Dance Revolution: Long Sequence Dance Generation with Music via Curriculum Learning

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Abstract

Dancing to music is one of human’s innate abilities since ancient times. In artificial intelligence research, however, synthesizing dance movements (complex human motion) from music is a challenging problem, which suffers from the high spatial-temporal complexity in human motion dynamics modeling. Besides, the consistency of dance and music in terms of style, rhythm and beat also needs to be taken into account. Existing works focus on the short-term dance generation with music, e.g. less than 30 seconds. In this paper, we propose a novel seq2seq architecture for long sequence dance generation with music, which consists of a transformer based music encoder and a recurrent structure based dance decoder. By restricting the receptive field of self-attention, our encoder can efficiently process long musical sequences by reducing its quadratic memory requirements to the linear in the sequence length. To further alleviate the error accumulation in human motion synthesis, we introduce a dynamic auto-condition training strategy as a new curriculum learning method to facilitate the long-term dance generation. Extensive experiments demonstrate that our proposed approach significantly outperforms existing methods on both automatic metrics and human evaluation. Additionally, we also make a demo video to exhibit that our approach can generate minute-length dance sequences that are smooth, natural-looking, diverse, style-consistent and beat-matching with the music. The demo video is now available at https://www.youtube.com/watch?v=P6yhfv3vpDI.

1 Introduction

Arguably, dancing to music is one of our innate abilities, as we can spontaneously sway along with the tempo of music we hear. The research in neuropsychology indicates that our brain is hardwired to make us move and synchronize with music regardless of our intention [10]. Another study in archaeology also suggests that dance is a social communication skill among early humans and connected to the ability of survival long time ago [11]. Nowadays, dance (to music) has become a means to cultural promotion, a method of emotional expression, a tool for socialization, and an art form to bring aesthetic enjoyment. The neurological mechanism behind dancing behavior and the unique value of dance to the society motivate us to explore a computational approach to dance creation from a piece of music in artificial intelligence research. Such work is potentially beneficial

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to a wide range of applications such as human creation assistant in art and sports, character motion generation for audio games and research on cross-modal human behavior.

However, the music-to-dance generation task needs to synthesize continuous movements, which suffers from the high spatial-temporal complexity in modeling human motion dynamics \[20, 14, 30, 16, 26\]. Besides, it also requires the synthesized movements to be in harmony with the given music, which raises several new challenges: (1) the movements need to be consistent with the music in terms of style, rhythm and beat; (2) the generation model needs to capture the multimodal nature of dance since one pose at a moment could have highly diverse following movements; (3) the predicted dance sequence needs to be long enough to cover the full range of music clip. For instance, composing a dance for a 1-minute music clip under 30 Frame Per Second (FPS) means the generation of 1800 poses. While sequence generation models, especially when dealing with highly complex human motions, are prone to collapse only after a few steps, e.g. poses begin to freeze, due to the severe error accumulation problem \[27\].

Previous works \[13, 24\] try to synthesize dance from music by retrieval based methods, which severely rely on the index and show limited creativity. Recent Dancing2Music \[22\] formulates the task from the generative perspective and further proposes a decomposition-to-composition framework to generate dance from music. While their Generative Adversarial Network (GAN) based approach only considers a global style feature extracted by a music style classifier in the dance generation, which fails to capture more fine-grained correspondences between music and dance.

In this work, we formalize music-driven dance generation as a sequence-to-sequence learning problem whereby temporal dependency within music and dance is represented through sequence modeling and their alignment is established via mapping from a sequence of acoustic features of the music to a sequence of movements of the dance. The model consists of a music encoder and a dance decoder. The encoder transforms low-level acoustic features of an input music clip into high-level representations via self-attention with a receptive field restricted in $k$-nearest neighbors of an element. Thus, the encoder can efficiently process long musical sequences, e.g. a sequence with more than 1000 elements, and model local characteristics of the music such as chord and rhythm patterns. The decoder exploits a recurrent structure to predict the dance movement frame by frame conditioned on the corresponding element in the musical sequence. To further alleviate error accumulation in human motion synthesis \[27\], we propose a dynamic auto-condition training strategy to facilitate the long-term dance generation, which mixes ground-truth sub-sequences and predicted sub-sequences to predict the next pose and length of the predicted sub-sequences is gradually increased with respect to the training epochs. In addition, we also corrupt the input dance movements of the decoder with random noise in training to further enhance the robustness of the model.

Our contributions in this work can be summarized as follows: (1) We propose a novel seq2seq architecture and a dynamic auto-condition training strategy for long sequence dance generation with music. Extensive experiments demonstrate our approach remarkably outperforms the state-of-art method by reducing 18.4 on FID and improving 18.1% on style accuracy. The human evaluation consistently validates the superior performance of our approach. (2) We present a high-quality dataset with paired music and dance that will be public with our source code later.

## 2 Related Work

Our work can be viewed as an interdisciplinary study of cross-modal learning and human motion prediction. We take advantage of the state-of-the-arts in human motion prediction while deal with the new challenges in cross-modal modeling.

**Cross-Modal Learning.** Cross-modal perception is the unique ability of human brain, which involves the interactions of multi-sensory modalities and has been studied in the psychology and neuroscience \[29, 6, 36, 47\] for a long time. In machine learning research, most existing works focus on the modeling between vision and text, such as image caption \[28, 49\], image-text matching \[23, 32\] and text-to-image generation \[35, 53, 50\]. There are some other works to study on the translation between audio and text like Automatic Speech Recognition (ASR) \[18, 11\] and Text-To-Speech (TTS) \[33, 37\]. While the modeling between audio and vision is less explored and the music-to-dance generation task is a typical cross-modal learning problem from audio to vision.
**Human Motion Prediction.** Prediction of human motion dynamics has been a challenging problem in computer vision. Existing works \cite{8,9,44,46} represent the human pose as 2D or 3D body keypoints \cite{7} and address the problem via sequence modeling. Early methods, such as hidden markov models \cite{25}, Gaussian processes \cite{45} and restricted boltzmann machines \cite{40}, have to balance the model capacity and inference complexity due to complicated training procedures. Recently, neural networks dominate the human motion modeling. For instance, Jain et al. \cite{20} propose a structural-RNN to model human-object interactions in a spatio-temporal graph; Fragkiadaki et al. \cite{44} present LSTM-3LR and Encoder-Recurrent-Decoder (ERD) as two recurrent architectures for the task; Martinez et al. \cite{30} propose a seq2seq architecture with a sampling-based loss to alleviate the discontinuity issue in motion prediction; and Ghosh et al. \cite{16} equip LSTM-3LR with a dropout autoencoder to enhance the long-term prediction. Besides, convolutional neural networks (CNNs) have also been utilized to model the human motion prediction \cite{26,52} in recent years.

## 3 Approach

In this section, we present our approach to music-driven dance generation. After formalization of the problem in question, we elaborate the model architecture and the learning approach that facilitates long-term dance generation according to the given music.

### 3.1 Problem Formalization

Suppose that there is a dataset \( \mathcal{D} = \{(X_i, Y_i)\}_{i=1}^N \), where \( X = \{x_l\}_{l=1}^n \) is a music clip with \( x_l \) a vector of acoustic features at time-step \( t \), and \( Y = \{y_l\}_{l=1}^n \) is a sequence of dance movements with \( y_l \) aligned to \( x_l \). The goal is to estimate a generation model \( g(\cdot) \) from \( \mathcal{D} \), and thus given a new music input \( X \), the model can synthesize dance \( Y \) to music \( X \) based on \( g(X) \).

We formulate \( g(\cdot) \) within the encoder-decoder framework \cite{39}. While the framework provides a general approach to modeling correspondence between parallel sequences, the key to successfully adapt it to a specific task lies in properly instantiating the encoder and the decoder with neural architectures that well fit the nature of the data \cite{2,15,42}. We first present our seq2seq architectures chosen for music-driven dance generation in the following section. Later in the experiments, we empirically justify the choice by comparing the architectures with other alternatives.

### 3.2 Model Architecture

In the architecture of \( g(\cdot) \), a music encoder first transforms \( X = (x_1, ..., x_n) \) \( (x_i \in \mathbb{R}^{d_x}) \) into a hidden sequence \( Z = (z_1, ..., z_n) \) \( (z_i \in \mathbb{R}^{d_z}) \) using a local self-attention mechanism to reduce the memory requirement for long sequence modeling, and then a dance decoder exploits a recurrent structure to autoregressively predicts movements \( \hat{Y} = (y_1, ..., y_n) \) conditioned on \( Z \).

**Music Encoder.** Encouraged by the compelling performance on music generation \cite{19}, we define the music encoder with a transformer encoder structure. While the self-attention mechanism \cite{42} in transformer can effectively represent the multi-scale structure of music, the quadratic memory complexity \( O(nd_z + n^2) \) impede its application to long sequence modeling. To keep the effectiveness of representation and control the cost, we introduce a local self-attention mechanism that modifies the receptive field of self-attention by restricting the element connections within \( k \)-nearest neighbors. Thus, the memory complexity is reduced to \( O(nd_z + nk) \). \( k \) could be small in our scenario since we only pursue a good representation for a given music clip. Therefore, the local patterns of music are encoded in \( Z \) that is sufficient for dance generation, yet we can handle long musical sequences, e.g. more than 1000 elements, in an efficient and memory-economic way.

Specifically, we first embed \( X = (x_1, ..., x_n) \) into \( U = (u_1, ..., u_n) \) with a linear layer parameterized by \( W^E \in \mathbb{R}^{d_z \times d_x} \). Then \( \forall i \in \{1, ..., n\} \), \( z_i \) can be formulated as:

\[
    z_i = \sum_{j=-\lfloor k/2 \rfloor}^{\lfloor i+k/2 \rfloor} \alpha_{ij}(u_j W_i^V).
\]  

Each \( u_j \) is only allowed to attend its \( k \)-nearest neighbors including itself, where \( k \) is a hyper-parameter referring to the size of the receptive field of local self-attention. Attention weight \( \alpha_{ij} \) is calculated
using a softmax function as:

\[ \alpha_{ij} = \frac{\exp e_{ij}}{\sum_{j'=j-k}^{j+k} \exp e_{i j'}} \quad (2) \]

\[ e_{ij} = (u_i W_j^Q)(u_j W_i^K)^\top \sqrt{d_k} \quad (3) \]

where for the the \(l\)-th head, \(W_j^Q \in \mathbb{R}^{d_q \times d_h}\) and \(W_i^K \in \mathbb{R}^{d_k \times d_h}\) are parameters that transform \(X\) into a \(query\), a \(key\), and a \(value\) respectively. \(d_z\) is the dimension of hidden state \(z_i\) while \(d_h\) is the dimension of \(query\), \(key\) and \(d_v\) is the dimension of \(value\).

**Dance Decoder.** We choose a recurrent structure as the dance decoder in consideration of two factors: (1) the chain structure can well capture the temporal dependency among motion dynamics; and (2) prediction of the next movement only relies on one previous step, which can improve the efficiency of our proposed learning approach, as will be described in the next section. Specifically, with \(Z = (z_1, \ldots, z_n)\), the dance movements \(Y = (\hat{y}_1, \ldots, \hat{y}_n)\) are synthesized by:

\[ \hat{y}_i = [h_i; z_i] W^S + b, \quad (4) \]

\[ h_i = \text{RNN}(h_{i-1}, \hat{y}_{i-1}), \quad (5) \]

where \(h_i\) is the \(i\)-th hidden state of the decoder with \(h_0\) randomly sampled from standard normal distribution to enhance variation of the movements, and \([; ;]\) denotes a concatenation operation. \(W^S \in \mathbb{R}^{d_c \times d_y}\) and \(b \in \mathbb{R}^{d_y}\) are parameters where \(d_c\) and \(d_y\) are the dimensions of \([h_i; z_i]\) and \(\hat{y}_i\).

### 3.3 Learning Approach

In natural language generation (NLG), exposure bias [21] [34] [48] [54] is a notorious issue, referring to the discrepancy between training and inference, since the model is never exposed to its own prediction errors in the training phase. This problem becomes much more severe when it comes to dance movement (complex human motion) synthesis of continuous space. First of all, most of generated sentences only contain less than 100 words in NLG while composing a dance sequence with 1-minute length under 30 FPS needs to generate 1800 dance poses. Secondly, the bias of predicted probability vectors can be corrected by sampling in the discrete NLG, for example, we can still obtain the right word with index 2 by sampling on probability vectors \([0.3, 0.3, 0.4]\) whose groundtruth is \([0, 0, 1]\). However, any small biases of predictions in the continuous space will be accumulated. As a result, prediction errors in long sequence generation of the continuous space are more likely to be accumulated and propagated to the future, which makes the generation process quickly converge to a “mean pose” only after a few steps in the inference phase.

Scheduled sampling [3], as a curriculum learning method [4], is proposed to alleviate exposure bias in NLG. The sampling-based strategy, however, does not help in human motion synthesis of continuous space [27], since it would feed long noisy autoregressive sequences into training at an early stage when the model is still far away from convergence, which causes gradient vanishing due to error accumulation. Motivated by this, we propose a dynamic auto-condition learning strategy as a new curriculum learning method for long-term dance movement (complex human motion) synthesis, which begins with teacher forcing and then gradually transits to the autoregressive training. The decoder predicts \(Y_{tgt} = \{y_2, \ldots, y_{m+1}, y_{m+2}, \ldots, y_{m+n+1}, y_{m+n+2}, \ldots\}\) from \(Y_m = \{\hat{y}_1, \ldots, \hat{y}_m, y_{m+1}, \ldots, y_{m+n}, y_{m+n+1}, \ldots\}\) which alternates autoregressively predicted sub-sequences with length \(m\) (e.g., \(\hat{y}_1, \ldots, \hat{y}_m\)) and ground-truth sub-sequences with length \(n\) (e.g., \(y_{m+1}, \ldots, y_{m+n}\)). During training, we fix \(n\) and gradually increase \(m\) according to a growth function \(f(t)\) where \(t\) is the number of training epochs. In this work, we set \(f(t) = [\lambda t]\) through empirical comparison among \[\{\text{const}, [\lambda t], [\lambda t^2], [\lambda e^t]\}\], where \(\lambda < 1\) controlling how frequently \(m\) is updated. Note that our learning strategy degenerates to the method proposed in [27] when \(f(t) = \text{const}\). The advantage of a dynamic strategy over a static strategy lies in the flexibility to learning, as the learning procedure needs an easy curriculum at early stages (e.g., small \(m\)) while can involve more autoregressive predictions to increase the difficulty of curriculum (e.g., large \(m\)) when the model gradually converges.

Besides, corrupting ground-truth with random noise, which is first introduced by Denoising Auto-Encoder (DAE) [43], has proven an effective way to enhance the robustness of generation models. Analogously, in our scenario, to further enhance the robustness of the dance decoder and reduce its
Table 1: Statistics of datasets.

| Category     | Num of Videos | Avg. Length (min) | FPS | Resolution |
|--------------|---------------|-------------------|-----|------------|
| Ballet       | 40            | 1.7               | 30  | 720P       |
| Hiphop       | 55            | 2.9               | 30  | 720P       |
| Japanese Pop | 60            | 3.5               | 30  | 720P       |

prediction errors at each time-step, we corrupt input movements with Gaussian noise $\epsilon$ to fake the motions with physical artifacts produced in the training phase:

$$\hat{y}_{i-1} = \hat{y}_{i-1} + \epsilon, \quad \epsilon \sim N(0, \sigma)$$  \hfill (6)

where $\hat{y}_{i-1}$ is the input of the recurrent structure in Eq. (5) and $\sigma$ is a hyperparameter. Finally, we estimate parameters of $g(\cdot)$ by minimizing the $\ell_1$ loss on $D$:

$$\ell_1 = \frac{1}{N} \sum_{i=1}^{N} ||g(X_i) - Y_{tgt}^{(i)}||_1$$  \hfill (7)

4 Experimental Setup

In this section, we describe the dataset collection and preprocess, followed by the implementation details of our model. After that, we introduce several baselines compared in our experiments.

4.1 Dataset Collection and Preprocess

We seek a dataset of high quality for research in the music-to-dance generation task and collect 155 solo dance videos from YouTube, as shown in Table. 1. The dataset consists of dances with three typical styles: Japanese Pop, Ballet and Hiphop. Then we trim the first and last several seconds for each video and split them into clips with 1 minute length. Besides, we also perform the data augmentation by dividing each clip with 30 FPS into two 15 FPS clips and extract video frames. To align with video frames under 15 FPS, we extract audio frames with 15.4kHz.

**Pose Preprocess.** For the human pose estimation, we leverage OpenPose [7] to extract 2D body keyjoints from videos. Each pose consists of 25 keyjoints$^3$ and is represented by a 50-dimension vector in the continuous space. In practice, we also interpolate the missing keyjoints from nearby frames to reduce the noise in extracted pose data.

**Audio Preprocess.** Librosa [31] is a well-known audio and music analysis library in the music information retrieval, which provides flexible ways to extract the spectral and rhythm features of audio data. Specifically, we extract the following features by Librosa: mel frequency cepstral coefficients (MFCC), MFCC delta, constant-Q chromagram, tempogram and onset strength [5]. To better capture the beat information of music, we also convert onset strength into a one-hot vector, called beat one-hot, where 1 denotes the occurrence of music beats. We concatenate these acoustic features as the representation of the input music, as detailed in Table. 2.$^2$

4.2 Implementation Details

The music encoder consists of a stack of $N = 2$ identical layers. Each layer has two sublayers: a local self-attention sublayer with $l = 8$ heads and a position-wise fully connected feed-forward sublayer with 1024 hidden units. Each head contains a scaled dot-product attention layer with $d_k = d_v = 64$ and its receptive yield is restricted by setting $k = 100$. Then we set the dimension of acoustic feature vector $d_x = 438$ and the dimension of hidden vector $d_z = 200$ respectively. The dance decoder is a 3-layer LSTM with 1024 hidden units and the dimension of pose vector $d_y = 50$. Finally, we set $\lambda = 0.01, n = 10$ and $\sigma = 0.1$ for the proposed learning approach and train the model using the Adam optimizer with the learning rate $1e - 4$ on two NVIDIA GeForce RTX 2080 GPUs.

$^2$https://github.com/CMU-Perceptual-Computing-Lab/openpose/blob/master/doc/output.md#pose-output-format-body_25
4.3 Baselines

Since generating dance from music is an emerging task from the generative model perspective, there are few methods proposed to solve this problem. In our experiment, we compare our proposed approach with the following baselines: (1) Dancing2Music. We use Dancing2Music [22] as our deterministic baseline. It is the state-of-art method on music-to-dance generation task, which proposes a synthesis-by-analysis learning framework to generate dance from music and achieves the compelling performance; (2) LSTM. Shlizerman et al. [38] propose a LSTM network to predict body dynamics from the audio signal. We modify their open-source code to take audio features of music as inputs and produce the human pose sequence; (3) Aud-MoCoGAN. Aud-MoCoGAN is an auxiliary baseline used in Dancing2Music, which is original from MoCoGAN [41], a video generation model. Here we also use it as a baseline in our experiment.

5 Experimental Results

We conduct extensive experiments to evaluate our approach and compare it with the aforementioned baselines. Specifically, our experiments answer four questions: (1) How does our approach perform compared to baselines on the automatic metrics and human evaluation? (2) What is the performance of our approach on long-term dance generation? (3) Is our encoder structure more efficient than other alternatives on long musical sequence modeling? (4) Does the proposed dynamic auto-condition strategy help in the training process? In the supplementary material, we attach a demo video to exhibit that our approach can generate minute-length dance sequences that are smooth, natural-looking, diverse, style-consistent and beat-matching with the music.

5.1 Automatic Metrics and Human Evaluation

We quantitatively evaluate different methods by automatic metrics and conduct a human evaluation on the motion realism and smoothness of dance movements as well as the style consistency of generated dances with the corresponding musics. Specifically, we randomly select 60 testing music clips to generate dances and divided the generated dances from three methods and the real dances into four pairs: (LSTM, ours), (Dancing2Music, ours), (real, ours) and (real, real). Then we ask annotators to answer three questions for each pair: (1) Which dance is more realistic regardless of music; (2) Which dance is more smooth regardless of music; (3) Which dance matches the music better in terms of style. Note that, we do not include Aud-MoCoGAN in the human evaluation since both it and Dancing2Music are GAN based models while the latter is the state-of-art.

Motion Realism, Style Consistency and Smoothness. We evaluate the visual quality and realism of generated dances by Fréchet Inception Distance (FID) [17] which is used to measure how close the distribution of generated dances is to the real. Similar to [22], we train a style classifier on pose sequences of three categories and use it to extract features for the given dances. Then we calculate FID between the synthesized dances and the real ones. As shown in Table. 3, our FID score is significantly lower than those of others and much closer to that of the real, which means our generated dances are more motion-realistic and more likely to the real dances. Besides, we use the same classifier to measure the style accuracy of generated dance to the music, and our approach achieves 78% accuracy and significantly outperforms Dancing2Music by 18.1%.

Human evaluation results in Figure. 2 consistently show the superior performance of our approach compared to baselines on motion realism, style consistency and smoothness. We observe the dances
Table 3: **Automatic metrics of different methods.** FID (lower is better) evaluates the quality and realism of dances by measuring the distance between the distributions of the real dances and the generated dances. ACC evaluates the style consistency between generated dances and music. Beat Coverage measures the ratio of total kinematic beats to total musical beats while Beat Hit Rate measures the ratio of kinematic beats aligned with musical beats to total kinematic beats. Diversity denotes the variations among a set of generated dances while Multimodality refers to the variations of generated dances for the same music, we measure these two metrics by the average feature distance.

| Method         | FID  | ACC (%) | Beat Coverage (%) | Beat Hit Rate (%) | Diversity | Multimodality |
|----------------|------|---------|-------------------|-------------------|-----------|---------------|
| Real Dances    | 2.6  | 99.5    | 56.4              | 63.9              | 40.2      | -             |
| LSTM           | 51.9 | 12.1    | 4.3               | 9.7               | 16.8      | -             |
| Aud-MoCoGAN    | 48.5 | 33.8    | 10.9              | 28.5              | 30.7      | 16.4          |
| Dancing2Music  | 22.7 | 60.4    | 15.7              | 65.7              | 30.8      | 18.9          |
| Ours           | 4.3  | 78.5    | 23.5              | 62.9              | 37.2      | 11.9          |

generated by LSTM have lots of floating dance movements and are prone to freeze after several seconds due to error accumulation, which results in lower preferences. While Dancing2Music can generate the smoother dance units, it is still found the generated dance movements have obvious jumps and vibration at the junction of adjacent dance units in practice. This is also reflected in the preference comparisons where only 35% of annotators prefer Dancing2Music on motion realism and our approach obtains 78.3% preferences on the smoothness of generated dances compared to Dancing2Music. The result on style consistency also shows our approach can generate more style-consistent dances with music. The possible reason is that we introduce more fine-grained features of music in our approach while Dancing2Music only considers a global style feature in the dance generation. In the comparisons to real dances, 41.2% of annotators prefer our method on motion realism and 30.3% on style consistency. Additionally, we found an interesting result that 57.9% of annotators prefer our approach compared to real dances on smoothness. This is caused by the noisy dance poses in the real dances due to the imperfect pose extraction with OpenPose, while our model can denoise the dance pose thanks to its robustness.

**Beat Coverage and Hit Rate.** In addition to above metrics, we also evaluate the beat coverage and hit rate of generated dances introduced in [22], which defines the beat coverage as $B_k / B_m$ and beat hit rate as $B_a / B_k$ where $B_k$ is the number of kinematic beats, $B_m$ is the number of music beats and $B_a$ is the number of aligned kinematic beats with music beats. Since there is no standard method to extract kinematic beats of dance poses, we use the standard deviation (SD) of motion to detect in practice just like [51], which observes the kinematic beats of dance usually occurs when the direction of motion changes drastically. The onset strength [12] is a common way to detect music beats. Figure 1 shows two short clips of motion SD curves and aligned music beats. We found that the music beat would occur when the kinematic beat occurs, which is consistent with our intuition that dancers would step on music beats during dancing while do not step on every music beat. As we can see in Table 3, LSTM and Aud-MoCoGAN generate dances with few kinematic beats and most of them do not match the music beats. Although Dancing2Music outperforms us by 2.8% on hit rate, our method achieves 7.8% higher beat coverage, which indicates the superior performance of our method on the matching degree of beat between music and dance.

![Beat tracking curves for music and dance by onset strength and motion standard deviation respectively. The left is a short clip of ballet while the right is a short clip of hip-hop. The red circles are kinematic beats and dash lines denote the music beats.](image-url)
Figure 2: Human evaluation results on motion realism, style consistency and smoothness. We conduct a human evaluation to ask annotators to select the dances that are more realistic and more smooth regardless of music, more style-consistent with music through pairwise comparison.

Diversity and Multimodality. The diversity among generated dances corresponding to various music reflects the generalization ability of the model and its dependence on the input music. The better the diversity, the less likely the model will fall into mode collapse. We use the average feature distance similar to [22] as the measurement where the features are extracted by the same extractor as used in measuring FID. We select 60 music to generate dances and randomly pick 500 combinations to compute average feature distance. Results show our method achieves the highest diversity score.

We evaluate the multimodality among dances generated from the same music and initial pose in a similar way. Specifically, we generate 5 dances for each of 60 musics and compute the average feature distance. The scores of Aud-MoCoGAN and Dancing2Music are higher than ours and the possible reason is that their GAN based models would introduce more randomness in the generation.

5.2 Long-Term Dance Generation

To further investigate the performance of different methods on long-term dance generation, we evaluate the quality of dances generated by different methods over time. Specifically, we first split a generated dance with 1 minute into 15 clips with 4 seconds and measure FID of each clip. Then we draw the FID curve over time for each method in Figure 3. As we can see, FID scores of LSTM and Aud-MoCoGAN grow quickly in the early stage due to the error accumulation and then converge to around 57 because the generated dances begin to freeze after that. Dancing2Music maintains the relatively stable FID scores all the time, which benefits from its decomposition-to-composition strategy. While its curve still has the subtle fluctuations since it needs to synthesize the whole dance from generated dance units. FID scores of our model are much lower compared to other methods and close to the real dance, which validates the good performance of our method on long-term generation.

Figure 3: FID curves of different methods over time. The lower FID is better.

5.3 Discussion

Comparison on Encoder Structures. We compare the different encoder structures in our model, as shown in Table 4. The transformer encoders outperform LSTM or the encoder in ConvS2S...
Table 4: Left: Automatic metrics of our model using different encoder structures. Right: Automatic metrics on different learning strategies.

| Encoder Structure     | FID  | ACC (%) | Learning Approach     | FID  | ACC (%) |
|-----------------------|------|---------|-----------------------|------|---------|
| LSTM                  | 7.9  | 45      | Auto-condition (const) | 13.7 | 38      |
| ConvS2S encoder       | 13.3 | 54      | Ours (⌊λe⌋)            | 4.2  | 71      |
| Global self-attention | 3.6  | 80      | Ours (⌊λt^2⌋)          | 9.7  | 75      |
| Local self-attention  | 4.3  | 78.5    | Ours (⌊λt⌋)            | 4.3  | 78.5    |

[15] on both FID and style consistency, due to the superior performance of self-attention on long sequence modeling. Although the transformer encoder with our proposed local self-attention slightly underperforms the original one by 0.7 higher in FID and 1.5% lower in ACC, it only has 2.16M parameters compared to 7.92M parameters of the original one in our setting. This confirms the effectiveness and efficiency of the local self-attention on long musical sequence modeling.

**Comparison on Different Learning Approaches.** To investigate the performance of our proposed learning approach, we conduct an experiment to compare the performances of our model using different learning strategies. As we can see in Table 4, the dynamic auto-condition learning strategies we proposed consistently perform better than the static auto-condition strategy [27]. Besides, we also found the linear curriculum function achieves the best performance among them, which might be that increasing the difficulty of curriculum too quickly would lead to the model degradation.

6 Conclusion

In this work, we propose a novel seq2seq architecture for long sequence dance generation with music, e.g. about one-minute length, which consists of a transformer based music encoder and a recurrent structure based dance decoder. To efficiently process long musical sequences, we introduce a local self-attention mechanism in the encoder to reduce the quadratic memory requirements to the linear in the sequence length. Besides, we also propose a dynamic auto-condition training strategy to alleviate the error accumulation problem in human motion prediction and thus facilitate the long-term dance generation. Extensive experiments have demonstrated the superior performance of our proposed approach. In future work, we consider the explicit modeling of style information in dance generation and incorporate more dance styles.

**Broader Impact**

The music-driven dance generation models have a wide range of beneficial applications for society, including human creation assistant in dancing art and sport, the motion generation of 2D & 3D character model for audio games. In principle, the contents generated by such generation models are all skeleton based dance motions and can hardly have harmful applications in most situations. While they still have the potential risk of portrait privacy violation when retargetting the generated dance motions to 2D characters using video generation models like [8] and [46]. Besides, it would also potentially lead to the misuses of copyrighted 3D character models when we applied the generated 2D dance motions to 3D character model by 3D reconstruction and animation driving technologies. But we believe the rational application of our model will eventually advance the development of related fields in industry and academia.

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