DCANet: Dense Context-Aware Network for Semantic Segmentation

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Abstract

As the superiority of context information gradually manifests in advanced semantic segmentation, learning to capture the compact context relationship can help to understand the complex scenes. In contrast to some previous works utilizing the multi-scale context fusion, we propose a novel module, named Dense Context-Aware (DCA) module, to adaptively integrate local detail information with global dependencies. Driven by the contextual relationship, the DCA module can better achieve the aggregation of context information to generate more powerful features. Furthermore, we deliberately design two extended structures based on the DCA modules to further capture the long-range contextual dependency information. By combining the DCA modules in cascade or parallel, our networks use a progressive strategy to improve multi-scale feature representations for robust segmentation. We empirically demonstrate the promising performance of our approach (DCANet) with extensive experiments on three challenging datasets, including PASCAL VOC 2012, Cityscapes, and ADE20K.

Keywords: Semantic segmentation, Dense Context-Aware module, Long-range contextual information, Progressive strategy

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1. Introduction

Semantic segmentation is a fundamental visual understanding task by solving a dense labeling problem, whose purpose is to assign different semantic categories for each pixel of the given image. It plays a crucial role in many potential applications such as scene understanding, autonomous driving, and human parsing, etc.

Recently, a lot of state-of-the-art semantic segmentation techniques based on the Fully Convolutional Network (FCN) [1] have achieved striking results. Among these works, one of the most effective approaches to enhance the robustness of segmentation is exploiting the scene context information to boost understanding of the various objects in semantic level. For example, some works [2][3] enlarge the kernel size with a decomposed structure or propose an effective context encoding layer to obtain rich global contextual information. And some works [4][5][6][7] aggregate multi-scale contextual information in the form of different pooling and dilated convolution operations to capture the correlation between regions. The pyramid pooling module in PSPNet [6] and atrous spatial pyramid pooling (ASPP) module in DeepLab [8][9][5] also provide effective parallel processing manners to help extract multi-scale context features to a certain degree. Besides, to establish long-range dependencies, the encoder-decoder structures [10][11][12] combine low-level and high-level semantic features by applying skip connections [13], which also achieves the multi-level context fusion.

Although the context fusion used in these approaches learns to generalize different scales objects to some extent, it can not leverage the relationship between objects in a global view, which is essential to capture the long-range contextual relationship for scene understanding [14][15]. Consequently, the segmentation networks with theses limited fusion methods such as concatenation or addition operation between global and local clues, have no sufficient understanding of objects in the scene. As a result, misclassification could occur, especially for some similar categories. To better illustrate the aforementioned issues, we show several representative examples in Fig. 1. Intuitively, we need to adaptively es-
Establish features dependencies in the spatial and channel dimensions to enhance the awareness of the scene context and collect the long-range dependencies from all pixels.

![Image](a) (b) (c)

(a) Image (b) FCN base model (c) Ground Truth

Figure 1: Illustration of hard examples from different datasets. (a) Input image. (b) the output of FCN based model. (c) Ground Truth label. These examples are from the PASCAL VOC 2012 and the Cityscapes dataset. In the first row, the left corner of the horse is recognized as a cow. In the second row, there are some obvious misclassified categories on the truck. The various scales, occlusion and similar appearance of objects need to dense contextual information to parse each pixel.

Towards the above issues, we design a Dense Context-Aware (DCA) module, a novel short-range module that captures the compact context relationship and explicitly enhances the capabilities of networks for multi-scale processing. Instead of directly utilizing the multi-scale context aggregation [4][6][11], our proposed DCA module extracts global descriptors and local features from two pathways under the contextual correlation. In detail, we regard the semantic level features as dense contextual awareness to adaptively apply attention to local clue in a data-driven manner, after which we apply the concatenation and addition operation to complete the fusion of different features, respectively.

Furthermore, we carry out a sequence of DCA modules at multiple scales to capture long-range contextual dependencies. Based on the DCA module, we further put forward two extended structures: (i) a novel network structure
named Cascade-DCA, which consists of several DCA modules working at different scales context. And we connect these modules in a cascading manner to get a finer long-range relationship. (ii) the Pyramid-DCA structure, following the pyramid design introduced in PSPNet, which performs multiple branches, each one utilizes cascaded DCA modules and finally accomplish feature fusion from different branches. With the long-range dependencies established, our network can progressively refine spatial relationships from a global view and improve feature representations for a comprehensive perception of complex scenes.

We extensively evaluate our DCANet on three most competitive semantic segmentation datasets, i.e., PASCAL VOC 2012, Cityscapes, and ADE20K. Experimental results show that our proposed method consistently outperforms strong baselines and obtains significant results. We will give all implementation details related to our decent performance in this paper and will make the code and trained models publicly available to the community upon publication of the paper with a license that allows free usage for research purposes. Our main contributions can be summarized as follows:

- We first improve the manner of the context fusion and propose a novel network module named Dense Context-Aware (DCA), taking advantages of the contextual awareness to aggregate the features from the perspective of position and channel.

- We further propose extended structures based on our DCA modules to model dense contextual guidance at several scales in a more efficient way. By capturing the semantic similarity and long-range contextual dependency, our DCANet improves the segmentation results.

- Extensive experiments on three challenging semantic segmentation datasets, including PASCAL VOC 2012, Cityscapes and ADE20K, demonstrate the superiority of our approach over other previous state-of-the-art methods. More importantly, we visualize the attention maps of our DCA module to enhance the interpretability of deep CNNs.
The rest of the paper is organized as follows. We first discuss related work in Section 2. After introducing our approach and network architectures in detail in Section 3, we present experimental results in Section 4. Finally, we briefly conclude the paper in Section 5.

2. Related Work

In the following, we review recent advances related to our method. For other ways, a comprehensive review can be found in [16].

Semantic Segmentation. Recently, benefiting from the advances of deep neural networks, semantic segmentation or scene parsing has achieved significant progress. Fully Convolutional Network (FCN) was the first approach to use convolution layers to replace the fully-connected layer for semantic segmentation. DeconvNet [17], SegNet [18] and RefineNet [11], etc., adopted the encoder-decoder structure to combine low-level and high-level information for the optimization of the segmentation results. Besides, Markov random field (MRF) [19] and conditional random field (CRF) [8][20][21] are broadly utilized to model the long-range dependencies for fine structure prediction in semantic segmentation. To obtain a larger receptive field of convolutional neural networks, Chen et al. [8][20] employed the dilated convolution operation to enlarge the spacing of values (insert ‘holes’) while increasing the feature resolution. In our work, we also employ the same dilated strategy as in [5][22] to preserve the intermediate features of high-resolution.

Context. The context always plays an important role in various computer vision tasks. Contextual information, with various forms such as global scene context and sampled spatial context, has been applied for image classification [23] and object detection [24], especially in the semantic segmentation. Works like [25][26][13][27] used the global average pooling (GAP) to obtain the global contextual prior. Moreover, Liu et al. introduced ParseNet [4] that applies
global pooling to attain the fusion of context information for scene parsing, and Zhao et al. proposed PPM [6] module to fuse multi-scale contextual information. The atrous spatial pyramid pooling (ASPP) [20] was developed to aggregate contextual information by different dilated rates. In addition, Zhang et al. [22] proposed a novel framework named Attentional Class Feature Network (ACFNet), to harvest the contextual information from a categorical perspective.

In reference to the above method but different from them, we aim to use the proposed dense context-aware (DCA) module to progressively achieve the transition from short-range attention to long-term contextual dependency.

**Attention.** Attention mechanism is widely used in deep neural networks and has achieved excellent performance. Mnih et al. [28] introduced an attention model that adaptively selects a sequence of regions or locations and only processes the selected regions. Chen et al. [29] learned several attention masks from different network branches to fuse weighted feature maps. Squeeze-and-Excitation Network (SENet) [30] was used to improve the representational power of deep features by modelling channel-wise relationships in an attention mechanism. Wang et al. [31] brought forward the non-local module for vision tasks to calculate the spatial-temporal dependencies through the self-attention form. OCNet [14] and DANet [32] utilized the self-attention mechanism to harvest the related contextual information. PSANet [15] also learned an attention map to aggregate contextual information for each individual point adaptively and specifically.

Our attention module is motivated by the success of attention mechanisms in the above works. We rethink the attention mechanism from the perspective of the context fusion and compute the attention masks about the global information for better improving the feature representations.
3. Approach

In this section, we first present a general framework of our network and introduce the key component—dense context-aware (DCA) module with the details of the specific formulations and operations. Then we elaborate on two long-range dense context-aware structures that we propose based on the DCA module. Finally, we describe the complete network structures of our method.

3.1. Overview

An input image \( I \) is fed into a fully convolution network (e.g., a ResNet backbone) to acquire the feature map \( X \). And then our approach lets the feature map \( X \) go through the long-range dense context-aware structure, generating a processed feature map \( \hat{X} \). Finally, the segmentation layer predicts the category of each pixel based on the generated feature map \( \hat{X} \), and upsamples the score map for eight times at last. The pipeline is presented in Fig. 2(a), and the whole structure is called DCANet. The critical contribution of DCANet to semantic segmentation lies in the long-range DCA structure, which is mainly composed of dense context-aware modules.

3.2. Dense Context-Aware Module

The intuition of dense context-aware module is to enhance the contextual awareness of features by applying the related context attention to the local information. To further improve the feature representation with the context fusion, our solution achieves through two aspects: fusion with the context attention and semantic supervision for later input features.

**Fusion with Context Attention.** Initially, in order to combine the local and global information for modelling rich contextual relationships, the DCA module comprises two pathways, the contextual pathway and the spatial pathway. We use \( F_c \) and \( F_s \) to represent the two inputs of the DCA module, where the subscript letters denote the pathway. In particular, we take the output of the
CNN network as the input to each pathway of the first DCA module in the long-range DCA structure. As the module shown in Fig. 2(b), its detailed process is described by two steps. The first step is to calculate the attention masks over the contextual pathway.

Inspired by [2][6][33], which were proposed to enlarge the receptive field on the input feature, we adopt the average pooling [34] for generating the context priors in a global view. In the DCA module, this operation is named context pooling, of which the outputs’ size is represented by the $r_1$. The input feature $F_c$ in the context pathway first passes through the context pooling to generate the features $F'_c$ with the specific scale context. The greater context but less detailed can be captured in the contextual pathway by decreasing the size $r_1$ of...
scale context. Thus, we can enlarge the receptive field via controlling $r_l$ that leads to a 'zoom out' behaviour over the features. The context pooling operation can be formulated as follows:

$$F'_c = P_{\text{context}}(F_c ; r_l)$$  \hspace{1cm} (1)

Here we can manually set the scale context size $r_l$ for different modules on the occasion of multiple modules used in the DCA structures (see Section 3.3).

Meanwhile, we keep the original scale size for the features $F_s$ which are rich in spatial details in the other pathway. Then the context features $F'_c$ goes through two convolutional layers with batch normalization and ReLU (the conv$_c$ in Fig. 2(b)), after which the features are further mapped by an element-wise sigmoid function to obtain the dense context attention masks $\Lambda_l$. To align with the other pathway, we apply an interpolation operation in the second convolutional layer to obtain the features of identical size as the original feature map. The process can be described in mathematical as follows:

$$\Lambda_l = \sigma(\text{conv}_c(F'_c))$$  \hspace{1cm} (2)

The module also generates two outputs, which serve as the input of the next attention module under connecting multiple DCA modules. We explain the second step, updating the two outputs of the module.

Having computed the context attention masks $\Lambda_l$, the spatial pathway $\hat{F}_s$ is updated by:

$$\hat{F}_s = \Lambda_l \otimes \text{conv}_s(F_s) + F_s$$  \hspace{1cm} (3)

where $\otimes$ denotes an element-wise multiplication. By multiplying the spatial features after two convolution layers (the conv$_s$ in Fig. 2(b)) with the attention masks $\Lambda_l$, we extract the dense pixel-wise prediction maps that are driven by the contextual awareness for adaptively achieving the optimal representation of features. Considering the preservation of the original spatial information, we employ the short-range residual connection to perform an element-wise plus. And the residual connection [13] helps capture the long-range contextual
relationship and achieves effective end-to-end training of the whole network, particularly when there are several DCA modules.

As the spatial pathway gets updated through the DCA module, the contextual pathway should keep being updated with the other pathway, which can complete the transmission of spatial features to the following module. Therefore, we incorporate the calculated spatial features with rich context information. The context features $F'_c$ further pass through the two convolutional layers in the previous step. Then, the transformed features are combined with the updated spatial features $\hat{F}_s$ by concatenation. Mathematically, the update can be formulated as follows:

$$\hat{F}_c = \text{conv}_c \left( F'_c \right) \parallel \hat{F}_s$$  \hspace{1cm} (4)

where $\parallel$ represents the concatenation of two feature maps along the depth axis. Note that the first convolutional layer of the $\text{conv}_c$ needs to reduce the feature map depth to be consistent with the other pathway feature map depth, when cascading multiple modules.

**Semantic Supervision.** In practice, we come up with the deep semantic supervision in the DCA module to enhance the semantic concepts of the contextual output as connecting multiple DCA modules. To fit the DCA module to establish the long-range context fusion, we assign the semantic supervision to the pathway of concatenation, which is beneficial for improving global semantic similarity in the context information. Fig. 2(b) presents the detailed structure of our Semantic Supervision block. We first refine the output of the contextual pathway through a $1 \times 1$ $\text{conv}$ to decrease the dimension of the feature map. After global average pooling, we build an additional fully connected layer to implement individual predictions for the object categories in the scene and learn with the binary cross-entropy loss for each category. Some similar supervision techniques [6][15][35] are generally utilized with related deep networks [36][25] to optimize the learning process. Therefore, the semantic supervision we applied in the DCA module can not only enhance the understanding of the class-level
contextual features, but also benefit the training process. The experiments in Section 4 shows how this method improve the performance of our segmentation networks.

3.3. Long-range DCA structure

We have introduced a separate dense context-aware module in detail, whose contextual pathway only works on one scale context. Next, we present the long-range DCA structures, which comprise a sequence of the DCA modules and refine the feature maps progressively. On the one hand, to capture the long-range contextual relationships for better improving dense feature representation, we implement a progressive strategy [37] by the DCA modules cascaded in sequence. Correspondingly, proper network depth can be obtained by varying the number of modules. On the other hand, inspired by the multi-scale network structure [6][5], we also enhance the capabilities of network structure for multi-scale processing, which can facilitate ambiguous classification due to only focusing on the local context. By adjusting the pixel size of scale context pooling for each DCA module (see Fig. 2(b)), hierarchical pyramid scales are composed when using several modules. We describe the two structures in the following, and the architectures of Cascade-DCA and Pyramid-DCA are shown in Fig. 3.

**Cascade-DCA.** The core of the cascade-DCA structure, consisting of four cascaded DCA modules, is to adopt a progressive strategy to cope with the understanding of segmentation scene adaptively. Specifically, to achieve the optimization of contextual attention from semantic level to detailed cues, we gradually increase the size \( r_l \) of context pooling in each module, using four pyramid scales: \( 1 \times 1 \), \( 4 \times 4 \), \( 8 \times 8 \) and \( 16 \times 16 \). Taking the progressive manner allows each DCA module to improve the local feature representations under the different contextual awareness, which further ensures the long-range contextual relationship. We feed the intermediate features to both pathways of the first module. Through the continuous optimization of these cascaded modules, the
features of the spatial pathway have enhanced the similarity of the semantic categories while maintaining rich spatial details, which helps to boost feature discriminability for classification. Therefore, the spatial pathway of the last module is taken as the final result. More details of this Cascade-DCA structure is illustrated in Fig. 3.

**Pyramid-DCA.** We employ four parallel branches, each of which consists of several DCA modules. Same as the Cascade-DCA structure, we use the cascaded
modules in each branch, with all modules in each branch using the identical size of context pooling. Inspired by PSPNet [6], we adopt four pyramid scales: $1 \times 1$, $2 \times 2$, $3 \times 3$, and $6 \times 6$, for the sizes $r_j$ of context pooling of the four branches. Meanwhile, considering the excellent performance of network structure with low computation complexity, we utilize two cascaded DCA modules in each branch to take full advantages of long-range contextual information. Finally, the spatial pathway outputs of the last module of the four branches are concatenated together to achieve cross-branch feature fusion. More details are illustrated in Fig. 3.

3.4. Network Architecture

With the two long-range DCA structures (Cascade-DCA and Pyramid-DCA), we propose the end-to-end network for semantic segmentation. Regardless of the long-range structure, our network is mainly composed of two separate parts, the backbone network and the DCA structure. It is worth noting that our module can be embedded into the existing FCN pipeline for exploiting different network variants.

**Baseline Network.** As for the baseline network, we use the ResNet-101 pre-trained on the ImageNet dataset [38]. And following [20], we make some modifications: remove the classification layer and last pooling layer, and replace the convolutions within the last two modules by dilated convolutions with dilation rates being 2 and 4, respectively. Then the output feature map size is $1/8$ of the input image.

**Long-range DCA structure.** We construct the entire network structures based on Cascade-DCA and Pyramid-DCA, respectively.

The detailed architecture of Cascade-DCA network is given as follows. We directly feed the output feature map of the backbone network into the Cascade-DCA structure which consists of four DCA modules connected in sequence and the dimension of the input feature map is reduced from 2048 to 512 in the first
module of the cascaded network. After going through the cascaded network, we further employ a $1 \times 1$ convolution on the output feature map with 1024 channels to obtain the final result.

For the Pyramid-DCA network, we first apply a $3 \times 3$ convolution layers (with batch normalization and ReLU layers) to reduce the output dimension of backbone from 2048 to 512 in advance, then we feed the features of dimension reduction into the Pyramid-DCA structure which contains four different branches, and we concatenate the four different spatial pathway outputs from the four parallel cascaded branches. Each of the four branches of output feature maps has 512 channels. We employ a $1 \times 1$ convolution on the concatenated feature map with 2048 channels to generate the final feature map with 512 channels.

**Loss Function.** In addition to the main supervision applied to the final output of our network, we employ the auxiliary supervision, and the deep semantic supervision in the DCA modules. For explicit feature refinement, we use extra deep supervision to refine the performance of the FCN backbone and make the network easier to optimize following PSANet [15]. For introducing the semantic information into related features, we apply the same deep semantic supervision for the last module in the Cascade-DCA and the last module of each branch in the Pyramid-DCA. The class-balanced cross entropy is employed for main segmentation loss, auxiliary loss, and semantic supervision losses. Finally, we use three parameters $\lambda_m, \lambda_a$ and $\lambda_s$ to balance the main segmentation loss $l_m$, the auxiliary loss $l_a$ and all semantic supervision losses $l_s$ as shown in Eq. 5.

$$L = \lambda_m \cdot l_m + \lambda_a \cdot l_a + \lambda_s \cdot l_s$$ (5)

**4. Experiments**

To evaluate the proposed approach, we carry out comprehensive experiments on three challenging datasets: object segmentation dataset PASCAL VOC 2012 [39], Cityscapes dataset [40], and ADE20K [41]. In the following, we first introduce the implementation details related to training strategies on different
datasets and hyper-parameters, then we report experimental results and ablation study on corresponding datasets. Finally, we present the progressive aggregation processing by the visualization of the learned masks generated by the DCA modules.

4.1. Implementation Details

We implement our experiments based on Pytorch. Following prior works [20], we adopt a poly learning rate policy where the initial learning rate is multiplied by \((1 - \frac{\text{iter}}{\text{max iter}})^{\text{power}}\). The initial learning rate is set to 0.01 for Cityscapes dataset and 0.001 for others, and the power is set to 0.9. We train our model with mini-batch stochastic gradient descent (SGD) [38] and set the batch size to 8 for Cityscapes and 16 for others, the momentum to 0.9, and the weight decay to 0.0001, respectively. The performance of the model can be improved by increasing the number of iterations, which is set to 30K for PASCAL VOC, 90K for Cityscapes and 150K for ADE20K. For data augmentation, we employ the random mirror, and random resize between 0.5 and 2.0 for all datasets and additionally add new random rotation between -10 and 10 degrees and random Gaussian blur for PASCAL VOC 2012 and ADE20K datasets. We notice that data augmentation does help improving performance and avoiding overfitting. In the experiments, the loss weights \(\lambda_m, \lambda_a\) and \(\lambda_s\) in Eq. 5 are set to 1.0, 0.2 and 0.05 respectively.

4.2. PASCAL VOC 2012

Dataset and Evaluation Metrics. We perform a series of experiments on the PASCAL VOC 2012 segmentation dataset, which is for object-centric segmentation and contains 20 object classes and one background. Following prior works [8][42], we use the augmented annotations from [43] resulting 10,582, 1,449 and 1,456 images for training, validation and testing. For evaluation metrics, the mean of class-wise intersection over union (Mean IoU) is adopted.
4.2.1. Ablation Study

We first use the atrous ResNet-101 as the backbone network, and the final segmentation results are obtained by directly upsampling the output. For starters, we evaluate the performance of the baseline network and conduct experiments based on the backbone (ResNet-101). It should be noted that all our experiments use the auxiliary supervision to optimize the learning process.

**Dense Context-Aware module.** We perform two comparison experiments to evaluate the effectiveness of our network structure with the DCA module. One is to explore the advantage of the DCA module in the Cascade-DCA structure by replacing it with the vanilla residual module [13][44] that results in a cascaded residual structure named ResNet-101 + CRS. Specifically, we use ResNet-101 and multiple residual modules, and the number of these residual modules is the same as in the Cascade-DCA structure. And the other is to exhibit the advantage of our Pyramid-DCA structure with the DCA modules. Similarly, for comparison, we use ResNet-101 + PPM to represent the PSPNet that applies pyramid pooling module on feature maps of multiple scales. The related experimental results with different settings are reported in Table 1, where the single scale testing is adopted in all the results. Especially, the performance of these methods has indicated the mean through several times to ensure that our results are reliable.

As shown in Table 1, our approaches with the DCA modules outperform the baseline network remarkably. Compared with the ResNet-101 + CRS, employing the cascaded modules in the Cascade-DCA structure yields a result of 77.45% in Mean IoU, which increases by almost 3%. Meanwhile, employing the Pyramid-DCA structure with the DCA modules exceeds the individual pyramid scale structure by 1.9%. Notably, our Pyramid-DCA network improves the segmentation performance over the Cascade-DCA network by 0.6% on the validation set, which shows that the former is a slightly better choice in terms of capturing long-range contextual information. The complexity of the Cascade-
DCA structure is relatively small, however, and only requires about 1/2 of the parameters of the Pyramid-DCA structure. Considering the balance between performance and complexity, the Cascade-DCA network is also a solution worth exploring.

Table 1: Detailed performance comparison of our proposed networks with different approaches on the validation set of PASCAL VOC 2012. Results are reported with the same settings.

| Method                  | Mean IoU(%) |
|-------------------------|-------------|
| ResNet-101 Baseline     | 73.64       |
| ResNet-101 + CRS        | 74.56       |
| ResNet-101 + PPM        | 76.14       |
| ResNet-101 + Cascade-DCA| 77.45       |
| ResNet-101 + Pyramid-DCA| 78.06       |

**Ablation Study for Improvement Strategies.** Following [5], we adopt some strategies to improve the performance of the network further. These improvement strategies are: DA (Data augmentation with random scaling), MS (We average the segmentation probability maps from 7 image scales \{0.5 0.75 1 1.25 1.5 1.75 2\} for inference), and SS (the semantic supervision loss in the corresponding DCA modules).

We conduct experiments on the basis of the ResNet-101 + Cascade-DCA structure, and the results are reported in Table 2. From the experimental results, we notice that using data augmentation with scaling improves the performance by almost 1.0% because of the enriching scale diversity of training data. Also, using the semantic supervision, our result can further exceed it by 1.5% and reach 79.95%, which shows that network benefits from the deep semantic supervisions’ capability of enhancing the context fusion. Finally, by applying the multi-scale testing, segmentation result fusion further improves the performance to 80.84%, which outperforms the original method by 3.4%.
4.2.2. Method Comparison

We show the comparison between our method and some previous methods in Table 3. With pre-training on the ImageNet dataset, our method based on ResNet-101 achieves the superiority over these previous state-of-the-art methods\textsuperscript{1}. In particular, our model is better than some methods, such as DeepLabv2-CRF \textsuperscript{20} and GCN \textsuperscript{2}, which use powerful pretrained models on the MS-COCO dataset. Comparing to state-of-the-art approaches of DANet \textsuperscript{32} and SANet \textsuperscript{45}, our method improves the performance to 84.41\%. Furthermore, we believe that our proposed approach (e.g., the DCA module and the cascaded structure) could be useful for many vision tasks.

4.2.3. Visual Improvements

To further demonstrate the effectiveness of our method, we show the visual comparison of the segmentation results in Fig. 4. Consistently, our methods improve the segmentation quality, where more accurate and detailed structures are obtained compared to the baseline. Some misclassified categories are now

\textsuperscript{1}The result link to the VOC evaluation server:
http://host.robots.ox.ac.uk:8080/anonymous/B3XPSK.html
Table 3: Methods comparison with results reported on PASCAL VOC 2012 testing dataset. Methods pre-trained on MS-COCO are marked with ′.

| Method                  | Backbone       | Mean IoU(%) |
|-------------------------|----------------|-------------|
| FCN[1]                  |                | 62.2        |
| CRF-RNN [21]            |                | 72.0        |
| DPN [19]                |                | 74.1        |
| DeepLabv2-CRF′ [20]     | ResNet-101     | 79.7        |
| GCN′ [2]                | ResNet-101     | 83.6        |
| ResNet38 [46]           | WideResNet-38  | 82.5        |
| RefineNet [11]          | ResNet152      | 83.4        |
| PSPNet [6]              | ResNet-101     | 82.6        |
| EncNet [3]              | ResNet-101     | 82.9        |
| DANet [32]              | ResNet-101     | 82.6        |
| APCNet [47]             | ResNet-101     | 84.2        |
| SANet [45]              | ResNet-101     | 83.2        |
| DCANet                  | ResNet-101     | 84.4        |

correctly classified, such as the horse in the second row and the sofa in the third row. Meanwhile, we find out that some details and object boundaries are clearer from the results, such as the cow in the lower right of the first row. Besides, in terms of integrity and boundary details, slightly better segmentation maps than Cascade-DCA are produced by the Pyramid-DCA.

4.3. Cityscapes Dataset. Cityscapes dataset [40] is collected for semantic segmentation on urban street scenes. It contains 5,000 finely annotated images captured from 50 cities in different seasons. And these images are divided into 2,975, 500, and 1,525 images for training, validation and testing. It has 30 annotated common classes of road, person, car, etc. and defines 19 classes for semantic segmentation evaluation. Besides, another 20,000 coarsely annotated images are also provided.
We carry out experiments on the Cityscapes dataset to evaluate the effectiveness of our method. We first show the improvement brought by our DCANet based on the FCN backbone with different layers (ResNet-50 or ResNet-101). Note that we also adopt different DCA structures in Table 4. The baseline (ResNet-50) yields Mean IoU 72.33%. Our DCA structure improves performance significantly, where DCANet-50 for better results exceeds the baseline by 6.6%. When we adopt a deeper network ResNet-101, the model achieves Mean IoU 80.13%. To further illustrate the performance of our method on the Cityscapes dataset, we show the comparison with some previous methods. The evaluation results of Cityscapes val set are shown in Table 5, and our method
achieves the best performance under both settings.

Table 4: Performance comparison between different strategies on Cityscapes val set. Results are reported with models for single-scale testing and.

| Method   | BaseNet  | Cascade-DCA | Pyramid-DCA | Mean IoU(%) |
|----------|----------|--------------|-------------|-------------|
| Baseline | ResNet-50|              |             | 72.33       |
| DCANet   | ResNet-50| ✓            |             | 78.05       |
| DCANet   | ResNet-50|             | ✓           | 78.92       |
| Baseline | ResNet-101|            |             | 74.72       |
| DCANet   | ResNet-101|           | ✓           | 79.55       |
| DCANet   | ResNet-101|            | ✓           | 80.13       |

We also provide the qualitative comparisons between DCANet and baseline network on several examples to present the visual improvement, as shown in Fig. 5. Similarly, better prediction is yielded with the DCA structure incorporated. For the parsing of complex scenes such as the traffic street, our network gets better performance than the baseline when dealing with objects of the various scales.

![Figure 5: Examples of DCANet results on Cityscapes dataset.](image-url)
Table 5: Methods comparison with results reported on Cityscapes set. We adopt the same improvement strategies as in PASCAL VOC 2012 to improve performance.

| Method          | Mean IoU(%) |
|-----------------|-------------|
| FCN [1]         | 65.3        |
| DeepLabv2-CRF [20] | 70.4        |
| RefineNet [11]  | 73.6        |
| DUC_HDC [48]    | 76.9        |
| PSPNet [6]      | 77.7        |
| PSANet [15]     | 79.3        |
| DenseASPP [49]  | 79.8        |
| CCNet [50]      | 81.3        |
| DANet [32]      | 81.5        |
| DCANet          | 81.8        |

4.4. ADE20K

Dataset. The ADE20K dataset [41] is a scene parsing dataset, which contains 150 classes and diverse complex scenes up to 1,038 image-level categories. The challenging dataset is divided into 20K/2K/3K for training, validation and testing, respectively. Note that both objects and stuffs need to be parsed in this dataset. For evaluation metrics, both pixel-wise accuracy (Pixel Acc.) and mean of class-wise intersection over union (Mean IoU) are used.

We perform experiments to verify the generalization of our proposed network on the ADE20K dataset. The comparisons with some previous methods are reported in Table 6. Under the same settings, we can observe that the DCANet (ResNet101 + Pyramid-DCA) overall achieves better results than these previous works on the validation set of ADE20K. Our method could capture the long-range contextual information effectively for more accurate segmentation results.
Table 6: Methods comparison with results reported on ADE20K validation dataset.

| Method             | Mean IoU(%) | Pixel Acc.(%) |
|--------------------|-------------|---------------|
| FCN [1]            | 29.39       | 71.32         |
| SegNet [18]        | 21.64       | 71.00         |
| CascadeNet [41]    | 34.90       | 74.52         |
| RefineNet [11]     | 40.20       | -             |
| PSPNet [6]         | 43.29       | 81.39         |
| DSSPN [51]         | 43.68       | 81.13         |
| PSANet [15]        | 43.77       | 81.51         |
| EncNet [3]         | 44.65       | 81.19         |
| CCNet [32]         | 45.22       | 81.61         |
| APCNet [47]        | 45.38       | -             |
| DCANet             | 45.49       | 81.65         |

4.5. Visualization of attention masks

In order to deeper understand how the progressive solution in multiple cascaded DCA modules improves the performance of the context fusion, we visualize the learned attention masks, as shown in Fig. 6. The example images are selected from the validation set of Pascal VOC 2012. The progressive convergence of attention masks under the awareness of the context is clear and interpretable, which also expounds the transfer process from the global information to the details well. For the several masks in the front (first two columns of masks), we note that the attention tends to distinguish between foreground and background in a global view, which can help improve the capability of feature for the intra-class inconsistency problem. And for the last two mask columns, we find that some clear boundaries for locating the detailed clues are generated by the attention masks. In short, the visualized masks further demonstrate that collecting semantic similarity and the long-range contextual dependencies are essential for improving feature representations in semantic segmentation.
Figure 6: Visualization of learned masks by DCANet on the validation set of PASCAL VOC 2012. The left column is the input images from dataset, the 2, 3, 4, 5 are pixel-wise masks from corresponding modules. 'DCA1' denotes the attention mask of the first DCA module and 'DCA2~4' likewise. In addition, the corresponding result and ground-truth are provided in the last two columns.

5. Conclusion

In this work, we propose the DCA module for semantic segmentation with the objective of improving the capabilities of neural networks for the context fusion. Based on the DCA module, we further propose two extended structures, named Cascade-DCA structure and Pyramid-DCA structure, to progressively and adaptively capture long-range contextual information for the robustness of segmentation results. We demonstrate the advantages of our proposed approaches with delightful performance on three challenging benchmarks, including PASCAL VOC 2012, Cityscapes, and ADE20K. In the future, we will concentrate on improving the computational efficiency of the dense context-aware module for semantic segmentation.

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