

Retraction

Retracted: Detection of Body Behavior Characteristics in Sports Training Based on Grey Relational Model

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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. Li and S. Zeng, "Detection of Body Behavior Characteristics in Sports Training Based on Grey Relational Model," *Security and Communication Networks*, vol. 2021, Article ID 3450712, 8 pages, 2021.

Research Article

Detection of Body Behavior Characteristics in Sports Training Based on Grey Relational Model

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In order to deal with the problems of low detection accuracy and efficiency existing in traditional detection methods of body behavior characteristics in sports training, this paper proposes a new detection method of body behavior characteristics in sports training based on the grey correlation model. According to this method, the foreground binary image is obtained by the interframe difference method, and the action information and contour information are extracted, firstly. And then, the behavior feature descriptor is obtained. After the description of body behavior characteristics in sports training is completed, the grey correlation coefficient is calculated, and the complete observation equation of time delay estimation of image grey value under complex sports training background is established to complete the detection of body behavior characteristics. The experimental results show that, compared with the traditional methods, the detection accuracy and efficiency of the text method can always maintain a high level, indicating that the practical application performance of this method is strong. In fact, the grey analysis does not attempt to find the best solution but does provide techniques for determining a good solution.

1. Introduction

In recent years, the development of computer has made amazing progress; people began to consider how to apply the computer to intelligent processing and apply it to the experience of practical problems in life to train the computer to work more like a real human brain [1]. In today's computer field, the detection and recognition of body behavior in sports training video has become an important research direction. It has an important application in human motion analysis [2]. Applied Behavior Analysis is used in sports and athletic training to teach and reinforce skills used in training and competition. Behavioral coaching has been used in sports from football to gymnastics to swimming to improve athlete training regimes, such as enforcing a healthy diet and regular exercise programs, and boost the performance of particular athletic skills, such as maintaining proper body form. However, due to the nonrigidity of human motion training and the complexity of video background, this

method is still a challenging research direction [3]. As a science of understanding and using information, information science provides a new way of thinking and method for the detection and recognition of body behavior in the sports training videos. Meanwhile, intelligent computing research aims at bringing intelligence, reasoning, perception, information gathering, and analysis to computer systems [4–6].

In sports training video images, how to obtain the body information in the image through computing technology, how to obtain related behaviors based on this information, and how to realize the recognition of the sports training machine target and related behaviors in the video have become a difficult point in this field. [7–9].

In [10], a feature descriptor-based motion training body behavior feature detection method is proposed to extract the optical flow field information in the motion training video and calculate the interframe acceleration optical flow. The acceleration information in a space-time block is analyzed by histogram statistics, and the histogram features of all space-

time blocks in several frames are spliced to obtain the acceleration descriptor of body motion, so as to describe the characteristics of body behavior in sports training. Reference [11] puts forward a method for detecting the behavior characteristics of sports training body based on infrared array sensor. The infrared sensor designed in this paper is small in size, is easy to install, is stable in any environment, and can collect low resolution information. Based on the information collected by the sensor, the k-nearest neighbor algorithm is used to detect the body behavior. Reference [12] puts forward a method for detecting the behavior characteristics of sports training body based on spatial clustering. This method uses spatial clustering algorithm to cluster the coordinate data of sports personnel into different clusters and carries out a single data processing for each cluster. Finally, machine learning method is used to detect the characteristics of body behavior. Reference [13] develops an algorithm to detect and classify goalkeeper training exercises using a wearable inertial sensor attached to a goalkeeper glove. Their approach first detects the exercises using an event detection algorithm based on a high-pass filter, a peak detector, and Dynamic Time Warping to detect and eliminate irrelevant motion instances. Then, it extracts a set of statistical and heuristic features to describe the different exercises and train a machine learning classifier. Reference [14] proposes a wearable flow-MIMU human motion capture device by incorporating a microflow sensor with a microinertial measurement unit. Motion velocity is detected by a microflow sensor and utilized to figure out the motion acceleration. The gravity accelerations are extracted by eliminating the motion accelerations from the accelerometer outputs. Finally, posture estimation is implemented using a tailor-designed Kalman-based data fusion of the gyroscope outputs and the extracted gravity accelerations. The flow-MIMU device with wireless communication is designed like a watch to be wearable. A method based on 2D skeleton and two-branch stacked Recurrent Neural Networks (RNNs) are reconstructed starting from RGB video streams, therefore allowing the use of the proposed approach in both indoor and outdoor environments [15]. Reference [16] proposes a novel Graph-Based Object Semantic Refinement based on Bi-GRU to extract multilevel semantic features for visual detection, which uses convolutional neural networks to extract visual features from images and collaborates with semantic features model to achieve better objection recognition results.

Although the above methods can complete the detection of sports training body behavior characteristics, the above methods have the problems of low detection accuracy and detection efficiency. To overcome the problems of low detection accuracy and efficiency existing in traditional detection methods of body behavior characteristics in sports training, a new detection method of sports training body behavior characteristics based on grey correlation model is proposed in this paper. A grey correlation model means a system in which part of the information is known and part of the information is unknown. Grey systems will give a variety of available solutions. Grey analysis does not attempt to find the best solution but does provide techniques for

determining a good solution, an appropriate solution for real-world problems. Furthermore, compared with the traditional methods, the detection accuracy and efficiency of the text method can always maintain a high level, indicating that the practical application performance of this method is strong. According to this method, the foreground binary image is obtained by the interframe difference method, and the action information and contour information are extracted, firstly. And then, the behavior feature descriptor is obtained. After the description of body behavior characteristics in sports training is completed, the grey correlation coefficient is calculated, and the complete observation equation of time delay estimation of image grey value under complex sports training background is established to complete the detection of body behavior characteristics.

The contributions of this paper can be described as follows:

- (1) This paper proposed a method which can detect the body behavior characteristics in sports training. According to this method, it takes the advantages of grey relational model, and the detection accuracy and efficiency of the text method can always maintain a high level.
- (2) According to the proposed method, it can detect the body behavior characteristics which is always very important but very difficult.

The rest of this paper is organized as follows. The framework and technical details of our proposed system are described in Section 2. In Section 3, we present extensive experimental results to demonstrate the effectiveness of the proposed model. Finally, we conclude our work in Section 4.

2. Detection of Body Behavior Characteristics in Sports Training Based on Grey Relational Model

Scientific and reasonable sports training is based on the feedback information of technical monitoring indicators, so as to regulate the intensity of sports training and related actions and realize a reasonable sports training mode. The realization of this technology lies in the detection of human body behavior characteristics [17]. However, the traditional detection methods of body behavior characteristics in sports training cannot feedback the athletes' key technology and range of action in real time and often need to use people's experience mode discrimination to achieve action analysis, which is not accurate and real-time. In addition, the traditional body behavior feature detection algorithm is manually interpreted, which seriously affects the feedback speed. Moreover, the accuracy and technicality of manual recognition are not high, and the workload is huge. For busy coaches, the operability is poor [18].

Therefore, in this research process, the grey correlation model is applied to the sports training body behavior characteristics, and the grey correlation theory is used to realize the accurate analysis of the training image, so as to detect the body behavior characteristics more effectively.

2.1. Body Behavior Characteristic Model of Sports Training.

The body behavior of sports training includes not only the static spatial information (such as posture) of sports training target, but also its dynamic information (such as limb or global motion information). The construction of body behavior feature model of sports training can avoid singularity problem and improve the accuracy of body behavior detection [19].

The body behavior of sports training includes action information and contour information. The foreground binary image is obtained by using the interframe difference method, and all the foreground binary images in the sports training video are merged to obtain the motion energy map of the sports training video [20], where $D(x, y, t)$ represents the two-value foreground image obtained after the t -frame and the $t - 1$ interval; the motion energy graph calculation formula of the video is

$$E_{\tau}(x, y, t) = \bigcup_{i=0}^{\tau-1} D(x, y, t - i). \quad (1)$$

In the same way, the calculation of motion energy map also requires the method of frame difference to find the binary image. However, the motion energy map can be used to represent the motion training information in the foreground image, and the specific formula is

$$\int_{-\infty}^{+\infty} P^2((\rho - \vec{x} \cos \theta - \vec{y} \sin \theta), (\rho - \vec{x} \cos \theta - \vec{y} \sin \theta)) d\rho = \int_{-\infty}^{+\infty} P^2(v, \theta) dv = R(\theta). \quad (4)$$

From this, it can be seen that the image translation does not change the result of the R transform, so it has translational invariance.

Similarly, R transform has rotational invariance, and the image rotation angle is γ ; it is

$$\int_{-\infty}^{+\infty} P^2(-\rho, \theta \pm \gamma) d\rho = \int_{-\infty}^{+\infty} P^2(v, \theta \pm \gamma) dv = (R\theta \pm \gamma). \quad (5)$$

From this, it can be seen that the cycle of R is γ , and the body region can be sufficiently described using the 180-dimensional vector [22].

When the scale changes to the image, the scale factor is α , obtained by

$$\frac{1}{\alpha^2} \int_{-\infty}^{+\infty} P^2(\alpha, \rho, \theta) d\rho = \frac{1}{\alpha^3} \int_{-\infty}^{+\infty} P^2(v, \theta) dv = \frac{1}{\alpha^3} \int_{-\infty}^{+\infty} R(\theta). \quad (6)$$

At this time, when the scale changes, the amplitude of the R transform changes, so it needs to be normalized or standardized to the image. R transformation definition and schematic are shown in Figure 1.

In order to realize image normalization, Fourier transform is used. In Fourier descriptors, the overall contour of

$$H_{\tau}(x, y, t) = \begin{cases} \tau & D(x, y, t) = 1 \\ \max(0, H_{\tau}(x, y, t - 1) - 1) & \text{otherwise.} \end{cases} \quad (2)$$

By adjusting its weight, it can be expressed by adjusting its weight to express the historical information of motion training. According to the motion energy map constructed above, the R conversion method is used to describe the motion training body behavior information [21].

R transformation is an improved algorithm for Radon transformation. R transform is translation, rotation, and scales unchanged compared to Radon transformations, so it is more suitable for describing motion training body behavior information.

R transformation is defined as

$$R(\theta) = \int_{-\infty}^{+\infty} P^2(\rho, \theta) d\rho. \quad (3)$$

The R transform has translation invariance, where the image $f(x, y)$ is translated to $\bar{u}f(x', y')$; the following results can be obtained:

the image determines the low-frequency component of the descriptor, while the detailed information of the image determines the high-frequency component of the descriptor. Therefore, when describing the body contour information, the low-frequency component and high-frequency component need to be taken into account at the same time [23]. Before Fourier transform, it is necessary to transform the image from space-time domain to frequency domain; that is, the point (x_i, y_i) on the plane contour line in XY space-time domain is transformed to the complex plane orderly, and its horizontal axis is the real axis and the vertical axis is the imaginary axis. The complex plane coordinates of each point on the contour line are defined as

$$C(i) = (x_i - x_c) + j(y_i - y_c). \quad (7)$$

In the formula, $(x_i - x_c)$ is the centroid coordinates of the contour. Fourier transform is performed on the set of contour points:

$$f(k) = \frac{1}{N} \sum_{i=0}^{N-1} C(i) \exp\left[-\frac{j2\pi ki}{N}\right], k = 0, 1, 2, \dots, N - 1. \quad (8)$$

In the formula, N represents the number of points on the outline. The characteristic description of the body behavior

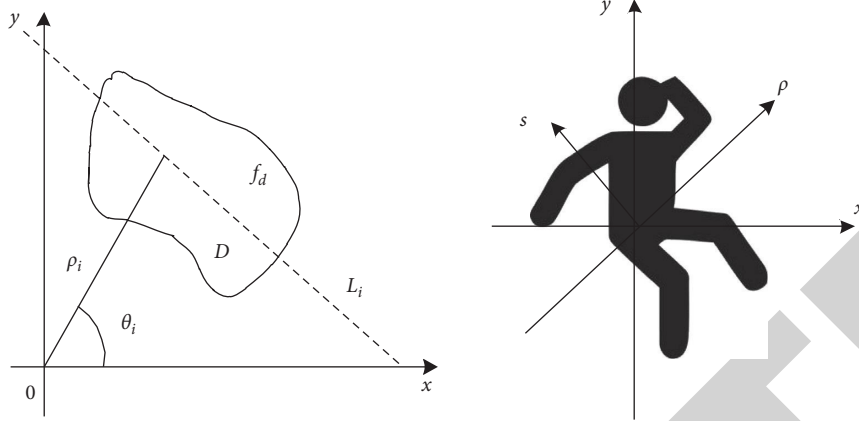


FIGURE 1: R transformation definition and schematic.

after normalization is normalized [24]. The normalization calculation formula is

$$\text{desc} = \left[\frac{\|f(1)\|}{\|f(0)\|}, \frac{\|f(12)\|}{\|f(0)\|}, \dots, \frac{\|f(N-1)\|}{\|f(0)\|} \right]. \quad (9)$$

The outline of body behavior is shown in Figure 2. According to this figure, the points in this figure represent the characteristic points, which can form the outline of body behavior. When the body behavior changes, the outline will change too. Generally speaking, the more the characteristic points are used, the higher the performance of the algorithm will be.

2.2. Detection of Body Behavior Characteristics in Sports Training. After the description of the body behavior characteristics of sports training, the grey correlation analysis method is used to detect the body behavior characteristics of sports training.

The theory of grey relational analysis system is a theory of Uncertainty Research founded by Professor Deng Julong of China in 1982. The research content is “small sample, poor information” uncertainty method of “some information is clear, some information is unknown.” It realizes the accurate description and cognition of display time through the generation and development of known “part” information. Grey correlation analysis mainly studies the object of “explicit denotation, unclear connotation” [25]. Grey relational theory mainly includes grey relational analysis, modeling, prediction, evaluation, decision-making, control, and optimization system. Grey relational analysis theory has been widely used in industry, agriculture, social economy, energy, transportation, and many other fields and has successfully solved a large number of practical problems.

Compared with the high dimension and huge amount of information contained in the image, the training body behavior image is a “small sample,” so the detection of body behavior feature is regarded as a “small sample” problem. Therefore, the application of grey relational analysis theory to the detection of body behavior characteristics has theoretical feasibility. The specific research process is as follows [26].

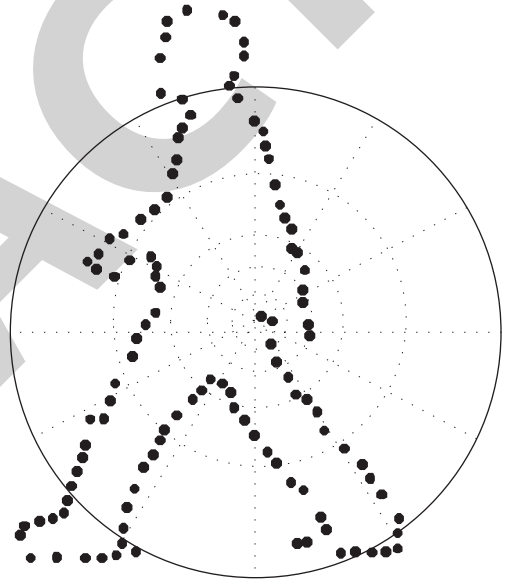


FIGURE 2: Outline description diagram.

Let $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ be the grey relational feature sequence, and

$$\begin{aligned} X_0 &= (x_0(1), x_0(2), \dots, x_0(n)), \\ X_1 &= (x_1(1), x_1(2), \dots, x_1(n)), \\ X_i &= (x_i(1), x_i(2), \dots, x_i(n)), \\ X_m &= (x_m(1), x_m(2), \dots, x_m(n)), \end{aligned} \quad (10)$$

is the sequence of related factors, given a real number $\gamma(x_0(k), x_i(k))$, if the real number

$$\gamma(X_0, X_i) = \frac{1}{n} \sum_{k=1}^n \gamma(x_0(k), x_i(k)) \quad (i=1, 2, \dots, m; k=1, 2, \dots, n). \quad (11)$$

Satisfaction:

$$(1) \text{ Normative: } \quad 0 < \gamma(x_0, x_i) \leq 1, \quad \gamma(x_0, x_i) = 1 \iff X_0 = X_i$$

- (2) Integrity: for $X_i, X_j \in X = \{X_s | s = 0, 1, 2, \dots, m; m \geq 2\}$, have $\gamma(X_i, X_j) \neq \gamma(X_j, X_i), i \neq j$
- (3) Even symmetry: $\gamma(X_i, X_j) = \gamma(X_j, X_i) \Leftrightarrow X = \{X_i, X_j\}$
- (4) Proximity: the smaller $|x_0(k) - x_i(k)|$ is, the larger $\gamma(x_0(k), x_i(k))$ is

Then $\gamma(X_0, X_i)$ is called the grey correlation degree of X_i and X_0 . Among them, normalization, integrity, even symmetry, and proximity become the four axioms of grey relation. The real number $\gamma(x_0(k), x_i(k))$ is the grey correlation coefficient between X_i and X_0 . $\gamma(X_0, X_i) \in (0, 1]$ indicates that any two behavior sequences cannot be strictly unrelated.

$$\gamma(X_0(k), X_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \xi |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|} \quad (12)$$

where the resolution coefficient $\xi \in (0, 1]$.

The calculation steps of grey correlation degree are as follows:

- (1) Find the initial value image or mean value image of each sequence, and record it as $X'_i = (x'_i(1), x'_i(2), \dots, x'_i(n))$, ($i = 0, 1, 2, \dots, m$). Let $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ be the behavior sequence of factor X_i , D_1 and D_2 are sequence operators, and the initial values are as follows: $X_i D_1 = (x_i(1)d_1, x_i(2)d_1, \dots, x_i(n)d_1)$, among $x_i(1)d_1 = x_i(k)/x_i(1); x_i(1) \neq 0; k = 1, 2, \dots, n$. The average image is as follows: $X_i D_2 = (x_i(1)d_2, x_i(2)d_2, \dots, x_i(n)d_2)$, among $x_i(1)d_2 = x_i(k)/\bar{X}_i, \bar{X}_i = 1/n \sum_{k=1}^n x_i(k); k = 1, 2, \dots, n$.
- (2) Subtraction sequence: $\Delta_i = (\Delta_i(1), \Delta_i(2), \dots, \Delta_i(n))$ ($i = 0, 1, 2, \dots, m$), among $\Delta_i(k) = |x'_0(k) - x'_i(k)|$.
- (3) Find the difference between the two levels: $M = \max_i \max_k \Delta_i(k), m = \max_i \max_k \Delta_i(k)$.
- (4) Calculate the relationship coefficient:

$$\gamma_{0i}(k) = \frac{m + \zeta M}{\Delta_i(k) + \zeta M}, \zeta \in (0, 1) (k = 1, 2, \dots, n; i = 1, 2, \dots, m). \quad (13)$$

- (5) Calculate the correlation degree:

$$\gamma_{0i} = \frac{1}{n} \sum_{k=1}^n \gamma_{0i}(k); (i = 1, 2, \dots, m). \quad (14)$$

On the basis of the above processing, according to the constructed sports training body behavior characteristics, calculate the correlation degree results, and carry out grey correlation analysis [27]. Based on the quantum evolution and particle filter algorithm of grey correlation, the motion training tracking is carried out. Firstly, whether the grey level range after greying meets the requirements of effectively displaying the behavior characteristics of the training body is judged, and the selection window is 3×3 . $X_{i,j}$ is used to

represent the grey value of the pixel at position (i, j) , and $M_{i,j}$ is the output vector of the enhanced image; the calculation formula is

$$M_{i,j} = \text{med}(X_{i-1,j-1} \cdots X_{i,j} \cdots X_{i+1,j+1}). \quad (15)$$

Through grey correlation analysis, finally generated greyscale histogram binary pixel features

$$F_{i,j} = \begin{cases} 1, & |X_{i,j} - M_{i,j}| \geq T \\ 0, & |X_{i,j} - M_{i,j}| < T \end{cases}, \quad (16)$$

where $F_{i,j}$ is the value of greyscale histogram binary pixel features.

According to the torque coefficient of each body shape, different thresholds w are obtained. When the pixel value is lower than (i, j) , the dilution value of the body motion sequence is expressed as containing noise. On the contrary, the point does not contain noise. The machine feature driven key frame feature under the effect of grey correlation is obtained; the smooth output of the image is as follows:

$$\begin{aligned} u^{(n+1)}(x, y) &= u^{(n)}(x, y) + \delta u_1^{(n)}(x, y), \\ u_1^{(n)}(x, y) &= M \Delta_s u^{(n)}(x, y) + N \Delta_t u^{(n)}(x, y; d). \end{aligned} \quad (17)$$

In the above formula, $n = 1, 2, \dots, T$ represents the number of iteration steps, T represents the total number of iterations, $u^{(n)}(x, y)$ represents the pixel value, and δ represents the grey correlation update speed. Through the difference between the current frame and the binary background image, the complete observation equation of time delay estimation of image grey value under complex motion training background is established:

$$s(k) = \phi \cdot s(k-1) + w(k). \quad (18)$$

Among them,

$$\phi = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}, w(k) = \begin{pmatrix} N(0, \sigma_{\theta(k)}) \\ 0 \\ N(0, \sigma_x(k)) \\ 0 \\ N(0, \sigma_y(k)) \end{pmatrix}. \quad (19)$$

When $k = 0$, the motion component in the initial state is obtained by solving $s(0)$, which represents the characteristics of the body action state in the sports training scene and realizes the detection of the body behavior characteristics of the sports personnel.

3. Experimental Verification

In order to verify the practical application effect of the proposed method based on grey correlation model, the simulation experiment is carried out. Before the beginning of the experiment, we need to set the experimental samples and experimental scheme.

3.1. Experimental Samples and Schemes. Experimental data: MySQL database is a more common database that selects 400 motion training images in the database, and the size of each image is 92×112 . The body behavior characteristics mainly include running, squatting, biblays, sit-ups, push-ups, and more. MySQL database is currently using the most widely used standard database, containing a lot of comparison results.

Experimental scheme: taking the detection accuracy and detection efficiency of body behavior features as experimental comparison indexes, the method in this paper is compared with the method based on infrared array sensor and the method based on spatial clustering.

Body behavior feature detection accuracy: feature detection accuracy refers to the degree of consistency between the detection results of different methods and the actual body behavior feature detection results. The higher the detection accuracy is, the better the detection performance of the method is.

Detection efficiency of body behavior features: detection efficiency refers to the detection time consumed when different methods detect the same number of images. The shorter the detection time, the higher the detection efficiency.

Experiments in this paper are carried out using one GPU (GeForce GTX 1050 ti) and an Intel CORE i7 with 16 GB RAM memory system.

3.2. Analysis of Experimental Results

3.2.1. Comparison of Detection Accuracy of Body Behavior Characteristics. Due to the rich movement of sports training, experimental samples are set to include a variety of body behavior, and different methods are used to detect the characteristics of body behavior. The detection results of different methods are compared with the actual results to verify the detection accuracy of different methods, containing a deep learning-based method.

Specifically, the infrared array sensor based method is a traditional type of method for body behavior detection, which typically relies on the speed of hardware and the improvement of the algorithm. This kind of hardware-based method requires some manual assistance to detect different types of body behaviors. Thus, the infrared array sensor based method is also to detect different body behaviors, and the detection accuracy and efficiency are summarized as the experimental results. The clustering-based method is also a traditional type of method for body behavior detection; technically, the input space is clustered by the clustering method, and based on the result, the clustering results are classified into different body behaviors based on the classification criterion and experience. Here, we choose the spatial clustering method as one baseline, which aims to partition spatial data into a series of meaningful subclasses, called spatial clusters, such that spatial objects in the same cluster are similar to each other and are dissimilar to those in different clusters. We choose the bidirectional recurrent convolutional network as the deep learning-based baseline method, which is a two-branch stacked LSTM-RNNs

model [15]; it restricts the receptive field of the original full connection to a patch rather than the whole frame, which can capture the temporal change of visual details. Meanwhile, it replaces all the full connections with weight-sharing convolutional ones, which largely reduces the computational cost. The loss function is the classification and regression loss. The optimizer we choose in the experiment is the commonly used Adam optimizer. The comparison results of the detection accuracy of the three methods are shown in Figure 3.

The results of the comparison of the accuracy of the measurement of the body behavior characteristics shown in Figure 3 show that the detection accuracy of this method keeps rising continuously in the course of many comparative experiments and is finally stable at 98%. The detection accuracy based on infrared array sensor method has a large increase, but the final detection accuracy is only 73%. Similarly, the maximum detection accuracy based on spatial clustering method is not more than 80%. Therefore, the above experimental results show that the method can effectively improve the accuracy of detecting the characteristics of the body behavior. Even compared with the deep learning-based method, the proposed method in this paper still shows its superiority.

3.2.2. Detection Efficiency of Body Behavior Characteristics. Because the process of sports training generally lasts half an hour or more, the sports training data is very large, so it is necessary to verify the detection efficiency of the detection method. Formally, the detection efficiency is defined as follows:

$$I_i = \frac{b_{\text{detection},i}}{b_{\text{groundtruth},i}}, \quad (20)$$

where I_i denotes the detection efficiency of the i -th time of the detection method. $b_{\text{detection},i}$ denotes the number of behaviors detected by the method at i -th time. $b_{\text{groundtruth},i}$ denotes the number of behaviors of the ground truth at i -th time.

According to the above analysis, the detection efficiency is selected as the experimental index, and the proposed method is compared with the infrared array sensor method and the spatial clustering method. Furthermore, a deep learning-based method is also compared to verify the superiority of the proposed method. The comparison results of detection efficiency of the three methods are shown in Figure 4.

By observing the comparison results of the detection efficiency of body behavior characteristics shown in Figure 4, it can be seen that the detection efficiency of this method is always higher than that of the two comparison methods in the experimental time of 30 minutes. The detection efficiency of this method is always above 95%, and the detection efficiency of the two comparison methods has strong volatility. Importantly, the efficiency of our proposed method is better than the deep learning-based method. Therefore, this method can effectively improve the efficiency of body behavior feature detection.

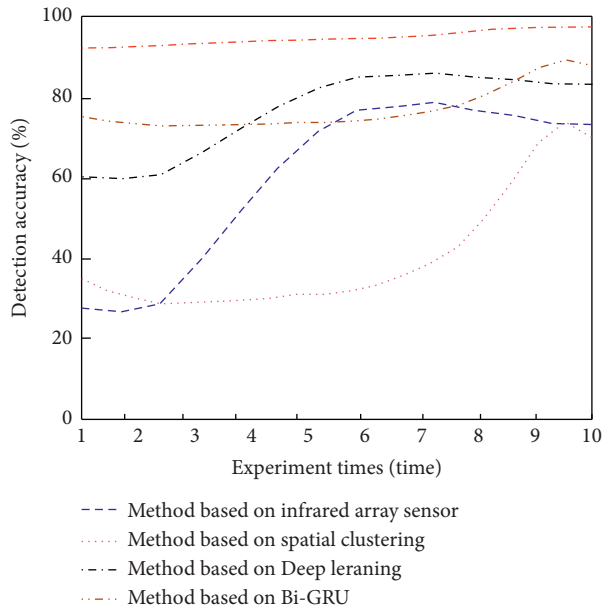


FIGURE 3: Comparison results of detection accuracy of body behavior characteristics.

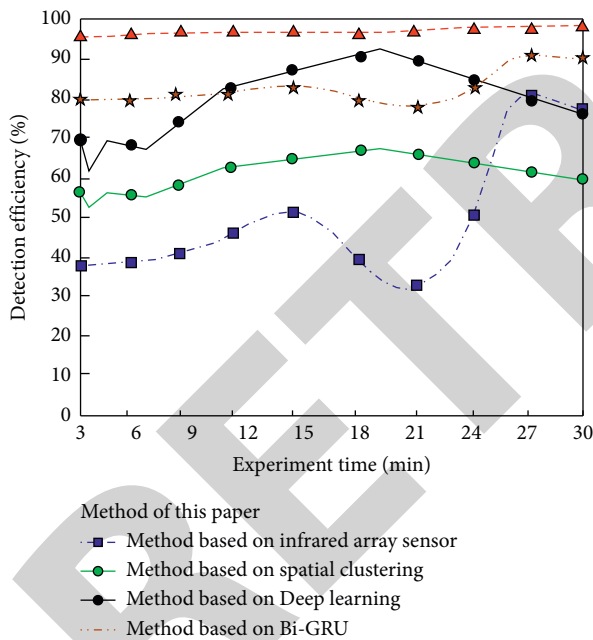


FIGURE 4: Comparison results of detection efficiency of body behavior characteristics.

4. Conclusion

In order to realize the effective detection of body behavior characteristics, a method of body behavior characteristics detection in sports training based on grey relational model is proposed. The performance of the method is verified theoretically and experimentally. This method has high detection accuracy and efficiency in the detection of body behavior characteristics. Specifically, compared with the method based on infrared array sensor, the detection accuracy is significantly improved, and the highest detection

accuracy is 98%. Compared with the spatial clustering method, the detection efficiency is greatly improved, and the detection efficiency is always above 95%. Therefore, it fully shows that the proposed detection method based on grey correlation model can better meet the requirements of body behavior feature detection in sports training. The experimental results show that the proposed method is better than the baselines in practical applications. Generally speaking, the algorithm is successful and meets the expected requirements of scene information collection in general football matches. However, there is still a lack of reasonable theoretical analysis of our method. In the future work, we will discuss the models and methods in the analysis theoretically.

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 conflicts of interest.

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