Proceedings

Design of a LIOR-Based De-Dust Filter for LiDAR Sensors in Off-Road Vehicles [†]

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Abstract: A LiDAR sensor has played an important role in a variety of related applications due to its merits of providing high-resolution and accurate information about the environment. However, its detection performance significantly degrades under dusty conditions, and thus it makes the whole perception of the vehicles prone to failure. To deal with this problem, we designed a de-dust filter using a LIOR filtering technique that offers a viable solution to eliminate dust particles from the measurement data. Experimental results confirm that the proposed method is robust to dust particles by successfully removing them from the measured point cloud with good filtering accuracy while maintaining rich information about the environment.

Keywords: de-dust filter; LiDAR; Low-Intensity Outlier Removal (LIOR); off-road vehicles

1. Introduction

Recently, many researchers are developing autonomous solutions for off-road vehicles in various industrial sectors, including construction and mining. One of the most widely used sensors for achieving autonomy in these vehicles is LiDAR (Light Detection and Ranging) as it can provide rich geometry and intensity information about the environment. Perception is a major issue in this field due to harsh working environments such as dust. For example, measured data by the LiDAR sensor can be corrupted due to light backscattering from dust particles [1], and thus it can make the whole perception of these vehicles prone to failure. However, there has been little effort to resolve the de-dusting issue despite its importance.

The author in [2] applied a voxel-based machine learning such as Support Vector Machine and Random Forest and neural network (NN) algorithm for dust classification. This study also compared the performance of both methods and showed the NN-based approach outperformed the machine learning method. A deep learning approach was also adopted for dust classification [3], in which point-wise classification and voxel-wise classification were proposed based on the input features to the network architecture.

A major drawback of the above AI (Artificial Intelligence)-based methods is that the filtering or classification performance is heavily dependent on the quality of training data. Moreover, tuning several parameters to find a good solution requires extremely high computation, especially when large training data sets are needed.

On the other hand, there have been non-AI-based methods due to the merit of requiring fewer parameters for optimization while considering fewer features compared to AI-based methods for classification. The non-AI-based methods such as Low-Intensity Removal (LIOR) filter and Dynamic Radius Outlier Removal (DROR) filter have been

used to de-noise LiDAR points for adverse weather conditions like snow [4,5] but to the best of our knowledge, no one has yet implemented these methods to the dust problem.

By taking the above advantage of the non-AI method and exploring its extensive applications to dust filtering, this study proposes a de-dusting algorithm based on LIOR filtering principles. The proposed algorithm was evaluated using labeled sensory data collected from a VLP-16 LiDAR. In the test results, the developed algorithm demonstrated superior de-dusting performance by achieving high accuracy with the mean F1 score of 82.88 percent.

The remainder of this paper is divided as follows. In Sections 2 and 3, the research methodology and corresponding results are described. The conclusion is provided in Section 4.

2. LIOR Method

The LIOR method [5] employs a two-step filtering procedure in this study. The first step is based on the fact that dust particles have a lower intensity than other non-dust objects. The gathered data was analyzed to determine a threshold intensity that can be used to distinguish dust from other non-dust objects. Then, points with intensity values below the selected threshold were eliminated through a filtering process. As the second step, a radius outlier removal (ROR) filter was applied to the points identified as outliers in the previous step. This step is required to preserve non-dust object points that have low intensity but are incorrectly classified as dust. Specifically, the ROR filter iterates through the points classified as dust in the previous step and counts the number of points located within the specified radius search. If the counted number is greater than a cut-off value, the corresponding points are considered as inliers; otherwise, they are eliminated as outliers.

To find an appropriate threshold intensity value, we gathered real data sets that contain 18 packets of data in various dusty conditions, each of which includes around 60 frames. We then manually labeled our data to identify dust and non-dust points. The histograms below illustrate the intensity values of dust and non-dust points for one example frame in Figure 1a and Figure 1b. As shown in Figure 1a, the intensity values of all of the dust points are low (less than 8). However, choosing a high threshold may result in the removal of low-intensity (non-dust) data from the environment. For example, it can be seen from Figure 1b that a minor portion of non-dust points has an intensity value below 10.
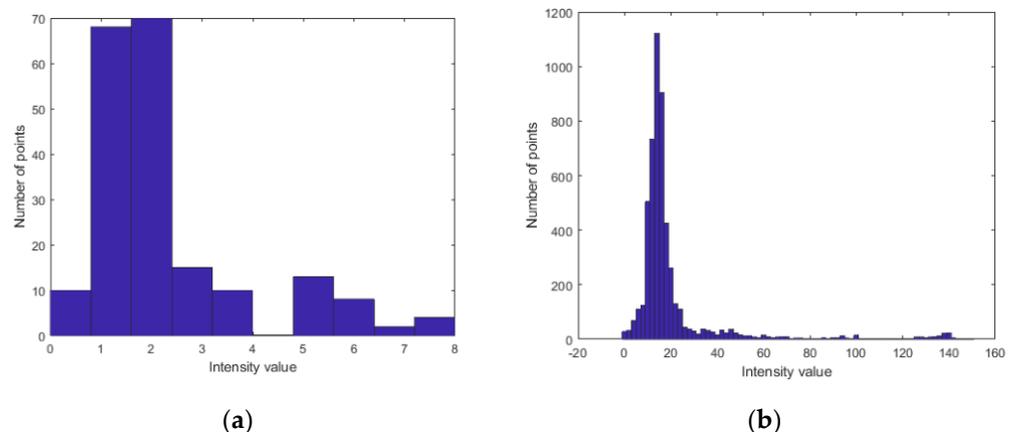

(**a**)   (**b**)

Figure 1. Histogram for intensity value: (**a**) dust points; (**b**) non-dust points.

An overview of the optimized LIOR conditions used in this experiment is presented in Table 1.

Table 1. Optimized LIOR parameters.

LIOR Parameters	Value
Threshold intensity	7
Radius search (m)	0.044
Cut-off value	6

3. Results and Evaluation

The performance of our developed filter was evaluated using the labeled data described in Section 2. Four different metrics including accuracy, precision, recall, and F1 score were used, which are defined in Equations (1)–(4). For one packet data containing 19 frames, the evaluation results of LIOR filtering are presented in Table 2. These values represent the mean, maximum, and minimum values in each criterion for the entire frames in the considered packet data. Figure 2 visualizes a point cloud before (Figure 2a) and after filtering (Figure 2b) to illustrate the effect of filtration.

$$\text{Accuracy} = \frac{TP + TN}{\text{Total number of points}} \qquad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3)$$

$$F1 \text{ score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \qquad (4)$$

where *TP* is the number of dust points that predicted truly, *TN* is the number of non-dust points that predicted truly, *FP* is the number of dust points that predicted falsely, and *FN* is the number of non-dust points that predicted falsely.
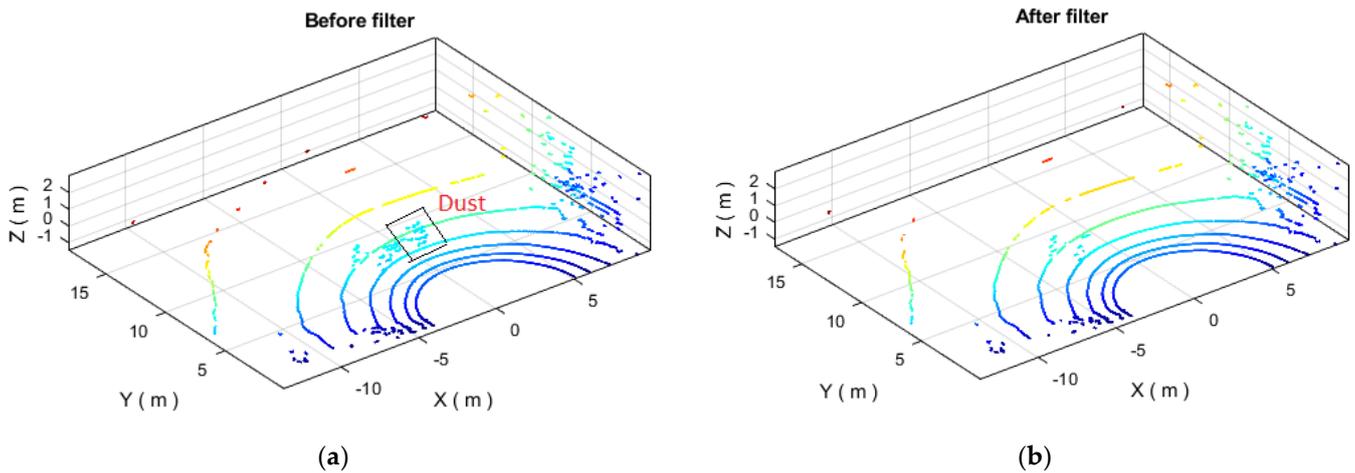

(**a**)   (**b**)

Figure 2. Visualization of LIOR filtering: (**a**) point cloud before filtering; (**b**) point cloud after filtering.

Experimental results confirm that the proposed LIOR-based de-dusting algorithm is robust to dust particles by successfully removing them from the measured point cloud while maintaining rich information about the environment.

Table 2. Results of LIOR filtering evaluation.

Evaluation Metrics	Mean Value	Min. Value	Max Value
Accuracy (%)	98.49	96.86	99.3
Precision (%)	75.44	55.43	82.13

Recall (%)	92.58	88.12	97
F1 score (%)	82.88	70.055	87.28

4. Conclusions

This study proposes a de-dusting filtering method for LiDAR sensors that stems from the LIOR technique. Experimental validation using four evaluation metrics shows the developed algorithm is capable of filtering dust particles from the original point cloud data. In addition, this approach has the advantage of simplicity and less computational costs over AI-based methods while providing satisfactory performance in removing dust. Therefore, the proposed method can be applied to LiDAR sensors mounted on off-road vehicles in various industrial fields with dust exposure, such as construction, mining, and agriculture.

Institutional Review Board Statement:

Informed Consent Statement:

Data Availability Statement:

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