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Computer-Aided Design AND APPLICATIONS

Using Deep Learning Algorithm to Analyze the Accurate Modeling of Dance Dynamics in CAD

Xi Liu[1] and Zhen Li[2]

[1]Jiangxi Normal University Science and Technology College, Jiujiang 332020, China, shyllliuxi@163.com
[2]School of Art and Design, Nanchang Hangkong University, Nanchang 330063, China, 70998@nchu.edu.cn

Corresponding author: Zhen Li, 70998@nchu.edu.cn

Abstract. The purpose of this article is to explore the dynamic analysis and CAD modeling method of dance based on DL (Deep learning) so as to realize efficient and accurate analysis and 3D visual reproduction of dance movements. In order to achieve this goal, this article first constructs a DL model to automatically extract and classify the key features of dance movements from dance videos. Furthermore, a method of transforming the analyzed dance dynamic data into a CAD model is innovatively proposed, and the 3D visualization of dance movements is realized by using CAD modelling technology. The experimental results show that this method has achieved remarkable performance improvement in dance dynamic analysis tasks and can generate realistic and accurate CAD dance models. These findings not only provide new tools and methods for digital and intelligent analysis of dance art but also open up new ways for dance creation, performance, education, and inheritance. To sum up, the research results of this article prove the effectiveness and superiority of the dance dynamic analysis and CAD modelling method based on DL and provide important references for future related research and application.

Keywords: Deep Learning; Dance Dynamics; Computer-Aided Design; Dance Model; 3D Visualization
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1 INTRODUCTION

With the swift advancement of computer technology, CAD has emerged as a crucial instrument across numerous domains. With the continuous development of artificial intelligence technology, the automatic generation of music and dance has become a hot research topic. In order to achieve a close integration between music and dance, Cai et al. [1] proposed a music-driven automatic generation method for ethnic dance movements based on a sequence-to-sequence network (Seq2Seq). This method converts the time series of music into the time series of dance actions, thereby achieving synchronization and mapping between music and dance. Music feature extraction, sequence-to-sequence network modelling, and dance action generation. Firstly, we extract features such as rhythm, melody, and harmony from music to construct a time series of musical features. Then, we use the Seq2Seq model to encode the music feature time series and convert it into a time series of dance actions. In the Seq2Seq model, we use Long Short Term Memory Network (LSTM) as the encoder and decoder to capture the long-term dependencies of music and generate corresponding dance actions. Finally, we generate specific dance actions based on the action labels output by the decoder. Specifically, in dance artistry, CAD technology enables dancers to translate abstract dance movements into tangible 3D representations, enhancing comprehension and creativity in dance choreography. With the advent of the digital age, the application of 3D human dance modelling technology in fields such as film and television production, game design, and virtual reality is becoming increasingly widespread. However, existing 3D human dance modelling methods often face problems such as complex parameter settings and unnatural movements. To address these issues, Chi et al. [2] proposed a new parameterized 3D human dance modelling method based on key position labelling and body part segmentation. It uses parameterized models to model dance movements. Generate various dance movements by adjusting model parameters. This method has strong flexibility and scalability and can adapt to various dance styles and movement requirements. Finally, a parameterized dance modelling method was used to generate some dance movements, and professional dancers were invited for evaluation. The evaluation results indicate that the dance movements generated by this method are natural, smooth, and have good diversity and scalability.

Nevertheless, conventional CAD modelling techniques often encounter difficulties when tackling intricate dance dynamics, such as ensuring the precision of motion capture and streamlining data processing. The analysis and modelling of three-dimensional dance movements is a challenging topic in the field of computer vision. It not only involves accurate capture and recognition of dance movements but also requires a deep understanding of the dynamic characteristics of dance. In recent years, with the rapid development of deep learning technology, we have been able to explore the potential patterns of dance movements more deeply and how to model them through computer vision technology. Farnoosh and Ostadababas [3] explored how to use computer vision technology to dynamically generate deep potential modelling of three-dimensional dance movements. Deep generative latent models are an effective representation learning framework that can map high-dimensional dance data to low-dimensional latent spaces, thereby extracting the intrinsic structure and dynamic patterns of dance actions. This model can learn the intrinsic structure and patterns of data, thereby predicting and generating new dance data. Through deep learning techniques, we can train efficient deep generative latent models, such as Variational Autoencoder (VAE) and Generative Adversarial Network (GAN), to achieve dynamic modelling of three-dimensional dance movements. With the popularization of dance in digital media, the application of dance motion tracking technology in the fields of education and entertainment is becoming increasingly widespread. To achieve accurate dance motion tracking, it is necessary to determine an appropriate sampling frequency. Fedasyuk and Marusenkova [4] proposed an algorithm for detecting the minimum sampling frequency used for tracking preset motion scenes in dance movements. This algorithm aims to find a sampling frequency that can meet the tracking accuracy requirements while avoiding excessive redundant data. In early research, dance motion tracking mainly relied on manual labelling or rule-based methods. However, these methods are often time-consuming and have low accuracy. In recent years, deep learning has achieved great success in the field of computer vision, providing new solutions for dance motion tracking. However, choosing an appropriate sampling frequency is crucial for achieving efficient tracking. To verify the effectiveness of the algorithm, experiments were conducted on a publicly available dance action dataset. The results indicate that the algorithm can accurately detect the minimum sampling frequency used for dance motion tracking in preset motion scenes. Compared with traditional fixed sampling frequency methods, this algorithm can adaptively adjust the sampling frequency according to different motion scenes, thereby improving tracking accuracy and reducing redundant data. Consequently, it's imperative to explore innovative methods for accurately modelling dance dynamics within the CAD realm.

This research aims to scrutinize dance dynamics by harnessing the power of DL algorithms for precise modelling within CAD. By leveraging DL technology, we can extract patterns and principles of dance movements from extensive dance datasets, subsequently applying these insights to CAD modelling. This approach not only elevates the precision of dance dynamic modelling but also mitigates the intricacies and expenses associated with data processing. Furthermore, precise dance dynamic modelling holds significant practical value for dance instruction, choreography, and performance, ultimately contributing to the advancement and evolution of dance artistry.

In this investigation, we will employ sophisticated deep learning algorithms, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to scrutinize dance dynamic data. For data acquisition, we will utilize a motion capture system to gather the dancers' movement information, followed by preprocessing and annotation. During data manipulation, techniques such as data augmentation and feature extraction will be leveraged to enhance the model's generalization capabilities and overall performance. In terms of modelling, we aim to investigate the integration of DL analysis outcomes with CAD modelling methodologies to achieve precise dance dynamic representations.

In this article, the following innovations have been made in the dance dynamic analysis and CAD modelling method based on DL:

(1) Construction and application of DL model: In this article, DL technology is introduced into the field of dance dynamic analysis, and an efficient DL model is successfully constructed. The model can automatically extract and classify the key features of dance movements, which breaks through the limitation of traditional methods relying on manual feature extraction and realizes a higher level of dance movement understanding and analysis.

(2) Transformation from dance dynamics to CAD model: This article innovatively puts forward a method to transform the analyzed dance dynamics data into a CAD model. By combining the feature extraction ability of DL with CAD modelling technology, the 3D visual reproduction of dance movements is realized. This method overcomes the limitation that dance movements can only be presented in the form of video in the past and provides a more intuitive and 3D display method for dance creation, teaching and inheritance.

(3) Interdisciplinary integration and application expansion: This article not only pays attention to the dynamic analysis of dance itself but also explores the possibility of combining dance art with interdisciplinary fields such as computer science and engineering design. By introducing CAD modelling technology, this article provides a new idea and application direction for the digital, virtual, and intelligent development of dance art. This interdisciplinary integration helps promote the cross-innovation between dance art and other fields and injects new vitality into the inheritance and development of dance art.

This article comprises six distinct sections. The initial section serves as an introduction, outlining the research's backdrop, objectives, importance, key elements, methodologies, and overall structure. The second section delves into the fundamental principles of dance dynamics and CAD modelling, providing a solid theoretical foundation for the subsequent research.

Moving on, the third section introduces the DL algorithm and its application in the context of dance dynamic analysis, paving the way for the experimental analysis that follows. The fourth section, which constitutes the heart of this article, details the methodology for dance dynamic analysis and CAD modelling utilizing DL.

Subsequently, the fifth section aims to validate the efficacy and superiority of the presented approach through rigorous experiments. It also includes a comprehensive analysis and discussion of the experimental findings. Finally, the sixth section summarizes the study's key accomplishments and contributions, identifies any potential shortcomings or limitations, and offers recommendations and future research directions.

2 RELATED WORK

The outstanding performance of deep learning algorithms in processing complex visual data has led to their increasingly widespread application in the field of human activity recognition. Girdhar [5] provides a comprehensive review of the methods and technologies related to visual human activity recognition using deep learning algorithms. The application of deep learning in human activity recognition mainly involves convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN). These network structures can extract features from the original image and classify activities based on these features. CNN performs well in processing spatial information in images, while RNN can process sequential data and is suitable for processing temporal information. GAN can be used to generate virtual activity data for training and enhancing model performance. Deep learning models can automatically extract features from raw images, which have better representation ability compared to manually designed features. Convolutional layers, pooling layers, and other structures can extract local and global features of images, while fully connected layers can integrate features and provide a basis for classification tasks. Music and dance, as forms of artistic expression, often have a non-linear and fluid creative process. Deep learning algorithms, as a powerful data analysis tool, can reveal the underlying mechanisms of this process. Hsueh et al. [6] explored how to use deep learning algorithms to analyze deconstructive creativity, particularly the nonlinear processes and flowing roles in contemporary music and dance. Deep learning algorithms have advantages in handling complex data structures, making them an ideal tool for analyzing creative processes. Creativity is often seen as a complex nonlinear process that involves the combination, variation, and reconstruction of various elements. Deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), can learn and simulate these complex internal connections. In music and dance, non-linear processes are reflected in the ups and downs of melodies, changes in rhythm, and the flow of movements. These elements interact with each other to form a dynamic system. Deep learning models can capture these dynamic relationships and reveal the hidden nonlinear patterns in music and dance. For example, the use of Long Short-Term Memory Networks (LSTM) can effectively process sequence data to analyze time dependencies in music and dance.

With the rise of online live streaming, real-time identification of crowd dance activities has become a hot research direction. This technology can help viewers better understand live streaming content, improve the viewing experience, and provide more diverse interactive methods for live streaming platforms. Kang et al. [7] introduced a crowd dance activity recognition method based on 3D ResNet and region graph convolutional networks. In early research, crowd dance activity recognition mainly relied on manually designed feature extraction methods, such as edge detection, motion tracking, etc. However, these methods often struggle to handle complex backgrounds and dynamic populations. In recent years, deep learning has achieved great success in the field of computer vision, and many researchers have begun to attempt to apply deep learning to crowd dance activity recognition. Among them, 3D-CNN and graph convolutional networks are two commonly used methods. A regional graph convolutional network is a special type of convolutional network that can handle graph-structured data. In crowd dance activity recognition, the region graph convolutional network can view individuals in the crowd as nodes, and the relationships between individuals as edges, thus constructing a graph structure. By performing convolution operations in the graph, the region graph convolutional network can better capture the dynamic relationships in the crowd, thereby improving the recognition accuracy of dance movements. Machine learning is a technique that enables computers to automatically learn and improve from data. In dance activity recognition, machine learning techniques can automatically identify different dance movements, styles, and states by analyzing dance videos. The application of this technology not only improves the accuracy of dance recognition but also makes the processing and analysis of dance data more convenient. Kulsoom et al. [8] reviewed the research on machine learning-based human dance activity recognition in various applications. Through machine learning techniques, the accuracy and skill level of dance movements can be automatically identified and analyzed, providing an objective basis for dance teaching and evaluation. The application of this technology can help teachers better guide students and improve their dance skills. Machine learning-based human dance activity recognition can also be applied in the fields of rehabilitation therapy and fitness. By analyzing the patient's dance movements, their physical condition and rehabilitation progress can be evaluated, providing a basis for rehabilitation treatment. In addition, this technology can also be used in the fitness field to help users exercise more effectively.

Human dance motion recognition and posture prediction are important research directions in the fields of computer vision and artificial intelligence. This technology has broad application prospects in fields such as dance performances, intelligent monitoring, human-computer interaction, and virtual reality. Deep learning algorithms have strong capabilities in processing image and video data, providing new solutions for human dance motion recognition and pose prediction. Ma et al. [9] reviewed the relevant research on using deep learning algorithms for human dance motion recognition and posture prediction. The application of deep learning in dance action recognition mainly involves convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN). These network structures can extract features from the original image and classify dance movements based on these features. CNN performs well in processing spatial information in images, while RNN can process sequential data and is suitable for processing temporal information. GAN can be used to generate virtual dance action data for training and enhancing model performance. With the continuous development of artificial intelligence technology, deep learning has achieved significant results in many fields. In the field of dance, deep learning-based human dance action prediction has become a hot research direction. This technology can help us better understand the generation mechanism of dance movements, and improve the performance and creative level of dance. Park et al. [10] introduced a deep learning-based human dance motion prediction method and explored its application in intention-aware motion planning. In early research, the prediction of dance movements mainly relied on manually designed feature extraction methods and motion models. These methods often struggle to handle complex dance movements and diverse performance styles. In recent years, the application of deep learning in computer vision and motion analysis has gradually received attention. Among them, Recurrent Neural Network (RNN) and Long Short Term Memory Network (LSTM) are two commonly used methods. It adopts a deep learning model based on LSTM for dance action prediction. This model can process sequential data and learn the temporal dependencies of dance movements. By training the model, we can obtain the probability distribution of each dance action and predict the next possible action. With the continuous development of deep learning technology, unsupervised learning has achieved significant results in processing large amounts of unlabeled data. Stacked Autoencoders (SAE), as a powerful unsupervised learning algorithm, have been widely used in feature learning and dimensionality reduction. In the field of 3D dance analysis, using deep learning algorithms to extract features of dance movements is of great significance for dance recognition, classification, and synthesis. Protopapadakis et al. [11] explored how to use stacked autoencoders to analyze unsupervised 3D dance. It trains the stacked autoencoder using unlabeled 3D dance data. By minimizing reconstruction errors, SAE can learn feature representations of dance movements. After the training is completed, the intermediate layer or output layer of the stacked autoencoder can be used as the feature representation. These features can reflect the spatial and temporal characteristics of dance movements, such as joint angles, velocity, and acceleration.

The dance interactive learning system is an innovative educational tool that utilizes technology to enhance students' learning experience, especially in the art field of dance. Deep learning algorithms have achieved significant results in multiple fields, such as image recognition, speech recognition, and natural language processing, providing new ideas and methods for the design and implementation of dance interactive learning systems. Raheb et al. [12] explored how to use deep learning algorithms to analyze the interactive workflow and teaching methods of dance interactive learning systems—using deep learning algorithms to automatically extract features related to dance movements, such as joint angle, velocity, acceleration, etc. These features can reflect the learner's movement characteristics and skill level. It utilizes deep learning models to train and recognize a large amount of dance action data. Common models include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). The model can automatically extract features and recognize dance movements by learning a large amount of dance action data. Provide real-time feedback and correction information to learners based on the recognition results of the model. These pieces of information can be conveyed to learners through sound, visual, or tactile means, helping them correct their movements and improve their skills during practice. With the continuous development of robotics technology, robots have been able to complete various complex actions, including dance movements. In order to achieve real-time recognition of robot dance movements, an efficient and accurate method is needed. Reily et al. [13] proposed a real-time dance action recognition method based on multi-sensor graphic-embedded robot learning. This method utilizes multi-sensor data, combined with graphic embedded technology and machine learning algorithms, to achieve real-time recognition of robot dance movements. Extract features from preprocessed data, such as temporal changes in joint angles, waveforms of velocity and acceleration, etc. These features can reflect the dynamic and static information of dance movements. Represent the extracted features as a graphical structure, where nodes represent joints and edges represent relationships between joints. This graphical representation can better handle complex and continuous dance action data. It uses machine learning algorithms to classify and recognize data represented by embedded graphics. These algorithms can learn the characteristics and patterns of dance movements from a large amount of data. Real-time recognition of dance movements is achieved by inputting real-time collected sensor data into a trained machine-learning model. For each dance action, the system can output corresponding labels or descriptions for the robot to perform corresponding action control.

The Creative Dance Collaboration System is an innovative platform that integrates artificial intelligence and dance art, aiming to achieve automation and intelligence in dance creation through human-computer interaction. Interaction modelling is the core component of the system, which can describe and predict the interaction behaviour in the system, thereby optimizing the generation and performance of dance movements. Deep learning algorithms have significant advantages in processing complex data and pattern recognition, providing new solutions for the interactive modelling of creative dance collaborative systems. Rezwana and Maher [14] explored how to use deep learning algorithms to analyze interactive modelling frameworks in creative dance collaboration systems. It extracts dance action-related features from preprocessed data, which can reflect the action characteristics and interaction behaviour of participants. It utilizes deep learning algorithms to train models, enabling the model to automatically extract features and recognize dance movements by learning a large amount of dance action data. Computer 3D assistance systems have shown enormous potential in various fields. Especially in the modelling and design of dance motion mechanics, this technology provides unprecedented accuracy and visualization effects. Tan and Yang [15] explore how to use computer-aided 3D systems for precise modelling and design of dance motion mechanics. Computer 3D assistance systems can capture the movements of dancers in real-time through high-precision capture devices and convert them into 3D data. These data not only include the spatial position of the action, but also mechanical parameters such as force and speed. Through these data, it is possible to conduct precise mechanical analysis of dance movements, thereby better understanding the skills and expressive power of dancers. Extracting mechanical parameters such as force and velocity from the data is crucial for understanding the mechanical characteristics of dance movements. Based on the extracted mechanical parameters, establish a mechanical model of dance movements. This can be a mathematical model, a physical model, or a simulation model, depending on the research purpose and field. Verify the accuracy and reliability of the model by comparing actual data with model predictions. Taking a specific dance action - jumping as an example, it can obtain three-dimensional data of the dancer's jumping process through a computer three-dimensional assistance system. Then, based on these data, we can establish a mechanical model for jumping actions and analyze various factors that affect jumping height and distance.

3 DL ALGORITHM AND ITS APPLICATION IN DANCE DYNAMIC ANALYSIS

3.1 The Principle of Dl Algorithm and the Construction of Dance Dynamic Data Set

Dance, as an art form, conveys emotions, stories and culture through body language. Its dynamic characteristics are rich and varied, including rhythm, strength, fluency, posture and space occupation (Figure 1). Every dance movement is a comprehensive embodiment of these characteristics.

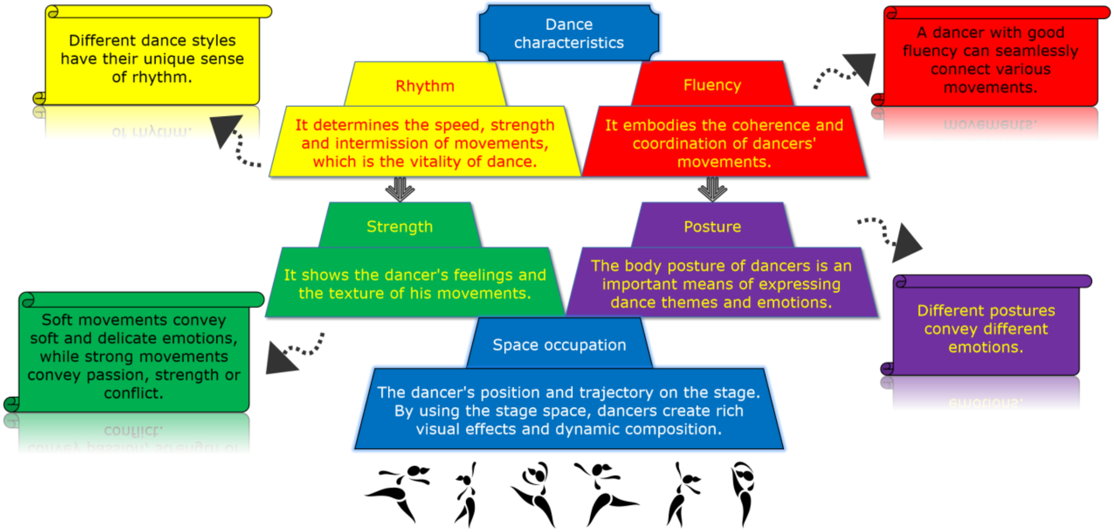

Figure 1: Dance characteristics.

Since its birth in the 1960s, CAD technology has experienced rapid development from 2D drawing to 3D modelling. It uses the powerful computing power and graphics processing power of computers to help designers design more efficiently and accurately. The core of CAD technology is digital and parametric design. Through digitalization, designers can convert real objects into data that computers can process. Parametric design allows designers to quickly adjust the design by modifying parameters, which greatly improves the design efficiency. Wireframe modelling is the most basic modelling method, which defines the outline of an object through lines and curves. Surface modeling adds the surface information of the object on this basis to make the model more realistic. Solid modeling is the most complete modeling method, which not only contains the surface information of the object but also defines the internal structure and quality attributes of the object.

Deep Learning (DL) is a specialized branch of machine learning that leverages neural network models to derive meaningful representations from data. In our discussion, we focus primarily on two DL algorithms: Convolutional Neural Networks (CNN) and a particular type of Recurrent Neural Network (RNN) known as Long Short-Term Memory (LSTM). CNN excels in handling data with a grid-like structure, particularly images. They employ a sequence of convolutional layers, pooling layers, and fully connected layers to extract relevant features from the input data. In the context of dance dynamic analysis, CNN can effectively extract spatial features such as dancers' postures and movements from video footage. They are functions that introduce nonlinear factors between the input and output of neurons and help neural networks learn and understand complex and nonlinear data patterns. The activation function must be non-linear because the combination of linear functions is still linear, and it is impossible to approximate complex non-linear functions. The nonlinear activation function allows the neural network to learn and approximate almost any type of function. (As shown in Figure 2).

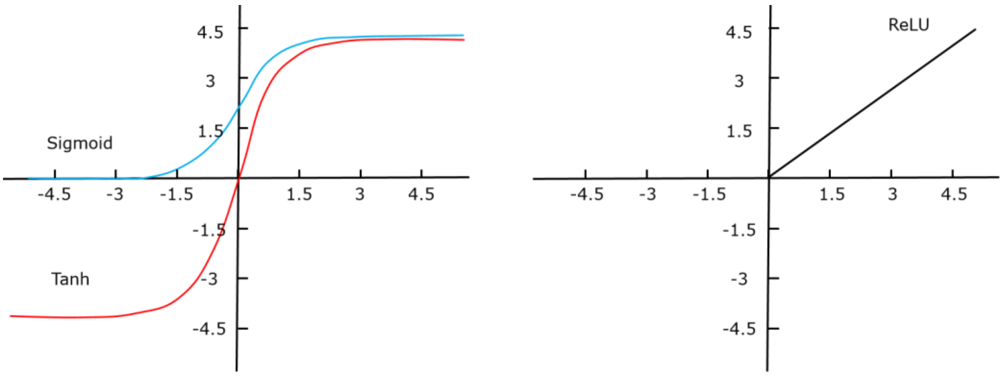

Figure 2: Activation function.

In this article, the LeakyReLU function is selected, which still has a small gradient when the half axis is negative, and can effectively avoid the "dead zone" state. Its formula can be expressed as:

$$f(x) = \begin{cases} 0.01x & x \le 0 \\ x & x > 0 \end{cases} \tag{1}$$

In this context, x denotes the input to the activation function, while $f(x)$ signifies its output. By using the correlation between the network model's actual and ideal outputs as the fitness function f, the correspondence between the actual output γ_j^k and the desired output δ_j^k for the k sample must meet certain criteria.

$$K_i = \theta - \sum_{k=1}^{\theta} \delta_j^k \text{-} \gamma_j^k \tag{2}$$

Where θ is a given constant, thus obtaining the fitness function:

$$f = \sum^{k} K_i \tag{3}$$

The optimal solution for the objective function outlined in the study can then be acquired.

First, collect a large number of dance dynamic data. This data can come from professional dance performances, dance teaching videos, or motion capture systems. In order to ensure the diversity and generalization of data, dance data of different styles, different difficulties, and different dancers will be collected. The collected raw data may contain noise or redundant or irrelevant information. Therefore, data preprocessing, such as denoising, normalization, clipping, and filtering, is needed to improve the quality of data. In addition, for video data, operations such as key frame extraction or motion trajectory extraction are needed to extract the key information about dance movements. In order to train the DL model, this article labels the processed data. The content of labelling includes the dancer's posture, action type, emotion, and so on. The marking process can be completed by professional dance teachers or motion capture systems. In order to ensure the accuracy and consistency of labelling, a variety of labelling methods and cross-validation strategies will be adopted.

3.2 Training and Optimization of DL Model

Model training strategy: use supervised learning to train the DL model. Specifically, using the marked dance dynamic data as input, the parameters of the model are optimized by minimizing the loss function between the predicted value and the real value. In the training process, batch training and random gradient descent methods are used to improve the training efficiency and stability of the model. The network training situation is shown in Figure 3.

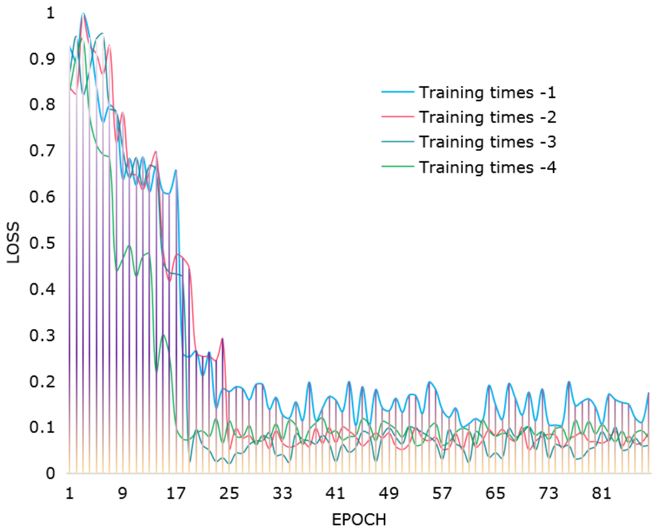

Figure 3: Network training situation.

Hyperparameter adjustment: Hyperparameter is one of the key factors affecting model performance. In this article, through experiments and adjustments, we choose the appropriate super-parameters, such as learning rate, batch size, network depth and width. Furthermore, in order to adjust the hyperparameter effectively, some automatic hyperparameter optimization methods are adopted, such as grid search, random search, and Bayesian optimization. Table 1 shows all kinds of superparameters adjusted in the experiment and their settings.

Hyperparameter	*Describe*	*Experimental setting range*	*This article chooses*
Learning Rate	Step size of model weight update	0.001, 0.005, 0.01, 0.05, 0.1	0.005
Batch Size	The number of samples input into the model at each training iteration.	32, 64, 128, 256	128
Depth	Number of layers in the model	3, 5, 10, 20	5
Number of Layers	The number of hidden layers in the model	64, 128, 256, 512	256
Number of Neurons	Number of neurons in each layer	According to the number of layers and width	-
Activation Function	Functions with nonlinear factors were introduced.	ReLU, Sigmoid, Tanh, Softmax, LeakyReLU	LeakyReLU

Table 1: Super parameter settings.

Optimization methods: To enhance the model's performance and generalizability, several optimization techniques are employed in this article. Regularization methods are utilized to mitigate overfitting, while data augmentation techniques are applied to diversify the dataset. Furthermore, ensemble learning is leveraged to integrate predictions from multiple models. Additionally, emphasis is placed on model interpretability and visualization technologies to facilitate a deeper understanding and analysis of the model's decision-making processes.

4 DYNAMIC ANALYSIS AND CAD MODELING METHOD OF DANCE BASED ON DL

4.1 Dance Dynamic Analysis Process

In the process of dynamic dance analysis, the application of the DL algorithm provides a powerful tool for accurately capturing and analyzing dance movements. The following are the specific steps to analyze dance dynamics by using the DL algorithm:

Data preprocessing: First, the collected dance video data is preprocessed, including video format conversion, key frame extraction, background removal, and so on, to ensure the quality and consistency of the data. This step is very important for the subsequent training of the DL model. In this article, the data model fusion method is used for preprocessing, and a large number of small data are normalized and mapped to [-1,1] intervals for processing. Then, limit the network input and output data to [0,1] or [-1,1], and the formula is as follows:

$$\hat{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

Where: x_i stands for input or output data, $x_{\min}, x_{\max}$ stand for minimum and maximum values in data respectively.

Feature extraction: Next, use the trained DL model to extract the features of the preprocessed dance video. These features include the dancer's posture, movement tracking, movement speed, and so on, which can effectively represent the dynamic characteristics of dance. The real-time dance action recognition process is shown in Figure 4.

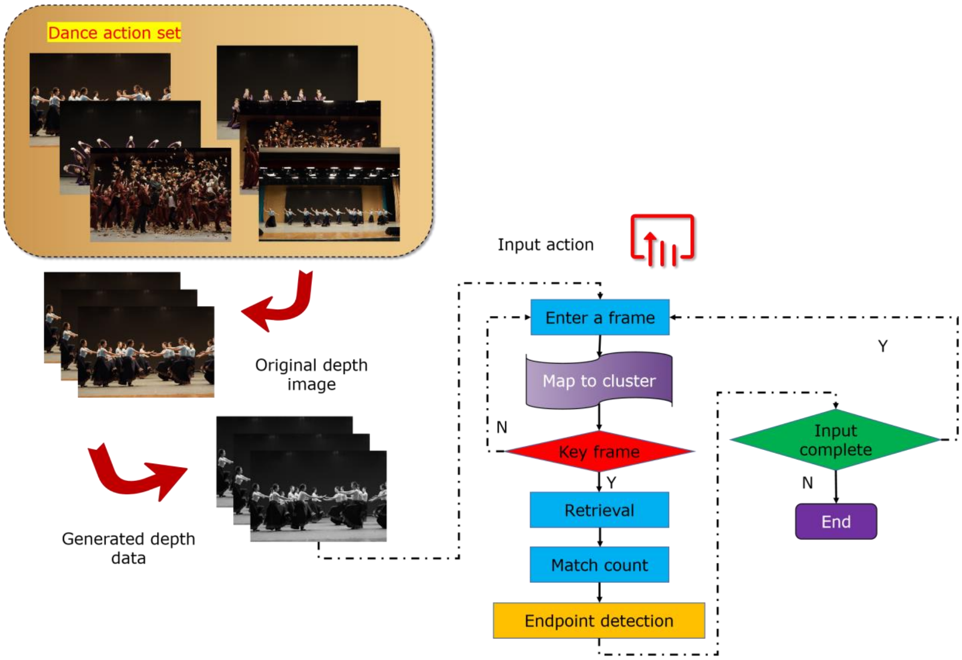

Figure 4: Process diagram of dance action recognition.

Action recognition and classification: After extracting the characteristics of dance movements, the DL model further analyzes these characteristics, identifies specific dance movements and classifies them. For example, the model can identify basic dance movements such as jumping, rotation, flexion and extension, and classify them into different action libraries.

Time series modelling: Because dance is an artistic expression in time series, the DL model also needs to model the identified dance movements in time series. Through sequence models such as LSTM, we can capture the time-dependent relationship between dance movements so as to analyze the whole dance sequence more accurately.

4.2 CAD Modeling Method

One of the core tasks of this study is to transform the analyzed dynamic dance data into a CAD model. The following are specific technologies to achieve this goal:

Data format conversion: First, the dance dynamic data analyzed by the DL model is converted into a data format recognizable by CAD software. This step involves transforming the spatial coordinates and posture parameters of dance movements into basic geometric elements such as points, lines, and surfaces in CAD software. In this article, the position of the center point of the image is calculated by the following formula:

$$\begin{cases} M\_med = \left(M+1\right)/2 \\ N\_med = \left(N+1\right)/2 \end{cases} \tag{5}$$

From top to bottom, scan the boundary point matrix edge from left to right and the point with a value of 1 (image boundary point). The center line of the root system is a binary image with a width of one pixel. In this article, the following formula is used to calculate the number of pixels with a gray value of 1 in the 8- neighbourhood of each pixel p on the root center line:

$$C\left(p_x,p_y\right) = \sum_{i=-1}^{1}\sum_{j=-}^{j} I\left(p_x+i,p_y+j\right)-1 \tag{6}$$

According to the value of $C\left(p_x,p_y\right)$, the branch point and the endpoint are extracted, the pixel point corresponding to $C\left(p_x,p_y\right)=1$ is the endpoint, $C\left(p_x,p_y\right)\geq 3$ and there is no pixel point corresponding to 4- neighbourhood between the pixels of the root center line of 8- neighbourhood as the branch point. Optimize the center coordinates and normal vectors of patches to maximize the average correlation coefficient. In the process of optimization, the center point of the patch is fixed on the light of the reference image, and the degree of freedom of optimization is 3. The z coordinates of the center of the patch represent two angles α,β of the normal vector. The equation of the inclined plane element is:

$$a\left(X-X_c\right)+b\left(Y-Y_c\right)+c\left(Z-Z_c\right)=0 \tag{7}$$

The relationship between the normal vector and direction angle is:

$$a=\cos\alpha\cos\beta, b=\sin\alpha\cos\beta, c=\sin\beta \tag{8}$$

Model building: In CAD software, the 3D model is built by using the converted dance dynamic data. This can be achieved by modelling tools in CAD software (such as stretching, rotating and lofting). According to the characteristics of dance movements, appropriate modelling methods and techniques are selected to create realistic and accurate dance dynamic models.

Texture mapping and rendering: In order to make the CAD model reflect the dynamic beauty of dance more realistically, texture mapping and rendering are also needed for the model. By adding appropriate materials and textures to the model, we can simulate the details of the dancer's clothing, skin, and other features and further enhance the realism of the model.

In dance dynamic CAD modelling, it is very important to improve the modelling accuracy. Therefore, it is necessary to optimize the data preprocessing process to reduce noise and redundant information, select a suitable DL model to accurately capture dance features, fuse multi-source information to obtain a comprehensive and accurate action description, and introduce transcendental knowledge in the dance field to guide modelling. The design and execution of dance movements all follow certain transcendental knowledge such as human anatomy and kinematics principles. Introducing this prior knowledge into the CAD modelling process can ensure that the model conforms to the characteristics and laws of actual dance movements in structure and dynamics. This not only improves the fidelity and credibility of the model but also provides a more accurate basis for the subsequent dance simulation and simulation. In addition, continuous iterative optimization and verification processes are also key to ensuring the accuracy and quality of CAD models.

5 EXPERIMENT AND ANALYSIS

5.1 Experimental Environment and Data

A comprehensive experimental setup was established to validate the efficacy of the dance dynamic analysis and CAD modelling approach grounded in deep learning (DL). High-performance computing resources, including NVIDIA GPUs, were harnessed to expedite the training and inference cycles of the DL models. Additionally, a state-of-the-art dance motion capture system was employed to acquire precise dance dynamic data. The experimental workflow encompassed various software tools, namely TensorFlow for DL operations, AutoCAD for CAD modelling, and Python and MATLAB for data processing and analysis. The experimental dataset was sourced from two primary channels: Firstly, publicly accessible dance motion datasets, encompassing a wide range of dance styles and performer attributes, were utilized. Secondly, data collected through our own dance motion capture system provided a more focused and practical perspective. Emphasis was placed on ensuring data diversity and generalizability by including dance performances varying in style, complexity, and performer profiles. Before utilization, the data underwent a rigorous preprocessing pipeline to enhance its quality and applicability to the analysis and modelling tasks.

5.2 Experimental Design and Implementation

In this section, a comprehensive set of experiments is devised to assess the efficacy of the introduced technique. The experimental framework encompasses comparisons across various model designs, training approaches, optimization techniques, and performance evaluations using distinct datasets. To this end, the article deploys multiple DL models, specifically CNN, RNN, and BPNN, to compare their relative efficiencies in dance dynamic analysis. The trained model's performance is then gauged against test datasets, and its decision-making processes are visually represented for intuitive understanding. Figure 5 presents a comparison of the accuracy rates achieved by these different methods in recognizing and classifying dance movements. The accuracy of this method on different data sets is shown in Figure 6. The real-time comparison of the algorithm is shown in Figure 7.

The experimental results show that the dance dynamic analysis and CAD modelling method based on DL has an excellent performance in many aspects. The following is an analysis and discussion of the experimental results:

Accuracy: This method has achieved high accuracy in the task of dance movement recognition and classification and can accurately capture and analyze the key features of dance movements.

Robustness: Experiments on different data sets show that this method is robust and can handle dance data with different styles, different difficulties, and different performers.

Real-time: Although the training and reasoning process of the DL model requires certain computational resources, the method in this article can still meet the needs of real-time analysis in practical application.

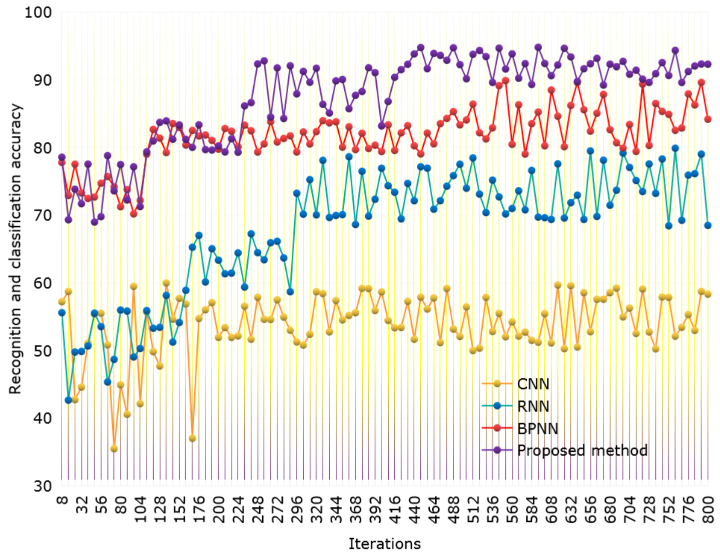

Figure 5: Accuracy of dance movement recognition and classification.

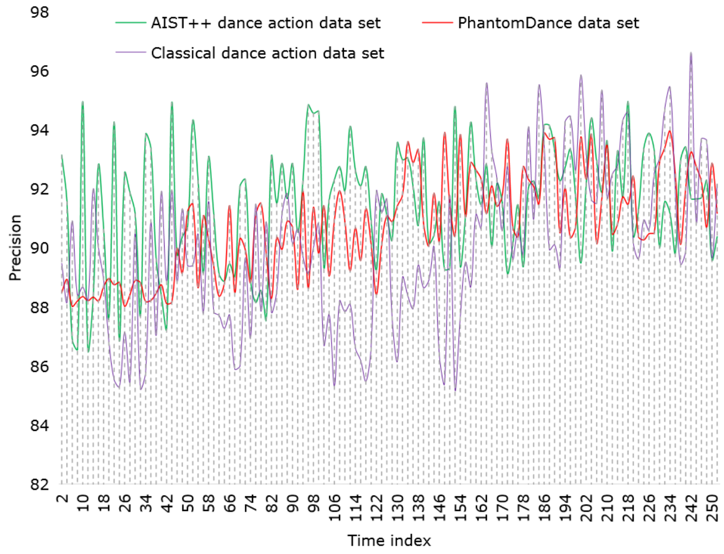

Figure 6: Accuracy of different data sets.

Compared with the existing methods, this method has the following advantages:

Abundant feature expression: The dynamic features of dance extracted by the DL model are richer and more comprehensive, which can better describe the characteristics and aesthetic feeling of dance movements.

Higher modelling accuracy: With the powerful fitting ability of the DL model, the CAD modelling method in this article can restore the spatial structure and dynamic trajectory of dance movements more accurately.

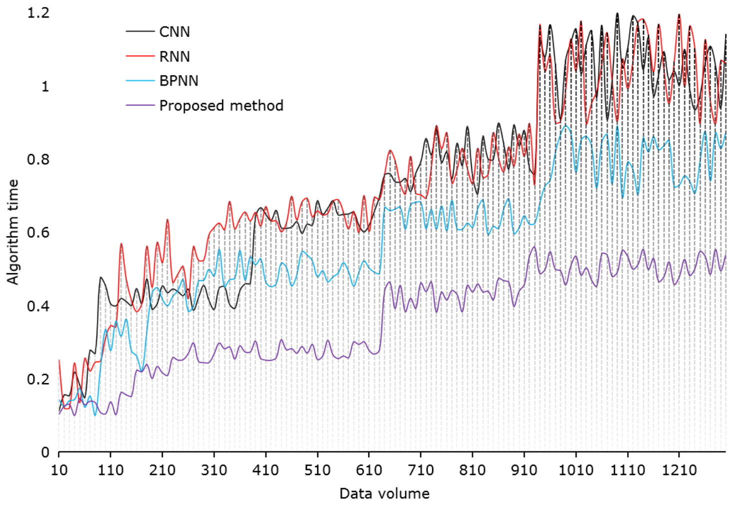

Figure 7: Real-time comparison of algorithms.

Wider application scenarios: Thanks to the DL model's robust generalizability, the approach outlined in this article can adapt to diverse dance genres and settings, thereby enriching the prospects for dance art's creation and preservation.

6 CONCLUSION AND PROSPECT

6.1 Summary of Research Results

This study focuses on dance dynamic analysis and CAD modelling methods based on DL and has achieved a series of important research results and discoveries. The main contributions can be summarized as follows:

Firstly, this article successfully constructs an efficient DL model for accurate analysis of dance dynamics. The model can accurately capture the key features of dance movements and realize automatic classification and recognition of action types. Through large-scale experiments, the model has achieved remarkable performance improvement in the dynamic analysis of dance, which provides strong support for the digital and intelligent analysis of dance art.

Secondly, this article innovatively puts forward a method to transform the analyzed dance dynamic data into a CAD model. This method uses the dynamic characteristics of dance extracted from the DL model and CAD modelling technology to realize the 3D visual reproduction of dance movements. This not only provides a brand-new visual experience for dance creation and performance but also opens up a new way for dance education and inheritance.

Finally, this article also explores the key technologies and methods to improve the modelling accuracy and further improve the fidelity and accuracy of CAD modelling by optimizing the data preprocessing process, selecting the appropriate DL model, and integrating multi-source information.

6.2 Research Deficiency and Future Work Prospect

Limited by the quality and quantity of data sets, there may be some deviations in the analysis of some specific dance styles in this study. In the future, we can consider collecting more diversified and high-quality dance data to enrich further and improve the data set, so as to improve the generalization ability and analytical accuracy of the model. In addition, although this study puts forward the method of transforming dance dynamic data into a CAD model, it still faces some technical challenges in practical application. For example, how to realize a more efficient model transformation algorithm and how to improve the processing speed of large-scale dance data. These problems need further study and exploration.

In the future, the DL model can be further improved and optimized to improve the accuracy of dance dynamic analysis. For example, we can try to use more advanced network architecture and introduce an attention mechanism to improve the performance of the model. Furthermore, we can explore more efficient CAD modelling methods and algorithms to realize the modelling and visualization of larger and more complex dance scenes. This may need to be supported by more powerful computing resources and optimization techniques.

Xi Liu, https://orcid.org/0009-0007-9917-4359
Zhen Li, https://orcid.org/0009-0009-5123-840X

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