

## Retraction

# Retracted: Research on Sports Class Load Monitoring System Based on Threshold Classification Algorithm

### Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

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.

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- [1] L. Zhao, "Research on Sports Class Load Monitoring System Based on Threshold Classification Algorithm," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 3891453, 10 pages, 2021.

## Research Article

# Research on Sports Class Load Monitoring System Based on Threshold Classification Algorithm

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In order to reduce the sports injury caused by high intensity sports classes, it is necessary to monitor the state of the sports load. Therefore, the sport's load monitoring system based on a threshold classification algorithm is proposed. In this paper, we design the hardware and software structures of the sports load monitoring systems in a physical education class. In this system, the state parameters of the sports load are collected by wireless sensor network nodes, and the feature parameters are fused and clustered by the integrated information fusion method. After that, we establish the movement target image acquisition model, which unifies the ZigBee networking realization to the high intensity sports classroom movement load monitoring. Simulation results show that the designed PE classroom sports load monitoring system based on the threshold classification algorithm has high performance for sports parameter monitoring and can effectively avoid sports injury caused by overload.

## 1. Introduction

As people pay more and more attention to their physical health, they begin to take intensive physical exercise gradually to improve their physical fitness [1]. But the nonprofessional athlete sometimes cannot grasp well the intensity of the movement load. Therefore, it is necessary to study an effective monitoring system of the sports class exercise load [2, 3]. It is of great significance to study the design method of the monitoring system of the sports load state in a PE class for promoting sports training and health monitoring.

Reference [4] proposes to monitor the athletic performance of male athletes and to measure the change of athletic performance in 1 year after arthroscopic treatment of femoral and acetabular impact injuries. Methods male athletes with the arthroscopic treatment of FAI were tested in preoperative and postoperative 1 year, including acceleration, steering speed, squatting depth, and reaction intensity index. Compared with the healthy athletes, the FAI with symptoms makes the athletes' performance drop significantly and puts the athletes in an obvious sports disadvantage. Reference [5] proposes a method for monitoring adolescent athletic professionalism in a hospital-based outpatient department of

pediatric sports medicine. Patients or other participants or athletes injured between the ages of 12 and 17 who visited clinics between 2015 and 2017 and who completed a sports participation survey were invited to participate. The methods mentioned above have the problems of poor anti-interference and low output stability in the monitoring of the sports class load. In order to improve the stability and reliability of the monitoring output, this paper puts forward the monitoring system of the sports class load status based on the threshold classification algorithm, which is based on the collection and information extraction of the parameters of the sports class load status, and combines the optimized information processing technology and the big data information processing technology to monitor the sports class load status and improve the stability and reliability of the monitoring output.

In Reference [6], the authors proposed a multilabel classification based on a random forest algorithm for a noninvasive load monitoring system. This paper proposes a multilabel classification method using random forest (RF) as a learning algorithm for noninvasive load identification. Multilabel classification can be used to determine which categories data belong to. This classification can help to identify

the operation states of independent loads from mixed signals without disaggregation. The experiments are conducted in a real environment and public data set. Several basic electrical features are selected as the classification feature to build the classification model. These features are also compared to select the most suitable features for classification by feature importance parameters. The classification accuracy and  $F$ -score of the proposed method can reach 0.97 and 0.98, respectively. In Reference [7], the authors proposed a load identification and classification in a nonintrusive load monitoring system based on the data stream. In order to enhance the classification accuracy and reliability of load detection in a nonintrusive load monitoring systems, novel approaches for general load switch detection were proposed. Based on the improved CUSUM algorithm which can determine the start and ending point of the transient process, the transient energy algorithm and correlation method was applied. Further, the comparison results of different ending points show the different differentiation degrees. The information fusion as a criterion was added, and the data fusion error rate threshold was determined to enhance reliability. After that, the correlation method was applied to verify the results. In the case study simulation, the effectiveness of this novel system was proven. In Reference [8], the authors have given the research on sports retrieval recognition of action based on feature extraction and the SVM classification algorithm. The feature extraction speed of the traditional athlete motion retrieval algorithm is slow, and it often takes dozens of minutes or even hours to analyze a video. The speed of this feature extraction obviously cannot meet the needs of big data video analysis. In response to these two problems exposed by Action Bank under large-scale data, this paper proposes to apply the template learning method based on spectral clustering to Action Bank, which replaces the cumbersome manual selection template step and is easy to generalize to different databases. Moreover, in view of the disadvantage of the slow speed of extracting Action Bank features, this paper proposes a fast algorithm for accumulating Action Bank. In addition, this study uses the lookup table method instead of the time-consuming steps of the correlation distance calculation in template matching, which greatly accelerates the time of feature extraction. Finally, this study designed experiments to analyze the performance of the algorithm.

In this paper, we use the threshold classification algorithm to study the sports class load monitoring system. The threshold classification algorithm classifies according to the preset threshold. Those within the set threshold range belong to one category, while those not within the threshold range are divided into another category. The main idea of this method is to divide the individuals within a certain threshold into a class, and the individuals outside that threshold into another class. Compared with other classification algorithms, this algorithm has the advantages of low time complexity and computational complexity.

The main contribution of this paper can be described as follows:

- (1) The author studies a new sports class load monitoring system. In recent years, motion detection has

been paid more and more attention by researchers, but at present, the research in this field is still in its infancy, and there are little research results

- (2) In this paper, a new motion state classification method is proposed, which is called the threshold classification algorithm. Threshold classification algorithm has low computational complexity and better classification effect than other algorithms, so this algorithm can be well applied to motion state monitoring

The structure of the rest of this paper is as follows: Section 2 gives the introduction of the design of a sports load monitoring system for a physical education class. Section 3 gives the object image monitoring model of the sports load state in a physical education class and fusion processing of monitoring sensing information. Section 4 gives the experimental analysis. The conclusion and prospect are given in Section 5.

## 2. Design of Sports Load Monitoring System for Physical Education Class

*2.1. System Hardware Architecture.* The hardware of the sports load monitoring system is mainly composed of two parts: the first part is the positioning label and photoelectric heart rate meter. The positioning tag is powered by the battery and can transmit an ultrawideband signal with a frequency of 10Hz. It is worn as a wristband [9, 10]. The photoelectric heart rate meter must be worn in contact with the skin, in the form of an arm band, and separately worn from the positioning label. The second part is the base station, which is fixed with known coordinates and can receive the UWB signal sent from the positioning tag. Base stations are connected by wire to form a LAN [11]. The parameters of each piece of hardware are shown in Table 1, and the appearance of each piece of hardware is shown in Figure 1.

*2.2. System Software Development.* The sports load monitoring system software of the physical education classroom is mainly composed of four layers: perception layer, transport layer, service layer, and display layer. The sensing layer is composed of a positioning base station, a positioning tag, and an optoelectronic heart rate meter and is mainly used for automatic data acquisition. When the positioning label enters the coverage of the base station, it automatically registers into the network, determines the configuration parameters of the positioning label, and uploads the relevant information in real time. The transport layer is the transmission channel between the location label, base station, server, and external network, which is transmitted wirelessly. The service layer is composed of a threshold classification algorithm positioning engine, interface software, and system computing software. The display layer is displayed by the service layer through the calculation of a real-time display location label and location information. The display layer displays primarily on the mobile or PC side [12].

Based on the threshold classification algorithm, the monitoring system software of the sports class load includes

TABLE 1: System hardware parameter list.

Label	Describe	Base station	Describe	Heart rate meter	Describe
Temperature range	-40°C-70°C	Working temperature	-40°C-70°C	Transmission mode	Low power consumption of Bluetooth
Renewal rate	0.01-200 Hz	Antenna gain	12.5 dBi	Software	Wireless upgrade
Frequency range	6.35-6.75 GHz	Frequency range	6.35-6.75 GHz	Frequency range	1 Hz
Power supply	Battery powered	Power supply	External power supply	Power supply	Battery powered
Protection level	IP67	Protection level	IP40	Protection level	30 m underwater
Transmission distance	200 cm	Transmission distance	100 m	Usage time	12 h
Size	7 × 4 × 1 cm	Size	35 × 25 × 8 cm	Size	2 × 2 × 1 cm
Weight	18 g	Weight	1.64 kg	Weight	15 g

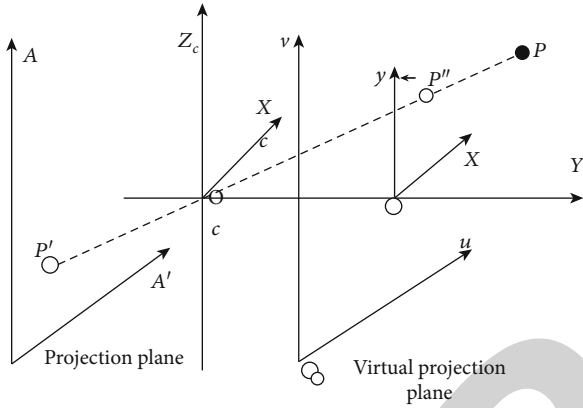


FIGURE 1: Image monitoring model of sports load target in physical education class.

the main control interface and positioning software. The main control interface is made up of a toolbar, menu bar, label bar, monitor interface, and status bar. The localization software includes four modules: data source setting, system configuration, database management, and network communication. The software development environment mainly uses Microsoft Visual Studio.net version 10 and uses MySQL as the system database and VB.NET as the software development language to complete the positioning software system design.

When the UWB signal is received by the base station whose coordinate position is known, the real-time position of the label is calculated according to the time information, angle information, or intensity information of the label. There are three main methods for a base station to obtain UWB signals: (1) by using the signal flight time (TOF), the signal arrival time (TOA) sent by the base station receiving the positioning label, and the difference between the arrival time of two base stations receiving the signal (TDOA) to obtain the time information; (2) by using the base station receiving signal arrival strength (RSSI) to obtain the signal strength information [13, 14]; and (3) by using the base station receiving signal arrival angle (AOA) to obtain the angle information. Two-dimensional positioning needs at least 2 base stations, and three-dimensional positioning needs at least 3 base stations.

### 3. Object Image Monitoring Model of Sports Load State in Physical Education Class and Fusion Processing of Monitoring Sensing Information

3.1. Establishment of Sports Load Target Image Monitoring Model in Physical Education Class. The camera that gets the sports load target image is taken as the center of the model  $O_c$ ;  $O_c$  and  $Y_c$  are the optical axes generated when getting the sports target. The optical axes are perpendicular to the plane A of the plane projection of the optical axes, and a virtual projection plane  $A'$  is created on the right side of the camera plane that gets the sports target image [15]. An image monitoring model of the PE classroom load target is established, which is based on  $O_c$  as the origin,  $Y_c$  as the Y-axis, and  $Z_c$  as the X-axis. The basic principle of the image monitoring model of the sports load target in the physical education class is shown in Figure 1.

In the camera moving target image acquisition model, P is any point in the process of image capture by the robot, the projection point of its imaging on plane A is P', the projection point on plane A' is P'',  $X_c$  is the X-axis projection, and the plane coordinates and pixel coordinates  $u$ ,  $o$ , and  $v$  of the X, O, and y images are set in the model in Figure 1. According to Figure 1, the relationship between the threshold classification algorithms is established. If the focal length of camera for obtaining the moving target image is  $f$ , then we can get the position of  $x$  and  $y$  as follows:

$$\begin{cases} x = X_c \frac{f}{Z_c}, \\ y = Y_c \frac{f}{Z_c}. \end{cases} \quad (1)$$

If (1) is brought in, then we can rewrite (1) as

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{f}{Z_c} & 0 & 0 & 0 \\ 0 & \frac{f}{Z_c} & 0 & 0 \\ 0 & 0 & \frac{f}{Z_c} & 0 \end{bmatrix} \begin{bmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{bmatrix}. \quad (2)$$

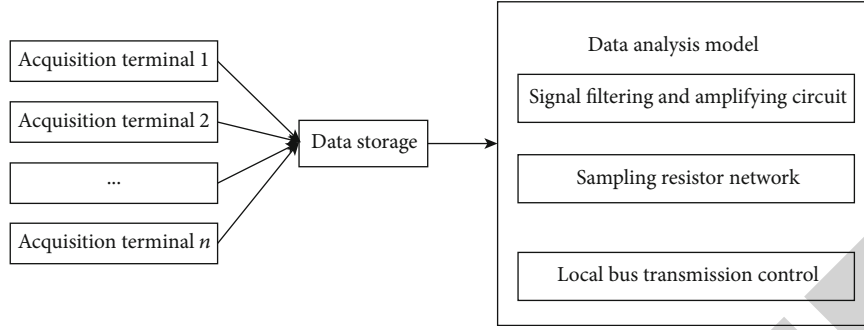


FIGURE 2: Data acquisition module of exercise load monitoring in physical education class.

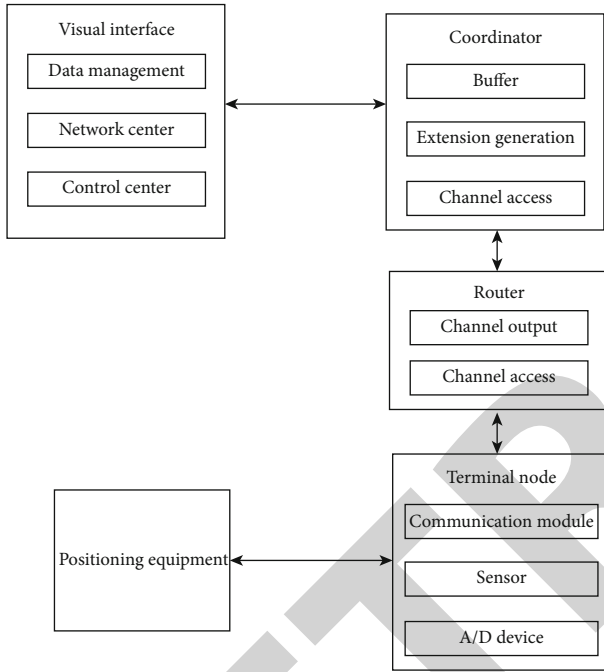


FIGURE 3: Overall structure module design of the system.

The formula is the mathematical matrix model of moving target image acquisition. In the competition system, the robot searches for the moving target robot which obtains the moving target image through the formula of Figure 1 or (2), and this image belongs to the moving target range graph. Therefore, after obtaining the target image of the sports load in the physical education classroom, it is necessary to calibrate the moving target. After calibrating the moving target image, the obtained image is segmented and processed, and then, the moving target features are extracted [16].

**3.2. Monitoring and Sensing Information Collection of Sports Load State in Physical Education Classroom.** Combining the design of the ZigBee sensor network, the paper constructs the data acquisition module of the sports classroom load condition monitoring system based on the threshold classification algorithm, as shown in Figure 2.

In the data acquisition module of the sports class load state monitoring shown in Figure 2, the local bus transmission control technology is adopted to realize the information

fusion of the sports class load state threshold classification algorithm, and the remote transmission control model of the sports class load state threshold classification algorithm is constructed; the TMS320C50 DSP chip is used as the core processing chip of the sports class load state feature monitoring system to realize the integrated information processing of the sports class load state feature [17]. The FIFO RAM buffer of the sports class load state feature monitoring system is designed, and the synchronous/trigger mode is used to realize the control instruction loading and information control. The overall structure of the system is obtained, and the module design is shown in Figure 3.

In the overall structure module design shown in Figure 3, the collected parameters of the sports class load state mainly include threshold classification algorithms such as  $VO_2\max$ , VE,  $o_2p$ , and HR, and the characteristic information display and optimization processing of the sports class load state are realized in the LED display interface [18].

### 3.3. Acquisition and Fusion Processing of Monitoring Sensor Information

**3.3.1. Image Data Information Fusion Processing.** When the window function  $k$  of the frequency spectrum signal of the threshold classification algorithm of the sports load state in the physical education classroom is determined, the threshold classification algorithm of the sports load state in the physical education classroom is fused and clustered, then

$$X = \sqrt{x(n-k)^2 + \dots + x(n)^2 + \dots + x(n+k)^2}. \quad (3)$$

Then, we can obtain the detection output of the spectrum signal of the classification algorithm of the sports load state threshold:

$$y(n) = \text{Mid}\{x(n-k), \dots, x(n), \dots, x(n+k)\}. \quad (4)$$

When the variance  $\sigma^2 = 1$ , the critical characteristic point of the transition from aerobic metabolism to anaerobic metabolism was taken as the threshold value, and the broadening of the recognition of the state information of the exercise load was obtained as follows:

$$d_n = -2eX_v. \quad (5)$$



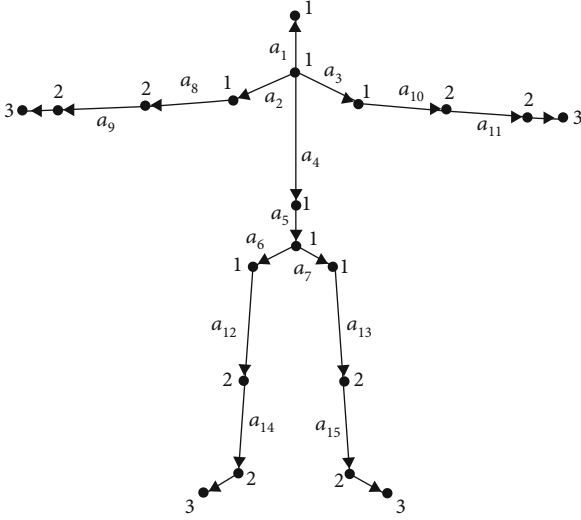


FIGURE 4: Joint point stratification and bone vector definition.

By using the network protocol model, the threshold classification algorithm of the sports load state in the physical education classroom is segmented. The characteristic parameter of the segmented spectrum is  $X_v$ , and  $V_b$  is the reference signal collected by the system. When  $\tilde{X}$  is the minimum, the fusion component of the sports load state in the physical education classroom is obtained as follows:

$$E = [x(n) - s(n)]^2 - \sum_{v=1}^V b_v x_v. \quad (6)$$

By using the method of three terminal linear estimation, this paper constructs the state clustering model of the sports load in the physical education classroom and obtains the threshold classification algorithm function of the sports load state in the physical education classroom:

$$W(n+1) = W(n) - b_v \times S(n). \quad (7)$$

According to the rotational characteristics of sports bones and the topological structure of athletes' bones, 20 athletes' joints collected by Kinect sensors are processed in layers.

- (i) *The first layer:* body trunk junctions [19]. The joint of the trunk is the support of the whole body, which is composed of the head, the left and right shoulders, and the spine.
- (ii) *The second layer:* limb joint. Most movements of athletes are expressed by limbs. Limb joints contain a lot of characteristic information related to athletes' posture, which is mainly composed of the left and right elbows, wrists, and knees and ankle joints [20, 21].

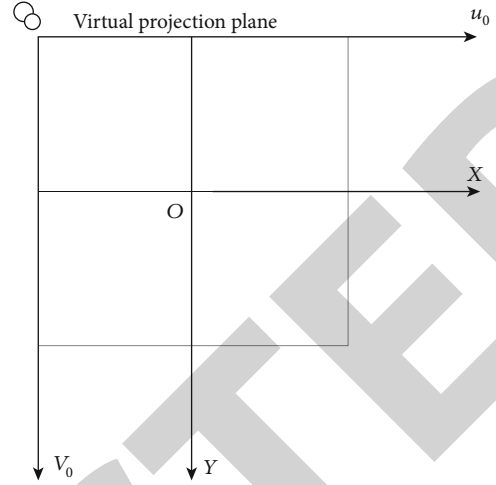


FIGURE 5: Pixel coordinate system and image plane coordinate system.

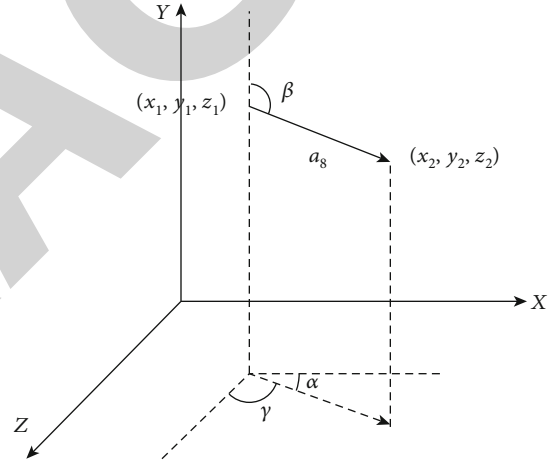


FIGURE 6: Calculation of direction cosine of bone vector.

- (iii) *The third layer:* hands and feet. Left and right hands and left and right foot joints are divided into the third layer.

Joint point stratification and bone vector definition is shown in Figure 4.

**3.3.2. Moving Target Image Acquisition.** In order to obtain the accurate position in the sports system of the physical education classroom, the geometric position and attribute parameters in Figure 5 need to be one-to-one corresponding to those in the coordinate system, and then, the image is segmented, the features of the moving object are extracted, and the image position of the moving object is determined. Therefore, the pixel coordinate system  $u, O, V$  and the image coordinate system  $X, O, y$  in the target image monitoring model of the sports load in physical education classroom are extracted, as shown in Figure 5.

In Figure 5, the optical axis coincides with the center of the image plane, so the coincidence point is taken as the

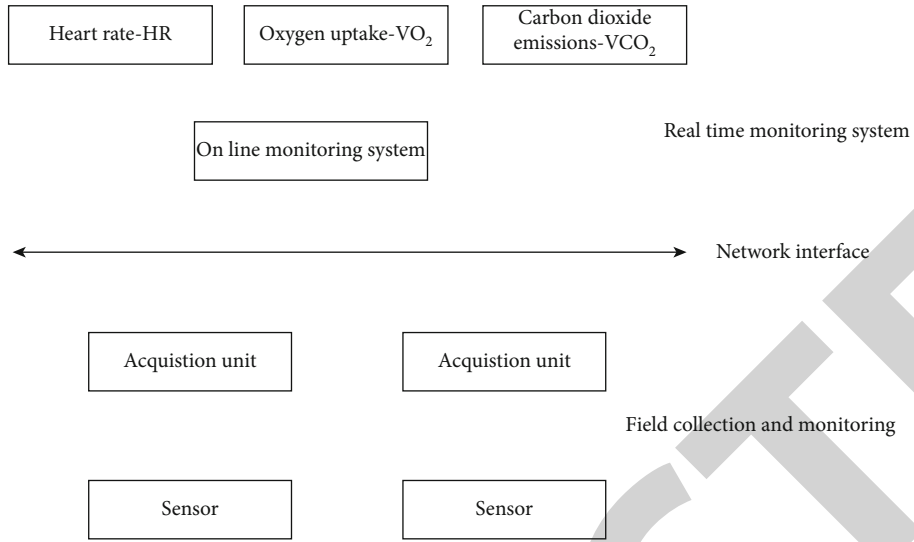


FIGURE 7: Exercise load monitoring and information fusion in physical education class.

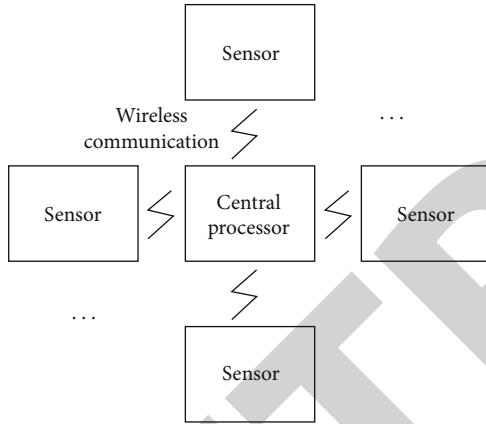


FIGURE 8: Wireless data acquisition system.



FIGURE 10: Results of image stabilization for motion amplitude feature monitoring.



FIGURE 9: Original moving image.

the unit distance of the image plane coordinate system are  $d_x$  and  $d_y$ , then there are

$$\begin{cases} u = \frac{x}{d_x} + u_0, \\ v = \frac{y}{d_y} + v_0. \end{cases} \quad (8)$$

According to the calibrated moving target, the moving target image can be acquired.

3.3.3. *Moving Target Direction Cosine Feature Extraction.* In order to reduce the dimension of the athlete's movement and speed up the calculation, the interested nodes need to be extracted and the ones with less information should be filtered out. Based on the above hierarchical analysis, only the key nodes of the first and second levels are studied [22].

center point  $O$  of the pixel coordinate system and the image coordinate system, and the pixel coordinate system is extracted as  $u_0$ ,  $o_0$ , and  $v_0$ . Therefore, if the pixel values in

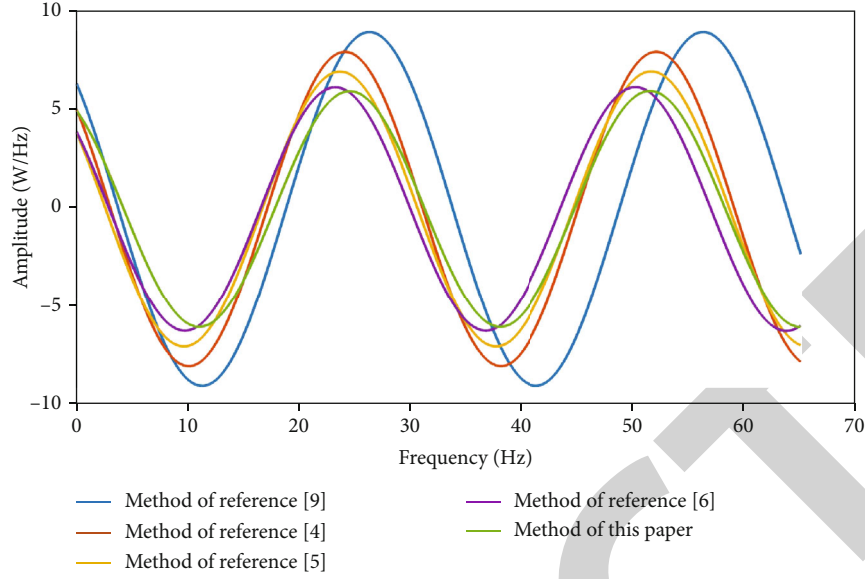


FIGURE 11: Comparison of double peaks.



FIGURE 12: Reference image.

In the case of making different movements, the position and angle information of each segment of the athletes' bones will be different. In this section, the direction cosine feature of the skeleton vector is defined to describe some kind of action.

Taking the right shoulder to elbow bone vector ( $a_8$  vector) as an example, the direction cosine feature extraction process is analyzed.

Suppose that the three-dimensional coordinates of the shoulder joint obtained by Kinect are described by  $(x_1, y_1, z_1)$  and the three-dimensional coordinates of the elbow joint are described by  $(x_2, y_2, z_2)$ , as shown in Figure 6. Then, the skeleton vector can be described as

$$a_8 = \{x_2 - x_1, y_2 - y_1, z_2 - z_1\}. \quad (9)$$

Assuming that the three directions of the  $a_8$  vector and the Kinect coordinate system are  $\alpha$ ,  $\beta$ , and  $\gamma$  in turn, the cosine values of the three directions of the skeleton vector can be obtained by the following formula:

$$\begin{aligned} \cos \alpha &= \frac{x_2 - x_1}{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}}, \\ \cos \beta &= \frac{y_2 - y_1}{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}}, \\ \cos \gamma &= \frac{z_2 - z_1}{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}}. \end{aligned} \quad (10)$$

Through the above process, the direction cosine values of 15 defined bone vectors are regarded as features in order to monitor them. To sum up, the integrated information processing model of the threshold classification algorithm monitoring of the sports load state in the physical education classroom is constructed [23]. According to  $VO_2\max$ , HR, and other index parameters, the sports load state monitoring and information fusion processing in the physical education classroom are realized, as shown in Figure 7.

**3.3.4. Wireless Data Acquisition.** In this paper, the data of the sensor is sent by wireless communication. As mentioned above, the system needs to collect the data of human movement, which cannot be transmitted through the wired network. The schematic diagram of the wireless transmission of motion data is shown in Figure 8.

## 4. Experimental Analysis

In order to test the performance and efficiency of the sport's load monitoring system based on the threshold classification algorithm, the simulation experiment was carried out. The



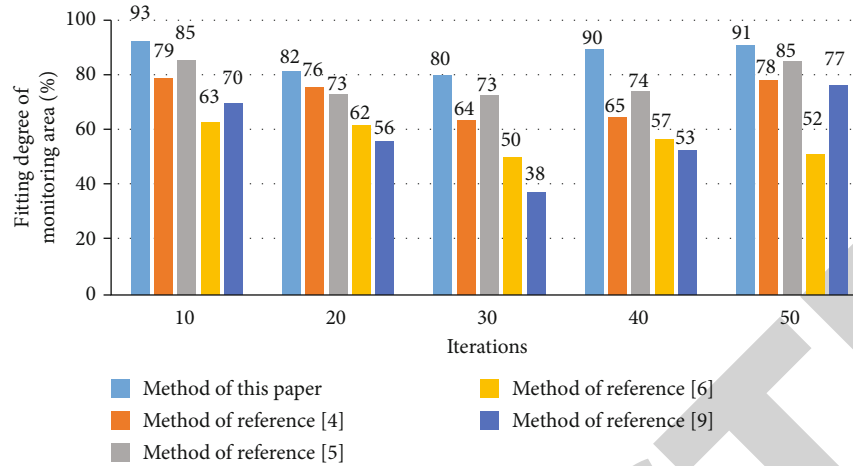


FIGURE 13: Comparison of monitoring effect of fixed point area of moving target.

hardware environment of the experiment platform was an ordinary desktop computer (CPU 3.30 GHz for Intel Core i3 processor, memory 4G DDR3). The original image of the experiment is taken by CCD, through which a series of functions such as photoelectric conversion signal storage, transfer (transmission), output, processing, and electronic shutter can be realized, and the CCD data rate can be adjusted. Therefore, CCD can be used to measure the dimension under dynamic, static, and other conditions. The resolution of the image is  $320 \times 240$ . Meanwhile, in the experiment, 100 test samples of each mode in a group of simulation data are  $100 \times 8$  to constitute the test set, and 20, 50, or all 100 of 100 training samples of each mode are randomly selected to constitute the training set of  $20 \times 8$ ,  $50 \times 8$ , and  $100 \times 8$ , respectively. Based on the edge detection results, the image segmentation threshold of the IKONOS and WorldView images is set at 50 and 80, respectively, and the original motion is shown in Figure 9.

Using this method, the original image is preprocessed, and the single frame vision difference analysis method is used to compensate the motion. The output image of motion amplitude detection is shown in Figure 10.

As can be seen from Figure 9, the proposed method can effectively extract the motion amplitude features of moving images and has good performance. Comparing this method with the methods proposed in References [4–6, 9], the paper verifies the position of the bimodal phenomenon. The higher the position is, the worse the monitoring effect is. The verification result is shown in Figure 11. According to this figure, we can draw that the method proposed in this paper has the best performance.

As can be seen from Figure 10, this method has great advantages in comparison with other methods, and its bimodal curve fluctuation range is smaller and lower than other methods, which shows that it is suitable for sports load monitoring in the PE class and has strong practical application.

Figure 11 is a standard MPEC image, which can be used as a reference image. When playing table tennis in the PE class, the scale and shape of the person being tracked have some changes, but do not affect the statistical distribution. The test results are shown in Figure 12.

But in Figure 13, the fitting degree of the monitoring area of the proposed method is up to 98%, which is higher than that of other four methods. According to the other four methods, especially for Reference [9], the original data used for prediction must have correlation; that is, the autocorrelation coefficient must be greater than 0.5, and the prediction effect of the data will be better; otherwise, the prediction result will be extremely inaccurate. Therefore, for these methods, the prediction effect of the method cannot be fully guaranteed. Not only can the monitoring method accurately monitor the new targets in the monitoring area but it can also embody the effect of the monitoring method on the nonrigid object scale transformation and the deformed area, which has good robustness. That is to say, once the objects have big shape difference, the target location will not be unclear or deformed, which can prove that the method has a good effect.

## 5. Conclusion and Prospect

**5.1. Conclusion.** The proposed method can effectively extract the motion amplitude feature of the motion image, the monitoring performance is good, and the practical application is strong. The motion target tracking system constructed in this paper can achieve up to 98% of the fitting degree of the tracking region, and the excessive bimodal phenomenon is suppressed, and finally, the tracking image is clear, and the probability of deformation is very small, which can effectively avoid the sports injury caused by overload movement.

The main disadvantage of the threshold classification algorithm is that the classification accuracy is not high. This is mainly because the threshold setting is too simple and the number is too small. If we want to improve the classification accuracy, we must set more thresholds, but this will also increase the computational complexity of classification.

### 5.2. Prospect

- (1) In the future, the monitoring rate of the sports load in the physical education classroom can be improved from the perspectives of a smart phone

sensor, raw data preprocessing, and movement recognition methods, so as to better serve the exercise monitoring

- (2) In future studies, the exercise volume can be monitored more accurately based on the association of the daily exercise volume with weight, height, and physique of the study users
- (3) During the implementation of the system, in order to reduce the randomness of the system, the data in the open data set can be used to train the classifier. But in fact, these data are optimal for a single user. In the future research, we can construct a personalized movement monitoring model by selecting training data online to improve the accuracy of exercise monitoring

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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