

Building Computer-Aided Interaction Model for Choreography Teaching and Learning

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Abstract. This paper deeply discusses the innovative application of computer-aided choreography and interactive teaching modes under the tide of modern science and technology. Based on the traditional essence of dance art, this research cleverly integrates the rich expressiveness of multimedia technology and the precise computing power of computer-aided technology algorithms, aiming to create an efficient, creative, and highly personalized dance teaching and creation environment. This paper combines virtual reality technology and dynamic sampling light projection algorithm to build a 3D reconstruction model of dance movements, realizes the extraction and matching of dance movements and music features through the directed graph neural network, and realizes the rationalization of dance choreography and teaching interaction. The experimental results show that the proposed model effectively improves the accuracy and recognition rate of the three-dimensional model of dance movements and can accurately extract the features of music and dance movements, enhancing the matching degree and coherence of the two. The final choreography effect shows that the model improves the rationality of choreography and the final choreography effect. In addition, this model effectively increases the number of interactions between teachers and students and improves the effectiveness of interaction.

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1 INTRODUCTION

As an art form with a long history, with the development of The Times and the changes in society, its arrangement mode, expression method, and cultural connotation constantly evolve, and dance arrangement is no longer limited to a certain style or culture [1]. Modern dance, street dance, national dance, classical dance, and other styles learn from each other and integrate, forming a diversified form of dance expression [2]. At the same time, the development of modern technology has provided new possibilities for choreography. With digital media technology, light and shadow effects, and other modern technological means, dance works can present more shocking visual

effects so that the audience can enjoy the dance but also feel the perfect combination of science, technology, and art [3]. Some stage designers cleverly used a variety of light sources such as laser, LED lamp strip and projection, and realized the complex transformation of light and shadow through programming control, so that the audience could enter a dreamy future world like a tunnel through time and space in the climax of the dance [4]. Some choreographers combine the holographic projection stage background to seamlessly integrate the virtual scene with the real stage. Through high-precision 3D modelling and real-time rendering, visual wonders such as colourful city skylines and vast cosmic stars appeared on the stage [5]. Although the choreography has been innovative in expression and technical means, it is still insufficient in the overall creativity and theme conception. Some works lack novelty in arrangement and rely too much on traditional arrangement patterns and expression techniques, resulting in a lack of uniqueness and attraction [6]. In the teaching of dance choreographers, although the teaching scale has gradually grown in recent years, its classroom teaching content is still relatively simple, and the choreography content mainly relies on manual design and experience accumulation [7]. This teaching mode is not only inefficient but also limits the development of students' innovative thinking and comprehensive ability to a certain extent. At the same time, some students are too limited in the ability of action creation and thinking and lack self-confidence and innovation ability.

The constructed human motion posture model library not only includes a wide range of basic dance movements but also can be flexibly combined and adjusted according to the creative needs of the choreographer. During the choreography process, the system can capture the choreographer's demonstration movements in real-time and compare them with the models in the pose library. By utilizing virtual reality (VR) or augmented reality (AR) technology, students can interact with dance models in a virtual environment, simulating exercises in real stage scenes. By using methods such as feature plane similarity matching, the system can accurately analyze students' dance performance, including multiple dimensions such as action accuracy, rhythm, and expressiveness. Based on the individual dance foundation and learning ability of students, the system can intelligently recommend suitable learning content and develop personalized learning plans. Real-time feedback on the similarity, fluency, and other information of movements helps choreographers accurately adjust every detail of the movement, ensuring that the dance work is both artistic and technical [8]. Through algorithm optimization, the system can automatically or semi-automatically generate novel dance sequences, stimulate the creativity of choreographers, and accelerate the creative process. By comparing students' practice movements with standard movements, the system provides targeted improvement suggestions to maximize learning outcomes. These evaluation results not only provide students with clear directions for self-improvement but also provide teachers with scientific teaching feedback, which helps optimize teaching strategies. At the same time, the system supports remote teaching, breaking geographical limitations and allowing high-quality dance education resources to be widely disseminated. Set up a dance community on the platform to encourage students to share their dance works, participate in online competitions, and create a positive learning atmosphere. At the same time, it also builds a bridge for communication and cooperation between choreographers and dancers, promoting the inheritance and innovation of dance art.

In the case of a clear dance theme, music and movement choreography are the key links of choreography, while traditional choreography mode requires a large manpower and time cost, and is constantly adjusted in practice to achieve the final choreography effect [9]. This mode is often limited by the environmental conditions of the choreography, and can not fully show the dance effect. In choreography and teaching, computer-aided technology can greatly improve work efficiency, significantly shorten the work cycle and reduce labour costs through automated and intelligent methods. Computer vision technology combined with dance style and dancer characteristics to achieve more personalized choreography, optimize dance movements, reduce trial and error costs, and improve choreography efficiency. At the same time, computer-aided technology can capture dance movements and musical features to build corresponding three-dimensional models, You can preview the overall effect of the dance, so that the creativity of the choreography can be displayed more intuitively. In the aspect of dance choreography teaching interaction, the application of computer-aided technology can enrich multimedia teaching resources, achieve personalized teaching

purposes, enhance teaching interaction, students can experience the scene and atmosphere of dance performance immersive, and improve immersion and participation in learning. First of all, this paper studies the computer-assisted dance choreography and teaching interaction mode, builds a dance choreography and teaching environment based on virtual reality technology, and realizes the presentation of dance choreography effect and teaching demonstration through the virtual three-dimensional model. Students can observe the choreography from multiple angles through the three-dimensional model to establish the overall view of the entire choreography effect. To improve the accuracy of the three-dimensional model of dance movements, this paper introduces the dynamic sampling light projection algorithm to improve the clarity and rendering speed of the movement model. Through the digraph neural network model, the characteristic data of dance movements and music are extracted, and the intelligent choreography is realized. At the same time, through the classification of dance movements and the characteristics of different students, personalized teaching interactive recommendation is realized to improve the learning efficiency of different students. To achieve the purpose of the research, the theory and principle of traditional ray projection algorithm and digraph neural network model are expounded at the beginning of the research. Then, on this basis, the key technologies of this paper are comprehensively introduced, including choreography motion capture, music feature extraction, dance motion feature extraction, and the final choreography and teaching interactive modules. Finally, the application effect of this model is verified and analyzed through performance experiments and application practice.

2 RELATED WORK

Based on the human body framework structure model, computer-aided choreography systems can intelligently combine and transform different action elements. Shahriar [10] has created dance sequence systems that conform to specific styles or emotional expressions. Combining fuzzy neural network theory, the system can automatically quantify these features and provide real-time feedback to choreographers, including the similarity, innovation, and fit with the overall style of actions, thereby helping choreographers quickly adjust and improve their work. During the choreography process, the system captures the creative movements of the choreographers in real time and uses graphic pattern recognition technology to analyze the characteristics of the movements quickly. Through mathematical representation methods, the system can accurately calculate key parameters such as the fluency and intensity distribution of movements, ensuring the artistic and technical quality of newly created dance works. By using fuzzy neural networks to analyze action features quantitatively, the system can accurately assess students' learning progress and existing problems, providing personalized learning suggestions and training plans for students. Combined with multimedia database technology, the system can select the most suitable teaching content from a vast database of dance movements based on students' dance levels and interest preferences. The system automatically quantifies and analyzes the action characteristics of each work, providing objective and fair scoring criteria for the competition and inspiring students' learning enthusiasm and creativity. The system provides real-time feedback and guidance based on students' actions, helping them correct errors and improve their skills. On the interactive teaching platform, students can share their dance works, participate in online collaborations and competitions, and exchange ideas with dancers from around the world. By utilizing virtual reality (VR) and augmented reality (AR) technologies, students can practice in simulated dance environments and gain an immersive learning experience. Through quantitative analysis of different dance genres and style characteristic variables, Tan and Yang [11] found that this system can gain a deeper understanding of the unique features of various dance styles, providing a scientific basis for dance education and creation. This article takes the analysis of the characteristic variables of the Nanquan movement style as an example, and similar methods can be applied to the study of dance style.

Capture technology is not only about collecting and transforming data but also a bridge connecting the real world and the virtual world. Tsuchida et al. [12] replicated human actions with extremely high precision, providing a realistic and dynamic aesthetic for computer-generated images or characters. In the field of computer-aided choreography, motion capture technology provides

unprecedented creative freedom and efficiency for choreographers. Choreographers can use this technology to pre-record a series of dance movements, and then freely combine and adjust these movement segments in a digital environment to create a brand-new dance sequence. In the field of dance, this means that every jump, rotation, and pose change of the dancer can be accurately captured and reproduced, providing a solid foundation for subsequent animation production, choreography creation, and teaching interaction. This non-linear creative method not only reduces the trial and error cost of traditional choreography but also inspires more creative inspiration. In terms of teaching interaction, motion capture technology has also shown great potential. Through this technology, students can intuitively observe and imitate standard dance movements. Valle et al. [13] enable choreographers to easily explore different dance styles and emotional expressions by adjusting action parameters and applying different animation effects, providing audiences with a richer and more diverse viewing experience. This instant feedback mechanism greatly improves learning efficiency and accuracy, making dance teaching more scientific and efficient. At the same time, the system can provide real-time feedback on students' completion of actions, identify existing problems, and provide improvement suggestions. In addition, combined with virtual reality (VR) technology, students can interact with virtual dancers in a virtual environment, experience dance performances in different scenarios, and deepen their understanding and experience of dance art.

Choreographing dance is undoubtedly a highly challenging artistic process, requiring constant iteration and improvement in order to pursue perfect dance performance. To address this challenge, Wang and Dong [14] innovatively developed the "DanceUnisoner" interactive group dance simulation interface, aiming to deeply integrate the concept of computer-aided choreography with teaching interaction modes, bringing revolutionary changes to dance creation. Traditionally, choreographers rely on paper and pencil sketches and limited on-site rehearsals to conceptualize and adjust their dances, which not only consumes time and energy but also limits the rapid realization of creativity and feedback loops. By adjusting the position, size, timing, and other parameters of each dancer in real-time, choreographers can quickly preview and modify dance layouts and movements without relying on actual dancers, greatly shortening the cycle from conception to implementation. It allows choreographers to directly arrange excerpts of dancers' solo dance videos in a virtual 3D environment, greatly expanding the freedom and flexibility of creation. DanceUnisoner is not only a technical tool but also an accelerator for choreographers' creative expression. Choreographers can demonstrate dance concepts to students in a simulated environment, answer questions in real-time, and visually demonstrate the effects of different choreography schemes by adjusting parameters, helping students better understand the structure and intention of dance. In terms of teaching interaction, DanceUnisoner has also demonstrated extraordinary value. It is not only a choreography tool but also a teaching platform that promotes in-depth communication and cooperation among choreographers, students, and dancers. Zhang [15] interacts and experiments through the interface, proposes his own ideas, and explores the infinite possibilities of dance art with choreographers.

3 COMPUTER-AIDED CHOREOGRAPHY AND TEACHING INTERACTIVE MODEL

3.1 Dance Motion Capture Module

The traditional ray projection algorithm is classical and widely used in the field of volume rendering. It is a direct volume rendering technology based on image space, which calculates and synthesizes two-dimensional images by simulating the process of light passing through three-dimensional volume data. In this process, the volume data is treated as a three-dimensional array of many tiny voxels, each containing certain physical or measured properties (such as density, temperature, velocity, pressure, etc.) that can be represented by colour and opacity. Then, according to the order from front to back or from back to front, the colour and resistance of the sampling points on the optical line are synthesized, and the colour value of the pixel on the screen is finally obtained. The biggest advantage of the ray projection algorithm is that the imaging quality is high, and the internal structural characteristics of the object can be displayed. This method is effective when dealing with static scenes or bulk data with a relatively small amount of data, but it has some problems, such as

large computation, high memory requirements, and limited real-time performance. In particular, when the observation direction or Angle of view changes, pixel values on the entire visual plane need to be recalculated, resulting in insufficient real-time performance. Therefore, in the process of Wu Tao choreographed motion capture, this paper introduces the dynamic sampling ray projection algorithm to optimize the shortcomings of the traditional algorithm, which can dynamically adjust the sampling strategy according to the characteristics of the volume data, the observer's perspective, and observation needs. The dynamic sampling ray projection algorithm may also be combined with other optimization techniques further to improve the efficiency and real-time performance of the algorithm. By dynamically adjusting the sampling strategy, the algorithm can reduce the unnecessary calculation and improve the rendering speed on the premise of ensuring the image quality, to meet the real-time requirements better.

3.2 Directed Graph Neural Network

A directed graph neural network is a subset of a graph neural network that deals with data from a directed graph structure. A directed graph is a special graph structure in which the connections between nodes are directional, that is, pointing from one node to another. In a directed graph neural network, the model takes this directionality into account to learn and represent nodes and edges in the graph. The typical models of directed graph neural networks include graph convolutional neural networks, gated graph neural networks, graph attention networks, and so on. In the process of application, the direction of the edge is usually explicitly considered in the aggregate function. Nodal v Described as h_v , whose incoming neighbour set is expressed as N_{in} v the updated formula is

shown in formula (1):

$$
h_v^{\text{new}} = \sigma(\sum_{u \in N_{in}(v)} \alpha_{uv} \cdot h_u \cdot W) \tag{1}
$$

Where the graph neural network after node update is represented as h_v^{new} the current vector h_u , the activation function is expressed as $\sigma(\cdot)$, edge (u, v) the weight is expressed as $\alpha_{_{uv}}$, W represents the weight matrix.

Temporal digraph neural networks are designed to process digraph data containing time dimensions. For temporal-directed graphs, the algorithm needs to consider both spatial structure and temporal dynamics. A common practice is to combine graph neural networks with time series models such as recurrent neural networks or time convolutional networks. Its updated formula is related to its model combination. A partial node of RNN in a temporal digraph neural network is set v At the time When its hidden state is expressed as h_v^t The updated formula is shown in (2):

$$
h_v^t = RNNCell(h_v^{t-1}, Aggregate(\lbrace h_u^{t-1} | (u, v) \in InEdges(v) \rbrace))
$$
\n
$$
(2)
$$

Where the aggregate function is described as *Aggregate* , the RNN unit is represented as. Spatial graph neural networks mainly focus on the spatial structure of graphs, that is, the spatial layout and relationship of nodes and edges. Although a spatial graph neural network is not directly equivalent to a directed graph neural network, it can process a directed graph as one of the input data. Spatial graph neural networks update node representations by aggregating information from neighboring nodes, a process that can be applied to directed graphs but also takes into account other types of graph structures. Let the sequence number be *i* The representation matrix of all nodes in the layer is described as H^l The updated formula is shown in (3):

$$
H^{l+1} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{l}W^{l})
$$
\n(3)

Where the sequence number is l the layer weight matrix is expressed as W^l , the eigenmatrix is expressed as $\ H^l$, the adjacency matrix is expressed as $\ \tilde{A}$, whose degree matrix is described as $\ \tilde{D}$

The normalized adjacency matrix is described as $\left.\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}\right.^{\frac{1}{2}}$ D ²*AD* \cdot

The dynamic sampling ray projection algorithm can dynamically adjust the sampling step size or the number of sampling points according to the complexity and importance of local data during the process of light passing through volume data. In areas where the data changes gently or the importance is low, the sampling points can be appropriately reduced to reduce the computation and memory requirements. In areas where the data changes dramatically or is of high importance, the sampling points are increased to improve the image quality. Figure 1 shows a schematic comparison of the principle of the traditional ray projection algorithm and dynamic sampling ray projection algorithm.

Figure 1: Comparison of a schematic diagram of traditional ray projection algorithm and dynamic sampling ray projection algorithm.

Set line of sight points as $\,M\,$, where the presence of two lines of sight are denoted as $\,F\hskip-3pt$, which line of sight *F* and the relationship between the edges of the surface is tangent, Pass through *M* Line of sight of point S The nearest point between the surface and the surface is SP. The surface and its section normals and line of sight $|F|$ Points of intersection are denoted as, and the partial derivative at this point is denoted as $z = f'x(x_{0}, y_{0})$, its expression is shown in (4):

$$
f'x(x_0, y_0) = \frac{\partial f}{\partial x}\bigg|_{\substack{x = x_0 \\ y = y_0}}\tag{4}
$$

The line of sight can be obtained from the above formula *F* and The slope between the axes, denoted by $k_{_0}$ And the slope is a point $\,P\,$ Sum of the corresponding tangent planes Z Maximum slope value between axes. There is a correlation between the slope and the concave and convex of the surface; that is, the convex surface indicates that the slope is positive, and the reverse is negative. The slope expression is:

$$
k_0 = \left| f'x(x_0, y_0) \right| \le 1 \tag{5}
$$

Line of sight F Summation point J_{0} The distance between them is:

$$
\left| FJ_0 \right| = \sqrt{(x_0 - x)^2 + (y_0 - y)^2 + (z_0 - z)^2}
$$
\n(6)

Attainable point J_{0} The sampling frequency is:

$$
rate = \frac{k_0}{|FJ_0|} = \frac{|f'x(x_0, y_0)|}{\sqrt{(x_0 - x)^2 + (y_0 - y)^2 + (z_0 - z)^2}}
$$
(7)

Where the sampling frequency is denoted as *rate* .

In the dynamic sampling ray projection algorithm, the relationship between the tangent point and the line of sight and the tangent point slope is a negative correlation, and the relationship between the distance and the sampling rate is also a negative correlation. When the sampling rate is smaller, the fewer pixels projected on the screen, that is, the lower the clarity of the image, and vice versa.

3.3 Dance Feature Extraction and Matching Module

If choreography wants to achieve the best effect from the visual and emotional aspects, it needs to fully understand the characteristics of music based on mastering the characteristics of dancers and organically combine music and dance movements. Musical characteristics are the key link to determine the tone of choreography, and the integration of musical characteristics and dance movement characteristics is also related to the continuity and integrity of choreography. In this paper, we will use the directed graph neural network to extract the features of dance music and choreography and make corresponding matching.

Musical features include musical intensity and rhythm, and dance movements are related to them. Therefore, this paper divides music into several segments and extracts the rhythm and intensity features of each segment of music through a directed graph neural network. Let the music of the whole piece be *^M* , the number of its segments is denoted as *i* then, each music set is represented as $M = [M_1, M_2, ..., M_i]$ then fragment M_n the characteristics of:

$$
MF(f) = \begin{bmatrix} F_n^M(f) \\ F_i^M(f) \end{bmatrix}, f \in M_n
$$
\n(8)

Among them, $1 \leq n \leq i$ the sequence number of the music clip frame is f , the music rhythm and intensity characteristics are respectively recorded as $\ F_R^M$ and $\ F_I^M$.

The rhythmic characteristics of music fragments are described as follows:

$$
F_R^M(f) = \begin{cases} 1, f = P_t \\ 0, other \end{cases}
$$
 (9)

Where the node time is expressed as $\left\vert P_{_{t}} \right\rangle$.

The sound pressure level is used as the characteristic of music intensity, which is calculated as shown in (10):

$$
F_I^M(f) = \log_{10} \left(\sum_{g=C4}^{C6} X_{peak}(g)^2 \cdot f_g^2 \right), f \in M_n \tag{10}
$$

Where the corresponding frequency value of C4-C6 is denoted as f_g .

Let the dance sequence be *N* , Actions are divided into segments and expressed as $N = [N_1, N_2, ..., N_i]$, i Represents the number of dance movement segments, and its rhythm and intensity characteristics are shown in (11):

$$
F_R^D(f) = \begin{cases} 1, f = P_t \\ 0, other, f \in N_t \\ F_I^D(f) = \sum_{i=f_R^c}^{f_R^c} \frac{W(i)}{f_R^e - f_R^s + 1} \\ W(i) = \sum_{k=1}^c \alpha^{(k)} \cdot \left\| x_{i+1}^{(k)} - x_i^{(k)} \right\| \end{cases}
$$
(11)

Where the frame number in the action fragment is represented as The start frame of its rhythm cycle is denoted as f^s_R , the end frame is denoted as f^e_R , the action vector is denoted by x , the number of dimension sequences in this frame is k The action data is marked as $x_i^{(k)}$, the action vector dimension of each frame is denoted as *^c* .

The formula for calculating the match of rhythm and intensity between music and action is shown in (12):

$$
\hat{S} = \max_{s, f_0} \sum_{f=1}^{L_M} \frac{F_R^M(f) \cdot F_R^D(s \cdot f + f_0)}{F_R^M(f) + F_R^D(s \cdot f + f_0)}
$$
\n
$$
\hat{B} = \sum_{f=1}^{L_M} \sqrt{\frac{F_R^M(f)}{F_R^M(f)} \cdot \frac{F_R^D(f)}{F_R^D(f)}}
$$
\n
$$
(12)
$$

Where the length of the musical segment is denoted as $\, L_{\scriptscriptstyle M}$, the length of the action segment is denoted L_{D} , $f_0 \in [0, L_D - s \cdot L_M]$, $s \in [0.9, 1.1]$, the scaling factor is denoted as s, and The translation is expressed as f_0 .

3.4 Interactive Module of Choreography

After obtaining the music and movement features, they are used as control signals to predict the movement sequences through the temporal-directed neural network and the spatial-directed neural network, respectively, to complete the choreography. Figure 2 shows the choreography network structure diagram.

The distribution of motion frames for dance movement prediction was obtained according to the

Gaussian mixture model. Namely
$$
G(x_i) \sum_{g=1}^{G} \alpha_g \phi(x_i \Big| v_g, D_g)
$$
, of which $\sum_{g=1}^{G} \alpha_g = 1, 0 \le \alpha_g \le 1, D_g > 0$, the

number of Gaussian models is denoted as $|G|$. The sequence number is $|g|$ The density function of the Gaussian model is expressed as $\phi(x_i|v_g, D_g)$ the mean vector is denoted by v_g , the covariance matrix

is denoted by $\left\langle D\right\rangle _{g}$, its loss function is shown in (13):

$$
S_{gmm} = -\log \sum_{g=1}^{G} \alpha_g \phi(x_i \Big| v_g, D_g) \tag{14}
$$

Figure 2: Schematic diagram of choreography network structure.

In this style, there are five ends of the dance movement: head, hands, and feet, the rotation of the action joint is denoted as r , the endpoint position is denoted as $\;m$, $\;S_{_{gmm}}\;$ the two can be calculated.

The presence of limited foot contact is denoted as $e_{contact}$ the exposure limit loss is calculated as:

$$
S_{contact} = \sum_{t} \sum_{i \in feet} e_t^i e_{t+1}^i \left\| l_t^i - T(l_{t+1}^i) \right\| \tag{15}
$$

Where the sequence number is i The joints are in contact with the ground at the moment, and the rotating seat is marked l_i^i , the equation converted to position coordinates is $T(l_{t+1}^i)$.

The comprehensive loss function is:

$$
S = S_{gmm} + \beta \cdot S_{contact} \tag{16}
$$

Among them, $\beta = 0.1$.

4 EXPERIMENTAL RESULTS AND ANALYSIS

To test the performance of computer-aided dance choreography and teaching interaction model and its practical application effect, this paper randomly selected A class of school students for the experiment. In the experiment, the class needs to choreograph and teach the interaction of three different music styles through the model of this paper. The experimental content is mainly divided into three parts, namely, the capture of dance movements, the extraction of dance music and movement features, and the application of dance choreography. Qualitative and quantitative experimental analysis is carried out in each part of the experiment.

4.1 Motion Capture Results

In this part of the experiment, the sampling time of moving limbs in different dance movements and the recognition rate of dance movements in the application process of the model are analyzed. Figure 3 shows the sampling time of students' limbs by the model. In addition to the model algorithm in this paper, the traditional ray projection algorithm is also selected for sampling time comparison. The results show that, on the whole, the sampling time of the traditional ray projection algorithm for different limb parts is above 20 and there is a certain range of fluctuation. However, the sampling time of the proposed algorithm is all lower than 18s, and the sampling time of the proposed algorithm tends to decrease slowly. This indicates that the model algorithm in this paper can significantly

shorten the sampling time in the reconstruction of the dance movement model, and the stability performance of the model sampling efficiency is better.

Figure 3: Sampling time of students' limbs by the model.

Figure 4 shows the comparison results of the recognition rates of different dance movements of Class A students by the three models. In addition, the model in this paper also includes the traditional light projection algorithm and the point cloud algorithm. To reduce the chance rate and error of recognition, the experiment selected 5 different sets of dance movements for recognition. The results show that in the same set of dance movement recognition results, the recognition rate of the traditional light projection algorithm is the lowest, the recognition rate of the point cloud algorithm is slightly improved, and the recognition rate of this algorithm is greatly improved. From the recognition rate of different dance movements, the recognition rate of the proposed algorithm is the best, all above 91%, while the traditional algorithm is the worst, the recognition rate is not more than 90%. This indicates that the proposed algorithm has certain advantages in dance movement recognition accuracy and shows good stability, which can provide effective and accurate basic data for future applications.

4.2 Extraction Results of Dance Features

Considering that there are some differences between different styles of dance music and dance movements, in this part of the experiment, this paper chooses three styles of dance choreography: street dance, house dance and modern dance. This part of the experiment is divided into two parts, one is to extract the dance movements and music features, and the other is to test the matching degree between them. Due to the limitation of space, this paper takes some dance movements as an example for analysis, and the results are shown in Figure 5. As can be seen from the results of Figure (a), in this set of dance movements, the arm movement speed of the sixth segment and the ninth segment varies greatly, and the arm movement speed of the sixth segment is the fastest, which indicates that the dance movements of this segment are highly variable. Figure (b) (c) shows the extraction of dance characteristic postures in the sixth and ninth segments. From the extraction postures, dance movements at both ends have significant changes, and the movement amplitude of the sixth paragraph is greater than that of the ninth paragraph, which is consistent with the analysis in Figure (a). This shows that the model in this paper can effectively extract dance movement features and provide accurate data for subsequent matching.

Figure 6 shows the matching degree results of three different styles of dance and music. In this experiment, traditional manual matching methods were also selected for comparison. As shown in the figure, in terms of the matching degree of music and dance, the traditional artificial matching method scores below 3.2 points, while the matching results of the model in this paper are above 4.2 points, and the error margin is significantly smaller. In terms of coherence and authenticity, the values of the model in this paper are above 4 points.

Much higher than traditional manual methods. This shows that the model in this paper can match music and dance movements according to the characteristics of the two, improve the matching degree of music and dance movements, increase the coherence of choreography, more in line with the characteristics of actual dancers, and help improve the final effect of choreography.

Figure 6: Matching degree results of three different styles of dance and music.

4.3 Choreography Application Results

This part of the experiment includes testing the rationality of the final choreography sequence and teaching interaction. In the rationality analysis experiment of choreography sequence, this paper also selected three choreography methods for comparison, and the results are shown in Figure 7. The FID index was introduced in this experiment, and there was a negative correlation between this index and the rationality of the dance choreography sequence; that is, the higher the value of this index, the lower the rationality of dance choreography, and vice versa. The results show that among the four dance choreography models, the index value of the LSTM algorithm is much higher than that of the other three algorithms, the manual choreography model is slightly lower than that of the DanceNet model, and the index value of this model is much lower than that of the other three models, and the performance is the best. At the same time, it can be seen from the rhythm coverage rate in the figure that the rhythm coverage rate of the model in this paper and the rhythm coverage rate of the manual arrangement model perform better. In the aspect of action rhythm, the action rhythm rate of this model is significantly higher than that of the other three models. To sum up, the model in this paper can effectively combine music and dance movements, the choreography sequence generated is more reasonable and the choreography effect is better.

Figure 7: Comparison of effects of four choreographic models.

Figure 8 shows the comparison of teaching interaction between the manual choreography teaching mode and the choreography teaching mode in this paper. The result shows that, compared with the manual choreography teaching mode, the interaction times of the teaching mode in this paper have been greatly improved, and the effective interaction rate is more than twice that of the manual choreography teaching mode. This shows that the model in this paper can carry out personalized teaching according to the characteristics of students, improve the interaction between teachers and students, strengthen the effectiveness of interaction, and improve the efficiency of choreography.

Figure 8: Comparison of teaching interaction between the manual choreography teaching mode and the choreography teaching mode in this paper.

Figure 9: Schematic diagram of choreography results for dance movements in the style of otaku dance.

The otaku dance is deeply loved by young people for its unique rhythm and dynamic body language. In Figure 9, the movements of the otaku dance are accurately captured, analyzed, and optimized through computer-aided choreography. The system may automatically adjust the speed, intensity, and coherence of movements based on the characteristics of otaku dance, such as fast hand movements, flexible body transitions, and distinct rhythm so that the entire arrangement retains the original flavour of otaku dance while adding precision and beauty of modern technology. In addition, computer-aided choreography can help teachers or choreographers quickly generate multiple choreography schemes, making it easier to compare and choose and improving work efficiency and creative freedom.

Mongolian dance is known for its roughness, boldness, and grandeur, with movements containing profound cultural connotations and ethnic characteristics. In Figure 10, computer-aided orchestration technology also plays an important role. The system may inject more cultural charm and emotional expression into the dance movements by analyzing the basic steps, gestures, body posture, and other elements of Mongolian dance combined with the historical background and artistic style of Mongolian culture.

Figure 10: Schematic diagram of the choreography results of Mongolian dance movements

At the same time, the system can also fine-tune dance movements to ensure they meet the normative and artistic requirements of Mongolian dance. In terms of teaching interaction, such arrangement effect diagrams can be visually displayed to students, helping them better understand the essence and charm of Mongolian dance, and improving learning effectiveness and interest.

5 CONCLUSIONS

Traditional dance choreography is based on the experience of teachers and involves a lot of time and labour costs, so there is often a lack of effective teaching interaction in the teaching process, and most of them are based on the completion of dance choreography training. To improve the quality of choreography teaching, this paper introduces computer-aided technology in teaching to improve the efficiency of choreography and increase teaching interaction. According to the characteristics of choreography, this paper constructs a choreography model based on virtual reality technology and improves the reconstruction accuracy of the three-dimensional model of dance movements by dynamic sampling light projection algorithm. At the same time, the characteristics of dance music and dance movements are obtained through the directed graph network, and the choreography is realized according to the dance tone and dancers' characteristics. The experimental results show that the proposed model can improve the sampling efficiency of the three-dimensional dance movement model, shorten the sampling time, improve the recognition rate of movements, and provide a more accurate data basis for model dance choreography. At the same time, the model in this paper can effectively extract the characteristics of music and dance movements, achieve movement matching according to different music styles, and improve the matching degree and coherence of the two. The rationality results of the final choreography sequence show that the model in this paper improves the matching of dance music and movements and the overall coherence, making the final choreography sequence more in line with the characteristics of dancers and more reasonable. In addition, the virtual reality environment constructed in this paper can effectively improve the interaction frequency and effectiveness between teachers and students, which is conducive to enhancing the final effect of choreography. Although some results have been obtained in this study, there are still many problems that need to be further solved and optimized. In the following research, this paper should strengthen the interaction of a virtual reality environment and improve the presentation of its choreography effect and teaching interaction.

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