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Digital modeling and computational analysis of human movement mechanisms in dance anatomy

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ABSTRACT
Dance Anatomy is a basic theory course for university dance majors, which reveals the structure and function of various parts of the human body and their important roles in dance training through an in-depth interpretation of dance anatomy. Using relevant equipment and instruments, we will set up a data acquisition environment for data acquisition and pre-processing. For the problem of coordinating music rhythm and dance movement, a time-series autoregressive model is used to realize music-driven dance synthesis, and the model loss function is clarified. Combining the above model, data, and modeling software, the task of modeling the human dance movement mechanism is completed, and the cosine similarity is adopted to analyze the problem of coordinating music rhythm and dance movement. In both the training and test sets, the music-driven dance sequences and the original sequences fluctuate within a certain range (-8, 13), and the scoreRatio value of this paper's method (1.505) is much better than that of the other four sets of models, which verifies the efficacy of its model in the application of the task of modeling the mechanism of human dance movement, and also verifies the reliability of cosine similarity method. This will enable better implementation of human movement mechanisms in dance anatomy into practical scenarios, help trainers to better perform dance training and performance, reduce dance injuries and prevent occupational diseases.

Keywords: dance anatomy, human movement mechanisms, similarity, time-series autoregressive modeling

1. Introduction

Different art forms have different material carriers and different material means, and the material carrier of dance is the human body. The material carrier of dance is the human body, and the means of expression of dance is human body movements. How to use one's body consciously and freely is the most basic quality that every qualified dancer should have [1-4]. Dance anatomy is a science based on

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the morphology and structure of the normal healthy human body, which studies the interrelationship between the morphology and structure functions of the human body and the laws of growth and development and dance training, and how to improve the human body's dance skills [5-7]. Dancers understand the dance anatomy is conducive to an objective, scientific understanding of the dance scientific training, understanding of the movement of the human body's organs of motion, improve dance technical skills, to avoid dance injuries caused by training as well as to prevent occupational diseases [8-11].

Dance digital is a broad definition, including dance digital dissemination, dance digital production, dance digital analysis and dance anatomy human movement digital modeling and so on are included. Dance digitization is a topic that is gaining widespread attention in the art of dance [12-15]. The digitization of dance has ostensibly diluted the power of theater and humanity in the name of technology, but on the other hand it has extended and expanded perception by diverse means [16-18]. With the digitization of video technology, the concept of multimedia in dance has been developed on a wider scale, and the incorporation of more technological elements and design in dance multimedia has enabled the medium to change the way dance is lived and created [19-22].

Literature [23] assessed dancers' perceived and actual knowledge of basic musculoskeletal anatomy and its relationship to function, revealing that both years of dance training and professional dancer status were significantly associated with increased anatomical knowledge, but not with perceived knowledge. Literature [24] discussed the forms of application of dance anatomy in the classroom teaching of basic training of Chinese classical dance based on analyzing dance anatomy and classroom teaching of basic training of Chinese classical dance. Literature [25] describes the reflective practice of functional awareness, which uses foundational information from anatomy and movement learning to facilitate the reader's understanding of individual body structures and through movement exploration and anatomical visualization, thereby improving dance skills and providing tools for lifelong physical fitness. Literature [26] examines classical ballet and reveals that when anatomical knowledge and instruction are integrated in ballet classes, it helps to open the black box of the “body” to allow for technical improvements. Literature [27] analyzes the application of digital methods to folk dance knowledge and discusses and proposes a framework for the digitization of folk dance, using the example of festival dance rituals. Literature [28] explored the impact of digitalized dance teaching on students' motivation and performance, pointed out that students' enthusiasm for learning was qualitatively improved under digital dance teaching, and suggested that schools should strengthen the construction of information technology to provide teachers and students with comprehensive educational resources and teaching facilities. Literature [29] examined the special and complex nature of dance teaching based on the literature review, and emphasized that in the context of digital teaching, the dance teacher's is not only teaching skills, but also an important role of integrating resources, guiding learning, and promoting interaction.

This paper shows the human movement mechanism in dance training through the analysis of the core concept of dance anatomy, and in order to reveal the human dance movement mechanism more intuitively, the research program of mathematical modeling and similarity calculation of human movement mechanism is carried out. First, we set up the experimental environment, collect the experimental data, clean and screen the experimental data, and store them in the corresponding file format. Then the above data are put into the time series autoregressive model for training, set the model loss function, and finally complete the mathematical modeling of human dance movement mechanism. The cosine similarity calculation formula is used to explore the efficacy of the human dance movement mechanism model, so that the trainers can correctly use the knowledge of dance anatomy in the basic dance training class, which ensures the beautiful and coordinated dance movements.

2. Dance anatomy

2.1. Core concepts

Dance anatomy is a branch of normal human anatomy, which is based on the morphology and structure of the normal healthy human body, and studies the interrelationship between the morphology and structure of the human body, the laws of growth and development, and dance training, and how to improve the human body's dance skills in science. Workers engaged in dance education and performance should be on the basis of dance anatomy, research on the impact of dance training on human morphology and structure, to explore the laws of mechanical movement of the human body structure, and the use of dance anatomy knowledge to analyze and study the technical movements of the dance. Dance Anatomy for the dance art category, both as a basic theory course, but also for the training practice has a significance to guide the application of the discipline.

2.2. Anatomical analysis of dance movements

Anatomical analysis of dance movement is based on the theory of human body's motion and static mechanics, taking the movement system as a complete structure, combining with the actual situation of human body, and exploring the universal laws of bones, joints, and muscles' activities during human body's movement. Through movement analysis, analyzing the working state of bones, joints and muscles of the basic movements in the basic dance training class, we have a comprehensive and systematic understanding of the technical specifications of the movements. Mastering the method of movement analysis, and citing the method of movement analysis, we can comprehensively understand the essentials of the various specifications of the basic training class and the purpose of the training, so as to achieve the purpose of improving the dance technical level and preventing the dance injury. Therefore, understanding and mastering the content of dance movement analysis has certain practical significance for improving the quality of dance teaching and training.

2.2.1. Lifting and kicking the front leg. In the dance movement of lifting, kicking the front leg, starting the leg is power restraining work, the original action muscle mainly has iliopsoas muscle, rectus femoris muscle, broad fascia tensor, suture muscle, pubococcygeus muscle, they are at the same time close to the fixed contraction, so that the thigh in the hip flexion (starting the front leg), the antagonist muscle mainly has the biceps femoris muscle, semitendinosus muscle, semimembranosus muscle, big retractor muscle.

Lifting and kicking the front leg often requires external rotation of the thigh at the same time. Some muscles have both thigh flexion and external rotation, such as the iliopsoas muscle, and the effect will be weakened if both functions are performed at the same time. Although some muscles have the function of flexing the thigh, they also have the function of making the thigh rotate internally, in order to make them only play the function of flexing the thigh, it is necessary to limit the internal rotation of the thigh to neutralize it, and further weakening the effect of flexing the thigh and rotating it externally. Therefore, the amplitude of the external rotation's lifting and kicking of the front leg is not as high as the amplitude of the single lifting and kicking of the front leg. The height of the externally rotated front leg movement increases, and the degree of external rotation is reduced by its effect.

2.2.2. Small jumps. The squatting speed before the jump is fast, it is explosive muscle contraction, the primary dynamic muscles for power restraint work are mainly biceps femoris and calf anterior group of muscles, when jumping up first to quadriceps femoris, broad fascia tensor, suture muscle, calf triceps main primary dynamic muscles, the contraction of the foot fixed under the outbreak of the contraction, so that the knee is straightened and produces the foot pushed to the ground, for power restraint work. Immediately after the far fixed point and then moved to the toes, all the muscles with the function of tensing the instep, tensing the toes - bunion flexor, long flexor toes, tibialis posterior, peroneus longus, peroneus brevis, bunion flexor, phalanges short flexor for the primary dynamic muscles, power restraint work, their explosive contraction of the heel, the foot, the toes pushed off the ground, so the body rose up in the air.

3. Digital modeling and computation of human movement

3.1. Data Acquisition and Preprocessing

3.1.1. Pre-preparation for data collection:

1) Choreography. This study will take "a well-known dance" as the teaching content for data collection, professional dancers are the inheritors of regional culture, in addition to being able to accurately show the dance, they have a deeper understanding of the dance, which can help dance learners better understand and master the movement.

2) Data acquisition environment construction. Figure 1 shows the schematic diagram of the experimental environment. The subject's body surface is labeled with reflective markers, and the camera captures the object's movement in real time by tracking the position of the reflected light from these markers. The marker points were categorized into 2.96mm, 9.43mm and 13.87mm sizes based on the physical characteristics and joints of the captured objects. In this lab, the ability to adjust the light more flexibly helps to minimize the interference of extraneous factors, thus improving the quality of the captured data.

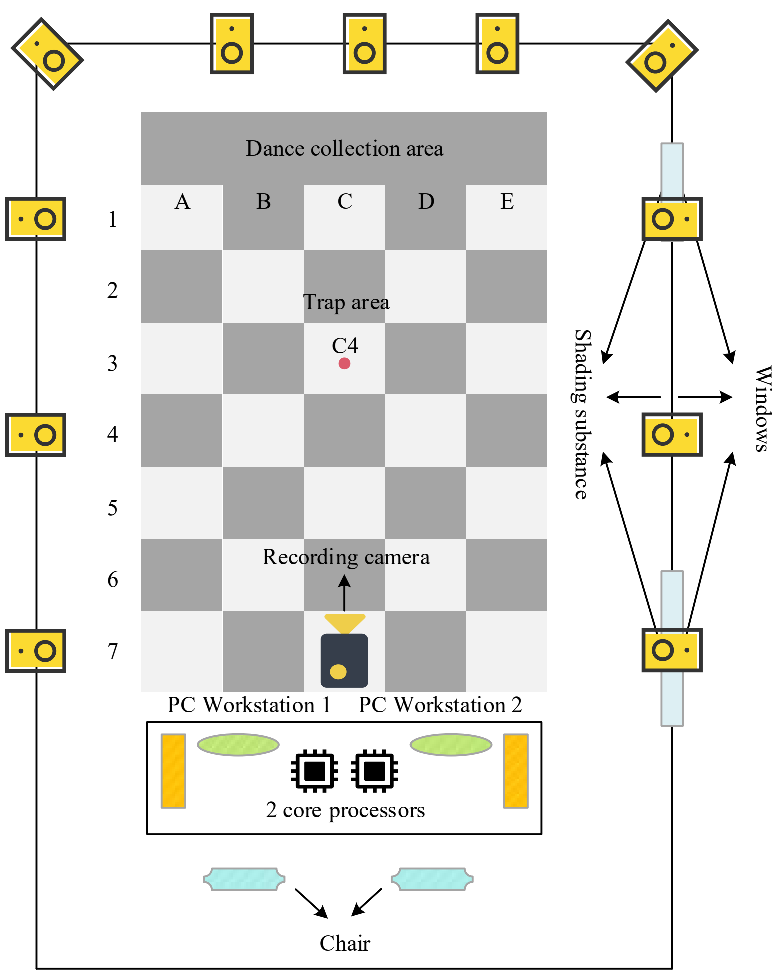


Fig. 1. The experimental environment was collected

3.1.2. Dance movement data acquisition:

1) Site calibration. After the construction of the motion capture system is completed, in order to better identify the reflective marking points and ensure the quality of the collected data. It is necessary to carry out camera calibration to determine the space center position, edge, ground position and front and back direction. Adjust the scope of recognizing the reflective marking points and swing the T-shaped calibration frame to calibrate the 12 cameras.

2) Marker Point Pasting. Paste Marker marker balls for the dancers wearing motion capture suits. Due to the complexity of this dance movement, 39 points could not satisfy the acquisition, so 14 auxiliary Marker points and 10 finger Marker points were added. Therefore a five-finger template was used for hand Marker point pasting. Finger Marker points were pasted on the tip of the middle finger of the left and right palm, totaling 10.

3) Acquisition of movement data. The dance contains rich finger movements, and when capturing finger movements, the data is easily lost due to occlusion in space, which makes it more difficult to capture compared to limbs.Vicon Shōgun Live can capture reflective Marker points on the moving human body through the camera, and solve their precise coordinates in 3D space, even if the occluded Marker points can be solved for the coordinates of partially occluded Marker points, realizing high-resolution and high-precision motion capture. Therefore, in this study, we chose to use the Vicon Shōgun system for data acquisition of dance movements, and two PC workstations were used to synchronize data acquisition in order to ensure data integrity and quality.

3.1.3. Restoration and smoothing of motion capture data. During the process of movement acquisition, the data will be affected by unavoidable errors such as marking point occlusion and misidentification of reflective points. Therefore, after the dance action acquisition is completed, it is necessary to use VICON's Shōgun Post software for action data correction, spatial and temporal calibration, complementary key points and other data preprocessing work, the software can be highly automated data processing, data reconstruction, automatic labeling of markers, data restoration and data solving, etc., and it can be exported to a variety of mainstream file formats.

3.1.4. Motion data export. After the data processing is completed, two formats of files are exported according to the requirements: one is FBX (skeletal humanoid animation) file, which is used for the teacher's dance movement demonstration in virtual teaching. The other one is HTR (motion analysis) file, which is used for subsequent digital modeling and motion similarity quantification calculation.

3.2. Dance movement-music synthesis

3.2.1. Time-Series Autoregressive Motion Synthesis Models. This subsection will focus on the timing autoregressive model, which inputs a series of control signals and outputs human actions. For simple movement control, the control signals are: movement type, role, speed and direction. For dance movement, the control signals are music style, rhythm and melody. Specifically for each frame synthesis, the current frame motion is synthesized based on many frames of previous motion as well as the control conditions at the current moment. It is important to note that the model output is modeled as a probability density function, i.e., the model predicts as a probability distribution of the current frame, rather than directly predicting the current frame. The whole model includes: a motion encoder, a residual motion control module, and a motion decoder. The model synthesizes the current frame based on the preceding k frames of motion as well as the control signals at the current moment, and the control signals may contain more than one. The model models the probability density function of the current frame based on the current control condition $c_t = [c_t^1, \ldots, c_t^s]$.

$$Pr(x \mid c^1,...,c^s) = \prod_{t=1}^{T} Pr(x_t \mid X_{pre}, c_t^l,...,c_t^s) \tag{1}$$

$$Pr(x_t \mid X_{pre}, c_t^l,...,c_t^s) = F(X_{pre}, c_t^l,...,c_t^s) = F_D(F_C(F_E(X_{pre}), c_t^l,...,c_t^s)) \tag{2}$$

where x is the motion sequence, x_t is the current motion frame, $X_{pre} = x_{t-k-1},\ldots,x_{t-1}$ is the previous sequence k frame motion, and k is the sensory field length. F is the temporal autoregressive model, including: motion encoder F_E, residual motion control module F_C and motion decoder F_D. In the following, we first introduce the motion encoder and decoder, and then specify the core module of the model: residual motion control module.

Motion Encoder. Two "Conv1D+Relu" modules are stacked as motion encoders to encode the human motion in the preamble of k frames, with the convolution kernel of the time-series convolution (ConvlD) set to 1, which ensures that the motion features obtained in each frame are independent of each other.

Motion decoder. Similar to the encoder, two "Relu+Conv1D" modules are stacked to decode the fused features obtained from the residual motion control module to obtain the probability distribution of the predicted motion frames. The order of the temporal convolution (ConvlD) and the nonlinear function (Relu) is reversed from that of the encoder.

3.2.2. Loss function. To predict the probability distribution of the current motion frame, GMM is used to model the probability density function of the current motion frame. In general, the GMM distribution is:

$$Pr(x_t) = \sum_{i=1}^{N} \omega_i \square (x_t \mid \mu_i, \Sigma_i) \tag{3}$$

The GMM model requires that the sum of the Gaussian components is 1 and the covariance matrix is positive definite, $\Sigma_{i=1}^{N}\omega_i = 1, 0 \le \omega_i \le 1, \Sigma_i > 0$. N is the number of Gaussian components, μ_i, Σ_i are the mean vector and covariance matrix of each component, respectively. To fulfill these requirements, the model output is defined as: $\hat{\omega}_i, \hat{\mu}_{i,j}, \hat{\sigma}_{i,j} (\hat{\omega}_i \subseteq \hat{\omega}, \hat{\mu}_{i,j} \subseteq \hat{\mu}, \hat{\sigma}_{i,j} \subseteq \hat{\sigma})$, j is the index of the motion features. The model output specifically consists of: $\hat{\omega}, \hat{\mu}, \hat{\sigma}$ and the above requirements can be satisfied. Namely:

$$\omega_i = \frac{e^{\hat{\omega}_i}}{\sum e^{\hat{\omega}_i}}, \mu_{i,j} = \hat{\mu}_{i,j}, \Sigma_{i,j} = e^{\hat{\sigma}_{i,j}} \tag{4}$$

At this point, the loss function can be defined as a negative log-likelihood. I.e:

$$L_{gmm} = -\log \Pr(x_t \mid \omega_i, \mu_i, \Sigma_i) = -\log \sum_{i=1}^{N} \omega_i \square (x_t \mid \mu_i, \Sigma_i) \tag{5}$$

Note that μ_i is a real motion frame during training. In addition, a smoothing loss is added to ensure the smoothness of the motion, i.e., to optimize the smoothness of the predicted mean vector:

$$L_S = \sum_t (\hat{\mu}_{t+1} + \hat{\mu}_{t-1} - 2\hat{\mu}_t) \tag{6}$$

After training, during model testing, synthesized motion frames can be obtained by sampling from the probability density function of the predicted motion frames.

3.2.3. Music-driven dance synthesis. The previous subsection has introduced the synthesis and control effect of the time-series autoregressive model on simple motions. The model has a strong modeling ability and high robustness, which can realize the long sequence stochastic synthesis without the accumulation of timing error, and also has both motion denoising and complementation functions. In the controllability method, the model can realize controllable movement type, controllable movement direction, controllable movement speed and so on.

In order to synthesize dance movements that match the music style, a large amount of music data needs to be collected to train the classifier so as to obtain the accurate music style. Music styles include two types: soothing music and fast-paced music. A large number of music songs were downloaded from music websites and then carefully labeled with music styles. Finally, about 40 hours of music were collected, of which 20 hours of soothing music (suitable for modern dance) and the rest of fast-paced music (suitable for house dance).

Once the model was validated on simple movements, it was migrated to dance synthesis. The timing complexity as well as the diversity of dances is higher than that of simple dances, and therefore more difficult. And it is also difficult to define the control signals. The goal is to realize natural and varied dance movements with consistent musical style, rhythm and melody. In this method, musical style, melody and rhythm are used as control signals, and a time-series autoregressive model is used to synthesize the dance movements.

Based on the temporal autoregressive model, a music context-aware encoder is added to form the complete DanceNet. Music rhythm and melody (music features) are first extracted, and music styles are categorized using a music style classifier. DanceNet consists of four components: a music context-aware encoder, a motion encoder, a residual motion control module, and a motion decoder. Compared to the temporal autoregressive model presented above, a musical context-aware encoder is added to encode local musical features.DanceNet uses the musical style ms as a global control signal, and the musical rhythmic and melodic features m_0 as local control signals, and outputs a conditional probability distribution $p\left(x \mid m_0, m_s\right)$, which can be described as:

$$p\left(x \mid m_o, m_s\right)=\prod_{t=1}^{T} p\left(x_t \mid x_{t-k-1}, \cdots, x_{t-1}, m_{o,t}, m_s\right) \tag{7}$$

The Music Context Awareness module was used as a newly added module to encode music features. Since music and dance movement are two different modalities, directly using music features as control signals will lead to difficulties in integrating the movement features with the control signal features, thus weakening the modeling ability of the model. Therefore, time-series convolution combined with bidirectional LSTM (BiLSTM) is used to construct an encoder to encode the music features. The aim is to fuse the rhythmic and melodic features of the music at each moment while taking into account the musical contextual information. In addition, since the dance movements are smooth, BiLSTM is added after temporal convolution to fuse the contextual information and ensure that the musical contextual features obtained by the encoder are smooth (there is a jitter problem with the musical rhythm and melody). During training and testing, music feature m_o is input to the encoder using a sliding window. To increase the training speed, the window size is fixed and set to 12 seconds during the training phase, and during the inference phase, the music context features of each segment are extracted by sliding the window (overlapping for 2 seconds) and then stitched together to form a complete music context feature.

The rest of the model is consistent with the temporal autoregression presented above and will not be repeated. When training the model, Gaussian noise was similarly added to the input versus real motion, and a 40% deactivation probability was imposed on the input motion features. Xavie was used to initialize the model and optimized with RMSprop. The entire model was trained for approximately 2000 rounds with an initial learning rate of 1×10^{-4} and decayed at the 1000th round (decay coefficient of 0.1). It is worth noting that clustering was performed on the dance movement data because the distribution of the dance data is inhomogeneous. In the training phase, the data sampling probabilities were based on the clustering results.

3.3. Mathematical modeling and similarity calculation

3.3.1. Mathematical modeling. Firstly, the model (timing autoregressive model) file, FBX file (mentioned in subsection 3.1.4), and HTR file are moved to the "Assets" folder, which will be automatically detected by Unity3d and displayed in the resource window [30-31]. After importing into the software, the avatar skeleton is bound to the joint numbers defined in this paper, and a hierarchical connection is established between the joints to drive the avatar skeleton while controlling the positional changes of the joints. Quaternions are a highly effective mathematical tool often used by 3D graphics programmers to describe rotations [32-33]. Quaternions make interpolation easier to implement, resulting in the generation of more continuous moving surfaces, which is essential for realizing the mechanisms of human motion. Equation (8) shows the calculation of quaternions. Namely:

$$q = < w, x, y, z > = w + xi + yi + zk \tag{8}$$

In this equation, a, b, c, d is the real part and i, j, k is the imaginary unit. Quaternions can be used to represent axes and angles of rotation. In standard form, the quaternion q can be expressed as equation (9):

$$q = \cos(\frac{\theta}{2}) + (x \cdot i + y \cdot j + z \cdot k) \cdot \sin(\frac{\theta}{2}) \tag{9}$$

(x, y, z) is the unit vector of the axis of rotation and θ is the angle of rotation. This representation allows quaternions to compactly represent rotation information.

Due to the special characteristics of the head and hand, they are slightly different from the body gaze rotation LookRotation and need to be calculated separately. To wit:

$$j_i^{f_\gamma} = tr(r, tb_i, tb_\tau) \tag{10}$$

$$j_{h_i}^{f_\varepsilon} = v(j_i, j_i \; j_i^{f_\gamma}) \tag{11}$$

Equations (10) and (11) are LookRotation calculations for the body part, i is the number of the body joint, and is the y vector of the forward facing direction of the current joint j, whose result is equal to the direction normal to the plane formed by the root joint r, the left hip joint, and the right hip joint. Is the z-vector of joint j that is perpendicular to y, and the resultant is a superposition of the current joint vector j, the subjoint vectors of joint j, and the vectors. i.e:

$$j_H^{f_s} = v(j_H, j_n) \tag{12}$$

Equation (12) is also solved directly in the same way for the head-to-nose vector as the z-vector of the head LookRotation. To wit:

$$j_k^{f_\gamma} = tr(w, t, mf) \tag{13}$$

$$i_{k_\gamma}^{f_\varepsilon} = v(t, mf) \tag{14}$$

$$i_{k_\gamma}^{f_\varepsilon} = v(mf, t) \tag{15}$$

Equations (13)~(14)~(15) are solving for the LookRotation vectors of the hand, where the normal vectors of the plane formed by the joints of the wrist, the thumb, and the coordinates of the middle finger together form the y-direction, whereas the left wrist is the vector from the thumb to the middle finger forms the z-direction of the left wrist, and the right wrist is the right hand z-direction formed from the middle finger to the thumb. Then:

$$J' = J^{Iniz} * Q \tag{16}$$

$$A * A^{-1} = 1 \tag{17}$$

$$Q^{-1} = J^{Init} * (J^{f})^{-1} \tag{18}$$

The character model LookRotation matrix combined with the model initial rotation can be obtained from Eq. (18) through Eqs. (16) and (17), where J^{f} is the model LookRotation matrix and $J^{\ln x}$ is the initial rotation InitRotation matrix, which will be solved for the represented intermediate alignment matrix Q in this step.

3.3.2. Similarity calculation. Dance movement scoring cares more about the coordination between the whole body and parts of the learner and the proportion of movements, and will not go overboard with the length characteristics between body joints, so the use of cosine similarity is considered to calculate the degree of similarity of the movement parameter vectors of the corresponding body parts of the two sets of movements in the same beat. During the assessment process, in order to ensure that the students' movements are synchronized with the template movements and to allow for a certain amount of time difference, a metronome interface needs to be designed with voice and text prompts for movement details, which requires the user to complete a specific movement within a given time frame, synchronizing the movement rhythm as much as possible. Namely:

$$s_i = cos\theta = \frac{\vec{a} \cdot \vec{b}}{|a| \times |b|} \tag{19}$$

Equation (19) illustrates that the feature vector of a body part used to represent a movement parameter when a learner follows a learned dance movement is $\vec{a}$, and the feature vector of the movement parameter of that part in a standard proto-language movement is $\vec{b}$. The closer the cosine similarity s_i is to 1 indicates that two identical body parts tend to be similar in their movement states in space.

4. Exploratory analysis of movement mechanisms in dance anatomy

4.1. Dance Movement-Music Synthesis Research Analysis

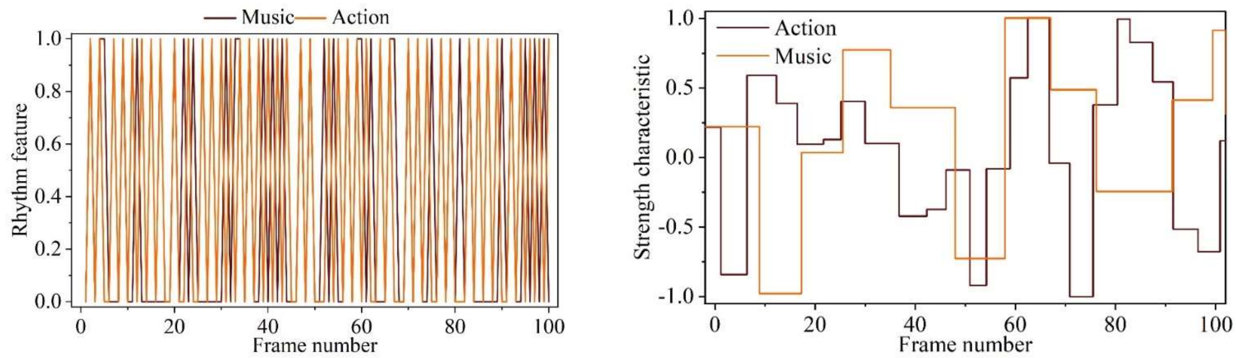
4.1.1. Analysis of loss function results. For training on the collected data, the sequence length was set to 800, the dimension of the dance movement and music feature vector d_x was 476, the dimension of the hidden vector d_z was 512, the dance movement decoder was a 3-layer GMM model, the number of nodes in the hidden layer of each GMM model was 512, and the dimension of the movement gesture vector d_y was 85. The model parameters were updated using the Adam Optimizer, and the initial learning rate was set to 0.0001, the experiments were conducted on a computing i.e. system with Ubuntu 19.0, eight NVIDIA GTX 3080Ti graphics cards were used to accelerate the training, the model was trained in 100 iterations, and the loss function results were analyzed as shown in Table 1. As can be seen from the table, the model in this paper after 70 times of training, the loss function reaches 0.0271, and is in a stable convergence state, the lower the value of its loss, indicating that the model training effect is better, and is fully able to carry out subsequent research and analysis work.

Table 1. Loss function result

N	Loss	N	Loss	N	Loss	N	Loss
1	0.1820	26	0.0902	51	0.0473	76	0.0271
2	0.1606	27	0.0897	52	0.0468	77	0.0271
3	0.1468	28	0.0892	53	0.0462	78	0.0271
4	0.1357	29	0.0887	54	0.0456	79	0.0271
5	0.1246	30	0.0882	55	0.0451	80	0.0271
6	0.1196	31	0.0876	56	0.0445	81	0.0271
7	0.1148	32	0.0862	57	0.0440	82	0.0271
8	0.1100	33	0.0842	58	0.0434	83	0.0271
9	0.1053	34	0.0822	59	0.0428	84	0.0271
10	0.1025	35	0.0802	60	0.0423	85	0.0271
11	0.1015	36	0.0779	61	0.0417	86	0.0271
12	0.1006	37	0.0748	62	0.0411	87	0.0271
13	0.0996	38	0.0718	63	0.0406	88	0.0271
14	0.0986	39	0.0687	64	0.0400	89	0.0271
15	0.0976	40	0.0656	65	0.0395	90	0.0271
16	0.0967	41	0.0625	66	0.0389	91	0.0271
17	0.0957	42	0.0610	67	0.0383	92	0.0271
18	0.0947	43	0.0594	68	0.0378	93	0.0271
19	0.0939	44	0.0579	69	0.0372	94	0.0271
20	0.0934	45	0.0563	70	0.0271	95	0.0271
21	0.0929	46	0.0548	71	0.0271	96	0.0271
22	0.0923	47	0.0532	72	0.0271	97	0.0271
23	0.0918	48	0.0517	73	0.0271	98	0.0271
24	0.0913	49	0.0501	74	0.0271	99	0.0271
25	0.0908	50	0.0486	75	0.0271	100	0.0271

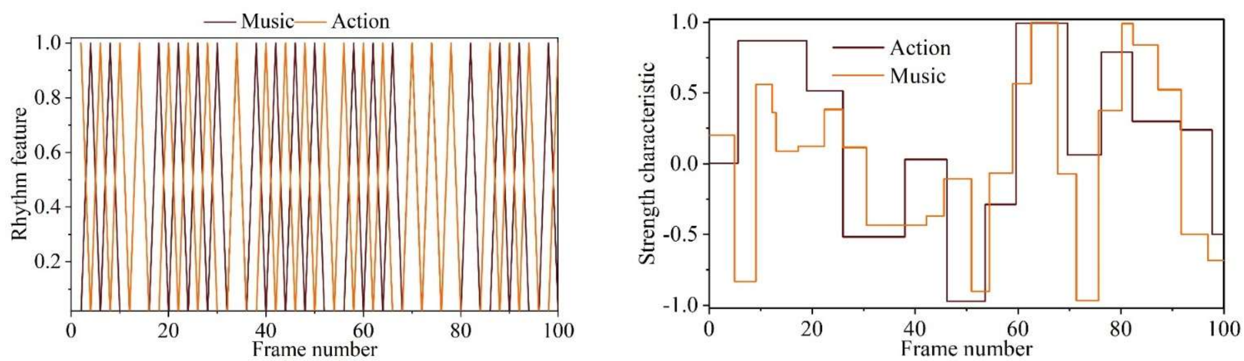
4.1.2. Analysis of synthetic effects. The above section utilizes the design of music-driven dance synthesis to solve the cross-modal matching problem of music and movement. In order to test the reasonableness of using music rhythm and intensity features and dance movement rhythm and intensity features for matching, it is set to be illustrated by comparing the feature relationship between the original matched dance and music and the feature relationship between the dance and music synthesized by the method of this paper.

It is illustrated by comparing the feature relationship between the original matched dance and music and the feature relationship between the dance and music synthesized by the method of this paper. Figure 2 shows the features of the original dance and music, where (a)~(b) are the rhythmic features, normalized intensity features, respectively, and Figure 3 shows the features of the dance and music synthesized for the model of this paper, where the rhythmic and intensity features of the music are computed according to the model, respectively, and the rhythmic and intensity features of the movements can be computed as well. As can be seen from the figure, the beat points of the movements basically coincide with the music, and the intensity distribution of the movements is similar to that of the music. Comparing Fig. 2 and Fig. 3, it can be seen that the synthesized dance based on the method of this paper and the original dance have comparable degree of audio special adaptation.



(a)Rhythm feature (b)Normalized strength characteristics

Fig. 2. Features of primitive dance and music



(a)Rhythm feature (b)Normalized strength characteristics

Fig. 3. This paper models the characteristics of synthetic dance and music

Meanwhile, this paper uses rhythm matching and intensity matching to quantify the original dance-music and synthetic dance-music respectively. The results of the number of rhythmic matches for original dance-music and synthetic dance-music are shown in Fig. 4, and the results of the intensity matching coefficients are shown in Fig. 5. From Fig. 4, it can be seen that the number of rhythmic matches of synthetic dance and the number of rhythmic matches of original dance are not much different. As can be seen from Fig. 5, the intensity matching coefficient of the synthesized dance is basically the same as that of the original dance. From the matching degree, the model proposed in this paper is feasible. However, the number of rhythmic matches and the intensity coefficient of some synthetic dances are slightly higher than that of the original dances, while the actual visual effect of the synthetic dances is slightly lower than that of the original dances. This is because the objective index is artificially defined, take the rhythmic matching number as an example, when synthesizing the dance, as far as possible, the action segments are selected for the music segments to make the rhythmic matching number as high as possible, resulting in the rhythmic matching number of the synthesized dance being slightly higher than that of the original dance, which is considered to be reasonable, not only verifying the effectiveness of the model of this paper in the application of the dance action-music synthesis, but also making the digital modeling more in line with the actual situation.

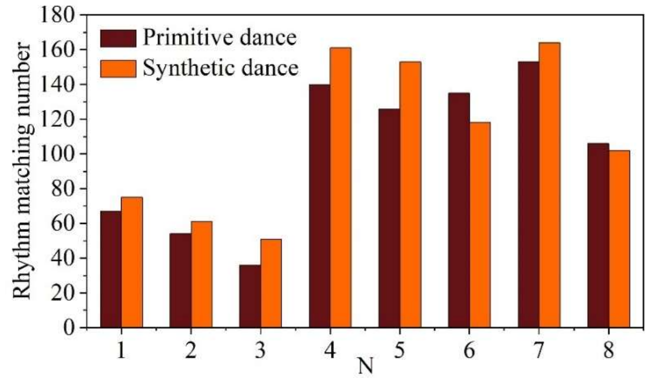


Fig. 4. Original dance - music and synthetic dance - music rhythm matching

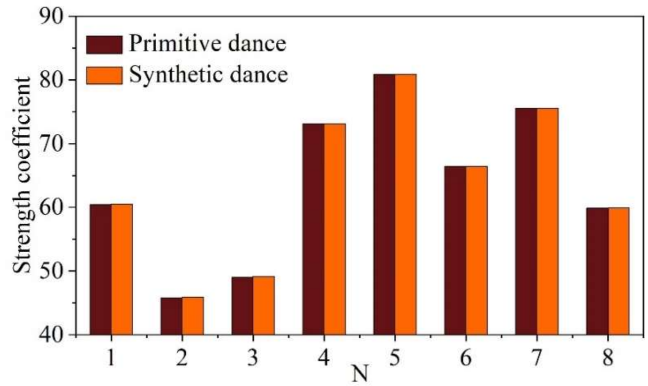
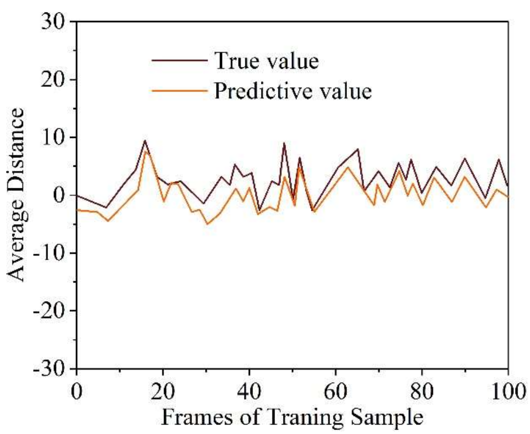


Fig. 5. Intensity matching coefficient of synthetic dance

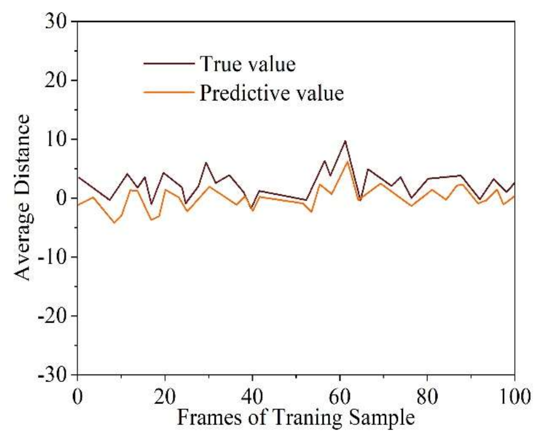
4.2. Analysis of Similarity Calculation Results

Two scoring methods are currently available: one is manual scoring from human subjective feelings, and the other is to design a network model for automatic scoring through deep learning. Both methods have some limitations, and an alternative processing strategy designed here is to focus on the dance sequence itself. Since both the original dance sequence i.e. and the synthetic dance sequence are known, it is possible to try to find the relationship between these two sequences, which in turn serves the purpose of scoring the synthesized dance sequence and judging the consistency of the music tempo and the dance movement coordination.

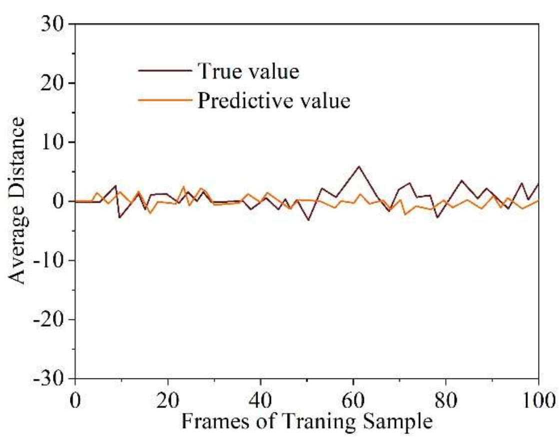
4.2.1. Method validation. In order to demonstrate the feasibility of calculating the cosine similarity between the original dance sequences and the music-driven dance sequences, we validated the method proposed in this section by dividing the study data proportionally into a training set and a test set. Firstly, we validated M1 (M1 represents the degree of deviation from the center point of the whole sequence, calculating the average distance value from each point to the center point of each of the 18 key points of the human body), and M2 (M2 is the calculation of the positional change of each key point in two consecutive frames, recording some special motion changes such as repetitive kicking, rotating, twisting the hips, and moving the arms up and down back and forth.) Validation was performed and secondly we calculated the cosine similarity between all music sequences and all synthesized dance sequences.CosA is used to represent the sum of cosine similarity between the original dance sequences based on the same music and the music-driven dance sequences. CosB is used to represent the sum of the cosine similarities between the original dance sequences based on different music and the music-driven dance sequences. Finally, the ratio of cosA to cosB is expressed using scoreRatio. The value of ScoreRatio indicates the performance of the corresponding model, and a larger value indicates a better performance of the corresponding model. Figure 6 represents the trend curve of the M1 feature extraction method based on cosine similarity, where (a) to (d) are the test set CosA, test set CosB, training set CosA, and training set CosA, respectively. It represents the average distance value from each point to the center point. Figures (a) and (b) show the variation of the first 100 frames of data in the training set, where the predicted dance sequence alignment and the original highly overlap. Fig. (c) and Fig. (d) are the data in the test set, which do not completely overlap, but the overall trend still largely matches. Figure 7 represents the trend curve of the M2 feature extraction method based on cosine similarity. It represents the position change of each point in two consecutive frames. It can be clearly seen from the figure that the music-driven dance sequences and the original sequences fluctuate within a certain range (-8, 13) in both the training and test sets. The cosine similarity validation of different dance sequence synthesis methods is shown in Table 2. The data in the table is the value of scoreRatio, and a higher score indicates a better performance of the corresponding dance sequence synthesis model. The method proposed in this paper achieves excellent results in both training and test sets. The scoreRatio value of this paper's method in the training set is as high as 1.505 which is much higher than that of 1.1409 for the AM network, and the data results of the test set do not span as much as the training set, but they still prove that the method of calculating the cosine similarity is feasible, which ensures the reliability of the following research and analysis work.



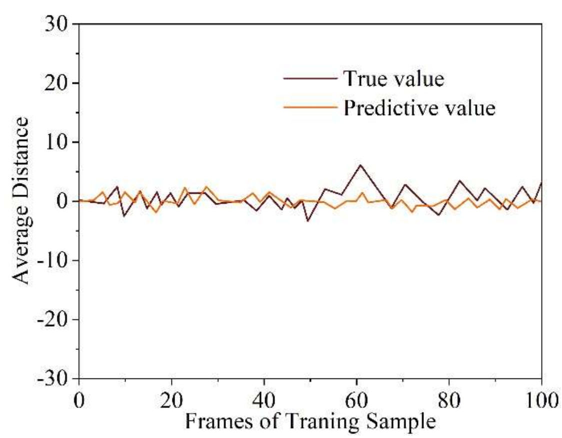
(a)Test set CosA



(b)Test set CosB

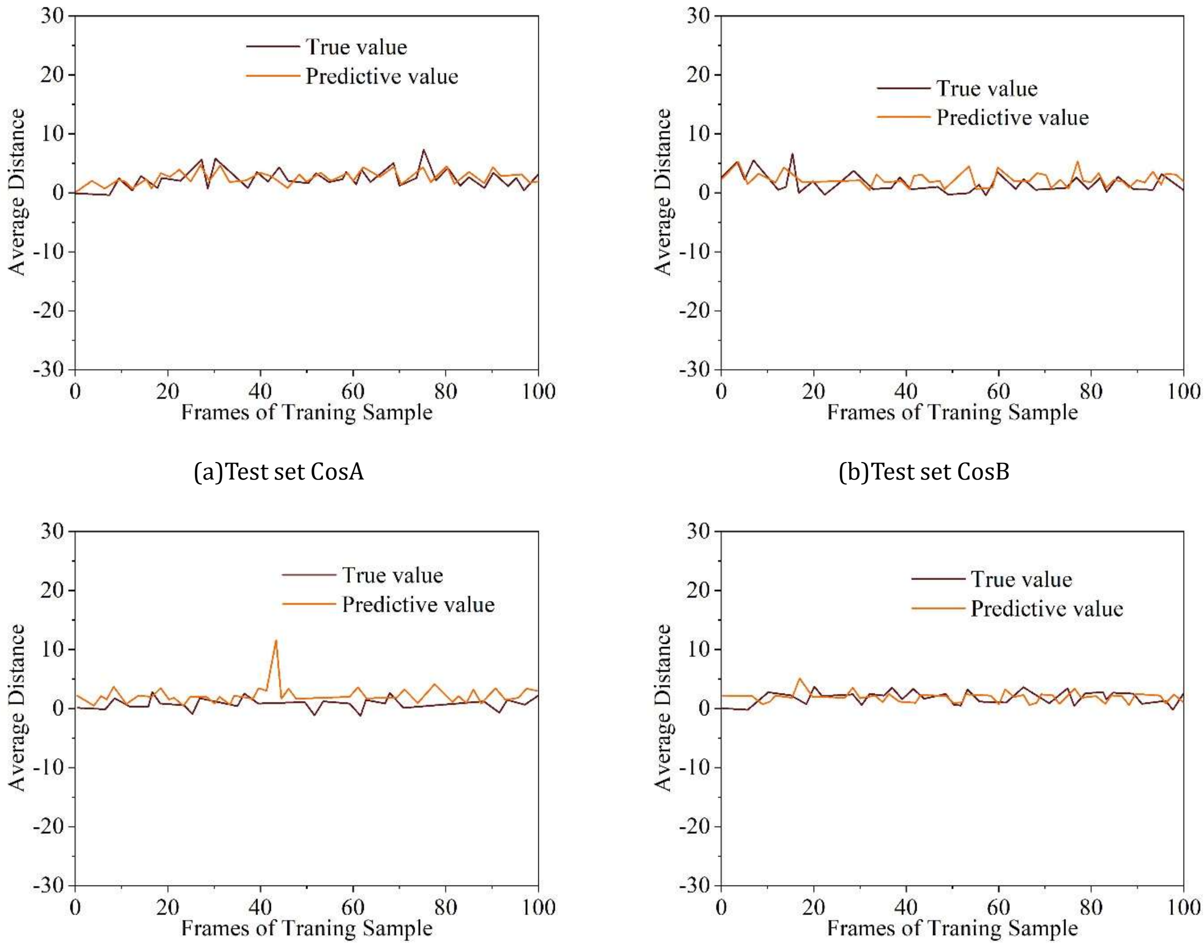


(c)Training set CosA



(d)Training set CosB

Fig. 6. M1 method verification based on cosine similarity



(a)Test set CosA (b)Test set CosB

(c)Training set CosA (d)Training set CosB

Fig. 7. M2 method validation based on cosine similarity

Table 2. Cosine similarity verification of different dance sequence synthesis methods

Train						Test				
Method	M2	M1	$\alpha=0.3$	$\alpha=0.6$	$\alpha=0.8$	M2	M1	$\alpha=0.3$	$\alpha=0.6$	$\alpha=0.8$
CNN	1.0008	1.2919	1.1214	1.1818	1.2522	1.0014	0.9905	0.9907	0.9941	0.9939
LSTM	1.1616	1.5535	1.3306	1.1414	1.5029	1.0026	0.9744	0.9923	0.9845	0.9812
AM	1.1224	1.1422	1.1313	1.1324	1.1409	0.9942	0.9542	0.9815	0.9723	0.9622
SA	1.1216	1.1547	1.1411	1.1447	1.1532	0.9844	0.9411	0.9626	0.9626	0.9433
Our	1.1605	1.5609	1.3313	1.4129	1.5105	1.0001	0.9912	0.9942	0.9933	0.9925

4.2.2. Analysis of similarity results. Figure 8 presents the results of the average scores based on cosine similarity for the five different dance synthesis models. From the data in the table, it can be seen that the scores of the training set are generally higher than those of the test set, and the scores of the test set are more distinguishable. As the predicted results above, the model proposed in this paper performs the best and is capable of modeling the human movement mechanism in dance anatomy and dance music synthesis, which not only ensures the aesthetics of the practitioner's dance, but also avoids injuries caused by substandard movements, and implements the human movement mechanism in dance anatomy in all aspects.

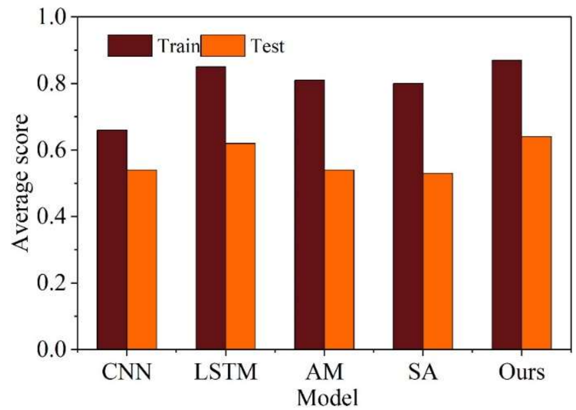


Fig. 8. The cosine similarity score of different models

5. Conclusion

This project firstly explains the interrelationship of morphological and structural features of various organs and systems of the human body, as well as the influence of dance training on the morphological structure of the human body through the systematic elaboration of dance anatomy. With the help of relevant equipment to build the experimental environment, the initial data of this study were collected and pre-processed, and the data were exported and saved in the corresponding file format. To address the problem of inconsistency between dance movements and music rhythms, a time-series autoregressive model is used to construct a dance movement-music synthesis model, and the loss function of the model is set. Finally, the research data, the model in this paper and the 3D modeling software are integrated to complete the mathematical modeling of the human dance movement mechanism, and the cosine similarity is used to explore and analyze the music-driven dance movements. Whether in the training set, test set, this paper's method has excellent application performance, its specific value of 0.8693, 0.6391, far better than the other four groups of models, indicating that this paper's method is well implemented in the dance anatomy of the human body movement mechanism, to prevent the physical injury of the dance training, but also to ensure that the rhythm of the music and the coordination of the dance movement, so that the dance movement rendering effect has been significantly improved.

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