Supplementary Information: 3D-OutDet: A Fast and Memory Efficient Outlier Detector for 3D LiDAR Point Clouds in Adverse Weather

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S1. Winter Adverse Driving Dataset

Kurup and Bos [1] published the Winter Adverse Driving Dataset or WADS. This dataset was collected in the snow belt region of Michigan's Upper Peninsula. Kurup and Bos [1] labeled more than 7 GB of LiDAR point cloud. At the time of writing our article, we have found that they have published 20 sequences of point-wise annotated LiDAR scans. These 20 sequences are 11, 12, 13, 14, 15, 16, 17, 18, 20, 22, 23, 24, 26, 28, 30, 34, 35, 36, 37, 76. We have found that there are 387 Million labeled points in these 20 sequences. We noticed that there are duplicate points in most of the point clouds hence we cleaned the point clouds. After removing the duplicates, we re-calculated the number of points to 227 Million, in other words 160 Million points are duplicate and we removed them before running any of the experiments. After removing the duplicates, the class distribution looks like Table S1. This dataset has been labeled like SemanticKITTI dataset [?], it has labels other than snow and accumulated snow which also gives an opportunity to test the effectiveness of snow removal for a downstream task e.g., semantic segmentation. But as you can see from Table S1, outlier class is available in 2 sequences, bus and lane-marking are available only in 1 sequence each. As we are following standard protocol, we have to split the dataset into training, testing and validation sets. So, if a class is available in less than 3 sequences, we cannot distribute them for training, testing and validation sets hence we mapped them to semantically similar classes. We mapped the outlier class to unlabeled class, bus to other-vehicle class, and lane-marking to road class. Finally, we mapped moving-car to car class as we are not doing anything related to motion. After remapping the dataset, we split the sequences to training, testing and validation sets such a way that each set would contain all instances from all the remaining 20 classes.

S2. SnowyKITTI

We utilized the SnowyKITTI dataset from Seppänen et al. [2] to evaluate different models for snow removal. At the time of writing this article, the SnowyKITTI dataset provided by Seppänen et al. [2] had 26 sequences. To keep similarity with SemanticKITTI [3] dataset we used 22 sequences. After removing dupicates from these 22 sequences we have found that about 97% points are classified as non-snow and about 3% points are classified as snow. As this dataset does not preserve the semantic classes from Semantic KITTI, we could not evaluate the effectiveness of snow removal on downstream semantic segmentaiton task for this dataset.

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S3. Runtime of LiSnowNet

Yu et al. [4] assumed that the LiDAR point cloud would be available as a batch hence they divided the runtime by batch size. In reality, each LiDAR scan generates a single point cloud at a time and by the time next point cloud is generated, the current point cloud will become obsolete hence in a real autonomous driving scenario, there is no option to make a batch of point cloud and run the inference on the batch. In our runtime calculation, we used the same hardware and software stack for all models to ensure fairness and we processes single point cloud at-at time to simulate real life autonomous driving scenario. We note that we assumed each point cloud may contain 250000 points at maximum and we used WADS testset to calculate run-time. We also note that for some model the run-time is dependent on the number of points inside the point-cloud hence the reader may see different runtime for a different dataset.

S4. Hyperparameters

For WADS and SnowyKITTI we used Adam Optimizer and for SemanticSpray dataset we used Quasi Hyperbolic Adam optimizer. Table S2 shows the list of parameters used in the result generation.

References

[1] A. Kurup and J. Bos, "Dsor: A scalable statistical filter for removing falling snow from lidar point clouds in severe winter weather," *arXiv preprint arXiv:2109.07078*, 2021.

[2] A. Seppanen, R. Ojala, and K. Tammi, "4denoisenet: Adverse weather denoising from adjacent point clouds," *IEEE Robotics and Automation Letters*, 2022.

[3] A. Geiger, P. Lenz, and R. Urtasun, "Are we ready for autonomous driving? the kitti vision benchmark suite," in *2012 IEEE conference on computer vision and pattern recognition*. IEEE, 2012, pp. 3354–3361.

[4] M.-Y. Yu, R. Vasudevan, and M. Johnson-Roberson, "Lisnownet: Real-time snow removal for lidar point clouds," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 6820–6826.

TABLE S1

POINT DISTRIBUTION AFTER REMOVING DUPLICATES

Label	**# Points**	**%**	**Available in # sequences**
unlabeled	14232109	6.27	20
outlier	45182	0.02	2
car	9549161	4.21	19
bus	39836	0.02	1
truck	506101	0.22	5
other-vehicle	50893	0.02	3
person	79450	0.04	5
road	22054161	9.72	20
parking	2748079	1.21	6
sidewalk	6466522	2.85	11
other-ground	6416848	2.83	8
building	53769871	23.70	19
fence	6964952	3.07	13
other-structure	3493672	1.54	13
lane-marking	5302	0.00	1
vegetation	21045978	9.28	19
trunk	71483	0.03	5
terrain	253169	0.11	4
pole	1683000	0.74	20
traffic-sign	708933	0.31	17
other-object	905389	0.40	16
snow	30864152	13.61	20
accum snow	44735234	19.72	19
moving-car	164381	0.07	6

TABLE S2

HYPERPARAMETERS OF PODNET

Dataset	k for kNN	# Layers	Optimizer	Learning Rate	Weight Decay	betas (β)	nus (ν)	# Epochs	Scheduler	Scheduler Factor
WADS	9	2	Adam	$1e-3$	$1e-4$	Default	N/A	50	Multi Step	0.1
SnowyKITTI	9	2	Adam	$1e-3$	$1e-4$	Default	N/A	50	Multi Step	0.1
SemanticSpray	9	2	QHAdam	$1e-3$	Default	[0.5, 0.99]	[0.7, 1.0]	30	Multi Step	0.1