Sport Fatigue Monitoring and Analyzing Through Multi-Source Sensors

Jiya Wang, Qiqihar University, China*
Huan Meng, Mudanjiang Medical University, China

ABSTRACT
During the process of daily training or competition, athletes may suffer the situation that the load exceeds the body’s bearing capacity, which makes the body’s physiological function temporarily decline. It is one of the characteristics of sports fatigue. Continuous sports fatigue may incur permanent damage to the athletes if they cannot timely get enough rest to recover. In order to solve this issue and improve the quality of athlete’s daily training, this paper establish a fatigue monitoring system by using multi-source sensors. First, the sEMG signals of athlete are collected by multi-source sensors which are installed in a wearable device. Second, the collected sEMG signals are segmented by using fixed window to be converted as Mel-frequency cepstral coefficients (MFCCs). Third, the MFCC features are used learn a Gaussian processing model which is used to monitor future muscle fatigue status. The experiments show that the proposed system can recognize more than 90% muscle fatigue states.

KEYWORDS
Gaussian Processing, Mel-Frequency Cepstral Coefficients, Sports Fatigue, Surface Electromyography

1. INTRODUCTION
Muscle fatigue is a common physiological phenomenon in daily sport exercises (Ghamkhar & Kahlaee 2019). The most intuitive feeling of muscle fatigue is muscle weakness or soreness. In physiology, muscle fatigue is the internal reason why the body cannot maintain the expected strength due to the temporary decline of the work or contraction ability of the muscle movement system (Oleksy et al. 2018). As for the mechanism of muscle fatigue, the central fatigue theory believes that fatigue is the result of protective inhibition of the cerebral cortex (McMorris et al. 2018). When a person feels tired, the active protection is taken to avoid body damage. From the perspective of the change of the content of chemical substances in cells, the occurrence of Ca+ movement disturbance, the accumulation of phosphate and other metabolites, the decrease of ATP etc. lead to the change of action conduction potential and the decrease of muscle fiber contraction strength, which causes the subjective feeling of powerlessness (Kanehisa 2019).

DOI: 10.4018/IJDST.317941 *Corresponding Author
This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.
When muscle fatigue occurs, it will cause the changes of electromyography (EMG) signals to reflect the body state of the muscle (Jebelli & Lee 2019; Hussain 2019). Through detecting the changes of EMG signals, it can provide early warning before fatigue to prevent further muscle damage, maintain the maximum activity of muscles, and enhance the protection of body. In daily sports, the fatigue caused by overload of muscles may induce permanent damage or injury (Wirth et al. 2021). The early fatigue analysis and evaluation has important role in sports injury recovery and auxiliary training. Therefore, an automatic system that can detect the occurrence of muscle fatigue is particularly useful in sports related scenes. The system can guide users to carry out conscious training and act as a warning device of early fatigue to avoid excessive muscle fatigue and prevent body injury.

The research shows that the contraction mode of muscle can be divided into isometric contraction and isometric contraction (Ato et al. 2019). When the static constant force is applied, it is isometric contraction. When the muscle is moving toward the belly, it is isotonic contraction. Both of these movements can lead to muscle fatigue. Under static contraction, when muscles tend to fatigue, the spectrum of EMG signals will shift to the left and the time domain amplitude will increase. However, due to the limitations of instruments, these studies have been in the exploratory stage. With the development of signal acquisition equipment, more attention has been paid to the research on muscle fatigue. When muscle fatigue occurs, the amplitude and spectral characteristics of EMG signals will change, which has become a consensus in the research.

Since the discovery of muscle fatigue, many researchers have taken a variety of methods to study and evaluate it. In terms of acquisition methods, there are mainly intrusive methods and non-intrusive methods (Nsugbe 2021). Invasive method can collect more accurate physiological signals, but may cause wound damage. It is not widely used in the study of muscle fatigue (Greco et al. 2019). The non-invasive method is easy to obtain through human body surface. Under the premise of ensuring the signal quality, non-invasive method is widely used in muscle analysis (Toro et al. 2019). At present, the mainstream non-invasive research methods include mechanical mapping (MMG) method based on muscle vibration (Cè et al. 2013) and electromyography (EMG) method based on motor unit discharge (Toro et al. 2019). From the research trend, EMG method is more suitable for clinical use. In addition, some studies have shown that MMG signal is the mechanical equivalent signal of surface electromyography (sEMG), which originates from the low-frequency vibration of muscle fibers during contraction and extension (Cifrek et al. 2009). The ultrasonic and infrared imaging methods cannot achieve promising accuracy of sEMG. Thus, this paper adopts sEMG to monitor the muscle fatigue during sports.

The main contributions of this paper are summarized as follows: First, a simple muscle fatigue monitoring system is proposed by using sEMG signals. Second, the features of sEMG are extracted by using Mel-frequency cepstral coefficients. Third, a Guassian Processing is used as classification model to monitor the muscle fatigue.

The rest of this paper is summarized as follows: the background and related work is introduced in Section 2; the architecture and implementation of proposed muscle fatigue monitoring system are provided in Section 3; the experimental evaluation is reported in Section 3; the last section is the conclusion and future work.

2. BACKGROUND AND RELATED WORK

Muscle fatigue mainly refers to the weakness of muscle groups in certain parts of the human body. The muscle mainly fatigue refers to local muscle fatigue in academia (Wan et al. 2017). Early research divided the fatigue process into fatigue state and non-fatigue state. Scholars believe that local muscle fatigue do not begin at a certain point (Weber et al. 2014). As long as the body starts to exert force, the fatigue process begin to occur.

In the study of local muscle fatigue, from the subjective perspective, Rating of Perceived Exercise (RPE) was proposed for the subjective force assessment (Halperin & Emanuel 2020). When the
human body is engaged in various kinds of sports or physical activities, the physical condition will produce some physiological reactions with the increase of exercise, such as increased heartbeat, asthma, sweating, muscle contraction, etc. With the increase of exercise intensity, the body reaction will become more intense. In order to prevent the damage of the body’s functional system, the body will appear fatigue and inhibit continued exercise. Rating of Perceived Exercise (RPE) is based on this different fatigue process. The fatigue assessment table is developed based on the subjective feelings of the subjects to determine the current state of the subject’s muscles and the fatigue degree. However, at present, there is still no uniform standard for academic classification of muscle fatigue.

In the study, there are two types of muscle contraction: isotonic contraction and isometric contraction (Rio et al. 2017). Isometric contraction is to maintain the muscle length without any movement, while isotonic contraction is to perform centripetal contraction and eccentric contraction. In general, static shrinkage is usually isometric, while dynamic shrinkage is isotonic. Generally, the surface electromyography (sEMG) refers to the detection of local muscle fatigue under static contraction (Yousif et al. 2019).

The characteristics of surface EMG signal are related to biochemical and physiological changes of skeletal muscle during fatigue contraction (Cifrek et al. 2009). In the research field of local muscle fatigue, a common sense is that the EMG signal have an obvious change trend in the time and frequency domains during the process of muscle fatigue. The time domain amplitude of the EMG signal will increase, while the associated frequency domain spectrum will shift to the left.

In addition, some researchers found out the changes of blood lactic acid content and surface electromyography signal under different muscle fatigue degrees to disclose the associated relationship and implement muscle status and fatigue monitoring according to the quantity ratio of electromyography signal corresponding to lactic acid content. Some scholars believe that lactic acid produced during exercise is considered to be a harmful metabolite, which is one of the reasons for the decline of exercise ability and induces exercise fatigue and metabolic acidosis (Westerblad et al. 2002). However, at normal pH, more than 99% of lactic acid in the human body is hydrolyzed into lactate ions and hydrogen ions. At present, there are still some controversies about whether lactic acid is produced in the process of human exercise and the impact of lactic acid on human pH and fatigue. The research shows that the change of lactic acid can indeed reflect the fatigue state of muscle. However, because the content of lactic acid in cells is a dynamic change process. Its generation and disappearance cannot be continuously detected, and the real-time online analysis of muscle fatigue using lactic acid faces limitations. The generation of muscle fatigue will be accompanied by changes in many physical, physiological and chemical signals of the human body. According to these signal characteristics, the current muscle fatigue state is reflected. Compared with other measurement methods, the sEMG signal is non-invasive, convenient, robust and repeated (Yun et al. 2020). It becomes the mainstream trend of muscle fatigue monitoring by using sEMG signal.

In terms of research means, the analysis of muscle fatigue includes two electrode analysis methods and high-density electromyography electrode analysis methods. The muscle fatigue state is analyzed by increasing or decreasing the number of electrodes. In terms of research objects, according to research purposes, there are studies on the improvement of athletes’ functions, on the wearability of intelligent artificial limbs and on the fatigue evaluation and early warning of normal people. In terms of research content, the current research fields mainly focus on the sensitivity, variability, fatigue characteristics and other indicators of sensor signals, as well as the best processing algorithms and technical solutions with high efficiency and low computational complexity. In the aspect of practicality, there are researches on real-time and controllable fatigue monitoring and early warning system.

An automatic fatigue detection system mainly includes two parts: signal acquisition system and signal analysis system (Abbas & Alsheddy 2020). The signal acquisition system includes sensors, amplification circuits, filtering circuits, main control chips and hardware control systems. At the same time, it should also include power modules and signal transmission modules. The signal analysis part mainly processes the digital signals, including signal filtering, preprocessing, feature extraction, dimension reduction,
classification and prediction. The workflow of the whole detection system is to obtain the sEMG signal in the process of fatigue through the lower computer part and transmit it to the upper computer signal processing part for analysis, output the decision results, and then realize the detection of the muscle state. An illustration of automatic fatigue detection system is shown in Figure 1.

In Figure 1, the fatigue monitoring system contains three parts. The left part is a wearable device to collect sEMG signals and send the collected sEMG signals to lower computer in time. The middle part is a lower computer which extracts useful features of sEMG signals and send the features to the upper computer. The right part is an upper computer which returns the fatigue detection results to the lower computer according to a stored intelligent model.

3. THE IMPLEMENTATION OF MUSCLE FATIGUE MONITORING DURING SPORTS

The sEMG signal is a kind of non-stationary time-varying characteristic signal. As one of the common electrophysiological signals of human body, it is widely used in many fields. As an external comprehensive representation of the potential activity of human muscle cells, sEMG signal can reflect the characteristics of the current human physiological state and the characteristics of the state of consciousness. Meanwhile, the sEMG signal changes are related to biochemical and physiological changes of skeletal muscle during fatigue contraction. In the process of skeletal muscle tending to fatigue, the degree of synchronization of motion unit is deepened, which is reflected by the obvious increase of amplitude through superposition effect. With the deepening of fatigue, the activity of low frequency transmitting unit is excited, and the activity of high frequency unit is reduced, which makes the signal spectrum shift to the left. According to these characteristics of EMG signals, the surface EMG signals of fatigue process can be analyzed.

With the development of signal processing methods, researchers began to conduct in-depth research on muscle fatigue. Up to now, the judgment method has been improved on the basis of the research that amplitude increase and frequency shift to the left during fatigue. It mainly includes time domain method, frequency domain method, time-frequency domain method, etc. (Cifrek et al. 200)

The sEMG signal is a kind of random signal that changes with time. In time domain analysis method, the sEMG is regarded as a time-varying function. After removing artifact noise, the sEMG signal is represented as statistical characteristics in time domain.

Modern signal and system analysis methods believe that any periodic function can be regarded as the superposition of sine waves with different amplitudes and phases. Through Fourier analysis, the sEMG signal can be converted into frequency domain signal to analyze the frequency and energy characteristics. Compared with the time-domain analysis method, the frequency-domain analysis method can analyze the recruitment of motion elements in the fatigue process. Meanwhile, it can find the change trend of frequency through analyzing the spectrum of sEMG signals.

In the development of signal processing methods, it is not feasible to separate time-domain analysis methods from frequency-domain analysis methods for signal analysis. Through the combination of time-domain and frequency-domain signal analysis methods, more signal components can be obtained.
such as wavelet transform and short-time Fourier transform. It can combine the advantages of both time-domain and frequency-domain analysis.

This paper adopts Mel-frequency cepstral coefficients (MFCC) (Siam et al. 2021) to extract the characteristics of sEMG signals, which is widely used in many applications. The flowchart of MFCC is shown in Figure 2.

In the framing stage, the sEMG signal is segmented into frames of $N$ sample points. The adjacent frames have $N - M$ overlapped sample points. In the Windowing stage, each individual frame is multiplied a window function to weaken the discontinuity. Hamming window is a common used window function, which is written as follows

$$w(n) = 0.54 - 0.46 \cos \left( \frac{2\pi n}{N - 1} \right), \quad 0 \leq n \leq N - 1.$$ (1)

In FFT stage, the discrete windowed sEMG segment is converted from time domain to frequency domain through Fourier transform. The associated samples $S(k)$ in frequency domain is written as follows:

$$S(k) = \sum_{n=0}^{N-1} s(n) e^{-j\frac{\pi nk}{N}}, \quad 0 \leq k \leq N - 1.$$ (2)

In the Mel frequency warping, the samples in frequency domain are warped into Mel scale through a set of filters, which are a series of overlapping triangular bandpass filters. The warping between linear frequency scale and Mel frequency scale is represented as follows:

$$Mel(f) = 2595 \cdot \log_{10} \left( 1 + \frac{f}{700} \right).$$ (3)

In DCT stage, the log of Mel scale of each frame is input into discrete cosine transform (DCT) to avoid complex numbers of MFCCs and eliminate the correlations between MFCCs. The output of Mel filters is written in the matrix form as follows:

$$S_{Mel} = W \cdot P.$$ (4)

Here, $W$ represents the Mel filters’ amplitudes and $P$ represents power spectrum. The output after DCT is represented as follows:

Figure 2. The flowchart of Mel-frequency cepstral coefficients
Here, $C_g$ is the Mel-frequency cepstral coefficient, $g = 0, 1, \ldots, J - 1$ ($J$ is the number of MFCCs), $N_f$ is the number of Mel filters. The sEMG segment is finally represented as an MFCC vector $C = [C_0, C_1, \ldots, C_{J-1}]$. The MFCC vectors of sEMG segments are used to learn a Gaussian Processing (GP) model for muscle fatigue monitoring.

Compared with support vector machine (SVM) (Zhu et al. 2016; Zhu et al. 2017a; Zhu et al. 2017b), the Gaussian Processing (GP) (Pérez-Cruz et al. 2013) is a probability model whose output is the probability of a test sample from each class rather than merely a predicted label. It is more meaningful for muscle fatigue monitoring. Additionally, GP does not need to manually set model parameters, which are automatically obtained when Gaussian function is used to solve a posteriori probability. In addition, there are relatively few parameters, and it is easier to optimize parameters.

Let $\mathbf{D} = \{\mathbf{x}_i, y_i\}_{i=1}^n$ represents the set of MFCC vectors and associated fatigue labels. Here, $\mathbf{x}_i$ represents the MFCC vector of sEMG segment $i$, $y_i$ is the associated fatigue label.

When $y_i \in \{-1, +1\}$, for a sample $\mathbf{x}_i$, the prior probability $p(y_i = +1 | \mathbf{D}, \theta, \mathbf{x}_i)$ is written as follows:

$$p(y_i = +1 | \mathbf{D}, \theta, \mathbf{x}_i) = \frac{1}{1 + \exp(-y_if_{\mathbf{x}_i})} \Phi(y_if_{\mathbf{x}_i})$$

Here, $\Phi(y_if_{\mathbf{x}_i})$ is the cumulative probability function following the standard normal distribution. For the implicit function $f$, it can be represented as a Gaussian prior function with mean 0 as follows:

$$p(f | \mathbf{X}, \theta) = N(f | 0, K)$$

Here, $\theta$ is a hyper-parameter of the prior function, $K$ is the positive definite covariance matrix whose element is represented as $K_{ij} = k(\mathbf{x}_i, \mathbf{x}_j, \theta)$. According to Bayesian theorem, the posterior distribution of implicit function is represented as follows:

$$p(f | \mathbf{D}, \theta) = \frac{N(f | 0, K)}{p(\mathbf{D} | \theta)} \prod_{i=1}^n \Phi(y_if_{\mathbf{x}_i})$$

For $p(f | \mathbf{D}, \theta)$, the Gaussian posterior distribution is approximated as follows:

$$p(f | \mathbf{D}, \theta, \mathbf{x}_i) = \int p(f | f, \mathbf{X}, \theta, \mathbf{x}_i) p(f | \mathbf{D}, \theta) df.$$ 

Then, it can obtain $q(f_i | \mathbf{D}, \mathbf{x}_i, \theta) = N(f_i | \mu_i, \sigma_i^2)$. Here, $\mu_i$ and $\sigma_i^2$ are mean and covariance.
Then, the approximate prediction probability of $x_*$ from +1 is represented as follows:

$$q(f | D, x_*, \theta) = \int p(y_* | f_*) p(f | D, \theta, x_*) df = \int \Phi(f_*) N(f, \mu_*, \sigma_*^2) df = \Phi \left( \frac{\mu_*}{\sqrt{1 + \sigma_*^2}} \right).$$  

(10)

For $c$-class classification problem, the strategy of GP is to learn $c$ binary classifiers. For a test sample $x_*$, a probability vector is obtained from these binary classifiers. The maximum probability indicates which class the test sample comes from.

4. EXPERIMENTS AND SIMULATIONS

In this section, we will evaluate the proposed muscle fatigue monitoring method during sports. Thirty healthy persons are recruited as volunteers in our experiments, including fifteen males and fifteen females. They all have no smoking history, no neuromuscular diseases, and no behavior of staying up late in the last week. Their age ranges 24 ± 2 years old. Their sEMG signals are collected through a multi-channel device in which the multi-source sensor is installed. The frequency of sEMG signal is set as 100 Hz. The collected sEMG signals are denoted as five fatigue levels, including relaxed state, weight bearing state, fatigue transition state, deep fatigue state and fatigue state. In both the relaxed state and the fatigue state, the target muscle group has no effect on external force. In the state of weight bearing, fatigue transition and deep fatigue, there is a state of force generation in the muscle group, and the deep fatigue state is a process of muscle exhaustion. By dividing the muscle state into five levels and combining the mapping relationship of the characteristic parameters of the sEMG signal, the muscle state can be detected during the occurrence of local fatigue, and the exercise can be stopped when the muscle reaches the deep fatigue state, so as to prevent muscle damage.

The sEMG signal is an extremely weak non-stationary time-varying signal. Its distribution parameters change with time. The amplitude of the signal is microvolt level, and most of the spectral energy is concentrated between 50 Hz and 150 Hz. After the surface EMG signal is collected by multi-channel surface EMG signal collectors, further data processing is required.

Because the surface EMG signal is very weak, it is easy to be interfered by the environment and the acquisition process. The main interference sources are the inherent noise of electronic components, power frequency noise, motion artifact and the inherent instability of random signals. These noises are removed by a band-pass filter and a notch filter.

In data acquisition, due to the imbalance phenomenon in the acquisition system or the charge exchange between the human body and the environment, the signal amplitude of some points will be far greater than the average value of the collected signal, which may cause sudden changes. It is necessary to eliminate these mutation points. If a point of signal exceeds the maximum sEMG amplitude threshold, this point is smooth by adjacent 5 points.

After removing noises and smoothing sudden points, the sEMG signals are segmented as segments with 3 seconds or 300 points. Each pair of adjacent segments have overlapped 1 second or 100 points. The segments are processed by Mel filters to extract MFCCs as features. The extracted MFCCs are further used to learn a GP model. Here, radial basis function (RBF) is adopted as kernel function in the GP. In order to demonstrate our method, we compare MFCC features with time domain features, frequency domain features and time-frequency domain features. The muscle fatigue recognition results are reported in terms of accuracy, recall and F1-score in Table 1.

From the results in Table 1, the precision reaches 82.36%, 83.68%, 85.64% and 90.37% when using time domain features, frequency domain features, time-frequency domain and MFCCs, respectively;
the recall reaches 84.17%, 83.93%, 86.29% and 89.82% when using time domain features, frequency domain features, time-frequency domain and MFCCs, respectively; the F1-measure reaches 0.836, 0.841, 0.872 and 0.918 when using time domain features, frequency domain features, time-frequency domain and MFCCs, respectively. It can be found that when using GP as classifier, MFCC features perform better than other features.

Furthermore, we compare GP with some other canonical classifiers, including k-nearest neighbor (kNN) (Bukhari et al. 2020), linear discriminant analysis (LDA) (Venugopal et al. 2014; Zhu et al. 2022) and neural network (NN) (Subasi & Kiymik 2010), logistic regression (LR) (Marri & Swaminathan 2015) when using MFCC features. The parameter \( k \) is tuned in the range from 1 to 10 stepped by 2. The results are reported in Table 2.

In Table 2, the precision reaches 87.63%, 88.52%, 88.27%, 88.04% and 90.37% for kNN, LDA, NN, LR and GP, respectively; the recall reaches 86.79%, 87.84%, 88.13%, 87.72% and 98.82% for kNN, LDA, NN, LR and GP, respectively; the F1-measure reaches 0.884, 0.897, 0.902, 0.891 and 0.918 for kNN, LDA, NN, LR and GP, respectively. When using MFCC features, GP perform better than other classifiers. From the results in Table 1 and 2, it can be found that MFCC features plus GP classifier can recognize most muscle fatigue states correctly. Furthermore, the accuracy of each fatigue level is reported in Table 3 for MFCC features plus GP classifier.

From the results in Table, it can be found that the accuracy of MFCC features plus GP classifier can reaches 88.57% ~ 96.31%.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>F1-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>kNN</td>
<td>87.63</td>
<td>86.79</td>
<td>0.884</td>
</tr>
<tr>
<td>LDA</td>
<td>88.52</td>
<td>87.84</td>
<td>0.897</td>
</tr>
<tr>
<td>NN</td>
<td>88.27</td>
<td>88.13</td>
<td>0.902</td>
</tr>
<tr>
<td>LR</td>
<td>88.04</td>
<td>87.72</td>
<td>0.891</td>
</tr>
<tr>
<td>GP</td>
<td>90.37</td>
<td>89.82</td>
<td>0.918</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>relaxed state</td>
<td>96.31</td>
<td>deep fatigue state</td>
<td>91.24</td>
</tr>
<tr>
<td>weight bearing state</td>
<td>90.43</td>
<td>fatigue state</td>
<td>94.86</td>
</tr>
<tr>
<td>fatigue transition state</td>
<td>88.57</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1. The performance of muscle fatigue recognition by using different features when using GP as classification model

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>F1-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time domain</td>
<td>82.36</td>
<td>84.17</td>
<td>0.836</td>
</tr>
<tr>
<td>Frequency domain</td>
<td>83.68</td>
<td>83.93</td>
<td>0.841</td>
</tr>
<tr>
<td>Time-frequency domain</td>
<td>85.64</td>
<td>86.29</td>
<td>0.872</td>
</tr>
<tr>
<td>MFCCs</td>
<td>90.37</td>
<td>89.82</td>
<td>0.918</td>
</tr>
</tbody>
</table>

Table 2. The performance of muscle fatigue recognition by using different classifiers when using MFCC features

Table 3. The accuracy of each fatigue level when using MFCC features plus GP classifier
5. CONCLUSIONS

In order to improve the efficient of daily sports training and avoid athlete’s permanent damage or injury, this paper establishes an automatically muscle fatigue system by using surface electromyography signals and machine learning technology. Compared with other physiological signals, electromyography signal can better reflect the body state of the muscle. Compared with electrode electromyography signal, the surface electromyography is non-invasive and easy to obtain. The surface electromyography signals are first collected through wearable device which installs multi-source sensors. Then, the collected surface electromyography signals are removed noises by using a band-pass filter and a notch filter. The denoised surface electromyography signals are segmented by a fixed window to extract Mel-frequency cepstral coefficients. Lastly, a Gaussian Processing model is learnt by using the Mel-frequency cepstral coefficients features, which is used to monitor and recognize the muscle fatigue state. The experiments demonstrate the effectiveness of the proposed muscle fatigue monitoring system. In the future, more intelligent functions can be developed for smart sports training.

ACKNOWLEDGMENT

This research was supported by the Provincial undergraduate university basic research business fee Youth Innovative Talent Project in Heilongjiang Province in 2021, China (Grant No.145109226 ), the Provincial undergraduate university basic research business fee Youth Innovative Talent Project in Heilongjiang Province in 2021, China (Grant No. 145109228), and the Provincial undergraduate university basic research business fee Youth Innovative Talent Project in Heilongjiang Province in 2021, China (Grant No. 145209234).
REFERENCES


