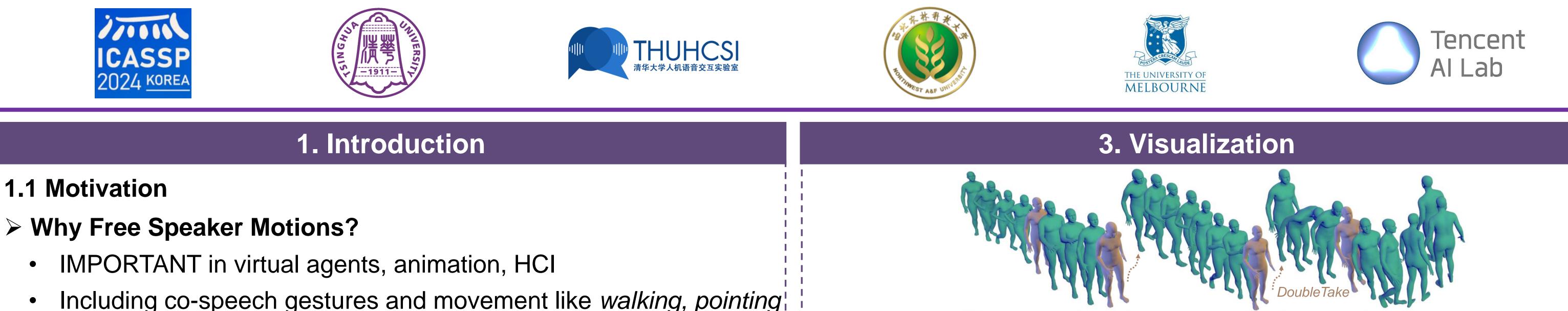
FreeTalker: Controllable Speech and Text-Driven Gesture Generation **Based on Diffusion Models for Enhanced Speaker Naturalness**

Sicheng Yang¹, Zunnan Xu¹, Haiwei Xue¹, Yongkang Cheng², Shaoli Huang³, Mingming Gong^{4,5}, Zhiyong Wu¹

¹ Tsinghua Shenzhen International Graduate School, Tsinghua University² Northwest A&F University

³ Tencent AI Lab ⁴ University of Melbourne, ⁵ Mohamed bin Zayed University of Artificial Intelligence



"A person runs forward then slows down" \rightarrow "a person raises right

- or interacting is crucial for realism and engagement
- Limitations of Current Work
 - Focus on co-speech gesture generation
 - Limited focus on free motion (spontaneous and non-spontaneous)

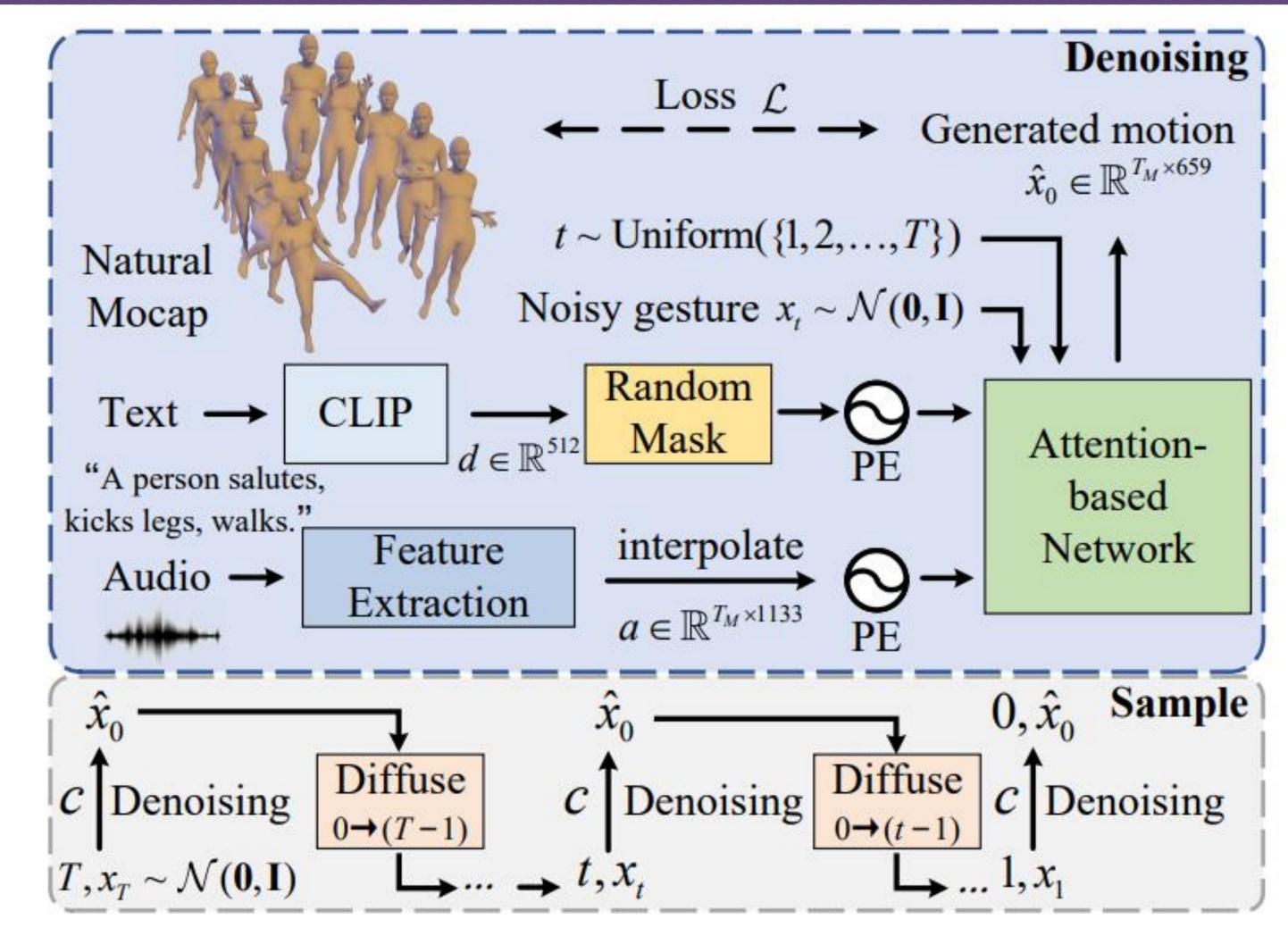
> Challenges

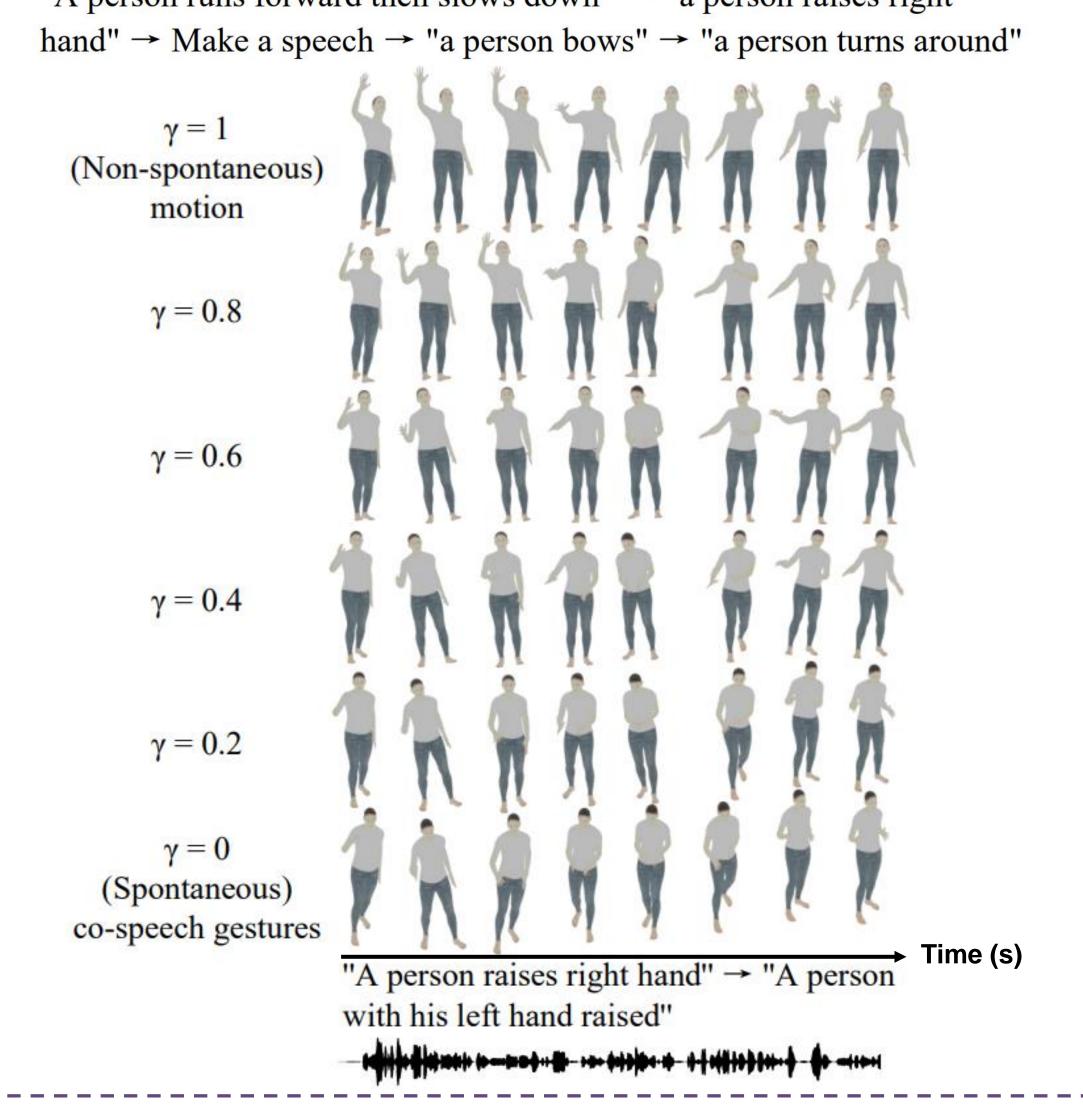
- Disjointed motion representations and diverse inputs handling \rightarrow multi-dataset utilization and multimodal learning
- Long sequence and controllable motion generation

1.2 Contributions

- \checkmark The first framework to generate free speaker motions
- \checkmark Employing classifier-free guidance and DoubleTake for controlled, flexible gesture generation
- Demonstrating increased naturalness in speaker motions

2. Methodology





4. Experiments

> Motion Processing

- Adaptation: converts BVH to axis-angle (SMPL-X) for detailed motion; adapts 3D positions to SMPL-X with Vposer with uniform scale and root joint translations
- Features: includes root height, linear/rotational velocities, joint rotation/position/velocity, and foot contact

- > **Datasets**: HumanML3D (text-driven) and BEAT (speech-driven)
 - **Preprocessing**: resampling to 20 FPS; HumanML3D spans 40-180 frames, texts up to 20 words; English speakers' gestures
 - **Split**: 80% train, 10% validate, 10% test; weighted sampling
 - **Normalization:** mean subtraction and standard deviation
- > Model: T=1000, cosine schedule, 256-dimension self-attention
- Training: 1M steps, batch size 256, learning rate 2e-4, over 3 days on one V100 GPU

Name	Co-speech gesture generation				
	$jerk \rightarrow$		acceleration \rightarrow	FID↓	Naturalness ↑
Natural Mocap	135.36 ± 58.61		12.39 ± 11.79	-	-
DiffuseStyleGesture	206.52 ± 83.65		5.68 ± 2.19	0.008	49%
MDM	-		_	-	_
Ours*	245.78 ±	108.27	6.03 ± 2.55	0.139	40%*
	-				-
Name	Motion Ger			Free-motion	
Namo	IVI	ouon Ge	neration	Fre	ee-motion
Name	SSIM ↑	$\frac{\text{outon Ge}}{\text{FID }\downarrow}$	neration Naturalness ↑	FID ↓	ee-motion Naturalness ↑
Name Natural Mocap					
Natural Mocap					

> Diffusion Model for Motion Generation

- **Conditioning**: integrates text and audio inputs to generate motion • Implementation:
 - T steps, and initial motion is derived from a normal distribution Ο
 - Predict clean motion \hat{x}_0 from noised inputs x_t , incorporating text Ο (CLIP) and audio features (WavLM etc.) as conditions
 - Huber loss function \bigcirc
- Controllable Long Motion Generation using DoubleTake
 - **Conditioning**: uses text / audio to generate gestures, balancing inputs through a mix parameter (γ)
 - Implementation: blend and smooth transitions between motion segments, ensuring seamless long-duration motion generation

> Results

- **Objective:** competitive results of our method with baselines
- **Subjective:** user study on *naturalness*, 25 participants; competitive performance in comparison to baselines, suggesting improvements with an expanded motion database

References

- [1] Tevet G, Raab S, Gordon B, et al. Human motion diffusion model//The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023. [2] Yang S, Wu Z, Li M, et al. Diffusestylegesture: Stylized audio-driven cospeech gesture generation with diffusion models[C]//Proceedings of the 32nd International Joint Conference on Artificial Intelligence, IJCAI 2023, Macao,
- S.A.R, 19th-25th August 2023.

