

Research on LiDAR Point Cloud Denoising Algorithms for Autonomous Driving Scenarios

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Abstract: LiDAR is one of the core sensors in the environmental perception system for autonomous driving. It acquires 3D point cloud data of the surrounding environment by transmitting and receiving laser signals, which provides fundamental information for object detection, obstacle recognition, localization and mapping. However, in real-world autonomous driving scenarios, factors such as rain, snow, fog, dust, direct sunlight, long-distance stray light, specular reflection of objects and inherent hardware errors of the sensor introduce numerous noisy points into the raw point cloud. Noise may lead to distorted object contours, misclassification of ground points, missed detection of dynamic objects and point cloud registration errors, which directly degrade the stability of perception algorithms and pose potential risks to driving safety. This paper sorts out the sources and classification of LiDAR point cloud noise in autonomous driving scenarios, compares and analyzes the principles, applicable conditions, advantages and disadvantages of existing classic point cloud denoising algorithms for such scenarios. Considering the special requirements of autonomous driving for algorithm real-time performance, edge feature preservation and adaptability to dynamic objects, the difficulties faced by current denoising algorithms are summarized, and the development trends of LiDAR point cloud denoising technology oriented to autonomous driving are prospected.

Keywords: Autonomous Driving; LiDAR; Point Cloud; Denoising; Environmental Perception

1. INTRODUCTION

With the continuous deployment of autonomous driving technology, environmental perception serves as the prerequisite for vehicles to realize autonomous decision-making and path planning. Featuring high ranging accuracy, insensitivity to illumination variations and the capability to acquire 3D geometric information, LiDAR has been widely equipped on platforms including passenger cars, unmanned delivery vehicles and mining autonomous vehicles. The real road environment is complex and changeable, far from ideal laboratory test conditions. Mixed with valid point clouds, noise points will significantly degrade the performance of downstream high-level algorithms such as object detection, segmentation and SLAM without preprocessing.

Point cloud denoising is an indispensable preprocessing step in the LiDAR perception pipeline. Most conventional 3D point cloud denoising algorithms are designed for reverse engineering and 3D reconstruction scenarios, which prioritize point cloud smoothing. They usually suffer from heavy computation overhead, tendency to erase edges of small-sized obstacles, and inability to distinguish dynamic objects from noise. Therefore, they can hardly meet the low-latency and high-safety requirements of autonomous driving. It is of great engineering value to investigate dedicated LiDAR point cloud denoising algorithms tailored to autonomous driving scenarios, so as to balance three objectives: noise suppression, feature preservation and real-time computation.

This paper first classifies point cloud noise types in autonomous driving scenarios, introduces the principles of mainstream denoising algorithms, analyzes the limitations of various algorithms in road scenarios, discusses current research challenges, and finally puts forward ideas for future technological development.

2. Sources and Classification of LiDAR Point Cloud Noise in Autonomous Driving Scenarios

According to the generation mechanism, LiDAR point cloud noise in autonomous driving is generally divided into three categories: outlier noise, distributed noise and structured false noise.

From the perspective of scenario dimension, the noise can also be classified into weather-related noise, illumination-related noise, inherent sensor noise and multi-sensor interference noise. Different types of noise vary greatly in spatial distribution and reflection intensity characteristics, so it is difficult for a single algorithm to handle all noise types simultaneously.

3. Review of Existing LiDAR Point Cloud Denoising Algorithms

Current point cloud denoising algorithms are mainly divided into four categories: algorithms based on statistical features, algorithms based on neighborhood geometry, algorithms based on surface fitting, and deep learning-based denoising algorithms. The following is the description of statistical feature-based algorithms and neighborhood geometry-based algorithms.

3.1 Denoising Algorithms Based on Statistical Features

The representative algorithm is Statistical Outlier Removal (SOR). Its core idea is to calculate the average distance from each point to other points in its neighborhood. Assuming that the neighborhood distances follow a Gaussian distribution, thresholds of mean value and standard deviation are set. Points whose distances exceed the thresholds are identified as outliers and removed. With a simple structure and fast computation speed, statistical filtering is suitable for deployment on embedded platforms and serves as the most

commonly used basic denoising method in autonomous driving engineering. Nevertheless, it has obvious drawbacks. When the thresholds are fixed, the algorithm adapts poorly to point clouds with drastic density variations. The point cloud is dense at close range and sparse at long range, so small real objects at a distance (such as traffic cones) are prone to being falsely removed. Relying only on distance statistics without utilizing reflection intensity information, it is almost ineffective against structured false noise.

3.2 Denoising Algorithms Based on Neighborhood Geometric Features

Such algorithms distinguish noise from valid points by using geometric information such as normal vectors, curvature and plane consistency in the point neighborhood. For planar regions like road surfaces, the normal vectors of points tend to be consistent and the curvature is small, while noisy points show chaotic neighborhood geometric relations and abrupt curvature changes. Typical methods include normal vector consistency check and region-growing filtering. The advantage of these algorithms lies in their ability to preserve object edges, making them suitable for handling disturbance noise attached to object surfaces and for ground point cloud preprocessing. Their limitations are as follows: normal vector calculation relies on neighborhood search, which increases computational overhead. For low obstacles and thin objects (railings, wires), the number of neighboring points is inherently small and their geometric features are unstable, so they are easily mistaken for noise and removed. Point cloud deformation caused by the motion of dynamic objects also interferes with geometric judgment.

4. Special Constraints and Existing Difficulties of Point Cloud Denoising in Autonomous Driving Scenarios

While conventional 3D reconstruction scenarios prioritize point cloud smoothness, autonomous driving scenarios impose multiple hard constraints, which also constitute the research challenges of current algorithms. The main difficulties are listed as follows:

Real-time constraint, feature preservation constraint, scene dynamics constraint, multi-noise coupling problem, adaptive requirement, functional safety constraint.

5. Development Directions of Point Cloud Denoising Technology for Autonomous Driving

In view of the above difficulties, future research on LiDAR point cloud denoising for autonomous driving can be carried out in several directions:

Adaptive Hybrid Filtering Framework with Multi-feature Fusion, Combination of Lightweight Deep Learning and Traditional Algorithms, Temporal Information Aided Denoising, LiDAR-Camera Fusion Aided Denoising, Interpretable Denoising Design for Functional Safety.

6. Conclusion

LiDAR point cloud denoising is a critical preprocessing step in the environmental perception of autonomous driving. Road scenarios for autonomous driving involve complex types of noise and impose stringent requirements on algorithm real-time performance, obstacle feature preservation and safety. Traditional statistical filtering, geometric filtering and surface fitting algorithms each have their applicable scope. Deep learning methods show potential for handling complex noise, yet they are currently limited by computing power, datasets and interpretability. Simply pursuing point cloud smoothness is not suitable for autonomous driving scenarios. Future research should focus on constructing denoising schemes that balance real-time performance, target preservation and complex noise suppression. By adopting ideas including multi-feature fusion, temporal correlation, multi-sensor cooperation and lightweight model combination, the robustness of LiDAR perception systems under extreme working conditions such as rain, fog and strong light can be improved to support the safe operation of autonomous vehicles.

References

- [1] Charron N, Phillips S, Waslander S L. De-noising of Lidar Point Clouds Corrupted by Snowfall[C]. 2018 15th Conference on Computer and Robot Vision. IEEE, 2018: 254-261.
- [2] Rusu R B, Cousins S. 3D is here: Point Cloud Library (PCL)[C]//2011 IEEE International Conference on Robotics and Automation. IEEE, 2011: 1-4.
- [3] Qi C R, Su H, Mo K, et al. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation[C]. 2017 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2017: 77-85.
- [4] Yan X Y, Yang J X, Zhu X, et al. Denoising Framework Based on Multiframe Continuous Point Clouds for Autonomous Driving LiDAR in Snowy Weather [J]. IEEE Sensors Journal, 2024, 24 (7): 10515-10527.