Variant Grid Size of PointNet++ for Point Cloud Semantic Segmentation

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***Abstract*— In this paper, a multi-scale grid based PointNet++ is proposed for 3D semantic segmentation. The proposed method decomposes a point cloud into multi-scale grids firstly. PointNet++ is adopted as the classifier that is trained with those multi-scale grids. The proposed algorithm also prunes and optimizes the obtained models by AdamW. In our simulation, the objects are classified into thirteen types, including floor, table, chair, etc. Experimental results show that the proposed method has good performance in mIoU and mAcc up to 54.1% and 64.9%.**

I. Motivation

Point Cloud Semantic Segmentation (PCSS) is a method that addresses this by working directly with regularly or irregularly distributed points in three-dimensional space, in contrast to the uniformly spaced pixels in 2D images. While many deep learning methods have been proposed for semantic segmentation in images, adapting them for PCSS often involves projecting the three-dimensional point cloud into images. However, this can lead to the loss of critical 3D features like depth information and normal vectors of points. Recently, novel deep learning networks such as PointNet [1] and PointNet++ [2] have been introduced to directly convolve 3D point clouds within deep learning networks. In this study, we employ PointNet++ as the foundational deep learning network, enhancing it through the addition of a multi-scale area partition and pruning optimization.

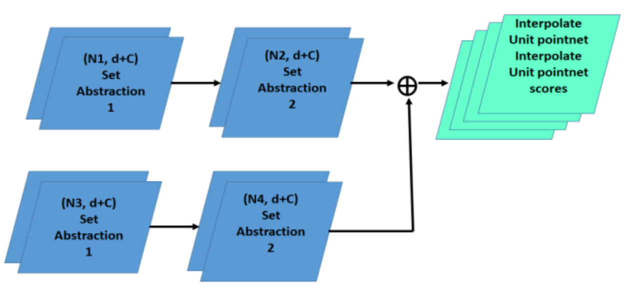
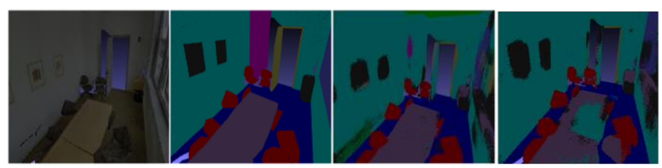


Fig 1. The proposed Variant-Grid based PointNet++.

II. Variant Grid Size of PointNet++

In PointNet++, scene data is separated along the x and y axes with the size of 1m×1m×H. For PCSS, the block size is too tiny that breaks the object's geometric structure and easily causes wrong segmentation. Based on the conventional PointNet++, a point cloud scene is separated along the x and y axes with the sizes of 1m×1m×H and 2m×2m×H into 2 type blocks. Two block sets are in the small block set P^1 and in the large block P^2 as shown in Fig. 1. The proposed algorithm firstly uses the P^1 to train the PointNet++ and reserve these weights and parameters. Then, the P^2 is used to refine the PointNet++. Since it is time-consuming to process all points in a block, a FPS (farthest point sampling) downsampling scheme was proposed in PointNet++.

The experimental data uses the S3DIS which has 13 types of objects, including ceilings, floors, walls, beams, columns, windows, doors, tables, chairs, sofas, bookcases, boards, and clutter. The experiment uses Areas 1, 2, 3, 4, and 6 as the training data and Area 5 as the test set. Compared to PintNet++ as shown in Tab. 1 and Fig. 2, for objects with less complicated spatial geometry, such as ceiling, floor, and walls, the results of the segmentation of IoU are not much different. In contrast, the results of windows, bookcases, and board are significantly different, at 7%, 16.6%, and 12.1%. Based on the above experimental results, the method proposed in this paper can effectively solve the problem of semantic segmentation errors caused by region cutting and improve the overall accuracy.



(a) (b) (c) (d)

Fig 2. (a) raw. (b) ground truth. (c) the proposed method. (d) PoimtNet++.

TABLE I. Compare with other algorithm results

Method	Mean IoU	mAcc	oAcc
PointNet	47.6%		78.5%
RSNet	51.9%	59.4%	
G + RCU	49.7%		81.1%
Ours	**54.1%**	**64.9%**	**83.1%**

References

[1] Charles R. Qi, Hao Su, Mo Kaichun, Leonidas J. Guibas, “Pointnet: Deep learning on point sets for 3d classification and segmentation”, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 652–660, 2017.

[2] Charles R. Qi, Li Yi, Hao Su, Leonidas J. Guibas, “Pointnet++: Deep hierarchical feature learning on point sets in a metric space” in *Advances in Neural Information Processing Systems*, pp. 5099–5108, 2017.

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