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Digital modeling and computational analysis methods for human dance movement mechanisms

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Abstract Traditional dance teaching mainly relies on empirical transmission and lacks scientific means of movement analysis, making it difficult to accurately quantify human movement characteristics. In this study, we constructed a digital modeling system for human movement mechanism in dance anatomy based on 3DResNet-LSTM cascade neural network. Methodologically, Kinect somatosensory technology was used to collect dance movement data, extract the skeletal information of 24 joint points, and process the data noise through the skeletal joint point motion smoothing algorithm. A 28-layer 3DResNet-LSTM cascade network model is constructed, in which 3DResNets are responsible for extracting spatial features and the LSTM network learns temporal features to realize accurate recognition of multi-view dance movements. The results show that the model performance is optimized when the number of LSTM neurons is 24, the learning rate is 0.0055, and the batch size is 200. In the test of more than 100 dance action segments, the recognition accuracy reaches 98.66%, which is 7.83% higher than the average of ST-GCNs and 22.94% higher than the average of LSTM. In the application validation of four professional dance types, the recognition accuracies are above 89.53%, up to 93.08%, and the shortest recognition time is only 22.87 s. The 3DResNet-LSTM cascade network model in this study demonstrates excellent generalization ability and robustness in the task of dance movement recognition, which provides an effective technical support for the digital teaching of dance anatomy.

Index Terms 3DResNet-LSTM, dance anatomy, Kinect somatosensory technology, digital modeling, human movement mechanism, cascade neural network

I. Introduction

Human movement in dance anatomy is a combination of human structure and dance movements to study the interaction of bones, muscles, and joints in movement [1]. In recent years, with the continuous development of computer technology, digital human modeling and motion simulation technology has gradually become a popular field [2]. This technology can simulate various movements, postures and expressions of the human body and is widely used in the field of dance [3].

Digital human modeling technology is based on the knowledge of human anatomy and physiology [4]. Through the study of human body structure and movement laws, the parts of the human body can be decomposed into small modules, and then they are combined to form a complete human body model through modeling software [5]-[7]. This model contains all the structural information of the human body, which can be easily and quickly used for various motion simulations and expression [8], [9]. In the process of model construction, the human body's morphology, structure, bones, muscles, etc. need to be finely analyzed and measured to ensure the authenticity and reliability of the model [10], [11]. In the field of dance, digital human modeling technology can realize the digitization of the human movement mechanism in dance anatomy, through which the digital human modeling technology can more accurately understand the physical condition and action rules of dancers, so as to provide more targeted guidance for their training and competition [12]-[15].

This study proposes a digital modeling method for dance anatomy that integrates computer vision and deep learning techniques. First, Kinect somatosensory technology is used to construct a dance movement data acquisition platform to realize real-time capture of human joint movements. Then, a 3DResNet-LSTM cascade neural network model is designed to extract spatial features through a 3D convolutional network and learn temporal features by combining with a long and short-term memory network to realize accurate recognition and analysis of complex dance movements. Finally, the validity of the model is verified by ablation and comparison experiments, and the application is verified in a variety of professional dance genres to provide technical support for the digital teaching of dance anatomy.

II. Design of human movement mechanism investigation

II. A. Dance Anatomy

II. A. 1) Overview of definitions

Dance anatomy can provide both theoretical guidance for dance learning and practical practice of dance movements. Therefore, dance teachers, dance students and choreographers should understand and use the knowledge of dance anatomy in their dance-related work and study, and utilize the knowledge of anatomy to answer the problems encountered by students in the process of dance learning and improve the quality of dance teaching. Dance anatomy is based on the structure of the human body, and the discipline takes the structure of the human body as the starting point to analyze the connection between the structure of the human body and human body growth and dance training, with a view to improving the level of students' dance technique and dance technical ability. Dance Anatomy is the basic subject of dance learning, which can guide students to learn dance movements. Learning dance anatomy can make dance-related workers and learners better understand the body structure, better use of their own bodies, combined with their own conditions to improve the efficiency of dance learning, to avoid sports injuries, and help the smooth progress of dance learning.

II. A. 2) Movement mechanisms

Dance anatomy in the analysis of dance movement mainly from the dynamic and static two aspects, analyze, explore the movement process of human body joints, bones and muscles of the law of change. Movement analysis mainly analyzes the state of human muscles, bones and joints in dance movements, and analyzing the state can promote students to understand the technical specifications of movements in a more comprehensive and systematic way. The mastery of analyzing method can make students understand the specifications of other movements and help them avoid sports injury.

The movement of lifting and kicking the front leg does power restraining work when the leg is just lifted up, which is mainly the proactive muscles such as the iliopsoas, suture muscles, broad fascia tensor, rectus femoris, pubococcygeus and other proactive muscles doing near-fixed contraction to allow the thigh to flex partially at the hip joint. Opposing muscles include the biceps femoris, semimembranosus, semitendinosus, and vastus lateralis.

When lifting and kicking the front leg, one's thigh rotates outward, and some of the muscles can both flex and externally rotate the thigh, such as the iliopsoas. It is important to note, however, that if one wants a muscle to perform both functions, the effect of each is diminished. Some muscles have the functions of both thigh flexion and internal rotation of the thigh, but in specific dance movements, the muscles are often only required to perform the function of thigh flexion, so other muscles need to be used to restrain the thigh muscles from performing the function of internal rotation, which weakens the effect of both thigh flexion and external rotation. Therefore, for the lifting and kicking movements, the amplitude of external rotation will be lower than the amplitude of a single movement, and the height of the front leg of the human body will become higher when performing external rotation, which affects the role of external rotation.

Many of the primary moving muscles in the lifting and kicking movements are multi-joint muscles, such as the quadriceps, the suture muscles across the hip joint, the vastus medialis tensor muscle and the knee joint, and if the thigh is flexed with the calf straightened, the contraction of the thigh will be significantly under-represented, which results in the amplitude of the foreleg movement not being as high in the straightened knee as it is in the bent knee. The effect of gravity on the externally rotated front leg movement as it descends often changes the work of flexing the thigh from a restraining work to a yielding work. And in order to make it slower, the muscles undergo a degree of contraction in which the working relationship does not change.

II. B. Data extraction and processing based on Kinect somatosensory technology

II. B. 1) Kinect somatosensory technology

The emergence of Kinect technology can improve the real-time of motion capture, and the sportsman can achieve the purpose of real-time recording of movements by utilizing the Kinect body sensor to obtain the human body movement data [16], [17]. The dance movements of the dancer acquired with Kinect are used to control the changes in the movements and body posture of the virtual character. Kinect data has many functions such as real-time data collection of moving images, voice color adjustment, image data analysis, microphone input and human interaction. If you use Kinect through the infrared scanning image collection area, so that the remote infrared receiver receives the object reflected light source, after processing the image data transmission, while the RGB image sensor is through the direct collection of image data.Windows, Kinect, SDK depth data and color data request through the Open Next Frame method, the detailed data acquisition steps are: first read the image frame information, followed by obtaining the color image data. The detailed data acquisition steps are: firstly, read the image frame information, secondly, get the color image frame information, and finally, use the event model to get the data to get the data frames.The application of Kinect somatosensory technology in digital dance is to use the dancer's movement to control the virtual character movement, and to judge whether one's own movement is standard or not by observing the virtual character's dance posture. From the practical effect, the research can improve the enthusiasm of learners to learn dance, which has certain significance for the reform and innovation of dance learning method.

II. B. 2) Skeletal data extraction

The human skeleton joint points in Kinect are divided into 24 joints. In the actual application process, when analyzing the skeleton through NITE middleware, only 14 joint point information can be obtained, and the list of available nodes can be obtained through trial and error. The translation vector is a general 3-dimensional space vector, and its rotation can be represented by its rotation matrix, Euler angle, or quaternion.

II. B. 3) Skeletal joint point motion smoothing

Skeletal joint point motion smoothing is mainly to increase the sampling frequency, i.e. to increase the frame rate of the camera in the smoothing of the skeletal joint points, and the process is mainly to increase the number of motion control nodes. Among them, the range of the floating point function is set from 0-2, according to the floating point function to do the smoothing processing of the value read, the larger the value after processing, then its processing results will be better, but in the process of processing, it will also lose the details of the information.

II. C.Digital modeling

In order to overcome the possible degradation problem when the number of neural network layers is too deep, this chapter builds a 3DResNet-LSTMs cascade neural network model based on ResNet and LSTMs for recognizing the dance movements of individuals with multiple viewpoints.The core of the 3DResNets is a three-dimensional convolutional layer, which is used to learn the appearance features of a sequence of pictures. LSTM is used to learn temporal features, and the combination of the two can learn both local and temporal features.

II. C. 1) The Keras Framework

The Keras framework, with Tensorflow or Theano as the backend, can seamlessly convert between CPU and GPU, and supports the rapid construction of various types of derived networks based on CNN and RNN. We use the Keras framework with TensorFlow as the backend to build network models, which is categorized into sequential models and function models. The topologies of the two models are different. The sequential model is similar to the structure of CNN, stacking all the network layers one by one; this model adopts modular programming, which has low development cost but lacks flexibility and is only suitable for building network models with linear topology. On the other hand, the function model uses a functional method to set the relationship between network layers, and can flexibly design networks with arbitrary topologies or a combination of topologies, such as directed acyclic networks, shared networks, etc. We use the function model in the Keras framework. We use the function model in the Keras framework to build the 3DResNet-LSTMs cascade network model, and the construction process is as follows: Define the model, create a function model to complete the network layers and network parameters at the same time. Compile the model, select the appropriate loss function and network optimization function, and use the compile( ) function to complete the compilation process. Train the model, use the fit( ) function to pass the training data and target values to train the network model. Perform prediction, define evaluate( ) function and predict( ) function to evaluate and predict the recognition effect in the validation set.

II. C. 2) Model Layer Structure Settings

The overall structure of 3DResNet-LSTMs cascade network model is shown in Fig. 1, which is divided into 3DResNets and LSTMs in most parts, and specifically contains the input layer, 3DConv layer, 3DPooling layer, batch normalization layer, activation layer, Reshape layer, LSTM layer, Dense layer, and the output layer. 3DResNets processing The process of input data is as follows: firstly, the pre-processed 3D data is input into the 3DConv layer for spatial and temporal feature extraction, aiming at reducing the training parameters and increasing the sparsity of the network; then the extracted features are downscaled through the 3DPooling layer to output the deeper features in the image sequence, preventing the model from overfitting problems. The activation layer and batch normalization layer are added after each 3DConv layer, which can accelerate the process of network training and increase the nonlinearity of the network.LSTM is used to extract the temporal features between adjacent frames in the picture sequence after 3DResNets.3DResNets outputs are five-dimensional feature vectors, and LSTM requires that the input data be three-dimensional, so we use the Keras Therefore, we use the Reshape function in the Keras library to transform the five-dimensional feature vector into a three-dimensional feature vector, and finally the extracted local features are integrated into the output through the fully connected layer.

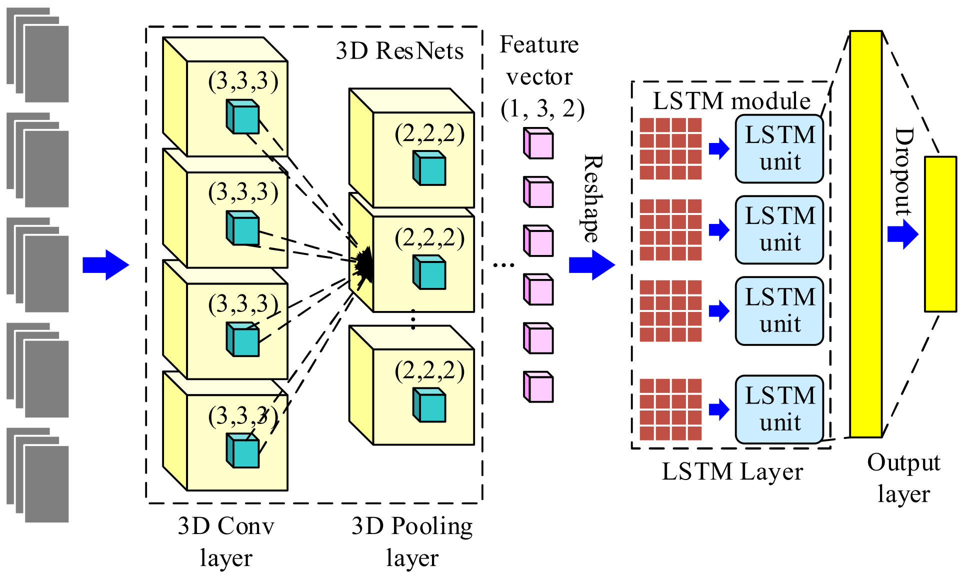


Figure 1: Cascading network model architecture of 3DResNet-LSTMs

The cascade network model includes two different structures of residual units, as shown in Fig. 2. The first residual unit has the same number and size of feature maps in all layers; the second residual unit has a convolutional layer for dimensionality reduction of the right branching network, which makes the size of feature maps in the network become twice the size of the upper layer, and the number of maps is reduced to half of the upper layer.

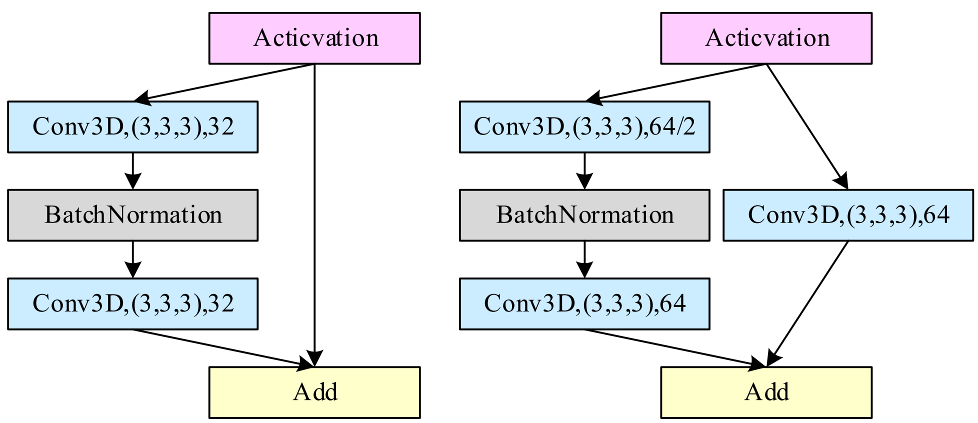


Figure 2: Two residual units

II. C. 3) Network parameterization

Try to build three different depths of 3DResnet-LSTMs cascade network model, respectively, 15 layers, 28 layers, 46 layers, after experiments to verify that the 28-layer network model of the recognition effect is better, the 28-layer network model structure is shown in Figure 3. The network model consists of an input layer, one 3DConv layer, three residual blocks, two 3DPooling layers, one Reshape layer, one LSTM and an output layer. Each residual block contains 5 residual units, and the residual unit in the 1st residual block consists of 2 3DConv layers with shortcut connections. One residual cell in the 2nd and 3rd residual blocks has a right branch passing through one 3DConv layer, and the rest of the residual cells also use the shortcut connection method. In addition, a batch normalization layer and an activation layer are set up after each 3DConv layer.

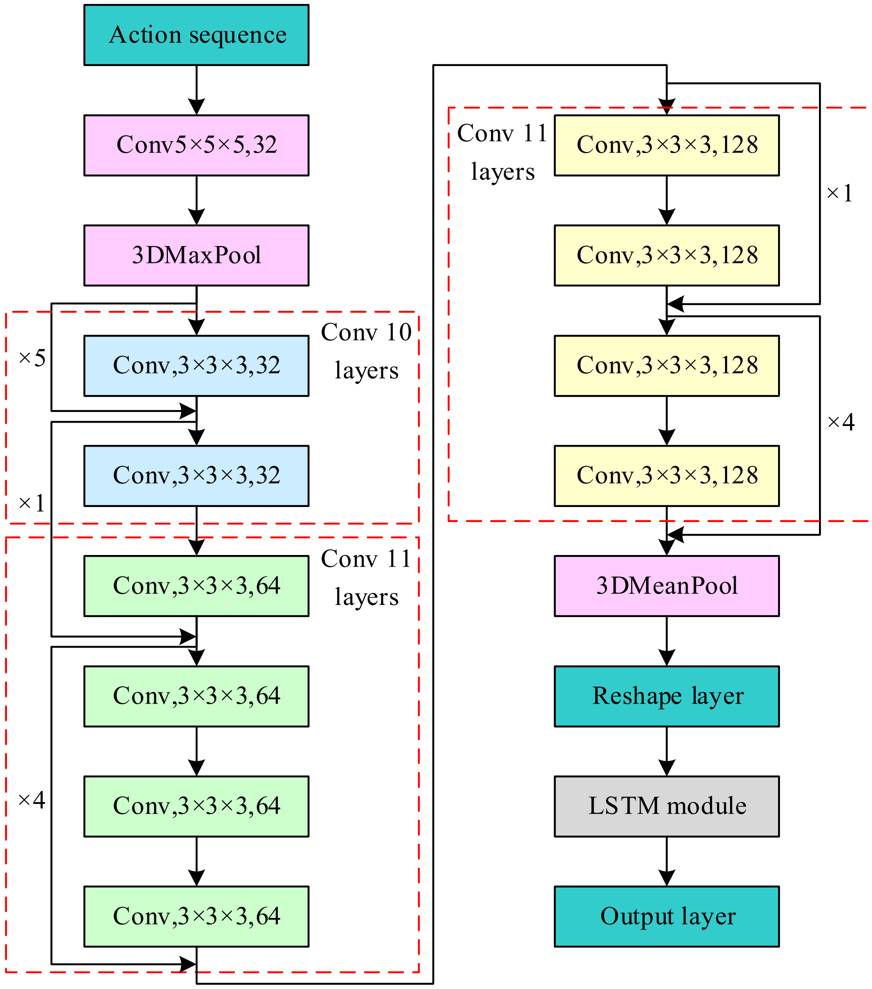


Figure 3: 3DResNet-LSTMs model layer

III. Analysis of empirical experiments

III. A. Experimental environment, dataset and experimental setup

III. A. 1) Experimental environment

The experiments were run in the following environment: the operating system was Windows 8 and the general-purpose parallel computing architecture cuda10.2. Deep neural network GPU acceleration library cudnn 7.6.5. Graphics card GeForce RTX 4080Ti with 16GB of video memory and graphics driver nvidia 450.80. Hard disk 512 GB, camera model HIKVISION 2DE2402IW-D3/W, 12 megapixels, internal memory card 512 GB.

III. A. 2) Experimental data sets

Considering that there are fewer existing motion capture databases about dance, this paper builds a motion capture experimental platform to collect dance motion capture data through Kinect somatosensory technology to form a dance motion database. At the same time, starting from the perspective of dance movement segmentation, more than 100 kinds of dance movement segment data were labeled by manual segmentation method.

III. A. 3) Experimental setup

In the section of multi-view action recognition method, this paper uses more than 100 kinds of dance action clip data in the dataset to conduct experiments, taking the position of the camera as different observation viewpoints. During the experiment, in order to reduce the model computation and improve the training speed, a number of frames are randomly taken out from the video frames that are cropped to 240×135, and continue to be cropped to 112×112 frames and input into the training model. The optimizer uses Adam with a learning rate of 1×10^{-4}~6×10^{-4}. In this paper, we follow the cross-topic evaluation method suggested in the NTURGB+D 120 dataset, i.e., out of the 100 presenters, 100 are classified into the training group, and the other 100 are classified into the testing group.

III. B. Analysis of model hyperparameters and training process

III. B. 1) Model Hyperparameter Analysis

The model training process and parameter settings are similar to the training process of the CNN model with multilayer feature fusion, and the main parameters that need to be adjusted in this model are: the number of LSTM neurons, the learning rate, and the Batch size. The initial parameters are set as: learning rate is 0.0055, epoch is 200, Batch size of each batch sample is 200, and the initial recognition rate on this basis is 93.74%.

(1) Determination of the number of LSTM neurons

The number of LSTM neurons is a very important parameter for this model, therefore, this subsection verifies the recognition rate on the test set when the number of neurons is 6, 12, 18, 24, 30, 36, 42, 48, 54, 60 respectively. The recognition rate on the test set for different number of neurons is shown in Fig. 4, and the highest accuracy is achieved when the number of neurons is 24.

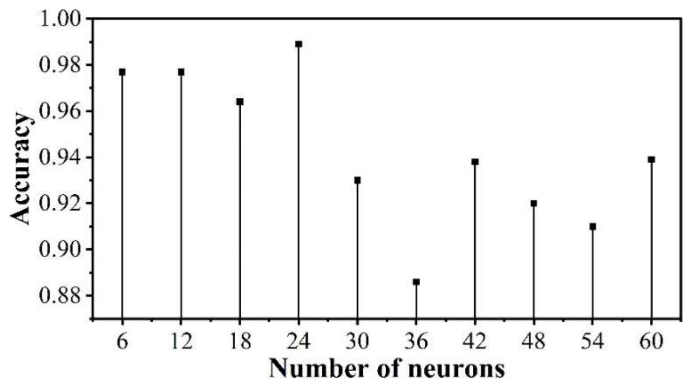


Figure 4: Recognition rate of different neurons on the test set

(2) Learning rate size determination

In order to get a suitable learning rate, this subsection conducts accuracy experiments when the learning rate is 0.001, 0.0015, 0.002, 0.0025, 0.003, 0.0035, 0.004, 0.0045, 0.005, 0.0055, 0.006, 0.0065, and 0.007, respectively. According to the performance on the test set, the recognition rate of different Learning rate on the test set is shown in Fig. 5, when the selected Learning rate is 0.0055, this model performs the best and the recognition rate reaches to 98.66%, so the Learning rate of this model is 0.0055 is the most appropriate.

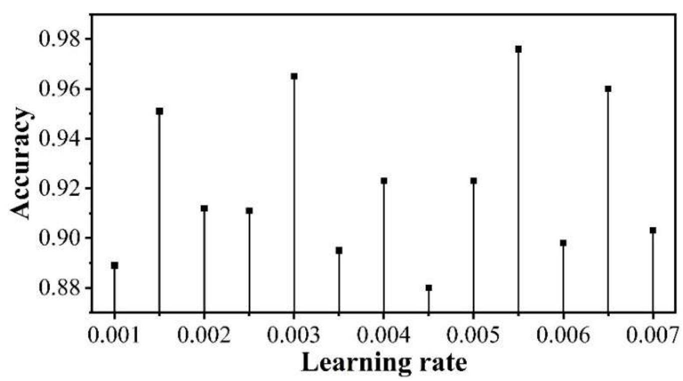


Figure 5: The recognition rate of different Learning rate on the test set

(3) Batch size determination

The recognition rates on the test set with different Batch size are shown in Fig. 6 as 50, 100, 150, 200, 250, 300, 350, 400, 450, 500. It can be seen that the recognition rate is highest when the Batch size is 200.

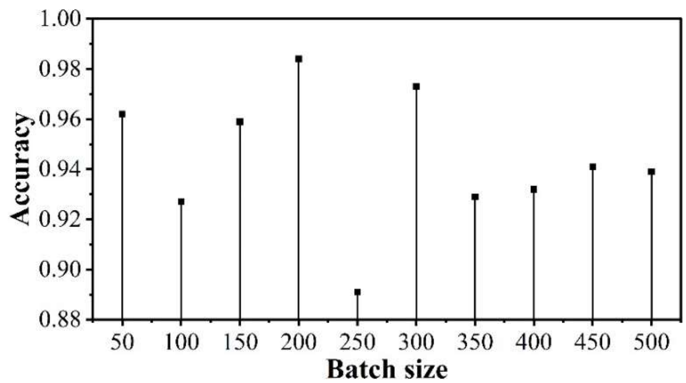
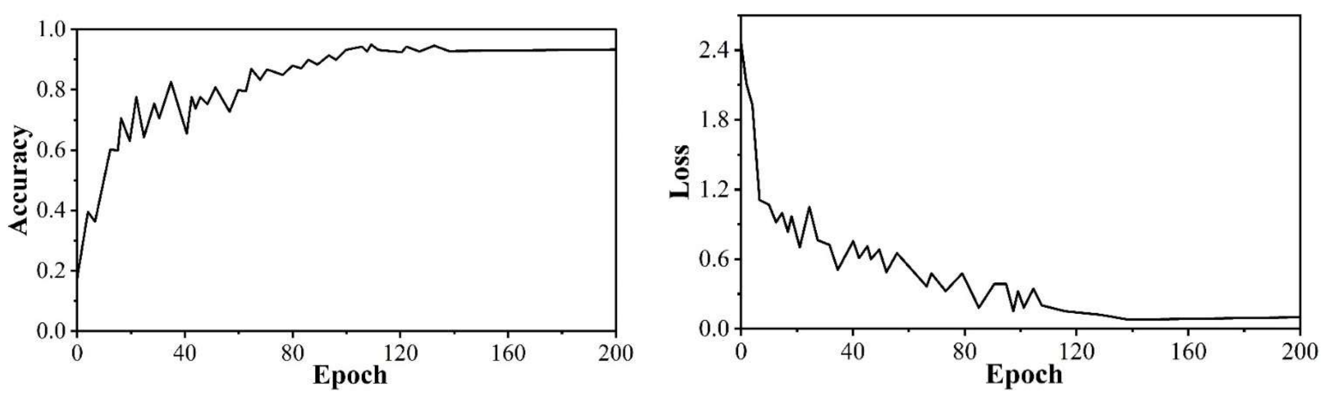


Figure 6: Recognition rate of different Batch sizes on the test set

After the series of experiments described above, the important parameters of the model were determined to facilitate the experimental analysis work described below.

III. B. 2) Analysis of model training process

The videos from all viewpoints are processed and input into the model. In order to analyze the model performance more intuitively, the accuracy and loss value curves of 3DResNet-LSTM model on the dataset are plotted, as shown in Fig. 7, where (a) ~ (b) are the accuracy and loss values, respectively, which can be seen that the fluctuation of both the accuracy and loss values are larger in the very first iteration training, and thereafter, with the increase in the number of iterations, the model begins to converge, and the curves tend to be smooth gradually, indicating that the The 3DResNet-LSTM model can well meet the needs of digital modeling and computational analysis of human movement mechanisms in dance anatomy.



(a)Accuracy rate

(b)Loss-Value

Figure 7: The accuracy rate of the 3D ResNet-LSTM model

III. C. Analysis of ablation experiments

In order to verify the effectiveness of 3D ResNet-LSTM network model in digital modeling and computational analysis of human movement mechanism in dance anatomy, ablation experimental analysis is used to explore and verify the analysis, taking LSTM as the baseline model, introducing different modules in turn, and verifying the effectiveness of 3D ResNet-LSTM network model by comparing the accuracy of dance movement recognition. The results of the ablation experiment analysis are shown in Fig. 8. In different perspectives, when the 3D ResNet module is introduced into the LSTM network model, the dance movement recognition accuracy rate is significantly improved, and the feasibility of the modular structure of the 3D ResNet-LSTM network model enables it to meet the user's needs for digital modeling and computational analysis of human movement mechanisms.

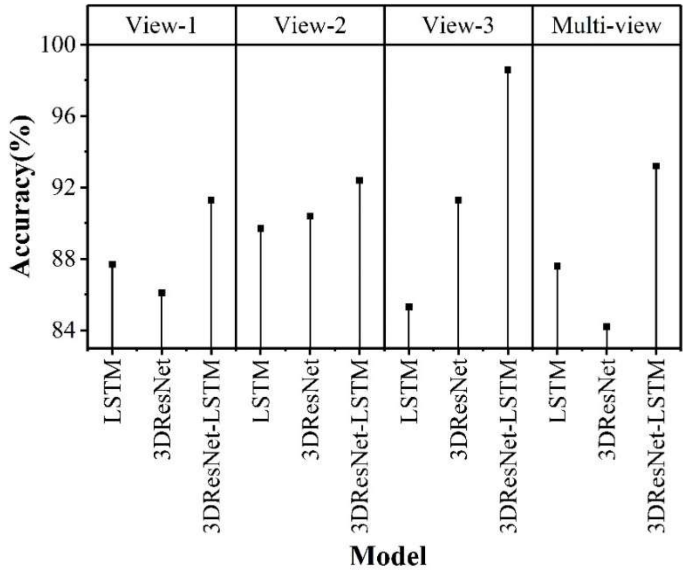


Figure 8: Analysis results of ablation experiments

III. D. Model validation analysis

III. D. 1) Statistical analysis of accuracy results

In order to verify the generalization ability as well as the robustness of the 3D ResNet-LSTM model, the study tested its recognition accuracy against the algorithms such as Two-stream Convolutional Networks (TSCNs), Long Short-Term Memory Networks (LSTMs), Convolutional Pose Machines (CPMs), and Spatiotemporal Graphic Convolutional Networks (ST-GCNs) with 10 video datasets of dance movements containing different complexities, and the result are shown in Fig. 9. From Fig. 9, it can be seen that the recognition efficiency of 3D ResNet-LSTM all maintains above 95%, which is about 7.83% higher than the average of ST-GCNs, 15.21% higher than the average of TSCNs, 19.77% higher than the average of CPMs, and 22.94% higher than the average of LSTMs. The results fully demonstrate that 3DResNet-lSTM has stronger generalization ability as well as robustness.

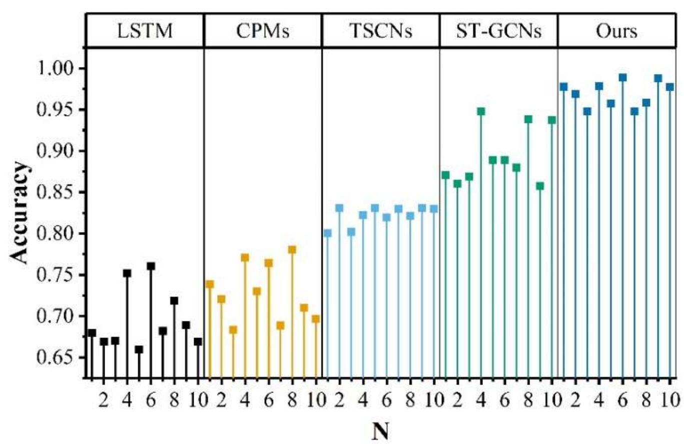


Figure 9: Statistical analysis of accuracy results

III. D. 2) Analysis of practical application effects

Finally, the proposed 3DResNet-LSTM model is applied to dance anatomy for the validation of practical effects. It is compared with 3DResNet, 2DResNet-LSTM and 3DCNN for the recognition experiments of basic movements in four professional dance types, including classical dance, ballet, folk dance and jazz dance, and the obtained results are shown in Figs. 10~11. Figure 10 shows the recognition accuracy of the four methods for professional dances, while Figure 10 shows the recognition time. As can be seen from Fig. 10, in the recognition of the basic movements of ballet and jazz dance, the accuracy of 3DResNet is below 85%, which is the lowest among the four methods. In the recognition of classical and folk dance movements, the accuracy of 2DResNet-LSTM is 87.25% and 82.92% respectively, which is the lowest. And the proposed 3DResNet-LSTM model has the highest accuracy in action recognition of all four dance types, which are above 89.53% and up to 93.08%, with obvious recognition advantages. As can be seen from Fig. 11, 2DResNet-LSTM takes the longest time in the recognition time of ballet, both close to 38.15s, and 3DResNet takes the longest time in folk dance and jazz dance, 35.79s and 35.22s, respectively. The 3DResNet-LSTM models all take the shortest time, with a minimum of only 22.87s and a maximum of 26.24s, which is more efficient. The performance of different algorithms in basic movement recognition of classical dance, ballet, folk dance and jazz dance is compared in the task of movement recognition of different professional dance types. 3DResNet-LSTM shows good overall performance in all the above tests.

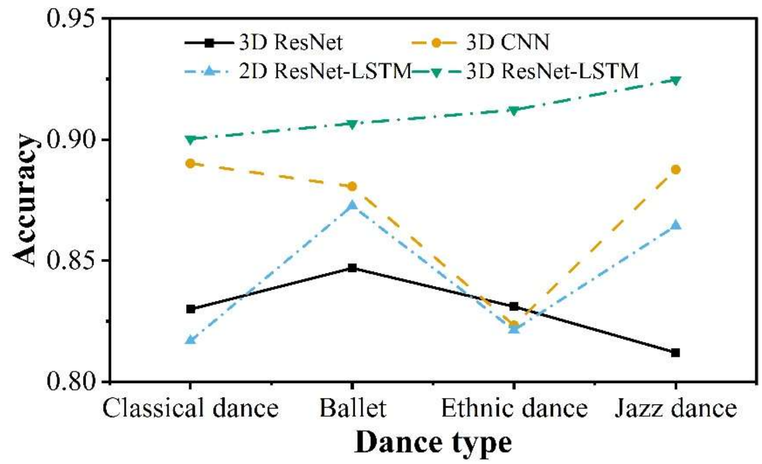


Figure 10: Four methods for identifying accuracy

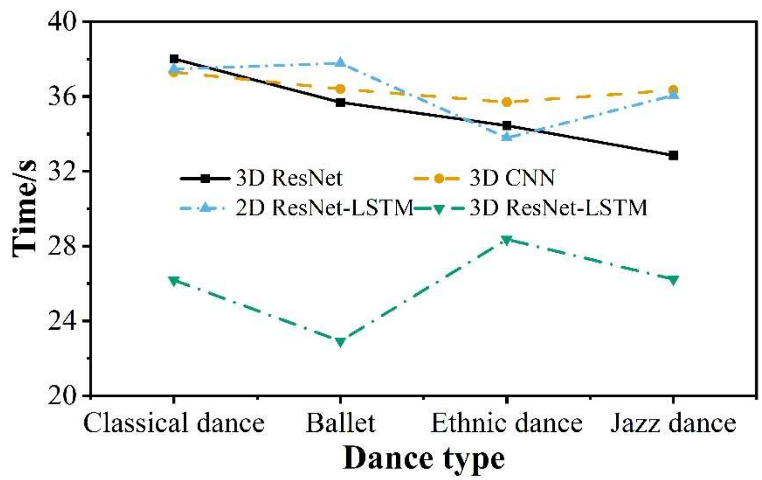


Figure 11: Four methods for identifying time

IV. Conclusion

In this study, digital modeling and accurate analysis of human movement mechanisms in dance anatomy were successfully achieved by constructing a 3DResNet-LSTM cascade neural network model. The experiment verifies the superior performance of the 28-layer network architecture, and the model recognition accuracy reaches 98.66% under the optimal parameter configuration, which significantly outperforms the existing mainstream algorithms. Compared with traditional methods, the model performs well in the complex dance movement recognition task, with an average improvement of 7.83% over the ST-GCNs algorithm and 22.94% over the LSTM algorithm, which fully proves the effectiveness of the cascade network architecture.

In the practical application validation, the model maintains a high accuracy of over 89.53% in the movement recognition of four professional dance types, up to 93.08%, while the recognition efficiency is significantly improved, with the shortest recognition time of only 22.87s, which provides a technical guarantee for real-time dance teaching. The ablation experiment further verifies the key role of the 3D ResNet module in feature extraction, and the recognition performance of the LSTM benchmark model is significantly improved when this module is introduced.

The fusion application of Kinect body sensing technology and deep learning algorithms provides a new digital solution for traditional dance anatomy teaching. The method not only accurately captures the human body movement trajectory, but also realizes intelligent analysis and evaluation of dance movements, effectively bridging the gap between theoretical teaching and practical training. In the future, the method can be further extended to recognize more dance types and complex movement sequences, laying a solid foundation for building an intelligent dance education platform.

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