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Filter Methods for Removing Falling Snow from Light Detection and Ranging Point Clouds in Snowy Weather

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For autonomous driving systems to effectively replace human drivers, they must be able to adapt to harsh weather conditions. Rain and snow can cause noise to be introduced into light detection and ranging (LiDAR) point cloud data, which can interfere with the work of the perception module of autonomous driving systems. In this work, we collected LiDAR point cloud data of snowy weather in Beijing, China, applied current state-of-the-art point cloud filtering methods such as dynamic statistical outlier removal (DSOR) and dynamic radius outlier removal (DROR) filters, verified the effectiveness of filtering and real-time performance of these methods under the snowy weather environment in Beijing, and proposed possible improvements to the methods. Experiments showed that the DSOR filter has better performance than the DROR filter in snowfall scenarios and is better suited for use in automated driving systems.

1. Introduction

A vehicle autonomous driving system consists of a variety of sensors working together to respond to various situations that occur while the vehicle is driving. Light detection and ranging (LiDAR) is one of the core sensors in the perception system of an autonomous vehicle (AV). Owing to its high precision and high acquisition frequency, LiDAR is a key sensor for prediction, ranging, and positioning functions in AV systems. With the continuous improvement of technology and the reduction of costs, the importance of LiDAR is increasing. Because of the short wavelength of the pulse signal and the inherent nature of the optical pulse signal, which easily diverges, the optical pulse signal is easily reflected by particles, resulting in the defect that it is easily disturbed in LiDAR. In harsh climates with, for example, sand, rain, and snow, noisy point signals reflected by these particles can obscure LiDAR point cloud data and reduce visibility. As a result, the signal-to-noise ratio of LiDAR sensor data obtained by an AV sensing system is significantly reduced, which will affect the performance of the AV perception system.

Noise caused by snow particles is removed while preserving details of environmental features, which are required for autonomous localization and navigation. Snow particle noise can

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easily lead to incorrect judgments in the AV perception system with LiDAR as the core sensor. For example, falling snow may occlude oncoming vehicles and evade Autoware's Euclidean clustering for object detection.(1) The mechanism of snow noise generation is shown in Fig. 1. Neural networks trained on large datasets exhibit reduced performance under winter snow conditions, and the lack of datasets containing snow conditions is one of the possible factors.(2) For this purpose, Matthew *et al.*(3) collected a dataset of winter snowfall scenes in the Waterloo region of Canada that contains 7000 frames of annotated data. Martin *et al.*(4) proposed a physically based method for a snowfall scene simulation algorithm to improve the robustness of 3D target detection.

Conventional point cloud noises are processed by corresponding noise filter methods, and good filtering effects have been achieved. However, for noise in some special scenes, the effectiveness of conventional filtering methods is poor. The noise points generated by snow or rain can easily interfere with the perception ability of an AV sensing system, resulting in false detections. Therefore, the LiDAR point cloud must be filtered before it can be used reliably. The density of snow particle noise is inversely proportional to the detection distance of the LiDAR sensor; as the distance increases, the density of noise gradually decreases. These characteristics endow snow particle noise with a unique noise distribution different from that of traditional point cloud noise, which requires special filtering methods to filter out.

2. Literature Review

LiDAR point cloud filtering methods can be divided into two categories: those based on 2D space and those based on 3D space. Filtering methods based on 2D space include spatial-coordinate-system-based, depth-and-color-based, and segmentation-based filtering methods. These methods are not only unable to effectively remove snow particle noise but also have the negative effect of smoothing the edges of key point features. Yao *et al.*(5) proposed the principal-

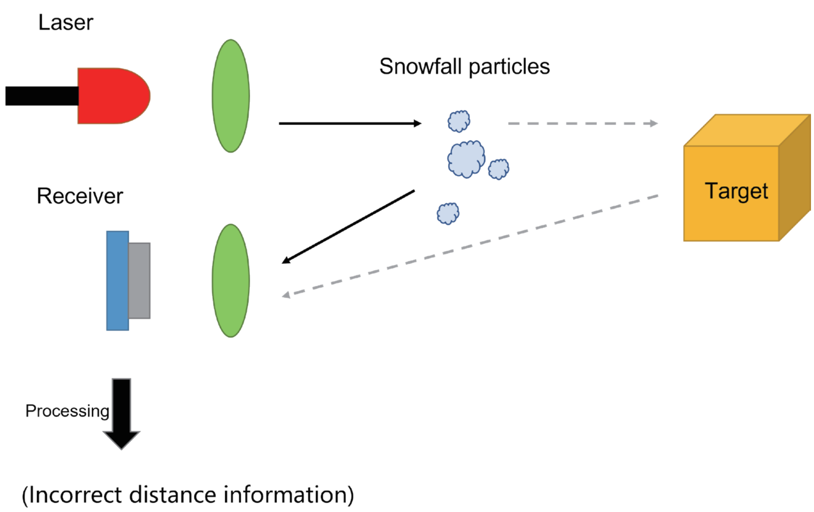

Fig. 1. (Color online) Mechanism of snow particle noise generation.

component-analysis-based adaptive clustering (PCAAC) filtering method by combining the principal-component-analysis and density-based clustering methods. The PCAAC method removes snow noise by filtering out sparse point cloud areas after reducing the dimensionality for 3D point clouds and has high scalability because of its low time complexity. However, owing to the inherent limitations of clustering methods, in high-density snow, their effectiveness in noisy areas is low, and clustering technology will classify high-density snow noise areas as environmental features. 3D-space-based filtering methods, including grid, statistical outlier, and radius outlier filtering methods, can directly process LiDAR point cloud data but lack adaptability to environments that are, for example, snowy. Usually, snowflake noise cannot be effectively filtered out. Ronnback *et al.*(6) analyzed the relationship between the distribution range of snowflakes and the LiDAR detection distance in a snowy weather environment and found that the gamma distribution is suitable for describing the distribution law of snowflakes in LiDAR sensor data. Charron *et al.*(7) proposed a point cloud filtering method based on an adaptive radius neighborhood search to obtain the local optimal solution by iteratively searching the neighborhood of the target point. This method has good filtering effectiveness on isolated noise points. However, since these methods are based on spatial proximity, single reflected signals that have no neighbors in the neighborhood are discarded, causing the number of signal points classified as noise to increase with the distance, thereby reducing the visibility of the sensor. Balta *et al.*(8) proposed a fast clustering statistical outlier filtering method based on the statistical outlier filtering method. This method down-samples the point cloud data and applies the fast clustering statistical method, which improves the algorithm performance compared with the statistical outlier removal (SOR) filtering method. The intensity-based filter method removes noise by presetting the LiDAR reflection intensity threshold. However, the reflection intensity depends on the laser wavelength and target reflectivity. If the target detection and classification is only based on the reflection intensity in a snow particle scene, it will be affected by a large area of snow or environmental features with the same reflection intensity as snowflakes, and it has the limitation of an unreliable single attribute in detection and classification. To resolve this problem, Park *et al.*(9) proposed a low-intensity outlier removal (LIOR) filtering method by combining the reflection intensity filtering method and radius outlier removal (ROR). This method sets the point cloud reflection intensity threshold for preliminary screening of the point cloud, and then applies ROR to the preliminary screening results as secondary screening to compensate for the unreliable limitation of a single attribute of the reflection intensity filtering method. On the basis of LIOR, Zhong *et al.*(10) optimized the ROR to the dynamic radius outlier removal (DROR), which further improved the effectiveness of the filtering method. Kurup *et al.*(11) proposed the dynamic statistical outlier removal (DSOR), which optimizes the SOR method by adaptively adjusting the standard deviation threshold in the SOR method as the LiDAR detection distance increases, which further improves the filtering accuracy compared with the DROR. Because it has low time complexity, there is space for further optimization in the future. In terms of deep-learning technology, Heinzle *et al.*(12) proposed a LiDAR point cloud filtering method based on the convolutional neural network deep-learning framework. Experiments showed very high filtering effectiveness in rainy scenes with this approach. Pfeuffer *et al.*(13) proposed a robust learning method that enables neural networks to learn to handle unknown noise, greatly improving robustness under adverse weather conditions. The filtering effect in snowy scenes must be further verified, and this method requires the additional use of sensors, such as visual cameras, to achieve filtering functions. The recognition classification effect can also be impacted in low light scenes such as at night.

Under the weather conditions of snowfall, the reflectivity of snowflakes on LiDAR light signals varies because of different sensor models. The collection of dataset information and the performance of filtering methods for datasets for adverse climate environments are very important in the research and development of datasets for AV performance. Michaud *et al.*(14) presented the behavioral characteristics of four LiDAR systems (Velodyne HDL-32E, SICK LMS151, SICK LMS200, and Hokuyo UTM-30LX-EW) under snowfall conditions and concluded that the snowfall has less impact outside a range of 10 m from the LiDAR.

In the present work, we collected snowy environment point cloud data in Beijing, China, based on vehicle LiDAR and applied current advanced noise removal methods to the data, explored the characteristics and filter methods of LiDAR point cloud noise under snowy climate conditions in north China, and analyzed these methods. Accordingly, we evaluated the specific performance of each method for the snowy climate of northern China and analyzed the space for improvement of future denoising methods.

3. Datasets and Methods

3.1 LiDAR datasets

The point cloud data used in this paper were collected from a 200-m-long road in the southeast of Beijing University of Civil Engineering and Architecture; a total of 100 GB of LiDAR data were captured with a volume of 3000 frames. The weather conditions were stable during the collection period, and there were no significant changes in snowfall, ensuring the stability of weather conditions in the data. The point cloud data contained environmental features, such as vehicles, signage, pedestrians, buildings, and streetlights, which are conducive to the subsequent observation of the filtering method to retain the effect of environmental features, as shown in Fig. 2.

The point cloud data collection equipment included an AgileX robot, which has a stable moving speed of 5 m/s and the ability to absorb shocks, ensuring a stable viewing angle for LiDAR and ensuring that point cloud data are obtained with a uniform transition in each frame. The 40-line LiDAR system used in this study (Hesai Pandar40) has a detection distance of up to 200 m, a total vertical field of view of 23° from −16° to +7°, a minimum vertical angle resolution of 0.33°, a minimum horizontal angle resolution of 0.2°, and an acquisition speed of 10 fps, enabling it to accurately obtain details of the environmental features in the collected road section, as shown in Fig. 3.

3.2 Filter methods

LiDAR point cloud noise will interfere with the perception module of the AV system, causing the AV planning module to make incorrect decisions, resulting in potential safety hazards. In

Fig. 2. (Color online) Road conditions during data collection.

Fig. 3. (Color online) Data collection equipment.

snowy weather, a large quantity of snow particles diffusing in space will generate a large amount of snow particle noise, much of it concentrated in the area near the LiDAR sensor, which will cause significant interference, affecting the LiDAR sensing performance. For this reason, methods have been proposed to reduce the influence of snow particle noise. In the 3D point cloud filtering method, ROR and SOR are traditional methods for removing noise from point clouds in 3D space.

ROR traverses each point in the point cloud data by predefining the threshold of the number of adjacent points and the search radius, and determines whether the number of adjacent points in the neighborhood of the search radius of the point is lower than the threshold number of adjacent points; if so, the point is classified as noise; otherwise, it is classified as an environmental feature, as shown in Fig. 4.

SOR uses a Gaussian distribution function to describe the point cloud data model and filters the noise by judging the distance between the point and the set of points in its neighborhood. The method predefines the number of adjacent points to be queried and the standard deviation

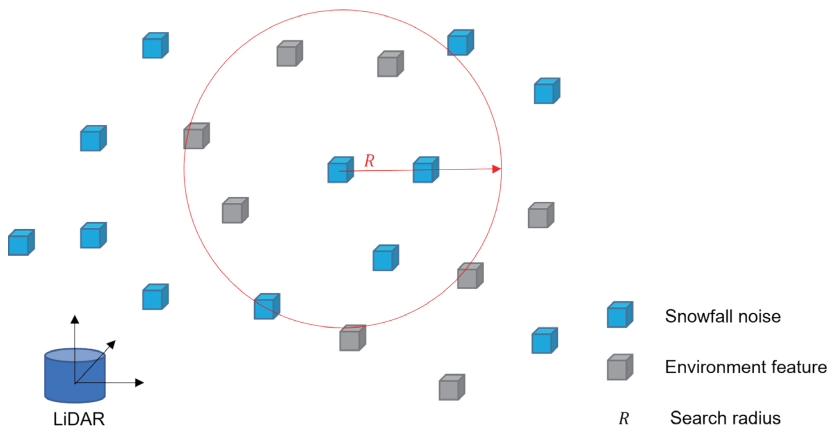

Fig. 4. (Color online) Principle of ROR method.

multiple threshold. By traversing each point in the point cloud data, the average distance between the point and the adjacent points is calculated, and the sum of the distances between the point and all adjacent points is judged as to whether it is greater than the classification threshold; if it is greater than the threshold, it is classified as noise; otherwise, it is classified as an environmental feature. The threshold calculation formula is

$$Threshold = \mu + (\sigma \times \beta), \tag{1}$$

where μ is the mean, σ the standard deviation, and β a constant.

The ROR and SOR methods cannot adapt to the special distribution law of snow particle noise and usually cannot retain the medium- and long-distance environmental characteristics while filtering out the noise. To this end, improvements have been made to these two methods to improve the effectiveness of filtering and time efficiency of the filtering method under snowy weather conditions.

DROR is an improved method of ROR that adapts the search radius of ROR by optimizing the algorithm structure, enabling DROR to retain more medium- and long-distance environmental characteristics than ROR, as shown in Fig. 5. DROR first performs k-dimensional tree (KD-tree) preprocessing on the point cloud data, then traverses each point in the data, and determines the number of adjacent points within the search radius. Points with less than a threshold number of neighboring points are classified as noise and other points are classified as environmental features. The search radius is calculated as

$$R = d \times \beta \times \alpha, \tag{2}$$

where R is the search radius, d the Euclidean distance from the point to the LiDAR sensor, β a constant, and α the horizontal angular resolution of LiDAR.

DSOR is an improved method of SOR that adapts the threshold of SOR by optimizing the algorithm structure so that the threshold is proportional to the Euclidean distance from the point to the LiDAR sensor to filter out more snow particle noise. DSOR first performs KD-tree

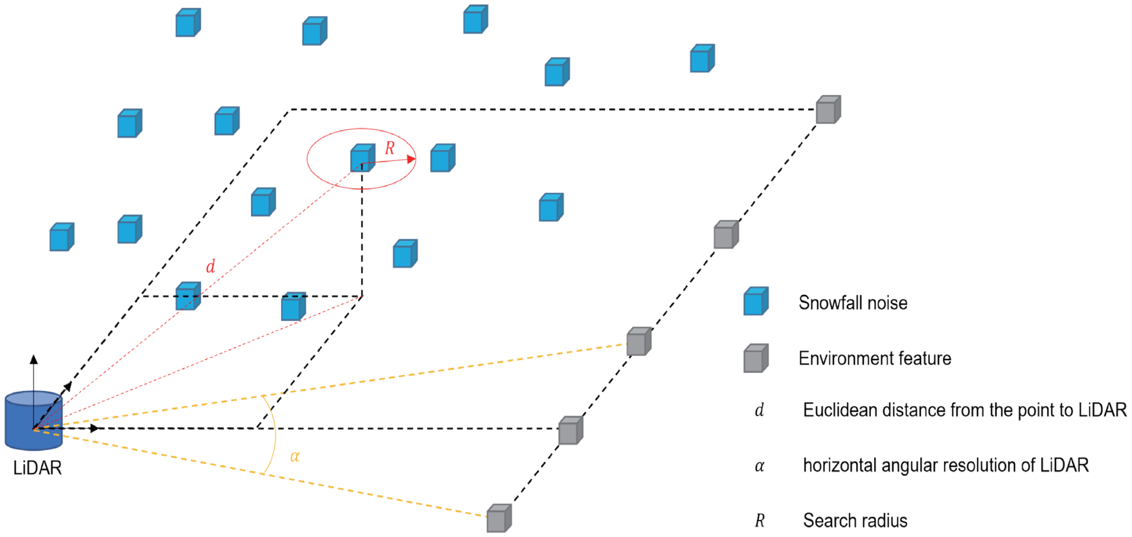

Fig. 5. (Color online) Principle of DROR method.

preprocessing on the point cloud data, then traverses each point in the data, calculates the average distance and standard deviation from the current point to all points in the data, and calculates the global threshold and dynamic threshold using Eqs. (3) and (4). Points with an average distance less than the dynamic threshold are classified as noise and other points are classified as environmental features.

$$T_g = \mu + (\sigma \times \beta) \tag{3}$$

Here, μ is the mean, σ the standard deviation, and β a constant.

$$T_d = T_g \times r \times d \tag{4}$$

Here, T_g is the global threshold, r a constant, and d the Euclidean distance from the point to the LiDAR sensor.

4. Results and Discussion

The algorithm proposed in this paper was verified using the data collected by the Hesai Pandar40 40-line LiDAR system. The hardware used was an AMD Ryzen 9 5800X CPU with 32 GB RAM; all the filters were implemented on this device. The LiDAR point cloud data used during the experiments were collected from Beijing University of Architecture and Civil Engineering. The experimental scene was sleet and snowy weather. The ROR, SOR, DROR, and DSOR were applied to the scenarios to verify the effectiveness of denoising and their real-time performance for this dataset. All results were obtained using at least 100 point cloud samples.

We uniformly sampled at least 100 frames from the collected 3000 frames of point cloud data as the original experimental data, applied different filtering methods to the same original data, and compared the experimental results of the filtering methods from multiple aspects to comprehensively evaluate their performance. The ground-truth data of the classification results used to verify the filtering method were created using Cloud Compare software.(15) By manually labeling the noise and environmental features of all of the sampled data frames, the noise and environmental features were classified and extracted to obtain accurate verification results.

4.1 Filter result

Figure 6 shows the visualization point cloud results of original data, ROR, SOR, DROR, and DSOR. The original point cloud shows clusters of snowflake points scattered in the area around the LiDAR system. Although the ROR removes the noise points, it also removes many environmental features. Compared with the SOR and DROR, the DSOR retains many

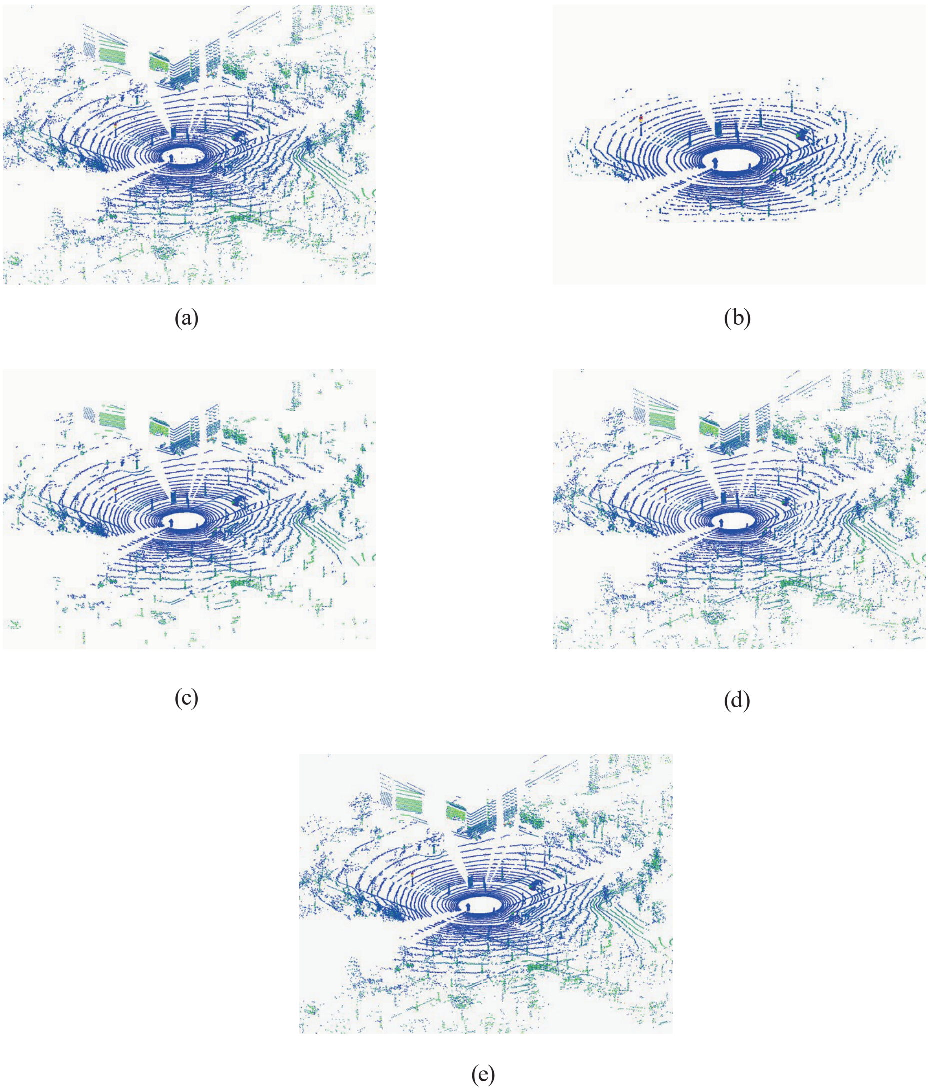

Fig. 6. (Color online) Visualization results of (a) original point cloud and filtered point clouds of (b) ROR, (c) SOR, (d) DROR, and (e) DSOR.

environmental features while removing noise points, but the DROR removes more noise in the area around the LiDAR system. For example, the SOR removes some of the tree branches and building features classified as noise at medium and long distances, and the DROR removes some of the vehicle feature points around the LiDAR area as noise, as shown in Figs. 7 and 8.

4.2 Precision and recall

The precision and recall are suitable evaluation indexes for the binary classification method. There are four types of classification results in the binary classification method, namely, true negative (TN), false negative (FN), true positive (TP), and false positive (FP). In Table 1, the column headings refer to the classification result of the ground-truth data and the row labels refer to the classification result of the sample data.

LiDAR point cloud denoising in snowy weather must preserve as many environmental features as possible while removing snow particle noise. When using precision and recall to

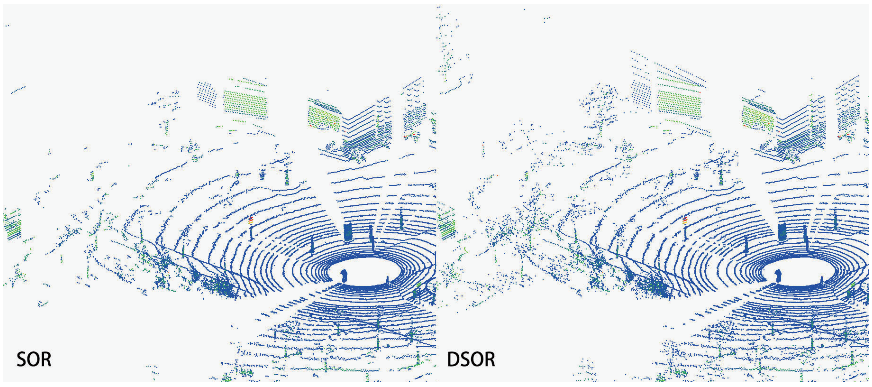

Fig. 7. (Color online) DSOR preserves more environmental features than SOR.

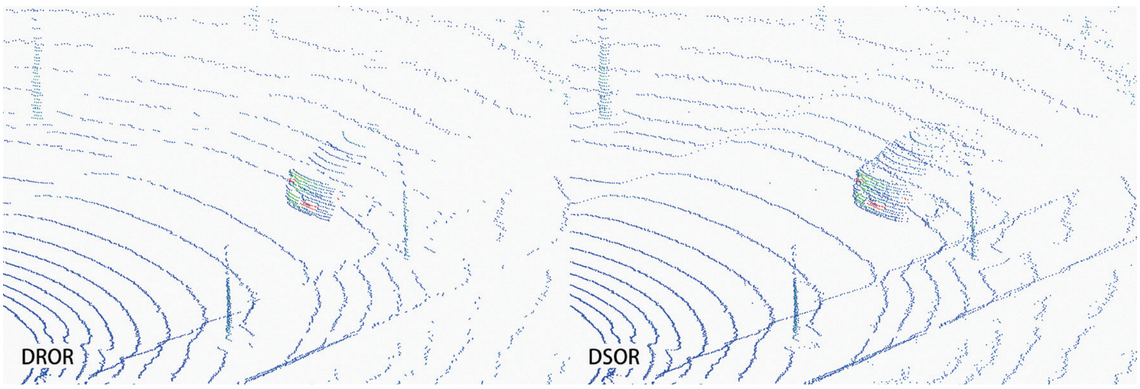

Fig. 8. (Color online) DSOR preserves more environmental features than DROR, but DROR removes more noise in the area around the LiDAR system.

Table 1
Four types of classification results.

Data type	Environmental feature	Noise
Environmental feature	TN	FN
Noise	FP	TP

evaluate the data quality for each filtering method, a higher precision value means that more environmental features are preserved, and a higher recall value means that more noise is removed. From the experimental results, we calculated the precision and recall using Eqs. (5) and (6), respectively.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

As shown in Fig. 9, the ROR and SOR filters have extremely low precision due to the removal of many environmental feature points. The DSOR has 26.41 percentage points higher precision (74.63%) than the DROR (48.22%). This means that the DSOR preserves more environmental feature points than the DROR. The DROR has 3.78 percentage points higher recall (63.88%) than the DSOR (60.10%). This means that the DROR removes more noise points than the DSOR.

4.3 Real-time performance

With increasing vehicle driving speed, the decision module of an AV system must acquire point cloud data with a higher frame rate to make timely corrections to the AV behavior during driving. The sampling frequency of the Hesai Pandar40 LiDAR sensor is 10 Hz. To make full use of the performance of the LiDAR sensor, the execution time of the filtering method must be as short as possible; the shorter the execution time of the filtering method, the stronger its real-time performance and the higher the driving speed for which it has satisfactory performance. The filtering algorithm used in the present work was designed in C++ programming language to ensure the execution efficiency of the filtering method. The point cloud data were read, written, and processed using the Point Cloud Library.(16) The simulated driving scenario and the effectiveness of filtering were demonstrated using the Robot Operating System.(17)

Table 2 shows the average execution times of the ROR, SOR, DROR, and DSOR, where all the results were obtained using at least 100 point clouds. The DROR has the longest execution time with an average of 706.97 ms. The ROR has the shortest execution time with an average of 99.02 ms. The SOR and DSOR have a longer execution time than the ROR filter but are much faster than the DROR, both filters having an approximately 82% shorter execution time than the DROR.

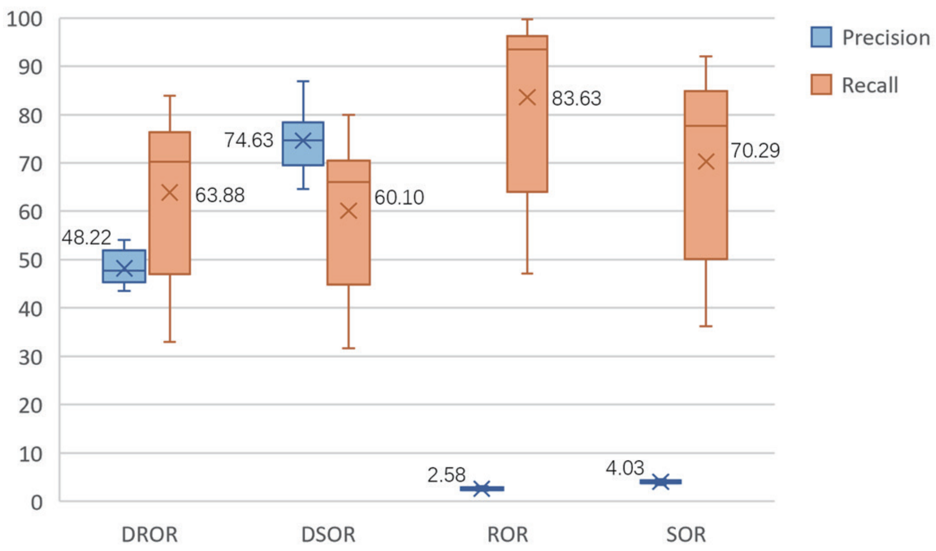

Fig. 9. (Color online) Statistical results for precision and recall.

Table 2
Execution times of four filters compared in this study.

Filter	Average execution time (ms)
ROR	99.02
SOR	138.14
DROR	706.97
DSOR	130.11

5. Conclusion

Snowy weather can interfere with the perception system of an AV and may cause its decision-making system to make incorrect decisions, therefore posing a potential safety hazard. In this paper, we introduced the current LiDAR point cloud filters for winter snowfall conditions, collected a winter snowfall LiDAR dataset in Beijing, China, and validated several filtering methods using the collected dataset to evaluate their filtering result and real-time performance.

The results show that the ROR and SOR are unable to preserve environmental features at medium and long distances and thus cannot meet the data requirements for autonomous driving under snowfall conditions. As state-of-the-art filters, both DROR and DSOR achieved good filtering results. Compared with the DROR, the DSOR preserves more environmental features, has a higher execution speed, and has a precision 54.77 percentage points higher than that of the DROR. In areas close to the LiDAR sensor, the DROR removes more noise points than the DSOR, but the DROR cannot be used in scenarios with real-time filtering due to its average running time of up to 706.97 ms. Therefore, the DROR is not suitable as a filtering method for LiDAR data in autonomous driving scenarios. If the DSOR is used in combination with the intensity-based filtering method, it will be able to preserve more environmental features without any reduction in processing speed. In the future, we will continue to evaluate the performance of these filtering methods in severe climatic environments such as rainfall and sleet.

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