UnifiedGesture: A Unified Gesture Synthesis Model for Multiple Skeletons

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1. Introduction

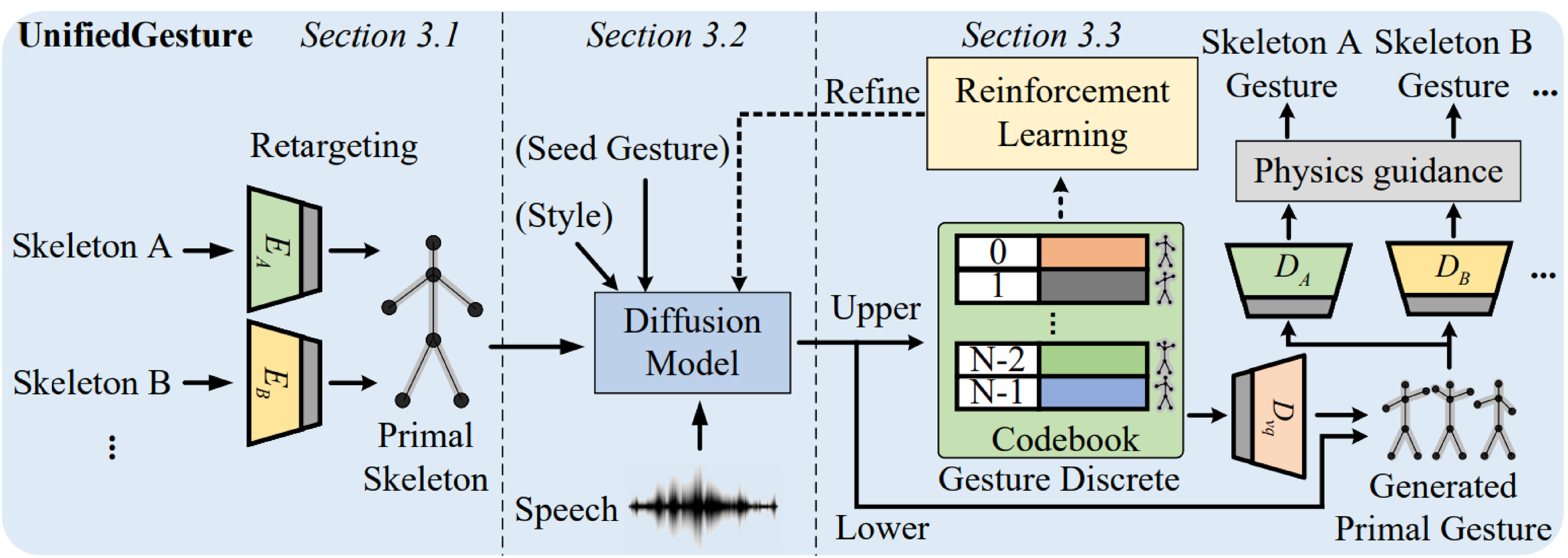
1.1 Motivation

- Goal:
  - ✓ Develop a comprehensive gesture synthesis model that can cater to multiple skeletons, ensuring natural and appropriate gestures in sync with speech
- Problem:
  - Existing gesture synthesis models are limited in their adaptability to various skeletons
  - The need for a model that can generate gestures that are both semantically relevant and natural in appearance

1.2 Contribution

- ✓ Introduction of a unified model that bridges the gap between different skeletal structures
- ✓ Present a temporally aware attention-based diffusion model on the primal skeleton for co-speech gesture generation
- ✓ Incorporation of advanced techniques like reinforcement learning and VQVAE to enhance gesture quality
- ✓ Extensive experiments show that our model can generate human-like, speech-matched, stylized, diverse, controllable, and physically plausible gestures

2. Methodology

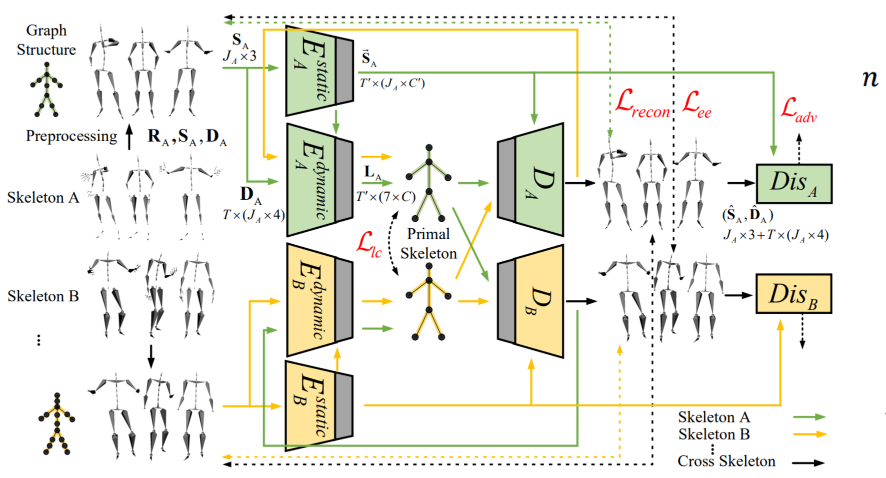


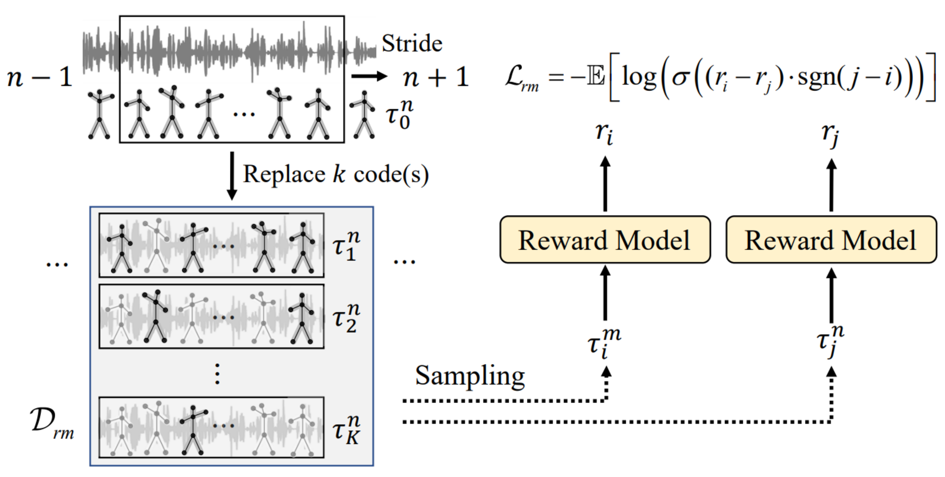
2.1 Multiple Skeletons Retargeting Network

The adjacency lists are expressed as $\mathcal{N}^d = \{\mathcal{N}_1^d, \mathcal{N}_2^d, \ldots, \mathcal{N}_J^d\}$

Two reference poses $\mathbf{P}_A$ and $\mathbf{P}_B$ can be aligned through global and local translation and rotation: $\mathbf{P}_B = \mathbf{Q}^{AB}\mathbf{P}_A\left(\mathbf{Q}^{AB}\right)^\top$

The motion of different skeletons consists of a static component $\mathbf{S} \in \mathbb{R}^{J\times 3}$ (joint offsets) and a dynamic one $\mathbf{D} \in \mathbb{R}^{T\times(J\times 4)}$ (joint rotations).To unify the motion of the different skeletons, we utilize a retargeting network architecture similar to [1]





2.2 Diffusion Model for Speech-driven Gesture Generation

Our goal is to synthesize a gesture $\mathbf{L}^{1:N}$ of length N given noising step t_d, noisy gesture $\mathbf{L}_{t_d}$ and conditions c (including audio a, style s, and seed gesture d). That is $\mathbf{L}_0 = \text{Denoise}\left(\mathbf{L}_{t_d}, t_d, c\right)$.

The Denoising module can be trained by optimizing the Huber loss between the generated poses $\mathbf{L}_0$ and the ground truth human gestures $\mathbf{L}_0$ on the training examples:

$$\mathcal{L}_{diff} = \lambda_{diff} E_{\mathbf{L}_0\sim q(\mathbf{L}_0|c), t_d\sim[1,T_d]}\left[\text{HuberLoss}(\mathbf{L}_0 - \mathbf{L}_0)\right]$$

2.3 Gesture Generation Refinement

2.3.1 Primal Gesture VQVAE

Each code represents a unique gesture. Besides, discrete spaces are more conducive to reinforcement learning for exploration. The VQVAE can be trained by optimizing $\mathcal{L}_{vq}$:

$$\mathcal{L}_{vq} = \left\|\mathbf{L}_0^{\text{upper}} - \mathbf{L}_0^{\text{upper}}\right\|_1 + \alpha_1\left\|\mathbf{L}_0^{\text{upper}'} - \mathbf{L}_0^{\text{upper}'}\right\|_1 + \alpha_2\left\|\mathbf{L}_0^{\text{upper}''} - \mathbf{L}_0^{\text{upper}''}\right\|_1 + \left\|\text{sg}[\mathbf{u}] - \mathbf{u_q}\right\| + \beta_{vq}\left\|\mathbf{u} - \text{sg}\left[\mathbf{u_q}\right]\right\|$$

2.3.2 Reinforcement Learning Finetuning

In this paper, we adopted Inverse Reinforcement Learning (IRL) to learn a neural network model from human demonstrations. Given the reward model, we use the REINFORCE algorithm to improve the model: $\mathcal{L}_{RL} = -\mathbb{E}_{\tau\sim\pi}\left[\log p_\pi(\tau) r(\tau)\right]$.

2.3.3 Physics Guidance

We consider that the foot should have contact with the ground when there is a left-right acceleration or an upward acceleration of the root. And we use standard Inverse Kinematics (IK) optimization for physics guidance.

3. Experiments

3.1 Experiment Preparation

- Retargeting network
  - Evaluation on the Trinity and ZEGGS datasets. d_{re}=4, then the primal gesture is 7.5 fps.
  - Adam optimizer with a batch size of 256 for 16000 epochs.
- Diffusion model
  - Gesture data are cropped to a length of N = 30 (4 seconds).
  - AdamW optimizer (learning rate is 3×10^{-5}) with a batch size of 256 for 1000000 steps.
- VQVAE
  - The size C_b of codebook $\mathcal{Z}_u$ is set to 512 with dimension n_z is 512. Down-sampling rate d_{vq}=2.
  - ADAM optimizer (learning rate is e^{-4}, β_1 = 0.5, β_2 = 0.98) with a batch size of 128 for 200 epochs.

3.2 Comparison to Existing Methods

- *Human-likeness*. Our model significantly surpasses the compared state-of-the-art methods.However, it is not significantly different from ExampleGestures.
- *Gesture and speech appropriateness*. Our model significantly outperforms StyleGestures, Audio2Gesture, and ExampleGestures, giving competitive results with DiffuseStyleGesture.

Name	Objective evaluation				Subjective evaluation	
	Global CCA	CCA for each sequence	FGD ↓	Diversity ↑	Human-likeness	Appropriateness
Ground Truth	1.000	1.00 ± 0.00	0.0	10.03	4.22 ± 0.11	4.22 ± 0.11
StyleGestures [4]	0.978	**0.98 ± 0.01**	15.89	**13.86**	3.56 ± 0.12	3.17 ± 0.13
Audio2Gesture [43]	0.969	0.97 ± 0.01	19.78	6.148	3.61 ± 0.11	3.15 ± 0.14
ExampleGestures [19]	0.914	**0.98 ± 0.01**	10.49	5.418	3.77 ± 0.12	3.17 ± 0.14
DiffuseStyleGesture [85]	0.987	0.97 ± 0.01	11.98	11.22	3.66 ± 0.12	**3.46 ± 0.14**
Ours	**0.988**	0.95 ± 0.02	**3.850**	7.039	**3.80 ± 0.11**	3.42 ± 0.14

3.3 Ablation Studies

- *Human-likeness*. the scale of the dataset has a significant effect on the results, which shows the importance of unifying the gesture dataset.
- *Speech and gesture appropriateness*. The scale of the dataset has the largest impact on this metric. The appropriateness also decreased without RL, shows the importance of data exploration.

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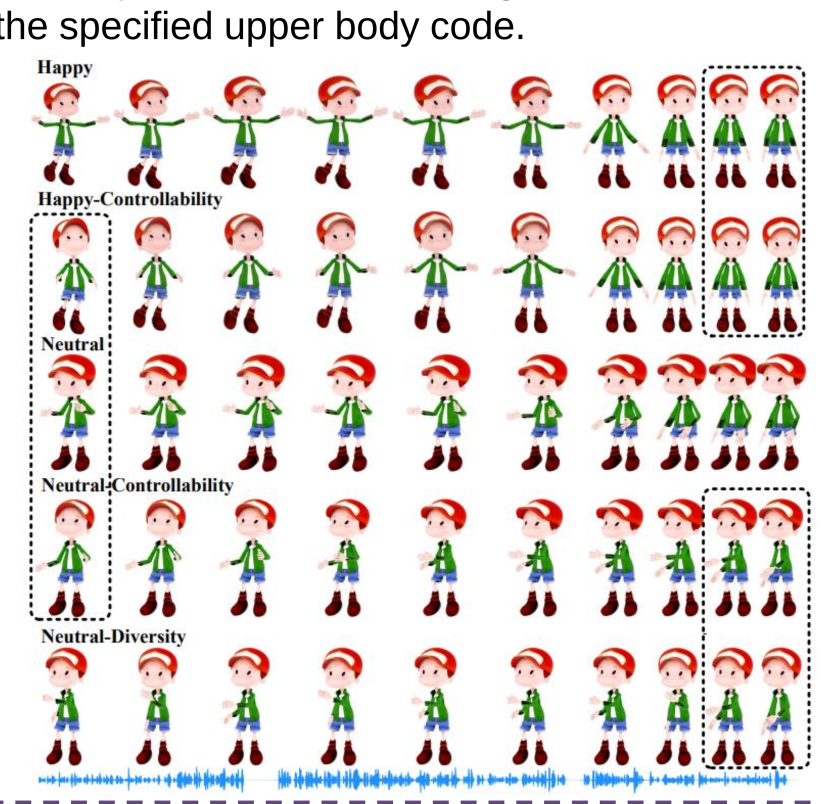
Ours	**0.988**	**0.95 ± 0.02**	3.850	**7.039**	3.80 ± 0.11	**3.42 ± 0.14**
- RL	0.987	0.94 ± 0.03	**3.132**	7.008	**3.82 ± 0.11**	3.24 ± 0.16
- RL - VQVAE	0.987	0.94 ± 0.03	3.568	6.971	3.79 ± 0.11	3.33 ± 0.12
- Skeleton A	0.972	0.94 ± 0.03	13.76	4.882	3.54 ± 0.12	3.00 ± 0.13
- Skeleton B	0.965	**0.95 ± 0.03**	12.45	5.566	3.59 ± 0.13	3.09 ± 0.13

3.4 Diverse, Controllable, and Stylized Gesture Generation

The **intensity of the stylization** can be controlled by the value of γ. Due to the diffusion model architecture, different noisy gesture and different seed gesture could **generate different gestures** even for the same speech and style. We can have a **high level of control** over speech-driven gestures at any time with the specified upper body code.



Reference

[1] Skeleton-Aware Networks for Deep Motion Retargeting
[2] DiffuseStyleGesture: Stylized Audio-Driven Co-Speech Gesture Generation with Diffusion Models
[3] Bailando: 3D dance generation via Actor-Critic GPT with Choreographic Memory
[4] Edge: editable dance generation from music

Project page