



VisHall3D: Monocular Semantic Scene Completion from Reconstructing the Visible Regions to Hallucinating the Invisible Regions

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Contents Title



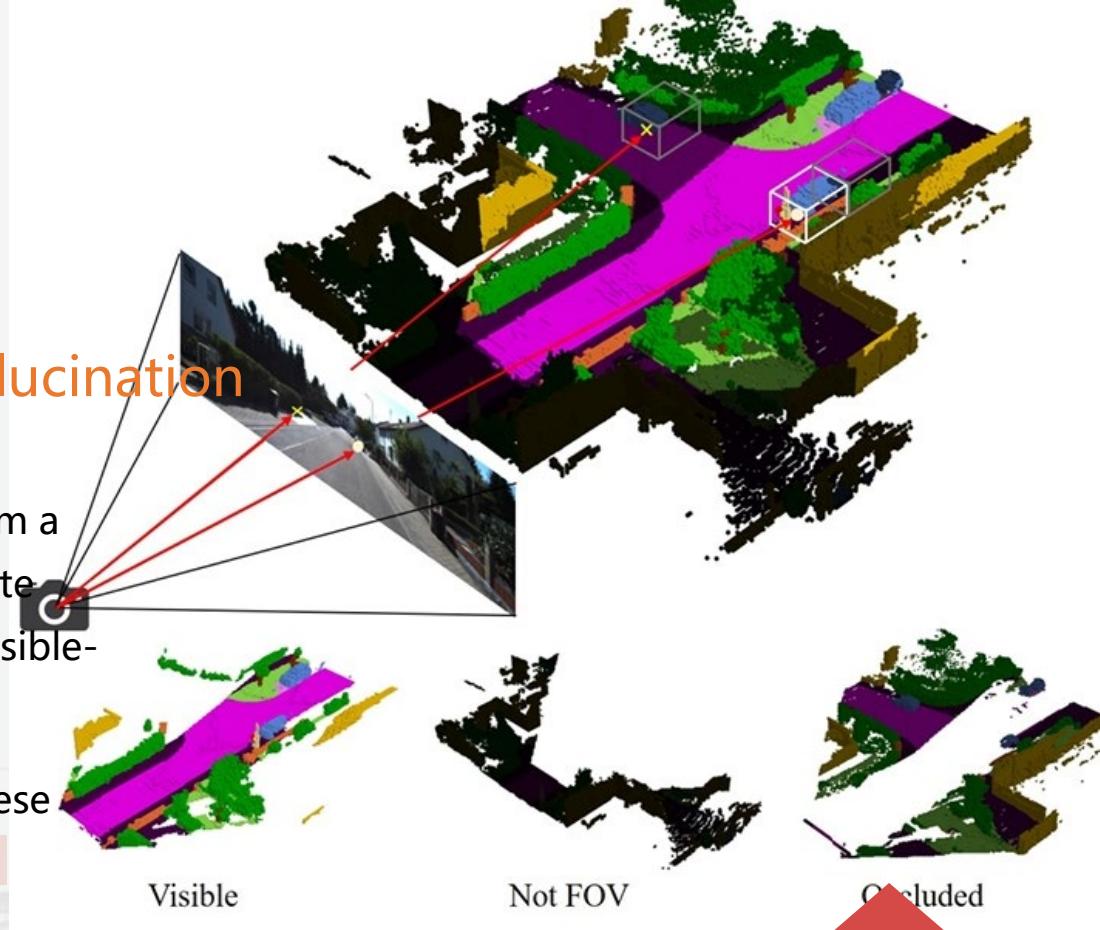
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VisHall3D

Monocular SSC: Vision vs. Hallucination

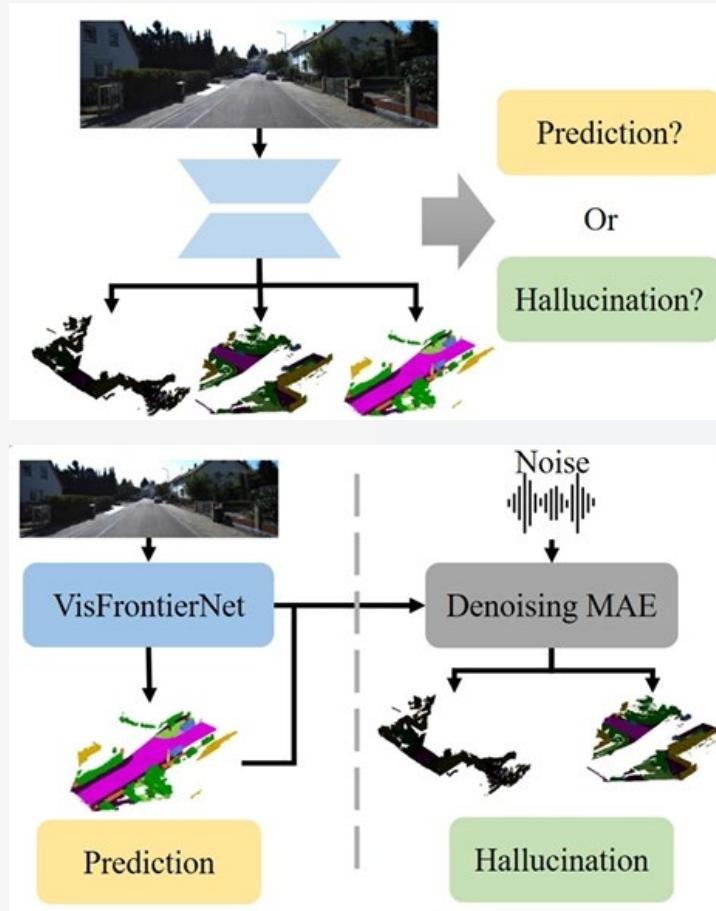
Monocular SSC reconstructs 3D scenes from a single RGB image, demanding both accurate visible-surface modeling and plausible invisible-region inference.

Existing single-stage methods entangle these tasks, causing **feature entanglement** and **geometric inconsistency**.





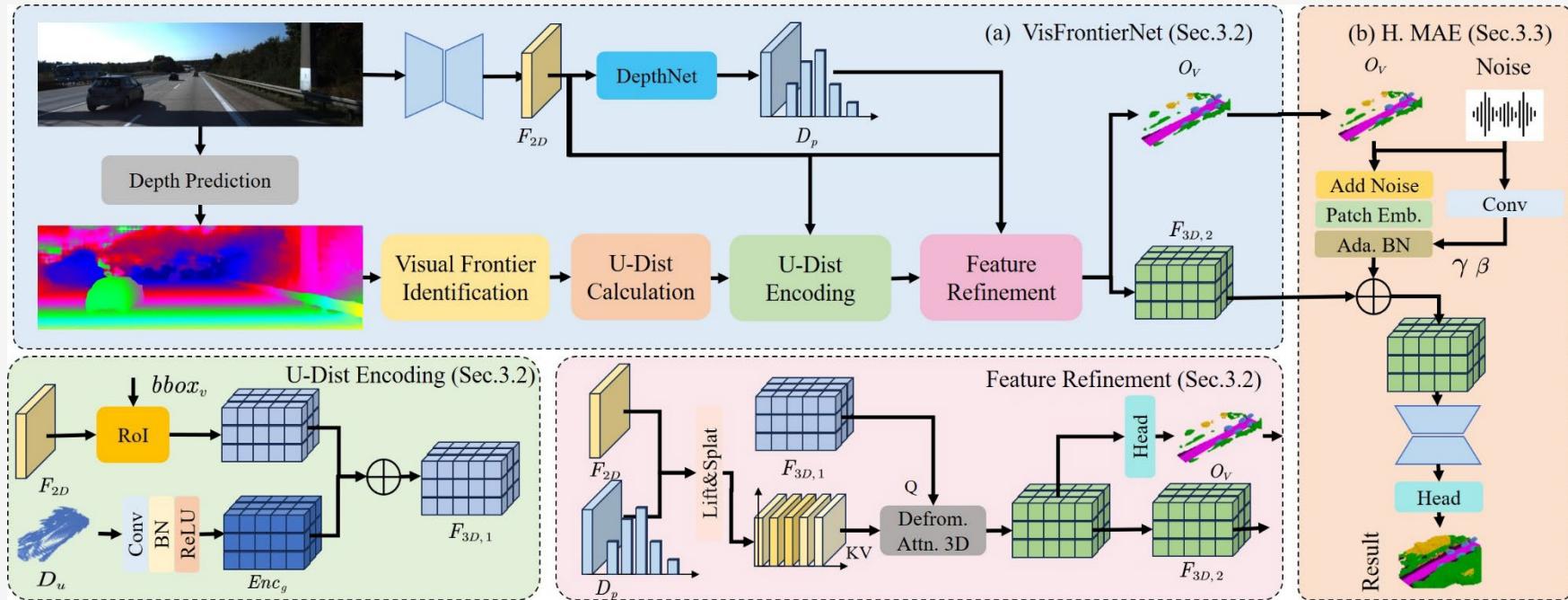
Motivation



Our Solution: Decoupling

We propose a two-stage framework:
VisFrontierNet for visible regions,
followed by OcclusionMAE for
invisible ones.

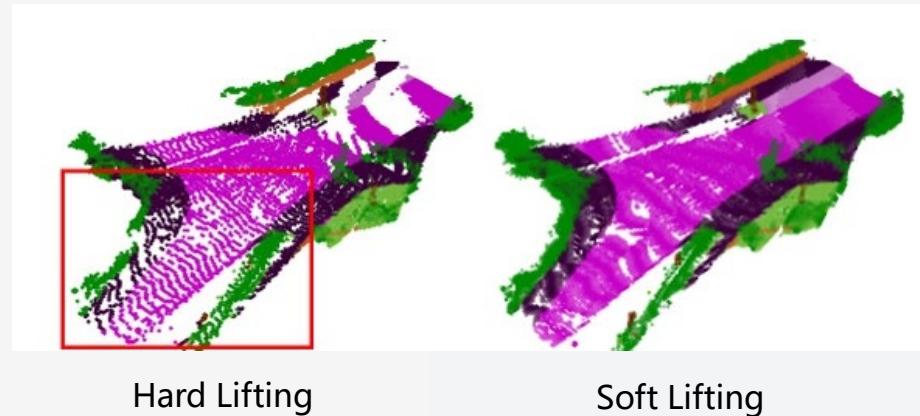
Pipeline



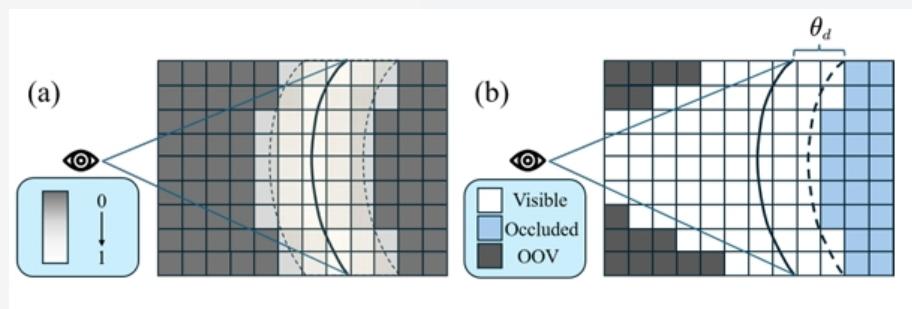
We propose **VisHall3D**, a two-stage monocular SSC framework that decouples vision and hallucination to reduce feature entanglement and geometric inconsistency.

- **VisFrontierNet**, a visibility-aware projection module that accurately traces the visual frontier by modeling the boundary between visible and invisible regions.
- **OcclusionMAE**, a hallucination network that generates plausible geometries for invisible regions using a noise injection mechanism.

Pipeline



➤ Problem: Far distant depth prediction exhibits significant errors, and hard-lifting methods lead to inconsistencies between near and far feature



We propose **Visual Frontier (Soft Lifting)**, a method that models uncertainty in depth prediction while preserving the network's ability to hallucinate missing regions.



Experiment

Method	Date	IoU↑	mIoU↑	road	sidewalk	parking	other-grnd.	building	car	truck	bicycle	motorcycle	other-veh.	vegetation	trunk	terrain	person	bicyclist	motorcyclist	fence	pole	traf.-sign	
Stereo camera-based methods																							
StereoScene[14]	IJCAI2024	43.34	15.36	61.90	31.20	30.70	10.70	24.20	22.80	2.80	3.40	2.40	6.10	23.80	8.40	27.00	2.90	2.20	0.50	16.50	7.00	7.20	
Monocular temporal methods																							
VoxFormer-T[20]	CVPR2023	43.21	13.41	54.10	26.90	25.10	7.30	23.50	21.70	3.60	1.90	1.60	4.10	24.40	8.10	24.20	1.60	1.10	0.00	13.10	6.60	5.70	
HASSC-T[36]	CVPR2024	42.87	14.38	55.30	29.60	25.90	11.30	23.10	23.00	2.90	1.90	1.50	4.90	24.80	9.80	26.50	1.40	3.00	0.00	14.30	7.00	7.10	
HTCL[15]	ECCV2024	44.23	17.09	64.40	34.80	33.80	12.40	25.90	27.30	5.70	1.80	2.20	5.40	25.30	10.80	31.20	1.10	3.10	0.90	21.10	9.00	8.30	
H2GFormer-T[37]	AAAI2024	43.52	14.60	57.90	30.40	30.00	6.90	24.00	23.70	5.20	0.60	1.20	5.00	25.20	10.70	25.80	1.10	0.10	0.00	14.60	7.50	9.30	
Monocular single-frame methods																							
MonoScene[3]	CVPR2023	34.16	11.08	54.70	27.10	24.80	5.70	14.40	18.80	3.30	0.50	0.70	4.40	14.90	2.40	19.50	1.00	1.40	0.40	11.10	3.30	2.10	
VoxFormer-S[20]	CVPR2023	42.95	12.20	53.90	25.30	21.10	5.60	19.80	20.80	3.50	2.60	0.70	3.70	22.40	7.50	21.30	1.40	2.60	0.20	11.10	5.10	4.90	
TPVFormer[11]	CVPR2023	34.25	11.26	55.10	27.20	27.40	6.50	14.80	19.20	3.70	1.00	0.50	2.30	13.90	2.60	20.40	1.10	2.40	0.30	11.00	2.90	1.50	
SurroundOcc[38]	ICCV2023	34.72	11.86	56.90	28.30	30.20	6.80	15.20	20.60	1.40	1.60	1.20	4.40	14.90	3.40	19.30	1.40	2.00	0.10	11.30	3.90	2.40	
OccFormer[46]	ICCV2023	34.53	12.32	55.90	30.30	31.50	6.50	15.70	21.60	1.20	1.50	1.70	3.20	16.80	3.90	21.30	2.20	1.10	0.20	11.90	3.80	3.70	
IAMSSC[39]	T-ITS2024	43.74	12.37	54.00	25.50	24.70	6.90	19.20	21.30	3.80	1.10	0.60	3.90	22.70	5.80	19.40	1.50	2.90	0.50	11.90	5.30	4.10	
DepthSSC[41]	arXiv2024	44.58	13.11	55.64	27.25	25.72	5.78	20.46	21.94	3.74	1.35	0.98	4.17	23.37	7.64	21.56	1.34	2.79	0.28	12.94	5.87	6.23	
HASSC-S[36]	CVPR2024	43.40	13.34	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
Symponize[12]	CVPR2024	42.19	15.04	58.40	29.30	26.90	11.70	24.70	23.60	3.20	3.60	2.60	5.60	24.20	10.00	23.10	3.20	1.90	2.00	16.10	7.70	8.00	
H2GFormer-S[37]	AAAI2024	44.20	13.72	56.40	28.60	26.50	4.90	22.80	23.40	4.80	0.80	0.90	4.10	24.60	9.10	23.80	1.20	2.50	0.10	13.30	6.40	6.30	
MonoOcc-L[47]	ICRA2024	-	15.63	59.10	30.90	27.10	9.80	22.90	23.90	7.20	4.50	2.40	7.70	25.00	9.80	26.10	2.80	4.70	0.60	16.90	7.30	8.40	
CGFormer[43]	NIPS2024	44.41	16.63	<u>64.30</u>	34.20	34.10	<u>12.10</u>	<u>25.80</u>	<u>26.10</u>	4.30	<u>3.70</u>	1.30	2.70	24.50	<u>11.20</u>	29.30	1.70	3.60	0.40	<u>18.70</u>	<u>8.70</u>	9.30	
Ours	ICCV2025	46.50	17.46	64.60	<u>34.10</u>	<u>32.00</u>	12.50	26.90	26.70	7.50	2.90	3.30	<u>6.20</u>	27.30	12.50	<u>28.00</u>	2.30	5.10	<u>1.90</u>	19.50	9.20	<u>9.20</u>	

Semantic-KITTI Comparison

- 3,834 train samples
- 815 validation samples
- 3,992 test samples
- 20 valid classes
- 1 invalid class

Experiment

Method	Date	IoU↑	mIoU↑	car	bicycle	motorcycle	truck	other-veh.	person	road	parking	sidewalk	other-grnd.	building	fence	vegetation	terrain	pole	traj.-sign	other-struct.	other-obj.
LiDAR-based methods																					
SSCNet [34]	CVPR2017	53.58	16.95	31.95	0.00	0.17	10.29	0.00	0.07	65.70	17.33	41.24	3.22	44.41	6.77	43.72	28.87	0.78	0.75	8.69	0.67
LMSNet [32]	3DV 2020	47.35	13.65	20.91	0.00	0.00	0.26	0.58	0.00	62.95	13.51	33.51	0.20	43.67	0.33	40.01	26.80	0.00	0.00	3.63	0.00
Monocular camera-based methods																					
MonoScene [3]	CVPR2023	37.87	12.31	19.34	0.43	0.58	8.02	2.03	0.86	48.35	11.38	28.13	3.32	32.89	3.53	26.15	16.75	6.92	5.67	4.20	3.09
TPVFormer [11]	CVPR2023	40.22	13.64	21.56	1.09	1.37	8.06	2.57	2.38	52.99	11.99	31.07	3.78	34.83	4.80	30.08	17.52	7.46	5.86	5.48	2.70
OccFormer [46]	ICCV2023	40.27	13.81	22.58	0.66	0.26	9.89	3.82	2.77	54.30	13.44	31.53	3.55	36.42	4.80	31.00	19.51	7.77	8.51	6.95	4.60
VoxFormer [20]	CVPR2023	38.76	11.91	17.84	1.16	0.89	4.56	2.06	1.63	47.01	9.67	27.21	2.89	31.38	4.97	28.99	14.69	6.51	6.92	3.79	2.43
IAMSSC [39]	T-ITS2024	41.80	12.97	18.53	2.45	1.76	5.12	3.92	3.09	47.55	10.56	28.35	4.12	31.53	6.28	29.17	15.24	8.29	7.01	6.35	4.19
DepthSSC [41]	arXiV2024	40.85	14.28	21.90	2.36	4.30	11.51	4.56	2.92	50.88	12.89	30.27	2.49	37.33	5.22	29.61	21.59	5.97	7.71	5.24	3.51
Symphonies [12]	CVPR2024	44.12	18.58	30.02	1.85	5.90	25.07	12.06	8.20	54.94	13.83	32.76	6.93	35.11	8.58	38.33	11.52	14.01	9.57	14.44	11.28
CGFormer[43]	NIPS2024	48.07	20.05	29.85	3.42	3.96	17.59	6.70	6.63	63.85	17.15	40.72	5.53	42.73	8.22	38.80	24.04	16.24	17.45	10.18	6.77
Ours	ICCV2025	49.12	20.95	30.77	1.91	6.60	17.99	8.72	8.67	64.35	18.83	41.53	4.48	43.87	9.07	39.75	24.94	16.52	20.66	10.30	7.99

KITTI360-SSCBench Comparison

- 8487 train samples
- 1812 validation samples
- 2566 test samples
- 19 valid classes



Experiment

Method	IoU↑	mIoU↑	Params (M)	Memory (M)
Baseline	42.11	14.56	57.2	15260
VisFrontierNet w/o Feature Refinement	46.44 (+4.33)	15.11 (+0.55)	74.3	17349
+ OcclusionMAE w/o Denoising	46.38 (-0.06)	15.99 (+0.88)	86.7	18746
+ Feature Refinement	45.88 (-0.50)	16.59 (+0.60)	125.5	21246
+ Denoising	46.14 (+0.26)	17.06 (+0.47)	127.8	22597

- Ablation on architectural components

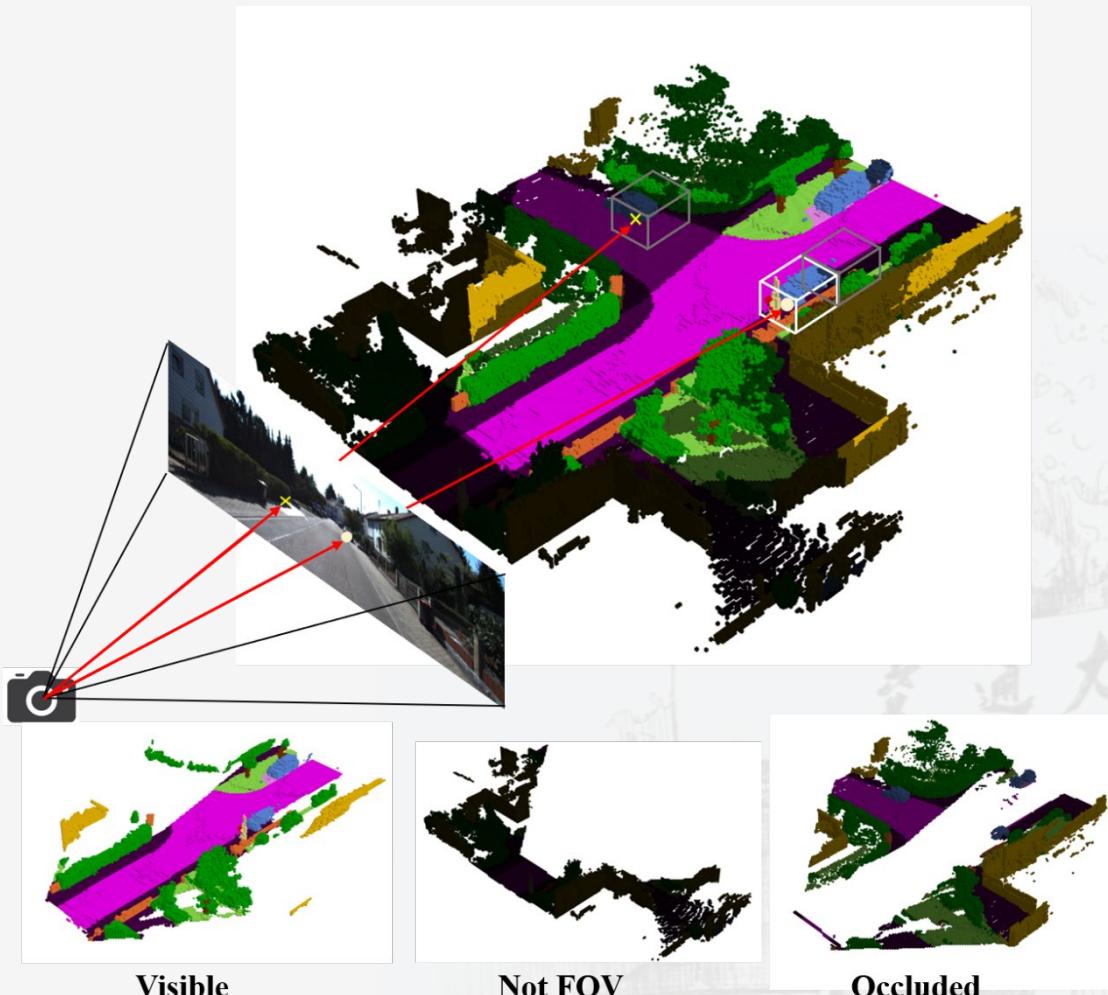
R_h (Voxel)	R_d (Voxel)	IoU↑	mIoU↑
0	0	46.03	16.32
0	2	45.92	16.79
0	3	45.83	16.92
0	4	45.73	16.66
1	3	46.19	16.52
1	4	46.12	16.69

Invisibility	Threshold θ_d (m)	IoU↑	mIoU↑
OOV	-	43.98	15.89
OOV + Occ.	1.5	45.87	16.65
OOV + Occ.	2.5	45.83	16.92
OOV + Occ.	3.5	46.14	17.06
OOV + Occ.	4.5	45.94	16.95

- Ablation on Visual Frontier

- Ablation on MAE noise

Conclusion



In this paper, we proposed VisHall3D. VisHall3D sets a new standard for Monocular SSC, paving the way for more accurate and reliable scene understanding in various applications



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Thank You

