LiDAR4D: Dynamic Neural Fields for Novel Space-time View LiDAR Synthesis

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Lab Page: https://www.embodiment.ai

Project Page: https://dyfcalid.github.io/LiDAR4D

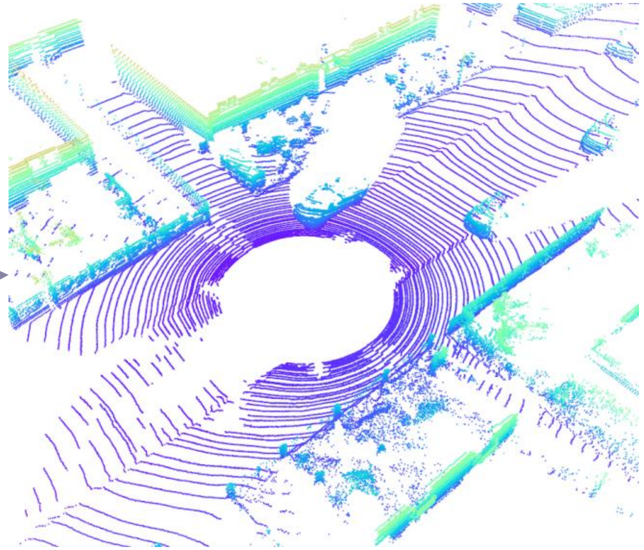
LiDAR Point Clouds

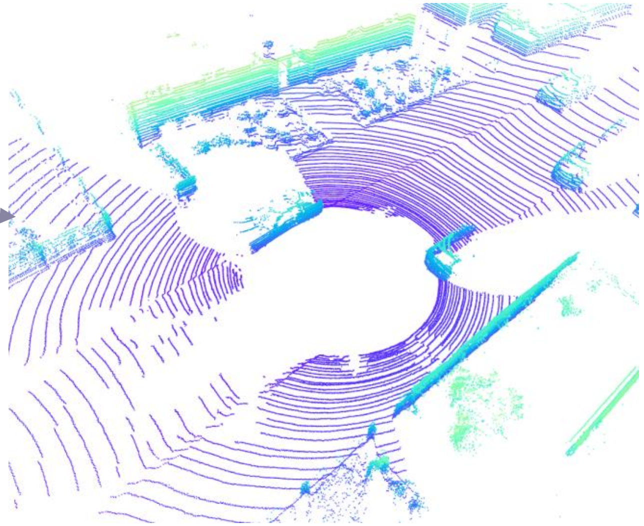
- LiDAR serves as the crucial sensor of autonomous driving for accurate 3D perception

- Sparsity and occlusion
- Varying at different locations and times

- Costly acquisition for a large-scale dataset
- Limited to specific sensor configuration and ego-vehicle trajectory

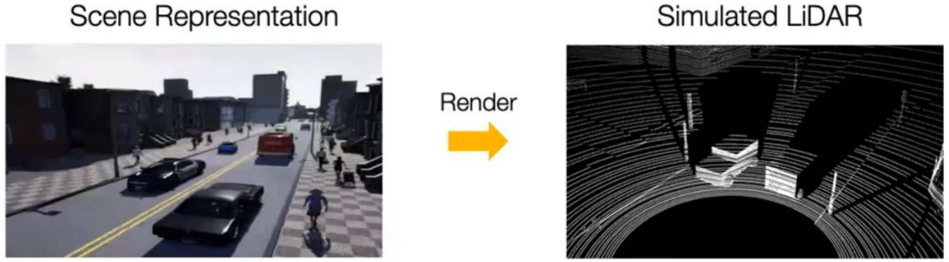
How can we generate/simulate novel point clouds?



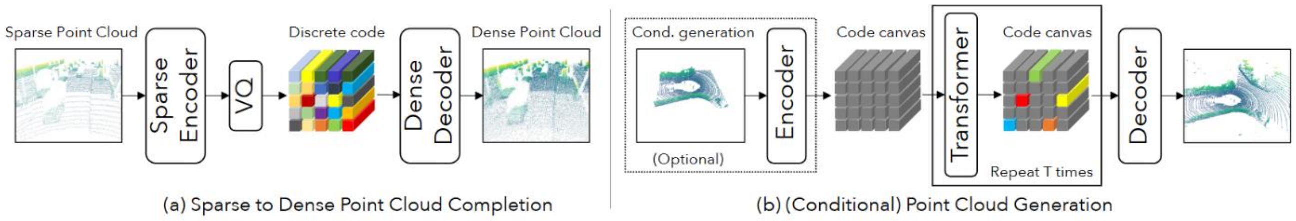


Previous Methods

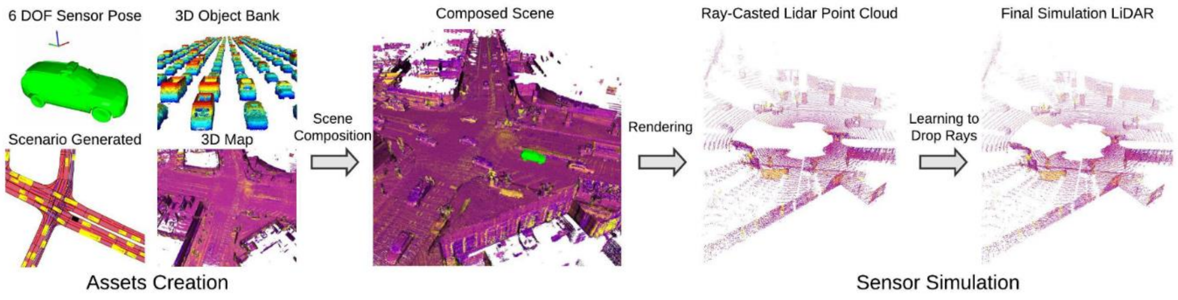
- Physical-based Simulation
  - ✕ Costly 3D assets
  - ✕ Domain gap
- Generative Models
  - ✕ Hard to control/edit
  - ✕ Poor generalization
- Scene Reconstruction
  - ✕ Complicated
  - ✕ Limited to static scenes



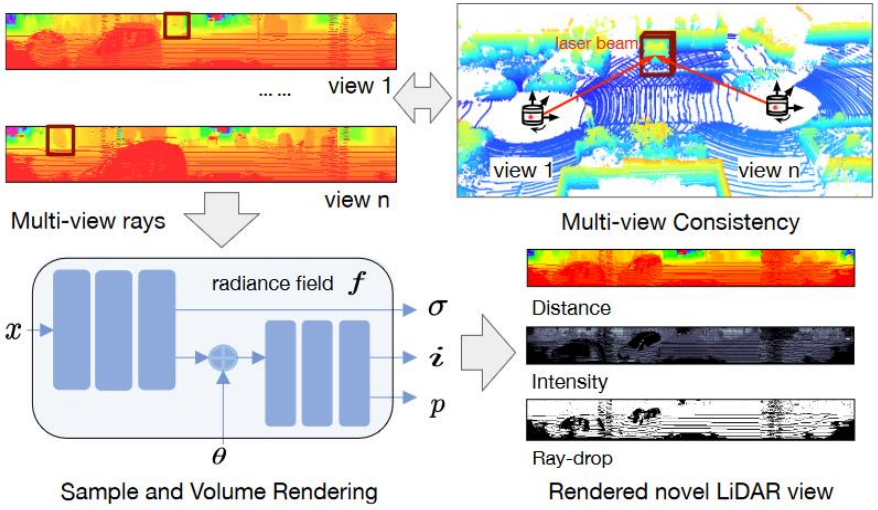
CARLA: An open urban driving simulator



Learning Compact Representations for LiDAR Completion and Generation



LiDARsim: Realistic LiDAR Simulation by Leveraging the Real World



LiDAR-NeRF: Novel LiDAR View Synthesis via Neural Radiance Fields

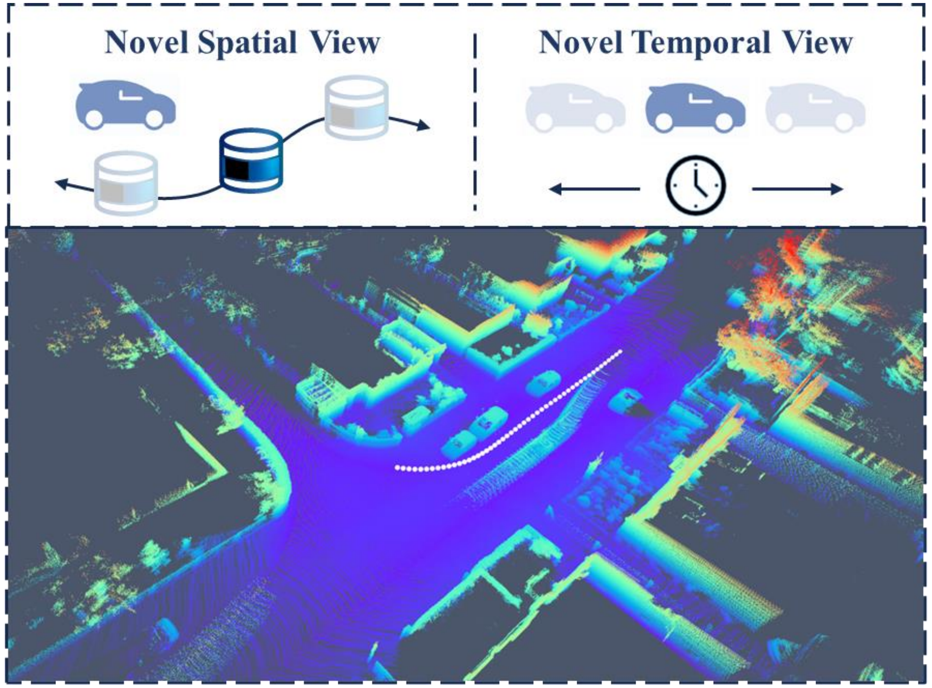
Novel Space-time View LiDAR Synthesis

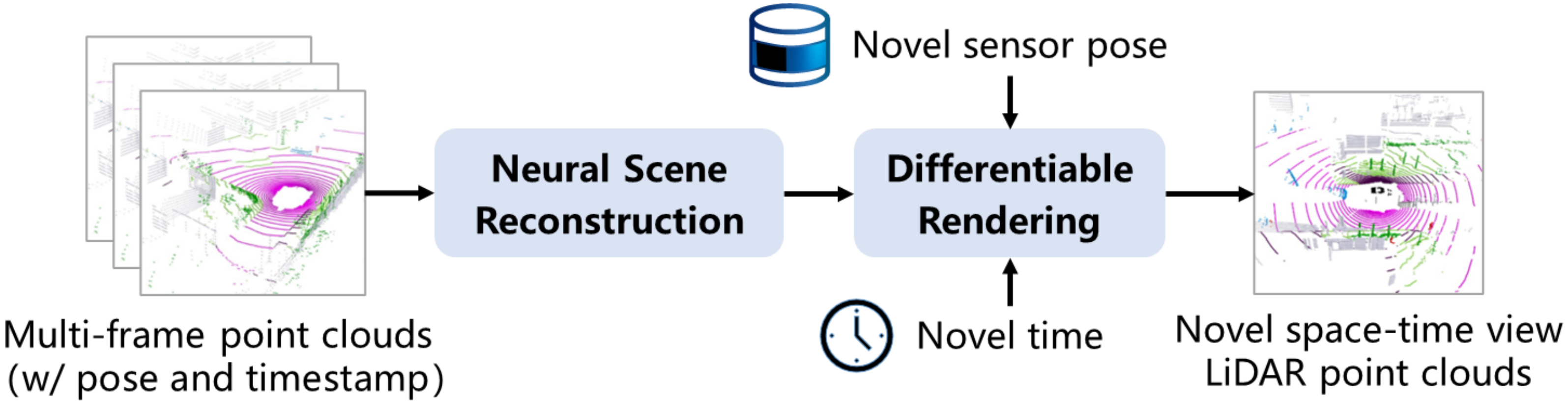
Input

- LiDAR point cloud sequence $S = \{S_0, S_1, \ldots, S_{n-1}\}$ ($S_i \in \mathbb{R}^{N\times 4}$, *including intensity*)
- sensor poses $P = \{P_0, P_1, \ldots, P_M\}$ ($P_i \in SE(3)$)
- timestamps $T = \{t_0, t_1, \ldots, t_{n-1}\}$ ($t_i \in \mathbb{R}$)

Output

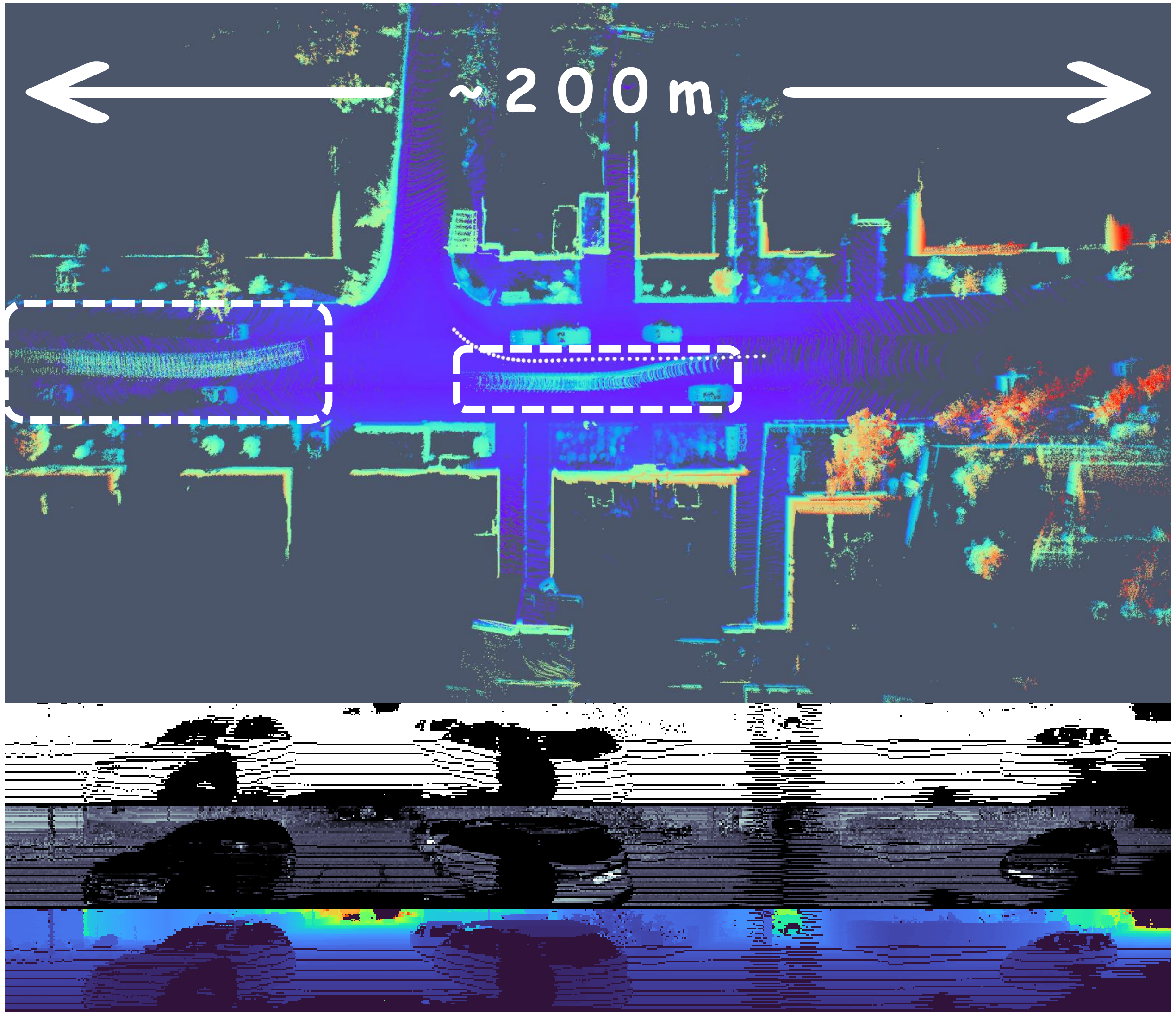
- LiDAR point cloud S_{novel} given novel pose P_{novel} and novel time t_{novel}





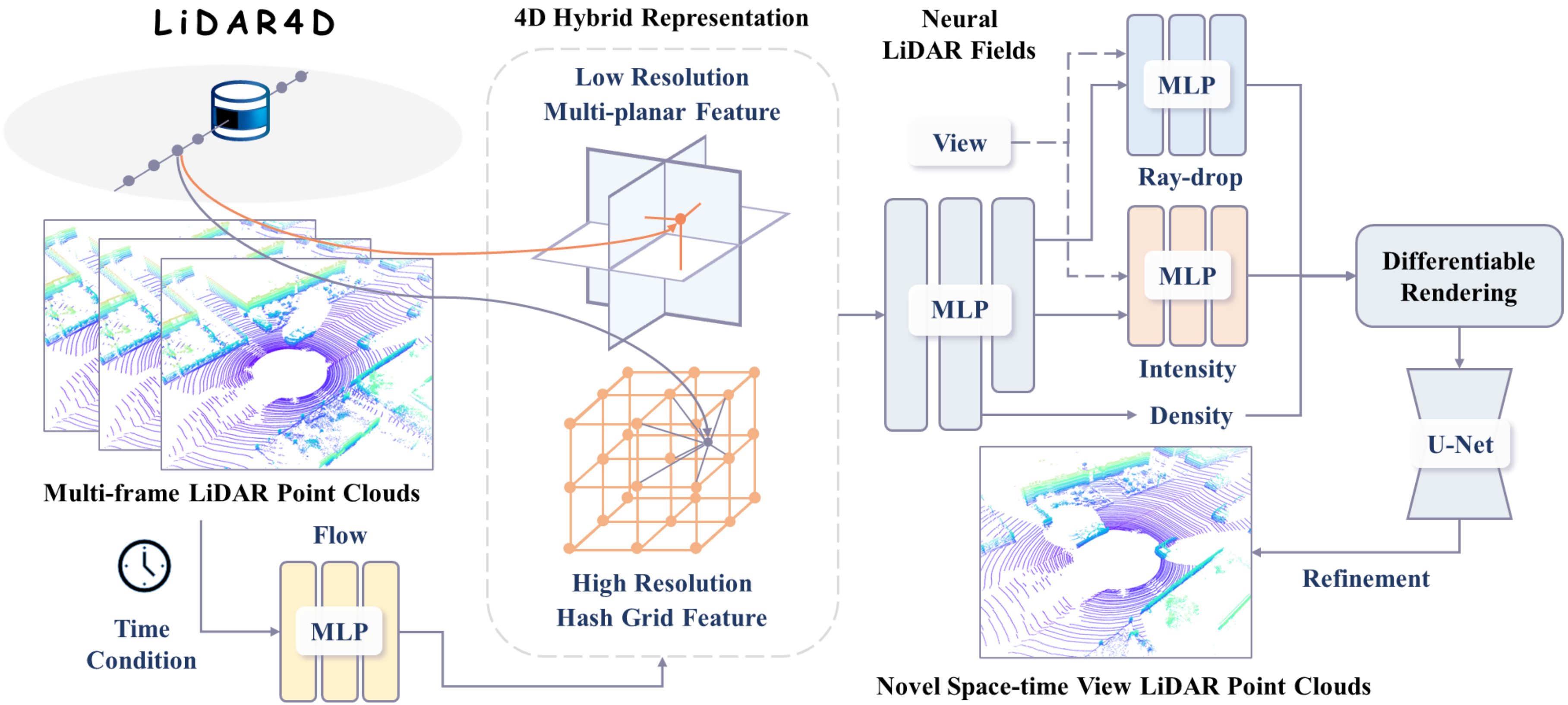
However, challenges remain …

- **Large-scale reconstruction**
  - Scenes spanning hundreds of meters
  - Representation resolution
  - Sparsity of point clouds
- **Dynamic scenarios**
  - Long-distance vehicle motion
  - Temporal consistency
- **Generation realism**
  - Intensity reconstruction
  - Ray-drop characteristic



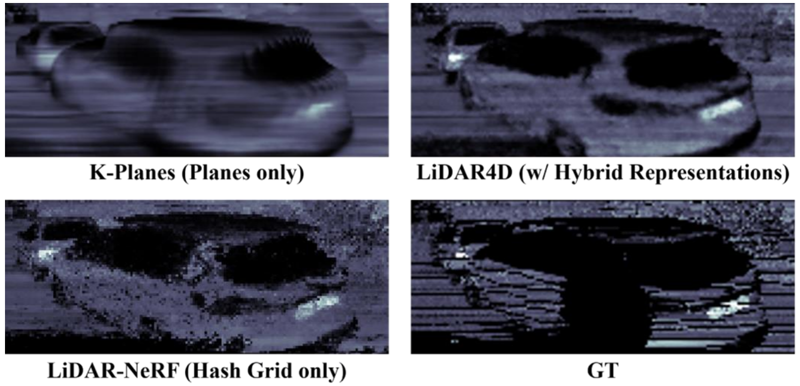
Methodology —— LiDAR4D

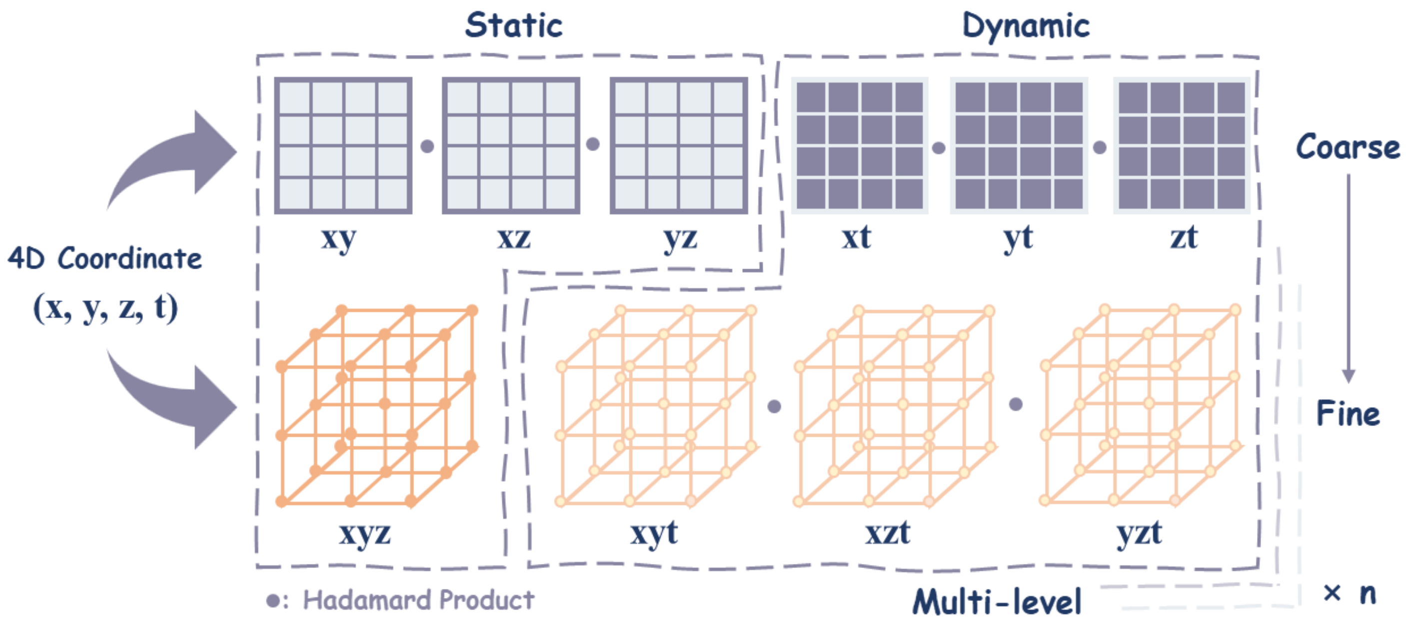
- ✓ Differentiable LiDAR-only framework for novel space-time LiDAR view synthesis
- ✓ Geometry-aware and time-consistent large-scale dynamic reconstruction
- ✓ Better generation realism with global refinement

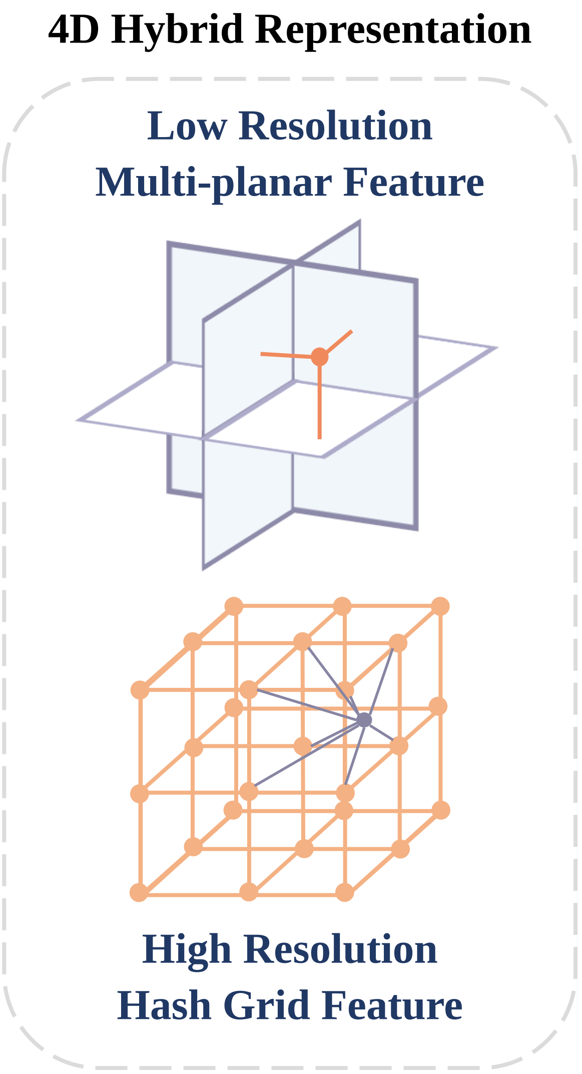


Methodology

- **Hybrid Representation**
  - Planes & Hash Grids
  - Coarse-to-fine Resolution
  - 4D Decomposition

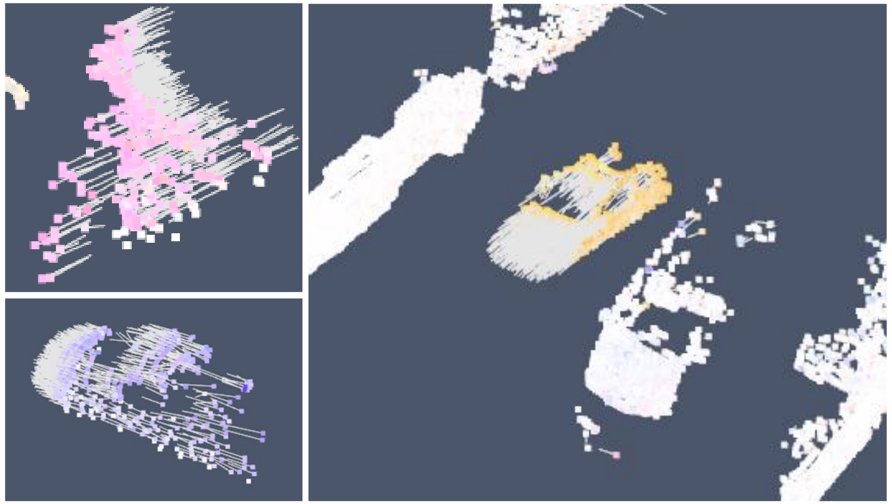


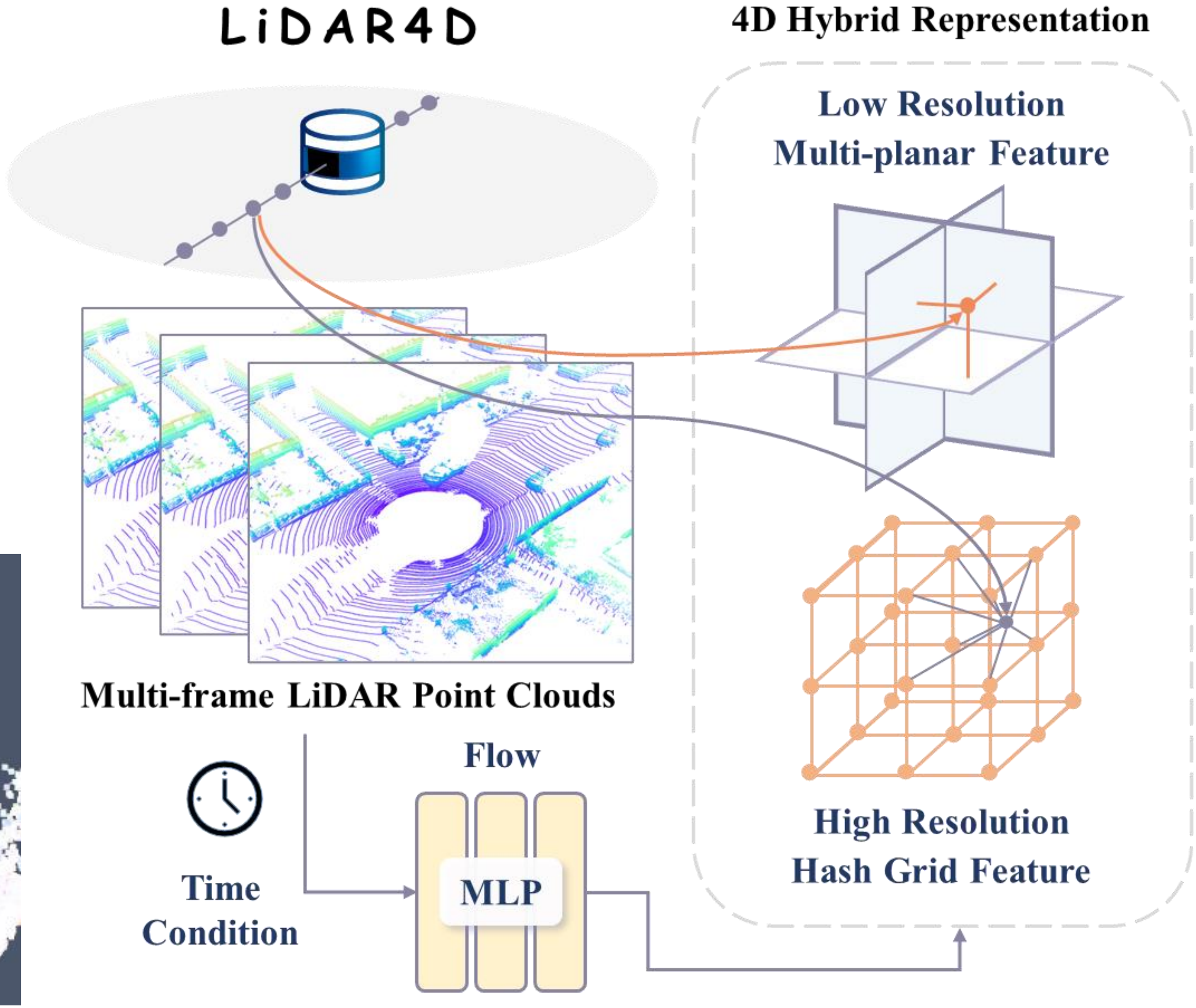




Methodology

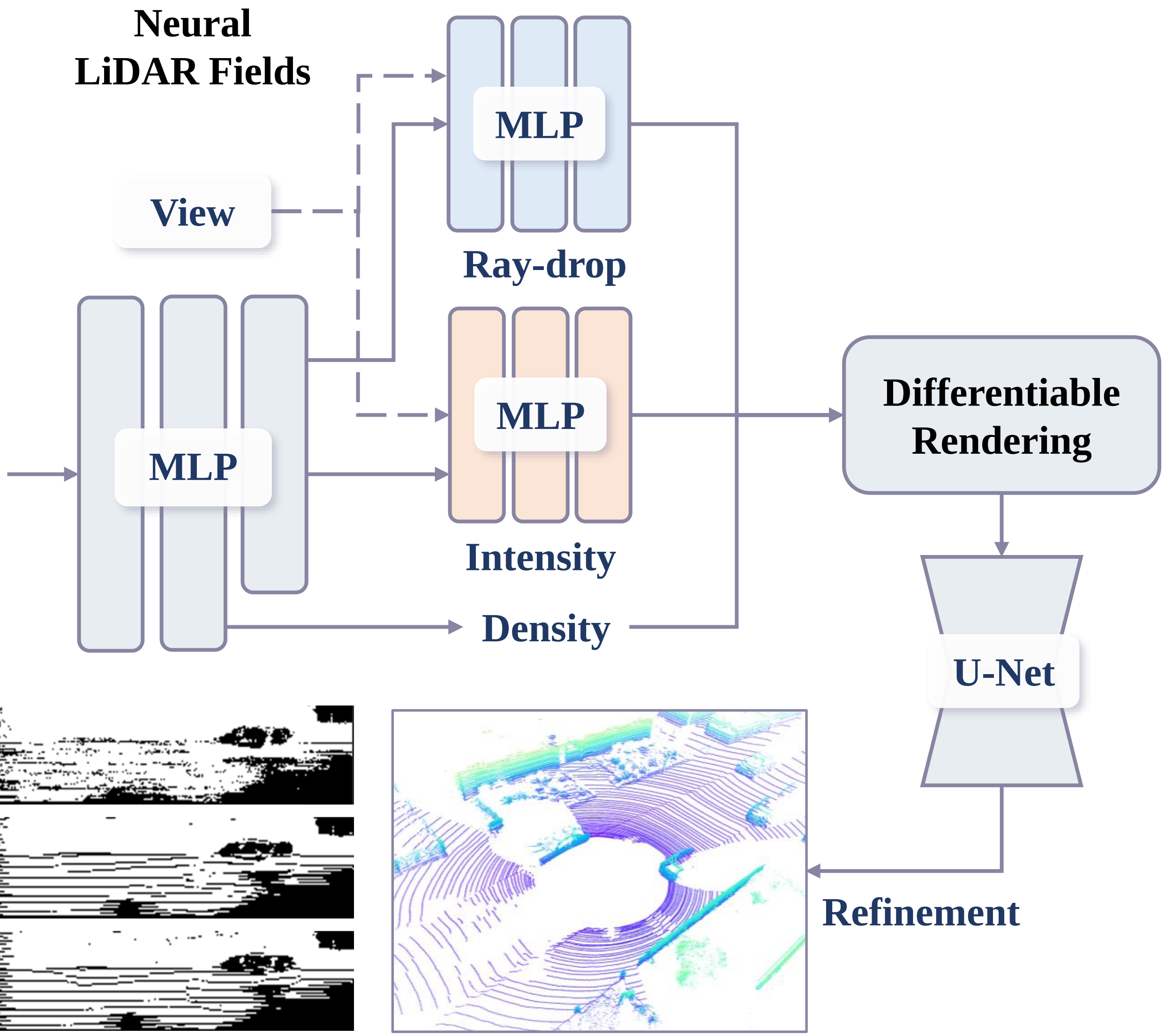
- Hybrid Representation
- **Scene Flow Prior**
  - Flow MLP
  - Geometry-aware Constraint (Chamfer Distance)
  - Temporal Feature Aggregation

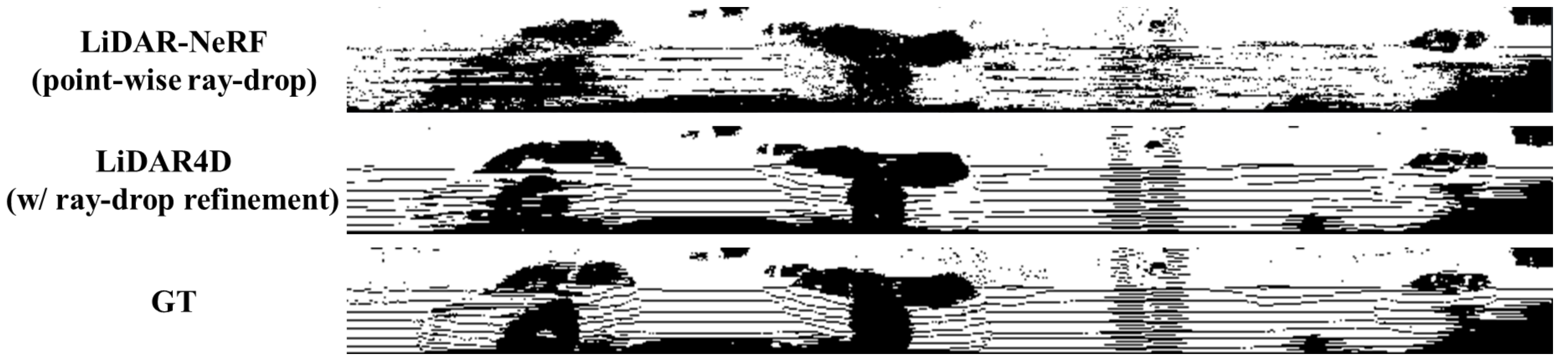




Methodology

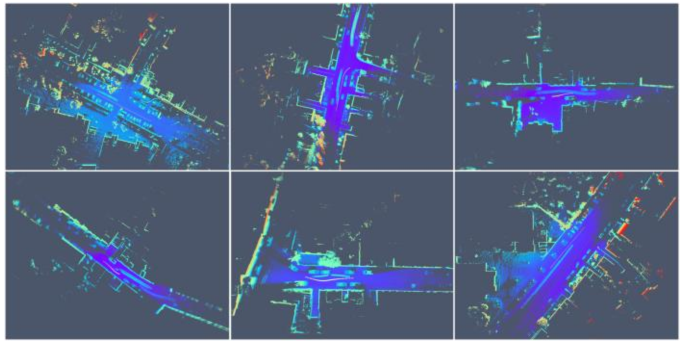
- Hybrid Representation
- Scene Flow Prior
- **Neural LiDAR Fields**
    - Separate MLPs for Depth/Intensity/Ray-drop
    - Global Optimization for Ray-drop Refinement via U-Net





Novel Space-time View LiDAR Point Clouds

Experiments



- **SOTA Results**
  - KITTI-360

Method	Type	Point Cloud		Depth					Intensity				
		CD↓	F-score↑	RMSE↓	MedAE↓	LPIPS↓	SSIM↑	PSNR↑	RMSE↓	MedAE↓	LPIPS↓	SSIM↑	PSNR↑
LiDARsim [25]	$\mathcal{E}$. / $\mathcal{S}$. / $\mathcal{M}$.	3.2228	0.7157	6.9153	0.1279	0.2926	0.6342	21.4608	0.1666	0.0569	0.3276	0.3502	15.5853
NKSR [15]	$\mathcal{E}$. / $\mathcal{S}$. / $\mathcal{M}$.	1.8982	0.6855	5.8403	0.0996	0.2752	0.6409	23.0368	0.1742	0.0590	0.3337	0.3517	15.2081
PCGen [19]	$\mathcal{E}$. / $\mathcal{S}$.	0.4636	0.8023	5.6583	0.2040	0.5391	0.4903	23.1675	0.1970	0.0763	0.5926	0.1351	14.1181
LiDAR-NeRF [39]	$\mathcal{I}$. / $\mathcal{S}$.	0.1438	0.9091	4.1753	0.0566	0.2797	0.6568	25.9878	0.1404	0.0443	0.3135	0.3831	17.1549
D-NeRF [32]	$\mathcal{I}$. / $\mathcal{D}$.	0.1442	0.9128	4.0194	0.0508	0.3061	0.6634	26.2344	0.1369	0.0440	0.3409	0.3748	17.3554
TiNeuVox-B [9]	$\mathcal{I}$. / $\mathcal{D}$.	0.1748	0.9059	4.1284	0.0502	0.3427	0.6514	26.0267	0.1363	0.0453	0.4365	0.3457	17.3535
K-Planes [12]	$\mathcal{I}$. / $\mathcal{D}$.	0.1302	0.9123	4.1322	0.0539	0.3457	0.6385	26.0236	0.1415	0.0498	0.4081	0.3008	17.0167
LiDAR4D (Ours)	$\mathcal{I}$. / $\mathcal{D}$.	**0.1089**	**0.9272**	**3.5256**	**0.0404**	**0.1051**	**0.7647**	**27.4767**	**0.1195**	**0.0327**	**0.1845**	**0.5304**	**18.5561**

Table 1. **Quantitative comparison on KITTI-360 dataset**. We compare our method to different types of previous approaches and color the top results as best and second best. $\mathcal{E}$: Explicit, $\mathcal{I}$: Implicit, $\mathcal{S}$: Static, $\mathcal{D}$: Dynamic, $\mathcal{M}$: Mesh.

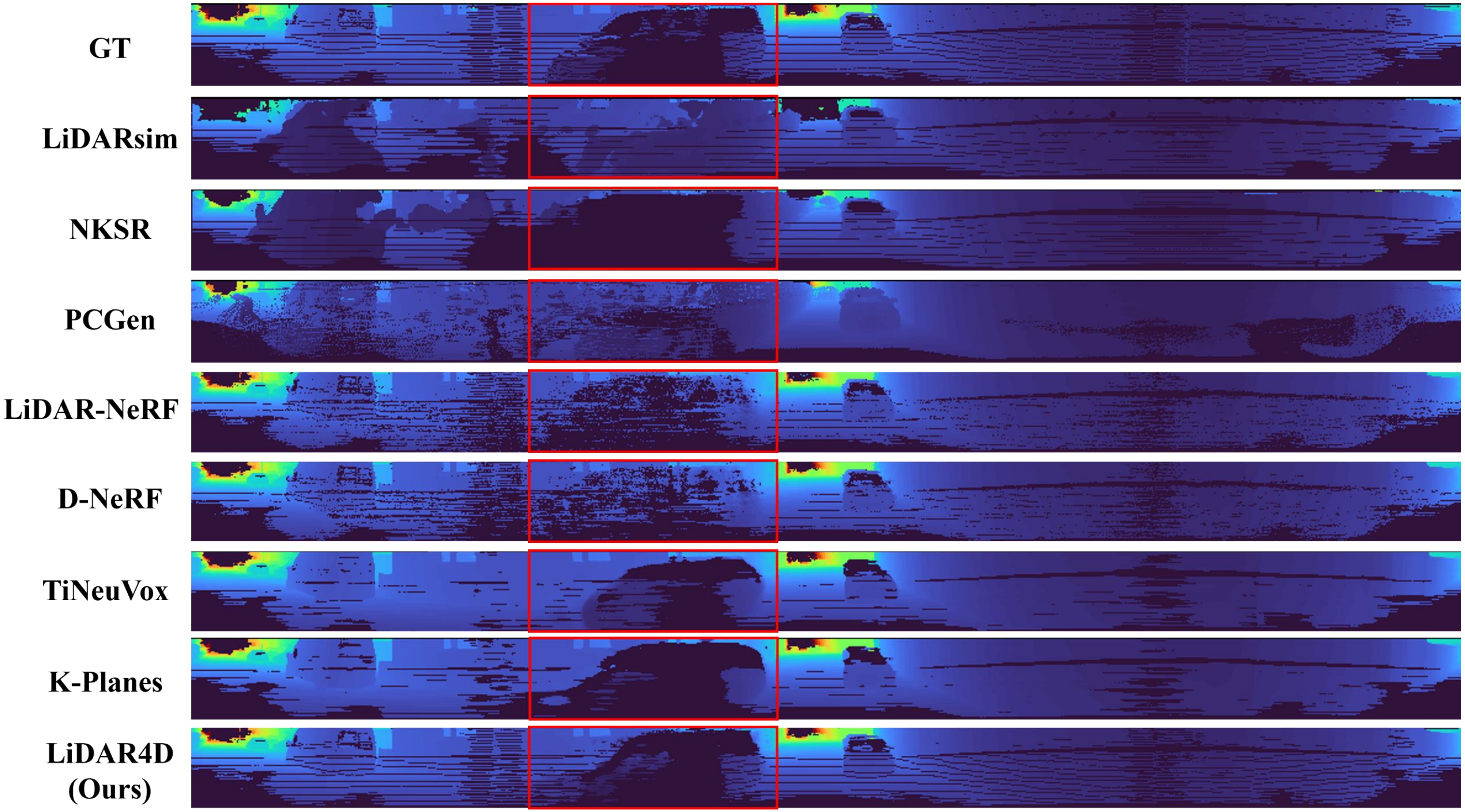
  - NuScenes

Method	Type	Point Cloud		Depth					Intensity				
		CD↓	F-score↑	RMSE↓	MedAE↓	LPIPS↓	SSIM↑	PSNR↑	RMSE↓	MedAE↓	LPIPS↓	SSIM↑	PSNR↑
LiDARsim [25]	$\mathcal{E}$. / $\mathcal{S}$. / $\mathcal{M}$.	12.1383	0.6512	10.5539	0.3572	0.1871	0.5653	17.7841	0.0659	0.0115	0.1160	0.5170	23.7791
NKSR [15]	$\mathcal{E}$. / $\mathcal{S}$. / $\mathcal{M}$.	11.4910	0.6178	9.3731	0.5763	0.2111	0.5637	18.7774	0.0680	0.0119	0.1290	0.5031	23.4905
PCGen [19]	$\mathcal{E}$. / $\mathcal{S}$.	2.1998	0.6341	8.8364	0.4011	0.1792	0.5440	19.2799	0.0768	0.0147	0.1308	0.4410	22.4428
LiDAR-NeRF [39]	$\mathcal{I}$. / $\mathcal{S}$.	0.3225	0.8576	7.1566	0.0338	0.0702	0.7188	21.2129	0.0467	0.0076	0.0483	0.7264	26.9927
D-NeRF [32]	$\mathcal{I}$. / $\mathcal{D}$.	0.3296	0.8513	7.1089	0.0368	0.0789	0.7130	21.2594	0.0467	0.0080	0.0492	0.7180	26.9951
TiNeuVox-B [9]	$\mathcal{I}$. / $\mathcal{D}$.	0.3920	0.8627	7.2093	0.0290	0.1549	0.6873	21.0932	0.0462	0.0080	0.1294	0.7107	26.8620
K-Planes [12]	$\mathcal{I}$. / $\mathcal{D}$.	0.2982	0.8887	6.7960	**0.0209**	0.1218	0.7258	21.6203	0.0438	0.0076	0.1127	0.7364	27.4227
LiDAR4D (Ours)	$\mathcal{I}$. / $\mathcal{D}$.	**0.2443**	**0.8915**	**6.7831**	0.0258	**0.0569**	**0.7396**	**21.7189**	**0.0426**	**0.0071**	**0.0459**	**0.7498**	**27.7977**

Table 2. **Quantitative comparison on NuScenes dataset**. The notations are consistent with the KITTI-360 Table 1 above.

Experiments

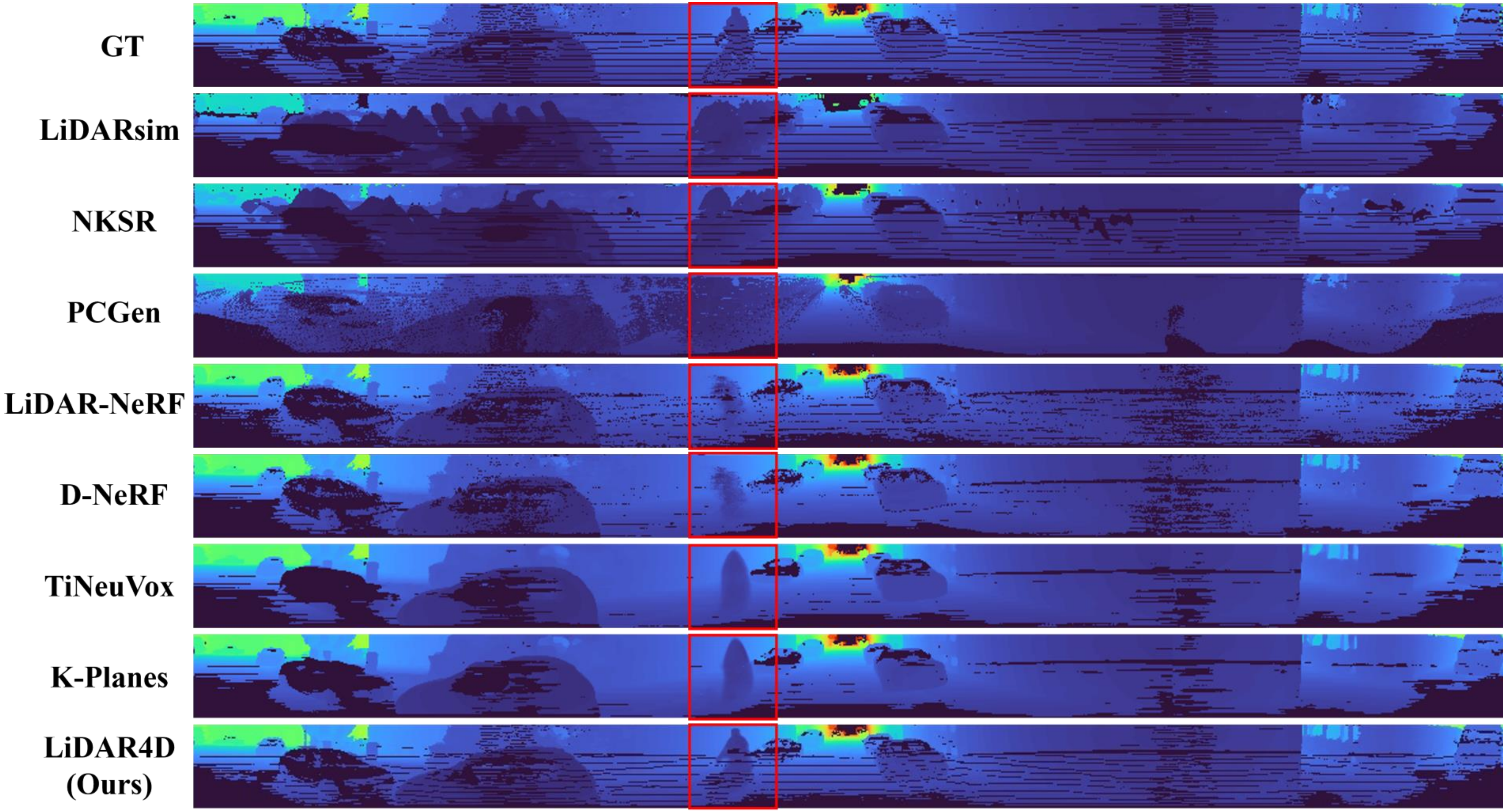
- **More Comparisons** Depth reconstruction on dynamic vehicles



Experiments

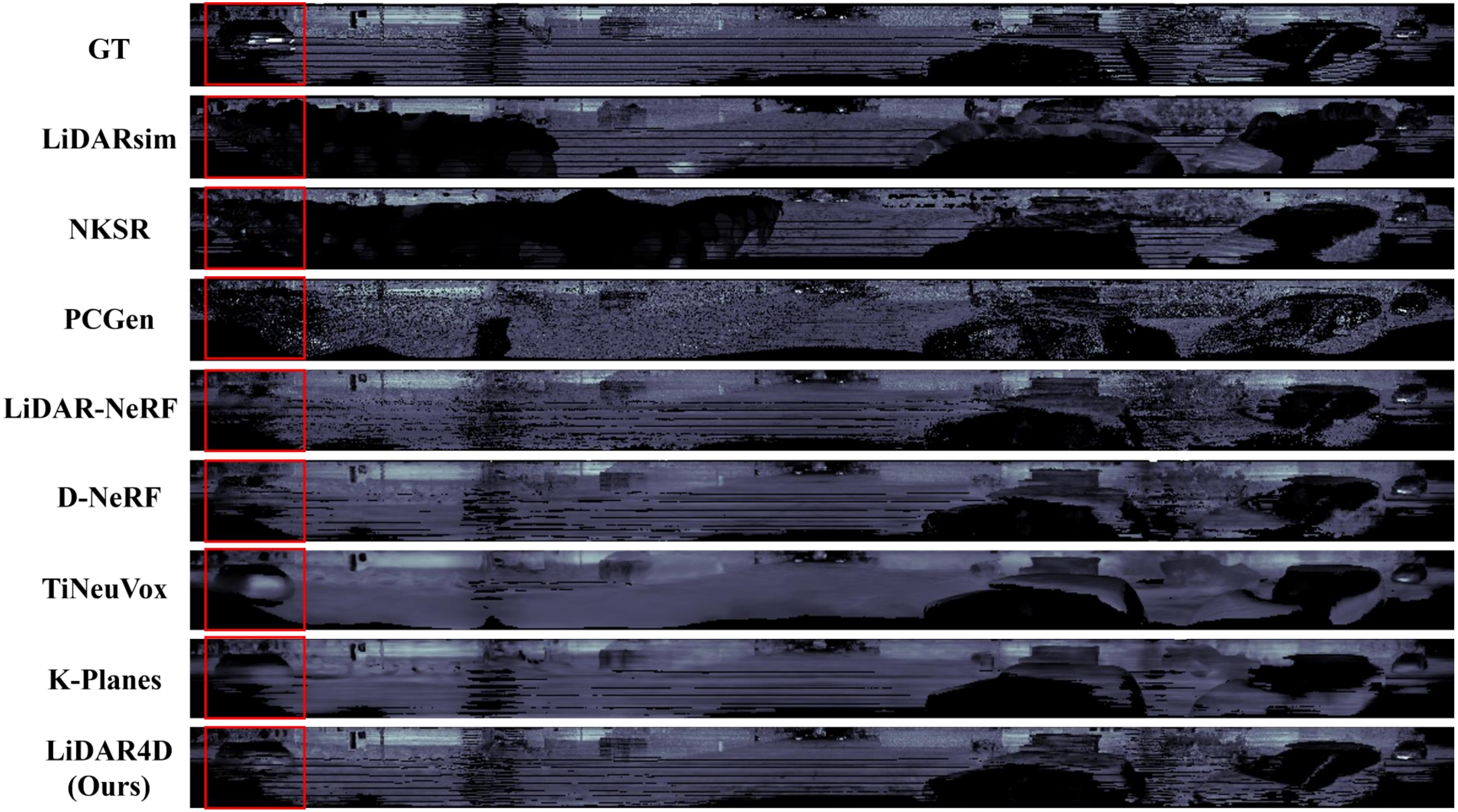
- **More Comparisons**

Even on small objects



Experiments

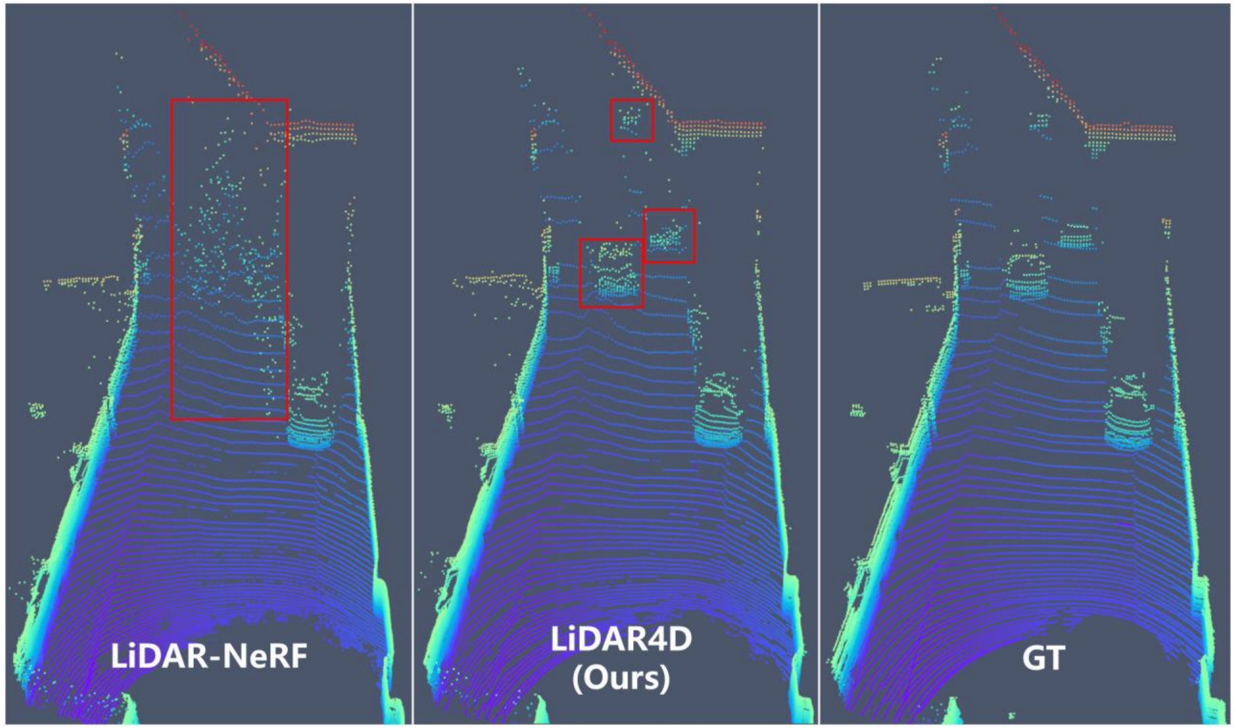
- **More Comparisons** Also the intensity reconstruction

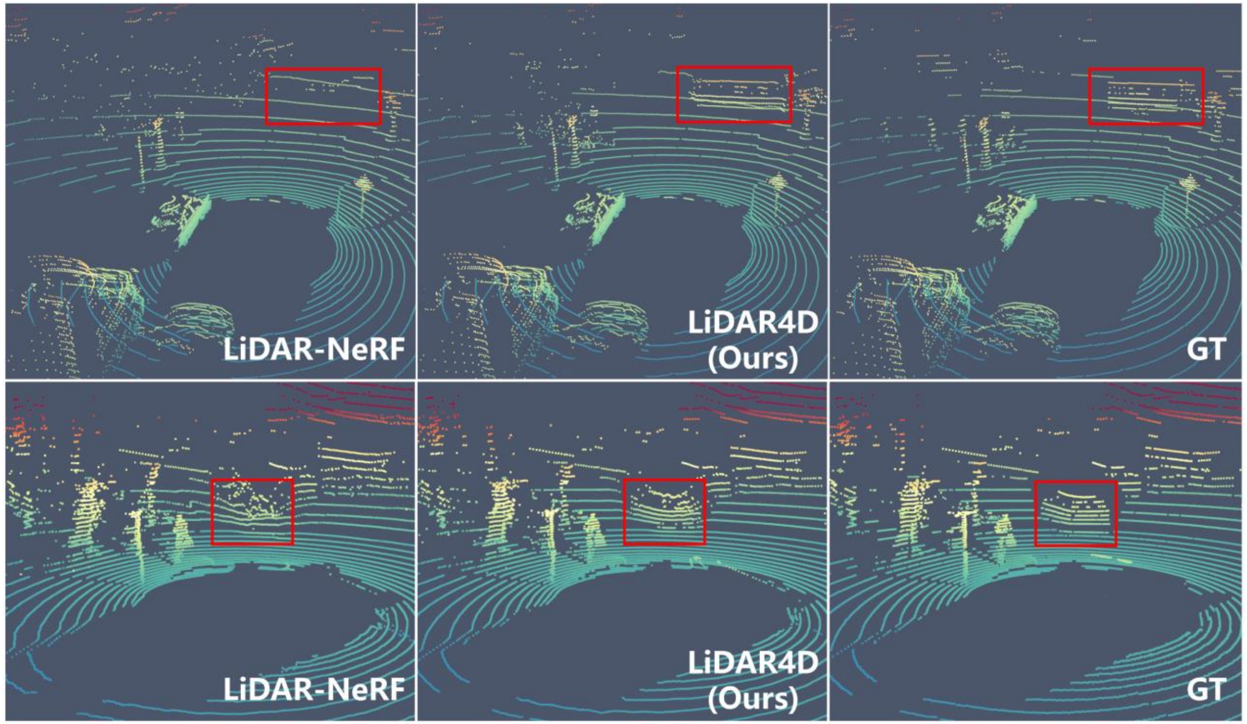


Experiments

- **More Comparisons**

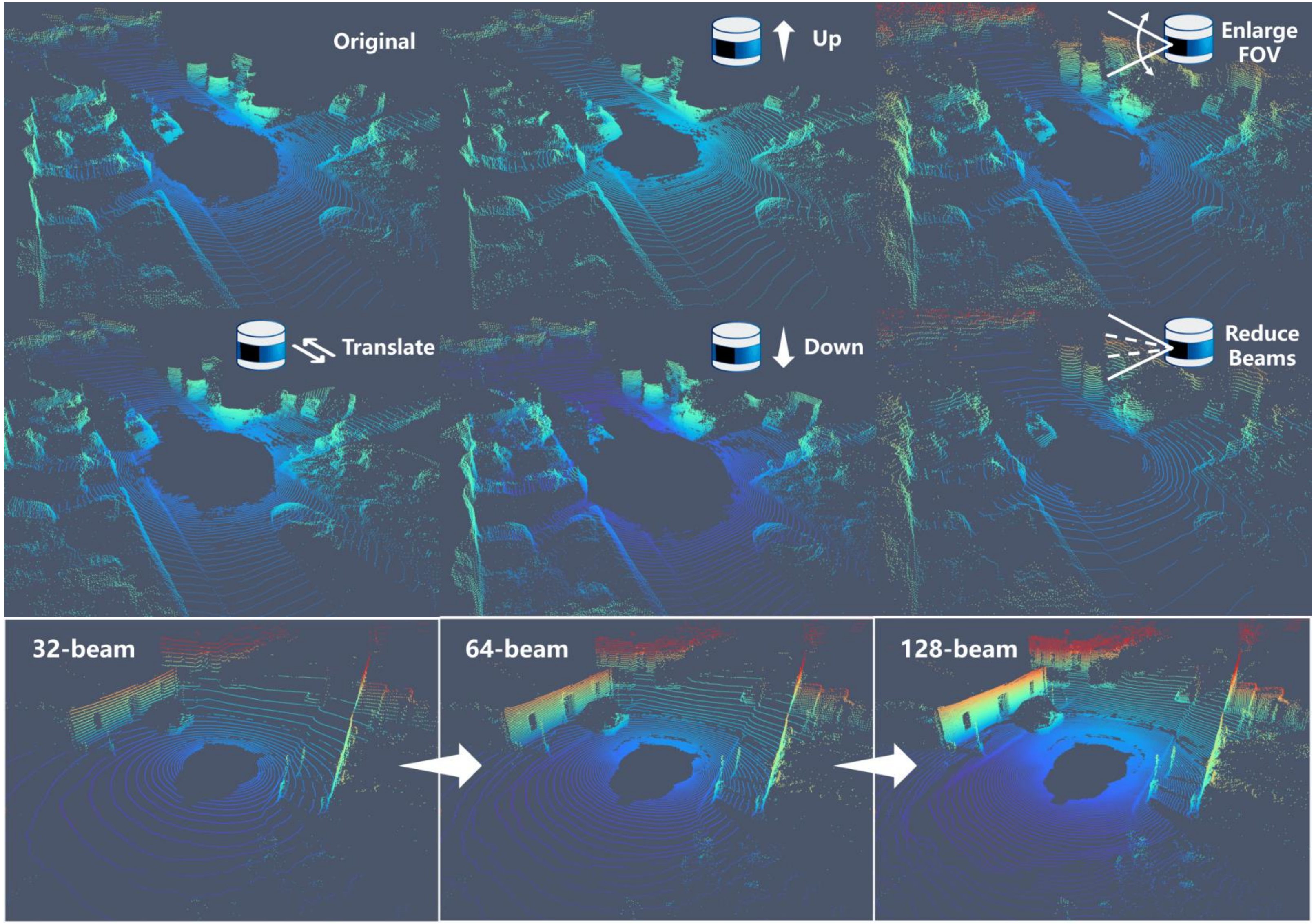
  ✓ LiDAR4D achieves much better ***dynamic*** reconstruction results





Application

- **Shift poses**
  - Sensor Height
  - Translation / Rotation
- **Configuration**
  - Field of View
  - Angular resolution
  - LiDAR beams
- **Simulation**
  - Scene Re-play
  - Novel Trajectory

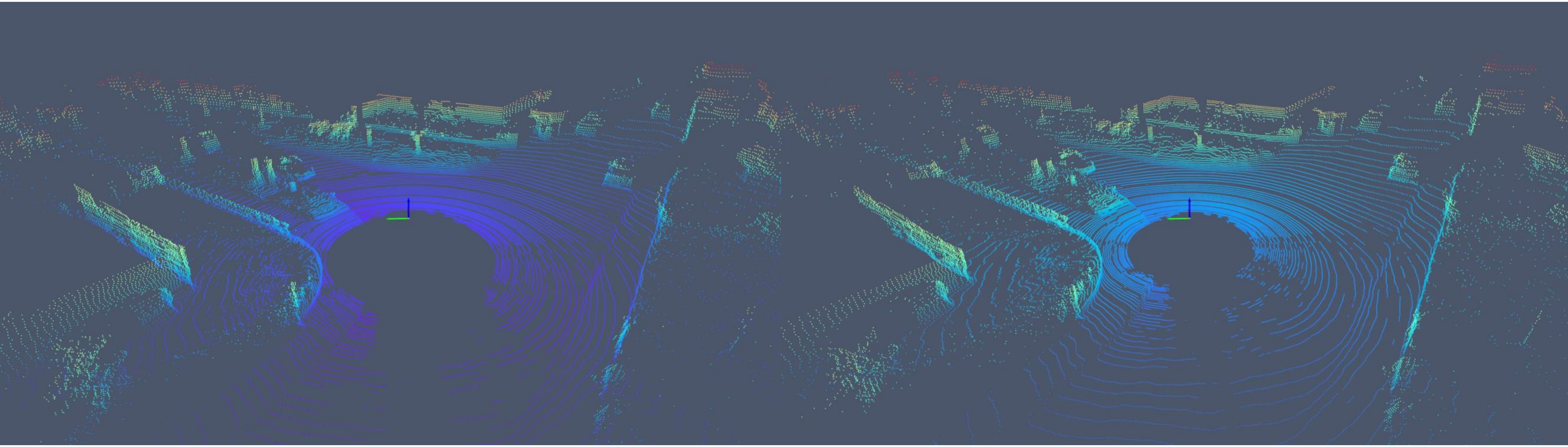


Application

Original Placement

simulate

Horizontal / Vertical Displacement



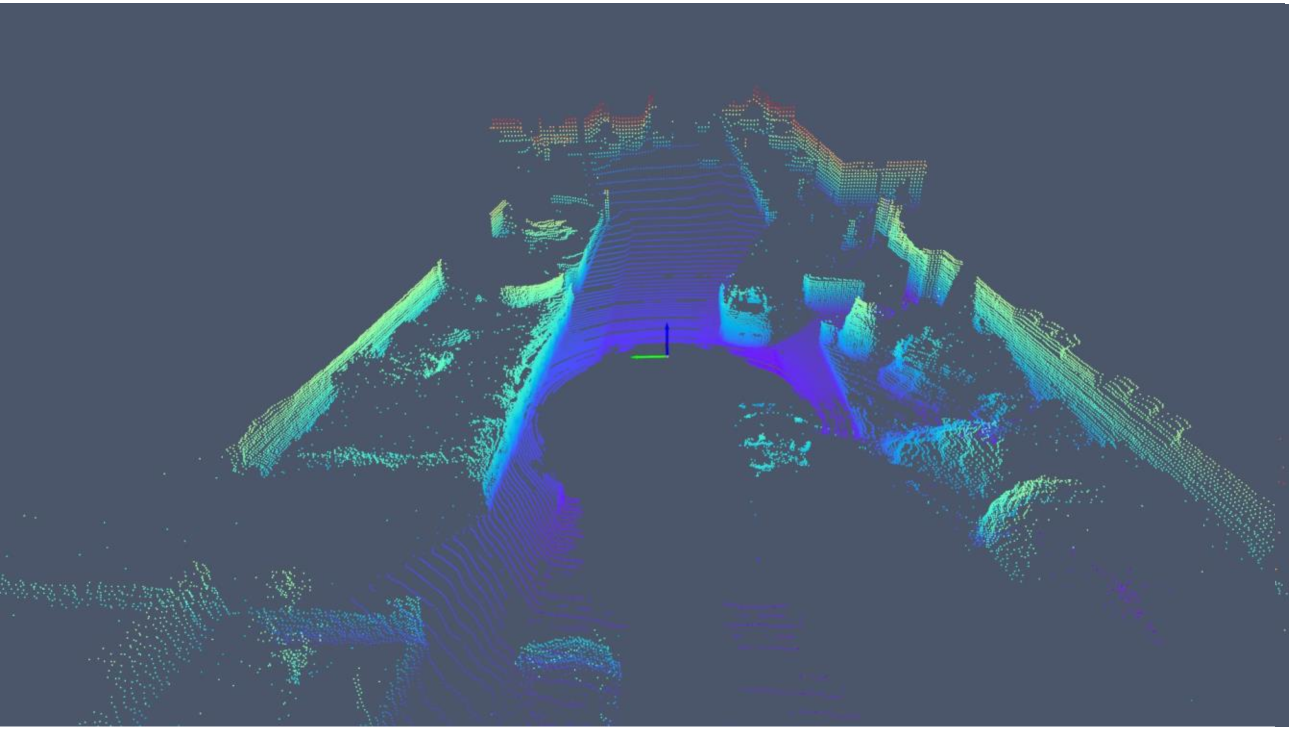
Application

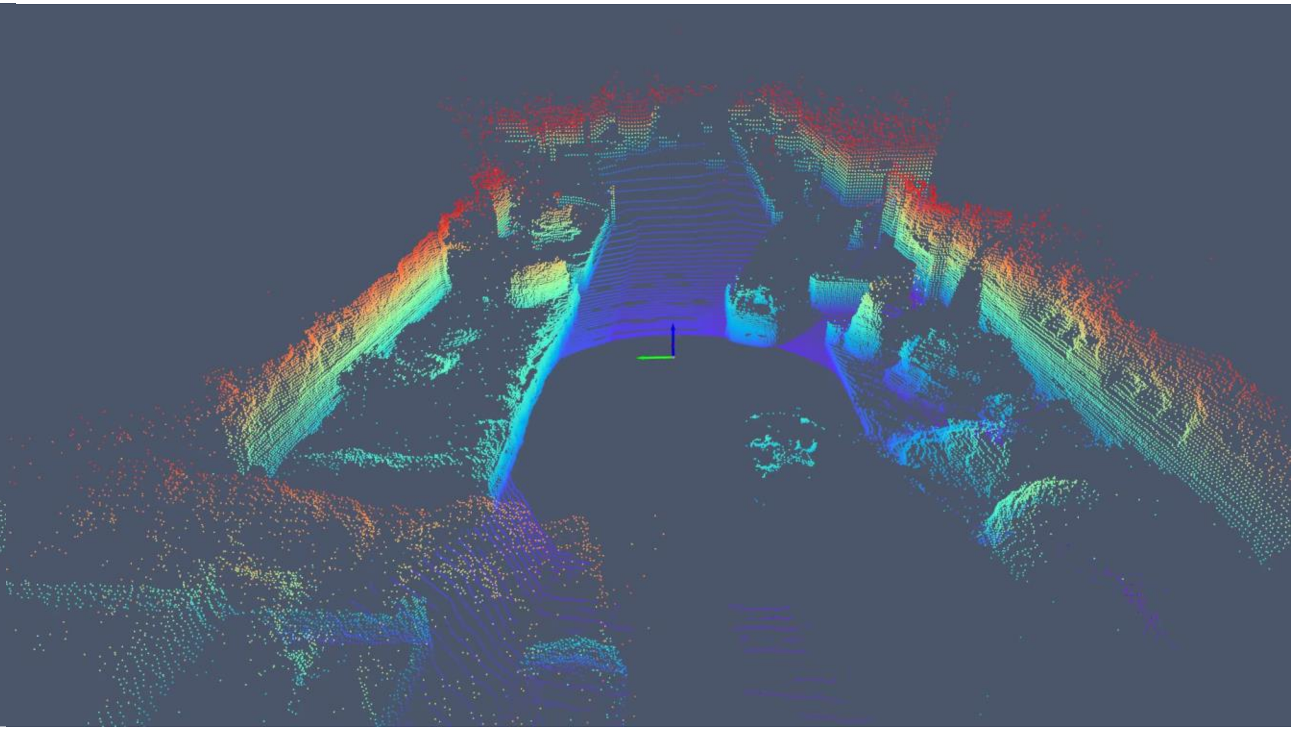
Original Field of View

simulate

Enlarge / Reduce

Field of View



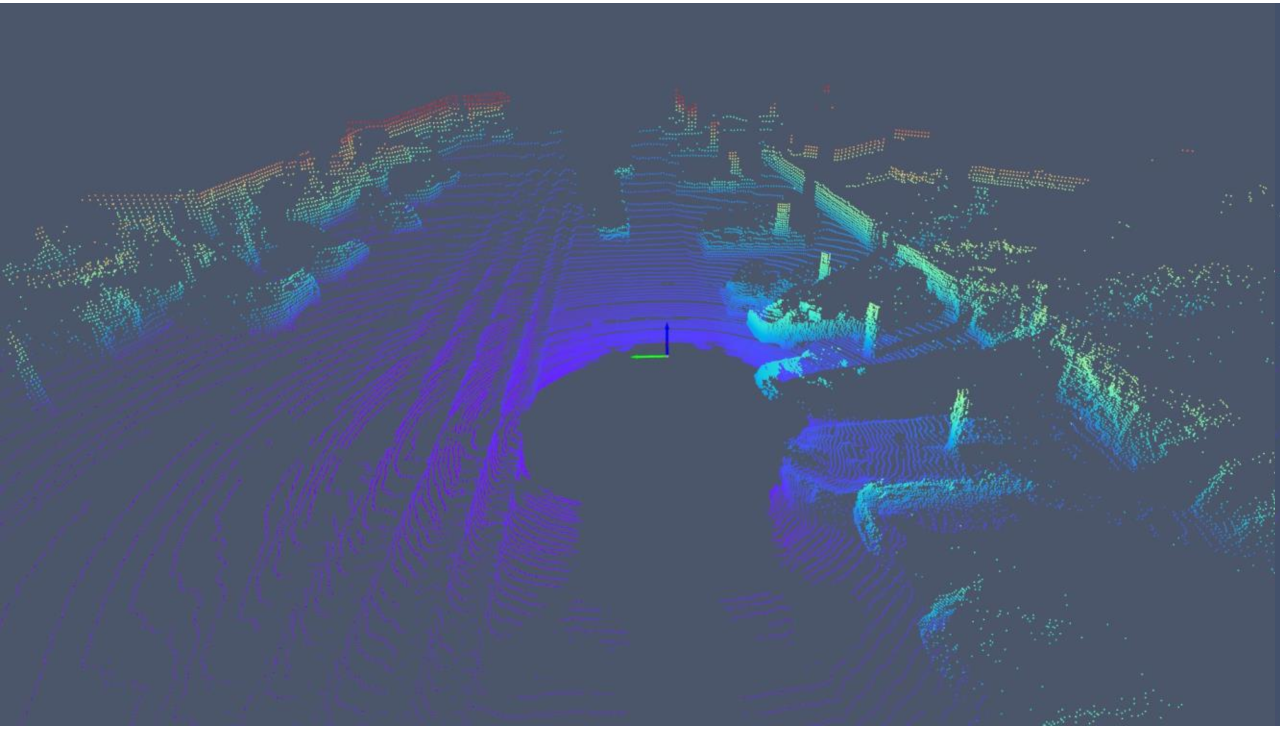


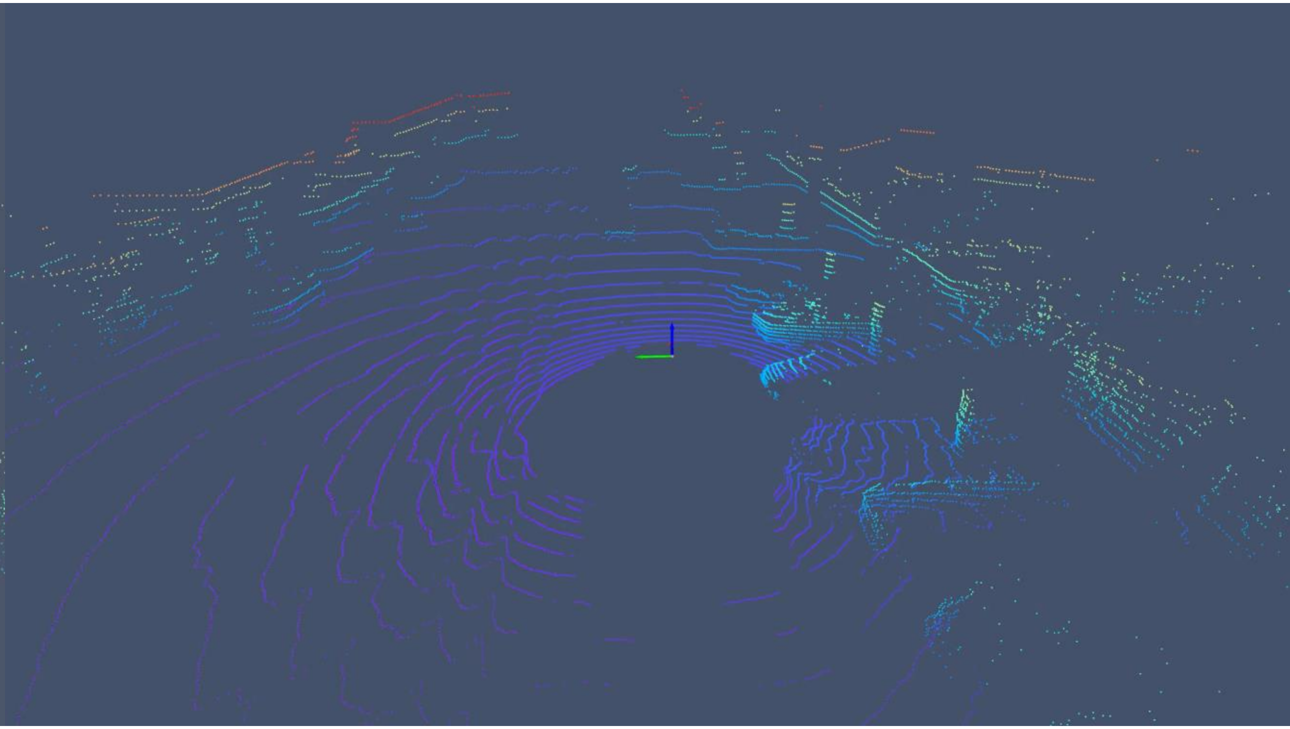
Application

simulate

Original Beams

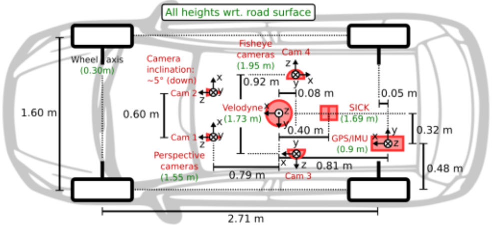
Increase / Decrease Beams





Application

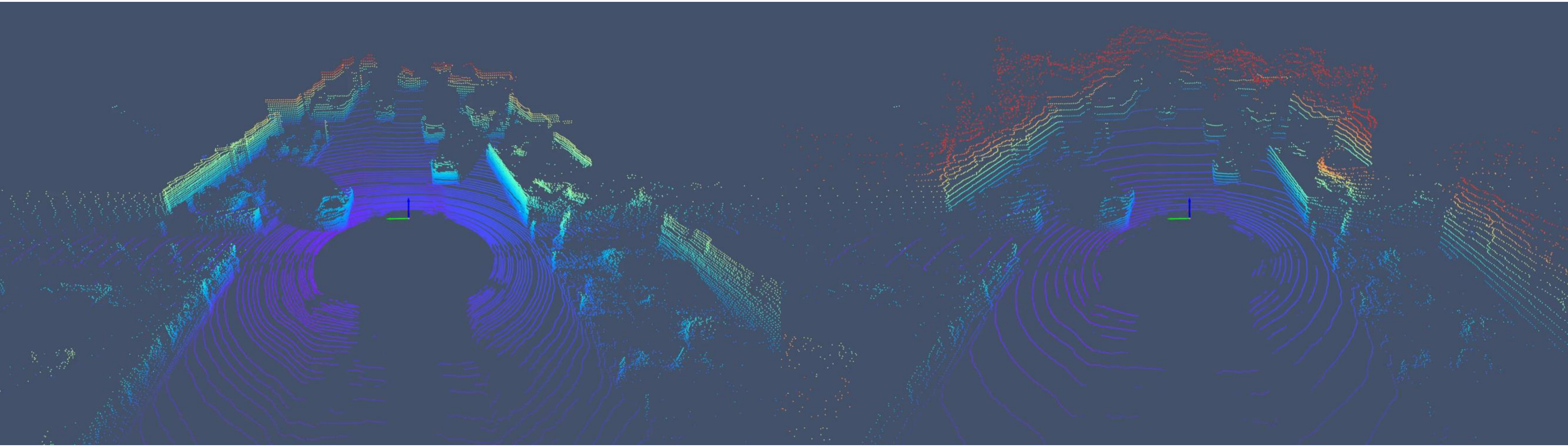
KITTI-360 LiDAR Configuration



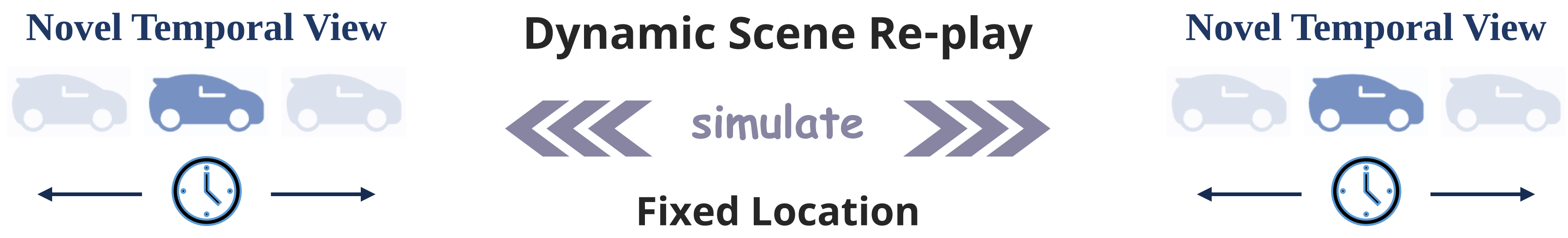
simulate

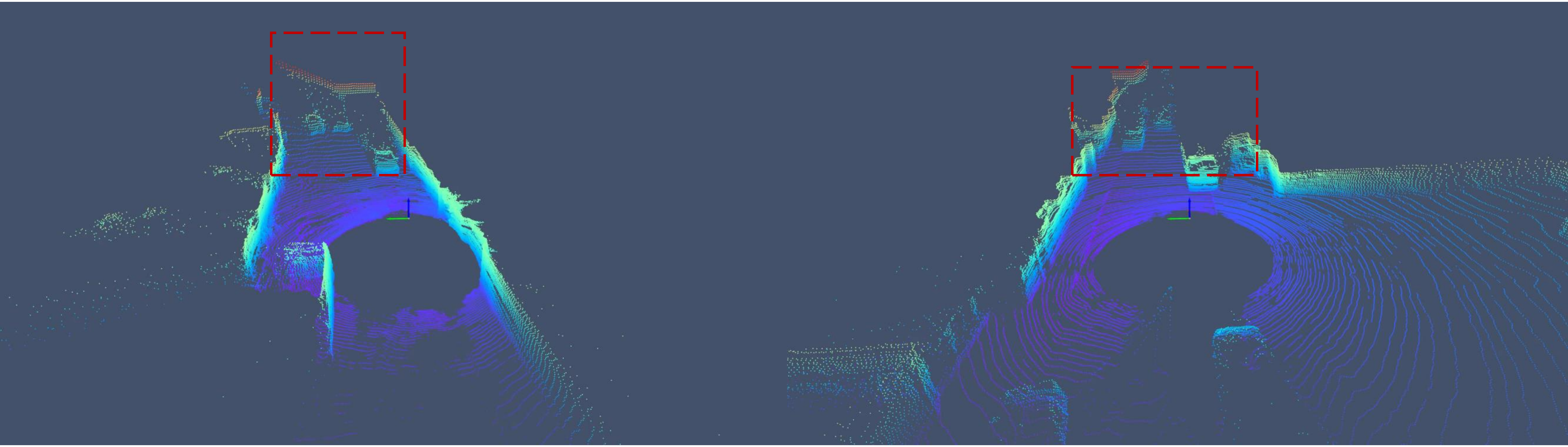
NuScenes LiDAR Configuration

FOV,
Height,
Beams,
Range...

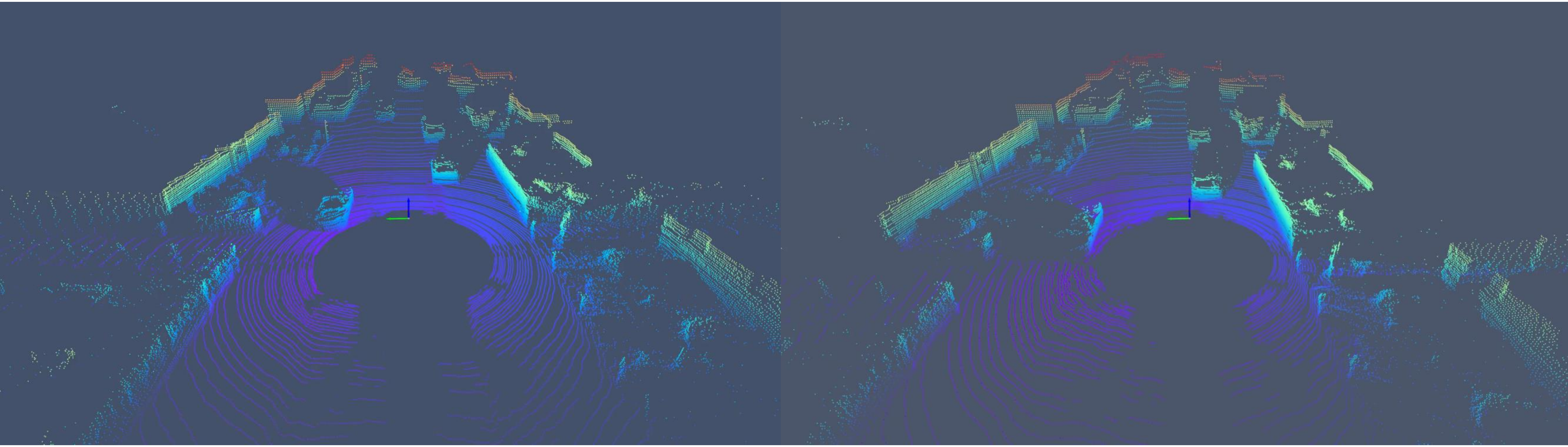


Application





Application



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Robotics & Embodied AI Lab

CVPR SEATTLE, WA JUNE 17-21, 2024

Thank you for listening

Project Page: https://dyfcalid.github.io/LiDAR4D

Codes are available at: https://github.com/ispc-lab/LiDAR4D