Rethinking Data Augmentation for Robust LiDAR Semantic Segmentation in Adverse Weather

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ECCV 2024 Oral

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1. Problem Statement

Overview

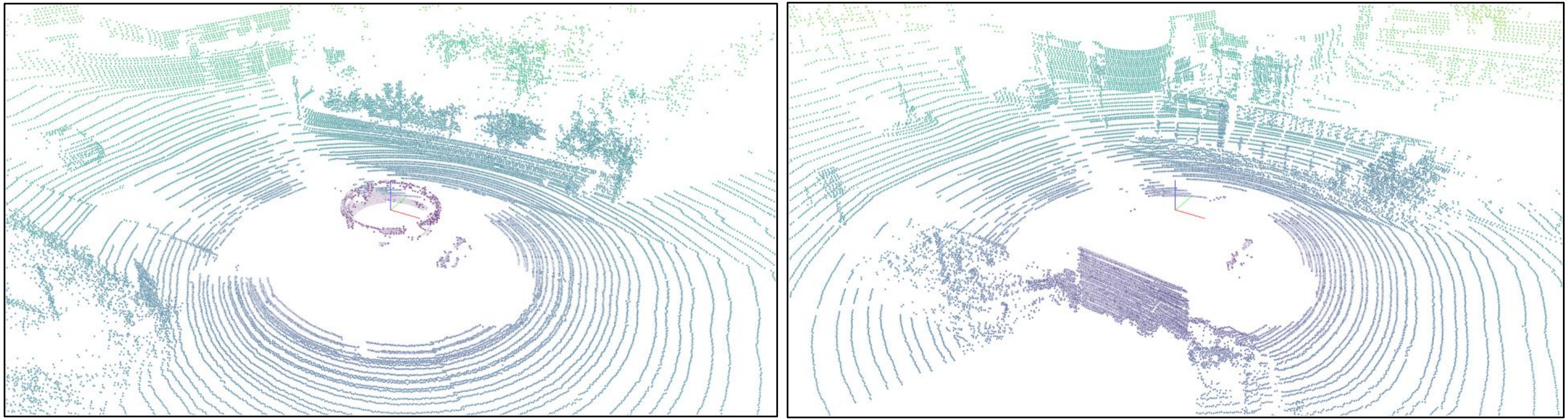


Fig 1. LiDAR Points in Clean Weather.

- Most of the driving scenes are acquired in clean weather conditions.
- Low noise and well-aligned LiDAR points

Bijelic, Mario, et al. "Seeing through fog without seeing fog: Deep multimodal sensor fusion in unseen adverse weather." CVPR. 2020.

Overview

Fig 2. LiDAR Points in Fog and Snow Weather.

- Adverse weather includes rain, snow, fog, etc. They are noisy and poorly aligned.
- It hinders the LiDAR semantic segmentation task.

Bijelic, Mario, et al. "Seeing through fog without seeing fog: Deep multimodal sensor fusion in unseen adverse weather." CVPR. 2020.

Previous Works

- **Acquiring data in adverse weather conditions is challenging.**

Many Adverse Weather Types

Fog, Rain, Snow…

Many Severity

Hard, Moderate, Easy…

- Previous works focused on **simulations.**

Flaticon: Lumi, Hasymi, Freepik, Bharat Icons

Previous Works

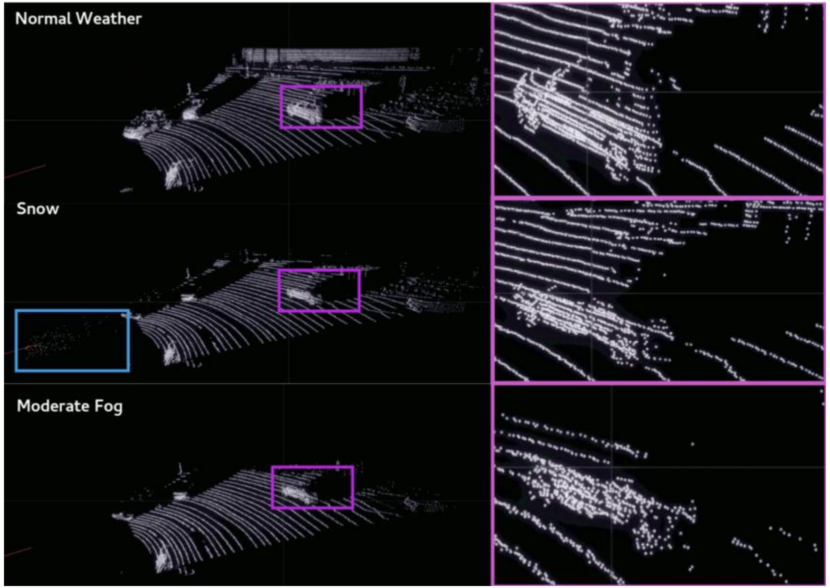


Fig 5. Weather Simulation.

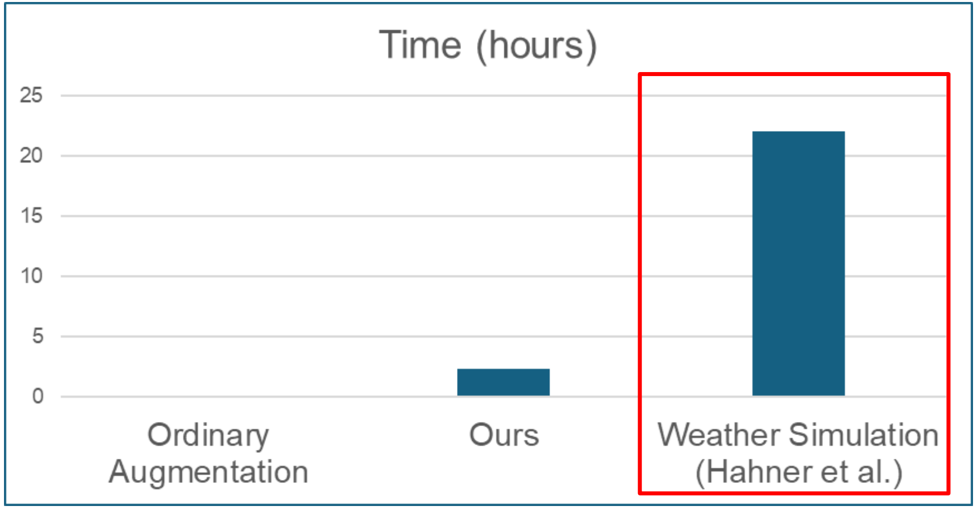
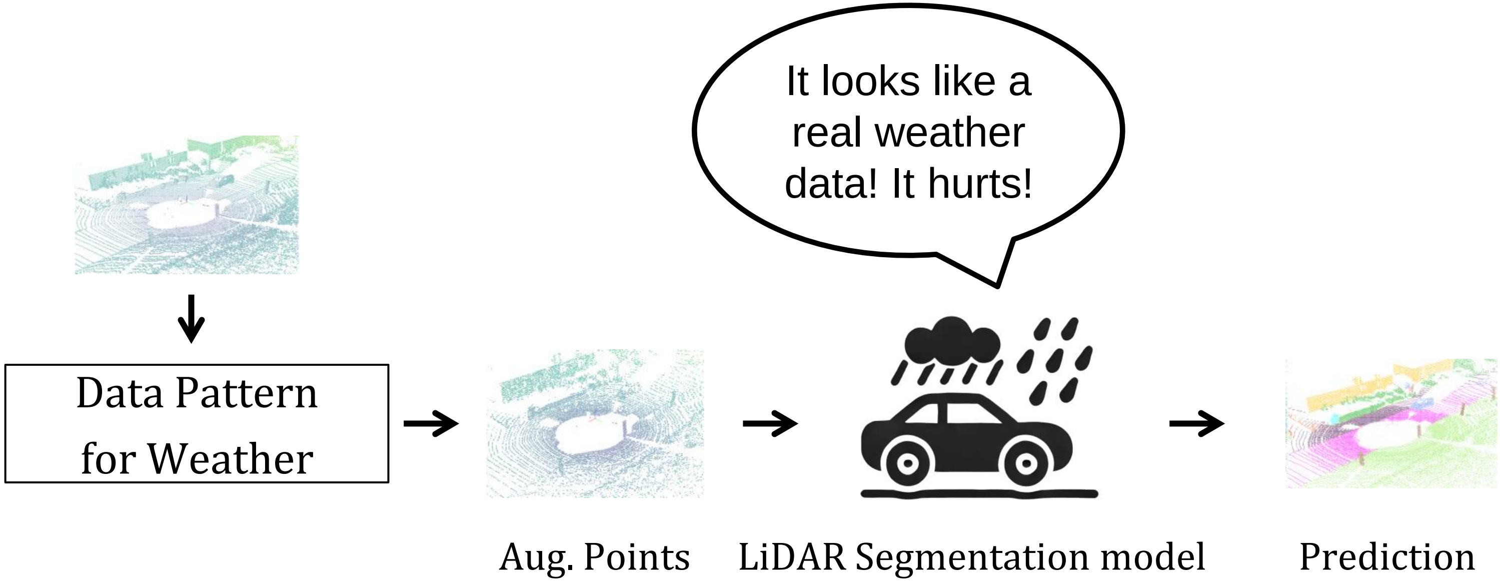


Fig 6. Time Spent on Augmentation.

- Simulation methods require substantial computational resources.

Kilic, Velat, et al. "Lidar light scattering augmentation (lisa): Physics-based simulation of adverse weather conditions for 3d object detection." arXiv preprint. (2021).

Problem Statement

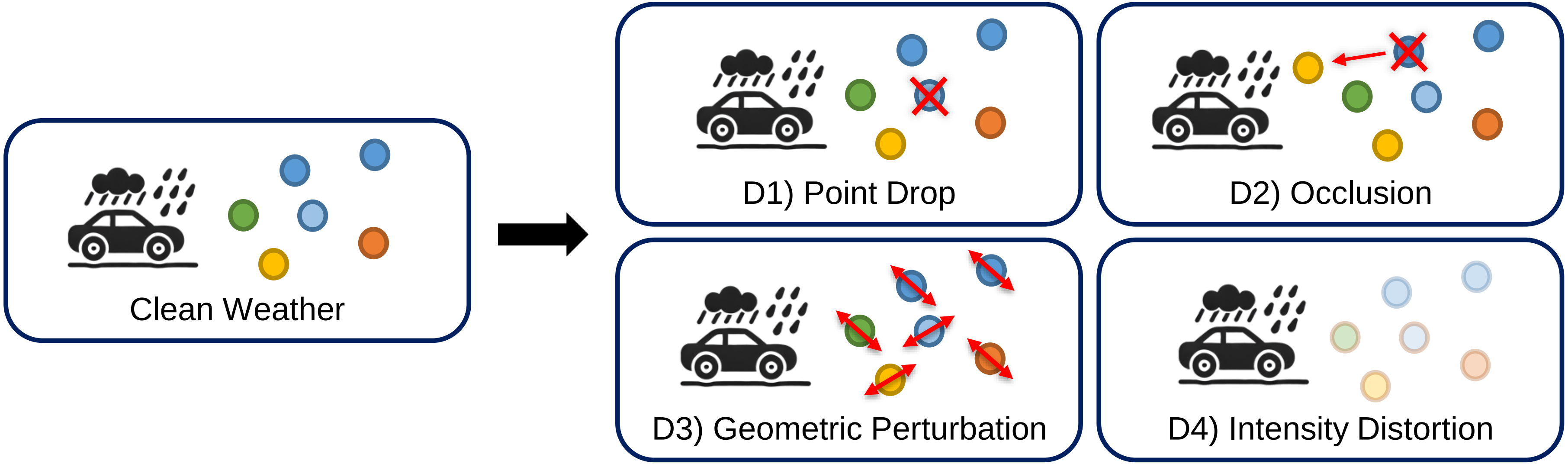


- Data pattern contributing to performance degradation ***in a data-centric manner***.
    - Utilize data pattern to generate weather-conditioned data.
- No need of precise weather simulation.

2. Toy Experiments

Previous Analysis of Adverse Weathers

- The common physical phenomena in previous research:



- What is "main factor" contributing to deterioration?
  - Toy experiments!

Toy Experiments

Distortion	car	bi.cle	mt.cle	truck	oth-v.	pers.	bi.clst	mt.clst	road	parki.	sidew.	oth-g.	build.	fence	veget.	trunk	terra.	pole	traf.	mIoU
Clean	96.8	22.2	66.9	89.1	65.2	67.0	84.7	0.0	93.8	50.6	81.4	0.1	91.1	63.0	88.1	67.7	74.5	63.8	47.7	63.9
D1 : Soft	96.3	17.9	63.4	87.1	63.7	64.3	81.4	0.0	92.7	47.5	79.7	0.1	90.1	62.3	87.3	64.2	74.1	61.1	41.6	61.8
D1 : Hard	86.1	0.2	12.7	21.0	40.0	10.1	24.4	0.0	4.2	10.2	11.1	0.0	71.7	47.8	77.0	34.6	27.6	30.4	17.6	**27.7**
D2 : Soft	94.8	16.3	51.7	66.3	53.9	59.2	52.1	0.0	92.5	44.9	79.2	0.1	89.7	61.4	87.3	63.2	74.3	59.2	40.2	57.2
D2 : Hard	81.3	0.5	5.4	13.1	35.5	7.6	0.7	0.0	2.6	8.5	10.8	0.0	71.1	45.7	76.3	32.9	27.3	26.7	16.1	**24.3**
D3 : Soft	96.2	15.4	56.7	58.6	51.3	51.8	78.1	0.0	66.3	33.9	46.1	0.0	86.1	61.6	84.4	62.0	56.8	61.5	44.0	53.2
D3 : Hard	93.8	9.7	38.3	19.4	31.4	35.2	55.2	0.0	9.9	12.3	12.2	0.0	48.9	40.8	71.4	55.5	31.2	58.7	40.8	**35.0**
D4 : Soft	96.3	21.7	61.1	89.4	61.8	68.9	83.2	0.0	92.9	44.4	79.1	0.1	90.4	56.7	86.9	68.2	71.1	63.9	48.3	62.3
D4 : Hard	95.0	17.2	50.4	81.4	57.0	64.9	79.7	0.0	90.7	38.8	64.7	0.9	88.4	45.3	83.5	62.8	50.5	60.1	47.9	56.8

Tab 1. Result of Toy Experiments.
D1) Point drop D2) Occlusion D3) Geometric perturbation D4) Intensity distortion

- Point drop, and geometric perturbation are critical factors.

Toy Experiments

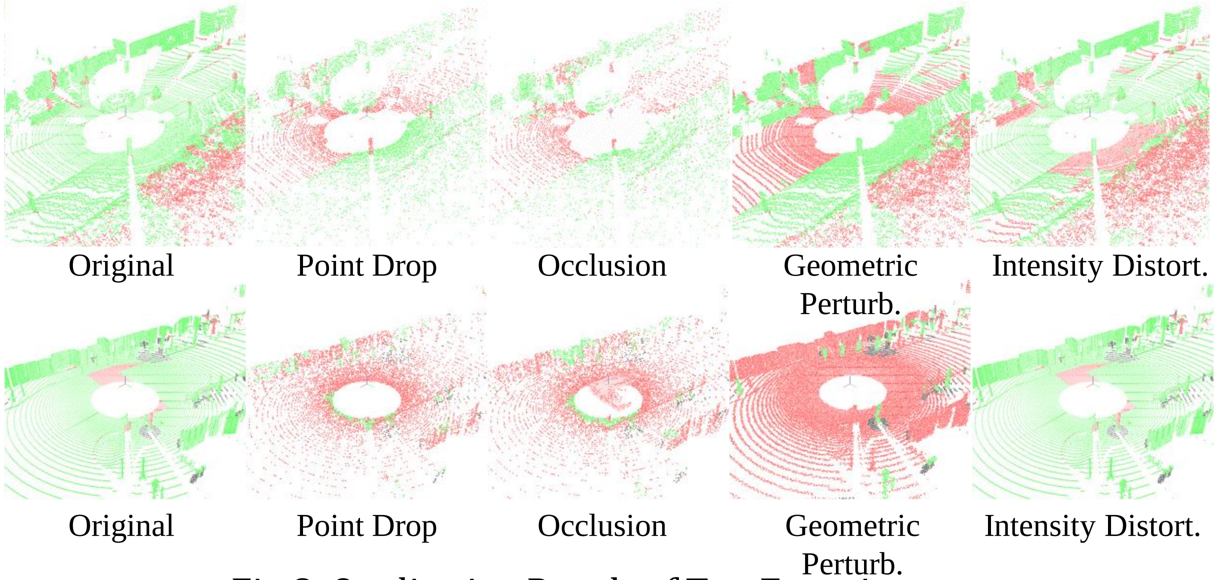


Fig 8. Qualitative Result of Toy Experiments.

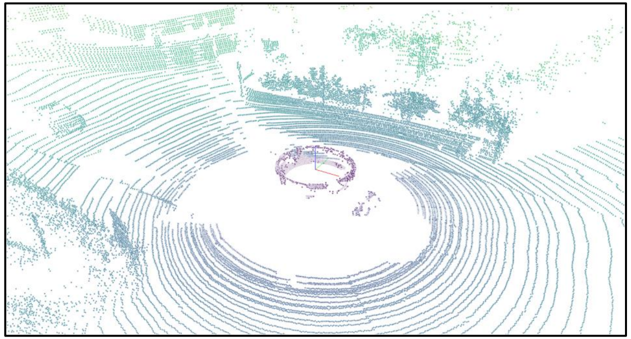
- Occlusion can be interpreted as point drop.

Our contribution!

- The main factors under adverse weather: **geometric perturbation** and **point drop**.

3. Methods

Concept of Methods



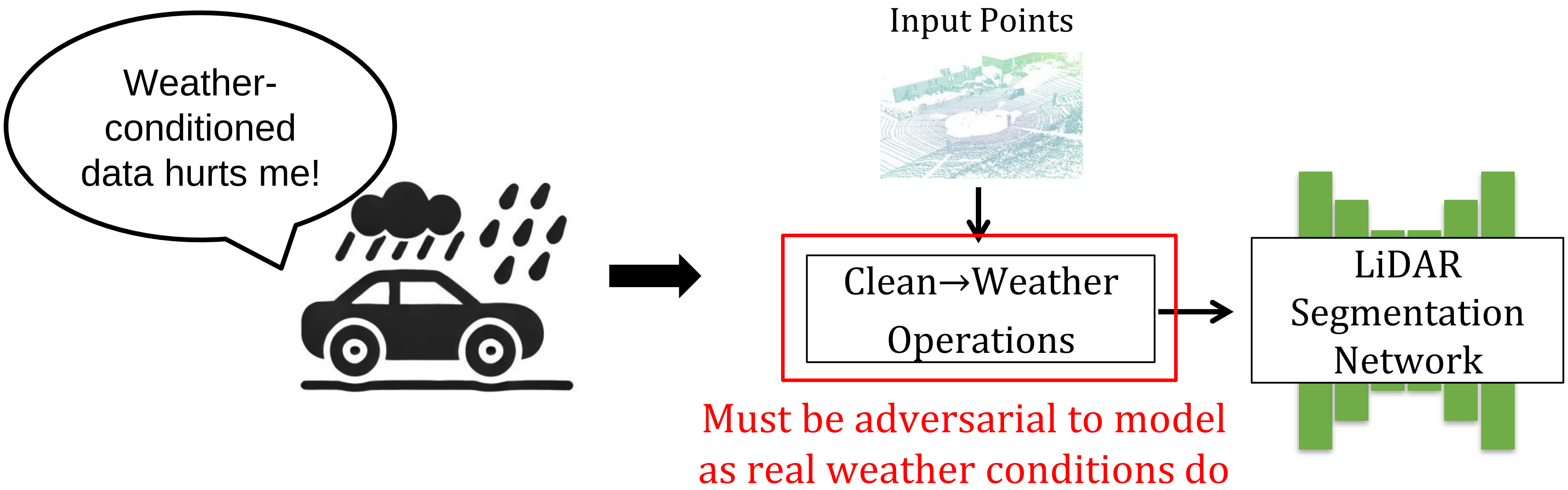
VS

LiDAR
Simple Representation:
XYZ coords, Intensity

Image
Complex Representation:
Curvature, Texture, Colors…

- LiDAR data have lower representation power to depict objects than images.
- Hand-crafted operation can be a transformation of source-to-target.

Concept of Methods



- Real weather conditions work adverse to LiDAR segmentation model.
- Our output of source-to-target operation should be adverse to the model, too.

Overall Methods

Our contribution!

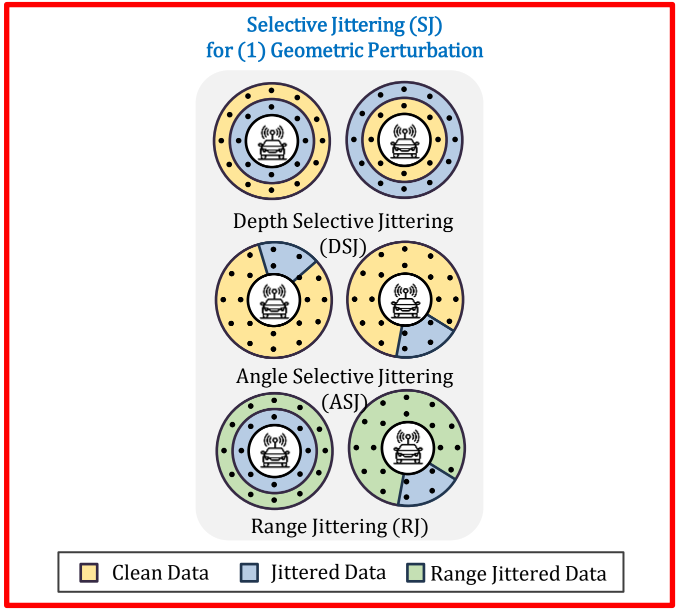


Fig 10. Selective Jittering.

- Selective Jittering (SJ) perturbs point coordinates within random regions.

Overall Methods

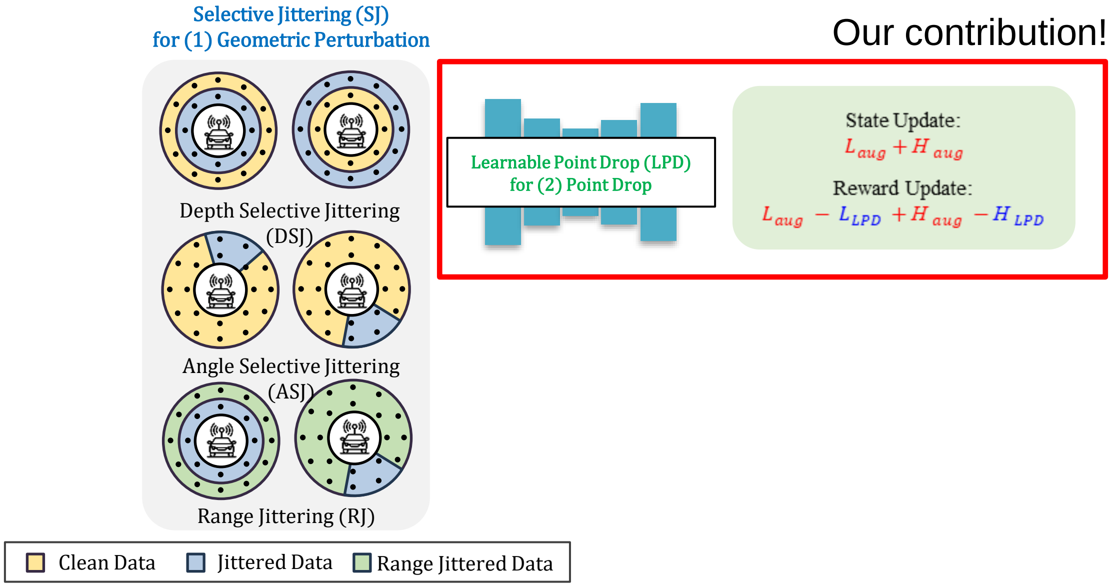


Fig 11. Learnable Point Drop.

- Learnable Point Drop (LPD) utilize a reinforcement learning model.
- LPD module drops points that make the model vulnerable.

Overall Methods

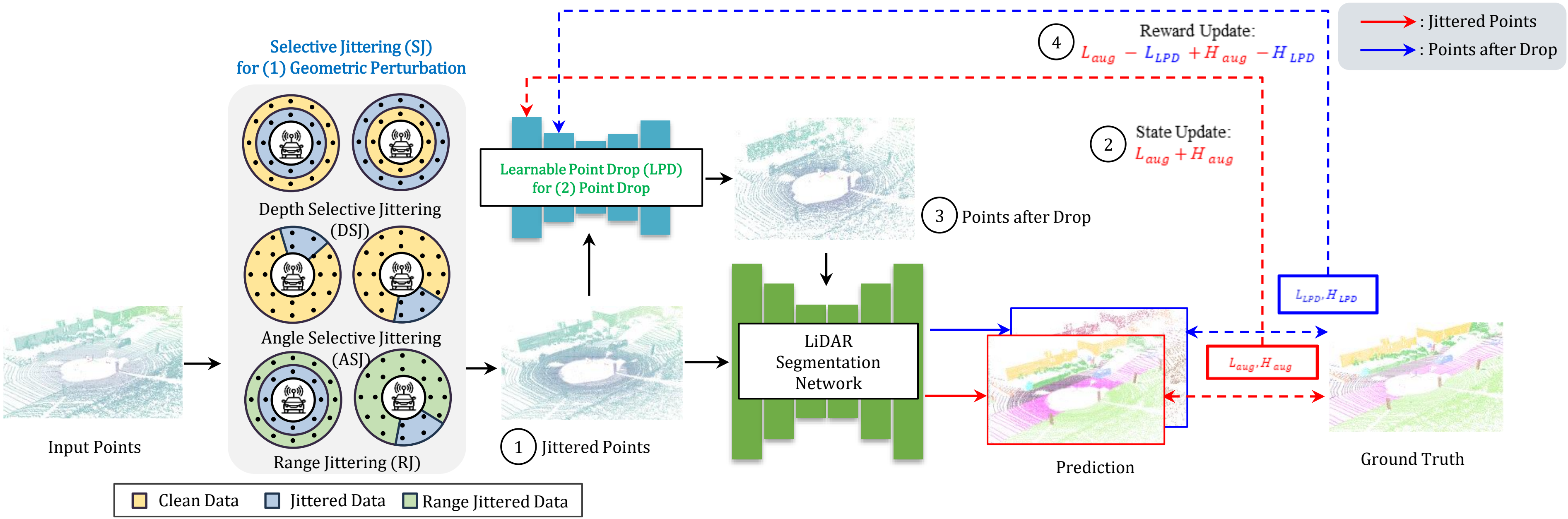


Fig 12. Overall Method.

4. Experiments

Main Experiments

(a) SemanticKITTI→SemanticSTF

Methods	D-fog	L-fog	Rain	Snow	mIoU
Oracle	51.9	54.6	57.9	53.7	54.7
Baseline	30.7	30.1	29.7	25.3	31.4
LaserMix [13]	23.2	15.5	9.3	7.8	14.7
PolarMix [31]	21.3	14.9	16.5	9.3	15.3
PointDR* [33]	**37.3**	33.5	35.5	26.9	33.9
Baseline+SJ+LPD	36.0	**37.5**	**37.6**	**33.1**	**39.5**
Increments to baseline	+5.3	+7.4	+7.9	+7.8	+8.1

(b) SynLiDAR→SemanticSTF

Methods	D-fog	L-fog	Rain	Snow	mIoU
Oracle	51.9	54.6	57.9	53.7	54.7
Baseline	15.24	15.97	16.83	12.76	15.45
LaserMix [13]	15.32	17.95	18.55	13.8	16.85
PolarMix [31]	16.47	18.69	19.63	15.98	18.09
PointDR* [33]	19.09	20.28	25.29	18.98	19.78
PointDR* ‡	**21.41**	20.94	**25.48**	**19.31**	20.47
Baseline+SJ+LPD	19.08	20.65	21.97	17.27	20.08
Increments to baseline	+3.8	+4.7	+5.1	+4.5	+4.6
Baseline+SJ+LPD‡	18.99	**21.22**	23.14	17.28	**20.51**
Increments to baseline	+3.7	+5.3	+6.3	+4.5	+5.1

Tab 2. Main Results of Experiments.

- Our method surpasses the previous state-of-the-art on the SemanticSTF dataset.
- No need of precise physics-based simulations.

Comparison with Domain Generalization(Adaptation) Methods

	Methods	mIoU
Utilize Real Weather Data →	CoSMix(DA)	28.4
	UniMix(DA)	37.2
Utilize Weather Simulation →	UniMix(DG)	31.4
	MinkowskiNet18+Ours	36.3

Tab 3. Comparison with Other Domain Generalization/Adaptation Methods.

- Specifically, our approach outperforms the previous state-of-the-art method, UniMix.

Qualitative Results

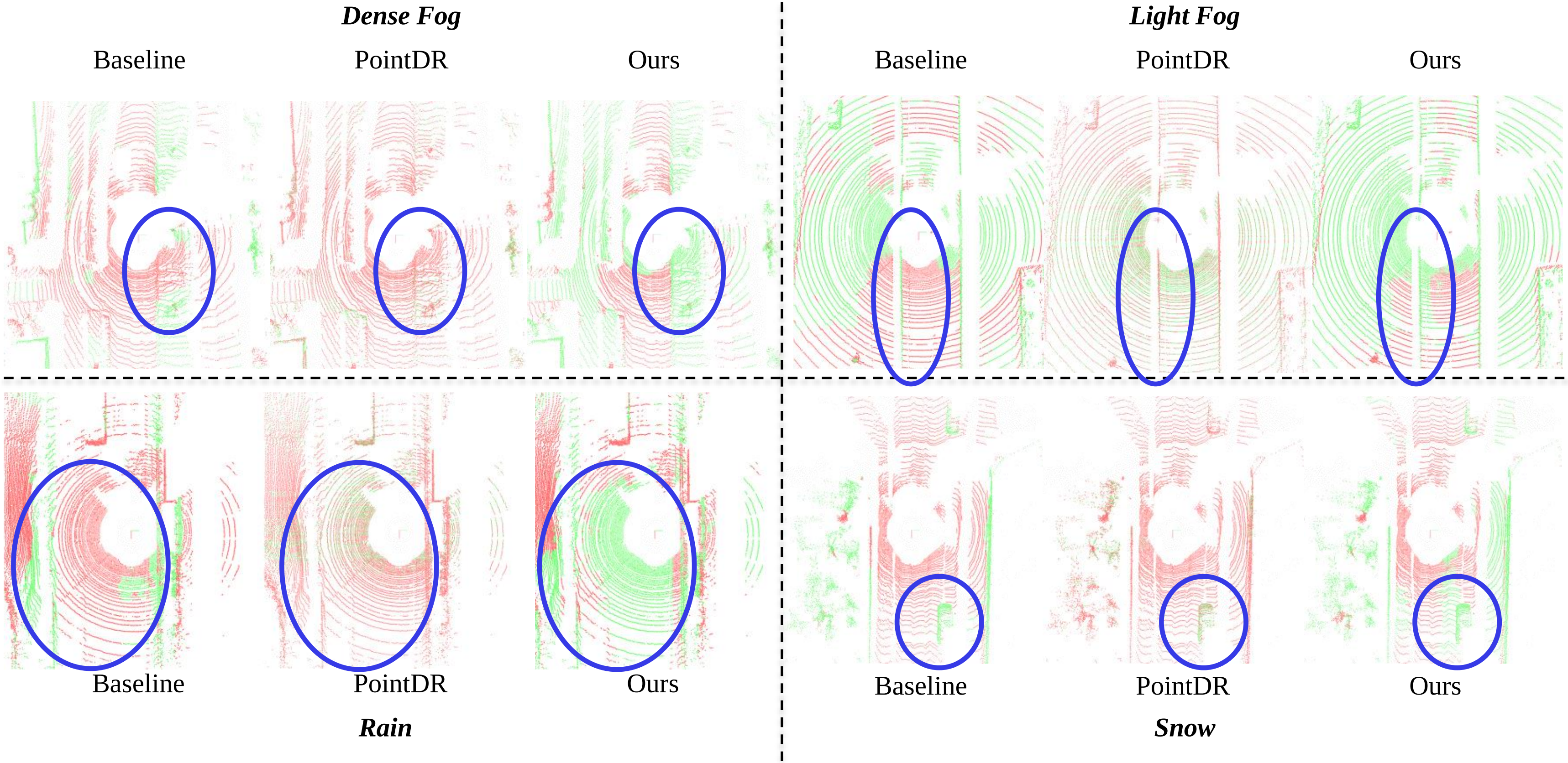


Fig 13. Qualitative Results. Green(Red) point is true(false) prediction.

Conclusion

- Identified key degradation factors of adverse weather.
- The first data-centric approach that integrate various weather types and severities.
- Addressed the challenges of synthesizing all specific weather types and severities.

Thank You for Listening!

See You in Poster #149

Project page:
https://engineerjpark.github.io/ECCV2024LiDARWeather/

Code:
https://github.com/engineerJPark/LiDARWeather

E-mail:
jshackist@kaist.ac.kr

Appendix

Details About LPD

$$L_{DQN} = \mathbb{E}_{i,s,a}\left[\left(r + \gamma \max_{a'} Q'(s', a'; \theta_{i-1}) - Q(s, a; \theta_i)\right)^2\right].$$

$$L_{total} = L_{aug} + L_{LPD} + L_{DQN}.$$

- Reward of LPD let point drop degrade or confuse LiDAR segmentation model.
- LPD module uses the same framework & loss as the original DQN did.

Toy Experiments in SynLiDAR

Methods	car	bi.cle	mt.cle	truck	oth-v.	pers.	bi.clst	mt.clst	road	parki.	sidew.	oth-g.	build.	fence	veget.	trunk	terra.	pole	traf.	mIoU
Clean	0.0	54.9	94.1	0.0	0.0	94.8	93.7	0.0	94.8	0.0	89.8	0.0	98.2	53.7	76.8	90.3	0.0	86	95.2	53.8
D1 : soft	0.0	37.0	86.7	0.0	0.0	89.5	87.8	0.0	92.6	0.0	85.1	0.0	93.8	32.4	39.5	80.9	0.0	84.7	93.0	50.2
D1 : hard	0.0	9.1	53.9	0.0	0.0	56.0	48.6	0.0	20.9	0.0	23.7	0.0	31.0	0.4	4.8	26.7	0.0	39.6	74.4	**21.6**
D2 : soft	0.0	4.2	86.7	0.0	0.0	88.2	87.8	0.0	92.5	0.0	48.4	0.0	52.1	7.0	1.4	68.8	0.0	28.8	26.8	31.2
D2 : hard	0.0	0.2	52.5	0.0	0.0	50.3	48.4	0.0	20.6	0.0	3.1	0.0	4.0	0.2	0.1	10.5	0.0	2.2	8.7	**11.1**
D3 : soft	0.0	55.7	79.6	0.0	0.0	86.5	87.4	0.0	45.0	0.0	50.4	0.0	55.3	22.3	6.8	74.1	0.0	69.5	29.1	34.8
D3 : hard	0.0	12.5	11.3	0.0	0.0	63.3	32.9	0.0	0.2	0.0	3.5	0.0	6.6	1.9	2.8	45.6	0.0	4.1	0.1	**9.7**
D4 : soft	0.0	54.8	94.1	0.0	0.0	94.8	93.8	0.0	94.8	0.0	89.8	0.0	98.2	53.8	76.6	90.2	0.0	86	95.2	53.8
D4 : hard	0.0	54.8	94.1	0.0	0.0	94.8	93.8	0.0	94.8	0.0	89.8	0.0	98.2	53.8	76.6	90.2	0.0	86	95.2	53.8

Tab A1. Result of Toy Experiments in SynLiDAR.
D1) Point drop D2) Occlusion D3) Geometric perturbation D4) Intensity distortion

- Point drop, occlusion, and geometric perturbation are also critical factors in SynLiDAR.

Class IoU on SemanticKITTI→SemanticSTF

Methods	car	bi.cle	mt.cle	truck	oth-v.	pers.	bi.clst	mt.clst	road	parki.	sidew.	oth-g.	build.	fence	veget.	trunk	terra.	pole	traf.	mIoU
Oracle	89.4	42.1	0.0	59.9	61.2	69.6	39.0	0.0	82.2	21.5	58.2	45.6	86.1	63.6	80.2	52.0	77.6	50.1	61.7	54.7
Baseline	67.1	5.0	**28.1**	38.5	14.6	45.8	8.3	13.8	40.1	**16.1**	26.1	3.3	71.6	**52.7**	53.8	33.9	39.2	25.3	12.7	31.4
LaserMix [4]	18.6	**5.4**	0.0	9.9	1.6	0.6	7.9	10.5	47.6	6	12.1	1.8	21.6	20.2	48.4	6.6	37.8	19	2.8	14.7
PolarMix [7]	21	2	0.0	3.8	1.6	2.8	0.6	0.0	58.3	4.4	17.4	1.4	40.7	36.4	41.3	6.6	35	14.6	2.8	15.3
PointDR* [9]	69.2	1	8.9	**41.9**	7.6	48.9	**17.0**	36.2	57.8	15.9	32.3	4.0	**75.7**	46.4	54.0	36.2	43.9	23.7	24.2	33.9
Baseline+SJ+LPD	**86.1**	4.8	13.8	39.7	**26.6**	**55.4**	8.5	**50.4**	**63.7**	14.9	**37.9**	**5.5**	75.2	**52.7**	**60.4**	**39.7**	**44.9**	**30.1**	**40.8**	**39.5**
Increments to baseline	+19.0	-0.2	-14.3	+1.1	+12.0	+9.6	+0.2	+36.6	+23.5	-1.2	+11.9	+2.2	+3.6	0.0	+6.7	+5.8	+5.7	+4.9	+28.2	+8.1

Tab A2. Class IoU on the SemanticKITTI→SemanticSTF.

- Performance enhancement in several classes.
- Performance drop in bicycles and motorcycles is due to their sparsity.

Class IoU on SynLiDAR→SemanticSTF

Methods	car	bi.cle	mt.cle	truck	oth-v.	pers.	bi.clst	mt.clst	road	parki.	sidew.	oth-g.	build.	fence	veget.	trunk	terra.	pole	traf.	mIoU
Oracle	89.4	42.1	0.0	59.9	61.2	69.6	39.0	0.0	82.2	21.5	58.2	45.6	86.1	63.6	80.2	52.0	77.6	50.1	61.7	54.7
Baseline	33.76	1.71	3.29	15.54	0.24	25.52	1.65	3.43	15.27	9.16	16.76	0.05	33.38	21.89	39.49	18.7	**44.03**	8.75	0.84	15.45
LaserMix [4]	**52.41**	**5.6**	1.05	7.91	1.96	25.59	1.62	2.92	**44.58**	6.44	21.21	0.88	16.95	23.61	40.75	18.91	41.45	5.65	0.7	16.85
PolarMix [7]	48.93	4.23	2.32	14.64	**2.37**	24.55	2.14	4.64	34.64	7.66	19.8	0.39	37.44	22.3	44.85	21.32	43.18	7.08	1.3	18.09
PointDR* [9]	41.07	2.81	**3.43**	18.05	0.17	**31.3**	**2.81**	3.3	34.39	**10.23**	19.72	0.96	**52.72**	21.98	**48.49**	21.33	38.31	19.19	5.61	19.78
PointDR*‡ [9]	36.13	3.47	2.15	**21.93**	0.31	28.72	1.69	**5.09**	42.92	9.31	20.71	0.58	50.83	26.88	46.85	**24.49**	37.69	22.74	6.45	20.47
Baseline+SJ+LPD	42.13	2.79	2.68	19.22	0.67	29.22	1.91	4.8	42.32	8.67	21.05	**1.56**	48.23	25.97	47.17	22.11	32.8	21.74	6.54	20.08
Increments to baseline	+8.4	+1.1	-0.6	+3.7	+0.4	+3.7	+0.3	+1.4	+27.0	-0.5	+4.3	+1.5	+14.9	+4.1	+7.7	+3.4	-11.2	+13.0	+5.7	+4.6
Baseline+SJ+LPD‡	39.26	2.89	0.89	19.39	0.75	27.68	2.19	3.78	42.5	9.35	**21.55**	0.3	51.89	**33.48**	47.38	23.11	33.31	**23.22**	**6.78**	**20.51**
Increments to baseline	+5.5	+1.2	-2.4	+3.8	+0.5	+2.2	+0.5	+0.4	+27.2	+0.2	+4.8	+0.3	+18.5	+11.6	+7.9	+4.4	-10.7	+14.5	+5.9	+5.1

Tab A3. Class IoU on the SynLiDAR→SemanticSTF.

- Performance enhancement in several classes.
- Performance drop in motorcycles is due to their sparsity.

Various Input Representations

	Method	SemanticSTF	SemanticKITTI-C
	CENet	14.2	49.3
	SPVCNN	28.1	52.5
	Minkowski	31.4	53.0
Range image based	CENet+Ours	22.0 (+7.8)	53.2 (+3.9)
Point-voxel based	SPVCNN+Ours	38.4 (+10.3)	52.9 (+0.4)
	Minkowski+Ours	39.5 (+8.1)	58.6 (+5.6)

Tab A4. Results across Various Input Representations.

- Strong performance across various datasets and input representations.

Ablation Study

Methods	Clean	D-fog	L-fog	Rain	Snow	mIoU
Baseline	**63.9**	30.7	30.1	29.7	25.3	31.4
+ASJ	62.1 (-1.8)	33.3	35.4	37.8	31.6	36.8 (+5.4)
+DSJ	63.0 (-0.9)	34.8	36.4	**39.0**	29.9	37.6 (+6.2)
+RJ	61.2 (-2.7)	33.4	37.0	35.7	**33.5**	38.7 (+7.3)
+LPD	62.8 (-1.1)	**36.0**	**37.5**	37.6	33.1	**39.5** (+8.1)

Tab A5. Ablation Study.

- All components contribute to performance enhancement.
- Reasonable performance maintenance in clean weather.

Hyperparameter Ablation Study

Selective Jittering					
DSJ range	mIoU	ASJ $\Delta\theta$	mIoU	Gaussian σ	mIoU
[2, 5]	39.3	$\frac{1}{2}\pi$	38.1	0.001	37.5
[3, 6]	38.8	$\frac{3}{4}\pi$	39.9	0.005	38.4
[4, 7]	37.8	π	**39.5**	**0.01**	**39.5**
[5,8]	**39.5**	$\frac{5}{4}\pi$	40.0	0.05	37.3
[6, 9]	37.8	$\frac{3}{2}\pi$	39.3	0.1	37.9
deviation	0.8	deviation	0.2	deviation	1.3

Learable Point Drop					
Batch size	mIoU	Discount γ	mIoU	Decay ϵ	mIoU
8	37.1	0.5	37.8	100	38.5
16	37.1	0.8	38.4	500	38.7
32	**39.5**	0.9	38.4	**1000**	**39.5**
64	38.2	**0.99**	**39.5**	2000	37.3
128	37.0	0.999	38.8	3000	40.3
deviation	1.7	deviation	0.9	deviation	0.7

Tab A6. Hyperparameter Ablation Study.

- Our methods are robust to change of hyperparameter.

Point Drop Ratio of LPD

Distance	0~10m	10~20m	20~30m	30~40m	40~50m	50~60m	60~70m	70~80m	80~90m
Ratio	80.6	78.6	78.7	77.4	76.2	75.5	76.2	76.4	72.5

Tab A7. Point Drop Ratio of LPD Module in Specific Depth Ranges.

- LPD drops more points when the distance of points is large.
- Physically feasible drop ratio with respect to real weather.

More Qualitative Results

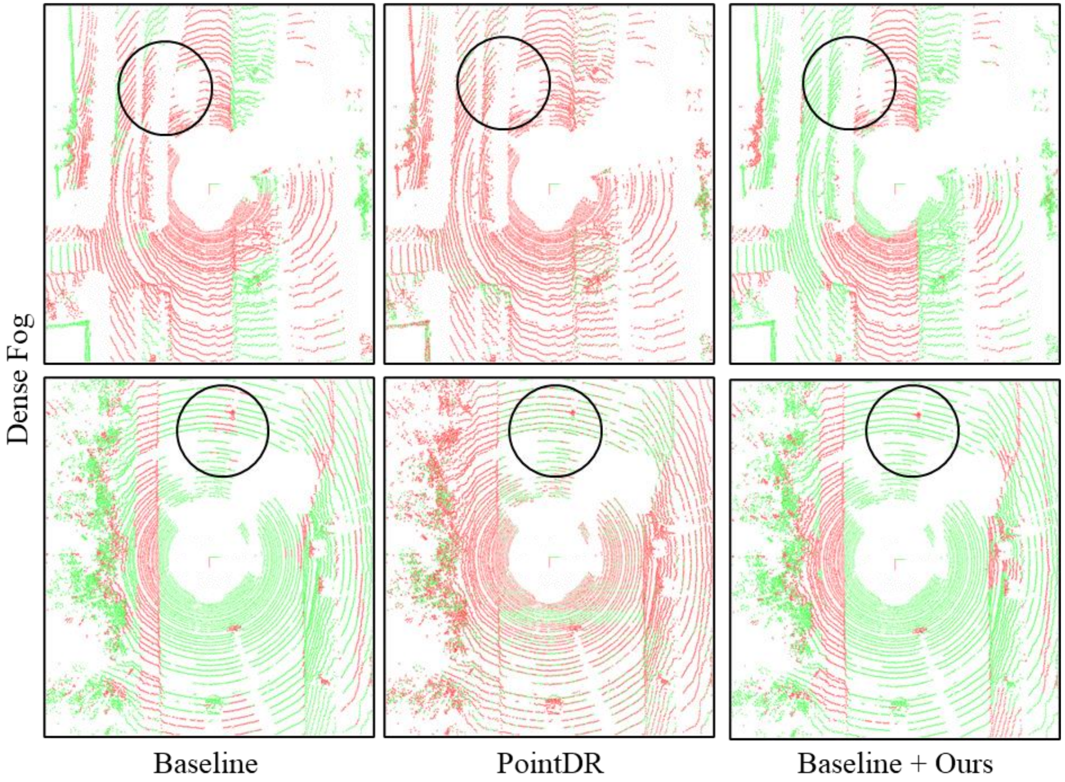


Fig A1. Qualitative Results in Dense Fog, SemanticKITTI→SemanticSTF

More Qualitative Results

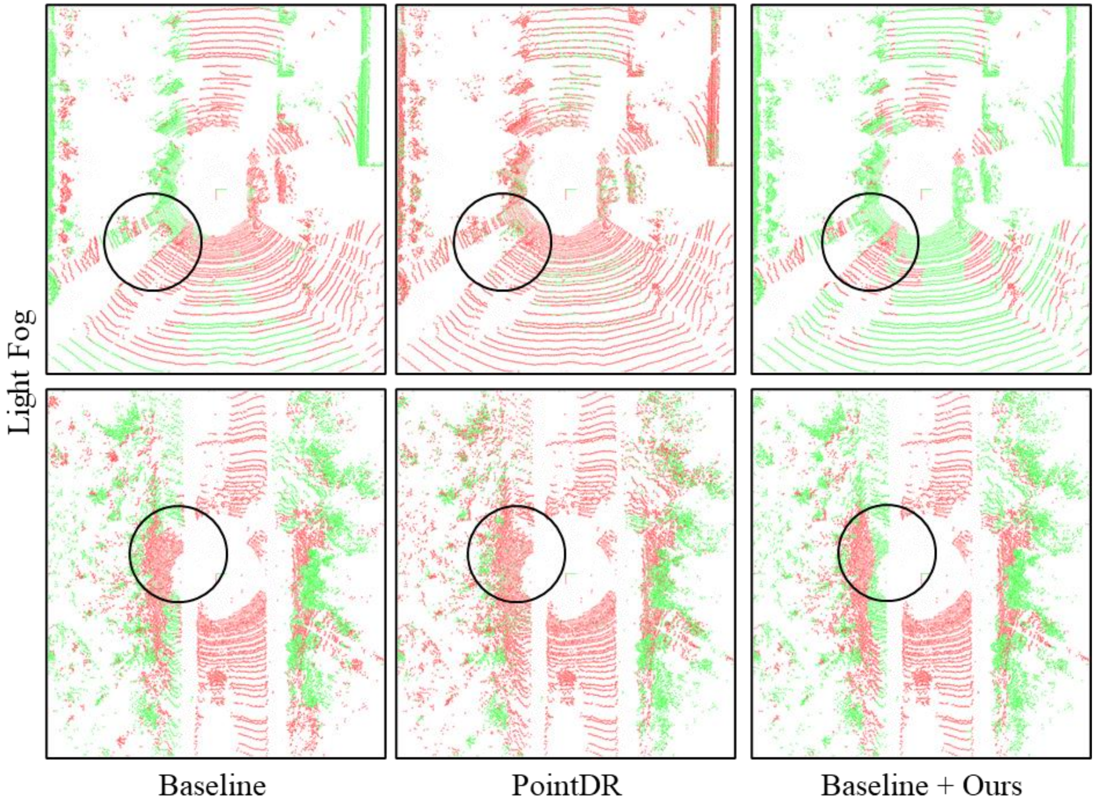


Fig A2. Qualitative Results in Light Fog, SemanticKITTI→SemanticSTF

More Qualitative Results

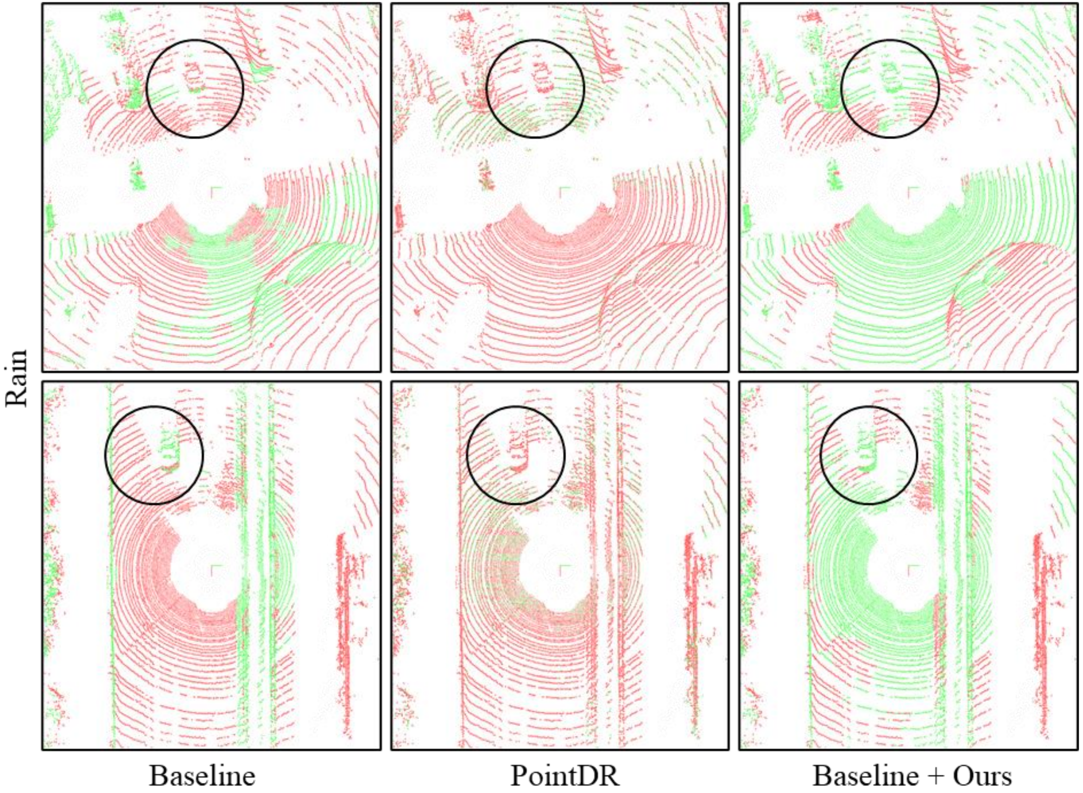


Fig A3. Qualitative Results in Rain, SemanticKITTI→SemanticSTF

More Qualitative Results

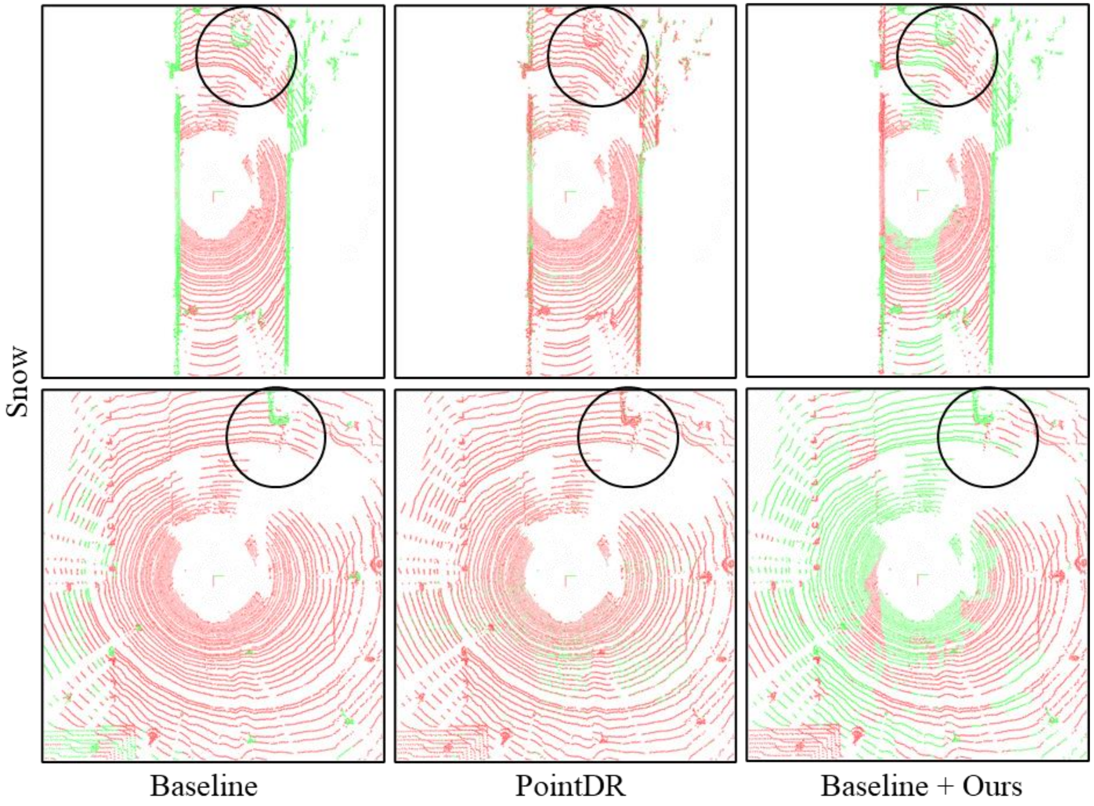


Fig A4. Qualitative Results in Snow, SemanticKITTI→SemanticSTF

More Qualitative Results

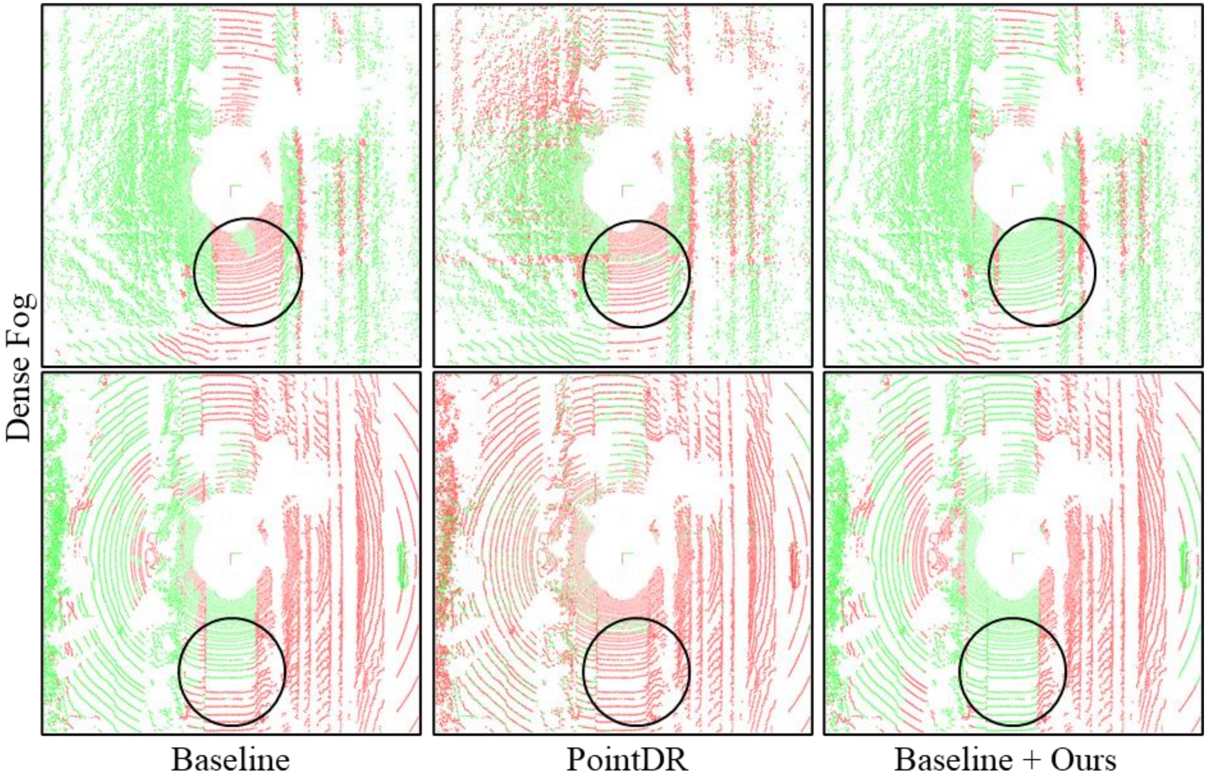


Fig A5. Qualitative Results in Dense Fog, SynLiDAR→SemanticSTF

More Qualitative Results

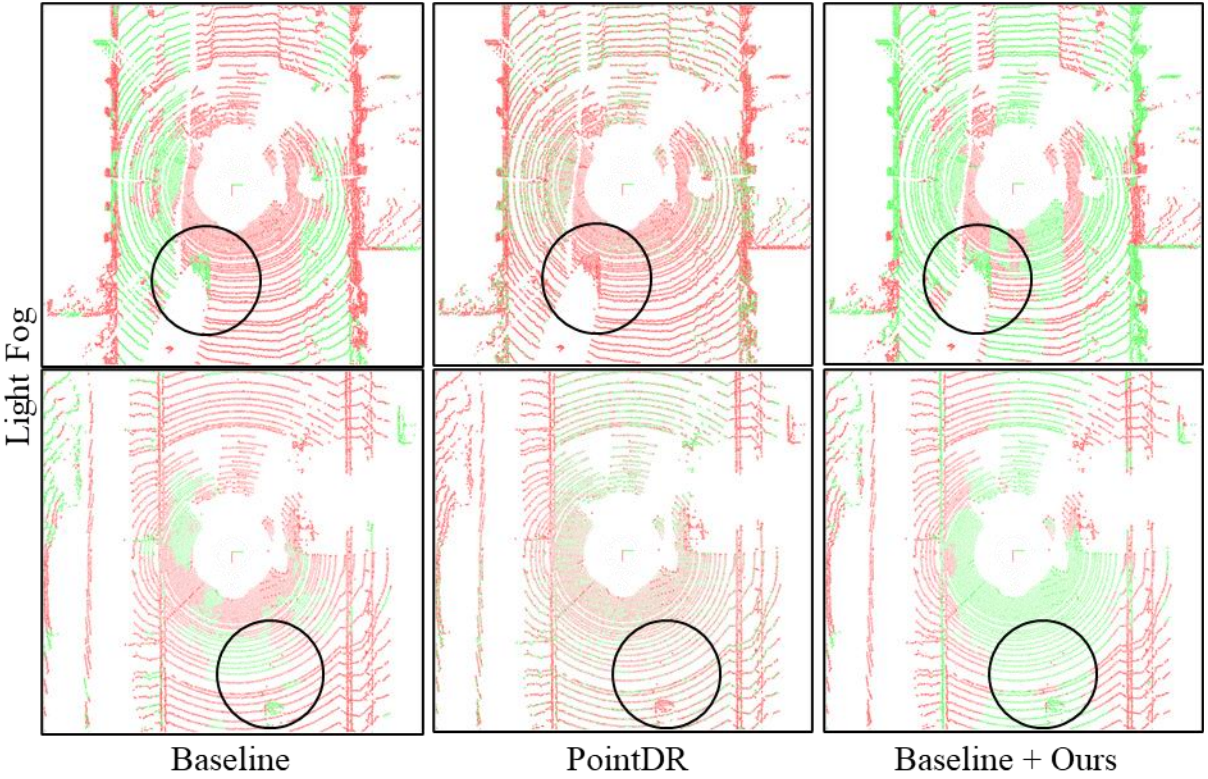


Fig A6. Qualitative Results in Light Fog, SynLiDAR→SemanticSTF

More Qualitative Results

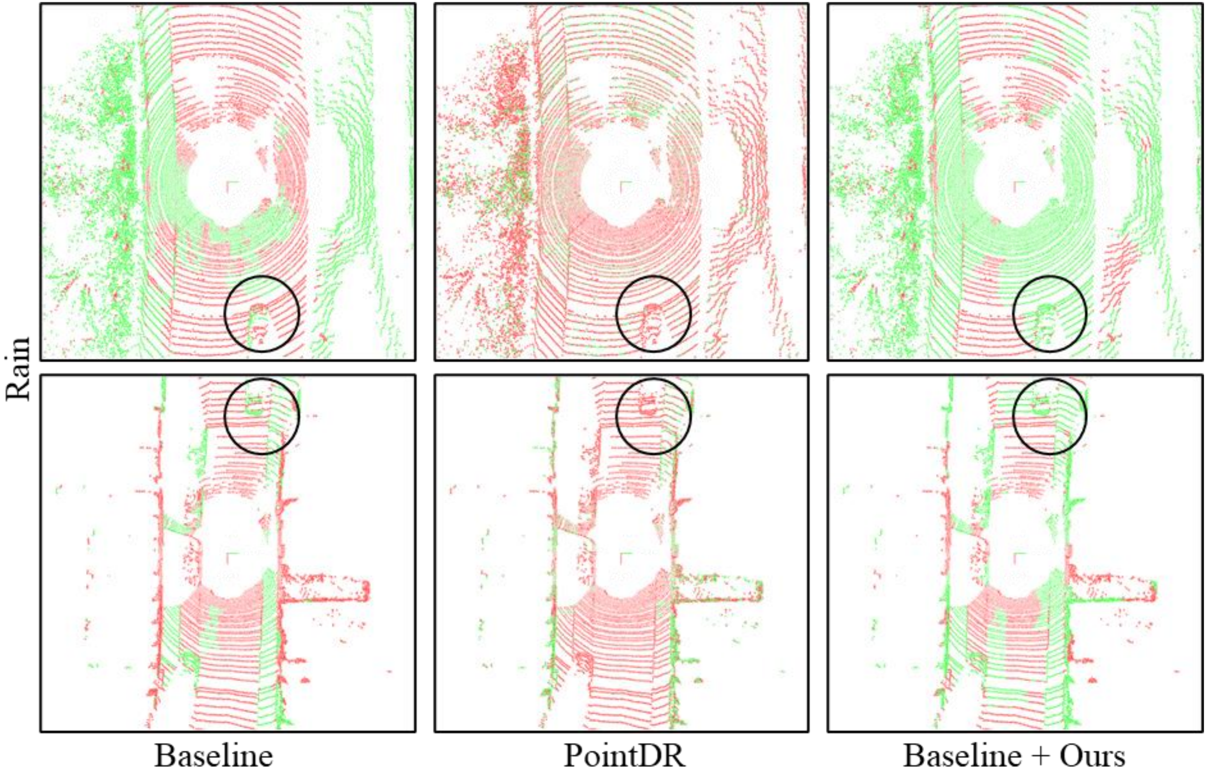


Fig A7. Qualitative Results in Rain, SynLiDAR→SemanticSTF

More Qualitative Results

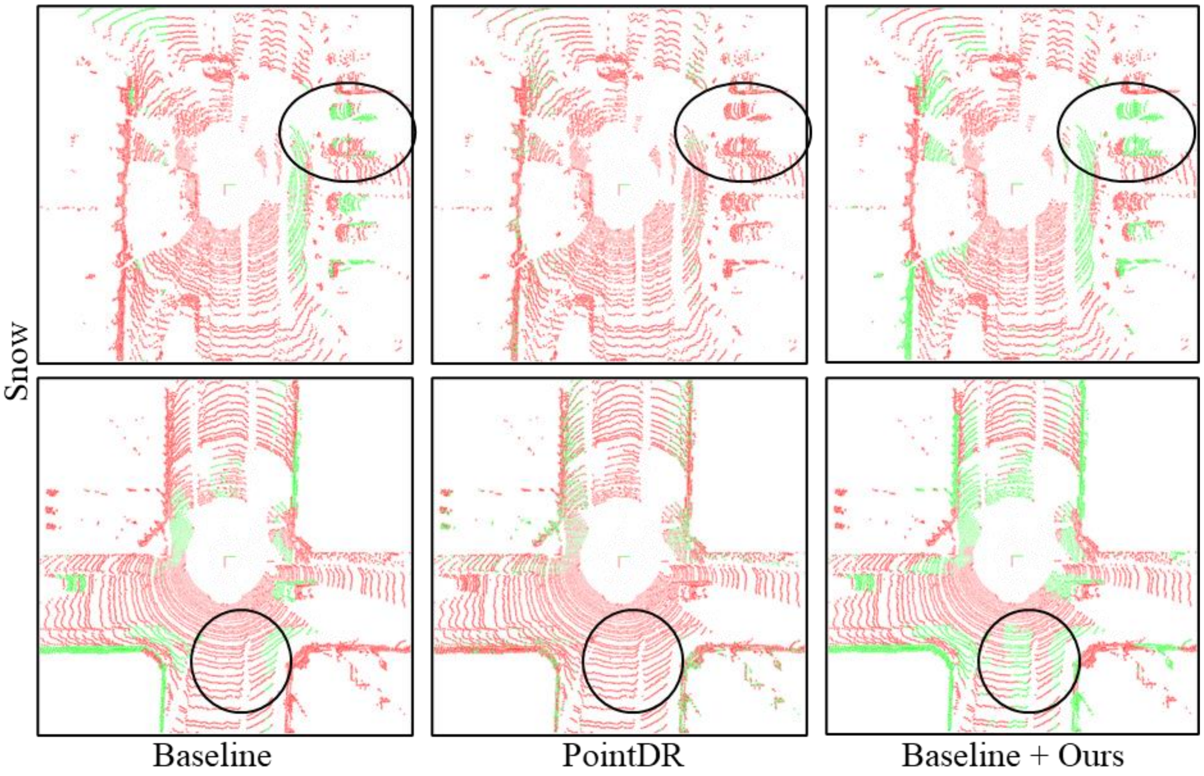


Fig A8. Qualitative Results in Snow, SynLiDAR→SemanticSTF