ShapeConv: Shape-aware Convolutional Layer for Indoor RGB-D Semantic Segmentation

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Abstract

RGB-D semantic segmentation has attracted increasing attention over the past few years. Existing methods mostly employ homogeneous convolution operators to consume the RGB and depth features, ignoring their intrinsic differences. In fact, the RGB values capture the photometric appearance properties in the projected image space, while the depth feature encodes both the shape of a local geometry as well as the base (whereabout) of it in a larger context. Compared with the base, the shape probably is more inherent and has a stronger connection to the semantics, and thus is more critical for segmentation accuracy. Inspired by this observation, we introduce a Shape-aware Convolutional layer (ShapeConv) for processing the depth feature, where the depth feature is firstly decomposed into a shape-component and a base-component, next two learnable weights are introduced to cooperate with them independently, and finally a convolution is applied on the re-weighted combination of these two components. ShapeConv is model-agnostic and can be easily integrated into most CNNs to replace vanilla convolutional layers for semantic segmentation. Extensive experiments on three challenging indoor RGB-D semantic segmentation benchmarks, i.e., NYU-Dv2(-13,-40), SUN RGB-D, and SID, demonstrate the effectiveness of our ShapeConv when employing it over five popular architectures. Moreover, the performance of CNNs with ShapeConv is boosted without introducing any computation and memory increase in the inference phase. The reason is that the learnt weights for balancing the importance between the shape and base components in ShapeConv become constants in the inference phase, and thus can be fused into the following convolution, resulting in a network that is identical to one with vanilla convolutional layers.

1. Introduction

With the widespread use of depth sensors (such as Microsoft Kinect \cite{31}), the availability of RGB-D data has boosted the advancement of RGB-D semantic segmentation, which contributes to an indispensable task in the computer vision community. Thanks to the flourishing of Convolutional Neural Networks (CNNs), recent studies mostly resort to CNNs for tackling this problem. Convolutional layers, deemed as the core building blocks of CNNs, are accordingly the key elements in RGB-D semantic segmentation models \cite{6,13,15,17,21,22}.

However, RGB and depth information are inherently different from each other. In particular, RGB values capture the photometric appearance properties in the projected image space, while the depth feature encodes both the shape of a local geometry as well as the base (whereabout) of it in a larger context. As a result, the convolution operator that is widely adopted for consuming RGB data might not be...
the optimal for processing the depth data. Taking Figure 1 as an example, we would expect the corresponding patches of the same chairs to have the same features, as they share the same shape. The shape is a more inherent property of the underlying object and has stronger connection to the semantics. We would expect to achieve shape invariance in the learning process. When a vanilla convolution operator is applied on these corresponding patches, the resulting features are different due to the differences in their base component, hindering the learning from achieving shape invariance. On the other hand, the base components cannot be simply discarded for pursuing the shape invariance in the current layer, as they form the shape in a followup layer with a larger context.

To address these problems, we propose a Shape-aware Convolutional layer (ShapeConv), to learn the adaptive balance between the importance of shape and base information, giving the network the chance to focus more on the shape information whenever necessary for benefiting the RGB-D segmentation task. We firstly decompose a patch into two separate components, i.e., a base-component and a shape-component. The mean of patch values depicts the whereabout of the patch in a larger context, thus constitutes the base component, while the residual is the relative changes in the patch, which depicts the shape of the underlying geometry, thus constitutes to the shape component. Specifically, for an input patch (such as $P_1$ in Figure 1), the base describes where the patch is, i.e., the distance from the observation point; while the shape expresses what the patch is, e.g., a chair corner. We then employ two operations, namely, base-product and shape-product, to respectively process these two components with two learnable weights, i.e., base-kernel and shape-kernel. The output from these two is then combined in an addition manner to form a shape-aware patch, which is further convolved with a normal convolutional kernel. In contrast to the original patch, the shape-aware one is capable of adaptively learning the shape characteristic with the shape-kernel, and the base-kernel serves to balance the contributions of the shape and the base for the final prediction.

In addition, since the base-kernel and shape-kernel become constants in the inference phase, we can fuse them into the following convolution kernel, resulting in a network that is identical to the one with vanilla convolutional layers. The proposed ShapeConv can be easily plugged into most CNNs as a replacement of the vanilla convolution in semantic segmentation without introducing any computation and memory increase in the inference phase. This simple replacement transforms CNNs designed for RGB data into ones better suited for consuming RGB-D data.

To validate the effectiveness of the proposed method, we conduct extensive experiments on three challenging RGB-D indoor semantic segmentation benchmarks: NYU-Dv2 [25](-13,-40), SUN RGBD [26], and SID [1]. We apply our ShapeConv to five popular semantic segmentation architectures and can observe promising performance improvements compared with baseline models. We found that ShapeConv can significantly improve the segmentation accuracy around the object boundaries (see Figure 5), which demonstrates the effective leveraging of the depth information.

2. Related Work

CNNs have been widely used for semantic segmentation on RGB images [3, 4, 19, 18, 23, 33]. In general, existing segmentation architectures usually involve two stages: the backbone and the segmentation stage. The former stage is leveraged to extract features from RGB images, wherein popular models are ResNet [12], ResNetXt [29] which are pre-trained on the ImageNet dataset [24]. The latter stage aims to generate predictions based on the extracted features. Methods in this stage include Upsample [19], PPM [33] and ASPP [3, 4], etc. It is worth noting that both stages adopt the convolutional layers as the core building blocks.

As RGB semantic segmentation has been extensively studied in literature, a straightforward solution for RGB-D semantic segmentation is to adapt the well-developed architectures from the ones designed for RGB data. However, implementing such a idea is non-trivial due to the asymmetric modality problem between the RGB and the depth information. To tackle this, researchers have devoted efforts into two directions: designing dedicated architectures for RGB-D data [6, 8, 13, 15, 17, 21, 28], and presenting novel layers to enhance or replace the convolutional layers in RGB semantic segmentation [5, 27, 30]. Our method falls into the second category.

Methods in the first category propose to feed RGB and depth channels to two parallel CNNs streams, where the output features are fused with specific strategies. For example, [6] presents a gate-fusion method, [8, 13, 21] fuse the features in multi-levels of the backbone stages. Nevertheless, these methods mostly leverage separate networks to consume RGB and depth features, they are yet faced with two limitations: 1) it is hard to decide when is the best stage for the fusion to happen; and 2) the two-stream or multi-level way often results in large increase of computation.

In contrast, methods along the second direction target at designing novel layers based on the geometric characteristics of RGB-D data, which are more flexible and time-efficient. For instance, Wang et al. [27] proposed the depth-aware convolution to weight pixels based on a hand-crafted Gaussian function by leveraging the depth similarity between pixels. [30] presents a novel operator called mal-

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1The operation unit of input features for the convolutional layer, whose spatial size is the same as the convolution kernel.

2Our code is released through https://github.com/hanchaoleng/ShapeConv.
leable 2.5D convolution, to learn the receptive field along the depth-axis. \cite{5} devises a S-Conv to infer the sampling offset of the convolution kernel guided by the 3D spatial information, enabling the convolutional layer to adjust the receptive field and geometric transformations. ShapeConv proposed a novel view of the content in each patch and a mechanism to leverage them adaptively with learnt weights. Moreover, ShapeConv can be converted into vanilla convolution in the inference phase, resulting in ZERO increase of memory and computation compared with the models with vanilla convolution.

3. Method

In this section, we first provide the basic formulation of the Shape-aware convolutional layer (ShapeConv) for RGB-D data, followed by its application in the training and inference phase. We end this section with the method architectures.

3.1. ShapeConv for RGB-D Data

**Method Intuition.** Given an input patch \( P \in R^{K_h \times K_w \times C_{in}} \), \( K_h \) and \( K_w \) are the spatial dimensions of the kernel; \( C_{in} \) represents the channel numbers in the input feature map, the output features from the vanilla convolution layer are obtained by,

\[
F = \text{Conv}(K, P),
\]

where \( K \in R^{K_h \times K_w \times C_{in} \times C_{out}} \) denotes the learnable weights of kernels in a convolutional layer (The bias terms are not included for simplicity); \( C_{out} \) represents the channel numbers in the output feature map. Each element of \( F \in R^{C_{out}} \) is calculated as,

\[
F_{cout} = \sum_{i} (K_{i,c_{out}} \times P_{i}).
\]

It can be easily recognized that \( F \) usually changes with respect to different values of \( P \). Take the two patches in the Figure\[P_1\] and \( P_2 \), as an example. The corresponding output features, \( F_1 \) and \( F_2 \) from the vanilla convolution layer are learned by: \( F_1 = \text{Conv}(K, P_1), F_2 = \text{Conv}(K, P_2) \). Since \( P_1 \) and \( P_2 \) are not identical (different distances from the observation points), accordingly, their features are usually different, and this may lead to distinct prediction results.

Nevertheless, \( P_1 \) and \( P_2 \), corresponding to the red regions in Figure\[P_1\] actually belong to the same class - chair. And vanilla convolutional layers cannot well handle such situations. In fact, there exists some invariants of these two patches, namely, the shape. It refers to the relative depth correlation under local features, which is however, unexpectedly ignored by the existing methods. In view of this, we propose to fill this gap via effectively modeling the shape for RGB-D semantic segmentation.

**ShapeConv Formulation.** Based on the aforementioned analysis, in this paper, we offer to decompose an input patch into two components: a base-component \( P_B \) describing where the patch is, and a shape-component \( P_S \) expressing what the patch is. Therefore, we refer the mean of patch values to be \( P_B \), and its relative values to be as \( P_S \):

\[
P_B = m(P), \quad P_S = P - m(P),
\]

where \( m(P) \) is the mean function on \( P \) (over the \( K_h \times K_w \) dimensions), and \( P_B \in R^{1 \times 1 \times C_{in}} \), and \( P_S \in R^{K_h \times K_w \times C_{in}} \).

Note that directly convolved \( P_S \) with \( K \) in Equation\[P_1\] is sub-optimal, as the values from \( P_B \) contributes the class discrimination across patches. Thus, our ShapeConv instead leverages two learnable weights, \( W_B \in R^{1 \times 1 \times C_{in}} \) and \( W_S \in R^{K_h \times K_w \times C_{in}} \), to separately compute the above two components. The outputted features are then combined in an element-wise addition manner, which forms a new shape-aware patch with the same size as the original one \( P \). The formulation of ShapeConv is given as,

\[
F = \text{ShapeConv}(K, W_B, W_S, P) = \text{Conv}(K, W_B \odot P_B + W_S \ast P_S) = \text{Conv}(K, P_B + P_S) = \text{Conv}(K, P_{BS}),
\]

where \( \odot \) and \( \ast \) denote the base-product and shape-product operator, respectively, which are defined as,

\[
\begin{align*}
P_B &= W_B \odot P_B, \\
P_{B_{1,1}} &= W_B \times P_{B_{1,1}}, \\
P_S &= W_S \ast P_S, \\
P_{S_{k_h,k_w}} &= \sum_{i} W_S \times P_{S_{k_h,k_w}}.
\end{align*}
\]

where \( c_{in}, k_h, k_w \) are the indices of the elements in \( C_{in}, K_h, K_w \) dimensions, respectively.

We reconstruct the shape-aware patch \( P_{BS} \) from the addition of \( P_B \) and \( P_S \), and \( P_{BS} \in R^{K_h \times K_w \times C_{in}} \), which enables it to be smoothly convolved by the kernel \( K \) of vanilla convolutional layer. Nevertheless, the \( P_{BS} \) is equipped with the important shape information which is learned by the two additional weights, making the convolutional layer to focus on the situations when merely using depth values fails.

3.2. ShapeConv in Training and Inference

**Training phase.** The proposed ShapeConv in Section 3.1 can effective leverage the shape information of the observation points, we notice that the rotational transformations cannot be addressed due to the angle of view limitation. As a result, we focus more on the translational transformations in this paper.
patches. However, replacing vanilla convolutional layer with ShapeConv in CNNs introduces more computational cost due to the two product operation in Equation 3 and 4. To tackle this problem, we propose to shift these two operations from patches to kernels,

$$\begin{align*}
\{ K_B = W_B \times K_B \\
K_{B_{i,1,c_{in},c_{out}}} = W_B \times K_{i,1,c_{in},c_{out}},
\end{align*}$$

$$\begin{align*}
\{ K_S = W_S \times K_S \\
K_{S_{i,k_h,k_w,c_{in},c_{out}}} = \sum_k K_h \times K_w \times (W_{S_{i,k_h,k_w,c_{in}}} \times K_{S_{i,c_{in},c_{out}}} ),
\end{align*}$$

where $K_B \in R^{1 \times C_{in} \times C_{out}}$ and $K_S \in R^{K_h \times K_w \times C_{in} \times C_{out}}$ denote the base-component of kernels and shape-component, respectively, and $K = K_B + K_S$.

We therefore re-formalize ShapeConv the Equation 2 to following:

$$\begin{align*}
F = ShapeConv(K, W_B, W_S, P) \\
&= Conv(W_B \circ m(K) + W_S \times (K - m(K)), P) \\
&= Conv(W_B \circ K_B + W_S \times K_S, P) \\
&= Conv(K_B + K_S, P) \\
&= Conv(K_{BS}, P),
\end{align*}$$

where $m(K)$ is the mean function on $K$ (over the $K_h \times K_w$ dimensions). And we require $K_{BS} = K_B + K_S$, $K_{BS} \in R^{K_h \times K_w \times C_{in} \times C_{out}}$.

In fact, the two formulations of ShpeConv, i.e., Equation 2 and Equation 5 are mathematically equivalent, i.e.,

$$\begin{align*}
F = ShapeConv(K, W_B, W_S, P) \\
&= Conv(K, P_{BS}) \\
&= Conv(K_{BS}, P),
\end{align*}$$

$$\begin{align*}
F_{cout} &= \sum_i (K_{i,c_{out}} \times P_{BS_i}) \\
&= \sum_i (K_{BS_{i,c_{out}}} \times P_i),
\end{align*}$$

please refer to the Supp. for detailed proof. In this way, we utilize the ShapeConv in Equation 5 in our implementation as illustrated in Figure 2(b) and (c).

**Inference phase.** During inference, since the two additional weights i.e. $W_B$ and $W_S$, become constants, we can fuse them into $K_{BS}$ as shown in Figure 2(c) with $K_{BS} = W_B \odot K_B + W_S \odot K_S$. And $K_{BS}$ shares the same tensor size with $K$ in Equation 1 thus, our ShapeConv is actually the same as the vanilla convolutional layer in Figure 2(a). In other words, when replacing vanilla convolution with ShapeConv, there would introduce zero additional inference time.

### 3.3. ShapeConv-enhanced Network Architecture

Different from devising specially dedicated architectures for RGB-D segmentation [21, 22, 27], the proposed ShapeConv is a more generalized approach that can be easily plugged into most CNNs as a replacement for the vanilla convolution in semantic segmentation, which is then transformed for adapting the RGB-D data.

Figure 5 depicts an example of the overall method architecture. In order to leverage the advanced backbones in semantic segmentation, we firstly require to convert the input features from RGB images to RGB-D data via the concatenation of the RGB and D information. In practice, D can be depth values [11, 20] or HHA images [10, 19, 16, 6]. We then replace the vanilla convolution layer with the ShapeConv in both the backbone and segmentation stages. It is worth noting that, $W_B$ is initialized to one, $W_S$ can be viewed as $C_{in}$ square ($K_h \times K_w \times (K_h \times K_w)$) matrices, which are initialized to the identity matrix. In this way, ShapeConv is equivalent to the vanilla convolution at the beginning of training since $K_{BS} = K$.

This initialization approach offers two advantages: 1) It makes the ShapeConv-enhanced networks do not interfere with the RGB data, i.e., the RGB features are processed in the same way as before. 2) It facilitates ShapeConv to reuse the parameters from pre-trained models.

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4Horizontal disparity, Height above ground and normal Angle to the vertical axis.
Thus, with this approach, future advances in RGB semantic segmentation architectures can be easily transferred to consuming the RGB-D data, greatly reducing the effort that would otherwise be spent on designing dedicated networks for RGB-D semantic segmentation. We have shown the results of building RGB-D segmentation networks with this style using several popular architectures \cite{3, 4, 18, 23} in Sec 4.2.

### 4. Experiments

**Datasets and metrics.** Among the existing RGB-D segmentation problems, the indoor semantic segmentation is rather challenging, as the objects are often complex and with severe occlusions \cite{5}. Thus, in order to validate the effectiveness of the proposed method, we conducted experiments on three indoor RGB-D benchmarks: NYU-DepthV2 (NYUDv2-13 and -40) \cite{25}, SUN-RGBD \cite{26} and Stanford Indoor Dataset (SID) \cite{1}. NYUDv2 contains 1,449 RGB-D scene images, where 795 images are split for training and 654 images for testing. We adopted two popular settings for this dataset, i.e., 13-class \cite{25} and 40-class \cite{9}, where all pixels are labeled with 13 and 40 classes, respectively. SUN-RGBD is composed of 10,355 RGB-D indoor images with 37 categories for each pixel label. We followed the widely used setting in \cite{26} to split the dataset into a training set of 5285 images and a testing set of 5050 images. SID contains 70,496 RGB-D images with 13 object categories. In particular, areas 1, 2, 3, 4, and 6 used for the training and Area 5 is for testing following \cite{27}.

We reported the results using the same evaluation protocol and metrics as FCN \cite{19}, i.e., Pixel Accuracy (Pixel Acc.), Mean Accuracy (Mean Acc.), Mean Region Intersection Over Union (Mean IoU), and Frequency Weighted Intersection Over Union (f.w. IoU).

**Comparison protocol.** We adopted several popular architectures with different backbones as our baseline methods to demonstrate the effectiveness and generalization capability of ShapeConv. For all the baseline methods, we only replaced the vanilla convolutional layers with our ShapeConv, without any change to other settings. This guarantees that the obtained performance improvements is due to the application of ShapeConv, but not other factors.

| Backbone | Setting | Pixel Acc. | Mean Acc. | Mean IoU | f.w. IoU |
|----------|---------|------------|-----------|----------|----------|
| Baseline | 80.0    | 72.5       | 60.8      | 67.6     |          |
| Baseline* | 80.6   | 72.7       | 61.6      | 68.5     |          |
| Ours     | 80.4    | 73.0       | 61.8      | 68.1     |          |
| Ours*    | 81.1    | 73.4       | 62.7      | 69.1     |          |
| +        | 0.4     | 0.5        | 1.0       | 0.3      |          |
| ⋆        | 0.5     | 0.7        | 1.1       | 0.6      |          |

| Backbone | Setting | Pixel Acc. | Mean Acc. | Mean IoU | f.w. IoU |
|----------|---------|------------|-----------|----------|----------|
| Baseline | 80.0    | 73.4       | 61.3      | 67.6     |          |
| Baseline* | 81.0   | 74.3       | 63.1      | 68.9     |          |
| Ours     | 81.2    | 74.9       | 62.9      | 69.1     |          |
| Ours*    | 81.9    | 75.7       | 64.0      | 70.1     |          |
| +        | 1.2     | 1.5        | 1.6       | 1.5      |          |
| ⋆        | 0.9     | 1.4        | 0.9       | 1.2      |          |

| Backbone | Setting | Pixel Acc. | Mean Acc. | Mean IoU | f.w. IoU |
|----------|---------|------------|-----------|----------|----------|
| Baseline | 81.8    | 73.9       | 63.2      | 70.1     |          |
| Baseline* | 82.2   | 74.4       | 63.7      | 70.6     |          |
| Ours     | 82.6    | 75.7       | 65.1      | 71.2     |          |
| Ours*    | 82.9    | 76.0       | 65.6      | 71.6     |          |
| +        | 0.8     | 1.8        | 1.9       | 1.1      |          |
| ⋆        | 0.7     | 1.6        | 1.9       | 1.0      |          |

**Implementation Details.** We used the ResNet \cite{12} and ResNeXt \cite{29} initialized with the pre-trained model on ImageNet \cite{24} in the backbone stage. If not otherwise noted, the inputs of both the baseline and ours are the concatenation of RGB and HHA images. We adopted both single-scale and multi-scale testing strategies during inference. For the latter one, left-right flipped images and five scales are exploited: [0.5, 0.75, 1.0, 1.25, 1.5, 1.75]. ⋆ in tables of this section denotes the multi-scale strategy. Note that, no
post-processing tricks like CRF is used in our experiments.

Table 2. Performance comparison with baselines on NYUDv2-40 dataset. Deeplabv3+ is the adopted architecture.

| Backbone | Setting | Pixel Acc.(%) | Mean Acc.(%) | Mean IoU(%) | f.w. IoU(%) |
|----------|---------|---------------|--------------|-------------|-------------|
| ResNet 50 | Baseline | 73.1 | 57.7 | 45.6 | 59.2 |
| Ours | 74.2 | 59.0 | 47.1 | 60.2 |
| + | 75.0 | 60.4 | 48.8 | 61.4 |
| ResNet 101 | Baseline | 73.4 | 58.9 | 45.9 | 59.7 |
| Ours | 74.4 | 60.2 | 47.6 | 60.7 |
| + | 75.5 | 60.7 | 49.0 | 61.7 |
| ResNet 101_32x8d | Baseline | 74.7 | 61.5 | 48.9 | 61.5 |
| Baseline* | 75.4 | 62.6 | 50.3 | 62.2 |
| Ours | 75.8 | 62.8 | 50.2 | 62.6 |
| + | 76.4 | 63.5 | 51.3 | 63.0 |
| ResNet 50 | Baseline* | 81.4 | 65.4 | 45.6 | 70.0 |
| Ours | 81.8 | 65.8 | 46.3 | 70.3 |
| + | 82.2 | 69.2 | 48.6 | 71.3 |
| ResNet 101 | Baseline | 81.6 | 65.7 | 46.4 | 70.4 |
| Ours | 82.0 | 65.8 | 47.6 | 70.5 |
| + | 82.2 | 69.2 | 48.6 | 71.3 |

Table 3. Performance comparison with other methods on NYUDv2-13 dataset.

| Method | Pixel Acc.(%) | Mean Acc.(%) | Mean IoU(%) | f.w. IoU(%) |
|--------|---------------|--------------|-------------|-------------|
| Eigen [17] | 75.4 | 66.9 | - | - |
| MVCNet [20] | 77.8 | 69.5 | 57.3 | - |
| Ours | 82.6 | 75.7 | 65.1 | 71.2 |
| MVCNet [20]* | 79.1 | 70.6 | 59.1 | - |
| PVNet [22]* | 82.5 | 74.4 | 59.3 | - |
| Ours* | 82.9 | 76.0 | 65.6 | 71.6 |

Table 4. Performance comparison with other methods on NYUDv2-40 dataset.

| Method | Pixel Acc.(%) | Mean Acc.(%) | Mean IoU(%) | f.w. IoU(%) |
|--------|---------------|--------------|-------------|-------------|
| FCN [19] | 65.4 | 46.1 | 34.0 | 49.5 |
| LSD-GF [6] | 71.9 | 60.7 | 45.9 | 59.3 |
| D-CNN [2] | - | 61.1 | 48.4 | - |
| MAAF-Net [8] | 72.2 | 59.2 | 44.8 | - |
| ACNet [13] | - | - | 48.3 | - |
| Ours | 75.8 | 62.8 | 50.2 | 62.6 |
| CFN [17] | - | - | 47.7 | - |
| 3DGNN [22] | - | 55.7 | 43.1 | - |
| RDF [21] | 76.0 | 62.8 | 50.1 | - |
| M2SD [10] | 76.9 | - | 50.9 | - |
| SGNet [5] | 76.8 | 63.3 | 51.1 | - |
| Ours | 76.4 | 65.3 | 51.3 | 63.0 |

Table 5. Performance comparison with baselines on SUN-RGBD dataset. The architectures adopted in this table is deeplabv3+ with different backbones.

| Backbone | Setting | Pixel Acc.(%) | Mean Acc.(%) | Mean IoU(%) | f.w. IoU(%) |
|----------|---------|---------------|--------------|-------------|-------------|
| ResNet 50 | Baseline | 81.1 | 56.5 | 45.5 | 69.7 |
| Baseline* | 81.4 | 57.5 | 46.6 | 70.0 |
| Ours | 81.6 | 56.8 | 46.3 | 70.3 |
| + | 82.2 | 59.2 | 48.5 | 71.3 |
| ResNet 101 | Baseline | 81.6 | 57.8 | 46.9 | 70.4 |
| Baseline* | 81.8 | 58.4 | 47.6 | 70.5 |
| Ours | 82.0 | 58.5 | 47.6 | 71.2 |
| + | 82.2 | 59.2 | 48.6 | 71.3 |

Table 5. Performance comparison with baselines on SUN-RGBD dataset. The architectures adopted in this table is deeplabv3+ with different backbones.

Table 6. Performance comparison on SUN-RGBD dataset.

| Method | Pixel Acc.(%) | Mean Acc.(%) | Mean IoU(%) | f.w. IoU(%) |
|--------|---------------|--------------|-------------|-------------|
| 3DGNN-101 [22] | - | 55.7 | 44.1 | - |
| D-CNN-50 [27] | - | 53.5 | 42.0 | - |
| MAAF-Net-152 [8] | 81.0 | 58.2 | 47.0 | - |
| SGNet-101 [5] | 81.0 | 59.8 | 47.5 | - |
| Ours-101 | 82.0 | 59.5 | 47.6 | 71.2 |
| CFN-101 [17] | - | - | 48.1 | - |
| 3DGNN-101 [22] | - | - | 45.9 | - |
| RDF-152 [21] | 81.5 | 60.1 | 47.7 | - |
| SGNet-101 [5] | 82.0 | 60.7 | 48.6 | - |
| Ours-101 | 82.2 | 59.2 | 48.6 | 71.3 |

SUN-RGBD Dataset. The comparison results between baseline and ours with SUN-RGBD dataset are reported in Table 2.

NYUDv2 Dataset. We adopted two popular settings for this dataset, i.e., 13-class and 40-class, and show the results of baseline and our method with different backbones on NYUDv2-13 and NYUDv2-40 in Table 4.

We also compare the performance of our ShapeConv with several recently developed methods in Table 5 and Table 6. As illustrated in Table 3, ShapeConv achieves the best over all the four metrics on NYUDv2-13. Compared to the recently proposed method [32], our approach yields around 6.3% improvements on Mean IOU which is the most commonly used metric for semantic segmentation. In addition, our method also achieves a competitive performance on NYUDv2-40 in Table 4.

4.1. Experiments on Different Datasets

NYUDv2 Dataset. We adopted two popular settings for this dataset, i.e., 13-class and 40-class, and show the results of baseline and our method with different backbones on NYUDv2-13 and NYUDv2-40 in Table 4. As illustrated in Table 3, ShapeConv achieves the best over all the four metrics on NYUDv2-13. Compared to the recently proposed method [32], our approach yields around 6.3% improvements on Mean IOU which is the most commonly used metric for semantic segmentation. In addition, our method also achieves a competitive performance on NYUDv2-40 in Table 4.

Note that SID dataset is much larger than NYUDv2-13 and NYUDv2-40 in Table 4 and Table 2 respectively. It can be seen that architectures with ShapeConv outperform the baselines with a large margin under all settings.

We also compare the performance of our ShapeConv with several recently developed methods in Table 6 and Table 4. As illustrated in Table 5, ShapeConv achieves the best overall over all the four metrics on NYUDv2-13. Compared to the recently proposed method [32], our approach yields around 6.3% improvements on Mean IOU which is the most commonly used metric for semantic segmentation. In addition, our method also achieves a competitive performance on NYUDv2-40 in Table 4.

Table 5. Performance comparison with baselines on SUN-RGBD dataset. The architectures adopted in this table is deeplabv3+ with different backbones.

Table 6. Performance comparison on SUN-RGBD dataset.

SUN-RGBD Dataset. The comparison results between baseline and ours with SUN-RGBD dataset are reported in Table 2.

SID Dataset. Note that SID dataset is much larger than the other two datasets, contributing to a better testbed for...
evaluating RGB-D semantic segmentation model capabilities. The results on SID dataset between the baseline with ours and the state-of-the-art methods are reported in Table [7]. We can observe that our ShapeConv surpasses these methods with a large margin. Note that even though we utilized a strong baseline (ResNet-101 backbone) which surpasses MMAF-Net-152 (ResNet-152 backbone) with 1.7% Mean IoU, our ShapeConv can still achieve a 6% Mean IoU improvement. This highlights the effectiveness of our method.

Table 7. Performance comparison on SID dataset. The architectures of baseline and ours adopted in this table is deeplabv3+ with ResNet-101 backbone and the “+” denote the deltas relative to the baseline method.

| Method       | Backbone Setting | Baseline | Ours | Ours+ |
|--------------|------------------|----------|------|-------|
| D-CNN [27]   | ResNet-101       | 73.4     | 58.9 | 45.9  |
| MMAF-Net-152 | ResNet-101       | 73.5     | 59.5 | 47.4  |
| Baseline-101 |                  | 73.1     | 51.7 | 43.6  |
| Ours-101     |                  | 74.1     | 59.1 | 47.3  |
| +            |                  | 1.0      | 1.4  | 1.7   |

4.2. Experiments on Different Architectures

Our proposed ShapeConv is a general layer for RGB-D semantic segmentation which can be easily plugged into most CNNs as a replacement for the vanilla convolution in semantic segmentation. To verify its generalization properties, we also evaluated the effectiveness of our method in several representative semantic segmentation architectures: Deeplabv3+ [4], Deeplabv3 [13], UNet [23], PSPNet [33] and FPN [18] with different backbones (ResNet-50 [12], ResNet-101 [12]) on NYUDv2-40 dataset, and reported the performance in Table 8. We can see that ShapeConv brings significant performance improvements under all settings, demonstrating the generalization capability of our method.

Table 8. Performance comparison with different baseline methods on NYUDv2-40 dataset.

| Architecture | Setting | Pixel Acc. (%) | Mean Acc. (%) | Mean IoU (%) | f.w. IoU (%) |
|--------------|---------|----------------|---------------|--------------|--------------|
| DeepLabv3+   | ResNet-101 Baseline | 73.4 | 58.9 | 45.9 | 59.7 |
|              | Ours    | 73.5 | 59.5 | 47.4 | 60.8 |
|              | +       | 1.1  | 0.6  | 1.5  | 1.1  |
| DeepLabv3    | ResNet-101 Baseline | 71.6 | 55.5 | 43.2 | 57.2 |
|              | Ours    | 72.8 | 56.6 | 44.9 | 58.5 |
|              | +       | 1.2  | 1.1  | 1.7  | 1.3  |
| U-Net        | ResNet-101 Baseline | 70.9 | 54.7 | 42.1 | 57.7 |
|              | Ours    | 72.3 | 56.5 | 45.9 | 58.8 |
|              | +       | 1.4  | 1.8  | 1.8  | 1.1  |
| PSPNet       | ResNet-101 Baseline | 72.8 | 56.8 | 44.4 | 58.9 |
|              | Ours    | 73.3 | 59.2 | 46.3 | 59.6 |
|              | +       | 0.5  | 2.4  | 2.1  | 0.7  |
| FPN          | ResNet-101 Baseline | 71.1 | 53.6 | 42.0 | 56.7 |
|              | Ours    | 72.0 | 56.2 | 44.0 | 57.7 |
|              | +       | 0.9  | 2.6  | 2.0  | 1.0  |

4.3. Visualization

Figure 4 illustrates the qualitative results on NYUDv2-13 and -40, more results can be found in the Supp. As shown in this figure, the depth information, especially the detailed one, can be well utilized by ShapeConv to extract the object features. For instance, the chair and table regions in the top example of Figure 4(a) are with gradually changed colors, making it hard to predict accurate segmentation boundaries of the baseline method. The shape fea-
features learned by ShapeConv makes the accurate cut following the geometric hints compare with the conventional convolutional layer. For other two cases, i.e., the chair in the bottom example of Figure 2(a) and the desk in the top example of Figure 2(b), the ShapeConv can also significantly improve the segmentation results in edge areas compared with the baseline. It is worth noting that for the multiple bookshelves in the bottom example of Figure 2(b), ShapeConv achieves more consistent predictions. This is because our ShapeConv yields a positive tendency for smoothing neighborhood regions within same classes.

To validate the effectiveness of our method on modeling the depth information, we adopted the comparison strategy proposed by Kohli et al. [14]. Specifically, we counted the relative number of misclassified pixels within a narrow band (“trimap”) surrounding ground-truth object boundaries. As shown in Figure 5, our method outperforms the baseline across all trimap widths. This further demonstrates the segmentation effectiveness of our method on edge areas, where the shape information matters.

4.4. Ablation Study

We conducted ablation experiments to validate the indispensability of the two introduced weights in Equation 5. As can be observed in Table 9, the model performance degrades when removing either \( W_B \) or \( W_S \), or both. This proves that both the base-kernel and shape-kernel are essential for the final performance improvement, and combing these two achieves the best results.

Table 9. Performance comparison with and without \( W_B \) and \( W_S \) in ShapeConv on NYUDv2-40. The architecture adopted in this table is deeplabv3+ with ResNet-101 as backbone.

| Setting | Pixel Acc. (%) | Mean Acc. (%) | Mean IoU (%) | lw. IoU (%) |
|---------|---------------|---------------|--------------|-----------|
| \( a \). RGB | 73.4 | 59.9 | 45.9 | 59.7 |
| \( b \). RGB+Depth | ✓ | 73.9 | 59.4 | 47.0 | 60.1 |
| \( c \). RGB+Depth ∗ | ✓ | 74.1 | 59.2 | 46.3 | 60.1 |
| \( d \). RGB+HHA | ∗ | 74.5 | 59.5 | 47.4 | 60.8 |
| \( e \). RGB+HHA+ShapeConv | ∗ | 75.5 | 60.7 | 49.0 | 61.7 |

To provide a more in-depth analysis of ShapeConv, we conducted detailed ablation studies on the NYUDv2-40 dataset with deeplabv3+ and ResNet-101 as baseline and backbone, respectively. Results on more datasets can be found at the Supp. Table 10 illustrates the results and the key observations from this table are as follows: 1) The input features with HHA outperform the Depth images for the baseline and ours; 2) Replacing the vanilla convolution with ShapeConv leads to considerable performance improvements on both Depth and HHA; 3) The multi-scale setting in testing phase brings more performance gains; 4) Cascading the ShapeConv with HHA and multi-scale testing can achieve the best result.

5. Conclusion

In this paper, we propose a ShapeConv layer to effectively leverage the depth information for RGB-D semantic segmentation. In particular, an input patch is firstly decomposed into two components, i.e., shape and base, which are then decorated with two corresponding learnable weights before the convolution is applied. We have conducted extensive experiments on several challenging indoor RGB-D semantic segmentation benchmarks and promising experimental results can be observed. Moreover, it is worth noting that our ShapeConv introducing no additional computation or memory in comparison with the vanilla convolution during inference, yet with superior performance.

In fact, the shape-component is inherent in the local geometry and highly relevant to the semantics in images. In the future, we plan to expand the application scope to other geometry entities, such as point clouds, where the shape-base decomposition is more challenging due to the additional degree of freedom.

Table 10. Ablation study of the proposed ShapeConv on the NYUDv2-40 dataset. RGB, Depth and HHA denote the inputs consisting of RGB images, depth images and HHA images.

| Setting | Pixel Acc. (%) | Mean Acc. (%) | Mean IoU (%) | lw. IoU (%) |
|---------|---------------|---------------|--------------|-----------|
| \( a \). RGB | 73.9 | 59.1 | 46.8 | 60.0 |
| \( b \). RGB+Depth | ∗ | 73.4 | 58.9 | 45.9 | 59.7 |
| \( c \). RGB+Depth ∗ | ∗ | 74.4 | 60.2 | 47.6 | 60.7 |
| \( d \). RGB+HHA | ∗ | 73.9 | 58.2 | 46.2 | 60.0 |
| \( e \). RGB+HHA+ShapeConv | ∗ | 74.5 | 59.5 | 47.4 | 60.8 |
| \( f \). RGB+HHA+ShapeConv | ∗ | 75.5 | 60.7 | 49.0 | 61.7 |

Figure 5. Segmentation accuracy around object boundaries. In this figure, the left is the visualization of the “trimap” measure; The right is the percent of misclassified pixels within trimaps of different widths.

| Trimap Width (Pixels) | Trimap(4pix) | Trimap(8pix) | Trimap(12pix) |
|-----------------------|-------------|-------------|-------------|
| 0 | 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 20 |
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