Dense Supervision Propagation for Weakly Supervised Semantic Segmentation on 3D Point Clouds

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Abstract—Semantic segmentation on 3D point clouds is an important task for 3D scene understanding. While dense labeling on 3D data is expensive and time-consuming, only a few works address weakly supervised semantic point cloud segmentation methods due to the labeling cost by learning from simpler and cheaper labels. Meanwhile, there are still huge performance gaps between existing weakly supervised methods and state-of-the-art fully supervised methods. In this paper, we propose Dense Supervision Propagation (DSP) to train a semantic point cloud segmentation network with only a small portion of points being labeled. We argue that we can better utilize the limited supervision information as we densely propagate the supervision signal from the labeled points to other points within and across the input samples. Specifically, we propose a cross-sample feature realocating module to transfer similar features and therefore reallocate supervision signals from the labeled points to other points within and across point cloud samples. We conduct extensive experiments on public datasets S3DIS and ScanNet. Our weakly supervised method with only 10% and 1% of labels can produce competitive results with the fully supervised counterpart.

Index Terms—3D point cloud, weakly supervised learning, semantic segmentation.

I. INTRODUCTION

With the development of 3D sensors, and point cloud data are playing important roles in multimedia applications. Semantic point cloud segmentation is vital for 3D scene understanding, which provides fundamental information for further applications like augmented reality and mobile robots. Recent developments in deep learning-based point cloud analysis methods have made considerable progress in 3D semantic segmentation [1], [2], [3], [4]. However, 3D semantic segmentation requires point-level labels, which are much more expensive and time-consuming than the labels of 3D classification and detection tasks.

Recently, in the realm of circuits and systems for video technology, many efforts have been put into weakly supervised semantic segmentation (WSSS) [5], [6], [7] on 2D images and achieved remarkable results. However, despite dense labeling on point clouds being even more expensive than dense image labeling, only a few works have been done on 3D WSSS [8], [9] and yet there remains a huge performance gap with the state-of-the-art fully supervised methods.

The existing 3D WSSS methods formulate the problem in different directions. Reference [10] utilize dense 2D segmentation labels to supervise the training in 3D by projecting the 3D predictions onto the corresponding 2D labels. However, each 3D sample is projected to 2D in several views and each projected 2D image needs pixel-level labeling. Thus, this method still requires a large amount of manual labeling. Reference [11] proposes to generate pseudo point-level label using 3D class activation map [12] from subcloud-level annotation, which is similar to the 2D WSSS methods using image-level labels. Reference [13] directly trains a point cloud segmentation network with 10 times fewer labels, which is close to point supervision [14] and scribble supervision [15], [16] in 2D WSSS methods. We adopt the 3D WSSS setting from [13] that takes only a small fraction of points to be labeled.

In this study, our primary objective is to optimize the use of scarce annotations by intensifying the dense propagation of supervision signals from labeled to unlabeled points. Initially, we employ the cutting-edge point cloud segmentation network, KPConv [4], as our foundational model. To overcome the aforementioned challenges, we introduce a novel two-stage training strategy, incorporating both our cross-sample feature reallocating module (CSFR) and the intra-sample feature reallocating (ISFR) module.

As depicted in Figure 1, the first stage of our training process draws inspiration from [17], [18], and [19]. Here, we select two samples with at least one overlapping class to serve as an input pair. The CSFR module is designed to facilitate the transfer of analogous features between these two

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samples. Unlike methods in [17], [18], and [19] which directly incorporate warped features from one sample to detect more active regions, we opt to reconstruct the features using the point correlation of the data pair, instead of mere addition. Consequently, each point in the restructured feature emerges as a weighted aggregate of all points from its counterpart sample. We then deploy a cross-regularization loss to gently enforce weak supervision upon these reallocated features. This approach enables us to effectively channel the gradients, allowing for a dense propagation of supervision from labeled points in one sample to their unlabeled counterparts in the other.

In the subsequent training stage, our ISFR module facilitates the transmission of supervision from labeled to unlabeled points within each individual sample, once again utilizing feature reallocation based on point correlation. This ensures that supervision is densely transmitted from labeled to unlabeled points within a given sample. Given the potential for non-overlapping classes between input pairs, which could introduce noise during the supervision propagation, our strategy involves training the network using the CSFR module to first acquire general representations. This is followed by employing the ISFR module for fine-tuning in the latter stage. As both modules function based on point correlation, supervision signals are effectively propagated to unlabeled points bearing resemblance in features to labeled ones. It is imperative to note that the primary role of these two modules is to enhance the training of the basic network. They are redundant for generating the final segmentation predictions during the inference phase. These modules indirectly steer the training of the basic segmentation network and remain unused during testing.

Compared to MulPro [8] and MP [9] which focus on exploring the information within the current input sample, our methods leverage to explore the information that contains inter-sample to find more supervision cues for weakly supervised 3D semantic segmentation task.

In summary, our contributions are:

- We propose a cross-sample feature reallocation module to reconstruct features and re-route gradients across the input pair based on point correlation. Hence, the supervision signals from labeled points can be propagated to unlabeled points across samples.
- We propose an intra-sample feature reallocation module to reallocate features within each sample based on point correlation. Then, the supervision signals can be propagated from labeled points to unlabeled points within each point cloud sample.
- We propose a two-stage training strategy so the cross-sample feature reallocation module and the intra-sample feature reallocation module can both contribute to the performance without interfering with each other.
- Our weakly supervised methods with only 10% and 1% of the points being labeled can produce compatible results with their fully supervised counterpart in S3DIS and ScanNet datasets.

II. RELATED WORKS

A. Semantic Segmentation on 3D Point Clouds

There are three categories for 3D semantic segmentation methods: projection-based methods, voxel-based methods and point-based methods. Multi-view projection-based methods [20], [21], [22] project the 3D data into 2D from multiple viewpoints, therefore they can easily process the projected data on 2D convolution networks. However, these methods suffer from occlusion, view-point selection, misalignment, and other defects that may limit the performance. Voxel-based methods like Submanifold Sparse Convolution [3], MinkowskiNet [2] and Occuseg [1] first quantize the point cloud data into voxels and perform sparse 3D convolution on the voxels. These methods can often achieve good segmentation performance but severely suffer from heavy memory and time consumption. Point-based methods directly take raw point cloud data as network input. PointNet [23] and PointNet++ [24] process point cloud data with stacked MLPs. DGCNN [25] proposes EdgeConv to capture local geometry by dynamically generating graphs for points with their neighbors. PointCNN [26] and PointConv [27] formulate convolution operations in 3D using KNNS for each point. KPConv [4] uses filters and kernel points in Euclidean space to formulate convolution operations with distances of points within the filter.

B.Weakly Supervised 2D Semantic Segmentation

Most 2D WSSS methods use image-level labels. Based on class activation map(CAM) [12], many methods [17], [18], [19], [28], [29], [30], [31], [32], [33] refines the CAM generated from a classification network to generate pseudo-pixel-level labels. Then, segmentation networks are trained using the pseudo-pixel-level labels. Besides the image-level label, other kinds of weak labels like point supervision [14] and scribble supervision [15], [16] which is similar to the weak setting in this work. Points and scribble supervision methods usually constrain the unlabeled points using label consistency with local smoothness.
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III. APPROACH

As illustrated in Figure 2, we propose a two-stage training strategy. In the first training stage, we train the basic segmentation network with the cross-sample feature reallocating module. And in the second stage, we train the basic segmentation network with the intra-sample feature reallocating module. We will explain each module in detail.

A. Basic Segmentation Network

The basic component of our method is a point cloud segmentation network. We take the state-of-the-art deep learning architecture Kernel Point Convolution (KPConv) [4] segmentation network as our backbone network. We denote each input point cloud sample as \( P_i \). We encode each input point cloud sample as \( Z_i \) and \( Z_{m} \). A bespoke cross-sample feature reallocation module is employed to redistribute these features and direct gradient flows, thereby facilitating the propagation of supervisory signals between the pair. This results in the formation of transformed features \( F^c_{i} \) and \( F^c_{m} \). Subsequently, in Stage 2, we train the basic segmentation network with the cross-sample feature reallocating module. And in the second stage, we train the basic segmentation network with the intra-sample feature reallocating module. We will explain each module in detail.

C. Weakly Supervised 3D Semantic Segmentation

Existing 3D WSSS methods utilize different kinds of weak supervisions. Reference [10] utilizes dense 2D segmentation labels to supervise the training in 3D by projecting the 3D predictions onto the corresponding 2D labels. Reference [11] proposes to generate pseudo point-level label using 3D class activation map [12] from subcloud-level annotation. Reference [13] directly trains a point cloud segmentation network with 10 times fewer labels. Scribble-Sup [34] use scribble annotations on the Lidar data as supervision. MulPro [8] incorporated prototypes during the training to expand the weak labels. PSD [35] proposed a Self-Distillation framework that leverages self-supervised learning principles. DAT [36] proposed dual adaptive transformations to learn localization cues from both point-level and region-level. WS3 [37] proposed a pretext task as point colorization to explore the information contained in the data. WS3D [38] focused on the region boundary with an energy-level loss to improve the segmentation results. Contrastive Scene Contexts [39] explores contrastive self-supervised learning to explore cues within the training data. HybridCR [40] employs a contrastive loss function computed not only on the original sample but also on augmented samples derived from the original data. Their primary emphasis lies in evaluating the similarity between the original sample and its augmented counterparts. However, all these methods failed to explore the inter-sample information in the 3D point cloud data.
Then, we use the normalized affinity to guide the feature reallocating:

\[
F_j^c = A_j^c F_j \in \mathbb{R}^{N_j^c \times K} \\
F_i^c = A_i^c F_i \in \mathbb{R}^{N_i^c \times K} 
\] (4)

The warped feature maps \(F_j^c\) and \(F_i^c\) have the same size and spatial shape as the original feature maps \(F_i\) and \(F_j\). However, all the features in \(F_j^c\) are collected from sample \(P_j\) and each point feature in \(F_j^c\) can be seen as a weighted sum of all point features from \(F_j\), which means we constructed a new feature \(F_j^c\) in the shape of \(F_j\) using the features from \(F_j\) and vice versa.

Unlike the previous methods [17], [18], [19] which utilize common semantics from other samples and directly discover more object regions by generating pseudo labels. We use the reallocated and original feature maps into the decoders with shared weights respectively. For sample \(P_i\) side, we feed the original feature map \(F_i\) and the reallocated feature map \(F_i^c\) from sample \(P_j\) into the decoder network and get the outputs \(Z_i = f_{dec}(F_i) \in \mathbb{R}^{N_i \times C}\) and \(Z_j^c = f_{dec}(F_j^c) \in \mathbb{R}^{N_j^c \times C}\).

In our approach, the weak labels are assigned to a sample \(P_i\), where each point in the set \(F_i^c\) can be interpreted as a weighted sum derived from all points within sample \(P_i\). This characteristic allows for the dense propagation of supervision from labeled points in \(P_i\) to unlabeled points in \(P_j\), facilitated through the re-routing of gradients using our feature reallocating module. However, it is essential to consider the presence of uncommon classes across input samples. Directly applying a weak segmentation loss to the output of the reallocated branch might introduce undesirable noise during the training process.

To mitigate this challenge, we opt not to compute the segmentation loss for the reallocated branch. Instead, drawing inspiration from previous works such as [41], [42], and [43], we initially calculate a weak segmentation loss, as denoted in Equation 1, on the original feature output \(Z_i\). Additionally, we introduce a novel cross regularization (CR) loss designed to maximize the alignment between \(Z_i\) and \(Z_j^c\). This strategic combination of weak segmentation loss and cross regularization ensures a robust training framework, effectively addressing the challenge posed by the presence of uncommon classes in the input samples.

\[
\mathcal{L}_{CR} = \|Z_i - Z_j^c\|_F^2 = \|f_{dec}(F_i) - f_{dec}(F_j^c)\|_F^2 
\] (5)

Indeed, our methodology allows for the implementation of soft propagation, enabling the seamless transfer of supervision signals from labeled points in sample \(P_i\) to unlabeled points in sample \(P_j\) and vice versa. Consequently, each labeled point effectively disseminates its supervision signals to points within the other sample that exhibit similar features. This intricate mechanism ensures a comprehensive and nuanced understanding of the dataset, enhancing the ability of the model to learn intricate patterns and relationships within and between samples.

C. Intra-Sample Feature Reallocation

In this section, we propose an intra-sample feature propagation (ISFR) module to further propagate supervision from
labeled points to unlabeled points within each sample and finetuning the network against the possible noise introduced by the CSFR module. For each input sample $P_i \in \mathbb{R}^{N_i \times K}$, we can get the feature map $\mathbf{F}_i \in \mathbb{R}^{N_i' \times K}$ from the same encoder network. Similar to the previous module, we can calculate a self-affinity matrix $A_i$ for the feature:

$$A_i = \mathbf{F}_i \mathbf{W}_i \mathbf{F}_i^T \in \mathbb{R}^{N_i' \times N_i'}$$

(6)

where $\mathbf{W}_i \in \mathbb{R}^{K \times K}$ is a learnable matrix. The self-affinity matrix describes the point-wise correlation between all points within the input sample. We then normalize the self-affinity matrix to guide the feature reallocating for each point:

$$A_i' = \text{softmax}(A_i^T)$$

(7)

Then, we use the normalized affinity to guide the feature warping:

$$\mathbf{F}'_i = A_i' \mathbf{F}_i \in \mathbb{R}^{N_i' \times K}$$

(8)

Unlike the classical self-attention [44], we remove the residual connection to retain the same activation intensity. Here each point in $\mathbf{F}_i$ can be considered as a weighted sum of all the points in the sample and the features are reallocated with respect to the point correlation. We separately feed the reallocated feature and the original feature to the decoder. Thus, the decoder outputs from the two branches are $Z_i^s = f_{\text{dec}}(\mathbf{F}_i^s) \in \mathbb{R}^{N_i \times C}$ and $\mathbf{Z}_i = f_{\text{dec}}(\mathbf{F}_i) \in \mathbb{R}^{N_i \times C}$.

Similar to the cross-regularization loss, we use a similar self-regularization (SR) loss on the two outputs to regularize the reallocated feature with the original output:

$$L_{SR} = \|Z_i^s - \mathbf{Z}_i\|^2_F = \|f_{\text{dec}}(\mathbf{F}_i^s) - f_{\text{dec}}(\mathbf{F}_i)\|^2_F.$$  

(9)

Given that our feature reallocation process occurs exclusively within samples and does not introduce supervision from absent classes, unlike methods such as CSFR, we employ an additional weak segmentation loss specifically on the self-reallocating branch.

$$L_{\text{seg},s} = -\frac{1}{B} \sum_n m_n \sum_c y_{nc} e^{s_{nc}} - \sum_c e^{s_{nc}}.$$  

(10)

here $B = \sum m_n$ represents a normalization factor. This normalization factor plays a crucial role, enabling the effective transfer of supervision signals from labeled points to unlabeled points with similar features.

D. Training

As shown in Figure 2, we use a two-stage training strategy to avoid interference between the two modules during training. In stage one, we train the basic segmentation network with the cross-sample feature reallocating module. In this stage, for each sample, the network learns from the weak labels of this sample and the supervision propagated from the weak labels of another sample.

The overall learning objective in stage one can be expressed as:

$$L_{stage1} = L_{\text{seg},\text{basic}} + L_{CR}$$

(11)

In the second stage, we train the basic segmentation network with the intra-sample feature reallocating module. The second stage propagates supervision from labeled points to unlabeled points. The overall training objectives in stage two are:

$$L_{stage2} = L_{\text{seg},\text{basic}} + L_{\text{seg},s} + L_{SR}$$

(12)

We argue that joint training of the two modules would hamper the performance of the basic segmentation network since the cross-regularization loss in the CSFR module and the self-regularization loss in the ISFR module may interfere with the training of each other as the CSFR module may bring wrong supervision from uncommon classes to the other sample, while the two-stage training can avoid this issue and improve the performance by taking advantage of both the modules. We will further discuss this through experiments in section IV-C.

The two modules implicitly guide the optimization of the basic network only at training time. In inference, we can simply discard the two modules and use the basic segmentation network as a normal point cloud segmentation network to get the segmentation predictions. Therefore, no extra memory and computational resources are introduced at test time.

IV. EXPERIMENTS

A. Dataset

1) Dataset: We conduct our experiments on the popular public dataset S3DIS [45]. S3DIS covers 6 areas of the entire floor from 3 different buildings with a total of 215 million points and covers over 6000m$^2$. The dataset is annotated with 13 classes. We follow the common practice that using Area 5 as the test scene to measure the generalization ability. We also perform experiments on ScanNet [46] which contains 1513 scenes and is annotated with 20 classes.

2) Weak Labels: We follow [13] to annotate only 10% of the points. We first sample 4% of the points from the original data as the network inputs. Then, we randomly label 10% of points in each class for the sampled input point clouds. The final predictions will be back-projected to the original point clouds. Therefore, only 10% of the network input training data and only 0.4% of the original point cloud data are labeled. We also perform experiments with fewer labels that only 1% of the input points are labeled.

B. Implementation Details

We use the KPConv [4] segmentation model KPFCNN as our backbone network. The network is an encoder-decoder fully convolutional network with skip connections. The encoder is composed by bottleneck ResNet blocks [47] with KP convolution layers. The decoder part is composed of the nearest upsampling layers with unary convolution layers. We put the CSFR and ISFR modules after the first upsampling layer for larger spatial resolution. Due to the limitation in computational resources, we use ball query to sample point cloud as input samples, the sample radius is set to 2m. We use a Momentum SGD optimizer, the initial learning rate is set to 0.01 and the momentum is set to 0.98. We train the
first stage for 600 epochs and the second stage for another 600 epochs.

In this study, the comprehensive duration of the training process, encompassing both stages, is approximately 33 GPU hours when executed on a single GTX2080Ti GPU. This duration, while marginally lengthier than the training time reported in the WeakSup [13], is notably shorter than the training time in the One-Thing-One-Click [48]. This brevity arises from the utilization of simpler backbone networks in WeakSup and the necessity for iterative training on the same network in One-Thing-One-Click. Notably, the inference duration of our proposed method aligns precisely with that of the fully supervised KPConv [4]. This parity in inference times stems from the exclusive involvement of the CSFR and ISFR modules solely during the training phase, while the network architecture during inference mirrors that of the KPConv model.

C. Ablation Studies

1) Two Stage Training Versus Joint Training: Table I compares one-stage training with two-stage training performances trained with 10% and 1% labels. For one-stage training, we perform experiments with only the CSFR module or ISFR module, each of the modules produces performance gain over the baseline method for both 10% and 1% label cases. However, when we jointly train CSFR and ISFR modules in one stage, we observe a performance drop, producing results lower than solely training one module and even lower than the baseline method in both cases. From the experiments, we argue that the training losses in the two modules may interfere with each other during optimization. Since the CR loss and SR loss from the two modules both trying to pull the segmentation output closer to the outputs of the two branches, the overall training objective may be deviated from our real target, better segmentation performance. With the losses from two modules being optimized together, the model may fail to find the global optimum and be optimized in the wrong direction. Therefore, by separating the training into two stages, we can avoid interference between the modules during training and take advantage of both modules.

2) Training Orders: We also compare the training orders of the two modules in Table I. ISFR-CSFR means we train the network with the ISFR module in the first stage and the CSFR module in the second stage. CSFR-ISFR means that we train the network with the CSFR module in the first stage and ISFR module in the second stage. We observe that CSFR-ISFR outperforms ISFR-CSFR under both 10% and 1% supervision. We argue that the CSFR module can help the network to learn more generalized coarse representations across samples while the ISFR module can act like a finetuning module that finetunes the learned representations and imposes constraints on unlabeled points within the samples. Therefore if we use the opposite training order, we can get worse results compared to even each single module.

3) Effects of Different Losses: We evaluate the effectiveness of each losses in Table III within each module. We compare results with different combinations of the losses for a single-stage training with only one module each. For the CSFR module, as shown in Table III(a), we suppose \( L_{\text{seg, basic}} + L_{\text{CR}} \) reaches the best performance for the CSFR module for both the label settings which means the cross regularization loss helps the segmentation performance. We also observe that training with \( L_{\text{seg, basic}} + L_{\text{CR}} + L_{\text{seg, c}} \) produces even lower score than solely using \( L_{\text{seg, basic}} \), which means adding another

| Method      | Dataset | Backbone | GPU Hour |
|-------------|---------|----------|----------|
| WeakSup [13]| S3DIS   | DGCNN [25] | 26.65    |
| Ours        | S3DIS   | KPConv [4]  | 33.85    |
| OTOC [48]   | ScanNet | PointGroup [49] | 175      |
| Ours        | ScanNet | KPConv [4]  | 33.32    |

| Combination | CSFR   | ISFR   |
|-------------|--------|--------|
| \( L_{\text{seg, basic}} + L_{\text{CR}} \) | 66.5   | 65.1   |
| \( L_{\text{seg, basic}} + L_{\text{SR}} \) | 66.7   | 66.8   |
| \( L_{\text{seg, basic}} + L_{\text{CR}} + L_{\text{seg, c}} \) | 66.3   | 64.8   |

(b)
segmentation loss on the cross propagated decoder branch would harm the performance. This supports our statement in section III-B that additional supervision on the propagate branch would introduce noise into the training process due to the inherent difference between the two samples.

Table III(b) shows that in the ISFR branch, training with all three losses $L_{seg\_basic} + L_{SR} + L_{seg\_i}$ produces better results than using $L_{seg\_basic} + L_{SR}$ and solely using the segmentation loss on the original branch. This result supports our statement in section III-C that the ISFR module imposes constraints on unlabeled points within the sample. Since the feature propagation is processed inside each sample, no noises would be introduced to the training. Thus, calculating a segmentation loss on the propagated feature branch would improve the training results.

4) Performance of Different Branches: Table IV compare the segmentation performance of different decoder branches in the two-stage settings. In both settings, the cross branches produce the poorest segmentation results the features of this branch are propagated from the other sample. However, the cross-branch can still produce reasonable scores as the network is learned to only propagate features from the same category for each point. The intra branch produces better results than the cross branch, but still lower than the basic branch. This supports our argument that the ISFR module imposes more constraints to unlabeled points as the features of unlabeled points can be propagated to the labeled points in the same category. But during inference, as the network already learned the representations, propagating the features is not helping the predictions. This is also a difference between our ISFR module with the self-attention module in many vision applications.

We also compare the results between the two settings. The outputs from all three branches in CSFR-ISFR perform better than those in ISFR-CSFR, which also supports our argument in section III-D. From the results, if the ISFR module is trained first, the network can overfit within samples and not generalize across samples. Thus the cross-branch performance is worse in ISFR-CSFR. Then, with the CSFR module trained in the second stage, the information from other samples may affect as noises. Therefore the performance from the basic branch is even lower than individual training with the two modules shown in Table I.

D. Qualitative Results

Figure 4(a) shows the affinity learned in CSFR between the input pairs. Figure 4(b) shows the affinity learned in ISFR in each sample. We show the affinity map on the left to the selected point on the right. The point clouds are sparse since we perform CSFR and ISFR in down-sampled features. Obviously, both modules have successfully learned to propagate features from the same class.

We provide visualizations of our final segmentation predictions in Figure 5. We compare our results with the ground truth and the predictions from the fully supervised counterpart. We can see that our method performs even better in label consistency and in hard examples like the fourth row.
TABLE V

| setting       | model   | backbone | mIoU | entail. | floor | wall | beam | col. | wind | door | chair | table | book | sofa | board | clut. |
|---------------|---------|----------|------|---------|-------|------|------|------|------|------|-------|-------|------|------|-------|------|
| Fully supervised | PointNet [23] | - | 41.1 | 88.8 | 97.3 | 69.8 | 0.1 | 3.9 | 46.3 | 10.8 | 52.6 | 58.9 | 40.4 | 5.9 | 26.4 | 33.2 |
| | PointNet++ [24] | - | 47.8 | 90.3 | 95.6 | 69.3 | 0.1 | 13.8 | 26.7 | 44.1 | 64.3 | 70.0 | 27.8 | 47.8 | 30.8 | 38.1 |
| | DGCNN [25] | - | 47.0 | 92.4 | 97.6 | 74.5 | 0.5 | 13.3 | 48.0 | 23.7 | 65.4 | 67.0 | 10.7 | 44.0 | 34.2 | 40.0 |
| | PointCNN [26] | - | 57.3 | 92.3 | 98.2 | 79.4 | 0.0 | 17.6 | 22.8 | 62.1 | 80.6 | 74.4 | 66.7 | 21.7 | 62.1 | 56.7 |
| | MinkNet [2] | - | 59.4 | 91.8 | 98.1 | 86.2 | 0.0 | 34.1 | 48.9 | 62.4 | 89.8 | 81.6 | 74.9 | 47.2 | 74.4 | 58.6 |
| | SENet [50] | - | 67.7 | 93.8 | 97.0 | 81.4 | 0.0 | 23.2 | 61.3 | 71.6 | 89.9 | 79.8 | 75.6 | 72.3 | 72.7 | 60.4 |
| Paper          | KPConv [4] | - | 67.1 | 92.8 | 97.3 | 82.4 | 0.0 | 23.9 | 58.0 | 69.0 | 91.0 | 81.5 | 75.3 | 75.4 | 66.7 | 58.9 |
| Retrain        | KPConv [4] | - | 67.3 | 94.8 | 98.4 | 82.3 | 0.0 | 28.3 | 56.6 | 71.2 | 90.5 | 82.6 | 74.6 | 67.8 | 67.4 | 59.9 |
| Fully supervised | DSP(Ours)  | KPConv [4] | 68.5 | 94.3 | 98.4 | 83.7 | 0.0 | 28.9 | 59.1 | 73.4 | 91.2 | 82.2 | 75.3 | 73.9 | 68.5 | 61.0 |

E. Segmentation Results

In Table V, we compare our proposed method with state-of-the-art methods, other weakly supervised methods, and our baseline method.

1) Comparison With Baseline Method: The baseline method is only the basic segmentation network trained with weak labels. Our method is the full model with cross- and intra-sample feature propagation modules and is trained with the two-stage strategy. The experiments show that our proposed method improves the performance of the baseline method with both 10% and 1% labels.

2) Comparison With Existing 3D WSSS Methods: We compare our proposed method with existing 3D WSSS methods [13], [41], [51]. For One-Thing-One-Click [48] and MulPro [8], we use the results reported from the MulPro [8] paper.
TABLE VI
THE SEGMENTATION RESULTS ON SCANNET VALIDATION SET. MPRM IS ANOTHER WEAKLY SUPERVISED METHOD USING SUB-CLOUD LEVEL SUPERVISION AND DEVELOPED ALSO BASED ON KPConv. THE KPConv-BASIC MEANS THE BASIC NETWORK DEVELOPED USING KPConv.

| Model       | Supervision | wall | floor | cabinet | bed | chair | sofa | table | door | window | B.S. | picture | counter | desk | curtain | S.C. | toilet | sink | bathtub | other | mIoU  |
|-------------|-------------|------|-------|---------|-----|-------|------|-------|------|-------|------|--------|---------|------|---------|------|--------|------|---------|------|--------|
| MPRM [11]  | subcloud    | 59.4 | 59.6  | 25.1   | 64.1| 55.7 | 58.7 | 45.6  | 36.4 | 40.3  | 67.9 | 16.1   | 22.6   | 42.9 | 66.9    | 24.1 | 39.6   | 47.0 | 21.2   | 44.7 | 28.0  | 43.2 |
| KPConv-basic| Full        | 83.9 | 95.5  | 68.5   | 79.4| 90.0 | 80.9 | 77.4  | 63.0 | 60.8  | 81.0 | 29.6   | 68.3   | 67.6 | 77.3    | 54.5 | 61.1   | 90.9 | 62.9   | 86.4 | 56.8  | 71.8 |
| KPConv-basic| 1%          | 82.7 | 94.9  | 68.2   | 77.8| 87.7 | 78.8 | 74.0  | 58.7 | 55.8  | 75.9 | 30.5   | 55.2   | 63.2 | 69.2    | 48.6 | 62.6   | 87.3 | 57.8   | 84.4 | 54.4  | 68.1 |
| KPConv-basic| 10%         | 83.6 | 95.1  | 66.1   | 79.9| 89.3 | 82.5 | 74.1  | 62.1 | 60.5  | 80.1 | 32.5   | 61.2   | 64.1 | 73.3    | 55.7 | 63.3   | 89.7 | 63.4   | 89.7 | 63.4  | 71.1 |
| DSP (Ours)  | 1%          | 82.8 | 95.4  | 64.7   | 78.8| 89.1 | 82.5 | 76.2  | 61.1 | 57.0  | 79.1 | 30.8   | 63.8   | 64.9 | 73.8    | 52.7 | 66.8   | 88.1 | 59.1   | 80.1 | 53.0  | 70.0 |
| DSP (Ours)  | 10%         | 84.2 | 95.5  | 68.1   | 80.0| 89.9 | 81.1 | 76.7  | 64.2 | 60.7  | 81.3 | 31.3   | 68.1   | 66.0 | 75.9    | 60.6 | 61.4   | 90.9 | 63.3   | 86.4 | 56.8  | 72.1 |

We compare 2D dense labels on 2D projections of the 3D point clouds and [13] utilize the same weak supervision technique by annotating 10% of the points. Reference [13] can also produce close or better results than its fully supervised counterpart, but the overall performance of these existing methods [8], [13], [41], [51] still remains a huge gap with existing state-of-the-art methods [2], [4]. Our proposed method surpasses the existing methods [8], [8], [13] by a large margin. We observe that with 10% points labeled, the fully supervised counterpart in S3DIS and ScanNet dataset. Our method outperforms the previous method MPRM [11] by a large margin. We observe that with 10% points labeled, the baseline results are already very close to the fully supervised results with only 0.7% margin. We argue that ScanNet is a very large-scale dataset, 10% of the label can already provide strong supervision. Our method with 10% points labeled improved 1% mIoU from the baseline and even outperformed the fully supervised result by a small margin of 0.3%. Since the 10% baseline is already close to the fully supervised result, our supervision propagation mechanism may help the network with more information than the fully supervised baseline model. Our method is more effective with only 1% labeled points, where we outperform the baseline method by 1.9% mIoU. In practice, it is not easy to collect a large-scale dataset like ScanNet, but we believe our method is meaningful in real-world applications.

V. LIMITATIONS

We present several failure cases in Figure 6. Consistent with numerous existing studies, our approach struggles when two categories exhibit similar geometric properties. This specific problem is a well-documented challenge, and its presence is notable even in methods that employ full supervision. The inherent limitations of our method, stemming from its lack of comprehensive supervision, further exacerbate its ability to effectively navigate and resolve this particular challenge. It underscores the need for enhanced techniques or additional guidance to improve differentiation in such cases.

VI. CONCLUSION

In this paper, we propose a weakly supervised point cloud segmentation method with only 10% or 1% percent of the points being labeled. We developed cross- and intra-sample feature reallocating modules to densely propagate supervision from labeled points to unlabeled points. We narrowed the performance gap between 3D weakly supervised semantic segmentation and current fully supervised methods while significantly reducing the human effort for annotation. Our proposed method with 10% and 1% of the points being labeled can produce compatible results with its fully supervised counterpart in S3DIS and ScanNet dataset.

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