Human Motion Synthesis: A Diffusion Approach for Motion Stitching and In-Betweening

Michael Adewole* Department of Computer Engineering Olabisi Onabanjo University Ago-Iwoye, Ogun State michaseyi@gmail.com

Oluwaseyi Giwa African Institute for Mathematical Sciences South Africa oluwaseyi@aims.ac.za

Favour Nerrise Department of Electrical Engineering Stanford University fnerrise@stanford.edu

Martins Osifeko Department of Computer Engineering Olabisi Onabanjo University osifeko.martins@oouagoiwoye.edu.ng

Ajibola Oyedeji Department of Computer Engineering Olabisi Onabanjo University oyedeji.ajibola@oouagoiwoye.edu.ng

Abstract

Human motion generation is an important area of research in many fields. In this work, we tackle the problem of motion stitching and in-betweening. Current methods either require manual efforts, or are incapable of handling longer sequences. To address these challenges, we propose a diffusion model with a transformer-based denoiser to generate realistic human motion. Our method demonstrated strong performance in generating in-betweening sequences, transforming a variable number of input poses into smooth and realistic motion sequences consisting of 75 frames at 15 fps, resulting in a total duration of 5 seconds. We present the performance evaluation of our method using quantitative metrics such as Frechet Inception Distance (FID), Diversity, and Multimodality, along with visual assessments of the generated outputs.

^{*}corresponding authors - michaseyi@gmail.com and giwaoluwaseyi475@gmail.com.

1 Introduction

Human motion data are important, perhaps evident by its extensive usage across various fields. Human motion generation techniques play important roles from driving character animation movies and video games to robotics striving for a more natural and human-like feel. Motion capture devices and hand-sculpted human motion sequences are common ways to acquire human motion. However, due to the high cost of quality motion capture devices, the skills required to keyframe human motion manually, and their flexibility and limitations, it is not feasible for many applications. The demand for high-quality human motion data has precipitated extensive research on human motion generation, with the primary goal of generating realistic and natural human motion.

Over the years, there have been numerous work leveraging the generative capabilities of artificial intelligence for this task. In particular, we have seen the use of neural network-based models such as diffusion transformer models [Shi et al., 2023], generative adversarial networks (GAN) [Lin and Amer, 2018], variable autoencoders (VAE) [Habibie et al., 2017], convolutional neural networks (CNN) [Zhou et al., 2019, Pavllo et al., 2019] and recurrent neural networks (RNN) [Martinez et al., 2017, Zhou et al., 2018a, Pavllo et al., 2018] producing promising results. These approaches offer the potential to overcome the limitations of traditional methods, making high-quality human motion more accessible for many applications.

Despite recent advances in human motion generation, there is relatively little research focused on motion stitching. Motion stitching involves generating a realistic motion sequence that passes through given keyframes. These keyframes can appear at any point in the sequence. Although existing studies address continuous motion generation from prior motion data, few explicitly tackle this challenge. For example, [Martinez et al., 2017] proposed a sequence-to-sequence RNN architecture with residual connections to enhance short-term human motion prediction by directly modeling motion velocities. The sampling-based loss function was used to ensure the model recovered from its prediction errors during training. QuaterNet [Pavllo et al., 2019], an extension of earlier [Pavllo et al., 2018], uses a CNN over its original RNN approach and focuses on quaternions for rotation representation, eliminating discontinuities and singularities that can hinder training. QuaterNet uses a positional geometric loss function, the predicted rotations are converted to joint positions using forward kinematics. However, these models are limited as they require all motion frames to follow each other and be positioned at the start of the sequence.

[Harvey et al., 2021] addressed this challenge by proposing the use of an adversarial RNN architecture with additive embedding modifiers to handle varying transition lengths. It also used scheduled target noise vectors for a diverse generation of realistic motions. However, their method operated primarily in the latent space of the RNN which could limit its ability to fully leverage the explicit temporal relationships that exist between motion frames.

To address these challenges, we propose a diffusion model approach. First, we pass the input motion frames encoded with their position in the motion sequence and the current diffusion step into an encoder transformer. Here, we capture the relationships between motion frames with the help of the self-attention mechanism as described in [Vaswani et al., 2017]. Next, the encoder output is used together with an initial Gaussian noise as input to another encoder transformer to predict the clean motion at the given time step. The role of the transformer is to serve as a denoiser as described in [Ho et al., 2020]. We incorporate the idea of predicting clean data instead of noise from [Shi et al., 2023]. The output of this transformer is then fed to a noise scheduler which adds random Gaussian noise based on the current time step to retrieve the noisy input for that time step. This noisy input is then returned in place of the initial Gaussian noise. The entire process is repeated for a predefined number of times.

Our contributions are as follows:

- We developed a diffusion model that generates realistic human motion, filling missing motion frames within a given sequence.
- We demonstrated the effectiveness of our method through extensive experiments on short-term and long-term motion generation tasks.



Figure 1: The workflow of our approach. Contextual information is extracted from the input poses c using a transformer encoder. The output is used to transform noisy motion data x_t to clean motion \hat{x}_0^t using another transformer encoder. The clean motion goes through the noise schedule to generate the noisy data x_{t-1} for the next timestep. This process is repeated for a predefined number of iterations.

2 Related Works

2.1 Human Motion Generation

Prior work on human motion generation can be classified according to the input condition used for motion generation. These classifications include text-to-motion, action class-to-motion, prior motion-to-motion, and video-to-motion.

Transformation of text into motion involves generating motion from a text description. An encoder like CLIP [Radford et al., 2021] is often used to encode the input. [Chen et al., 2022] used VAEs to learn a representation of human motion, then performed diffusion on this latent space representation instead of the raw motion data. MotionCLIP [Tevet et al., 2022] also used autoencoders, but instead mapped the CLIP representation of text to motion. MotionGPT [Zhang et al., 2024] employed LLMs fine-tuned with LoRA [Hu et al., 2021] for motion generation. Motion generation tasks are fed into it as a prompt. [Guo et al., 2022] used autoencoders to generate motion sequences with dynamic lengths from text by also predicting the length from the text. They also proposed the HumanML3D dataset. FG-MDM [Shi et al., 2023] further improved the generalization capabilities of these models by conditioning the input with LLMs. FG-MDM used LLMs to expand the text description of motion from the HumanML3D dataset [Guo et al., 2022] by including additional descriptions of several body parts through the motion encoded with CLIP.

Action class-to-motion methods focus on generating motion from a discrete number of classes describing the motion. Some of these classes may include 'running,' 'jumping,' 'walking,' etc. For example, Action2Motion, [Guo et al., 2020], proposed a temporal VAE with Lie algebra-based pose representation. This approach was tested on the NTU-RGB+D dataset with 120 action classes and HumanAct12 with 12 course-grained action classes. [Petrovich et al., 2021] also used a VAE and evaluated their approach on the same dataset as [Guo et al., 2020]. Unlike previous work that examined the loss in joint rotation or the loss in reconstruction in joint positions, the authors assessed the loss in reconstructed vertices of the SMPL body model [Loper et al., 2015] and also opted for a 6D rotation representation [Zhou et al., 2018b] for training. [Yang et al., 2018] proposed a pose sequence generative adversarial network (PSGAN) on labelled action classes to drive a human video generation model. PSGAN employed an encoder-decoder architecture with residual blocks and LSTM modules for temporal modeling.

In video-to-motion, [Sun et al., 2021] introduced a framework to forecast human motion from past video frames. The core idea was utilizing action-specific memory banks to capture motion dynamics. The system first predicts the action class from the observed video frames and then queries the memory bank associated with the predicted action class to get relevant motion dynamics. Another work by

[Pavllo et al., 2018] achieves a slightly different goal, the authors proposed a method to extract the human motion data described in a video sequence using a temporal convolution model. Their work has served as a tool for powering optical motion capture devices.

More closely related to this study is motion generation from prior motion. In addition to the work [Martinez et al., 2017, Pavllo et al., 2019] discussed in the previous section, [Hernandez et al., 2018] presented STIM-GAN, designed to preserve temporal coherence between generated motion and introduced frequency-based metrics for accessing motion quality. [Harvey et al., 2018] proposed a Recurrent Transition Network (RTN) to generate a realistic motion transition between different states. The core of RTN uses LSTM with initialized hidden states. [Zang et al., 2020] proposed MoPredNet, a few-shot human motion prediction model that leverages deformable spatio-temporal convolution network (DSTCN), sequence masks, and a parameter generation module to adapt to new motion dynamics and make accurate long-term predictions. [Qu et al., 2024] introduced FMP-OC, a framework that uses LLMs for predicting motion with a few shots without additional training. This framework bridges the gap between LLMs and numeric motion data. Unlike the classes of models discussed above, [Holden et al., 2016] presented a convolutional autoencoder that takes in high-level parameters such as the trajectory of a character over terrain and the movement of the end effectors (hands and feet) to generate full body motion.

2.2 Representing Rotation

The choice of rotation representation is important in training neural networks as it directly affects the stability and accuracy of the learning process. [Pavllo et al., 2019] highlighted two critical properties for rotation representation; continuity and interpolation. These properties rule out Euler angles as a suitable rotation representation. Exponential maps, another alternative to represent rotation, suffer the same fate. However, quaternions possess 3D interpolation properties, with only two quaternions encoding the same rotation. The authors presented an approach to resolve this ambiguity to ensure that the quaternion representation was continuous.

Upon further exploration of the rotation representation, [Zhou et al., 2018b] proposed the continuous rotation representation in higher dimensions. They proposed a method to represent rotation in 5D and 6D for any given 3D rotation. Another work by [Xiang and Li, 2020] discusses the effectiveness of higher-dimensional rotation representations such as 5D and 6D embedding. They revealed that even higher-dimensional representation could struggle in certain scenarios, particularly when dealing with point clouds with nontrivial rotational symmetry. The authors use ensembles of representation to mitigate these issues.

3 Methodology

Given a set of input poses $\mathbf{c} \in \mathbb{R}^{L \times F}$ and respective pose indices $\mathbf{c}_i \in \mathbb{R}^L$, $F = 3 + J \cdot D$, D represents the number of dimensions of the joint representation (e.g., a quaternion or 6D rotation representation [Zhou et al., 2018b]), and J is the number of joints, the objective is to generate output motion sequence $\mathbf{x} \in \mathbb{R}^{B \times F}$. L is the context length or the number of input poses. B is the block size or the length of the generated motion sequence. L ranges from 1 to B/2, F is the dimensionality of each pose representation, which includes the 3D position of the root joint relative to the first frame in the motion sequence, joint features (e.g., rotations), which are encoded in D dimensions for each of the J joints. \mathbf{x} is ensured to retain the poses in \mathbf{c} at specified index \mathbf{c}_i and to follow the dynamics and patterns observed in \mathbf{c} .

3.1 Denoising Diffusion Model

The proposed method uses a diffusion model for generating human motion. This process is inspired by the natural phenomenon of diffusion, where particles spread from regions of higher concentration to lower concentration until equilibrium is achieved. The exception here is that the aim is to learn the reverse process, from a state of high entropy (i.e. standard normal noise) to a state of low entropy (i.e. clean data). It consists of two sub-processes, the forward process and the reverse process. The primary component of the forward process is the noise scheduler. Starting with clean data \mathbf{x}_0 at t = 0, Gaussian noise $\mathcal{N}(\mu, \sigma^2)$ is gradually added to \mathbf{x}_0 . At each time step t, μ , and σ are determined by the noise schedule. The goal is to transform \mathbf{x}_0 into \mathbf{x}_t where \mathbf{x}_t is approximately a standard normal distribution $\mathcal{N}(0, I)$ with high entropy. The reverse process aims to reverse the forward process by predicting clean data \mathbf{x}_0 , or the standard normal noise added. This stage is performed by a denoiser. In our case, at each time step, the denoiser takes in noisy data \mathbf{x}_t and predicts clean data $\hat{\mathbf{x}}_0^t$. This step is done iteratively for the number of given time steps to generate the final clean data.

3.2 Noise Schedule

The choice of the beta schedule determines how noise is introduced during the forward process. Our method uses a noise schedule with a sample linear beta schedule [Ho et al., 2020] among others including the cosine [Nichol and Dhariwal, 2021] and the sigmoid [Jabri et al., 2022] beta schedule. The noise schedule, denoted by β_t , is defined as:

$$\beta_t = \beta_{\min} + t \cdot \frac{\beta_{\max} - \beta_{\min}}{T} \tag{1}$$

where β_{\min} and β_{\max} are the minimum and maximum noise levels, respectively, and T is the total number of time steps. With β_t defined, the forward diffusion process for any given time step t can be described as in equation 2. $\bar{\alpha}_t$ represents the cumulative product of noise coefficients up to time step t, and $\epsilon \sim \mathcal{N}(0, I)$ is Gaussian noise.

$$x_t = \sqrt{\bar{\alpha}_t} \, x_0 + \sqrt{1 - \bar{\alpha}_t} \, \epsilon \tag{2}$$

$$\bar{\alpha}_t = \prod_{s=1}^t (1 - \beta_s) \tag{3}$$

3.3 Denoiser Network

The denoiser network is built on the transformer architecture. It consists of two encoders. For each sampling step, a masked input encoded with the current time step is generated using c and c_i and passes through a stack of transformer encoder layers. The output, together with x_t , which is initially standard normal noise, is fed into another stack of transformer encoder layers to predict clean motion \hat{x}_0^t . If the current time step is greater than zero, x_{t-1} , noisy data for the next denoising step are obtained from equation 4. \hat{x}_0^t is the predicted clean motion at time step t, $\tilde{\beta}_t$ is the posterior variance at time step t and $\epsilon \sim \mathcal{N}(0, I)$ denotes standard normal noise. This process continues until T iterations are completed and the final clean motion \hat{x}_0^0 is obtained.

$$x_{t-1} = \hat{x}_0^t + \sqrt{\tilde{\beta}_t} \cdot \epsilon \tag{4}$$

3.4 Forward Kinematics

To reconstruct the joint positions from individual local joint rotations and the global root position, we define a function FK(x; A(i), B) to perform the forward kinematic process. x is a tensor of rotation matrices representing local rotation for each joint. A(i) is a function that returns the kinematic chain of the target joint with index i, this chain is an ordered set of joints connecting the root joint to the target joint. B is an ordered set of position vectors for each joint defining the rest pose. For a joint at index i, the position is calculated as shown in equation 5. j_p denotes the index of the parent to j in the kinematic chain A(i). For the case where j is the index of the root joint, we set B_{j_p} to a zero vector.

$$p_i = \left(\prod_{j \in A(i)} \begin{bmatrix} x_j & 0\\ B_j - B_{j_p} & 1 \end{bmatrix}\right) \begin{bmatrix} 0\\ 1 \end{bmatrix}$$
(5)

3.5 Training Objective

The training objective at any time step is to minimize the error between x_0 and \hat{x}_0^t . We define a composite loss function l with five components for this.

• Model Loss l_g : Measures the distance between the predicted clean motion \hat{x}_0 at time step t and the ground truth motion x_0 .

$$l_g = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\hat{x}_0^{t(i)} - x_0^{(i)}\right)^2} \tag{6}$$

• Reconstruction Loss l_r : Measures the distance between the reconstructed joint position of the predicted clean motion and the ground truth.

$$l_r = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(FK(\hat{x}_0^{t(i)}) - FK(x_0^{(i)}) \right)^2}$$
(7)

• Context Loss l_c : Measures the distance between the reconstructed joint positions of context keypoints in the predicted clean motion \hat{x}_0^t and the ground truth motion x_0 for the context indices c_i .

$$l_{c} = \sqrt{\frac{1}{|c_{i}|} \sum_{i \in c_{i}} \left(FK(\hat{x}_{0}^{t(i)}) - FK(x_{0}^{(i)}) \right)^{2}}$$
(8)

Rotation Velocity Loss l_{r_vel}: Measures the distance between the rotation velocities of the predicted clean motion x⁰₀ and the ground truth motion x₀.

$$l_{r_vvel} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} \left((\hat{x}_0^{t(i+1)} - \hat{x}_0^{t(i)}) - (x_0^{(i+1)} - x_0^{(i)}) \right)^2}$$
(9)

• Position Velocity Loss l_{p_vel} : Measures the distance between the position velocities of the predicted clean motion \hat{x}_0^t and the ground truth motion x_0 .

$$l_{p_vel} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} \left((FK(\hat{x}_0^{t(i+1)}) - FK(\hat{x}_0^{t(i)})) - (FK(x_0^{(i+1)}) - FK(x_0^{(i)})) \right)^2}$$
(10)

FK is a function that computes the joint positions from joint orientation and root position using the forward kinematic process. The total loss is a sum of these components:

$$l = l_g + l_r + l_c + l_{r_vel} + l_{p_vel}$$
(11)

4 **Experiments**

4.1 Dataset and Preprocessing

Our experiment used five AMASS data sets [Mahmood et al., 2019]. This included CMU mocap [Carnegie Mellon University], BMLrub [Troje, 2002], DanceDB [Aristidou et al., 2019], SFU [University and of Singapore], and MPI Limits [Akhter and Black, 2015]. We trained our model on CMU mocap, BMLrub, and DanceDB. We then evaluated the zero-shot performance of our model on SFU and MPI Limits. The CMU mocap dataset consists of 1983 motions from 96 subjects totaling 543 minutes of motion data. The dataset covers various human activities, including walking, running, dancing, and other everyday activities. The BMLrub dataset consists of 3061 motion sequences performed by 111 subjects covering 522 minutes of motion data. DanceDB consists of a wide range of dance styles and performances. It includes over 150 motions, with 20 subjects and a total duration of 203 minutes. SFU and MPI Limits are on the smaller side, with a total duration of 15 and 20 minutes, respectively. SFU consists of 44 motions with 7 different subjects, while MPI Limits includes 35 motion sequences with 3 subjects. We executed a pipeline with three stages to preprocess the datasets. First, each motion sequence is downsampled to a target frame rate of 15 fps. This is done by selecting frames at an interval determined by the source and target frame rate. The second stage of the pipeline involves generating chunks of motion sequences for training purposes. Here, we split motion sequences into chunks of 75 frames each, representing 5 seconds. The final stage involves increasing the output of the previous stage. We extended the data size by rotating each motion sequence randomly twice around the vertical axis. We utilized a data split of 80-10-10 for training, validating and testing respectively.

4.2 Experimental Setup

In our experiment, we used 6D rotation representation [Zhou et al., 2018b] and two encoder transformers with the following configurations. Each encoder consists of six layers, an input dimension of 512, a feed-forward dimension of 2048, eight attention heads, and drop-out layers of 0.1 drop rate. The model was trained with a batch size of 128 and 300 diffusion time steps on a single NVIDIA P100 GPU provided by Kaggle.

4.3 Evaluation Metrics

To evaluate the effectiveness of our model in generating high quality and diverse motion sequences, we employ three different metrics: Frechet Inception Distance (FID), Diversity, and Multimodality. These metrics are discussed in the following.

- Frechet Inception Distance (FID): FID was originally introduced to measure the performance of GANs on image generation tasks. It has continued to be used in general on generation tasks. It measures the distance between the extracted feature distribution of real and generated data. It works by comparing the mean and covariance matrix of the extracted features from both real and generated data. A lower FID score indicates the feature distribution of generated data is closer to real data and can be considered to be realistic and of high quality.
- Diversity: Diversity measures the variation in the model's generated output across various input condition. It can be calculated by averaging the pairwise distance between generated samples in feature space. High diversity indicates that the model can generate a wide variety of distinct outputs.
- Multimodality: This measures the ability of the model to generate varied motion sequences from similar input or context. This is useful for a generative model where there could be multiple valid outputs for the same input condition, and we want the model to capture the full range of this space. Calculated by measuring the average pairwise distance between generated samples that share the same input condition.

To extract the required features for computing these metrics, we trained an autoencoder to extract a feature embedding of \mathbb{R}^{256} from a given motion sequence, mapping $f : \mathbb{R}^{B \times F} \to \mathbb{R}^{256}$.

5 Results and Analysis

We present the results of our evaluation as follows:

5.1 Visual Evaluation of Generated Motion

The following figures 2 to 5 illustrate the generated motion sequence output of our model. These images represent various frames of the generated sequences which illustrates motion dynamics over time. The generated frames have been downsampled for clearer visualization.



Figure 2: Sample output from our model on unseen input motion. The red body indicates the input poses. This has been downsampled for clearer visualization and the ratio of input poses to generated output is maintained.



Figure 3: Sample output from our model on unseen input motion. This has been downsampled for clearer visualization. Each frame has been sufficiently spaced to prevent overlapping.



Figure 4: Sample output from our model on unseen input motion. Each frame has been sufficiently spaced to prevent overlapping.

5.2 Quantitative Evaluation Metrics

In table 1, we present the evaluation results of our model with input lengths of 10 and 20 across multiple datasets. The multimodality scores decrease as the number of input poses increases, due to stronger constraints imposed by the increased input length, reducing the ambiguity in the generated motion sequence. It is important to mention that this table does not include multimodality scores for real data as it is not grouped by identical motion frames.

6 Conclusion

In this study, we explored the use of diffusion models for motion stitching and in-betweening. We trained a transformer-based denoiser on datasets from AMASS and presented the output of sampling our model using the reverse diffusion process for 300 timesteps. Furthermore, we present the performance evaluation of our model using FID, Diversity, and Multimodality metrics. Some limitations of this study include the fixed output sequence length, motion generation from unrealistic input key poses and model performance degradation on smaller input context length. For future work, we aim to consider additional input conditions to capture more contextual information about



Figure 5: Sample output from our model on unseen input motion. Each frame has been sufficiently spaced to prevent overlapping. Root position and orientation are not visualized.

Dataset	Method	FID \downarrow	Diversity \uparrow	Multimodality \uparrow
CMU	Real	$0.026^{\pm 0.003}$	$2.788^{\pm 0.032}$	-
	$Ours_{ c =20}$	$0.392^{\pm 0.006}$ 0.514 ^{\pm 0.009}	$2.991^{\pm 0.039}$ $3.147^{\pm 0.033}$	$0.165^{\pm 0.027}$ 0.173^{\pm 0.019}
BMLrub	Real	$\frac{0.014}{0.015^{\pm 0.003}}$	$\frac{3.147}{2.545^{\pm 0.038}}$	-
	$\frac{\text{Ours}_{ c =20}}{\text{Ours}_{ c =10}}$	$\begin{array}{c} 0.253^{\pm 0.006} \\ 0.265^{\pm 0.007} \end{array}$	$2.625^{\pm 0.037} \\ 2.472^{\pm 0.028}$	$\begin{array}{c} 0.097^{\pm 0.008} \\ 0.117^{\pm 0.011} \end{array}$
DanceDB	Real	$0.073^{\pm 0.006}$	$3.610^{\pm 0.019}$	_
	$Ours_{ c =20}$ $Ours_{ c =10}$	$\begin{array}{c} 0.716^{\pm 0.003} \\ 0.924^{\pm 0.002} \end{array}$	$3.751^{\pm 0.057} \\ 3.788^{\pm 0.015}$	$\begin{array}{c} 0.362^{\pm 0.035} \\ 0.488^{\pm 0.048} \end{array}$
SFU	Real	$0.199^{\pm 0.094}$	$3.033^{\pm 0.049}$	-
	$\frac{\text{Ours}_{ c =20}}{\text{Ours}_{ c =10}}$	$\begin{array}{c} 0.742^{\pm 0.011} \\ 0.801^{\pm 0.005} \end{array}$	$\begin{array}{c} 3.139^{\pm 0.053} \\ 3.202^{\pm 0.038} \end{array}$	$\begin{array}{c} 0.209^{\pm 0.018} \\ 0.235^{\pm 0.039} \end{array}$
MPI Limits	Real	$0.319^{\pm 0.087}$	$2.743^{\pm 0.046}$	-
	$\frac{\text{Ours}_{ c =20}}{\text{Ours}_{ c =10}}$	$\frac{1.550^{\pm 0.001}}{2.268^{\pm 0.001}}$	$\begin{array}{c} 2.937^{\pm 0.040} \\ 3.0124^{\pm 0.068} \end{array}$	$\begin{array}{c} 0.235^{\pm 0.031} \\ 0.355^{\pm 0.042} \end{array}$

Table 1: Evaluation metrics for different datasets

the desired output motion sequence, for example, a textual description of the desired output motion. Conditioning on more contextual information is important to guide stitching and in-betweening on longer motion generation tasks.

References

- Xu Shi, Wei Yao, Chuanchen Luo, Junran Peng, Hongwen Zhang, and Yunlian Sun. Fg-mdm: Towards zero-shot human motion generation via fine-grained descriptions. 12 2023. URL http: //arxiv.org/abs/2312.02772.
- Xiao Lin and Mohamed R. Amer. Human motion modeling using dvgans. 4 2018. URL http: //arxiv.org/abs/1804.10652.
- Ikhsanul Habibie, Daniel Holden, Jonathan Schwarz, Joe Yearsley, and Taku Komura. A recurrent variational autoencoder for human motion synthesis. *British Machine Vision Conference 2017*, *BMVC 2017*, 2017. doi: 10.5244/C.31.119.
- Dongsheng Zhou, Xinzhu Feng, Pengfei Yi, Xin Yang, Qiang Zhang, Xiaopeng Wei, and Deyun Yang. 3d human motion synthesis based on convolutional neural network. *IEEE Access*, 7:66325–66335, 2019. ISSN 21693536. doi: 10.1109/ACCESS.2019.2917609.
- Dario Pavllo, Christoph Feichtenhofer, Michael Auli, and David Grangier. Modeling human motion with quaternion-based neural networks. *International Journal of Computer Vision*, 128:855–872, 1 2019. doi: 10.1007/s11263-019-01245-6. URL http://arxiv.org/abs/1901.07677http://dx.doi.org/10.1007/s11263-019-01245-6.
- Julieta Martinez, Michael J. Black, and Javier Romero. On human motion prediction using recurrent neural networks. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition*, *CVPR 2017*, 2017-January:4674–4683, 5 2017. doi: 10.1109/CVPR.2017.497. URL https: //arxiv.org/abs/1705.02445v1.
- Yi Zhou, Zimo Li, Shuangjiu Xiao, Chong He, Zeng Huang, and Hao Li. Auto-conditioned recurrent networks for extended complex human motion synthesis. 6th International Conference on Learning Representations, ICLR 2018 Conference Track Proceedings, 2018a.

- Dario Pavllo, Christoph Feichtenhofer, David Grangier, and Michael Auli. 3d human pose estimation in video with temporal convolutions and semi-supervised training. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2019-June:7745–7754, 11 2018. ISSN 10636919. doi: 10.1109/CVPR.2019.00794. URL https://arxiv.org/abs/ 1811.11742v2.
- Félix G. Harvey, Mike Yurick, Derek Nowrouzezahrai, and Christopher Pal. Robust motion inbetweening. ACM Transactions on Graphics, 39:12, 2 2021. doi: 10.1145/3386569.3392480. URL http://arxiv.org/abs/2102.04942http://dx.doi.org/10.1145/3386569.3392480.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in Neural Information Processing Systems*, 2017-December:5999–6009, 6 2017. ISSN 10495258. URL https://arxiv.org/abs/1706.03762v7.
- Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. Advances in Neural Information Processing Systems, 2020-December, 6 2020. ISSN 10495258. URL https://arxiv.org/abs/2006.11239v2.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. *Proceedings of Machine Learning Research*, 139:8748–8763, 2 2021. ISSN 26403498. URL https://arxiv.org/abs/ 2103.00020v1.
- Xin Chen, Biao Jiang, Wen Liu, Zilong Huang, Bin Fu, Tao Chen, and Gang Yu. Executing your commands via motion diffusion in latent space. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2023-June:18000–18010, 12 2022. ISSN 10636919. doi: 10.1109/CVPR52729.2023.01726. URL https://arxiv.org/abs/2212. 04048v3.
- Guy Tevet, Brian Gordon, Amir Hertz, Amit H. Bermano, and Daniel Cohen-Or. Motionclip: Exposing human motion generation to clip space. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 13682 LNCS:358–374, 3 2022. ISSN 16113349. doi: 10.1007/978-3-031-20047-2_21. URL https: //arxiv.org/abs/2203.08063v1.
- Yaqi Zhang, Di Huang, Bin Liu, Shixiang Tang, Yan Lu, Lu Chen, Lei Bai, Qi Chu, Nenghai Yu, and Wanli Ouyang. Motiongpt: Finetuned llms are general-purpose motion generators. *Proceedings* of the AAAI Conference on Artificial Intelligence, 38:7368–7376, 3 2024. ISSN 23743468. doi: 10.1609/aaai.v38i7.28567.
- Edward Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *ICLR 2022 10th International Conference on Learning Representations*, 6 2021. URL https://arxiv.org/abs/2106.09685v2.
- Chuan Guo, Shihao Zou, Xinxin Zuo, Sen Wang, Wei Ji, Xingyu Li, and Li Cheng. Generating diverse and natural 3d human motions from text. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2022-June:5142–5151, 2022. ISSN 10636919. doi: 10.1109/CVPR52688.2022.00509.
- Chuan Guo, Xinxin Zuo, Sen Wang, Shihao Zou, Qingyao Sun, Annan Deng, Minglun Gong, and Li Cheng. Action2motion: Conditioned generation of 3d human motions. *MM 2020 Proceedings of the 28th ACM International Conference on Multimedia*, pages 2021–2029, 7 2020. doi: 10.1145/3394171.3413635. URL http://arxiv.org/abs/2007.15240http://dx.doi.org/10.1145/3394171.3413635.
- Mathis Petrovich, Michael J. Black, and Gül Varol. Action-conditioned 3d human motion synthesis with transformer vae. *Proceedings of the IEEE International Conference on Computer Vision*, pages 10965–10975, 4 2021. ISSN 15505499. doi: 10.1109/ICCV48922.2021.01080. URL https://arxiv.org/abs/2104.05670v2.

- Matthew Loper, Naureen Mahmood, Javier Romero, Gerard Pons-Moll, and Michael J. Black. Smpl: A skinned multi-person linear model. ACM Transactions on Graphics, 34, 11 2015. ISSN 15577368. doi: 10.1145/2816795.2818013/SUPPL_FILE/A248-LOPER.ZIP. URL https: //dl.acm.org/doi/10.1145/2816795.2818013.
- Yi Zhou, Connelly Barnes, Jingwan Lu, Jimei Yang, and Hao Li. On the continuity of rotation representations in neural networks. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2019-June:5738–5746, 12 2018b. ISSN 10636919. doi: 10.1109/CVPR.2019.00589. URL https://arxiv.org/abs/1812.07035v4.
- Ceyuan Yang, Zhe Wang, Xinge Zhu, Chen Huang, Jianping Shi, and Dahua Lin. Pose guided human video generation. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11214 LNCS:204–219, 7 2018. ISSN 16113349. doi: 10.1007/978-3-030-01249-6_13. URL https://arxiv.org/abs/1807. 11152v1.
- Jiangxin Sun, Zihang Lin, Xintong Han, Jian-Fang Hu, Jia Xu, and Wei-Shi Zheng. Action-guided 3d human motion prediction. *Advances in Neural Information Processing Systems*, 34:30169–30180, 12 2021.
- Alejandro Hernandez, Jurgen Gall, and Francesc Moreno. Human motion prediction via spatiotemporal inpainting. *Proceedings of the IEEE International Conference on Computer Vision*, 2019-October:7133–7142, 12 2018. ISSN 15505499. doi: 10.1109/ICCV.2019.00723. URL https://arxiv.org/abs/1812.05478v2.
- Félix G Harvey, Polytechnique Montreal, Ubisoft Montreal, and Canada Christopher Pal. Recurrent transition networks for character locomotion. *SIGGRAPH Asia 2018 Technical Briefs, SA 2018*, 10 2018. doi: 10.1145/3283254.3283277. URL https://arxiv.org/abs/1810.02363v5.
- Chuanqi Zang, Mingtao Pei, and Yu Kong. Few-shot human motion prediction via learning novel motion dynamics. *IJCAI International Joint Conference on Artificial Intelligence*, 1:846–852, 7 2020. ISSN 1045-0823. doi: 10.24963/IJCAI.2020/118. URL https://www.ijcai.org/ proceedings/2020/118.
- Haoxuan Qu, † Zhaoyang He, Zeyu Hu, Yujun Cai, and Jun Liu. Off-the-shelf chatgpt is a good few-shot human motion predictor. 5 2024. URL https://arxiv.org/abs/2405.15267v1.
- Daniel Holden, Jun Saito, and Taku Komura. A deep learning framework for character motion synthesis and editing. *ACM Transactions on Graphics*, 35, 7 2016. ISSN 15577368. doi: 10.1145/2897824.2925975.
- Sitao Xiang and Hao Li. Revisiting the continuity of rotation representations in neural networks. 6 2020. URL https://arxiv.org/abs/2006.06234v2.
- Alexander Quinn Nichol and Prafulla Dhariwal. Improved denoising diffusion probabilistic models, 2021. URL https://openreview.net/forum?id=-NEXDKk8gZ.
- Allan Jabri, David J. Fleet, and Ting Chen. Scalable adaptive computation for iterative generation. *Proceedings of Machine Learning Research*, 202:14569–14589, 12 2022. ISSN 26403498. URL https://arxiv.org/abs/2212.11972v2.
- Naureen Mahmood, Nima Ghorbani, Nikolaus F. Troje, Gerard Pons-Moll, and Michael J. Black. AMASS: Archive of motion capture as surface shapes. In *International Conference on Computer Vision*, pages 5442–5451, October 2019.
- Carnegie Mellon University. CMU MoCap Dataset. URL http://mocap.cs.cmu.edu.
- Nikolaus F. Troje. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. *Journal of Vision*, 2(5):2–2, September 2002. doi: 10.1167/2.5.2.
- Andreas Aristidou, Ariel Shamir, and Yiorgos Chrysanthou. Digital dance ethnography: Organizing large dance collections. J. Comput. Cult. Herit., 12(4), November 2019. ISSN 1556-4673. doi: 10.1145/3344383. URL https://doi.org/10.1145/3344383.

- Simon Fraser University and National University of Singapore. SFU Motion Capture Database. URL http://mocap.cs.sfu.ca/.
- Ijaz Akhter and Michael J. Black. Pose-conditioned joint angle limits for 3D human pose reconstruction. In 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 1446–1455, June 2015. doi: 10.1109/CVPR.2015.7298751.