Sports Athlete Error Action Recognition System Based on Wireless Communication Network

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Abstract. Incorrect actions not only affect the training effect, but also cause certain harm to the athlete's body. A sports athlete incorrect action recognition system based on wireless communication network is proposed. Build a wireless communication network architecture, obtain sports athletes' sports videos, extract key frames, determine athletes' positions, extract sports athletes' action characteristics (STIP characteristics, Cuboids characteristics, enhanced dense trajectory characteristics and covariance characteristics), based on the extraction of sports athletes' action characteristics, build a Hyperplane based on support vector mechanism, and finally realize the recognition of sports athletes' wrong actions. The experimental data shows that after the application of the system in this article, the maximum recognition rate of incorrect movements of sports athletes obtained is 96.35%.

Keywords: Sports Athletes · Standard Action · Movement Characteristics · Action Recognition · Wireless Communication Network · Wrong Action

1 Introduction

Sports are various activities that are gradually carried out in the process of human development to consciously cultivate one's physical fitness. It adopts various forms of physical activities such as walking, running, jumping, throwing, and dancing. These activities are commonly referred to as physical exercise processes, with rich content, including athletics, ball games, swimming, martial arts, aerobics, mountain climbing, ice skating, weightlifting, wrestling, judo, cycling, and other events [1]. The state encourages and supports the exploration, organization, protection, promotion, and innovation of excellent ethnic, folk, and folk traditional sports projects, and regularly holds ethnic minority traditional sports games. The newly revised Sports Law makes clear provisions on the inheritance and development of traditional sports projects. Modern sports were first introduced to China's Christian school by Western missionaries in the late Qing Dynasty. The so-called Christian school is a new school established by missionaries in accordance with the western educational model and philosophy to spread Christian culture and scientific knowledge. Different from the traditional Chinese private schools or academies, Christian school, while focusing on intellectual education, also vigorously

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promote sports; Not only are there specialized physical education courses in the curriculum, but also amateur sports teams and sports competitions have been established. All this originates from the Olympic tradition and belief in ancient Culture of Greece, that is, sound thoughts need healthy bodies to carry them. Sports have functions such as physical fitness, entertainment, and education, politics, and economy. It can also be said that sports have different functions in different historical stages, but since the emergence of sports, physical fitness and entertainment have always been the main functions of sports. Sports is a complex social and cultural phenomenon that uses physical activity as the basic means to enhance physical fitness, enhance health, and cultivate various psychological qualities of individuals. In recent years, sports competitions have become one of the world's key exchange activities, especially the Olympics. Athletes have also received widespread attention from various countries and the general public.

Athletes often face various technical requirements in training and competition. However, due to the limitations of human vision and training environments, coaches often find it difficult to accurately identify and correct athletes' incorrect movements. The traditional manual guidance method requires coaches to have rich experience and professional knowledge, and consumes a lot of time and energy. Developing a sports athlete error recognition system has important research significance and practical application value. Firstly, this system can help coaches more accurately identify and analyze athlete's incorrect actions, providing timely and effective guidance and correction [2]. Secondly, by automatically identifying and analyzing erroneous movements, the system can provide personalized training suggestions for athletes, helping them improve their technical skills faster. In addition, the system can also be used to evaluate and monitor the training progress of athletes, providing scientific basis for the formulation of training plans. In short, the research and development of a sports athlete error recognition system will greatly improve the guidance effect of coaches and the training efficiency of athletes, which is of great significance for promoting the development of sports.

In recent years, more and more coaches and researchers have begun to study how to conduct efficient replay analysis based on competition videos. The analysis method gradually transformed from direct observation of records to data analysis combined with computer technology. For example, the Chinese national team of table tennis has successively introduced table tennis technical and tactical analysis software such as Simi Scout developed by Germany and "Table Tennis Military" developed by the Software Architecture Laboratory of Northern Polytechnical University. These software achieve diversified needs such as technical and tactical data statistics and analysis, as well as the editing and synthesis of exciting fragments. They also recognize technical and tactical actions through manual processing based on the experience of coaches, This method can relatively accurately identify athlete movements, but with the sudden increase in the number of videos that need to be analyzed, manual processing alone will consume a lot of time and manpower, and will reduce accuracy. Therefore, how to use computer technology to efficiently and accurately identify sports athlete movements is a current research hotspot. The above methods can be applied to the training process of sports athletes to identify their erroneous movements, facilitate timely adjustment and change of training plans, and maximize the quality of athletes' training.

In order to achieve the above objectives, a design and research on a sports athlete error action recognition system based on wireless communication networks is proposed. The designed system is based on a wireless communication network architecture, extracting key frames from sports athlete motion videos and determining the athlete's position. After extracting multiple features of sports, support vector machines are used to identify incorrect actions of sports athletes.

2 Sports Athletes' Error Action Recognition System

2.1 Wireless Communication Network Architecture Building Module

Wireless communication network is the basis and premise of sports athletes' action data collection, so the first step of research is to build a wireless communication network architecture.

Due to the large number of sports athletes, the wireless communication network architecture has been set up as a hierarchical distributed topology structure. The topology structure of the wireless communication network is shown in Fig. 1.

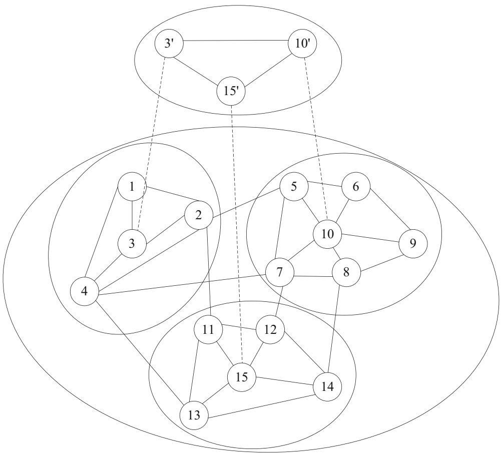

Fig. 1. Schematic diagram of wireless communication network topology

As shown in Fig. 1, the nodes in a hierarchical distributed topology are generally divided into cluster head nodes, gateway nodes, and ordinary nodes. From a structural perspective, the hierarchical distributed topology can be seen as a combination of the star-shaped structure and the fully distributed topology structure. It is commonly used in systems with a large number of nodes [3].

The topology structure of wireless communication networks has been studied earlier. Another important component in wireless communication networks is routing protocols. Routing, as the name suggests, is to choose the best path for data transmission in the network. A suitable routing protocol can improve the stability and access efficiency of the entire network system. For traditional routing protocols such as OSPF and RIP, they cannot respond in a timely manner to rapidly changing topologies, and are likely to encounter various unknown errors when updating routing information, such as the appearance of routing loops. According to the routing method, the routing of wireless communication networks can be divided into active routing and on-demand routing.

Among them, active routing requires nodes to actively exchange routing information regardless of whether the topology structure in the network has changed, in order to update the routing changes in the network in a timely manner. It can continuously monitor the topology structure changes in the network and track updates. The advantage of active routing is that for networks with high throughput, its routing is always in the latest state. This way, for a data transmission process, available routing information can be directly found without initiating the route discovery process. However, for networks with low throughput and topology that are not easily changed, frequent updates of routing are particularly wasteful of system resources when there is no data transmission. Common active routing protocols include DSDV, WRP, etc. The DSDV routing protocol distinguishes between new and old routes by managing the sequence number of the route. Each route is assigned a sequence number, and the quality of the route is judged by determining the size and parity of the sequence. The size of the sequence is directly proportional to the quality of the route. The main feature of DSDV protocol is that it can distinguish the old and new routes through serial numbers, and can also avoid routing loops. The WRP routing protocol requires nodes in the network to send routing packets to exchange routing information with neighboring nodes during idle time, in order to update routing information. Due to the routing exchange between adjacent nodes, routing loops can be avoided. However, WRP requires nodes to exchange information with neighboring nodes, resulting in a huge cost for the entire network in routing updates, which is not suitable for networks with a large number of nodes.

The main difference between on-demand routing and active routing is that on-demand routing does not require scheduled and active updates of routing information. It only updates the route in a certain way when network nodes exchange data. In general, when the source node needs to send data to the target node, on-demand routing will first check the routing table or local cache for routing information from the source node to the target node. Assuming it exists, it will be sent according to this route. Otherwise, a route discovery process will be initiated to update the routing information in the routing table [4]. On demand routing can alleviate the pressure on network system resources in situations or topologies where real-time requirements are not strong due to its on-demand update characteristics. Common on-demand routing protocols include DSR, AODV, TORA, ABR, SSR, etc. DSR is a typical on-demand routing protocol designed based on the concept of source routing. The source route contains all the information of the data transmission process route, and is also forwarded according to the routing information in the group when forwarded by the intermediate node. The DSR routing protocol can route as needed and update routes in a timely manner, but due to the complete routing information contained in packets, it can cause a lot of overhead. AODV is also an on-demand routing protocol that combines the advantages of DSR. The difference is that AODV abandons the complete information of routes in DSR packets and instead uses a hop by hop forwarding method for routing. AODV can quickly establish effective routes, but the establishment of routes has a long delay. The TORA routing protocol adopts an analogy to the "high mountains and flowing water" approach, comparing the destination nodes to other nodes in the network with specific routing heights. The data transmission path can only be transmitted in the direction of height from large to small, which can effectively avoid the generation of loops.

Based on the above description and combined with the needs of sports athlete action data collection, TORA is selected as the routing protocol for wireless communication network.

In order to ensure the stable operation of wireless communication networks, it is necessary to scientifically manage their resources, which are mainly divided into three stages: channel adjustment, power adjustment, and load balancing, as follows:

First, channel adjustment
Reasonable use of non overlapping channels for each AP within a certain wireless coverage range is crucial for wireless network management. For example, on a 2.4G network, there are only three non overlapping channels, and achieving intelligent channel allocation for APs is crucial for wireless applications. At the same time, a large number of possible interference sources, such as radar and microwave ovens, exist in the frequency band of wireless network operation, and the normal operation of the AP will be interfered by them [5]. To ensure that the optimal channel can be allocated to each AP and minimize or avoid adjacent channel interference, channel adjustment functions can be used to achieve this; At the same time, in order to enable the AP to avoid interference sources such as radar and microwave in real-time, real-time channel detection can be used to achieve this. Continuous communication is achieved through dynamic channel adjustment, providing reliable transmission for the network. The schematic diagram of channel adjustment is shown in Fig. 2.

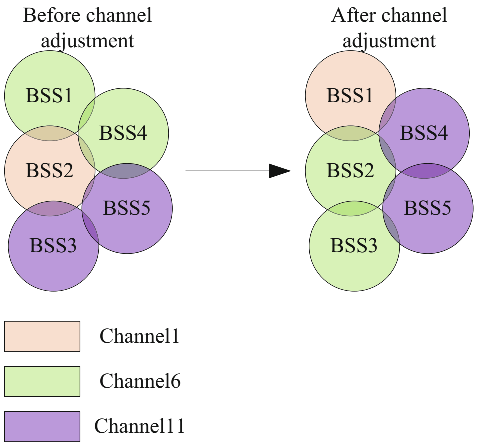

Fig. 2. Schematic diagram of channel adjustment

Second, power adjustment
The traditional RF power control method only statically sets the transmission power to the maximum value in order to simply pursue the signal coverage, but excessive

power may cause unnecessary interference and affect other wireless devices. Therefore, it is necessary to select the best power to balance the coverage and system capacity. Power adjustment is to allocate power dynamically and reasonably in the whole wireless network operation process according to the real-time wireless environment. When the AP starts to run for the first time, it uses the maximum transmission power; When it detects other neighbor APs and gets reports from other neighbor APs, the power will increase or decrease according to the actual situation of the environment. The power increase or decrease ultimately depends on the detection conclusion:

1. When the neighbor AP is added, the power will decrease. The wireless signal covers the same area, and the default maximum number of neighbors is 3; After adding AP4, the maximum number of neighbors is 3, and each AP will run the power adjustment function. The power after adjustment is less than the power required by the first three APs.
2. When the neighbor AP is reduced, the power will increase. When AP3 is reduced and the number of neighbors is 2, each AP will run the power adjustment function to repair the black hole covered by the signal caused by the offline neighbor APs, and the adjusted power is greater than the power required by the first three APs.

Third, load balancing
The purpose of wireless communication network load balancing is to ensure the performance and bandwidth of each wireless user, and accurately balance the load of users in WLAN network according to the actual wireless network situation. WLAN load balancing can effectively ensure the reasonable access of wireless users, and is suitable for the wireless network environment of high-density applications [6]. The AC is responsible for performing load balancing when the client connects to the AP. The AC will periodically receive the information sent by the AP to the connected wireless client. The AC performs load balancing according to the neighbor information. When the client connects to the AP, AC will check whether it exceeds the set load; If the set responsibility is not exceeded, accept the current requested connection; Otherwise, the current connection will be accepted or rejected based on the configured load balancing:

1. When the configuration is in session mode, the operation of load balancing mainly depends on the number of users connected to the AP and RF. Client 1 is associated with AP1, and client 2 to client 6 are associated with AP2. To start user based load balancing on the AC, the threshold number of users is 5 and the maximum load difference is 4. When client 7 sends a connection request to AP2, the number of users on AP2 has simultaneously exceeded the threshold of 5 and the session difference threshold of 4. So client 7 is associated with AP1.
2. When configuring for traffic mode, load balancing mainly considers using traffic snapshots. Client 1 and Client 2 are associated with AP1. Start the traffic based load balancing on the AC. If the traffic of AP1 is greater than the set traffic threshold and the traffic difference threshold at the same time, the final client 3 will be associated to AP2.

Through the above process, the wireless communication network was built, and its resources were scientifically managed, which laid a solid foundation for the follow-up research.

2.2 Movement Data Collection Module of Sports Athletes

Based on the wireless communication network built above, obtain sports video of sports athletes, extract key frames, determine the position of athletes, and provide support for the subsequent extraction of sports athletes' action characteristics.

The visual word bag model, being an image recognition algorithm for image processing, requires the conversion of video data into image data. To accomplish this, the key frame extraction method is employed to extract the significant frames from the video [7]. Nonlinear editing technology in Direct Show plays a major role in this extraction process. Given that sports involve high-speed movements and variations in poses for the same action, it is crucial to ensure the completeness of the action. Therefore, when extracting feature points, the key frame extraction rate is constrained based on the video's frame rate attribute. The key frame extraction algorithm is as follows:

Input: video data A
Output: keyframe image data
Begin:

(1) Get the video frame rate as p
(2) Get the total number of video frames, recorded as N
(3) Calculate key frame capture rate $S = \frac{1000}{p}$
(4) Extract keyframe images based on S and save them

End

The time complexity of this algorithm is $O(1)$, and only the frame rate of video data is used as the standard for keyframe extraction rate to complete keyframe extraction. After the keyframe extraction is completed, it is necessary to preprocess the keyframe data. The preprocessing operation first randomly selects 80% of the extracted keyframe images as the training set, and the remaining 20% keyframe images as the test set.

Based on the extracted keyframes mentioned above, a real-time and high recognition rate human detector, C4, was adopted. This method utilizes boundary signals from video frames and uses the CENTRIST visual descriptor, followed by a cascaded classifier for classification and recognition. This method can quickly recognize the human body in video frames, with a resolution of 640×480 images can achieve a detection effect of over 90% when the thread reaches 20 fps. Using C4 human detector for athlete position detection on the BSMDataset dataset. The schematic diagram of the position detection results for sports athletes is shown in Fig. 3.

To evaluate the detection accuracy of C4 on the BSMDataset dataset, this study utilizes the first frame image of each video segment as the experimental sample. Only the first frame is used for detector performance testing since subsequent frames can rely on the human body's position in the previous frame to determine its location. The C4 human body detector is employed to detect the position of the human body in these samples. The results indicate that the C4 human detector achieves a detection accuracy of 86.25% on these experimental samples, with a processing speed of 20 fps on the visual system's modest hardware. These findings meet the requirements of this study regarding the accuracy and speed of sports athlete position detection. Hence, this detector is selected for further detection purposes.

Fig. 3. Schematic diagram of sports athletes' position detection results

After detecting the position of the athlete in the video frame, a rectangular area containing the athlete is obtained. This article uses the rectangular area obtained by the human body detector as a mask, and by only detecting feature points within the area where the human body is located, it reduces the computational complexity of the algorithm while enhancing its robustness [8]. When human detection is not used, feature points need to be detected throughout the entire video frame, which not only consumes a lot of computational resources and time, but also includes many feature points in the background, causing interference to subsequent tracking and classification recognition. When using a human body detector to detect the human body, a large amount of useless calculations and background interference are eliminated. After the application of C4 detector, the detection range of feature points has increased from the original 800 × 450, dropped to 90 × 270, the detection range has been reduced by 93.25%, which not only reduces the computational complexity, but also avoids the interference of useless feature points on the recognition effect and increases the robustness of the algorithm.

The above process completed the collection of sports athlete videos, extracted key frames, and detected the position information of sports athletes, providing convenience for subsequent sports athlete motion feature extraction.

2.3 Sports Athletes' Action Feature Extraction Module

Based on the aforementioned collected data of sports athlete movements, the extracted features of sports athlete movements (including STIP features, Cuboids features, enhanced dense trajectory features, and covariance features) serve as a foundation for recognizing the final erroneous movements.

The STIP feature was proposed by Laptev, who extended the feature extraction method from two-dimensional spatial images to three-dimensional spatiotemporal videos. Firstly, a Gaussian mean function was used to calculate the first-order spatiotemporal derivative mean, which was used to construct the second-order spatiotemporal matrix used in the feature extraction process [9]. The Gaussian mean function expression is

$$\mu(\sigma, \tau) = g\left(\sigma^2, \tau^2\right) * \left[\nabla L(\sigma, \tau)(\nabla L(\sigma, \tau))^T\right] \tag{1}$$

In Eq. (1), $\mu(\sigma, \tau)$ represents the Gaussian mean function; σ and τ represent independent spatial and temporal parameters, and there is no mutual influence between the two; $g\left(\sigma^2, \tau^2\right)$ represents the time function; $\nabla L(\sigma, \tau)$ represents the spatial gradient value.

By utilizing the local maximum value, the position of the point of interest can be accurately determined, enabling the retrieval of the corresponding point of interest. Consequently, the time-space value of the point of interest can be calculated as a descriptor for further analysis.

The calculation formula of local maximum value is:

$$H = \det(\mu) - ktrace^3(\mu) \tag{2}$$

In Eq. (2), H represents the local maximum value; $\det(\mu)$ and $ktrace(\mu)$ represent the maximum and minimum values of the Gaussian mean function.

Cuboids was proposed by Dollar et al., who independently calculated the points of interest in space and time. For spatial dimension, 2D Gaussian kernel smoothing filter is used for detection, while for temporal dimension, 1D Gabor filter is used for detection. The response equation is:

$$R = (I * g * h_1)^2 + (I * g * h_2)^2 \tag{3}$$

In Eq. (3), R represents the characteristic value of Cuboids; I represents the size of the image; g represents the average grayscale value of the keyframe image; h_1 and h_2 represent an orthogonal pair of 1D Gabor filters.

The local maximum value of formula (3) represents the final point of interest detected. After detecting Cuboids' interest points, each pixel generated within the cube is considered as a center point for gradient calculation. These gradient values are then concatenated. To enhance computational efficiency, simplify feature data, and reduce dimensionality, linear discriminant analysis is employed as a dimensionality reduction method. Research analysis suggests that applying PCA can reduce the feature dimension to 100 dimensions, while extracting 200 cube feature blocks from each video.

The calculation method for dense trajectory features mainly involves calculating the optical flow field of the entire video that needs to extract features. The optical flow field is a two-dimensional instantaneous velocity field composed of all pixels in each frame of the video image. This two-dimensional velocity field is the projection of the three-dimensional velocity field of visible points in the image onto the two-dimensional imaging surface. After calculating the optical flow field of the entire image, pixel dense sampling is performed on the first frame of the video that requires feature extraction. Generally, sampling is set every W pixels, and this study sets $W = 5$. To enhance the dense trajectory features, the image is first densely sampled at intervals of W pixels in the spatial dimension. In order to ensure that the extracted feature points can express all the action information as much as possible and reduce the influence of the surrounding environment on the action information, independent sampling under different spatial scales is needed. In the study, sampling was carried out at most on 8 different spatial scales, and each sampling space was reduced $\sqrt{2}$ times in turn according to the resolution of the video. Then the sampled points are tracked to facilitate the tracking and calculation of the optical flow space ω_t of the image. In this study, a 3 × 3 kernel median filter is used to calculate the optical flow field, and the expression is

$$\omega_t = (\mu_t, v_t) \tag{4}$$

In Eq. (4), μ_t represents the horizontal component of the optical flow field; v_t represents the vertical component of the optical flow field.

For a given sampling point P_t in one frame of image I_t, its tracking point in the next frame of image I_{t+1} is P_{t+1}. By connecting the points in the following image using this method, the trajectory feature of the point can be obtained: $\{P_t, P_{t+1}, P_{t+2}, \cdots\}$.

The covariance feature is obtained on the basis of enhancing dense trajectory features. Select the HOF feature portion from each frame of image features and calculate its corresponding covariance features, represented as:

$$C_i = \frac{1}{n-1}\sum_{i=1}^{n}(\sigma_i - \mu)(\sigma_i - \mu)^T \tag{5}$$

In Eq. (5), C_i represents the covariance feature; σ_i represents the standard deviation; μ represents variance.

In order to facilitate the application of movement characteristics of sports athletes in the future, they are integrated into set $X = \{x_1, x_2, \cdots, x_M\}$ to provide accurate data support for subsequent research.

2.4 Identification Module of Sports Athletes' Wrong Actions

Based on the extracted movement feature $X = \{x_1, x_2, \cdots, x_M\}$ of sports athletes, support vector machine is used to identify incorrect movements of sports athletes, providing certain assistance for sports athlete training.

Support Vector Machine (SVM) is a generalized linear classifier that employs the supervised learning method for binary classification of data. Its decision boundary is determined by maximizing the margin of the training samples. SVM utilizes the hinge loss function to calculate empirical risk and incorporates a regularization term into the solution system to optimize structural risk. As a classifier, SVM demonstrates sparsity and robustness. By utilizing kernel methods, SVM can also perform nonlinear classification, making it one of the commonly used kernel learning methods.

The properties of support vector machines are as follows:

Robustness and sparsity: The optimization problem of SVM considers both empirical risk and structural risk minimization, so it is stable. From the geometric point of view, the stability of SVM is reflected in that it requires the maximum margin when constructing the hyperplane Decision boundary, so there is sufficient space between the interval boundaries to contain the test samples [10]. SVM uses hinge loss function as proxy loss, and the value of hinge loss function makes SVM sparse, that is, its Decision boundary is only determined by the support vector, and the rest of the sample points do not participate in empirical risk minimization. In nonlinear learning using kernel method, the robustness and sparsity of SVM ensure reliable solution results while reducing the computation and memory overhead of the kernel matrix.

Relationship with other Linear classifier: SVM is a generalized Linear classifier, and other types of Linear classifier can be obtained by modifying the loss function and optimization problems under the algorithm framework of SVM. For example, replacing the loss function of SVM with a logistic loss function can get an optimization problem close to logistic regression. SVM and logistic regression are classifiers with similar functions. The difference between the two is that the output of logistic regression has probability significance and is easy to expand to multi classification problems. However, the sparsity and stability of SVM make it have good generalization ability and less computational complexity when using kernel methods.

As a property of kernel methods, SVM is not the only machine learning algorithm that can use kernel techniques. Logistic regression, ridge regression, and linear discriminant analysis (LDA) can also obtain kernel logistic regression, kernel ridge regression, and kernel linear discriminant analysis (KLDA) methods through kernel methods. Therefore, SVM is one of the implementations of generalized kernel learning.

The hyperplane and interval boundary of support vector machine are expressed as:

$$\begin{cases} \zeta^T X + \alpha = 0 \\ \begin{cases} \zeta^T X + \alpha \geq +1 \\ \zeta^T X + \alpha \leq +1 \end{cases} \end{cases} \tag{6}$$

In Eq. (6), ζ and α represent the normal vector and intercept of the hyperplane.

Load a clear set of sports athletes' correct action characteristics $Y = \{y_1, y_2, \cdots, y_N\}$ and wrong action characteristics $Z = \{z_1, z_2, \cdots, z_q\}$, which are distributed on both sides of the hyperplane. Calculate the similarity between sports athletes' action characteristics $X = \{x_1, x_2, \cdots, x_M\}$, correct action characteristics and wrong action characteristics, and the expression is:

$$\begin{cases} \psi(X, Y) = \frac{\mathrm{cov}(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \\ \psi(X, Z) = \frac{\mathrm{cov}(X,Z)}{\sqrt{D(X)}\sqrt{D(Z)}} \end{cases} \tag{7}$$

In Eq. (7), $\psi(X, Y)$ and $\psi(X, Z)$ represent the similarity between the movement characteristics of sports athletes and the correct and incorrect movement characteristics; $\mathrm{cov}(\cdot)$ represents covariance; $D(\cdot)$ represents variance.

According to the calculation result of formula (7), the athletes' action judgment rules are formulated as follows:

$$\begin{cases} \psi(X, Y) \geq \xi \quad right \\ \psi(X, Y) < \xi \quad wrong \end{cases} \cup \begin{cases} \psi(X, Z) \geq \Psi \quad right \\ \psi(X, Z) < \Psi \quad wrong \end{cases} \tag{8}$$

In Eq. (8), ξ and Ψ represent the athlete's action judgment threshold, which needs to be set according to the actual situation.

Through the above process, the recognition of sports athletes' wrong actions is realized, which provides assistance for athletes' training and skill improvement.

3 System Performance Test

3.1 Experiment Preparation Stage

In order to ensure the smooth progress of the follow-up experiment, the badminton athletes were taken as the experimental objects, and their action data were accurately intercepted in the preparation stage of the experiment, providing certain convenience for the follow-up experiment.

Because the segmentation of experimental data is offline, the motion data can be observed well without considering the real-time. The most accurate window segmentation method is naturally the event based window segmentation method, followed by the action window based data segmentation method. However, the event based window segmentation method is relatively strict in determining the start point and end point, and this paper does not require too much experimental data, so the action window based segmentation method is selected.

In order to illustrate the process of capturing experimental data, take a section of action data in which the swing action type is flat gear as an example. For the experimental data used, the existence of the swing action is known, so the size and position of the action window can be determined only by determining the start and end positions of the action. First of all, we need to find the general position of the swing action. In this paper, we choose to determine the general position of the swing action according to the position of the hitting point, and then determine the starting point and ending point of the swing action. Through the comparison and observation of several experimental data, it is found that the position of the hitting point always appears near the peak of the action data.

Through a large number of tests, it can be seen that the average time spent on a badminton swing action is about 0.8 s, and the sampling frequency of the data acquisition system is 50 Hz, that is, the size of an action window should be 40 groups of data. Here, set the hitting point as the center point of an action window, take the 19 groups of data in front as the first half data, and the remaining 20 groups of data are the 20 groups of data after the hitting point.

In the actual situation, the swing action cannot be continuous all the time, and there must be non swing action data in the middle, and it needs to ensure real-time, so it is necessary to process the data immediately after collecting certain data. This paper uses the method of combining sliding window and action window to intercept real-time action data. First, judge whether there is swing action in the sliding window data. If there is no swing action, discard this part of data and directly read the next sliding window data; If there is swing action, find the hitting point first, and then intercept the swing action data according to the size of the action window determined by the hitting point.

3.2 Analysis of Experimental Results

Based on the contents of the above experimental preparation stage, the video action recognition system based on HOF-CNN and HOG features and the fitness action recognition system based on deep learning are selected as the comparison systems 1 and 2 to design the contrast experiment of sports athletes' wrong action recognition.

The design system is applied to identify the wrong actions of sports athletes, and the recognition results are shown in Fig. 4.

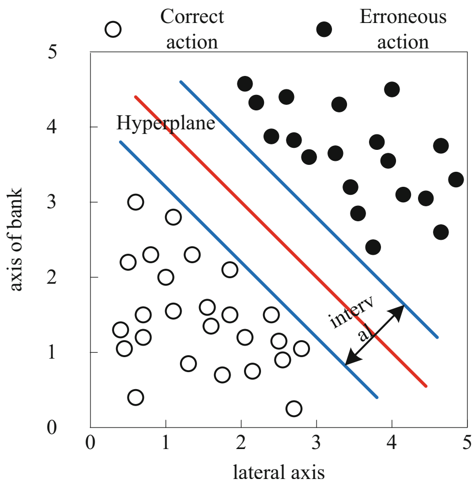

Fig. 4. Schematic diagram of sports athletes' error action recognition results

As shown in Fig. 4, the design system can effectively identify the wrong actions of sports athletes, but in order to highlight the advantages and disadvantages of the application performance of the design system, the recognition rate of wrong actions is calculated under different experimental conditions, as shown in Table 1.

Table 1. Results of error action recognition rate of athletes/%

Test conditions	design system	Comparison system 1	Comparison system 2
1	89.45	45.23	35.02
2	90.45	50.12	45.10
3	91.20	36.26	42.11
4	96.35	50.48	43.59
5	94.25	45.69	50.12
6	92.10	51.78	54.78
7	85.45	46.19	53.46
8	86.23	45.23	52.49
9	91.25	48.79	50.14
10	95.12	46.23	40.16

As shown in the data in Table 1, after the application of the design system, the error action recognition rate of sports athletes obtained is higher than that of the comparison systems 1 and 2, with the maximum value of 96.35%, which fully confirms that the application performance of the design system is better.

4 Conclusion

High-performance sport have various effective rules to prevent injustice, which is an artistic creation and gives people a feeling of intense, wonderful, harmonious and beautiful. With the continuous development of High-performance sport, sports athletes have also been widely concerned by the public. In order to continuously improve the skills of sports athletes, it is necessary to conduct scientific training and correct their incorrect actions. This requires precise identification of the correctness and error of sports athletes' actions. Therefore, a design and research on a sports athlete's incorrect action recognition system based on wireless communication networks is proposed. The design system has significantly improved the recognition rate of incorrect actions by sports athletes, providing more effective system support for sports athlete training. In future research work, multiple sensor data (such as images, videos, inertial sensors, etc.) can be fused to obtain more comprehensive and accurate motion information. By comprehensively analyzing the data of different sensors, we can better capture and identify wrong actions.

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