OCCGen : Generative Multi-modal 3D Occupancy PPrediction for Autonomous Driving

Guoqing Wang, Zhongdao Wang, Pin Tang, Jilai Zheng, Xiangxuan Ren, Bailan Feng, Chao Ma

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- Problem/Objective
  - Semantic Occupancy Prediction

- Contribution/Key Idea
  - Noise-to-occupancy prediction
  - Efficient Encoder-Decoder runner mechanism
  - Improve performance

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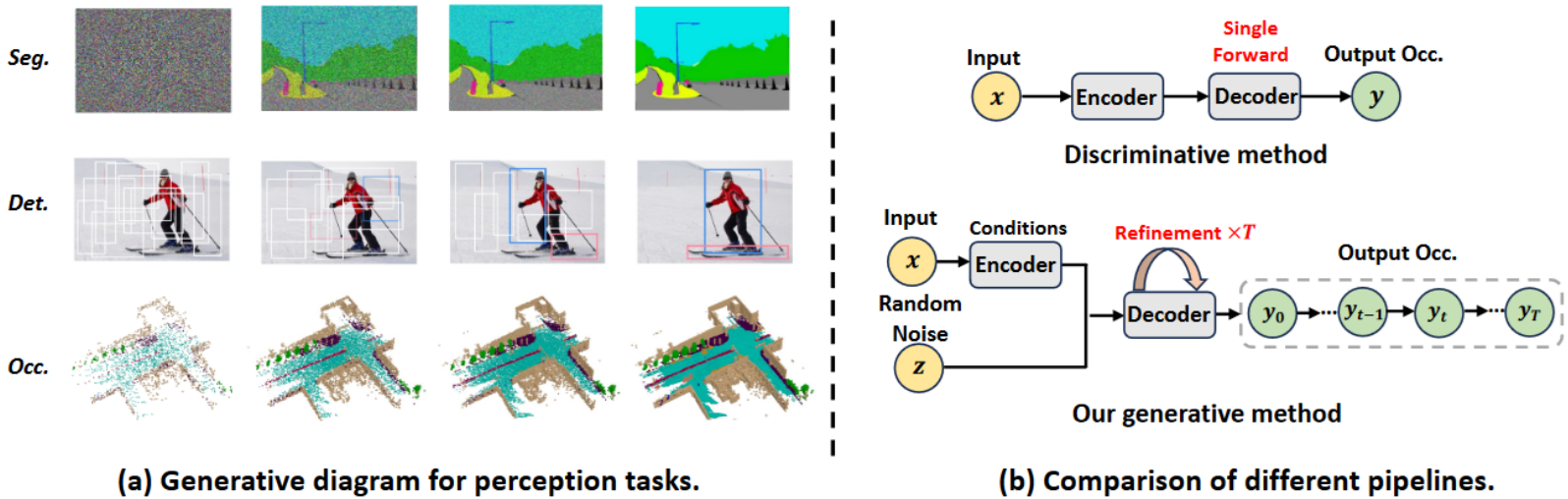

(a) Generative diagram for perception tasks.

(b) Comparison of different pipelines.

기존 방법 : One-shot voxel wise segmentation problem with a single forward step

본 모델 : Progressive refinement decoder (Coarse-to-fine)

(1) 계산량 - 품질 사이의 trade off 선택가능

(2) occupancy prediction과 동시에 uncertainty estimation 가능

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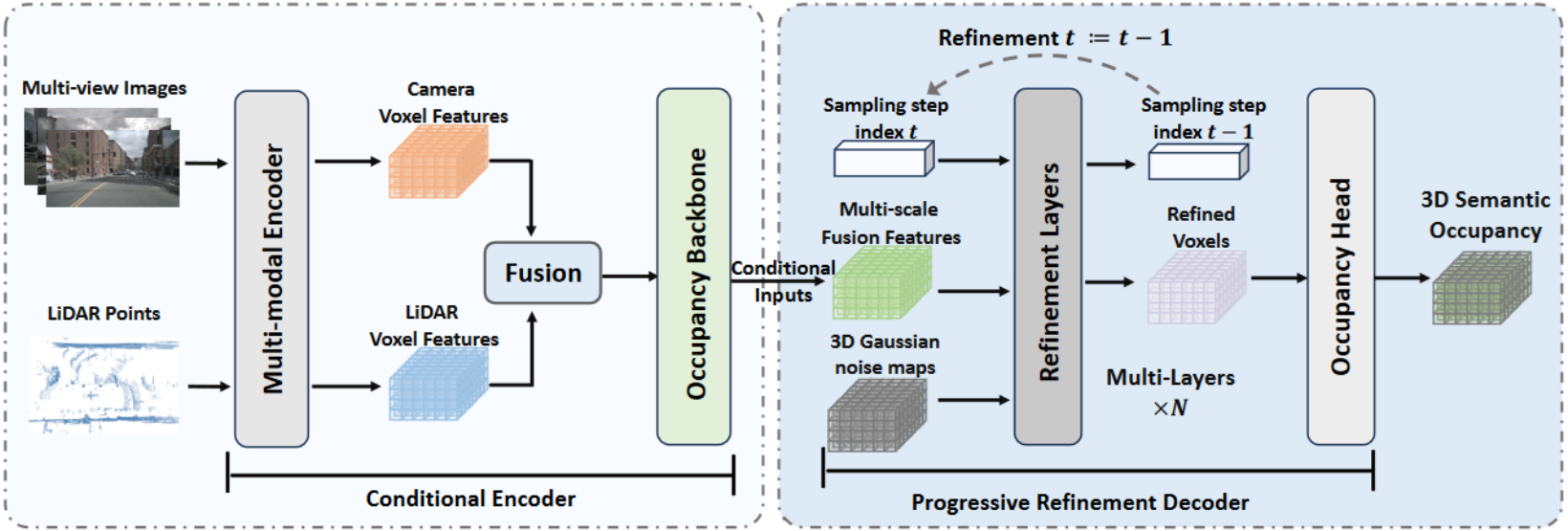

$$X_p \in \mathbb{R}^{N_L \times (3+d)}$$

$$X_c \in \mathbb{R}^{N_C \times H_C \times W_C \times 3}$$

$$Y \in \{c_0, c_1, ..., c_N\}^{H \times W \times Z}$$

$$\Delta Y_t = f_\theta\left(x, t, Y_{t+1}\right), \quad Y_t = Y_{t+1} \oplus \Delta Y_t$$

$$Y_T \xrightarrow{f_\theta} Y_{T-1} \xrightarrow{f_\theta} \dots \xrightarrow{f_\theta} Y_0$$

3D Gaussian voxel map

Refined Occupancy

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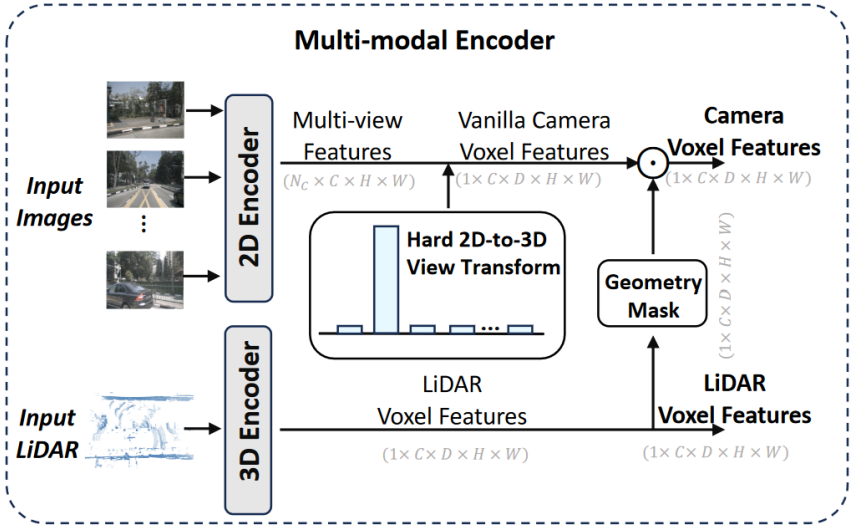

(a) The architecture of multi-modal encoder.

$$W = \mathcal{G}_{\mathrm{C}}\left(\left[\mathcal{G}_{\mathrm{C}}\left(F_p\right), \mathcal{G}_{\mathrm{C}}\left(F_c\right)\right]\right),$$
$$F_m = \sigma(W) \odot F_p + (1 - \sigma(W)) \odot F_c$$

Different from the previous 2D-to-3D view transformation [30, 33, 36, 41] methods that estimate the probabilistic of a set of discrete depths, OccGen proposes a hard 2D-to-3D view transformation to guarantee more accurate depth. We opt for predicting a one-hot vector for depth, as opposed to utilizing softmax on discrete depth values when lifting each image individually into a frustum of features for each camera. However, obtaining one-hot encoding directly through $argmax$ operation is non-differentiable. To address this issue, we propose using Gumbel-Softmax [20] to convert the predicted depth into one-hot encoding.

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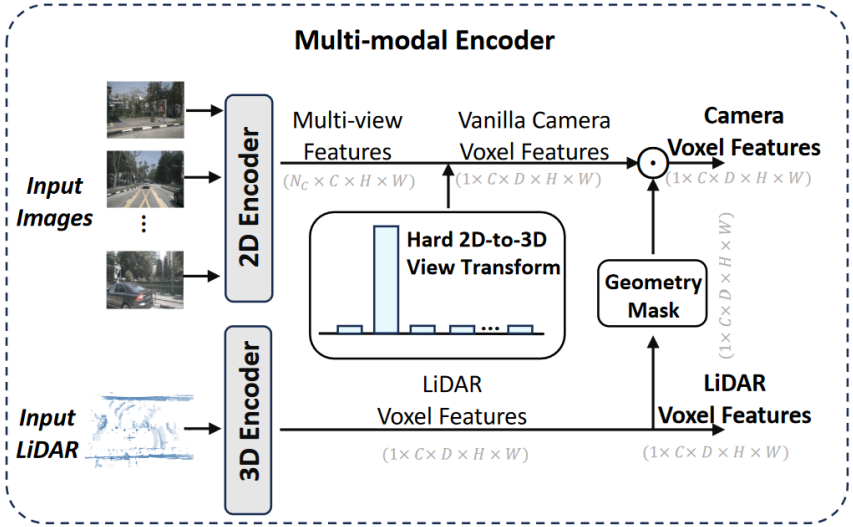

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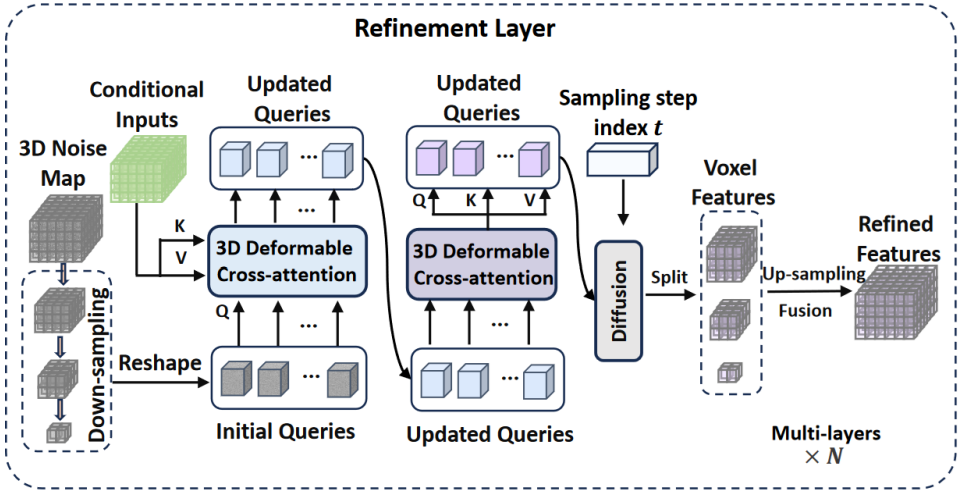

(b) The architecture of refinement layer.

Directly operating on the original 3D Gaussian noise map Y_t with high resolution is computationally intensive. Therefore, we first downsample it to obtain smaller multi-scale noise maps $Y_t^i \in \mathbb{R}^{\frac{D}{2^i} \times \frac{H}{2^i} \times \frac{W}{2^i} \times C_i} (i = 1, 2, 3)$. Then, we re-

$$\mathrm{DCA_{3D}}\left(Y_t^i, F_m\right) = \sum_{n \in F_m} \mathrm{DA_{3D}}\left(q, proj(q, n), F_m\right)$$

$$\mathrm{DSA_{3D}}\left(Y_t^i, Y_t^i\right) = \sum_{n \in Y_t^i} \mathrm{DA_{3D}}\left(q, p, \mathbf{Y}_t^i\right)$$

$$Y_t^i := \mathrm{Diff}(Y_t^i, \mathrm{ToEmbed}(t))$$

x N times

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Table 1: Semantic occupancy prediction results on nuScenes-Occupancy validation set. The C, D, L, M denotes **camera, depth, LiDAR** and **multi-modal**. For **Surround**=✓, the method directly predicts surrounding semantic occupancy with 360-degree inputs. Best camera-only, LiDAR-only, and multi-modal results are marked **red**, **blue**, and **black**, respectively.

Method	Input	Surround	IoU	mIoU	barrier	bicycle	bus	car	const. veh.	motorcycle	pedestrian	traffic cone	trailer	truck	drive. suf.	other flat	sidewalk	terrain	manmade	vegetation
MonoScene [5]	C	✗	18.4	6.9	7.1	3.9	9.3	7.2	5.6	3.0	5.9	4.4	4.9	4.2	14.9	6.3	7.9	7.4	10.0	7.6
TPVFormer [19]	C	✓	15.3	7.8	9.3	4.1	11.3	10.1	5.2	4.3	5.9	5.3	6.8	6.5	13.6	9.0	8.3	8.0	9.2	8.2
3DSketch [8]	C&D	✗	25.6	10.7	12.0	5.1	10.7	12.4	6.5	4.0	5.0	6.3	8.0	7.2	21.8	14.8	13.0	11.8	12.0	21.2
AICNet [28]	C&D	✗	23.8	10.6	11.5	4.0	11.8	12.3	5.1	3.8	6.2	6.0	8.2	7.5	24.1	13.0	12.8	11.5	11.6	20.2
LMSCNet [42]	L	✓	27.3	11.5	12.4	4.2	12.8	12.1	6.2	4.7	6.2	6.3	8.8	7.2	24.2	12.3	16.6	14.1	13.9	22.2
JS3C-Net [61]	L	✓	30.2	12.5	14.2	3.4	13.6	12.0	7.2	4.3	7.3	6.8	9.2	9.1	27.9	15.3	14.9	16.2	14.0	**24.9**
C-OpenOccupancy [57]	C	✓	19.3	10.3	9.9	6.8	11.2	11.5	6.3	8.4	8.6	4.3	4.2	9.9	22.0	15.8	14.1	13.5	7.3	10.2
L-OpenOccupancy [57]	L	✓	30.8	11.7	12.2	4.2	11.0	12.2	8.3	4.4	8.7	4.0	8.4	10.3	23.5	16.0	14.9	15.7	15.0	17.9
OpenOccupancy [57]	M	✓	29.1	15.1	14.3	12.0	15.2	14.9	13.7	15.0	13.1	9.0	10.0	14.5	23.2	17.5	16.1	17.2	15.3	19.5
C-CONet [57]	C	✓	20.1	12.8	13.2	8.1	**15.4**	17.2	6.3	11.2	10.0	8.3	4.7	12.1	31.4	18.8	18.7	16.3	4.8	8.2
L-CONet [57]	L	✓	30.9	15.8	17.5	**5.2**	13.3	18.1	7.8	5.4	9.6	5.6	13.2	13.6	34.9	21.5	22.4	21.7	19.2	23.5
CONet [57]	M	✓	29.5	20.1	23.3	13.3	21.2	24.3	**15.3**	15.9	18.0	13.3	15.3	20.7	33.2	21.0	22.5	21.5	19.6	23.2
C-OccGen	C	✓	**23.4**	**14.5**	**15.5**	**9.1**	15.3	**19.2**	**7.3**	**11.3**	**11.8**	**8.9**	**5.9**	**13.7**	**34.8**	**22.0**	**21.8**	**19.5**	**6.0**	**9.9**
L-OccGen	L	✓	**31.6**	**16.8**	**18.8**	5.1	**14.8**	**19.6**	**7.0**	**7.7**	**11.5**	**6.7**	**13.9**	**14.6**	**36.4**	**22.1**	**22.8**	**22.3**	**20.6**	24.5
OccGen	M	✓	**30.3**	**22.0**	**24.9**	**16.4**	**22.5**	**26.1**	14.0	**20.1**	**21.6**	**14.6**	**17.4**	**21.9**	**35.8**	**24.5**	**24.7**	**24.0**	**20.5**	**23.5**

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Table 2: Semantic Scene Completion results on SemanticKITTI [2] validation set. † denotes the results provided by MonoScene [5].

Method	IoU	road. (%)	sidewalk. (%)	parking. (%)	otherground. (%)	building. (%)	car. (%)	truck. (%)	bicycle. (%)	motorcycle. (%)	othervehicle. (%)	vegetation. (%)	trunk. (%)	terrain. (%)	person. (%)	bicyclist. (%)	motorcyclist. (%)	fence. (%)	pole. (%)	trafficsign. (%)	mIoU
LMSCNet† [42]	28.61	40.68	18.22	4.38	0.00	10.31	18.33	0.00	0.00	0.00	0.00	13.66	0.02	20.54	0.00	0.00	0.00	1.21	0.00	0.00	6.70
AICNet† [28]	29.59	43.55	20.55	11.97	0.07	12.94	14.71	4.53	0.00	0.00	0.00	15.37	2.90	28.71	0.00	0.00	0.00	2.52	0.06	0.00	8.31
JS3C-Net† [61]	38.98	50.49	23.74	11.94	0.07	15.03	24.65	4.41	0.00	0.00	6.15	18.11	4.33	26.86	0.67	0.27	0.00	3.94	3.77	1.45	10.31
MonoScene [5]	37.12	57.47	27.05	15.72	**0.87**	14.24	23.55	7.83	0.20	0.77	3.59	18.12	2.57	30.76	1.79	1.03	0.00	6.39	4.11	2.48	11.50
TPVFormer [19]	35.61	56.50	25.87	20.60	0.85	13.88	23.81	8.08	0.36	0.05	4.35	16.92	2.26	30.38	0.51	0.89	0.00	5.94	3.14	1.52	11.36
VoxFormer [29]	44.02	54.76	26.35	15.50	0.70	17.65	25.79	5.63	0.59	0.51	3.77	24.39	**5.08**	29.96	1.78	3.32	0.00	**7.64**	7.11	4.18	12.35
OccFormer [65]	36.50	58.85	26.88	19.61	0.31	14.40	25.09	**25.53**	0.81	1.19	8.52	19.63	3.93	**32.62**	2.78	2.82	0.00	5.61	4.26	2.86	13.46
Symphonize [23]	41.44	55.78	26.77	14.57	0.19	**18.76**	**27.23**	15.99	**1.44**	2.28	9.52	**24.50**	4.32	28.49	3.19	**8.09**	0.00	6.18	**8.99**	**5.39**	13.44
OccGen (ours)	36.87	**61.28**	**28.30**	20.42	0.43	14.49	26.83	15.49	**1.60**	**2.53**	**12.83**	20.04	3.94	32.44	**3.20**	3.37	0.00	6.94	4.11	2.77	**13.74**

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	Encoder	Decoder	IoU	mIoU
(a)	-	-	28.1	20.4
(b)	✓	-	28.6	20.7
(c)	-	✓	30.1	21.6
(d)	✓	✓	30.3	22.0

Hard LSS	Geo. Mask	IoU	mIoU
-	-	29.8	21.4
✓	-	30.2	21.5
-	✓	30.3	21.6
✓	✓	30.3	22.0

Models	Latency(ms)	IoU	mIoU
C-Baseline [57]	172.4	19.3	10.3
C-CONet [57]	285.7	20.1	12.8
C-OccGen(step1)	294.1	23.0	14.2
C-OccGen(step2)	312.5	23.3	14.4
Baseline [57]	243.9	29.1	15.1
CONet [57]	344.8	29.5	20.1
OccGen(step1)	357.1	29.3	21.7
OccGen(step2)	400.0	29.7	21.8

performance is further boosted to 21.8% and 14.4% on the multi-modal and camera-only benchmarks, at a loss of 20 $\sim$ 50 ms. These results show that OccGen can progressively refine the output occupancy multiple times with reasonable time cost.

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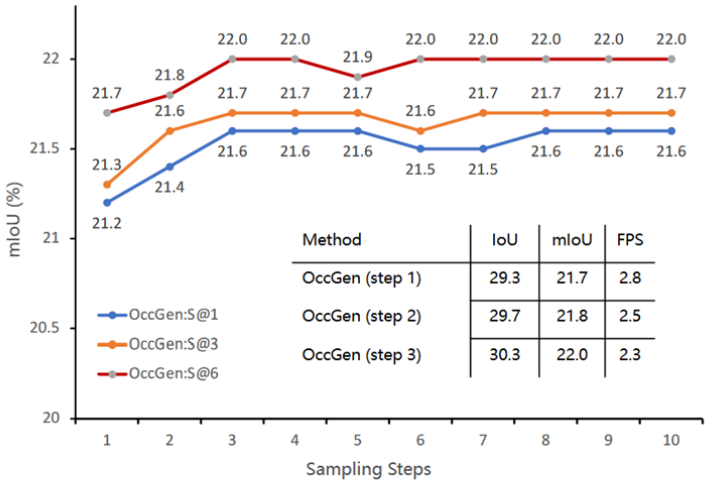

Fig. 5: The results of multiple inferences on nuScenese-Occupancy under multi-modal setting.

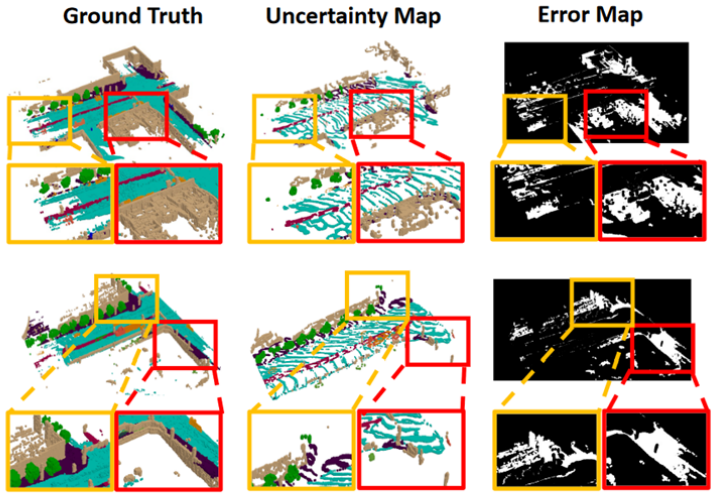

Fig. 6: The visualization of uncertainty map and error map on nuScenese-Occupancy under multi-modal setting.

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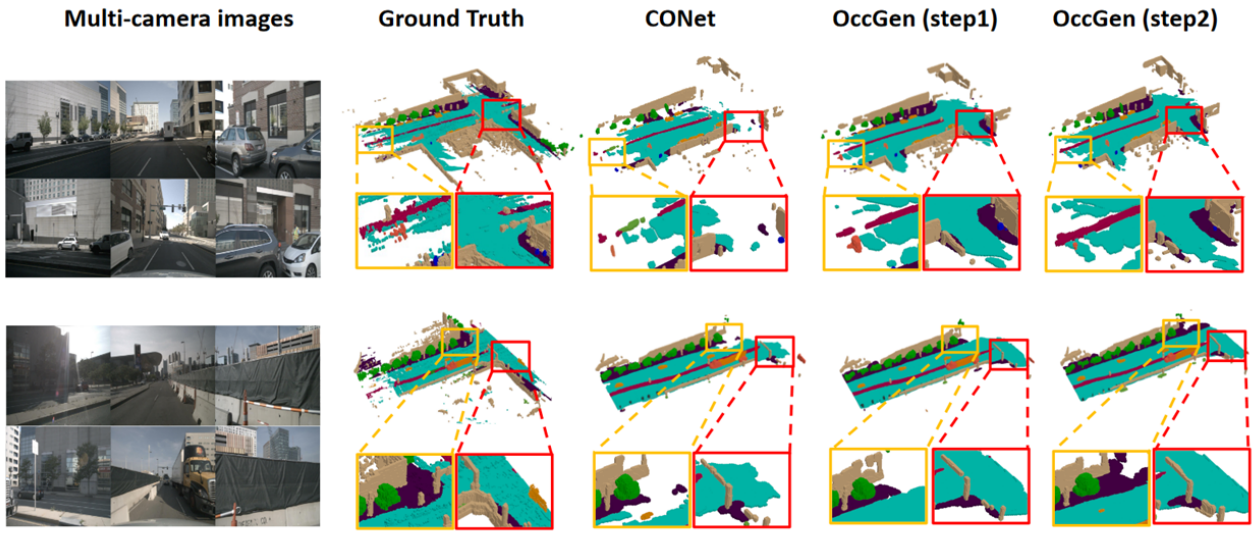

Fig. 4: Qualitative results of the 3D semantic occupancy predictions on nuScenes-Occupancy. The leftmost column shows the input surrounding images, and the following four columns visualize the 3D semantic occupancy results from the ground truth, CONet [57], OccGen(step1), and OccGen(step2). The regions highlighted by rectangles indicate that these areas have obvious differences (better viewed when zoomed in).