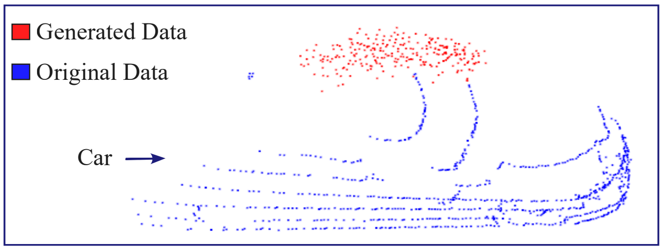
Supplementary Material



Side View

Fig. 1. The result of the dynamic object completion by PF-Net [1]. The car consists of original point clouds colorized (blue) and generated point clouds colorized (red). It can be seen this method only interpolates the local part of the car instead of completing the detailed profile.

I. Overview

In this supplementary material, we first demonstrate the effect of completing point clouds on classification in Section II-A. Besides, we show the ensemble learning classification results of different network combinations in Section II-B.

II. Additional Experiment

A. Point Clouds Completion Experiments

We utilize PF-Net [1] to interpolate point clouds of dynamic objects in a single scan before using other classification networks. The interpolation effect is shown in Fig. 1. According to the results in Table I, this method still cannot meet the classification requirements. We believe the reason is that this method is mainly applied to the occlusion scene of dense point clouds. That is to say only some parts of the object have blind spots, while the other point clouds are detailed enough to obtain a better interpolation effect. Therefore, it is once again verified that the feature-level fusion method adopted by PointLE provides more sufficient information in the classification of low-resolution data.

B. Ensemble Learning Performance

Table II shows the ensemble learning classification results of different network combinations. During the experiment, we select one of the above types of point cloud classification networks for association. According to the results, the combination of PointNet++ [6], 3DmFV [4] and DGCNN [5] has a relatively significant classification ability for motorcycles. We think that it is due to PointNet++ [6] and DGCNN [5] outperforming other networks in classifying low-resolution point clouds of motorcycle, thus showing the highest overall classification accuracy.

TABLE I
Performance of different point cloud classification networks on our proposed dataset. Best results in bold.

	Car	Pedestrian	Motorcycle	OA
PointNet++ [6]	6.65	0.6	5.37	4.52
3DmFV [4]	43.87	78.443	0	41.13
DGCNN [5]	**99.58**	0	0.6	41.83
RSCNN [2]	28.90	12.57	0.30	15.83
PointASNL [7]	32.43	20.06	0.9	19.65
PointConv [3]	31.19	24.25	0	20.09
PF-NET [1] + PointNet++ [6]	16.22	-	2.39	10.54
PF-NET [1] + 3DmFV [4]	14.55	-	0	8.58
PF-NET [1] + DGCNN [5]	27.23	-	0.3	16.18
PointLE	96.06	**86.86**	**88.72**	**91.48**

TABLE II
Performance of different network combinations on our proposed dataset. A refers to PointASNL [7], B to PointNet++ [6], C to PointConv [3], D to 3DmFV [4], E to RSCNN [2] and F to DGCNN [5]. Best results in bold.

	Car	Pedestrian	Motorcycle	Overall Accuracy
A + C + F	91.83	85.59	76.92	86.26
A + D + F	96.06	86.44	75.90	88.17
A + E + F	96.06	**88.98**	81.54	90.33
B + C + F	**97.46**	84.32	80.51	89.31
B + E + F	97.18	87.29	78.46	89.57
B + D + F	96.06	86.86	**88.72**	**91.48**

References

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