TADNet: A Time and Attention-Based Point Cloud Denoising Network for Autonomous Driving in Adverse Weather

Yidan Zhang [1], He Huang [1], Xinyuan Yan [1], Yu Liang [1], Yida Li [1],Junxing Yang [1*]

[1] School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, Beijing, China-
zhangyidan0925@gmail.com,huanghe@bucea.edu.cn,yan1075783878@126.com,yu748240@gmail.com,yida.li@foxmail.com,yangjunxing@bucea.edu.cn

Keywords: autonomous driving, LiDAR, adverse weather, point cloud denoising, deep learning.

Abstract

Lidar technology is widely used in the field of autonomous driving by virtue of its high precision. However, under special weather conditions such as rain, snow, fog, etc., suspended particles in the air can contaminate the point cloud data collected by LIDAR, which leads to a significant performance degradation of the vehicle sensing system and increases the driving safety risk. To address this problem, we propose A **T**ime and **A**ttention-Based Point Cloud **D**enoising **Net**work for Autonomous Driving in Adverse Weather (TADNet). The method is based on the 3D-OutDet network with the addition of Convolutional Block Attention Module (CBAM), which highlights important features and suppresses minor ones. The original ResNet base network architecture is changed to Temporal-Bottleneck ResNet (TB-ResNet) to improve the network's ability to recognize rain, snow and fog noise. We conducted comparative experiments between the TADNet method proposed in this paper and the filter-based point cloud denoising method and the deep learning-based point cloud denoising method. The experimental results show that the denoising effect of TADNet in three kinds of bad weather, namely rain, snow and fog, is better than other methods, which can remove different kinds of noise with different intensities and retain the environmental features, and has the best performance of IoU and MIoU in all kinds of weather conditions.

1. Introduction

With the continuous advancement of autonomous driving technology, vehicles have been able to realize autonomous driving in most scenarios. However, under special weather conditions such as snow, rain, and fog, LiDAR's perception performance suffers, which in turn affects its accuracy. Therefore, enhancing the perception performance of LiDAR in bad weather conditions has become a key issue to be solved in the field of autonomous driving.

Currently, laser point cloud denoising techniques mainly include two categories: traditional filtering methods and deep learning methods.In 2011, Rusu and other researchers proposed two well-known filtering algorithms: the Radius Outlier Removal (ROR) and the Statistical Outlier Removal (SOR) (Rusu & Cousins, 2011). Both algorithms are based on the premise that noisy points usually exist in isolation.The ROR algorithm calculates the number of neighbors of each point by counting the number of neighboring points within a set radius, and if the number is lower than a preset threshold, the point is determined to be noisy.The SOR algorithm, on the other hand, iteratively calculates the average of the distances between each point and its K nearest neighbors and compares them with the global distance mean and standard deviation, and if the average exceeds a set global threshold, the point is determined to be a noisy point. However, relying only on the premise of noise point isolation may ignore environmental features, so Charron et al. proposed the Dynamic Radius Outlier Removal (DROR) algorithm in 2018 (Charron et al., 2018).The DROR algorithm optimizes the ROR by setting a threshold for each point based on its distance from the sensor and the horizontal angular resolution of the laser dynamically changes the search radius. In this way, DROR solves the problem of misclassification that a fixed radius may lead to in long-range low-density areas, while retaining key environmental feature points and effectively removing noise. Similar to DROR, the Dynamic Statistical Outlier Removal (DSOR) filtering algorithm was proposed by Kurup et al. in 2021 (Kurup & Bos, 2021), which improves on SOR.DSOR overcomes the limitation of SOR in dealing with non-uniform point cloud density by dynamically adjusting the threshold value and achieves better denoising effect. In addition to the spatial characteristics of the noise points, researchers have also found the intensity characteristics of the noise points.Huang et al. proposed the Low-Intensity Dynamic Statistical Outlier Removal (LIDSOR) filter in 2023 (Huang et al., 2023), which is an improvement of DSOR. LIDSOR added distance and intensity threshold parameters to optimize point cloud filtering. In recent studies, researchers have also introduced temporal characterization of noise points.2024 Yan et al. proposed a denoising framework for snowy point clouds based on the disordered nature of snowflakes (Yan et al., 2024). This framework contains the Time Outlier Removal (TOR) filter. Its core idea is to let the ordered objects strengthen each other while let the disordered objects weaken each other. The experimental results prove that it not only removes the disordered snowflakes from the air, but also removes some other disordered noise points, which provides a favorable guarantee for the realization of autopilot in snowy days.

Although traditional denoising methods can be directly applied to 3D sparse point cloud data, they are often limited by preset fixed parameters, which leads to unsatisfactory denoising results when the point cloud density increases. Therefore, deep learning technology in the field of point cloud denoising gradually highlights its advantages, and has made significant progress. Currently, the networks for denoising point clouds for severe weather are mainly divided into two categories: one is for eliminating rain and fog noise points, and the other is for eliminating snow noise points.Heinzler et al. firstly applied convolutional neural network to the field of point cloud denoising in 2020, and proposed WeatherNet(Heinzler et al., 2020).In 2022, Luo et al. proposed SunnyNet based on WeatherNet (Luo et al., 2022), which is a semantic segmentation network for removing rain and fog noise from point clouds. By introducing attention modules such as SENet (Szegedy et al., 2014), CBAM (Woo et al., 2018), and ECANet (Wang et al., 2020), SunnyNet is able to focus more on features in specific regions, which, in turn, improves the performance of recognition differentiation under rainy and foggy conditions. Meanwhile, point cloud denoising networks specifically designed for snowy days are gradually starting to be proposed. liSnowNet is a CNN-based unsupervised denoising network released in 2022 (Yu et al., 2022) for processing LiDAR point cloud data damaged by snowflakes. Previous research has focused on point cloud denoising networks for one or two severe weather conditions, and in order to broaden the application scope of the network, researchers have developed a variety of integrated networks to cover more kinds of severe weather denoising needs. In 2023, Seppänen's team developed SMEDNet (Seppänen et al., 2023), a technique that filters out valid echoes of targets from LiDAR multi-echo data while excluding noise caused by airborne particles (e.g., rain, snow, fog, etc.).SMEDNet utilizes self-supervised learning to generate a clean point cloud without precise labeling in inclement weather Data. More recent works are 3D-OutDet proposed by Raisuddin et al. in 2024 (Raisuddin et al., 2024) and AdverseNet proposed by Yan et al. in 2025 (Yan et al., 2025).AdverseNet adopts Cylindrical Tri-Perspective View representation to represent the point cloud, and uses the Cylindrical Tri-Perspective View representation. method to represent the point cloud and uses a two-stage training strategy. In the first training phase, generic features of rain, snow and fog noise points are learned; in the second training phase, weather-specific features are learned. While traditional deep learning methods usually rely on MLP or standard convolution operations, 3D-OutDet reduces computational requirements and maintains efficient denoising performance by directly convolving the neighborhood.However, the network suffers from deficiencies in the functionality of determining major spatial regions and lacks the ability to capture key information about the time series.

Therefore, we propose A Time and Attention-Based Point Cloud Denoising Network for Autonomous Driving in Adverse Weather (TADNet) based on our previous research on the characteristics of rain, snow, and fog noise point distribution. We add the Convolutional Block Attention Module (CBAM) to the 3D-OutDet network and change the original ResNet base network architecture to Temporal-Bottleneck ResNet (TB-ResNet), in order to improve the network's rain, snow and fog noise Recognition ability. The main contribution of this study is:

1. We propose TADNet, a point cloud denoising network capable of simultaneously handling three types of severe weather, namely rain, snow and fog.
2. TADNet integrates the CBAM attention mechanism, which dynamically adjusts the feature map channel importance through channel attention, while spatial attention captures the feature map spatial saliency.
3. TADNet enhances time series feature capture, effectively extracts continuous frame context information, and improves the recognition accuracy of time series noise point patterns and features.

2. Methodology

2.1 NeighborHood (NH) Convolution

Most of the existing point cloud processing methods rely on multilayer perceptron (MLP) or convolutional neural network (CNN), but these methods suffer from high computational complexity and memory consumption when processing point cloud data. To solve these problems, we apply a new convolution operation, NeighborHood (NH) Convolution, which deals only with nearest neighbor points, thus reducing computational complexity and memory consumption.The core idea of NH Convolution is to directly perform a convolution operation on the point cloud's nearest neighbors of the point cloud, rather than through complex approximation or learning of convolution kernels. Specifically: for each point in the point cloud, its k nearest neighbors are found using the kNN (k-Nearest Neighbors) algorithm. Apply the convolutional kernel to these nearest neighbors instead of the entire point cloud.

The traditional convolution formula:

$$(f * g)(x) = \sum_{-\infty}^{\infty} f(i) g(x - i), \quad (1)$$

Where， f is the convolution kernel, g is the data, and x is the position in the data.
NH Convolution formula:

$$(f * g)_{nh}(x) = \sum_{-\infty}^{\infty} f(i) g(KNN(x) - i), \quad (2)$$

Where, $KNN(x)$ denotes the nearest neighbor of the point.

2.2 TB-ResNet

In this study, the original ResNet base network architecture is changed to Temporal-Bottleneck ResNet (TB-ResNet).The core idea of TB-ResNet is to retain the temporal dimension through (Temporal-Bottleneck Residual Block, TB-ResBlock) the information. While the traditional ResNet residual block (ResBlock) reduces the spatial dimension (including the temporal dimension) by convolution operation, TB-ResBlock recovers the temporal dimension by introducing transposed convolution, which avoids the loss of temporal information.
The structure of TB-ResBlock is as follows:

$$y = ReLU\left(G_2\left(G_1(x)\right) + I(x)\right), \quad (3)$$

Where: G_1 is a 3×3 convolution operation with step size (S,2) followed by Batch Normalization (BN) and ReLU activation function. G_2 is a 3×3 transposed convolution operation with step size (1,2) followed by Batch Normalization. $I(x)$ is a skip connection.If the dimension of the input x matches the dimension of $G_2\left(G_1(x)\right)$,then $I(x)$ is a constant mapping;Otherwise, $I(x)$ is a 1×1 convolution operation for dimension adjustment.

2.3 CBAM（Convolutional Block Attention Module）

To further improve the denoising accuracy, the features of CBAM Attention Module are selectively enhanced and incorporated into TADNet. The feature representation capability is enhanced by (Channel Attention Module,CAM) and (Spatial Attention Module,SAM).CBAM sequentially infers the attention maps along two independent dimensions (channel and spatial) and then multiplies the attention maps by the input

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-1733-2025 | © Author(s) 2025. CC BY 4.0 License.

feature maps for adaptive feature modification.As shown in Fig. 1.

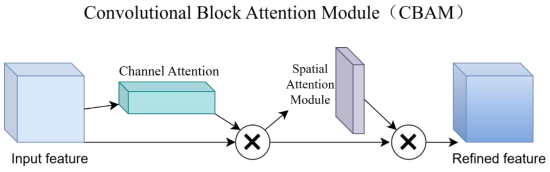


Figure 1 Convolutional Block Attention Module.

Channel Attention Module（CAM）

$$M_c(F) = \sigma\Big(MLP\big(AvgPool(F)\big) + MLP\big(MaxPool(F)\big)\Big) \\ = \sigma\Big(W_1\Big(W_0\big(F_{avg}^c\big)\Big) + W_1\big(W_0(F_{max}^c)\big)\Big), \quad (4)$$

As shown in Fig. 2, the input feature map F (H×W×C),where C is the number of channels, and H and W are the height and width, respectively. Global max pooling and global average pooling are performed for each channel to obtain two 1 × 1 × C vectors, and these two operations capture the global information and salient features of the channel, respectively. Next, the results of GAP and GMP are each passed through a shared two-layer fully connected network (MLP), where the number of neurons in the first layer is C/r (r is the reduction rate) and the activation function is Relu, and the number of neurons in the second layer is C. And after that, the features outputted from the MLP are subjected to element-wise based summing operation and sigmoid activation operation to generate the final channel attention feature, i.e., M_c. Finally, element-wise multiplication operation is done between M_c and the input feature map F to generate the input features required by the Spatial attention module.

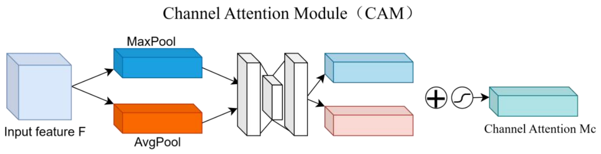


Figure 2 Channel Attention Module.

Spatial Attention Module（SAM）

$$M_s(F) = \sigma\big(f^{7\times7}([AvgPool(F); MaxPool(F)])\big) \\ = \sigma\Big(f^{7\times7}\big([F_{avg}^s; F_{max}^s]\big)\Big), \quad (5)$$

As shown in Fig. 3, the feature map F' output from Channel attention module is used as the input feature map of this module. First do a channel-based global max pooling and global average pooling to get two H×W×1 feature maps, and then these 2 feature maps are subjected to a splicing operation based on channel. Then go through a 7 × 7 convolution operation to downsize to 1 channel, i.e.,H×W×1.Then go through sigmoid to generate spatial attention feature, i.e., M_s. Finally do multiplication between this feature and the input feature of the module to get the final generated feature.

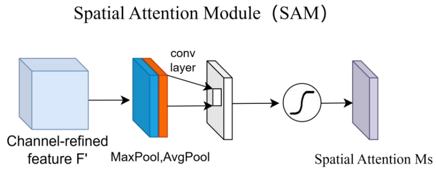


Figure 3 Spatial Attention Module

2.4 TADNet Design

Our proposed point cloud denoising network TADNet applied to rain, snow and fog is shown in Fig. 4. It consists of several modules, including customized convolution blocks (NHConvBlock) and convolution operations (NHConv), which enable the network to efficiently process the local structural information of point cloud data. The core of the network is a deep neural network consisting of multiple layers of convolutional blocks and pooling layers, where each convolutional layer is followed by a CBAM (Convolutional Block Attention Module) with a temporal bottleneck module, and residual connectivity is added to each layer to ensure effective information transfer. In addition, a pooling operation (PoolTree) performs feature compression between appropriate layers to reduce computation and improve abstraction. Finally, the output after deep feature processing is passed through the fully connected layers for category prediction. The architecture effectively integrates spatial and temporal features and attention mechanisms, which significantly improves the processing accuracy and robustness of point cloud data in time-series scenarios, and can achieve better results in different 3D point cloud denoising tasks.

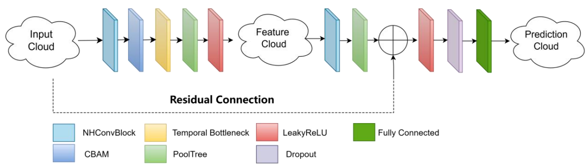


Figure 4 Architecture of our proposed TADNet

3. Experiments

3.1 Datasets

In the experiments of this study, we use two datasets, DENSE and SnowyKITTI. the DENSE dataset records four very realistic road scenarios in the CLIMATE CHAMBER containing two types of inclement weather, rain and fog; the SnowyKITTI dataset generates a snowy point cloud dataset by means of a highly realistic physical simulation model, and provides each point with a non category labels such as noise point or snow for each point.

We removed duplicate points in the dataset and performed a more detailed classification based on the severity of the weather. We divided the dataset into three parts: training set, validation set, and test set based on the dataset studied by AdverseNet (Yan et al., 2025), and the details of the division are shown in Table 1.

Classification	Light Snow	Medium Snow	Heavy Snow
Snowfall Rate	[0.5, 1.5)	[1.5, 2.5)	[2.5, 3.0]

Number of Frames	20546	10539	12467
Train	0,2,19	1,5,9,10	6,13,15,21
Valid	17,18	3,4,20	16
Test	8	11,12	7,14
Classification	FogA	FogB	FogC
Visibility	10-100 m		
Number of Frames	14601	7376	7800
Train	22,24,25	27,28,31	32,35,36,37
Valid	26	29	33
Test	23	30	34
Classification	Rain15	Rain33	Rain55
Rainfall Rate	15 mm/h	33 mm/h	55 mm/h
Number of Frames	8626	10157	9854
Train	39,41,42,43,44,45	46,47,49,50,51,53	55,56,57,59,60,61
Valid	38	52	54
Test	40	48	58

Table 1. Division of the severe weather dataset

3.2 Comparison with the State-of-the-art Methods

3.2.1 Evaluation metric: We use IoU, MIoU, and total execution time as quantitative evaluation metrics, and the formulas for the quantitative metrics are as follows:

$$IoU = \frac{TP}{TP+FP+FN}, \tag{6}$$

$$MIoU = \frac{1}{N}\sum_{i=1}^{N} IoU_i, \tag{7}$$

In the formula, *TP* denotes the number of noise points correctly identified as noise points, *TN* denotes the number of non-noise points correctly identified as non-noise points, *FP* denotes the number of non-noise points incorrectly identified as noise points, and *FN* denotes the number of noise points incorrectly identified as non-noise points.MIoU is the average of all the category IoUs.

3.2.2 Quantitative Results: We conducted denoising comparison experiments between TADNet and the state-of-the-art (SOTA) method under rain, snow, and fog, respectively, where the data for the control experiment part is from AdverseNet.

According to Table 2, it can be seen that the IoU values of TADNet are generally higher in all test scenarios (Rain15, Rain33, Rain55, FogA, FogB, FogC, Clear). This indicates that TADNet has higher accuracy. In addition, TADNet's IoU values fluctuated less under different weather conditions TADNet's Mean Intersection and Merger Ratio (MIoU) value was 94.86%, which was the highest among all the compared methods. However, the average running time of TADNet is longer compared to the other methods, but given its performance and accuracy, this time extension is acceptable because the time increase of the denoising process is not significant.

Method	Rain15 IoU (%)	Rain33 IoU (%)	Rain55 IoU (%)	FogA IoU (%)	FogB IoU (%)	FogC IoU (%)	Clear IoU (%)	MIoU (%)	Average Runtime (ms)
SOR	8.33	11.91	13.88	3.61	5.30	4.77	70.65	16.92	6.16
ROR	1.74	17.89	5.99	2.16	5.45	6.66	81.58	17.35	5.87
DSOR	10.22	23.13	18.81	27.41	17.89	14.60	83.23	27.90	5.67
DROR	10.63	21.12	21.16	24.89	19.32	14.63	82.88	27.80	9.43
SunnyNet	96.92	83.10	96.13	91.72	92.65	80.99	96.27	91.11	3.82
3D-OutDet	97.07	87.95	97.39	97.34	94.52	82.61	99.5	93.76	82.11
TADNet	98.51	88.25	98.07	97.37	95.74	84.63	99.86	94.63	76.56

Table 2.Quantitative Denoising Experiment Results for Rainy and Foggy Weather

In Table 3, we present the results of denoising experiments in snowy environments, where the deep learning denoising method SunnyNet is replaced by LiSnowNet. By comparing the different methods, we find that TADNet has the highest IoU for most of them, which again proves its excellent performance in the snowy day detection task. Also, TADNet has the highest MIoU on Light Snow, Medium Snow, Heavy Snow and Clear categories. This indicates that TADNet is extremely adaptable to different snow levels and is able to provide stable and reliable performance in a variety of environments. Although TADNet's average runtime (81.03ms) is not the fastest, such a runtime is relatively acceptable considering its excellent performance. In real-world applications, the balance between performance and runtime is critical, and TADNet provides a good compromise in this regard.TADNet incorporates the advantages of the temporal attention mechanism, which helps the model capture key information in the time series, allowing TADNet to perform well in the snowy day scenario task, which is in line with its performance in rainy and foggy weather.

Method	Light Snow IoU (%)	Medium Snow IoU (%)	Heavy Snow IoU (%)	Clear IoU (%)	MIoU (%)	Average Runtime (ms)
SOR	10.36	12.23	14.42	85.46	30.62	70.41
ROR	10.70	15.23	20.73	93.46	35.03	67.02
DSOR	67.00	67.02	63.88	98.68	74.15	61.44
DROR	54.00	59.44	59.84	98.27	67.89	110.48
LiSnowNet	40.16	25.10	18.18	97.76	45.30	2.44
3D-OutDet	90.11	94.13	92.06	98.69	93.75	79.21
TADNet	92.35	93.98	94.56	99.54	95.11	81.03

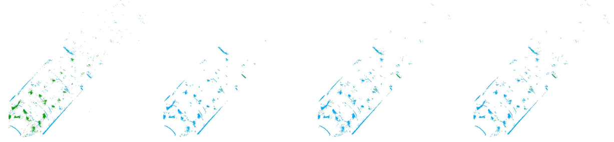
https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-1733-2025

Table 3.Quantitative Denoising Experimental Results under Snowy Conditions

3.2.3 Qualitative Results:We present qualitative results of denoising comparison experiments under different severe weather conditions such as rain, snow, and fog, as well as qualitative results for various weather conditions with different degrees of severity, respectively.

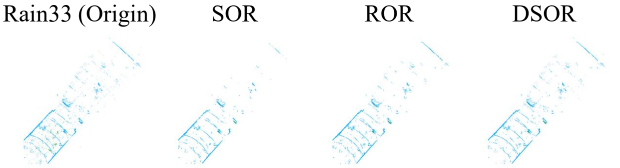
Figure 5 shows the visualization results of the rainy day scene, where the blue dots indicate CLEAR, while the green dots indicate rain noise points. The de-noising effects of SOR and ROR are observed under Rain15, Rain33 and Rain55 conditions, and the results show that both of them have a large number of noise points that are not removed, while many non-noise points are mistakenly deleted. In contrast, ROR generally outperforms SOR. further analysis of the denoising performance of DSOR and DROR under the same conditions reveals that they remove more noise points while retaining the non-noise points better. When evaluating the denoising performance of SunnyNet and 3D-OutDet in Rain15, Rain33, and Rain55, it is found that these two methods effectively remove most of the noise points, and their denoising performance is significantly better than that of DSOR and DROR.When comparing all the methods comprehensively, the denoising performance of TADNet in Rain15, Rain33, and Rain55 is the best, which verifies the effectiveness of our method in dealing with these three different intensity rainy day point cloud scenes.

Rain15 (Origin) SOR ROR DSOR

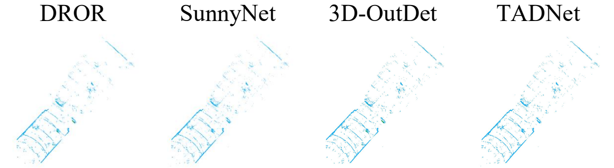


DROR SunnyNet 3D-OutDet TADNet

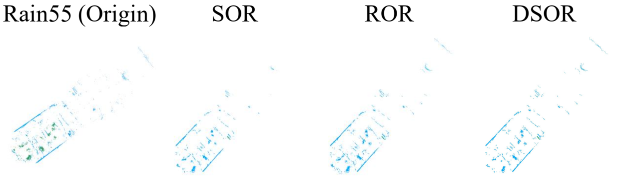
Rain33 (Origin) SOR ROR DSOR



DROR SunnyNet 3D-OutDet TADNet



Rain55 (Origin) SOR ROR DSOR

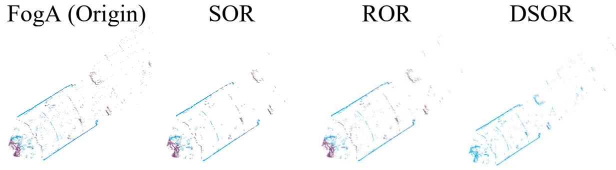


DROR SunnyNet 3D-OutDet TADNet

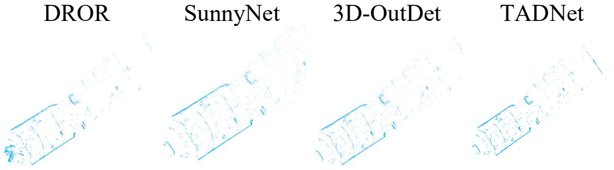
Figure 5. Visualization of denoising results for rainy weather

Figure 6 shows the visualization analysis for the foggy case, where blue dots indicate CLEAR, while purple dots indicate fog noise points. Similar to the rainy day case, SOR and ROR denoising for the FogA, FogB, and FogC cases are not effective, and many noise points are not removed while numerous non-noise points are mistakenly deleted.DSOR and DROR denoising is better than SOR and ROR, but there are still some noise points remaining.SunnyNet and 3D-OutDet successfully remove most of the noise points, with only a small amount remains.TADNet almost completely removes the noise points, which verifies the effectiveness of our method in processing three different concentrations of foggy sky point clouds, FogA, FogB and FogC.

FogA (Origin) SOR ROR DSOR

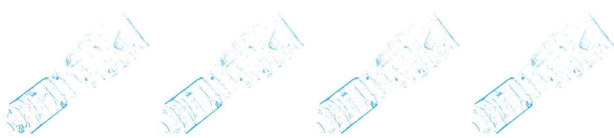


DROR SunnyNet 3D-OutDet TADNet

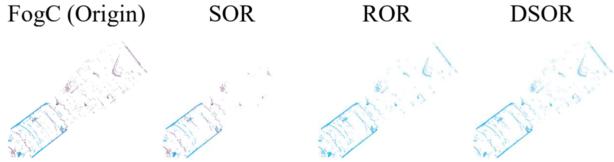


FogB (Origin) SOR ROR DSOR

DROR SunnyNet 3D-OutDet TADNet



FogC (Origin) SOR ROR DSOR



DROR SunnyNet 3D-OutDet TADNet

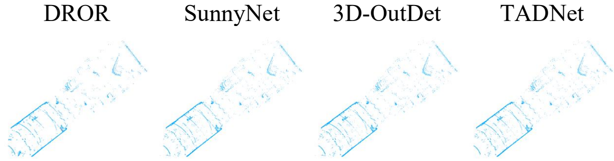
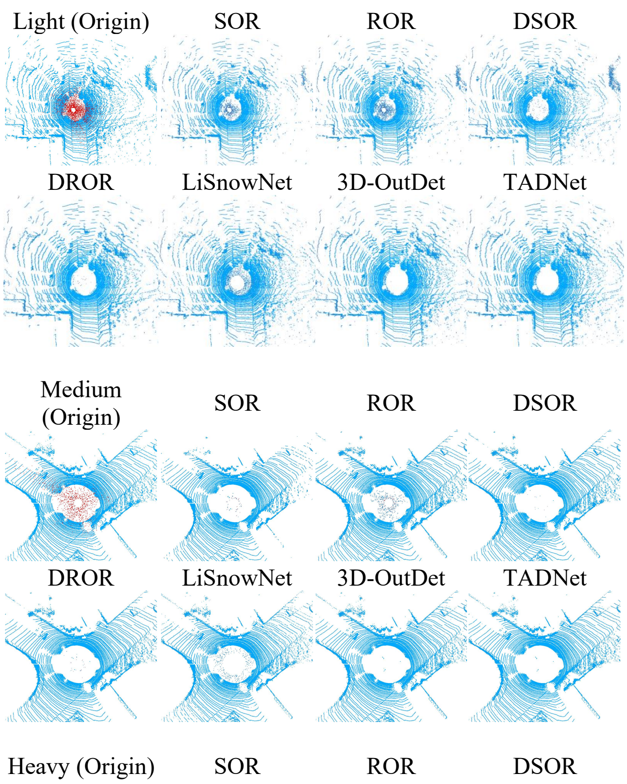


Figure 6. Visualization of denoising results for foggy weather

Fig. 7 represents the visualization results for a snowy day, where the blue dots indicate CLEAR, while the red dots indicate snow noise points. By comparing the denoising effect of SOR and ROR, we notice that both of them fail to remove numerous noise points completely, although ROR outperforms SOR in preserving the environmental features.Further observing the denoising performance of DSOR, we find that it outperforms light snow in medium snow and heavy snow cases.This suggests that the DSOR method has a This shows that the DSOR method has a limitation: it cannot achieve the same denoising effect for point clouds with different degrees of snowfall using a uniform parameter. Comparatively speaking, the denoising effect of DROR is more consistent in the light snow, medium snow and heavy snow cases, which shows a stronger robustness to the point clouds with different snowfall levels. Although there are still a few noise points left in the denoising results of DSOR and DROR, the performance of these two methods is better in snowy weather compared to the performance in rainy and foggy weather.LiSnowNet's denoising results have a large number of noise points left in the denoising results, which is not as effective as DSOR and DROR, which indicates that although setting more threshold hyperparameters can shorten the average running time of the model, it also limits the performance of the model in snowy weather. This shows that although setting more threshold hyperparameters can shorten the average running time of the model, it also limits the advantage of deep learning over traditional filters in parameter setting, and cannot automatically adjust the threshold hyperparameters according to the amount of snowfall.3D-OutDet eliminates almost all the noise points in the light snow, medium snow, and heavy snow scenarios, and achieves excellent denoising effect. And our proposed TADNet achieves a slight performance improvement based on 3D-OutDet. Since the denoising effect of these two methods is close to complete denoising, it becomes more difficult to improve the accuracy. Considering the denoising results of three kinds of bad weather, namely rain, snow and fog, our proposed 3D-OutDet shows good denoising performance under different kinds and degrees of bad weather.



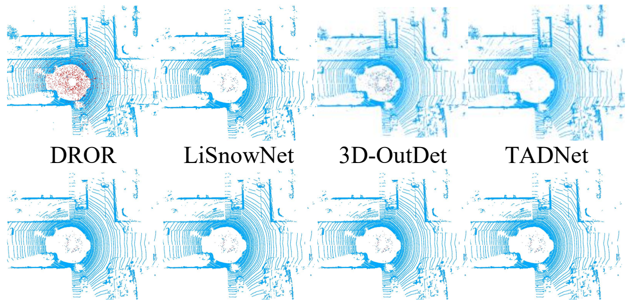


Figure 7. Visualization of denoising results for snowy weather

3.3 Ablation Study

In order to verify the effectiveness of TB-ResNet and CBAM attention mechanisms, we designed ablation experiments with gradual transition from the 3D-OutDet model to the TADNet model to evaluate the effects of both on the experimental results, and the results of the ablation experiments are shown in Table 4. Four groups of experiments are included in each data type, the first group is using the 3D-OutDet base model, the second group replaces the network framework of 3D-OutDet with TB-ResNet, the third group of experiments incorporates the CBAM attention mechanism on top of 3D-OutDet, and the fourth group is the TADNet proposed in this paper.

The results of the comparison experiments show that TB-ResNet and CBAM attention mechanisms generally have a positive effect on model performance. The use of TB-ResNet and CBAM attention mechanism improves the IoU and MIoU metrics of the model under different intensity of rain, snow and fog weather conditions, and only slightly reduces them in very few cases. Taken together, the introduction of TB-ResNet and CBAM attention mechanism is effective.

Method	3D-OutDet	3D-OutDet +TB-ResNet	3D-OutDet +CBAM	TADNet
Rain15 IoU (%)	97.07	97.11	97.97	98.51
Rain33 IoU (%)	87.95	88.03	88.14	88.25
Rain55 IoU (%)	97.39	97.51	97.84	98.07
FogA IoU (%)	97.34	97.34	97.37	97.37
FogB IoU (%)	94.52	95.39	94.93	95.74
FogC IoU (%)	82.61	83.63	82.92	84.63
Clear IoU (%)	99.5	99.6	99.73	99.86
Rain Fog MIoU (%)	93.76	94.09	94.13	94.63
Light Snow IoU (%)	90.11	91.28	91.76	92.35
Medium Snow IoU (%)	94.13	94.06	93.99	93.98
Heavy Snow IoU (%)	92.06	93.83	92.6	94.56
Clear IoU (%)	98.69	99.21	99.21	99.54
Snow MIoU (%)	93.75	94.6	94.39	95.11

Table 4 Module Effectiveness Analysis

4. Conclusion

In this paper, a novel point cloud denoising network, TADNet, is proposed to solve the noise problem of LiDAR point cloud data under rain, snow and fog. The number of temporal frames is preserved by changing the ResNet base network architecture to Temporal-Bottleneck ResNet (TB-ResNet). By enhancing the temporal information, TADNet is able to aggregate well-preserved temporal features.The Convolutional Block Attention Module (CBAM) is incorporated into TADNet, which further strengthens the extraction of noisy features and significantly improves the denoising accuracy. Experimental results show that TADNet significantly outperforms existing traditional filtering techniques and deep learning methods in removing noise under severe weather conditions such as rain, snow, fog, etc., and exhibits stable performance under weather conditions of different intensities. Compared to other methods, TADNet achieves the highest accuracy in both MIoU and IoU evaluation metrics. Under severe weather conditions, TADNet enhances the perception capability of LiDAR and promotes the stability of the environment perception of the autonomous driving system, which in turn promotes the utilization of autonomous driving technology and its performance under severe weather conditions.

References

Charron, N., Phillips, S., & Waslander, S. L. (2018). De-noising of Lidar Point Clouds Corrupted by Snowfall. 2018 15th Conference on Computer and Robot Vision (CRV), 254–261. https://doi.org/10.1109/CRV.2018.00043

Heinzler, R., Piewak, F., Schindler, P., & Stork, W. (2020). CNN-Based Lidar Point Cloud De-Noising in Adverse Weather. IEEE Robotics and Automation Letters, 5(2), 2514–2521. https://doi.org/10.1109/LRA.2020.2972865

Huang, H., Yan, X., Yang, J., Cao, Y., & Zhang, X. (2023). LIDSOR: A FILTER FOR REMOVING RAIN AND SNOW NOISE POINTS FROM LIDAR POINT CLOUDS IN RAINY AND SNOWY WEATHER. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-1/W2-2023,733-740.https://doi.org/10.5194/isprs-archives-XLVIII-1-W2-2023-733-2023

Kurup, A., & Bos, J. (2021). DSOR: A Scalable Statistical Filter for Removing Falling Snow from LiDAR Point Clouds in Severe Winter Weather (arXiv:2109.07078). arXiv. http://arxiv.org/abs/2109.07078

Luo, Z., Ma, J., Xiong, G., Hu, X., Zhou, Z., & Xu, J. (2022). Semantic Segmentation Based Rain and Fog Filtering Only by LiDAR Point Clouds. 2022 IEEE International Conference on Unmanned Systems (ICUS), 90–95. https://doi.org/10.1109/ICUS55513.2022.9986567

Raisuddin, A. M., Cortinhal, T., Holmblad, J., & Aksoy, E. E. (2024). 3D-OutDet: A Fast and Memory Efficient Outlier Detector for 3D LiDAR Point Clouds in Adverse Weather. 2024 IEEE Intelligent Vehicles Symposium (IV), 2862–2868. https://doi.org/10.1109/IV55156.2024.10588582

Rusu, R. B., & Cousins, S. (2011). 3D is here: Point Cloud Library (PCL). 2011 IEEE International Conference on Robotics and Automation, 1–4. https://doi.org/10.1109/ICRA.2011.5980567

Seppänen, A., Ojala, R., & Tammi, K. (2023). Multi-Echo Denoising in Adverse Weather (arXiv:2305.14008). arXiv. http://arxiv.org/abs/2305.14008

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2014). Going Deeper with Convolutions (arXiv:1409.4842). arXiv. https://doi.org/10.48550/arXiv.1409.4842

Wang, Q., Wu, B., Zhu, P., Li, P., Zuo, W., & Hu, Q. (2020). ECA-Net: Efficient Channel Attention for Deep Convolutional Neural Networks (arXiv:1910.03151). arXiv. https://doi.org/10.48550/arXiv.1910.03151

Woo, S., Park, J., Lee, J.-Y., & Kweon, I. S. (2018). CBAM: Convolutional Block Attention Module (arXiv:1807.06521). arXiv. https://doi.org/10.48550/arXiv.1807.06521

Yan, X., Yang, J., Liang, Y., Ma, Y., Li, Y., & Huang, H. (2025). AdverseNet: A LiDAR Point Cloud Denoising Network for Autonomous Driving in Rainy, Snowy, and Foggy Weather. IEEE Sensors Journal, 1–1. https://doi.org/10.1109/JSEN.2024.3505234

Yan, X., Yang, J., Zhu, X., Liang, Y., & Huang, H. (2024). Denoising Framework Based on Multiframe Continuous Point Clouds for Autonomous Driving LiDAR in Snowy Weather. IEEE Sensors Journal, 24(7), 10515–10527. https://doi.org/10.1109/JSEN.2024.3358341

Yu, M.-Y., Vasudevan, R., & Johnson-Roberson, M. (2022). LiSnowNet: Real-time Snow Removal for LiDAR Point Clouds. 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 6820–6826. https://doi.org/10.1109/IROS47612.2022.9982248