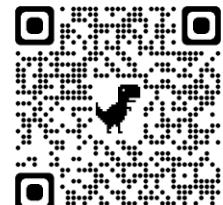


Self Introduction

- Education
 - [MS] UNIST, Graduate School of Artificial Intelligence [2021.09 ~ 2023.08]
 - [BS] Seoultech University, Electricity and Information Engineering [2015.03 ~ 2021.08]
- Publication
 1. “**DITTO: Dual and Integrated Latent Topologies for Implicit 3D Reconstruction**”, [under review](#).
Jaehyeok Shim, Kyungdon Joo.
 2. “**ContactGen: Contact-Guided Interactive 3D Human Generation for Partners**”, [AAAI 2024](#).
Dongjun Gu, Jaehyeok Shim, Jaehoon Jang, Changwoo Kang, Kyungdon Joo.
 3. “**Diffusion-Based Signed Distance Fields for 3D Shape Generation**”, [CVPR 2023](#).
Jaehyeok Shim, Changwoo Kang, Kyungdon Joo.



Github: <https://github.com/Kitsunetic>

Homepage: <https://kitsunetic.github.io>

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Research Project

2023.07 ~ 2024.01

p03 ~ p15

1. DITTO: Dual and Integrated Latent Topologies for Implicit 3D Reconstruction

(under review)

Research Project

2022.07 ~ 2023.01

p16 ~ p28

2. SDF-Diffusion: Diffusion-Based Signed Distance Fields for 3D Shape Generation

(CVPR 2023)

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2023.05 ~ 2022.09

p29 ~ p39

3. Contact-Gen: Contact-Guided Interactive 3D Human Generation for Partners

(AAAI 2024)

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4. Various AI Challenge Experiences

(Total 4th Place in DACON)

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5. Server Management Experiences

Research Project

2023.09 ~ 2023.12

1. DITTO:

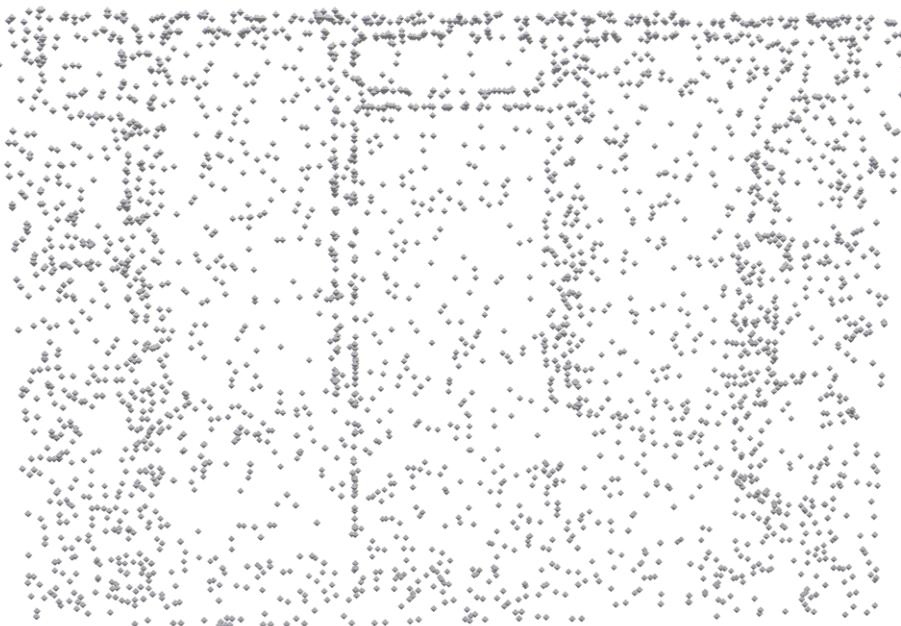
**Dual and Integrated Latent Topologies
for Implicit 3D Reconstruction**

Jaehyeok Shim, Kyungdon Joo
under review

Introduction

Problem Statement

- Reconstructing meshes from input point clouds.



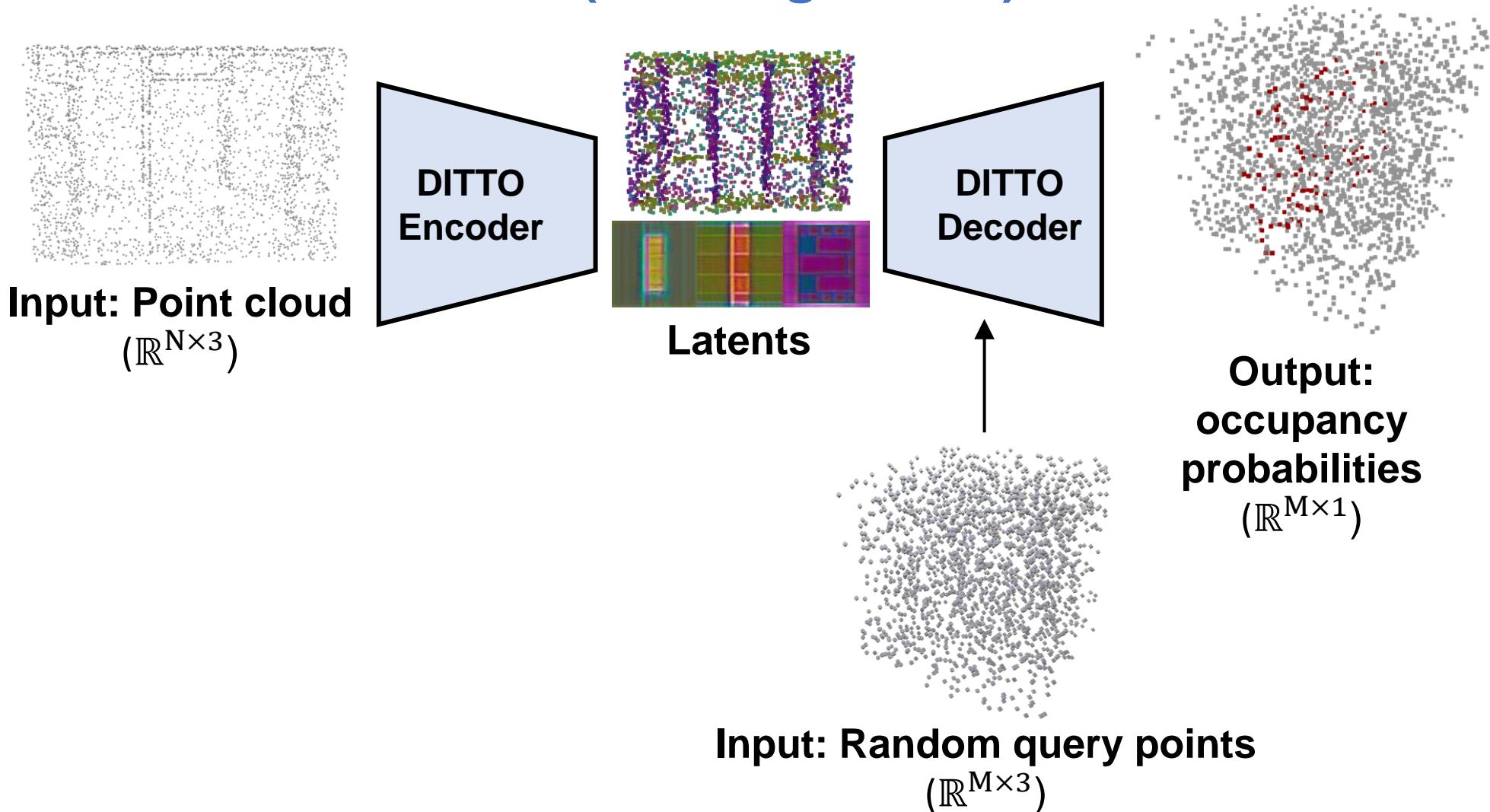
Input: Point cloud
 $(\mathbb{R}^{N \times 3})$

Output: Mesh
(vertices: $\mathbb{R}^{M \times 3}$, faces: $\mathbb{R}^{L \times 3}$)

- **Fundamental ill-posed problem** in 3D vision similar to super-resolution of image domain.

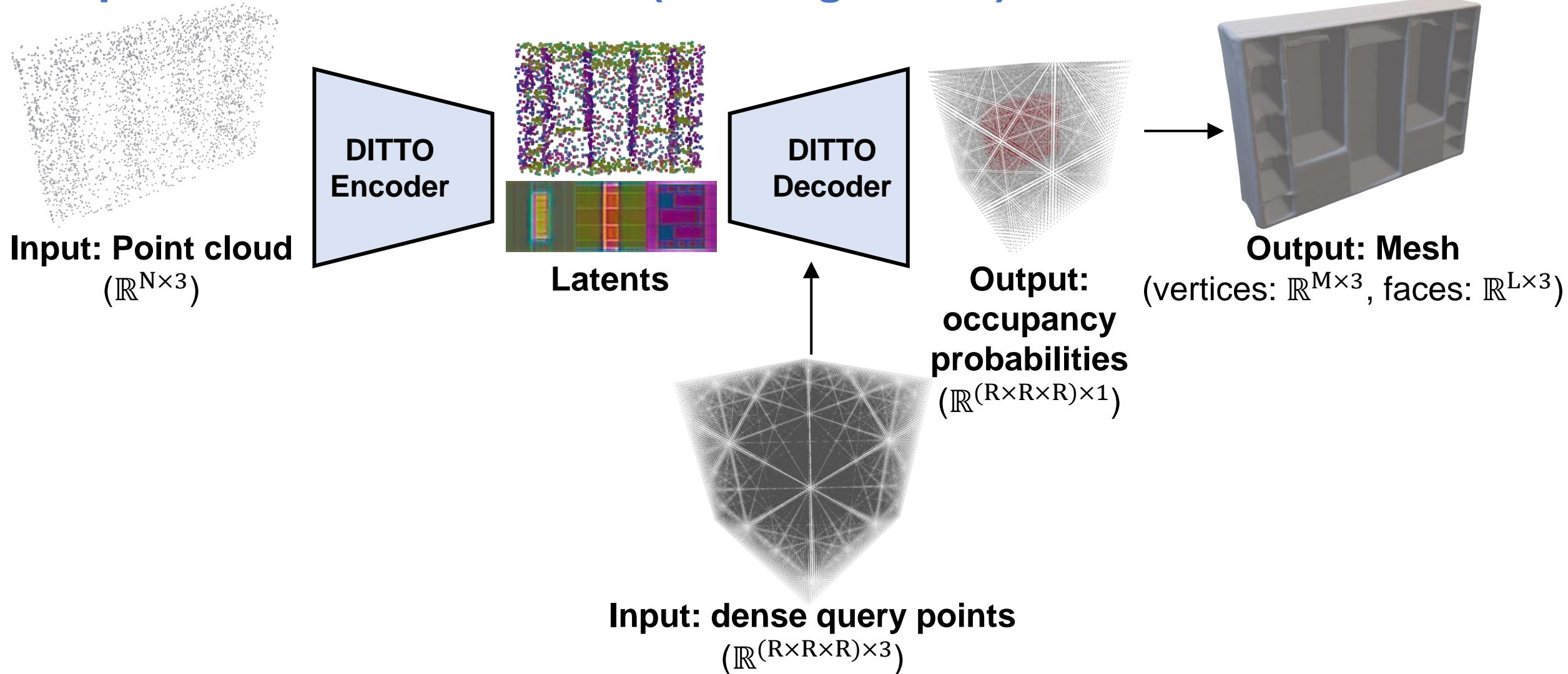
Introduction

Implicit 3D Reconstruction (Training Phase)



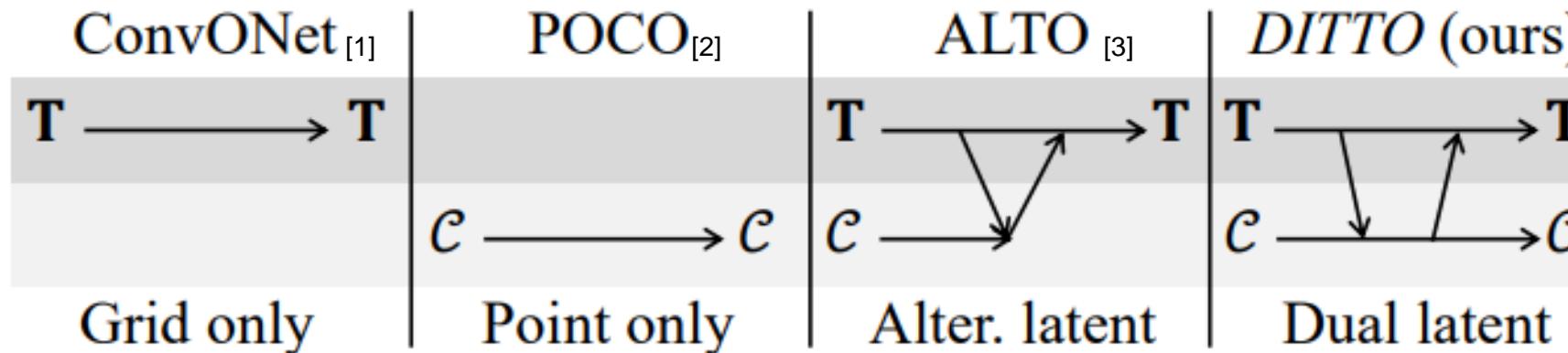
Introduction

Implicit 3D Reconstruction (Training Phase)



Methods

Concept of our DITTO Encoder



Conceptual Comparison of Encoder Architectures

- **DITTO** encoder uses both grid \mathbf{T} and point \mathcal{C} latents at once.
- Previous methods mainly depend on a single latent type.
- Utilizing complementary strengths of each latent is important.

$\mathbf{T} \in \mathbb{R}^{3 \times d \times H \times W}$: grid latent

$\mathcal{C} \in \mathbb{R}^{N \times d}$: point latent

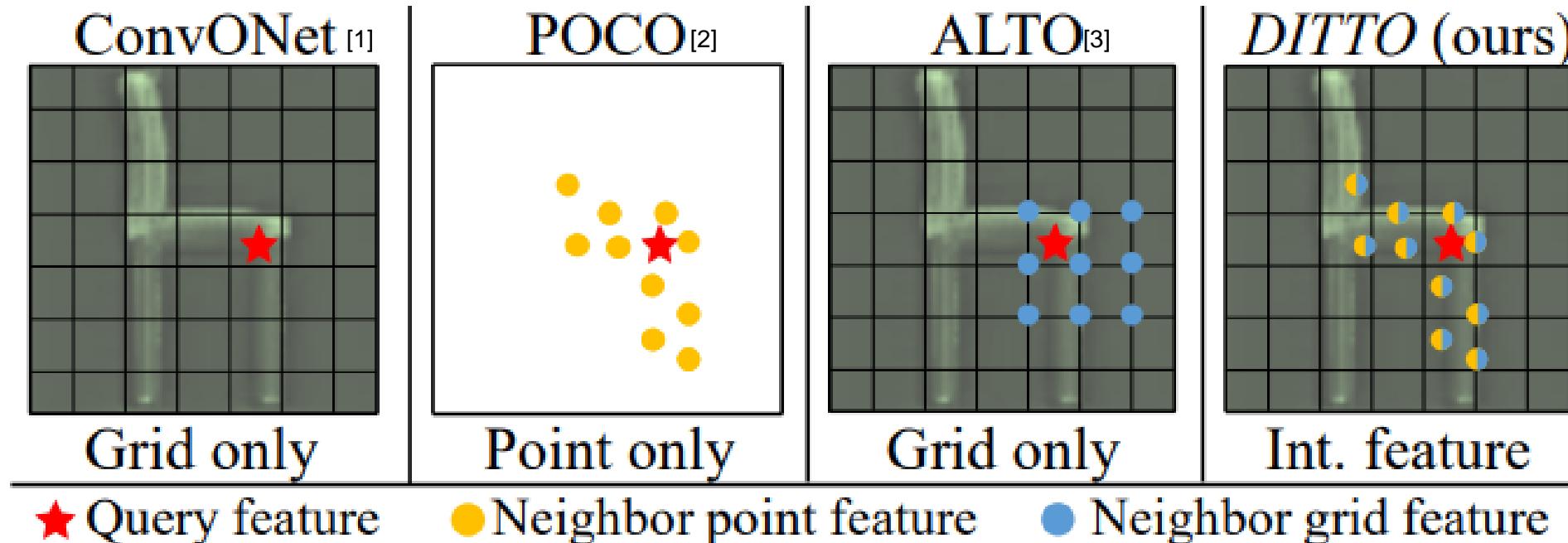
[1] Peng, Songyou, et al. "Convolutional occupancy networks." ECCV 2020.

[2] Boulch, Alexandre, and Renaud Marlet. "Poco: Point convolution for surface reconstruction." CVPR 2022.

[3] Wang, Zhen, et al. "Alto: Alternating latent topologies for implicit 3d reconstruction." CVPR 2023.

Methods

Concept of our DITTO Decoder



Conceptual Comparison of Decoder Architectures

- **DITTO** decoder integrates both grid and point latents to estimate occupancy.
- All previous methods use depend on a single latent.

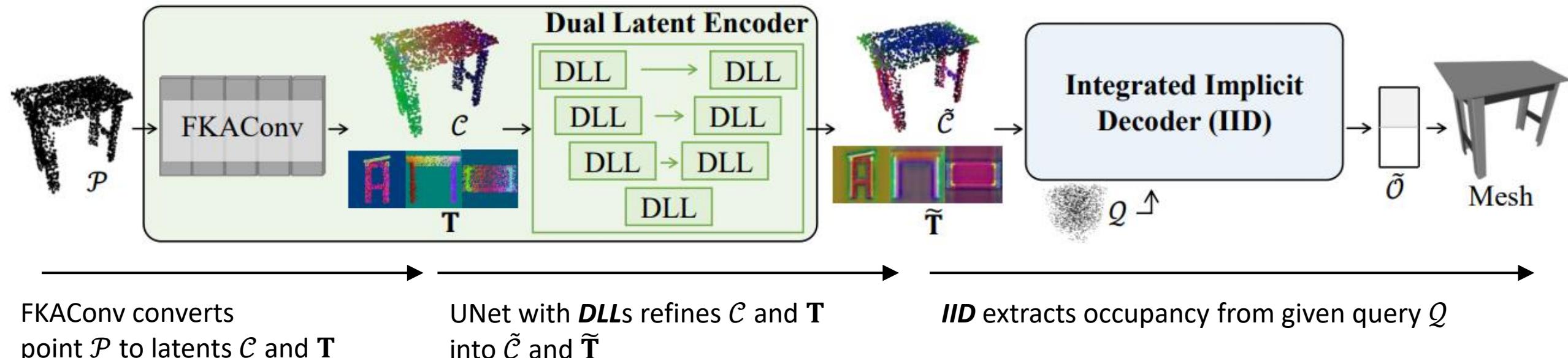
[1] Peng, Songyou, et al. "Convolutional occupancy networks." ECCV 2020.

[2] Boulch, Alexandre, and Renaud Marlet. "Poco: Point convolution for surface reconstruction." CVPR 2022.

[3] Wang, Zhen, et al. "Alto: Alternating latent topologies for implicit 3d reconstruction." CVPR 2023.

Methods

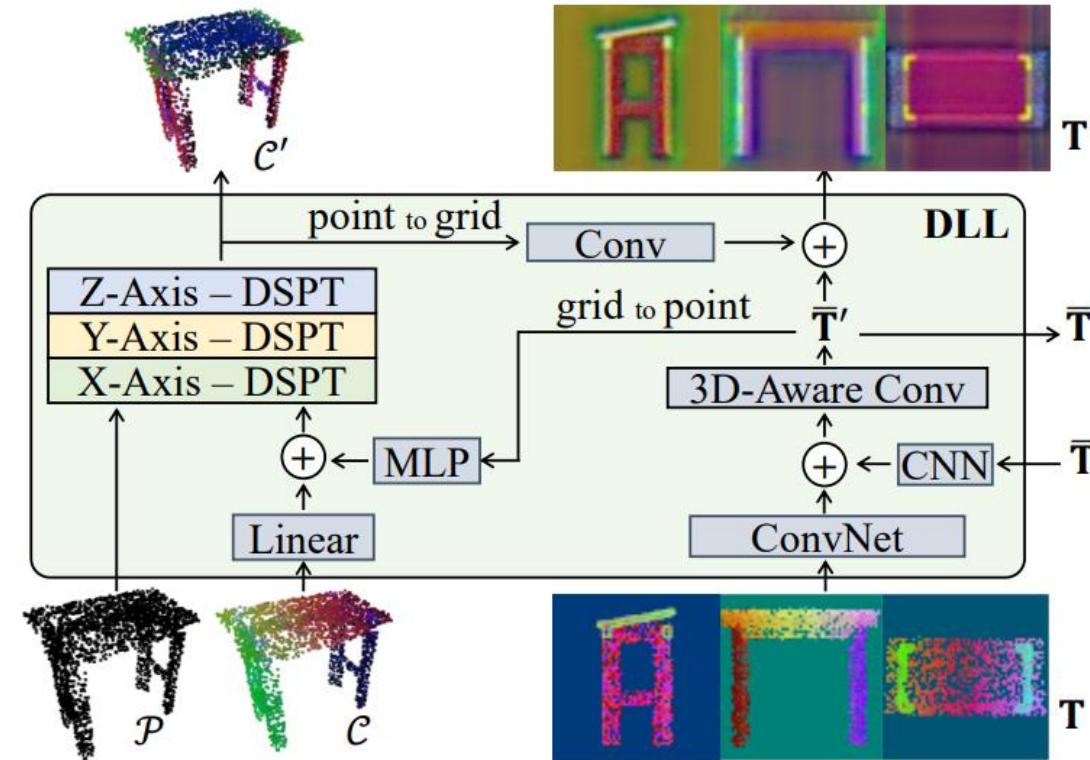
DITTO Overview



- **Notation**
- $\mathcal{P} \in \mathbb{R}^{N \times 3}$: point cloud
- \mathcal{C} or $\tilde{\mathcal{C}} \in \mathbb{R}^{N \times d}$: point latent
- \mathbf{T} or $\tilde{\mathbf{T}} \in \mathbb{R}^{3 \times d \times H \times W}$: grid latent
- $\mathcal{Q} \in \mathbb{R}^{M \times 3}$: query point
- \mathcal{O} or $\tilde{\mathcal{O}} \in \mathbb{R}^{M \times 1}$: occupancy

Methods

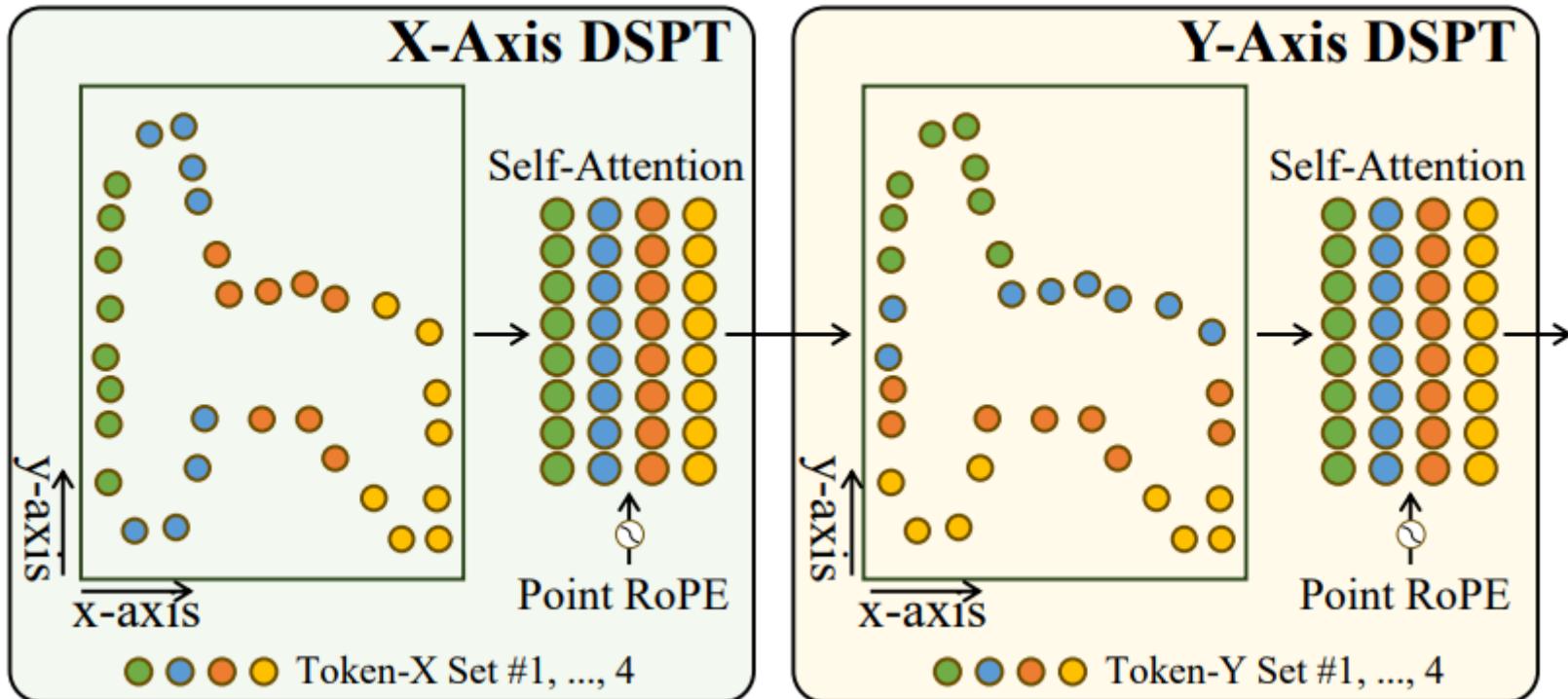
Dual Latent Layer (DLL)



- Enhances both grid T and point C latents to produce \bar{T}' and \bar{C}' .
- **DSPT** especially enhances point latent C .

Methods

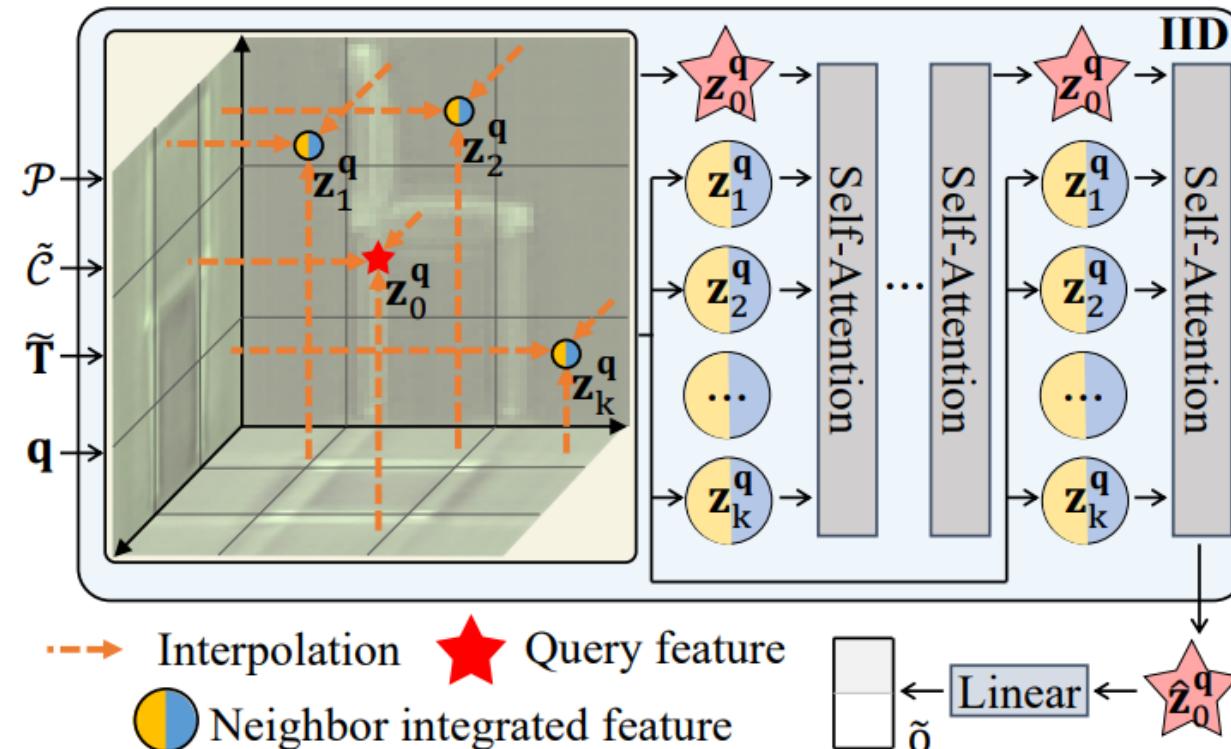
Dynamic Sparse Point Transformer (DSPT)



- Similar to SwinTransformer^[4]. The windows are split based on point coordinates.

Methods

Integrated Implicit Decoder (IID)

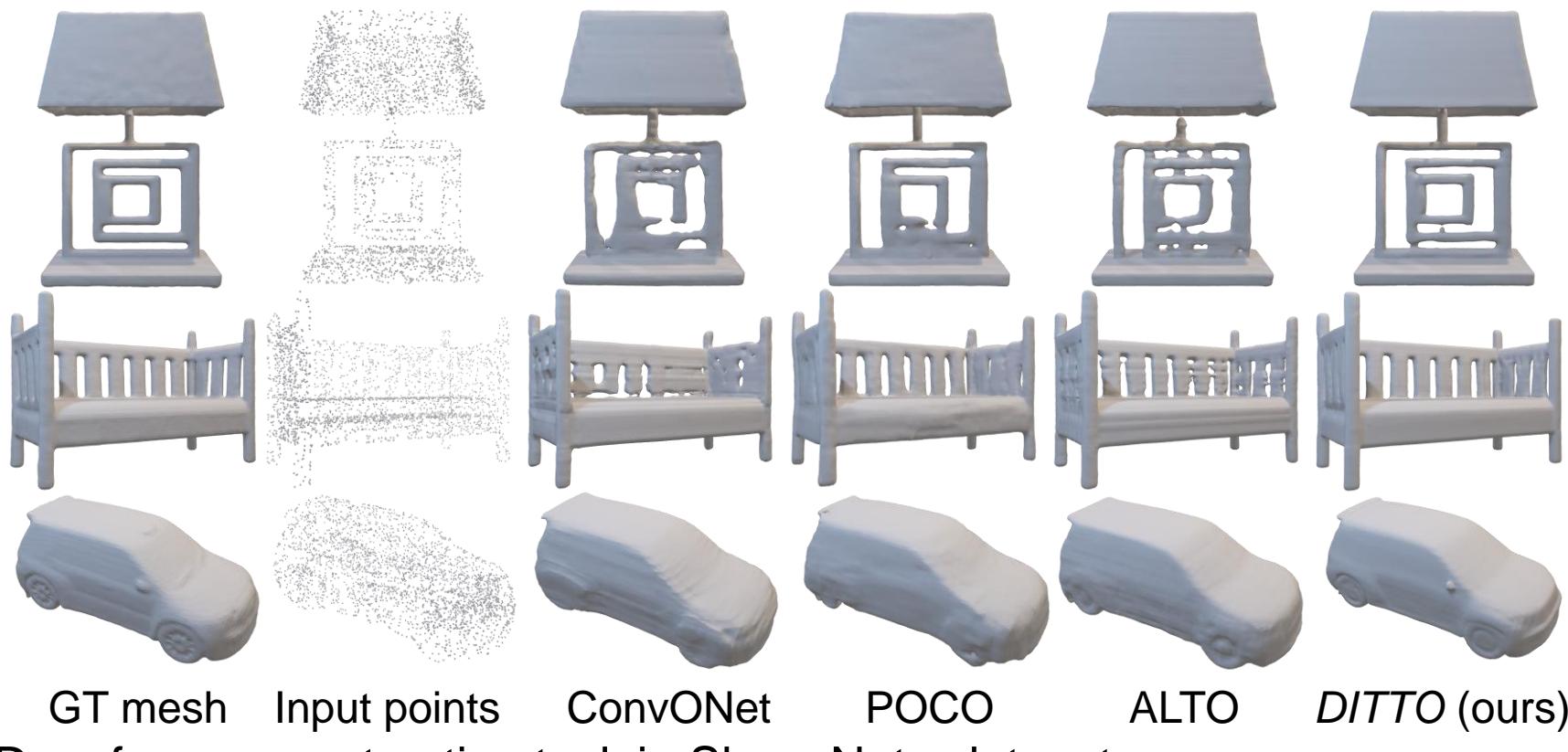


1. Find neighbor points $\tilde{\mathcal{P}}^{\mathbf{q}}$ and their latents $\tilde{\mathcal{C}}^{\mathbf{q}}$ of a query \mathbf{q} .
2. Combine $\tilde{\mathcal{C}}^{\mathbf{q}}$ with grid latent to make $Z^{\mathbf{q}} = \{\mathbf{z}_1^{\mathbf{q}}, \dots, \mathbf{z}_k^{\mathbf{q}}\}$.
3. Interpolate grid feature at \mathbf{q} to make $\mathbf{z}_0^{\mathbf{q}}$.
4. Apply self-attention multiple times to a sequence $\{\mathbf{z}_0^{\mathbf{q}}, \dots, \mathbf{z}_k^{\mathbf{q}}\}$ to make final occupancy.

Experiments

Object-Level 3D Surface Reconstruction

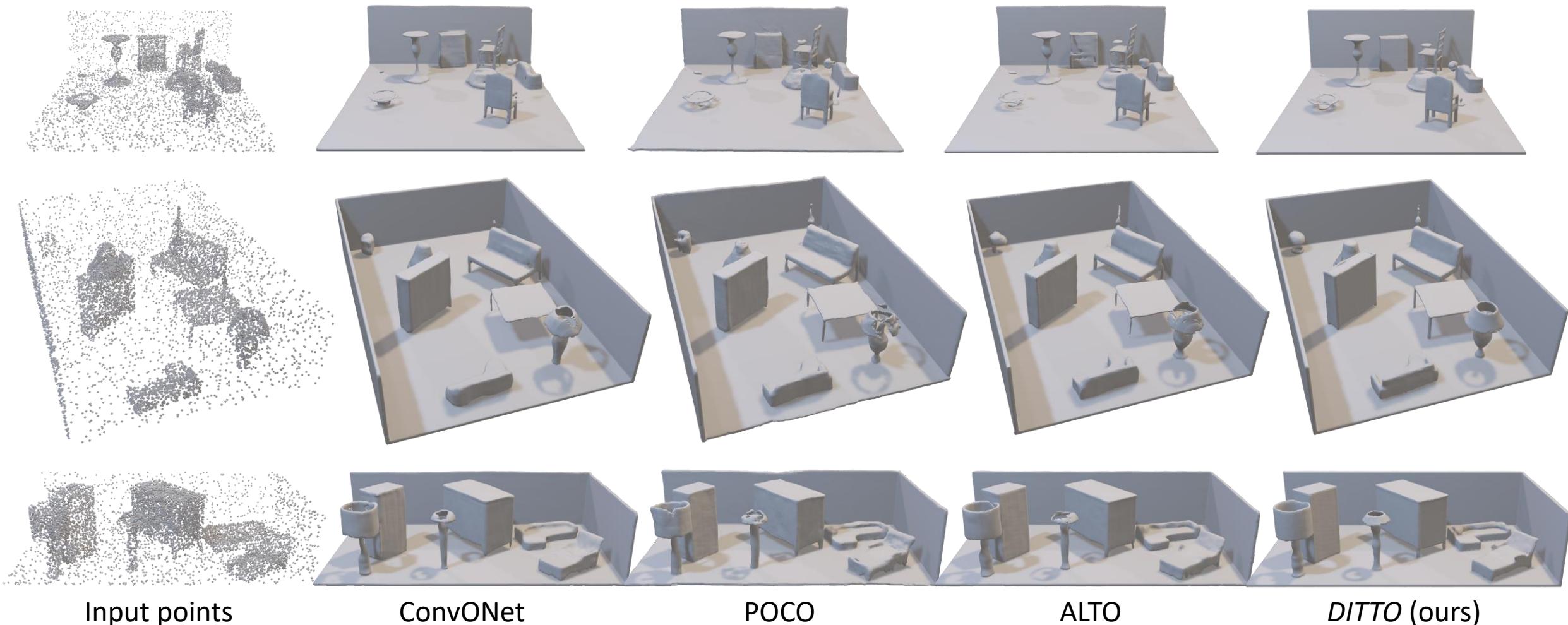
Method	normal (3K points & noise level 0.005)				sparse (1K points & noise level 0.005)				sparse (300 points & noise level 0.005)			
	IoU ↑	Chamfer- L_1 ↓	NC ↑	F-score ↑	IoU ↑	Chamfer- L_1 ↓	NC ↑	F-score ↑	IoU ↑	Chamfer- L_1 ↓	NC ↑	F-score ↑
ONet [25]	0.761	0.87	0.891	0.785	0.772	0.81	0.894	0.801	0.778	0.80	0.895	0.806
ConvONet [30]	0.884	0.44	0.938	0.942	0.859	0.50	0.929	0.918	0.821	0.59	0.907	0.883
POCO [1]	0.926	<u>0.30</u>	0.950	<u>0.984</u>	0.884	0.40	0.928	0.950	0.808	0.61	0.892	0.869
ALTO [45]	<u>0.930</u>	<u>0.30</u>	<u>0.952</u>	0.980	<u>0.905</u>	<u>0.35</u>	<u>0.940</u>	<u>0.964</u>	<u>0.863</u>	<u>0.47</u>	<u>0.922</u>	<u>0.924</u>
DITTO (ours)	0.949	0.27	0.957	0.988	0.926	0.32	0.949	0.975	0.882	0.43	0.931	0.940



- SoTA in 3D surface reconstruction task in ShapeNet^[5] dataset.

Experiments

Scene-Level 3D Surface Reconstruction



- SoTA in 3D surface reconstruction task in SyntheticRooms dataset.

Conclusion

- New method how to handle data types including both grid and point cloud.
- New model architecture **DITTO**, based on proposed **DLL**, **DSPT**, **IID** modules.
- Achieve SoTA in implicit 3D reconstruction tasks.

Research Project

2023.09 ~ 2023.12

2. SDF-Diffusion: Diffusion-Based Signed Distance Fields for 3D Shape Generation

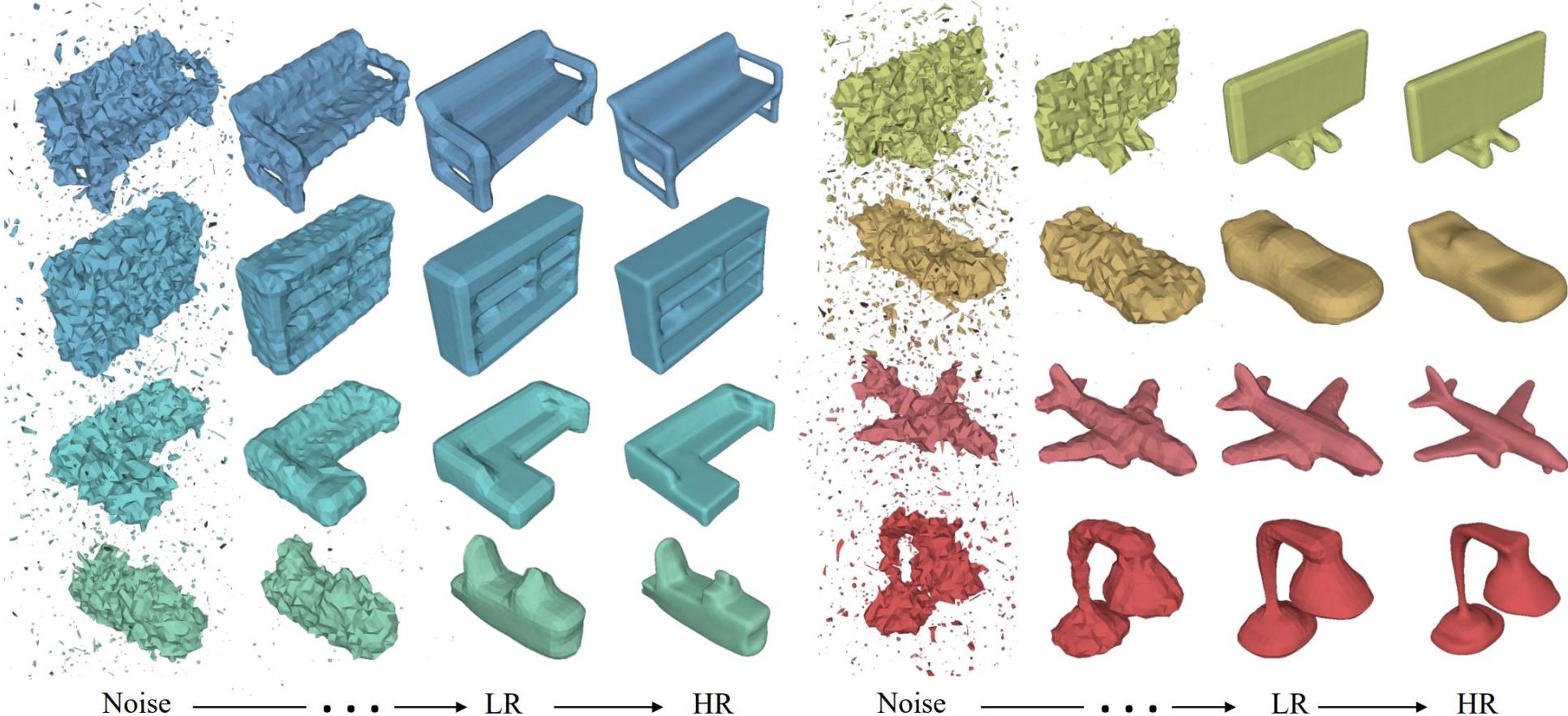
CVPR 2023



Introduction

Problem Statement

- Make a **diffusion-based 3D shape generative model** in the form of **meshes**.

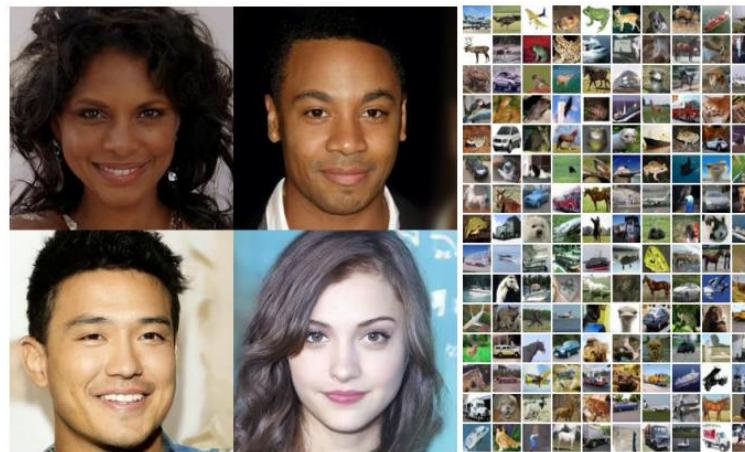


- **Input:** **TSDF Grid** (from mesh), **Output:** New **TSDF Grid** (can be converted into mesh)

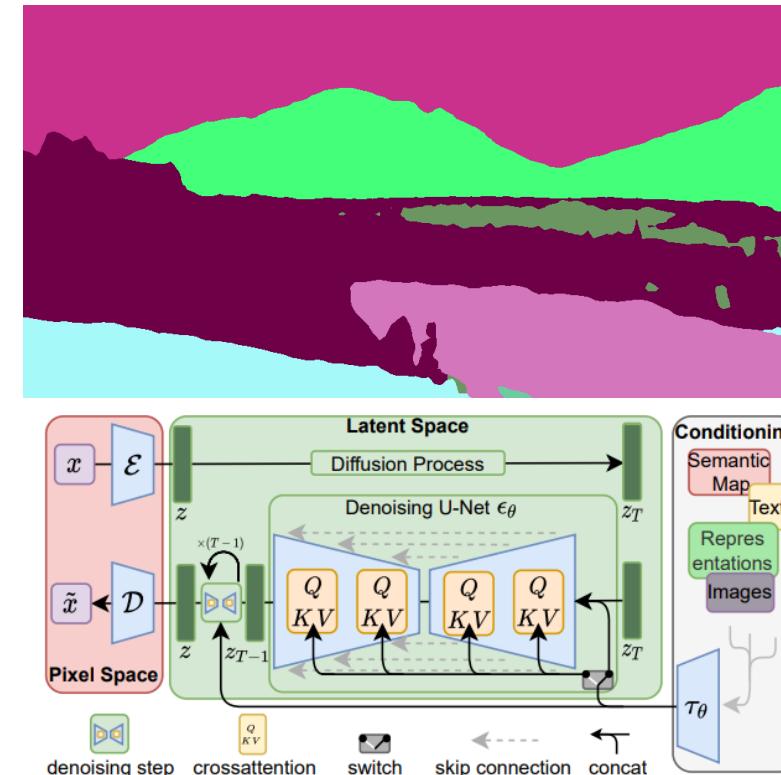
Introduction

Motivation: Emergence of Denoising Diffusion Models for Image

DDPM (NIPS 2020) [1]



LDM (CVPR 2022) [2]



CDM (JMLR 2022) [3]



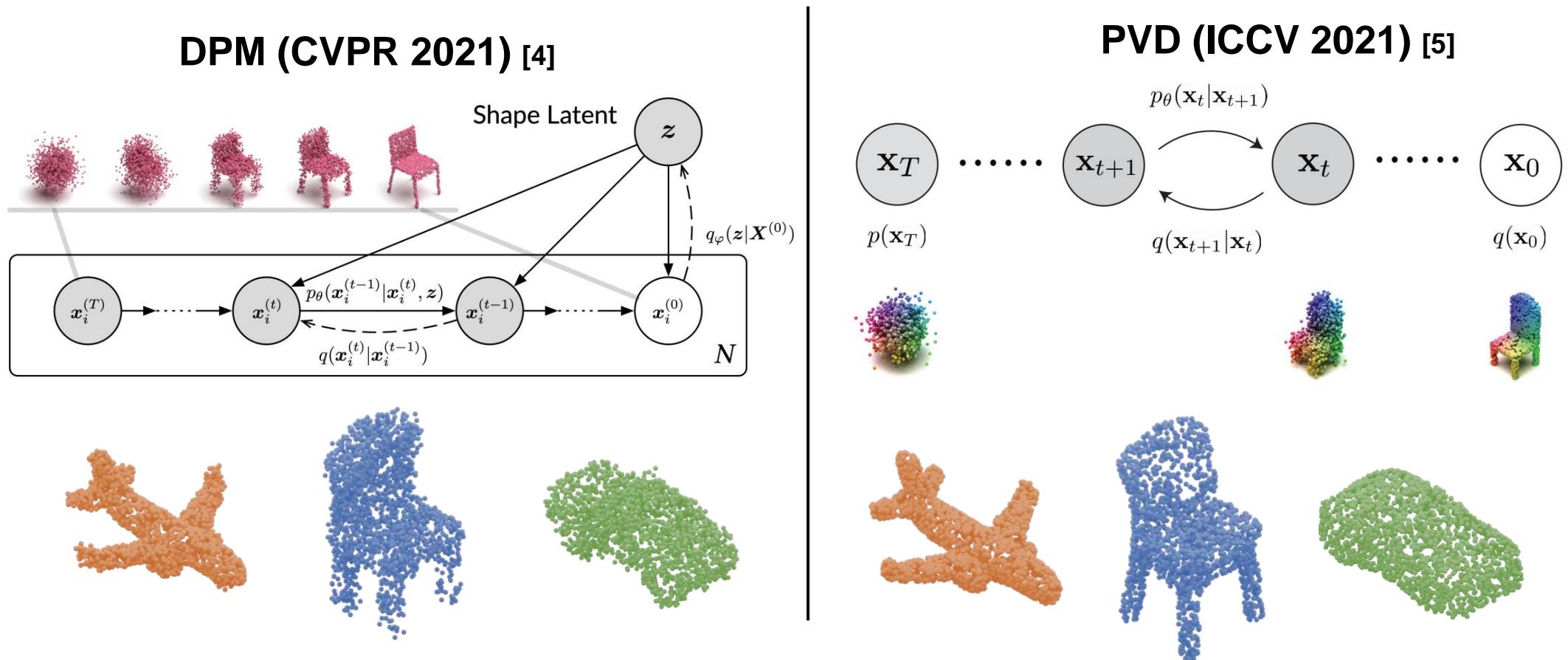
[1] Ho et al. "Denoising diffusion probabilistic models." NeurIPS 2020.

[2] Rombach et al. "High-resolution image synthesis with latent diffusion models." CVPR 2022.

[3] Ho et al. "Cascaded Diffusion Models for High Fidelity Image Generation." JMLR 2022.

Introduction

Observation: Limitation of Previous Methods

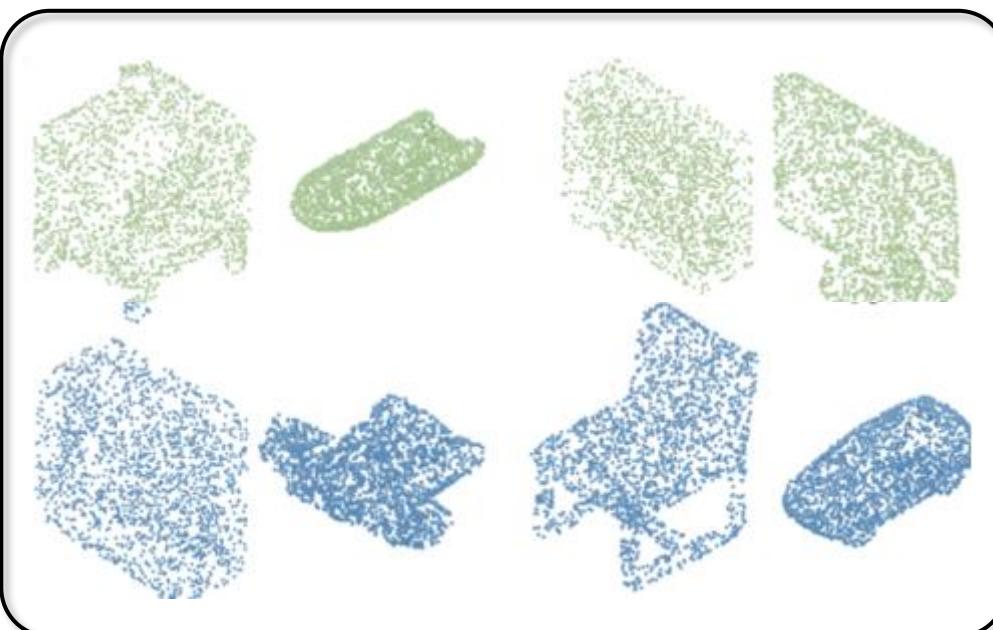


- Previous diffusion-based 3D shape generative models are based on point cloud representation.

Introduction

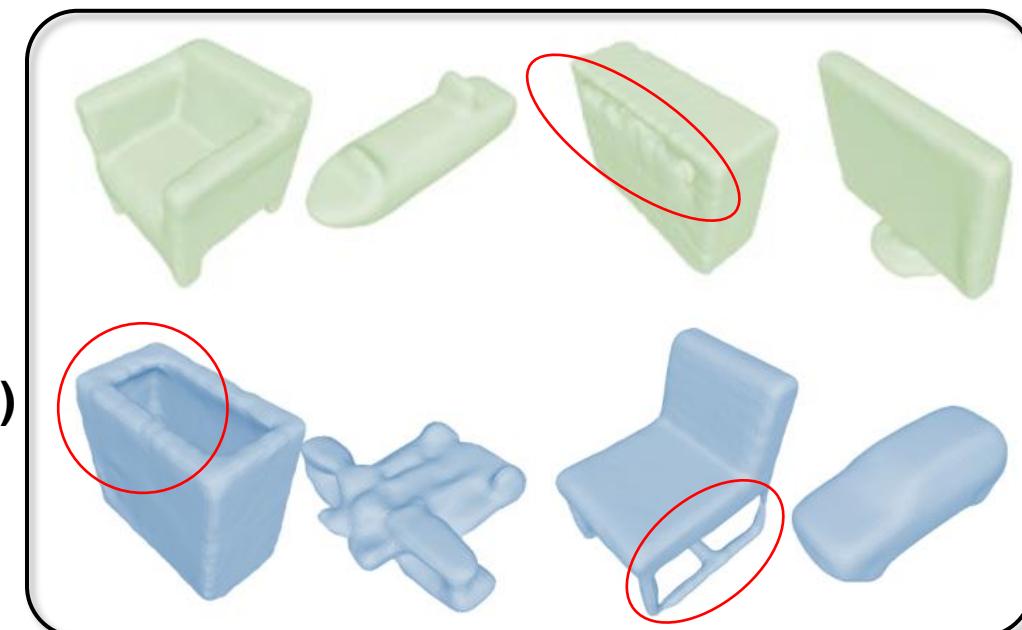
Observation : Limitation of Point Cloud

Point Cloud (from PVD [6])



→
Remeshing
(pretrained SAP [7])

Reconstructed Mesh



- Point cloud requires **complex processes** to reconstruct mesh.
- Reconstructed mesh has **imperfect surface** due to partial characteristic of point cloud.

Introduction

Challenge: Processing High-Resolution Voxel

- Training deep neural network requires thousands of features maps.

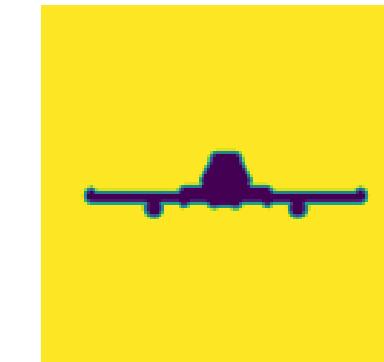
Data Type	Spatial Complexity	Capacity	
Image (2D)	128 x 128	2 Mbytes	
Voxel (3D)	128 x 128 x 128	256 Mbytes	→ Out of memory!

(for 32 channels of float32)

- Processing voxel like 2D image will exceeds **GPU memory and computation limitation**.



$$2D \ 128^2 = 2^{14}$$

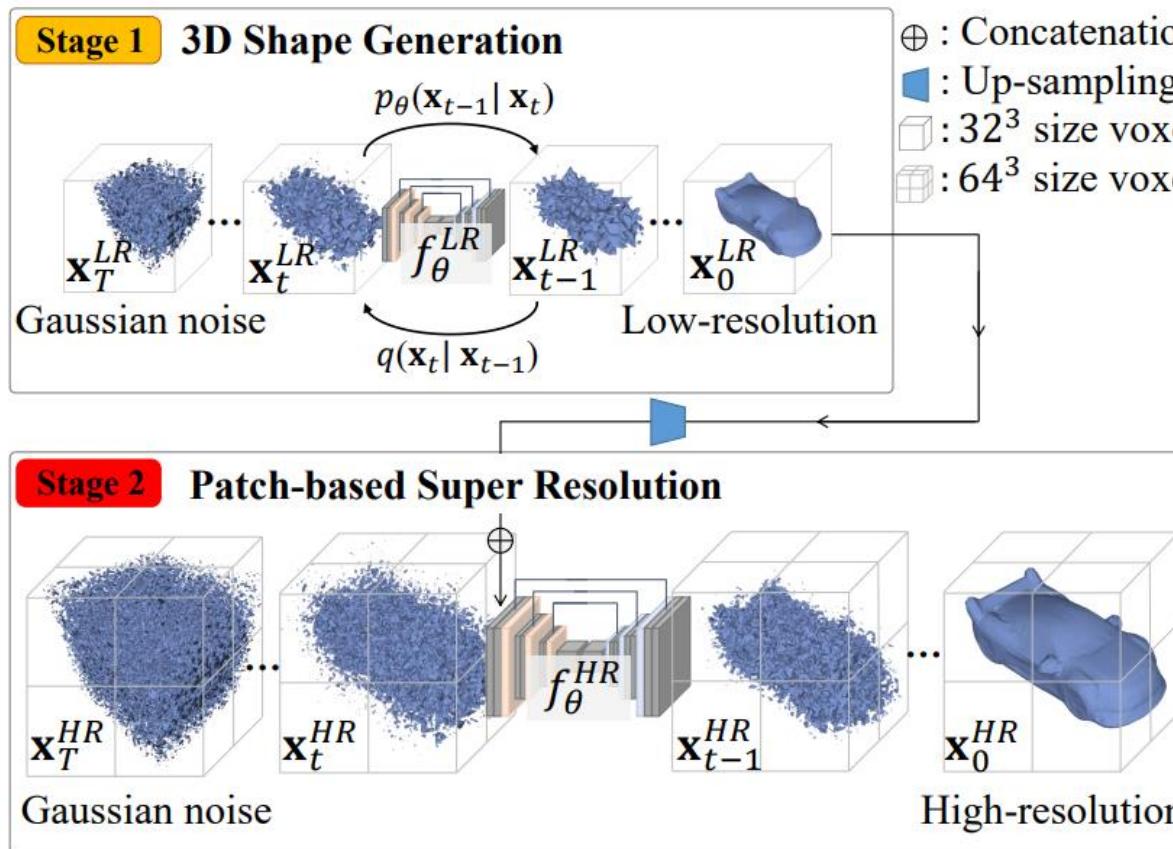


$$3D \ 128^3 = 2^{21}$$

Methods

Two-Stage Diffusion Framework for TSDF Voxel

- Stage 1: Generates **low-resolution TSDF voxel** (at 32^3 resolution).
- Stage 2: **Upsamples TSDF voxel** into high-resolution ($32^3 \rightarrow 64^3$ or $64^3 \rightarrow 128^3$)

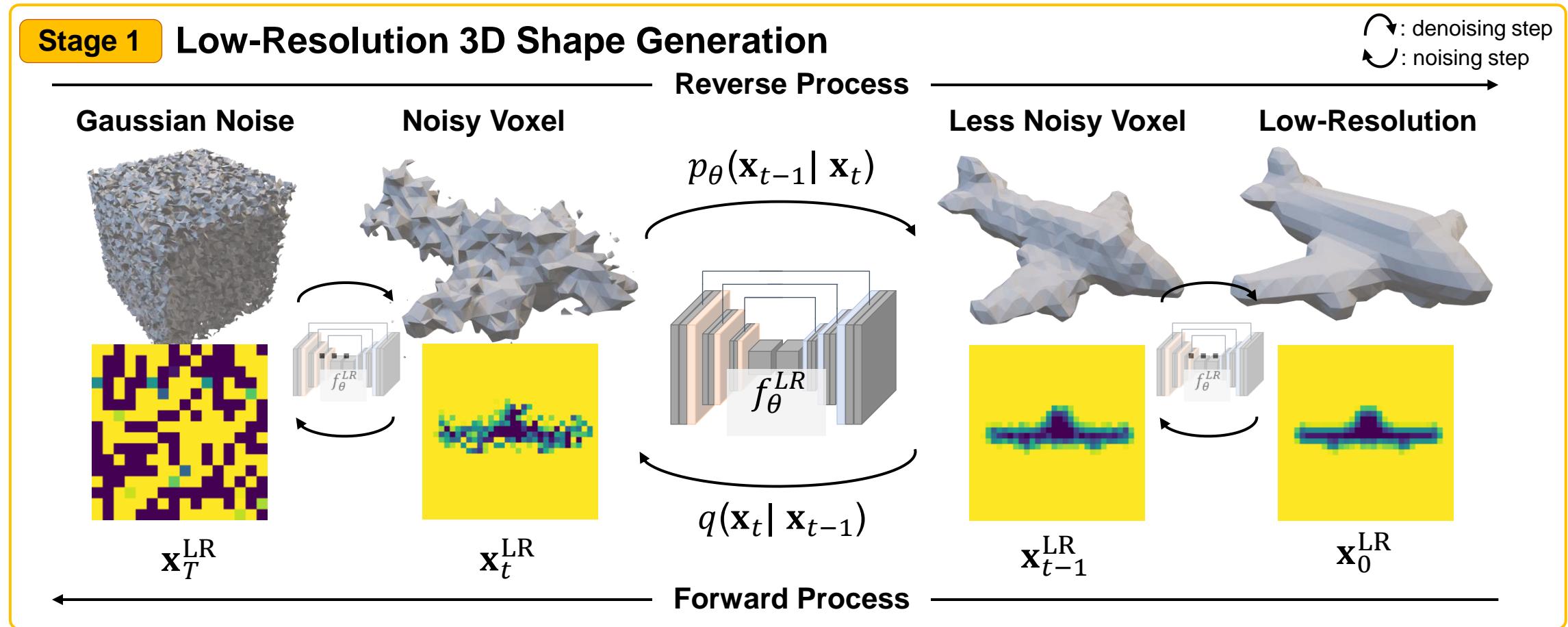


- \mathbf{x}_t^{LR} : low-resolution TSDF voxel at timestep t .
- \mathbf{x}_t^{HR} : high-resolution TSDF voxel at timestep t .
- f_θ^{LR} : first-stage generation model.
- f_θ^{HR} : second-stage super-resolution model.
- $q(\mathbf{x}_t | \mathbf{x}_{t-1})$: diffusion forward process.
- $p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t)$: diffusion reverse process.

Methods

Stage 1: Diffusion Models for Low-Resolution Generation

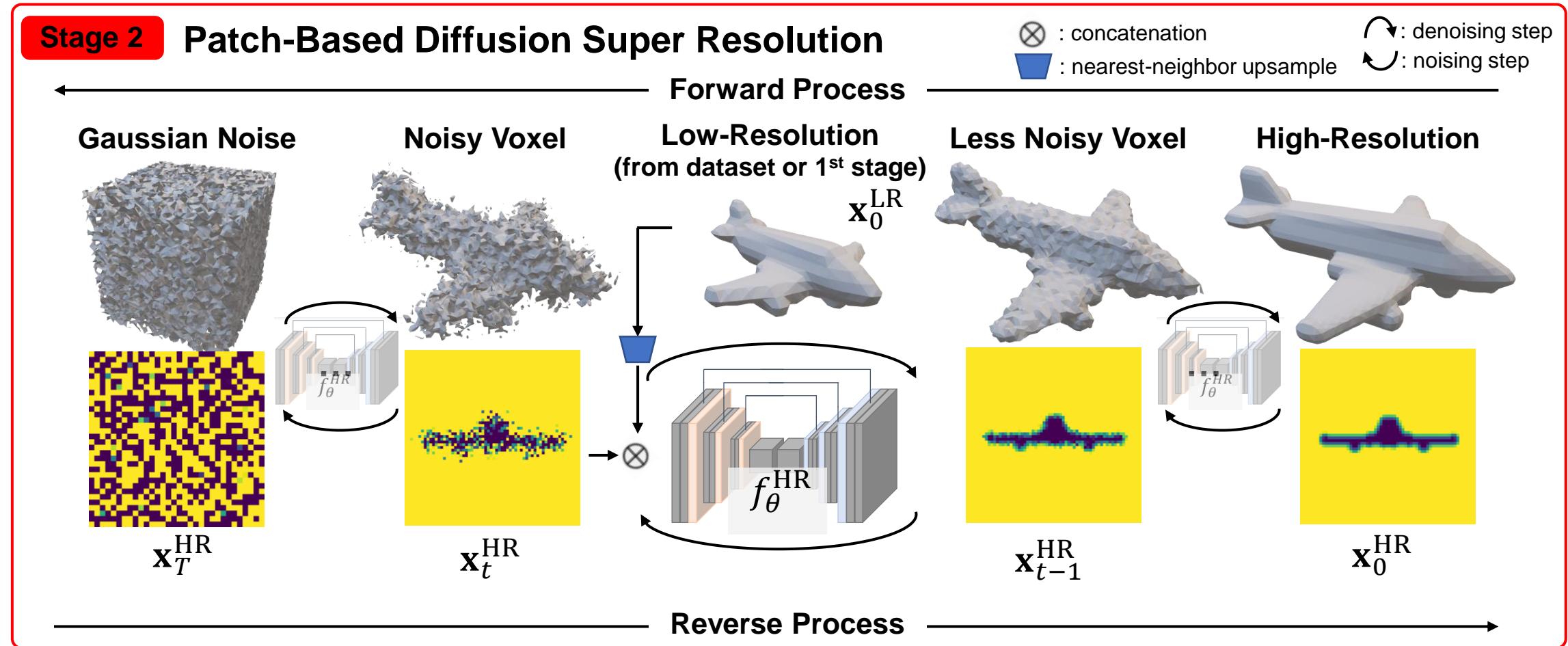
- Stage 1: generate low-resolution TSDF voxel using diffusion framework.



Methods

Stage 2: Diffusion Models for High-Resolution Super-Resolution

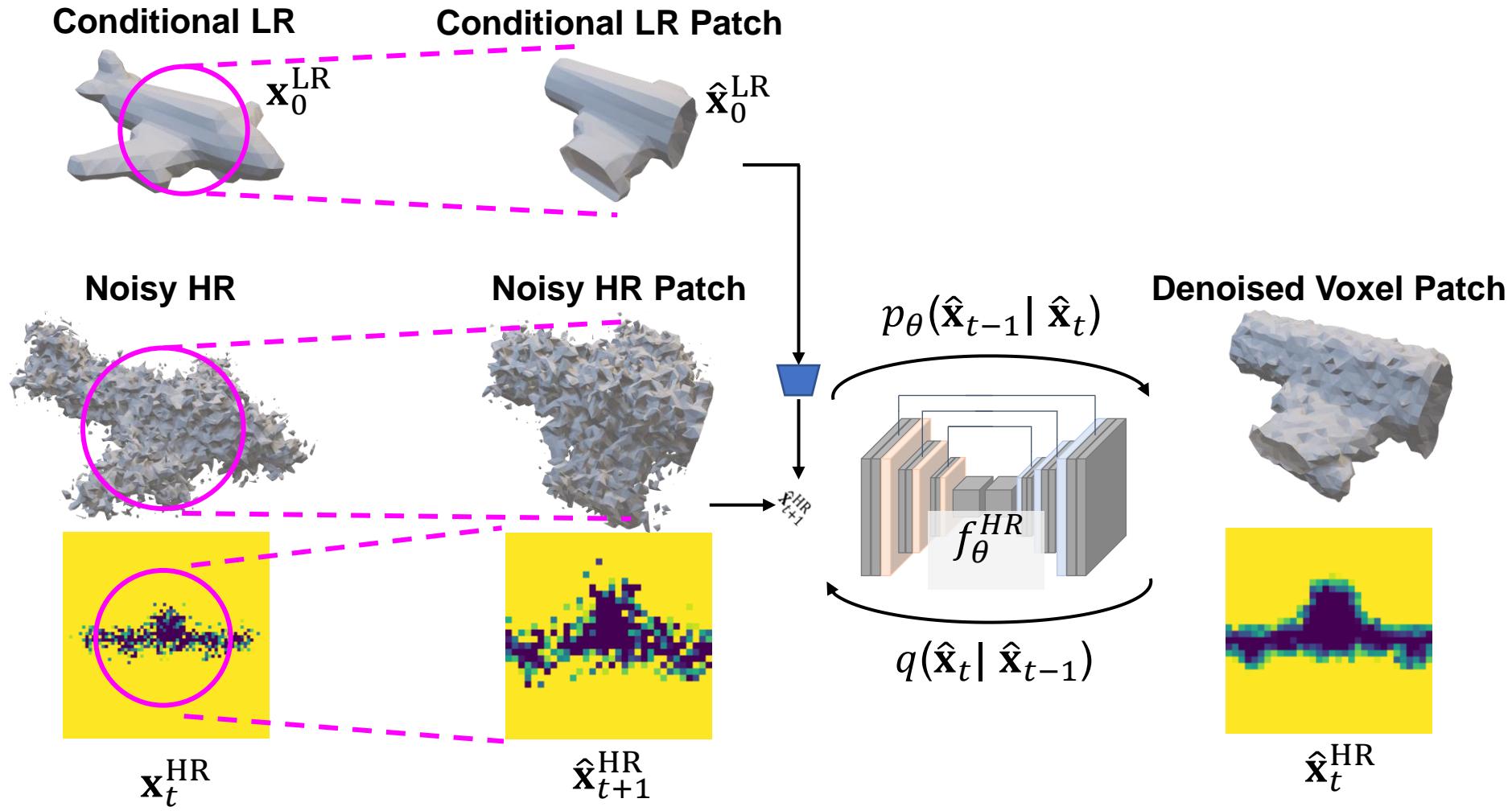
- Stage 2: generate high-resolution TSDF voxel using **diffusion-based super-resolution**.



Methods

Stage 2: Patch-Based Training Scheme

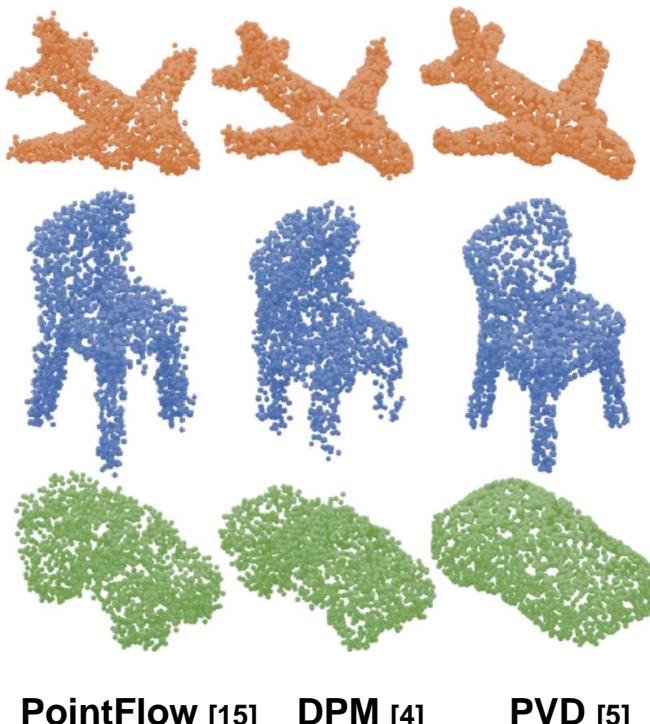
- Stage 2 is trained in **patch-by-patch** to alleviate **memory and computation**.



Experiments

Generation Performance

- Quantitative / qualitative evaluation of **single-category generation**.



		Trainset	PointFlow [15]	DPM [4]	PVD [5]	ours
Airplane	MMD (CD)	1.51	2.43	2.24	2.46	2.37
	COV (CD)	56.93	50.50	50.00	45.30	50.25
	1-NNA (CD)	45.92	72.28	67.45	62.62	56.56
Car	MMD (EMD)	2.33	1.67	1.64	1.55	1.49
	COV (EMD)	57.43	52.97	52.23	53.96	55.20
	1-NNA (EMD)	47.40	62.50	63.37	52.72	48.14
Chair	MMD (CD)	2.44	2.61	2.57	2.48	2.48
	COV (CD)	54.07	41.92	44.19	44.33	47.26
	1-NNA (CD)	49.47	74.50	75.57	58.48	58.28
Chair	MMD (EMD)	1.28	1.39	1.39	1.30	1.28
	COV (EMD)	52.34	41.92	41.92	48.33	52.47
	1-NNA (EMD)	50.53	71.90	71.90	51.13	53.20
Chair	MMD (CD)	8.05	8.27	7.65	7.87	8.00
	COV (CD)	54.95	46.53	47.86	48.89	49.78
	1-NNA (CD)	52.88	70.83	66.40	55.61	53.69
Chair	MMD (EMD)	3.57	4.21	4.08	3.56	3.61
	COV (EMD)	53.47	49.63	41.65	50.37	49.31
	1-NNA (EMD)	48.74	74.74	76.66	53.03	51.77

- Our framework **outperforms in most metrics** even though our **output is mesh, not point cloud**.

[15] Yang, et al. "Pointflow: 3d point cloud generation with continuous normalizing flows." ICCV 2019.

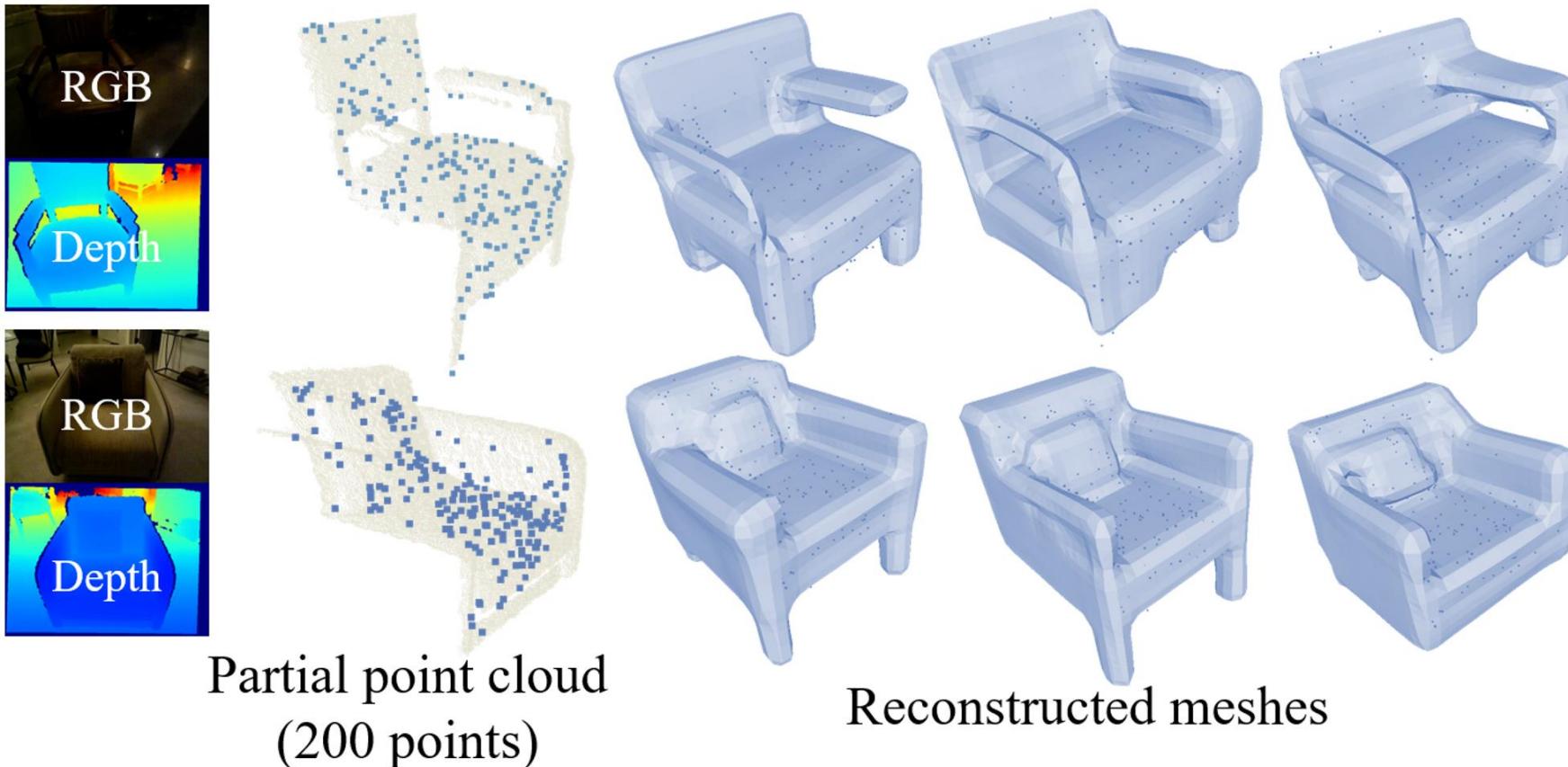
[4] Luo and Hu. "Diffusion probabilistic models for 3d point cloud generation." CVPR 2021.

[5] Zhou et al. "3d shape generation and completion through point-voxel diffusion." ICCV 2021.

Experiments

Application: Out-of-Distribution Shape Completion

- We test our shape completion method trained with **point cloud condition** about **unseen dataset** [16].



- Our model can generate various 3D shapes even from unseen dataset.

Conclusion

- New 3D mesh generative model based on diffusion.
- Comparable results than SoTA with more complicated representation (point v.s. mesh)

Research Project

2023.09 ~ 2023.12

3. ContactGen:

Contact-Guided Interactive

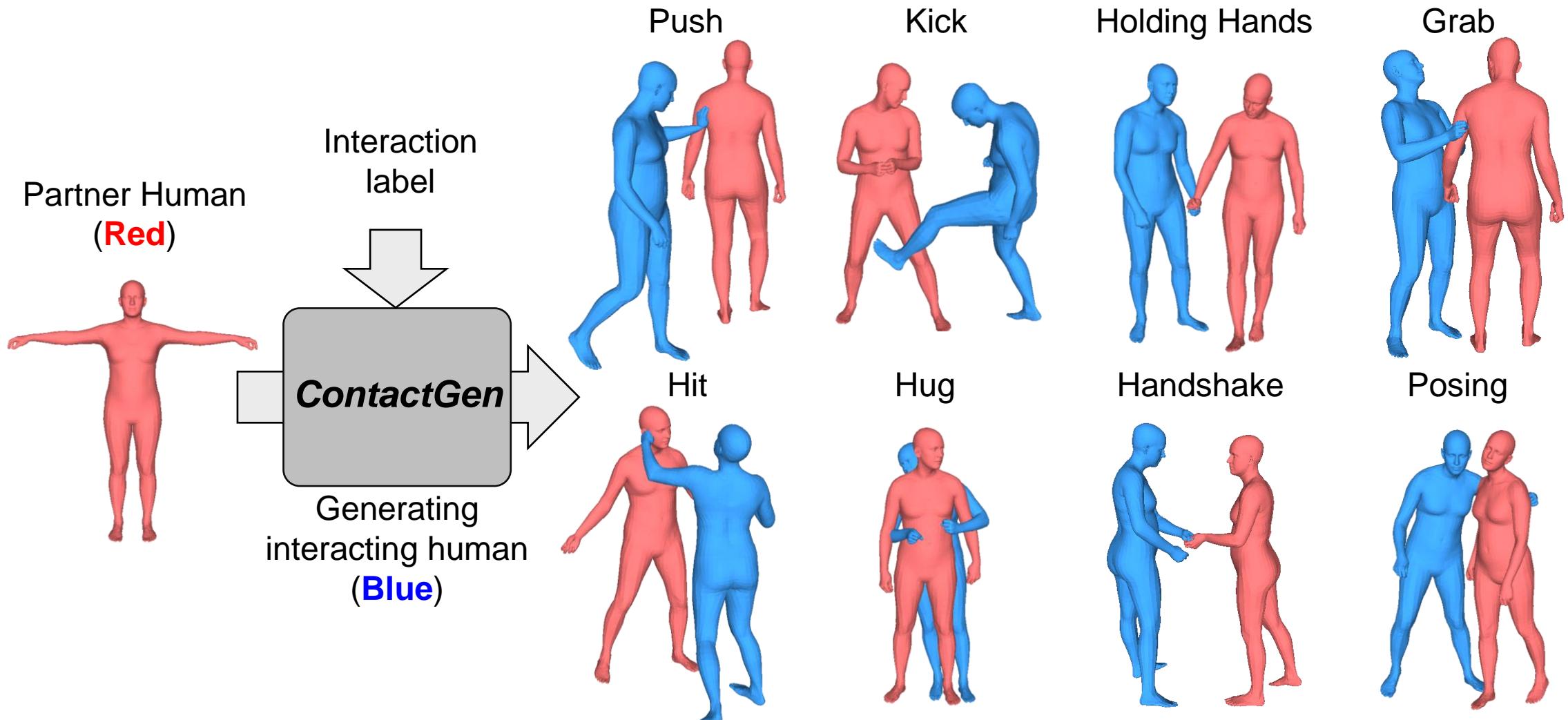
3D Human Generation for Partners

Dongjun Gu, Jaehyeok Shim, Jaehoon Jang, Changwoo Kang, Kyungdon Joo



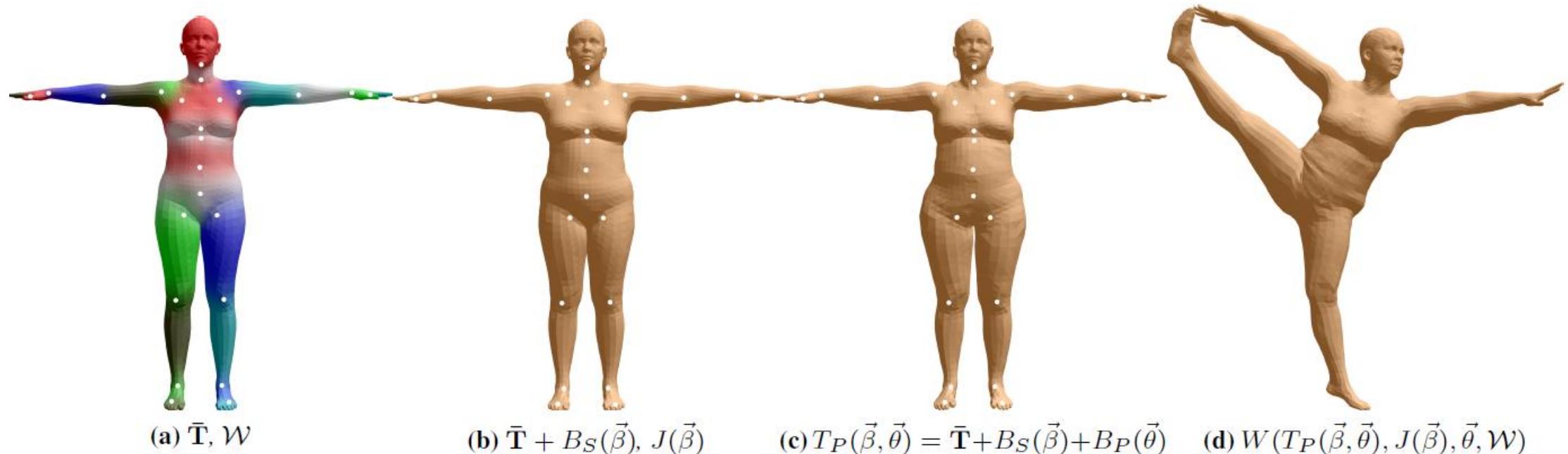
Introduction

Problem Statement

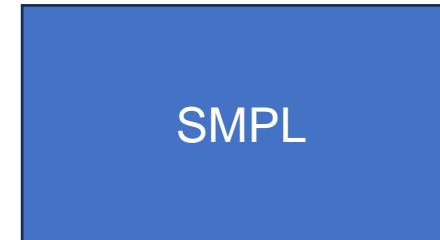


Background

SMPL-X_[1] Parameters



Body parameters:
 translation
 global rotation
 joint rotation
 body shape



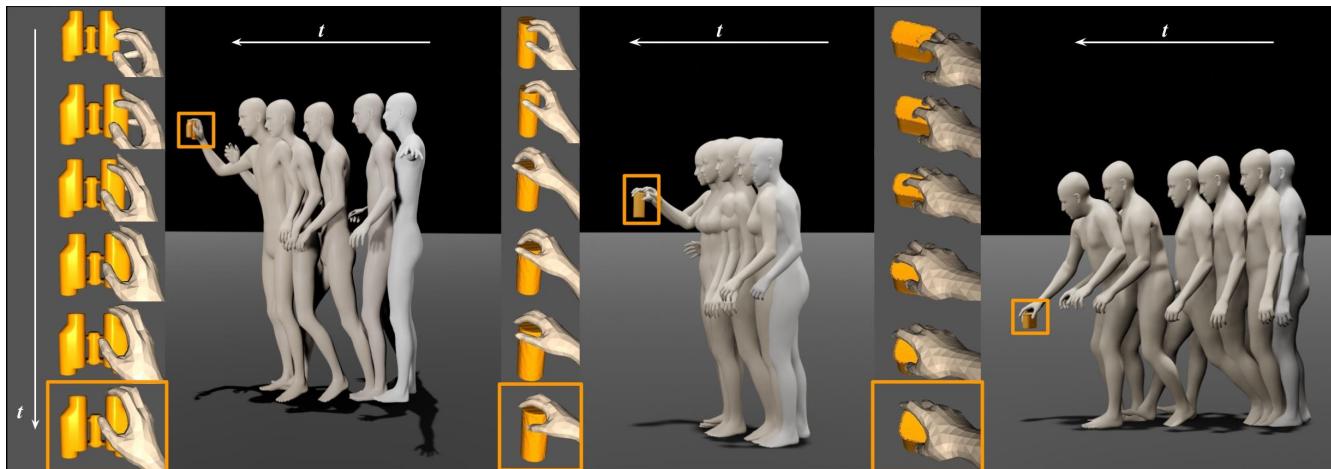
SMPL mesh
 (vertices & faces)

...

Related Works

Previous Works: Human-Object Interaction

- **SAGA_[2] (ECCV 2022):**
 - Generates human to grasp a given object.
 - **SceneDiffuser_[3] (CVPR 2023):**
 - Generates human conditioned to scene.
- Biased to contact with simple and static object.



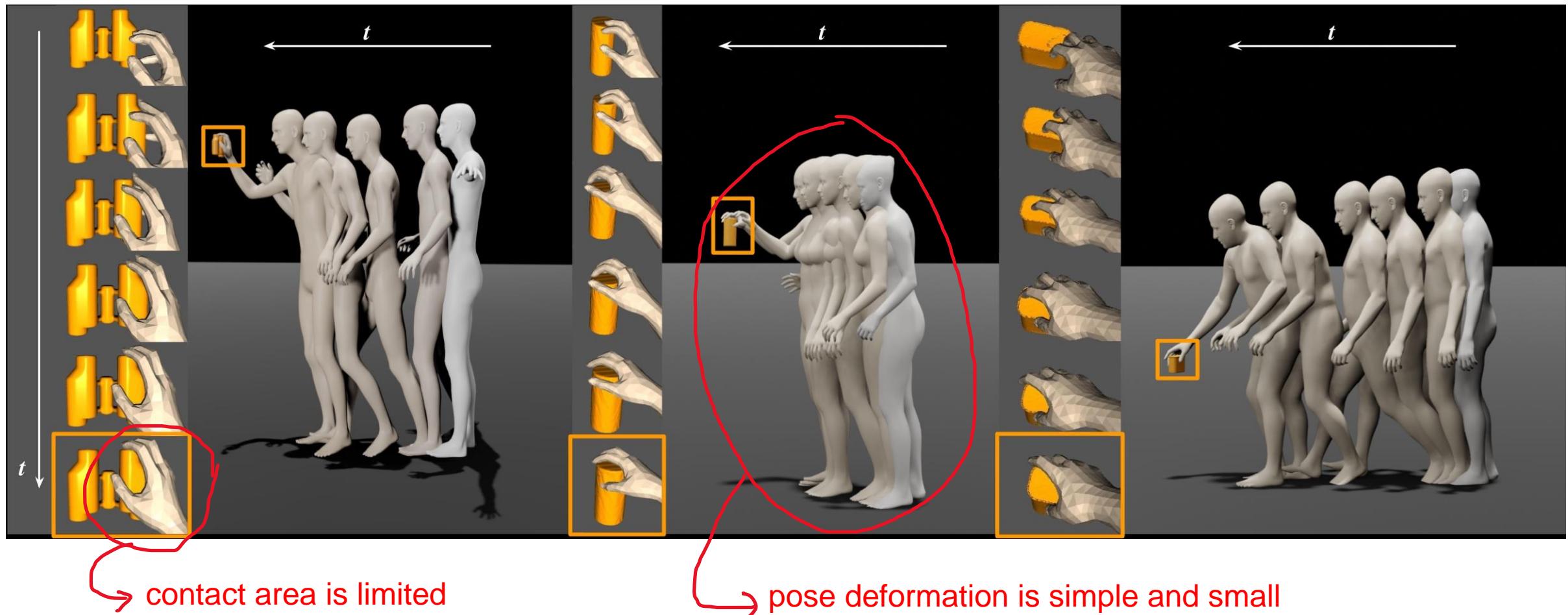
SAGA



SceneDiffuser

Related Works

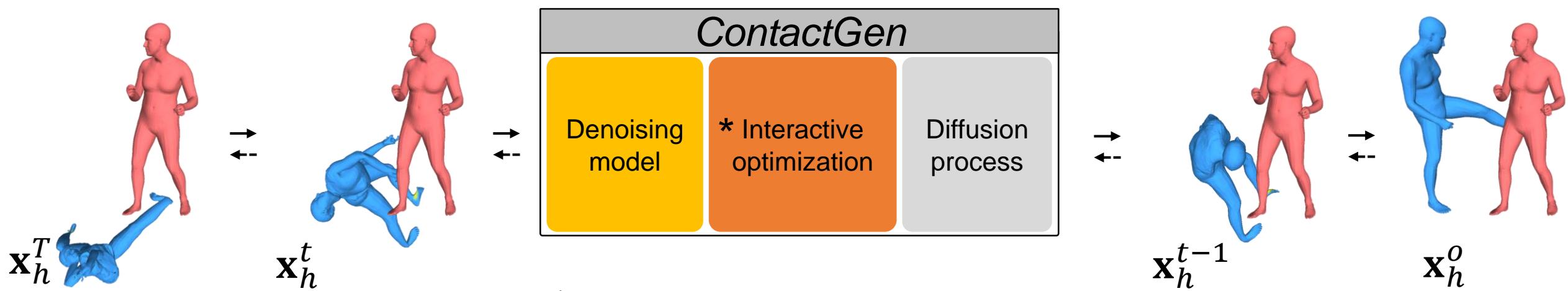
Limitation of Human-Object Interaction



Methods

ContactGen: Method Overview

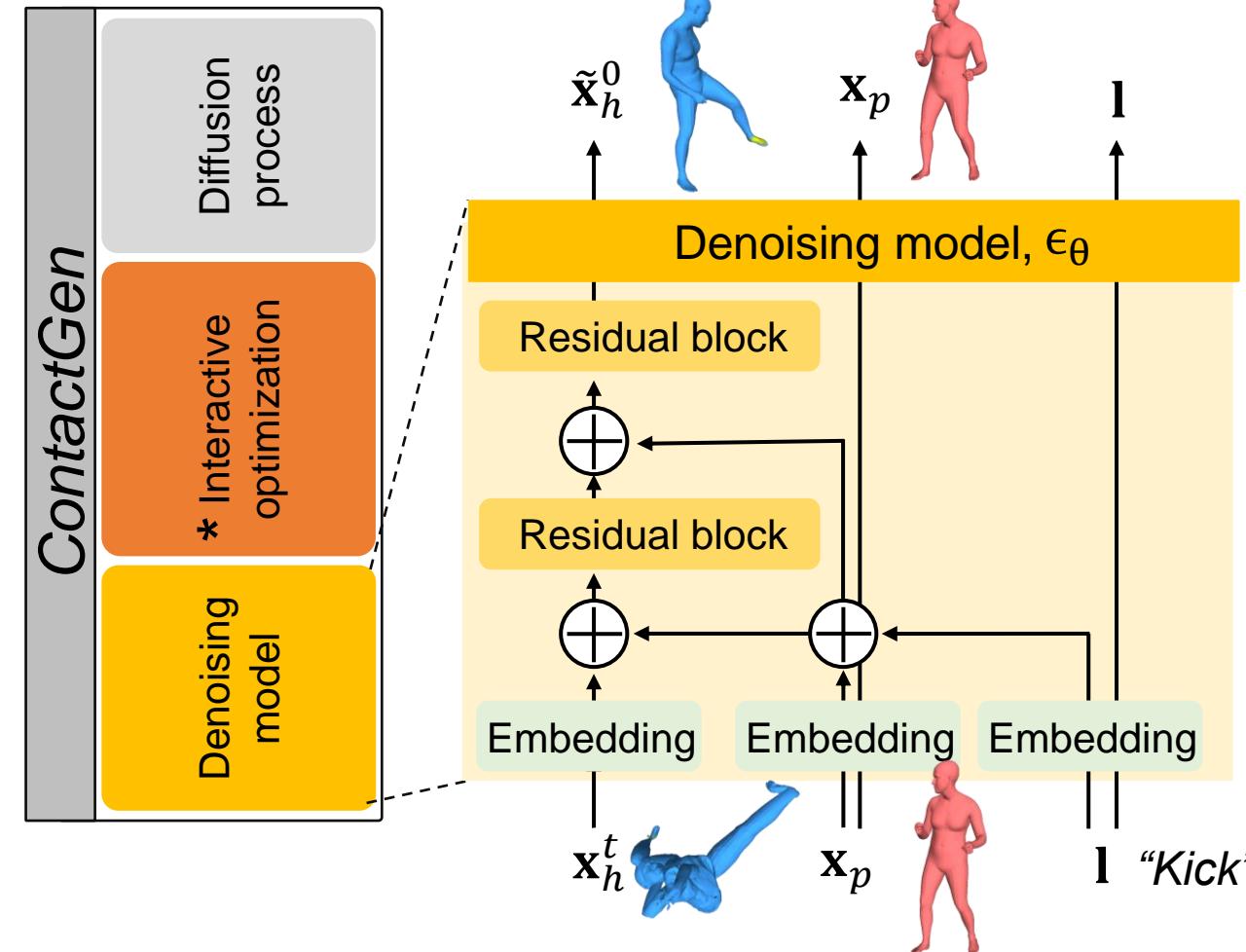
- Generate new human pose based on given partner's pose with diffusion models.



\mathbf{x}_h^t : human at diffusion timestep t
 \mathbf{x}_p : partner human
 \mathbf{l} : interaction label
 \rightarrow : forward process
 \rightarrow : reverse process
 * : sampling only

Methods

ContactGen: Denoising Model



Training Phase

- Diffusion model ϵ_θ learns how to denoise SMPL.
- Predict SMPL noisy: $\tilde{\epsilon} = \epsilon_\theta(x_h^t, t, x_p, \mathbf{l})$
- Calculate loss: $\mathcal{L} = \sum_i \frac{1}{N_i} \|\tilde{\epsilon}_i - \epsilon_i\|_2^2$

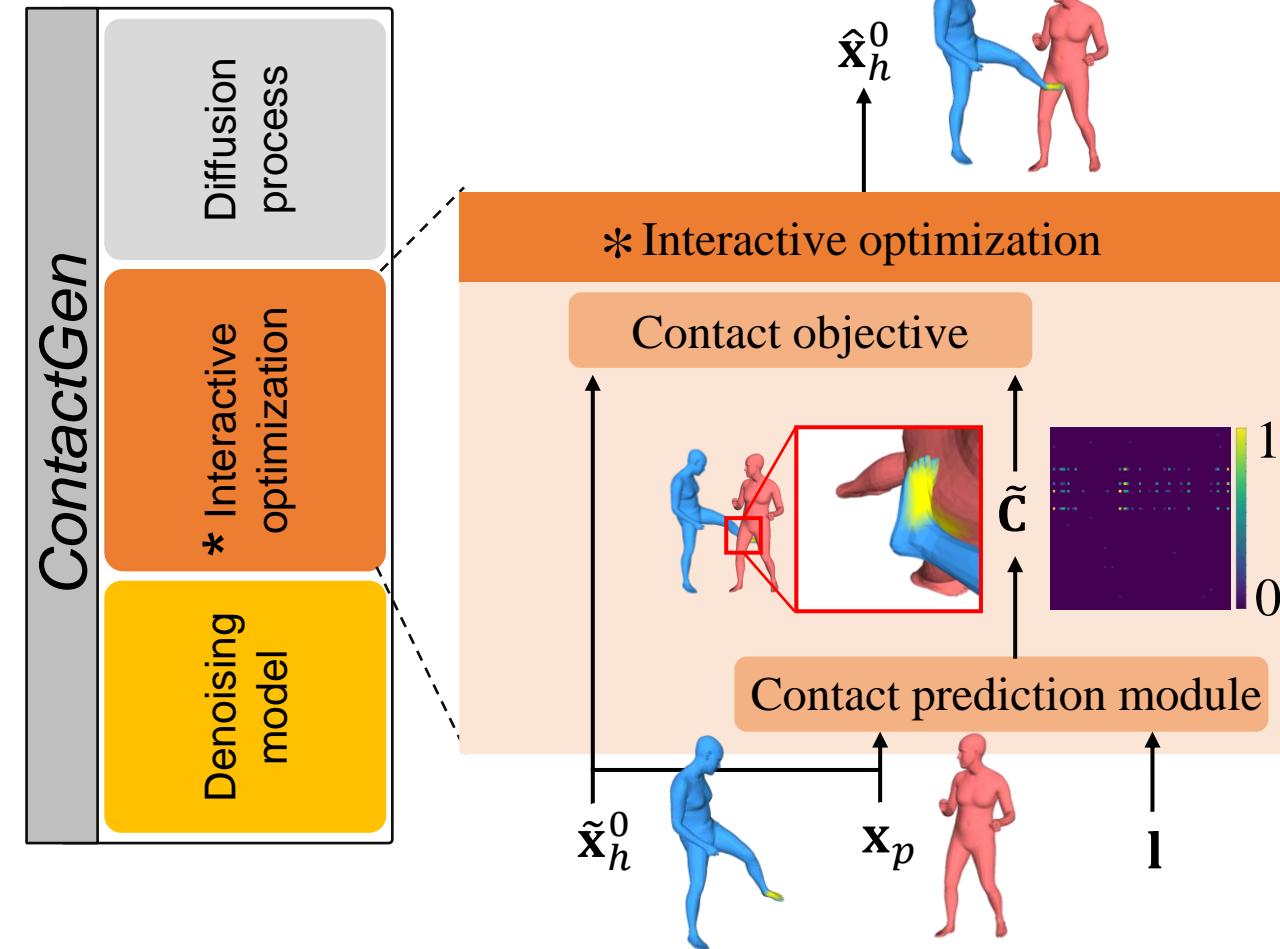
Inference Phase

- Predict denoised SMPL:

$$\bullet \quad \tilde{x}_h^0 = f_\theta(x_h^t, t, x_p, \mathbf{l}) = \frac{x_h^t - \sqrt{1-\hat{\alpha}_t} \epsilon_\theta(x_h^t, t, x_p, \mathbf{l})}{\sqrt{\hat{\alpha}_t}}$$

Methods

ContactGen: Interactive Optimization



Inference Phase

- Contact prediction module estimates contact \tilde{C} .
- Denoised human \tilde{x}_h^0 is updated contact objective \mathcal{O} .
- Guidance g is applied with as a gradient form following Guided Diffusion^[5].
- $$\mathcal{O}_{contact}(\mathbf{x}_h, \mathbf{x}_p, \mathbf{l}) = \sum_{(r_i, r_j) \in \mathbb{C}} d_{CD}(V_h^{r_i}, V_p^{r_j})$$
- $$g = \nabla_{\mathbf{x}_h} \mathcal{O}(\mathbf{x}_h, \mathbf{x}_p, \mathbf{l}) \Big|_{\mathbf{x}_h = \tilde{\mathbf{x}}_h^0}$$
- $$\hat{\mathbf{x}}_h^0 = \tilde{\mathbf{x}}_h^0 - \lambda \odot g$$

Results

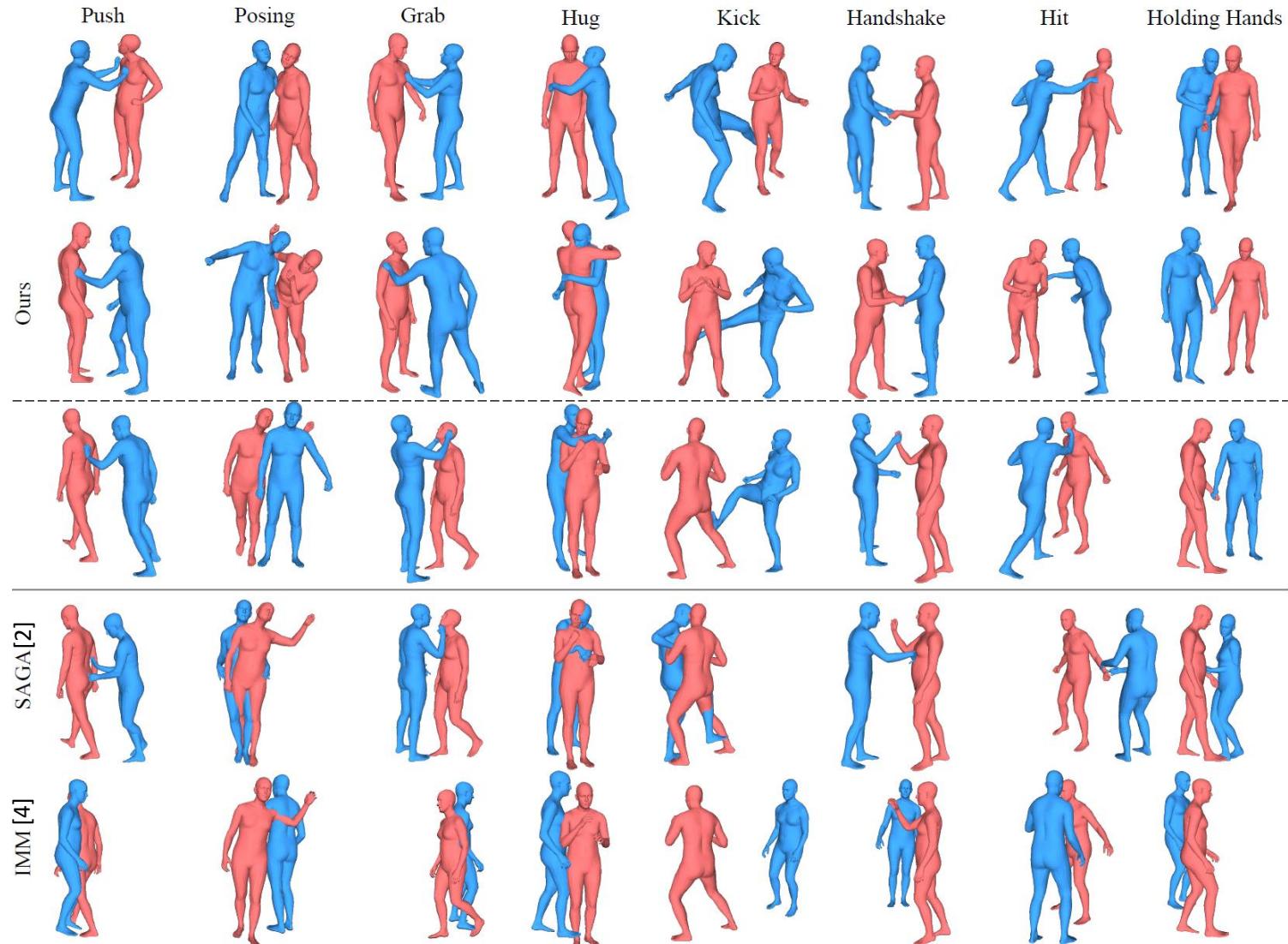
Quantitative Comparison

Interaction	IMM [4]					SAGA [2]					Ours				
	FHID↓	top-1↑	top-3↑	contact↓	non-coll↑	FHID↓	top-1↑	top-3↑	contact↓	non-coll↑	FHID↓	top-1↑	top-3↑	contact↓	non-coll↑
Push	51.00	0.00	82.89	17.52	94.08	34.54	18.43	72.74	7.44	95.10	56.78	87.52	98.85	3.61	94.77
Posing	174.78	11.90	23.13	14.81	93.54	53.23	62.50	94.51	4.33	92.15	71.70	84.15	99.54	8.58	92.72
Grab	59.23	92.78	100.00	13.26	96.98	46.70	84.41	94.06	5.95	97.00	28.88	91.32	96.92	4.76	96.50
Hug	235.84	18.72	34.76	12.45	88.17	57.16	93.38	99.24	3.16	76.21	21.43	99.75	100.00	5.96	78.71
Kick	29.89	66.67	92.59	10.01	99.70	42.04	30.17	64.22	4.62	97.41	46.55	95.69	100.00	11.98	98.49
Handshake	146.90	11.90	45.24	16.14	99.10	34.39	66.12	92.12	4.14	98.16	12.97	92.12	99.63	7.34	99.13
Hit	43.01	61.40	100.00	10.94	98.52	44.10	50.60	96.99	6.22	96.98	20.38	67.47	99.40	5.16	96.55
Holding Hands	499.84	0.00	0.00	15.17	96.80	54.07	73.93	92.62	4.27	96.41	26.20	99.02	100.00	6.42	97.12
All	92.25	34.49	58.93	14.24	94.41	24.26	67.47	90.76	5.23	94.62	6.15	90.30	98.67	6.07	94.89

- ContactGen shows better qualitative and quantitative results than baseline methods: IMM_[6] and SAGA_[2].

Methods

Qualitative Comparison



Conclusion

- New task suggested, human generation for partner.
- New human generative model based on diffusion.
- Outperforming baseline methods about human generation with contact.

Research Project

2020.05 ~ 2022.12

4. Various AI Challenges

DACON: Human Pose Estimation Challenge



Problem Statement

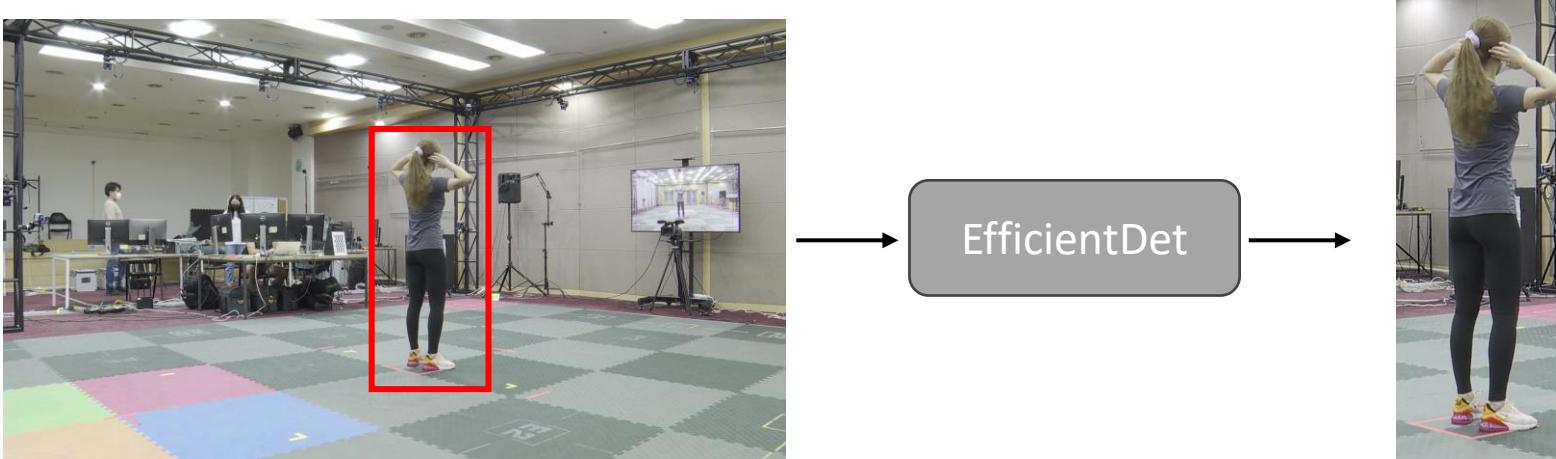
- **Goal:** Find human keypoint from given image.
- **Input:** Image, **Output:** Human Keypoint



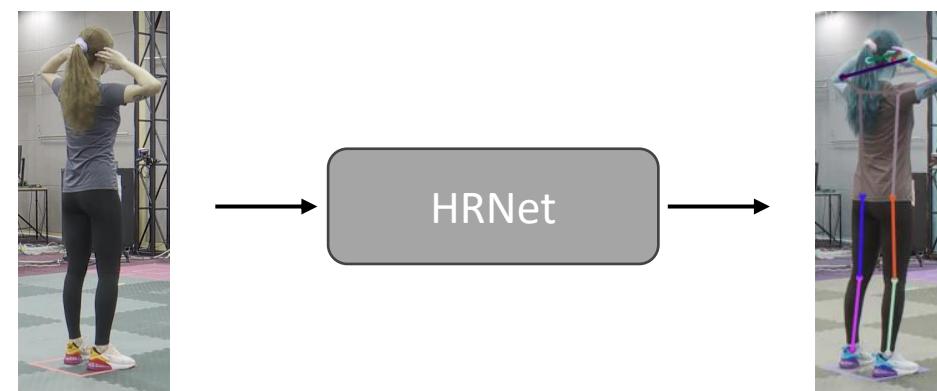
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Approaches

1. Detect humans using pretrained EfficientDet^[1], crop RoI.



2. Detect human keypoints by finetuning pretrained HRNet^[2].



[1] Tan, Mingxing, Ruoming Pang, and Quoc V. Le. "Efficientdet: Scalable and efficient object detection." CVPR 2020.

[2] Sun, Ke, et al. "Deep high-resolution representation learning for human pose estimation." CVPR 2019.

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Challenge

1. Occlusion: Occlusion bothers pose model detecting keypoints.



2. Irregular bbox aspect ratio: aspect ratio of person largely differs regarding to pose.



Warping to feed pose model



Outputs of detection model

Warped images has large distortion

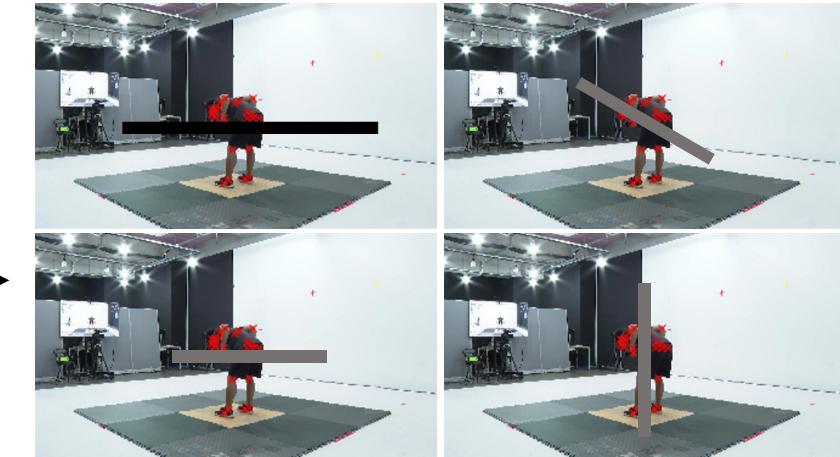
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Approaches

1. Occlusion: Propose new augmentation imitating occlusions.



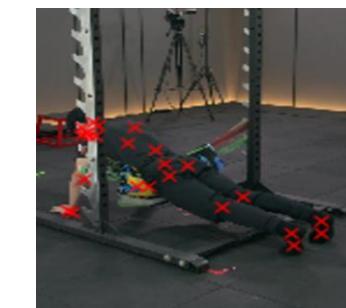
Augmentation →



2. Irregular bbox aspect ratio: Padding and resizing instead of warping to reduce distortion.



Padding/resize to make square →



Outputs of detection model

Padded image has less distortion

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Result

1st place win against 819 participants.

모션 키포인트 검출 AI 경진대회
 운동 | Keypoint Detection | 비전 | RMSE
 상금 : 400만원
 2021.02.10 ~ 2021.04.05 17:59 [+ Google Calendar](#)
 819명 마감



참여중

대회안내 데이터 코드 공유 토크 리더보드 제출

PUBLIC PRIVATE AWARDS RANKING CHART 순위기준

● WINNER ● 1% ● 4% ● 10%

#	팀	팀 멤버	최종점수	제출수	등록일
1	여우는여우여우		5.54628	19	2년 전
1	여우는여우여우		5.54628	19	2년 전
2	에르모		5.59514	43	2년 전
3	yanado		6.53785	12	2년 전
4	woojin		6.59228	4	2년 전
5	오케익		7.24578	20	2년 전

Other Experiences

- Participated various AI challenges alone.
- Win various challenges especially in DACON.
- Total 4th place in DACON when highest rank.



- [OCR Challenge](#), from KYOWON Group with DACON, 2022.12, 7th place win from 430 players (top 2%). OCR task of Korean language. I improved accuracy with transfer learning of ConvNeXT by proposing language specific loss.
- [NAVER CLOVA AI-RUSH 2022 Round 2](#), from NAVER CLOVA, 2022.08, 7th place from 15 players. Regress specific scores from given images. I improved accuracy with transfer learning of CoAT with various augmentation.
- [NAVER CLOVA AI-RUSH 2022 Round 1](#), from NAVER CLOVA, 2022.07, 15th place win from 27 players. Classifies given images. I improved accuracy through transfer learning of EfficientNetV2 with various augmentations.
- [Ego-Vision Hand Gesture Recognition AI Contest](#), from DACON, 2021.06, 3th place win from 290 players (top 1%). Classifies hand gesture from given images. I achieved high-accuracy with transfer learning of EfficientNetV2 with cross validation.
- [News Topic Classification AI Contest](#), from DACON, 2021.05, 3 th place win from 256 players (top 1%). This competition is to classify topics of given text articles. I improved accuracy with noisy student training strategy about BeRT-based model.
- [NAVER CLOVA AI-RUSH 2021 Round2](#), from NAVER CLOVA, 2021.05, 6th place from 13 players. Clustering of given text dataset. I improved model performance with self-supervised learning.
- [NAVER CLOVA AI-RUSH 2021 Round1](#), from NAVER CLOVA, 2021.04, 4th place win from 35 players. Classification of given image dataset with limited model capacity. I achieved high-accuracy with transfer learning of EfficientNetV2 with careful hyper-parameter tuning.
- [Predicting Danger of System Log Messages](#), from DACON, 2021.04, 2th place win from 152 players (top 1%). Finding out-of-distribution data not appeared in training dataset. I achieved high-accuracy with DistilBeRT-based anomaly detection.
- [Finding Human Key-Points from Motion Images](#), from DACON, 2021.02, 1th place win from 156 players (top 0.6%). Estimating human key-points from given image dataset. I achieved high-accuracy with fine-tuning HRNet for pose estimator and EfficientDet for human detector, and with data-driven augmentations.
- [The 2th Computer Vision AI Contest](#), from DACON, 2021.02, 30th place from 216 players (top 13%).
- [Motion Classification AI Contest](#), from DACON, 2021.01, 21th place from 336 players (top 6%). Classifies human motions from acceleration of human body parts captured with various sensors.
- [정보통신대학 ICT AI 및 알고리즘 경진대회](#), from SNUT, 2021.01, 1th place win.
- [태양광 발전량 예측 AI 경진대회](#), from DACON, 2020.11, 94 place from 461 players (top 20%).
- [공공데이터 활용 수력 댐 강우예측 AI 경진대회](#), from DACON, 2020.10, 39 place from 132 players (top 29%).
- [컴퓨터 비전 학습 경진대회](#), from DACON, 2020.08, 11th place from 356 players (top 3%).
- [NAVER CLOVA AI-RUSH 2020 Round1](#), from NAVER CLOVA, 2020.06, 37th place.
- [위성관측 데이터 활용 강수량 산출 AI 경진대회](#), from DACON, 2020.05, 72th place from 213 players (top 33%).

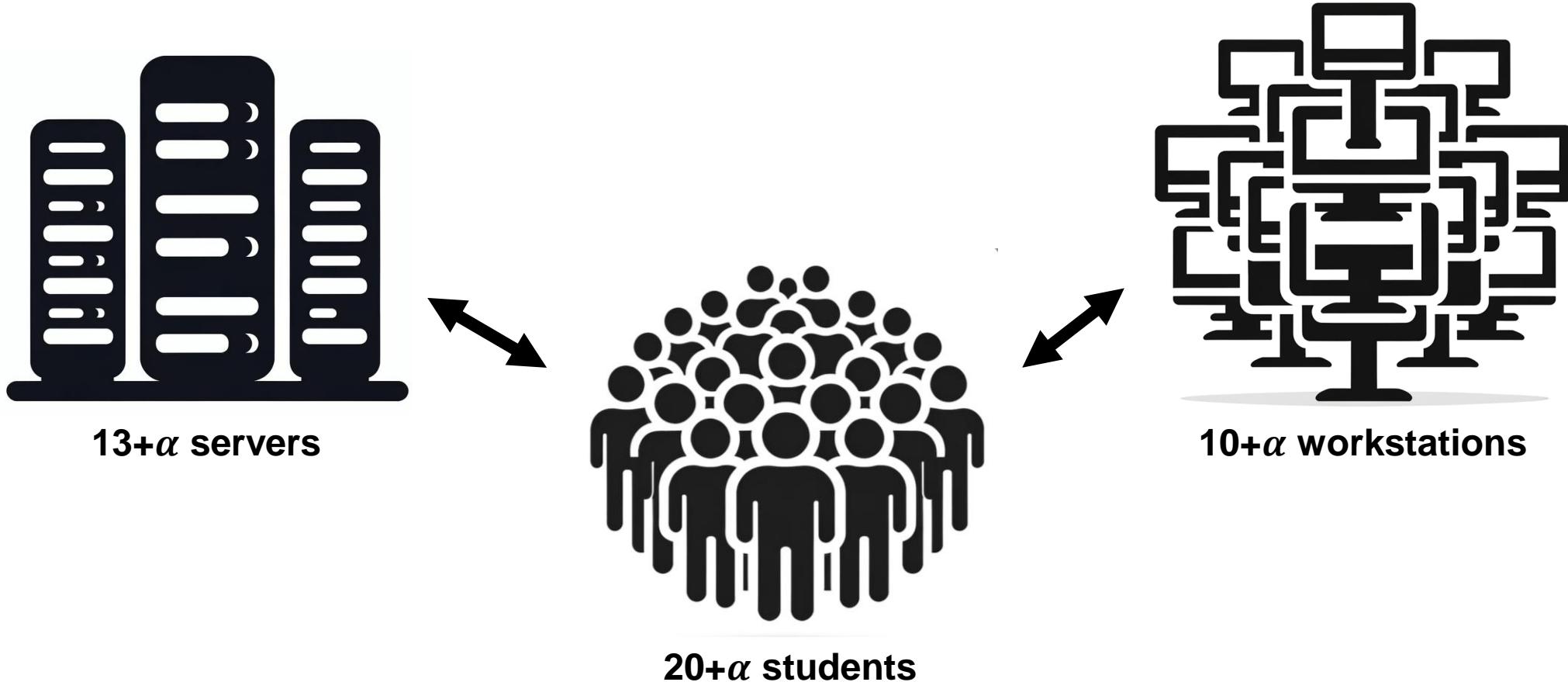
Research Project

2021.09 ~ 2023.02

5. Server Management Experience

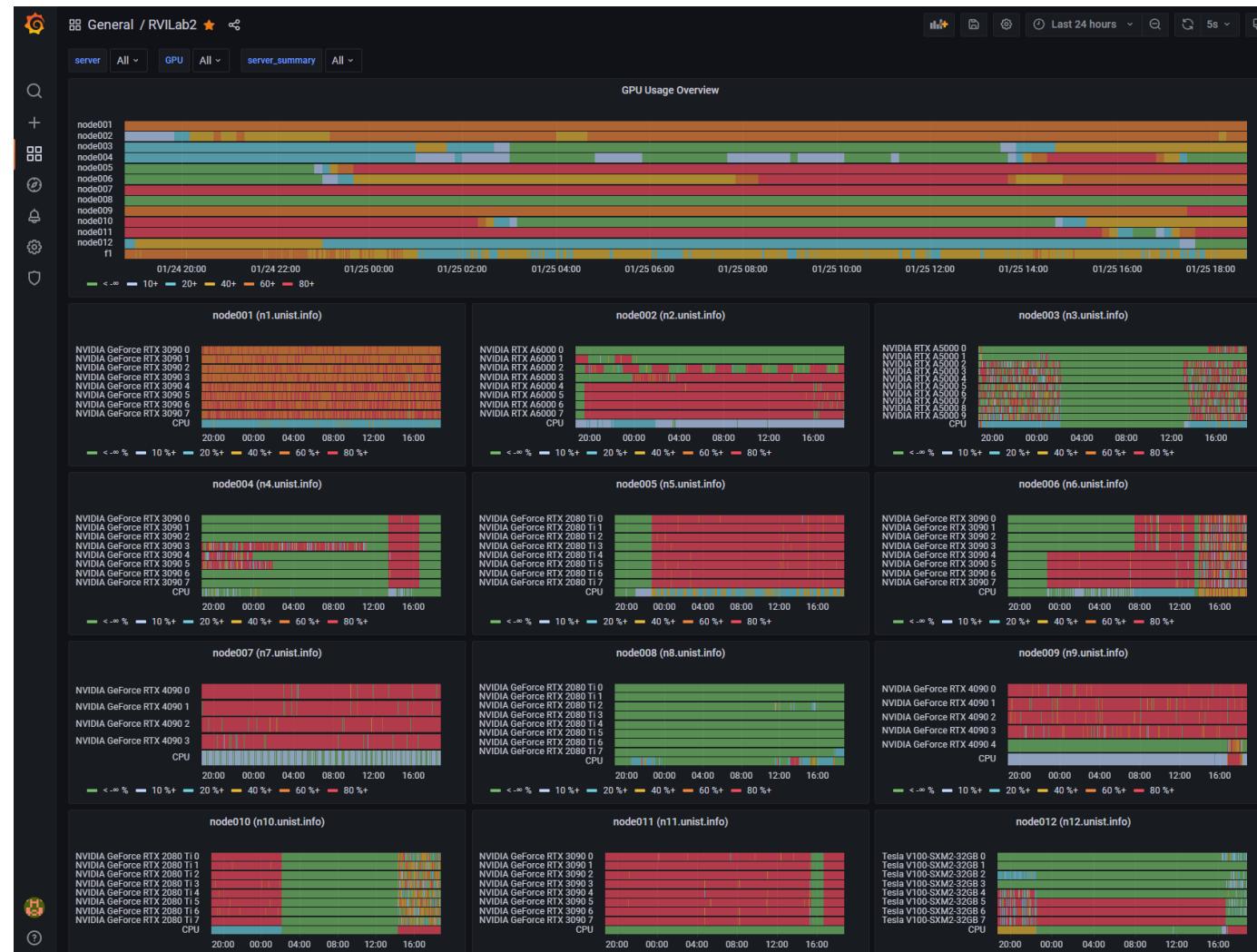
Lab Server Managing

- For more than 2 years, manager rule for lab servers.
- There are more than 20 students, 13 servers, 10 workstations.



Integrated Monitoring System

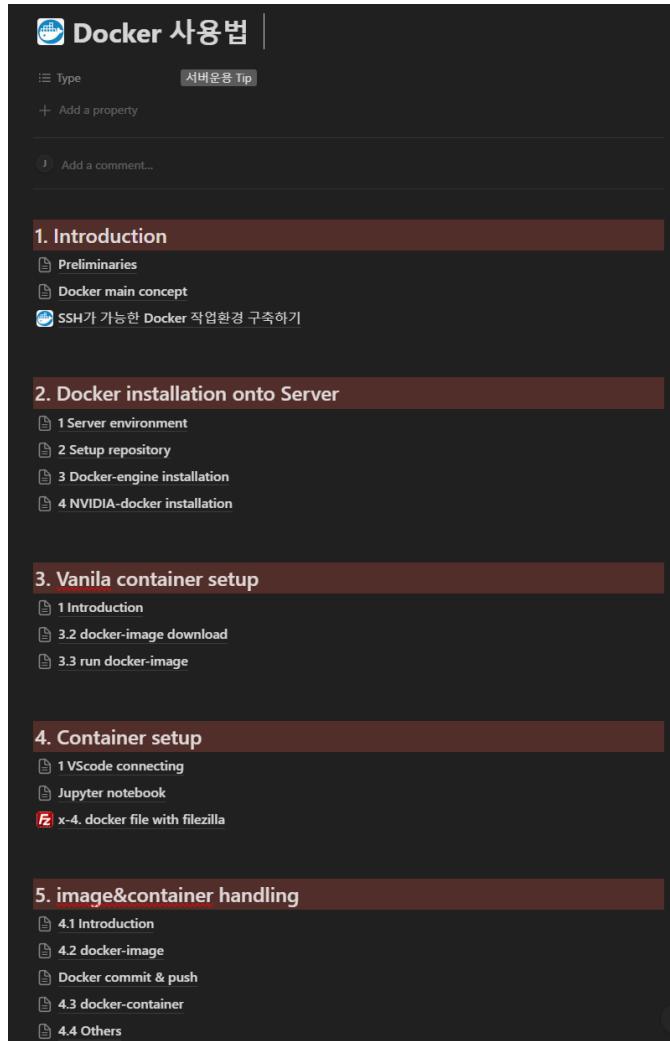
- For convenience of managing, have built monitoring system using Prometheus and Grafana.



Grafana page

Integrated Monitoring System

- For students ease of use, have built guide, custom docker image and docker hub.



Server usage guide

Docker Registry Frontend

You are here: Home / Repositories

Repositories

Filter repositories on this page			Repositories (20/20)
2d_dreamer	1		
2d_dreamer			
3dgen	1		
3dgen			
aisdf_hyper	1		
aisdf_hyper			
canon_dj	1		
canon_dj			
contrail	1		
contrail			
ddgs	1		
ddgs			
deepvio	1		
deepvio			
econ_dj	1		
econ_dj			

Custom docker hub

dockerenv-public Public

Pin Unwatch 2 Fork 0 Star 11

master Go to file + <> Code

Kitsunetic support for cuda... 1de58d2 - 10 months ago 9 Commits

- cuda10.2-cudnn8-mini... Add 10.2 2 years ago
- cuda11.3.0-cudnn8-... add parallel 2 years ago
- cuda11.4.0-cudnn8-... support for cuda 11.4.... 10 months ago
- cuda11.5.1-cudnn8-... add parallel 2 years ago
- cuda9.0-cudnn8-mini... 9.0 2 years ago
- .gitignore Initial commit 3 years ago
- README.md Initial commit 3 years ago

README

dockerenv-public

No description, website, or topics provided.

Readme Activity 11 stars 2 watching 0 forks

No releases published Create a new release

No packages published Publish your first package

Dockerfile 98.3% Shell 1.7%

Custom docker image base

Thank You