A CAUSAL CONVOLUTIONAL NEURAL NETWORK FOR MOTION MODELING AND SYNTHESIS

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Abstract

We propose a novel deep generative model based on causal convolutions for multi-subject motion modeling and synthesis, which is inspired by the success of WaveNet in multi-subject speech synthesis. However, it is nontrivial to adapt WaveNet to handle high-dimensional and physically constrained motion data. To this end, we add an encoder and a decoder to the WaveNet to translate the motion data into features and back to the predicted motions. We also add 1D convolution layers to take skeleton configuration as an input to model skeleton variations across different subjects. As a result, our network can scale up well to large-scale motion data sets across multiple subjects and support various applications, such as random and controllable motion synthesis, motion denoising, and motion completion, in a unified way. Complex motions, such as punching, kicking and, kicking while punching, are also well handled. Moreover, our network can synthesize motions for novel skeletons not in the training dataset. After fine-tuning the network with a few motion data of the novel skeleton, it is able to capture the personalized style implied in the motion and generate high-quality motions for the skeleton. Thus, it has the potential to be used as a pre-trained network in few-shot learning for motion modeling and synthesis. Experimental results show that our model can effectively handle the variation of skeleton configurations, and it runs fast to synthesize different types of motions on-line. We also perform user studies to verify that the quality of motions generated by our network is superior to the motions of state-of-the-art human motion synthesis methods.

Keywords Deep learning · Temporal convolutional neural network · Motion synthesis and control · Optimization · Motion denoising · Motion completion

1 Introduction

It is a challenging task to learn a powerful generative motion model from prerecorded human motion data because human motion is intrinsically governed by highly nonlinear dynamical systems. An appealing solution for generative motion models should scale up well to motion datasets across multiple subjects. In addition, it should be accurate and compact, efficient for runtime evaluation, and amenable to various forms of applications, such as motion synthesis with or without control inputs, motion prediction, motion denoising, and motion completion.
Recent deep learning-based motion synthesis algorithms show great potentials in resolving these issues. The deep neural network with nonlinear activation functions can well model nonlinear dynamics and generate different motions without the motion capture data used for network training to save the memory footprint. Autoregressive models, such as restricted Boltzmann machines (RBMs) and recurrent neural networks (RNNs) \cite{1,2,3}, have been applied to motion synthesis by predicting the possibility of motions in the future. However, to avoid causal error accumulation in such models, careful training strategies must be employed. Conditioned on control signals, convolutional neural networks (CNN), phase-functioned neural network (PFNN), Long-short term memory (LSTM) networks, and variational autoencoders have been applied to generate controllable motions to interact with the environment for a specific person \cite{4,5,6,7}. Despite significant progress in deep learning-based motion modeling, there is no accurate generative model that can scale up well to motion datasets across multiple subjects and support different applications in a unified way.

This paper proposes a novel causal convolutional neural network (CCNet) to address the aforementioned issues in generative motion modeling and synthesis. The network architecture is inspired by the success of causal-convolution-based WaveNet \cite{8} in multi-subject speech synthesis. The causal convolution is appealing to generative human motion modeling since it can explicitly model the correlation among a long-range temporal window, which is demonstrated to be more effective than the hidden states used in RNNs and their variations in speech synthesis experiments. However, it is a non-trivial task to apply WaveNet to motion synthesis because motion data is a high dimensional signal, and one needs to pay attention to foot contact to synthesize plausible motions. To this end, we adapt the network architecture of the WaveNet by adding an encoder and a decoder to translate the motion data into features and back to the predicted motions. Moreover, we add 1D convolution layers to allow the CCNet to take skeleton configurations as an input, which is critical for the network to handle the skeleton variations of different subjects. The output of the CCNet is the probabilistic density function (PDF) of the motion at the next time step that is conditioned on the motions at previous time steps, control signals, and the skeleton configuration. Consequently, with a meticulously-designed training strategy, our CCNet can capture personalized style variation of different skeletons and effectively support random and controllable motion synthesis in a unified way using a single set of network parameters.

The CCNet possesses the desirable properties of the generative motion model. It is a compact model of size ~4.5M bytes. Combined with a Gaussian loss that penalizes the deviation of joint angles, positions, and velocities simultaneously in training, the drifting or freezing issues that are frequently encountered in RNN models can be effectively mitigated. Thus, the CCNet can be applied to random motion synthesis, i.e., synthesizing long-time motion sequences of different subjects without control signals. This renders it suitable for motion generation, denoising, and completion applications. The CCNet can also be applied to the controllable motion synthesis. After training on the motion capture (mocap) data across multi-subjects, we allow the user to control the motion synthesis result through various control signals, such as heading direction, velocity, and motion type. The skeleton is also called control signals hereafter and processed in the same way as other control signals in the CCNet. Moreover, the CCNet can synthesize motions for novel skeletons not in the training dataset. After fine-tuning the network with a few motion data of the novel skeleton, it is able to capture...
2 Related Work

Human motion modeling and synthesis is a long-standing problem in the area of computer graphics. In the following, we focus our review on data-driven human motion modeling, as well as their applications in human motion synthesis and processing.

Motion Control and Synthesis. Data-driven motion synthesis is built successfully on the interpolation of motions in a database. For example, Rose et al. [9] classified the motion database into verbs and adverbs. Then human motions are interpolated by the constructed radial basis as well as low-order polynomials. However, interpolation-based methods can not adapt to the rich repertoire of human behaviors. Generative statistical models, which describe human movements by hidden parameters and the associated probability distributions, became the mainstream in the previous decades. Tanco et al. [10] learned a statistical model from the data set, and motion is then interpolated by giving the start and end frames, as well as a few keyframes with the learned statistical model. Other varieties of different statistical models, including Hidden Markov Models (HMMs) [11, 12], spatial-causal dynamic models [13, 14], and low-dimensional statistical models [15, 16] are developed one after the other for human pose analysis and synthesis. Furthermore, motion graphs [17, 18] and their various extensions [19, 20] are proposed to extend the statistical models for representing complex human motions. These directed graphs also provide benefits for the interactive editing and control for complex human motions. In [21], a generative motion graphs named MotionGraph++ is proposed to process motions at semantic and kinematic levels.

In this paper, we propose an end-to-end deep learning framework for human motion modeling and synthesis. Our deep-learning model is much more compact than motion graph++. Besides, our model has a much better generalization ability than motion graph++. Our experiments show that it can model not only a rich set of human actions and their transitions but also delicate motion variations across multiple subjects, a capability that has not been demonstrated in previous work.

Motion Style. Our method has superior performance for generating different motion styles associated with different people, even when they possess the same type of human motions. It is noted that motion style and motion type are
clearly differentiated in this paper. For example, a fat man and a thin man would have different walking styles for the same motion type, i.e., walking. The critical challenge is how to model the motion style. In the work of [12], the motion style is parameterized to learn a statistical model, and different types of motion can be synthesized from the learned model according to the input style parameters. Arikan et al. [19] proposed categorizing the human motions into different motion types, such as turning left and turning right, and then generating motion sequences according to the input motion types through a dynamic programming search algorithm. In the work of [26], the motion style for a single person has been proposed for addressing the problem of unlabeled heterogeneous motions. However, all the methods mentioned above only focus on the motion styles for a specific person. None of them can model the variations of human motion styles across different people. Similar to [27], our deep generative model can handle personalized style variations across multiple subjects. However, unlike [27], which can only model personalized style variations for a particular human motion such as walking or running, our generative model can scale up well to a rich repertoire of human motions as well as their transitions. Aberman et al. [28] handled the skeleton variations by representing skeletons as the static offsets in some arbitrary initial pose together with the dynamic motions in a tree graph structure. However, they focused on motion retargetting while we are interested in motion synthesis.

**Deep Learning based Motion Synthesis.** In recent years, deep learning has gained lots of attention in computer vision and computer graphics. Like many other tasks, such as image segmentation, classification, and object recognition, human motion synthesis has also benefited from the rapid progress of deep learning. It provides a remarkable tool for directly learning a compact, low-dimensional motion space from a dataset without any motion feature designations. By comparison, traditional successful generative statistical models for human motion synthesis heavily rely on the human-made ad-hoc motion features [16, 29, 20]. Holden et al. [30] proposed a convolutional auto-encoder to learn compact motion representation, termed as the motion manifolds, for human motion synthesis. Such motion representation can be utilized to fill in the missing data and perform the motion interpolation in the manifold space.

In [4], user-friendly high-level parameters for motion control, such as character motion trajectory and foot contact information, are investigated for synthesizing the human motions. Phase variable for cyclic motions is explicitly used as an input to control the weights in the network [5]. In contrast, the hidden state in LSTM can model the causal dependence of the motion implicitly. Thus motion synthesis with multi-objective control can be realized without the phase information [6]. Mixture-of-expert (MoE) architecture [31, 32, 33] are used to ease the burden of phase labeling for motions and improve the capacity of the networks for motion synthesis. Ling et al. [7] leveraged MoE as the decoder of motion VAEs to model the distribution of possible next poses. Starke et al. [34] added local motion phase feature to MoE to learn asynchronous movements of each bone and its interaction with external objects and environments. Reinforcement learning has been widely applied [35, 36, 37, 38, 39] to train physics-based motion controllers. Peng et al. [40] adopted a two-level hierarchical control policy with high-level environment information to make the character be aware of the surroundings. Won et al. [33] clustered the reference library of motions generated by the kinematic controller to construct experts and then combined these experts by deep reinforcement learning. The adversarial training strategy is adopted in [41, 36] to improve the quality of generated motions. Recently, mapping the features extracted from music [42] or language [43] to the motion space is utilized to generate character motions synchronizing with such multi-modal inputs.

Enormous neural networks are proposed to address long-term motion prediction problem, which include recurrent neural networks (RNNs) [2, 44, 45, 46], fully connected networks [47, 48], reinforcement learning [49, 50], graph networks [51, 52], and generative adversarial networks (GAN) [53]. To better model the randomness of human motions, Aliakbarian et al. [54] combined the root of variations with previous pose information to force the network to learn the motion variations. At the same time, Zhao et al. [55] exploited Bayesian Hierarchical Hidden semi-Markov Model(BH-HSMM) as generator and discriminators for adversarial learning. To solve the error accumulation problem for long-term motion prediction, practical strategies, including adding residual blocks and introducing sampling in training, are applied to improve RNN [3], and the auto-condition scheme is adopted in RNN in the work of [56]. QuaterNet [57] conducts extensive experiments to demonstrate that the quaternion representation is beneficial to improve the quality of synthesized motions.

Despite significant progress in deep-learning-based motion modeling and synthesis, constructing a generative model capable of accurately modeling motion data sets across different subjects remains challenging. The CCNet is more appealing to human motion modeling because the explicit causal convolution adopted in CCNet has a larger and more efficient receptive field than widely used networks such as RNNs or their variations. As shown in our comparisons (see Sec. 6), in the case of multiple subjects, the CCNet can capture personalized style variation and produce superior results than alternative deep learning models in terms of both motion synthesis quality and motion control accuracy, a capability that has not been demonstrated in previous work. Finally, as shown in Tab. 1 our model is more flexible and powerful for motion synthesis and processing. In contrast, traditional motion graph techniques [22, 23, 17, 21] are hard to scale up to handle large scale motion data, and the required memory footprint is usually large. For fair comparisons,
ERD-LSTM models [2] [3] [24] [6]. DAE-LSTM models [25] and PFNN [5] are extended to model multi-subject motion data by taking skeleton configuration as an input (see Sec. [6] for details).

3 Overview

The overall framework of our system is illustrated in Fig. 1. Given the processed motion data (Sec. 4), we train a CCNet to predict the PDF of the future pose conditioned on the poses of past frames and optional control signals, where the details of control signals are discussed in (sec. 4.2). The designed CCNet has three types of functional blocks, i.e., encoder, separate residual block, and decoder, and it outputs the mean and variance of the PDF (Sec. [5.1]). A variety of motion synthesis applications, such as motion denoising, motion completion, and motion control, can be realized by this unified generative model with a single set of network parameters. We also test how the network generalizes to novel skeletons not in the training dataset (Sec. [6]).

During training, we use Gaussian loss, foot contact loss, and smoothness loss to learn the network parameters (sec. 5.2). Noises are added to the sampled training motion data such that the trained network is robust to the accumulated error in the motion synthesis and can produce high-quality, non-freezing motions. The slight foot sliding in the generated motion is removed by an inverse kinematic (IK) algorithm according to the predicted foot contact label by the CCNet. To ease the interactive control, we also train the proposed network to output the direction and velocity control signal for the next frame.

4 Data Processing and Representation

We build a human motion database of 12 different subjects using the mocap technique. Three of the subjects are female, and the rest of them are male. The database includes 10 types of motions: walking, running, jumping with the left foot, jumping with the right foot, jumping with both feet, back walking, zombie walking, kicking, punching and kicking while punching. All subjects are asked to perform the first 7 types of motions, and 5 of them are asked to perform the last 3 types of complex motions additionally. The motion recording speed is 120fps, and the recording time for each subject is within 2 hours. Thus, there are around 80,000 frames of motion data for each subject. During recording, we ask each subject to perform two types of motions in one motion sequence to facilitate the learning of transition between different motion types. Afterwards, We down-sample the recorded motion data to 60fps and obtain a total of 486,282 frames to be used as our training and validation datasets. The validation dataset is formed by randomly selecting one motion sequence of each subject. Moreover, all the motion sequences of subject 7 are removed from the training dataset and only present in the validation dataset, which is used to test how our network can handle the skeleton variation after training on multi-subject motion data. As a result, the validation dataset contains 41 motion sequences and a total of 88,649 frames. The rest motion data is used in the training dataset.

4.1 Motion representation

The character skeleton in the mocap data is modeled as an articulated figure with rigid links connected by ball-and-socket joints. The motion at each frame is recorded as the translation and rotation at the root joint and the relative rotations at other joints. However, such motion representation is a relatively local feature since most rotations at ball-and-socket joints are relative to their parent joint. Thus, we add 3D joint positions and the joints’ angular and linear velocities into the representation to better model the global influence of joint rotations on rigid links’ positions and orientations. Overall, the motion information at nth frame is represented as \( x_n = \{ x_n^e, x_n^p, x_n^\omega, x_n^v_0, x_n^v_f \} \), where \( x_n^e \) denotes the vector of relative joint rotations represented using exponential coordinates [58], \( x_n^p \) the vector of relative angular velocities of the joints, \( x_n^\omega \) the 3D joint positions, and \( x_n^v_0 \) denotes the vector of joint linear velocities. The foot contact information at nth frame is represented as a 2-dimensional binary vector \( x_n^f \).

Before converting the mocap data into our representation, we first align each recorded motion clip by translating its first frame to the origin of the global coordinate system on the XOZ plane and setting the root’s rotation around the global Y-axis to be zero. For the nth frame in the clip, we first rotate the root orientation represented in the global coordinate system of frame \( n-1 \) to a coordinate system whose Y-axis is \( \{0, 1, 0\} \). We then represent the root position and orientation of nth frame to the rotated coordinate system at frame \( n-1 \). However, we still represent the \( y \) coordinate of the root joint in the global coordinate system to emphasize this quantity in network training. The rotations for non-root joints remain the same with the motion capture data. The linear and angular velocities are computed by subtracting the corresponding joint positions and rotations in exponential coordinates at frame \( n \) and \( n-1 \) and representing the difference vectors in the rotated coordinate system of frame \( n-1 \). The motion alignment makes our motion representation invariant to translation and facing orientation in the plane, which means that no matter where the
where $h$ is the height of the root joint, and the 3D positions of non-root joints, i.e., \( \{t_1^x, t_1^y, t_1^z, \ldots, t_m^x, t_m^y, t_m^z\} \), are set to be relative to the root. The number of joints $m$ is set to be 27, which is the number of non-finger joints in our database. The 27 non-finger joints’ relative 3D positions and the root joint’s height form the 82 dimensions $c_n^d$. Note that the skeleton configuration is input to the network all the time, but other control signals are optional in the motion synthesis.

5 CCNet

In this section, we first describe the network structure of CCNet and then proceed to its training details.
There are a total of 20 SRBs in our network. The superscript \( \psi \) in Eq. (2) indicates that the SRBs in the network are recursively executed, and each \( i \)th block takes the output of \((i - 1)\)th block and the control signals as its inputs. The first separate residual block \( \psi_R^1 \) takes the output from the encoder and the control signals as inputs. The output PDF \( p(x_n) \) is set to be the Gaussian \( N(\mu_n, \sigma_n) \). where its mean \( \mu_n \) and standard deviation \( \sigma_n \) are the output of the decoder \( \psi_D \). Since the decoder \( \psi_D \) might output a negative standard deviation value after convolution, we compute the final standard deviation values as \( \sigma_n = e^{\sigma_n} \), where \( \sigma_n \) is the direct output of the \( \psi_D \).

**Encoder.** The motion representation \( X \) of past \( l \) frames are first input to an encoder \( \psi_E \) to map the data into features, and the encoder is of a simple "Conv1D-ReLU" structure where the size of 1D convolution kernel is 1 and use ReLU as the activation function. Note that the kernel of size 1 makes sure that the feature of the motion at each input frame is independent.

**Separate residual blocks:** The core component of the CCNet is the set of separate residual blocks \( \psi_R^i \). It is similar to the residual blocks used in WaveNets [8], which use dilated causal convolution to guarantee the input motion data’s ordering. The control signals are also inputted to the residual blocks through convolution layers with kernel size 1. The difference is that we use two separate dilated causal convolution layers and 1D convolution layers to compute separate features for the gated activation. This is designed to disentangle the information to increase the capacity of our network. Moreover, the features from the motion data and control signals are fused through summation. This enables us to switch on/off the control signals online during the training and inferring. The dilated Causal Convolution is implemented as in [8]. Specifically, zeros are padded before the feature of the \( \psi_E(x_{n-i-1}) \) so that the output of the convolution of a frame \( i \) only depends on the frames before it. The padding size can be easily computed as \((k - 1) \ast d\), where \( k \) is the kernel size and \( d \) the dilation size. The kernel size of the causal convolution and dilation size in SRBs are set to be 2. As a result, the causal receptive field of the CCNet is 41 frames, which can be computed using the following formula:

\[
F = (k - 1) + \sum_{i=0}^{19}(k - 1) \ast 2
\]
where $k$ is 2, the kernel size of the dilated Causal Convolution used in our CCNet.

Fig. 3 shows the details on how the control signals are input to the separate residual blocks: each type of control signal is input to its own Conv1D layer, and the kernel size of Conv1D is 1. The input motion feature (channel number: 32) for SRB$_i^{−1}$ is the feature $O_{i−1}^r$ output by SRB$_i^{−2}$. The output feature $O_i^s$ (dimensionality of the output features: 512) is sent to the decoder.

**Decoder.** The decoder $\psi_D$ maps the summed features from the SRBs to the PDF of the predicted motion. It is of a simple "ReLU-Conv1D" structure, where the convolution kernel size is also set to be 1.

### 5.2 Training Loss

The training loss consists of four terms, a Gaussian loss $L_G$, a motion smoothness loss $L_s$, a foot contact label loss $L_f$ and a direction control loss $L_d$. It can be formulated into:

$$L = L_G + \lambda_1 * L_s + \lambda_2 * L_f + \lambda_3 * L_d$$  \hspace{1cm} (4)

where the weight $\lambda_1$ is set to be 10.0, $\lambda_2$ be 2.0 and $\lambda_3$ be 1.0 in all our experiments.

The first term $L_G$ is the Gaussian loss. This term follows the Gaussian mixture loss in [2], while we only use one mode and set the covariance matrix to be diagonal to reduce the number of parameters. It can be written into:

$$L_G = -\ln(p(x_n | \hat{\mu}_n, \hat{\sigma}_n)),$$  \hspace{1cm} (5)

where $x_n$ is the motion representation extracted at $n_{th}$ frame. This term enforces the network to output the values of mean $\hat{\mu}_n$ and standard deviation $\hat{\sigma}_n$ so that the captured motion data is of high probability. The binary foot contact label in $x_n$ is handled in $L_f$ and thus not included in this term. We add a constraint in our implementation to ensure the standard deviation $\hat{\sigma}_n$ is greater than 1e-4 by a clipping operation, and we observe that the standard deviation output by the trained CCNet is usually between 1e-4 and 1e-3. Consequently, in motion synthesis, we can sample a motion according to the Gaussian distribution to enrich the variation of the synthesized motion. Note that the Gaussian function is used to maximize the probability of the motion representation vector of the ground-truth mocap data during training. Thus, the joint positions and linear velocities included in this term can help to model the correlations between the rotational degrees of freedom of different joints since such quantities are affected by all the parent joints on the kinematic chain connected to the joints.

The second term is the smoothness term to prevent the sudden change of the motion among neighboring frames, which is as follows:

$$L_s = \sum_{n=2}^N (\hat{\mu}_{n−2} + \hat{\mu}_n - 2\hat{\mu}_{n−1}).$$  \hspace{1cm} (6)

The smoothness loss is only optimized for the mean of predicted Gaussian distributions since the motion generated by the network is usually close to the mean at each frame. This term is a soft constraint to prevent the sudden change of accelerations at joints and make the synthesized motion smoother.
The third term is used to train the network to predict whether the foot is in contact with the supporting plane at \( n \)th frame. Specifically, we adopt binary cross entropy (BCE) loss function to compute this term:

\[
L_f = \text{BCE}(x^f_n, \hat{x}^f_n),
\]

where \( x^f_n \) is the ground-truth foot contact label from the data, and \( \hat{x}^f_n \) is the network prediction. The foot contact label is used to trigger IK algorithms to remove the foot sliding in the synthesized motion.

The last term is used when the direction and velocity controls are switched on. It can be simply written as:

\[
L_d = \| \hat{c}^d_n - c^d_n \|^2 + \| \hat{c}^v_n - c^v_n \|^2
\]

where \( c^d_n \) and \( c^v_n \) are the direction and velocity control signals computed from the motion data, and \( \hat{c}^d_n \) and \( \hat{c}^v_n \) are the predicted values. This term is useful in interactive motion control applications when control signals might be input by the user occasionally. In this case, the predicted control signal values will be fed into the network to continue the motion synthesis.

5.3 Training Details

We train our CCNet using the RMSProp optimizer \footnote{59}. The initial learning rate is 1e-4 and will be decayed by multiplying it by 0.5 every 500 epochs. The loss curve usually converges around 1000 epochs. The batch size is set to be 256, and each sample in the batch is a motion sequence of 240 consecutive frames. There are two steps to generate 240 samples in a batch: 1) randomly select a motion clip from the database and then the starting frame index in the clip. 2) Sample 240 frames in the clip repeatedly using a one frame interval, i.e., the starting frame index, \( F_s+1 \), of the next 240 frames sequence is equal to \( F_s+1 \). For an input sequence, \( X = \{x_0, x_1, ..., x_{n-1}\} \), the CCNet can produce the output \( Y = \{y_1, y_2, ..., y_n\} \) due to the guaranteed causal ordering in all the dilated causal convolutional operations in CCNet. Thus, we can compute the training loss for all the output motions at different frames, which helps the CCNet learn to handle the input motions of different lengths.

Data augmentation. We add additional independent identically distributed Gaussian noises to each sampled motion representation vector of training motion data to train the network to handle accumulated errors in the motion synthesis. The mean and standard deviation of the noise is selected to be 0 and 0.03.

6 Experiments

We have implemented our algorithm using Pytorch 1.6 on a desktop PC with Intel(R) Xeon(R) Gold 5120 CPU, 128G RAM, and one Tesla V100 SXM2 32GB graphics card. The trained CCNet has 1.16M parameters, resulting in a model of size ~4.5M Bytes. The skeleton information is always input to the CCNet in both random and controllable motion synthesis since they are required to differentiate between subjects in the experiments. Although the network can generate high-quality motion, slight foot sliding might still occur. If not mentioned, the inverse kinematics algorithm is adopted to completely remove the foot sliding in the generated motion according to the predicted foot contact label. Besides, we denote the initial frames input to the CCNet to begin the motion generation as seed frames hereafter.

Baseline networks: We compare the CCNet to state-of-the-art motion synthesis networks that are listed below:
Figure 5: Random motion synthesis results. (a) Random motion generation result for subject 3 (the fourth skeleton shown in Fig. 4). Different colors of the clothing indicate the different random motions generated by the trained CCNet. (b) and (c) A motion denoising result for subject 7 (the eighth skeleton shown in Fig. 4). (d) and (e) A motion completion result for subject 5 (the sixth skeleton shown in Fig. 4).

- ERD-4LR: the encoder-recurrent-decoder network structure in [2]. We implement the network using 4 LSTM layers as in [6].
- DAE-LSTM: the network structure in [25] that uses a dropout autoencoder to filter the predicted poses output by an LSTM network.
- PFNN: the network structure in [5] that adopts a cyclic function to compute the neural network’s weights by taking the motion phase as an input.

To test these three network structures’ performance in multi-subject motion synthesis, we add parameters at their first layer to accept as input the skeleton configuration and the same set of control signals. For clarity, we refer to the modified networks for random motion synthesis as ERD-4LR-rand and DAE-LSTM-rand and the modified networks for controllable motion synthesis as ERD-4LR-cond and DAE-LSTM-cond. Since PFNN is mainly designed for controllable motion synthesis, not for a generative model, we only compare the CCNet with PFNN on controllable motion synthesis. We refer to the modified PFNN as PFNN-cond. Please refer to the supplementary_material.pdf in "other supplementary materials" for the detailed network parameters of the modified networks.

We separately train these five networks, namely ERD-4LR-rand, DAE-LSTM-rand, ERD-4LR-cond, DAE-LSTM-cond, and PFNN-cond, and our CCNet, on the multi-subject motion dataset. For all the networks, the initial learning rate is set to 1e-4, and it will be decayed by multiplying it by 0.5 every epoch. The batch size is 256, and each sample in the batch is a motion sequence of 240 consecutive frames. We train these networks for 2000 epochs. The rest training settings for baseline networks remain the same as reported in their papers. Please refer to [2], [6], [25] and [5] for the detailed settings. Finally, we choose the best-performed network snapshots that achieve the lowest validation loss as the final networks used in the comparisons. Specifically, the network snapshots are selected as follows: CCNet, ERD-4LR-rand, and ERD-4LR-cond: 1510th epoch, the PFNN-cond network: 1045th epoch, DAE-LSTM-rand: 1650th epoch, and DAE-LSTM-cond: 1120th epoch.

6.1 Random motion synthesis

Random motion generation: In this experiment, the skeleton configuration and seed frames are fed to the CCNet to generate high-quality motions. However, we do not input control signals, such as direction, velocity, and motion type, to the CCNet. Also, we use 120 seed frames to facilitate the comparisons since such length is chosen in ERD-4LR and DAE-LSTM [6, 25]. As illustrated in Fig. 5a for the fourth skeleton shown in Fig. 4, five motion sequences are generated by sampling the pose at frame \( n \) using the predicted Gaussian distribution. The sampled pose is fed back to the network to generate future frames. The random motion generation can be used in motion prediction given a long motion sequence as an input, which is useful in on-line pose detection in computer vision or RGBD-based motion capture [60].

We also feed ERD-4LR-rand and DAE-LSTM-rand with the same 120 seed frames and the skeleton configuration to synthesize random motions for fair comparisons. As a result, we found that the CCNet, ERD-4LR-rand, and DAE-LSTM-rand can all synthesize long period motion sequences with more than 20,000 frames. The random motion generated by ERD-4LR-rand is also of good quality but a little bit less smooth than the motion generated by the CCNet. Comparisons conducted in the user study (Sec. 6.4) also show that the quality of the random motions generated by the CCNet is superior.

Motion denoising and completion: To test how the CCNet perform in motion denoising, we randomly select a motion sequence \( X = \{x_0, x_1, ..., x_k\} \) of a subject and then add independent identically distributed Gaussian noise (mean 0, standard deviation 0.01~0.1) to the motion data \( \hat{X} \). The network takes \( \hat{X} \) as an input and outputs the denoised motion \( Y \). However, the denoised pose is not fed back into the network, which is different from the random motion generation. For those frames with indices less than the casual receptive length, 41 frames in our network, they are denoised according to all the frames before them since the CCNet is trained to handle motions of different lengths. Fig. 5b and 5c illustrate...
### Table 2: Motion denoising comparison. STD: standard deviation. IK is disabled in this experiment. The errors of the motions denoised by the CCNet are less than the errors of the motions denoised by ERD-4LR-rand and DAE-LSTM-rand.

| Noise STD | Denoising Errors (mean±std) | ERD-4LR-rand | DAE-LSTM-rand | CCNet       |
|------------|----------------------------|--------------|---------------|-------------|
| 0.03       | 0.768±0.357               | 0.687±0.384  | 0.528±0.126   |
| 0.05       | 0.768±0.357               | 0.687±0.384  | 0.539±0.125   |
| 0.1        | 0.77±0.361                | 0.687±0.384  | 0.584±0.117   |

Figure 6: Trajectory-following results of two subjects. (a) A synthesized motion transiting from walking to running then to zombie walking for subject 10 (the eleventh skeleton shown in Fig. 4). (b) A synthesized motion transiting from jumping with the right foot to jumping with the left foot then to jumping with both feet for subject 11 (the twelfth skeleton shown in Fig. 4). We use different colors to represent different motion types at the different part of trajectories as follows: red-> walking, magenta->running, green->jumping with the left foot, cyan->jumping with the right foot, green-yellow->jumping with both feet, blue->back walking, pink->zombie walking, orange->kicking, purple->punching, and brown->kicking while punching.

6.2 Controllable motion synthesis

Motion control using user-specified trajectories: Synthesizing different types of motions along a specified trajectory is a desirable function in motion planning. We allow users to specify a motion trajectory $J$ on the XOZ plane with additional velocity and motion type information and then map the trajectory information into the control signals $c_d^i$ and $c_t^i$ supported in our system. Specifically, the trajectory $J$ is represented as $J = \{J_i, t_i, v_i\}, i = 1, \ldots, k$, where $J_i$ is the $i^{th}$ part of the whole trajectory represented as an ordered densely sampled 2D points, the motion type information $t_i$, and a scalar velocity value $v_i$ are also associated to the $J_i$. For two adjacent parts of the trajectory with different motion types, we set up 20 transitional frames with interpolated motion type control signal (see Sec. 4 for the details of motion type interpolation).

Suppose we already synthesize frame $n$, and its root position projected on the XOZ plane, denoted by $t_p^n$, might deviate from the input trajectory. We first find the closest point $t^J$ on the $J$, and then extract the part of trajectory $J^E$ lasting for one second starting from $t^J$ using the specified velocities. We then linearly interpolate between $J^E$ and the line connecting $t_p^n$ and the endpoints of the expected trajectory $j^E$ to obtain a blended trajectory $\hat{J}^b$. The blending weight for the $\hat{J}^E$ starts with 0 and increases towards 1 according to the time parameter. Afterward, 6 2D points are uniformly...
Figure 7: Our CCNet can synthesize (a) motions heading along a complex trajectory and (b) Complex motions for subject 5 (the eighth skeleton shown in Fig. 4).

Figure 8: The user interface for interactive control. The green dots on the ground represent the direction control signal. IK is disabled.

As shown in Fig. 6, our system can synthesize motions following two user-specified trajectories. Different trajectory colors indicate different types of motion. Fig. 7a illustrates that the synthesized motions can well follow a trajectory with large curvatures and frequent change of motion types. In Fig. 7b, we show that the CCNet can generate complex motions, such as kicking and punching motions present in our training dataset, when the user specifies these two motion types along a trajectory.

Interactive control: The CCNet can be easily integrated into interactive applications, and we demonstrate this capability by developing a demo that allows the user to control the direction, velocity, and motion type through a keyboard. Direction and velocity signals are used to generate future motion trajectory $\hat{c}_n$ online similar to PFNN [5]. The PyTorch implementation is exported to C++ through the LibTorch API to ease the implementation of this demo.

Specifically, to control the motion type, the user can use the number keys from 1 to 5 to select among 5 motion types: walking, running, jumping with the left foot, jumping with the right foot, and jumping with both feet. Once a key (for instance, 2) is pressed down, we update the motion type label by interpolating the new type label with the previous one in 20 frames, which means the character can transition from the previous motion type to the new one more smoothly. The user can also control the velocity by pressing up and down keys and heading direction of the character by pressing the left and right keys. Once the left key is pressed, the trajectory will be turned left. It is achieved by first computing a small offset vector $o_n = [1, 0] \times h \times 0.015$, where $h$ is the root’s height. This offset will be added to the $c_n$ by $o_n \times w_i$, where $w_i = i/5$, $i = 0.5$. Thus, the offset will be added to the 6 points in the predicted control signal $\hat{c}_n$ through the corresponding $w_i$. The distance between the 2D points in the updated $\hat{c}_n$ is then adjusted according to the user-specified velocity $v_u$. Since the $\hat{c}_n$ represents the future motion trajectory within one second, we can adjust the distance between its 2D points by multiplying it by the ratio between the current scalar velocity of the character $v_{cur}$ (computed by the length of the 2D points in $c_n$) and $v_u$, which is $v_u/v_{cur}$. The velocity is changed from the current velocity to the user-specified velocity with 20 frames interval. Fig. 8 illustrates the user interface used in interactive control.
Comparisons: We first compare the CCNet with baseline models on how accurate the generated motion is with respect to the user-specified trajectory. Thus, we leverage the average distance between the user-specified trajectory and the root trajectory on the XOZ plane as the criterion. In this accuracy experiment, with six different trajectories manually specified by users, we extract the direction control signals and randomly assign motion type information to trajectory segments. Afterward, we synthesize motions using the first 120 frames of the 33 locomotion sequences in the validation dataset as the seed frames for each specified trajectory and get a total of 198 controllable motion synthesis results. The trajectory distance is computed by summing the closest distance between a projected root position and a target trajectory at each frame. The mean and standard deviation of the averaged trajectory distance is as follows: $27.878 \pm 8.516$ for the CCNet, $158.67 \pm 30.94$ for PFNN-cond, and $171.973 \pm 31.862$ for ERD-4LR-cond. Fig. 9 shows an example. The result of the CCNet is more accurate than the baseline models. We will show the six trajectories in the supplementary material.

We also compare the motion quality in the case of controllable motion synthesis through a user study (see Sec. 6.4 for details). The user study results also verify that the CCNet can generate controllable motions of better quality in the setting of multi-subjects.

6.3 Generalization to Unseen Skeletons

After training with multi-subject motion data, the CCNet can generate motions for skeletons not in the training dataset. As illustrated in Fig. 4, 5b, 5c and 7a, we have applied the trained CCNet to automatically generate denoised and controllable motions for the skeleton of subject 7 not in the training dataset. We also test the generalization ability of the CCNet by applying it to a particularly designed skeleton generated by scaling the skeleton of subject 7. Fig. 10 illustrates that the CCNet can generalize well to the new skeleton. Since there is no mocap data for it, we utilize motion...
Table 3: The influence of the fine-tuning of CCNet with partial motion data of an unseen skeleton subject 7. Dataset1 contains motions of subjects 1, 3, 4, 8 and dataset2 contains motions of subjects 0, 5, 6, 11. Fine-tuning with walking and running mocap data of subject 7 with our entire training dataset (third row) achieves the lowest relative pose difference. IK is disabled in this experiment.

Table 4: T-test of user-study in the cases of random and controllable motion synthesis (confidence interval=0.95). VS: performing t-test between the results of the CCNet and all the results of baseline models in the second row. RAND: random motion synthesis. CONTR: controllable motion synthesis. Mean: the average number of generated sequences selected by all the participants after comparing to mocap sequences in the same group. Std: the standard deviation of the number being selected.

retargetting \cite{61} algorithm to generate 120 seed frames for the new skeleton. Besides, we use ERD-4LR-cond and PFNN-cond to generate motions for the skeleton. The results show that motions generated by both of them contain big sudden changes between seed frames and generated frames, which is inferior to the motion generated by the CCNet.

Moreover, the CCNet can be used as a pre-trained network in few-shot learning for motion modeling and synthesis. Given a few motion data of a novel skeleton, it can learn to capture the personalized style implied in the motion for the skeleton. Tab.\[4\] shows that, after finetuning the network on the walking and running motion of subject 7, the relative pose difference, rel$^p$, for all mocap data of this subject in the validation dataset can be significantly reduced. We compute relative pose difference as $rel^p = \frac{1}{N} \sum_{n=0}^{N} (\frac{\|\hat{x}_n - x_n\|_2}{\|x_n\|_2})$, where $N$ is the number of frames, and $\hat{x}_n$ and $x_n$ are the motion representation vectors of motions generated by the finetuned CCNet and the corresponding mocap data. The ability of generalization to new skeletons is crucial since it can save efforts to capture a large number of high-quality mocap data for a new skeleton in the motion synthesis applications.

To evaluate how the number of subjects in the dataset influences the generalization ability of the CCNet, we intentionally put the motions of subjects 1, 3, 4 and 8 into dataset1 and the rest motions of subjects 0, 5, 6 and 11 to dataset2. Tab.\[5\] lists the statistics of $rel^p$ of the motion generated by the CCNet finetuned on dataset1 (CCNet on dataset1) and dataset2 (CCNet on dataset2). Since the heights of subjects 1, 3, 4 and 8 are closer to subject 7’s height, the $rel^p$ of CCNet on dataset1 is less than that of dataset2, but still larger than that of CCNet trained with all mocap data in the training dataset. Thus, to improve the generalization ability of the CCNet to new skeletons, it is better to construct a database with more subjects for the network to learn how to handle skeleton variations.

6.4 User Study

We perform a t-test to verify the hypothesis that the CCNet can generate motions of better quality than baseline models. To this end, we design the user study as follows. First, we present 16 participants with all groups of motion sequences; three groups for random motion synthesis and four groups for controllable motion synthesis. Each group contains 16 pairs of motion sequences. One is the mocap sequence, and the other is generated by the CCNet or one of the baseline models (Please refer to the supplementary_material.pdf in "other supplementary materials" for the details of motion generation in the user study). Second, we ask the participants to select which sequence in a pair is of better motion quality. If the chosen number of CCNet-generated motion sequences is larger than the chosen number for other baseline models with statistical significance, we deem that our hypothesis is verified. The participants include six females and ten males, and all of them have experience with 3D animation or games. Before the user study, we present a few mocap sequences to the participants as examples of gooch-quality motions. Besides, if there are sudden changes or
Figure 11: Foot-ground penetrations in the motions generated by DAE-LSTM-rand, ERD-4LR-cond and PFNN-cond. (a) The 611th frame generated by DAE-LSTM-rand for subject 9 in random motion synthesis. (b) The 450th frame generated by ERD-4LR-cond for subject 7 in controllable motion synthesis. (c) The 666th frame generated by PFNN-cond for subject 8 in controllable motion synthesis. DAE-LSTM-rand, ERD-4LR-cond and PFNN-cond cannot effectively differentiate styles of different skeletons and lead to the foot-ground penetrations, as indicated by red rectangles. Furthermore, the motions generated by the CCNet is smoother.

| Groups              | numbers for CCNet (mean±std) |
|---------------------|------------------------------|
| ERD-4LR-rand vs. CCNet | 10.94±1.56                  |
| DAE-LSTM-rand vs. CCNet | 12.31±2.34                  |
| ERD-4LR-cond vs. CCNet | 11.63±2.87                  |
| DAE-LSTM-cond vs. CCNet | 16±0.0                      |
| PFNN-cond vs. CCNet  | 11.445±1.87                 |

Table 5: The average selected number for CCNet-generated motion sequences. Baseline-X vs. CCNet: a group of 16 pairs of motion sequences generated by a baseline model and the CCNet. Mean±std: mean and variance of the number of CCNet-generated motion sequences selected by all the participants.

foot penetrations into the ground plane, the sequence should be regarded as the worse one. At last, we get 15 valid questionnaires for random motion synthesis and 16 for controllable motion synthesis.

The t-test results are shown in Tab.4 The P-values of the CCNet vs. other baseline models are all less than the selected threshold (0.05). Therefore, the motions generated by the CCNet are significantly different from the motions generated by baseline models. According to the average number of motion sequences selected by the participants (mean in Tab.4), the average number of selected motion sequences of CCNet is larger than that of other baseline models. It verifies that the CCNet can generate better motions than state-of-the-art baseline models in different scenarios (The ANOVA test result in the supplementary material also verifies the statistical significance of the user study). Furthermore, we prepare another 5-group data that contain pairs of motion sequences generated by the CCNet and each baseline model. As listed in Tab.5, the number of CCNet-generated motion sequences selected by participants is still larger than that of the sequences generated by baseline models. Fig.14 shows examples of generated motion sequences used in this study. Motion jittering and penetrations into the ground plane frequently happen for motion sequences generated using ERD-4LR-cond, ERD-4LR-cond, and PFNN-cond, indicating that these models can’t handle the skeleton variations as well as the CCNet. In addition, we observe that DAE-LSTM-cond fails to generate long-period, controllable motion.

6.5 Evaluation of Network hyper-Parameters and Training Settings

In this section, we report the experiments conducted to figure out the hyper-parameters and training settings selected for the CCNet, including causal receptive length (CRL), numbers of consecutive frames of each sample in a batch (NCF), the length of seed frames, and the choice of smoothness loss term. We conduct all the experiments on the same training and validation datasets to verify our choices. Precisely, the chosen hyper-parameters for our CCNet in the random and controllable motion synthesis experiments above are as follows: CRL=41 and NCF=240. They are selected to minimize the loss in Eq.4 computed on mocap data in the validation set. For better visualization, the loss curves are plotted...
Figure 12: Loss curves obtained using different hyper-parameters of the CCNet. Left: Training. Right: Validation. We modify each hyper-parameter, including CRL, NCF and with/without skeleton configuration (w/_sk or w/o_sk), and compute the losses on the training and validation datasets respectively.

Figure 13: Ablation study of smoothness loss term. We remove the smoothness loss term and evaluate the corresponding re-trained model. Left: Training. Right: Validation.

using the formula $\log_{10}(\text{loss} + 320)$, where the loss is computed using Eq. 2. A bias 320 is added to make $\text{loss} + 320$ positive since the loss value is usually around $-300$.

Causal receptive length: We conduct experiments to choose the causal receptive length among three choices: 31 (with dilations of SRBs being repeatedly 1, 2), 41 (with dilations of SRBs being 2), and 46 (with dilations of SRBs being repeatedly 1, 2, 4), numbers of SRBs are fixed at 20 and we keep all the other settings the same as described in Section 5.1. When the causal receptive length is 31 and 46, the network converges to higher loss after training on the training dataset, as shown by the red dashed lines and green dash-dot lines in Fig. 12. We choose CRL as 41 that can lead to the lowest loss in this experiment.

NCF in a batch: We also test the NCF of each sample in a batch, which is set to be 60, 120, and 240, respectively. These numbers correspond to 1 second, 2 seconds, and 4 seconds long sequences. This can be easily achieved by changing the frame numbers in a batch and keep the other parameters the same. For the comparison’s convenience, we keep the numbers of consecutive frames of each sample in a batch fixed as 240 when computing the loss on the validation dataset. The cyan dashed lines in Fig. 12 illustrate that both training and validation loss exploded before converging when NCF is 60. The magenta dashed lines in Fig. 12 show that the network converges to a higher loss in the case of NCF=120, comparing to NCF=240. We hypothesize that 60 and 120 consecutive frames result in inadequate training data in a batch and too noisy gradient when training the network. Thus, we set NCF to 240 frames in training.

The importance of the skeleton configuration and the smoothness loss term: It is implemented by disconnecting the 1D convolution module for the skeleton configurations signal to the network and check whether the loss on the validation set increases significantly. The black dash-dot lines in Fig. 12 indicate that the network without skeleton configuration converges to a much higher loss when training on our multi-subject training dataset. However, the loss explodes at around 700 epochs on the validation dataset. Thus, the skeleton configuration plays an important role in the network to disambiguate different subjects’ motions. To verify the importance of smoothness loss term to the CCNet, we train the network by removing it from the loss terms. Fig. 13 indicates that the loss curves on both training and validation datasets explode before converging without smoothness term, which means the smoothness term is essential for the network to prevent the generated motions from big sudden changes and converge to a better result.

Seed frame length: The influence of seed frame length on the quality of generated motions is measured by computing the relative pose differences between generated motion and corresponding mocap data. Specifically, we extract seed frames from mocap data in the validation dataset and then let the networks predict a frame to be compared with the corresponding mocap frame in the case of controllable motion synthesis. Tab. 6 shows the computed relative pose
Table 6: Ablation study on the length of seed frames in the case of controllable motion synthesis. We synthesize motion sequences using different lengths of seed frames to check their influences on the generated motions. IK is disabled in this ablation study.

difference \( \text{rel}_p \) (see its definition in Sec. 6.3) for different seed frame length, such as 1, 5, 10, 30, 60 and 120. The lower difference value indicates that the generated motion is more similar to mocap data and thus of better quality. It can be seen that the CCNet is robust to the variation of the length of seed frames comparing to ERD-4LR-cond and DAE-LSTM-cond, and it doesn’t need too long seed frames to synthesize high-quality motions. However, we observe that there are more obvious jitters between the seed frames and the generated frames in the cases of 1 and 5 seed frame lengths. We hypothesize that, for such short length seed frames, the CCNet can’t get enough information to generate smooth motions.

7 Conclusion

We have designed a deep generative motion model, i.e., CCNet, based on causal convolution proposed in WaveNet [8] to synthesize high-quality motions for multiple subjects. The trained CCNet can also synthesize several types of complex motions, such as punching, kicking, and kicking while punching, included in our database. The CCNet can be applied to various applications, such as random motion generation, motion denoising, motion completion, and controllable motion synthesis. Moreover, the CCNet can generate motions for novel skeletons. Given sample motions of a novel skeleton, the pre-trained CCNet can be fine-tuned to capture the skeleton’s motion style.

Limitation and future work: Currently, the CCNet trained on our database can not handle arbitrary skeleton variation. For instance, if we scale the lower body of a skeleton in our database with a ratio less than 0.6, the CCNet without fine-tuning will generate motions with severe foot-ground penetration for the scaled skeleton. We hypothesize that it is because that 11 different skeletons in our training set might not be enough for the network to learn how to handle the large space of skeleton variation. Therefore, we plan to increase the number of subjects in the database to investigate the capacity of the CCNet. In addition, we also plan to increase the number and types of complex motions in the database to improve the quality of complex motion generation. Another issue with our CCNet is the number of seed frames required to initialize the motion synthesis. When seed frame length is set to between 1 and 5, jitters will occur in the generated motion, which might limit the application of the CCNet to model swift motions. We are also interested in investigating to take more temporal information as input, for instance, phase-like information in PFNN or joint accelerations, to mitigate this issue.

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8 Supplementary Material

8.1 Details of Network Parameters

CCNet: The detailed parameters of the separate dilation blocks (SRB) used in the CCNet are shown in Tab.8 and Tab.9 respectively. The format of the "output size" column is #channel×#NCF, where #channel indicates the numbers of feature channels and #NCF indicates the number of consecutive frames (NCF) of each sample in a batch.

The modification of ERD-4LR and DAE-LSTM: Both original ERD-4LR and DAE-LSTM networks in Sec.6 of our paper have 1024 hidden units in the linear layers and 512 hidden units in the LSTM layers. To test the performance of these two types of networks in the multi-subject motion synthesis, we add additional parameters to let the network accept as inputs the skeleton configuration. Specifically, we add a Linear-Tanh module (with 1024 hidden units in the Linear layer) for ERD-4LR and DAE-LSTM to map skeleton configurations to features and then add them to the feature output by the encoder. The summed features are fed to LSTM layers for the random motion synthesis. We denote these two adapted networks for random motion synthesis as ERD-4LR-rand and ERD-4LR-rand. Their network parameters are shown in Tab.10.

Similarly, to extend ERD-4LR and DAE-LSTM to support multi-subject, controllable motion synthesis, we additionally add a Linear-Tanh module (with 1024 hidden units in the Linear layer) to convert each of the control signals into features. Similarly, these features are added to the encoder output to form the input of subsequent LSTM layers. We denote the two adapted networks for controllable motion synthesis as ERD-4LR-cond and ERD-4LR-cond. Their network parameters are shown in Tab.11.

The modification of PFNN: We also adapt the network architecture of PFNN [5] to take the skeleton configuration as an input. It is implemented by replacing terrain data in its original inputs with the skeleton configuration since we only test the synthesis of motions on a ground plane. The rest inputs of PFNN remain the same as in [5]. Since PFNN is mainly designed for controllable motion synthesis, not a generative model, we only compare the CCNet with PFNN on controllable motion synthesis. The modified PFNN is denoted as PFNN-cond, and its network parameters are shown in Tab.12.

8.2 Trajectory-following Error Comparisons

Fig.14 illustrates the six manually specified trajectories used in the trajectory-following error comparison of controllable motion synthesis (the "comparisons" paragraph in Sec. 6.2 in our paper). The trajectory-following error for all the trajectories is visualized in Fig.9.

8.3 User Study

Motion generation: To conduct the user study, we first randomly select 16 mocap sequences from the validation dataset, including five motion sequences of subject 7 and one motion sequence of each of the rest of subjects in our database. Since subject 7 is not included in the training dataset, we thus choose more number of its motions to check the motion quality, in this case, more carefully. Secondly, for the user study on random motion synthesis, we initialize the
Table 7: ANOVA-test of user study for confidence interval=0.95 in the cases of random and controllable motion synthesis. SS: sum-of-squares for between-group variability. Df: degrees of freedom. MS: mean squares. F: F ratio. -: not applicable.

CCNet and baseline models using the first 120 frames of each mocap sequence as seed frames. Consequently, we obtain 16 sequences generated by CCNet, ERD-4LR-rand, and DAE-LSTM-rand, respectively, to form three groups of motion pairs. For controllable motion synthesis, seed frames are the same 120 frames of each sequence, and control signals are extracted from the 16 mocap sequences as described in section 4.2. The extracted control signals guarantee that these networks generate motions with the same motion types as the mocap sequences. We apply CCNet, ERD-4LR-cond, DAE-LSTM-cond, and PFNN-cond to generate 16 motion sequences separately. The average length of selected motion sequences is around 10 seconds, and the length of each generated motion sequence is chosen to be the same length as the corresponding mocap sequence. All the motion sequence pairs are present to the participants in a random order for their evaluation.

We name the videos of the generated motion sequences as follows: "rand0" and "cond0" are used for the videos of mocap data; "rand1" and "cond1" for the videos of motions generated by the CCNet; "rand2" and "cond2" for ERD-4LR-rand and ERD-4LR-cond; "rand3" and "cond3" for DAE-LSTM-rand and DAE-LSTM-cond; and "cond4" for PFNN-cond.

ANOVA-test: We also perform an ANOVA-test on the user study results as illustrated in Tab.7, which also verifies the statistical significance of the user study.

| Block name       | Output size | Filter size |
|------------------|-------------|-------------|
| CausalConv1      | 32x240      | 1x1, 32, stride 1, dilation 2, padding (2, 0); input: motion frames |
| cond1_conv1+ReLU | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: c1 |
| cond2_conv1+ReLU | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: c2 |
| cond3_conv1+ReLU | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: c3 |
| CausalConv2      | 32x240      | 1x1, 32, stride 1, dilation 2, padding (2, 0); input: the same as it to CausalConv1 |
| cond1_conv2+ReLU | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: the same as it to cond1_conv1 |
| cond2_conv2+ReLU | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: the same as it to cond2_conv1 |
| cond3_conv2+ReLU | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: the same as it to cond3_conv1 |
| sigmoid          | 32x240      | input: the sum of CausalConv1, cond1_conv1+ReLU, cond2_conv1+ReLU and cond3_conv1+ReLU |
| Tanh             | 32x240      | input: the sum of CausalConv2, cond1_conv2+ReLU, cond2_conv2+ReLU and cond3_conv2+ReLU |
| element-wise multiply | 32x240      | input: sigmoid and Tanh |
| conv_res         | 32x240      | 1x1, 32, stride 1, padding 1, dilation 1; input: element-wise multiply output(SRB_res): the sum of conv_res and the input to CausalConv1 |
| conv_skip        | 512x240     | 1x1, 512, stride 1, padding 1, dilation 1; input: element-wise multiply output(SRB_skips): the output of conv_skip |

Table 8: Network parameters of a single SRBi. The dilation of SRBi is 2.
Table 9: Network parameters of the CCNet. The input to the CCNet includes 240 frames of motions, the skeleton configuration c1, the direction and velocity c2, and the motion type c3. The network architecture of the CCNet is inspired by [8].

| Block name | Output size | Input/Output |
|------------|-------------|--------------|
| conv1+ReLU | 32×240      | 191, 32, stride 1, padding 1, dilation 1 |
| conv2+ReLU | 32×240      | 191, 32, stride 1, padding 1, dilation 1 |

| Encoder |                |
|---------|----------------|
| SFR0    | dilation 2; input: conv2, c1, c2 and c3 |
| SFR1    | dilation 2; input: SFR_res0, c1, c2 and c3 |
| SFR2    | dilation 2; input: SFR_res1, c1, c2 and c3 |
| SFR3    | dilation 2; input: SFR_res2, c1, c2 and c3 |
| SFR4    | dilation 2; input: SFR_res3, c1, c2 and c3 |
| SFR5    | dilation 2; input: SFR_res4, c1, c2 and c3 |
| SFR6    | dilation 2; input: SFR_res5, c1, c2 and c3 |
| SFR7    | dilation 2; input: SFR_res6, c1, c2 and c3 |
| SFR8    | dilation 2; input: SFR_res7, c1, c2 and c3 |
| SFR9    | dilation 2; input: SFR_res8, c1, c2 and c3 |
| SFR10   | dilation 2; input: SFR_res9, c1, c2 and c3 |
| SFR11   | dilation 2; input: SFR_res10, c1, c2 and c3 |
| SFR12   | dilation 2; input: SFR_res11, c1, c2 and c3 |
| SFR13   | dilation 2; input: SFR_res12, c1, c2 and c3 |
| SFR14   | dilation 2; input: SFR_res13, c1, c2 and c3 |
| SFR15   | dilation 2; input: SFR_res14, c1, c2 and c3 |

| Decoder |                |
|---------|----------------|
| ReLU+conv1 | 512×240      | 191, 32, stride 1, padding 1, dilation 1; input: the sum of SFR skip0, SFR skip1, ..., SFR skip14 |
| ReLU+conv4 | 613×240      | 191, 313, stride 1, padding 1, dilation 1 |

Table 10: Network parameters of the ERD-4LR-rand and ERD-4LR-cond. The inputs to the ERD-4LR-rand and ERD-4LR-cond include 240 frames of motions, the skeleton configuration c1, the direction and velocity c2, and the motion type c3. The overall network architectures of ERD-4LR-rand and ERD-4LR-cond are the adaptation of [2] to multi-subject motion synthesis, but implemented with 4-layers LSTM as in [6].

| Block name | Output size | Input/Output |
|------------|-------------|--------------|
| linear1+Tanh | 1024×240 | input: motion frames output: linear1 |
| linear2+Tanh | 1024×240 | input: linear1 output: linear2 |
| cond1_linear+Tanh | 1024×240 | input: c1 output: cond1_linear |
| cond2_linear+Tanh | 1024×240 | input: c2 output: cond2_linear |
| cond3_linear+Tanh | 1024×240 | input: c3 output: cond3_linear |
| LSTM1 | 512×240 | input: lstm1 output: lstm2 |
| LSTM2 | 512×240 | input: lstm1 output: lstm2 |
| LSTM3 | 512×240 | input: lstm1 output: lstm3 |
| LSTM4 | 512×240 | input: lstm1 output: lstm4 |
| linear3+Tanh | 1024×240 | input: lstm1 output: linear3 |
| linear4+Tanh | 613×240 | output: the predicted motion frames |

(a) ERD-4LR-rand.

| Block name | Output size | Input/Output |
|------------|-------------|--------------|
| linear1+Tanh | 1024×240 | input: motion frames output: linear1 |
| linear2+Tanh | 1024×240 | input: linear1 output: linear2 |
| cond1_linear+Tanh | 1024×240 | input: c1 output: cond1_linear |
| cond2_linear+Tanh | 1024×240 | input: c2 output: cond2_linear |
| cond3_linear+Tanh | 1024×240 | input: c3 output: cond3_linear |
| LSTM1 | 512×240 | input: lstm1 output: lstm2 |
| LSTM2 | 512×240 | input: lstm1 output: lstm2 |
| LSTM3 | 512×240 | input: lstm1 output: lstm3 |
| LSTM4 | 512×240 | input: lstm1 output: lstm4 |
| linear3+Tanh | 1024×240 | input: lstm1 output: linear3 |
| linear4+Tanh | 613×240 | output: the predicted motion frames |

(b) ERD-4LR-cond.
| Block name | Output size | Input/Output |  |
|------------|-------------|--------------|---|
| dropout+linear1+ReLU | 1024x240 | dropout probability: 0.3  
input: motion frames  
output: linear1 |  |
| linear2+ReLU | 1024x240 | input: linear1  
output: linear2 |  |
| linear3+ReLU | 1024x240 | input: linear2  
output: linear3 |  |
| linear4 | 305x240 | input: linear3  
output: linear4 |  |
| LSTM1 | 512x240 | input: linear2, output: lstm1 |  |
| LSTM2 | 512x240 | input: lstm1  
output: lstm2 |  |
| LSTM3 | 512x240 | input: lstm2  
output: lstm3 |  |
| linear5 | 613x240 | input: lstm3  
output: the predicted motion frames |  |

(a) DAE-LSTM-rand.

Table 11: Network parameters of DAE-LSTM-rand and DAE-LSTM-cond. The inputs to the DAE-LSTM-rand and DAE-LSTM-cond include 240 frames of motions, the skeleton configuration $c_1$, the direction and velocity $c_2$, and the motion type $c_3$. The overall network architectures of DAE-LSTM-rand and DAE-LSTM-cond are the adaptation of the network in [25] to multi-subject motion synthesis.

| Block name | Output size | Input/Output |  |
|------------|-------------|--------------|---|
| dropout+linear1+ReLU | 1024x240 | dropout probability: 0.3  
input: motion frames  
output: linear1 |  |
| linear2+ReLU | 1024x240 | input: linear1  
output: linear2 |  |
| linear3+ReLU | 1024x240 | input: linear2  
output: linear3 |  |
| linear4 | 305x240 | input: linear3  
output: linear4 |  |
| cond1_linear+Tanh | 1024x240 | input: $c_1$  
output: cond1_linear |  |
| cond2_linear+Tanh | 1024x240 | input: $c_2$  
output: cond2_linear |  |
| cond3_linear+Tanh | 1024x240 | input: $c_3$  
output: cond3_linear |  |
| LSTM1 | 512x240 | input: the sum of the linear4, cond1_linear, cond2_linear and cond3_linear  
output: lstm1 |  |
| LSTM2 | 512x240 | input: lstm1  
output: lstm2 |  |
| LSTM3 | 512x240 | input: lstm2  
output: lstm3 |  |
| linear5 | 613x240 | input: lstm3  
output: the predicted motion frames |  |

(b) DAE-LSTM-cond.

Table 12: Network parameters of the PFNN-cond. The input to the PFNN-cond is described in Sec.1 in the supplementary material.

| Block name | Output size | Input/Output |  |
|------------|-------------|--------------|---|
| dropout+pfnn_linear1+ELU | 512x1 | dropout probability: 0.7  
input: the concatenation of motion frames and control signals  
output: pfnn_linear1 |  |
| dropout+pfnn_linear2+ELU | 512x1 | dropout probability: 0.7  
input: pfnn_linear1  
output: pfnn_linear2 |  |
| dropout+pfnn_linear3 | 437x1 | dropout probability: 0.7  
input: pfnn_linear2  
output: the predicted motion frames and control signals |  |

Figure 14: Six trajectories used in trajectory-following comparisons. The green color indicates the starting point of a trajectory, while the red color indicates the terminal point.