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Computer-Aided Design AND APPLICATIONS

Dance Analysis and Visualization Method Based on Motion Capture Technology

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Abstract. Motion capture and CAD technology, as emerging technological means, have certain application value in dance teaching. Based on the research of motion capture technology and CAD technology, this article analyzes the sources of motion capture data and the characteristics of CAD technology. Through the study of the theory and methods of dance motion analysis, a method for dance motion analysis and visualization teaching is proposed, and this method is verified through examples. The experimental results of this study indicate that this method can accurately obtain key information about dance movements and has a certain reference value for the analysis and visualization of dance movements.

Keywords: Action Capture; CAD Technology; Particle Swarm Optimization Tracking Algorithm; Analysis of Dance Movements; Visual Teaching
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1 INTRODUCTION

Dance is an art form with human body movements that express people's thoughts and emotions, convey life information, and enable people to enjoy beauty through body movements. Dance teaching is an important component of dance art education, which is a process of mutual communication and influence between teachers and students. However, in the process of dance teaching, it is difficult for teachers to guide students in their movements accurately, and students cannot fully understand and master dance movements. Dance action analysis refers to the analysis, recognition, and extraction of key information in dance teaching and the transformation of this information into graphics or images that can be understood by computers through certain technical means in order to facilitate better teaching by teachers. With the rapid development of computer technology and multimedia technology, it has become possible to use computers to analyze dance movements. In order to obtain more accurate information on dance movements and analyze human movements using computers. At present, many scholars have begun to study this method, but this method can only obtain partial action information and has some limitations in practical applications. Bavil et al. [1] established the LHRNet model, which has lower parameters and computational complexity compared to HRNet. By introducing the CBAM attention mechanism in the lightweight

Basicblock residual module, more effective human keypoint features are obtained from channel and spatial dimensions. The test results of the dataset and actual scenarios show that the established ELHRNet can accurately estimate human postures under different scales and complex backgrounds with low parameter counts and computational complexity. However, for severe occlusion conditions, the attitude estimation performance needs to be further improved. Firstly, in order to make YOLOv4 suitable for human object detection tasks, the multi-class detection model is simplified into a single-class detection model that only detects the human body. Subsequently, in response to the problems of low detection accuracy and seriously missed detection of small and medium-sized human targets in complex visual scenes in reality, the ASPP module was introduced on the basis of YOLOv4. And add middle-level convolution input to establish double-layer Bi FPN. The performance of the model was validated on a publicly available dataset, and the results showed that it had higher accuracy and lower parameter count, achieving a balance between accuracy and parameter count.

To test the generalization of the dance human motion model, Guo et al. [2] tested the detection performance of the model in actual scenarios. It used a camera to capture 10 action categories in different scenes for experimentation. The results indicate that the ABYOLOv4 human object detection model has an overall good detection performance and is not easily affected by changes in human scale. But when there is a large overlap in the human body, there will be missed detections. The VTTransPose human pose estimation model responds to changes in the human scale. The detection effect is good for angle changes and slight occlusion, with good robustness. But when there is a large range of occlusion, inaccurate prediction of joint points and fluctuations in joint position may occur. The TPoseC3D human motion recognition network has high accuracy in recognizing movements with significant changes in limbs. Moreover, it can accurately identify action categories even in the event of partial loss of historical information, with strong robustness. In the process of human-machine collaboration, in order to achieve flexible production while ensuring human safety, Hu et al. [3] analyzed that collaborative robots have certain human motion recognition and prediction functions, which can better interact with humans during the operation process. Human motion recognition and prediction are effective means to achieve intelligent manufacturing and human-machine cooperation, which can help robots perceive the external environment. Through human action recognition, collaborative robots can identify the categories of human actions of operators, understand their intentions, and make corresponding decisions for efficient interaction between humans and machines. Human motion prediction can help collaborative robots predict the position of joints in each frame when performing future actions. Improve real-time collaboration control, respond quickly to work orders, maintain a safe distance when interacting with people, deal with uncertainties in the collaboration process, and avoid the occurrence of dangerous accidents. Therefore, identifying and predicting human movements is crucial for human-machine cooperation, intelligent obstacle avoidance, and trajectory tracking.

Li et al. [4] established a human action recognition model based on attention enhancement networks. It performs spatiotemporal modelling on each frame of an image obtained by the human pose estimation model, achieving human action recognition of video image sequences. Based on the ST-GCN human action recognition model, an attention enhancement model is established by introducing a spatiotemporal keypoint attention mechanism to obtain key features of human t action sequences. Introducing residual connections in the graph convolution module preserves underlying features and enriches input attention mechanism information. It established an attention-enhancing human action recognition model. According to the collected and actual i-field N test results, the constructed attention enhancement model can accurately recognize actions. The category of human body movements in videos with clear features has slightly increased in parameter count. For actions related to hand key points and actions where two-person key points intersect, there is still room for improvement in the model's action recognition performance. Li et al. [5] established a human pose estimation model based on the ELHRNet network and obtained the skeletal information of the human body in the image. Based on the HRNet human pose estimation model, an LHRNet model was established by lightweight the parameter proportion difference module in the HRNet model. Compared to HRNet, it has lower parameters and computational complexity. By introducing the CBAM attention mechanism in the lightweight Basicblock residual module. Obtaining more effective human keypoint features from channel and spatial dimensions, establishing an ELHRNet human pose estimation model enriches the feature information of human key points. The test results of the dataset and actual scenarios show that the established ELHRNet can accurately estimate human pose under different scales and complex backgrounds with low parameter counts and computational complexity. However, for severe occlusion conditions, the attitude estimation performance needs to be further improved.

Skeleton-based human motion recognition has broad application prospects in the field of virtual reality, as skeleton data is more resistant to data noise such as background interference and camera angle changes. It is worth noting that recent work treats human skeletons as non-grid representations, such as skeleton graphs, and then learns spatiotemporal patterns through graph convolution operators. However, stack graph convolution plays a marginal role in modelling long-range dependencies that may contain key action semantic clues. Liu et al. [6] introduced a Skeleton Large Kernel Attention Operator (SLKA) that can expand the receptive field and improve channel adaptability without adding too much computational burden. Then, the spatiotemporal SLKA module (ST-SLKA) was integrated, which can aggregate long-range spatial features and learn long-range temporal correlations. 3D pose estimation technology can accurately capture the body movement trajectory of dancers, including key information such as joint angles and limb positions. By using deep learning algorithms to process and analyze these data, we can effectively extract the features of the dancer's movements, thereby achieving accurate recognition of their dance movements. This technology not only improves the accuracy of recognition but also provides real-time feedback on the dancer's movement status, providing timely guidance and suggestions for the dancer. Matsuyama et al. [7] constructed a classification model with time and trajectory perception. This model can capture the continuity and dynamic characteristics of dancer movements by conducting a time series analysis of their motion data. At the same time, the model can also predict and classify the movements of dancers, achieving automatic recognition and classification of different dance movements. Peng et al. [8] proposed a long-term action recognition method based on Two MLPs to address issues such as the inability of existing methods to capture long-term dependencies of actions and to segment the connections between spatial and temporal information of long-term actions. Design a network layer consisting of multi-layer perceptrons (MLPs) to capture long-term dependency relationships of action features from both spatial and temporal dimensions. MLP eliminates inductive bias and achieves fully autonomous learning of the network. Add a norm penalty term to the loss function to constrain the learning direction of the network and explore the relationship between spatial and temporal information. And use the proximal gradient descent algorithm to solve non-convex programming problems. This method achieved good long-term action recognition accuracy on long and complex datasets, and the effectiveness of the relationship between spatial and temporal information was experimentally verified.

In order to better explore and utilize human motion data, this study attempts to combine motion capture technology with CAD technology to analyze the motion process of the human body during dancing. When analyzing dance movements, it is necessary to obtain key information. Therefore, this study summarizes the problems and commonly used methods in human motion, proposes a dance action analysis method based on motion capture and CAD technology, and calls this method the dance action analysis and visualization teaching method based on motion capture and CAD technology.

2 RELATED WORKS

In recent years, with the development of computer technology and the increasing popularity of digital media technology, scholars at home and abroad have begun to combine motion capture technology with computer graphics technology and apply it to dance teaching. In foreign countries, some scholars use motion capture data to analyze motion techniques and visualize movements. Some domestic scholars have also applied motion capture technology to dance teaching and combined it with computer graphics technology to visually analyze dance movements. In terms of motion capture, some scholars use motion capture data to analyze the problem of centre of gravity transfer in dance movements, while others use dynamic capture technology to analyze movements in dance teaching and propose a dance teaching design method based on motion capture data. Analyzing and visualizing dance movements in CAD technology has a positive impact on the development of dance teaching. Scholars have proposed a dance teaching method based on motion capture data analysis, using computer-aided teaching systems as a platform and human motion laws as research objects, through experimental research on the relationship between human motion laws and motion changes. Some scholars also use motion capture data to analyze and visualize changes in human posture in dance. Scholars have applied dance teaching methods based on motion capture data to dance teaching practice and proposed a dance teaching design method based on motion capture. In terms of constructing dance action analysis models, most scholars mainly use computer-aided teaching systems to construct dance action analysis models and use computer graphics technology to visualize dance actions. In this regard, some foreign scholars have also proposed some solutions, such as using virtual reality systems based on motion capture technology to construct virtual environments for dance teaching or using motion capture technology to analyze dance movements. However, some domestic scholars advocate using dynamic capture technology to analyze and visualize dance movements or using virtual reality technology to visualize dance movements.

In the learning and teaching of contemporary dance, action decomposition is a crucial aspect. By finely decomposing movements, students can gradually master complex dance movements and improve their skill levels. Meanwhile, with the development of human-computer interaction technology, ACM (Motion Capture and Modeling) technology provides new possibilities for the decomposition and learning of dance movements. Rivière et al. [9] explore the application and advantages of capturing motion decomposition in supporting contemporary dance learning and teaching from the perspective of ACM human-computer interaction. ACM technology utilizes high-precision sensors and algorithms to capture real-time motion data of dancers and convert it into digital models. This technique provides precise data support for the decomposition of dance movements. Dance teachers can decompose complex dance movements one by one, use ACM technology to capture the key points and details of each movement, and form a detailed action database. Senecal et al. [10] mainly studied human motion recognition and prediction in video sequences. Firstly, based on the human pose estimation model, obtain the skeletal structure of the human body in each frame of the video. Then, the obtained human skeleton information is correlated from the temporal and spatial dimensions, and the category of actions that the human body is executing in the video is obtained through a human action recognition model. Finally, based on the observed video sequence, predict the human joint position information and human action sequence for future video frames. Existing methods often increase model complexity and computational costs due to modelling video action timing information. Meanwhile, as increasingly long and complex video datasets are proposed, the time dimension of long-term actions becomes longer, and the motion information becomes more complex. This presents new challenges for existing methods in capturing long-term dependencies over the entire time range. Existing methods ignore the connection between spatial and temporal information. In addition, the conflict between video action recognition models with increasingly deep network structures and smaller datasets is becoming increasingly severe, and video data in existing datasets is usually more ideal. However, existing data augmentation methods face significant issues such as loss of target semantic information when improving model generalization ability and robustness. Therefore, Wang and Tong [11] have proposed new methods for learning temporal features of video actions, long-term action recognition, and data augmentation, respectively.

In the field of human motion recognition, recognition methods based on skeleton data have received widespread attention due to their efficiency and accuracy. With the development of deep learning technology, the application of skeleton data is becoming increasingly widespread. However, how to process and analyze this data to achieve more accurate action recognition is still a challenging problem. Layered softification, as an effective data processing method, provides a new solution for skeleton-based human motion recognition. Yang et al. [12] effectively integrated feature information from different levels by layering the skeleton data. They specifically, layered soft quantization first layers the skeleton data according to the human body structure, with each layer corresponding to a specific part or joint group of the human body. Then, within each layer, the position, angle, and other information of the joint points are transformed into a series of discrete quantization values through soft quantization. These quantified values not only reduce data redundancy but also retain key features of actions. Yang et al. [13] constructed a human action recognition model based on convolutional neural networks. It generates a 3D heatmap stack of key points to achieve recognition of human movements. To address the issue of difficult differentiation of actions with similar time rates, a TPN (Temporary Pyramid Network) temporal pyramid is constructed. It is introduced between the backbone network of the original PoseC3D and the prediction head, integrating features between actions with different visual rhythms to enhance the network's action discrimination ability. The experimental results indicate that TPoseC3D can effectively complete human motion recognition tasks.

In the learning and research of dance, analyzing and understanding body movements is crucial. With the development of deep learning technology, Convolutional Neural Networks (CNNs) have achieved significant results in the field of biological image visualization. Zhang [14] explored how to use convolutional neural network bioimage visualization technology to analyze the body changes of high-level dance movements, providing new perspectives and methods for dance learning and teaching. High-level dance movements typically have the characteristics of complexity, precision, and rapid change. The dancer's body undergoes various changes in shape and posture during the dance process, including joint bending, muscle contraction, and body rotation. These physical changes are not only the external manifestations of dance movements but also the embodiment of dance emotions and artistry. Therefore, precise and meticulous technical support is needed for the analysis of body changes in high-level dance movements. Zhou et al. [15] proposed a video action temporal feature learning method based on a dynamic temporal shift to address the issue of increased model complexity and computational cost caused by modelling temporal information. There are differences in the connections between features on different channel dimensions. Choosing channel features with close connections for temporal shifts can obtain effective interaction information. So we constructed a double-layer fully connected approach to learn the relationship between features in different time dimensions on each channel and obtained the attention distribution of channels at different levels. Then, a dynamic temporal shift module (DTSM) is designed to dynamically select channels with attention values greater than the threshold and perform temporal shifts along the time dimension to obtain temporal features. Finally, the fixed double-layer fully connected network parameters are used to learn global spatiotemporal features and fused with temporal features to enhance action feature representation. This method improves recognition accuracy on short and uniform datasets with lower model complexity.

3 METHODS

3.1 Hardware Platform Construction

At present, in dance teaching, research is often focused on dance movements while neglecting the principles and laws of movement. There is a lack of systematic, in-depth, and comprehensive analysis of dance action teaching. With the continuous development of science and technology, people have made significant breakthroughs in computer technology and digital image processing, providing new avenues for studying action principles and motion laws. Based on this, this article adopts a combination of computer vision technology and human bone models to construct a dance action analysis model. This method combines action capture technology with computer vision technology to establish a system platform consisting of data acquisition, data processing, 3D modelling, and 3D animation display, achieving comprehensive research on action principles and motion laws. Dance motion capture technology obtains information on the movement process of human bones and muscles through the motion characteristics of relevant parts such as joints, bones, and muscles. Therefore, a dance motion analysis system based on motion capture technology includes the following modules: data acquisition module, data display module, 3D modelling module, and 3D animation display module.

In the design of the data acquisition module, wireless sensor technology plays a crucial role in accurately capturing the most complex and subtle dynamic changes of the human body during dance movements. These sensors not only need to have high sensitivity and accuracy but also must be able to maintain stable performance in different environments. Specifically, when dancers begin their dance, wireless sensors quickly capture the subtle movements of joints and muscle tremors in the human body. This information is recorded in real-time and then transmitted wirelessly to servers connected to computer networks, where the data is encrypted and further analyzed through the powerful computing power of the computer. This process involves in-depth mining and interpretation of a large amount of data to identify the muscle movement patterns and joint coordination behind each dance movement. This data collection technology enables dance coaches and professional dancers to receive valuable feedback, continuously improving their dance steps and movements. This approach provides the possibility for personalized training and a new tool for scientific research, helping dancers better understand and master the complexity of human movements. The corresponding formulas in this process are as follows:

$$A(f)=\int\left(ef_i+\left(\frac{\alpha+\beta}{e}\right)f_{i+1}\right) \tag{1}$$

$$B(f)=\int\left(\frac{\alpha}{\beta+1}f_{i-1}+e\beta f_i+\left(\frac{e+\alpha\beta}{\alpha\beta}\right)f_{i+1}\right) \tag{2}$$

After a collaborative data processing, the following formula can be further derived：

$$C(f)=\int\left(\alpha\beta+\frac{ef_{i-1}+\alpha\beta f_i+\ e+r\ f_{i+1}}{e\alpha\beta+\beta^2}\right) \tag{3}$$

$$D(f)=\int\left(\frac{\alpha d_{i-1}+e\beta d_i+\ e-\alpha\ d_{i+1}}{\sqrt{2e\alpha\beta+\alpha^2+\beta^2}}\right) \tag{4}$$

$$E(f)=\iint\frac{ef_{i-1}+e\alpha\beta f_i+\ e+2\alpha\ f_{i+1}}{e^2\beta^2+\sqrt{\beta^3+\alpha e^3}} \tag{5}$$

The formula $A(f)$、$B(f)$、$C(f)$、$D(f)$、$E(f)$ represents the data collection function, data node judgment function, action fitting judgment function, CAD advanced fitting analysis function, and feature extraction function in the dance action analysis model f_i represents indoor dance action data elements, and e,α,β represents action capture, action decomposition, and feature values, respectively.

In the design of the data display module, this study used 3DsMax software, which is a powerful 3D modelling and rendering software. This module converts the collected human motion data into image format through an accurate data acquisition system. These images are then enhanced by professional image processing techniques, resulting in high-definition and detail-rich dynamic images presented to users. In the processing process, this study pays special attention to the motion trajectories of key parts of the human body, as they are crucial for simulating real-world movements. Therefore, wireless sensor systems are used to capture video data of human activities. These sensors can track human movements in real time and convert them into digital signals for use by 3DsMax software.

In the 3D modelling module, the bones are modelled separately using "bones" and "bone nodes", and the two modelling methods are mixed to achieve a high simulation of human actions. In the 3D animation display module, the 3D animation is displayed on the screen using Adobe Flash software. By designing these modules, the dance action analysis model can be effectively built, as shown in Figure 1.

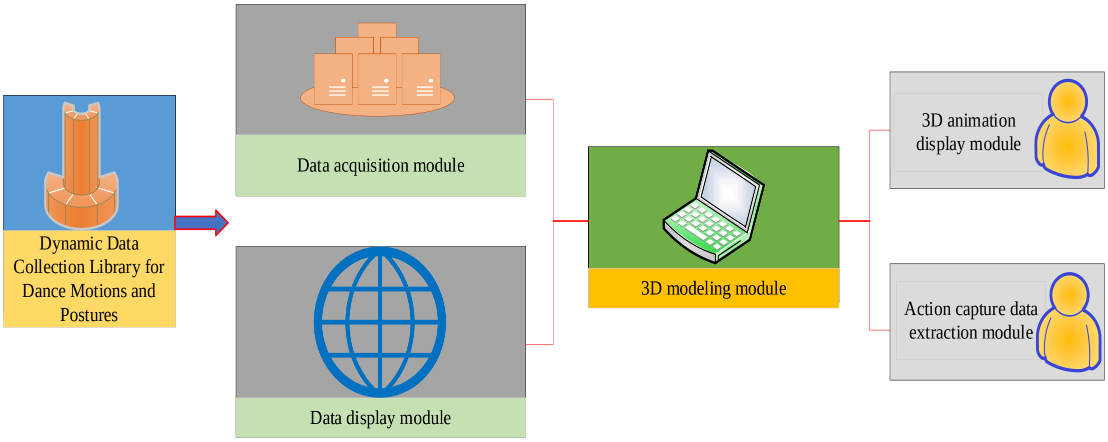

Figure 1: The hardware platform construction process of a dance motion analysis model based on motion capture and CAD technology.

3.2 Data Analysis Strategy

In the process of motion data analysis, it is necessary to consider issues such as large data volume, complex collection equipment, and slow sampling speed in order to improve the effectiveness of motion capture technology for adaptive data analysis. Particle Swarm Optimization (PSO) is a stochastic optimization algorithm based on swarm intelligence, which has the characteristics of fast convergence and strong robustness. It simulates the behaviour of biological populations in foraging, searching, and other aspects, allowing local optimal solutions in the solution space to converge to globally optimal solutions continuously. Using particle swarm optimization algorithm to optimize multiple parameters of the system and achieve adaptive analysis of motion data. In order to effectively improve the data analysis efficiency of the dance motion capture model, this study improved the particle swarm tracking algorithm and introduced it into this model. In this study, the particle swarm tracking algorithm adopted the idea of "fitness function", which is mainly divided into three strategies throughout the entire motion data analysis process.

Firstly, a carefully designed algorithm was used to conduct a thorough global search of the particle swarm, aiming to find the best solution from it. This process involves evaluating all possible solutions in the entire space and selecting data collection locations that can maintain efficient performance in different situations. Once these optimal solutions are found, they can be used to select new data collection points, providing an accurate starting point for subsequent analysis work. Subsequently, in order to ensure the continuity and consistency of the data, this study used interpolation processing techniques to connect the selected new data points with the original data points. This method allows this study to ensure the accuracy of the analysis results still when dealing with dynamically changing action data. The corresponding formulas in this process are as follows:

$$A'(f)=\frac{\alpha\beta}{\alpha+\beta}\int\left(\frac{\alpha}{e}f_i+\left(\frac{\alpha+\beta}{e}\right)f_{i+1}\right) \tag{6}$$

$$B'(f)=\int\left(\sqrt{\frac{e\alpha}{\beta+1}f_{i-1}+\frac{\alpha\beta}{e}f_i+\left(\frac{e+\alpha\beta}{e\alpha\beta}\right)f_{i+1}}\right) \tag{7}$$

After the secondary data collaborative processing, the following formula can be further obtained:

$$C'(f)=\int\left(\alpha\beta+\sqrt{\frac{ef_{i-1}+\alpha\beta f_i+\ e+r\ \ f_{i+1}}{e\alpha\beta+\beta^2}}\right) \tag{8}$$

$$D'(f)=\int\left(\beta+\alpha\frac{\sqrt{\alpha d_{i-1}+e\beta d_i+\ e-\alpha\ d_{i+1}}}{\sqrt{2e\alpha\beta+\alpha^2+\beta^2}}\right) \tag{9}$$

$$E'(f)=\iint\sqrt{\frac{ef_{i-1}+e\alpha\beta f_i+\ e+2\alpha\ f_{i+1}}{\sqrt{e^2\beta^2+\sqrt{\beta^3+\alpha e^3}}}} \tag{10}$$

The formula $A(f)$、$B(f)$、$C(f)$、$D(f)$、$E(f)$ represents the data collection function, data node judgment function, action fitting judgment function, CAD advanced fitting analysis function, and feature extraction function in the dance action analysis model f_i represents indoor dance action data elements and e,α,β represents action capture, action decomposition, and feature values, respectively.

Secondly, when changes are observed in the collection points of motion data, the particle swarm tracking algorithm will intervene and update the velocity, position, and acceleration parameters of its internal particles to adapt to new environmental conditions. The purpose of doing so is to avoid calculation results deviating from the actual situation due to locally optimal solutions, thereby ensuring the stability and reliability of the entire analysis system. Therefore, through the optimization of the particle swarm tracking algorithm, the action capture model has significantly improved in analysis speed. Especially when analyzing dance movements in detail, this algorithm can quickly locate the key target points of each action, greatly reducing the analysis cycle and improving efficiency. The corresponding formulas in the calculation process of this algorithm are as follows:

$$A''(f)=\int\left(\sqrt{ef_i}+\sqrt{\left(\frac{\alpha+\beta}{e}\right)}f_{i+1}\right) \tag{11}$$

$$B''(f)=\int\left(\sqrt{\frac{\alpha}{\beta+1}}f_{i-1}+\sqrt{e\beta}f_i+\left(\sqrt{\frac{e+\alpha\beta}{\alpha\beta}}\right)f_{i+1}\right) \tag{12}$$

After a collaborative data processing, the following formula can be further derived：

$$C''(f)=\int\left(\alpha\beta+\sqrt{e\beta+\alpha\frac{ef_{i-1}+\alpha\beta f_i+\ e+r\ f_{i+1}}{e\alpha\beta+\beta^2}}\right) \tag{13}$$

$$D''(f)=\int\left(\frac{e}{\alpha+\beta}+\frac{\sqrt{\alpha d_{i-1}+e\beta d_i+\ e-\alpha\ d_{i+1}}}{\sqrt{2e\alpha\beta+\alpha^2+\beta^2}}\right) \tag{14}$$

$$E''(f)=e\alpha\beta+\iint\frac{\sqrt{ef_{i-1}+e\alpha\beta f_i+\ e+2\alpha\ f_{i+1}}}{e^2\beta^2+\sqrt{\beta^3+\alpha e^3}} \tag{15}$$

The formula $A(f)$、$B(f)$、$C(f)$、$D(f)$、$E(f)$ represents the data collection function, data node judgment function, action fitting judgment function, CAD advanced fitting analysis function, and feature extraction function in the dance action analysis model, f_i represents indoor dance action data elements and e,α,β represents action capture, action decomposition, and feature values, respectively.

Moreover, this improvement is not only reflected in speed but more importantly, it enhances the data-adaptive analysis ability of the dance motion capture model, greatly enhancing the adaptability and flexibility of the model. More importantly, the accuracy of motion data analysis has been improved, which means that even in complex and ever-changing motion scenes, the model can accurately capture and interpret every subtle action detail, making dance motion analysis more accurate and professional. The simulation results are shown in Figure 2.

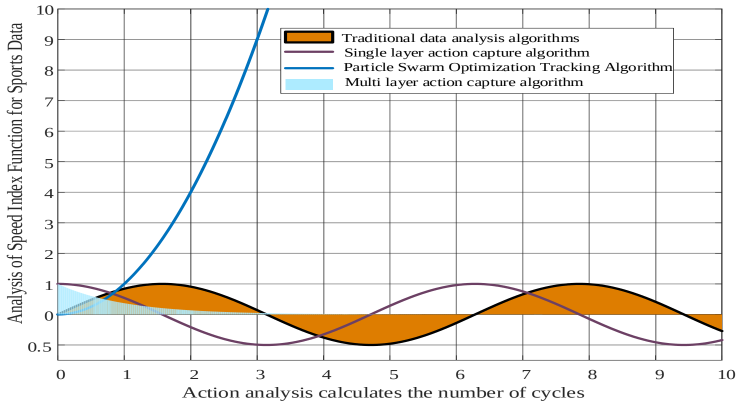

Figure 2: Analysis of speed Changes in action capture by different algorithms at different cycle times.

Finally, after an in-depth analysis of the limitations of existing dance motion capture models, this study further aims to improve their data adaptive analysis capabilities. Therefore, this study considers the analysis of speed and accuracy as key optimization objectives and takes these two indicators as the main considerations for designing particle swarm tracking algorithms. In order to achieve this goal, this study has carried out a series of technological innovations on the motion capture model, including but not limited to enhancing the particle memory mechanism, adjusting the learning strategy of particle swarm, and accelerating algorithm update speed. These measures aim to enhance the adaptability of algorithms to unknown parameters in complex and variable data environments in order to capture subtle changes in dance movements more accurately. The simulation results are shown in Figure 3.

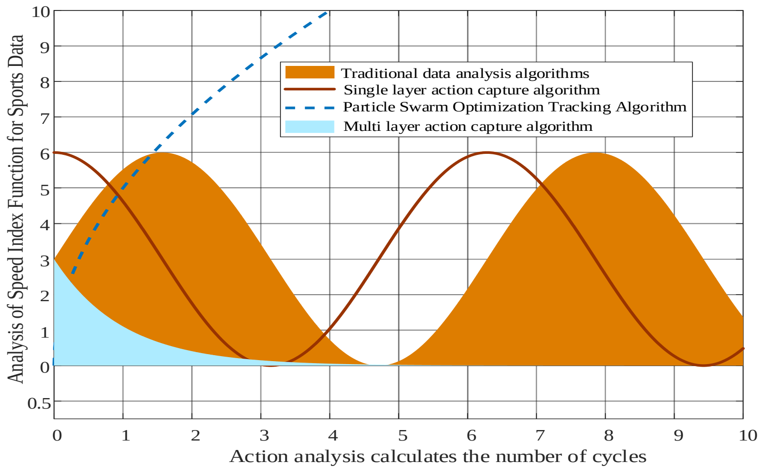

Figure 3: The analysis of speed changes in action capture by different improved algorithms under different numbers of cycles.

From the results in Figures 2 and 3, it can be seen that through systematic testing and evaluation, the results show that when the particle swarm tracking algorithm is applied in the motion capture model, it not only significantly improves the analysis speed of motion data but also can quickly and accurately locate the key points of motion analysis. This is because the particle swarm optimization algorithm itself has strong data processing ability, which can efficiently classify and recognize a large amount of information in a short period of time. In addition, after multiple parameter optimizations and adjustments, the analysis accuracy of the dance motion capture model has been further improved, ensuring that the model can provide stable and reliable data analysis results in various dance scenes.

3.3 Optimization of Dance Motion Analysis Model

Due to the influence of factors such as data quality, device spatial location, and environment on the acquisition of motion data, how to efficiently and accurately transmit high-quality motion data to computers and combine it with visual teaching applications is currently a problem faced by dance motion capture technology. On the other hand, in order to further improve the data analysis efficiency of dance motion capture models, this study takes the analysis efficiency of dance motion capture models as the optimization goal of particle swarm optimization algorithms. In order to achieve this optimization goal, this study introduces the particle swarm tracking algorithm into the dance motion capture model and improves it using a genetic algorithm.

In this study, a genetic algorithm generates new individuals by randomly selecting a gene segment to replace known positional elements. This approach ensures that individuals can avoid both global and local optima. The goal of combining the motion data analysis strategy of the motion capture model with a genetic algorithm is to minimize dependence on unknown parameters and improve the efficiency of motion data analysis. The preliminary results are shown in Figure 4.

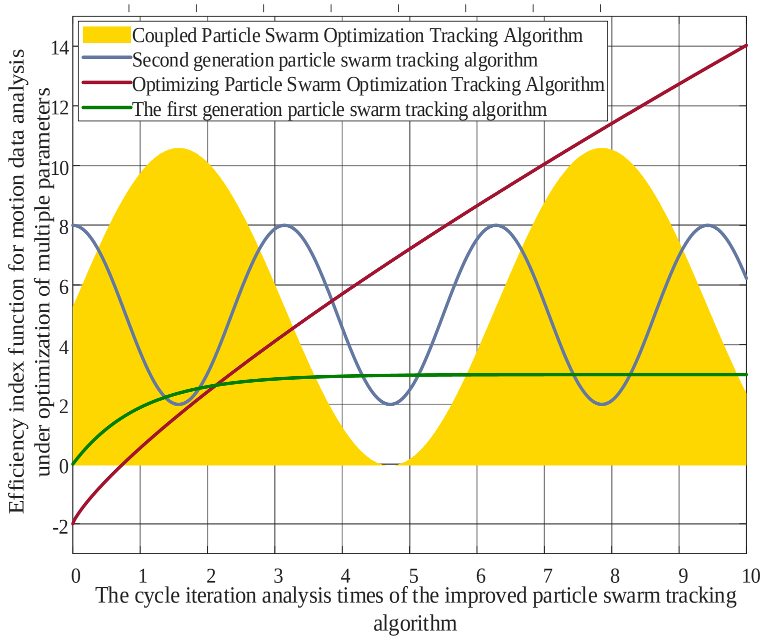

Figure 4: Efficiency index results of motion data analysis for improved particle swarm optimization algorithm.

Specifically, in order to avoid excessive dependence of action capture models on unknown parameters, this study designed multiple parameters in the algorithm, including particle count, position and velocity update step size, and learning factors. Among them, the number of particles and learning factors is selected based on the characteristics of the parameters themselves and the goals they aim to achieve; The updated step size of position and speed is determined based on the environment in which the parameters are located. After testing, it was found that the improved particle swarm optimization algorithm can effectively improve the analysis efficiency of dance motion capture models, and under the optimization of multiple parameters, the efficiency of motion data analysis has also been further improved. The optimization results are shown in Figure 5.

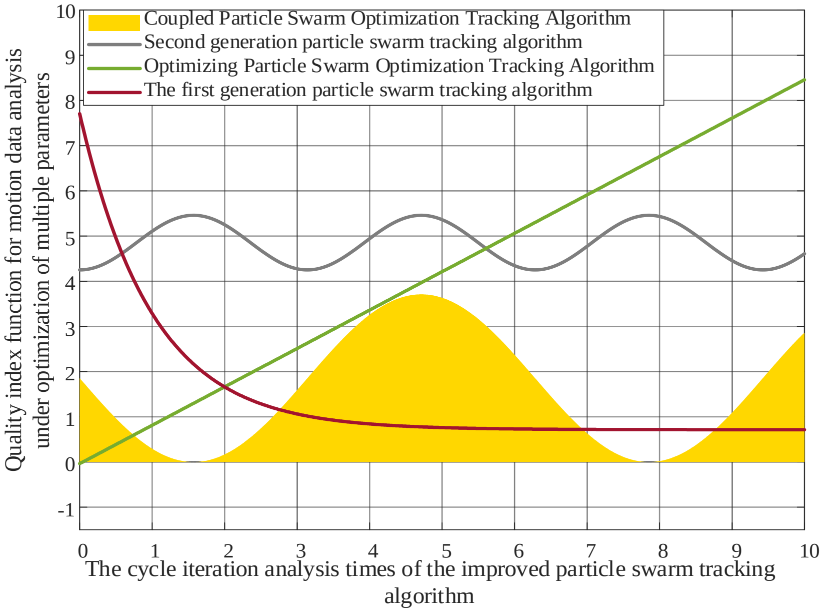

Figure 5: The quality results of motion data analysis for dance movement analysis models under optimization of multiple parameters.

From the results in Figures 4 and 5, it can be seen that the model has also achieved good results in simulation experiments, further proving its practicality. This is because due to time constraints, this study did not process dance action data or extract action features in this section. Therefore, only a brief description of action feature extraction and data preprocessing was provided. In simulation experiments, different methods of feature extraction for action data will yield different results, that is, the action data features obtained through action capture technology have higher credibility than those obtained through CAD technology. This study utilizes motion capture technology to extract dance motion feature data and then utilizes CAD technology to visualize dance motion feature data.

4 EXPERIMENTAL DESIGN, VALIDATION, AND RESULT ANALYSIS

4.1 Experiment Design

This study adopts dance action analysis and visualization teaching methods to analyze a dance action and presents the analysis results in the form of pictures and tables using CAD software. The motion capture data collection device used is the Hanislab human motion capture system, which collects human body data from six different directions: front, side, back, left and right, front and rear. Store these data in a database, classify and organize them using Excel, and create corresponding tables. Edit them using Excel when drawing charts. All action data is processed and saved to the server as the basis for analysis, as shown in Figure 6.

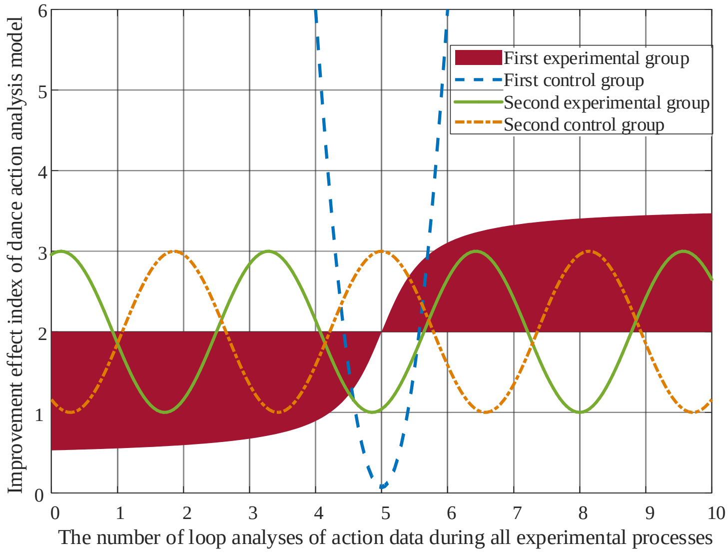

Figure 6: Preliminary results of visual teaching experiment on dance motion analysis based on motion capture and CAD technology.

From the experimental results in Figure 6, it can be seen that the dance motion analysis model based on motion capture and CAD technology has a significant improvement effect. This is because this study used advanced features from CAD software and 3DsMax software to process relevant data. The built-in timeline tool in the software allows us to set specific "timestamps" to record the time when each joint begins to move accurately. With these timestamps, the specific start time of joint movements can be determined, ensuring the accuracy and completeness of the entire motion trajectory. Finally, using the "frame difference method" to analyze video frames can help us identify the motion angles between each joint. By comparing the angle changes between different frames, not only can we observe the motion patterns of each part in detail, but we can also gain a deeper understanding of the details of joint activity. This detailed data analysis is crucial for further simulating and optimizing human motion models, helping to improve training effectiveness and guide the development of personalized rehabilitation plans.

4.2 Analysis of Experimental Results

In order to further objectively analyze and characterize the experimental results of the dance action analysis model, this study combined multiple objective evaluation models to evaluate and analyze the experimental results in terms of accuracy, teaching quality improvement, student learning efficiency, classroom interaction effect, etc. When analyzing the experimental data and related charts, this study used advanced functions in CAD software and 3DsMax software. In CAD software, data is stored in the form of nodes and the motion trajectories of each joint are plotted using the "curve graph" tool in 3DsMax software. In the graph, compare the changes in motion angles at different time nodes by drawing the rotation axis. This method not only visually displays the action process, but also helps students better understand the details of dance movements. The analysis results are shown in Figure 7.

From the results in Figure 7, it can be seen that as the number of loop analyses increases, its accuracy, teaching quality improvement, student learning efficiency, and classroom interaction effect all perform well. This is because this study combines multiple objective evaluation models and takes different values in various evaluation indicators. Among them, the analysis accuracy of the action capture model is the highest, which can ensure the integrity of the data.

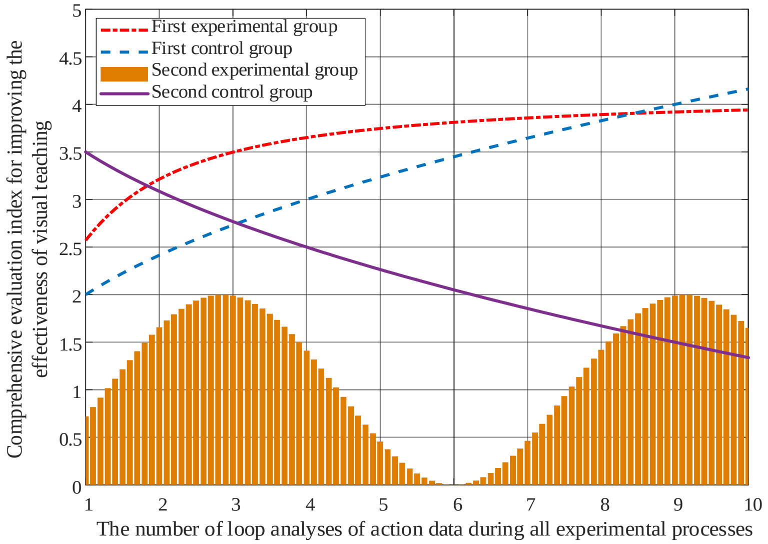

Figure 7: Evaluation of the objectivity improvement effect of experimental results of the dance action analysis model.

The most significant improvement in teaching quality is due to its ability to ensure the professionalism and accuracy of the analysis process. The maximum learning efficiency of students indicates that the model can effectively promote their understanding of knowledge; Classroom interaction has the best effect because it can greatly alleviate the tension between teachers and students and promote emotional communication between them. Therefore, the dance motion analysis model based on motion capture and CAD technology has a significant improvement in visual teaching.

5 CONCLUSIONS

This article is based on motion capture technology and CAD technology and proposes a method for dance motion analysis and visualization teaching by analyzing the sources of motion capture data and the characteristics of CAD technology. This method can quickly identify, extract, analyze, and process movements, accurately obtain key information about dance movements, and can serve as an auxiliary means for dance teaching. This method is suitable for analyzing and visualizing dance movements for students in the classroom, as well as other teaching methods such as dance teaching videos and dance teaching software. In addition, the motion capture technology used in this article is based on simulating specific motion scenes and does not consider the impact of different motion scenes on motion capture data. In future research, it can be considered to use more motion scenes to simulate different dance movements in order to obtain data that is more in line with the actual situation, thus making the method proposed in this paper more applicable.

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