LISTEN TO DANCE: MUSIC-DRIVEN CHOREOGRAPHY GENERATION USING AUTOREGRESSIVE ENCODER-DECODER NETWORK

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ABSTRACT

Automatic choreography generation is a challenging task because it often requires an understanding of two abstract concepts - music and dance - which are realized in the two different modalities, namely audio and video, respectively. In this paper, we propose a music-driven choreography generation system using an auto-regressive encoder-decoder network. To this end, we first collect a set of multimedia clips that include both music and corresponding dance motion. We then extract the joint coordinates of the dancer from video and the mel-spectrogram of music from audio, and train our network using music-choreography pairs as input. Finally, a novel dance motion is generated at the inference time when only music is given as an input. We performed a user study for a qualitative evaluation of the proposed method, and the results show that the proposed model is able to generate musically meaningful and natural dance movements given an unheard song.

Index Terms— Choreography, dance motion generation, autoregressive encoder-decoder network

1. INTRODUCTION

Choreography is a kind of art that designs a series of movements. In particular, in performing art, choreography extends to the use of human bodies to express movements, and these are often performed with music. The choreography suitable for music has significance in that it is not only an artwork itself, but also maximizes the expression of music. [1][2] For this reason, choreography has become an essential element in many pop music works in recent years. Therefore, the process of creating choreography for music is also considered to be important, and research on a system capable of automatically generating choreography is actively conducted. However, automatic choreography generation is a challenging task because both music and dance are abstract art concepts, and the clear relationship between the two concepts is also not defined by established rules.

Recent advances in machine learning and deep learning techniques have led to a variety of attempts to study the relationship between dance and music. Lee et al. proposed a choreography generation algorithm that retrieves the motions corresponding to the most similar pieces of music in the predefined motion-music-paired database for given new music segment. [3]. This method selects dance motion from a predefined database, so choreography retrieved with high correlation with music is guaranteed. However, it has limitations in that it can not create novel dance movements that are not included in the database. Ofil et al. proposed a HMM-based model that categorizes the genre of music based on the Mel-Frequency Cepstrum Coefficients (MFCC) feature and generates matching choreography based on the results [4]. But since the choreography is determined by the categorical value obtained through the genre classifier, there is a limit to generate a novel choreography. Omid et al. proposed a music-driven choreography model named Groovenet [5]. They used pairs of music and three-dimensional motion data to train the Factored Conditional Restricted Boltzmann Machines (FCRBM) [6]. They attempted to directly train the relationship between music and dance by using the mel-spectrogram in the training process. However, they reported that their model created awkward dance moves for unheard song, so they conclude that the model was overfitted and the dance moves according to music were not generalized enough.

Lee et al.’s and Ofil et al.’s studies have a limitation in that they can not create novel choreography because the former synthesizes motion by reusing the choreographic samples in a predefined database, and the latter creates choreography only for music input categorized by its genre. Omid et al. did succeed to create novel dance motion, but failed to yield good results mainly due to insufficient training data of merely 23 minutes. In this study, we propose a neural network-based model that can generate novel and natural choreography trained on large amount of data that is easily obtained from the online video sharing community. An overview of the proposed system is illustrated in Figure 1.

The rest of the paper is organized as follows. In Section 2 we explain in detail our proposed method for choreography generation based on the encoder-decoder network. We describe the datasets for experiments and the training process in Section 3. The evaluation scheme and the results are presented in Section 4 followed by conclusions and directions for future work in Section 5.
2. LISTEN TO DANCE: PROPOSED APPROACH

In order to learn the relationship between the time-series data of two different modalities, i.e., music and dance, we need a model that performs multi-modal sequence-to-sequence transformations. We modified the Dilated Convolution Text-To-Speech model [7] that performed well in the text-to-speech domain and used it as a our choreography generation network. Our model consists of two encoders and one decoder, and the detailed structure is explained below.

2.1. Causal Dilated Highway Conv. Block

The encoders and decoder used in the proposed model contain causal dilated highway convolutional blocks (CDHC). Causal means that only the input data from time 0 to \(t - 1\) can be referred to when calculating the output at time \(t\). We used a causal convolution layer because our network must be an auto-regressive model to generate the next frame that is not yet known from the preceding frames. In addition, we used the dilated convolution used in the Wavenet [8] to ensure that the model has a wider receptive field. Finally, to enable efficient training even in deep model structures, we used a highway network architecture [9] where gated function could be trained. That is, the output of the CDHC block is calculated as:

\[
\text{output} = \text{tanh}(H1) \cdot \text{relu}(H2) + (1 - \text{tanh}(H1)) \cdot \text{input} \tag{1}
\]

\([H1, H2]\) is the tensor calculated through the causal dilated convolution layer of the input tensor. The output channel of this convolution layer is twice the input channel, and the kernel size is 3.

2.2. Encoder & Decoder

Both the skeleton encoders and the audio encoders all consist of three convolution layers and 10 CDHC blocks. The first convolution layer of each encoder increases the input channel to 256 dimensions, and the other two layers perform 1x1 convolution. Thereafter, the output values from last convolutional layer are connected in sequence to 10 CDHC blocks with a dilation factor of \((1,3,9,27,1,3,9,27,3,3)\), and the corresponding operations result in audio and skeleton data are encoded to have a sufficiently wide receptive field to reflect sufficient past information.

A decoder is a network that generates skeleton data for the next frame from an encoded skeleton and an encoded audio. First, the encoded skeleton input to the decoder is combined with the encoded audio in the following:

\[
H1 = \text{conv}(E_{skeleton}) + E_{audio}[:128] \tag{2}
\]

\[
H2 = \text{conv}(E_{skeleton}) + E_{audio}[128:] \tag{3}
\]

\[
\text{comb} = \sigma(H1) \cdot \text{tanh}(H2) \tag{4}
\]

Where \(E_{skeleton}\) and \(E_{audio}\) refer to the encoded skeleton and encoded audio, respectively, and conv means the convolution layer with an output channel of 128 and a kernel size of 1. The combined comb tensor then goes through six CDHC blocks with a dilation factor of \((1,3,9,27,3,3)\) and then through three 128-channel convolutional layers with a tanh activation function. Finally, after passing through a convolution layer with the same output channel as the dimension of the target, the final decoder output is obtained via sigmoid activation.

2.3. Proposed network

This network receives motion and music data from time 0 to \(t - 1\) as input. Both data are encoded via encoders and

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Fig. 1: A schematic diagram of the proposed music-driven choreography generation system.
combined at the beginning of the decoder. The final output of the decoder is compared with the ground truth motion data at time 1 to t and we used it as a L1 loss. Since all convolution operations included in the network are with kernel size 1 or causal operations, the kth value of output refers to only the 0 to k-1 time step of the input during the operation. Therefore, the model satisfies the auto-regressive condition.

3. EXPERIMENT

3.1. Data

We have collected 100 YouTube choreography videos and corresponding audios. The genre was selected mainly for K-pop dance, and the total length of collected data was 6.26 hours.

3.1.1. Skeleton data

We extracted the x, y coordinates of 15 human body joints from each frame using the Openpose algorithm [10] from the collected video as shown in Fig. 2. Next, we min-max normalize the extracted coordinate values for each video, and use the linear-interpolation for the unrecognized coordinate values.

Since we cannot measure the exact 3d angle between the human body limbs using the 2d joint coordinate, we used the absolute coordinates values of each point as the training target. However, in this case, the length of each limb in the projected skeleton can vary, and awkward motion can be generated if the model learns it incorrectly. So we additionally calculated the lengths of the 14 main limbs together and added a loss to compare with the limb length of the skeleton that the model generated. Therefore, the x, y coordinates of the total 15 joints, and the total of 14 main limb length are used as skeleton data.

3.1.2. Music data

We separated the audio contained in the collected video and used it as music data. The mel-spectrogram was extracted from the audio waveform with the window size of 1024 samples, and 80 mel-frequency bins. Because we need time-aligned audio-video pairs for training, we adjusted the hop size when extracting the mel-spectrogram so that audio data has the same frame rate as that of video.

3.2. Training

We have trained proposed network that creates the next skeleton coordinate for a given previous skeleton sequence and music sequence. To do this, we first input skeleton data and music data from 0 to t-1 frames. Then, the output of the network is compared with the ground truth choreographic data corresponding to 1 to t frame by use L1 loss as a cost function. In addition, we calculated the length of each limb from the skeleton data of the generated frame, and compared with the actual ground truth length through the L1 loss. We used the adam optimizer [11] for training and set the learning rate to 0.0002.

3.3. Inference

The choreography inference process is performed in an auto-regressive manner different from training. That is, the initial position of each joint is given as an input skeleton frame, and at the same time, the first frame of mel-spectrogram is input to the trained model. When inference is performed once, estimated skeleton at t = 1 is output. Then we concatenate skeleton at t = 0 and t = 1, then input them back into the model with mel-spectrogram at t = 0 and t = 1. After that, we get estimated skeleton at t = 1 and t = 2. Therefore, we can generate the choreography by repeating the above process for the length of music input, and used it to evaluate the generated choreography.

4. EVALUATION & RESULTS

4.1. User study

We conducted a user study to evaluate whether the generated choreography was natural and whether it was produced in accordance with the music. First, we generated 20 videos for each of the three groups: Real, Generated, and Random. Group Real consists of music Ai and actual choreography for music Ai. Group Generated consists of music Bi and novel choreography generated by our model given music Bi. Finally, the group Random consists of music Ci and novel choreography generated by our model but with randomly selected music rather than Ci. Music Ai, Bi, and Ci were randomly selected among the songs included in the validation dataset that was not used in training, and the length of each audio/video was 16 seconds.1

After mixing the three groups of videos in a random order, we asked the participants whether each video’s choreography is natural (Question 1) and whether it fits well with music (Question 2), and to give a score in a Likert scale [12]. After collecting the responses, we performed isoquantity and

1 The generated result can be found at: listentodance.strikingly.com.
normality tests using data averaging 20 responses from each
group, to see if there was a difference in the mean of the re-
sponses of the groups. After evaluating significance through
repeated-measure ANOVA test, further post-hoc analysis
was performed to calculate the p-value, and the difference
between the groups was examined [13].

A total of 33 participants answered the questionnaire and
the results are shown in the Fig.3. The results of the statis-
tical tests confirmed that the mean scores between the three
groups were significantly different for both questions. Aver-
age user score for both questions were highest in Real
group and lowest in Random group. It is clear that the Real
group score is the highest, because it is made up of the choreogra-
phy created by the human. The average score of the Generated
group surpassed the Random group in both questions. If
the proposed model generates choreography that is not asso-
ciated with music, participants will have a similar response,
regardless of what music is played with the generated chore-
ography. However, from the fact that the video received a sig-
nificantly higher score when played with the music used in
choreography generation, we judged that the proposed model
produced choreography that listen and reflects the music.

4.2. Autocorrelation Analysis

We also performed an autocorrelation analysis to further in-
vestigate the differences between the generated choreography
and the actual choreography. Autocorrelation is a correlation
between a given sequence with itself, reflecting the periodic
properties of the sequence. We can identify the periodic com-
ponent of a given sequence through the location of the peaks
observed in the autocorrelation results. Using this, we ana-
alyzed the motion by calculating the autocorrelation on the x,
y coordinates of the choreography movement and compared it
with the tempo of corresponding music. Our hypothesis was
that if the model can produce dance by listening to the music,
the autocorrelation peak position of the motion will appear at
the same point as the beat of the music.

Fig. 4 shows the autocorrelation results of two choreogra-
phy samples along with the tempo of corresponding music. In
actual choreography, a clear peak is observed in y-direction
movement, but not in x-direction movement. This tendency
is also observed in the generated choreography. From this
we can determine that the proposed network has learned the
periodic tendency of the real choreography used in training.
Also, In actual choreography, the first or second peak of the y-
direction auto-correlation appears at the same position as the
music beat. This means that music and choreography have
similar periodic properties. This tendency can be confirmed
also in the case of the generated sample. From this, it is judged
that the proposed model has generated the choreography that
listen the music and reflects its periodic nature.

5. CONCLUSION

In this study, we proposed an auto-regressive encoder-decoder
network that generates matching choreography for a given
music input. We used audio-video pairs data obtained from
YouTube for training. As a result, it was found that motions
matching with the music were generated through comparison
of user study and autocorrelation analysis. This study has a
significance in that it shows a significant performance in the
area of learning-based choreography generation, in which suf-
ficient performance has not been secured yet. Also, it is mean-
ful not only to learn the movement of dance but also to use
the relationship with music together for generation.

This research has limitations that generated choreography
reflects only the periodicity among various properties of mu-
ic. Ultimately, it is necessary to create appropriate choreog-
raphy according to various genres, moods, and contexts of
music as well as periodicity. In order to do this, we plan to es-
ablish data sets that satisfy various conditions and carry out
further research. In addition, we use 2-d skeleton position for
training, and it is difficult to use this type of data in case of
needing actual implementation such as a robot. Therefore, the
extension of the model to 3-d choreography generation using
the improved 3-d pose estimation algorithm is also a future
research topic.
6. ACKNOWLEDGEMENTS

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7. REFERENCES

[1] Carol L Krumhansl and Diana Lynn Schenck, “Can dance reflect the structural and expressive qualities of music? a perceptual experiment on balanchine’s choreography of mozart’s divertimento no. 15,” Musicae Scientiae, vol. 1, no. 1, pp. 63–85, 1997.

[2] Sommer Gentry and Eric Feron, “Modeling musically meaningful choreography,” in Systems, man and cybernetics. 2004 IEEE international conference on. IEEE, 2004, vol. 4, pp. 3880–3885.

[3] Minho Lee, Kyogu Lee, and Jaeheung Park, “Music similarity-based approach to generating dance motion sequence,” Multimedia tools and applications, vol. 62, no. 3, pp. 895–912, 2013.

[4] Ferda Ofli, Yasemin Demir, Yücel Yemez, Engin Erzin, A Murat Tekalp, Koray Balci, Idil Kizoğlu, Lale Akarun, Cristian Canton-Ferrer, Joëlle Tilmanne, et al., “An audio-driven dancing avatar,” Journal on Multimodal User Interfaces, vol. 2, no. 2, pp. 93–103, 2008.

[5] Omid Alemi, Jules François and Philippe Pasquier, “Groovenet: Real-time music-driven dance movement generation using artificial neural networks,” networks, vol. 8, no. 17, pp. 26, 2017.

[6] Graham W Taylor and Geoffrey E Hinton, “Factored conditional restricted boltzmann machines for modeling motion style,” in Proceedings of the 26th annual international conference on machine learning. ACM, 2009, pp. 1025–1032.

[7] Hideyuki Tachibana, Katsuya Uenoyma, and Shunsuke Aihara, “Efficiently trainable text-to-speech system based on deep convolutional networks with guided attention,” arXiv preprint arXiv:1710.08969, 2017.

[8] Aäron Van Den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew W Senior, and Koray Kavukcuoglu, “Wavenet: A generative model for raw audio,” in SSW, 2016, p. 125.

[9] Rupesh Kumar Srivastava, Klaus Greff, and Jürgen Schmidhuber, “Highway networks,” arXiv preprint arXiv:1505.00387, 2015.

[10] Zhe Cao, Tomas Simon, Shih-En Wei, and Yaser Sheikh, “Realtime multi-person 2d pose estimation using part affinity fields,” in CVPR, 2017.