Sensor Fusion for Car Accident Detection in Taiwan

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Abstract. With the advent of the Autonomous Driving Assist System (ADAS), automobile accidents with L2 / L2+ capability have increased. There is a need to devise an Al-assisted apparatus mounted on construction vehicles or TMA and its method to alert potential head-on vehicles under various weather conditions.

Keywords: Sensor Fusion, Point Cloud, ADAS, Lidar, Camera, Object Detection, Truck-Mounted Attenuator

1 Introduction

With the advent of the Autonomous Driving Assist System (ADAS), automobile accidents with L2 / L2+ capability have increased. According to Freeway Bureau, MOTC, from 2021 to 2023, the number of collisions of construction vehicles or Truck Mounted Attenuator (TMA) in national highway was 79 (2021), 114 (2022) and 128 (2023) respectively, of which 36, 47 and 80 were chased by ADAS-equipped vehicles, of which 6 (16.67%), 26 (55.32%), 53 (66.25%) incidents, ADAS were activated during accidents causing 149 people killed or injured. There is a need to devise an Al-assisted apparatus mounted on construction vehicles or TMA, and its method is to alert potential head-on vehicles under various weather conditions.

2 Method

In this paper, we present a method (Fig. 1) that evaluates the performance of commonly used object recognition models comprising four steps. To begin, we select KITTI dataset[1] that contains 2D images and 3D point cloud. KITTI dataset is an open-source database comprising vehicle field testing data. Secondly, out of all the selected KITTI dataset, we sort out 100 dataset with far-away vehicles. In the third step, we apply on each KITTI dataset 5 different object detection models involving two 2D (Yolo v5x, Yolo v5s) [2] and three 3D (Complex-Yolo v4, complex-Yolo v3, [3] and SFA3D[4]) object detection models. Lastly, probabilities of successful object detection for each object detection model are tabulated as shown in Table 1.

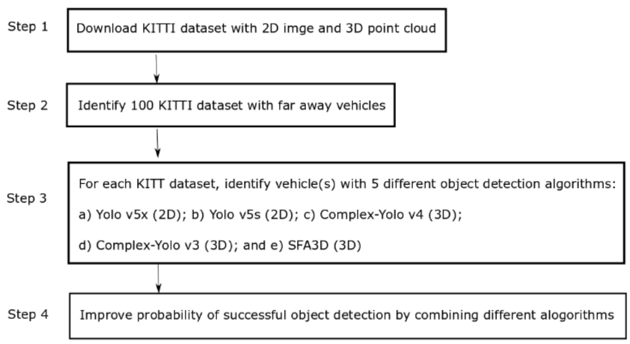

Fig. 1: A method to evaluate the performance of various object detection models on KITTI dataset.

3 Discussion

Table 1 recognition rate on various object detection models

Model	Yolo v5x	Yolo v5s	Complex-Yolo v4	Complex-Yolo v3	SFA3D
Recognition rate	95%	88%	55%	49%	33%

Table 1 shows the recognition rate on various object detection models. Yolo v5x (2D) has the highest recognition rate (95%) among all five models, followed by Yolo v5s (2D) (88%). Both models are based on 2D image object detection models while all three 3D point cloud object detection models have lower recognition rates. From this, we concluded that 2D image object detection models are better schemes to identify objects than 3D point cloud object detection models. Therefore it is apparent that camera performs better than LiDAR to identify objects, and camera is sufficient in object identification.

However, we also found out that out of the 5% that Yolo v5x fails to recognize 5% can be detected by Complex-Yolo v4, and out of the 12% which Yolo v5s fail to recognize 8% can be detected by Complex-Yolo v4. Table 2 shows the recognition rate of combining various object detection models. By combining Yolo v5x and complex-Yolo v4, the recognition rate increases from 95% to 100%, and by combining Yolo v5s and complex-Yolo v4, the recognition rate increases from 88% to 96%. From this, we can conclude that by combining 2D and 3D object detection models, the recognition rate improves; therefore LiDAR is of necessary importance in object detection when combining with camera.

Table 2 recognition rate on combining various object detection models

Model	Yolo v5x + Complex-Yolo v4	Yolo v5s + Complex-Yolo v4
Recognition rate	**100%**	**96%**

4 Conclusion

Sensor fusion for ADAS is the process of combining data from Lidar and camera to improve the accuracy and reliability of a vehicle's perception of its surroundings. In this paper, we present a method to evaluate various 2D and 3D object detection models. The method was tested with 100 field road tests and indicated a 5% to 8% improvement in object detection.

Future Work. The authors expect to install an apparatus comprising a camera and a LiDAR on a TMA placed on a Taiwan highway for further field data collection.

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