Pyramidal Dense Attention Networks for Lightweight Image Super-Resolution

Huapeng Wu, Jie Gui, Senior Member, IEEE, Jun Zhang, Member, IEEE, James T. Kwok, Fellow, IEEE, and Zhihui Wei, Member, IEEE

Abstract—Recently, deep convolutional neural network methods have achieved an excellent performance in image super-resolution (SR), but they can not be easily applied to embedded devices due to large memory cost. To solve this problem, we propose a pyramidal dense attention network (PDAN) for lightweight image super-resolution in this paper. In our method, the proposed pyramidal dense learning can gradually increase the width of the densely connected layer inside a pyramidal dense block to extract deep features efficiently. Meanwhile, the adaptive group convolution that the number of groups grows linearly with dense convolutional layers is introduced to relieve the parameter explosion. Besides, we also present a novel joint attention to capture cross-dimension interaction between the spatial dimensions and channel dimension in an efficient way for providing rich discriminative feature representations. Extensive experimental results show that our method achieves superior performance in comparison with the state-of-the-art lightweight SR methods.

Index Terms—Super-resolution, pyramidal dense learning, group convolution, joint attention.

I. INTRODUCTION

Single image super-resolution (SISR) is a low-level vision problem that recovers a high resolution (HR) image from a low resolution (LR) observation, which is an ill-posed problem because multiple HR images can be degraded to the same LR image. To address this issue, researchers have proposed many approaches, which can be divided into three subclasses including interpolation-based methods [11], reconstruction-based methods [12,13], and learning-based methods [14,15].

Benefit from the powerful learning ability, various deep convolutional neural network methods have been introduced and achieved a significant performance in image SR community [11]. Firstly, Dong et al. [14] proposed a three-layer super-resolution convolutional neural network (SRCNN) to learn the nonlinear mapping function between LR and HR. Later, inspired by ResNet [12] and DenseNet [13], many complex deep neural networks [14,15] have been presented to boost reconstruction performance. However, doing so will cause an increase in model parameters and computational cost, which greatly limit their practical applications in some computing devices, such as mobile and embedded applications. For solving these problems, some network architectures have been proposed by integrating recursive learning and lightweight models. For example, Deeply-Recursive Convolutional Network (DRCN) [5] and Deep Recursive Residual Network (DRRN) [6] used a recursive network to reduce the number of network parameters by parameter sharing strategies. Although DRCN and DRRN show favorable performances with a few parameters, they have a deeper model (DRRN ups to 52 convolutional layers) and require heavy computational costs. To further save computational overhead, some works proposed to directly extract feature in LR domain, and then upscale the features by deconvolution [16] or sub-pixel convolution [17] at the end of the network. Afterward, Enhanced Deep Super-Resolution network (EDSR) [8] adopted this post-processing strategy and employed a simplified ResNet architecture, which has about 165 convolutional layers. Zhang et al. [18] utilized residual-in-residual structure by adding channel attention block to construct a very deep model (up to 400 layers) for training a SR model. From these efforts, we find that the deeper network is helpful to extract more feature information to reconstruct HR images, but most of them suffered from large network parameters and computational cost.

Recently, some other researchers began to focus on design lightweight and efficient neural networks for image SR. Ahn et al. introduced a cascading residual network (CARN) [19] to achieve efficient SR by using several cascading connections with group convolution [20]. The information distillation network (IDN) [21] employed information distillation mechanism to divide the intermediate features into two parts, one part was retained and another part was further processed by succeeding convolution operations. To better balance performance and inference applications, Hui et al. [22] further proposed a lightweight information multi-distillation network (IMDN) that extracted hierarchical features at a granular level, and split the preceding extracted features along channel dimension. At each step, its partial feature information was retained and the other features were processed in a subsequent step. It won the first place in the AIM 2019 constrained image super-resolution challenge [23]. In addition to the above-mentioned strategies, some other efficient methods (e.g. MobileNet [24], self-
In recent years, attention mechanisms have been widely used in many computer vision tasks and achieved good results. Hu et al. [28] proposed the squeeze-and-excitation block to learn the channel-wise information and improve the representation ability of the model. Inspired by [28], Zhang et al. [28] introduced a residual channel attention network (RCAN) by integrating the squeeze-and-excitation block into the residual architecture for image SR. In [29], the channel attention and spatial attention are combined to adaptively capture rich contextual information. Although these attention-based networks have provided performance improvements, they have some shortcomings. For example, SENet [28] only concentrate on channel-wise attention and ignore the importance of spatial information. Its variant, [29] uses the channel and spatial attention mechanisms, but they are only computed independently, which is also not beneficial to capture rich discriminative feature representations.

In this paper, we propose a novel lightweight pyramidal dense attention network (PDAN) for SISR (illustrated in Fig. 1). Unlike most previous dense networks with a fixed channel growth rate, we introduce a lightweight pyramidal dense block with a variable channel growth rate inspired by [30]. The proposed feature extractor adopts the pyramidal dense learning strategy that the output channel dimensionality grows up while the convolutional layers are deepening in each pyramidal dense block, which can effectively aggregate contextual information (shown in Fig. 2). While increasing the output feature dimensionality is beneficial to enhance the feature learning ability of the networks, the parameter explosion needs to be noted. Therefore, we use group convolution with the dimension cardinality (i.e., the number of groups in each convolutional layer) which increases linearly to relieve the parameter explosion. Besides, to further improve the discriminative representation ability of the network, we propose a novel joint attention to capture cross-dimension interaction between the channel dimension and the spatial dimensions [31] for high-frequency information extraction. The detail of joint attention is shown in Fig. 2(b), where an input tensor (the size is C × H × W) is transferred to four branches, two of which are responsible for modeling channel attention (C × 1 × 1) and spatial attention (H × W) respectively, and the other two branches are used to build cross-dimension interaction between the channel dimension C and the spatial dimension H or W.

The main contributions of this paper are summarized as follows:

1) We propose a lightweight pyramidal dense attention network (PDAN) for SISR. The proposed lightweight model can effectively improve SR performance via the pyramidal dense feature learning and joint attention mechanism with a few parameters.

2) We introduce a pyramidal dense block to fully exploit multi-level features as well as boost the flow of information with a few parameters. Moreover, the proposed joint attention can efficiently capture cross-dimension interaction between the channel dimension and the spatial dimensions to provide richer and more discriminative contextual information for feature rescaling. In comparison with state-of-the-art lightweight SR methods, our method achieves competitive results in terms of model size and performance.

The remainder of this paper is organized as follows. In Section II, we introduce the proposed PDAN for image SR in detail. Extensive experimental results and analysis are provided in Section III. Finally, the conclusion is given in Section IV.

II. PROPOSED METHOD

In this section, we will show the proposed lightweight pyramidal dense attention networks for SISR in details.

A. Network Architecture

As illustrated in Fig. 1, the proposed PDAN consists of two modules: 1) feature extraction module, 2) reconstruction module. In this paper, we denote $I^{LR}$ and $I^{SR}$ as the input LR image and output HR image of our PDAN. The LR image is first fed to one $3 \times 3$ convolution layer for initial feature extraction. Next, the learned initial features are fed into several stacked lightweight pyramidal dense attention blocks to produce powerful feature maps. Lastly, we apply the reconstruction module that consists of a $3 \times 3$ convolution...
layer and a sub-pixel convolution layer [17] to reconstruct the desired SR image. The SR procedure of the proposed PDAN can be written as following:

$$I^{\text{SR}} = F_{\text{PDAN}} (I^{\text{LR}}, \theta) = F_{\text{UP}} (F_{e} (I^{\text{LR}})),$$  

(1)

where $F_{\text{PDAN}}$ represents the reconstruction function of our PDAN, $\theta$ denotes the learnable parameters of the network, $F_{e}$ is the feature extraction step and $F_{\text{up}}$ denotes the up-sampling and reconstruction step.

Our PDAN is optimized with the $L_{1}$ loss [18] by measuring the difference between a reconstructed SR image $I^{\text{SR}}$ and its HR ground-truth $I^{\text{HR}}$. Given a set of training image pairs $\{I_{i}^{\text{LR}}, I_{i}^{\text{HR}}\}_{i=1}^{N}$, where $N$ denotes the number of training images. The loss function of our method can be expressed as:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \|F_{\text{PDAN}}(I_{i}^{\text{LR}}, \theta) - I_{i}^{\text{HR}}\|_{1}.$$  

(2)

Next, we will give more details about the proposed lightweight pyramidal dense attention block.

### B. Pyramidal Dense Attention Block (PDAB)

As illustrated in Fig. 2 (a), our pyramidal dense attention block (PDAB) is mainly constructed by two stages: pyramidal dense feature learning, and feature refinement based on joint attention mechanism. Moreover, local residual learning is also adopted to improve the gradient information flow. Let $H_{d-1}$ and $H_{d}$ denote the input and output of the $d$-th PDAB, respectively. The process flow with PDAB can be formulated as following:

$$H_{d} = H_{d-1} + F_{\text{PDAB}}(H_{d-1}),$$  

(3)

where $F_{\text{PDAB}}$ is the mapping function of the proposed PDAB.

#### 1) Pyramidal Dense Feature Learning: Dense skip connections have been widely exploited in deep learning methods, which is beneficial to boost the flow of feature information and
enhance the representation ability of the network. However, on the other hand, the dense connections will need large resources and memory for extracting and storing features. Additionally, due to the inconsistency between the number of input and output channels, the dense connections with a fixed channel growth rate can cause the loss of information and degrade the learning ability of the network. In this paper, we introduce a pyramidal dense connection mechanism with a varying growth rate, where the output feature dimensionality of convolutional layers gradually increases when the network layers are deepening to relieve this problem. However, when the convolution layers increase, this method will result in the parameter explosion. Specifically, the input channel dimensionality of two different dense connection layers can be written as follows.

The conventional dense connections with a fixed growth rate are

\[
C_i = c_0 + \sum_{j=1}^{i-1} c_j = c_0 + (i - 1) \times g_0, \quad (4)
\]

\[
c_j = g_0. \quad (5)
\]

The pyramidal dense connections with a varying growth rate are

\[
\tilde{C}_i = c_0 + \sum_{j=1}^{i-1} \tilde{c}_j = c_0 + (i - 1) \times g_0 + g \times \frac{(i - 1)(i - 2)}{2}, \quad (6)
\]

\[
\tilde{c}_j = g_0 + g \times (j - 1), \quad (7)
\]

where \(c_0\) is the number of initial input channels, \(g\) is a growing factor of growth rate \(g_0\). \(C_i\) and \(\tilde{C}_i\) are the number of input channels in the \(i\)-th layer, \(c_j\) and \(\tilde{c}_j\) denote the output feature dimensionality of \(j\)-th convolutional layer.

From the above analysis, the group convolution is adopted to avoid the problem of parameter explosion. Note that we choose group convolution instead of conventional convolution since the former can reduce the number of parameters efficiently. Specifically, the corresponding parameters of them are given as

\[
P_i = C_i^{\text{out}} \times C_i^{\text{in}} \times K \times K, \quad (8)
\]

\[
P_i^G = G_i \times (\frac{C_i^{\text{out}}}{G_i} \times \frac{C_i^{\text{in}}}{G_i} \times K) = \frac{P_i}{G_i}, \quad (9)
\]

where \(C_i^{\text{in}}\) and \(C_i^{\text{out}}\) are the number of input and output channels in the \(i\)-th layer, \(K\) indicates the corresponding kernel size, \(G_i\) is the group size and the bias is omitted for simplicity. Obviously, the parameters of group convolution \(P_i^G\) are less than the parameters of conventional convolution \(P\). However, when \(G_i\) is fixed, this will also cause the parameter to increase sharply since the output feature channels \(C_i^{\text{out}}\) grows up linearly with the dense layers. Therefore, we introduce the adaptive group convolution to further alleviate the parameter explosion. In the experiment, the group size is set to grow linearly with dense convolutional layers,

\[
G_i = i + 1. \quad (10)
\]

Moreover, the bottleneck architecture \((1 \times 1\) convolutional filters) is also designed to refine the input cascaded features to be consistent with the output channels of the corresponding layer, which can keep them divisible by the group size and boost the information propagation among different group features in each layer.

2) Joint Attention Mechanism (JA): The aim of the attention-based SR methods is to selectively focus on more important high-frequency details of the input feature for HR image recovery. Here, we introduce a novel joint attention that can capture cross-dimension dependencies [31] for improving the discriminative feature representations. First, we will revisit some attention mechanisms including channel attention and spatial attention [28, 29].

**Convolutional Block Attention Module:** Unlike SENet [28], convolutional block attention module (CBAM) [29] compute channel attention by using global average pooling and global max pooling. Specifically, let \(X \in \mathbb{R}^{C \times H \times W}\) denote the input feature where \(C\) is the number of input channels, \(H\) and \(W\) are height and width of the input features, respectively. The channel-wise global statistics are defined as

\[
\text{GAP}(X) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_{i,j}, \quad (11)
\]

\[
\text{GMP}(X) = \max_{H,W}(X_{i,j}). \quad (12)
\]

Next, the multi-layer perception is shared to compute channel attention,

\[
A_c = \sigma(W_2 \delta(W_1 \text{GAP}(X))) + W_2 \delta(W_1 \text{GMP}(X))), \quad (13)
\]

where \(\sigma\) and \(\delta\) are the sigmoid function and the Rectified Linear Unit [32], \(W_1 \in \mathbb{R}^{C \times H \times W\times C_{1}}, W_2 \in \mathbb{R}^{C \times H \times W\times C_{2}}\), and \(r\) is the reduction radio. Moreover, the above average pooling and max pooling operations along the channel dimension are also used to produce the spatial attention weights in CBAM. The formulation can be written by

\[
A_s = \sigma(w^{k \times k}(X_{a}^{\text{avg}}, X_{s}^{\text{max}})), \quad (14)
\]

where \(X_{a}^{\text{avg}}, X_{s}^{\text{max}} \in \mathbb{R}^{1 \times H \times W}\), \(W^{k \times k}\) denotes a convolution layer with the filter size of \(k \times k\) and \(\sigma\) is the sigmoid function.

**Joint Attention module:** Although CBAM [29] introduces channel attention and spatial attention to improve the feature representations, they ignore the importance of cross-dimension interaction. For this problem, we propose the joint attention to effectively model channel attention and spatial attention with few parameters.

As shown in Fig. 2 (b), joint attention consists of four branches, two branches are responsible for modeling the channel attention \((C \times 1 \times 1)\) and the spatial attention \((H, W)\). The rest two branches aim to capture the interaction between the channel dimension and the spatial dimensions \((H, C)\) or \((C, W)\). Specifically, given a input feature map \(X \in \mathbb{R}^{C \times H \times W}\). In the channel attention branch, like SENet [28], the channel attention weights are used to refine the feature \(X_{C}\). In the spatial attention branch, we first aggregate channel information to produce two 2D maps \(1 \times H \times W\) by the above average-pooling and max-pooling operations across the channel axis. Then, a \(3 \times 3\) dilated convolution [33]
with dilation value 3 followed by a batch normalization [33] and a sigmoid activation function are used for producing the attention weights \((1 \times H \times W)\). Finally, the spatial attention weights are multiplied with the input tensor \(X\) to generate the recalibrated feature \(\hat{X}_{H \times W}\). For the remaining two branches, the input tensor \(X\) is first permuted and then passed to the above similar operations to generate the corresponding attention weights \((1 \times H \times C\) or \(1 \times C \times W\) ), respectively. Subsequently, the generated attention weights are applied on the permuted feature and then rotated 90° clockwise along the width axis or the height axis to retain the original input shape \((C \times H \times W)\). Finally, the refined features of four branches \((\hat{X}_C, \hat{X}_{H \times W}, \hat{X}_{H \times C}, \hat{X}_{C \times W})\) are aggregated by the averaging operation to enhance the discriminative representation ability of the network, which can be written as

\[
\hat{X} = \frac{\hat{X}_C + \hat{X}_{H \times W} + \hat{X}_{H \times C} + \hat{X}_{C \times W}}{4}, \tag{15}
\]

where \(\hat{X}\) is the output recalibrated feature. In addition to simple averaging, other simple and efficient aggregation methods can also be explored to further improve the performance.

### III. Experimental Results and Analysis

#### A. Datasets and Metrics

In our experiments, we use DIV2K dataset [35] as our training set, which contains 800 high-quality training images. We employ five standard benchmark datasets for testing our model, including Set5 [36], Set14 [37], Bsd100 [38], Urban100 [39] and Manga109 [40]. We conduct three different experiments with bicubic (BI), blur-downscale (BD) and downsampling-noise (DN) degradation models. The peak signal-to-noise ratio (PSNR) and the structural similarity index measurement (SSIM) [41] are used for measuring the quality of the SR images on the luminance (Y) channel of the transformed YCbCr space.

#### B. Implementation Details

To construct the training pairs, we downsample the original HR images to generate LR Images by using bicubic interpolation. Data augmentation is performed on the above training dataset by randomly rotating 90°, 180°, 270° and flipping horizontally. In each training batch, 16 LR RGB patches with the size of 48 × 48 are randomly sampled as inputs. We adopt Adam optimizer [42] to train the model by setting \(\beta_1 = 0.9\), \(\beta_2 = 0.999\), and \(\varepsilon = 10^{-8}\). The learning rate is initialized as \(10^{-4}\) and reduced to half every 200 epochs. We implement the proposed method by using the PyTorch framework [43] with a NVIDIA RTX 2080Ti GPU.

In our proposed model, the convolutional layers are set to 64 filters with \(3 \times 3\) kernel size except for \(1 \times 1\) convolutional layers for feature fusion. Additionally, in each pyramidal dense block, the initial input features are first reduced to \(c_0\) and then passed to the subsequent pyramidal dense connection layers. For simplicity, the channel number of pyramidal dense layers can be expressed linearly as \(c_j = (j + 1) \times c_0\).

The operations of each pyramidal dense layer consists of a \(1 \times 1\) convolution filter, activation function ReLU, \(3 \times 3\) adaptive group convolution and ReLU. Specifically, \(c_0\) is set to 16 and the number of pyramidal dense layers is 4 in a pyramidal dense block. Following the previous papers, we use the recently popular sampling method ESPCNN [17] to perform the upsampling operation. The final convolution layer has 3 filters with kernel size of \(3 \times 3\) that are used to reconstruct the HR image.

#### C. Ablation Study

In this subsection, we analyze the effects of the key configurations in our proposed method. For fair comparisons, our method and its variants are set with the same baseline structure. As shown in Table I, we can see that the baseline method \(P_1\) (without any attention) performs not very well and PSNR only reaches 30.47 dB on Manga109 (×4). It is noticed that when we compare the joint attention \((P_4)\) with other attention mechanisms \((P_2\) and \(P_3)\), we can see that our joint attention module can achieve better performance (i.e., 30.64 v.s. 30.59 dB v.s. 30.46 dB).

In addition, we also compare other metrics, including parameters and FLOPs to demonstrate the effectiveness of our method. FLOPs is computed on the HR image with 512 × 512 pixels. From Table I it is observed that our joint attention model can improve the PSNR with less additional parameters and FLOPs. The results clearly indicate that joint attention is more effective than other attention mechanisms [28, 29].

#### D. Results with Bicubic Degradation (BI)

We compare our proposed method with some state-of-the-art SR methods, Bicubic, SRCNN [4], FSRCNN [16], VDSR [44], DRCN [5], LapSRN [45], DRRN [6], SRMDNF [46], SRRResNet [47] and CARN [19]. Table II shows quantitative results for three different scaling factors \((×2, ×3, ×4)\). In addition, the number of parameters of these methods is also provided to show the model complexity. The results show

| Channel attention [28] | Channel and Spatial attention [29] | Joint attention |
|------------------------|-----------------------------------|----------------|
| | ✓ | ✓ | ✓ | ✓ |

| Channel attention [28] | Channel and Spatial attention [29] | Joint attention |
|------------------------|-----------------------------------|----------------|
| | ✓ | ✓ | ✓ | ✓ |

| Params (K) | FLOPs (G) | PSNR (dB) |
|------------|-----------|-----------|
| 1471 | 31.78 | 30.47 |
| 1866 | 31.85 | 30.59 |
| 1588 | 31.87 | 30.46 |
| 1587 | 31.87 | 30.46 |

| Channel attention [28] | Channel and Spatial attention [29] | Joint attention |
|------------------------|-----------------------------------|----------------|
| | ✓ | ✓ | ✓ | ✓ |

| Channel attention [28] | Channel and Spatial attention [29] | Joint attention |
|------------------------|-----------------------------------|----------------|
| | ✓ | ✓ | ✓ | ✓ |

| Params (K) | FLOPs (G) | PSNR (dB) |
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| 1866 | 31.85 | 30.59 |
| 1588 | 31.87 | 30.46 |
| 1587 | 31.87 | 30.46 |
| Method     | HR PSNR/SSIM | Bicubic PSNR/SSIM | SRCNN PSNR/SSIM | VDSR PSNR/SSIM |
|------------|--------------|-------------------|-----------------|----------------|
| Bicubic    | 18.14/0.4593 | 26.92/0.7250      | 29.69/0.8098    | 29.69/0.8308   |
| SRCNN      | 19.03/0.5506 | 29.30/0.8393      | 30.30/0.8648    | 32.27/0.8768   |
| VDSR       | 19.38/0.5925 | 29.69/0.8308      | 30.30/0.8648    | 32.27/0.8768   |
| LapSRN     | 19.34/0.5968 | 29.69/0.8393      | 30.30/0.8648    | 32.27/0.8768   |
| DRCN       | 19.34/0.5921 | 29.69/0.8308      | 30.30/0.8648    | 32.27/0.8768   |
| CARN       | 20.08/0.6449 | 29.69/0.8308      | 30.30/0.8648    | 32.27/0.8768   |
| PDAN (Ours)| 21.18/0.7023 | 29.69/0.8308      | 30.30/0.8648    | 32.27/0.8768   |

In Fig. 3, we present visual comparison with upscaling factor ×4 on Urban100 dataset. We can see that our method yields best visual results among all existing compared methods. For “image_024”, the other compared methods generate the blurred detailed textures. Our method can recover more accurate lines and details. For “image_073”, most methods suffer from the blurry effects while our method produces the sharper edges and finer details.

E. Results with BD and DN Degradations

Following [14, 48], we also carry out experiments with blur-downscale (BD) and downscale-noise (DN) degradation models. The proposed method PDAN is compared with some state-of-the-art SR methods: SRCNN [4], FSRCNN [16], VDSR [44], IRCNN G [48], IRCNN C [48], SRMDNF [46], and RDN [14]. As shown in Table III, our PDAN achieve the best performance on almost all quantitative results compared with other SR methods with scaling factor ×3. In particular, in comparison with RDN [14], our proposed PDAN still obtains comparable results. It is worth noting that PDAN has fewer parameters than RDN (1.6 M v.s. 22.3 M, 14× less).
### TABLE II

Quantitative results of different image SR methods with B1 degradation module. The parameters and PSNR/SSIM comparison results for scaling factor ×2, ×3 and ×4. Red/blue text: best/second-best among all methods.

| Methods       | Scale | Params | Set5 | Set14 | Bsd100 | Urban100 | Mang109 | PSNR | SSIM |
|---------------|-------|--------|------|-------|--------|----------|---------|------|------|
| Bicubic       | 2     | –      | 33.66| 0.9299| 30.24  | 0.8688   | 29.56   | 0.8431| 26.88| 0.8403|
| SRCNN [4]     | 2     | 57K    | 36.66| 0.9542| 32.45  | 0.9067   | 31.36   | 0.8879| 29.50| 0.8946|
| FSRCNN [16]   | 2     | 13K    | 37.00| 0.9558| 32.63  | 0.9088   | 31.53   | 0.8920| 29.88| 0.9020|
| VDSR [44]     | 2     | 666K   | 37.53| 0.9587| 33.03  | 0.9124   | 31.90   | 0.8960| 30.76| 0.9140|
| DRCN [5]      | 2     | 1774K  | 37.63| 0.9588| 33.04  | 0.9118   | 31.85   | 0.8942| 30.75| 0.9133|
| LapSRN [45]   | 2     | 251K   | 37.52| 0.9591| 32.99  | 0.9124   | 31.80   | 0.8952| 30.41| 0.9103|
| DRRN [6]      | 2     | 298K   | 37.74| 0.9591| 33.23  | 0.9136   | 32.05   | 0.8973| 31.23| 0.9188|
| SRMDNF [46]   | 2     | 1511K  | 37.79| 0.9601| 33.22  | 0.9159   | 32.05   | 0.8985| 31.33| 0.9204|
| SRResNet [47] | 2     | 1370K  | 38.05| 0.9607| 33.64  | 0.9178   | 32.22   | 0.9002| 32.23| 0.9295|
| CARN [19]     | 2     | 1592K  | 37.76| 0.9590| 33.52  | 0.9166   | 32.09   | 0.8978| 31.92| 0.9256|
| PDAN (ours)   | 2     | 1439K  | 38.05| 0.9607| 33.65  | 0.9182   | 32.20   | 0.8998| 32.36| 0.9300|
| Bicubic       | 3     | –      | 30.39| 0.8682| 27.55  | 0.7742   | 27.21   | 0.7385| 24.46| 0.7349|
| SRCNN [4]     | 3     | 57K    | 32.75| 0.9090| 29.30  | 0.8215   | 28.41   | 0.7863| 26.24| 0.7989|
| FSRCNN [16]   | 3     | 13K    | 33.18| 0.9140| 29.37  | 0.8240   | 28.53   | 0.7910| 26.43| 0.8080|
| VDSR [44]     | 3     | 666K   | 33.66| 0.9213| 29.77  | 0.8314   | 28.82   | 0.7976| 27.14| 0.8279|
| DRCN [5]      | 3     | 1774K  | 33.82| 0.9226| 29.76  | 0.8311   | 28.80   | 0.7963| 27.15| 0.8276|
| LapSRN [45]   | 3     | 502K   | 33.81| 0.9220| 29.79  | 0.8325   | 28.82   | 0.7980| 27.07| 0.8275|
| DRRN [6]      | 3     | 298K   | 34.03| 0.9244| 29.96  | 0.8349   | 28.95   | 0.8004| 27.53| 0.8378|
| SRMDNF [46]   | 3     | 1528K  | 34.12| 0.9254| 30.04  | 0.8382   | 28.97   | 0.8025| 27.57| 0.8398|
| SRResNet [47] | 3     | 1554K  | 34.41| 0.9274| 30.36  | 0.8427   | 29.11   | 0.8055| 28.20| 0.8535|
| CARN [19]     | 3     | 1592K  | 34.29| 0.9255| 30.29  | 0.8407   | 29.06   | 0.8034| 28.06| 0.8493|
| PDAN (ours)   | 3     | 1624K  | 34.44| 0.9276| 30.39  | 0.8437   | 29.11   | 0.8063| 28.34| 0.8563|

### TABLE III

Quantitative results with BD and DN degradation modules for scaling factor ×3. Red/blue text: best/second-best among all methods.

| Methods       | Model  | PSNR | SSIM |
|---------------|--------|------|------|
| Bicubic       | BD     | 28.78| 0.8308|
|               | DN     | 24.01| 0.5369|
| SRCNN [4]     | BD     | 32.05| 0.8944|
|               | DN     | 25.01| 0.6950|
| FSRCNN [16]   | BD     | 26.23| 0.8124|
|               | DN     | 24.18| 0.6932|
| VDSR [44]     | BD     | 33.25| 0.9150|
|               | DN     | 25.20| 0.7183|
| IRCNN_G [38]  | BD     | 33.38| 0.9182|
|               | DN     | 27.50| 0.7379|
| IRCNN_C [38]  | BD     | 33.17| 0.9157|
|               | DN     | 27.48| 0.7925|
| SRMDNF [16]   | BD     | 34.09| 0.9242|
|               | DN     | 28.51| 0.8156|
| PDAN (ours)   | BD     | 34.47| 0.9270|
|               | DN     | 28.47| 0.8151|
| RDN [14]      | BD     | 34.58| 0.9280|
|               | DN     | 28.47| 0.8156|
PDAN obtains superior performance with comparable model size. It demonstrates that our method achieves a better trade-off between the performance and model size. Extensive experiments on image super-resolution using deep recursive residual network, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017.

F. Model size

The number of parameters is a key factor for constructing a lightweight image SR model. From Table II we can observe that our method achieves better results than other state-of-the-art lightweight methods. As shown in Fig. 4, we illustrate the comparisons about parameters and PSNR on Urban100 with upscaling factor $\times 4$. In comparison with other methods, our PDAN obtains superior performance with comparable model size. It demonstrates that our method achieves a better trade-off between the performance and model size.

IV. Conclusion

In this paper, we propose a lightweight pyramidal dense attention network (PDAN) for image SR. Specifically, in the proposed pyramidal dense attention block, the pyramidal dense connections can efficiently exploit feature information in different layers. Meanwhile, the adaptive group convolution whose group size increases linearly with layers is presented to relieve the parameter explosion. In addition, we introduce a new joint attention mechanism to recalibrate the feature responses more accurately by considering cross-dimension interaction in an efficient way. Extensive experiments on image SR demonstrate the superior performance of our PDAN in terms of quantitative and qualitative results.

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