DCANet: Differential Convolution Attention Network for RGB-D Semantic Segmentation

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Abstract

Combining RGB images and the corresponding depth maps in semantic segmentation proves the effectiveness in the past few years. Existing RGB-D modal fusion methods either lack the non-linear feature fusion ability or treat both modal images equally, regardless of the intrinsic distribution gap or information loss. Here we find that depth maps are suitable to provide intrinsic fine-grained patterns of objects due to their local depth continuity, while RGB images effectively provide a global view. Based on this, we propose a pixel differential convolution attention (DCA) module to consider geometric information and local-range correlations for depth data. Furthermore, we extend DCA to ensemble differential convolution attention (EDCA) which propagates long-range contextual dependencies and seamlessly incorporates spatial distribution for RGB data. DCA and EDCA dynamically adjust convolutional weights by pixel difference to enable self-adaptive in local and long range, respectively. A two-branch network built with DCA and EDCA, called Differential Convolutional Network (DCANet), is proposed to fuse local and global information of two-modal data. Consequently, the individual advantage of RGB and depth data are emphasized. Our DCANet is shown to set a new state-of-the-art performance for RGB-D semantic segmentation on two challenging benchmark datasets, i.e., NYUDv2 and SUN-RGBD.

1. Introduction

Semantic segmentation is an essential task in computer vision, which infers semantic labels of every pixel in a scene. With the widespread use of 3D sensors such as Kinect, Xition etc., the 3D geometry information of objects can be easily obtained to boost the advancement of RGB-D semantic segmentation. After encoding the real-world geometric information, the RGB-D images can be applied to overcome the challenge of 2D only displaying the photometric appearance properties in the projected image space and enrich the representation of RGB images. The information of RGB and depth images are presented in entirely different forms. In particular, RGB images capture the photometric appearance properties in the projected image space, while the depth maps capture the photometric appearance properties in the projected image space, while the depth maps can produce plentiful complementary information for the appearance cues of local geometry. As a result, it is vital to enhance and fuse the strengths of RGB and depth data in semantic segmentation task.

In a real scenario, there are too many challenging images with complex appearances. Take Fig. 1 as an example, while the chair and the table are inseparable according to the 2D appearance in RGB image, they can be easily distinguished in depth map based on geometric information. In DCANet, we exploit DCA to capture local-range geometric consistency in depth map and EDCA to focus on long-range dependence for RGB.
ance. In fact, the depth data provide more fine-grained local geometry difference information and theoretically leading to better segmentation performance compared to only using RGB images. In contrast, as verified in the classic self-attention [54, 60, 63] mechanisms that RGB data focuses on more global information.

The existing methods [3, 9–11, 20, 24, 26, 29, 36, 39] try to fuse RGB-D data by introducing new convolution layer and pooling layer, attention mechanism, noise-cancelling module, etc., to obtain better semantic segmentation results. These methods ignore the intrinsic differences between RGB and depth features, using homogeneous operators instead. The weights of both types of data are equally treated so as to make the same contribution to the segmentation, which is obviously not appropriate. Besides, the information of RGB images and depth maps is mainly achieved from the combined final channel, where specific semantic information in different channels is not considered.

To address the aforementioned problems, we propose two attention mechanisms, namely differential convolution attention (DCA) and ensemble differential convolution attention (EDCA) to improve the cross-modal ability between RGB and depth data in semantic segmentation. DCA dynamically augments the standard convolution with a pixel difference term and forces pixels with a similar difference to the center of the kernel to contribute more to the output than other pixels. DCA incorporates local geometric information and improve local-range adaptability for depth data. EDCA absorbs the advantage of dynamic convolution of DCA to propagate long-range contextual dependencies and seamlessly incorporate spatial distribution for RGB data. Meanwhile, both DCA and EDCA avoid common drawbacks such as ignoring adaptability in channel dimension. Our main contributions are summarized as follows.

- We propose a DCA module which incorporates long-range intricate geometric patterns and enables self-adaptive by considering subtle discrepancy of pixels in local regions for depth data.
- We extend DCA to EDCA for achieving long-range correlations and seamlessly incorporating spatial distribution for RGB data.
- Based on DCA and EDCA, we propose a DCANet that achieves a new state-of-the-art performance on NYUDv2 [47] and SUN-RGBD [48] datasets. We also provide a detailed analysis of design choices and model variants.

2. Related Work

2.1. RGB-D Semantic Segmentation

With the help of additional depth information, the combination of such two complementary modalities achieves great performance in semantic segmentation [3, 9, 17, 27, 28, 45, 47]. Many works simply concatenate the features of RGB and depth images to enhance the semantic information of each pixel [45, 47]. The fusion method can be classified into three types: early fusion, middle fusion and late fusion. Cao et al. [3] concatenate the RGB and depth data decomposed by a shape and a base component in the depth feature in the early stage. However, due to the complexity of these two modalities, a single model cannot fit their data well due to their differences. Jiao et al. [27] design two encoder-decoder modules for fully consideration the RGB and depth information, where both modal are fused in late stage. In this method, the interaction between the different features of RGB and depth data is insufficient, since the rich information of the modalities is gradually compressed and even lost. After overcoming the drawback of early stage and late stage fusion strategy, middle stage fusion performs better by fusing the intermediate information of the two different modalities. Gupta et al. [18] concatenate the geocentric embedding for depth images and with depth images to contribute the final semantic information in the middle stage. Notably, the distribution gap is reduced in the middle stage fusion strategy, and multi-modal features are combined with ample interaction. As a result, recent studies mainly focus on middle stage fusion. Chen et al. [9] propose a spatial information-guided convolution, which generates convolution kernels with different sampling distributions to enhance the spatial adaptability of network and receptive field regulation. Chen et al. [10] unify the most informative cross-modality features from data for both modalities into an efficient representation. Lin et al. [29] split the image into multiple branches based on geometry information, where each branch of the network semantically segments relevant similar features.

Our method applies two branches and each branch focuses on extracting modality-specific features, such as color and texture from RGB images and geometric, illumination-independent features from depth images. To be specific, similar to middle stage fusion, attentive depth features generated by the DCA are fused into the attentive RGB from the EDCA at each of the resolution stages in the encoders. The depth and RGB data focus on local and long range information, respectively.

2.2. Attention Modules

What has greatly contributed to the popularity of attention modules is the fact that they can be applied to model the global dependencies of features almost in any stage of the network. Woo et al. [56] adaptively refined the information in spatial and channel dimensions through the convolutional block attention module. Inspired by the self-attention network in Natural Language Processing [51], such self-attention related module achieves widespread focus in computer vision [44, 50, 61]. Many researchers focus on the global and local dependencies. In [54], Wang et al. pro-
Figure 2. The instances of DCA and EDCA when taking a 3 × 3 local grid as an example.

pose a non-local model to extend the self-attention to a more general type of non-local filtering method for capturing the long-range dependencies. Fu et al. [15] propose two attention modules to capture spatial and channel interdependencies, respectively. Cao et al. [4] propose a lightweight non-local network based on a query independent formulation for global context modeling. Zhu et al. [63] integrates the features of different levels while considering long-range dependencies and reducing redundant parameters.

Our method integrates DCA and EDCA to build relationship between different points for depth and RGB data, respectively. The DCA module supports that the same objects have more substantial depth similarity in a local-range of depth data, and we make use of the pixel-wise difference to force pixels with more consistent geometry to make more contributions to the corresponding output. The EDCA module enables long-range dependencies for RGB data.

3. Method

RGB-D semantic segmentation requires fusing features from RGB and depth modalities, which are inherently different. Specifically, RGB data has long-range contextual dependencies and global spatial consistency, while depth data contains local geometric consistency. The intrinsic characteristics of the two modalities should be considered separately to identify the strengths of each, while enhancing the two feature representations. To this end, we put forward two attention modules called DCA and EDCA to capture the intrinsic features of depth and RGB data, respectively. In this section, we elaborate the details of the proposed DCA and EDCA, followed by the description of the proposed differential convolution attention network (DCANet).

3.1. Differential Convolution Attention

The attention mechanism can be considered as an adaptive selection process that selects discriminative features based on input features and automatically ignores noisy responses [16]. The key point of the attention mechanism is to learn the relationship between different points and generate an attention map that indicates the importance of different points. The well-known method for establishing relationship between different points is self-attention mechanism [15, 54, 57, 61], which is used to capture long-range dependence. However, due to its intrinsic properties, the depth data is only relevant in a local region and long-range dependencies may introduce more interference terms. For this, we explore convolution to build relevance and produce attention map by considering a local region in depth data.

Given a feature map \( F \in \mathbb{R}^{h \times w \times c} \); \( h, w, \) and \( c \) are the height, width and the channel of input feature map, respectively. For simplicity, we note \( X \in \mathbb{R}^{h \times w \times 1} \) as the input feature map. For each point \( p \in \mathbb{R}^2 \) on \( X \), the vanilla convolution is calculated as:

\[
Y(p) = \sum_{i=1}^{k \times k} K_i \cdot X(p + p_i),
\]

where \( p_i \) enumerates the local locations around \( p \). \( K \) is the learnable weights of the convolution kernel with the size of \( k \times k \) (the bias terms are ignored for simplicity).

In Eq.(1), the convolution kernel \( K \) of the vanilla convolution is fixed for any input, which cannot perceive the
changes of the input dynamically. However, for depth data, we expect the attention map generated by convolution to sense the geometric information on-the-fly while learning the correlations between different points in a local region. To this end, we explore a pixel difference term to weight the vanilla convolution kernel called differential convolution kernel $K^*$:

$$K^*_i = K_i \cdot \exp(-|X(p) - X(p + p_i)|),$$

The difference term in $K^*$ implies the geometric information in depth data and is then regularized to (0,1], which ensures that the larger the difference between any two points, the smaller the correlation, and vice versa. It is intuitive that the depth at a point is locally continuous. With the blessing of the difference term, the differential convolution kernel $K^*$ depends not only on the input features, but also on the convolution position. Thus it is geometry-aware for depth data. With differential convolution kernel $K^*$, the differential convolution (DC) for input feature map $X \in \mathbb{R}^{h \times w \times 1}$ can be written as:

$$Y(p) = \sum_{i=1}^{k \times k} K^*_i \cdot X(p + p_i),$$

As mentioned above, we use differential convolution kernel $K^*$ to calculate the relevance between different points in a local receptive field, and the field size is input-dependent. In our experiments, the receptive field size for depth data is $9 \times 9$. To reduce computations, we apply the depth-wise separable convolution [12] to decouple a differential convolution into a differential depth-wise convolution and a point-wise convolution ($1 \times 1$ convolution). For generalized input feature map $F \in \mathbb{R}^{h \times w \times c}$, our DCA module is defined as:

$$Attention = Conv_{1 \times 1}(DC-DW(F)),$$

$$Output = Attention \otimes F.$$  

Here, $Conv_{1 \times 1}$ represents $1 \times 1$ convolution, and DC-DW denotes differential depth-wise convolution whose differential kernel is generated by Eq.(2). $Attention \in \mathbb{R}^{h \times w \times c}$ means attention map which has the same size of input feature map $F$. Each value in the attention map integrates the geometric information in the local range of the depth image to indicate the importance of each feature. $\otimes$ denotes element-wise product. The whole process of DCA is illustrated at the top part of Fig. 2.

Convolution kernel that introduces difference term can dynamically rebalance the convolution weights according to the input. And the proposed DCA module forces points with more consistent geometry to make more contributions to the corresponding output for depth data. In summary, DCA achieves flexibility not only in the local spatial dimension, but also in the channel dimension, and integrates geometric information of the local extent. It is worth noting that channels-wise information often represents different objects in CNNs [5,43], which is also crucial for segmentation tasks.

### 3.2. Ensemble Differential Convolution Attention

As mentioned above, RGB data has long-range contextual dependencies and global spatial consistency. Although self-attention [54, 60, 63] is the practical methods to learn relationship between different points to capture long-range dependence, it only obtains spatial-wise adaptability and lacks the channel-wise adaptability. The proposed DCA module has flexibility in both spatial dimension and channel dimension, and it considers local-range correlations which is appropriate for depth data. Therefore, as for RGB data it is intuitive to extend DCA to propagate long-range contextual dependencies.

The most straightforward approach is to use larger kernel differential depth-wise convolution in DCA. In order to capture long-range relationship with less computational costs and parameters than directly apply larger kernel operations, we decomposed large kernel-based DC to a differential depth-wise convolution, a differential depth-wise dilation convolution and a point-wise convolution, called ensemble differential convolution (EDC). With EDC, the propose EDCA can be written as:

$$F_1 = DC-DW(F),$$

$$F_2 = DC-DWD(F_1),$$

$$Attention = Conv_{1 \times 1}(F_1 + F_2),$$

$$Output = Attention \otimes F.$$  

Similar to DCA, $F \in \mathbb{R}^{h \times w \times c}$ is the input feature map. $Conv_{1 \times 1}$ represents $1 \times 1$ convolution and $\otimes$ denotes element-wise product. DC-DW and DC-DWD mean differential depth-wise convolution and differential depth-wise dilation convolution with differential convolution kernel $K^*$, respectively. Fig. 2 shows the proposed EDCA module.

The size of EDC kernels are also input dependent. In our experiments, the DC kernel size of DC-DW is $5 \times 5$, and that of DC-DWD is $9 \times 9$ with dilation $3$. With the above settings, the receptive field size of EDC is approximated to $29 \times 29$. Fig. 3 (d) shows the convolution strategies in EDC, for convenience, we show the $5 \times 5$ convolution and $5 \times 5$ convolution with dilation $3$. Accordingly, EDCA can obtain long-range dependence, while the differential term dynamically adjust the convolution weights and provides spatial distribution information for RGB data. In summary, the discriminative features are boosted and the noisy responses are ignored based on the spatial and channel-wise adaptability of EDCA.
3.3. Understanding DCA and EDCA

As verified by the prior works that pixels with same semantic labels have similar depths [29, 36, 53] in a local region. The DCA integrates geometric perception ability to vanilla convolution and generates an attention map which indicates the importance of each point in depth data. EDCA absorbs the advantage of dynamic convolution of DCA to propagate long-range contextual dependencies and seamlessly incorporate spatial distribution for RGB data.

As shown in Tab. 1, our proposed DCA and EDCA combine the advantages of convolution and self-attention. By augmenting the convolution kernel with a pixel difference term, DCA captures geometry with a local receptive field. Compared with vanilla convolution, the learnable weights of DCA are adjusted by the geometric variance. Based on this, with the help of our decomposed large kernel, the EDCA is extended to further capture refined pixel discrepancy in the satisfied receptive field.

Table 1. Desirable characteristics of convolution, self-attention, DCA, and EDCA. Notably, DCA and EDCA are applied for depth and RGB data, respectively.

| Properties                      | Convolution | self-attention | DCA          | EDCA          |
|---------------------------------|-------------|----------------|--------------|---------------|
| Geometry Structure              | ✓           | ✓              | ✓            | ✓             |
| Local-range dependence          | ✓           | ✓              | ✓            | ✓             |
| Long-range dependence           | ✓           | ✓              | ✓            | ✓             |
| Spatial adaptability            | ✓           | ✓              | ✓            | ✓             |
| Channel adaptability            | ✓           | ✓              | ✓            | ✓             |

3.4. DCANet Architecture

The architecture of DCANet for RGB-D semantic segmentation is shown in Fig. 4. Our DCANet adopts DeepLabv3+ [8] as the baseline for RGB-D semantic segmentation task, where the encoder is ResNet-101 [19] and retain the original decoder of DeepLabv3+. We apply a two-branch structure in our DCANet, one for RGB and another for depth data.

At each of the four resolution stages in the ResNet-101, depth features are fused into the RGB encoder by attention and fusion block. Specifically, the channel dimension of both modalities are first squeezed to $1/8$ for dimensionality reduction. Next, we apply the DCA for depth data and EDCA for RGB data simultaneously. Third, the outputs of DCA and EDCA are convolved to match the dimensionality of the original features and performed an element-wise sum with the original features separately. Finally, the depth data extracting complementary geometric information is integrated into the RGB data by element-wise sum to obtain better feature representations. The outputs of attention and fusion block are as follows:

$$ \text{Depth}_{\text{out}} = \mathcal{W}_2 (\text{DCA}(\mathcal{W}_1(\text{Depth}_{\text{in}}))) + \text{Depth}_{\text{in}}, $$

$$ \text{RGB}_{\text{out}} = \mathcal{W}_2' (\text{EDCA}(\mathcal{W}_1'(\text{RGB}_{\text{in}}))) + \text{RGB}_{\text{in}}, $$

$$ \text{RGB}_{\text{out}} = \text{RGB}_{\text{out}} + \text{Depth}_{\text{out}} $$

where $\mathcal{W}_1$ ($\mathcal{W}_1'$) and $\mathcal{W}_2$ ($\mathcal{W}_2'$) represent $1 \times 1$ convolution to squeeze and recover the channel, respectively. Notably, the fused output RGB feature of last block is propagated to the segmentation decoder.

4. Experiments

4.1. Dataset and metrics

Evaluation is performed on two popular RGB-D datasets:

NYUDv2 [47]: NYUDv2 contains 1449 RGB-D images with pixel-wise labels. We follow the 40-class settings and the standard split with 795 training images and 654 testing images.

SUN-RGBD [48]: This dataset has 37 categories of objects and consists 10335 RGB-D images, with 5285 as training and 5050 as testing.

We evaluate the results using two common metrics, i.e., Pixel Accuracy (Pixel Acc.), and Mean Intersection Over Union (mIoU).

4.2. Implementation Details

We use dilated ResNet-101 [19] pretrained on ImageNet [46] as the backbone network for feature extraction and adding another auxiliary loss in the last stage of ResNet-101. We keep all the other settings of DeepLabv3+ [8] the same. We implement our network using the PyTorch deep learning framework [40], and all the models are trained with two Nvidia Tesla V100 GPUs. We use the “poly” policy [34] with initial learning rate 0.008, crop size $480 \times 480$, batch size 8, fine-tuning batch normalization parameters [25] and data augmentation method (i.e., random scaling, random cropping, and left-right flipping) during training. For the optimizer, we use the SGD with a momentum of 0.9 and a weight decay of 0.0001. In addition, we train the NYUDv2 dataset for 500 epochs and train the SUN-RGBD dataset for 200 epochs. For fair comparisons with other methods, we adopted both single-scale and multi-scale testing strategies during inference. If not otherwise noted, the experiments are single-scale testing, and ‘*’ in tables denote the multi-scale strategy.

4.3. Ablation Study

DC kernel size of DCA. Our DCA module applies the DC kernel of $9 \times 9$, dilation 1 to capture local geometry information for depth data. To confirm the effectiveness of applying $9 \times 9$ DC kernel, we hence attempt DCA with other
Figure 4. The overview of our network. The network consists of two ResNet-101 encoders, where DCA and EDCA are plugged into CNNs as an attention module for each block of each ResNet-101 encoder in RGB and Depth branches, respectively. We employ the original decoder DeepLabv3+. During training, each pair of feature maps are fused by the attention and fusion block and propagated to the next stage of the encoder for further feature transformation.

Table 2. The results of DCA with different DC kernel sizes on NYUDv2 test set.

| DC kernel size | Pixel Acc.% | mIoU% |
|----------------|-------------|-------|
| 3 x 3          | 75.3        | 49.1  |
| 5 x 5          | 75.7        | 49.7  |
| 7 x 7          | 76.0        | 50.1  |
| 9 x 9          | 76.5        | 50.9  |
| 11 x 11        | 76.4        | 50.9  |

Table 3. Ablation study on DCA and EDCA modules on NYUDv2 test set.

| Method | DCA | EDCA | Pixel Acc.% | mIoU% |
|--------|-----|------|-------------|-------|
| Baseline |     |      | 75.1        | 47.4  |
| Model1  | ✓   | ✓    | 76.5        | 50.9  |
| Model2  | ✓   | ✓    | 76.9        | 51.3  |
| DCANet  | ✓   | ✓    | 77.3        | 52.1  |

Table 4. Superiority of EDCA compared with Self-Attention [54] and EDCA- on NYUDv2 test set. EDCA- denotes EDCA without differential term. All the three modules are for RGB data to capture long-range dependence and no operations are performed on the depth data.

| Self-Attention | EDCA- | EDCA | Pixel Acc.% | mIoU% |
|----------------|-------|------|-------------|-------|
| ✓              | ✓     | ✓    | 76.1        | 49.3  |
| ✓              | ✓     | ✓    | 76.3        | 50.1  |
| ✓              | ✓     | ✓    | 76.9        | 51.3  |

DC kernel sizes on depth data and no operations are performed on the RGB data. The results shown in Tab.2 prove that larger DC kernels do not bring significant performance gains due to the local geometric nature of depth data and our setup works.

**Effectiveness of DCA and EDCA modules.** We conduct ablation studies on NYUDv2 dataset to prove the indispensability of the DCA and EDCA modules. We perform two parallel DeepLabv3+ (ResNet-101) as baseline. As shown in Tab. 3, the two attention modules improve the performance remarkably. Compared with baseline, employing only DCA on depth data improves mIoU by 3.5%, while using only EDCA on RGB data brings 3.9% improvement.

When we apply both modules together, the performance is further improved to 77.3% (Pixel Acc.) and 52.1% (mIoU). The results indicate that both modules are critical for the performance improvement and work best when combined.

**EDCA vs. Self-Attention.** Self-attention mechanism, *e.g.*, Non-local neural networks [54], are the well-known method to capture long-range dependence. We compare the performance of self-attention with our proposed EDCA. As illustrated in Tab. 4, EDCA outperforms self-attention in mIoU and Pixel Acc. by 2% and 0.8%, respectively. Self-attentive mechanisms are spatially adaptive, but not simultaneously channel-adaptive as EDCA. Nevertheless, channel adaptability plays a crucial role in segmentation tasks. Furthermore, we also verify the effectiveness of differential term in EDCA by removing the differential term in EDCA, called EDCA-. The results in Tab. 4 show that differential term brings 1.2% improvement in mIoU. This term in EDCA provides long range spatial distribution information for RGB data while dynamically sensing the scene.

**Suitability of DCA and EDCA.** In the proposed
DCANet, we apply DCA on depth data to capture local-range dependence and geometric information and EDCA on RGB data to garner long-range correlations and spatial distribution information. We also confirm the suitability of such two modules by applying EDCA for depth data and DCA for RGB. As shown in Tab. 5, applying DCA on depth improves mIoU by 1.7% compared to EDCA and 1.6% improvement in mIoU using EDCA over DCA on RGB. The results illustrate that DCA and EDCA are appropriate for Depth and RGB data, respectively. This also explains that depth maps are more suitable for providing intrinsic geometric information of objects due to their local depth continuity, while RGB images effectively provide a global view.

### 4.4. Experiments on Different Architectures

Our proposed DCA and EDCA are general modules for RGB-D semantic segmentation, which can be easily plugged into CNNs as attention modules in semantic segmentation. Our method is also assessed with respect to several representative semantic segmentation architectures: Deeplabv3+ [8], Deeplabv3 [7], PSPNet [33] and FPN [62] with different backbones (ResNet-50, ResNet-101 [19]) on NYUDv2 dataset to verify the generalizability. As is shown in Tab. 6, our method outperforms the baseline by a desirable margin under all settings, demonstrating the generalization capability of our method.

### 4.5. Comparing with State-of-the-arts

NYUDv2. The comparison results are shown in Tab. 7. Our method achieves leading performance. Compared with these methods, our model focuses more on the variability within RGB and depth data and apply different modules to enhance the feature representation. The depth-aware convolution proposed by D-CNN [53] is more similar to our approach. For fair comparison, under single testing, D-CNN

| Method       | Backbone | Setting | Pixel Acc. (%) | mIoU (%) |
|--------------|----------|---------|----------------|----------|
| Deeplabv3+   | ResNet-101 | baseline | 75.1 | 47.4 |
|              |          | ours    | 77.3 | 52.1 |
|              |          | +       | 2.2  | 4.7  |
| Deeplabv3    | ResNet-50 | baseline | 74.5 | 46.5 |
|              |          | ours    | 76.8 | 51.2 |
|              |          | +       | 2.3  | 4.7  |
| PSPNet [33]  | ResNet-101 | baseline | 72.7 | 45.2 |
|              |          | ours    | 75.8 | 49.4 |
|              |          | +       | 3.1  | 4.8  |
| FPN [62]     | ResNet-101 | baseline | 72.8 | 44.3 |
|              |          | ours    | 75.6 | 49.2 |
|              |          | +       | 2.8  | 4.9  |
|              | ResNet-50 | baseline | 72.2 | 43.6 |
|              |          | ours    | 75.1 | 48.5 |
|              |          | +       | 2.9  | 4.9  |

### Table 7. Performance comparison with the state-of-the-art methods on NYUDv2 test set. '*' means multi-scale testing.

| Method       | Pixel Acc. (%) | mIoU (%) |
|--------------|----------------|----------|
| LSD-GF [11]  | 71.9           | 45.9     |
| D-CNN [53]   | -              | 48.4     |
| MMAF-Net [14]| 72.2           | 44.8     |
| ACNet [23]   | -              | 48.3     |
| ShapeConv [3]| 75.8           | 50.2     |
| RDF [39]*    | 76.0           | 50.1     |
| M2.5D [58]*  | 76.9           | 50.9     |
| SGNet [9]*   | 76.8           | 51.1     |
| SA-Gate [10]*| 77.9           | 52.4     |
| InverseForm [2]* | 78.1 | 53.1 |
| ShapeConv [3]* | 76.4 | 51.3 |
| DCANet       | 77.3           | 52.1     |
| DCANet*      | 78.2           | 53.3     |

### Table 8. Performance comparison with the state-of-the-art methods on SUN RGB-D test set. '*' means multi-scale testing.

| Method       | Pixel Acc. (%) | mIoU (%) |
|--------------|----------------|----------|
| 3DGNN [42]   | -              | 44.1     |
| D-CNN [53]   | -              | 42.0     |
| MMAF-Net [14]| 81.0           | 47.0     |
| SGNet [9]    | 81.0           | 47.5     |
| ShapeConv [3]| 82.0           | 47.6     |
| ACNet [23]   | -              | 48.1     |
| 3DGNN [42]*  | -              | 45.9     |
| CRF [29]*    | -              | 48.1     |
| RDF [39]*    | 81.5           | 47.7     |
| SA-Gate [10]*| 82.5           | 49.4     |
| SGNet [9]*   | 82.0           | 47.6     |
| ShapeConv [3]* | 82.2 | 48.6 |
| DCANet       | 82.2           | 48.1     |
| DCANet*      | 82.6           | 49.6     |

Note: Our proposed method applies DCA for Depth and EDCA for RGB data.
achieves the mIoU of 48.4, while our model achieve the score of 52.1, a 3.7% improvement. This because depth-aware convolution is used to produce a feature map while our DCA and EDCA are employed to generate an attention map that indicates the importance of different points. Moreover, depth-aware convolution only compares the similarity of local regions in the depth map and ignores the long-range dependence and global spatial consistency in RGB data, which can be captured by our EDCA.

SUN RGB-D. Tab. 8 shows testing results on SUN RGB-D dataset. The DCANet achieves the best results compared with other state-of-the-art methods under both single-scale and multi-scale testing.

5. Visualization of DCANet

Fig. 5 illustrates the qualitative results of the NYUDv2 and SUN RGB-D dataset. From the results, we can confirm that the local geometric information in depth image and global dependence in RGB image are well enhanced by our DCA and EDCA modules. As illustrated in the second row on the right part, our DCANet successfully recognize the whole lamp including its bracket while it is even unrecognizable under strong lighting conditions. That is because our model effectively combines the advantages of both modal data. Specifically, when the 2D information of the object is unreliable, the model will make reasonable use of the corresponding geometric information. Similar examples can be found in the second row on the left part.

To validate the effectiveness of the DCA and EDCA of our model, we apply the response maps of the baseline model and our DCANet. As shown in Fig. 6, the refined feature maps demonstrate the segmentation effectiveness of our method on capturing pixel-level subtle information (edge areas), where the pixel differential convolution matters. The attention maps of the RGB and depth data also explain that the DCA provide intrinsic fine-grained local geometry difference information for depth data, while EDCA effectively provide a global view for RGB data.

6. Conclusion

Considering the intrinsic difference between RGB and depth data, we present a state-of-the-art differential convolution attention network by introducing two plug-and-play modules: DCA and EDCA. DCA dynamically perceives
subtle geometric information that occurs in local regions in depth data. EDCA absorbs the advantage of dynamic convolution of DCA to propagate long-range contextual dependencies and seamlessly incorporate spatial distribution for RGB data. Attention maps generated by DCA and EDCA are employed to boost feature representations and further improve model performances.

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