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Full Length Article

Muscle fatigue identification and prediction in motion using wearable device with power and torque-based features

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ABSTRACT

Monitoring muscle fatigue is a critical area of research in both the fields of rehabilitation medicine and sports science. Despite its importance, practical measurement remains challenging due to constraints in equipment size and cost. This study leverages a commercially available, wearable high-resolution goniometer to capture joint angles during single-degree-of-freedom curling movements. From these data, we can deduce the torque and power of the biceps in the upper arm using an elbow musculoskeletal model. We proposed nine fatigue indicators, all of which showed significant correlations with the Root Mean Square (RMS) and Median Frequency (MDF) indicators derived from Electromyography (EMG) signals. Spectral clustering was utilized for the identification and classification of fatigue. Subsequently, we employed a K-Nearest Neighbors (KNN) model to predict muscular fatigue, achieving an impressive overall accuracy of 95%, an effective recall rate of 95%, an F1-score of 95%, and an Area Under the Curve (AUC) of 99%. This research presents an innovative and comprehensive approach to the identification and prediction of muscle fatigue.

1. Introduction

Muscle fatigue monitoring is a widely-discussed research topic across daily care, rehabilitation medicine, and sports science[1]. The contemporary understanding of muscle fatigue generally pertains to the decline in the body's maximum voluntary contraction force or power during physical exertion, where the muscular system is unable to maintain a specific level of functionality or sustain a set exercise intensity [2–5]. Monitoring muscle fatigue in athletes during their regular training regimens can optimize training efficiency, boost performance, and minimize the risk of muscle injuries. Muscle fatigue monitoring techniques can be broadly classified into three categories: invasive methods, cardiopulmonary methods, and wearable methods [6,7]. Given that invasive and cardiopulmonary methods are often uncomfortable and not conducive to daily training for patients or athletes, wearable methods stand out as a viable alternative [8–10].

In the realm of wearable electronics, the predominant technique for fatigue assessment involves the acquisition and analysis of surface electromyography (sEMG) signals [11]. Despite its widespread use, the sEMG method encounters limitations when applied to muscles situated immediately beneath the skin, particularly due to its vulnerability to crosstalk from EMG signals of adjacent muscles [11,12]. Studies focusing on EMG signals confront several challenges that are not easily surmountable. Firstly, EMG signals are effective primarily in low-frequency bands, are highly sensitive to environmental noise, and are prone to variations in operating conditions. Moreover, noise signals can markedly affect measurement precision during dynamic muscle contractions. Additionally, factors such as torque magnitude, muscle fiber diversity, and electrode positioning can exacerbate the non-linearity and non-stationarity of EMG signals during dynamic isotonic contractions. As a result, relying exclusively on EMG signals for fatigue identification during dynamic muscle contractions is deemed inadequate [13–19].

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Recently, the use of machine learning to predict muscle activity and fatigue has gained considerable traction. Scholars have employed both traditional and deep learning algorithms on electromyography (EMG) and surface electromyography (sEMG) data to extract relevant features and anticipate fatigue states, thereby facilitating the detection and prevention of muscle fatigue. For instance, Papakostas et al. leveraged wearable EMG devices for real-time fatigue detection, extracting a range of time-frequency domain features and utilizing algorithms such as Support Vector Machines (SVM) and Random Forests to forecast fatigue states [20]. In a similar vein, Moniri et al. introduced a Convolutional Neural Network (CNN)-based model for real-time fatigue prediction, which enhanced the accuracy and stability of fatigue predictions in trunk muscles, underscoring the benefits of deep learning for long-term and intricate applications [12,21–24]. These studies underscore the pivotal role of machine learning in the monitoring of muscle fatigue, presenting valuable tools for the fields of sports medicine and rehabilitation.

Skeletal muscle fatigue manifests through both external and intrinsic indicators, with the latter predominantly characterized by a decline in force. This force decay is intricately linked to power signals and torque, as muscle fatigue invariably results in a reduction of muscle tension and output power [25,26]. Consequently, this study constructs and employs a wearable sensing platform for curling exercises. In addition to utilizing traditional EMG sensors to gather signals associated with muscle fatigue, the platform will measure the elbow joint angle. This measurement will be integrated into the elbow musculoskeletal model to extract the elbow flexion torque and power of the biceps brachii during isotonic contractions. Spectral clustering and K-Nearest Neighbors (KNN) algorithms are deployed for fatigue recognition and prediction, while eXtreme Gradient Boosting (XGBoost) is leveraged to assess the efficacy of the proposed features. Following an analysis grounded in physical principles, two sets of fatigue indices will be developed, correlating with the Zero Crossing Rate (ZCR) and median frequency (MDF) of EMG signals. This correlation will substantiate our findings, leading to a more accurate identification of muscle fatigue [27,28].

2. Methods devices and participants

2.1. Devices and participants

In this study, we employed a commercial wireless portable sEMG sensor, the BIOM-LE2 (Biometrics Ltd., USA), and a wireless portable goniometer, the BIOM-WS150 (Biometrics Ltd., USA), to establish a wearable multi-signal acquisition system (Fig. 1**(a)**). The EMG sensor BIOM-LE2 was configured with a sampling frequency of 2000 Hz, and the goniometer BIOM-WS150 with 1000 Hz, ensuring high-fidelity real-time capture of EMG potentials and joint angle curves during daily exercises.

To uphold the scientific rigor and reliability of our experiment, we selected 32 healthy male volunteers (age range: 20–25 years, height: 1.77 ± 0.05 m, weight: 70 ± 10 kg, arm circumference: 25–35 cm, body mass index/BMI: 23.5 ± 3.3) to participate. Prior to the commencement of the study, participants were briefed on the objectives, procedures, and potential risks involved, and they provided their written informed consent. The Ethics Committee at the College of Information Science and Technology of Donghua University reviewed and approved the research protocol, which was conducted in compliance with the ethical standards of the Declaration of Helsinki and adhered to local legal requirements. All participants were in good health, free from cardiovascular diseases or muscle injuries, and were not in a state of fatigue following adequate rest. Notably, some

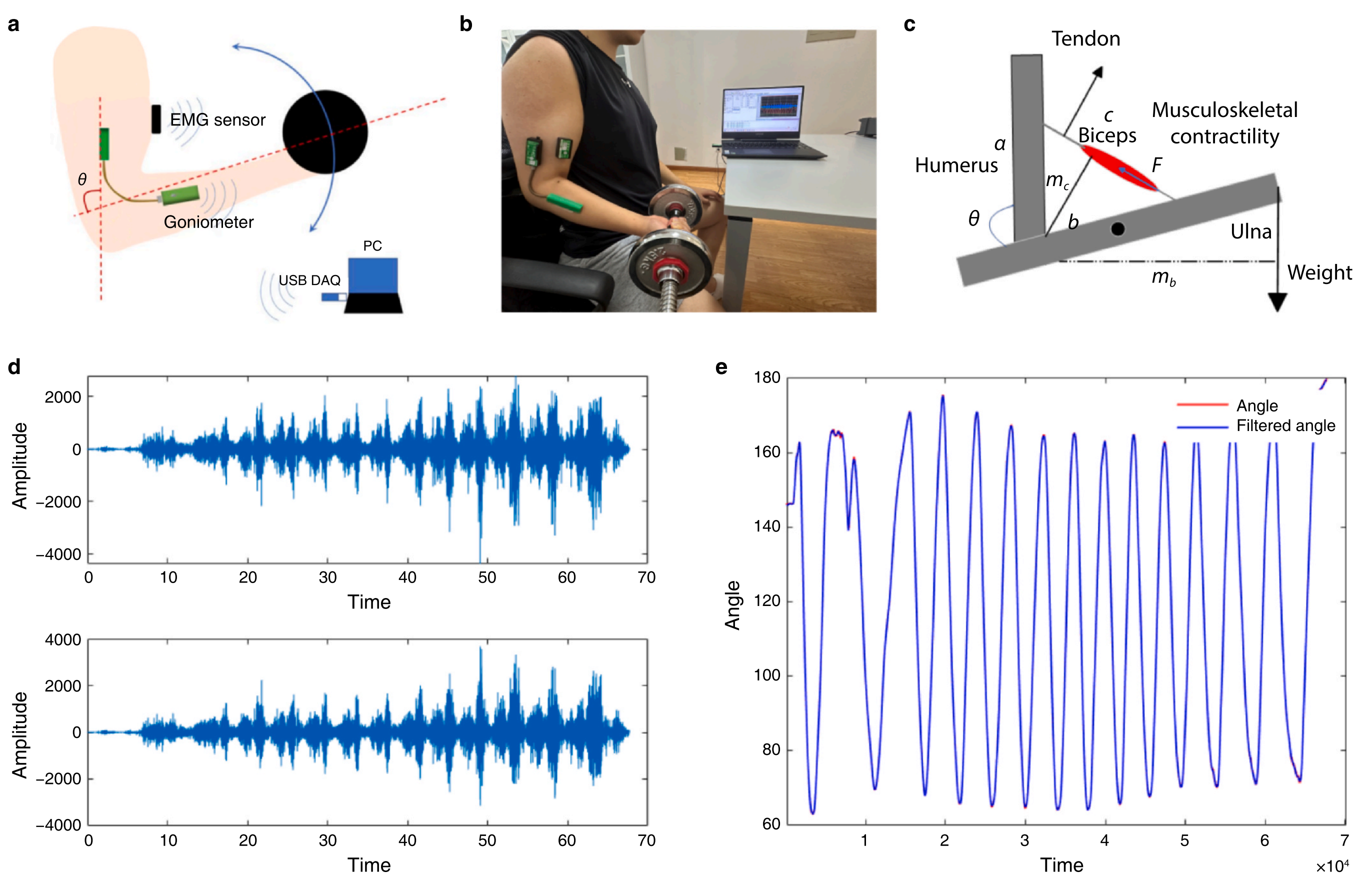

Fig. 1. (a) schematic diagram of sensor configuration and data acquisition scheme; (b) field experimental photo; (c) musculoskeletal model of elbow flexion; (d) collected EMG of biceps brachii in test; (e) collected elbow joint angle in test.

participants had a background in physical training. Importantly, none of the participants had engaged in strenuous exercise within the 24 hours preceding the experiment.

2.2. Experimental design

As previously mentioned, continuous collection and storage of surface electromyography (EMG) signals from the biceps brachii and elbow joint angle data are essential. We selected standard bicep curls with the upper arm held upright as our target test protocol. Participants were offered a range of dumbbell weights to select the most appropriate one for achieving biceps fatigue after performing 8–12 repetitions of uniform standard bicep curls. They were instructed to maintain a consistent posture: standing with legs apart, seated on a chair with a forward lean, elbows resting on the inner front of their thighs, and ensuring that the support point remained stationary during the curls [29–31]. This setup ensures that the primary loading is on the biceps brachii, making the external signs of muscle fatigue more evident. When participants were unable to sustain the standard uniform bicep curl, their arm muscles were deemed fatigued. The schematic diagram and field photo of the experimental setup are presented in Fig. 1**(a-b)**.

2.3. Data preprocessing and Modeling

Elbow joint angle signal was denoised using a nine-level wavelet transform to produce a smoother curve[32]. The EMG signal of biceps brachii underwent band-pass filtering at 50 Hz to remove power line interference, followed by additional band-pass filtering between 10 and 200 Hz to eliminate unwanted noise [11]. A wavelet transform was then applied to reduce white noise interference. Finally, the EMG signal was reconstructed using wavelet transform to enhance the signal-to-noise ratio and eliminate baseline drift. The comparison of the EMG and Angle signals before and after pretreatment is shown in Fig. 1**(d-e)**.

The musculoskeletal model of elbow flexion is shown in Fig. 1**(c)**. Based on this configuration, the following formulas were used to construct the upper arm biceps power model[33]. The construction of the upper arm biceps energy model is as follows:

$$F(t)\cdot m_c - mg\cdot m_b = -M_1\ddot{\theta} \quad (1)$$

$$p(t) = F(t) \times v_1 \quad (2)$$

$$M = L \times F \quad (3)$$

Where θ satisfies $\cos(\pi - \theta) = \frac{a^2+b^2-c^2}{2ab}$, $M_1 = mg\cdot b^2$, $v_1 = \frac{\Delta c(\theta)}{\Delta t}$.

In the equation, $p(t)$ represents the power output signal of the skeletal muscle; $F(t)$ denotes the real-time skeletal muscle tension, i.e., contraction force; $\Delta c(\theta)$ stands for the change in skeletal muscle length, v_1 signifies the rate of change of skeletal muscle length per unit time, i.e., velocity; θ represents the real-time joint flexion angle, $\ddot{\theta}$ is the second derivative of angular velocity, representing joint angular acceleration, M denotes torque, F denotes skeletal muscle tension, a represents the length of the humerus (upper arm bone), b represents the length at the connection point of muscles in the forearm, and c represents the length of the biceps brachii, m_c represents the length of the lever arm from the joint to the biceps brachii, m_b represents the length of the lever arm from the joint to the biceps brachii.

3. Extraction and selection of muscle fatigue features

3.1. Fatigue feature in power of biceps

Literature has established that the energy expenditure curve during exercise is not a straightforward linear progression; it is more complex. Initially, the body demands a surge in energy to sustain high-intensity activities, leading to a sharp rise in energy consumption [34]. However, as time elapses, the body adapts to these demands, which results in a deceleration of the energy expenditure rate. In our experiment, after analyzing the energy signals for each exercise repetition (Rep), as depicted in Figure S1 in supplementary information, we observed that participants performing standard bicep curls experienced an initial spike in energy expenditure followed by a subsequent decline. The fluctuation in energy consumption across Reps is detailed in Fig. 2**(a)**.

It is evident that with an increasing number of exercise Reps, the energy consumption indicator follows a characteristic pattern of initial increase and subsequent decrease. This pattern can be utilized as a fatigue feature for monitoring muscle fatigue in the biceps brachii. Similar to EMG signals, the Root Mean Square (RMS) amplitude of the biceps brachii power in the contralateral limb shows a significant increase shortly after the initiation of movement, indicating a substantial rise in amplitude. The sensitivity of the RMS to these changes suggests its potential for early detection of muscle fatigue onset. As the exercise progresses, RMS values continue to ascend, peaking at exhaustion, which underscores RMS's capacity to accurately reflect the severity of muscle fatigue [35–37]. In this study, RMS was also analyzed in relation to the human body's energy signal, revealing an initial increase followed by a decrease post-fatigue onset, as shown in Fig. 2**(b)**. This pattern is consistent with the physical interpretation of RMS, which provides average amplitude information for periodic signals.

Observing the trend of RMS values as the number of Reps increases, we see an initial rise followed by a decline, suggesting that RMS can serve as an additional indicator for detecting muscle fatigue in the biceps brachii."

3.2. Fatigue features in elbow flexion torque

The temporal flexion torque and power model examined in this paper, as outlined in Eq. (1), are both derived from the musculoskeletal

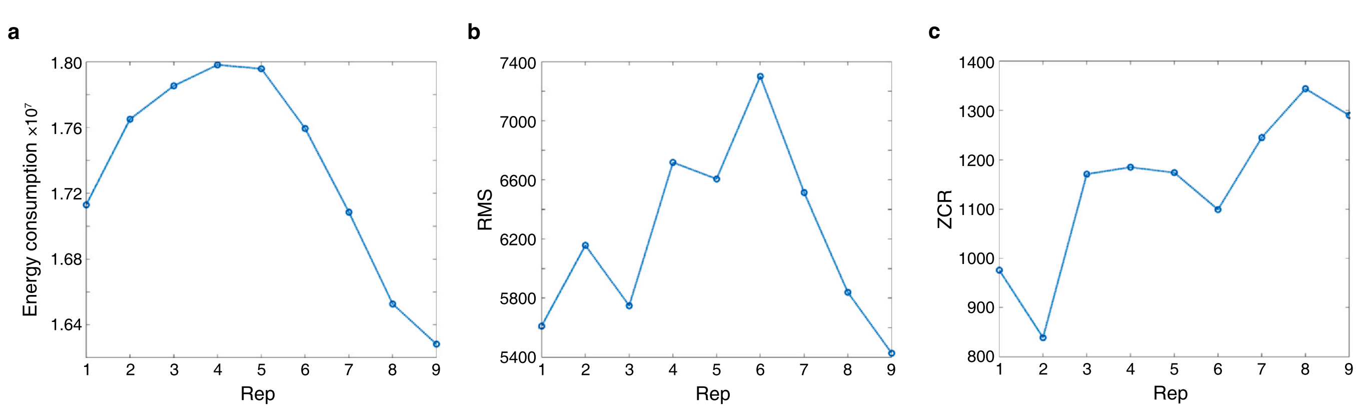

Fig. 2. (a) RMS of the energy signal of randomly selected subject varies with the reps of curling; (b) RMS of torque signals of randomly selected subjects with reps of curling; (c) ZCR of flexion torque of randomly selected subject with reps of curling.

model using real-time joint angle signals. By segmenting each cycle of flexion into increasing and decreasing phases of the joint angle, we can calculate the flexion torque, as illustrated in Figure S2 in supplementary information.

The Zero Crossing Rate (ZCR) is a measure that quantifies the number of times a signal crosses the zero amplitude line (from positive to negative or vice versa) within a defined segment of the signal[27]. This metric has been extensively utilized in speech recognition, music information retrieval, and has also been applied in several studies analyzing EMG signals. In the context of the torque signals derived from the model presented in this paper, ZCR can effectively reflect the body's control over fatigue-affected muscles, thereby indicating the state of muscle fatigue. A higher ZCR suggests increased muscle tremor. Consequently, this study presents the ZCR of torque signals as shown in Fig. 2**(d)**.

From the aforementioned figure, it is clear that the ZCR of torque signals escalates with the progression of exercise Reps, manifesting an upward trend. Thus, this paper identifies the ZCR of torque signals as a promising indicator for monitoring muscle fatigue.

3.3. Correlation and feature intensity analysis of fatigue indicators

Accounting for the variability in the number of curling exercise repetitions among participants, this study uniformly selected the first three repetitions, the last three repetitions, and the middle repetitions for analysis. During the experimental design phase, EMG (electromyography) signals were collected to capture muscle activity. In the feature correlation analysis phase, this study employed RMS (Root Mean Square) and MDF (Median Frequency), two well-established fatigue indicators derived from EMG signals, to assess the correlation and significance levels of the three selected indicators. Pearson correlation coefficients (R) and significance levels (P) between the electromyography-based fatigue indicators and muscle thickness were calculated through correlation analysis, as detailed in Table 1.

Table 1 clearly demonstrates that the indicators selected for this study show strong correlations with established metrics. These results highlight that the fatigue indices derived from the biceps brachii power and flexion torque model are effective in monitoring muscle fatigue. This finding points to potential applications in enhancing wearable devices for sports and other physical activities.

To find out the most-important features of muscle fatigue, this study employed the XGBoost algorithm and conducted a feature importance test on fatigue indicators derived from the biceps brachii muscle power and torque model [38,39]. The choice of XGBoost is justified by its superior predictive performance among commonly used methods such as CART, Optimal Trees, XGBoost, and SHAP. XGBoost stands out as a "black-box" model, particularly suitable for studies where the underlying mechanisms are not fully understood. While SHAP offers more detailed interpretability, its efficiency is comparatively lower; hence, XGBoost was chosen for its role in aiding muscle fatigue prediction in this study [20,40]. The detailed results of these analyses are presented in Tables S1 and S2 in supplementary information.

The XGBoost algorithm, a sophisticated tree-based model, is utilized in this study for model determination. Our objective is to harness a probabilistic model to pinpoint fatigue indicators and to delve into the regression relationship that exists between various features and levels of fatigue. Given this, there is a strategic preference for employing neural networks to model the intricate relationship between features and fatigue, capitalizing on their capacity for greater generalizability across different data scenarios. Concurrently, XGBoost is integrated into our feature engineering process, where it plays a pivotal role in enhancing the feature set before these are input into the neural network for fatigue prediction.

Table 1
Pearson correlation coefficients and significance levels.

	RMS of EMG		MDF of EMG	
	R	P	R	P
Energy Consumption	−0.8121	0.0023	0.7882	0.0039
RMS of Power	0.7044	0.0772	−0.5413	0.2095
ZCR of Torque	0.7038	0.0156	−0.6245	0.0391

4. Identification and prediction of fatigue

4.1. Fatigue reorganization using power and torque-based features

This study has meticulously constructed a self-collected database comprising a total of 55 tests, each rich in nine unique features. The dataset, consisting of 495 observations, underwent standardization and was subsequently analyzed using spectral clustering. The visualization of the results is presented with the number of exercise repetitions (Reps) on the horizontal axis and one of the eight dimensions on the vertical axis. A representative example, as depicted below, demonstrates the spectral clustering outcomes for a dataset encompassing a total of nine Reps.

As depicted in Fig. 3**(a)**, the red segments are predominantly found in the initial three repetitions (Reps), while the blue and green segments are less discernible. This observation suggests that the nine features selected for fatigue clustering in this experiment did not yield the desired results. The silhouette coefficient for the spectral clustering outcome is 0.217, the Calinski-Harabasz Index is 158.64, and the Davies-Bouldin Index is 1.33. Consequently, the authors opted to refine the XGBoost algorithm. When clustering was performed using the Slope of Torque, as shown in Figure S3**,** supplementary information, the differentiation in fatigue clustering was minimal. Thus, the authors decided to exclude this feature from the dataset, retaining only the remaining eight features per group. The 440 data points were standardized once more and subjected to spectral clustering. The results are presented with the number of action Reps on the horizontal axis and one of the eight dimensions on the vertical axis, as shown in Fig. 3**(b)**, where the red segments are mainly concentrated in the first three Reps, the blue segments in the middle three Reps, and the green segments in the last three Reps. Based on the spectral clustering results of this eight-dimensional dataset, it can be inferred that during the performance of bicep curls for a total of nine Reps, the first three Reps predominantly represent a non-fatigued state, Reps 4–7 indicate a transition from non-fatigued to fatigued states, and Reps 8–9 predominantly represent a fatigued state. This conclusion is consistent with experimental observations, where arm tremors were noted as fatigue set in. Furthermore, the silhouette coefficient for this spectral clustering result is 0.235, the Calinski-Harabasz Index is 225.73, and the Davies-Bouldin Index is 1.24 [41,42].

Given that visualization based on a single feature may be biased, we applied Principal Component Analysis (PCA) to the standardized feature indicators, using the first and second principal components as the y and z axes, respectively, to achieve a three-dimensional visualization of the clustering effect, as shown in Fig. 3**(c)**. This three-dimensional visualization effectively distinguishes the three fatigue statuses of the biceps brachii. Therefore, the authors decided to apply PCA to the original eight fatigue indicators, selecting the first, second, and third principal components for spectral clustering. The results are displayed with the number of action Reps on the horizontal axis and one of the three-dimensional data points on the vertical axis.

An example illustrating the spectral clustering results for data from a total of nine Reps was shown in Fig. 3**(d)**. As can be observed from the figure, the red segments are predominantly concentrated in the first three repetitions (Reps), the blue segments in the middle three Reps, and the green segments in the last three Reps, mirroring the outcomes achieved with the eight muscle fatigue indicators used for spectral clustering. Furthermore, the silhouette coefficient for this spectral clustering result stands at 0.268, the Calinski-Harabasz Index reaches

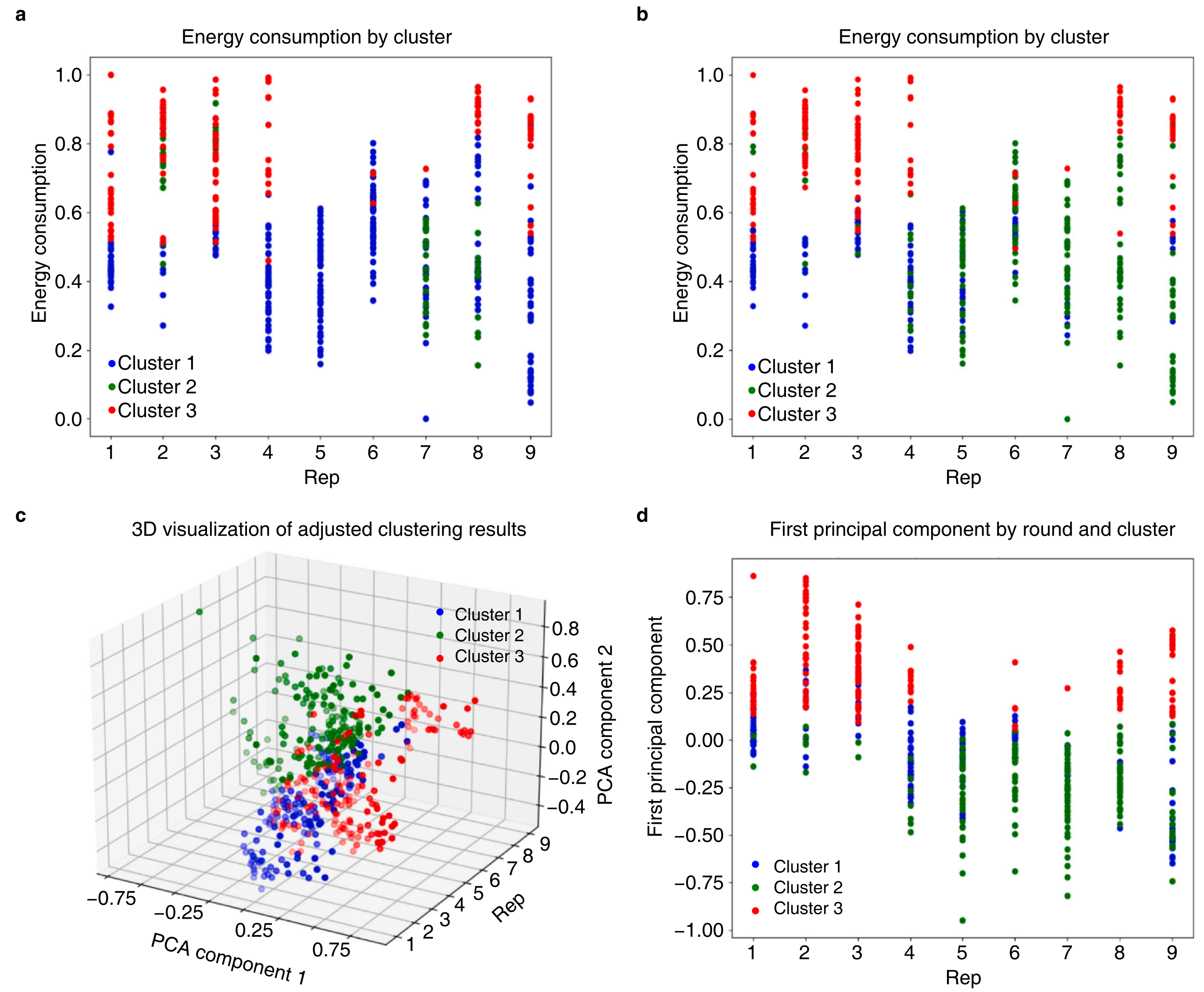

Fig. 3. (a) Clustering results using original nine features. (b) Clustering results of the eight-dimensional features, with Slope of torque excluded. (c) 3D visualization of well-distinguished fatigue clustering. (d) Visualization of fatigue clustering after dimensional reduction based on PCA results. Where in this figure, the red sections indicate the non-fatigue state, the blue sections represent the transition to fatigue state, and the green sections denote the fatigue state.

240.63, and the Davies-Bouldin Index is 1.26. This spectral clustering method exhibits a marked improvement over the previous clustering with eight fatigue indicators, signifying enhanced cluster cohesion and separation, and thus, demonstrating a superior clustering performance. Consequently, these clustering results can be effectively utilized to identify fatigue states within the dataset's samples and to label the data, thereby preparing it for the subsequent application of supervised classification algorithms aimed at predicting muscle fatigue states.

4.2. Prediction of muscle fatigue using labeled data

In this study, we allocated 70 % of the PCA-reduced sample set for training, with the remaining 30 % designated as the test set [43–45]. Following the spectral clustering of the data as previously described, all samples were labeled, setting the stage for the selection of a supervised classification method for feature recognition. Given the inherent variability in human data, the performance of the algorithm model cannot be assessed solely by accuracy. A comprehensive set of evaluation metrics is essential, encompassing precision, recall, F1-score, ROC curve, and AUC [46–48]. These metrics are derived from the confusion matrix, as depicted in Fig. 4**(a)**.

The AUC is derived from the ROC curve, which is presented below. The horizontal axis of the ROC curve indicates the False Positive Rate (FPR), representing the proportion of negative samples mistakenly classified as positive. The vertical axis signifies the True Positive Rate (TPR), also known as recall, which denotes the proportion of positive samples accurately identified as such.

As shown in Fig. 4**(b),** the model excels in fatigue prediction accuracy, achieving a recall rate of 95 %, an F1-score of 95 %, and an AUC of 99 %. These results meet and exceed the benchmarks for predicting muscle fatigue states.

5. Discussion and conclusions

This study introduces dynamic dumbbell bending fatigue experiments to develop a model and a wearable electronic platform for muscle fatigue monitoring based on features of the torque and power of the biceps brachii. After features evaluation, three effective muscle fatigue indicators were derived from this model, all of which exhibit significant correlations with established indicators such as the RMS and MDF of EMG signals. Those effective features contribute in machine learning models that provides successful categorization among non-fatigue,

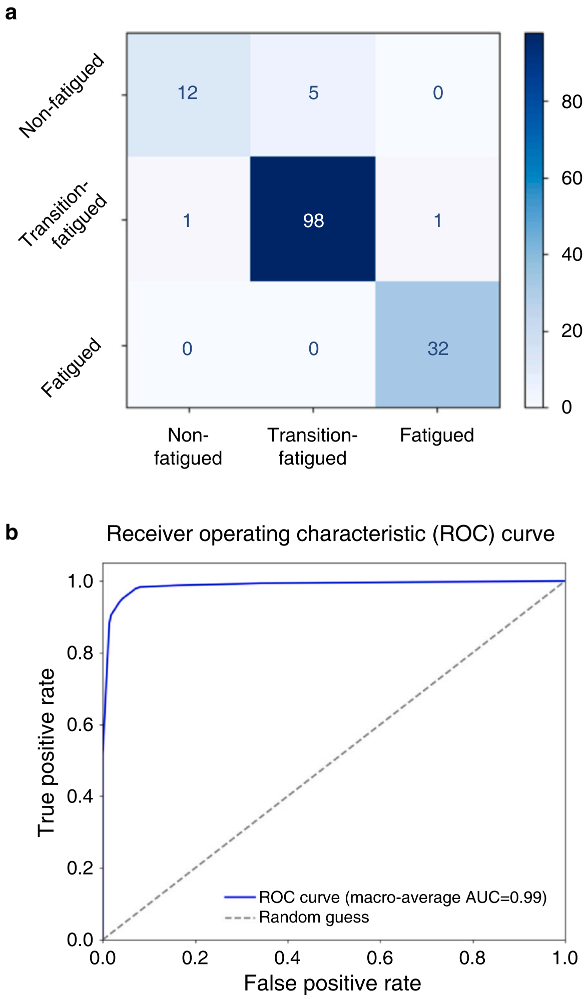

Fig. 4. (a) Confusion Matrix; (b) ROC curve of fatigue prediction.

transition and fatigued. This result indicates that the biceps brachii torque and power model, constructed using only angle sensors, has enabled effective identification and prediction of muscle fatigue, yielding promising results. Compared to traditional methods with EMG or sEMG signals, the collection and processing of angle signals proved more convenient, particularly suitable for field training environments. It can be consequently concluded that, biceps brachii torque and power model offers a complementary approach in the study of skeletal muscle fatigue and provides valuable insights for research in sports rehabilitation, which may pave the way for novel perspectives and applications in muscle fatigue recognition in future research.

However, the generalizability of our current data is limited due to the homogeneity of our participant pool. The experimental design was constrained by the inclusion of only male participants, potentially overlooking gender-specific differences in muscle fatigue. Future studies should encompass both female participants and patients to provide a more holistic assessment of gender disparities in muscle fatigue.

Ethics approval and consent to participate

Ethics approval for the involvement of human subjects in this study was granted by the Ethics Committee at the College of Information Science and Technology of Donghua University, Shanghai, China, and conducted in good compliance with the relevant laws and institutional guidelines. The participants provided their informed consent to participate in this study.

CRediT authorship contribution statement

Zhangding Li: Writing – original draft, Visualization, Data curation. **Xi Wang:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Qiao Li:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Fei Wang:** Resources, Investigation. **Xiaoming Tao:** Supervision, Conceptualization.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.wees.2024.12.005.

References

[1] G. Theofilidis, G.C. Bogdanis, Y. Koutedakis, C. Karatzaferi, Monitoring exercise-induced muscle fatigue and adaptations: making sense of popular or emerging indices and biomarkers, Sports 6 (4) (2018) 153.
[2] R.T. Thorpe, G. Atkinson, B. Drust, W. Gregson, Monitoring fatigue status in elite team-sport athletes: implications for practice, Int. J. Sports Physiol. Perform. 12 (s2) (2017) S2-27–S2-34.
[3] S.-H. Liu, C.-B. Lin, Y. Chen, W. Chen, T.-S. Huang, C.-Y. Hsu, An EMG patch for the real-time monitoring of muscle-fatigue conditions during exercise, Sensors 19 (14) (2019) 3108.
[4] J. Finsterer, Biomarkers of peripheral muscle fatigue during exercise, BMC Musculoskelet. Disord. 13 (2012) 1–13.
[5] C. Twist, J. Highton, Monitoring fatigue and recovery in rugby league players, Int. J. Sports Physiol. Perform. 8 (5) (2013) 467–474.
[6] M.R. Al-Mulla, F. Sepulveda, M. Colley, A review of non-invasive techniques to detect and predict localised muscle fatigue, Sensors 11 (4) (2011) 3545–3594.
[7] H. Abbood, W. Al-Nuaimy, A. Al-Ataby, S.A. Salem, H.S. AlZubi, Prediction of driver fatigue: Approaches and open challenges, 2014 14th uk Workshop On Computational Intelligence (ukci), IEEE, 2014.
[8] F.B. Stulen, C.J. De Luca, Muscle fatigue monitor: a noninvasive device for observing localized muscular fatigue, IEEE Trans. Biomed. Eng. (12) (1982) 760–768.
[9] T.J. Freeborn, Fatigue Monitoring Techniques Using Wearable Systems, in *Wearable Sensors*, Elsevier, 2021, pp. 575–592.
[10] V.P. Singh, D.K. Kumar, B. Polus, S. Fraser, Strategies to identify changes in SEMG due to muscle fatigue during cycling, J. Med. Eng. Technol. 31 (2) (2007) 144–151.
[11] M. Cifrek, V. Medved, S. Tonković, S. Ostojić, Surface EMG based muscle fatigue evaluation in biomechanics, Clin. Biomech. 24 (4) (2009) 327–340.
[12] D. Farina, P. Madeleine, T. Graven-Nielsen, R. Merletti, L. Arendt-Nielsen, Standardising surface electromyogram recordings for assessment of activity and fatigue in the human upper trapezius muscle, Eur. J. Appl. Physiol. 86 (2002) 469–478.
[13] R.H. Chowdhury, M.B. Reaz, M.A.B.M. Ali, A.A. Bakar, K. Chellappan, T.G. Chang, Surface electromyography signal processing and classification techniques, Sensors 13 (9) (2013) 12431–12466.
[14] C.J. De Luca, A. Adam, R. Wotiz, L.D. Gilmore, S.H. Nawab, Decomposition of surface EMG signals, J. Neurophysiol. 96 (3) (2006) 1646–1657.
[15] R. Merletti, D. Farina, Surface electromyography: physiology, engineering, and applications, John Wiley & Sons. DOI, 2016.
[16] C.J. De Luca, The use of surface electromyography in biomechanics, J. Appl. Biomech. 13 (2) (1997) 135–163.
[17] W. Chen, Z. Wang, H. Xie, W. Yu, Characterization of surface EMG signal based on fuzzy entropy, IEEE Trans. Neural Syst. Rehabil. Eng. 15 (2) (2007) 266–272.
[18] A. Merlo, D. Farina, R. Merletti, A fast and reliable technique for muscle activity detection from surface EMG signals, IEEE Trans. Biomed. Eng. 50 (3) (2003) 316–323.
[19] C.J. De Luca, L.D. Gilmore, M. Kuznetsov, S.H. Roy, Filtering the surface EMG signal: Movement artifact and baseline noise contamination, J. Biomech. 43 (8) (2010) 1573–1579.

[20] M. Papakostas, V. Kanal, M. Abujelala, K. Tsiakas, and F. Makedon. Physical fatigue detection through EMG wearables and subjective user reports: a machine learning approach towards adaptive rehabilitation. Proceedings of the 12th ACM international conference on pervasive technologies related to assistive environments. (2019) 475-481, https://doi.org/10.1145/3316782.3322772.
[21] P. Karthick, D.M. Ghosh, S. Ramakrishnan, Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms, Comput. Methods Prog. Biomed. 154 (2018) 45–56.
[22] P.M. Kuber, A.R. Kulkarni, E. Rashedi, Machine learning-based fatigue level prediction for exoskeleton-assisted trunk flexion tasks using wearable sensors, Appl. Sci. 14 (11) (2024) 4563.
[23] A. Moniri, D. Terracina, J. Rodriguez-Manzano, P.H. Strutton, P. Georgiou, Real-time forecasting of sEMG features for trunk muscle fatigue using machine learning, IEEE Trans. Biomed. Eng. 68 (2) (2020) 718–727.
[24] C. Wang, X. Wang, Q. Li, X. Tao, Recognizing and predicting muscular fatigue of biceps brachii in motion with novel fabric strain sensors based on machine learning, Biomed. Signal Process. Control 96 (2024) 106647, https://doi.org/10.1016/j.bspc.2024.106647.
[25] D.G. Allen, G.D. Lamb, H. Westerblad, Skeletal muscle fatigue: cellular mechanisms, Physiol. Rev. 88 (1) (2008) 287–332.
[26] W. Ament, G.J. Verkerke, Exercise and fatigue, Sports Med. 39 (2009) 389–422.
[27] G. Inbar, O. Paiss, J. Allin, H. Kranz, Monitoring surface EMG spectral changes by the zero crossing rate, Med. Biol. Eng. Comput. 24 (1986) 10–18.
[28] A. Phinyomark, S. Thongpanja, H. Hu, P. Phukpattaranont, C. Limsakul, The usefulness of mean and median frequencies in electromyography analysis, Comput. Intell. Electromyogr. Anal. -A Perspect. Curr. Appl. Future Chall. 23 (2012) 195–220.
[29] H.-J. Hwang, W.-H. Chung, J.-H. Song, J.-K. Lim, H.-S. Kim, Prediction of biceps muscle fatigue and force using electromyography signal analysis for repeated isokinetic dumbbell curl exercise, J. Mech. Sci. Technol. 30 (2016) 5329–5336.
[30] Y. Wang, T. Hua, B. Zhu, Q. Li, W. Yi, X. Tao, Novel fabric pressure sensors: design, fabrication, and characterization, Smart Mater. Struct. 20 (6) (2011) 065015.
[31] L. Shu, T. Hua, Y. Wang, Q. Li, D.D. Feng, X. Tao, In-shoe plantar pressure measurement and analysis system based on fabric pressure sensing array, IEEE Trans. Inf. Technol. Biomed. 14 (3) (2010) 767–775.
[32] N. Sobahi, Denoising of EMG signals based on wavelet transform, Asian Trans. Eng. 1 (5) (2011) 17–23.
[33] X. Wang, X. Tao, R.C. So, L. Shu, B. Yang, Y. Li, Monitoring elbow isometric contraction by novel wearable fabric sensing device, Smart Mater. Struct. 25 (12) (2016) 125022.
[34] T. Zhuang, B. Sun, A comparative study about energy consumption of young men when walking and running, Chin. J. Tissue Eng. Res. 16 (37) (2012) 6937.
[35] J.S. Petrofsky, Frequency and amplitude analysis of the EMG during exercise on the bicycle ergometer, Eur. J. Appl. Physiol. Occup. Physiol. 41 (1979) 1–15.
[36] T.I. Arabadzhiev, V.G. Dimitrov, N.A. Dimitrova, G.V. Dimitrov, Interpretation of EMG integral or RMS and estimates of "neuromuscular efficiency" can be misleading in fatiguing contraction, J. Electromyogr. Kinesiol. 20 (2) (2010) 223–232.
[37] M. Bilodeau, S. Schindler-Ivens, D. Williams, R. Chandran, S. Sharma, EMG frequency content changes with increasing force and during fatigue in the quadriceps femoris muscle of men and women, J. Electromyogr. Kinesiol. 13 (1) (2003) 83–92.
[38] H. Zheng, J. Yuan, L. Chen, Short-term load forecasting using EMD-LSTM neural networks with a Xgboost algorithm for feature importance evaluation, Energies 10 (8) (2017) 1168.
[39] S. Ramraj, N. Uzir, R. Sunil, S. Banerjee, Experimenting XGBoost algorithm for prediction and classification of different datasets, Int. J. Control Theory Appl. 9 (40) (2016) 651–662.
[40] S. Solorio-Fernández, J.A. Carrasco-Ochoa, J.F. Martínez-Trinidad, A review of unsupervised feature selection methods, Artif. Intell. Rev. 53 (2) (2020) 907–948.
[41] X. Wang and Y. Xu. An improved index for clustering validation based on Silhouette index and Calinski-Harabasz index. IOP Conference Series: Materials Science and Engineering. 569 (5) (2019), Article 052024, https://doi.org/10.1088/1757-899X/569/5/052024.
[42] U. Maulik, S. Bandyopadhyay, Performance evaluation of some clustering algorithms and validity indices, IEEE Trans. Pattern Anal. Mach. Intell. 24 (12) (2002) 1650–1654.
[43] J. Qi, G. Jiang, G. Li, Y. Sun, B. Tao, Surface EMG hand gesture recognition system based on PCA and GRNN, Neural Comput. Appl. 32 (2020) 6343–6351.
[44] N.F. Güler, S. Koçer, Classification of EMG signals using PCA and FFT, J. Med. Syst. 29 (2005) 241–250.
[45] G.R. Naik, S.E. Selvan, M. Gobbo, A. Acharyya, H.T. Nguyen, Principal component analysis applied to surface electromyography: a comprehensive review, IEEE Access 4 (2016) 4025–4037.
[46] B. Frauscher, A. Iranzo, C. Gaig, V. Gschliesser, M. Guaita, V. Raffelseder, L. Ehrmann, N. Sola, M. Salamero, E. Tolosa, Normative EMG values during REM sleep for the diagnosis of REM sleep behavior disorder, Sleep 35 (6) (2012) 835–847.
[47] E. Gokgoz, A. Subasi, Comparison of decision tree algorithms for EMG signal classification using DWT, Biomed. Signal Process. Control 18 (2015) 138–144.
[48] C. Morbidoni, A. Cucchiarelli, V. Agostini, M. Knaflitz, S. Fioretti, F. Di Nardo, Machine-learning-based prediction of gait events from EMG in cerebral palsy children, IEEE Trans. Neural Syst. Rehabil. Eng. 29 (2021) 819–830.