Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

The value of kinematic modeling-based dance teaching methods in enhancing the effectiveness of complex movement training

Le Chen[1,✉], Yaqi Hao[2]

[1] School of Sports and Health Education, Nanjing Normal University Taizhou College, Taizhou, Jiangsu, 225300, China
[2]. Faculty of Education and Science, Yangzhou University, Yangzhou, Jiangsu, 225000, China

ABSTRACT
The dance teaching method that effectively combines motion capture and posture estimation can effectively differentiate itself from the traditional dance teaching mode, realize the teaching interaction between the 3D virtual world and the real technology, and help to improve the quality of dance movement teaching. In this paper, HRNet network is selected under the framework of human posture estimation for the extraction of key points of human posture, and SPIN algorithm is composed of two parts, namely, regression network and SMPLify, to complete the three-dimensional expansion of human posture information. Design the flow of the dance visual movement tracking decomposition method, and perform feature point labeling and labeling parameter setting for multiple key points and key movement parts in the dance movement. Select the specific parts of the dancer as the motion tracking points, record and record the dancer's action images, and track and fit the dance action trajectory using the 3D visual motion tracking decomposition method proposed in this paper. Compare the dance trajectory fitting effect of this paper's method with that of the degree-of-freedom vector method and the tracking differentiator method, and obtain the performance of the three-dimensional visual motion tracking decomposition method. Analyze the students' physical flexibility, balance ability, and the completion of complex movements after a two-month dance teaching. After the dance teaching utilizing dance movement posture analysis, the students' body flexibility (shoulder) and balance ability improved by 12.8cm, 18.74s (left), and 22.2s (right), respectively.

Keywords: SPIN algorithm, HRNet network, human posture estimation, movement tracking decomposition, dance teaching

1. Introduction

Dance is a true reflection of culture, so the modernized teaching of dance has become the focus of

✉ Corresponding author.
E-mail address: 18861010909@163.com (L. Chen).
Received 10 January 2024; Revised 15 March 2024; Accepted 25 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-508

attention in the field of education in China. In the stage of basic movement training in dance teaching, the main purpose is to learn and train some simple typical movements. In this stage, the main dance teaching movement demonstration and learning are generally divided into paper illustration learning and classroom direct learning, movement learning through traditional pictures and text descriptions, or learning according to the movement video burned in the CD-ROM [1-2]. Paper illustrations and videos are more likely to result in incomplete demonstration of movements, and the learners will have deviations or errors in movement understanding, and their learning effect is general, and they are more likely to be limited by factors such as venue and time [3-4]. In addition, in the traditional dance teaching mode, basically can only rely on the coach with experience to judge and analyze the degree of completion of the movement, but this way to bring the dance teacher teaching pressure, teaching resources can not keep up with the increase in demand [5-7]. Therefore, in the face of teaching dance techniques with complex movements, traditional dance teaching methods have largely hindered the speed of development of dance art and the progress of each dance student in the dance program [8-9]. In recent years, with the wide application of machine vision, the use of machine vision to recognize and classify images has achieved better application results [10-11]. Using the dance movement recognition method to establish the motion model of complex dance can help dance trainers to find out the problems of the movement, so as to make targeted improvements and corrections, and achieve better complex dance results [12-15].

The establishment of a framework for analyzing the movement model of dance movements not only broadens the dance teaching and training methods, but also provides a means of auxiliary training for students who need feedback on the results of self-study and for teachers who batch-check the results of their training, which is of some significance for the development and inheritance of the art of dance [16]. Huang, Y. integrates ballet teaching with motion capture and computational modeling, analyzes ballet postures by using coordinate transformation and D-H method, and verifies the correctness of the spatial analysis of exoskeleton motion by using Monte Carlo method, which enhances the teaching effect of ballet by solving the dynamics of ballet postures [17]. Liu, Y. analyzed the rotational movements of dancers of different skill levels using the APAS system with kinematic indicators such as center of gravity displacement and joint angles, aiming to help dance learners to better control the fluidity and stability of movements and to improve the completion rate of complex movements [18]. Yang, H. et al. explored the application of three-dimensional motion capture technology in Latin dance movement teaching, using image processing technology to analyze the movement of Latin dance front walk and back swing, and to dig out the technical characteristics of its different movement phases, and the experiments showed that the students who received experimental teaching had stable control of the center of gravity, smooth and fluent movements, which were in good agreement with the results of the movement scoring [19]. Jiao, Y. showed that dance gesture recognition and prediction is an important part of dance training, and proposed that it can recognize complex human gestures and dynamic movements MKFF-ST-GCN model, which utilizes multi-head attentional mechanism for the fusion of multiple kinematic features at key points and spatio-temporal graphical attentional mechanism for computation in order to improve the performance of recognition and prediction of dance gestures [20]. Shi, J. believes that the analysis of dance physical and verbal movements is a favorable way to inherit and develop the art of dance, due to the hidden nature of dance itself and high difficulty and other characteristics, the traditional dance teaching program is inefficient, the study of dance movement teaching program based on visual recognition technology can provide support for the sustainable development of the art of dance [21]. Ni, S. et al. proposed a sports dance movement recognition system oriented to human motion monitoring and sensing for the high complexity and human body self-obscuration problem in complex dance movements, and the experiments showed that the system had a high accuracy in recognizing complex movements in dance training and competitions [22].

This paper takes dance as the core of basic training, integrates motion capture and posture estimation technology, and proposes a dance teaching method based on kinematic modeling. Briefly analyze the advantages of dance teaching by fusing motion capture technology and posture analysis technology. The HRNet network is used to extract the key points of the dancer's human body posture, and the SPIN algorithm is utilized to obtain the 3D model of the human body and the motion sequence on the basis of the 2D human body posture key points. The 3D visual motion tracking decomposition technique based on the improved inverse kinematics method is proposed, and the dance visual motion feature marker points are parameterized. The fitting effect of the proposed 3D visual motion tracking decomposition technique on the dancer's dance trajectory is tested. Analyze the usefulness of the dance teaching method based on dance movement gesture analysis in conjunction with a two-month dance teaching training.

2. Methods of teaching dance based on movement and gesture

2.1. Analysis of the Advantages of Dance Teaching by Integrating Motion Capture and Gesture Analysis Technology

The effective combination of motion capture and gesture estimation technology in the field of dance teaching can dissolve the shortcomings of the traditional teaching mode. Thus, it can greatly improve the quality of teaching, improve the efficiency of teaching, and realize the perfect interaction between the three-dimensional virtual world and the real technology. This part will briefly analyze the advantages of motion capture technology combined with posture estimation technology in dance teaching [23].

This paper takes dance as the core of basic training, and integrates motion capture and posture estimation technology to develop a dance-assisted teaching method. For professional dancers or dance enthusiasts, only an ordinary monocular camera can realize mobile learning. Helping the spread of dance culture has a profound significance for the inheritance and protection of dance.

Considering the complexity and professionalism of some of the dance movements, obtain the 3D data of professional dancers and record their motion capture paths and track data. According to the body mechanics analysis data, record the three-dimensional movement coordinates of the marking points and save them to establish a complete and precise database of Dunhuang dance movement data. A virtual learning environment is established, proposing a one-to-one “teacher-to-student” incarnation learning method, with a standard movement database as a control, using posture analysis technology to capture the user's learning posture, and participating in the assessment to strengthen the key details of the dance movement, so as to achieve a more precise and comprehensive teaching. Dancers and enthusiasts through such a combination of gesture analysis and motion capture technology innovative teaching system, will have a new experience different from the traditional dance 3D animation display, to obtain good learning results.

2.2. Human Body Posture Estimation Algorithm

2.2.1. HRNet-based human pose estimation. In order to realize the human posture estimation for dancers, this paper chooses the top-down human posture estimation framework with higher accuracy. Among them, HRNet still maintains the highest accuracy level in the field of human posture estimation due to its multi-branch network structure. Therefore, in this paper, based on the target detection algorithm, HRNet is chosen to realize the high-precision extraction of the key points of the dancer's human posture.

The HRNet network is able to continuously retain the high-resolution representation in the forward propagation and gradually add low-resolution branches to form multiple feature processing stages. Eventually, the branch networks of multiple resolutions are connected in parallel to realize multi-scale feature fusion [24-25].

The overall network structure of HRNet is relatively simple, similar to an hourglass network, but the difference is that the high-resolution representation is maintained all the time rather than just from low-resolution up-sampling, which makes the feature map richer in high-resolution features and more conducive to the localization of key points in the human body.77 Maintaining its resolution is based on the use of convolution for feature extraction. The fusion of different resolution features is performed between the two stages and is the key to the whole network. Its first step is to complete the fusion of the feature maps by up and down sampling to generate branches of the corresponding resolution.

HRNet adopts the heat map to output the detection results of key points, and uses the comparison between the predicted heat map and the real heat map to calculate the gradient during the training of the network, which reflects the gap between the real labeling data and the predicted results. Where the real heat map is generated using a two-dimensional Gaussian distribution with standard variance centered on each key point and using the mean square error as the loss function. The final output of the model is a human skeleton model that includes a total of 17 human keypoints in COCO format.

2.2.2. SPIN-based 3D human pose estimation. In order to further complete the three-dimensional expansion of human posture information and obtain a three-dimensional human model, this subsection selects the SPIN algorithm on the basis of obtaining the two-dimensional human posture key points. Combined with the 2D human body keypoints to complete the 3D estimation of the human body posture, the final 3D human body model as well as the motion sequence is obtained, which can be displayed and edited in common 3D modeling software.

There are generally two types of 3D human pose estimation methods that target the human model. The first one is the iterative optimization method, which needs to obtain the 2D human body keypoints first and iteratively fit the parametric human body model (e.g., SMPL) to the 2D keypoints, and the 3D human body model obtained by this method can be accurately aligned to the picture. However, it is slow and sensitive to initialization. The second is direct regression, i.e., using convolutional neural network to extract image features to directly regress the parameters of the human body 3D model, which is faster but difficult to accurately align with the original image. SPIN algorithm combines the above two ways, and its algorithm flow is as follows.

The whole algorithm consists of two parts: regression network and SMPLify. The regression network directly regresses the parameters of the human body model through the images and serves as the initial parameters for iterative optimization. SMPLify is based on the initial human body model parameters, through iterative fitting of the human body model to the existing 2D human body key points, and the final fitting results are used in the regression network training supervision, so that the two parts of the formation of mutually reinforcing cycle, to achieve the construction of the human body 3D model.

The regression network takes the image as input data, first goes through a convolutional encoder to complete feature extraction, then feeds the obtained features into the 3D parametric regression module to infer possible 3D representations of the human body, and finally uses a discriminator with a priori information to determine whether the model parameters are reasonable or not. The loss function of its network in the absence of 3D supervised data includes reprojection loss and discriminator loss, and the computational expression is shown in Equation (1):

$$L = \lambda L_{reproj} + L_{adv} \tag{1}$$

where, L_{reproj} is the reprojection loss, L_{adv} is the discriminator loss, and λ is the adjustment parameter.

The heavy projection loss calculation formula is shown in Equation (2):

$$L_{reproj} = \Sigma_i \left\| v_i \left(x_i - x_i \right) \right\|_1 \tag{2}$$

where x_i and $\hat{x}_i$ denote real human 2D points and projected 2D points, respectively, and v_i denotes the visibility of each point, which takes the values 0 and 1.

The expressions for calculating the discriminator loss are shown in Eqs. (3) and (4):

$$\min L_{adv}(E)=\sum_i E_{\Theta-p_E}\left[\left(D_i\left(E(I)\right)-1\right)^2\right] \tag{3}$$

$$\min L(D_i)=E_{\theta-p_{data}}\left[\left(D_i(\Theta)-1\right)^2\right]+E_{\Theta-p_t}\left[D_i\left(E(I)\right)^2\right] \tag{4}$$

where $\min L(D_i)$ is the individual discriminator loss and $\min L_{adv}(E)$ is the total discriminator loss.

The SMPLif module uses iterative computation to fit the SMPL human parameterized model to the given 2D human keypoints. And in order to achieve a better fitting result, the overall objective function consists of five parts, joint-based data items, three pose a priori and one shape a priori.

Among them, the objective function is shown in Equation (5):

$$\begin{aligned}E(\beta,\theta)&=E_J(\beta,\theta;K,J_{est})+\lambda_\theta E_\theta(\theta)\\&+\lambda_\alpha E_a(\theta)+\lambda_{sp}E_{sp}(\theta;\beta)+\lambda_\beta E_\beta(\beta)\end{aligned} \tag{5}$$

where, β is the body shape parameter, θ is the position parameter, K is the camera parameter, λ_θ, λ_a, λ_{sp} and λ_β are the scalar weights, E_J is the penalty term for joint data, E_θ, E_a and E_{sp} are the penalty terms for the pose a priori and E_β is the penalty term for the shape a priori.

In summary, the SPIN algorithm can get a better 3D model construction effect through the cyclic optimization of regression network and iterative fitting module. In this paper, the 2D human body keypoints obtained from HRNet are passed into the SPIN algorithm, so as to obtain a 3D human body model that fits the target body shape and posture.

2.3. Design of Dance Visual Movement Tracking Decomposition Methods

In this paper, an improved inverse kinematics method is used for video action tracking decomposition, and feature point labeling and labeling parameter setting are performed for multiple key points and key action parts in dance movements.

The flow of the visual action tracking decomposition method designed in this paper is shown in Figure 1.

Through the principle of visual action tracking decomposition to calculate the static replacement data of the dance action, after the image is segmented and labeled clearly, dynamic capture is carried out. If the image is not segmented and labeled clearly, the coefficients are corrected and recalculated until the dance movement image is segmented and labeled clearly. When analyzing a movement in detail, the system automatically tracks the decomposition without the need for the teacher to make the corresponding movements. Through the projection system or teaching monitor can be three-dimensional movement tracking decomposition imaging. The display process can be set at any time, so that the movements in the process of basic dance training can be tracked and decomposed without limitation.

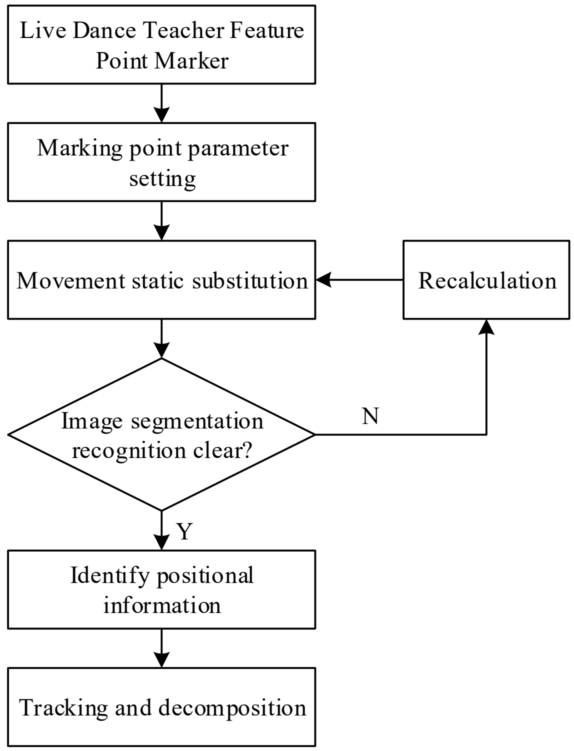

Fig. 1. Dance visual action tracking decomposition method process

2.3.1. Dance visual movement tracking design. In the process of visual movement tracking for basic dance training, the spatial limit range of the 3D movement tracking system should be selected first, after which the extreme value points of the 3D movement tracking system should be located. In the extreme point array, obtain each key action point array data and each key action point array vector parameter. The key point array feature vectors are then calculated, and the multi-directional dual-camera spatial plane imaging system is applied to complete the 3D tracking decomposition of the dance visual motion. The 3D visual motion tracking decomposition method designed in this paper is as follows.

Let $I(x,y,\tau)$ be a visual action spatially variable Gaussian function representing dance action paths and displacements. Where τ is a spatial scale coordinate and (x,y) is a spatial plane coordinate point. Detect the spatial extreme points of the 3D motion tracking system as follows:

$$D(x,y,\tau)=\frac{\sqrt{I(x,y,\tau)-(x,y)}\times O(x,y)}{L(x,y,\tau)} \tag{6}$$

where, $O(x,y)$ is the initial image coordinates. $L(x,y,\tau)$ is the image convolution generated. (x,y) The planar spatial array of points is shown in Fig. 2.

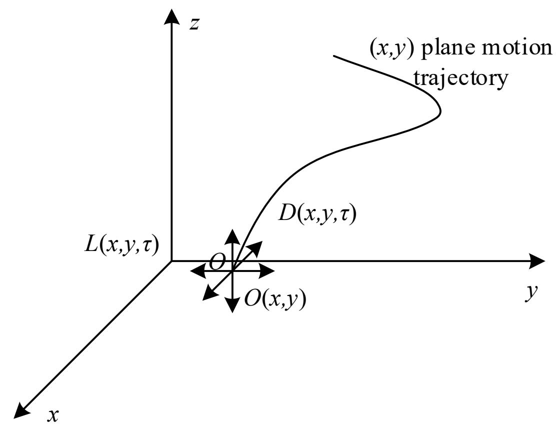

Fig. 2. Plane space lattice

Let $L'(a,b)$ be the Euclidean distance between the dance action key marker points a and b, L be the action amplitude feature spacing threshold, $L'_{\min}$ be the closest Euclidean distance between this action feature point and the next action feature point, $\omega(W)$ be the length where each feature point is located, and $L''_{\min}$ be the action amplitude sub-neighborhood distance. According to equation (7) locate the extreme point of the 3D action tracking system. That is:

$$\mu = \frac{L'_{\min} \times L''_{\min}}{L'(a,b)} \times \omega(W) \tag{7}$$

Let $Q(x,y)$ be the cumulative value of the gradient direction of the action feature point, $H(x,y)$ be the clustering center where the action feature point is located, $W(x,y)$ be the histogram of the gradient of the acquired action feature point, B_i be the normalized value of the length of the feature vector, and $\varepsilon(\lambda)$ be the direction vector of the feature point. Each key action point array vector parameter is obtained according to equation (8):

$$\eta(Q) = \frac{W(x,y) \times Q(x,y)}{H(x,y)} \times \varepsilon(\lambda) \times B_i \tag{8}$$

Let $H(a,b,c)$ be the spatial action feature point coordinates, W be the action amplitude, A, B be the external and internal camera parameters. The key point feature vectors are calculated according to equation (9):

$$\partial''(x,y,z) = \frac{WK \times H(a,b,c)}{A \cdot B} \times \tau(o) \tag{9}$$

Let T be the distance from the action amplitude to the two-camera plane, S be the distance between the two cameras, f be the camera focal length, R_1 and R_2 be the two-camera optical centers, F_f represent the individual camera distortion coefficients, R_P represent the two-camera in-parameters, and p^T represent the two-camera out-parameters. According to equation (10), the imaging relationship in the two-camera image plane space is obtained:

$$\{x_{pr}, y_{pt}, z_{pt}\} = \frac{z \times (R_1, R_2)}{f \times S} \times \frac{(R)}{p^T(R_P)} \times (F_f) \tag{10}$$

Let $G(v)$ be the set of motion space matching points, and complete the 3D tracking decomposition of the dance visual action according to Eq. (11):

$$\phi\left(V_x,V_y\right)=\frac{G\left(v\right)\times\left\{x_{pr},y_{pt},z_{pt}\right\}}{\partial''\left(x,y,z\right)} \tag{11}$$

Visual movement tracking is accomplished by applying the above principles of spatial movement tracking decomposition to basic dance training.

2.3.2. Parameterization of Marker Points for Dance Visual Movement Features. Characteristic marker points are dynamic capture marker points. Dynamic capture markers can be categorized into hand and foot markers, major limb markers, and contour markers in terms of capture location. From the frequency, it can be divided into high-frequency markers, medium-frequency markers, and low-frequency markers. Frequency less than or equal to 2 MHz is a low-frequency marker, frequency between 2 and 4 MHz is an intermediate-frequency marker, and frequency greater than 4 MHz is a high-frequency marker.

High-frequency marking point transmission frequency is high, sensitive to the positional accuracy information, suitable for the movement of small, inconvenient to observe the position with skill, such as fingers, muscle force parts. Low-frequency transmission has good anti-interference and transmission stability, applicable to the main joint position information transfer, such as shoulder joint, knee joint. The mid-frequency marking point has good comprehensive performance and is suitable for transferring and analyzing the body contour information in sports, mainly applied to the outer body contour marking. In this paper, in order to ensure the accuracy of the information, the IF marker point is chosen as the main marker.

Let the marker frequency be λ, the marker diameter be D, the marker propagation correction coefficient be K, and the propagation stabilization coefficient be q. The following relationship exists between transmission sensitivity F and stability W:

$$F=K\cdot\lambda/D \tag{12}$$

$$W=q\cdot K/F \tag{13}$$

In the hand and foot marking point setting parameters, the highest sensing frequency was selected for the finger marking point, followed by the palm and foot marking points. Finger marker diameter is the smallest, foot and palm marker diameter is the largest, the reason is that the smaller diameter of the finger can prevent visual obstacles, the palm and the foot to choose a large diameter of the marker can guarantee the transmission accuracy.

3. Complex dance movement decomposition and teaching training effect

3.1. Dance Training Movement Tracking Breakdown

A school is a comprehensive art school, the school's dance academy is based on the front line of traditional ethnic education, and strives to build a regional dance art research base and a traditional dance inheritance base. In recent years, the dance works choreographed and performed by the teachers and students of the school's dance academy have won many championships in national dance competitions and also gained good results in international dance competitions. In this paper, a dance teacher of the school's dance academy was taken as an experimental subject, and the head, shoulder, elbow, hand, waist, knee and foot of the teacher were taken as the motion tracking points, and the dance movement images of the teacher were recorded with a dynamic imager, and various basic dance training movements in the images were tracked.

Normally, when fitting the various associated dance training movements in the image, the fitting deviation was within 5 pixels, which indicated that the various associated dance trajectories of the dancer in the image were fitted effectively and the dance trajectory of the dancer could be derived completely. If the error value is greater than 5, it means that there is frame dropping or lagging phenomenon when fitting the dance trajectory of the dancer in the image. This indicates that the dance trajectory of the dancer in the image has not been fitted completely and should be reextracted.

In order to test the completeness of this paper's method (3D visual motion tracking decomposition) for fitting the dancer's dance trajectory, the degree of freedom vector method and the tracking differential method are used as the experimental comparison methods to test the overall fitting of the three methods to the dancer's dance trajectory.The fitting errors of the three methods to the dance trajectory are shown in Figure 3.

As can be seen from the figure, the fitting deviations of the three methods are all controlled within pixels, indicating that the dance trajectory of the dancer is effectively fitted. However, the fitting deviation values of the Degree of Freedom Vector Method and the Tracking Differential Method for the teacher's dance trajectory at different frame counts are larger than the fitting deviation values of this paper's method. This paper's method has a large fitting deviation value in the interval of 60-105 frames, but this fitting deviation value is smaller than the other two methods.

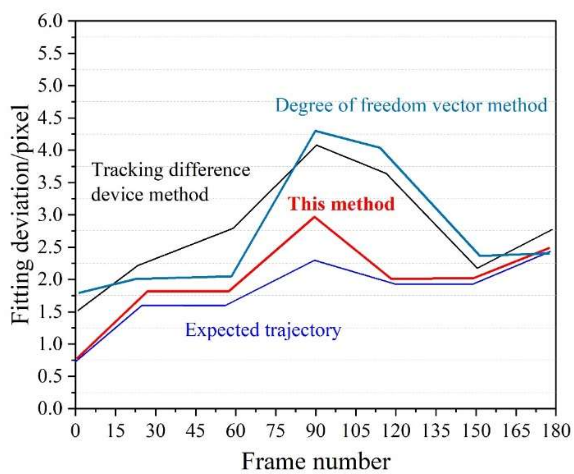

Fig. 3. Three approaches to the fitting error of the dance trajectory

This experimental spreading arm dance training movement tracking situation is the test object to test the effect of background complexity in the image on the tracking accuracy of the method in this paper. The background is set up to have no other clutter, one clutter and more than one clutter, respectively. The tracking of various dance movements by this paper's method in these three cases is tested, and the tracking results of the dance movements in different backgrounds are shown in Fig. 4. The completeness of the 7-point correlation movement extraction of the spreading arm movement using this paper's method in the three different backgrounds is also different.

When there is no clutter in the background, the average extraction completeness of each point in the spreading arm dance movement can reach 99.19%. When there are one or more clutter in the background, the average extraction completeness of this method for each point is 97.52% and 95.13%, respectively. This indicates that when tracking the basic dance training movements, the background complexity will affect the completeness of the extraction of the target movements by this paper's method to a certain extent. Thus, it affects the tracking results of this paper's method, but the completeness of movement extraction is above 95%. Therefore, the tracking of dance basic training movements using the method of this paper is less affected by the complexity of the background.

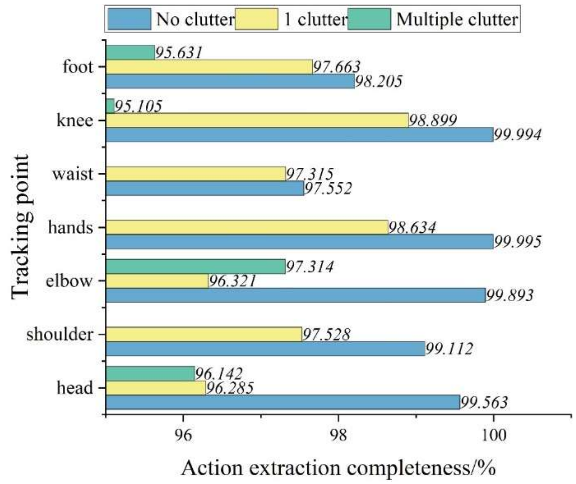

Fig. 4. The tracking results of dance movements in different backgrounds

A twisting action video is taken as an experimental object, from which left twisting and right twisting datasets are collected, and real-time tracking of the target action is accomplished using this method in order to validate the extraction, recognition and tracking performance of the method. Different actions are used as the recognition targets, and the time reduction multiplicity is tested to recognize the targets in the two datasets before and after the use of this method. The results of the time speed multiplier required for recognition before and after the use of the method in this paper are shown in Table 1.

Before the use of this method, the time taken to recognize the different actions in the two datasets varies from 233s to 354s. Among them, the time taken to recognize the left twisting action is the most, as high as 354 s. After the use of this paper's method, the mean value of the time taken to recognize the different motion actions is 57.5 s. The minimum and maximum time-speed multipliers can be up to 40 s and 86 s, respectively, which is a huge reduction. Therefore, it is shown that this method can realize the efficient recognition of motion actions and can meet the demand of subsequent real-time tracking.

Table 1. The time speed ratio of the time before and after the use

Action	Experiment number	Use the previous time/s	Use the post-use/s	Speed ratio
Right-handed	1	235	41	5.732
	2	274	52	5.269
	3	305	63	4.841
	4	296	59	5.017
	5	325	74	4.392
Left twist	1	268	48	5.583
	2	233	40	5.825
	3	287	50	5.740
	4	354	86	4.116
	5	312	62	5.032

3.2. Effectiveness of dance movement training

Based on the requirements of dance teaching, the principles and basic laws of dance movement training, combined with the physical and mental characteristics of dance majors and the training content of basic skills teaching, the following teaching practice plan is set:

1) Teaching objective: to improve students' basic ability and thinking space through gesture estimation and dance movement tracking training, to stimulate students' interest in learning, and to broaden the horizons of dance training.

2) Teaching task: to develop complex movement training that meets the needs of first-year dance majors and to skillfully integrate it into the teaching of basic dance skills.

3) Teaching Objects: The students of a dance teacher in the school's dance academy were selected as the research objects, and 20 students were in the first year of dance majors. Divided into two groups, one for the traditional dance teaching method group, one for the kinesiology-based dance teaching method group. Dance teaching was conducted simultaneously for a period of two months.

3.2.1. Physical Flexibility. Before and after the dance teaching practice of integrating movement tracking and postural technique analysis, 10 students were tested for body flexibility and balance. Due to financial and other factors, the measuring equipment was mainly tape measure, angular device, and stopwatch. The measurement of shoulder flexibility was based on the students' nearest over-the-shoulder distance, and the balance test used a stopwatch to record the students' adherence time to stand on one leg (left and right) in a balanced soft pedal as the data for the specific before and after comparisons.

The before and after comparisons of the dance students' body flexibility are shown in Table 2. The maximum improvement in the students' body (shoulder) flexibility was 19.9 cm.

Table 2. The physical flexibility of the dance is compared

Serial number	1	2	3	4	5	6	7	8	9	10
Preexperiment/cm	45.8	65.3	79.5	65.9	60.1	62.3	67.9	51.5	50.7	75.3
After the experiment/cm	36.8	50.1	59.6	57.8	49.6	47.3	55.2	41.7	42.3	55.9
Added value/cm	9	15.2	19.9	8.1	10.5	15	12.7	9.8	8.4	19.4

3.2.2. Balance capacity. The before and after comparisons of dance students' balance ability (left) are shown in Table 3. 10 students' balance ability (left) was improved with a mean of 18.74s after instruction based on postural estimation and movement tracking decomposition.

Table 3. The dance life balance is compared to the ability (left)

Serial number	1	2	3	4	5	6	7	8	9	10
Preexperiment/s	21.5	22.3	22.9	9.6	31.1	13.5	35.4	9.8	8.1	18.3
After the experiment/s	39.2	29.6	36.7	38.4	52.4	42.6	49.8	30.1	28.5	32.6
Added value/s	17.7	7.3	13.8	28.8	21.3	29.1	14.4	20.3	20.4	14.3

The before and after comparisons of balance ability (right) of the dance students are shown in Table 4. The kinesiology-based dance teaching method was more prominent in improving the balance ability (right) of the dance students. The mean value of balance ability (right) improvement was 22.2s.

Table 4. The balance of the dance is compared to the right

Serial number	1	2	3	4	5	6	7	8	9	10
Preexperiment/s	13.2	9.3	10.6	14.6	15.2	22.6	16.8	17.4	16.2	15.4
After the experiment/s	46.9	29.5	31.4	45.1	38.4	41.3	39.4	40.7	24.8	35.8
Added value/s	33.7	20.2	20.8	30.5	23.2	18.7	22.6	23.3	8.6	20.4

3.2.3. Complex movement completion. In the first two weeks of class, the teachers mainly taught the basic steps of dance singles and basic steps of pairs, and other teachers scored the students in four dimensions: technical quality, music interpretation, coordination skills, choreography and presentation, and the data measured by the students in the experimental class and the control class were collated, and an independent samples t-test was conducted using SPSS 27 software. The results of the independent sample t-test of the specialized dance movement skills of the students in the two classes before the experiment are shown in Table 5.

After the independent samples T-test, the T-test P-value of the four dimensions scores of the students in the experimental class and the control class are all greater than 0.05. It indicates that there is no significant difference between the scoring results of the specialized dance movement skills of the two classes before the experiment ($P>0.05$), and the samples are statistically significant. And the students of the two classes participating in the experiment are all students of the dance special selection general class, effectively ensuring the homogeneity of the experimental research object, which can be carried out for two months of teaching experimental intervention.

Table 5. Test results of the independent sample t of the two classes

Test item	Cross-reference class (N=10)	Laboratory class (N=10)	T value	P
Dance quality	16.253 ± 1.635	15.892 ± 1.307	0.852	0.346
Music interpretation	15.827 ± 1.302	15.217 ± 1.543	1.714	0.125
Matching skill	15.205 ± 1.519	15.824 ± 1.331	0.352	0.869
Choreography and presentation	14.506 ± 1.875	14.235 ± 1.496	0.743	0.584

The comparative analysis of the test results of the special dance movement skills of the students in the control class and the experimental class after the experiment is shown in Table 6.

The correlation analysis of the special dance movement skills of the students in the two classes after the experiment was carried out, in which the P-values of the four evaluation dimensions of matching skills, choreography and presentation, quality of dance movements, and music interpretation were less than 0.05, indicating significant differences.

To analyze the reasons, the experimental class formulated the learning objectives according to the students' differences before the beginning of the course, adopted the kinesiology-based dance teaching method, and used the coaching teaching techniques of dance movement posture estimation and complex movement tracking decomposition to “prescribe the right medicine” for the problems arising from students' self-study, so that the students actively participated in the study and motivated the students to practice on their own after the class. At the same time, students were motivated to practice on their own after class to improve the effectiveness of the training of complex dance movements. Therefore, after the two-month dance course, the students made significant progress in the degree of tacit understanding between dance partners, the choreography of group presentation and the overall expressiveness.

The kinesiology-based dance teaching method is integrated into the complex dance movement practice, which is based on different students' individualized practice methods, and the teacher plays a guiding role and provides assistance to give students the space for independent learning, which cultivates the students' ability to find problems, think about them, and solve them. At the same time, it greatly improves the students' motivation to learn and motivates them to practice independently after class.

Table 6. Test results of special dance action skills after experiment

Test item	Cross-reference class	Laboratory class	T value	P
Dance quality	16.763 ± 1.532	18.594 ± 1.042	-0.635	0.034*
Music interpretation	16.591 ± 1.235	16.007 ± 1.593	0.547	0.061*
Matching skill	15.966 ± 1.707	16.893 ± 1.524	-2.304	0.079*
Choreography and presentation	15.304 ± 1.512	15.248 ± 1.279	-2.336	0.043*

4. Conclusion

This paper proposes a dance teaching method that integrates motion capture technology and posture analysis technology. The SPIN algorithm is used to optimize the key points of the 2D human body based on HRNet, and a 3D human body model that meets the target body shape and posture is obtained. Through the tracking decomposition of dance movements, key practice guidance is proposed for complex dance movements.

The head, shoulder, elbow, hand, waist, knee and foot of a dance teacher are used as motion tracking points to track her dance movements. The 3D visual motion tracking decomposition method combined with the spatial motion tracking decomposition principle in this paper can better fit the trajectory of the dance movement, and the fitting error is less than 5. Using a waist dance movement as a test movement, the method in this paper can realize the efficient recognition of the motion movement, which can satisfy the subsequent real-time tracking needs. By applying the kinematics-based dance teaching method to actual dance movement practice, the flexibility and balance of dance majors are improved to different degrees. The mastery of complex dance movements is also effectively improved. There were significant differences in the four dimensions of technical quality, music interpretation, coordination skills, and choreography and presentation from the pre-dance teaching period.

References

[1] Vinken, P. M. (2024). Kinematic motion characteristics and observer's expertise in perceived aesthetics of dance jumps. Research in Dance Education, 25(1), 32-48.

[2] Wang, Y. (2022). Research on Dance Movement Recognition Based on Multi-Source Information. Mathematical Problems in Engineering, 2022(1), 5257165.

[3] Zhang, R. (2022). Analyzing body changes of high-level dance movements through biological image visualization technology by convolutional neural network. The Journal of Supercomputing, 78(8), 10521-10541.

[4] Zhang, X. (2023, October). The Application of Artificial Intelligence Technology in Dance Teaching. In First International Conference on Real Time Intelligent Systems (pp. 23-30). Cham: Springer Nature Switzerland.

[5] Yuan, X., & Pan, P. (2022). Research on the Evaluation Model of Dance Movement Recognition and Automatic Generation Based on Long Short-Term Memory. Mathematical Problems in Engineering, 2022(1), 6405903.

[6] Zhou, L. (2021, December). Research and Implementation of Specific Action Generation Model in Dance Video Based on Deep Learning Technology. In 2021 International Symposium on Advances in Informatics, Electronics and Education (ISAIEE) (pp. 243-247). IEEE.

[7] Pang, Y., & Niu, Y. (2023). Dance video motion recognition based on computer vision and image processing.

Applied Artificial Intelligence, 37(1), 2226962.

[8] Lin, Z. (2023, May). Dance movement recognition method based on convolutional neural network. In 2023 4th International Conference on Computer Vision, Image and Deep Learning (CVIDL) (pp. 255-258). IEEE.

[9] Yang, X., Lyu, Y., Sun, Y., & Zhang, C. (2021). A new residual dense network for dance action recognition from heterogeneous view perception. Frontiers in Neurorobotics, 15, 698779.

[10] Zhou, Q., Wang, J., Wu, P., & Qi, Y. (2021). Application development of dance pose recognition based on embedded artificial intelligence equipment. In Journal of Physics: Conference Series (Vol. 1757, No. 1, p. 012011). IOP Publishing.

[11] Jia, R., Zhao, L., Yang, R., Yang, H., Wu, X., Zhang, Y., ... & Su, Y. (2024). HFA-GTNet: Hierarchical Fusion Adaptive Graph Transformer network for dance action recognition. Journal of Visual Communication and Image Representation, 98, 104038.

[12] Mao, Y. (2022, December). Design of Calisthenics Choreography and Recording System Based on Action Recognition Algorithm. In International Conference on Machine Learning, Image Processing, Network Security and Data Sciences (pp. 186-193). Cham: Springer Nature Switzerland.

[13] Qiao, L., & Shen, Q. (2021). Human action recognition technology in dance video image. Scientific Programming, 2021(1), 6144762.

[14] Matsuyama, H., Hiroi, K., Kaji, K., Yonezawa, T., & Kawaguchi, N. (2019, May). Hybrid activity recognition for ballroom dance exercise using video and wearable sensor. In 2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR) (pp. 112-117). IEEE.

[15] Wang, Q., Tong, G., & Zhou, S. (2023). A study of dance movement capture and posture recognition method based on vision sensors. HighTech and Innovation Journal, 4(2), 283-293.

[16] Jiang, J. (2023, May). Dance Movement Recognition Technology Based on Multi Feature Fusion. In 2023 4th International Conference for Emerging Technology (INCET) (pp. 1-5). IEEE.

[17] Huang, Y. (2025). Enhancing ballet posture Teaching: Evaluation of a scientific computing model with motion capture integration. Entertainment Computing, 52, 100824.

[18] Liu, Y. (2024). Rotational movement of Chinese dance based on the analysis of kinematic mechanics. Molecular & Cellular Biomechanics, 21(1), 128-128.

[19] Yang, H., & Lv, C. (2022, June). A Study on Using Three-dimensional Motion Capture to Teach and Evaluate Latin Dance Techniques of Forward Walk followed by Swing. In 2022 2nd International Conference on Information Technology and Contemporary Sports (TCS) (pp. 62-69). IEEE.

[20] Jiao, Y. (2024). Optimizing Dance Training Programs Using Deep Learning: Exploring Motion Feedback Mechanisms Based on Pose Recognition and Prediction. International Journal of Advanced Computer Science & Applications, 15(8).

[21] Shi, J. (2021). Dance Action Recognition Technology Based on Multi Feature Fusion in the Internet Era. In Application of Intelligent Systems in Multi-modal Information Analytics: 2021 International Conference on Multi-modal Information Analytics (MMIA 2021), Volume 2 (pp. 352-357). Springer International Publishing.

[22] Ni, S., & Yao, D. (2021). Sports dance action recognition system oriented to human motion monitoring and sensing. Wireless Communications and Mobile Computing, 2021(1), 5515352.

[23] Gang Hao & Ling Cao. (2024). Action capture and VR interactive system for online experimental teaching. Entertainment Computing100669-.

[24] Jinzhen Liao,Wenhua Cui,Ye Tao,Tianwei Shi & Lijia Shen. (2024). Lightweight HRNet: A Ligtweight Network for Bottom-Up Human Pose Estimation. Engineering Letters(3).

[25] Bin Lu,Yang Sun,Zhenyu Yang,Ran Song,Haiyan Jiang & Yonghuai Liu. (2024). HRNet: 3D object detection network for point cloud with hierarchical refinement. Pattern Recognition110254-.