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Article

Research on Data-Driven Teaching Evaluation Methods for Dance Education Intelligent Platforms

Jing Wang *

Art Education Center, Zhengzhou University of Light Industry, Zhengzhou, Henan, 450002, China;
18569939397@163.com

Abstract: In this paper, a Springboot-based online learning service visualization and analysis system is first developed to show the overall situation of the dance education intelligent platform through visual analysis. A camera-aware Z-regression regression module is designed to realize gesture-based dance movement recognition. Unsupervised motion recognition based on S-SOFM neural network is proposed to complete dance movement evaluation using OE-DTW algorithm. The advantages of this system are verified through comparative tests and system application analysis. At the level of dance movement recognition, Z-regression performs optimally in all scenarios, and in the JHMDB dataset, the recognition rates of upper body, lower body and whole body reach 69.4%, 63.9% and 70.1%, respectively, which are significantly higher than that of RGB and Flow. Combined with the ratings of experts in the field of dance, the average Spearman correlation coefficient, ρ, of the system in this paper reaches 97.1%, which is able to effectively evaluate and analyze the dance movements.

Keywords: dance education; Z-regression; S-SOFM; dance movement recognition; dance movement evaluation

1. Introduction

Dance education is one of the important components of aesthetic education. As an important part of university quality education, dance education activities can not only cultivate students' aesthetic concepts and appreciation ability, make students form correct aesthetic concepts, and stimulate students' ability to create beauty, but also cultivate students' role consciousness and cooperation ability, and promote students' inner temperament shaping and intelligence level improvement [1-4]. Especially in the context of the new educational reform, dance education pays more attention to the cultivation of students' comprehensive ability [5]. By establishing a scientific evaluation system, it can collect more comprehensive information about students' comprehensive performance, help teachers understand students' learning status and needs, and then adjust teaching strategies to improve teaching quality [6-7].

With the advancement of education informatization, the field of education is committed to promoting the digital transformation of education, building an education intelligence platform, and promoting the digitalization of teaching, management, evaluation, service and other educational tasks [8-9]. Based on this background, dance education has also turned to the combination of online and offline education models, making full use of online and offline education data to achieve scientific teaching assessment [10]. The scientific all-round teaching assessment can enable teachers to understand the learning characteristics of each student more accurately, in addition to the level of dance skills, teachers can also observe the creativity, expressiveness, and teamwork ability shown by students in the process of dance learning, so that they can experience a sense of achievement, self-confidence, and stimulate the learning potential of students in the learning process [11-14]. However, colleges and universities are still using teaching evaluation based on teachers' experience, which makes it difficult to provide students with real-time and accurate teaching feedback. Literature [15] analyzed the problems of dance course evaluation in colleges and universities under the guidance of multiple intelligences theory, and emphasized the need to adopt a comprehensive intelligent evaluation framework and timely feedback mechanism in teaching evaluation. And data-driven teaching assessment precisely solves this problem.

Literature [16] proposed a mobile technology-enabled peer assessment method for assessing dance choreography courses, which improves the accuracy of assessment with objective attributes, and timely feedback among peers promotes the development among students. Literature [17] constructed a creative dance teaching assessment system, which processed relevant dance teaching data and then used fuzzy comprehensive evaluation method for teaching assessment, and the validation showed that the system had a better assessment effect. Literature [18], in order to assess the quality of classroom teaching in dance aesthetics education, used the probabilistic hesitant fuzzy set based on gray correlation analysis to eliminate the uncertainty in the data of assessment indexes, introduced information entropy to weight the indexes, and used the multi-attribute decision-making method for assessment. And the literature [19] provides a CIIC model based on CIIC soft rough set for the comprehensive assessment of dance teaching standards in colleges and universities, and the study adopts rough set and CIIC soft set to effectively deal with the ambiguity data in the evaluation data.

With the application of artificial intelligence and motion capture technology, data-driven assessment of teaching and learning achieves smarter support. Literature [20] provided an AI-assisted dance practice application, the mobile program was realized with the help of 3D pose assessment algorithm and reaction canvas video cropping and compression technology, the effectiveness of the application for dance teaching was evaluated by questionnaires and scales. Literature [21] constructed an artificial intelligence based framework for assessing the movement fluency of professional dancers, the framework contains the entire dance process data, with the help of performance algorithms, a comprehensive dance quality assessment is carried out, the framework will be based on the real-time analysis and assessment, based on real-time feedback. Literature [22] created a body-driven system which captures the data of dance body movement changes through wearable devices and introduces motion capture technology for movement recognition to provide a basis for dance teaching assessment. Literature [23] used a data-driven method based on clustering to transform lyrics and dance movements into symbols and analyzed the relationship between lyrics and dance movements, and this application can be used to assess students' dance works and provide a reference for teaching assessment. Literature [24] established a dance movement recognition and feedback model in dance teaching based on the graph attention mechanism and two-way gated loop unit model, which can effectively recognize and output effective feedback even for complex dance movements. Literature [25] senses data such as teaching information and teacher-student dialogues in dance education through a variety of digital technologies, and develops a teacher-student feedback mechanism, in which students can efficiently receive feedback given by the teacher and make timely adjustments to their mistakes. Literature [26] establishes teaching quality assessment indexes for online dance teaching and introduces an assessment model of back propagation neural network and particle swarm optimization algorithm, based on which teachers and students can improve teaching and learning based on this assessment feedback. Literature [27] used artificial intelligence technology to design a dance system integrating dance skill teaching, teaching assessment, and visual feedback, with the assistance of this system, students improved their dance skills and self-efficacy through online learning and timely assessment feedback.

In this paper, we first constructed a visualization analysis system relying on the online teaching platform of dance in a university. B/S architecture is adopted to realize the visual mining of teaching data. The Z-regression module is proposed for human posture estimation, which improves the traditional fully connected layer module. Utilizing 2D truth input with camera perception as the main task. Construct dance movement templates based on S-SOFM and measure movement similarity by Euclidean distance. Calculate the differences using the OE-DTW algorithm, and quantify the movement standardness by combining the normalized inner product. Multi-source databases are selected to verify the accuracy of the proposed method for dance movement recognition and assessment. Demonstrate the focus of movement assessment through Spearman's correlation coefficient and attention visualization. Introduce the comparison of dance expert ratings to evaluate the effectiveness of the system in this paper.

2. Design of a data-driven assessment system for teaching dance

With the deep integration of artificial intelligence technology and online education, dance education, as an important branch of art education, is in urgent need of intelligent means to enhance the scientific and precise nature of teaching evaluation. Dance teaching lacks an effective real-time feedback mechanism in remote or large-scale online teaching. To address this problem, this paper constructs a data-driven dance teaching evaluation system based on the data-driven teaching evaluation needs of dance education intelligent platform.

2.1. Construction of the Visualization and Analysis System

2.1.1. Data pre-processing

The data studied in this paper comes from the dance online teaching platform used by a university, with more than 300 courses, more than 120,000 users, and a total of more than 4 million visits to the system. By analyzing the database management system of the online course platform, it is found that the whole system consists of more than fifty data tables, and after eliminating the system operation support data tables that have nothing to do with teaching, 10 tables that are closely related to online teaching are exported, and the raw data of online teaching are shown in Table 1.

Table 1. Original data of online teaching.

Serial Number	Data table overview	Table name	Data volume
1	Teacher List	Octeacher	938
2	Community topic List	forumtopie	17037
3	Monthly course data record sheet	moocsummary	609
4	List of teaching units	Ocorg	45
5	Daily summary table of teaching units	ocrunsummary	264613
6	Community topic reply form	forumresponse	59366
7	Student table	Ocuser	9017
8	Daily record sheet of the teaching unit	Ocdata	603751
9	Course schedule	Oclog	518
10	User login log table	LogLogin	893827

After data cleaning, data conversion is performed. The original data of the teaching platform is stored in SQL Server, and this system is proposed to adopt the architecture of Java+MySQL for development, so it is necessary to import the data into MySQL database after converting the format from SQL Server. Use the data export function that comes with SQL Server to store the data as SQL files, and then use the import data function of the database management software Navicat for MySQL to restore the SQL files to the database structure, data tables and data.

2.1.2. Data mining

The purpose of data mining is to build a model from data, which mainly includes two categories: predictive model and descriptive model. In this paper, the purpose of data mining for online learning platforms is to build a descriptive model to discover the overall operational status of the platform since its launch, which can be used to assess the performance of all parties involved in online teaching and learning. Specific data mining methods in online education systems are divided into two categories: statistics and visualization and Web mining, which are used in this paper. Visualization (VS) visualizes information or knowledge, and visualization techniques can help people understand educational data more intuitively. The learning platform itself comes with a weak visualization and analysis function, for this reason this study developed a visualization and analysis system.

The system adopts the mainstream Browser/Server architecture, using Springboot technology, JDK8 (Java SE Development Kit8) as the development language, the front-end framework selects VUE component-based development framework, Element UI page rendering framework and jQuery framework, the back-end framework selects Springboot integrated development middleware framework, the database uses MySQL, data visualization and analysis framework selected Echarts, the implementation of front-end and back-end data interaction select Ajax asynchronous communication. The system architecture is shown in Figure 1.

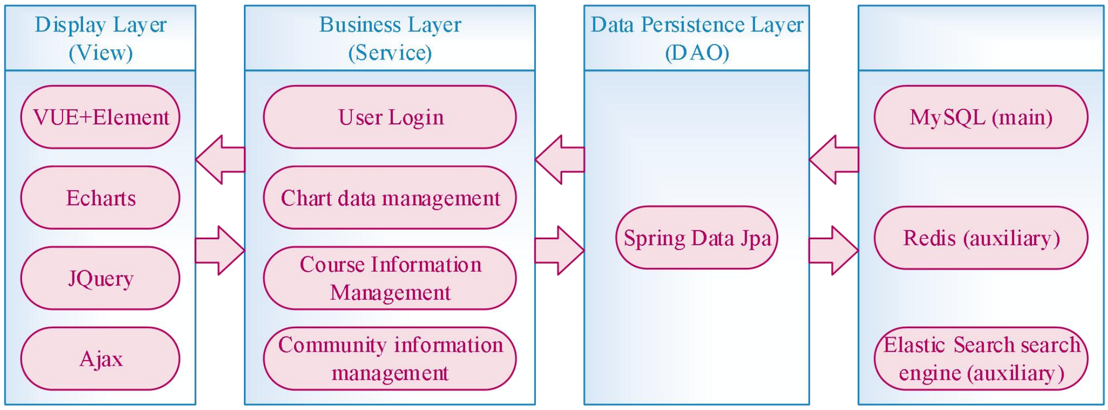

Figure 1. System architecture.

The implementation principle of visual analysis is to draw visual charts based on the data accumulated in the database table, and display the complicated data through visual charts such as bar charts, curve charts, etc., so as to facilitate the interpretation of the educational significance behind the data.

In terms of technical implementation, in order to realize the reuse of visual analysis charts in the system, each visual chart is drawn using a VUE component respectively. The drawing of the charts mainly relies on the Echarts.min.js file, through the front-end JavaSeript language to create option objects and set different attributes to achieve the different effects of the chart display. Due to the huge amount of data, if each time to send Ajax requests to the MySQL database to read the data, will cause the database query is slow, the front-end display effect is not good. Therefore, Redis is used to cache the huge course data, so that each Ajax access will first get the cached course data from the memory, compared with each direct access to the database, the use of Redis middleware can greatly improve the efficiency of the query and reduce the query pressure on the database.

Data visualization and analysis indicators As shown in Table 2, the online course data visualization system visualizes and analyzes 10 data tables. As can be seen from Table 2, the data visualization analysis in this paper takes the teaching unit as the statistical caliber, and analyzes the total amount of teaching behaviors and the trend of changes in teaching behaviors by time period respectively, which helps to form an intuitive understanding of the overall situation and the trend of changes in the operation of online courses in each teaching unit.

Table 2. Data visualization analysis indicators.

Serial number	Primary indicator	Secondary indicator
1	Total amount of teaching activities(measured in terms of teaching units)	Course click-through rate
		Course release volume
		Test release volume
		Number of students participating in the test
		The number of students participating in the test and submitting their responses
		Total number of reviews
		Topic posting volume
2	The trend of teaching behaviors over different time periods (calculated based on teaching units)	Trend of click volume by time period for the course
		Test the release trends by time periods
		Trend of time-period-based course participation and testing
		Time-based topic release trend

2.2. Human Body Posture Estimation

As is common for 2d to 3d lifting tasks, the network first generates a feature map from the original 2d input via a spatio-temporal alternation converter, followed by a Z-regression that splits the feature map into two parts, and the divisions pass through the fully-connected layer before performing the inverse projection lifting operation. The input part specifies the shape of the network input. The Alternating Space-Time Transformer section explains the network hierarchy and data flow of the Alternating Space-Time Transformer. The feature map section specifies the shape of the feature map and how the feature map is split. The Perspective section, the Depth section, and the Inverse Projection Lifting section describe the operations on the split feature graph after it passes through the fully connected layer, and the operation symbols are illustrated below the picture, and finally, the Output section gives the output of the network and its shape.

Of the two parts derived from the feature map split, the first part (the depth part) is used to regress the z-coordinate, which is the depth information D_z of that 2d image. Z-regression will cause the model to no longer predict the x-axis coordinates and y-axis coordinates, but only the z-axis coordinates, and compute the x-axis coordinates and y-axis coordinates using the 2d input from the original input to the network. The network will predict the projection plane of the real camera and add this z-axis coordinate as its missing depth information. In this process, a virtual coordinate system $O_{virtual}$ can be thought of as constructed by obtaining three non-orthogonal vectors, and combining the 2d inputs with the predicted z-coordinates into a coordinate system that provides a way to convert the 2d inputs in the screen space coordinate system back into coordinates in the world coordinate system.

The second part (the perspective part) constructs this virtual coordinate system $O_{virtual}$. This part of the feature map regresses three 3D points, the first point P_{offset} indicates the coordinates of the origin of this virtual coordinate system in the world coordinate system, which is also the world coordinate corresponding to the pixel at the center of the 2D screen image predicted by the model. The second point P_{up} indicates the "up" direction of the virtual coordinate system, which is also the world coordinate of the pixel at the center of the 2D screen as predicted by the model. The third point P_{cam} indicates the world coordinates of the camera.

The way the feature map is divided is determined by a hyperparameter, and in the optimal model, 52 dimensions (about 1/10) of the 512-dimensional feature map are taken out of the 512-dimensional feature map to regress the z-axis coordinates through a simple fully connected layer called z-head, which is the depth part, and the remaining 460 dimensions are regressed to the three three three-dimensional coordinates mentioned above through another fully connected layer called the view-head $P_{offfset}, P_{up}, P_{cam}$ totaling 9 floating point numbers, which is the view-head part. After trying other hyperparameter settings in this paper, it was found that simply equalizing the split based on data size gives the best results. After finding that splitting based on data size works well, it also went a step further and tried to regress the 512 dimensions as a whole directly to 10 dimensions, but unexpectedly found that the modeling results become worse if this is done. The experiments and analysis related to establishing the optimal hyperparameters are detailed in the ablation experiments section of this work.

For each joint point, after generating its corresponding $P_{offset}, P_{up}, P_{cam}, D_z$ for each frame, this work obtains the unit vector projection of the x-axis and y-axis of the virtual coordinate system $O_{virtual}$ under O_{world} in the following way, which is solved by the equations (1), (2)) equations, and (3) equations:

$$Axisy = \frac{P_{up} - P_{offset}}{\left| P_{up} - P_{offset} \right|} \tag{1}$$

$$CamDir = \frac{P_{cam} - P_{offset}}{\left| P_{cam} - P_{offset} \right|} \tag{2}$$

$$Axis_x = Axis_y \times CamDir \cdot \frac{16}{9} \tag{3}$$

Since the network scales the x- and y-coordinates of the 2d input from screen coordinates to the

$[-1,1]$ model during data preprocessing, it is important to note that the unit vector of the x -axis will be a little bit longer than that of the y -axis, and the exact scale is determined by the aspect ratio of the image. In equation (3), the vector fork multiplication is utilized to find out the projection vector of the x-axis, which is unitarized, and then rescaled to make its length is 16/9 of the y-axis unit vector, this is due to the fact that the 2D image input to the model is drawn at a resolution of 1920×1080.

The plane formed by the x-axis and y-axis of $O_{virtual}$ is similar to the projection plane of the camera, the difference between the two is that the plane calculated by the above equation is not necessarily perpendicular to the direction of the camera's viewpoint, the reason for this design is that the plane obtained by this method will be closer to the character's limbs, which will result in the values of the z-coordinate to be centered around the zero point, and these compact data will be easier to train.

Since the positional state of this plane is associated with another prediction, the z-axis coordinate, which is difficult to set by manually designing features, the network will be left to learn the specific state of this plane on its own.

Next, as in equation (4), the 2d input i.e., x, y coordinates are multiplied by the coordinate axis projections $Axis_x$ and $Axis_y$, and the resulting coordinates i.e., Pos_{xy} joints are in the xy-plane of $O_{virtual}$ in the xy-plane.

$$Pos_{xy} = input_x \cdot Axis_x + input_y \cdot Axis_y \tag{4}$$

After this, the depth information in the $O_{virtual}$ coordinate system needs to be supplemented for the final output. A ray is shot from the camera position, and all points on the ray are located at the same point in the camera view, so as in equation (5), Pos_{xy} is subtracted from the camera position P_{cam} and unitized as the projection of the $O_{virtual}Z$ -axis under O_{world} , which is physically a ray from the camera, and the actual position of the joints is on that ray. The physical meaning is a ray from the camera, and the actual position of the joint is on that ray. Next, using the coordinates of the z -axis predicted by the depth part of the network, the actual position of the joint is calculated by equations (6) and (7).

$$Axis_z = \frac{Pos_{xy} - P_{cam}}{|Pos_{xy} - P_{cam}|} \tag{5}$$

$$Pos_{depth} = D_z \cdot Axis_z \tag{6}$$

$$Output = Pos_{xy} + Pos_{depth} \tag{7}$$

The coordinates obtained through the above process are the output of the network.

It should be noted that in the final depth calculation of the inverse projection boost, $Axis_z$ is directly unitized without adjusting it based on the length of $Axis_x$ as in the case of using $Axis_y$, this is because in this operation, the depth information represented by the z-axis is not directly related to the camera information represented by the x , y axes represented by the camera information are not directly related to each other, if the $Axis_y$ length is introduced, it will form an unnecessary correlation between the irrelevant information, which will lead to worse modeling results.

2.3. Recognition and Evaluation of Action

2.3.1. Construction and metrics of dance movement templates

After training on the S-SOFM network model, each node represents a typical dance gesture. The description of an action fragment is to discretize a dance action into a set of gesture sequences and project this gesture sequence onto the gesture space of the S-SOFM sphere model, for each input gesture, the projection process is to identify the input gesture by using this node's index label after finding the best matching node on the output sphere (also known as the winning node), so that the following equation Therefore, as shown in the following equation, after a complete dance action segment (a sequence of gestures with time T) is projected to the output space, it forms a “trajectory” in the output space and also obtains a set of index numbers containing temporal information.

$$O_{c,n}(t) = \{o_1\}, t \in T \tag{8}$$

Therefore, each category of dance action can be identified by such a set of "unique" index number sequences $O_{c,n}$, which we refer to as the basic information template that defines a dance action fragment. better describe the action fragment, on top of that, we describe the basic information template of the dance action fragment at a high level based on the sparse coding of the dance action and use it as the dance action template used for recognition.

The basic information template of dance is logically similar to the bag-of-words (BOW) bag-of-words model that is popular in the field of natural language processing and information retrieval (IR). The gesture represented by each node in the output sphere model can be viewed as a special lexical entry, and similarly, an action fragment can be viewed as a set of lexical entries combined together according to specific grammatical rules. In the study of document classification applying bag-of-words modeling, the frequency of occurrence of statistical keywords can be used as an important feature for training classifiers. In this paper, we count the sequence of gestures inside a dance action segment according to the frequency of occurrence, thus forming a "histogram" of an action segment or a set of similar actions. Therefore, we transform the dance action segment from the original description by the index number of the gesture sequence to the histogram representation of the frequency of the action, and the histogram of each dance action segment is the statistical value of the frequency of the gesture contained in the action, and the similarity of two dance actions can be measured by the similarity distance between the histograms. According to the histogram statistics rule, the histogram of a movement sequence (containing n gestures) can be expressed by the following formula:

$$H\left(o_u\right)_{c,n}=\frac{f_u}{n} \tag{9}$$

f_u is the frequency of occurrence of the u th output node in the dance action, and n denotes the number of gestures included in the dance. The movement templates of the new input movements are matched with the known movement templates for the matching computation, here the template similarity metric uses the Euclidean distance to discriminate the category to which the unknown movement belongs, in a dance self-learning system, this recognition process can be done offline or online.

$$L_2=\left|h_s,h_c\right|=\sqrt[2]{\sum_{i=1}^{D}\left|h_{s,i}-s_{c,i}\right|^2} \tag{10}$$

2.3.2. Dance movement assessment

For the variability measure of gestures p_i and p_j , based on the need to unify the evaluation criteria, it is necessary to normalize the gesture distances, so the following formula is used to measure the variability of the two actions by means of the normalized inner product of the eigenvectors of the two gestures.

$$d\left(p_i,p_j\right)=\sqrt{\sum_{k=1}^{N}w_k\left(\frac{f_{i,k}-f_{j,k}}{f_k(\max)-f_k(\min)}\right)} \tag{11}$$

where $f_{i,k},f_{j,k}$ are the kth feature vector values of the gestures p_i and p_j respectively, $f_k(\max)$ denotes the maximum value of the kth feature, $f_k(\min)$ denotes the minimum value of the kth feature, and w_k is the weight of the kth feature. Let the input action $Q=\left\{p_{q,1},p_{q,2},\cdots,p_{q,n}\right\}$, and the template action $R=\left\{p_{r,1},p_{r,2},\cdots,p_{r,n}\right\}$, in order to compare the similarity between two actions Q and R. first obtain the following distance matrix for the two actions.

$$\begin{pmatrix} d\left(p_{q,1},p_{r,1}\right) & d\left(p_{q,1},p_{r,2}\right)\cdots d\left(p_{q,1},p_{r,m}\right) \\ d\left(p_{q,2},p_{r,1}\right) & d\left(p_{q,2},p_{r,2}\right)\cdots d\left(p_{q,2},p_{r,m}\right) \\ d\left(p_{q,n},p_{r,1}\right) & d\left(p_{q,n},p_{r,2}\right)\cdots d\left(p_{q,n},p_{r,m}\right) \end{pmatrix} \tag{12}$$

The curved path that exists between two actions $T,T=\left\{t_1,t_2,\cdots,t_k\right\}$ where

$t_k = \left(n_k, m_k\right) \in [1,n] \times [1,m]$, then the distance between X and Y is:

$$D_T(Q,R) = \sum_{t=1}^{k} d\left(q_{q,n_i}, r_{r,m_j}\right) \tag{13}$$

Based on the OE-DTW dynamic planning strategy algorithm, the OE-DTW distance $D_{OE}(Q,R)$ of the action Q and R is the optimal path, i.e.:

$$\begin{aligned} D_{OE}(Q,R) &= \min_{j=1,2,\cdots,m} D_{DTW}\left(Q,R^j\right) = D_T\left(Q,R^j\right) \\ &= \min\left\{D_T\left(Q,R^j\right)\right\} \end{aligned} \tag{14}$$

Since OE-DTW is the minimum value of the distance in the last column of the DTW results in the input and template movements. $D_{OE}(Q,R)$ is used as the difference distance between the two movements, based on the start frame of the optimal subsequence, and its mean value is used as the score of the overall dance or body localization movement $D_{score} = 1 - \left|\frac{D_{OE}(Q,R)}{L}\right|$.

3. Application Analysis of Data-Driven Dance Teaching Evaluation System

3.1. Dance Movement Recognition

The databases used in this paper include the dance video self-collected using motion capture equipment (Self-collected) and three more popular databases, JHMDB and MPII Cooking, respectively. The human body posture can either be used directly as feature information and then recognized by statistical methods for action recognition, or the human body region can be segmented by the posture estimator to obtain the human body posture information. Under the condition that the S-SOFM model is also selected for recognition, a comparison of the effect of dance action recognition based on RGB features, Flow features and Z-regression is shown in Table 3. Z-regression performs optimally in all scenes, with recognition rates of 69.4%, 63.9%, and 70.1% for upper body, lower body, and whole body, respectively, in the JHMDB dataset, which is significantly higher than that of RGB with Flow. In the MPII Cooking dataset, Z-regression continues to lead the way in recognizing the upper body, lower body, and whole body, and is better at recognizing the overall image at 62.9%.

Table 3. Comparison of dance movement recognition effect(%).

Human body parts	JHMDB			MPII Cooking		
	RGB	Flow	Z-regression	RGB	Flow	Z-regression
Upper body	49.2	57.5	69.4	33.1	46.3	56.9
Lower body	50.3	62.3	63.9	42.9	50.2	58.7
Entire body	54.9	56.2	70.1	30.1	58.5	60.4
The entire image	63.4	68.3	75.6	45.8	60.7	62.9

Further different parts of the upper body, lower body and whole body regions of the human body are selected respectively and the recognition rates based on RGB features, Flow features, RGB features combined with Flow features and Z-regression camera perception are compared. The recognition results of different human body regions based on different estimation methods are shown in Table 4. The recognition rate of the lower body in a single region (51.2%) is slightly higher than that of the upper body (50.5%), the highest recognition rate is found in the case of using a combination of human body regions (59.7%), and the recognition rate of the case of direct recognition of the whole body region of the human body (54.8%) is lower than that of the combination of all human body regions. The reason for this is that the number of dances in which the upper or lower body movements are dominant is close to the number of dances in which the upper or lower body movements are dominant when the movement category is selected, and the number of lower body dominant movements is high. The application of the whole body region of the human body, when the movement for only the upper body region or lower body region movement, the two regions will affect each other, and dance movement naming often use the lower body and upper body movements named separately, separate training can improve the accuracy of recognition.

Table 4. Recognition effect based on different estimation methods(%).

Human body parts	Self-collected			
	RGB	Flow	RGB+Flow	Z-regression
Upper body	9.8	24.2	31.6	50.5
Lower body	10.2	25.6	32.4	51.2
Upper body+Lower body	21.9	31.7	41.3	59.7
Entire body	20.4	29.8	39.8	54.8

3.2. Dance movement assessment

In this study, the key action posture of the left arm was analyzed as an object, and a certain dance in the self-collected dataset was selected as an example to quantitatively assess the standardization of the dance action by calculating the correlation parameters between the action to be tested and the standard action. Comparing the correlation parameters of the key movement of the subject to be tested with the standard movement, the correlation parameters of the left arm standard movement and the posture of the movement to be tested are shown in Tables 5 and 6, respectively. The correlation parameters of the standard movements were highly stable in each time period, and the fluctuation of the parameters of the movements to be tested was more significant, and there were errors in the coordination and standardization fit in some time periods.

Table 5. Standard posture correlation parameters of the left arm.

Sequence	$sim(V_2,V_{stand})$	$corr(V_{LLarm},V_{LFarm})$	$corr(V_{LFarm},V_{stand})$
0~1s	0.6286	0.9175	0.9472
1~2s	0.6934	0.9536	0.9825
2~3s	0.7176	0.9662	0.9711
3~4s	0.7037	0.9801	0.9645
4~5s	0.7011	0.9645	0.9624
5~6s	0.6736	0.9617	0.9901
6~7s	0.5921	0.9628	0.9635
7~8s	0.7018	0.9771	0.9806
8~9s	0.6735	0.9783	0.9554
9~10s	0.6452	0.9724	0.9825

Table 6. Motion posture correlation parameters of the left arm.

Sequence	$sim(V_2,V_{stand})$	$corr(V_{LLarm},V_{LFarm})$	$corr(V_{LFarm},V_{stand})$
0~1s	0.6309	0.9211	0.9504
1~2s	0.7026	0.9609	0.9902
2~3s	0.7098	0.9723	0.9816
3~4s	0.7471	0.9388	0.9773
4~5s	0.7145	0.9714	0.9728
5~6s	0.6873	0.9592	0.9844
6~7s	0.6095	0.9584	0.9738

7~8s	0.7132	0.9815	0.9912
8~9s	0.6694	0.9846	0.9645
9~10s	0.6522	0.9892	0.9738

The left arm movement correlation parameters are numbered as X1~X3 respectively, and the difference comparison results of the left arm movement posture are shown in Figure 2, from which it is obvious that there is a significant difference between the 3~4s to-be-tested movement and the standard movement. Through the comparison of the experimental results to verify that the method of this paper on the analysis of the movement posture can clearly and efficiently detect the difference between the movement object and the standard, with high robustness, for the dance scientific training to lay a foundation.

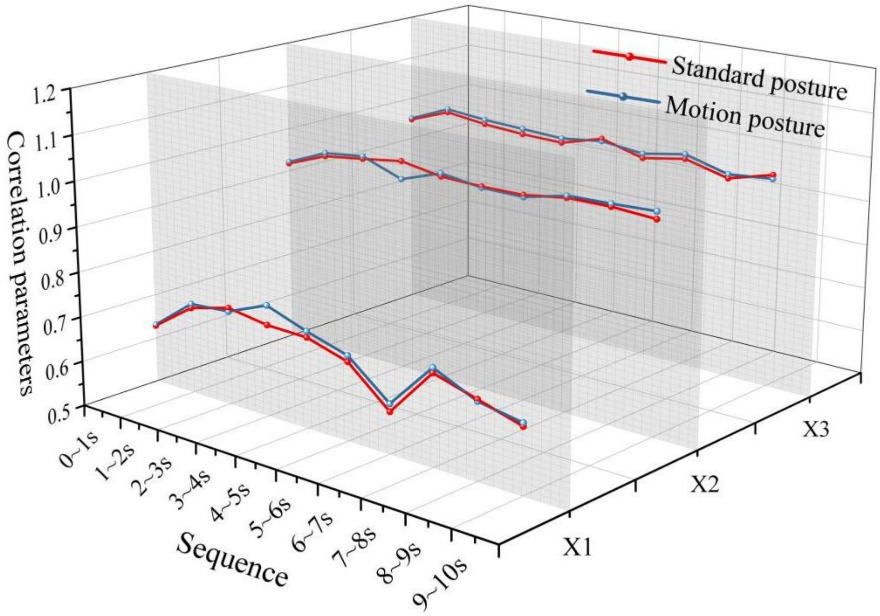

Figure 2. Results of differential comparison of left arm movement postures.

3.3. Visualization of experimental results

Spearman's correlation coefficient is a nonparametric measure of correlation between two variables. It is calculated based on the rank order of the data, rather than the actual magnitude of the values, and is commonly used to assess the monotonic relationship between two variables. This monotonic relationship can be linear or nonlinear and can take values between -1 and 1. When the correlation coefficient is 1/-1, it indicates that there is a perfect positive/correlation between the two variables; when the correlation coefficient is equal to 0, it indicates that there is no monotonic relationship between the two variables. For comparison, the calculated Spearman correlation coefficients are taken as absolute values as shown in Figure 3. In nodes such as video 12 and 15, the absolute value of the correlation coefficient is low, implying that attention is weakly correlated in different quality dimensions.

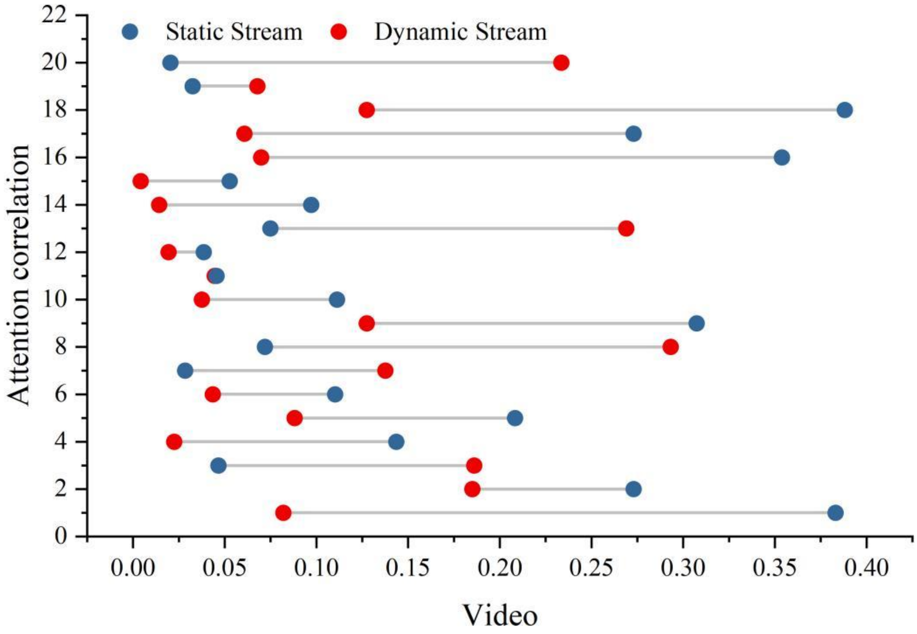

Figure 3. Absolute value of Spearman's correlation coefficient.

Visualizing the attention in the quality score decoupling module of the algorithm of this paper, the results are shown in Fig. 4, demonstrating the attention to a high quality score feature for a sample of dynamic stream branches. In node 110, a good dance move is accomplished with perfect body control, thus the attention reaches 0.0094. In node 40, the dance move is not accomplished and the control of the body posture is poor, thus a lower attention is obtained.

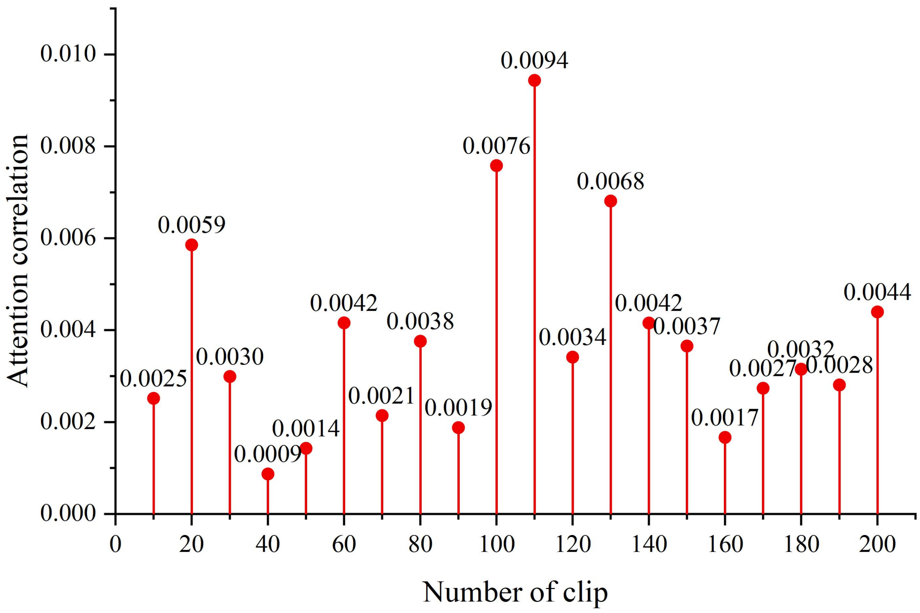

Figure 4. Visualization results of attention.

3.4. System effectiveness analysis

Two dancers' movement video samples are randomly selected from each kind of dance movement dataset constructed in this paper, the samples include 15 kinds of dance movements, and each kind of movement contains 6 dance movement videos. These dance movement samples were scored by the above evaluation method, and five experts in the field of dance were also invited to score the dance movement samples professionally, and the effectiveness of the movement evaluation method proposed in this paper was verified by comparing the scoring gap. The experimental results of some videos are shown in Figure 5. The experiments evaluated different dance movements, and the average Spearman's correlation coefficient ρ reached 97.1%. According to the guidance and analysis of experts in the field of dance, the dance evaluation movement evaluation system proposed in this paper has a high accuracy rate, and is able to effectively evaluate and analyze dance movements.

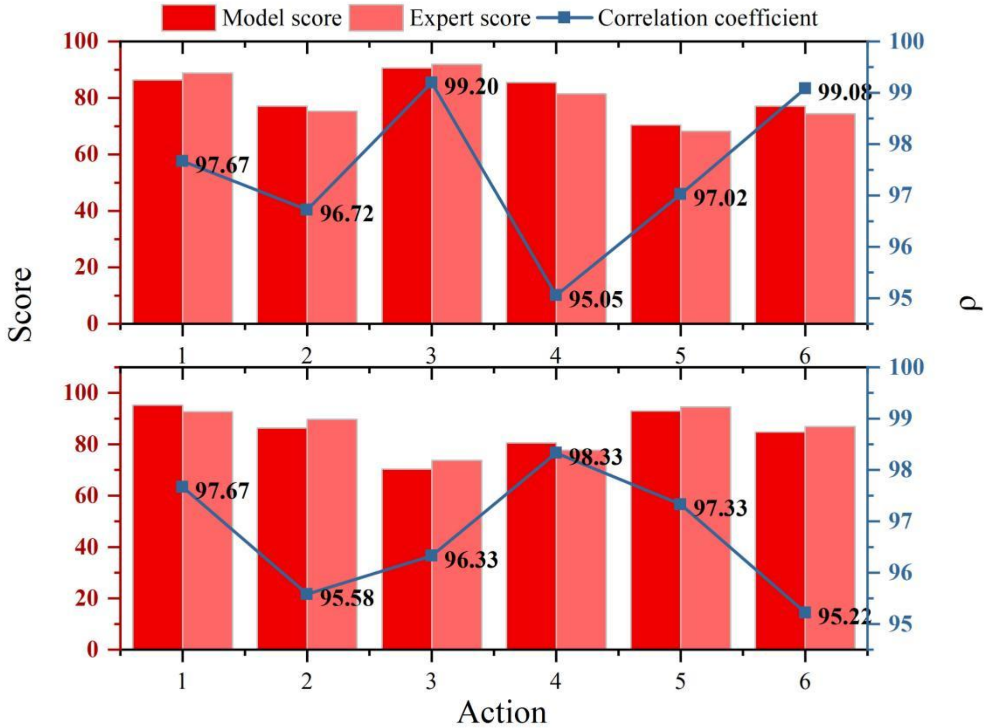

Figure 5. Experimental results.

4. Conclusion

Based on big data, this paper designs a set of teaching assessment methods for dance education intelligent platform, and verifies the effectiveness of the proposed system through experiments and application analysis.

At the level of dance movement recognition, Z-regression performs optimally in all scenarios, with 69.4%, 63.9%, and 70.1% recognition rates for upper body, lower body, and whole body, respectively, which are significantly higher than those of RGB and Flow in the JHMDB dataset. In the MPII Cooking dataset, Z-regression continues to lead the way in recognizing the upper body, lower body, and whole body, and is better at recognizing the overall image at 62.9%. At the level of dance movement evaluation, the method of this paper has a high robustness to the analysis of movement postures that can clearly and efficiently detect the differences and standards between movement objects. Visualizing the experimental results, it is found that in node 110, a good dance movement is accomplished with perfect limb control, so the attention reaches 0.0094. In node 40, the dance movements were not completed and the control of the body posture was poor, thus obtaining lower attention. The different dance movements were evaluated with an average Spearman correlation coefficient ρ of 97.1%.

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