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Vehicle Detection and Tracking Using Machine Learning Techniques

1. Introduction

The Vehicle Detection System is a simple solution that promotes pedestrian safety and deters vehicle-pedestrian accidents by activating a sign to alert pedestrians of an approaching vehicle. It is a critical task in the development of autonomous vehicles. Utilizing a variety of sensor modalities, including LiDAR, radar, and cameras, it entails recognizing and localizing vehicles inside a given environment. Vehicle detection and tracking finds its applications in traffic control, car tracking, creating parking sensors and many more. Vehicle detection remains a challenging task due to the complex and dynamic nature of the driving environment.

2. Literature Review

2.1 3D Fully Convolutional Network for Vehicle Detection in Point Cloud

The voxelated grid representation of the point cloud is processed directly in the proposed 3D FCN approach in order to detect cars in point clouds. On benchmark datasets for 3D object detection, the approach has demonstrated state-of-the-art performance.

Result: On the KITTI benchmark dataset for 3D object detection, the suggested technique delivered state-of-the-art results. The suggested method beat prior state-of-the-art techniques on the KITTI dataset, achieving a 91.03% recall rate and a 74.20% average precision for the automobile class. The "Baidu ApolloScape dataset," which includes over 10,000 frames of point cloud data recorded from a moving vehicle. The results showed that the proposed method achieved competitive performance compared to other state-of-the-art methods. Overall, the results show that the proposed 3D FCN technique can perform at the cutting edge on benchmark datasets and is useful for vehicle detection in point clouds.

Limitations: The suggested 3D FCN approach uses a lot of computation resources, particularly during training. The proposed approach might not be workable for real-time applications with constrained processing resources as a result. The research does not examine the expansion of the suggested approach to identify other types of objects, such as bicycles and pedestrians. Uncertainty exists over how well the suggested approach will handle point clouds that are noisy and opaque.

2.2 Joint Monocular 3D Vehicle Detection and Tracking

The proposed method is designed to jointly detect and track vehicles in monocular RGB video sequences. When applied to the KITTI benchmark dataset for 3D object detection and tracking, the approach has demonstrated state-of-the-art performance.

Result: Achieving an average accuracy (AP) of 81.96% for the 3D object detection task on the KITTI dataset, ID F1 score of 86.81% for the object tracking task on the KITTI dataset. On the KITTI dataset, which measures the accuracy of the projected object positions in the following frame, the suggested technique has a tracking accuracy of 89.90% and an occlusion handling accuracy of 91.16%.

Limitations: In this paper, has a few limitations that should be noted. Some of these limitations:

1. Only monocular RGB photos can be used.
2. Only cars are intended to be detected and tracked using.
3. Only the KITTI dataset, which is a frequently used benchmark dataset for autonomous driving, has been utilized to evaluate.
4. It may be difficult to build and deploy the technology in practical applications due to its complexity.

2.3 Cityscapes 3D: Dataset and Benchmark for 9 DoF Vehicle Detection

The research offers a new evaluation framework for existing approaches rather than a brand-new solution for 3D vehicle detection. A new evaluation framework for 3D vehicle detection algorithms in urban settings is offered by the suggested dataset and benchmark. The problem of recognizing and localizing automobiles in intricate urban environments is one that the authors think will spur the development of new techniques.

Result: The publication makes no mention of any performance data for particular 3D vehicle detecting techniques. The suggested Cityscapes 3D dataset is evaluated as a benchmark in the paper, and it quantifies the precision of 3D vehicle detection in terms of 9 degrees of freedom (DoF). The benchmark test demonstrates that based on the particular DoF being examined as well as the particular vehicle class being recognized, the performance of 3D vehicle detection algorithms differs dramatically.

Limitations: The limitations of the paper including a narrow focus on 3D vehicle detection in urban environments, a dataset that is only moderately diverse and only covers European cities, potential errors or inconsistencies in the dataset's annotations, and a lack of in-depth comparison with other datasets and benchmarks for 3D vehicle detection.

2.4 RRPN:RADAR REGION PROPOSAL NETWORK FOR OBJECT DETECTION IN AUTONOMOUS VEHICLES

In this paper, uses radar data to provide region proposals for object detection in autonomous cars. A proposal generator that creates 2D bounding boxes and related confidence ratings as well as a 3D radar feature extractor are both included in the network. The suggested approach is ideally suited for practical applications in autonomous driving because it is built to handle difficult situations like occlusions and poor sight.

Result: The Fast R-CNN object detection results for the two RPN networks on NS-F and NS-FB datasets and the per-class AP results for the NS-F and NS-FB datasets. For the NS-F dataset, RRPN outperforms Selective Search in the Person, Motorcycle and Bicycle classes with a wide margin, while following Selective Search closely in other classes. For the NS-FB dataset, RRPN outperforms Selective Search in all classes except for the Bus class. RRPN was able to generate proposals for anywhere between 70 to 90 images per second, depending on the number of Radar detections, while Selective Search took between 2-7 seconds per image.

Limitations: One of the main limitations of the paper is that the proposed method is designed specifically for radar data, which may not be available in all autonomous driving scenarios. The proposed approach can only provide 2D bounding boxes, which might not be adequate for other applications that need more specific data on the position and orientation of objects in 3D space. Finally, the proposed method does not address the issue of false positives, which can be a significant challenge for object detection in real-world driving scenarios.

3. Result and Analysis

Compare the results of all four methods:

i. The "3D Fully Convolutional Network for Vehicle Detection in Point Cloud" method delivers great precision and real-time performance, making it appropriate for LiDAR-based autonomous vehicle applications.

ii. The "Joint Monocular 3D Vehicle Detection and Tracking" method offers a collaborative architecture that can recognize and track monocular 3D vehicles in real-time without the use of pricey LiDAR sensors. On the KITTI benchmark, the technique delivers state-of-the-art performance.

iii. The "Cityscapes 3D: Dataset and Benchmark for 9 DoF Vehicle Detection" method which provide the benchmark and dataset serve as an invaluable resource for analyzing and contrasting various vehicle detection strategies.

iv. The "RRPN: RADAR REGION PROPOSAL NETWORK FOR OBJECT DETECTION IN AUTONOMOUS VEHICLES" method delivers good performance on radar data by generating candidate regions for object detection using a unique region proposal network.

4. Conclusion

Vehicle detection is a crucial task for autonomous vehicles to operate safely and efficiently. It is a challenging task that requires continued research and development to improve the accuracy, robustness, and efficiency of autonomous vehicles.

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