

Retraction

Retracted: The Importance of Traditional Sports into College Physical Education Based on Big Data Dynamic Programming Algorithm

Wireless Communications and Mobile Computing

Received 3 October 2023; Accepted 3 October 2023; Published 4 October 2023

Copyright © 2023 Wireless Communications and Mobile Computing. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external

researchers and research integrity experts for contributing to this investigation.

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

References

- [1] Z. Zheng, "The Importance of Traditional Sports into College Physical Education Based on Big Data Dynamic Programming Algorithm," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 2996940, 13 pages, 2021.

Research Article

The Importance of Traditional Sports into College Physical Education Based on Big Data Dynamic Programming Algorithm

Zhibin Zheng 

Jilin University, Changchun, Jilin 130012, China

Correspondence should be addressed to Zhibin Zheng; zhengzb@jlu.edu.cn

Received 13 August 2021; Accepted 20 September 2021; Published 29 October 2021

Academic Editor: Thippa Reddy G

Copyright © 2021 Zhibin Zheng. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Physical education teaching is conducive to the cultivation of students' lifelong sports consciousness, which can improve students' health and enhance their physique. In order to explore the importance of traditional sports based on big data dynamic programming algorithm into college physical education, the video action recognition and segmentation technology based on big data dynamic programming algorithm is designed. The complex actions in traditional sports teaching video are divided into a series of atomic actions with single semantics. The human action results are modeled according to the relationship between complex actions and atomic actions, and the actions are completed, and the changes of students' sports level were compared under different teaching modes. Compared with the no segment method, the average accuracy of the experimental design method increased by 2.80% and 3.50%, respectively, and the action recognition rate increased by 11.50%, 8.40%, 13.60%, 13.50%, and 13.60%, respectively. Before and after the experiment, there was a significant difference in the performance of the experimental group ($P = 0.021 < 0.05$). The results show that the traditional sports teaching mode based on video action recognition technology of big data dynamic programming algorithm can effectively improve the teaching quality of sports teaching. This research has a certain reference value to promote the current physical education teaching reform policy.

1. Introduction

Physical education can effectively enhance students' physique, cultivate their sports skills, and improve their health. Physical education is the main way for students to acquire sports technology and skills [1]. Professional sports video learning is an essential part of college physical education; students watch professional technical video repeatedly, analyze the athletes' actions in the video, and then establish the correct action representation, so as to lay a solid foundation for the cultivation of follow-up sports skills [2]. Aiming at the long PE teaching video, the big data dynamic programming algorithm is used to segment the video optimally and recognize the specific action of a single video segment [3]. For complex action video, a discriminant model with hidden variables is established to detect complex action and atomic action (single semantic meaning action decomposed from complex action), and the mapping matrix is used to reflect the many to one relationship between video segment and atomic action, so as to realize the goal of accurately identify-

ing complex action in video segment and reduce the difficulty of students' video learning [4].

For long and complex videos, Liu et al. put forward a time boundary regression method based on time series segmentation, which uses clustering algorithm to deal with the boundary regions of high-probability behaviors in time domain and combines the maximum inhibition method to formulate the segmentation scheme. Each behavior is described by the characteristics of three subsegments (proposal segment, start sub segment, and end subsegment), and the recognition rate of behavior actions reaches 30.1% [5]. Moving object recognition in video survey is a potential leap forward development opportunity among different PC vision system applications. Thangaraj and Monikavasagom have designed a robust video object detection and tracking technology, which is composed of detection stage, tracking stage, and evaluation stage. In the evaluation stage, video segment feature extraction and classification are realized, and texture-based features are obtained from the processed frames [6]. Semantic segmentation is a research hotspot in

the field of computer vision. Lyu et al. plan to capture the urban scene from the angle of inclined UAV and propose a new high-resolution UAV semantic segmentation data set UAVid data set, which is composed of 30 video sequences. At the same time, the feature extraction of corresponding images is realized by multiscale extended network [7]. Image segmentation is the main part of target recognition in image analysis. Its purpose is to identify the notification regions of images belonging to different targets. Combined with the region merging algorithm, Lian et al. proposed a noise robust edge detection technology based on anisotropic Gaussian kernel and obtained high-quality edge detection results. The experimental results show that it has good noise robustness and positioning accuracy [8]. Huang et al. expressed the object as shape and appearance and used it as the constraint of segmentation, so as to ensure that the object segmentation mask is consistent with the object area and the knowledge in the image [9].

Online segmentation and skeleton-based gesture recognition are very difficult, especially for incomplete gestures, whose early recognition easily falls into local optimum. Chen et al. use a temporal hierarchical dictionary to guide the decoding process of hidden Markov model and propose a measure called “relative entropy mapping,” which guides HMM decoding according to time context [10]. Gao et al. proposed a fiber recognition framework based on image segmentation, deep convolution neural network, and vision to segment overlapping and adhesive translucent fibers. The results show that the accuracy of multi fiber recognition strategy can reach 99.5% [11]. Saifuddin Saif et al. use convolutional neural network combined with compression function to extract spatial and temporal information features in image segmentation, which significantly improves the performance of human behavior recognition [12]. Reddy et al. studied two important dimensionality reduction techniques, linear discriminant analysis (LDA) and principal component analysis (PCA), on four popular machine learning (ML) algorithms [13]. Patil and Sunitha believe that in the dynamic video survey system, the location and detection of moving items in the video scene are very important, which are affected by obstacles, shadows, and noise. The basic development direction of the multicamera video survey system is the horizontal coordination and rerecognition of moving object detection and tracking on multiple cameras [14]. Ma and Song proposed a moving object detection method in H.264/AVC compressed domain for video surveillance applications, which uses H.264 to compress the information in the bit stream, while reducing the computational complexity and memory requirements, and completes the detection and segmentation of moving objects through motion vectors and quantization parameters [15].

It can be seen from the above research results that there are a lot of researches on dynamic video segmentation, human behavior recognition in video, video monitoring, and other different directions in the current society, but the research on big data dynamic programming algorithm for segmentation, recognition, and annotation of sports teaching video or professional athletes’ skill display video is limited. At the same time, most scholars ignore the role of

video action recognition technology based on big data dynamic programming algorithm in traditional sports teaching to a certain extent and lack of related research on the connection between video action recognition and college physical education. Therefore, the importance of video action recognition technology based on big data dynamic programming algorithm in traditional sports teaching in colleges and universities will be discussed. This paper is performed to discuss and analyze.

This paper is divided into four parts. The first part expounds the importance of traditional sports based on big data dynamic programming algorithm in college sports teaching, and the second part expounds the sports segmentation and recognition in sports video. The third part expounds the analysis content of the application effect of sports teaching video. The last part summarizes that the traditional physical education teaching mode of video action recognition technology based on big data dynamic programming algorithm can effectively improve the teaching quality of physical education. This study has a certain reference value for promoting the current physical education reform policy.

2. Motion Segmentation and Recognition in Sports Video

2.1. Action Segmentation and Recognition of Long Video. The complex actions in traditional physical education teaching video are divided into a series of atomic actions with single semantics. In this section, a structured discriminant model with hidden variables is designed, by which the continuous video stream is divided into a series of video segments with only a single action, and the action type of each video segment is marked.

The different states in the implicit state sequence in Figure 1 can reflect the potential semantic concepts in the corresponding unit video segment. In the model, an action is represented by the interaction among the learning video segment features, the contained latent semantic concepts, and action categories, and the corresponding temporal context between learning video segments is mined from the latent semantic level [16]. For the test video containing multiple actions, the big data dynamic programming algorithm is used to find the optimal video segment mode, and the video segment action category is judged [17].

The long video X is divided into a series of unit video segments, and the spatiotemporal feature x_t of each unit video segment is extracted. At this time, the long video $X = \{x_1, x_2, \dots, x_T\}$, the number of unit video segments T , and the video length are proportional [18]. If $S = \{s_1, s_2, \dots, s_M\}$ is a long video, X is divided into M video segments, and $Y = \{y_1, y_2, \dots, y_M\}$ belongs to the action tag of video segment, and $s_M = T$ exists, then the m th video segment is $X_M = X_{(s_{m-1}, s_m)} = \{x_{s_{m-1}+1}, \dots, x_{s_m}\}$, and its corresponding action tag is y_m . The state variable $H = \{h_1, h_2, \dots, h_T\}$ is introduced into the model, and the semantic meaning of unit video segment x_t is represented by h_t [19]. In this paper, we expect to learn a discriminant function $f_w(X)$, which can

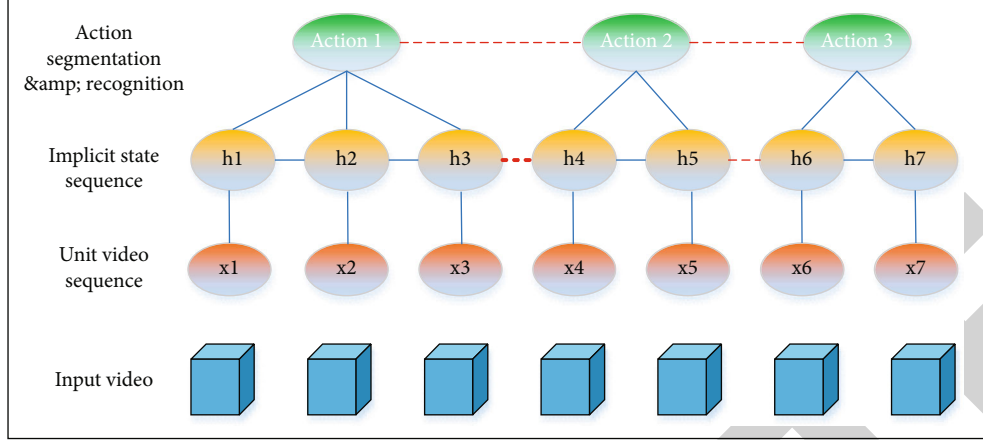


FIGURE 1: Schematic diagram of action segmentation and recognition method.

segment the video $X = \{x_1, x_2, \dots, x_T\}$ in $S = \{s_1, s_2, \dots, s_M\}$ mode and label the action tag $Y = \{y_1, y_2, \dots, y_M\}$:

$$f_w(X) = \max_{Y,S,H} F(X, Y, S, H) = \max_{Y,S,H} w^T \cdot \Phi(X, Y, S, H). \quad (1)$$

In equation (1), w is the model parameter, and the feature vector of the interaction among X , CC , DD , and EE is described by FF . GG is defined as the sum of several potential energies.

In equation (1), w is the model parameter; video X , video segment division S , video segment corresponding label Y , implied variable H , and the eigenvector of the interaction among the four variables are described by $\Phi(X, Y, S, H)$. $w^T \cdot \Phi(X, Y, S, H)$ is defined as the sum of several potential energies.

$$\begin{aligned} w^T \cdot \Phi(X, Y, S, H) = & \sum_{m=1:M} \alpha^T \cdot \phi_1(X_m, y_m) \\ & + \sum_{m=1:M} \beta^T \cdot \phi_2(X_m, H_m) \\ & + \sum_{m=1:M} \gamma^T \cdot \phi_3(y_m, H_m) \\ & + \sum_{m=1:M} \eta^T \cdot \phi_4(H_{m-1}, H_m) \\ & + \sum_{m=1:M} \delta^T \cdot \phi_5(y_{m-1}, y_m). \end{aligned} \quad (2)$$

In equation (2), $w = \{\alpha; \beta; \gamma; \eta; \delta\}$ is the model parameter. The potential energy functions shown in equations (3), (4), and (5) are only related to the video segment containing a single action.

$$\alpha^T \cdot \phi_1(X_m, y_m) = \sum_{y'} \alpha_{y'}^T \cdot X_m \cdot I(y_m = y'). \quad (3)$$

Equation (3) evaluates the matching degree between the global feature X_m of the whole video segment and the action category template of the video segment, where $\alpha_{y'}$ is the classi-

fication template of action y and $I(y_m = y')$ is the indicator function; when $y_m = y'$, then $I(y_m = y') = 1$, otherwise $I(y_m = y') = 0$.

$$\beta^T \cdot \phi_2(X_m, H_m) = \sum_{t=s_{m-1}+1:s_m} \sum_{h'} \beta_{h'}^T \cdot x_t \cdot I(h_t = h'), \quad (4)$$

$$\begin{aligned} \gamma^T \cdot \phi_3(y_m, H_m) = & \sum_{y'} \sum_{t=s_{m-1}+1:s_m} \sum_{h', h''} \gamma_{y' h' h''}^T \cdot I(y_m = y') \\ & \cdot I(h_t = h') \cdot I(h_{t+1} = h''). \end{aligned} \quad (5)$$

Formula (4) reflects the constraint relationship between local features and latent semantic state of video segment. Formula (5) is the modeling of cooccurrence relationship between the overall action category and the corresponding implied state of a video segment, reflecting the semantic constraints between two unit video segments in the sequential adjacent state of a certain action [20].

$$\eta^T \cdot \phi_4(H_{m-1}, H_m) = \sum_{h'} \sum_{h''} \eta_{h' h''}^T \cdot I(h_{s_{m-1}} = h') \cdot I(h_{s_{m-1}+1} = h''), \quad (6)$$

$$\delta^T \cdot \phi_5(y_{m-1}, y_m) = \sum_{y'} \sum_{y''} \delta_{y' y''}^T \cdot I(y_{m-1} = y') \cdot I(y_m = y''). \quad (7)$$

Formula (6) is the potential energy function based on the relationship between adjacent video segments X_m and X_{m+1} in the semantic concept level, and formula (7) is the potential energy function based on the relationship between adjacent video segments X_m and X_{m+1} in the action category level. Before segmenting the whole long video X , first, understand the best segmentation method of the first u unit video segments $\{x_1, x_2, \dots, x_u\}$ of X [21]. If the action label of the U th unit video segment $\{x_1, x_2, \dots, x_u\}$ is y and the corresponding hidden state is h , the best segmentation method can be

described by the function $g(X, h, y, u)$, and the maximum potential energy function value can be taken at this time [22].

$$\begin{aligned}
g(X, h, y, u) &= \max_{h_{u-}, y_{-}, u_{-}} \{g(X, h_{u-}, y_{-}, u_{-}) \\
&\quad + \theta(X_{u-+1:u}, H_{u-+1:u}, y, y_{-}, h_{u-})\} \\
&= \max_{h_{u-}, y_{-}, u_{-}} \{g(X, h_{u-}, y_{-}, u_{-}) \\
&\quad + \max_{H_{u-+1:u-1}} \theta(X_{u-+1:u}, H_{u-+1:u}, y, y_{-}, h_{u-})\}, \tag{8}
\end{aligned}$$

$$\begin{aligned}
&\theta(X_{u-+1:u}, H_{u-+1:u}, y, y_{-}, h_{u-}) \\
&= \alpha^T \cdot \phi_1(X_{u-+1:u}, y) + \beta^T \cdot \phi_2(X_{u-+1:u}, H_{u-+1:u}) \\
&\quad + \gamma^T \cdot \phi_3(y, H_{u-+1:u}) + \eta^T \cdot \phi_4(h_{u-}, h_{u-+1}) \\
&\quad + \delta^T \cdot \phi_5(y_{-}, y). \tag{9}
\end{aligned}$$

Equation (8) gives the incremental form of the function $g(X, h, y, u)$ and defines the relationship between it and the function value $g(X, h_{u-}, y_{-}, u_{-})$ of the previous video segment. Suppose that the last unit video in the previous video segment is x_{u-} , which meets the condition $l_{\min} \leq u - u_{-} \leq l_{\max}$. h_{u-} is used to reflect the hidden state of x_{u-} , and y_{-} is used to represent the action tag of x_{u-} , where l_{\min} and l_{\max} are the minimum length and the maximum length of an action in turn [23]. The model is trained by a set of videos $\{(X^i, S^i, Y^i)\}_{i=1:N}$ marked with action segments and their categories, including long video X^i , real video segmentation S^i , and action label Y^i of each video segment. The training framework based on maximum interval is used to learn the model parameter w :

$$\begin{aligned}
&\min_w \quad 0.5 \|w\|^2 + C \cdot \sum_i \xi_i \\
\text{s.t.} \quad &\max_H w^T \cdot \Phi(X^i, S^i, Y^i, H) - \max_H w^T \cdot \Phi(X^i, Y, S, H) \\
&\geq \Delta[(Y^i, S^i), (Y, S)] - \xi_i, \forall i, Y, S. \tag{10}
\end{aligned}$$

In equation (10), the standard maximum interval constraint condition is used to constrain, and the model parameter w should reasonably divide the video and accurately label the action category of each video segment. ξ_i is the penalty factor, which acts on action segmentation and action recognition, and C is the penalty factor coefficient.

$$\Delta[(Y^i, S^i), (Y, S)] = \frac{1}{T} \cdot \sum_{t=1:T} I(\chi_t^i \neq \chi_t). \tag{11}$$

Equation (11) is the definition of loss function, where χ_t^i is the action tag of unit video segment x_t , determined by (Y^i, S^i) , and χ_t is the action tag of unit video segment x_t , determined by (Y, S) . In this case, the definition of function $g(X, h, y, u)$ is shown in the following equation:

$$\begin{aligned}
g(X, h, y, u) &= \max_{h_{u-}, y_{-}, u_{-}} \left\{ g(X, h_{u-}, y_{-}, u_{-}) + \frac{1}{T} \sum_{t=u-+1:u} \right. \\
&\quad \left. \cdot I(y \neq \chi_t^i) + \theta(X_{u-+1:u}, H_{u-+1:u}, y, y_{-}, h_{u-}) \right\} \\
&= \max_{h_{u-}, y_{-}, u_{-}} \left\{ g(X, h_{u-}, y_{-}, u_{-}) + \frac{1}{T} \sum_{t=u-+1:u} I(y \neq \chi_t^i) \right. \\
&\quad \left. + \max_{H_{u-+1:u-1}} \theta(X_{u-+1:u}, H_{u-+1:u}, y, y_{-}, h_{u-}) \right\}. \tag{12}
\end{aligned}$$

2.2. Complex Action Analysis Based on Semantic Decomposition. Sports teaching video contains a series of complex movements, such as “three-step layup” and “triple jump.” Complex actions consist of a series of simple actions with a single semantic, which are called “atomic actions” in this section.

Figure 2 shows the expression of an action video through complex actions, atomic actions contained in complex actions, and video segments of atomic actions. A discriminant model with hidden variables is used to show the relationship among high-level action categories, middle-level atomic actions, and low-level video segments. While detecting atomic actions in video, the temporal structure of atomic actions is discussed [24]. Then, the mapping matrix is introduced to associate the video segment with the atomic action, and the many to one correspondence between them is established; that is, multiple video segments show the same atomic action.

Let the training sample set be $\{(x^n, y^n, h^n) | n = 1, 2, \dots, N\}$, x^n and y^n to represent the n th video and the complex action category that the video belongs to. The atomic action of the video is marked as $h^n = [h_1^n, h_2^n, \dots, h_V^n]$. When the i th atomic action appears in the video, there is $h_i^n = 1$ and vice versa $h_i^n = 0$. The mapping matrix between video segment and atomic action is used as the hidden variable $\{g^n | n = 1, 2, \dots, N\}$ in the model [25].

$$f_w(X) = \max_{y, h, g} F(x, y, h, g) = \max_{y, h, g} w^T \cdot \Phi(x, y, h, g). \tag{13}$$

Equation (13) is the prediction function of expected learning, and the eigenvectors of the relationships among video x , complex action y , atomic action h , and mapping matrix g are described by $\Phi(x, y, h, g)$. Firstly, the video segment atomic action mapping matrix is established, the atomic action h of video x is labeled as h , and the video x is divided into equal size r subvideo segment $x = [x_1, x_2, \dots, x_r]$, and the mapping matrix $g = \{g_{ij}, i = 1, 2, \dots, N; j = 1, 2, \dots, V\}$ is introduced [26]. If the i th video segment is labeled as the j th atomic action, there is $g_{ij} = 1$, otherwise $g_{ij} = 0$. Then, the model is built according to the relationship among video segment, atomic action, and complex action category, as shown in the following equation:

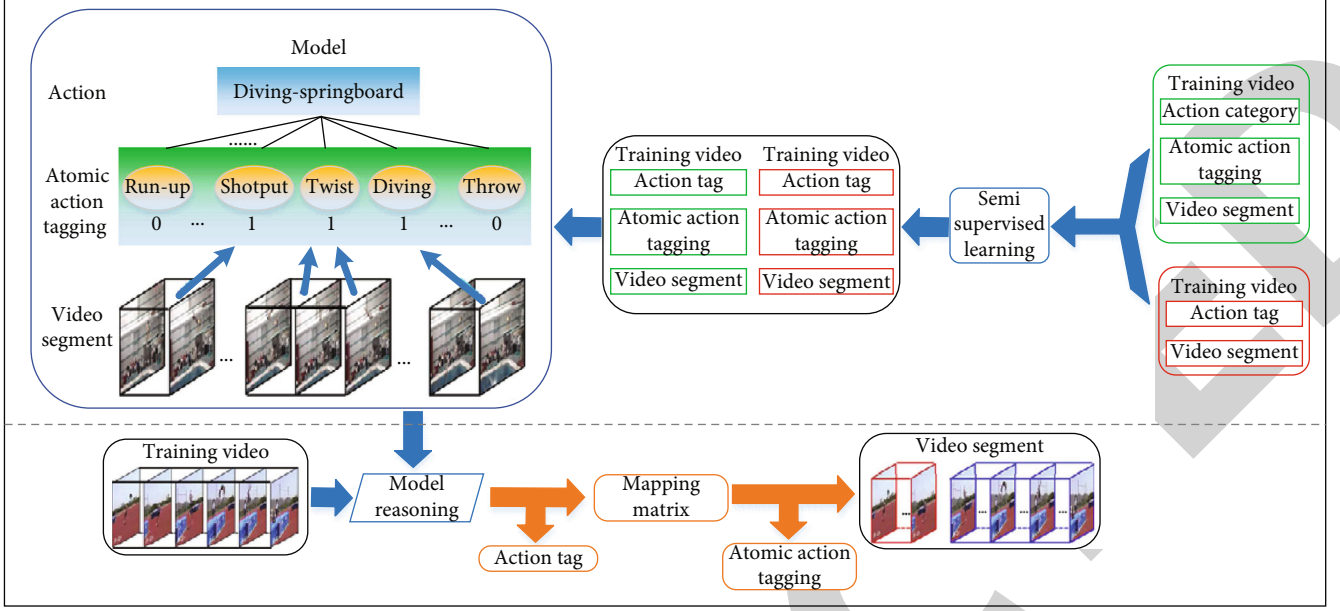


FIGURE 2: Complex action analysis method based on semantic decomposition.

$$w^T \cdot \Phi(x, y, h, g) = \alpha^T \phi(x, g) + \beta^T \psi(x, y) + \gamma^T \varphi(h, y). \quad (14)$$

Equation (14) is the potential energy function $w^T \cdot \Phi(x, y, h, g)$ and the model parameter $w = (\alpha; \beta; \gamma)$.

$$\alpha^T \phi(x, g) = \sum_{i=1}^R \sum_{j=1}^V \alpha_j^T \cdot x_i \cdot g_{ij}. \quad (15)$$

Equation (15) is a video segment atomic action interaction model, which reflects the matching degree between video segment and atomic action. The template of the j th atomic action is α_j , the feature of the i th video segment is x_i , and there is a constraint $\max_i g_{ij} = h_j$.

$$\beta^T \psi(x, y) = \beta_y^T \cdot x. \quad (16)$$

Equation (16) shows the matching degree between the video x and the action template and uses the standard linear model to predict the possibility that the video x belongs to the action y .

$$\gamma^T \varphi(h, y) = \sum_{j=1}^V [\gamma_{j,1}^y \cdot h_j + \gamma_{j,0}^y \cdot (1 - h_j)]. \quad (17)$$

Formula (17) shows the semantic relationship between atomic actions and complex actions. Different complex actions have different decomposition modes, and different videos of the same complex action have different decomposition modes. The training set $\{(x^n, y^n, h^n) | n = 1, 2, \dots, N\}$ and learning parameter W are given to train the model, and the SVM framework with hidden variables is used to learn the model parameter W :

$$\min_{w, \xi^n} 0.5 \|w\|^2 + C \sum_{n=1}^N \xi^n$$

$$\begin{aligned} \text{s.t.} \quad & \max_g w^T \cdot \Phi(x^n, y^n, h^n, g) - \max_g w^T \cdot \Phi(x^n, y, h, g) \\ & \geq \Delta[(y^n, h^n), (y, h)] - \xi^n, \forall n, \forall y, \forall h. \end{aligned} \quad (18)$$

In equation (18), $\Delta[(y^n, h^n), (y, h)]$ predicts the loss function of tag (y, h) with video x^n , and the definition of the loss function is $\Delta[(y^n, h^n), (y, h)] = \ell(y^n, y) + \sum_{j=1}^V \ell(h_j^n, h_j)$, with

$$\ell(a, b) = \begin{cases} 1, & \text{if } a \neq b, \\ 0, & \text{if } a = b. \end{cases} \quad (19)$$

In the test stage, the model is used to predict the complex action category y^* of video X and the atomic action annotation h^* , with $(y^*, h^*) = \arg \max_{y, h} [\max_g w^T \Phi(x, y, h, g)]$ [27].

The big data dynamic programming algorithm is used to complete the segmentation and recognition of each action in sports video. Students can improve their mastery of sports professional skills and enrich the content of college sports teaching by marking the unit video segment.

As shown in Figure 3, in the teacher's position, teachers can play sports-related action videos during the teaching process and explain the key points and difficulties of corresponding professional sports actions to students according to the video segment labels, so as to clarify the demonstration points of professional sports. From the perspective of students' position, students follow the teacher's explanation, master the way and focus of watching the video, mark the main points of action, and then communicate with each other and practice in groups [28].

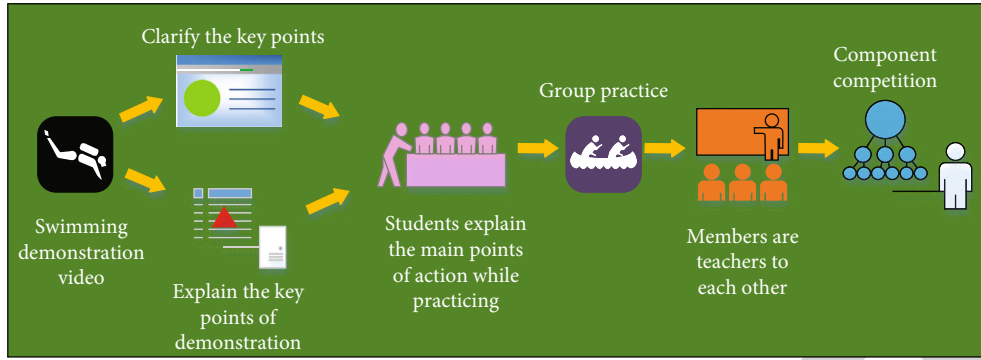


FIGURE 3: High-efficiency physical education teaching with sports video.

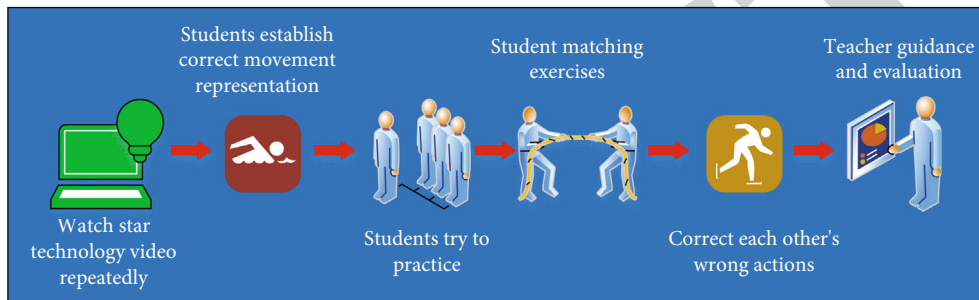


FIGURE 4: The cultivation of students' ability to correct mistakes.

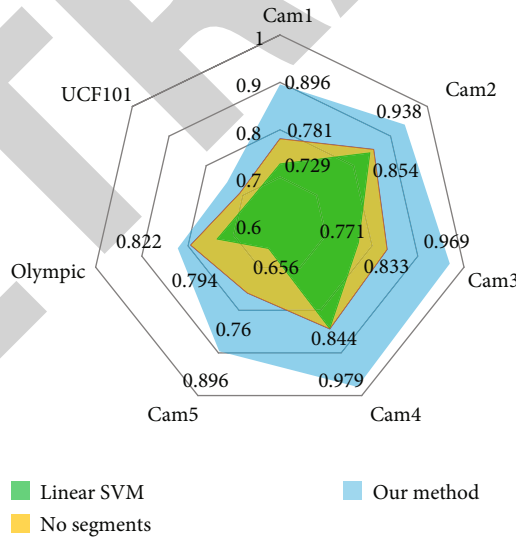
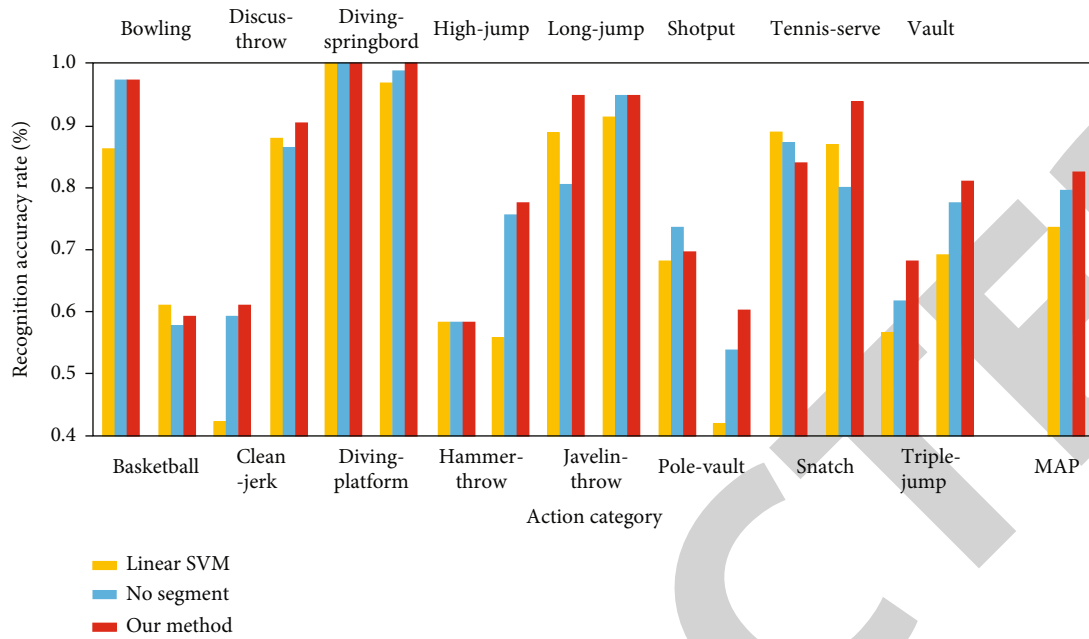


FIGURE 5: Comparison of action recognition results on three databases.

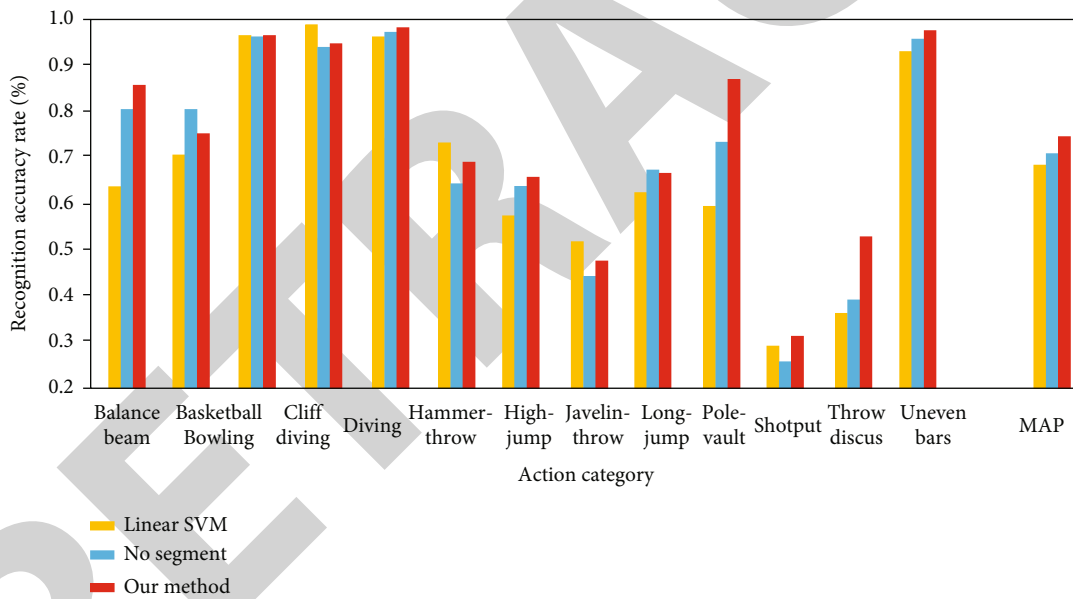
As shown in Figure 4, students can watch and learn professional sports videos repeatedly and initially establish correct action representation. The annotation of single action in video segments, combined with mutual communication and action practice between students, can gradually correct the action errors in the learning process. At the same time, according to the content of the teaching video, teachers pay for the wrong actions of students [29].

3. Analysis on the Application Effect of Sports Teaching Video

3.1. Sports Video Action Recognition Effect. Two reference algorithms are set up. The first one uses linear SVM classifier to classify video features, which is called linear SVM algorithm for short. The second is the simplification of the algorithm described in Section 2, which constructs the model of



(a) Effect comparison of several methods for action recognition on the Olympic dataset



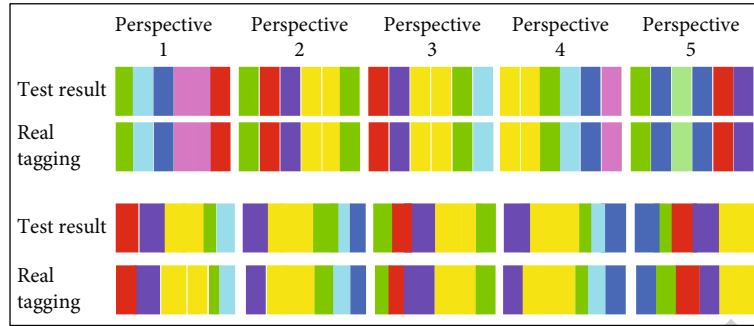
(b) Effect comparison of several methods for action recognition on the UCF101 dataset

FIGURE 6: Comparison of recognition effects of different types of actions on two data sets.

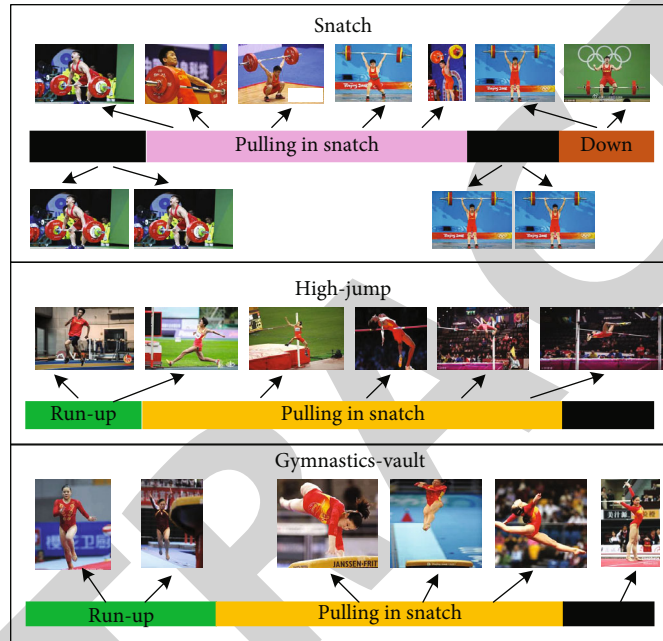
the relationship between complex actions and atomic actions through the structured SVM framework. This method does not consider the video segmentation features and ignores the relationship between video segments and atomic actions, which is called no segments for short. The synthetic data set, Olympic data set, and ucf101 data set were selected to compare the action recognition rate (synthetic data set) and mean average precision (map) (Olympic data set and ucf101 data set) of the two reference algorithms and the design algorithm.

Figure 5 shows that the overall action recognition rate of no segment method is higher than that of linear SVM method on the composite data set, and the action recogni-

tion rates of different subdata sets are increased by 5.20% (CAM1), 1.00% (CAM2), 6.20% (CAM3), 0.00% (CAM4), and 10.40% (CAM5), respectively; the average accuracy of no segment method is higher than that of no segment method on the Olympic data set and ucf101 data set. The results show that the introduction of atomic action concept is conducive to learning more discriminative complex action classifier. Compared with the no segment method, the motion recognition rate of the experimental design method increased by 11.50% (CAM1), 8.40% (CAM2), 13.60% (CAM3), 13.50% (CAM4), and 13.60% (CAM5), and the average accuracy rate increased by 2.80% (Olympic data set) and 3.50% (ucf101 data set). To sum up, the effect of



(a) Temporal localization results of atomic actions on composite datasets



(b) Hierarchical description of complex actions on Olympic dataset

FIGURE 7: Effect analysis of complex action description in teaching video.

the proposed method is better than that of linear SVM and no segments, because the proposed method takes the relationship between complex actions and atomic actions into account and establishes the corresponding relationship between atomic actions and video segments to show the temporal structure of atomic actions.

Figure 6(a) shows the comparison results of the recognition effects of the linear SVM method, the no segment method, and the proposed method on the Olympic data set. It can be seen from Figure 6(a) that the recognition effect of the proposed method is better than that of the linear SVM method and no segment method for all action categories except pole vault. Figure 6(b) shows the results of the comparison of the recognition effects of 13 categories of actions on the ucf101 data set by the linear SVM method, no segment method, and the experimental method. On the whole, the experimental method has better action recognition effect.

Figure 7(a) compares the prediction results of the proposed method and the real atomic action annotation on the same video segment on several videos of the composite

data set. One of the colors corresponds to an atomic action, and the duration of atomic action is represented by color width. It can be seen that in most cases, the proposed method can achieve the goal of detecting atomic action in video and accurately locate the time sequence position of atomic action. Figure 7(b) shows an example of video description on the Olympic data set. Complex action categories are marked on the top of the time bar. The time bar is responsible for displaying the detected atomic actions. One color corresponds to one atomic action. Black means that the video segment is not associated with any atomic actions. Taking “high jump” as an example, it can be seen from Figure 7(b) that it can be divided into “run-up,” “somersault,” “landing,” and other three atomic actions, and the relationship between atomic actions and video segments is roughly correct; most black video segments are static or only contain irrelevant actions; different complex actions can share a group of atomic actions. According to the detailed description of complex movements in the video, teachers or students can accurately learn the professional sports skills, sports posture, and power way in sports.

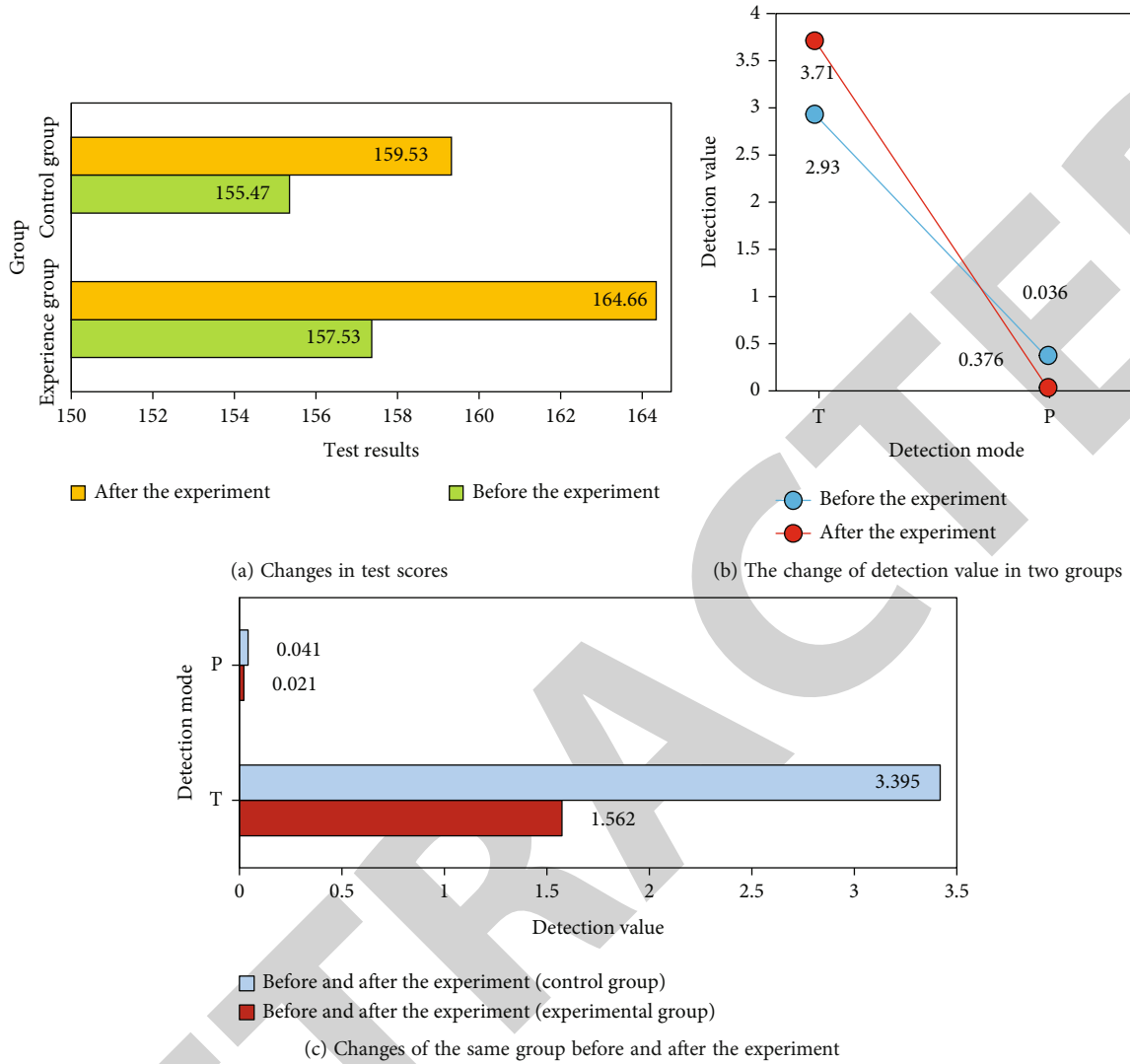


FIGURE 8: Before and after the experiment, the scores of the experimental group and the control group were compared.

3.2. The Effect of Application in College Physical Education.

In order to test the application effect of sports video segmentation and recognition technology in College Physical Education Teaching under big data dynamic programming algorithm and understand the importance of traditional sports in College Physical Education Teaching under big data dynamic programming algorithm, a college physical education major student is selected as the experimental object. After a period of teaching experiment, taking Fosbury Flop as a test item, the test results of the experimental group were compared with those of the control group.

The experimental group introduced the traditional sports video teaching link of sports video action recognition technology based on big data dynamic programming algorithm, while the control group taught in the normal way (no video action recognition). It can be seen from Figure 8 that before the experiment, there was no significant difference between the two groups ($P = 0.376 > 0.05$); after the experiment, there was a significant difference between the two groups (experimental group and control group)

($P = 0.036 < 0.05$), and there was a significant difference between the two groups ($P = 0.021 < 0.05$). It shows that the introduction of traditional sports based on big data dynamic programming algorithm can improve students' sports performance to a certain extent.

Sports skills are the ability that students in sports colleges and departments must master and also the important foundation for students to engage in sports-related work in the future. Therefore, in the introduction of traditional sports based on big data dynamic programming algorithm to cultivate students, we should pay attention to the improvement of sports-related students' professional skills. In order to verify the influence of the introduction of traditional sports based on the video action recognition technology of big data dynamic programming algorithm on the students' skill level, the change of students' skill level before and after the experiment is taken.

As shown in Figure 9, before the beginning of the teaching experiment, there was no significant difference in the skill level between the experimental group and the control

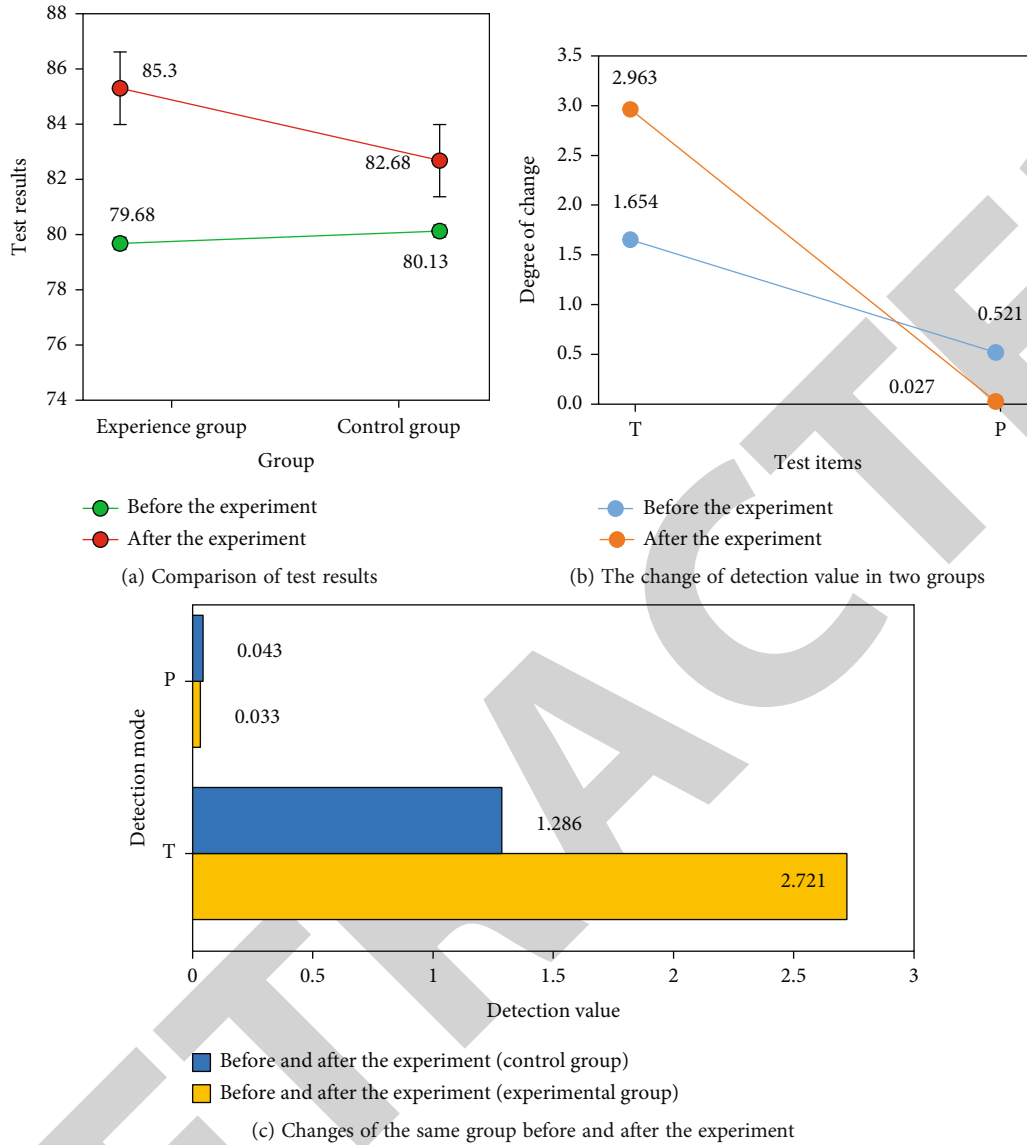


FIGURE 9: Comparison of technical evaluation between the experimental group and the control group before and after the experiment.

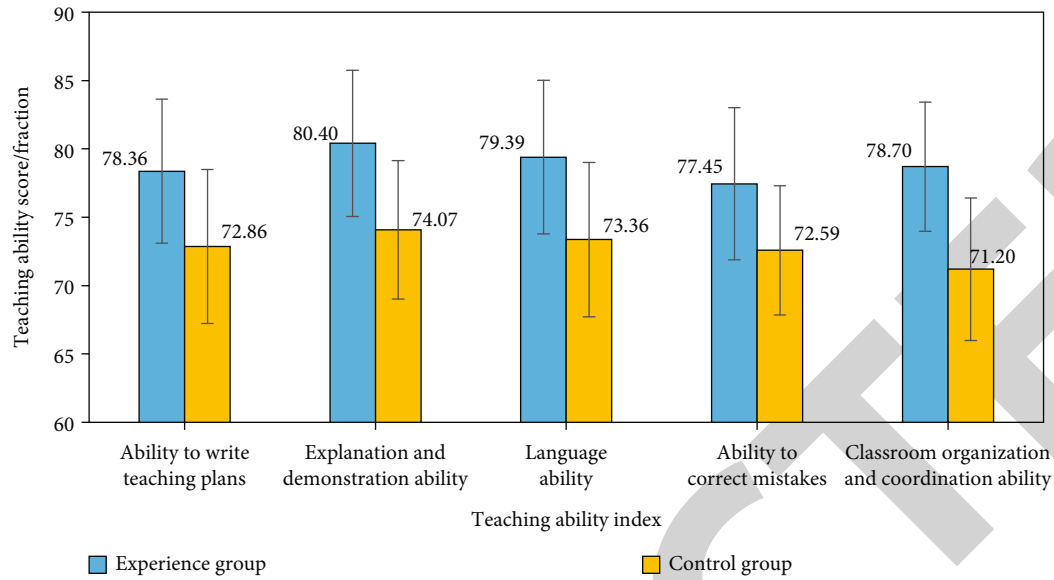
group ($P = 0.392 > 0.05$); after the end of the teaching experiment, there was a significant difference between the two groups ($P = 0.027 < 0.05$), there was a significant difference in the skill level of the students before and after the experimental group ($P = 0.033 < 0.05$), and there was a significant difference in the skill level of the students before and after the control group ($P = 0.043 < 0.05$), which shows that the progress of the experimental group is significantly stronger than that of the control group, indicating that the introduction of traditional sports based on big data dynamic programming algorithm video action recognition technology can effectively improve the students' skill level.

Figure 10 shows the comparison of teaching ability between the experimental group and the control group after the experiment. It can be seen from Figure 10 that after the experiment, under the guidance of the teaching mode of video action recognition technology based on big data

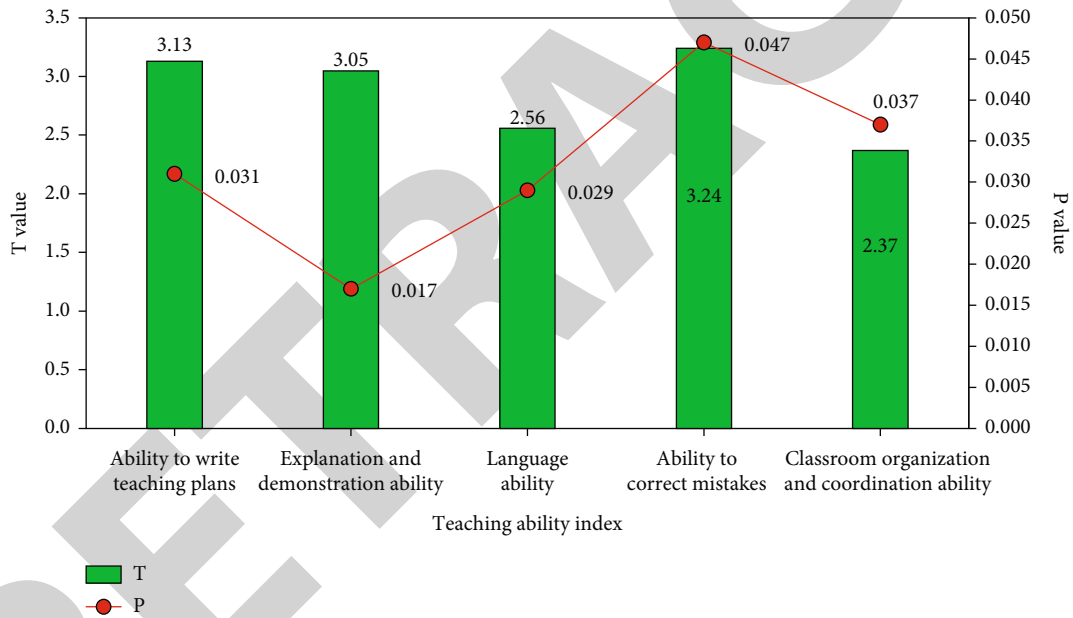
dynamic programming algorithm, the five teaching abilities of the experimental group have been improved, and the improvement of teaching ability is significantly higher than that of the control group ($P < 0.05$). The improvement of students' teaching ability is conducive to learning. The degree of mastering the students' professional ability is improved, and the employment probability is increased.

4. Conclusion

Physical education is an important part of school education. In order to verify the importance of traditional sports based on big data dynamic programming algorithm into college physical education, the video action recognition technology under big data dynamic programming algorithm is designed to recognize the action of traditional sports teaching video, guide students to watch and learn, and compare the changes



(a) Teaching ability score



(b) P value and T value of teaching ability score

FIGURE 10: Comparison of teaching ability between the experimental group and control group after experiment.

of students' sports level. Compared with the no segment method, the motion recognition rate of the experimental design method was increased by 11.50% (CAM1), 8.40% (CAM2), 13.60% (CAM3), 13.50% (CAM4), and 13.60% (CAM5), and the average accuracy rate was increased by 2.80% (Olympic data set) and 3.50% (ucf101 data set), respectively, with better effect of motion recognition and accurate video description. There was a significant difference in the achievement of motor standard ($P = 0.021 < 0.05$), and there was a significant difference in the skill level of the experimental group ($P = 0.033 < 0.05$). To sum up, the introduction of the traditional sports teaching mode of video action recognition technology based on big data

dynamic programming algorithm can effectively improve the teaching quality of physical education in colleges and universities and improve the level of students' professional sports skills. The experiment has achieved some results, but in the experiment, the initial segmentation of the video in the way of equal division easily causes the end of the previous atomic action combined with the beginning of the latter atomic action to be divided into the same video segment, resulting in wrong video segment annotation results. Therefore, a future research work is to improve the effectiveness of the initial video segmentation through the video segmentation method based on motion information.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no competing interest.

Acknowledgments

The project is supported by the “Research on the Construction of College Students’ Sports and Health Evaluation System, China (Grant No. 371202901405).”

References

- [1] A. Neuprez, J. F. Kaux, M. Locquet, C. Beaudart, and J. Y. Reginster, “The presence of erosive joints is a strong predictor of radiological progression in hand osteoarthritis: results of a 2-year prospective follow-up of the Liège Hand Osteoarthritis Cohort (LIHOC),” *Arthritis Research & Therapy*, vol. 23, no. 1, pp. 1–9, 2021.
- [2] M. A. Lopez-Gordo, N. Kohlmorgen, C. Morillas, and F. Pelayo, “Performance prediction at single-action level to a first-person shooter video game,” *Virtual Reality*, vol. 25, no. 3, pp. 681–693, 2021.
- [3] F. Gurkan and B. Günsel, “Integration of regularized L_1 tracking and instance segmentation for video object tracking,” *Neurocomputing*, vol. 423, pp. 284–300, 2021.
- [4] U. Cosimo, C. Matteo, and A. Alessio, “Neuroanatomical substrates of action perception and understanding: an anatomic likelihood estimation meta-analysis of lesion-symptom mapping studies in brain injured patients,” *Frontiers in Human Neuroscience*, vol. 8, p. 344, 2016.
- [5] J. Liu, C. Wang, and Y. Liu, “A novel method for temporal action localization and recognition in untrimmed video based on time series segmentation,” *IEEE Access*, vol. 7, pp. 135204–135209, 2019.
- [6] M. Thangaraj and S. Monikavasagom, “A competent frame work for efficient object detection, tracking and classification,” *Wireless Personal Communications*, vol. 107, no. 2, pp. 939–957, 2019.
- [7] Y. Lyu, G. Vosselman, G. S. Xia, A. Yilmaz, and M. Y. Yang, “UAVid: a semantic segmentation dataset for UAV imagery,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 165, pp. 108–119, 2020.
- [8] J. Lian, K. Jia, Y. Li, Q. Zhang, Z. Zhang, and B. Zhang, “Area segmentation of images using watershed and anisotropic Gaussian kernels,” *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 33, no. 04, p. 1954012, 2019.
- [9] W. Huang, H. Yu, W. Zheng, and J. Zhang, “A framework to coordinate segmentation and recognition,” *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, pp. 8473–8480, 2019.
- [10] H. Chen, X. Liu, J. Shi, and G. Zhao, “Temporal hierarchical dictionary guided decoding for online gesture segmentation and recognition,” *IEEE Transactions on Image Processing*, vol. 29, pp. 9689–9702, 2020.
- [11] F. Gao, J. Lin, H. Liu, and S. Lu, “A novel VBM framework of fiber recognition based on image segmentation and DCNN,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 4, pp. 963–973, 2020.
- [12] A. F. M. Saifuddin Saif, M. A. Shahriar Khan, A. Mohammad Hadi, R. Prashad Karmoker, and J. Julian Gomes, “Aggressive action estimation: a comprehensive review on neural network based human segmentation and action recognition,” *International Journal of Education and Management Engineering*, vol. 9, no. 1, pp. 9–19, 2019.
- [13] G. T. Reddy, M. P. K. Reddy, K. Lakshmana et al., “Analysis of dimensionality reduction techniques on big data,” *IEEE Access*, vol. 8, pp. 54776–54788, 2020.
- [14] C. M. Patil and Y. N. Sunitha, “A review of the multiple object detection, tracking and recognition in video surveillance systems using different approaches,” *Restaurant Business*, vol. 118, no. 7, pp. 34–43, 2019.
- [15] M. Ma and H. Song, “Effective moving object detection in H.264/AVC compressed domain for video surveillance,” *Multimedia Tools and Applications*, vol. 78, no. 24, pp. 35195–35209, 2019.
- [16] M. J. Hussain, S. H. Wasti, G. Huang, L. Wei, Y. Jiang, and Y. Tang, “An approach for measuring semantic similarity between Wikipedia concepts using multiple inheritances,” *Information Processing & Management*, vol. 57, no. 3, p. 102188, 2020.
- [17] S. Jain, K. R. Seeja, and R. Jindal, “A new methodology for computing semantic relatedness: modified latent semantic analysis by fuzzy formal concept analysis,” *Procedia Computer Science*, vol. 167, pp. 1102–1109, 2020.
- [18] R. L. Moseley and F. Pulvermüller, “What can autism teach us about the role of sensorimotor systems in higher cognition? New clues from studies on language, action semantics, and abstract emotional concept processing,” *Cortex*, vol. 100, pp. 149–190, 2018.
- [19] A. Tejero-de-Pablos, Y. Nakashima, T. Sato, N. Yokoya, M. Linna, and E. Rahtu, “Summarization of user-generated sports video by using deep action recognition features,” *IEEE Transactions on Multimedia*, vol. 20, no. 8, pp. 2000–2011, 2018.
- [20] F. R. Dreyer and F. Pulvermüller, “Abstract semantics in the motor system? –an event-related fMRI study on passive reading of semantic word categories carrying abstract emotional and mental meaning,” *Cortex*, vol. 100, pp. 52–70, 2017.
- [21] X. Jiang, J. Yang, X. Tan, and H. Xi, “Observation-based optimization for POMDPs with continuous state, observation, and action spaces,” *IEEE Transactions on Automatic Control*, vol. 64, no. 5, pp. 2045–2052, 2019.
- [22] Y. Zhan, S. Dai, Q. Mao et al., “A video semantic analysis method based on kernel discriminative sparse representation and weighted KNN,” in *IEEE international conference on Green Computing & Communications, IEEE & Internet of things*, pp. 1360–1372, 2015, IEEE.
- [23] L. Y. Tarhan, C. E. Watson, and L. J. Buxbaum, “Shared and distinct neuroanatomic regions critical for tool-related action production and recognition: evidence from 131 left-hemisphere stroke patients,” *Journal of Cognitive Neuroscience*, vol. 27, no. 12, pp. 2491–2511, 2015.
- [24] A. Mubashar, K. Asghar, A. R. Javed et al., “Storage and proximity management for centralized personal health records using an IPFS-based optimization algorithm,” *Journal of Circuits, Systems and Computers*, p. 2250010, 2021.
- [25] C. Beaudry, R. Peteri, and L. Mascarilla, “An efficient and sparse approach for large scale human action recognition in

- videos,” *Machine Vision and Applications*, vol. 27, no. 4, pp. 529–543, 2016.
- [26] J. Lei, G. Li, J. Zhang, Q. Guo, and D. Tu, “Continuous action segmentation and recognition using hybrid convolutional neural network-hidden Markov model model,” *IET Computer Vision*, vol. 10, no. 6, pp. 537–544, 2016.
- [27] J. Hou, X. Wu, Y. Sun, and Y. Jia, “Content-attention representation by factorized action-scene network for action recognition,” *IEEE Transactions on Multimedia*, vol. 20, no. 6, pp. 1537–1547, 2018.
- [28] X. Wang, D. Huang, and X. Zhao, “Design of the sports training decision support system based on improved association rule, the Apriori algorithm,” *Intelligent Automation and Soft Computing*, vol. 26, no. 4, pp. 755–763, 2020.
- [29] N. Kumar and N. Sukavanam, “A cascaded CNN model for multiple human tracking and re-localization in complex video sequences with large displacement,” *Multimedia Tools and Applications*, vol. 79, no. 9-10, pp. 6109–6134, 2020.