*Retraction*

# Retracted: Application Analysis of Wearable Technology and Equipment Based on Artificial Intelligence in Volleyball

## Mathematical Problems in Engineering

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] X. Dai and S. Li, "Application Analysis of Wearable Technology and Equipment Based on Artificial Intelligence in Volleyball," *Mathematical Problems in Engineering*, vol. 2021, Article ID 5572389, 10 pages, 2021.

*Research Article*

# Application Analysis of Wearable Technology and Equipment Based on Artificial Intelligence in Volleyball

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Today, while people's satisfaction with materials is high, the pursuit of health has begun and sports are becoming increasingly important. Volleyball is a good physical and mental exercise, which helps improve the health of the body. However, excessive exercise usually leads to muscle strain and more serious accidents. Therefore, how to effectively prevent excessive fatigue and sports injuries becomes more and more important. In the past, some methods of exercise fatigue detection were mostly self-assessment through some indicators, which lacked real-time and accuracy. With the advancement of smart technology, in order to better detect sports fatigue, smart wearable technology and equipment are used in volleyball. Firstly, surface electromyography signals (sEMG) are collected through wearable technology and equipment. Secondly, the signal is preprocessed to extract features that are conducive to exercise fatigue assessment. Finally, a motion fatigue detection algorithm is designed to identify and classify features and evaluate the motion status in real-time. The simulation results show that it is feasible to collect ECG signals and EMG signals to detect exercise fatigue. The algorithm has good recognition performance, can evaluate exercise conditions in real-time, and prevent fatigue and injury during exercise.

## 1. Introduction

With the rapid growth of our country's economy, the pace of people's lives is also accelerating. Most people are in a two-point living situation and a line at home and at work. In this fast-paced state of life, although it can bring better living conditions, people pay for it is the cost of health. According to the study, the age of patients with cardiovascular and cerebrovascular diseases is not limited to the elderly, the proportion of young patients is gradually increasing, and the number of deaths from cardiovascular and cerebrovascular diseases worldwide is as high as 15 million people each time, ranking first among all causes of death. Stimulated by these shocking data, people are slowing down their pace of life and devoting more energy to their health problems. Nowadays, people are willing to devote more time to sports. According to the "China Sports Report 2016" based on QQ sports released by QQ big data,

the average number of walking steps per day in China is 5112. Walking and running have become the most popular sports. In sports, although young people have devoted more enthusiasm than before, middle-aged and old people also pay more attention to health. Therefore, with more and more people's enthusiasm for sports, how to exercise scientifically and reasonably has become one of the hot spots of people's attention [1].

Volleyball is a good sport for physical and mental health. Since it was introduced to China, it has been loved by the majority of people. Especially with the advancement of artificial intelligence technology [2], venues and training have been greatly strengthened, and the viewing and safety have been continuously improved. More and more people are beginning to pay attention to volleyball, and the popularity of volleyball at the grassroots level is increasing, which greatly promotes the healthy development of volleyball in China.

In the process of volleyball, there are many cases of sudden death and morbidity caused by excessive intensity of sports beyond the endurance of the players themselves. Therefore, only scientific and reasonable sports can achieve the purpose of physical exercise without damaging the body. Scientific and reasonable exercise can not only achieve the purpose of physical exercise but also prevent athletes from sports injury due to excessive intensity of exercise. Monitoring the changes of physiological parameters can help athletes to achieve scientific and rational exercise. The commonly used physiological parameters include heart rate, body temperature, respiratory rate, and blood oxygen concentration. Because heart rate is sensitive to physiological changes and easy to monitor, it is used as an indicator of exercise intensity by most sports enthusiasts and athletes [3]. In addition, the acceleration can be used to calculate the energy consumption of sports so that the athletes can control their own sports consumption.

Among the traditional methods of heart rate measurement, common methods of heart rate measurement include electrocardiogram measurement, pressure method, and pulse diagnosis of Chinese medicine for heart rhythm diagnosis. However, ECG measurement requires electrodes to be connected to the body to extract the heart rate from the ECG signal of the body. The pressure measurement equipment is very large and requires an air pump; TCM pulse diagnosis requires the experience of a doctor. These methods all show that we cannot provide real-time monitoring of physical conditions in our daily lives. In recent years, with the rapid development of artificial intelligence technology, it is possible to develop portable body fatigue monitoring equipment [4]. At the same time, as mobile smart devices such as smartphones and tablet computers are increasingly integrated into people's daily lives, combined with their good interactive interfaces and powerful data processing capabilities, a portable real-time detection and analysis of human fatigue data can be developed. And the analysis function of cloud storage technology is realized.

Wearable technology is a technology that studies and intellectualizes the design and develops wearable equipment that meets the needs of users [5]. It mainly includes integration technology, recognition technology (voice, motion, and eyeball), detection technology, connection technology, and flexible screen technology. It refers to the integrated use of different technologies for identifying, detecting, connecting, and interacting cloud and storage services [6–10]. Wearable technology is a technology integrated in people's daily belongings, along with the daily activities of users, and users can operate at any time. Its intelligence in physical space manifests itself in the user-centered access, which can help extend the human body's limbs and memory function. At the same time, it processes the data and presents the data results to users in a visual form.

In recent years, wearable equipment based on wearable technology has become popular in the market. The so-called "wearable intelligent device" is the general term for the application of wearable technology to the intelligent design of daily wearable items or the development of wearable equipment, such as glasses, watches, and clothing. Wearable intelligent devices in the broad sense include comprehensive functions and appropriate size and can achieve complete or partial functions without relying on smart phones. For example, smart watches or smart glasses, as well as applications that focus only on a certain category, need to be used in conjunction with other intelligent devices such as mobile phones, smart bracelets for signs monitoring, and smart head wear and constantly derived a large number of medical, health, sports, and other wearing equipment. According to Gartner-Research, a well-known market research company, "Worldwide, wearable income for sports and personal health and fitness categories will be about $1.6 billion in 2013 and $5 billion in 2016."

With the rise of wearable medical devices, heart rate monitoring devices have appeared on the market. Although they are still in the embryonic stage, they can also enable users with such devices to measure the rate anytime, anywhere, simply, quickly, and conveniently. At present, the wearable devices of heart rate monitoring on the market are in full blossom, ranging from heart rate to heart rate meter.

Based on the above conditions, it is feasible to apply wearable technology and equipment to volleyball sport. It is of great significance to develop wearable testing equipment for volleyball sport fatigue. It is helpful for people to monitor their physical condition in real-time in volleyball sport and avoid sports fatigue and injury. The specific contributions of this paper are as follows:

(1) Using wearable technology and equipment to collect surface EMG signals

(2) Preprocessing the signals and extracting the features which are beneficial to the evaluation of sports fatigue

(3) Designing a motion fatigue detection algorithm to recognize and classify the features and evaluate the motion situation in real-time

## 2. Proposed Method

### 2.1. Wearable Technology and Signal Acquisition

*2.1.1. Wearable Technology.* In the 1960s, MIT Laboratory put forward the wearable technology as an innovative technology. This technology integrates multimedia, wireless sensor, and wireless communication technology skillfully through the media and carries on the induction-feedback-interaction experience through our basic body movements. Wearable technology action process, also known as human-computer interaction (HCI) [11, 12], is a technology to study human, computer, and their interaction. The purpose of human-computer interaction is to make the computer system and wireless sensor technology cooperate and influence each other and to complete user instructions more efficiently and safely. The details are shown in Figure 1.

Early wearable devices were just conceptual products. Historically, in 1975, Hamilton Watch launched Pulsar computer watches, which opened the era of smart wearability [13]. Limited by the social development environment and technological capabilities at that time, as well as the
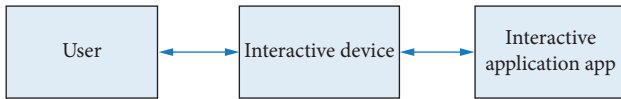
FIGURE 1: Wearable technical schematic.

attributes of the product, Pulsar could not be widely promoted. It was not until Sony released smart watch-generation in 2012 that smart wear technology came into the public eye [14]. Of course, with the advancement of science and technology and the strengthening of awareness of innovation, after years of fermentation and development, portable equipment also introduced the period of explosion of product development. Because of its more and more comprehensive functions and wider application, the statistical analysis of wearable devices of Vandrico company shows 291 pieces, and the functions of wearable devices (for example, bracelets) are gradually increasing. From the initial movement monitoring to today's daily life services (heart rate, sleep quality, smart calls, and intelligent wake-up), this also reflects the rapid development of wearable technology since entering the new century.

With the rapid development of wearable technology in society, there is a diversified development trend in aerospace, military special technology, medical and health technology, and sports science monitoring. Of course, the most frequent wearable technology to enter the public's vision is sports wear technology such as Huawei, NIKE, millet, and other electronic or sports equipment giants that have launched their own brand of wearable equipment, which is used in health monitoring, sports data collection, and other fields.

*2.1.2. Signal Acquisition.* EMG signals originate from motor neurons in the spinal cord, which are part of the central nervous system. The cell body of motoneurons is located in which the axons extend to the muscle fibers and are coupled to the muscle fibers via the endplate region, and there is more than one muscle fiber associated with each neuron. These parts are combined to form a so-called motion unit. The movement of muscle is controlled by consciousness. When the brain sends out excitation and transmits downward, the cell bodies and dendrites of motor neurons in the central nervous system produce electrical impulses (action potentials) stimulated by synapses, which are transmitted along the axons of neurons to the junctions of nerves and muscles at the terminals. When the motor nerve touches the muscle, its axons branch to many muscle fibers, and each branch terminates to form synapses on the muscle fibers, which are called motor endplates [15]. The action potential conducting to the axonal endings releases acetylcholine, a chemical at the nerve-muscle junction. Acetylcholine changes the ionic permeability of the motor endplate and produces the endplate potential. This endplate potential makes the myocyte membrane reach the depolarization threshold potential, generates the action potential of muscle fibers, and propagates along the muscle fibers to both sides, causing a series of changes in the

muscle fibers, resulting in the contraction of muscle fibers, and a large number of muscle fibers contraction produces muscle force. It can be seen that the transmission of electrical signals (action potentials of muscle fibers) leads to muscle contraction, while the electrical signals in transmission cause electric current field in human soft tissues and show potential difference between detection electrodes, that is, EMG signals.

Surface electromyogram (SEMG) is a bioelectrical signal recorded from the muscle surface when the nerve and muscle system is moving through electrodes. It is mainly the combined effect of EMG of superficial muscle and electrical activity of nerve trunk. It is related to the state of muscle activity and function in varying degrees, so it can reflect the activity of neuromuscles to a certain extent and diagnose neuromuscular diseases in clinical medicine. The ergonomic analysis of muscle work in the field of ergonomics has important practical value in the evaluation of muscle function in the field of rehabilitation medicine and in the determination of fatigue in sports science and in the analysis of the rationality of sports technology, the type of muscle fibers, and the noninvasive prediction of anaerobic thresholds.

Surface EMG signal is very weak, distributed in $\mu V \sim mV$ order of magnitude, so the weak signal needs to be amplified to meet the requirements of AD acquisition unit. Because the human body is a conductive body, power frequency interference and external electric and magnetic field induction will form measurement noise in the human body, interfering with the detection of EMG information, so signal filtering and circuit shielding become the focus of amplifier circuit research. The structure of a typical weak signal amplifier circuit is shown in Figure 2.

As can be seen from Figure 2, the design of the digital sensor for facial EMG signal includes the following parts: input electrode, preamplifier, high-pass circuit, low-pass circuit, secondary amplifier, power frequency interference notch circuit, and A/D conversion circuit.

## 2.2. Preprocessing of Surface Electromyography Signal and Extraction of Fatigue Characteristics

*2.2.1. Surface EMG Signal Preprocessing.* Due to the nonstationary, nonlinear, and weak amplitude ($10\mu V \sim 6mV$) of sEMG, it is often submerged in various noises and disturbances during detection. For example, 50 Hz power frequency, harmonic interference, ECG, and low-frequency noise caused changes in muscle and joint angles. For this reason, the pretreatment process of EMG signal is designed as follows. Firstly, the baseline drift is removed by high-pass filter [16–18] (cut-off frequency is 5 Hz). The band-pass filter (the range of band frequency is 5–200 Hz) is used to extract the effective frequency band signal, and then the signal is amplified. Finally, the 50 Hz power frequency interference and harmonics are separated and removed by independent component analysis (ICA).

   (1) Adaptive high-pass filter removes baseline drift, and band-pass filter extracts the effective frequency band
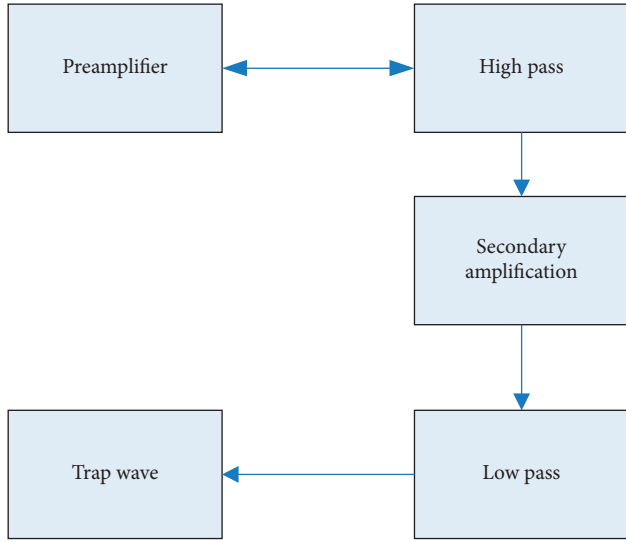
Figure 2: Typical structure of weak signal amplifier circuit.

of EMG signal. In the process of EMG signal acquisition, low-frequency noise is generated by the relative movement of muscle and joint, the change of joint angle, and so on. These noises are generally less than 5 Hz, and the amplitude is very large (usually several times of EMG signal). Therefore, high-pass filter is used to remove low-frequency interference signal (baseline drift). Digital filters are divided into FIR filters and IIR filters [19–21]. Because FIR filters are more stable than IIR filters and can achieve linear phase characteristics, this paper uses FIR-based adaptive high-pass filters to remove baseline drift [22, 23]. Adaptive filtering consists of two parts: FIR digital filter and adaptive algorithm for modifying digital filter.

The weight iteration formula of the adaptive filter designed in this paper is as follows:

$$
\begin{aligned}
h(n+1) &= h(n) - \mu \widehat{\nabla}_n, \\
&= h(n) + 2\mu e(n)x(n)e(n), \\
&= z(n) - h * x(n),
\end{aligned}
\tag{1}
$$

where $\mu$ represents the iteration step, $x(n)$ is the input vector of the adaptive filter, $e(n)$ is the error, $h$ is the weight of the filter, and $z(n)$ is the expected output of EMG signal.

(2) *Independent Component Analysis to Remove Power Frequency Interference.* Independent component analysis (ICA) effectively solves the problem of blind source separation, especially for nonlinear and nonstationary signals. Therefore, ICA separation has been well applied in pattern recognition, medical signal, and other fields. Independent component analysis (ICA) can be used to remove noise from EEG and EMG signals. For the collected EMG signal, there will be power frequency interference. The traditional 50 Hz notch wave will remove the

corresponding useful EMG signal while eliminating the power frequency. In order to solve this problem, this paper uses the independent component analysis method. Fast ICA is the most commonly used method in ICA. Fast ICA belongs to nonlinear convergence, and processing speed is relatively fast. Therefore, Fast ICA is chosen to remove power frequency interference. The 50 Hz power frequency interference is separated from sEMG by Fast ICA, and the useful EMG information is retained, which improves the quality of the signal.

*2.2.2. Fatigue Feature Extraction of Surface Electromyography.* According to the existing research results, the time domain and frequency domain indices of surface electromyography signal are analyzed in this paper.

(1) Time domain analysis parameters are as follows:

(1) *Integrated EMG (IEMG).* Integral EMG value [24, 25] is used to represent the excitation characteristics of muscle fibers in unit time. It is shown that the amplitude of sEMG signal changes with the change of movement time. It is the area of EMG curve and transverse axis in unit time domain. IEMG can reflect the change of sEMG signal:

$$
\text{IEMG} = \int_t^{t+T} |\text{EMG}(t)| \, dt,
\tag{2}
$$

where $T$ is the length of time and $\text{EMG}(t)$ is the EMG signal at $t$ time.

(2) *Root Mean Square (RMS).* The root mean square value [26–29] indicates the change characteristics of sEMG in unit time. The root mean square value is proportional to the magnitude and is positively related to the number of exciting muscle fiber units. With the deepening of muscle fatigue, more exciting units are recruited. The formula is as follows:

$$
\text{RMS} = \sqrt{\frac{1}{N} \int_t^{t+T} |\text{EMG}(t)|^2 \, dt}.
\tag{3}
$$

(3) *Zero-Crossing Rate (ZCR).* ZCR [30, 31] refers to the speed at which sEMG sets its zero value artificially. ZCR can reflect the oscillation frequency of sEMG. As the amount of training continues, the muscles begin to feel tired. At this time, the conduction current of muscle fibers decreases, and the ZCR changes rapidly.

$$
\text{ZCR} = \frac{\text{count}}{N},
\tag{4}
$$

where $N$ is the number of surface electromyographic signal value $x_N$ and count is the count of $x_i * x_{i+1} < 0$.

(2) Frequency domain analysis parameters are as follows:

(1) *Mean Power Frequency (MPF).* MPF [32] is the function index of sEMG in time. The size of MPF is mainly affected by the conduction speed of action potential and the type of excitation unit of peripheral excitation unit. The surface EMG signal changes obviously when the load is very low.

$$\text{MPF} = \frac{\int_0^\infty f \cdot \text{PSD}(f)\mathrm{d}f}{\int_0^\infty \text{PSD}(f)\mathrm{d}f}, \tag{5}$$

where $\text{PSD}(f)$ is the spectral density function of surface EMG signal.

(2) *Median Frequency (MF).* Similar to the above average power frequencies, MF represents the median of the frequency of muscle fiber emission signals during exercise, which corresponds to the frequency of 1/2 area of the surface EMG energy spectrum. The MF value is less disturbed by noise and is suitable for high intensity and sustained gentle motion and has a wide range of applications. Normally, the proportion of muscle fibers in different parts of skeletal muscle is different, and the MF value of muscle cells in different parts of the human body varies greatly. The principle is that muscle fibers are divided into high-frequency and low-frequency discharges due to the different rate of expression of characteristics.

$$\text{MF} = \frac{1}{2} \int_0^\infty \text{PSD}(f)\mathrm{d}f, \tag{6}$$

where $\text{PSD}(f)$ is the spectral density function of surface EMG signal.

Based on the analysis of the five characteristics, the frequency domain index MF and the time domain index IEMG are finally selected for the classification experiment of sports fatigue.

### 2.3. Volleyball Fatigue Estimation.

Due to the influence of individual differences, subjective emotions, and environmental changes in the detection of different human bodies, the traditional algorithm model SVM pattern recognition cannot resolve the above changes and the accuracy of the classification is affected. The optimal decision-making surface of classification is fixed after training. It cannot effectively utilize the current input and output optimization model and cannot retain historical information in the model. Its application flexibility and scope are limited. In order to better solve the above problems, the motion fatigue detection technology based on the LSTM neural network model is proposed. The principle and application of LSTM neural network are introduced below.

### 2.3.1. LSTM Neural Network Model.

LSTM is an improved RNN network. By adding long-term and short-term memory function RNN to the hidden layer structure change, it can maintain the persistence and long-term dependence of RNN network [33]. LSTM hidden layer structure solves the problem of gradient explosion and gradient disappearance of long-distance information transmission so that information will not decay.

The standard hidden RNN network level unit contains only one tanh layer, and its structure is very simple. The LSTM network improved by the standard RNN network mainly improves the structure of the hidden level unit. The traditional RNN network unit has only one layer, but the improved LSTM unit has four layers. LSTM network hiding layer module includes three multiplication units and multiple self-connected storage units. The three multiplication units represent forgetting gates, input gates, and output gates, which can realize unit module reading, writing, and resetting operations.

The key of LSTM network is cell state Ct. Cell state is represented by upper straight line, which includes two point-by-point operations. Cell states are transmitted and updated in this straight line, involving only some linear operations. Therefore, the cell state is like conveying information along the LSTM network on the conveyor belt. The cell state does not involve nonlinear changes, so it will not change or disappear.

The LSTM neural network unit controls discarding or adding information from the cell state through some "gates" structures, which consist of a nerve layer and a pointwise multiplication operation. The output of the Sigmoid layer is a value between 0 and 1, which is used to control the degree of information flow. When the output of Sigmoid layer is 0, it means that the "door" is closed and no letter is passed at this time; when the output is 1, it means that the "door" is opened, allowing all information to pass through. There are three gates in LSTM network unit to control the discarding and retention of cell state, which are called "input gate," "output gate," and "forgetting gate." The "forgetting gate" is used to control the degree to which information in the cell state should be discarded; then, the "forgetting gate" and the "input gate" determine what information will be retained and added to the new cell state; finally, the "output gate" is used to control what information is output in the cell state.

### 2.3.2. Volleyball Sports Fatigue Estimation Based on LSTM.

In this paper, the extracted physiological signal characteristic parameters are expressed as multivariate characteristic matrices, which are used for input of the LSTM neural network model, and a fatigue estimation model of volleyball sports based on LSTM neural network is constructed. The training steps of the model are shown in Figure 3.

The physiological signal characteristic parameters of the input layer are further studied in the LSTM network layer. The invalid information is discarded by using the excitation functions of the hidden layer neuron units. The useful features of the neural network are retained in the network structure. The appropriate excitation functions are set on the output layer of the model, and the prediction is changed to the classification problem. The excitation function selected in this paper is the softmax function. Softmax is used in the
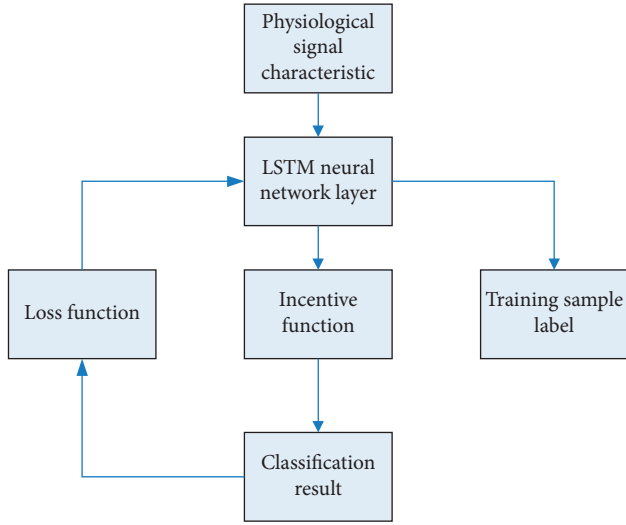
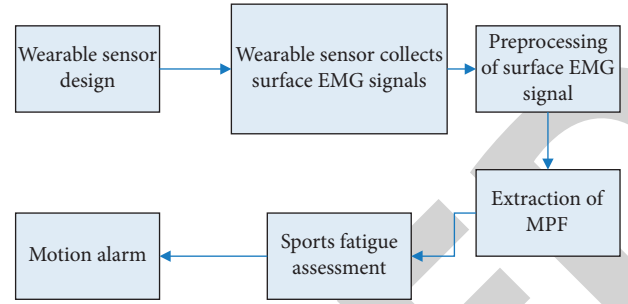FIGURE 3: Volleyball fatigue estimation process.



FIGURE 4: The flow chart of the article.

recognition rate is used as the evaluation index, and the expression is as follows:

$$\text{recognition rate} = \frac{\text{number of samples correctly identified}}{\text{total number of test samples}} \times 100\%.$$

(8)

## 4. Discussion

According to the principle of psychology, Borg, a Swedish psychologist, identified subjective fatigue and local muscle fatigue as a subjective fatigue sensation in subjects' exercise. This paper classifies muscle states into three categories: nonfatigue, imminent fatigue, and already fatigue. If the exercise evaluation finds that the muscles of the body are in a state of fatigue, wearable equipment reminds the athletes that the muscles are in a state of fatigue and pay attention to rest.

Firstly, after the preprocessing of surface electromyography signal, the frequency domain index MF and the time domain index IEMG are used as the analysis characteristics of fatigue assessment. It is necessary to analyze the changes of the two indexes with different fatigue degrees and to verify the feasibility of the two indexes as the analysis of volleyball sports fatigue. In this paper, 12 volleyball players were asked to take part in volleyball. Wearable devices were used to extract information and analyze the changes of their frequency domain index MPF and time domain index RMS. The average results were observed for one hour, as shown in Table 1.

According to Table 1, we draw a broken line chart of the change of integral EMG value with exercise time, as shown in Figure 5. As can be seen from the figure, with the increase in exercise time, the degree of muscle fatigue gradually increases, and the integral EMG value shows a decreasing trend.

Similarly, a broken line diagram of the median frequency MF varying with the time of motion is drawn as shown in Figure 6. It can also be seen that with the increase in exercise time, the degree of muscle fatigue gradually increases, and the median frequency also shows a significant decreasing trend.

From the above analysis, it can be found that the frequency domain index MF and time domain index IEMG used in this paper will gradually decrease with the increase in fatigue degree, and their changes are related to fatigue

multiclassification process. It maps the output of many neurons into the $(0, 1)$ interval. It can be understood as probability, and then multiclassification can be carried out.

The input sample is calculated by the excitation function of LSTM neural network, and the class label of the sample is output. Then, the difference between the output label and the sample label is calculated by comparing the loss function, and a non-negative number is output. The numerical size indicates the difference between the output tag and the sample tag. The smaller the value, the closer to the ideal value. The process of training the LSTM neural network model is to reduce the output value of loss function by feedback and iteration.

The calculation method of loss function selected in this paper is as follows:

$$L(B, P(B|X)) = \log_2 P(B|X) \tag{7}$$

where $B$ represents the sample label and the minimum value of $L(B, P(B|X))$ is the maximum value of $-\log_2 P(B|X)$. The process of solving the maximum value is to find the $B$ in $X$ to maximize $P(B|X)$ according to the classification results.

## 3. Experiments

In this paper, portable technology and equipment are applied to volleyball. The main objective is to avoid athletic fatigue and injury caused by excessive exercise and to monitor in real-time its situation. The wearable sensor is mainly designed to collect the surface EMG signal of the human body, then preprocess the EMG signal, extract the frequency domain index MF and time domain index IEMG, and then use the method of fatigue assessment based on LSTM neural network to carry out fatigue analysis and real-time monitoring of body condition. The specific flow chart is shown in Figure 4.

In order to better evaluate the performance of the volleyball fatigue assessment method designed in this paper, the

TABLE 1: Characteristic indicators change with movement.

| Time (min) | IEMG ($mV$) | MF (Hz) |
| --- | --- | --- |
| 5 | 1.79 | 119 |
| 10 | 1.76 | 109 |
| 15 | 1.69 | 106 |
| 20 | 1.58 | 101 |
| 25 | 1.52 | 91 |
| 30 | 1.48 | 87 |
| 35 | 1.42 | 83 |
| 40 | 1.31 | 79 |
| 45 | 1.20 | 75 |
| 50 | 1.07 | 67 |
| 55 | 0.89 | 61 |
| 60 | 0.71 | 50 |



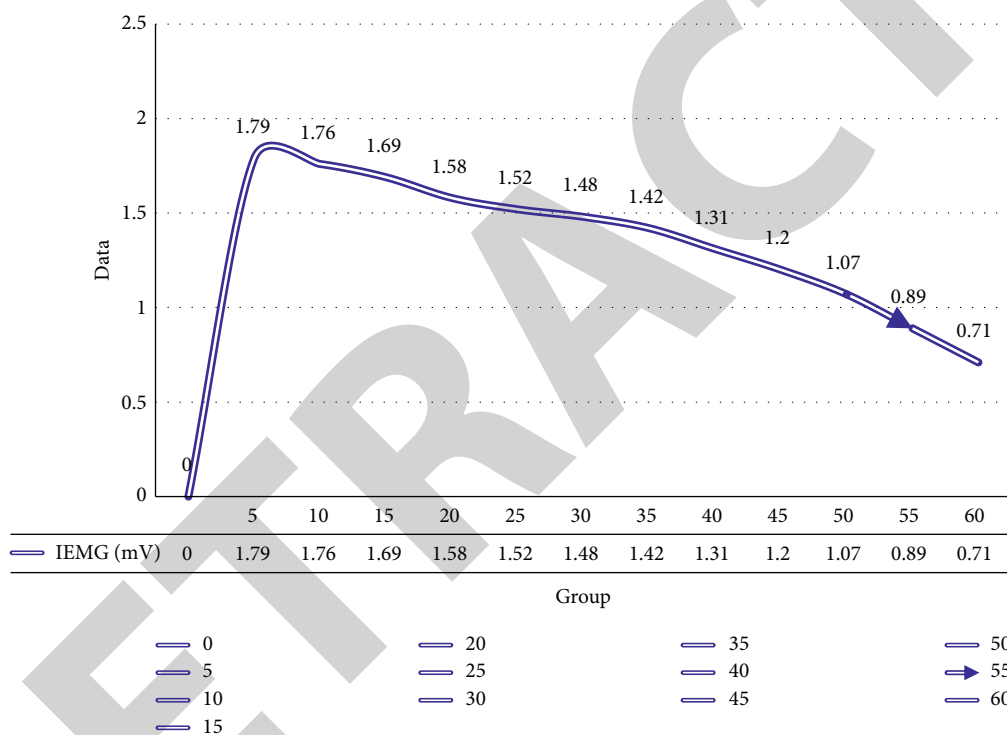| | IEMG (mV) | 0 | 1.79 | 1.76 | 1.69 | 1.58 | 1.52 | 1.48 | 1.42 | 1.31 | 1.2 | 1.07 | 0.89 | 0.71 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |

FIGURE 5: The change of integral EMG with exercise time.

degree, which can be used as an evaluation index of sports fatigue.

Secondly, the classification accuracy of using frequency domain index MF and time domain index IEMG as evaluation index and using frequency domain index MF and time domain index IEMG as classification index is analyzed. The analysis results are shown in Table 2. It can be seen from the table that the effect of using characteristic parameters in frequency domain or time domain as evaluation index is not as good as using time domain and frequency domain as evaluation index at the same time. The worst one is frequency domain index MF, with the recognition rate of 75.61%, followed by time domain index IEMG, with the recognition rate of 81.08%; the best one is that IEMG and

frequency domain MF are used as evaluation index at the same time, with the recognition rate of 93.62%.

Finally, this paper uses SVM "one-to-one" and SVM "one-to-many" classifiers as classification performance comparison and takes IEMG in time domain and MF in frequency domain as evaluation indicators to analyze the recognition performance of the fatigue classifier in this paper. The results are shown in Table 3, and the histogram is shown in Figure 7.

Combining Table 3 and Figure 7, it can be seen that the classification performance of the proposed fatigue assessment method is much better than that of SVM "one-to-one" and SVM "one-to-many" classifiers. The recognition rate of the proposed method is 10.47% higher than that of SVM
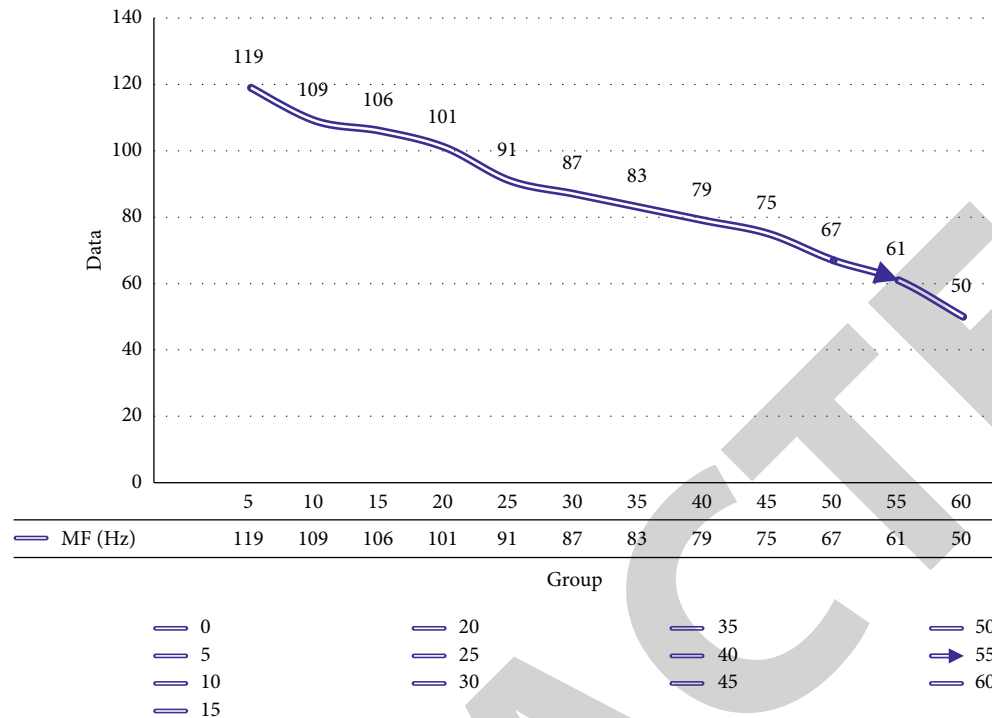
Figure 6: Variation of median frequency with motion time.

Table 2: Fatigue classification accuracy of different evaluation indicators.

| Indicator | Recognition rate (%) |
| --- | --- |
| IEMG | 81.08 |
| MF | 75.61 |
| IEMG and MF | 93.62 |

Table 3: Fatigue assessment performance of different methods.

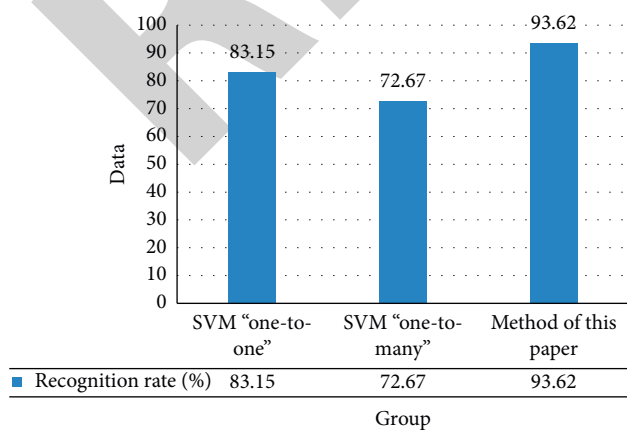| Method | Recognition rate (%) |
| --- | --- |
| SVM "one-to-one" | 83.15 |
| SVM "one-to-many" | 72.67 |
| Method of this paper | 93.62 |



Figure 7: Comparison of fatigue evaluation performance of different methods.

"one-to-one" classifiers and 20.95% higher than that of SVM "one-to-many" classifiers. It can be seen that the performance of the proposed fatigue assessment analysis method is good.

In conclusion, the simulation analysis shows that it is feasible to apply wearable technology and equipment in volleyball, and it can identify the fatigue of the body well, realize real-time monitoring of the body in sports, and prevent the occurrence of sports fatigue and sports injury.

## 5. Conclusions

Today, the rapid development of portable devices has a very wide range of applications in life, and application to sport has attracted more and more attention. Volleyball is a good exercise for the human body and mind and body, which contributes to improving the physical health of the body. However, due to the fierceness of the exercise, it is easy to produce sports fatigue and cause sports injuries. Therefore, the application of wearable technology based on artificial intelligence is used in volleyball. The real-time monitoring of fatigue has important research significance and practical significance. Based on the analysis of sports fatigue assessment methods, this paper designs an artificial intelligence-based wearable technology sports fatigue assessment method. The wearable sensor is designed to collect the SEMG signal of the human body. Low-frequency noise and power frequency interference can be eliminated by preprocessing the surface EMG signal. The time domain integrated EMG value IEMG and the frequency domain intermediate frequency MF are extracted

as the characteristics of exercise fatigue assessment. Input the sports fatigue assessment method based on LSTM neural network to classify sports fatigue and realize the assessment of volleyball human fatigue. Through simulation analysis, it can be found that the IEMG in the time domain and the MF in the frequency domain can reflect human muscle fatigue, and it is better to use the time domain and frequency domain features at the same time than to use them alone. In addition, compared with the support vector machine classifier, the performance of this method is good.

## Data Availability

No data were used to support this study.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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