석사 학위 논문 심사 발표

확산 모델을 활용한 사람 모션 기반 주변 사물 생성 모델
Human Motion-based Interacting Object Generation using Diffusion

2024.12.16

Neuro-Machine Augmented Intelligence Lab (NMAIL)

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Committee: 김태균 교수님, 최성희 교수님

NMAIL

Introduction

Tesla

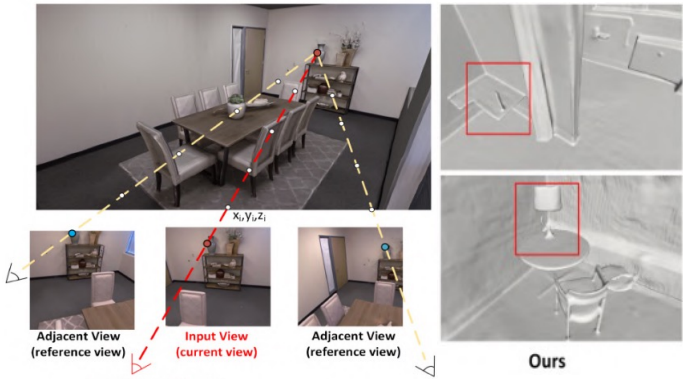
NVIDIA

Humane Ai Pin

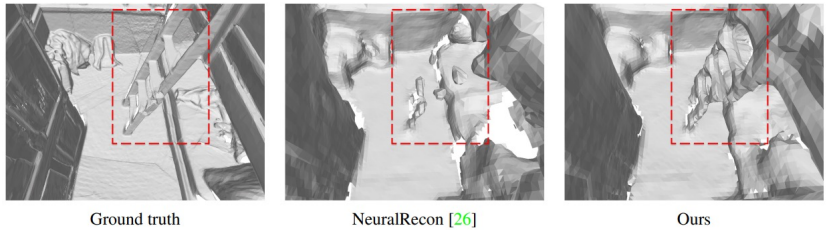
Apple Vision Pro

Meta

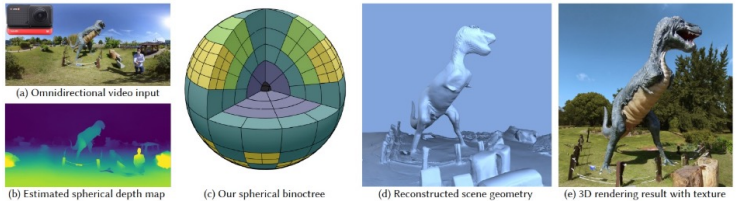
Introduction



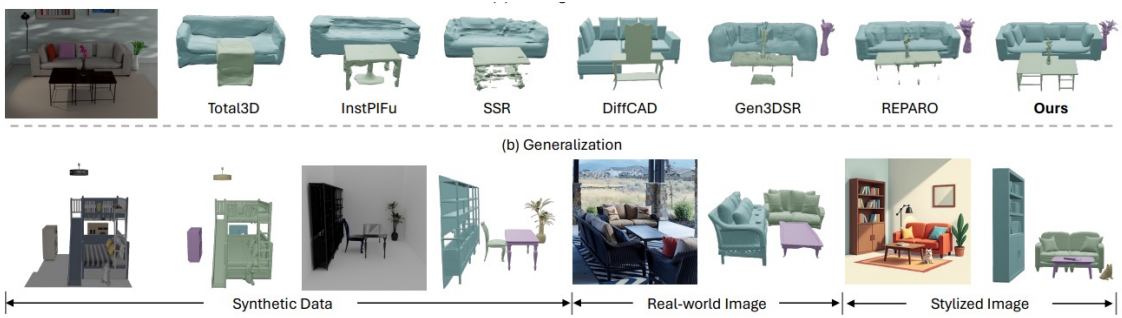
PMVC [Chushan Zhang et al. CVPR. 2024]



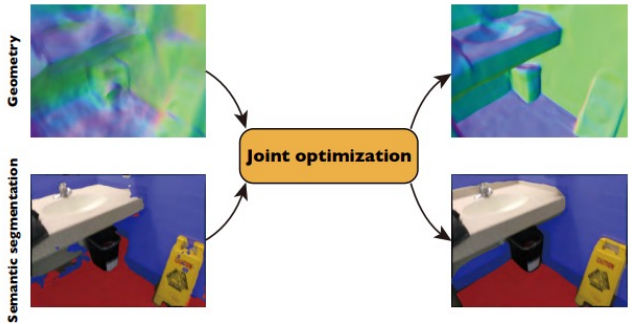
VisFusion [H Gao et al. CVPR. 2023]



EgocentricReconstruction [H Jang et al. SIGGRAPH. 2021]

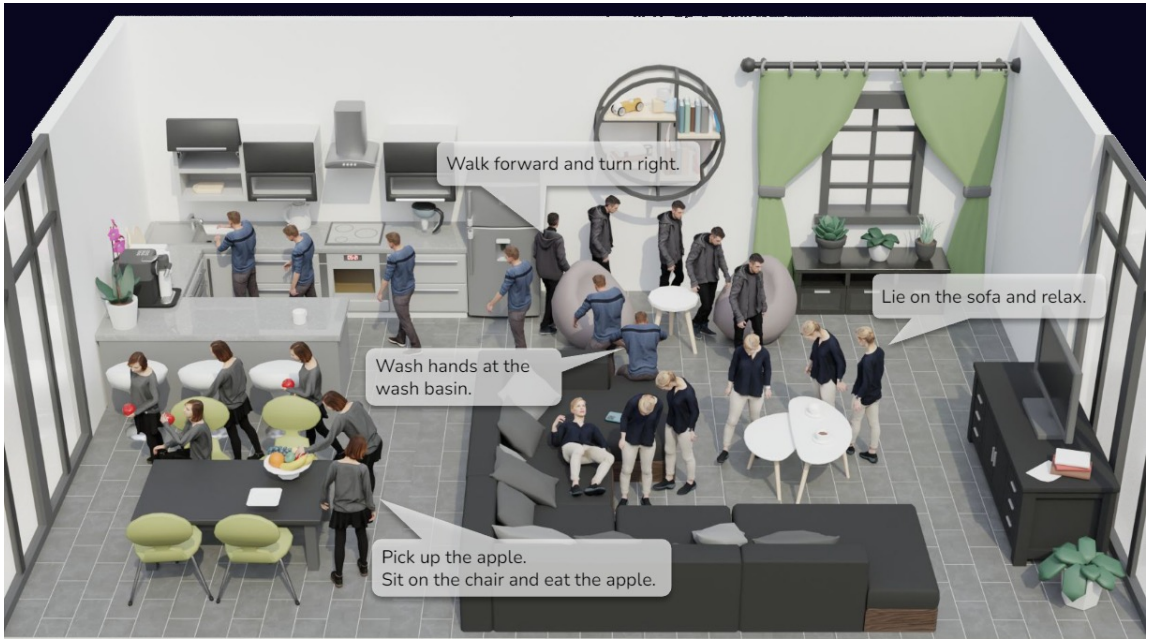


MIDI [Ze huang et al. arxiv. 2024]



Neural 3D Scene Reconstruction [Haoyu Guo et al. CVPR. 2022]

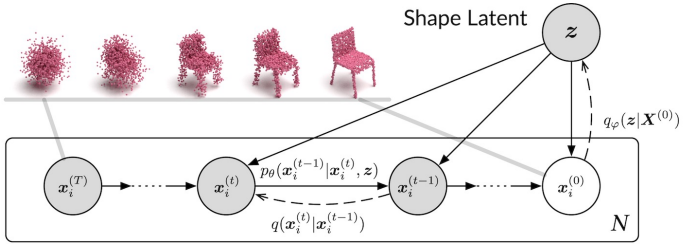
Introduction



If Human Motion is in the Scene, Motion will be interacting constantly!

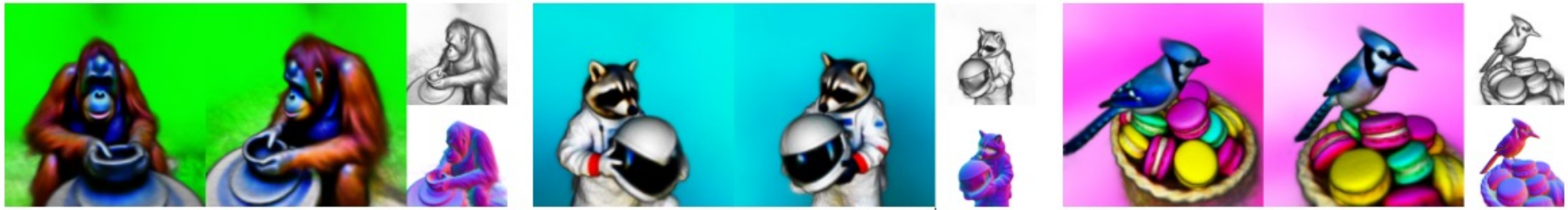
-> Generate Interacting Object and Scene from Human Motion

Generating Using Diffusion



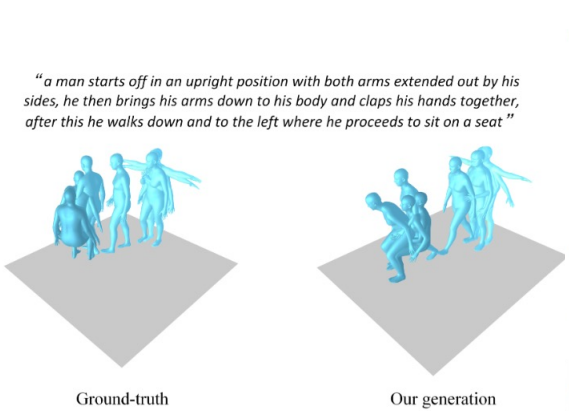
Diffusion-point-cloud, [Shitong Luoet al. CVPR. 2021]

MeshGPT, [Yawar Siddiqui al. CVPR. 2024]

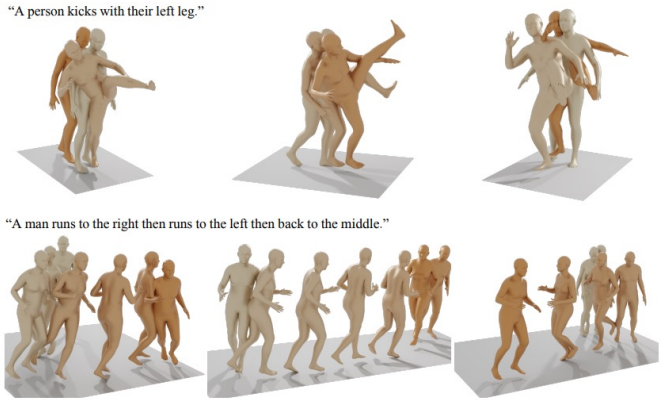


DreamFusion [Poole B et al. arxiv. 2022]

Generating Motion

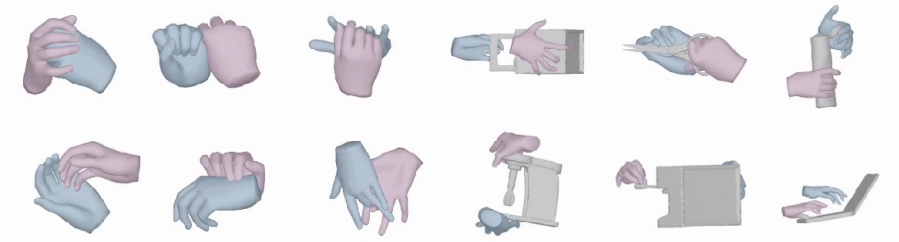


T2M GPT, [J Zhang et al. CVPR. 2023]



MDM [Guy Tevet et al. ICLR. 2023]

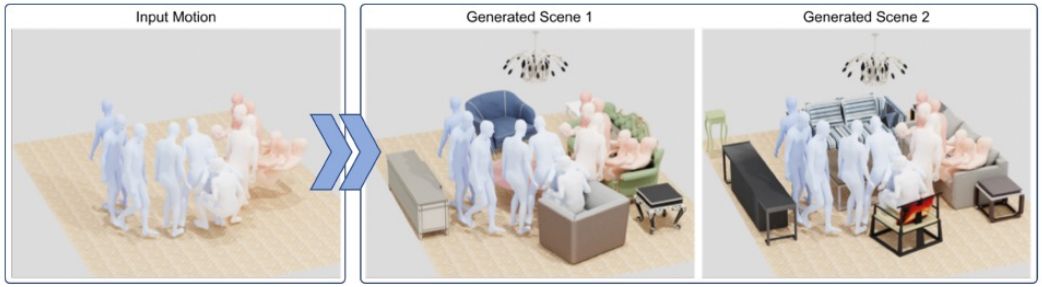
GMD [Korrawe K. et al. ICCV. 2023]



InterhandGen, [Jihyun Lee et al. CVPR. 2024]

SceneDiffuser, [S Huang et al. CVPR. 2023]

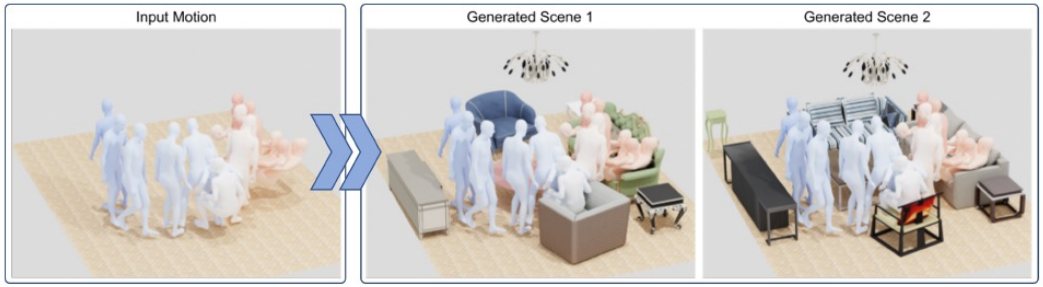
Most Related Works



MIME [Yi et al. CVPR. 2023]

LSDM [An Vuong et al. NeurIPS. 2023]

Most Related Works



MIME [Yi et al. CVPR. 2023]

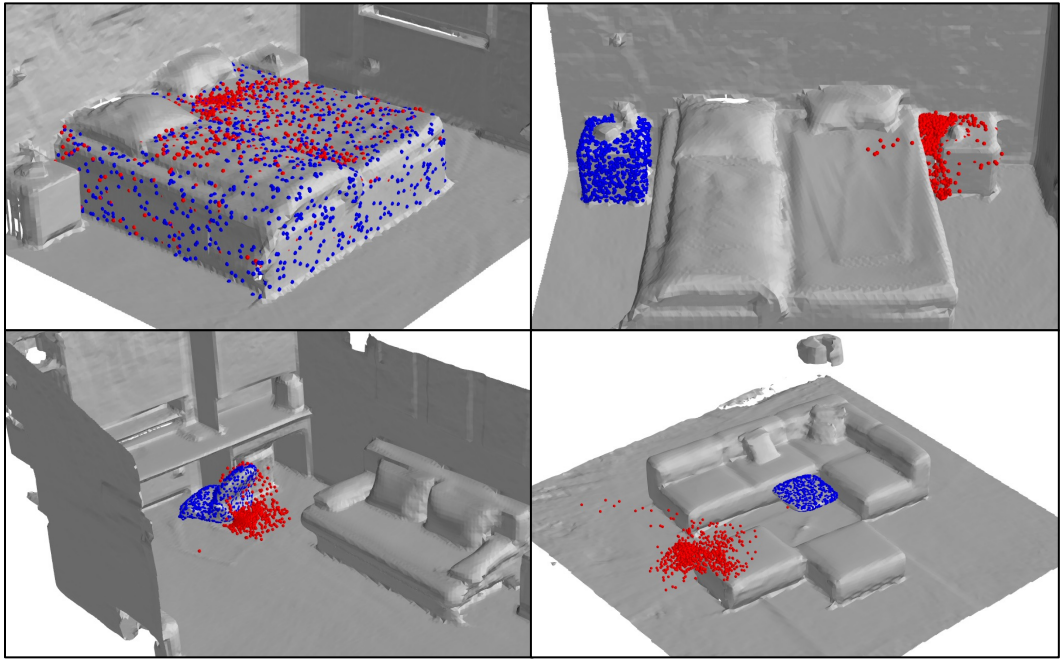
How about using short motions for Live?
How about predicting objects directly?

LSDM [An Vuong et al. NeurIPS. 2023]

How about predicting
without any text-guidance?

ex. *Put Chair Under the me and Next to bed*

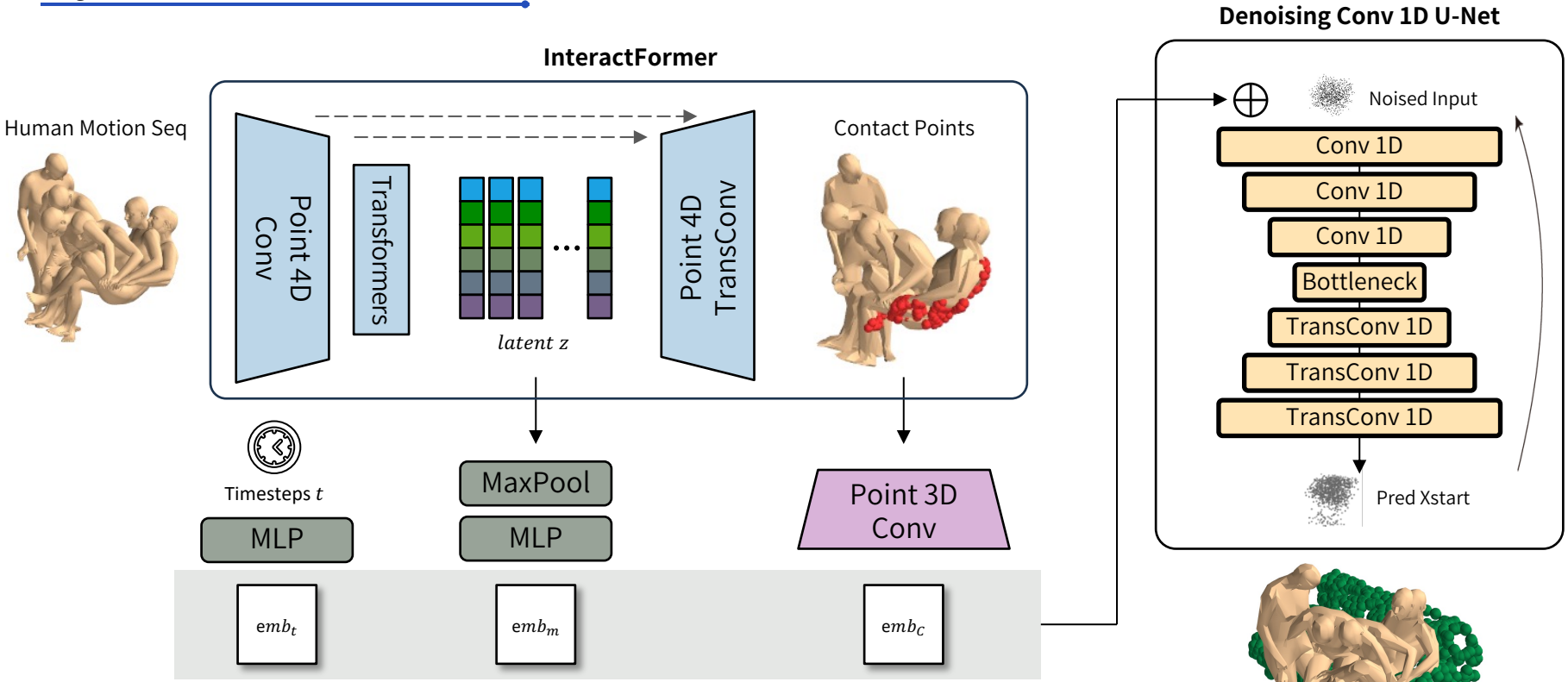
Limitations



Ground Truth (Blue), Predicted (Red)

Baseline	PRO-teXt CD ↓	PRO-teXt EMD ↓	PRO-teXt F1 ↑
Paschalidou et al., 2021)	2.0756	1.4140	0.0663
MMON (Ye et al., 2022)	2.1437	1.3994	0.0673
MIME (Yi et al., 2023)	2.0493	1.3832	0.0990
2023) + text embedding	1.8424	1.2865	0.1032
MCDM	0.6301	0.7269	0.3574
LSDM w.o. text (Ours)	0.9134	1.0156	0.0506
LSDM (Ours)	**0.5365**	**0.5906**	**0.5160**

System Architecture

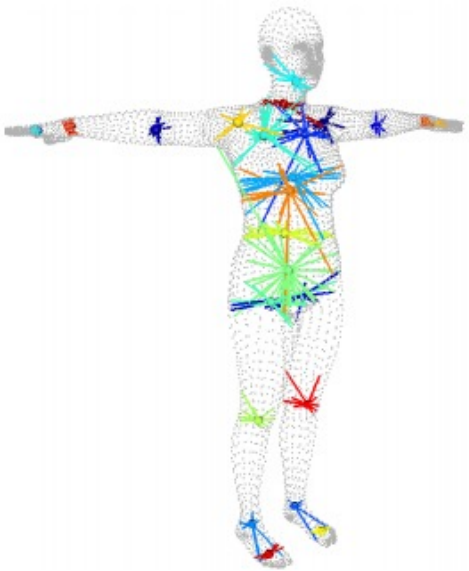


Main Purpose: Generating 3D Object, from Human Motion, Using Contact Points

Final Output (3D Object in Point Cloud)

Efficient Motion Data Format

SMPL Parameters (axis-angle)

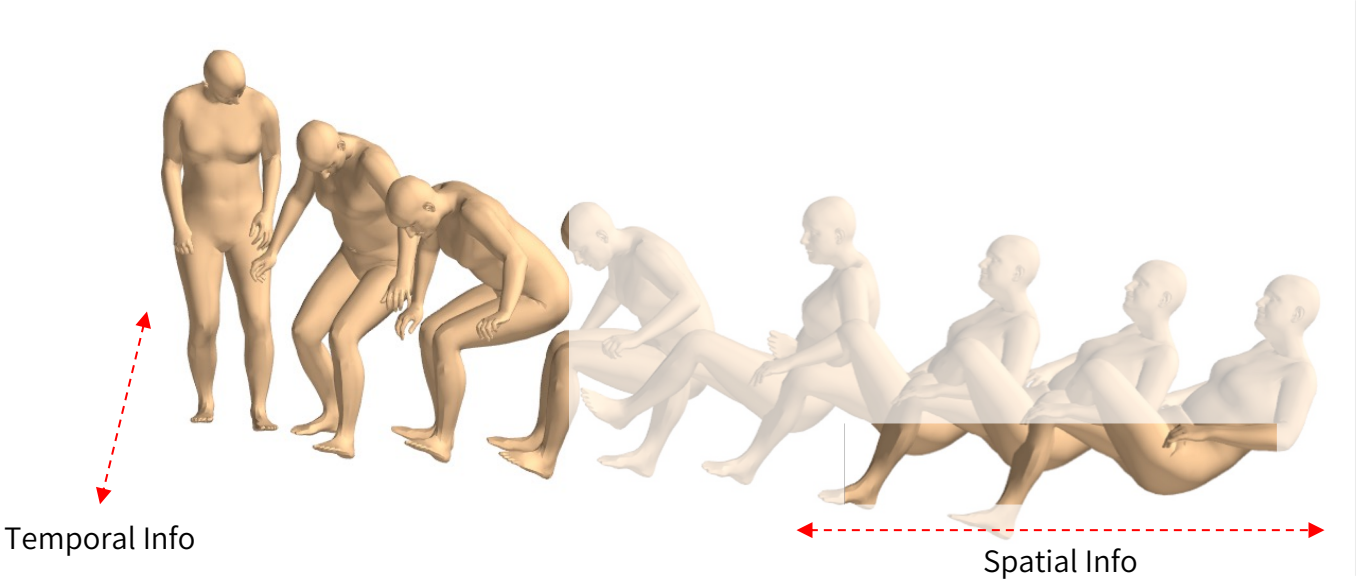


Easy to Understanding Full Body
Low Computation Cost
Less into about specific body (like Hand)

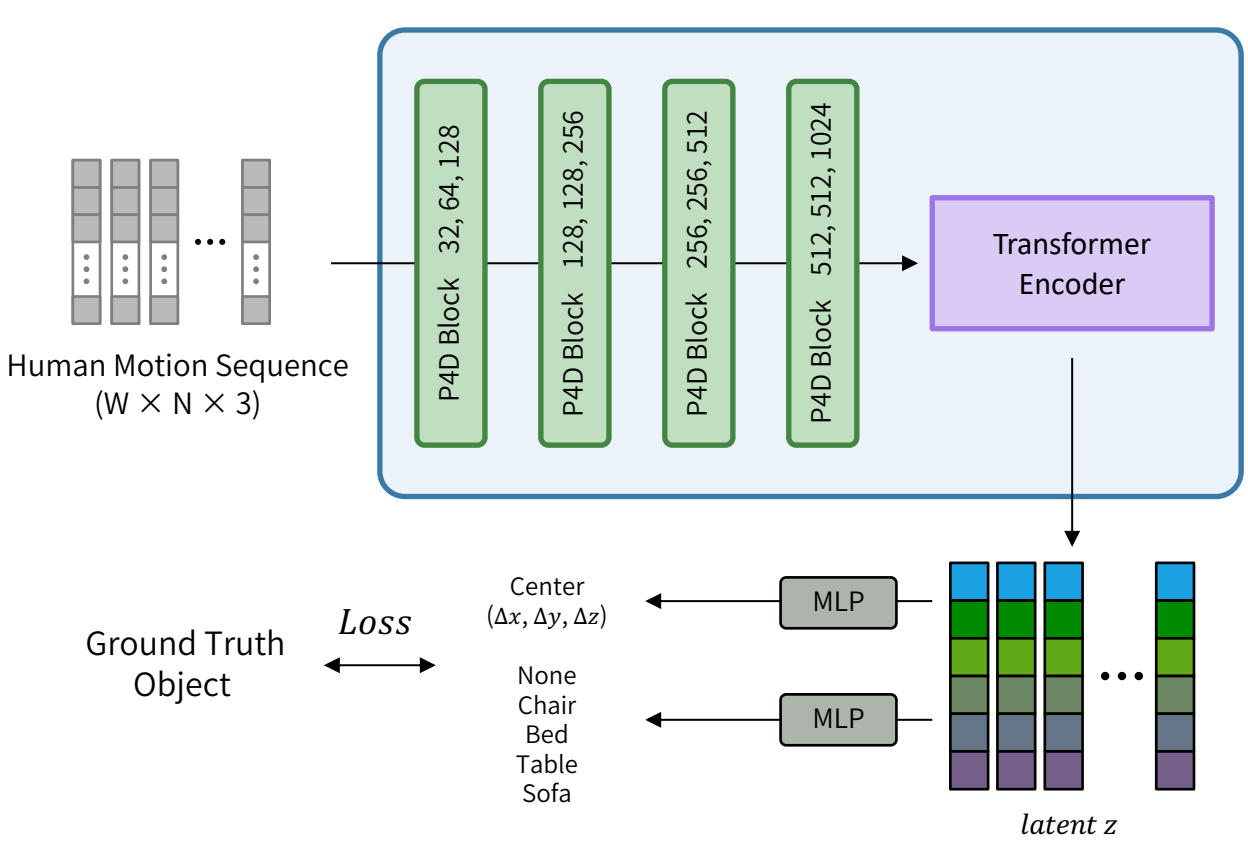
Point Cloud of Human Body Surface

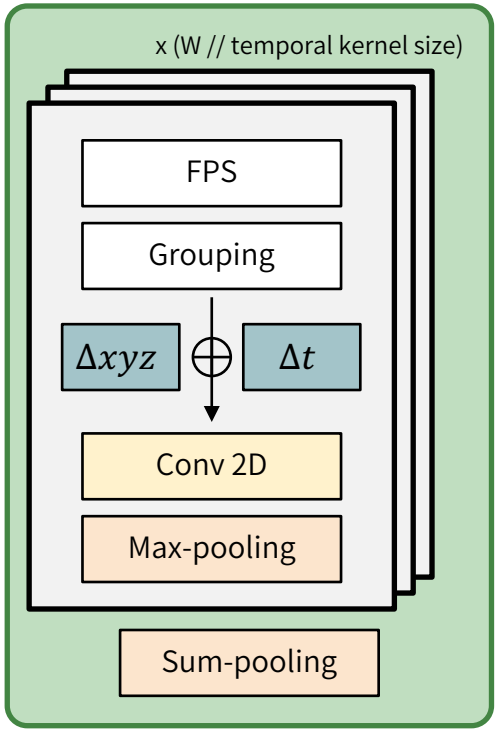
High Computation Cost
Helpful for providing condition
to Generating 3D Object

Dealing with 4D Data (3D Point Cloud + 1D Time)



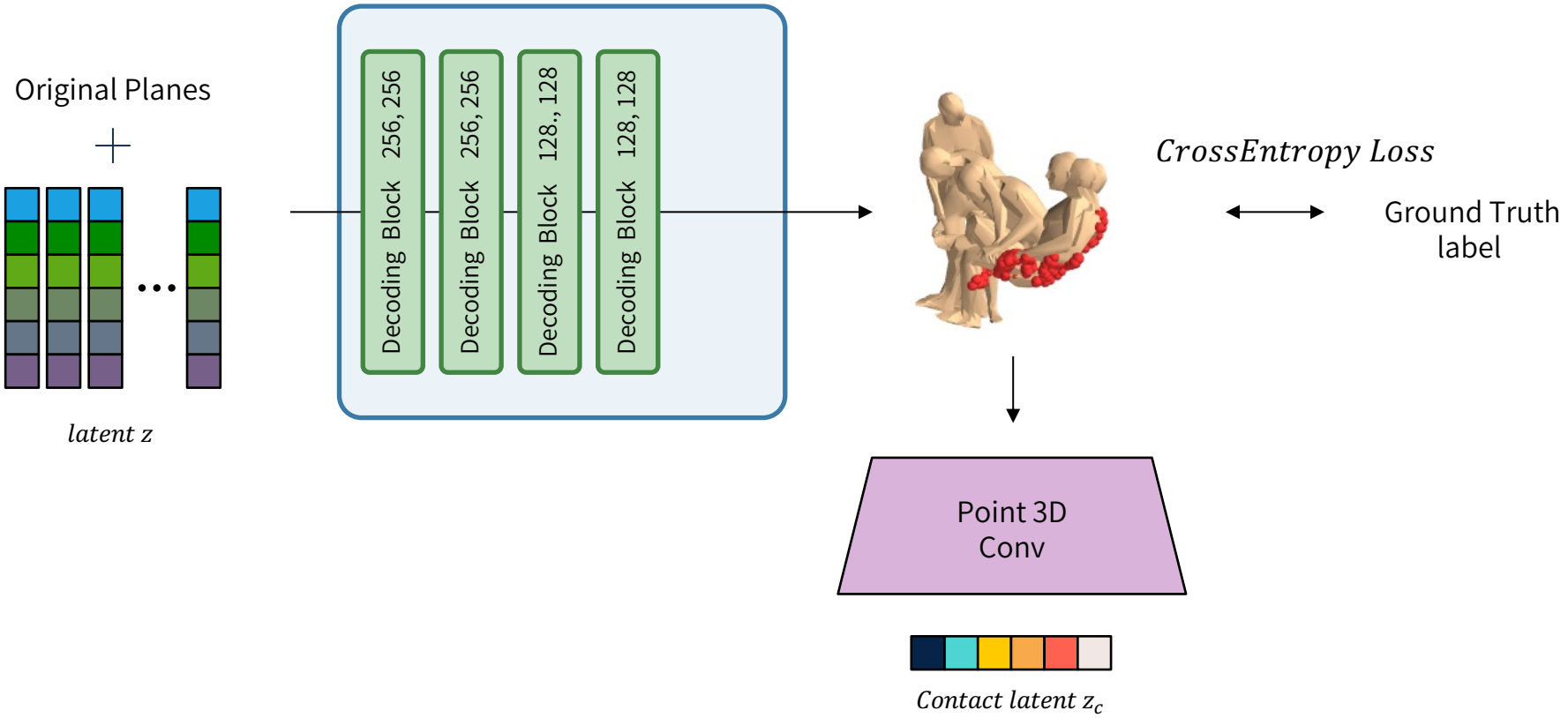
Encoding Human Motion Sequence



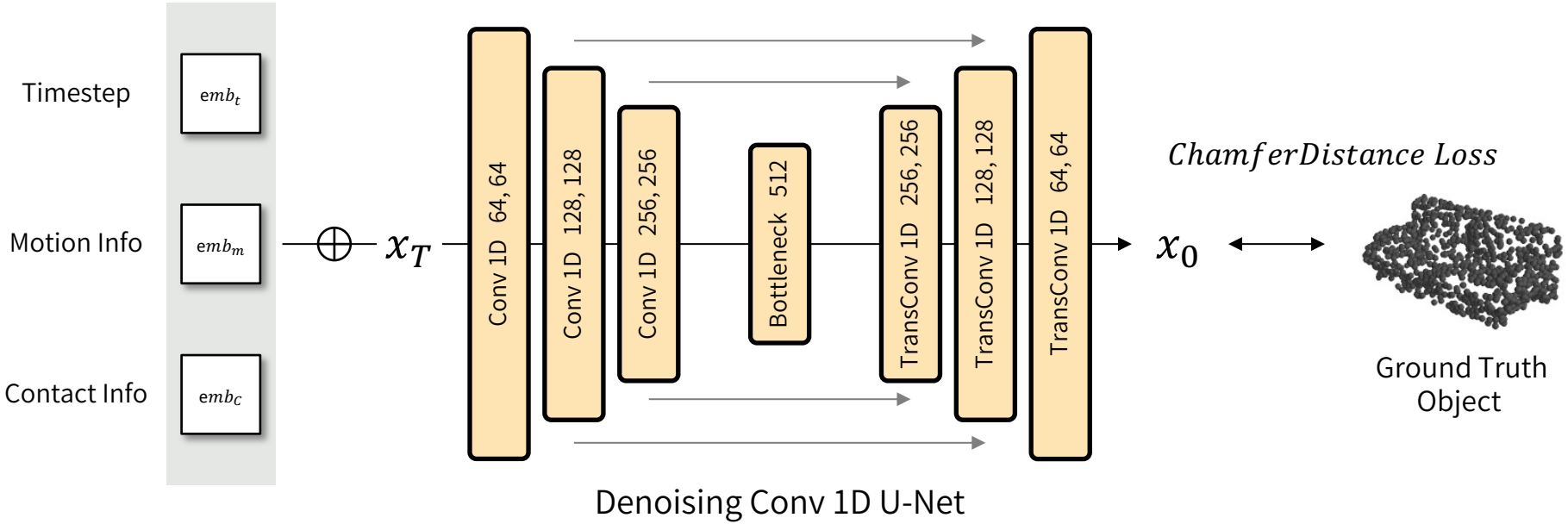


Loss Calculation for Latent Space, with Object Center and Category

Decoding Human Motion Sequence for Contact Points



Conditional Denoising U-Net for Generating Object



Conditional Diffusion – Forward Processing

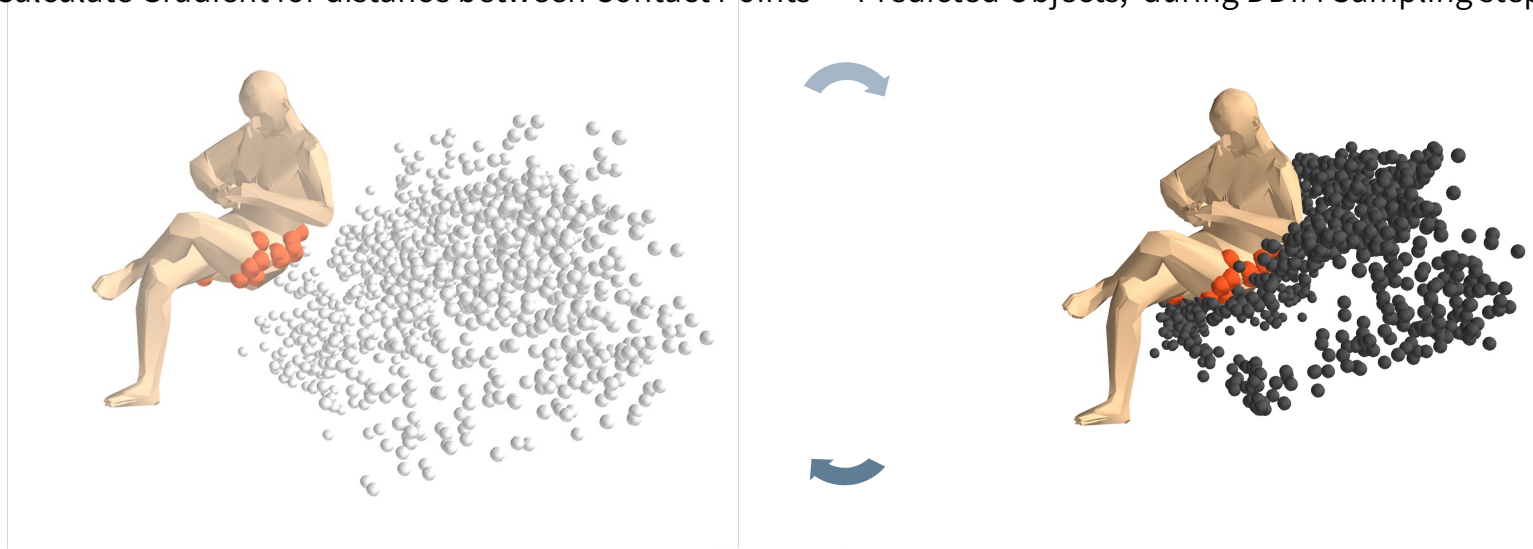
$$q(\mathbf{x}_{t+1}|\mathbf{x}_t) = \mathcal{N}\left(\sqrt{1-\beta_t}\,\mathbf{x}_t,\ \beta_t\mathbf{I}\right), q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=0}^{T-1} q(\mathbf{x}_{t+1}|\mathbf{x}_t)$$

Given Point Cloud X_0, add Gaussian noise each timestep with specific noise standard deviation

Using Cosine Scheduler for adding noise

Conditional Diffusion – CPG Sampling

Based on DDIM sampling, We used Contact Points Guidance (CPG) Sampling.
Calculate Gradient for distance between Contact Points ↔ Predicted Objects, during DDIM Sampling steps



$$\mathbf{x}_{t-1} = \sqrt{\alpha_{t-1}} \left(\frac{\mathbf{x}_t - \sqrt{1-\alpha_t}\,\hat{\epsilon}}{\sqrt{\alpha_t}} \right) + \sqrt{1-\alpha_{t-1}-\sigma_t^2}\,\hat{\epsilon} + \sigma_t \epsilon_t$$

$$\mathbf{x}_{t-1} \leftarrow \mathbf{x}_{t-1} - w_{cpg} \cdot \nabla_{\mathbf{x}_{t-1}} CD(p_{cnt}, \mathbf{x}_{t-1})$$

Datasets

Real Data

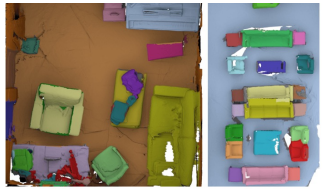
PROX

PROX, 43 sequences (about 1 min)
HUMANISE, 126 sequences (less 1 min)

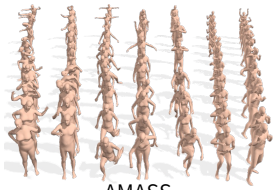
↓

Split it into 1-second short sequences, with the object it is most frequently in contact

Synthetic Data (Only Testing)



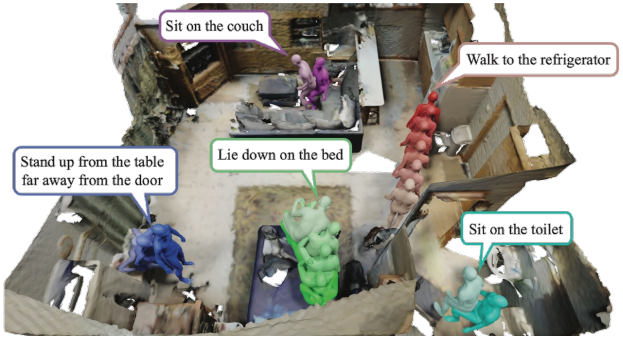
ScanNet v2

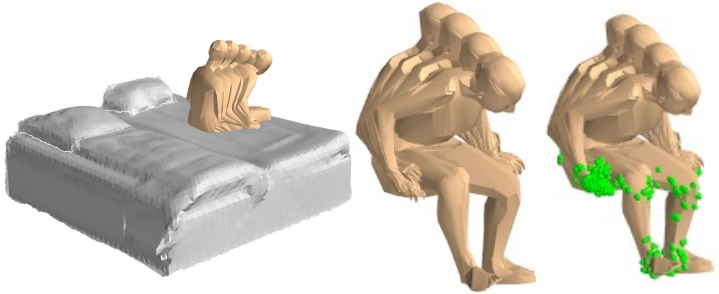


AMASS

→

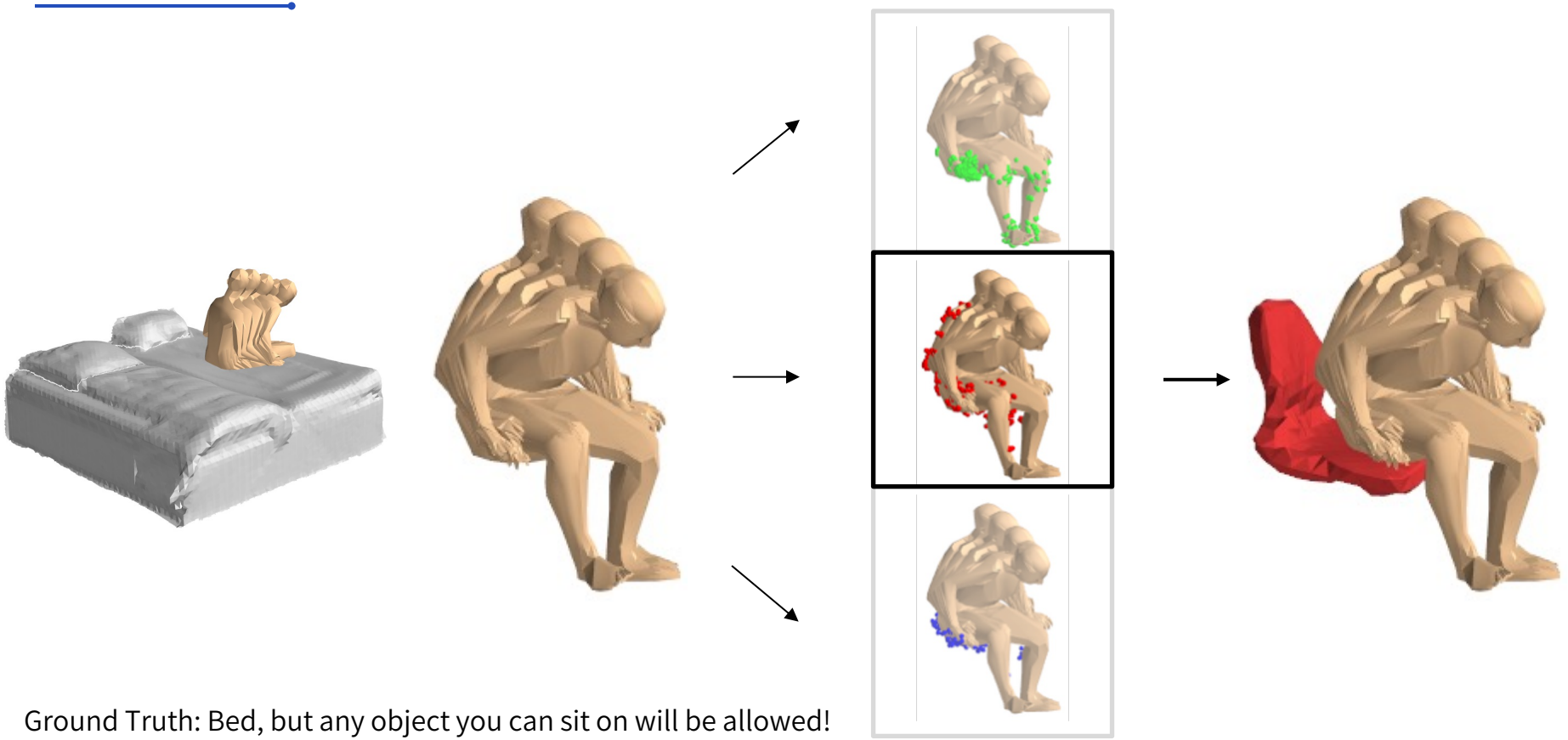
HUMANISE





Human Motion Sequence: (W × N × 3)
Target Object : (M × 3)
Contact Label: (W × N × num_class)

Datasets



Ground Truth: Bed, but any object you can sit on will be allowed!

Quantitative Results – InteractFormer

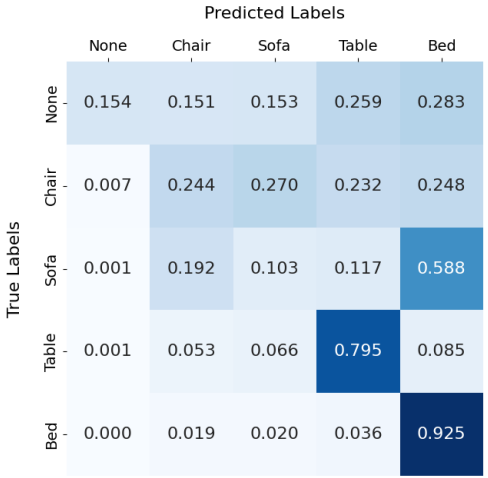
	PROX			HUMANISE		
	F1 ↑	Acc. ↑	Contact. ↑	F1 ↑	Acc. ↑	Contact. ↑
POSA	0.1269	0.1964	0.2257	0.0607	0.1100	0.1550
ContactFormer	0.2548	0.7646	0.7793	0.2151	0.7195	0.7416
Ours	**0.4577**	**0.8828**	**0.9029**	**0.2279**	**0.8048**	**0.8423**

Contact*: Evaluates whether points are in contact with any object,

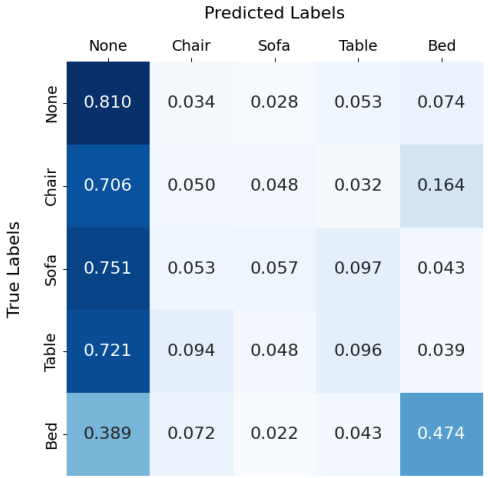
Our model achieves the best results in all three metrics for predicting Contact Points.

Quantitative Results – InteractFormer

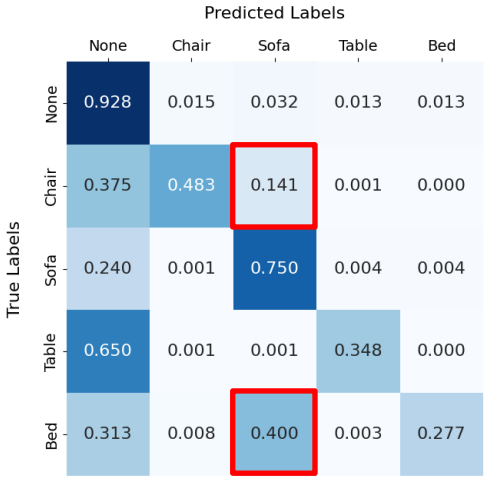
POSA



ContactFormer



InteractFormer (Ours)



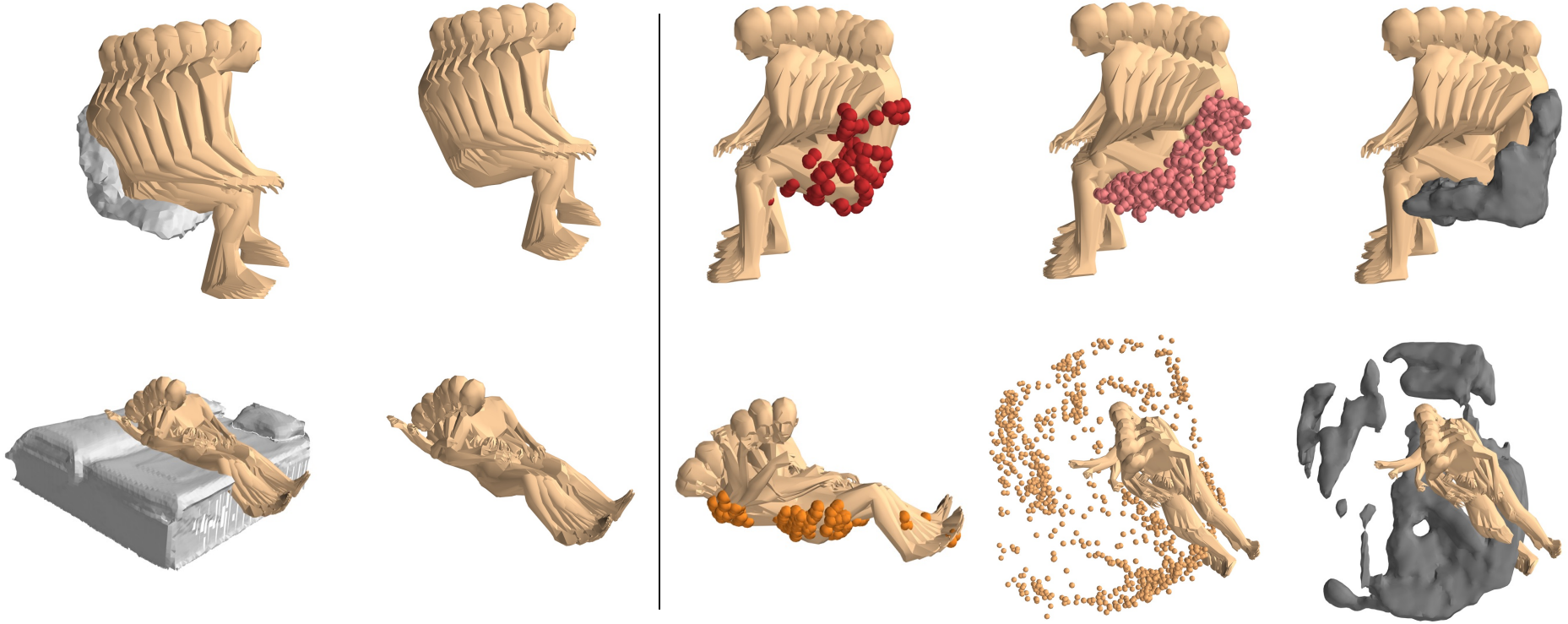
Confusion matrices for each of the three models

Quantitative Results

	PROX			HUMANISE		
	CD ↓	EMD ↓	F1 Score ↑	CD ↓	EMD ↓	F1 Score ↑
LSDM with no text	0.6252	0.9319	0.1961	0.8239	0.8665	0.1521
LSDM with GT Category text	0.5854	0.8874	0.2416	0.6098	0.8428	0.0826
Ours	**0.2982**	**0.6134**	**0.3662**	**0.4259**	**0.7704**	**0.1940**

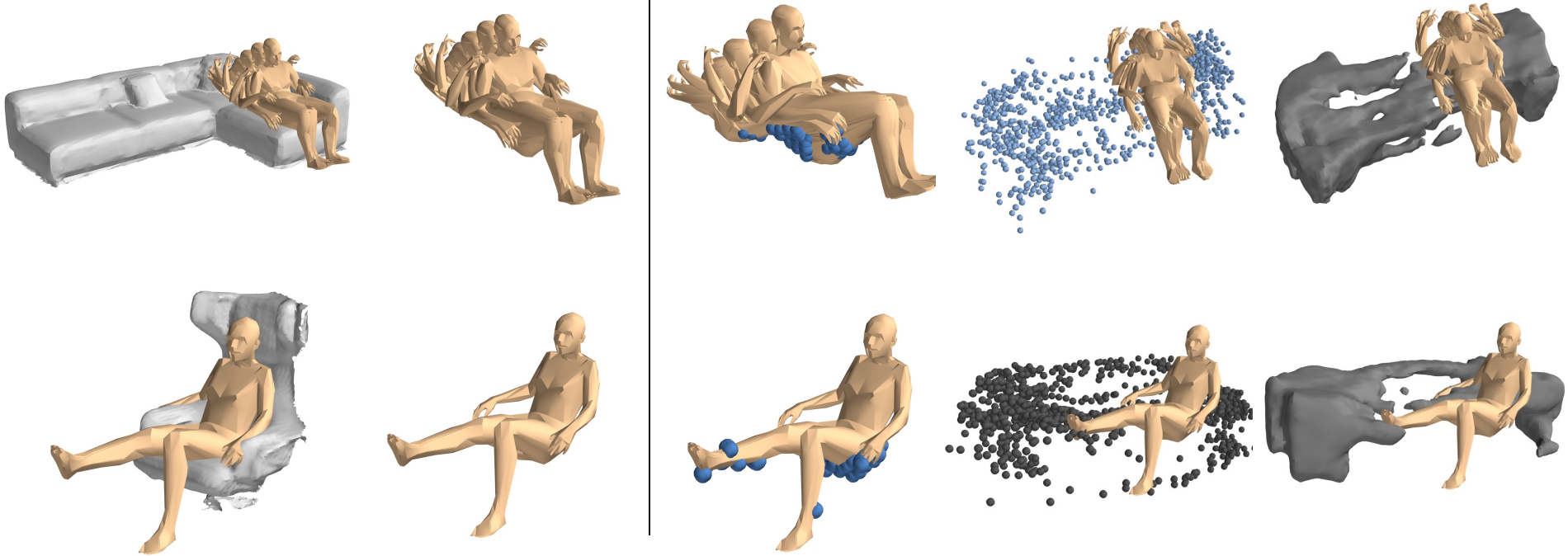
Our model achieves the best results in all three metrics

Qualitative Results



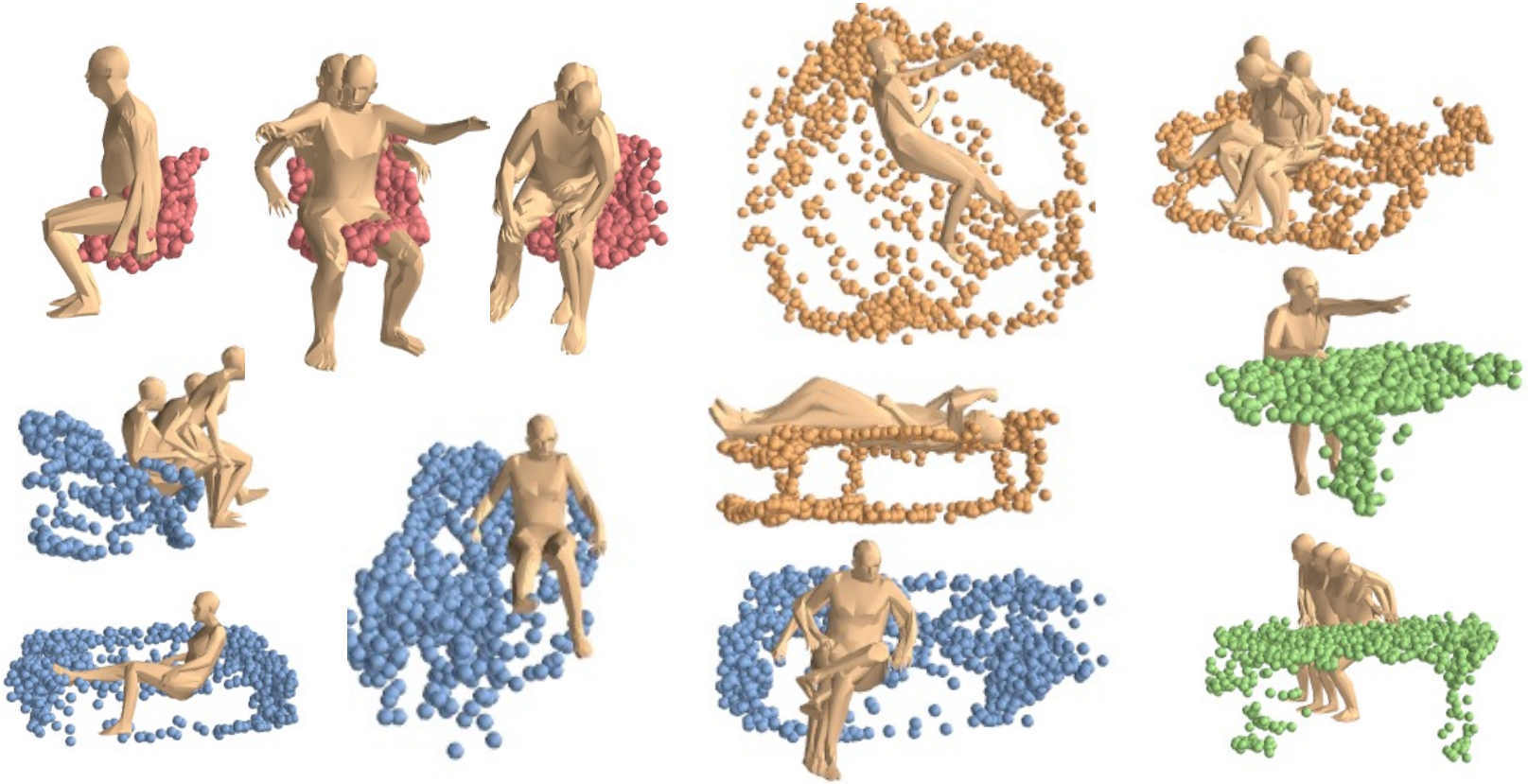
Ground Truth | Input | Pred Cont. Points | Pred Object | Applying SAP

Qualitative Results



Ground Truth | Input | Pred Cont. Points | Pred Object | Applying SAP

Qualitative Results



Conclusion

1. **Without any guidance or other information**, Generating interactive objects using only human motion.

2. **Using contact points predicting models,** Explainable results are derived.

3. **Live applications** are possible using short motion sequences (about 1 second).

Future Works

1. Using Synthetic data with exist Motion Diffusion Model

2. Apply for Scene Reconstruction, using Generated Objects

3. Combine with Sensor-to-Motion, for Sensor-to-Object

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감사합니다

Q&A

2024.12.16

Neuro-Machine Augmented Intelligence Lab (NMAIL)

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Committee: 김태균 교수님, 최성희 교수님

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