetting gates. The LSTM model was used to build a muscle fatigue recognition model in dynamic muscle contraction based on the multiple fractal features of sEMG signals extracted in the preceding section; its structure and hyperparameter settings are shown in Table 2, and its workflow is shown in Fig. 5. First, a feature vector is created by extracting the multiple fractal feature data from the pre-processed data using the sliding time window method. Next, the experimental feature dataset is combined to produce a total of 14,400 items, 80% of which are used for the training set, and the rest 20% are used for the test set. Finally, a stochastic gradient descent algorithm is used to optimize learning.

**Table 2.** Configuration of LSTM parameters

Hyperparameter	Value
Number of layers	3
LSTM unit	120
Optimizer	Adam
Loss function	RTRL
Activation function	Relu
Batch size	100
Initial learning rate	0.001

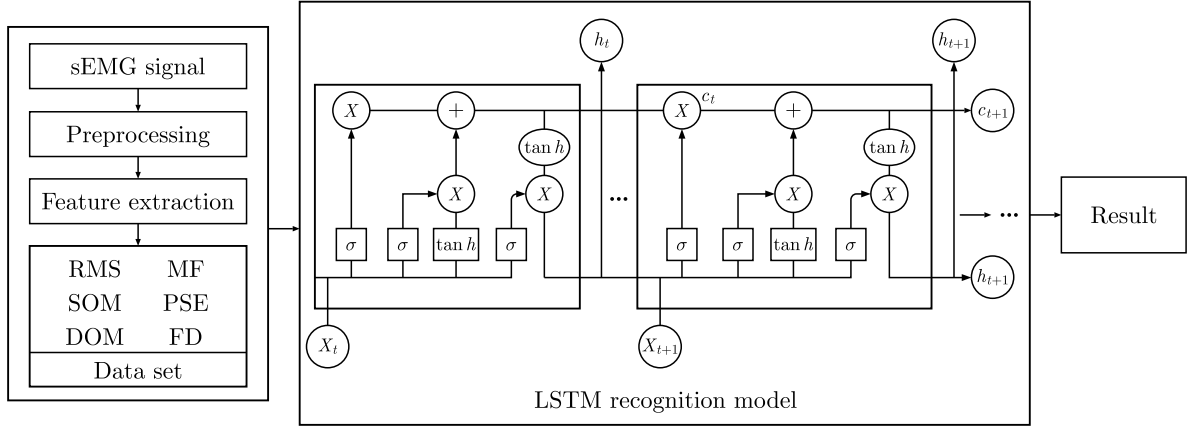


Fig. 5. LSTM model for identifying muscle fatigue

## 5. Experimental results of muscle fatigue recognition

### 5.1. The LSTM model performance for recognition using a single feature

The identification accuracy of the LSTM model was examined for each individual feature of SOM, DOM, PSE, root mean square (RMS), median frequency (MF), and fractal dimension (FD) (Xu *et al.*, 2022) in order to investigate the performance of each feature in describing muscle tiredness. The accuracy of model recognition is shown for each feature test set, as depicted in Fig. 6. The red line within the box in the image indicates the median of the experimental findings,

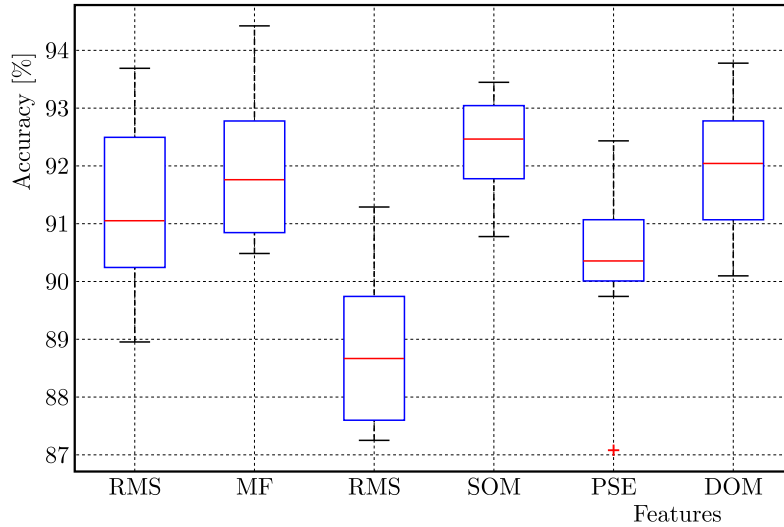


Fig. 6. Feature recognition accuracy for various characteristics

and the top and lower bounds of the box in the figure reflect the upper and lower quartiles of the 10 times recognition accuracy. In terms of the recognition accuracy, the single fractal dimension feature FD has the worst performance in the fatigue recognition model. The reason can be considered that the single fractal dimension is not sufficient to portray subtle changes of the motor unit recruitment. The highest recognition accuracy of the frequency domain feature MF and the time domain feature RMS reach 94.32% and 93.82%, respectively, but the main range of recognition accuracy of both is concentrated in 90.24% to 92.56% and 90.89% to 92.91%, with a relatively scattered distribution and low stability. The reasons for this can be considered as a large number of different types of motor units with an irregular discharge order and discharge frequency during dynamic muscle contraction due to fatigue, resulting in the time domain and frequency domain features of sEMG not changing significantly. The highest recognition accuracy



of multifractal features SOM, DOM and PSE are 93.23%, 93.92% and 92.67%, respectively, and the recognition accuracy of SOM performs the best. The highest recognition accuracy of SOM is slightly lower than that of MF and RMS, but the main range of recognition accuracy is concentrated in 91.61% 92.57%, and the distribution is more concentrated compared with MF and RMS. In addition, the main ranges of recognition accuracy of DOM and PSE are concentrated in 89.92% 91.03% and 91.04% 92.67%, with a more concentrated distribution and higher reliability. The results demonstrate that the MFDMA feature extraction method can characterize the nonlinear dynamics of EMG signals during dynamic muscle contraction. These multifractal features vary slightly with a change in the collected local motion units, so the recognition accuracy distribution is stable. This establishes a theoretical foundation for the feature fusion of the following fatigue recognition model.

### 5.2. Results of the LSTM model for different feature set combinations in recognizing muscle fatigue

To further optimize the feature set and achieve a muscle fatigue recognition model with high accuracy, the evaluation metrics of the LSTM model were investigated under different combinations of feature sets. The confusion matrix was utilized to calculate the accuracy, precision, recall, and F1\_score of the LSTM model for different feature set combinations. Each metric parameter was calculated 10 times, and the average was taken as the final reference result. The features, combinations, and their evaluation metric parameters are presented in Table 3. The findings demonstrate that: 1) combining feature sets generally enhances muscle fatigue recognition performance compared to using single features; 2) the recognition accuracy rises as the number of features increases; and 3) combining multifractal features on conventional EMG time- and frequency-domain features can achieve 98.91% recognition accuracy, which is an increase by 4.73% over conventional feature combinations. This outcome shows how combining numerous fractal characteristics with conventional time-frequency domain features can increase the precision of muscle fatigue detection.

**Table 3.** The evaluation metric parameters for different combinations of feature sets

Feature combination	Accuracy	Precision	Recall	F1_score
RMS+MF	94.18	95.89	93.95	94.57
SOM+DOM	95.93	97.01	95.04	96.14
RMS+MF+SOM+DOM	97.84	98.93	96.88	98.06
RMS+MF+SOM+DOM+PSE	98.91	99.27	98.68	99.19

### 5.3. Recognition outcomes for various models using the ideal feature set

The recognition accuracy of the LSTM model was compared with that of  $K$  nearest neighbors (KNN) (Zhang *et al.*, 2018), support vector machines (SVM) (Burges, 1998), and back propagation (BP) neural network (LeCun *et al.*, 1989) under the ideal set of characteristics in order to investigate the superiority of the models. SVM apply a non-linear transformation of the kernel function to map the solution of a non-linear problem to a high-dimensional feature space; KNN uses distance measurements between different feature values to classify; BP neural networks consist of two processes: forward propagation and backward propagation of the error, i.e., calculating the error output in the direction from the input to output while adjusting the weights.

The numerical values of evaluation metric parameters for each model are shown in Table 4. The accuracy of LSTM is as high as 98.91%, which is 3.02% higher than that of KNN, 2.08% higher than that of BP neural network, and 1.89% higher than that of SVM, as can be seen

from the figure. Since the sEMG signal features before and after a specific time segment in the process of muscle fatigue are correlated, the LSTM network can deeply capture the important details of the EMG features and preserve a specific time interval while forgetting some redundant information, so the model has better accuracy in identifying muscle fatigue.

**Table 4.** The evaluation metric parameters for several categorization models

Recognition models	Accuracy	Precision	Recall	F1_score
LSTM	98.91%	99.27%	98.68%	99.19%
BP	96.83%	94.97%	93.63%	94.26%
KNN	95.89%	93.84%	92.42%	93.09%
SVM	97.02%	92.62%	94.55%	93.95%

The experimental results confirm that our idea of using multifractal analysis to improve the recognition rate of muscle fatigue is effective. To begin with, unlike static contraction, the discharge sequence and frequency of a large number of different types of motor units are irregular when the muscle is dynamically contracted to fatigue, which has a high degree of non-stationarity, nonlinearity, complexity, and is a typical multifractal system. The complicated nonlinear dynamic evolution process formed during dynamic muscle exhaustion is challenging to define using the time-domain, frequency-domain, and single fractal analysis approaches. Contrarily, multifractal analysis is used to analyze datasets. The technique entails distorting datasets extracted from patterns to generate multifractal spectra that illustrate how scaling varies over the dataset. According to the experimental results, the multifractal feature can characterize complex characteristics of the muscle discharge rate, motor unit recruitment, and degree of nonlinear coupling of motion of the unit in space-time, making it an effective method for analyzing muscle dynamic fatigue.

## 6. Conclusion

- A muscle fatigue identification approach based on a combination of sEMG multifractal technology and LSTM was presented in order to address the issue of inaccurate assessment of muscle fatigue caused by complex properties of the sEMG signal, such as non-stationarity, nonlinearity and self-similarity.
- A new reference feature for the muscle fatigue recognition model based on deep learning is provided by the introduction of the MFDMA method to analyze and extract nonlinear properties of sEMG signals. Additionally, the *t*-test method is used to assess the significance of differences between the multifractal characteristics under fatigue and non-fatigue conditions.
- A methodology for recognizing muscle fatigue based on LSTM networks was created. The recognition accuracy of the model was as high as 98.91% by fusing the combined feature set of multifractals, which was 4.73% higher than that of the conventional EMG feature set. In addition, the recognition accuracy of the LSTM network model was 2.08%, 3.02%, and 1.89% higher than that of BP neural networks, K-nearest neighbors, and SVM, respectively, for the same feature set. The findings of the study might lead to the development of a novel technique for precisely identifying muscle exhaustion during physical activity and rehabilitation therapy.

### *Acknowledgement*

This work was supported by the Science and Technology Project of the Chongqing Municipal Education Commission (grant: KJZD-K201900702).

## References

1. BERETTA-PICCOLI M., CESCO C., VISTARINI A., PISEGNA C., VANNINI B., ZAMPELLA C., CALANNI L., SOLDINI E., BARBERO M., D'ANTONA G., 2023, Motor unit synchronization and firing rate correlate with the fractal dimension of the surface EMG: A validation study, *Chaos, Solitons and Fractals: the Interdisciplinary Journal of Nonlinear Science, and Nonequilibrium and Complex Phenomena*, **167**
2. BIANCARDI C.M., CHUMINO R., GIANNECHINI G., 2021, Linear correlation between the fractal dimension of surface EMG signals and the peak power of vertical jumps, *IEEE URUCON*, 223-226
3. BOYER M., BOUYER L., ROY J.S., CAMPEAU-LECOURS A., 2021, A real-time algorithm to estimate shoulder muscle fatigue based on surface EMG signal for static and dynamic upper limb tasks., *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 100-106
4. BURGESS C.J.C., 1998, A tutorial on support vector machines for pattern recognition, *Data Mining and Knowledge Discovery*, **2**, 2, 121-167
5. CAO A., ZHANG S., LIU R., ZOU L., FAN C., 2018, A muscle fatigue state classification system based on surface electromyographic signals, *Computer Applications*, **38**, 6, 1801-1808
6. CHEN X., PAN X., JI T., YU S., SUN Y., 2023, Fusion classification of stroke patients' biosignals by weighted cross-validation-based feature selection (W-CVFS) method, *Biomedical Signal Processing and Control*, **80**, 104282
7. FRANÇA L.G.S., MIRANDA J.G.V., LEITE M., SHARMA N.K., WALKER M.C., LEMIEUX L., WANG Y., 2018, Fractal and multifractal properties of electrographic recordings of human brain activity: toward its use as a signal feature for machine learning in clinical applications, *Frontiers in Physiology*, **9**, 1767
8. GHISLIERI M., CERONE G.L., KNAFLITZ M., AGOSTINI V., 2021, Long short-term memory (LSTM) recurrent neural network for muscle activity detection, *Journal of NeuroEngineering and Rehabilitation*, **18**, 1-15
9. GU G.F., ZHOU W.X., 2010, Detrending moving average algorithm for multifractals, *Physical Review*, **82**, 1, 011136
10. HOCHREITER S., SCHMIDHUBER J., 1997, Long short-term memory, *Neural Computation*, **9**, 8, 1735-1780
11. KANTELHARDT J.W., ZSCHIEGNER S.A., KOSCIELNY-BUNDE E., HAVLIN S., BUNDE A., STANLEY H.E., 2002, Multifractal detrended fluctuation analysis of nonstationary time series, *Physica A: Statistical Mechanics and its Applications*, **316**, 1-4, 87-114
12. KARTHICK P.A., RAMAKRISHNAN S., 2016, Surface electromyography based muscle fatigue progression analysis using modified B distribution time-frequency features, *Biomedical Signal Processing and Control*, **26**, 42-51
13. LECUN Y., BOSER B., DENKER J., HENDERSON D., HOWARD R.E., HUBBARD W., JACKEL L.D., 1989, Backpropagation applied to handwritten zip code recognition, *Neural Computation*, **1**, 4, 541-551
14. LI S., 2020, Multifractal detrended fluctuation analysis of congestive heart failure disease based on constructed heartbeat sequence, *IEEE Access*, **8**, 205244-205249
15. LIU G., DONG M., ZHANG S., XU L., ZHOU G., CAI J., 2021a, Study on fatigue classification of surface EMG signals based on KPCA-SVM, *Journal of Electronic Measurement and Instrumentation*, **35**, 10, 1-8
16. LIU Q., LIU Y., ZHANG C., RUAN Z., MENG W., CAI Y., AI Q., 2021b, sEMG-based dynamic muscle fatigue classification using SVM with improved whale optimization algorithm, *IEEE Internet of Things Journal*, **8**, 23, 16835-16844

17. MAHANANTO F., RIKSAKOMARA E., ADITYA R.Z., 2019, Multifractal detrended fluctuation analysis of heart rate variability predicts short-term outcomes of patients with sepsis, *2019 International Biomedical Instrumentation and Technology Conference (IBITeC)*
18. MARRI K., SWAMINATHAN R., 2016, Analysis of concentric and eccentric contractions in biceps brachii muscles using surface electromyography signals and multifractal analysis, *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, **230**, 9, 829-839
19. NA Y., KIM J., 2016, Dynamic elbow flexion force estimation through a muscle twitch model and sEMG in a fatigue condition, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **PP**, 99, 1-1
20. SKROBEK D., KRZYWANSKI J., SOSNOWSKI M., KULAKOWSKA A., ZYLKA A., GRABOWSKA K., CIESIELSKA K., NOWAK W., 2020, Prediction of sorption processes using the deep learning methods (long short-term memory), *Energies*, **13**, 24, 6601
21. SKROBEK D., KRZYWANSKI J., SOSNOWSKI M., KULAKOWSKA A., ZYLKA A., GRABOWSKA K., CIESIELSKA K., NOWAK W., 2022, Implementation of deep learning methods in prediction of adsorption processes, *Advances in Engineering Software*, **173**, 103190
22. TOMOHIRO K., TADASHI M., TOHRU K., TSUGUTAKE S., 2006, *Biomechanism Library Practical Usage of Surface Electromyogram* (in Japanese), Japan Society of Biomechanisms
23. TUNCER S.A., ALKAN A., 2022, Classification of EMG signals taken from arm with hybrid CNN-SVM architecture, *Concurrency and Computation: Practice and Experience*, **34**, 5, e6746
24. WANG J.-H., SUN S.-M., SUN Y.-N., CHEN J., PENG W., LI L., 2022, Research on muscle fatigue recognition model based on improved wavelet denoising and long and short term memory network, *Journal of Biomedical Engineering*, **39**, 3, 9
25. WANG Z.L., ZHOU Y.Q., 2000, Multifractal spectrum and its calculation, *Journal of Beijing University of Aeronautics and Astronautics*, **2000**, 3, 256-258
26. XI C.-P., ZHANG S.-N., XIONG G., *et al.*, 2015, Comparative analysis of fractal spectrum algorithms by multifractal descending fluctuation analysis and moving average method, *Journal of Physics*, **13**, 14
27. XIONG A.-B., ZHAO X.-G., HAN J.-D., LIU G.-J., 2013, Chaotic analysis of EMG on the patients of facial paralysis, *Science Bulletin*, **58**, S2, 152-165
28. XU Q.S., BAI R., LI S., 2022, Dual regulation of surface EMG nonlinear parameters by strength training load and muscle fatigue, *Chinese Sports Science and Technology*, **58**, 8, 8
29. YE L.-H., LI Q.-S., LU Q., 2023, Feature extraction and classification of electrocardiogram signals based on ensemble empirical mode decomposition and multifractal analysis, *Journal of Signal Processing*, **39**, 1, 143-153
30. ZHANG S., LI X., ZONG M., ZHU X., WANG R., 2018, Efficient kNN classification with different numbers of nearest neighbors, *IEEE Transactions on Neural Networks and Learning Systems*, **29**, 5, 1774-1785
31. ZHANG Y., CHEN S., CAO W., GUO P., GAO D., WANG M., ZHOU J., WANG T., 2021a, MFFNet: Multi-dimensional Feature Fusion Network based on attention mechanism for sEMG analysis to detect muscle fatigue, *Expert Systems with Applications*, **185**, 115639
32. ZHANG Y.A.L., ZHANG S.W., SUN S.H., *et al.*, 2021b, A novel method for muscle fatigue detection by fusing EMG signals with A-type ultrasound, *Journal of Electronic Measurement and Instrumentation*, **2022**, 6, 036