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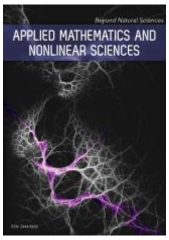

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Research on the Innovation of Physical Education and Physical Education Teaching Based on Big Data Analysis

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Abstract

In this paper, Openpose is used to process the sports teaching video to get the coordinates data of the human body joint point positions in each frame of the video, and Kalman filter data fusion is used to establish the human skeleton model. According to the results of the division of the five major parts of the human body, after establishing the limb vectors of the human body's torso, left arm, right arm, left leg, and right leg in three-dimensional spatial coordinates, the distances between the joints of the five human body skeletons based on the DTW posture matching algorithm were used to extract the characteristics of the sports error technical movements. From the demand of sports digital teaching, the design and implementation of sports basic movement teaching evaluation system based on the DTW posture matching algorithm, and the research and analysis of sports teaching under the background of big data. The results show that the IoU values of batting action localization in 6 segments of physical education teaching are 85.6%, 91.6%, 77.7%, 75.1%, 87.4% and 77.7%, respectively, and the average reach 82.5%, i.e., it shows that the research on action localization and recognition based on the DTW posture matching algorithm has a good performance. In the assessment of movement standardization in physical education, the maximum moment of stretching angle corresponds to the moment of hitting the ball, and its value reaches 3.79, i.e., it reflects that the evaluation system of physical education basic movement teaching can accurately determine whether the students' movements are accurate or not, and make timely feedbacks to carry out the corrections of physical education movements. This study has the potential to enhance students' interest and performance in sports and contribute to the advancement of digital sports teaching.

Keywords: DTW; Kalman filter; Human skeletal model; Action recognition; Physical education teaching system.
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1 Introduction

Today's world is experiencing a big change that has not been seen in a hundred years. With the rapid rise of artificial intelligence, big data and other technologies, digital technology has become the key to leading the development of human society, digital transformation has become an inevitable trend in the development of education, and the twentieth party congress has provided a fundamental guideline to do a good job of digitalization of education in the new era [1]. Big data technology is widely used in college physical education teaching and college physical education teaching management. College physical education teaching from traditional collective teaching rapidly transformed into personalized digital, physical education, and college physical education classroom teaching has become more scientific, flexible and lively, the students' classroom participation has been significantly improved, and the digitization of college physical education teaching, science and precision has also been further improved [2]. At the same time, big data technology has also been rapidly applied in the management of college sports teaching. Through the data pairs, intelligent teaching deployment can be more scientific, accurate and efficient to serve college sports teaching and students' learning and growth. Big data plays a key role in the evaluation of college physical education teaching, and deep data mining is the core of rapidly improving the quality of college physical education teaching and realizing students' personalized learning [3-4].

Digital empowerment is a new teaching mode for big data sports teaching. The big data sports teaching platform provides a one-stop resource service with a rich variety of teaching resources such as audio, video, picture and text, and a flexible and diversified display form, which can meet the needs of different types of teaching, and it is more convenient for teachers to obtain and filter high-quality teaching resources so that the process and way of sports teaching practice are increasingly informatized and intelligentized. At the same time, digital empowerment has enabled the data-based teaching evaluation of sports in colleges and universities, and the evaluation of sports teaching has become more specific and precise. Big data sports allow sports training to be carried out flexibly by combining online and offline activities, and sports teaching practice is more dynamic and vivid [5-6].

The breadth and depth of teaching content are limited to a certain extent by traditional teaching materials and teaching methods. And digital empowerment can bring more diversified content for college teaching. Literature [7], based on the big data science education platform, proposes indicators for screening teaching resources, science content itself, science-related phenomena, the value of science and the application of science, and the argument can also be extrapolated to teaching management. Literature [8] designed an experiment using a non-equivalent pre-test and post-test control group and concluded that a digitally flipped classroom improves learning outcomes and enhances students' willingness to learn on their own compared to the traditional mode of delivery. Literature [9] suggests that participatory teaching methods based on digital technologies, combined with formal and informal learning, lead to a more flexible and active digital classroom. Literature [10] used equation structure modeling to analyze the changes in the quality of teaching and learning after teachers and students were familiarized with the technology of digital teaching and learning platforms using digital distance education as a complete replacement for face-to-face education. The results of the study showed a higher correlation of students' effort. Literature [11] proposed a classroom feedback system based on big data through oral test recognition and head movement recognition, analyzed and processed by the system to give feedback to the teacher as a reference for teaching practice, and the experimental results proved that the system functions well, enhances the interaction in the classroom, and improves the learning experience of students.

The importance of physical education for the younger generation is recognized worldwide, and educators and scholars continue to optimize and improve the teaching and education of physical education based on the existing foundation and the context of the times. Literature [12] junction and digital flipped classroom learning, with 131 physical education students as the subject of a post-hoc study using a quasi-control group retrospective design in a blended and digital learning environment, can improve students' performance and overall ability development. Literature [13], on the other hand, suggests that previous research on the motivational role of situational interest in physical education, while individual situational interest is an empty beat, and that there is a need to enhance research on the interaction of individual and situational interest to better explain the fourth-order theory of interest development in physical activity. Literature [14] used a Latin student as a research object and, using a stratified logistic regression model assessment, concluded that PE has the role of reducing stress and bringing pleasure.

In this paper, firstly, after completing the acquisition of skeletal point data by Openpose technology, the human skeletal motion model is established by Kalman filtering, and the state transfer matrix, observation matrix and parameter values corresponding to students' movement training in the process of physical education are solved. Secondly, according to the understanding of the human body structure, the human body can be divided into five parts that is the torso, the left arm, the right arm, the left leg, and the right leg. The torso is an important part of the support of the human body. The use of the DTW posture matching algorithm calculates the center of mass coordinates of the recognition area of the sports error technology movement to generate the tracking image of the sports error technology movement and to achieve the positioning and recognition of the sports error technology movement. Then, based on the DTW posture matching algorithm, we constructed the evaluation system for teaching basic sports movements, and made a detailed descriptive analysis of the main functional modules of the system. Finally, the experimental environment and training parameters are determined, and simulation experiments are used to research and analyze sports teaching in the context of big data.

2 A study of physical movement recognition in physical education

2.1 Modeling the human skeleton

2.1.1 Skeletal point data acquisition

Openpose output is data files in json, xml, yml formats, for image processing, each image generates a data file containing human skeletal point coordinate data, for each video, the human joint point position coordinate data is obtained for each frame in the video. Using the output json data, the command write_json is used to save the results of the human posture data in json format, and a json file is generated for each frame of each video, and each json file contains an array of people. One of the arrays pose_keypoints_2d contains the coordinate data of the human body joint point position and the confidence level of detection, its format is: $\left[x_1, y_1, c_1, x_2, y_2, c_2, \cdots\right]$ c is the confidence score in the range of [0, 1], the other arrays are composed and their meanings are similar to pose_keypoints_2d.

2.1.2 Preprocessing of human skeletal joint points

The Taylor expansion of the position and velocity formula of the joint point movement in the X -axis is:

$$x_i(k) = x_i(k-1) + \dot{x}_i(k-1)\Delta t + \frac{\Delta t^2}{2!}\dot{x}_i(k-1) + \cdots \tag{1}$$

$$\dot{x}_i(k) = \dot{x}_i(k-1) + \ddot{x}_i(k-1)\Delta t + \frac{\Delta t^2}{2!}\dddot{x}_i(k-1) + \cdots \tag{2}$$

Similarly, the position and velocity in the Y-axis and Z-axis directions can be expanded by Taylor, then the filtering mathematical model of this experiment is obtained according to equations (1) and (2):

$$X_i(k+1) = AX_i(k) + W(k) \tag{3}$$

Among them:

$$X_i(k+1) = \begin{bmatrix} x_i(k+1) \\ \dot{x}_i(k+1) \\ y_i(k+1) \\ \dot{y}_i(k+1) \\ z_i(k+1) \\ \dot{z}_i(k+1) \end{bmatrix} \quad A = \begin{bmatrix} 1 & \Delta t & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$W(k) = \begin{bmatrix} w_{x_i}(k) & w_{\dot{x}_i}(k) & w_{y_i}(k) & w_{\dot{y}_i}(k) & w_{z_i}(k) & w_{\dot{z}_i}(k) \end{bmatrix}^T \tag{5}$$

The mathematical model of the observation matrix in question is as follows:

$$Z_i(k) = HX_i(k) + V(k) \tag{6}$$

Among them:

$$Z_i(k) = \begin{bmatrix} x_i^m(k) \\ y_i^m(k) \\ z_i^m(k) \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}, V(k) = \begin{bmatrix} v_x(k) \\ v_y(k) \\ v_z(k) \end{bmatrix} \tag{7}$$

The observed variables are $Z \in R^m, H$ for the measurement matrix, utilizing $R(k)$ as the covariance matrix of the measurement noise $V(k)$, and also the diagonal matrix, which can be obtained using a large number of statistical methods for observational data.

The estimated value of the current bone point in x dimensions is as follows:

$$x_i(k) = \begin{bmatrix} x_i(k) \\ \dot{x}_i(k) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_i(k-1) \\ \dot{x}_i(k-1) \end{bmatrix} + \begin{bmatrix} w_{x_i}(k) \\ w_{\dot{x}_i}(k) \end{bmatrix} \tag{8}$$

$$z_i(k) = [1 \quad 0] \begin{bmatrix} x_i(k) \\ \dot{x}_i(k) \end{bmatrix} + v_x(k) \tag{9}$$

Where, $A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 \end{bmatrix}, Q(k)$ and $R(k)$ can be statistically derived using the experimental data, this experiment is calculated through multiple data collection to finally obtain $Q(k)$ as a diagonal matrix with a value of 0.25 on the diagonal, and $R(k)$ as a diagonal matrix with a value of 3 on the diagonal.

2.1.3 Kalman filter data fusion

Figure 1 shows the schematic diagram of the traditional Kalman filter, whose measurements are continuously updated by prediction and correction. The fusion of data is accomplished by modeling the human skeletal motion through Kalman filtering. Nowadays, there are many applications and improvements based on the classical Kalman filter model, in which under the classical Kalman filter model, which contains state equations and observation equations, the state variables can be represented by $x \in R^n$. The state equations of the system are as follows:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{10}$$

The observed variable defined in the system is $z \in R^m$, and the observed equation is:

$$z_k = Hx_k + v_k \tag{11}$$

Where (10) for the system's state equation, is predicted by the last moment of the control variables and state of the current moment of the state, k on behalf of the time, x_k, x_{k-1} were k moments, $k-1$ moments under the system state value, u_{k-1} on behalf of the $k-1$ moments under the system control value, w_{k-1} for the system's process noise, which A, B, respectively, for the system's state transfer matrix and the input control matrix, in the practical application of the general do not need to take into account the B,. Eq. (11) is the observation equation of the system, z_k represents the measured value of the system at k moments, v_k is the observation noise of the system, and H is the measurement matrix. Where w_{k-1} and v_k are independent of each other, here can be replaced by white noise that satisfies the Gaussian distribution, which can be utilized Q represents the covariance matrix of the process noise, $w_{k\text{-}1} \sim N(0,Q)$. R represents the covariance matrix of the observation noise, $v_k \sim N(0,R)$. The classical Kalman filtering algorithm can be divided into two phases of prediction and updating, which formally corresponds to the five equations. The time update equation consists of computing the a priori state estimate and the a posteriori estimated covariance. The measurement update equation computes the reconstructed a posteriori estimate. Kalman filtering utilizes the measured values to get to the current optimum. It is a recursive prediction-correction method that continuously performs "prediction-measurement-correction".

The time update equation for the Kalman filter is:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \tag{12}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{13}$$

The state update equation is:

$$K_k = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1} \tag{14}$$

$$\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - H\hat{x}_k^-\right) \tag{15}$$

$$P_k = \left(I - K_k H\right) P_k^- \tag{16}$$

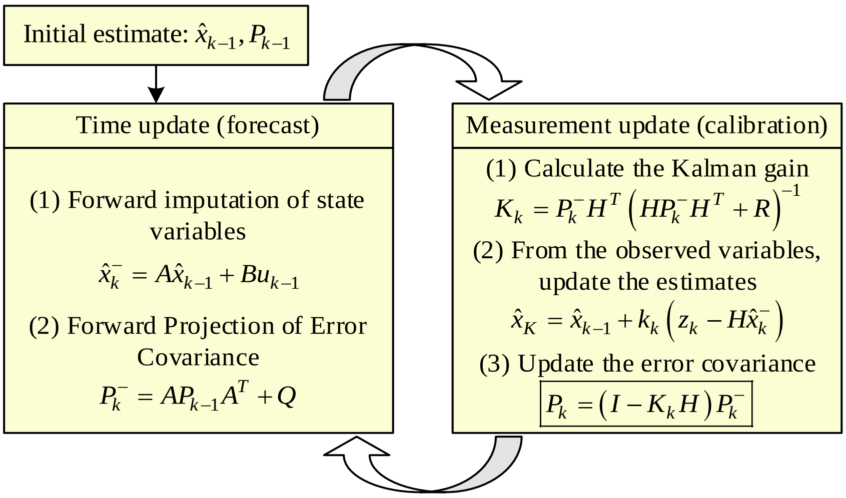


Figure 1. Kalman filter principle

2.2 Sports action recognition based on DTW pose matching algorithm

2.2.1 Extracting technical movement characteristics of sports errors

The result of the division of the five major parts of the human body is shown in Figure 2. Through the division of the human body structure, the combination of these five parts can be used to represent some basic movements of the human body, so a hierarchical strategy is used in the classification. For the five major parts of the human body, such as the torso, left arm, right arm, left leg, right leg, etc., their limb vectors within the three-dimensional spatial coordinates are established, which are expressed as:

$$\begin{cases} GT^{\{3\}}(t) = T^{\{3\}}(t) - G^{\{3\}}(t) \\ AJ^{\{3\}}(t) = J^{\{3\}}(t) - A^{\{3\}}(t) \\ BK^{\{3\}}(t) = K^{\{3\}}(t) - B^{\{3\}}(t) \\ EP^{\{3\}}(t) = P^{\{3\}}(t) - E^{\{3\}}(t) \\ FQ^{\{3\}}(t) = Q^{\{3\}}(t) - F^{\{3\}}(t) \end{cases} \tag{17}$$

Where {3} denotes the three-dimensional space. t denotes the moment of movement of a limb. $GT^{\{3\}}, AJ^{\{3\}}$, $BK^{\{3\}}, EP^{\{3\}}$ and $FQ^{\{3\}}$ denote the limb vectors of the human body's torso, left arm, right arm, left leg and right leg in three-dimensional space, respectively. In physical education sports, the human body movement is expressed with different contributions, and two joint angles are chosen from each part as the active action joint angles, respectively. The magnitude of each joint angle of the human body in three-dimensional space can be found by using the following equation, and the angular velocity of the joint angles of the human body is:

$$\omega(t) = \theta(t+1) - \theta(t) \tag{18}$$

The sequence of movements of the human body is continuous and varies over time. Changes in joint angles produce angular velocity values. The limb vectors and angular velocities of the active joint angles are an expression of the overall synergistic motion of the human torso and limbs, and the bending of the human limbs and torso represents the changes in the distances between the joints. The human body is also projected from the left view direction to the YOZ plane. The distances from the five parts of its athlete to the joint points are:

$$\begin{cases} d_{Gr}(y,z) = \sqrt{\left(y_G(t) - y_r(t)\right)^2 + \left(z_G(t) - z_r(t)\right)^2} \\ d_{CL}(y,z) = \sqrt{\left(y_C(t) - y_L(t)\right)^2 + \left(z_C(t) - z_L(t)\right)^2} \\ d_{CM}(y,z) = \sqrt{\left(y_C(t) - y_M(t)\right)^2 + \left(z_C(t) - z_M(t)\right)^2} \\ d_{GR}(y,z) = \sqrt{\left(y_G(t) - y_R(t)\right)^2 + \left(z_G(t) - z_R(t)\right)^2} \\ d_{GS}(y,z) = \sqrt{\left(y_G(t) - y_S(t)\right)^2 + \left(z_G(t) - z_S(t)\right)^2} \end{cases} \tag{19}$$

Where, $d(y,z)$ represents the Euclidean distance between two joints of the human body of a sportsman, and in order to eliminate the variability of different individuals in sports, each term in Eq. (17) and Eq. (18), as well as the width of the shoulder of the human body and the mean of the Euclidean distance between the joints, were standardized to obtain:

$$d_{AB}(x,y,z) = \sqrt{\left(x_A - x_B\right)^2 + \left(y_A - y_B\right)^2 + \left(z_A - z_B\right)^2} \tag{20}$$

$$\bar{d}(y,z) = \frac{\sum_{t=1}^{n} d(t)}{n} \tag{21}$$

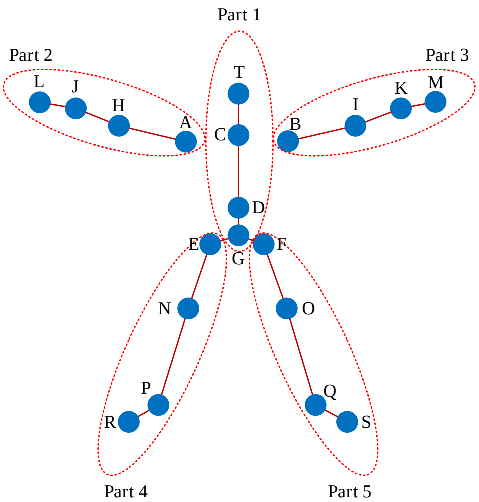


Figure 2. The results of the five parts of the body

2.2.2 Erroneous technical movement tracking and adjustment

In a sports teaching video or a live video of a game, the position of the camera is dynamic. Therefore, there are more non-static images in the sports competition videos, which cannot reflect the information of the athletes well because the camera is moving at all times. Therefore, it is necessary to track the moving target using the DTW pose matching algorithm to obtain the domain in which the athlete is active and to adjust the athlete’s image within this range to counteract the influence of external factors. Within the unfolded tracking target area, symmetric vertical and horizontal tracking is carried out to generate an image of the moving target and adjust it. Equation (21) is used to calculate the “center of mass” coordinates $\left(m_x, m_y\right)$ of the target area, and the center of mass coordinates are shifted according to the center of the area to generate the tracking image of the athlete’s target:

$$\begin{cases} m_x = \dfrac{\sum\limits_{x\in R}\sum\limits_{y\in R} x\cdot f(x,y)}{\sum\limits_{x\in R}\sum\limits_{y\in R} f(x,y)} \\ m_y = \dfrac{\sum\limits_{x\in k}\sum\limits_{y\in R} y\cdot f(x,y)}{\sum\limits_{x\in R}\sum\limits_{y\in R} f(x,y)} \end{cases} \tag{22}$$

As a result of this processing, it is possible to realize the adjustment of the image sequence for target tracking. The adjusted image sequence includes only the movement of the athlete’s limbs and the movement due to the racket, and it does not reflect the camera movement in the original image. By tracking the sports target and obtaining the activity area of the athlete, the tracking image of the sports error technique movement is generated by calculating the center-of-mass coordinates of the region identified by the sports error technique movement, so as to realize the tracking and adjustment of the sports error technique movement.

2.2.3 The process of recognizing incorrect technical movements in physical education

Based on the sports error technical action, the sports error technical action recognition process is designed by calculating the sports error technical action descriptor, and the background color elimination centered on the athlete is shown in Fig. 3. According to the sharpness of the camera, the user can manually adjust the sports error technical action image sequence and subsequently estimate the length of the light field. Firstly, the brightness of the sports error technique action images is tracked in real-time according to the flash and intensity of the camera’s degree of change, which can make the results of the optical flow calculations incorrect. So, the image difference is used to distinguish the brightness and eliminate the effect due to the change of brightness. Secondly, analyzing the theory of biological visual system, it is known that the machine vision cells are sensitive to the edge movement of the object, in the direction and speed, for the different optical flow formed due to the difference of the image, as a way of reflecting how the human visual system affects the logistics movement. On the basis of differential images, the Horn-Schunck algorithm is used to estimate how athletes track the Horn-Schunck optical flow field as follows:

$$\begin{cases} DI_i = HC_i - HC_{i-1} \\ OFF_i = HS\left(DI_i\right), i = 2,\cdots,N \end{cases} \tag{23}$$

Where DI_i denotes the difference image between the tracking sports error technique action image HC_i and HC_{i-1}. HS denotes the Horn-Schunck algorithm estimation expression. OFF_i denotes the optical flow field. N denotes the number of sports error technique action image sequence alignments.

The position of the athlete in the aligned sports error technique action images correlates with the relative displacement of the body, which exists in the corresponding image region. The spatial distribution of the optical flow field is different for different postures of the athlete.

The amplitude $M(P)$ and direction angle $\theta(P)$ of the sports player's erroneous technical action can be defined using the following equation, denoted as:

$$\begin{cases} M(p) = \sqrt{G_x^2(p) + G_y^2(p)} \\ \theta(p) = \arctan \dfrac{G_x(p)}{G_y(p)} \end{cases} \tag{24}$$

In summary, based on the DTW posture matching algorithm, the sports error technical movement features were extracted, and the sports error technical movement descriptors were computed by tracking and adjusting the sports error technical movements to realize the recognition of sports error technical movements.

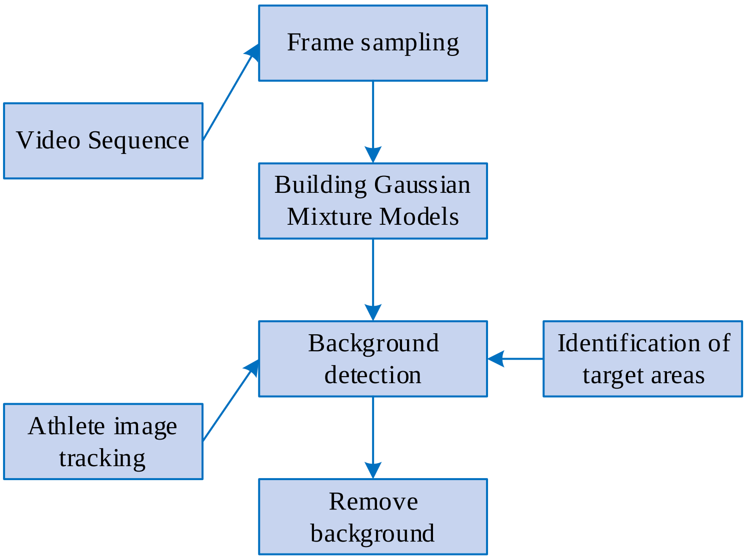


Figure 3. The background color of the athlete is eliminated

3 Design and realization of the evaluation system for teaching basic movements in sports

3.1 Development environment and system design

3.1.1 Development environment

The development environment of this system is as follows:

1) Computer configuration: 64-bit windows10 operating system, GTX1660 above performance GPU

2) Qt5.9.0, Visual Studio 2015 or above environment, OpenCV.

3) CMU Lab Openpose model: for outputting 25 skeletal points.

3.1.2 System design

The overall process of the evaluation system for teaching basic sports movements is shown in Fig. 4. In order to realize the evaluation of the standard degree of movements based on DTW posture matching in the teaching of basic sports movements, the basic process of the sports teaching system is designed as follows: firstly, students refer to the template movement video uploaded by the teacher on the client side for learning, constantly practice the basic movements therein, and according to the requirements, imitate the teacher's standard movements in the video. Take action and strive to achieve the required action. At the end of the study, students use their cell phones to shoot videos of their learning results and submit their assignments to the system for evaluation. The system will further process the video after the students upload the video. The system designed in this paper is developed on the Qt5 software development platform, using OpenCV to perform video processing. Both have the advantage of cross-platform support, and Qt5 has a good support configuration for OpenCV, which allows it to flexibly call all the visual libraries of OpenCV. Users can perform the basic process of action evaluation by uploading the action video to match and query the evaluation results through the friendly visualization interface.

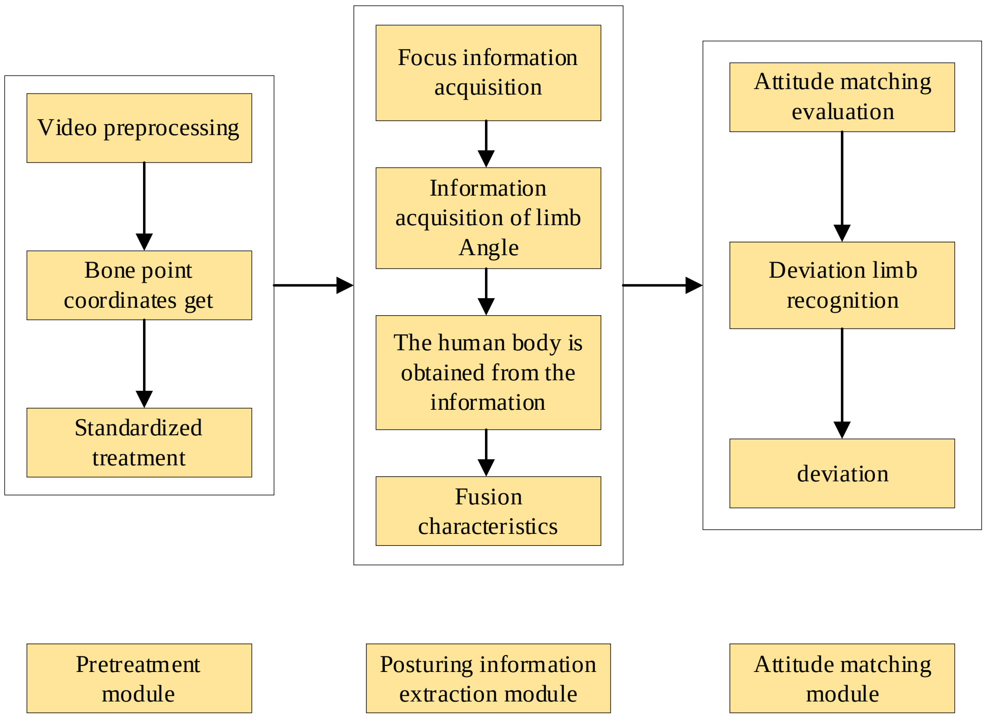


Figure 4. Sports basic action teaching evaluation system

3.2 System Main Functional Modules

3.2.1 Pre-processing module

The preprocessing module mainly focuses on acquiring and standardizing data. In this paper, the original data is based on the Openpose action video input to achieve the output of the human bone point coordinate data in the video. First of all, the resolution of the input video is standardized, mainly using the VideoCapture() function in OpenCV to adjust the resolution to 480*360 for resolution scale standardization. Then, the human skeletal point coordinate data in the video is acquired, and after obtaining the skeletal point coordinates, the information about the bone points to be matched is scaled according to the skeleton space ratio of the standard action, eliminating the effect of resolution adjustment on the size of the skeleton space. For the preprocessing module mainly occurs in the earliest period of the gesture matching process, students for action gesture matching and the formation of the teacher's template library need to be obtained first of all the original skeletal point data preprocessing operations, the formation of standardized coordinate data.

3.2.2 Feature Information Extraction Module

The feature information extraction module mainly realizes the computational extraction and fusion function of the differential posture features proposed in this paper, forming the human posture feature data available for the posture matching algorithm in this paper. This module is mainly divided into four steps. First of all, through the standardized skeletal point data obtained for the calculation of the center of gravity information, according to the principle of moment synthesis method, combined with the inertia coefficient of the human limb, the gravity component of each limb is calculated and deposited into an array, and then the gravity component is used to obtain the center of gravity coordinate by accumulating and summing function, and then the $acos(x)$ function is used to calculate the radian of the angle between the center of gravity vector and the spine vector, as the first posture feature. , as the first stance feature. Then, through the skeletal point coordinates data, the skeletal points are assigned to each limb block and the limb pinch angle array contained therein, and the function $acos(x)$ is called inside each array to solve for each limb pinch angle to get the basic limb pinch angle features, and then the skeletal points contained in the limb block are defined as the mean function $average(x)$ to calculate the centroid, and the limb block centroid vectors and vertebral vectors pinch angle features are computed to get the orientation of the four limb blocks. The features constrain the limb pinch angle features. Finally, to solve the human body orientation features, according to the skeletal point data, through the feet together vector, call the function library $atan2(y,x)$ function to find its rotation angle for the transverse axis, as a discrimination of the human body's left and right orientation information, the use of the shoulder joint and hip joint vector positive direction definition and its change, to discriminate the upper and lower limbs of the back and front of the body orientation information. Finally, the individual features are fused into a 21-dimensional array using the splicing method to form usable differential posture features. This module is a part of both the student posture-matching process and the teacher template-building process.

3.2.3 Attitude Matching Module

The posture matching module mainly realizes the functions of action evaluation, deviant limb recognition and labeling. The module first calculates the similarity between the obtained discrepant human gesture features in the students' actions and the features in the template library, defines function $similarityDistance(array[],\ array[])$ to solve the feature similarity by using the power function $pow(doublex,\ doubley)$ in the C++ library, and defines function $convScores(intd)$ to realize the conversion of the similarity distance into the gesture action scores to form the scoring matrix of the action sequences to be matched and the template action sequences. Then based on the DTW algorithm to realize the regularized path search on the scoring matrix to get the best match. Definition $finalScore(array)$ Find the final score of the student for the action. After the matching of the action is completed, the standard degree of posture is analyzed, and the five posture frames that have the greatest influence on the standard degree of the action, i.e., the lowest scores, are taken out, and the deviation factor function $devFactor()$ is defined to calculate the degree of deviation of the limb features, and the skeletal points contained in the limb with the greatest deviation are obtained, and the function $rectangle()$ in the OpenCV library is utilized to draw a rectangular frame outside the deviating limb in the image where the limb is located, and mark the deviating limb in the image of the frame with the deviating limb. That frame image to label the deviated limb. The posture matching module is only used in the process of matching and evaluating students' movements, and the teacher's template building module provides the feature information of the standard movements and participates in its calculation.

4 Analysis of Physical Education Teaching Research in the Context of Big Data

4.1 Empirical analysis of action recognition based on DTW pose matching algorithm

4.1.1 Experimental environment and training parameters

In this paper, the experimental environment is configured with Intel Xeon Platinum8160Ts CPU, Ge Force GTX 1080 Ti GPU, with CU-DA10 and CUDNN7.6 as GPU acceleration libraries, and is completed with the deep learning framework PyTorch1.1 in the Ubuntu18.0 system, and the configuration of training parameters is shown in Table 1. The evaluation metrics include the average recall rate $\left(\overline{R}\right)$, the average checking accuracy rate $\left(\overline{P}\right)$, and the micro-averaging (micro-AUC) of the area under the curve (AUC) of the subjects' work features with its macro-averaging (macro-AUC). Among them, the mean recall rate $\left(\overline{R}\right)$ and the mean finding rate $\left(\overline{P}\right)$ are calculated as:

$$\begin{cases} \overline{R} = \sum_{i}^{N} \frac{TP_i}{TP_i + FN_i} \\ \overline{P} = \sum_{i}^{N} \frac{TP_i}{TP_i + FP_i} \end{cases} \tag{25}$$

where TP is the true example, FN and FP are the false counterexample and false positive example, respectively, and N represents the category overview of the batting maneuver.

Table 1. Training parameter configuration

Parameter	Configuring
Rotation	50
Bulk size	63
Dropout Hyperparameter	0.7
Initial learning rate	2.5E-4
Pretraining model	BN-inception_caffe*
Optimizer	SGD
L2 Regularization coefficient η	5E-4
Momentum	0.9

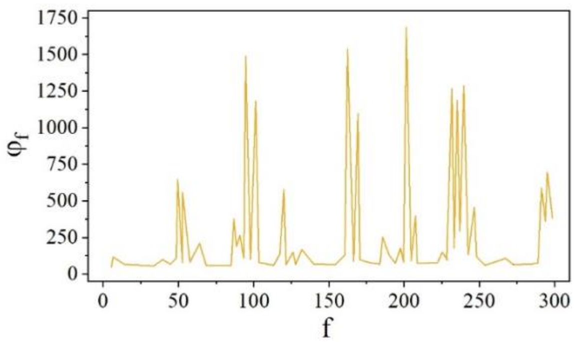
4.1.2 Data sets

In this paper, the sports teaching videos were collected from the Internet, and the tournaments were mainly the tennis matches of the 2012 London Olympics and the 2016 Rio Olympics, as well as the 2018 and 2019 Badminton World Federation tours.

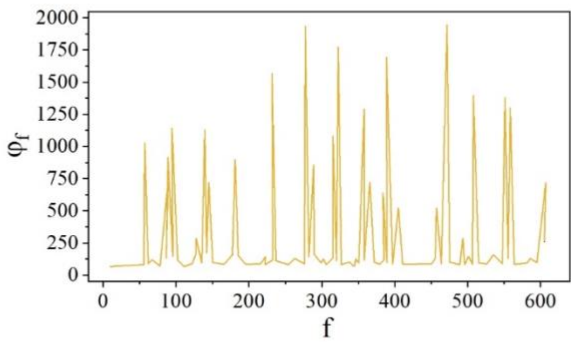
For the categorization of the main player's hitting action in the meta-video, in order to maximize the completeness of the meta-video hitting action in the dataset, this paper produces the dataset by manual means. For the sufficient amount of video clips of tennis matches collected and extracted in the previous period, 5160 sports teaching meta-videos were segmented using video merge segmentation software and manually labeled with categories of hitting actions as the dataset, and the labels included forehand hit, backhand hit, head hit and pick.

4.1.3 Analysis of movement localization and meta-video extraction in physical education

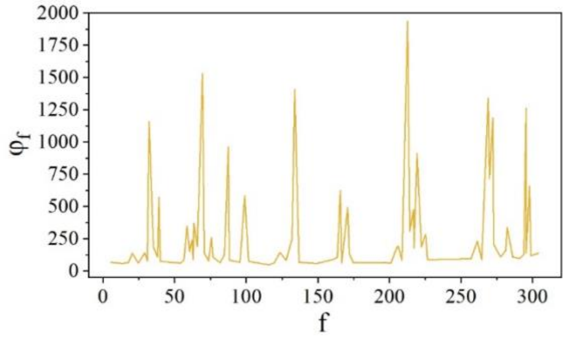
For video clip batting action localization, parameter λ is assigned a value of 0.35, swing amplitude threshold φ_τ is assigned a value of 500, and the frame range t on both sides of f_m takes the value of 15. If an extracted piece of meta-video V_p and the real meta-video V_T contain the same batting action, then V_p and V_T are the same. For a video clip, the set of extracted meta-videos is denoted as P and the set of real meta-videos is denoted as T , and loU denotes the intersection ratio of sets P and T . Higher IoU indicates better performance. The change state curves of the swing amplitude of the batting arm of the main player in the six video clips are shown in Fig. 5, in which (a)~(f) are $IoU = 85.6\%$, $IoU = 91.6\%$, $IoU = 77.7\%$, $IoU = 75.2\%$, $IoU = 87.3\%$, $IoU = 77.6\%$, respectively, and the frames corresponding to the dotted lines vertically intersecting with the horizontal coordinate axes are the frames in which the main player actually hits the ball, and the swing amplitudes of the neighboring domains of these frames show drastic undulation and other ranges of the frames tend to be stable. The measures of batting motion localization IoU for the six video clips were 85.6%, 91.6%, 77.7%, 75.1%, 87.4%, and 77.7%, respectively, with an average of 82.5%. The IoU metrics of video clip hitting action localization are related to the selection of swing amplitude thresholds and the main player's movement characteristics. Sometimes, the player is not at the moment of hitting the ball, the swinging amplitude of his racket-carrying arm will still be too large, or the player's elbow or wrist swing is not violent enough when hitting the ball, and there is a situation in which the localized hitting action is not the real hitting action, then the meta-video extracted in the above case is a false meta-video, which will interfere with the training and testing of the network model to a certain degree if inputted into the neural network for training. The experimental results show that the method of localizing the hitting action through the racket-holding arm swing amplitude discrimination based on the DTW posture matching algorithm has a better performance in general.



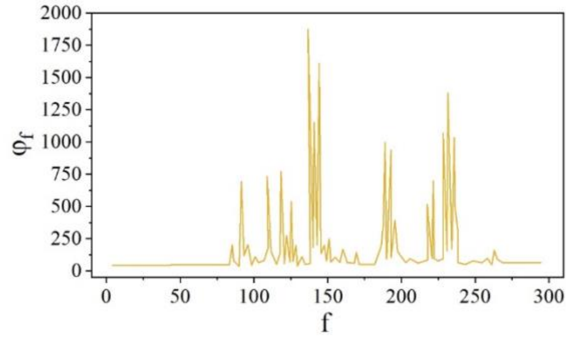
(a) $IoU = 85.6\%$



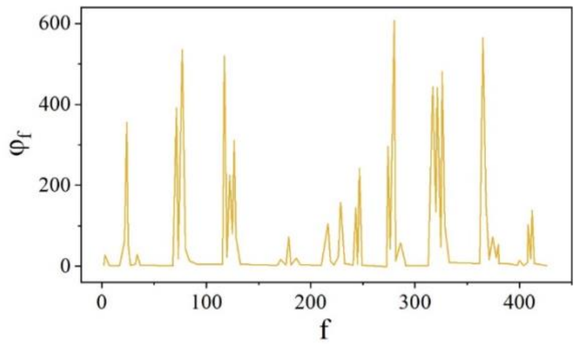
(b) $IoU = 91.6\%$



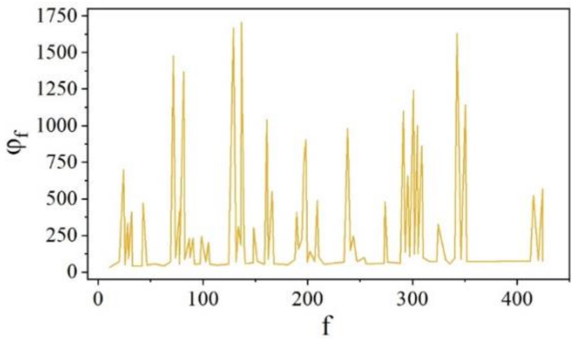
(c) $IoU = 77.7\%$



(d) $IoU = 75.2\%$



(e) $IoU = 87.3\%$



(f) $IoU = 77.6\%$

Figure 5. The master player's arm wave amplitude changes the state curve

4.1.4 Movement Recognition in Physical Education

In this paper, we adopt the leave-out method for recognizing actions in physical education and follow the stratified sampling method, i.e., the overall data is divided into several categories that do not intersect with each other at the time of sampling, and then a certain percentage of samples from each category of data are independently taken according to a certain ratio, and the extracted samples are combined as a sample set. Experimentally, 10% of the samples from each category of the meta-video dataset are categorized as the test set, and the rest of the samples are categorized as the training set. The test set is used to evaluate the model's performance after the network has been trained on the training set. In the training process, hierarchical 10-fold cross-validation is used. At the beginning of the training phase before each validation, each category of meta-video data in the training set is divided into 10 folds. 1 fold is taken in turn and categorized as the validation set, and the remaining 9 folds are involved in network training. When training to 30epoch and 40epoch, the learning rate is reduced to 10% of the original. Assign K to 1~5 respectively, and the trend of the training loss of the model when K takes different values is shown in Fig. 6, and the training loss is output once every 20 times (iteration) of training. It can be seen that when K is from 1 to 2, the convergence tendency value of the training loss (loss) decreases significantly, and from 2 to 5, the training loss curve is almost viscous, and the performance has not achieved significant improvement. When iterating to about 35 rounds, the overall trend of training loss is no longer decreasing and has converged. When the number of segments K is 3, the recognition rate and accuracy reach a relative equilibrium state, and the ROC of the trained classifier model for the recognition performance of the four categories, including forehand, backhand, overhead and pick, is shown in Fig. 7, in which TPR (true positive rate) is the true positive rate and FPR is the false positive rate, and the AUC metrics of all the four categories reach 0.5 and 0.5. The AUC metric of all four action categories reaches more than 0.8. The micro-AUC and macro-AUC are both about 0.985, which indicates that the DTW gesture-matching algorithm can be closer to the level of human judgment to a greater extent. It can effectively complete the task of recognizing the sports actions in physical education, which is a guide for the reform of digital teaching of sports in colleges and universities.

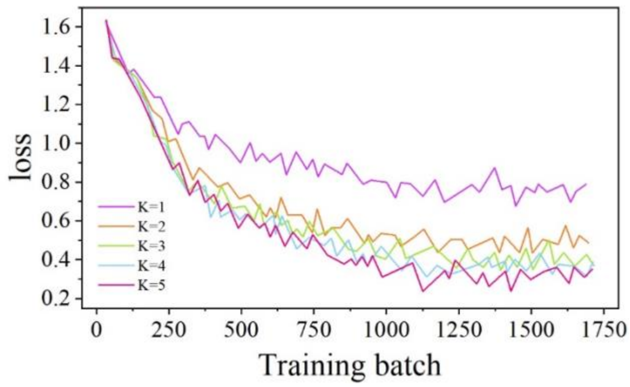


Figure 6. The loss of the validation set in the number of sections K is different

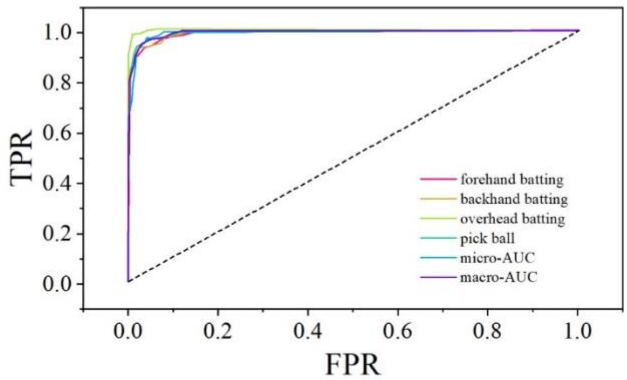


Figure 7. Measurement of ROC-AUC measurement

4.2 Empirical analysis of the evaluation system for teaching basic physical education movements

4.2.1 Parameter Settings of the Serving Machine and Outgoing Error Checking

The three-parameter settings of the serves and their minimum and maximum variance of the outgoing indexes are shown in Table 2. By adjusting the two parameters, topspin speed and bottom spin speed, of the OUKEI automatic serves, the three preset difficulty levels of serves, slight topspin, strong topspin and bottom spin, can be realized. It is possible to evaluate the variability of each serve. This paper counts the maximum and minimum variance of each characteristic, which corresponds to the three difficulty serves, in more than 300 experiments.

Table 2. Three parameter Settings for the service machine

Difficulty in serving	Upper turning parameter	Lower rotation parameter	*Cu / mm*	*Hd / mm*	*Ft / mm*	*Ot / mm*
Slight spin	5.5	2.5	0.05/0.17	6.4/30.4	0.05/5.6	0.02/27.5
Strong spin	7.5	2.3	0.08/0.14	35.6/69.7	0.03/4.4	0.1/25.6
Lower spin	3	3.5	0.8/1.61	7.7/48.2	0.06/5.2	0.1/42.2

In the case of a fixed position of the tee, the distribution of the landing point of the ball sent out can comprehensively reflect the variance of curvature, flight time and other indicators. Figure 8 shows the distribution of the landing point of the three kinds of difficulty serves received by the No. 1 trainee. It can be seen that the variance of the landing point of the three kinds of difficulty serves received by the subjects respectively, with a range of values of 0.98 to 1.32, which can be used as a reference for the stability of the ball, and the slight topspin and the bottomspin of the serve stability is better than strong topspin. It can be guessed that smaller server speeds have higher stability.

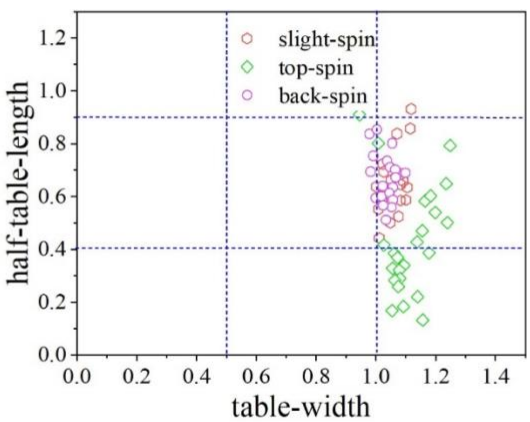


Figure 8. The fall point distribution of three difficult serve received by the trainee

4.2.2 Analysis of return quality in physical education

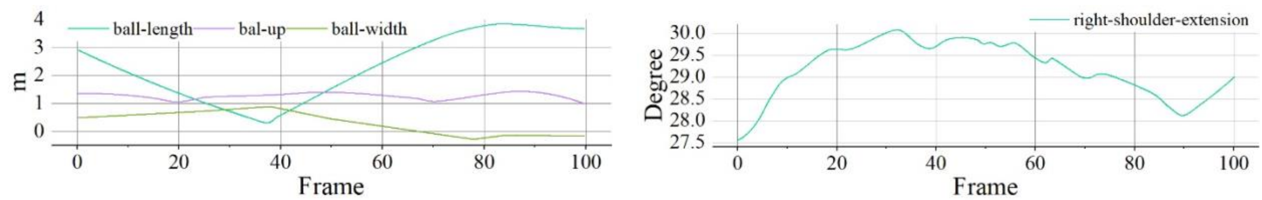
In order to better compare the catch and return levels of the four trainees, the mean values of the return metrics and the return success rates of the four subjects under slight topspin and strong topspin and downspin serves are shown in Table 3. Curvature Cu/m is the distance from the highest point of the ball flight arc to the table, the horizontal distance Hd/m is the horizontal straight line distance from when the ball leaves the racket to when it falls to the opponent's table, flight time Ft/s is the flight time from when the ball leaves the racket to when it falls to the opponent's table, offset distance Ot/m is the deviation of the landing point calculated according to the ideal parabola after the ball leaves the racket from the actual landing point, racket acceleration $Ra/m/s^2$ is the instantaneous acceleration of the racket before touching the ball, and the success rate of return RT is the ratio of the success rate of return to total shots. 6 is the ratio of the return success rate to the total number of balls hit. The higher the value of each index, the higher the trainee's ability to catch and return the ball. The treatment of Ft and Ot is to promote the athlete's level to grow in the same direction as the four indicators. Subject No. 1 scored higher in the indicators positively correlated with the skill level, such as speed, rotation, and power, and was able to have a high return rate under all three serving difficulties, indicating that subject No. 1 had the highest level among all subjects, with Ft values of 0.27 and Ot of -0.14. Subjects No. 3 and No. 4 subjects had relatively low scores on the relevant indicators, which is consistent with the actual situation. The main indexes constituting the first group of principal components of strong topspin are curvature Cu and flight time Ft, and the main indexes constituting the first group of principal components of bottom spin data are flight time Ft and racket acceleration Ra. Therefore, it can be preliminarily determined that the differences in the quality of catch and return among the four subjects are mainly reflected in the speed, i.e., the time from the time when the ball leaves the racket to the time it falls to the opponent's table is different, and still the horizontal distribution of the standard of the movement is consistent with the actual situation, which proves that the design of the paper is consistent with the actual situation. The actual situation is consistent with the actual situation, which proves that the system and algorithm designed in the paper are effective under small samples and lays a good foundation for more comprehensive and accurate sports teaching movement evaluation and feedback afterward.

Table 3. Return ball quality analysis

No	*Cu / m*			*Hd / m*			*Ft / s*		
	slight-spin	top-spin	back-spin	slight-spin	top-spin	back-spin	slight-spin	top-spin	back-spin
1	0.26	0.32	0.22	2.28	2.34	2.33	0.35	0.33	0.27
2	0.34	0.41	0.25	2.26	2.18	2.01	0.44	0.43	0.51
3	0.34	0.48	0.61	1.94	2.08	2.47	0.47	0.51	0.62
4	0.32	0.32	0.28	2.21	2.31	2.28	0.33	0.34	0.46
No	*Ot / m*			$Ra / m / s^2$			*RT*		
	slight-spin	top-spin	back-spin	slight-spin	top-spin	back-spin	slight-spin	top-spin	back-spin
1	-0.31	-0.21	-0.14	137	56.7	197	0.76	0.78	0.66
2	0.54	-0.53	-0.71	36.8	65.8	51.5	0.81	0.51	0.53
3	-0.57	-0.14	-0.23	14.1	17.1	15.5	0.47	0.31	0.22
4	-0.24	-0.38	-0.78	82.1	73.2	48.1	0.34	0.25	0.32

4.2.3 Assessment of movement standards in physical education

The results of the assessment of movement standardization in physical education are shown in Fig. 9, where (a)~(b) are the trajectory of the ball under the same round time slot and the trainee's right arm extension movement, respectively. The trainee's body movements are temporally correlated with the batting round, and the assessment of movement standardization refers to the assessment of movements corresponding to a particular batting round. An increase in the absolute value of the extension angle reflects the forward swing of the trainee's arm, and the moment of maximum extension corresponds to the moment of hitting the ball, with a ball width value of 3.79. If the value of the relevant movement index is within a reasonable threshold, the trainee is considered to have reached the corresponding movement standard, which is labeled as 1. Otherwise, the system marks the trainee as failing to meet the requirements of the index, which is labeled as 0, and gives a speech cue. Reminders. The trainee will be able to recognize the problem and make targeted corrections in future training or physical education.



(a) The trajectory of the ball at the same time (b) The trainee's right arm stretches

Figure 9. The results of action standard assessment in physical education

5 Conclusion

With the rapid development of computer technology and its continuous application in the field of teaching, it has become an inevitable trend to realize efficient and convenient teaching with the help of technology. Therefore, this paper proposes an evaluation system for teaching basic sports movements based on the DTW posture matching algorithm, aiming at realizing the extraction of deviated limbs and helping movement learners to correct their movements. These conclusions are drawn:

1) Through the empirical analysis of action recognition based on the DTW gesture matching algorithm, it is concluded that the AUC metrics of the four action categories all reach more than 0.8, and the micro-AUC and macro-AUC are about 0.985, which indicates that the DTW gesture matching algorithm takes into account the time-domain localization of sports actions and action classification, and makes the process of action recognition in physical education more intelligent and useful for the analysis of sports teaching videos. It is more intelligent and provides important application value for sports teaching and video analysis.

2) Through the empirical analysis of the evaluation system for teaching basic sports movements, it is concluded that subject No. 1 has the highest level among all subjects, with a Ft value of 0.27 and Ot of -0.14. Subjects No. 3 and No. 4 have relatively low scores on the relevant indexes, which is consistent with the actual situation. That is, it confirms the effective feasibility of the evaluation system for teaching basic movements in sports based on the DTW posture matching algorithm, which is of profound value for the research of digital recording and automated training in sports.

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