Research on the Application of Big Data in the Innovation of Physical Education Teaching Model

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Abstract

In view of the problem that traditional teaching scoring is often based on the experience of the scoring teacher, which results in imprecise scoring, this research proposes an intelligent recognition aerobics action scoring system based on big data. Firstly, the framework of the system is constructed, and the module for collecting 3D data is designed. Secondly, by supplementing and expanding the standard movements in MSR action 3D database, the aerobics evaluation database is established, and then the bone features and depth features are fused by using the principle of Fourier pyramid filtering. Finally, the fusion result data is classified by support vector machine to realize the design of Aerobics action recognition and evaluation function.

Keywords: *MSR Action3D; Aerobics; Action Recognition; Feature Fusion*

1.INTRODUCTION

With the increasingly prominent shortcomings of traditional physical education methods, there is an increasing need to realize physical education through information and intelligent methods. Traditional physical education often relies on the subjective experience of teachers in the fair competition and action scoring of sports movements, which leads to many teaching movements that cannot be effectively corrected. Therefore, how to build an action evaluation system that can be used for teaching based on big data and artificial intelligence technology has become the focus of current thinking and application.

At present, there are many innovative applications in physical education based on big data in academia. For example, Zhang Boyu (2020) proposed a method of human movement recognition based on points of interest in time and space [4], which improves the ability of human movement recognition, but cannot recognize combined movements; Fei Tingting (2020) Combining personalized modeling and depth data three-dimensional body pose estimation, increased the ability to recognize combined actions, but the efficiency is not satisfactory [5]. This research refers to the above literature, trying to build a teaching-oriented aerobics auxiliary review system design. In theory, the system can build a database of various difficulty combinations of aerobics, and establish an independent, fair and effective scoring system based on the database.

2.BUILD SYSTEM

2.1. System architecture

The system architecture is mainly composed of 5 parts, including: data processing layer, application layer, hardware layer, communication layer and data acquisition layer. The system architecture diagram is as follows:

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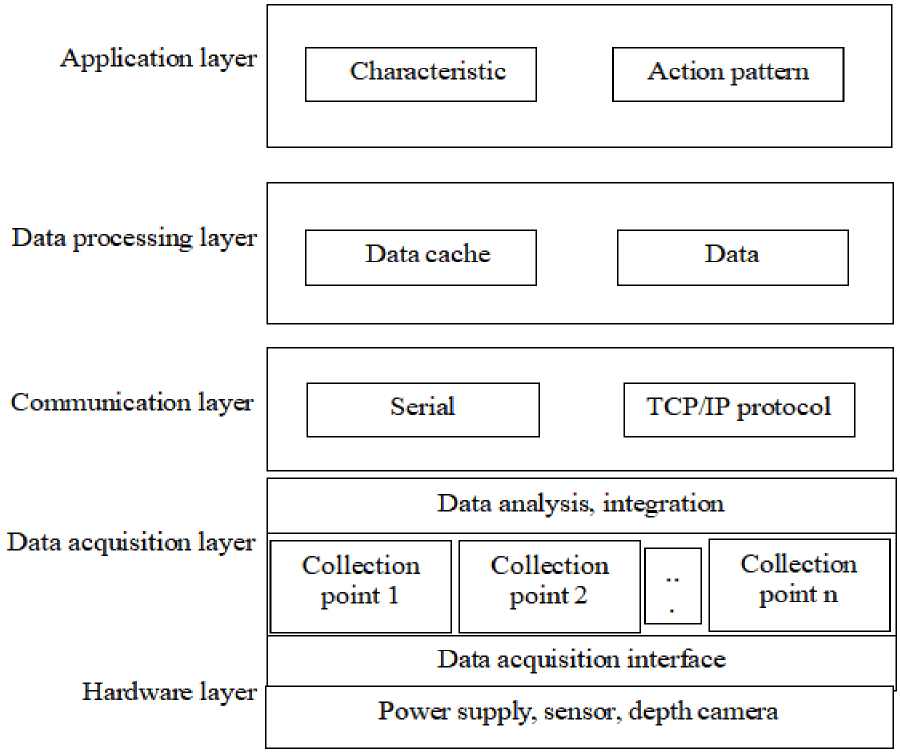

Figure 1. Schematic diagram of system architecture

As shown in Figure 1, the application layer includes characteristic signal analysis and action recognition functions, which can calculate and process the collected data to perform action recognition and auxiliary scoring. It is the core of the entire system function. The data acquisition layer will use its own several points and the data collection interface analyze and integrate the data uploaded to this layer. The communication layer uses the serial communication protocol and TCP/IP protocol to receive the data uploaded from the lower layer, and then transmits the data to the data processing layer to save, determine the order and filter the useless data [2]. The hardware layer collects initial physical information from nature through external hardware, including battery power, circuit sensors and three-dimensional vision data acquisition cameras.

2.2. Action data collection

The premise of motion recognition needs to collect data based on a variety of sensor systems, such as laser rangefinders, porous cameras, and microsoft KINECT. The microsoft KINECT sensor can better capture joint and Google feature data. The data collection process is shown in Figure 2:

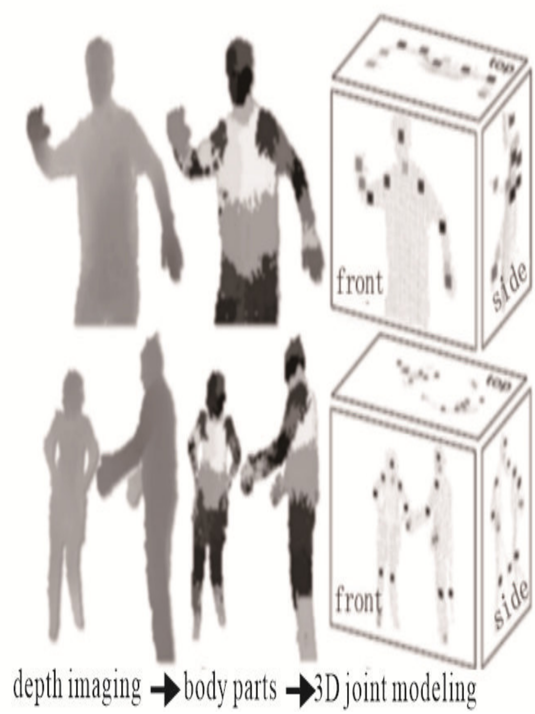

Figure 2. Architecture diagram of action data collection

The KINECT camera has an excellent depth imaging function. Even if a 640x480 resolution picture is taken at a frequency of 30 frames/s, the depth resolution is only a few centimeters. In addition, KINECT cameras are more suitable for photography and shooting in the first light environment than traditional sensors in the past, and the scale estimation and pose contours of the resulting photos are clearer. The most important thing is that the depth images taken by the camera can directly synthesize portraits, making the cost of building a training database not high. This study defines a part of the feature points of local body parts, which will cover the body parts on a large scale. Half of the feature points will be located at the designated joints, and the other half will be used to fill the gaps and predict the designated joints [6].

In this experiment, 31 body parts will be set for testing:

Head and neck LU, RU, LW and RW; Shoulders L/R; Arms LU, RU, LW and RW; Arms L/R; Trunk LU, RU, LW and RW; Legs L/R; Palms LU, RU, LW and RW; Wrist L/R; Ankle L/R; Foot L/R.

A simple operation in 3D modeling is to use a known calibration depth to model. However, edge pixels greatly reduce the estimation quality. Therefore, this paper uses a local search method based on a weighted Gaussian kernel. The depth model should be calibrated first in the process of building a 3D model. In the calibration process, once the edge pixels are of poor quality, the entire model will be affected. Therefore, this study uses the local search method based on the Gaussian kernel weighting to define the density of each part:

$$f_e(\hat{x}) \infty \sum_{i=1}^{N} w_{ic} \exp\left(-\left\|{(\hat{x}-\hat{x}_i)}\big/{b_c}\right\|\right) \tag{1}$$

In formula (1), $\hat{x}$、$\hat{x}_i$、b_c、ω_{ic} and N represent three-dimensional coordinates, pixel projection, learning bandwidth, pixel weight, and pixels, respectively. The mode at this density can be obtained by the average displacement, and then the final confidence estimation value can be obtained through the sum of the weight of each mode pixel. The detection mode is placed on the surface of the object to form a 3D model.

2.3. Action recognition and comparison

This method is based on depth features and bone joint features. Figure 3 shows the detailed identification steps.

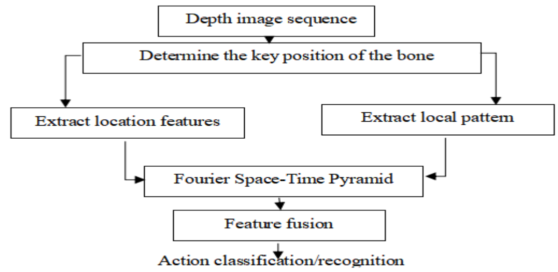

Figure 3. Flow chart of aerobics action recognition

When using the feature numbers of bones and joints to distinguish and recognize aerobics actions, the feature data should be robust. Therefore, the selection of bone and joint features should be based on location features. The calculation formula is as follows:

$$P_{i,k}^{t} = J_i^t - J_k^t \tag{2}$$

In formula (2), J_i^t represents the coordinate of the joint feature in the t-th group of data, and J_k^t is the coordinate of the k-th joint feature

The steps of extracting local bone joint features are: mapping depth images from 3D space to 4D space.

a. If the spatial point data exists, it is expressed as 1.

b. If the spatial point data does not exist, it is expressed as 0.

Because the existence of spatial point data is far greater than the nonexistent situation, it is uncommon to determine the features found by the local query feature pattern [1]. Then each depth image is divided into cubes with a volume of 1. Next, each depth image is then divided into cubes of 1 volume. Finally, the sigmoid standardization function is used to calculate the characteristics of each joint area, and the formula is as follows:

$$A_{xyz} = 1\Big/\left(1+e^{-\beta\sum_i u_i}\right) \tag{3}$$

In formula (3), A_{xyz} , β and u_i respectively represent the local feature value, standard constant and the data of the pixel point i in 4D space. If it exists, the value is 1, otherwise it is 0.

In this study, the three-layer Fourier space-time pyramid technology was selected to eliminate external interference in the process of taking images and collecting data from the KINECT camera, so that the accuracy of recognizing aerobics movements was improved. Suppose the bone joint feature unknown and the deep local feature matrix are denoted as

$U = ax$ and $V = by$ respectively. The correlation coefficients of the two matrices are denoted as:

$$corr(U,V)/(\delta_U \delta V) \tag{4}$$

In order to maximize the correlation coefficient, a specific set of U and V needs to be obtained, and then the optimal coefficient solutions of a and b are calculated. Finally, the matrix $\prod$ is defined as the combined vector covariance matrix of, which is expressed as follows:

$$\prod = Var\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} \prod_{11} \prod_{12} \\ \prod_{21} \prod_{22} \end{bmatrix} \tag{5}$$

According to the Lagrangian median method to solve the largest correlation coefficient a and b, we get:

$$\prod\nolimits_{11}^{-1} \prod\nolimits_{12} \prod\nolimits_{22}^{-1} \prod\nolimits_{21} a = \lambda^2 a \tag{6}$$

$$\prod\nolimits_{22}^{-1} \prod\nolimits_{21} \prod\nolimits_{11}^{-1} \prod\nolimits_{12} b = \lambda^2 a \tag{7}$$

After solving (6) and (7) to obtain the maximum values of correlation coefficients a and b, the two eigenvectors are combined to obtain the eigenmatrices U and V, and then the two eigen matrices are fused:

$$z = \begin{bmatrix} U \\ V \end{bmatrix} = \begin{bmatrix} a^T & \\ & b^T \end{bmatrix}^T \begin{bmatrix} x \\ y \end{bmatrix} \tag{8}$$

Then use support vector machine to identify and classify the fused action feature data. Suppose the sample provided to the support vector machine is $D_i =$ (x_i, y_i), x denoted as a feature vector, and y denoted as an action label. The distance between the input sample and the hyperplane is:

$$\delta_i = y_i(wx_i + b) \tag{9}$$

Finally, by minimizing the value $\|w\|$ to maximize the geometric interval, it will also minimize the number of misclassifications. Now considering the effect of noise, slack variables ξ are added while minimizing $\|w\|$ to ensure accuracy. In summary, all optimization problems can be expressed as:

$$\begin{aligned} &\min \ \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{l} \xi_i \\ &s.t.\ y_i\left[(wx_i) + b\right] \geq 1 - \xi_i \end{aligned} \tag{10}$$

In the formula（10）, l and C respectively represent the number of samples and the importance of the penalty factor to outliers. The larger the value of the calculation result of formula (10), the worse the optimization result, and vice versa. After using the support vector machine to classify and identify the features, the completion degree and difficulty of aerobics will be scored according to the database established in the next section.

3.BUILD A SCORING DATABASE

Based on the MSR Action3D database, this research will collect the athletes' difficult movements and add them to the database. Then, the scoring system of the database is combined with the Olympic Games scoring standard. The final score database constructed includes hundreds of aerobics pose sequences.

The MSR Action3D database is a commonly used database for 3D technology, providing bone data corresponding to more than 500 depth sequences. A variety of human movements can be constructed, such as basic movements like waving, squatting, and turning. These basic movements can be used as a breakdown of the various combined movements of aerobics [7].

In aerobics, movements of different difficulty can coexist to form a combination. Each combination will also be set with additional points for details and minimum completion. Taking group A as an example, the deductions are shown in Table 1:

Table 1. score reduction for group A with special difficulty errors

group A with special difficulty errors	Points reduction
Hand position adjustment	0.1
Shoulder and forearm are not in a horizontal line	0.1
The elbow is falling sideways and back in the wrong direction	0.3
"Vincent"-legs raised below the upper end of triceps or legs not on the arm	0.3
Completed full rotation and Thomas, but did not stand hip	0.3
Incomplete rotation	0.3
The helicopter ends in a straight-arm attitude	0.1

It can be seen that the establishment of the score database should contain more local actions, such as left and right rotation, up and down kicks and other movements. This can improve database functionality.

4.SYSTEM TESTING AND PERFORMANCE ANALYSIS

Based on the MSR Action3D database, this research adds and supplements a series of aerobics overall or decomposed actions [3]. Using the action characteristic data collected by the KINECT camera, performance analysis and system testing are now performed on the newly formed database. The local pattern features and bone joint features are extracted from the acquired data, and the 2-4 layer Fourier spatiotemporal pyramid technique mentioned above is used for denoising operation. After the denoising operation, feature fusion and classification recognition are performed, and the test results are shown in Table 2:

Table 2. System test result table

Difficulty group	Two-layer recognition	Three-layer recognition	Four-layer recognition
A-	78.6	85.2	96.0
A	79.1	88.7	98.1
B-	78.9	86.3	96.8
B	80.0	90.4	99.0
C-	78.8	86.0	95.9
C	78.9	89.0	98.4
D-	79.1	84.6	95.1
1)	79.8	89.9	99.1

In the table, A-, B-, C-, and D- represent the special deduction actions for each group. A, B, C, and D represent the minimum standard actions completed by each group.

It can be seen from the test results shown in Table 2 that the scoring system designed in this study still has a high action recognition function, and the accuracy calibration is also relatively good. At the same time, it also shows that the operation of feature fusion of depth characteristics and skeletal characteristics can effectively identify the action posture in aerobics.

5.CONCLUSIONS

In conclusion, the proposed scoring system for intelligent recognition of aerobics movements based on big data is feasible and effective. Through this system, the accurate recognition of complex actions can be realized. The experimental results show that in the recognition of special actions and standard actions, the recognition accuracy of this system for special actions can be up to 96.8%, the recognition accuracy of standard actions can be up to 99.1%. As can be seen, the recognition accuracy of the proposed system is high, and the system has a good ability to recognize and score aerobics movement. Comprehensive analysis shows that based on big data and action recognition algorithm, the intelligent auxiliary evaluation system of aerobics constructed in this paper can be vigorously promoted and applied in physical education scoring. The application of this system is conducive to ensuringthe fairness of physical competition in the future, and strict scoring can stimulate students' enthusiasm of sports competitions.

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