Methods

In order to investigate the impact of beams damaging on original model performance. Some points from particular beams may be lossed after long-term use or in certain environments, which may affect the effectiveness of the model trained with intact point clouds dataset. We hope that our experiments can provide some guidance when we need to replace new sensors.

Four models (PartA2, pointPillar, PV-RCNN and SECOND) are evaluated on KITTI dataset, while two models (VoxelNeXt and SECOND-MultiHead) are evaluated on nuScenes dataset. For each combination of model and dataset, the performances are compared two more beams damaged each step. In each step, a specific number of beams are randomly selected and removed. Then, the original pretrained models downloaded from OpenPCDet is used to evaluate on the damaged dataset without fine-tune or retraining. For each step with a particular number of damaged beams, the experiments are conducted 10 times by randomly selected beams and calculated the mean metrics. The psuducode of this process is depicted below:

Alg. 1 Psuducode of beams damaging evaluation

for n\_beam from 2 to total\_beams step 2:

for i in 10:

recover data

dmg\_beam\_list = randomly select n\_beam integers from [0:total\_beams]

remove points in dmg\_beam\_list

reconstruct meta data

evaluate reducted beams dataset

endfor

endfor

calcuate the mean values for each metric

The way of removing beams

For any point in point cloud data, where are the coordinate values on x-axis, y-axis and z-axis respectively, the z-axis span of each beam can be calculated by:

Where the total\_beams is the total number of beams for the sensors which are used for collecting point cloud data, the P is the set of points in a point cloud, and is the z-axis value of the point . The points are assigned into particular beam by the z-coordinate value of the point:

When we “damage” beams in the point cloud, the points belong to dmg\_beam\_list which are randomly selected are filter out from the ordinary ponit cloud and keep the remaining points. Although in reality the distribution of different beams on the z-axis is not of equal length, our approach roughly simulates the real sensor environment and simplifies the algorithm implementation.

Result and discussion

1. The impact of the number of beams damaged

Various models evaluated on KITTI or nuScenes datasets show relatively consistent trends and results. Fig. 1 shows the performance impact of varying numbers of beams damaged for SECOND and pointPillar on KITTI dataset.

A graph of a number of people

AI-generated content may be incorrect.

(I) panel: pointPillar on KITTI; (II) panel: SECOND on KITTI

Figure 1. Models’ performance impact of various number of damaged beams

It reveals that the models suffered a minor performance degradation until 22 beams (about 30%) were removed.

1. The impact of positions

It is observed that when the same number of beams are deleted, the impact of removing beams at different positions on the performance is different. Fig 2 illustrates the varying performance degradation of pointPillar on KITTI while different beams are removed although the same number of beams are deleted.

AS only a small number of beams are removed, the performance degradation of the model is uniformly. However, when a large number of beams are removed, the removal of beams at different positions will have a significant impact on the performance. As shown in Fig 2, when the beams of [33, 8, 53, 49, 4, 40, 47, 15] are removed, the performance decreases more seriously than when the beams of [0, 17, 29, 36, 12, 42, 9, 7] are removed.

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