ABSTRACT

This paper studies the 3D instance segmentation problem, which has a variety of real-world applications such as robotics and augmented reality. Since the surroundings of 3D objects are of high complexity, the separating of different objects is very difficult. To address this challenging problem, we propose a novel framework to group and refine the 3D instances. In practice, we first learn an offset vector for each point and shift it to its predicted instance center. To better group these points, we propose a Hierarchical Point Grouping algorithm to merge the centrally aggregated points progressively. All points are grouped into small clusters, which further gradually undergo another clustering procedure to merge into larger groups. These multi-scale groups are exploited for instance prediction, which is beneficial for predicting instances with different scales. In addition, a novel MaskScoreNet is developed to produce binary point masks of these groups for further refining the segmentation results. Extensive experiments conducted on the ScanNetV2 and S3DIS benchmarks demonstrate the effectiveness of the proposed method. For instance, our MaskGroup achieves a 66.4% mAP with the 0.5 IoU threshold on the ScanNetV2 test set, which is 1.9% higher than the state-of-the-art method.

Index Terms— Point Cloud, 3D Instance Segmentation, Hierarchical Point Grouping

1. INTRODUCTION

To tackle the 3D instance segmentation problem, a series of detection-based methods [1,2] are explored for predicting 3D bounding boxes from the observed point data. These methods produce a mask to obtain the instance inside the bounding box. Moreover, the embedding-based approaches [3,4,5,6,7] learn a spatial or feature embedding vector for each point, and utilize the clustering algorithm to obtain the instance. For example, Jiang et al. [6] proposed PointGroup, an end-to-end bottom-up architecture which groups the 3D points by considering the void space between objects. PointGroup first learns a space offset to move the object points towards their instance centers. Then, all points are clustered according to the distance of the blank space. Two points within a certain distance are merged into one group. However, it is hard to decide on a specific single distance to meet a variety of situations, because objects are lying from each other with different distances (As shown in Fig. 1). Additionally, since the objects in the 3D space are of high complexity, noisy points are usually existing in the grouped instances, which hinders the performance.

To enhance the performance of 3D instance segmentation, we present a masked hierarchical point grouping approach, namely MaskGroup. In practice, we first learn the offsets and semantic labels for the input 3D points. Since the sizes of observed 3D objects in the given environment are often various, we then propose a Hierarchical Point Grouping (HPG) algorithm for carefully merging the points of each object progressively. Specifically, a small gap is utilized to cluster points into several initial groups. Then we exploit progressively enlarged distances to merge small groups from the previous step into larger groups. The clustered groups obtained in different steps contain multi-scale information which can be further used for the final instance predictions with better results.

In addition, the clustered points obtained using the hierarchical grouping may have some noisy points for each instance due to the complex environment of 3D point data. To effectively refine and evaluate these groups, we propose a tiny MaskScoreNet to mask out the background points via a mask branch and simultaneously evaluate the quality of each mask via a score branch. The mask branch predicts a binary mask for the points in a group to distinguish the actual points in object instances. The score branch further predicts a binary
quality score for the masked group.

Our contributions are summarized as follows: (1) In order to make full use of the multi-scale information of 3D instances, we propose a Hierarchical Point Grouping algorithm to merge the points into different groups progressively. (2) We proposed a novel MaskScoreNet to refine the clustered groups, which produces binary point masks for all grouped instances to eliminate noisy points and predicts confidence scores for final instances, simultaneously. (3) The proposed method, i.e., MaskGroup, achieves state-of-the-art results on the challenging ScanNetV2 and S3DIS benchmarks, demonstrating its effectiveness for 3D instance segmentation.

2. RELATED WORK

3D instance segmentation for large scale point clouds has attracted great research interest in recent years. Similar to the detection-based 2D instance segmentation methods, Kundu et al. [10] proposed 3D-RCNN, which builds upon Faster R-CNN to predict 3D bounding boxes from point clouds. Yang et al. [1] proposed BoNet, which predicts the box from the global point features and produces a point mask for the bounding box.

The embedding-based idea in 2D instance segmentation is also extended into the 3D domain. Wang et al. [11] proposed to learn the neighborhood relationship for each pair of points and access the instance according to similar relations. Several methods [3, 4] extended the 2D embedding idea to point cloud, which encourage points in the same instance to lie close in the embedding space, and adopt mean-shift algorithm for clustering. Qi et al. proposed VoteNet [12], which learns shift vectors to move points towards their instance centers and can be seen as a kind of spatial embedding. Engelmann et al. [5] proposed to learn a spatial embedding of points and group points within a certain distance into one group, and use learned feature embedding to merge the group. Jiang et al. [6] proposed PointGroup, which also learns the spatial embedding, but groups the points connected with each other into an instance. OccuSeg [7] utilizes both spatial and feature embedding to progressively group the point into an instance.

The hierarchical approach is also used in 3D scene analysis [13, 14], which is mainly utilized for bottom-up context aggregation for hierarchical scene graph. Our paper proposes the hierarchical grouping and masking to capture multi-scale information for instance prediction, which is quite different from the above mentioned papers.

3. THE PROPOSED MASKGROUP

3.1. Method Overview

3D instance segmentation task aims to separate different objects in 3D scene and predict the semantic label of each instance. Our proposed method is depicted in Fig. 2.

The input 3D scene is represented as a point cloud $P$ with $N$ points in total, i.e., $P = \{p_i\}_{i=0}^N \in \mathbb{R}^{N \times k_0}$, where $k_0$ is the channel number of point feature such as the point location $\mu_i = (x_i, y_i, z_i)$ and color $q_i = (r_i, g_i, b_i)$. Then a voxel-based backbone network [15] is applied to extract the 3D features $F^b = \{F^b_i\}_{i=0}^N \in \mathbb{R}^{N \times k_1}$, where each point $i$ has a corresponding feature vector $F^b_i \in \mathbb{R}^{k_1}$, $k_1$ is the feature length. After that, two sub-branches are exploited to obtain the semantic labels $S = \{s_i\}_{i=0}^N \in \mathbb{R}^N$ and the offset vectors $D = \{d_i\}_{i=0}^N \in \mathbb{R}^{N \times 3}$, where $d_i = (\Delta x_i, \Delta y_i, \Delta z_i)$. Adding the offsets to original coordinates, we obtain the estimated object centroids $O = \{o_i\}_{i=0}^N \in \mathbb{R}^{N \times 3}$, where $a_i = \mu_i + d_i$.

In order to separate objects with the same semantics, we explore the void space in $O$ or $P$. Given a clustering radius $r_1$ manually, we can merge the points within $r_1$ into $|G^1|$ groups $G^1 = \{G^1_i\}_{i=0}^{|G^1|}$. However, it is difficult to select a proper $r_1$ that works well for instances with different scales. To this end, we proposed a hierarchical point grouping algorithm to cluster the points via a multi-scale scheme. First, a small radius is utilized to cluster points into several small groups. Then we exploit progressively enlarged clustering radius to merge small groups into larger groups for $H$ steps. The clustered groups $G = \{G^1 \cup \ldots \cup G^H\} = \{G^i\}_{i=0}^{|G|}$ obtained in different steps contain multi-scale information and are further used for final instance prediction.

However, the roughly clustered groups $G$ may contain some noisy points. We then propose a MaskScoreNet to refine and evaluate these groups. For each group $G_i$, MaskScoreNet predicts a binary mask $M_i$ to eliminate noisy points in this group and also outputs a score $E_i$ to indicate the confidence score of this masked group.

In inference stage, the groups $G = \{G^i\}_{i=0}^{|G|}$, masks $M = \{M_i\}_{i=0}^{|G|}$, and their corresponding scores $E = \{E_i\}_{i=0}^{|G|}$ are fed into the Non Maximum Suppression (NMS) module to obtain final instance predictions.

3.2. Backbone Network Architecture

The backbone network consists of a feature extraction network and two sub-branch networks for semantic prediction and object centroid regression. The feature extraction network takes points $P$ as input and obtains point features $F^b$.

A multi-layer perceptron (MLP) is applied to produce semantic scores $B = \{b_i\}_{i=0}^N \in \mathbb{R}^{N \times C}$ for the $N$ points, where $C$ is the number of semantic classes. The semantic labels $S = \{s_i\}_{i=0}^N \in \mathbb{R}^N$ are the classes with the highest score. This semantic branch is supervised by a semantic segmentation loss $L_{sem} = \frac{1}{N} \sum_{i=1}^N H(b_i, s_i)$, where $s_i$ is the ground truth semantic label of point $i$, $H(\cdot)$ represents the cross entropy function.

Another MLP encodes $F^b$ to produce 3-dimensional offset vectors $D$ for the $N$ points. This centroid branch is super-
vised using the following $L_1$ regression loss:

$$
\mathcal{L}_{\text{off}} = \frac{1}{|I|} \sum_{i=1}^{|I|} \frac{1}{N_i} \sum_{i=1}^{N_i} |d_i + \mu_i - \hat{o}_i|,
$$

(1)

where $\hat{o}_i$ is the ground truth centroid of $i$-th point that belongs to $i$-th instance, $N_i$ is the number of points in the $i$-th instance and $|I|$ is the number of ground truth instances.

To ensure that the points are moving towards their instance centroids, following [16], we adopt a direction loss $\mathcal{L}_{\text{dir}}$ to constrain the direction of predicted offset vectors:

$$
\mathcal{L}_{\text{dir}} = -\frac{1}{|I|} \sum_{i=1}^{|I|} \frac{1}{N_i} \sum_{i=1}^{N_i} |d_i| \cdot \left| \frac{\hat{o}_i - \mu_i}{|\hat{o}_i - \mu_i|} \right|,
$$

(2)

where $\mu_i$ represents the 3D position of the $i$-th point of the $i$-th instance. With the learned offset vector $d_i$, we can obtain the estimated object centroid $o_i = \mu_i + d_i$.

3.3. Hierarchical Point Grouping

With spatial information like 3D point positions and estimated object centroids, we can cluster points into different groups. Traditional methods for instance clustering in 3D instance segmentation rarely consider the multi-scale information, e.g., PointGroup [6] utilized a single radius threshold for point grouping, which is insufficient for capturing information for instances with different scales. Multi-scale information has been widely used in 2D object detection and instance segmentation [17] [18]. And some hierarchically ideas are used for analyzing 3D scenes [19] [20]. However, it is still less explored for 3D instance segmentation.

To this end, we propose a hierarchical point grouping algorithm that takes multiple spacing distance into consideration. Specifically, we take the groups $G^{h-1}$ found in $(h-1)^{th}$ round as input. Especially, when $h = 1$, each group in $G^0$ is a single point. In the $1^{st}$ round, we use a small spatial distance $r_1$ to group the points. If two points have the same semantics and the distance between them is smaller than $r_1$, then we put them into the same group. At the end of the $1^{st}$ round, we obtain a set of initial groups $G^1 = \{G^1_i\}_{i=0}$ with a number of $|G^1|$.

In the next round, we take groups $G^1$ in the first round as inputs. For two groups $G_i^1$ and $G_j^1$ with the same semantics, we merge them into a new group if the distance between two groups is smaller than radius $r_2$. All point within a group has the same semantics, so the semantic label of a group $G_i$ is defined as the label of its point. We denote the semantic label of group $G_i$ as $S_i(G_i)$. The distance $|G_i, G_j|$ between group $G_i$ and $G_j$ is calculated as the minimum distance between points in these two groups. In this way, we obtain some new groups $G^2 = \{G^2_i\}_{i=0}$ with a number of $|G^2|$.

We repeat this process for $H$ times. For each round, we have $r_{h-1} < r_h$, so we can merge groups in last round into larger groups gradually. We collect the groups in all rounds and eliminate the groups in which the number of its points is fewer than $N_g$, finally get $G = \{G^1 \cup ... \cup G^H\}$. These point groups obtained in different stages contain clustering information for different scales. For example, since $G^1$ is clustered with a small radius, point group in $G^1$ can better segment instances with small scales. Meanwhile, larger instances are better segmented in $G^H$. Point groups with multiple scales $G$ will be exploited for final instance prediction, which is beneficial for more accurate 3D instance segmentation.

3.4. MaskScoreNet

After the hierarchical point grouping step, we obtain a set of groups $G = \{G_i\}_{i=0}$, where $|G|$ is the total number of groups collected from all grouping steps. Group $G_i$ consists of $N_g$ points, i.e., $G = \{p_j\}_{j=0}^{N_g}$ (we omit $i$ for simplicity). Some groups in $G$ are well grouped and some contain inaccurate points. Therefore, we design a novel MaskScoreNet to refine the groups $G$ and also evaluate the quality of each group.

Recall that, each point $i$ has a corresponding backbone feature vector $F^b_i \in \mathbb{R}^{k_1}$. So, for a group $G = \{p_j\}_{j=0}^{N_g}$, we can create a group feature $F^g \in \mathbb{R}^{N_g \times k_2}$ by selecting the

![Fig. 2. The overall architecture of our proposed MaskGroup.](image-url)
corresponding point features from $F^m$.

The group $G$ assigned with group feature $F^g$ is fed into a small U-Net to better aggregate the group information, the output features $F^{m}$ are fed into a MLP (mask branch) to predict a binary mask $M = \{ m_j \}_{j=0}^{N_g}$ (we omit $i$ for simplicity), where $m_j$ is the confidence score for $j$-th point in $G$, which indicates the probability of this point belonging to $G$. The mask loss function for all groups is formulated as:

$$L_{\text{mask}} = -\frac{1}{|G|} \sum_{j=0}^{N_g} \sum_{i=0}^{N} (\hat{m}_i \log(m_i) + (1 - \hat{m}_i) \log(1 - m_i)),$$

where $\hat{m}_i$ is the ground-truth mask value corresponding to $m_i$. To obtain the ground-truth mask, we first found out the ground-truth instance $\hat{I}_g$ which has the largest Intersection Union (IoU) between cluster $G$:

$$\hat{g} = \arg\max_{\{\text{IoU}(G, I_i) \mid I_i \in \hat{I}\}},$$

where $\hat{I}$ is a set of ground-truth instances. Then we can get the value of $\hat{m}_i$:

$$\hat{m}_i = \begin{cases} 1, & \text{if point } i \text{ in both } G \text{ and } \hat{I}_g \\ 0, & \text{otherwise} \end{cases}.$$

To evaluate the quality of the masked groups, we propose a MaskPooling layer that uses the predicted mask $M$ to average pool the group feature $G$ across the points, and obtain a feature vector $F^e$ to represent the masked group. After that, a score branch (MLP and Sigmoid) is utilized to predict the quality score $E$ for the masked group based on $F^e$. The score loss is defined as:

$$L_{\text{score}} = -\frac{1}{|G|} \sum_{i=1}^{N} (\hat{E}_i \log(E_i) + (1 - \hat{E}_i) \log(1 - E_i)),$$

where $\hat{E}_i$ is the ground-truth score between 0 and 1 for $M_i$, which is decided by the IoU between $M_i$ and its corresponding ground-truth instances [21][22].

3.5. Network Training

We train the whole framework in an end-to-end manner with the total loss as:

$$L = L_{\text{sem}} + L_{\text{off}} + L_{\text{dir}} + L_{\text{mask}} + L_{\text{score}}.$$

4. EXPERIMENTS

4.1. Experimental Setting

We evaluate the proposed method on two large scale 3D indoor scene datasets, i.e., ScanNetV2 [32] and S3DIS [28]. ScanNetV2 contains 1613 scenes with 18 object categories, in which all points are annotated with semantic and instance labels. S3DIS [28] contains 6 sub-datasets and has 271 scenes in total. All points are annotated with instance labels and one of the 13 semantic labels. In the data processing part, we set the voxel size to 0.02m. We randomly crop the scene to make sure the number of points in each scene is equal to or fewer than 250k. In the inference phase, all scenes are fed into the network without cropping. In the hierarchical point grouping part, we set the clustering radii $r$ as 0.01m, 0.03m, and 0.05m in different stages. We use the same cluster radius setting for ScanNetV2 and S3DIS datasets. We have tried to use a different combinations of clustering radii for S3DIS, but observe no performance improvement. It demonstrate that our method has good generalization performance on different datasets. The minimum cluster point number $N_g$ is empirically set as 50. The threshold of IoU for NMS is set to 0.7. The proposed method is trained via Adam optimizer with a base learning rate of 0.001.

4.2. Comparisons with state-of-the-arts

Instance Segmentation on ScanNetV2 [32]. We compare our MaskGroup on the testing set of ScanNetV2 with a number of prior methods, including 3D-BoNet [1], 3D-MPA [5], PointGroup [6], GICN [25], OccuSeg [7], DyCo3D [26] and PE [27]. We report the results of AP$_{50}$, AP$_{25}$, and AP of different models in Table 1. Our MaskGroup achieves the highest AP$_{50}$ score of 66.4% and outperforms all prior methods. Specifically, the AP$_{50}$ score of our method is 2.6% and 2.3% higher than GICN [25] and DyCo3D [26], respectively. Moreover, our MaskGroup obtains 1.9% higher AP$_{50}$ than the for-

| Methods          | Publication | AP$_{50}$ | AP$_{25}$ |
|------------------|-------------|-----------|-----------|
| 3D-SIS [2]       | CVPR’19     | 16.1      | 38.2      | 55.8     |
| SALoss [23]      | IROS’20     | 26.2      | 45.9      | 69.5     |
| PanopticFusion [24] | IROS’19     | 21.4      | 47.8      | 69.3     |
| 3D-BoNet [1]     | NeurIPS’19  | 25.3      | 48.8      | 68.7     |
| 3D-MPA [5]       | CVPR’20     | 35.5      | 61.1      | 73.7     |
| OccuSeg [7]      | CVPR’20     | 44.3      | 63.4      | 73.9     |
| PointGroup [6]   | CVPR’20     | 40.7      | 63.6      | 77.8     |
| GICN [25]        | arXiv’20    | 34.1      | 63.8      | 78.8     |
| DyCo3D [26]      | CVPR’21     | 39.5      | 64.1      | 76.1     |
| PE [27]          | CVPR’21     | 39.6      | 64.5      | 77.6     |
| MaskGroup (Ours) |             | 43.4      | 66.4      | 79.2     |

Table 1. Quantitative results on the ScanNetV2 testing set in terms of AP, AP$_{50}$ and AP$_{25}$.

| Methods          | Area5 | mPrec | mRec | 6-Fold | mPrec | mRec |
|------------------|-------|-------|------|--------|-------|------|
| GICN [25]        | 61.5  | 43.2  | -    | 68.5   | 50.8  |
| PointGroup [6]   | 61.9  | 62.1  | -    | 69.6   | 69.2  |
| OccuSeg [7]      | 62.5  | 49.0  | -    | 68.4   | 53.7  |
| IMFin [9]        | 61.3  | 48.5  | -    | 67.2   | 51.8  |
| DyCo3D [26]      | 64.3  | 64.2  | -    | -      | -     |
| ICM-3D [31]      | 57.4  | 45.0  | -    | 65.9   | 49.8  |
| MaskGroup (Ours) | 65.0  | 62.9  | 64.7 | 69.9   | 66.6  | 69.6 |

Table 2. Comparisons with state-of-the-arts on S3DIS [28].
Table 3. Ablation results using different modules on the ScanNet v2 validation set.

| Score  | HPG | Mask | MaskPool | AP   | AP50 | AP25 |
|--------|-----|------|----------|------|------|------|
| A ✓✓   | 39.9| 58.9 | 70.3     |
| B ✓✓✓  | 39.2| 58.3 | 71.5     |
| C ✓✓✓✓ | 40.4| 59.8 | 70.5     |
| D ✓✓✓✓ | 39.4| 61.1 | 72.7     |
| E ✓✓✓✓ | 41.9| 62.7 | 73.6     |

Table 4. Ablation results using different grouping radii.

| Hierarchical Grouping | AP   | AP50 | AP25 |
|-----------------------|------|------|------|
| (0.01)                | 37.5 | 59.4 | 71.0 |
| (0.03)                | 41.5 | 61.9 | 72.3 |
| (0.05)                | 41.4 | 61.3 | 72.0 |
| (0.01, 0.03)          | 41.5 | 62.6 | 72.9 |
| (0.01, 0.03, 0.05)    | 41.9 | 62.7 | 73.6 |
| (0.01, 0.03, 0.05, 0.07) | 42.1 | 63.0 | 73.8 |
| (0.01, 0.03, 0.05, 0.07, 0.09) | 42.2 | 63.3 | 74.0 |
| (0.01, 0.03, 0.05, 0.07, 0.09, 0.11) | 42.0 | 63.3 | 74.2 |

Impacts of Multi-scale Groups. By using hierarchical point grouping, we could make use of clusters in multi-scales for final predictions. Here we elaborate the effectiveness of this multi-scale strategy. Table 4 shows the results of using groups obtained with different clustering radii. If we use only one clustering radius for grouping, the hierarchical grouping algorithm degrades into a common single-step algorithm. A small grouping radius $r=0.01m$ can mainly group small objects that are closely located. It achieves the AP/AP50/AP25 scores of 37.5%/59.4%/71.0%, which are not satisfactory, because it will drop many points in an object and makes the segmented instances incomplete. The radius of $r=0.03$ can achieve the best performance among all single radius settings. With a larger radius $r=0.05$, the results begin to decrease as the large radius will cause some over-grouped instances.

Even though $r=0.01$ can not perform well as other two larger radii, combining the groups obtained by $r=0.01$ and $r=0.03$ takes advantage of both scales, which results in better performance than single scale setting, i.e.62.6% vs (59.4%, 61.9%) AP50 scores. Combining all multi-scale groups obtained with $r=\{0.01, 0.03, 0.05\}$, it achieves better performance. With even more multi-scale groups, i.e., 4 to 6 scales, the performance will be further improved and begin to converge. These results demonstrate that our hierarchical grouping algorithm can take advantage of multi-scale information to obtain better 3D instance segmentation results. Considering the trade-off between accuracy and complexity, we choose $r=\{0.01, 0.03, 0.05\}$ in our model.
5. CONCLUSION

In this paper, we propose a novel framework named MaskGroup for accurate 3D instance segmentation. To better group the points in 3D scenes, we propose a Hierarchical Point Grouping algorithm to merge them progressively into groups with different distances. These multi-scale groups are then exploited for instance prediction, which is beneficial for predicting instances with different scales. What’s more, we propose a MaskScoreNet to produce binary point masks for all grouped instances and effectively eliminate noisy points from the instances. MaskGroup achieves 66.4% AP$_50$ on the testing set of ScanNetV2 and outperforms prior methods, demonstrating the effectiveness of our proposed method.

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Table 5. 3D instance segmentation results on ScanNetV2 testing set with AP50 scores. Our method yields the highest average AP50 performance among all existing methods published in the literature.
Fig. 4. Visualization of some failure cases.

Fig. 5. Comparisons of PointGroup and our proposed MaskGroup.

Fig. 6. Visualization of the hierarchical point grouping and the mask prediction.