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Article

Enhancement of Innovativeness of Dance Works by Artificial Intelligence-Based Dance Creation System

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Abstract: The gradual development and maturation of artificial intelligence technology has driven its deep integration and application in the field of dance choreography. This paper proposes a music-dance generation model based on generative adversarial networks (GANs), which consists of a generator and a discriminator. The generator employs the CL-K2M model, while the discriminator determines whether the generated dance sequence is authentic under the condition of known music. Additionally, the model calculates the pose differences between two frames based on the differences in degrees of freedom, and combines dance movement characteristics with motion interpolation techniques to achieve smooth transitions between two sequences. The dance movements generated by the designed model achieved the highest average user ratings in three metrics: rhythm (7.57), coordination (7.35), and style retention (8.45), demonstrating significantly superior performance compared to similar model algorithms.

Keywords: artificial intelligence; music and dance choreography; generative adversarial network; motion interpolation method

1. Introduction

Currently, advancements in artificial intelligence have expanded the scope of information dissemination, bringing about significant transformations in social life and sparking multifaceted innovations within the realm of aesthetic arts. These developments have exerted profound influences across multiple dimensions, including aesthetic experiences, artistic expression forms, and creative models [1-3]. Within the broad domain of the arts, the driving force of artificial intelligence on artistic creation activities and its promotional role in artistic form innovation will be comprehensive and deeply transformative [4-5]. As an important branch of artistic expression, dance art is inevitably caught up in this technological revolution, with its creative concepts, forms of expression, and aesthetic standards facing new challenges and opportunities [6]. Choreographers and artists are no longer solely focused on the study of movement styles or the exploration of movement development, but are instead dedicated to continuously exploring new forms of artistic innovation and developing a series of novel choreographic concepts and principles [7]. With the powerful support of deep learning technology, artists and choreographers utilize large datasets and efficient learning algorithms to systematically train artificial intelligence to accurately capture and understand movement patterns [8-9]. This training process not only enables artificial intelligence to innovate highly novel movement sequences but also achieves accurate prediction and visual reproduction of dancers' movement patterns [10]. This discovery not only broadens our understanding of the boundaries of AI applications but also provides important theoretical and practical foundations for exploring new paths for the synergistic development of AI and dance innovation.

Currently, the common practice in AI interaction within the dance field involves using deep learning and other technologies to track and identify dancers' movements, with the captured data applied to dance innovation choreography and visual effects generation or transformation. For example, Jiao [11] conducted research on dance motion human posture recognition and prediction using deep learning algorithms. The model developed in this study can effectively capture dynamic information of dance motions, and compared with the reference algorithm, the proposed model demonstrates superior posture recognition and prediction performance. Ji et al. [12] reported in 2024 that a deep learning model based on convolutional neural networks and multi-layer perceptron modules achieved an accuracy rate, precision, recall rate, and F1 score of 90.74%, 87.12%, 83.78%, and 84.39%, respectively, highlighting the effectiveness of deep learning models in dance movement recognition. Additionally, Matsuyama et al. [13] developed a dance motion recognition model based on long short-term memory (LSTM) networks, achieving a dance motion prediction accuracy of 93%, an 8.3% improvement over the baseline model and results close to human predictions.

For research on dance choreography, Broadwell et al. [14] applied a deep learning-based dance pose detection algorithm to a K-pop music video corpus and analyzed the time-series data of dance movements. Through case studies, they demonstrated the effectiveness of the model in dance choreography. Wu et al. [15] designed a robot automatic choreography system using deep learning technology, which can generate dance sequences matching the input music, and the generated dance sequences achieve human-level diversity and innovation. Ferreira et al. [16] addressed the issue of mismatch between intelligent dance generation and music using a graph convolutional network model, which can generate more natural dance styles based on qualitative and various quantitative metrics, outperforming most existing models in dance generation performance. Ban [17] optimized LSTM and GRU as music encoders to generate high-quality dances, reconstructing music features from the generated dances, the results show that this method can create natural dance movements that match the music.

Although AI-based algorithms can achieve good choreography effects, ensuring the novelty, coherence, and rhythm of the choreography movements with the target music, research on music and movement feature extraction, feature matching, and dance evaluation is still insufficient and requires further study [18-19].

This paper first describes the methods and mathematical expressions for extracting the characteristics of dance movement sequences, which serve as the prerequisites for dance choreography. It then explains the basic principles of the generator network and the architectural composition of the discriminator network, and integrates them to build a dance choreography model based on generative adversarial networks (GANs). Additionally, based on the defined content of dance movement attributes, it analyzes the methods for calculating the distances between the four elements of a movement and between two consecutive frames of a movement. A brief overview of the operational process of motion interpolation is provided, and action combination techniques in dance choreography are proposed. Music features are selected to analyze the matching effectiveness of the proposed model between music and action features. The effectiveness of the proposed model in generating dance actions is evaluated through feature assessment and matching degree. Qualitative assessment and user assessment comparison experiments are designed to verify the visual performance of the proposed model in generating dance actions. Finally, the effectiveness of introducing motion interpolation strategies is validated by comparing the effects before and after their application.

2. Dance Choreography Model Based on Generative Adversarial Networks

2.1. Problem Description

Given a piece of music data A and the corresponding real dance movement sequence $\left\{M_1,\ldots,M_n\right\}$. The music sequence $\left\{A_1,\ldots A_n\right\}$ is obtained by dividing A into segments of equal duration based on action frequency. Features are extracted from this sequence to obtain $\left\{A_1^F,\ldots A_n^F\right\}$. Features are extracted from the dance action sequence to obtain equation (1):

$$M^F=\left\{M_1^F,\ldots M_n^F\middle|M_i^F\in\mathbb{R}^{e*1}\right\} \tag{1}$$

Given the first frame M_0, whose feature is M_0^G, assume that a music dance generation function G and a discriminant function D can be obtained. The generation function G is divided into two parts: music encoding G^A and motion generation G^M. When $i=1$ to n, equations (2)-(3) apply:

$$A_i^E=G^A\left(A_i^F\right) \tag{2}$$

$$M_i^G=G^M\left(M_{i-1}^G,A_i^E\right) \tag{3}$$

When $i=0$, M_0^G is already given. Therefore, by iteratively calculating G, we can obtain the generated action feature sequence as shown in equation (4) and the encoded music features as shown in equation (5):

$$M^G = \left\{ M_1^G, \ldots, M_n^G \,\middle|\, M_i^G \in \mathbb{R}^{e*1} \right\} \tag{4}$$

$$A^E = \left\{ A_1^E, \ldots, A_n^E \,\middle|\, A_i^E \in \mathbb{R}^{e*1} \right\} \tag{5}$$

The discriminative function D can determine the probability that the input comes from a real action. Let M^{Fd} represent the probability of the function output when the input is a real action, as shown in equation (6), and let M^{G_d} represent the probability of the function output when the input is a generated action, as shown in equation (7).

$$M^{F_d} = D\left(M^F \,\middle|\, A^E \right) \tag{6}$$

$$M^{G_d} = D\left(M^G \,\middle|\, A^E \right) \tag{7}$$

The purpose of function D is to maximize $\log\left(M^{F_d}\right) + \log\left(1 - M^{G_d}\right)$, while the purpose of function G is to minimize it, as shown in equation (8):

$$\min_G \max_D V\left(M^{F_d}, M^{G_d}\right) = \log\left(M^{F_d}\right) + \log\left(1 - M^{G_d}\right) \tag{8}$$

By transforming the features of the generated action sequence M^G, we obtain the generated action sequence $\left\{ M_1^i, \ldots, M_n^i \right\}$.

2.2. Network Structure

2.2.1. Generator Network

In the music and dance generation model CL-K2M based on CNN and LSTM, the generation network is divided into two parts: the music encoding subnetwork and the action generation subnetwork. The music encoding subnetwork encodes the underlying features of a frame of music A_i^F to obtain the music encoding features A_i^E. The motion generation subnetwork concatenates the encoded music features A_i^B with the motion features from the previous frame M_{i-1}^G to output the motion features for the current frame M_i^G. Therefore, given the initial motion features M_0^G and a music sequence $\left\{ A_1, \ldots A_n \right\}$ as input, this model can iteratively generate an encoded music feature sequence $\left\{ A_1^E, \ldots, A_n^E \right\}$ of the same length as the music sequence, as well as the corresponding action feature sequence $\left\{ M_1^G, \ldots, M_n^G \right\}$. This model meets the requirements for the generation network in this paper, so its network structure is retained.

2.2.2. Discrimination Network

The design of the discriminator network mainly refers to CGAN and DCGAN. CGAN uses image labels as conditional inputs to determine whether an image conforms to the distribution of real data. In this paper, the auxiliary condition for the discriminator is a piece of music feature. The structure of the discriminator network is shown in Figure 1.

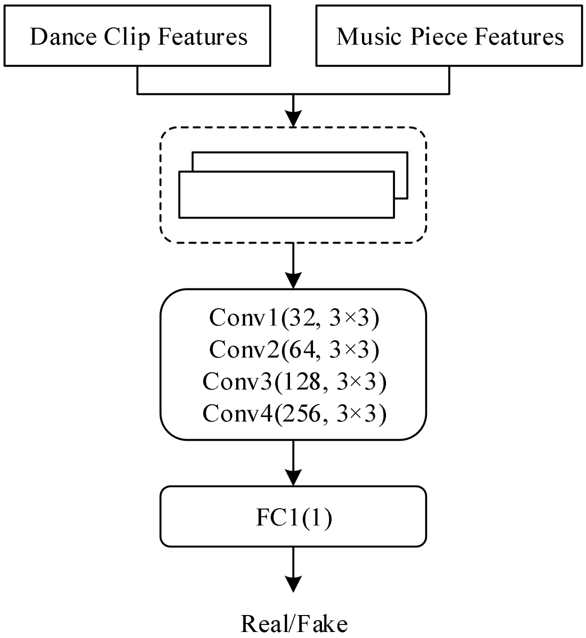


Figure 1. Discriminator network structure.

The music features and action features obtained from the generator are both vectors of size $1*60*1$. Based on the training window length N_w, the generated music features and action features can be stacked in chronological order to obtain a feature image of size N_w*60*1.

There are two ways to connect the music features and motion features as inputs to the discriminator: one is to directly connect the motion features and music features in the width dimension according to the standard CGAN method, and then form a feature image of size $N_w*120*1$. The other method is to connect the motion features and music features in the channel dimension to form a feature image of size N_w*60*2. Through experiments, this paper found that using the channel connection method makes the discriminator network converge more easily, so the channel connection method is used.

The discriminator network consists of four convolutional layers and one fully connected layer, where each layer has a $3*3$ size convolution kernel, a sliding stride of $2*2$, and uses edge zero padding. The number of convolutional kernels in the first to fourth convolutional layers are 32, 64, 128, and 256, respectively. Each convolutional layer is followed by an activation layer. Through experimentation, it was found that the Leaky ReLU activation function converges more stably than the ReLU activation function, so the Leaky ReLU activation function is used in the discriminator's activation layer. Finally, a fully connected layer with a sigmoid activation function outputs a value between 0 and 1. The larger the output value, the higher the probability that the input sample comes from the true data distribution; conversely, the smaller the output value, the lower the probability that the input sample comes from the true data distribution.

3. Dance Combination Techniques

3.1. Definition of Action Attributes

In the process of character animation design, dance movements are viewed at the physical level as composed of the local movement characteristics of four main joints: the head, upper limbs (chest and arms), lower limbs (chest and legs), and trunk. These are then combined to form a full-body dance movement. This concept of joint movement provides a reference and basis for evaluating the degree of movement correlation in later stages.

For each characteristic movement unit in the original chime dance movement database, the joint movements are divided based on their dance characteristics at the physical level, which can be represented by a simple four-equation system, as shown in Equation (9):

$$F_i = \left(\Sigma Ai \,\&\, \Sigma Bi \,\&\, \Sigma Ci \,\&\, \Sigma D_i\right) \tag{9}$$

Among them, Fi represents the overall movement of the human body, with four main joint movements: ΣAi for head movements, ΣBi for trunk movements, ΣCi for hand movements, and ΣDi for lower limb movements. Taking mulberry picking as an example, the overall characteristics of the movements are defined based on the specific descriptions of each joint movement.

For a dance choreographer, determining the joint definitions of a movement establishes its overall characteristics. By default, the starting movement of the next characteristic dance unit connected to the current movement's termination state should be selected based on its degree of association. Excluding external constraints based on emotion and environment, the internal constraints between movements are related to the four-variable equations of the preceding and following movements.

3.2. Distance between Two Frames

The distance between two frames, i.e., the pose difference between two frames, is calculated based on the differences in degrees of freedom.

(1) Distance between the four elements

Let the reference vector be $P_0 \in R^3$ and the unit quaternion be q_1 that rotates P_0 to P_1, and q_2 rotates P_0 to P_2, yielding equations (10)-(11):

$$[0, P_1] = q_1 [0, P_0] q_1^{-1} \tag{10}$$

$$[0, P_2] = q_2 [0, P_0] q_2^{-1} \tag{11}$$

Let the unit quaternion be as in (12):

$$q_2 q_1^{-1} = [w, x, y, z] = [\cos\theta, \sin\theta(a,b,c)]\left(\|(a,b,c)\| = 1, \theta = \arccos(w) \in [0, \pi]\right) \tag{12}$$

Apply it to vector P_1 as in equation (13):

$$\begin{aligned} \left(q_2 q_1^{-1}\right)[0, P_1]\left(q_2 q_1^{-1}\right)^{-1} &= \left(q_2 q_1^{-1}\right)\left(q_1 [0, P_0] q_1^{-1}\right)\left(q_2 q_1^{-1}\right)^{-1} \\ &= \left(q_2 q_1^{-1}\right)\left(q_1 \left[0, P_0 \mid q_1^{-1}\right)\left(q_1 q_2^{-1}\right) \\ &= q_2 \left(q_2^{-1} q_3\right)[0, P_0]\left(q_1^{-1} q_1\right) q_2^{-1} \\ &= q_2 [0, P_0] q_2^{-1} = [0, P_2] \end{aligned} \tag{13}$$

From equation (13), we can see that $q_2 q_1^{-1}$ transfers P_1 to P_2, so θ can be used to measure the distance between q_1 and q_2, that is, the difference between the rotations produced by q_1 and q_2. If there is equation (14):

$$q_2 q_1^{-1} = [w, x, y, z] \tag{14}$$

Then, the distance between q_1 and q_2 is defined by equation (15):

$$d\left(q_1, q_2\right) = \arccos(w) \tag{15}$$

(2) Distance between two frames

Let f_i^{m1} and f_j^{m2} be two frames in M1 and M2, respectively. The distance between them is defined by equation (16):

$$D\left(f_i^{m1}, f_j^{m2}\right) = \sum_{i=1}^{n} \alpha_i d\left(q_i\left(f_i^{m1}\right), q_i\left(f_j^{m2}\right)\right) \tag{16}$$

Where $\alpha_i (i = 1, 2, \ldots, n)$ are weighting coefficients representing the importance of each joint and their differing effects on human posture. $d\left(q_i\left(f_j^{m2}\right), q_i\left(f_j^{m2}\right)\right)$ is calculated based on the four-element distance. The human body structure is a tree-like chain of joints, where the movement of parent joints drives the movement of child joints. Therefore, from a movement perspective, parent joints are more important, such as the shoulder, elbow, leg, and knee joints, for which α_r is set to 1. For joints that have a smaller impact on human movement, such as the neck and wrist joints, α_i is set to 0.

The differences in pose between consecutive frames of f_i^{m1} and f_j^{m2} are also included in the calculation, resulting in equation (17):

$$T\left(f_i^{m1}, f_j^{m2}\right) = \sum_{I=-k}^{k} w_i D\left(f_i^{m1}, f_j^{m2}\right) \tag{17}$$

Among them, k is the frame window size, selecting 15 frames before and after, and w_1 is the weight.

3.3. Motion Interpolation

After determining the spline centers for the two motion segments, first translate the root joint position of the second segment's spline center point to the root joint position of the first segment's spline center point. Merge the root joint trajectories of the two segments to avoid the unnatural appearance caused by direct interpolation of the root joints. In addition to connecting the two trajectories at the center point, rotation of motion segment 2 is required to ensure that the performer's orientation at the center point is consistent after rotation.

After merging the root joint trajectories, interpolate the other joints outside the root joint. Select an appropriate interpolation range. Overlap the 20 frames before and after time point $t1$ in $M1$ with the 20 frames before and after time point $t2$ in $M2$, and use a smooth interpolation method during this overlap period. The specific interpolation method used is linear interpolation of the Euler angles of each joint.

4. Evaluation and Analysis of Dance Choreography Models

4.1. Coordination between Music and Dance Movements

4.1.1. Selection of Musical Characteristics

This paper uses the Librosa library as a tool for music processing, which is often used for music signal analysis, music feature extraction, sound waveform and spectrum diagram plotting, and other functions. The amplitude envelope of the waveform of the target music (audio generated after the choreography module) is plotted, and its shape is shown in Figure 2. Then, the beat of the audio is extracted to prepare for the choreography module.

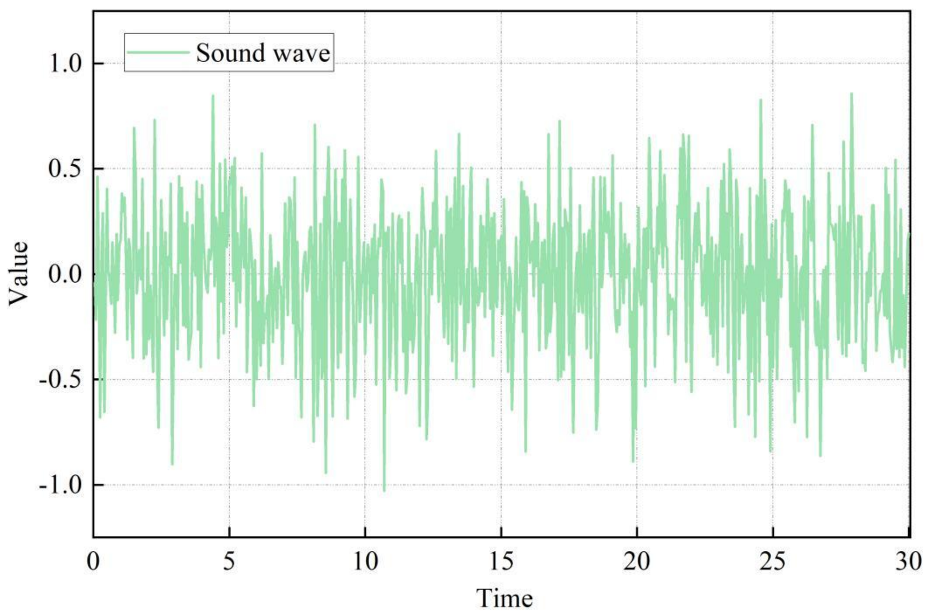
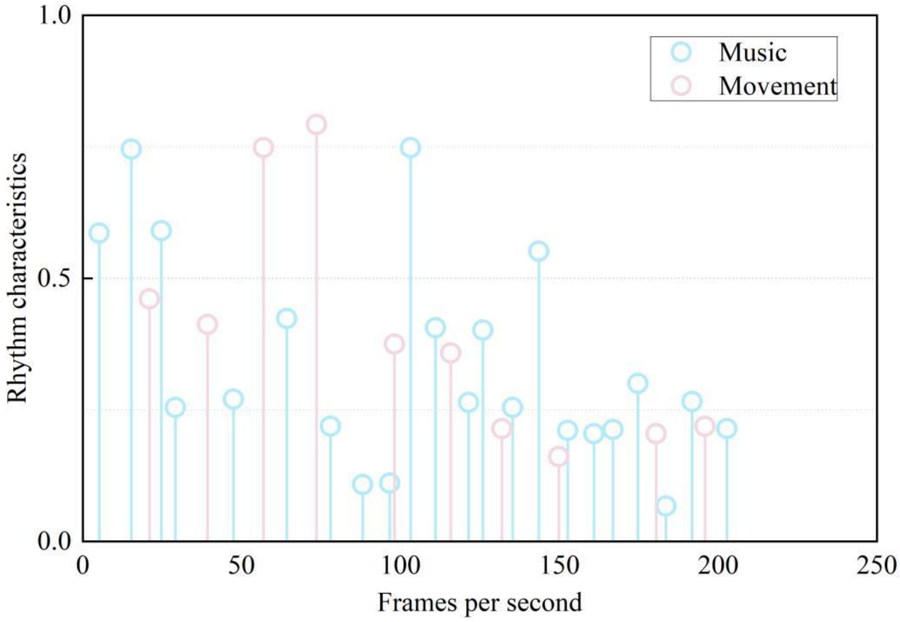


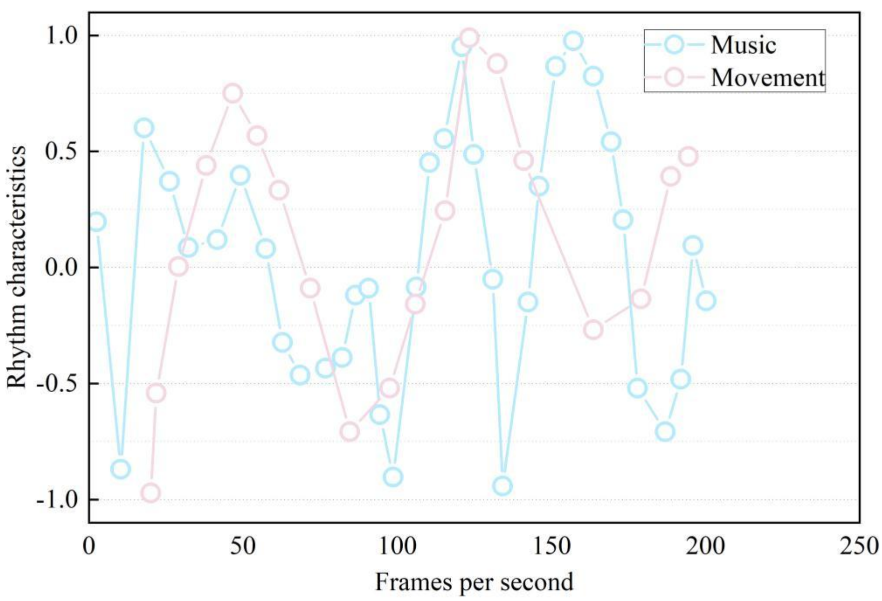
Figure 2. Target audio waveform.

4.1.2. Matching Music and Motion Characteristics

To further validate the proposed algorithm, this paper compares the existing matched dance-music relationships with the dance-music relationships synthesized in this paper. For the audio and BVH motion data of the original Greek dance Haniotikos, rhythm and intensity features were extracted using the feature extraction algorithm proposed in this paper, as shown in Figure 3. Specifically: 1 frame duration is 1/30s, and the average rhythm period of the Haniotikos audio is 0.25s. As shown in Figure 3, the average rhythm period of the dance movements is longer than that of the music, but the beat points of the movements largely align with the music. The intensity distribution of the movements is not perfectly matched with the music but is quite similar.



(a) The rhythmic characteristics of music and movements



(b) The intensity characteristics of music and movements

Figure 3. Music and motion features of Haniotikos.

4.2. Generating Effects

4.2.1. Feature Evaluation

To validate the model's effectiveness, FID and Diversity are used as evaluation metrics. FID is a metric that measures the distance between the feature vectors of real dance and generated dance. A lower FID value indicates that the generated movements are closer to the real movements. Diversity (Div) is the average distance in the feature space of generated dance movements. A higher Diversity value indicates better diversity in the generated movements. The following models were selected for comparison with the model proposed in this paper: (M1) Ground truth, (M2) Liet al., (M3) DanceNet, (M4) DanceRevolution, (M5) FACT, and (M6) Bailando. The experimental results are shown in Table 1, where FID and Div include two sub-metrics, denoted by k and v, respectively, to assess the motion and geometric features of dance actions. The Beat Align Score measures the beat alignment rate by calculating the distance between each music beat and its nearest dance beat.

Table 1. Experimental results of different models.

Model	$FID_k\downarrow$	$FID_g\downarrow$	$Div_k\uparrow$	$Div_g\uparrow$	Beat Align Score↑
M1	17.55	11.05	8.64	7.9	0.3608
M2	86.88	43.91	7.3	3.77	0.2841
M3	69.63	26.37	3.97	5.32	0.3184
M4	73.87	26.37	3.97	5.32	0.3184
M5	35.8	22.56	6.39	6.63	0.3443
M6	28.61	10.07	8.28	6.79	0.3566
M7	7.94	8.42	9.38	8.87	0.4371

Observing Table 1, (M7) the motion characteristics and geometric characteristics of the dance movements generated by the model in this paper are 7.94 and 8.42, respectively, which are the closest to real dance movements among the seven models. The beat alignment rate is 0.4371, which is also the best among the seven models.

4.2.2. Matching Degree

The results of the rhythm matching count and intensity matching coefficient between the original dance-music and the dance-music synthesized by the proposed model are shown in Table 2. In terms of rhythm matching count, the maximum difference between the dance synthesized by the proposed model and the original dance is only 4. In terms of intensity matching coefficient, the difference between the dance synthesized by the proposed model and the original dance ranges from 0.0038 to 0.1387. That is, the rhythm matching count between the model-synthesized dance-music and the original dance is not significantly different, and the intensity matching coefficients are largely consistent, indicating that the model proposed in this paper is feasible in terms of matching accuracy.

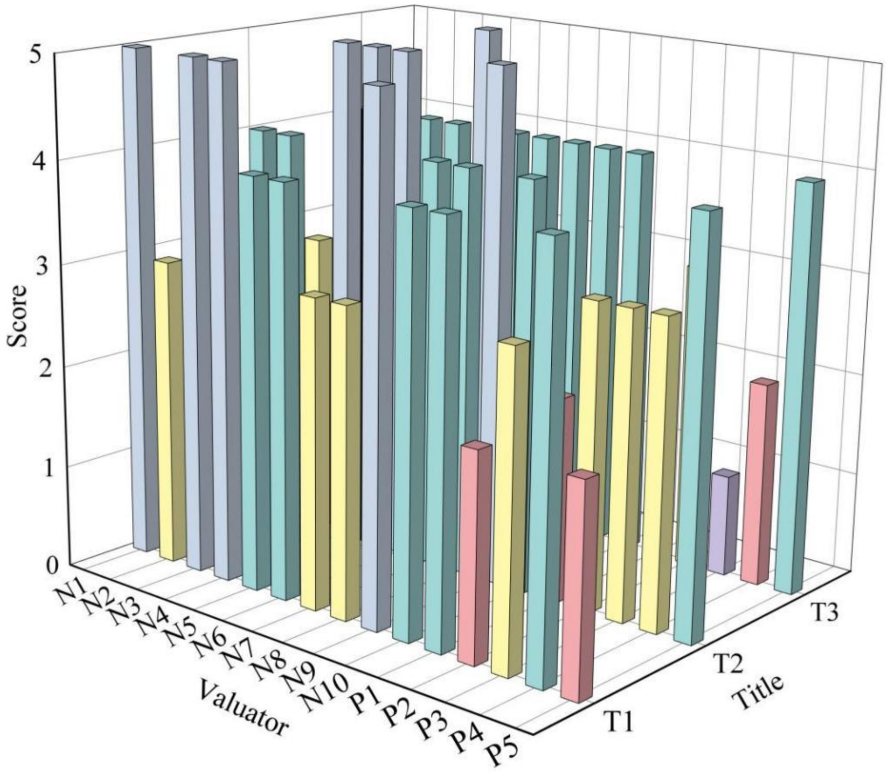
Table 2. Rhythm matching quantity and intensity matching coefficient.

Dance type		Primitive dance	Synthetic dance
Rhythm matching coefficient	Antl	71	79
	Ant2	58	65
	Ant3	40	55
	Han	144	165
	Has	130	157
	Mal	139	122
	Zeil	157	168
	Zei2	110	106
Intensity matching coefficient	Antl	61.6359	61.7255
	Ant2	47.0369	47.0643
	Ant3	50.2535	50.3922
	Han	74.365	74.3484
	Has	82.1244	82.1642
	Mal	67.6791	67.6829
	Zeil	76.8446	76.8256
	Zei2	61.0851	61.1195

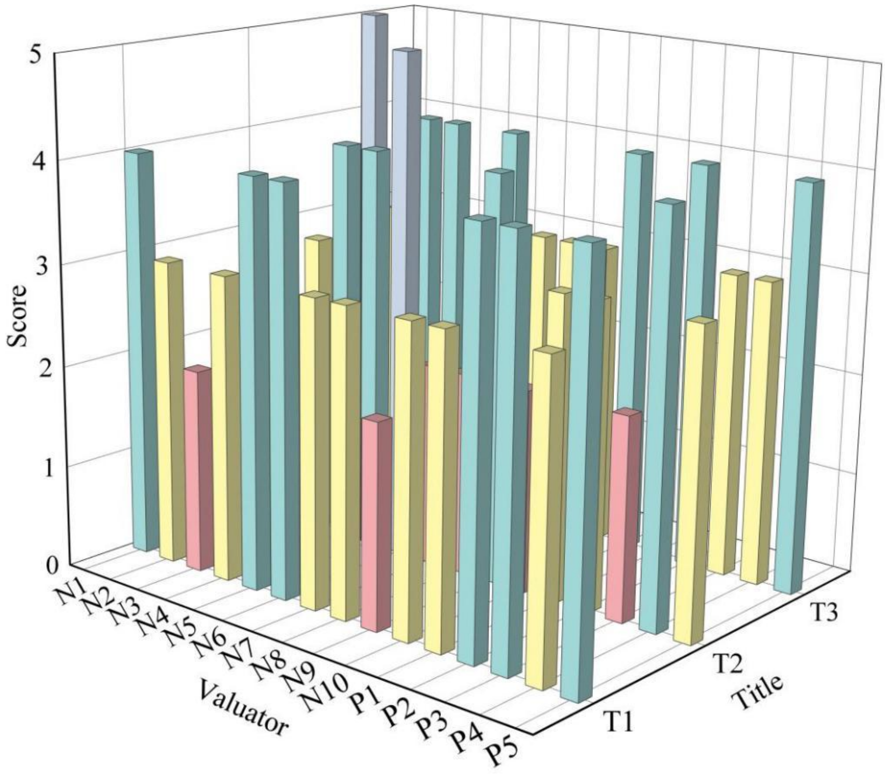
4.3. Visual presentation Effects

4.3.1. Qualitative Assessment

To assess the influence of subjectivity on dance evaluation, user research was employed to compare the quality of dance generated by the (M1) Ground truth model and the (M7) model method described above, which demonstrated superior overall performance. The survey participants included 5 professional dancers (P1-P5) and 10 non-professional dancers (N1-N10). The survey content provided to participants consisted of experimental results videos generated using both methods on the AIST++ dataset. Each set of videos featured the same input movements and music. Each participant was required to randomly select 10 out of 40 video sets and then evaluate each set based on the following three questions: (T1) The quality level of the dance in the video without considering the music. (T2) The extent to which the dance movements in the video follow the music. (T3) The level of creativity in the dance movements in the video. Each question was scored on a scale of 5 points: very poor (-1 point), poor (-2 points), average (-3 points), good (-4 points), and excellent (-5 points). The statistical results of the feedback from the two groups of participants are shown in Figure 4.



(a) M1



(b) M7

Figure 4. User research results.

As shown in Figure 4, the (M1) Ground truth model received higher scores from non-professional dancers, with multiple non-professional dancers giving it a score of 5. However, in evaluations by professional dancers, the overall scores were lower, concentrated between 2 and 3. This indicates that the (M1) Ground truth model is more oriented toward the perspective of spectators in generating dance movements, but lacks professionalism. In contrast, the (M7) model method used in this paper received scores mostly concentrated between 3 and 4 from both non-professional and professional dancers. Although the number of 5-point scores was lower than that of the (M1) Ground truth model, the number of 2-point evaluations was also significantly fewer than that of the (M1) Ground truth model. This indicates that the dance movements generated by the model method in this paper can balance both aesthetic appeal and professional rigor, possessing a richer depth of meaning.

4.3.2. User Evaluation Comparison

To comprehensively evaluate the visual effects of the generated dance, this section conducted a user study based on the following evaluation criteria: (E1) realism, (E2) rhythm, (E3) coordination, and (E4) style consistency. A survey questionnaire was designed with two questions for each criterion, each scored out of 10 points. The average user ratings for each criterion across the three model methods (M1, M4, and M7) are shown in Figure 5. Overall, all three model methods scored below 7 on the (E1) realism criterion and require improvement. However, in the (E2) rhythm, (E3) coordination, and (E4) style consistency metrics, the (M7) model achieved the highest average user evaluation scores, with scores of 7.57, 7.35, and 8.45, respectively.

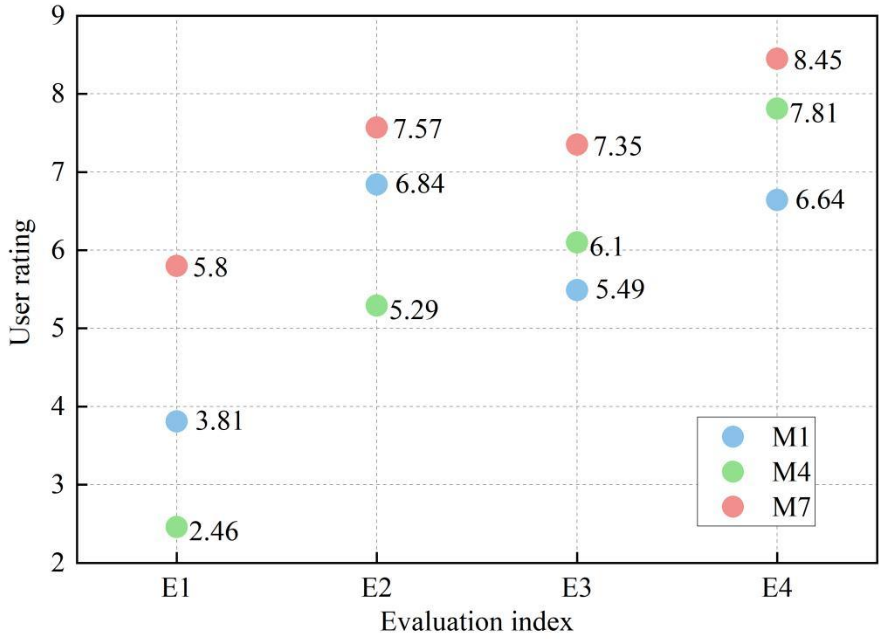
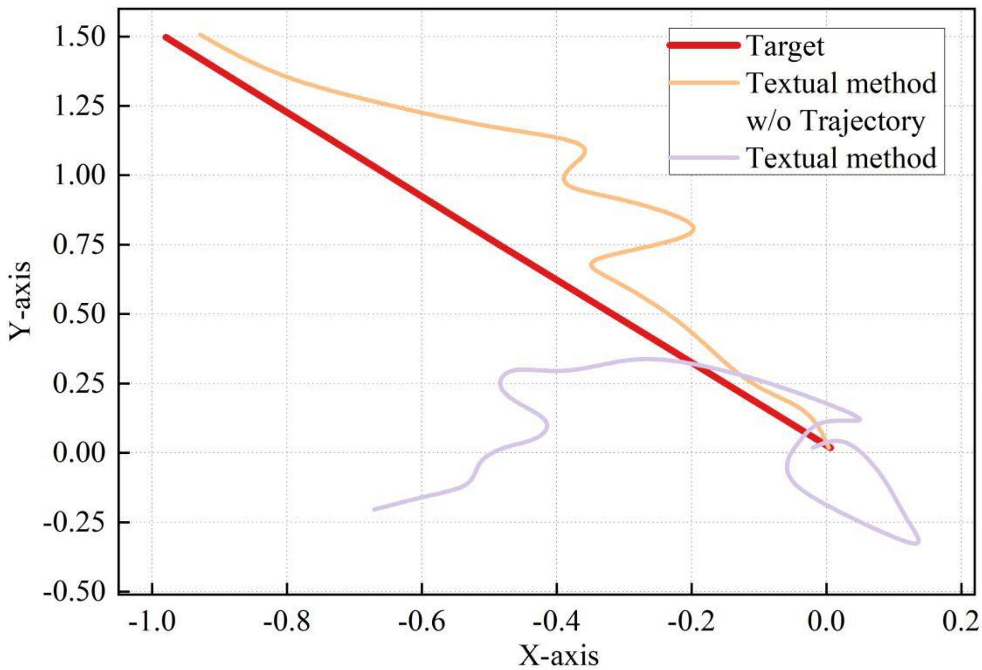


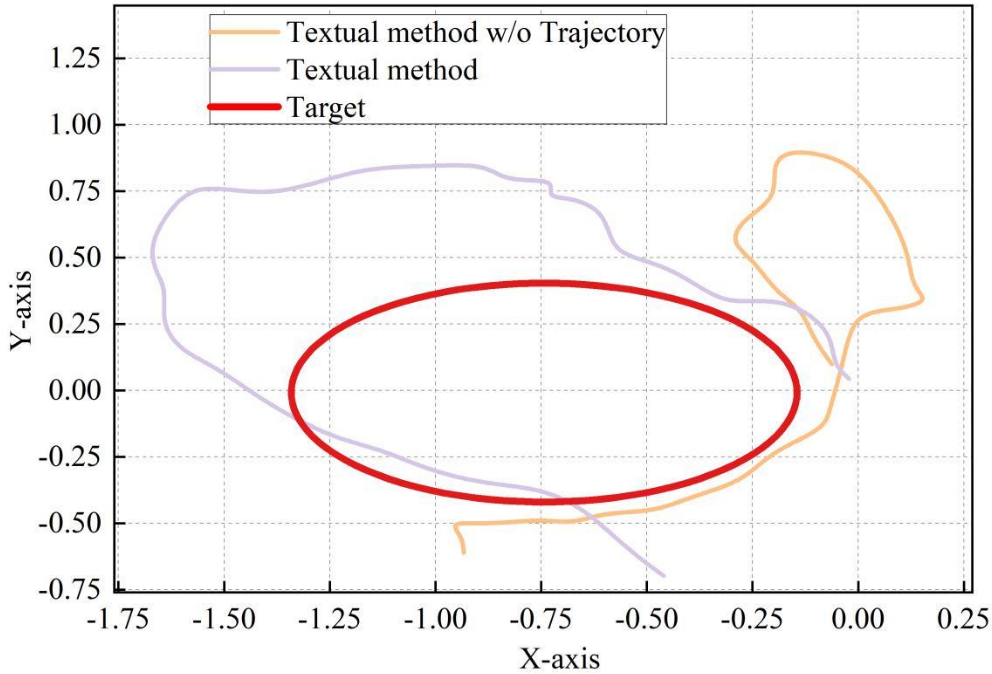
Figure 5. The average score of user ratings of the three model methods.

4.4. Effectiveness of Motion Interpolation Strategies

Furthermore, Figure 6 visually compares the results of dance motion visualization with and without the use of motion interpolation strategies. As can be clearly seen from the figure, the motion interpolation strategy generates dance motions that more closely align with the expected trajectory, significantly improving the continuity of the motions and the accuracy of spatial positioning. In contrast, the generation method without the motion interpolation strategy exhibits deviations in the execution of certain key motions, resulting in reduced fluidity and naturalness of the overall dance.



(a) Before applying the motion interpolation strategy



(b) After applying the motion interpolation strategy

Figure 6. Trajectory comparison.

5. Conclusion

This paper proposes a dance choreography model based on generative adversarial networks (GANs). The model employs a generator-discriminator architecture and utilizes motion interpolation to achieve smooth transitions between two dance sequences by centering on the interpolation region. The generated dance movements exhibit high fluidity, strong overall expressiveness, and a balance of aesthetic appeal and professional quality, providing valuable references for innovative dance content creation.

The beat points of the actions generated by the proposed model are largely aligned with the music. In terms of generation effects, the motion characteristics and geometric feature values of the actions are 7.94 and 8.42, respectively, with a beat alignment rate of 0.4371. The difference between the generated actions and the original dance ranges from 0.0038 to 0.1387. In terms of visual presentation, the model received consistent recognition from both non-professional and professional dancers (3–4 points) and achieved high average user ratings in three metrics: rhythm, coordination, and style retention, with scores of 7.57, 7.35, and 8.45, respectively. After applying the motion interpolation strategy, the generated dance movements exhibit greater continuity and spatial positioning accuracy.

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