Towards 3D Dance Motion Synthesis and Control

Wenlin Zhuang
wlzhuang@seu.edu.cn
Southeast University

Yangang Wang
yangangwang@seu.edu.cn
Southeast University

Joseph Robinson
robinson.jo@husky.neu.edu
Northeastern University

Congyi Wang
artwang007@gmail.com
XMov

Ming Shao
mshao@umassd.edu
University of Massachusetts Dartmouth

Yun Fu
yunfu@ece.neu.edu
Northeastern University

Siyu Xia
xia081@gmail.com
Southeast University

Figure 1: Framework of our TC-LSTM model. We take 3D dance synthesis as an autoregressive process conditioned on control signals. Our model can synthesize diverse and controllable dance motion for different dance types, and achieve multiple applications: random synthesis, Music2Dance and user control. "Conv": convolution, "D conv": dilated convolution.

ABSTRACT

3D human dance motion is a cooperative and elegant social movement. Unlike regular simple locomotion, it is challenging to synthesize artistic dance motions due to the irregularity, kinematic complexity and diversity. It requires the synthesized dance is realistic, diverse and controllable. In this paper, we propose a novel generative motion model based on temporal convolution and LSTM, Temporal Convolution-LSTM (TC-LSTM), to synthesize realistic and diverse dance motion. We introduce a unique control signal, the dance melody line, to heighten controllability. Hence, our model, and its switch for control signals, promote a variety of applications: random synthesis, Music2Dance and user control. Compared with existing methods, our method achieved start-of-the-art results.

CCS CONCEPTS

• Computing methodologies → Motion Processing, Motion and Animation; • Networks → Generative Model.

KEYWORDS

Motion synthesis and control, 3D dance motion, Generative Model

1 INTRODUCTION

Dance and concepts thereof are embroidered in our society, culture, and history [3]– whether it is freestyle (i.e., on-the-fly), a specific dance to a certain song (e.g., the macarena), a spiritually or culturally inspired dance-off, or even just solo acts of dancing while alone and replaying a melody from memory. Hence, dance moves have the power to allow one-to-many individuals express emotions, all the while having the persistence to inspire, spread knowledge, show culture, and promote believes. As a part of the mobile-age,
dance performances are easily main-streamed, making it possible to broadcast or view from just about anywhere at given moment. Now, we aim to best leverage our scientific research to directly enhance the melody of life we call dancing.

Dancing can be considered a form of art. It requires professional choreographers to create and design artistic movements to express emotions. For this, professional dancers are trained and equipped with a rich repertoire of dance steps - the more creative, the better. Different dancers perform quite differently, even to the same music or melody. Nonprofessionals would typically find it challenging to create a dance. Therefore, to acquire the ability to automatically create dances is a daunting task, as dancing contains high kinematic complexity that span long-term spatio-temporal structures (i.e., temporal 3D human dance motion), which make it difficult to synthesize realistic dance. More importantly, dance motion is diverse, irregular, complex, and often designed for specific music or melody. In addition, it is important to note that dancing is inherently a multi-modal problem [20], spanning multiple views (i.e., various dances for the same song). Lastly, different music or melodies should yield a whole variety of dance types. The challenges and specifications mentioned here demand an effective generative model to handle the complex and diverse dance motions. Furthermore, with such high powerful model, it should be adequate for various applications: freestyle (random synthesis [25]), dancing through the user-defined melody line (i.e., drawing) as the control signal. The type control signal can be obtained by a classifier matched, so we directly use the music melody line as the melody control signal. The type control signal can be obtained by a classifier matched, so we directly use the music melody line as the melody control signal.

Early on, researches mainly adopted similarity-based retrieval methods to synthesize simple locomotion [24, 29, 33]. Then, others proposed methods to synthesize long-term dance motions in accordance to musical inputs [7, 23, 30]. However, these strategies lack flexibility, creativity, and are difficult to apply to irregular, complex dance motion. More recently, deep learning-based motion synthesis algorithms have shown higher potential [8, 25, 26, 31, 32]. The deep neural network (NN) can well model spatio-temporal structures with high kinematic complexity without taking up too much memory. Recurrent Neural Network (RNN) [8, 26] has been proposed in recent years to model human motions for human motion prediction. However, these methods can easily fall into the temporal accumulation error (i.e., get stuck in static poses). Li et al. proposed the auto-condition training strategy to train the model based on RNNs to synthesize complex dance motion [25]. The method can only achieve random motion synthesis (long-term motion prediction), but not controllable motion synthesis. Considering the control signal, the method based on long short-term memories (LSTMs) [22] can synthesize controllable simple locomotion to interact with the environment, and it is difficult to synthesize complex controllable dance motion. Recently, some learning-based methods [20, 35, 40] have been used to synthesize controllable dance motion from music. Lee et al. designed a NN based on variational autoencoder (VAE) and generative adversarial network (GAN) to synthesize 2D dance movement [20]. The LSTMs-autoencoder (AE) [35] is proposed to synthesize 3D dance motion from music feature, but the synthesized dance motion is far from realistic and diverse. The DanceNet, based on Temporal Convolution Network (TCN), have been applied to synthesize diverse dances for different dance types [40]. However, the method can not synthesize various dances for the same music. Different from the direction and speed control in the locomotion synthesis [22], the control signal adopted by the method is directly extracted from the music. Although there is the rhythmic consistency between music and dance, it is difficult to completely determine the dance motion. This is a weak (i.e., not strong) control signal, so the controllability of their synthesized dance motion is lacking. Moreover, existing methods do not span various applications with the same model.

We first propose a dance control signal. Unlike in [40], we introduce a control signal, called dance melody line, and it is highly correlated to the dance since it is extracted directly from the dance motion. We sum up the speed of the salient joints frame-by-frame to capture the melody control signal (i.e., a 1D control signal). Provided a low-dimensional signal produced directly by motion, its coupling is notably strong, i.e., different dance motions correspond to the same dance melody line. This helps to synthesize different dance motions conditioned with the same control signal.

We also introduce a novel generative model with encoding and decoding stages. TCNs are robust to noisy inputs [40], so we adopt it to extract motion features and fuse control signals to obtain controllable motion features, which is done as part of the the encoding stage. To strengthen the long-term spatio-temporal dependence of the output frames, we adopt the LSTMs as the decoder. Our model overcomes the shortcomings of the LSTMs that is not robust to noise, while ensuring that the output frames leverage long sequence dependency. Our model obtains the controllable motion features based on the TCN, and then LSTMs decode to synthesize controllable dance motion. As a whole, we call our framework the Temporal Convolution-LSTMs (TC-LSTMs). The output of TC-LSTMs is designed as a probability density function (PDF) (i.e., Gaussian mixture model), which also makes our model more robust. With a careful training strategy (i.e., mix training), our model supports switch melody control signal to synthesize dance motion, meaning that our model can use the same parameters for random and controllable motion synthesis.

**Applications.** We ran experiments on music-dance pair dataset [40]. The results show that our model can generate realistic and diverse dance motions for different applications. Listed as follows: Random synthesis. We can switch off the melody control signal, and our model synthesizes long-term (i.e., arbitrary length), diverse dance sequences (without the temporal accumulation error).

Music2Dance. From the analysis of the music-dance paired data [40], we found that the melody lines of music and dance are highly matched, so we directly use the music melody line as the melody control signal. The type control signal can be obtained by a classifier as in [40] or user given. Through the music melody line and dance type to synthesize the dance motion consistent with the melody and style of music.

**User control.** The dance melody line is a 1D signal, which is easily given by ordinary users. Therefore, our approach allows ordinary users to design dance motions. We can synthesize the controllable dance through the user-defined melody line (i.e., drawing) as the melody control signal.

**Research contributions.** Along with the direct, tangible benefits, we propose the following contributions in research:
Table 1: Compare against state-of-the-art (SOTA) methods about 3D dance synthesis for different applications. Model extensibility means the model can synthesis dance for different dance types. ✓ means the method can achieve the application. × means the method cannot achieve the application.

| Method      | Model extensibility | Random synthesis | Music2Dance | User control |
|-------------|---------------------|-------------------|-------------|--------------|
| ac-LSTM[25] | ×                   | ✓                 | ×           | ×            |
| LSTM-AE[35] | ×                   | ×                 | ✓           | ×            |
| DanceNet[40]| ✓                   | ✓                 | ✓           | ✓            |
| Ours        | ✓                   | ✓                 | ✓           | ✓            |

Controllability. To our knowledge, we are the first to propose a controllable dance synthesis framework.

Robust to noisy inputs and long-term dependencies. Our encoder-decoder structure ensures robustness to noise, and building long-term spatio-temporal dependence of the output frames.

SOTA results with various applications. Our experiments show that our approach can achieve SOTA results for different applications.

2 BACKGROUND

We review three research areas most related to the proposed (i.e., motion synthesis and control, dance motion, and generative model).

Motion synthesis and control. Researchers tend to synthesize motions via data-driven methods, i.e., Hidden Markov Models (HMM) [2, 4], spatial-temporal dynamic models [6, 19, 37, 38], and low-dimensional statistical models [5, 11]. In addition, other methods to synthesize locomotion were based on motion graphs [18, 21, 24, 29, 33]. A common strategy among the aforementioned methods is the formulation of similarity-based retrieval to synthesize simple locomotion, which are completely dependent on the availability of dataset, hence, lacks flexibility and tend not to generalize well. Nowadays, deep NN-based methods [8, 15] gradually started being used to synthesize motion. For instance, the RNN-based methods that were proposed to predict short-term human motion, while being unable to synthesize long-term locomotion due to the temporal accumulation error [8, 16, 26]. Li et al. adopted the auto-conditioned training strategy to synthesize simple locomotion, but lacking the ability to control the generated motion [25]. Phase-functional networks [14] and LSTMs-based method [22] were introduced to synthesize controllable locomotion. However, these methods are still limited - either by simple-random or simple-controlled locomotion, thus they are unable to synthesize complex dance motion with complete control. These limitations can be overcome in our approach. Our method can synthesize realistic, complex, diverse and controllable dance motion sequences.

Dance motion. As mentioned, earlier research tended to focus on synthesizing dance motions by adopting similarity retrieval strategies (e.g., motion graph [21, 24]). Fan et al. divided the long-term dance motion into multiple short-term clips, which were then used to build a motion graph [7]. Shiratori et al. retrieved each dance segment where the music and dance rhythm were consistent [34]. However, these methods rely entirely on the dataset, and lack the ability to truly creativity are music-consistency. Recently, various types of NNs emerged as solutions to generate dance movements. For instance, VAE and GAN models were proposed to synthesize 2D dance motion from music [20]. Tang et al. built an LSTM-AE to generate 3D dance motions; however, the generated motions are unrealistic [35]. Li et al. proposed auto-conditioned LSTM to synthesize 3D dance motion; however, this work lacked motion control (just random synthesis) [25]. A model based on temporal convolution was proposed to generate 3D, controllable dance motions, but the controllability is limited in its inability to synthesize multimodal dances provided the same control signals [40]. Our model overcomes the limitations in being controllable, as we are able to synthesize realistic, diverse, and controllable multimodal dances. Furthermore, we use just a single model in a wide-range of applications: random synthesis, music2dance, and user control (Fig 1).

Generative model. In the motion synthesis model, the common autoregressive model is an LSTMs [8, 16, 25, 26]. Like most others, these models can only generate random outputs, and lack the ability to control the synthesized motion. Lee et al. designed the control signal at the model input, but lacked robustness to noise [22]. Zhuang et al. proposed an autoregressive model based on temporal convolution [40], although the model is robust to input noise, it was unable to capture temporal dependencies across output frames. We carefully consider the pros and cons of the temporal convolution and LSTMs-based methods - leveraging the strengths of each to design our model. During the encoding phase, we train our model to be insensitive to input noise via temporal convolution to encode features. Thereafter, we employ an LSTMs to decode, as it enhances the temporal correlation of the output motion so that our method synthesizes realistic, complex, diverse and controllable dance motions.

3 OVERVIEW

The proposed framework is shown in Figure 1. We take 3D dance synthesis as an autoregressive process conditioned on control signals. Specifically, to synthesize current frame, we take the previous dance frames and control signals (dance melody line and dance type) as inputs. We will introduce dance motion and control signal processing in Section 4. The model consists of two parts: encoder based on temporal convolution and decoder based on LSTMs. We will elaborate on our model in Section 5. After decoding, the model outputs the PDF of current dance frame, then we sample from the PDF to get the current frame. Our model can realize different applications with a set of parameters: dance random synthesis, Music2Dance, and user control, which are introduced in Section 6.
We proposed quantifying the melody lines as 1D signals. Specifically, we extract the melody line relative to the motion of the root joint by summing of speeds–different motions may have the same melody line (Section 4.1), and then the dance motion representation as an one-hot vector $c^t$, similar to [40]. We next describe the dance melody line extractor to encode speed information of the motion. Mathematically speaking, the motion feature at frame $t$ is represented as $x^t = (x^t_x, x^t_y, x^t_z, \omega^t_x, \omega^t_y, \omega^t_z)$, like in [15]. In summary,

$$
  x_t = (x^t_x, x^t_y, x^t_z, \omega^t_x, \omega^t_y, \omega^t_z)
$$

Equation (3)

where $\omega^t_z$ of the current and previous frames (i.e., the rotation about the Y-axis), and the $x$ and $z$ translations of the root joint are defined on the local coordinates of the previous frame $(\Delta p_x, \Delta p_z)$, like in [15]. We extract motion features from two aspects (i.e., rotation and position) to maximize the amount of motion information. Then, we add the angular velocity and linear velocity to more fully represent the motion feature. In addition, the information about the foot contact labels (ground-truth) are extracted by the height and speed of toe contact per frame.

4 DATA PROCESSING

Zhuang et al. introduced a high-quality music-dance pair dataset to synthesize dance-from-music [40]. This dataset consists of two types of dances - modern dance ($\approx$26.15 minutes, 94,155 frames at 60 FPS) and Korean dance ($\approx$31.72 minutes, 114,192 frames at 60 FPS) - we used to train the proposed model. The aim of this work was to develop a system for controlling dance motions with the control signal made-up of two parts, i.e., dance melody line (characterize the dance rhythm, local condition), and dance type (characterize the dance style, global condition). The dance type can be quantified as a strong signal (Fig. 2). Meanwhile, the signal is highly coupled to the speed and, thus, the melody control signal,

$$
  c^t_i = [L(t + t_{int}) - L(t), ..., L(t + n + t_{int}) - L(t), ...],
$$

Equation (2)

where $t_{int}$ is the sampling interval and $n$ is the sampling index.

4.2 Motion representation

Human motion is modeled as an articulated figure with rigid links (i.e., socket joints) connected ball-to-ball. Each frame is represented by the root translation $(p_{t,x}, p_{t,y}, p_{t,z})$, rotation $(r_{t,x}, r_{t,y}, r_{t,z})$, and the other joint rotations with respect to the parents (i.e., $r_{jx}, r_{jy}, r_{jz}$, and $j$ is the joint index). However, such a motion representation is a relative feature with local information related their parents. In addition, the translation and rotation of the root joint is relative to world coordinates. Ultimately, this increases the motion feature space, which increases the modeling complexity. Thus, we adopt the relative translation and rotation of root joint and add 3D joint positions, angle, and position velocities to the representation. This allows us to better model human motions. In our method, the motion feature at frame $t$ is represented as the rotations using quaternion exponential mapping $x^t_f$ [10], the angular velocities $x^t_v$, the 3D joint positions $x^t_p$, the joint linear velocities $x^t_x$, and foot contact information $x^t_c$. For the rotation of the root joint, we use the relative rotation $\Delta r_{t,y}$ of the current and previous frames (i.e., the rotation about the Y-axis), and the $x$ and $z$ translations of the root joint are defined on the local coordinates of the previous frame $(\Delta p_x, \Delta p_z)$, like in [15]. In summary,

$$
  x_t = (x^t_f, x^t_x, x^t_y, x^t_z, \omega^t_x, \omega^t_y, \omega^t_z)
$$

Equation (3)

where $\omega^t_z$ of the current and previous frames (i.e., the rotation about the Y-axis), and the $x$ and $z$ translations of the root joint are defined on the local coordinates of the previous frame $(\Delta p_x, \Delta p_z)$, like in [15]. In summary,

$$
  x^t_f = ((r_{t,x}, \Delta r_{t,y}, r_{t,z}, ..., r_{t,jx}, r_{t,jy}, r_{t,jz}))
$$

Equation (4)

$$
  x^t_v = \Delta p_t, t_{1,y}, \Delta p_z, ..., p_{t,jx}, p_{t,jy}, p_{t,jz}
$$

Equation (5)

We extract motion features from two aspects (i.e., rotation and position) to maximize the amount of motion information. Then, we add the angular velocity and linear velocity to more fully represent the motion feature. In addition, the information about the foot contact $x^t_c$ is added to reduce the foot sliding in the generated frames. Like in [14, 40], the foot contact labels (ground-truth) are detected by the height and speed of toe end per frame.

5 GENERATIVE MODEL

Next, we introduce the structure of the proposed model, and then we discuss the training details.

5.1 Encoder-decoder structure

Our end-to-end framework is shown in Figure 1: the proposed models the PDF of the predicted motion conditioned on control
Training loss. The output of TC-LSTM is the PDF of frame \( t \), which we model as a Gaussian Mixture Model (GMM), with a loss defined as the negative log likelihood. Specifically,

\[
L_G = -\log \Pr(x_t|o_t, \mu_t^f, \Sigma_t) = -\log \sum_{i=1}^N \omega_i \mathcal{N}(x_t|\mu_t^f, \Sigma_t^f),
\]

where \( N = 1 \), \( \omega_i \), \( \mu_t^f \), \( \Sigma_t^f \) are the mean vector and co-variance matrix, respectively. Note that \( \mu_t^f \) is the ground-truth motion frame. To ensure temporal smoothness of the output motion, the smoothness loss is optimized for just the mean vector via \( L_S = \sum_t (\mu_{t+1} - \mu_t)^2 \). Note that the binary foot contact in \( x_t \) is omitted from \( \mu \). Instead, we use the binary cross entropy (BCE) loss to compute the foot contact loss as \( L_F = BCE(\hat{x}_t^f, x_t^f) \), with \( x_t^f \) and \( \hat{x}_t^f \) as the ground-truth and predicted foot contact, respectively.

In the end, our training loss can be described as a sum of losses:

\[
\begin{align*}
\mathcal{L} &= L_G + \lambda L_S + \beta L_F,
\end{align*}
\]

where the balance parameters \( \lambda = 0.1 \) and \( \beta = 1 \).

Then, at inference, the generated motion frame can be obtained by sampling from the predicted PDF.

**Implementation details.** To achieve dance synthesis with and without the dance melody line control signal, we adopt a mix training strategy. That is, we pass the probabilistic input (i.e., melody control signal) during training with a probability of 0.5. To obtain robustness, we apply data augmentation: (1) mirror transformations for additional dance motion, (2) added Gaussian noise (i.e., \( \mu_{\text{noise}} = 0 \) and \( \sigma_{\text{noise}} = 0.05 \)) to the input and ground-truth to learn to handle temporal accumulation error, and (3) apply dropout (i.e., 0.4) at the input to resolve the problems of over-fitting. We initialize our model we use Xavier normal [9], and optimize via RM-Sprop [36]. Training runs for 500 epochs, starting with a learning rate of \( 4 \times 10^{-4} \), and then dropping by a factor of 10 at epoch 300. The batch-size is 128, setting each sample as a motion sequence of 600 continuous frames. Our system is implemented using PyTorch 1.2 on a PC with Intel i7 CPU, 32G RAM, and a GeForce-GTX 1080Ti.

6 EXPERIMENT

The proposed melody control signal allows it to be toggled on and off for different applications (i.e., random synthesis, Music2Dance, and user control). As far as we know, this is the first dance motion synthesizer proposed for a wide range of applications with the same model (the same parameters). Furthermore, this is the first user-controlled dance motion synthesizer for specific motions.

In this section, we describe each application, and compare with SOTA methods (Table 1). The SOTA random synthesis model (i.e., the ac-LSTM [25]), adopts a unique strategy (i.e., auto-condition) to train the LSTM. However, it lacks controllability for dance motion. Tang et al. proposed an AE-based LSTM (i.e., LSTM-AE) to synthesize dance motion from music [35], but its synthesized dances are unrealistic and out of sync with the music. Furthermore, it lacks an ability to be used in other applications. DanceNet was proposed to synthesize dance from music [40]. However, it lacks the ability to synthesize a variety of dance motions from the same music. Our model synthesizes realistic and diverse dance motions of different dance types, and the dance motions synthesized from same music...
Table 2: Comparison of realism (FID; lower is better) and diversity (Diversity-I: synthesized conditioned different initial frames, Diversity-II: synthesized conditioned same initial frames; higher is better).

| Method             | Modern Dance | Korean Dance |
|--------------------|--------------|--------------|
|                    | FID| Diversity-I | Diversity-II | FID| Diversity-I | Diversity-II |
| Real Dances        |   |             |              |   |             |              |
| ac-LSTM [25]       | 23.4| 41.1       | 7.8          | 22.5| 28.9       | 7.5          |
| Ours (w/o LSTM decoder) | 15.6| 48.1       | 37.9         | 11.7| 36.2       | 24.8         |
| Ours               | 10.6| 50.9       | 40.1         | 7.4| 38.5       | 26.3         |

Figure 4: The user studies of different applications: (a) Random synthesis, we asked 10 users to score the synthesized dances of acLSTM, our method(no melody control signal), and the real dances(the dances in dataset); (b) Music2Dance (realism), we asked 10 users to score the realism of synthesized dances of DanceNet, our method(with music melody line), and the real dances; (c) Music2Dance (consistency), score the music-consistency of synthesized dances; (d) User control, score the realism and melody-consistency of synthesized dances of our method(user given melody line).

6.1 Random synthesis

Given the dance type and initial dance motion frames(30 frames), our model can generate realistic and diverse dance sequences with its own style. With the same initial input frames, our model can generate different dance motion sequences, as shown in Figure 5. Since the predicted motion frame needs to be sampled from thePDFof the model output, which can effectively increase motion diversity. Then the sampled motion frame is fed back to the input to generate follow-up frame. To demonstrate our method, we compared with the SOTA model: ac-LSTM [25]. We randomly synthesize 15 dance motion sequences for each dance type, and every three synthesized sequences share the same initial input frames. We evaluate the random synthesized dance motion from realism and diversity. The realism can be evaluated by Fréchet Inception Distance(FID)[12], similar to [20, 39]. We adopt 3 temporal convolution layers and 1 Bi-LSTM layer as a feature extractor to obtain the FID score since the FID needs an action classifier to extract dance features. Our method can synthesize diverse sequences with the different/same initial frames, so we can evaluate the diversity by the dance features extracted by the action classifier, that is, the average feature distance among different sequences. Diversity-I evaluates the diversity of synthesized different dance sequences conditioned on different initial frames, Diversity-II evaluates the diversity conditioned on same initial frames, and the result is shown in Table 2. For better comparison, we use user study to score the realism and diversity of dance(10 users), as shown in Figure 4a. Our model can synthesize more realistic dance motion sequences, close to real dance sequences. It is worth noting that the dances generated by our model are diverse, while ac-LSTM [25] can not synthesize diverse dances at all for the same initial frames. Their explanation is that their training strategy avoids the temporal accumulation error, but the model completely loses diversity(just overfit to the train data). Our method can achieve the random synthesis of diverse motion sequences. Because our model has complex and robust modelling capabilities and the output of our model is the probabilistic density (we need to sample for predicted frame), which increases dance diversity.

6.2 Music2Dance

Synthesizing music-consistent dance is an interesting and challenging task. It requires that the synthesized dance can be consistent with the music rhythm, style and melody. However, music and dance are weakly related, and it does not determine the specific dance posture, that is, music does not determine whether the dance moves are leg lifting, jumping, or circling. Therefore, how to establish a correlation between music and dance is very important. Tang et al. [35] synthesized dance directly from music, and did
not explicitly establish the relationship between music and dance, so the synthesized dance is not realistic. Zhuang et al. [40] added music feature in the process of auto-regressive synthesis motion, but did not establish the relationship between music and dance.

How to determine the relationship between music and dance is the core difficulty of music2dance task. From professional choreographers, we know the relationship between music and dance is reflected in the melody and rhythm. Therefore, we construct the relationship between music and dance through the melody line of music and dance. In section 4.1, we propose the dance melody line to express the melody and rhythm of dance. In order to extract the music melody line, we introduce a simple and effective extraction method: extract onset strength by librosa [28] or madmom [1] and then smooth it through a Gaussian filter.

We select a segment from the music-dance pair data to obtain the melody lines of music and dance, and compare the relationship between them, as shown in Figure 6. Although the melody value of each frame is not necessarily the same, the change trend and peak value of the two melody lines are basically the same, indicating that the consistency of the melody rhythm between music and dance can be reflected through the melody line. In section 4.1, we introduce that the melody control signal of the model is the change trend of the melody line relative to the current frame, so we can directly adopt the change trend of the music melody line as the melody control signal.

To demonstrate the effectiveness of our approach, we compare with two SOTA methods, LSTM-AE [35] and DanceNet [40]. We use the FID to evaluate the dance realism, and the average feature distance to evaluate the dance diversity. For this application, dance diversity is evaluated from three views: (1) Diversity-I, the diversity of the different synthesized dance sequences conditioned on different initial frames and different melody line; (2) Diversity-II, the diversity is conditioned on same initial frame and different melody lines; and (3) Diversity-III, the diversity is conditioned on same initial frame and the same melody line. Diversity-III reflects the multi-modality power of Music2Dance. In addition, we use the rhythm consistency (i.e., the rhythm hit rate) to evaluate our methods like in [20, 40]. We randomly select 5 initial sequences to synthesize 30 dance motion sequences for each dance type using the two methods mentioned and our approach. For each, three were synthesized conditioned on the same initial sequence and the same melody line, and three were synthesized conditioned on the same initial sequence and a different melody line. The quantitative results are shown in Table 3. We conduct a user study to evaluate the realism of the music-consistency (Fig. 4, b & c). Our results significantly outperform LSTM-AE. We believe that directly mapping music to get the dance movement is unreasonable due to the weak correlation between dance and music. DanceNet [40] uses music features as the conditions to synthesize dance, but this method directly inputs music features without explicitly analyzing the correlation between music and dance. So, the model takes a long
Table 3: Comparison of realism (FID), diversity (Diversity-I: synthesized conditioned different initial frames and different melody line, Diversity-II: synthesized conditioned same initial frames and different melody line, Diversity-III (Multi-modal): synthesized conditioned same initial frames and same melody line), rhythm-consistent (rhythm hit rate, higher is better).

|                      | Morden Dance | Korean Dance |
|----------------------|--------------|--------------|
|                      | FID Diversity-I Diversity-II Diversity-III Rhythm | FID Diversity-I Diversity-II Diversity-III Rhythm |
| Real Dances          | 6.5 55.4     | – – 57.9%    | 5.6 42.5 – – 68.3% |
| LSTM-AE[35]          | 81.3 12.4    | 9.4 8.9 13.6% | 75.6 10.2 7.9 7.6 15.1% |
| DanceNet[40]         | 15.2 49.3    | 40.1 7.6 56.7% | 10.4 36.3 30.2 6.5 64.3% |
| Ours(w/o LSTMs decoder) | 13.8 50.3 50.1 42.5 55.4% | 7.8 36.5 31.9 24.9 67.3% |
| Ours                 | 11.2 50.8    | 48.9 43.4 56.2% | 7.8 36.5 31.9 24.9 66.8% |

Figure 8: User controls - the melody line is drawn by users.

6.3 User control
Given the dance type, our model synthesizes realistic, diverse dance motions conditioned on the melody line. The melody line is a simple 1D signal (Fig. 2, 6, and 7). Thus, allowing an ordinary user to create dances, opposed to depending on a professional choreographer - there is a variety of ways the melody line can be described: e.g., drawing (Fig. 8). We built an end-to-end system based on two steps: (1) the user draws the melody line via mouse inputs and (2) the synthesizer generates a dance according to the melody line. Note that since the lines drawn by the user are evenly sampled as melody lines, our model synthesizes melody-consistent dance motions.

In the end, this is the first model with such controls for synthesizing dances. Thus, we evaluate our method by user study. We asked 10 users to draw 3 melody lines. Then, they scored each dance sequence separately by measuring dance realism and melody-consistency (Fig. 4 d). Our method synthesizes realistic dances, while ensuring melody-consistency, especially for the modern dance.

6.4 Discussion and future work
Ablation study. We propose the TC-LSTM model, which is composed of two parts: an encoder (temporal convolution) and a decoder (LSTM). In order to verify the ability of our model, we conducted a comparative experimental. We directly use the temporal convolution model (without LSTM) to model the dance, and adopt same training strategy. We perform quantitative evaluations on two different applications, random synthesis and Music2Dance (Table 2 and 3). When the LSTMs is omitted from the decoder, the synthesized dances worsen, and especially the in realism (i.e., FID), which shows that building temporal dependencies via LSTMs in decoder improves modeling capabilities.

Result discussion. Our method realizes different dance synthesis applications (i.e., more than the three applications described above). For example, musical notation synthesis dance (i.e., to extract a melody line from musical notation). For these applications, we found a worthwhile phenomenon in the experiment. That is, the melody-consistency (i.e., controllable effect) of modern dance is superior to that in Korean dance; also, the diversity of Korean dance is inferior to modern dance. The first reason lies in the dance data. The dance steps of Korean dance in dataset are inconsistently distributed, which makes it difficult to model such unevenly distributed data. The second reason is that the rhythm and melody of Korean dance is very fast, which causes poor temporal smoothness and high dynamic complexity.

Future work. To the best of our knowledge, we are the first to propose a generative model with controllable dance synthesis via the simple and effective use of 1D control signals. However, there are some topics worth discussing: i.e., how to quantitatively evaluate the controls effectiveness, mediocre modeling ability for fast-rhythm Korean dance (mentioned above), the foot sliding (it is difficult to solve by IK for complex dance motion). The topics raised here are subject of future work.
7 CONCLUSION

We introduced a novel generative model, TC-LSTMs. Based on temporal convolutional neural networks (CNNs) and LSTMs, TC-LSTMs synthesize realistic, diverse dances (i.e., motion sequence). Our model can handle different dance types for various applications: random synthesis, music×dance, and user control. We demonstrated quantitative results and user studies establishing the effectiveness of our method, and our model can synthesize more realistic and diverse dance motion sequences, achieving state-of-the-art results.

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