

# Residual Dense Network for Image Restoration

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**Abstract**—Convolutional neural network has recently achieved great success for image restoration (IR) and also offered hierarchical features. However, most deep CNN based IR models do not make full use of the hierarchical features from the original low-quality images, thereby achieving relatively-low performance. In this paper, we propose a novel residual dense network (RDN) to address this problem in IR. We fully exploit the hierarchical features from all the convolutional layers. Specifically, we propose residual dense block (RDB) to extract abundant local features via densely connected convolutional layers. RDB further allows direct connections from the state of preceding RDB to all the layers of current RDB, leading to a contiguous memory mechanism. To adaptively learn more effective features from preceding and current local features and stabilize the training of wider network, we proposed local feature fusion in RDB. After fully obtaining dense local features, we use global feature fusion to jointly and adaptively learn global hierarchical features in a holistic way. We demonstrate the effectiveness of RDN with three representative IR applications, single image super-resolution, Gaussian image denoising, and image compression artifact reduction. Experiments on benchmark datasets show that our RDN achieves favorable performance against state-of-the-art methods for each IR task.

**Index Terms**—Residual dense network, hierarchical features, image restoration, image super-resolution, image denoising, compression artifact reduction.

## 1 INTRODUCTION

SINGLE image restoration (IR) aims to generate a visually pleasing high-quality (HQ) image from its degraded low-quality (LQ) measurement. Image restoration is used in various computer vision tasks, such as security and surveillance imaging [1], medical imaging [2], and image generation [3]. However, it is an ill-posed inverse procedure due to the irreversible nature of the image degradation process. Recently, deep convolutional neural network (CNN) has shown its excellent performance in different image restoration tasks, such as image super-resolution (SR) [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], image denoising (DN) [15], [16], [17], [18], [19], [20], and image compression reduction (CAR) [15], [17], [21].

Among them, Dong et al. [9] firstly introduced a three-layer convolutional neural network (CNN) into image SR and achieved significant improvement over conventional methods. Dong et al. [21] also applied such shallow CNN for image CAR. Kim et al. increased the network depth in VDSR [12] and DRCN [22] by using gradient clipping, residual learning, or recursive-supervision to ease the difficulty of training deep network. By using effective building modules, the networks for image SR are further made deeper and wider with better performance. Zhang et al. incorporated such a residual learning into denoising network [17]. Lim et al. used residual blocks (Figure 1(a)) to build a very wide network EDSR [23] with residual scaling [24] and a

very deep one MDSR [23]. Tai et al. proposed memory block to build MemNet for image restoration [18]. As the network depth grows, the features in each convolutional layer would be hierarchical with different receptive fields. However, these methods neglect to fully use information of each convolutional layer. Although the gate unit in memory block was proposed to control short-term memory [18], the local convolutional layers don't have direct access to the subsequent layers. So, it's hard to say memory block makes full use of the information from all the layers within it.

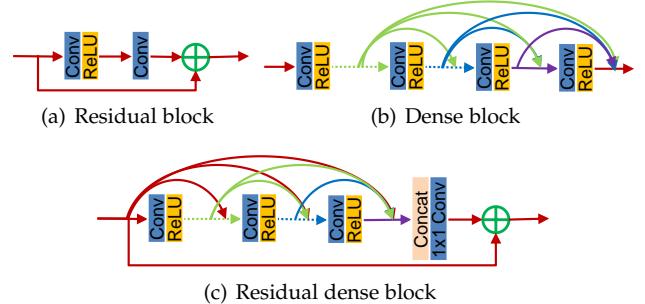


Fig. 1. Comparison of prior network structures (a,b) and our residual dense block (c). (a) Residual block in MDSR [23]. (b) Dense block in SRDenseNet [13]. (c) Our residual dense block, which makes better use of local features.

Furthermore, objects in images have different scales, angles of view, and aspect ratios. These aspects can be captured by hierarchical features, which would give more clues for reconstruction. While, most deep learning (DL) based methods (e.g., VDSR [12], LapSRN [25], IRCNN [19], and EDSR [23]) neglect to use hierarchical features for reconstruction. Although memory block [18] also takes information from preceding memory blocks as input, the multi-level features are not extracted from the original LQ image (e.g., the LR image). Taking image SR as an example, MemNet interpolates the original LR image to the desired size to

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form the input. This pre-processing step not only increases computation complexity quadratically, but also loses some details of the original LR image. Tong et al. introduced dense block (Figure 1(b)) for image SR with relatively low growth rate (e.g., 16). According to our experiments (see Section 5.1), higher growth rate can improve the performance of the network. While, it is hard to train a wider network with dense blocks.

To address these limitations, we propose a residual dense network (RDN) (Figure 2) to fully make use of all the hierarchical features from the original LQ image with our proposed residual dense block (Figure 1(c)). It's hard and impractical for a very deep network to directly extract the output of each convolutional layer in the LQ space. We propose residual dense block (RDB) as the building module for RDN. RDB consists of dense connected layers and local feature fusion (LFF) with local residual learning (LRL). Our RDB also supports contiguous memory among RDBs. The output of one RDB has direct access to each layer of the next RDB, resulting in a contiguous state pass. Each convolutional layer in RDB has access to all the subsequent layers and passes on information that needs to be preserved [26]. Concatenating the states of preceding RDB and all the preceding layers within the current RDB, LFF extracts local dense feature by adaptively preserving the information. Moreover, LFF allows very high growth rate by stabilizing the training of a wider network. After extracting multi-level local dense features, we further conduct global feature fusion (GFF) to adaptively preserve the hierarchical features in a global way. As depicted in Figures 2 and 3, each layer has direct access to the original LR input, leading to an implicit deep supervision [27].

In summary, our main contributions are three-fold:

- We propose a unified framework residual dense network (RDN) for high-quality image restoration. The network makes full use of all the hierarchical features from the original LQ image.
- We propose residual dense block (RDB), which can not only read state from the preceding RDB via a contiguous memory (CM) mechanism, but also fully utilize all the layers within it via local dense connections. The accumulated features are then adaptively preserved by local feature fusion (LFF).
- We propose global feature fusion to adaptively fuse hierarchical features from all RDBs in the LR space. With global residual learning, we combine the shallow features and deep features together, resulting in global dense features from the original LQ image.

A preliminary version of this work has been presented as a conference version [28]. In the current work, we incorporate additional contents in significant ways:

- We investigate a flexible structure of RDN and apply it for different IR tasks. Such IR applications allow us to further investigate the potential breadth of RDN.
- We investigate more details and add considerable analyses to the initial version, such as block connection, network parameter number, and running time.

- We extend RDN for Gaussian image denoising and compression artifact reduction. Extensive experiments demonstrate that our RDN still outperforms existing approaches in these IR tasks.

## 2 RELATED WORK

Recently, deep learning (DL)-based methods have achieved dramatic advantages against conventional methods in computer vision [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39]. Here, we focus on several representative image restoration tasks, such as image super-resolution (SR), denoising (DN), and compression artifact reduction (CAR).

### 2.1 Image Super-Resolution

Dong et al. [9] proposed SRCNN, establishing an end-to-end mapping between the interpolated LR images and their HR counterparts for the first time. This baseline was then further improved mainly by increasing network depth or sharing network weights. VDSR [12] and IRCNN [19] increased the network depth by stacking more convolutional layers with residual learning. DRCN [22] firstly introduced recursive learning in a very deep network for parameter sharing. Tai et al. introduced recursive blocks in DRRN [40] and the memory block in MemNet [18] for deeper networks. All these methods need to interpolate the original LR images to the desired size before applying them into the networks. This pre-processing step not only increases computation complexity quadratically [41], but also over-smooths and blurs the original LR image, from which some details are lost. As a result, these methods extract features from the interpolated LR images, failing to establish an end-to-end mapping from the original LR to HR images.

To solve the problem above, Dong et al. [41] directly took the original LR image as input and introduced a transposed convolution layer (also known as deconvolution layer) for upsampling to the fine resolution. Shi et al. proposed ESPCN [42], where an efficient sub-pixel convolution layer was introduced to upscale the final LR feature maps into the HR output. The efficient sub-pixel convolution layer was then adopted in SRResNet [43] and EDSR [23], which took advantage of residual learning [44]. All of these methods extracted features in the LR space and upscaled the final LR features with transposed or sub-pixel convolution layer. By doing so, these networks can either be capable of real-time SR (e.g., FSRCNN and ESPCN), or be built to be very deep/wide (e.g., SRResNet and EDSR). However, all of these methods stack building modules (e.g., Conv layer in FSRCNN, residual block in SRResNet and EDSR) in a chain way. They neglect to adequately utilize information from each Conv layer and only adopt CNN features from the last Conv layer in LR space for upscaling.

### 2.2 Deep Convolutional Neural Network (CNN)

LeCun et al. integrated constraints from task domain to enhance network generalization ability for handwritten zip code recognition [45], which can be viewed as the pioneering usage of CNNs. Later, various network structures were proposed with better performance, such as AlexNet [46], VGG [47], and GoogleNet [48]. Recently, He et al. [44]

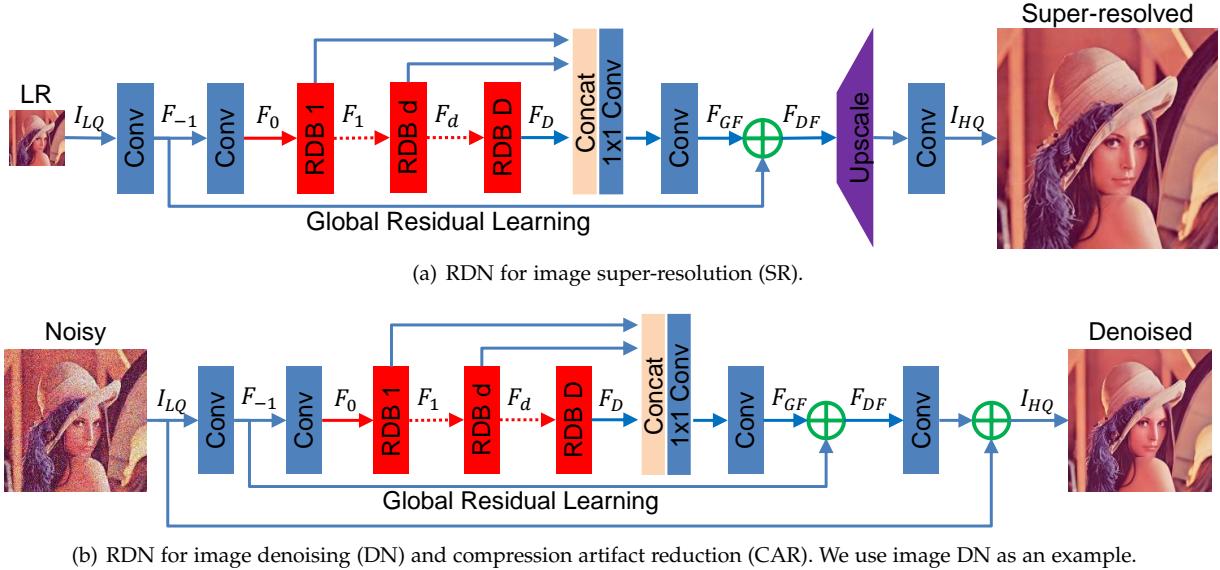


Fig. 2. The architecture of our proposed residual dense network (RDN) for image restoration.

investigated the powerful effectiveness of network depth and proposed deep residual learning for very deep trainable networks. Such a very deep residual network achieves significant improvements on several computer vision tasks, like image classification and object detection. Huang et al. proposed DenseNet, which allows direct connections between any two layers within the same dense block [26]. With the local dense connections, each layer reads information from all the preceding layers within the same dense block. The dense connection was introduced among memory blocks [18] and dense blocks [13]. More differences between DenseNet/SRDenseNet/MemNet and our RDN would be discussed in Section 4.

### 2.3 Deep Learning for Image Restoration

Dong et al. [21] proposed ARCNN for image compression artifact reduction (CAR) with several stacked convolutional layers. Mao et al. [16] proposed residual encoder-decoder networks (RED) with symmetric skip connections, which made the network go deeper (up to 30 layers). Zhang et al. [17] proposed DnCNN to learn mappings from noisy images to noise and further improved performance by utilizing batch normalization [49]. Zhang et al. [19] proposed to learn deep CNN denoiser prior for image restoration (IRCNN) by integrating CNN denoisers into model-based optimization method. However, such methods have limited network depth (e.g., 30 for RED, 20 for DnCNN, and 7 for IRCNN), limiting the network ability. Simply stacking more layers cannot reach better results due to gradient vanishing problem. On the other hand, by using short term and long term memory, Tai et al. [18] proposed MemNet for image restoration, where the network depth reached 212 but obtained limited improvement over results with 80 layers. For  $31 \times 31$  input patches from 91 images, training an 80-layer MemNet takes 5 days using 1 Tesla P40 GPU [18].

The aforementioned DL-based image restoration methods have achieved significant improvement over conventional methods, but most of them lose some useful hierarchical features from the original LQ image. Hierarchical features produced by a very deep network are useful for

image restoration tasks (e.g., image SR). To fix this case, we propose residual dense network (RDN) to extract and adaptively fuse features from all the layers in the LQ space efficiently.

## 3 RESIDUAL DENSE NETWORK FOR IR

In Figure 2, we show our proposed RDN for image restoration, including image super-resolution (see Figure 2(a)), denoising, and compression artifact reduction (see Figure 2(b)).

### 3.1 Network Structure

we mainly take image SR as an example and give specific illustrations for image DN and CAR cases.

**RDN for image SR.** As shown in Figure 2(a), our RDN mainly consists of four parts: shallow feature extraction net (SFENet), residual dense blocks (RDBs), dense feature fusion (DFF), and finally the up-sampling net (UPNet). Let's denote  $I_{LQ}$  and  $I_{HQ}$  as the input and output of RDN. Specifically, we use two Conv layers to extract shallow features. The first Conv layer extracts features  $F_{-1}$  from the LQ input.

$$F_{-1} = H_{SFE1}(I_{LQ}), \quad (1)$$

where  $H_{SFE1}(\cdot)$  denotes convolution operation.  $F_{-1}$  is then used for further shallow feature extraction and global residual learning. So, we can further have

$$F_0 = H_{SFE2}(F_{-1}), \quad (2)$$

where  $H_{SFE2}(\cdot)$  denotes convolution operation of the second shallow feature extraction layer and is used as input to residual dense blocks. Supposing we have  $D$  residual dense blocks, the output  $F_d$  of the  $d$ -th RDB can be obtained by

$$\begin{aligned} F_d &= H_{RDB,d}(F_{d-1}) \\ &= H_{RDB,d}(H_{RDB,d-1}(\dots(H_{RDB,1}(F_0))\dots)), \end{aligned} \quad (3)$$

where  $H_{RDB,d}$  denotes the operations of the  $d$ -th RDB.  $H_{RDB,d}$  can be a composite function of operations, such as convolution and rectified linear units (ReLU) [50]. As  $F_d$  is produced by the  $d$ -th RDB fully utilizing each convolutional

layers within the block, we can view  $F_d$  as local feature. More details about RDB will be given in Section 3.2.

After extracting hierarchical features with a set of RDBs, we further conduct dense feature fusion (DFF), which includes global feature fusion (GFF) and global residual learning (GRL). DFF makes full use of features from all the preceding layers and can be represented as

$$F_{DF} = H_{DFF}(F_{-1}, F_0, F_1, \dots, F_D), \quad (4)$$

where  $F_{DF}$  is the output feature-maps of DFF by utilizing a composite function  $H_{DFF}$ . More details about DFF will be shown in Section 3.3.

After extracting local and global features in the LQ space, we stack an up-sampling net (UPNet) in the HQ space. Inspired by [23], we utilize ESPCN [42] in UPNet followed by one Conv layer. The output of RDN can be obtained by

$$I_{HQ} = H_{RDN}(I_{LQ}), \quad (5)$$

where  $H_{RDN}$  denotes the function of our RDN.

**RDN for image DN and CAR.** When we apply our RDN to image DN and CAR, the resolution of the input and output keep the same. As shown in Figure 2(b), we remove the upscaling module in UPNet and obtain the final HQ output via residual learning

$$I_{HQ} = H_{RDN}(I_{LQ}) + I_{LQ}. \quad (6)$$

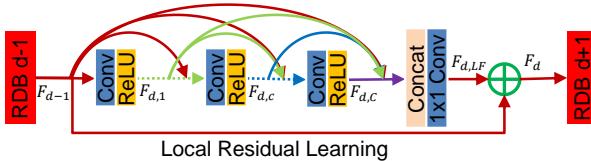


Fig. 3. Residual dense block (RDB) architecture.

### 3.2 Residual Dense Block

We present details about our proposed residual dense block (RDB) shown in Figure 3. Our RDB contains dense connected layers, local feature fusion (LFF), and local residual learning, leading to a contiguous memory (CM) mechanism.

**Contiguous memory (CM) mechanism.** It is realized by passing the state of preceding RDB to each layer of the current RDB. Let  $F_{d-1}$  and  $F_d$  be the input and output of the  $d$ -th RDB respectively and both have  $G_0$  feature-maps. The output of  $c$ -th Conv layer of  $d$ -th RDB can be formulated as

$$F_{d,c} = \sigma(W_{d,c}[F_{d-1}, F_{d,1}, \dots, F_{d,c-1}]), \quad (7)$$

where  $\sigma$  denotes the ReLU [50] activation function.  $W_{d,c}$  is the weights of the  $c$ -th Conv layer, where the bias term is omitted for simplicity. We assume  $F_{d,c}$  consists of  $G$  (also known as growth rate [26]) feature-maps.  $[F_{d-1}, F_{d,1}, \dots, F_{d,c-1}]$  refers to the concatenation of the feature-maps produced by the  $(d-1)$ -th RDB, convolutional layers  $1, \dots, (c-1)$  in the  $d$ -th RDB, resulting in  $G_0 + (c-1) \times G$  feature-maps. The outputs of the preceding RDB and each layer have direct connections to all subsequent layers, which not only preserves the feed-forward nature, but also extracts local dense feature.

**Local feature fusion (LFF).** We apply LFF to adaptively fuse the states from preceding RDB and the whole Conv layers in current RDB. As analyzed above, the feature-maps of

the  $(d-1)$ -th RDB are introduced directly to the  $d$ -th RDB in a concatenation way, it is essential to reduce the feature number. On the other hand, inspired by MemNet [18], we introduce a  $1 \times 1$  convolutional layer to adaptively control the output information. We name this operation as local feature fusion (LFF) formulated as

$$F_{d,LF} = H_{LFF}^d([F_{d-1}, F_{d,1}, \dots, F_{d,c}, \dots, F_{d,C}]), \quad (8)$$

where  $H_{LFF}^d$  denotes the function of the  $1 \times 1$  Conv layer in the  $d$ -th RDB. We also find that as the growth rate  $G$  becomes larger, very deep dense network without LFF would be hard to train. However, larger growth rate further contributes to the performance, which will be detailed in Section 5.1.

**Local residual learning (LRL).** We introduce LRL in RDB to further improve the information flow and allow larger growth rate, as there are several convolutional layers in one RDB. The final output of the  $d$ -th RDB can be obtained by

$$F_d = F_{d-1} + F_{d,LF}. \quad (9)$$

It should be noted that LRL can also further improve the network representation ability, resulting in better performance. We introduce more results about LRL in Section 5.2. Because of the dense connectivity and local residual learning, we refer to this block architecture as residual dense block (RDB). More differences between RDB and original dense block [26] would be summarized in Section 4.

### 3.3 Dense Feature Fusion

After extracting local dense features with a set of RDBs, we further propose dense feature fusion (DFF) to exploit hierarchical features in a global way. DFF consists of global feature fusion (GFF) and global residual learning (GRL).

**Global feature fusion (GFF).** We propose GFF to extract the global feature  $F_{GF}$  by fusing features from all the RDBs

$$F_{GF} = H_{GFF}([F_1, \dots, F_D]), \quad (10)$$

where  $[F_1, \dots, F_D]$  refers to the concatenation of feature maps produced by residual dense blocks  $1, \dots, D$ .  $H_{GFF}$  is a composite function of  $1 \times 1$  and  $3 \times 3$  convolution. The  $1 \times 1$  convolutional layer is used to adaptively fuse a range of features with different levels. The following  $3 \times 3$  convolutional layer is introduced to further extract features for global residual learning, which has been demonstrated to be effective in [43].

**Global residual learning (GRL).** We then utilize GRL to obtain the feature-maps before conducting up-scaling by

$$F_{DF} = F_{-1} + F_{GF}, \quad (11)$$

where  $F_{-1}$  denotes the shallow feature-maps. All the other layers before global feature fusion are fully utilized with our proposed residual dense blocks (RDBs). RDBs produce multi-level local dense features, which are further adaptively fused to form  $F_{GF}$ . After global residual learning, we obtain deep dense feature  $F_{DF}$ .

It should be noted that Tai et al. [18] utilized long-term dense connections in MemNet to recover more high-frequency information. However, in the memory block [18], the preceding layers don't have direct access to all the subsequent layers. The local feature information is not fully

used, limiting the ability of long-term connections. In addition, MemNet extracts features in the HQ space, increasing computational complexity. While, inspired by [23], [25], [41], [42], we extract local and global features in the LQ space. More differences between our proposed RDN and MemNet would be shown in Section 4. We would also demonstrate the effectiveness of global feature fusion in Section 5.2.

### 3.4 Implementation Details

In our proposed RDN, we set  $3 \times 3$  as the size of all convolutional layers except that in local and global feature fusion, whose kernel size is  $1 \times 1$ . For convolutional layer with kernel size  $3 \times 3$ , we pad zeros to each side of the input to keep size fixed. Shallow feature extraction layers, local and global feature fusion layers have  $G_0=64$  filters. Other layers in each RDB has  $G=64$  filters and are followed by ReLU [50]. For image SR, following [23], we use E-PCNN [42] to upscale the coarse resolution features to fine ones for the UPNet. For image DN and CAR, the up-scaling module is removed from UPNet. The final Conv layer has 3 output channels, as we output color HQ images. However, the network can also process gray images, for example, when we apply RDN for gray-scale image denoising.

## 4 DIFFERENCES WITH PRIOR WORKS

Here, we give more details about the differences between our RDN and several representative works.

**Difference to DenseNet.** Inspired from DenseNet [26], we adopt the local dense connections into our proposed residual dense block (RDB). In general, DenseNet is widely used in high-level computer vision tasks (e.g., object recognition [26]). While RDN is designed for image restoration. Moreover, we remove batch normalization (BN) layers, which consume the same amount of GPU memory as convolutional layers, increase computational complexity, and hinder performance of the network. We also remove the pooling layers, which could discard some pixel-level structural information. Furthermore, transition layers are placed into two adjacent dense blocks in DenseNet. While in RDN, we combine dense connected layers with local feature fusion (LFF) by using local residual learning, which would be demonstrated to be effective in Section 5.2. As a result, the output of the  $(d - 1)$ -th RDB has direct connections to each layer in the  $d$ -th RDB and also contributes to the input of  $(d + 1)$ -th RDB. Last not the least, we adopt GFF to fully use hierarchical features, which are neglected in DenseNet.

**Difference to SRDenseNet.** There are three main differences between SRDenseNet [13] and our RDN. The first one is the design of the basic building block. SRDenseNet introduces the basic dense block from DenseNet [26]. Our residual dense block (RDB) improves it in three ways: (1). We propose contiguous memory (CM) mechanism, which allows the state of preceding RDB to have direct access to each layer of the current RDB. (2). Our RDB allows larger growth rate by using local feature fusion (LFF), which stabilizes the training of the wider network. (3). Local residual learning (LRL) is utilized in RDB to further encourage the flow of information and gradient. The second one is that there are no dense connections among RDB. Instead, we use

TABLE 1  
PSNR (dB) comparisons under different block connections. The results are obtained with Bicubic (BI) degradation model for image SR ( $\times 4$ ).

Block connection	Dense connections		Contiguous memory		
	Datasets	SRDenseNet [30]	MemNet [25]	RDN (w/o LRL)	RDN (with LRL)
Set5 [51]		32.02	31.74	32.54	32.61
Set14 [52]		28.50	28.26	28.87	28.93
B100 [53]		27.53	27.40	27.75	27.80
Urban100 [11]		26.05	25.50	26.72	26.85

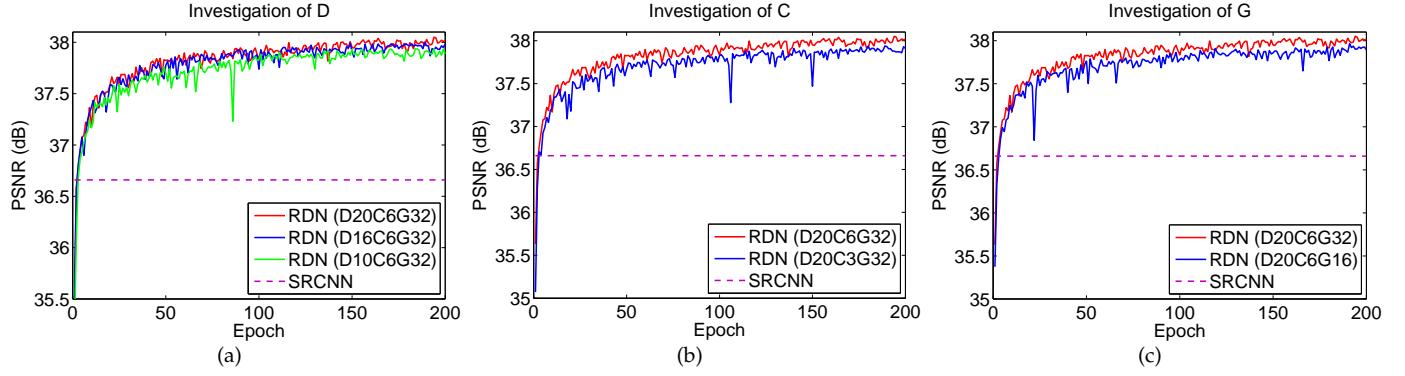
global feature fusion (GFF) and global residual learning to extract global features, because our RDBs with contiguous memory have fully extracted features locally. As shown in Sections 5.1 and 5.2, all these components increase the performance significantly. The third one is that SRDenseNet uses  $L_2$  loss function. Whereas we utilize  $L_1$  loss function, which has been demonstrated to be more powerful for performance and convergence [23]. As a result, our proposed RDN achieves better performance than that of SRDenseNet. In Table 1, our RDN with or without LRL would outperform SRDenseNet [13] for image SR on all the datasets.

**Difference to MemNet.** In addition to the different choice of loss function ( $L_2$  in MemNet [18]), we mainly summarize another three differences between MemNet and our RDN for image SR. First, MemNet needs to upscale the original LR image to the desired size using Bicubic interpolation for image SR. This procedure results in feature extraction and reconstruction in HR space. While, RDN extracts hierarchical features from the original LR image, reducing computational complexity significantly and improving the performance. Second, the memory block in MemNet contains recursive and gate units. Most layers within one recursive unit don't receive the information from their preceding layers or memory block. While, in our proposed RDN, the output of RDB has direct access to each layer of the next RDB. Also, the information of each convolutional layer flow into all the subsequent layers within one RDB. Furthermore, local residual learning in RDB improves the flow of information and gradients and performance, which is demonstrated in Section 5.2. Third, as analyzed above, the current memory block doesn't fully make use of the information of the output of the preceding block and its layers. Even though MemNet adopts densely connections among memory blocks in the HR space, MemNet fails to fully extract hierarchical features from the original LR inputs. While, after extracting local dense features with RDBs, our RDN further fuses the hierarchical features from the whole preceding layers in a global way in the LR space. As shown in Table 1, RDN achieves better results than that of MemNet. For other image restoration tasks, such as image DN, RDN also reconstructs better outputs (see Section 6.3).

## 5 NETWORK INVESTIGATIONS

### 5.1 Study of D, C, and G.

In this subsection, we investigate the basic network parameters: the number of RDB (denote as D for short), the number of Conv layers per RDB (denote as C for short), and the growth rate (denote as G for short). We use the performance of SRCNN [54] as a reference. As shown in Figures 4(a) and 4(b), larger D or C would lead to higher performance.

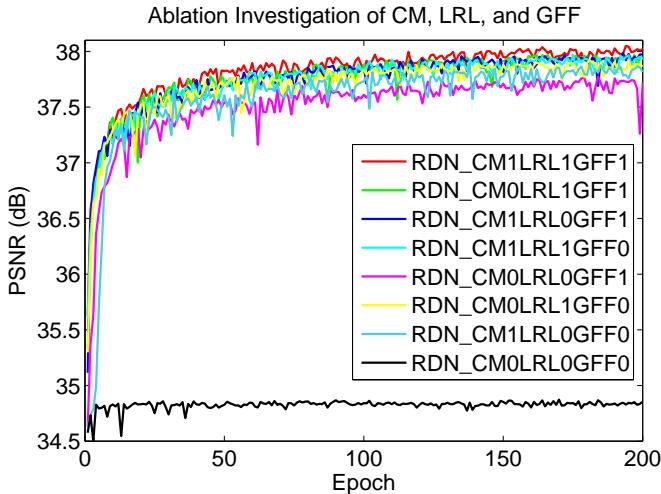
Fig. 4. Convergence analysis of RDN for image SR ( $\times 2$ ) with different values of D, C, and G.

This is mainly because the network becomes deeper with larger D or C. As our proposed LFF allows larger G, we also observe larger G (see Figure 4(c)) contributes to better performance. On the other hand, RND with smaller D, C, or G would suffer some performance drop in the training, but RDN would still outperform SRCNN [54]. More important, our RDN allows deeper and wider network, where more hierarchical features are extracted for higher performance.

TABLE 2

Ablation investigation of contiguous memory (CM), local residual learning (LRL), and global feature fusion (GFF). We observe the best performance (PSNR) on Set5 with scaling factor  $\times 2$  in 200 epochs.

	Different combinations of CM, LRL, and GFF							
	X	✓	X	X	✓	✓	X	✓
CM	X	✓	X	X	✓	✓	X	✓
LRL	X	X	✓	X	✓	✓	✓	✓
GFF	X	X	X	✓	X	✓	✓	✓
PSNR	34.87	37.89	37.92	37.78	37.99	37.98	37.97	38.06

Fig. 5. Convergence analysis on CM, LRL, and GFF. The curves for each combination is based on the PSNR on Set5 ( $\times 2$ ) in 200 epochs.

## 5.2 Ablation Investigation

Table 2 shows the ablation investigation on the effects of contiguous memory (CM), local residual learning (LRL), and global feature fusion (GFF). The eight networks have the same RDB number ( $D = 20$ ), Conv number ( $C = 6$ ) per RDB, and growth rate ( $G = 32$ ). We find that local feature fusion (LFF) is needed to train these networks properly, so LFF isn't removed by default. The baseline (denote as

RDN\_CM0LRL0GFF0) is obtained without CM, LRL, or GFF and performs very poorly (PSNR = 34.87 dB). This is caused by the difficulty of training [54] and also demonstrates that stacking many basic dense blocks [26] in a very deep network would not result in better performance.

We then add one of CM, LRL, or GFF to the baseline, resulting in RDN\_CM1LRL0GFF0, RDN\_CM0LRL1GFF0, and RDN\_CM0LRL0GFF1 respectively (from 2<sup>nd</sup> to 4<sup>th</sup> combination in Table 2). We can validate that each component can efficiently improve the performance of the baseline. This is mainly because each component contributes to the flow of information and gradient.

We further add two components to the baseline, resulting in RDN\_CM1LRL1GFF0, RDN\_CM1LRL0GFF1, and RDN\_CM0LRL1GFF1 respectively (from 5<sup>th</sup> to 7<sup>th</sup> combination in Table 2). It can be seen that two components would perform better than only one component. Similar phenomenon can be seen when we use these three components simultaneously (denote as RDN\_CM1LRL1GFF1). RDN using three components performs the best.

We also visualize the convergence process of these eight combinations in Figure 5. The convergence curves are consistent with the analyses above and show that CM, LRL, and GFF can further stabilize the training process without obvious performance drop. These quantitative and visual analyses demonstrate the effectiveness and benefits of our proposed CM, LRL, and GFF.

## 5.3 Model Size, Performance, and Test Time

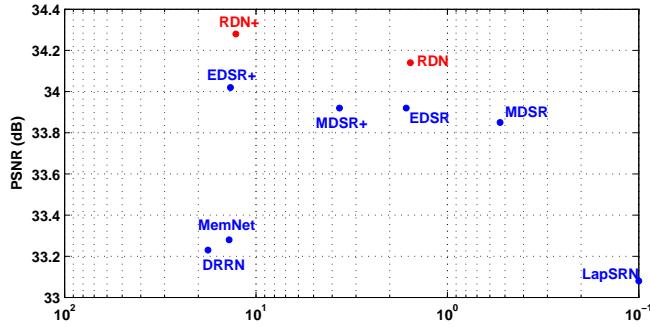
We also compare the model size, performance, and test time with other methods on Set14 ( $\times 2$ ) in Table 3. Compared with EDSR, our RDN has half less amount of parameter and obtains better results. Although our RDN has more parameters than that of other methods, RDN achieves comparable (e.g., MDSR) or even less test time (e.g., MemNet). We further visualize the performance and test time comparison in Figure 6. We can see that our RDN achieves good trade-off between the performance and running time.

TABLE 3  
Parameter number, PSNR, and test time comparisons. The PSNR values are based on Set14 with Bicubicu (BI) degradation model ( $\times 2$ ).

Methods	LapSRN [13]	DRRN [24]	MemNet [25]	MDSR [16]	EDSR [16]	RDN (ours)
# param.	812K	297K	677K	8M	43M	22M
PSNR (dB)	33.08	33.23	33.28	33.85	33.92	34.14
Time (s)	0.10	17.81	13.84	0.53	1.64	1.56

TABLE 4  
Quantitative results with BI degradation model. Best and second best results are **highlighted** and underlined

Method	Scale	Set5		Set14		B100		Urban100		Manga109	
		PSNR	SSIM								
Bicubic	$\times 2$	33.66	0.9299	30.24	0.8688	29.56	0.8431	26.88	0.8403	30.80	0.9339
SRCCNN [54]	$\times 2$	36.66	0.9542	32.45	0.9067	31.36	0.8879	29.50	0.8946	35.60	0.9663
FSRCCNN [41]	$\times 2$	37.05	0.9560	32.66	0.9090	31.53	0.8920	29.88	0.9020	36.67	0.9710
VDSR [12]	$\times 2$	37.53	0.9590	33.05	0.9130	31.90	0.8960	30.77	0.9140	37.22	0.9750
LapSRN [25]	$\times 2$	37.52	0.9591	33.08	0.9130	31.08	0.8950	30.41	0.9101	37.27	0.9740
MemNet [18]	$\times 2$	37.78	0.9597	33.28	0.9142	32.08	0.8978	31.31	0.9195	37.72	0.9740
EDSR [23]	$\times 2$	38.11	0.9602	33.92	0.9195	32.32	0.9013	32.93	0.9351	39.10	0.9773
SRMDNF [14]	$\times 2$	37.79	0.9601	33.32	0.9159	32.05	0.8985	31.33	0.9204	38.07	0.9761
D-DBPN [34]	$\times 2$	38.09	0.9600	33.85	0.9190	32.27	0.9000	32.55	0.9324	38.89	0.9775
RDN (ours)	$\times 2$	<b>38.30</b>	<b>0.9617</b>	<u>34.14</u>	<u>0.9235</u>	<u>32.41</u>	<u>0.9025</u>	<u>33.17</u>	<u>0.9377</u>	<u>39.60</u>	<u>0.9791</u>
RDN+ (ours)	$\times 2$	<b>38.34</b>	<b>0.9618</b>	<u>34.28</u>	<u>0.9241</u>	<u>32.46</u>	<u>0.9030</u>	<u>33.36</u>	<u>0.9388</u>	<u>39.74</u>	<u>0.9794</u>
Bicubic	$\times 3$	30.39	0.8682	27.55	0.7742	27.21	0.7385	24.46	0.7349	26.95	0.8556
SRCCNN [54]	$\times 3$	32.75	0.9090	29.30	0.8215	28.41	0.7863	26.24	0.7989	30.48	0.9117
FSRCCNN [41]	$\times 3$	33.18	0.9140	29.37	0.8240	28.53	0.7910	26.43	0.8080	31.10	0.9210
VDSR [12]	$\times 3$	33.67	0.9210	29.78	0.8320	28.83	0.7990	27.14	0.8290	32.01	0.9340
LapSRN [25]	$\times 3$	33.82	0.9227	29.87	0.8320	28.82	0.7980	27.07	0.8280	32.21	0.9350
MemNet [18]	$\times 3$	34.09	0.9248	30.00	0.8350	28.96	0.8001	27.56	0.8376	32.51	0.9369
EDSR [23]	$\times 3$	34.65	0.9280	30.52	0.8462	29.25	0.8093	28.80	0.8653	34.17	0.9476
SRMDNF [14]	$\times 3$	34.12	0.9254	30.04	0.8382	28.97	0.8025	27.57	0.8398	33.00	0.9403
RDN (ours)	$\times 3$	<b>34.78</b>	<b>0.9299</b>	<u>30.63</u>	<u>0.8477</u>	<u>29.33</u>	<u>0.8107</u>	<u>29.02</u>	<u>0.8695</u>	<u>34.58</u>	<u>0.9502</u>
RDN+ (ours)	$\times 3$	<b>34.84</b>	<b>0.9303</b>	<u>30.74</u>	<u>0.8495</u>	<u>29.38</u>	<u>0.8115</u>	<u>29.18</u>	<u>0.8718</u>	<u>34.81</u>	<u>0.9512</u>
Bicubic	$\times 4$	28.42	0.8104	26.00	0.7027	25.96	0.6675	23.14	0.6577	24.89	0.7866
SRCCNN [54]	$\times 4$	30.48	0.8628	27.50	0.7513	26.90	0.7101	24.52	0.7221	27.58	0.8555
FSRCCNN [41]	$\times 4$	30.72	0.8660	27.61	0.7550	26.98	0.7150	24.62	0.7280	27.90	0.8610
VDSR [12]	$\times 4$	31.35	0.8830	28.02	0.7680	27.29	0.7026	25.18	0.7540	28.83	0.8870
LapSRN [25]	$\times 4$	31.54	0.8850	28.19	0.7720	27.32	0.7270	25.21	0.7560	29.09	0.8900
MemNet [18]	$\times 4$	31.74	0.8893	28.26	0.7723	27.40	0.7281	25.50	0.7630	29.42	0.8942
SRDenseNet [13]	$\times 4$	32.02	0.8930	28.50	0.7780	27.53	0.7337	26.05	0.7819	N/A	N/A
EDSR [23]	$\times 4$	32.46	0.8968	28.80	0.7876	27.71	0.7420	26.64	0.8033	31.02	0.9148
SRMDNF [14]	$\times 4$	31.96	0.8925	28.35	0.7787	27.49	0.7337	25.68	0.7731	30.09	0.9024
D-DBPN [34]	$\times 4$	32.47	0.8980	28.82	0.7860	27.72	0.7400	26.38	0.7946	30.91	0.9137
RDN (ours)	$\times 4$	<b>32.61</b>	<b>0.8999</b>	<u>28.93</u>	<u>0.7894</u>	<u>27.80</u>	<u>0.7436</u>	<u>26.85</u>	<u>0.8089</u>	<u>31.45</u>	<u>0.9187</u>
RDN+ (ours)	$\times 4$	<b>32.69</b>	<b>0.9007</b>	<u>29.01</u>	<u>0.7909</u>	<u>27.85</u>	<u>0.7447</u>	<u>27.01</u>	<u>0.8120</u>	<u>31.74</u>	<u>0.9208</u>
Bicubic	$\times 8$	24.40	0.6580	23.10	0.5660	23.67	0.5480	20.74	0.5160	21.47	0.6500
SRCCNN [54]	$\times 8$	25.33	0.6900	23.76	0.5910	24.13	0.5660	21.29	0.5440	22.46	0.6950
FSRCCNN [41]	$\times 8$	20.13	0.5520	19.75	0.4820	24.21	0.5680	21.32	0.5380	22.39	0.6730
SCN [55]	$\times 8$	25.59	0.7071	24.02	0.6028	24.30	0.5698	21.52	0.5571	22.68	0.6963
VDSR [12]	$\times 8$	25.93	0.7240	24.26	0.6140	24.49	0.5830	21.70	0.5710	23.16	0.7250
LapSRN [25]	$\times 8$	26.15	0.7380	24.35	0.6200	24.54	0.5860	21.81	0.5810	23.39	0.7350
MemNet [18]	$\times 8$	26.16	0.7414	24.38	0.6199	24.58	0.5842	21.89	0.5825	23.56	0.7387
MSLapSRN [56]	$\times 8$	26.34	0.7558	24.57	0.6273	24.65	0.5895	22.06	0.5963	23.90	0.7564
EDSR [23]	$\times 8$	26.96	0.7762	24.91	0.6420	24.81	0.5985	22.51	0.6221	24.69	0.7841
D-DBPN [34]	$\times 8$	27.21	0.7840	25.13	0.6480	24.88	0.6010	22.73	0.6312	25.14	0.7987
RDN (ours)	$\times 8$	<b>27.23</b>	<b>0.7854</b>	<u>25.25</u>	<u>0.6505</u>	<u>24.91</u>	<u>0.6032</u>	<u>22.83</u>	<u>0.6374</u>	<u>25.14</u>	<u>0.7994</u>
RDN+ (ours)	$\times 8$	<b>27.40</b>	<b>0.7900</b>	<u>25.38</u>	<u>0.6541</u>	<u>25.01</u>	<u>0.6057</u>	<u>23.04</u>	<u>0.6439</u>	<u>25.48</u>	<u>0.8058</u>

Fig. 6. PSNR and test time on Set14 with BI model ( $\times 2$ ).

## 6 EXPERIMENTAL RESULTS

The source code and models of the proposed method can be downloaded at <https://github.com/yulunzhang/RDN>.

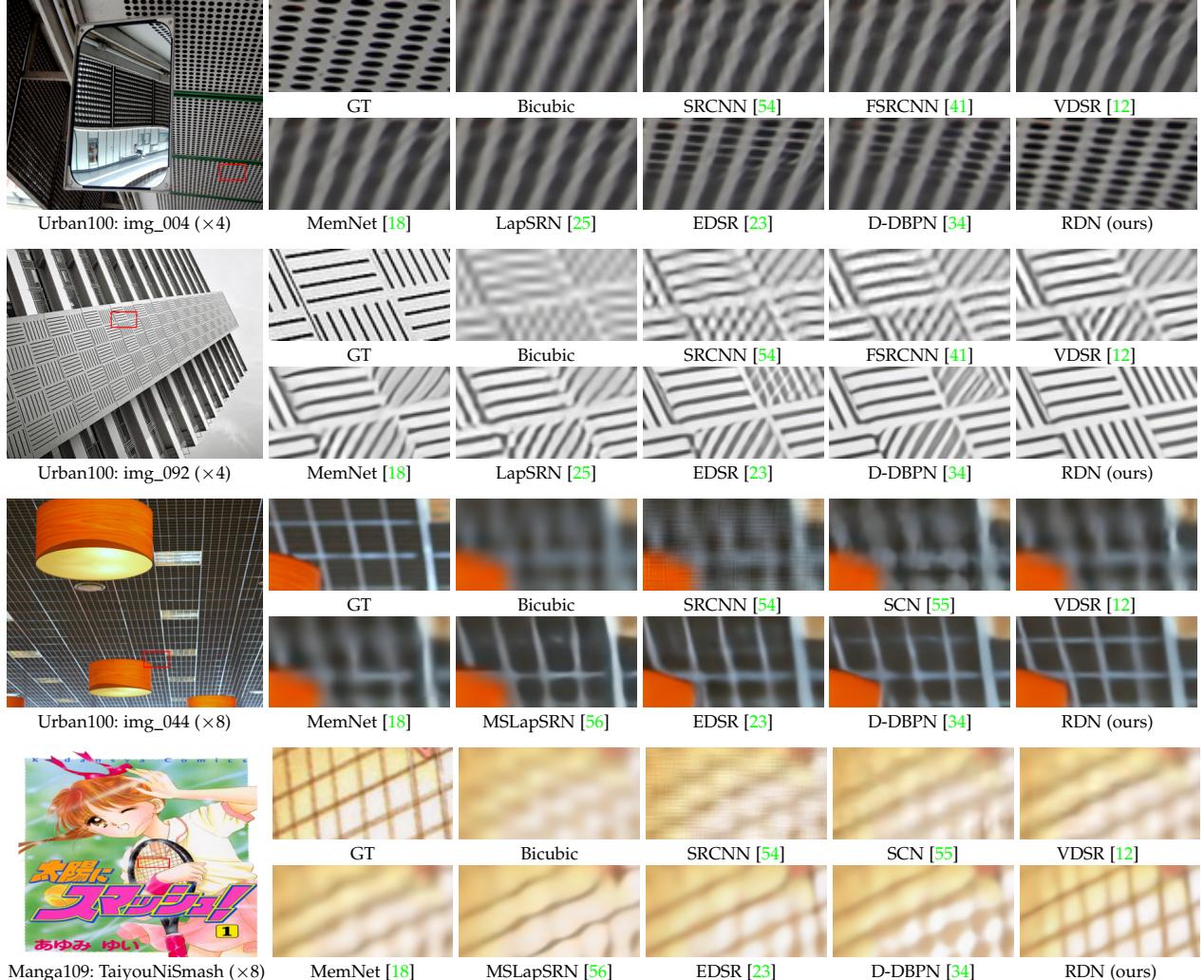
### 6.1 Settings

**Datasets and Metrics.** Recently, Timofte et al. have released a high-quality (2K resolution) dataset DIV2K for image restoration applications [33]. DIV2K consists of 800 training images, 100 validation images, and 100 test images. We train all our models with 800 training images and use 5 validation

images in the training process. For testing, we use five standard benchmark datasets: Set5 [51], Set14 [52], B100 [53], Urban100 [11], and Manga109 [57] for image SR. We use Kodak24 (<http://r0k.us/graphics/kodak/>), BSD68 [53], and Urban100 [11] for color and gray image DN. LIVE1 [58] and Classic5 [59] are used for image CAR. The image SR and CAR results are evaluated with PSNR and SSIM [60] on Y channel (i.e., luminance) of transformed YCbCr space.

**Degradation Models.** In order to fully demonstrate the effectiveness of our proposed RDN, we use three degradation models to simulate LR images for image SR. The first one is bicubic downsampling by adopting the Matlab function `imresize` with the option `bicubic` (denote as **BI** for short). We use **BI** model to simulate LR images with scaling factor  $\times 2$ ,  $\times 3$ ,  $\times 4$ , and  $\times 8$ . Similar to [19], the second one is to blur HR image by Gaussian kernel of size  $7 \times 7$  with standard deviation 1.6. The blurred image is then downsampled with scaling factor  $\times 3$  (denote as **BD** for short). We further produce LR image in a more challenging way. We first bicubic downsample HR image with scaling factor  $\times 3$  and then add Gaussian noise with noise level 30 (denote as **DN** for short).

**Training Setting.** Following settings of [23], in each training batch, we randomly extract 16 LQ RGB patches

Fig. 7. Image super-resolution results with scaling factors  $s = 4$  (first two rows) and  $s = 8$  (last two rows).

with the size of  $48 \times 48$  as inputs. We randomly augment the patches by flipping horizontally or vertically and rotating  $90^\circ$ . 1,000 iterations of back-propagation constitute an epoch. We implement our RDN with the Torch7 framework and update it with Adam optimizer [61]. The learning rate is initialized to  $10^{-4}$  for all layers and decreases half for every 200 epochs. Training a RDN roughly takes 1 day with a Titan Xp GPU for 200 epochs.

## 6.2 Image Super-Resolution

### 6.2.1 Results with BI Degradation Model

Simulating LR image with BI degradation model is widely used in image SR settings. For BI degradation model, we compare our RDN with state-of-the-art image SR methods: SRCNN [54], FSRCNN [41], SCN [55], VDSR [12], LapSRN [25], MemNet [18], SRDenseNet [13], MSLapSRN [56], EDSR [23], SRMDNF [14], and D-DBPN [34]. Similar to [23], [62], we also adopt self-ensemble strategy [23] to further improve our RDN and denote the self-ensembled RDN as RDN+. Here, we also additionally use Flickr2K [33] as training data, which is also used in SRMDNF [14], and D-DBPN [34]. As analyzed above, a deeper and wider RDN would lead to a better performance. On the other hand, as most methods for comparison only use about 64 filters per

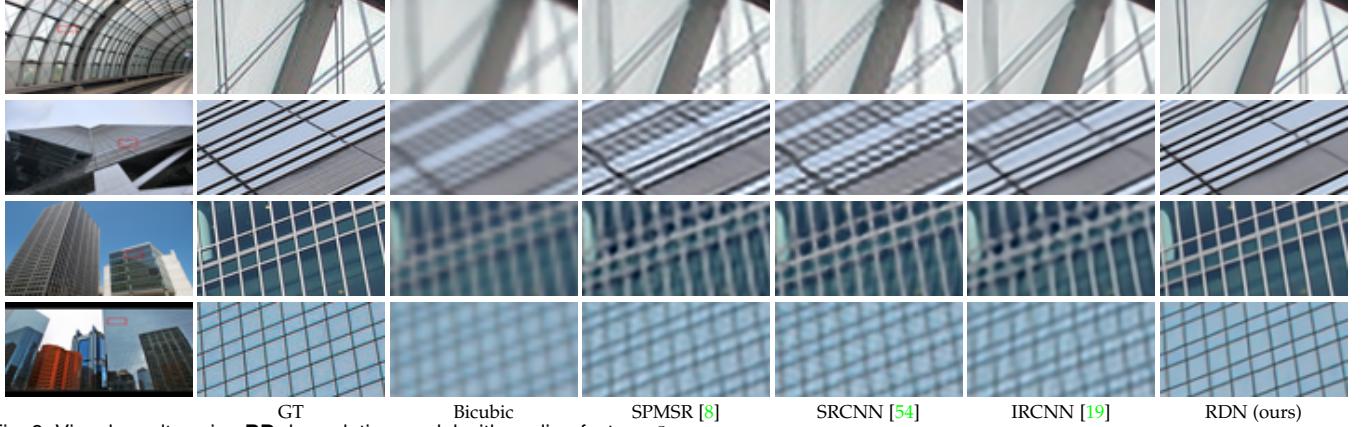
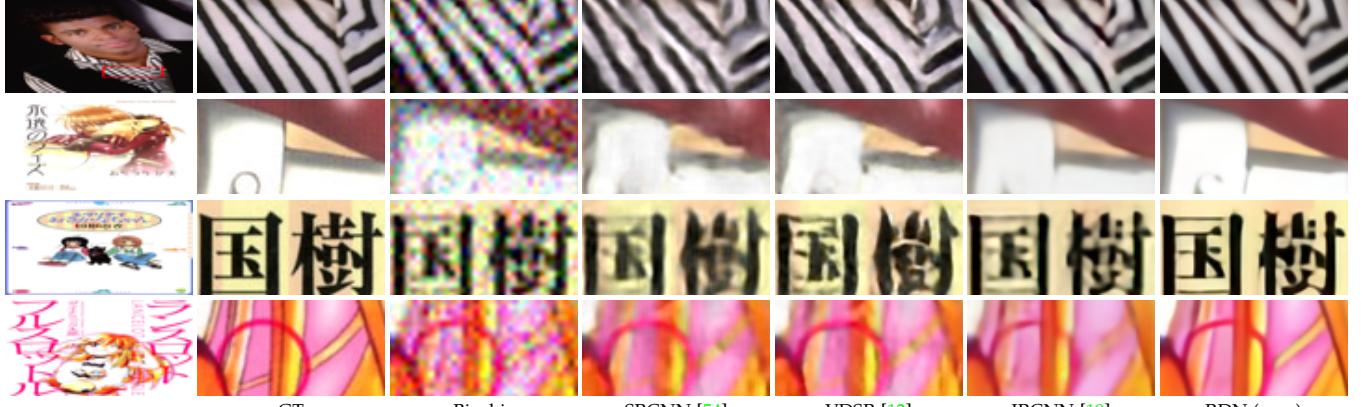
Conv layer, we report results of RDN by using  $D = 16$ ,  $C = 8$ , and  $G = 64$  for a fair comparison.

Table 4 shows quantitative comparisons for  $\times 2$ ,  $\times 3$ , and  $\times 4$  SR. Results of SRDenseNet [13] are cited from their paper. When compared with persistent CNN models (SRDenseNet [13] and MemNet [18]), our RDN performs the best on all datasets with all scaling factors. This indicates the better effectiveness of our residual dense block (RDB) over dense block in SRDenseNet [13] and the memory block in MemNet [18]. When compared with the remaining models, our RDN also achieves the best average results on most datasets. Specifically, for the scaling factor  $\times 2$ , our RDN performs the best on all datasets. EDSR [23] uses far more filters (i.e., 256) per Conv layer, leading to a very wide network with a large number of parameters (i.e., 43 M). Our RDN has about half less network parameter number and achieves better performance.

In Figure 7, we show visual comparisons on scales  $\times 4$  and  $\times 8$ . We observe that most of compared methods cannot recover the lost details in the LR image (e.g., “img\_004”), even though EDSR and D-DBPN can reconstruct partial details. In contrast, our RDN can recover sharper and clearer edges, more faithful to the ground truth. In image “img\_092”, some unwanted artifacts are generated in the degradation process. All the compared methods would fail

TABLE 5  
Benchmark results with **BD** and **DN** degradation models. Average PSNR/SSIM values for scaling factor  $\times 3$ .

Dataset	Model	Bicubic	SRCCNN [54]	FSRCNN [41]	VDSR [12]	IRCNN_G [19]	IRCNN_C [19]	RDN (ours)	RDN+ (ours)
Set5	<b>BD</b>	28.78/0.8308	32.05/0.8944	26.23/0.8124	33.25/0.9150	33.38/0.9182	33.17/0.9157	34.58/0.9280	<b>34.70/0.9289</b>
	<b>DN</b>	24.01/0.5369	25.01/0.6950	24.18/0.6932	25.20/0.7183	25.70/0.7379	27.48/0.7925	28.47/0.8151	<b>28.55/0.8173</b>
Set14	<b>BD</b>	26.38/0.7271	28.80/0.8074	24.44/0.7106	29.46/0.8244	29.63/0.8281	29.55/0.8271	30.53/0.8447	<b>30.64/0.8463</b>
	<b>DN</b>	22.87/0.4724	23.78/0.5898	23.02/0.5856	24.00/0.6112	24.45/0.6305	25.92/0.6932	26.60/0.7101	<b>26.67/0.7117</b>
B100	<b>BD</b>	26.33/0.6918	28.13/0.7736	24.86/0.6832	28.57/0.7893	28.65/0.7922	28.49/0.7886	29.23/0.8079	<b>29.30/0.8093</b>
	<b>DN</b>	22.92/0.4449	23.76/0.5538	23.41/0.5556	24.00/0.5749	24.28/0.5900	25.55/0.6481	25.93/0.6573	<b>25.97/0.6587</b>
Urban100	<b>BD</b>	23.52/0.6862	25.70/0.7770	22.04/0.6745	26.61/0.8136	26.77/0.8154	26.47/0.8081	28.46/0.8582	<b>28.67/0.8612</b>
	<b>DN</b>	21.63/0.4687	21.90/0.5737	21.15/0.5682	22.22/0.6096	22.90/0.6429	23.93/0.6950	24.92/0.7364	<b>25.05/0.7399</b>
Manga109	<b>BD</b>	25.46/0.8149	29.47/0.8924	23.04/0.7927	31.06/0.9234	31.15/0.9245	31.13/0.9236	33.97/0.9465	<b>34.34/0.9483</b>
	<b>DN</b>	23.01/0.5381	23.75/0.7148	22.39/0.7111	24.20/0.7525	24.88/0.7765	26.07/0.8253	28.00/0.8591	<b>28.18/0.8621</b>

Fig. 8. Visual results using **BD** degradation model with scaling factor  $\times 3$ .Fig. 9. Visual results using **DN** degradation model with scaling factor  $\times 3$ .

to handle such a case, but enlarge the mistake. However, our RDN can alleviate the degradation artifacts and recover correct structures. When scaling factor goes larger (e.g.,  $\times 8$ ), more structural and textural details are lost. Even we human beings can hardly distinguish the semantic content in the LR images. Most compared methods cannot recover the lost details either. However, with the usage of hierarchical features through dense feature fusion, our RDN reconstruct better visual results with clearer structures.

### 6.2.2 Results with BD and DN Degradation Models

Following [19], we also show the SR results with BD degradation model and further introduce DN degradation model. Our RDN is compared with SPMsr [8], SRCNN [54], FSRCNN [41], VDSR [12], IRCNN\_G [19], and IRCNN\_C [19]. We re-train SRCNN, FSRCNN, and VDSR for each degradation model. Table 5 shows the average PSNR and SSIM

results on Set5, Set14, B100, Urban100, and Manga109 with scaling factor  $\times 3$ . Our RDN and RDN+ perform the best on all the datasets with BD and DN degradation models. The performance gains over other state-of-the-art methods are consistent with the visual results in Figures 8 and 9.

For **BD** degradation model (Figure 8), the methods using interpolated LR image as input would produce noticeable artifacts and be unable to remove the blurring artifacts. In contrast, our RDN suppresses the blurring artifacts and recovers sharper edges. This comparison indicates that extracting hierarchical features from the original LR image would alleviate the blurring artifacts. It also demonstrates the strong ability of RDN for **BD** degradation model.

For **DN** degradation model (Figure 9), where the LR image is corrupted by noise and loses some details. We observe that the noised details are hard to recovered by other methods [12], [19], [54]. However, our RDN can not

only handle the noise efficiently, but also recover more details. This comparison indicates that RDN is applicable for jointly image denoising and SR. These results with **BD** and **DN** degradation models demonstrate the effectiveness and robustness of our RDN model.

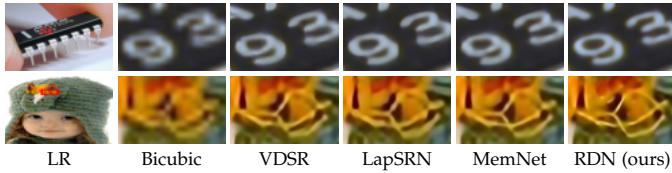


Fig. 10. Visual results on real-world images with scaling factor  $\times 4$ . The two rows show SR results for images “chip” and “hatc” respectively.

### 6.2.3 Super-Resolving Real-World Images

We also conduct SR experiments on two representative real-world images, “chip” (with  $244 \times 200$  pixels) and “hatc” (with  $133 \times 174$  pixels) [64]. In this case, the original HR images are not available and the degradation model is unknown either. We compare our RND with VDSR [12], LapSRN [25], and MemNet [18]. As shown in Figure 10, our RDN recovers sharper edges and finer details than other state-of-the-art methods. These results further indicate the benefits of learning dense features from the original input image. The hierarchical features perform robustly for different or unknown degradation models.

## 6.3 Image Denoising

We compare our RDN with recently leading Gaussian denoising methods: BM3D [63], CBM3D [65], TNRD [15], RED [16], DnCNN [17], MemNet [18], IRCNN [19], and FFDNet [20]. Kodak24 (<http://r0k.us/graphics/kodak/>), BSD68 [53], and Urban100 [11] are used for gray-scale and color image denoising. Noisy images are obtained by adding AWGN noises of different levels to clean images.

### 6.3.1 Gray-scale Image Denoising

The PSNR results are shown in Table 6. One can see that on all the 3 test sets with 4 noise levels, our RDN+ achieves the highest average PSNR values. On average, for noise level  $\sigma = 50$ , our RDN achieves 0.22 dB, 0.11 dB, and 0.88 dB gains over FFDNet [20] on three test sets respectively. Gains on Urban100 become larger, which is mainly because our method takes advantage of a larger scope of context information with hierarchical features. Moreover, for noise levels  $\sigma = 30, 50$ , and  $70$ , the gains over BM3D of RDN are larger than 0.7 dB, breaking the estimated PSNR bound (0.7 dB) over BM3D in [66].

We show visual gray-scale denoised results of different methods in Figure 11. We can see that BM3D preserves image structure to some degree, but fails to remove noise deeply. TNRD [15] tends to generate some artifacts in the smooth region. RED [16], DnCNN [17], MemNet [18], and IRCNN [19] would over-smooth edges. The main reason should be the limited network ability for high noise level (e.g.,  $\sigma = 50$ ). In contrast, our RDN can remove noise greatly and recover more details (e.g., the tiny lines in “img\_061”). Also, the gray-scale visual results by our RDN in the smooth region are more faithful to the clean images (e.g., smooth regions in “119082” and “img\_061”).

### 6.3.2 Color Image Denoising

We generate noisy color images by adding AWGN noise to clean RGB images with different noise levels  $\sigma = 10, 30, 50$ , and  $70$ . The PSNR results are listed in Table 7. We apply gray image denoising methods (e.g., MemNet [18]) for color image denoising channel by channel. Larger gains over MemNet [18] of our RDN indicate that denoising color images jointly perform better than denoising each channel separately. Take  $\sigma=50$  as an example, our RDN obtains 0.56 dB, 0.35, and 1.24 dB improvements over FFDNet [20] on three test sets respectively. Residual learning and dense feature fusion allows RDN to go wider and deeper, obtain hierarchical features, and achieve better performance.

We also show color image denoising visual results in Figure 12. CBM3D [65] tends to produce artifacts along the edges. TNRD [15] produces artifacts in the smooth area and is unable to recover clear edges. RED [16], DnCNN [17], MemNet [18], IRCNN [19], and FFDNet [20] could produce blurring artifacts along edges (e.g., the structural lines in “img\_039”). Because RED [16] and MemNet [18] were designed for gray image denoising. In our experiments on color image denoising, we conduct RED [16] and MemNet [18] in each channel. Although DnCNN [17], IRCNN [19], and FFDNet [20] directly denoise noisy color images in three channels, they either fail to recover sharp edges and clean smooth area. In contrast, our RDN can recover sharper edges and cleaner smooth area.

## 6.4 Image Compression Artifact Reduction

We further apply our RDN to reduce image compression artifacts. We compare our RDN with SA-DCT [59], AR-CNN [21], TNRD [15], and DnCNN [17]. We use Matlab JPEG encoder [67] to generate compressed test images from LIVE1 [58] and Classic5 [59]. Four JPEG quality settings  $q = 10, 20, 30, 40$  are used in Matlab JPEG encoder. Here, we only focus on the compression artifact reduction (CAR) of Y channel (in YCbCr space) to keep fair comparison with other methods.

We report PSNR/SSIM values in Table 8. As we can see, our RDN and RDN+ achieve higher PSNR and SSIM values on LIVE1 and Classic5 with all JPEG qualities than other compared methods. Taking  $q = 10$  as an example, our RDN achieves 0.48 dB and 0.60 dB improvements over DnCNN [17] in terms of PSNR. Even in such a challenging case (very low compression quality), our RDN can still obtain great performance gains over others. Similar improvements are also significant for other compression qualities. These comparisons further demonstrate the effectiveness of our proposed RDN.

Visual comparisons are further shown in Figure 13, where we provide comparisons under very low image quality ( $q=10$ ). Although AR-CNN [21], TNRD [15], and DnCNN [17] can remove blocking artifacts to some degree, they also over-smooth some details (e.g., 1st and 2nd rows in Figure 13) and cannot deeply remove the compression artifacts around content structures (e.g., 3rd and 4th rows in Figure 13). While, RDN has stronger network representation ability to distinguish compression artifacts and content information better. As a result, RDN recovers more details with consistent content structures.

TABLE 6  
Quantitative results about gray-scale image denoising. Best and second best results are **highlighted** and underlined

Method	Kodak24				BSD68				Urban100			
	10	30	50	70	10	30	50	70	10	30	50	70
BM3D [63]	34.39	29.13	26.99	25.73	33.31	27.76	25.62	24.44	34.47	28.75	25.94	24.27
TNRD [15]	34.41	28.87	27.20	24.95	33.41	27.66	25.97	23.83	33.78	27.49	25.59	22.67
RED [16]	35.02	29.77	27.66	26.39	33.99	28.50	26.37	25.10	34.91	29.18	26.51	24.82
DnCNN [17]	34.90	29.62	27.51	26.08	33.88	28.36	26.23	24.90	34.73	28.88	26.28	24.36
MemNet [18]	N/A	29.72	27.68	26.42	N/A	28.43	26.35	25.09	N/A	29.10	26.65	25.01
IRCNN [19]	34.76	29.53	27.45	N/A	33.74	28.26	26.15	N/A	34.60	28.85	26.24	N/A
FFDNet [20]	34.81	29.70	27.63	26.34	33.76	28.39	26.30	25.04	34.45	29.03	26.52	24.86
RDN (ours)	<u>35.17</u>	<u>30.00</u>	<u>27.85</u>	<u>26.54</u>	<u>34.00</u>	<u>28.56</u>	<u>26.41</u>	<u>25.10</u>	<u>35.41</u>	<u>30.01</u>	<u>27.40</u>	<u>25.64</u>
RDN+ (ours)	<b>35.19</b>	<b>30.02</b>	<b>27.88</b>	<b>26.57</b>	<b>34.01</b>	<b>28.58</b>	<b>26.43</b>	<b>25.12</b>	<b>35.45</b>	<b>30.08</b>	<b>27.47</b>	<b>25.71</b>

TABLE 7  
Quantitative results about color image denoising. Best and second best results are **highlighted** and underlined

Method	Kodak24				BSD68				Urban100			
	10	30	50	70	10	30	50	70	10	30	50	70
CBM3D [65]	36.57	30.89	28.63	27.27	35.91	29.73	27.38	26.00	36.00	30.36	27.94	26.31
TNRD [15]	34.33	28.83	27.17	24.94	33.36	27.64	25.96	23.83	33.60	27.40	25.52	22.63
RED [16]	34.91	29.71	27.62	26.36	33.89	28.46	26.35	25.09	34.59	29.02	26.40	24.74
DnCNN [17]	36.98	31.39	29.16	27.64	36.31	30.40	28.01	26.56	36.21	30.28	28.16	26.17
MemNet [18]	N/A	29.67	27.65	26.40	N/A	28.39	26.33	25.08	N/A	28.93	26.53	24.93
IRCNN [19]	36.70	31.24	28.93	N/A	36.06	30.22	27.86	N/A	35.81	30.28	27.69	N/A
FFDNet [20]	36.81	31.39	29.10	27.68	36.14	30.31	27.96	26.53	35.77	30.53	28.05	26.39
RDN (ours)	<u>37.31</u>	<u>31.94</u>	<u>29.66</u>	<u>28.20</u>	<u>36.47</u>	<u>30.67</u>	<u>28.31</u>	<u>26.85</u>	<u>36.69</u>	<u>31.69</u>	<u>29.29</u>	<u>27.63</u>
RDN+ (ours)	<b>37.33</b>	<b>31.98</b>	<b>29.70</b>	<b>28.24</b>	<b>36.49</b>	<b>30.70</b>	<b>28.34</b>	<b>26.88</b>	<b>36.75</b>	<b>31.78</b>	<b>29.38</b>	<b>27.74</b>

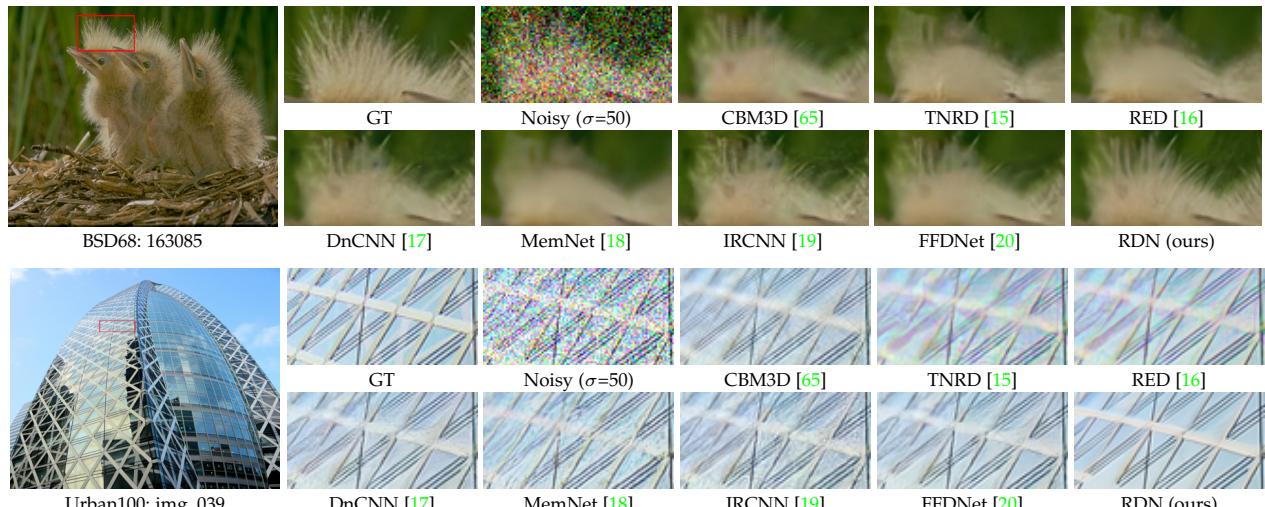
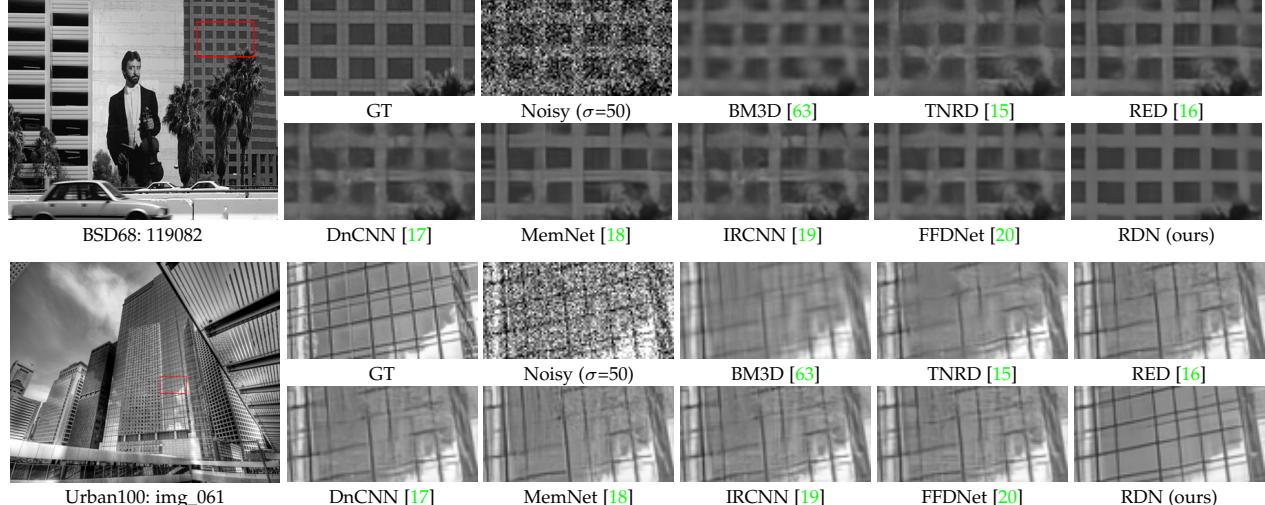
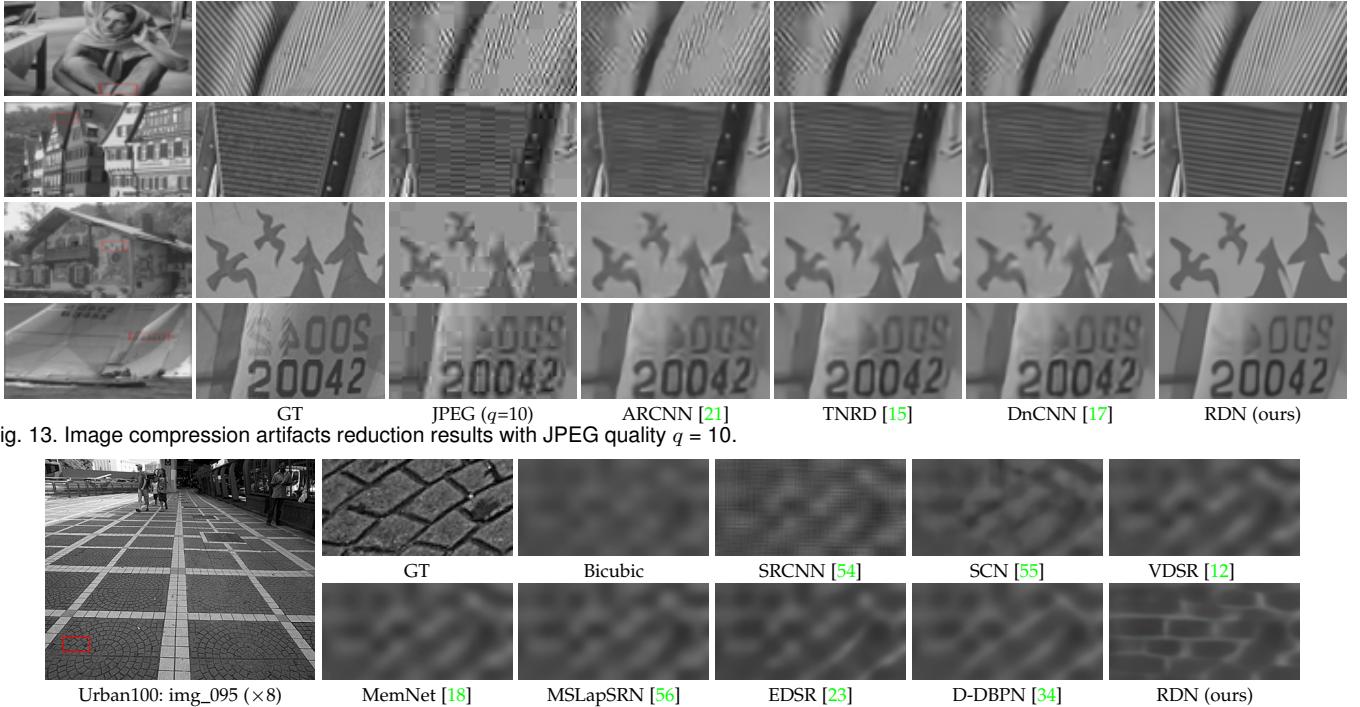
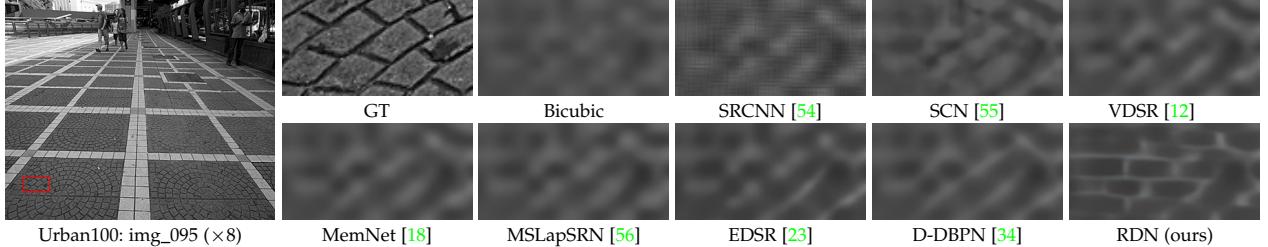


TABLE 8

Quantitative results about image compression artifact reduction. Best and second best results are highlighted and underlined

Dataset	Quality	JPEG		SA-DCT [59]		ARCNN [21]		TNRD [15]		DnCNN [17]		RDN (ours)		RDN+ (ours)	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
LIVE1	10	27.77	0.7905	28.65	0.8093	28.98	0.8217	29.15	0.8111	29.19	0.8123	29.67	0.8247	29.70	0.8252
	20	30.07	0.8683	30.81	0.8781	31.29	0.8871	31.46	0.8769	31.59	0.8802	32.07	0.8882	32.10	0.8886
	30	31.41	0.9000	32.08	0.9078	32.69	0.9166	32.84	0.9059	32.98	0.9090	33.51	0.9153	33.54	0.9156
	40	32.35	0.9173	32.99	0.9240	33.63	0.9306	N/A	N/A	33.96	0.9247	34.51	0.9302	34.54	0.9304
Classic5	10	27.82	0.7800	28.88	0.8071	29.04	0.8111	29.28	0.7992	29.40	0.8026	30.00	0.8188	30.03	0.8194
	20	30.12	0.8541	30.92	0.8663	31.16	0.8694	31.47	0.8576	31.63	0.8610	32.15	0.8699	32.19	0.8704
	30	31.48	0.8844	32.14	0.8914	32.52	0.8967	32.78	0.8837	32.91	0.8861	33.43	0.8930	33.46	0.8932
	40	32.43	0.9011	33.00	0.9055	33.34	0.9101	N/A	N/A	33.77	0.9003	34.27	0.9061	34.29	0.9063

Fig. 13. Image compression artifacts reduction results with JPEG quality  $q = 10$ .Fig. 14. Failure cases for image super-resolution ( $\times 8$ ).

## 7 DISCUSSIONS

Here, we give a brief view of the benefits and limitations of our RDN and challenges in image restoration.

**Benefits of RDN.** RDN is built on the RDB modules, where features from local layers are fully used with the dense connections among each layer. RDB allows direct connections from preceding RDB to each Conv layer of current RDB, resulting in a contiguous memory (CM) mechanism. LFF adaptively preserves the information from the current and previous RDBs. With the usage of LRL, the flow of gradient and information can be further improved and training wider network becomes more stable. Such local feature extraction and global feature fusion lead to a dense feature fusion and deep supervision.

**Limitations of RDN.** In some challenging cases, RDN may fail to reconstruct proper structures. As shown in Figure 14, although other methods fail to recover proper structures, our RDN generates wrong structures. The reason of this failure case may be that our RDN concentrates more on the local features and doesn't extract enough global features. As a result, RDN generates better local structures than others, while the global recovered structures are wrong.

**Challenges in image restoration.** Extreme cases make the image restoration tasks much harder, such as very large

scaling factors for image SR, heavy noise for image DN, low JPEG quality in image CAR. Complex desegregation processes in the real world make it difficult for us to formulate the degradation process. Then it may make the data preparation and network training harder.

## 8 CONCLUSIONS

In this paper, we proposed a very deep residual dense network (RDN) for image restoration, where residual dense block (RDB) serves as the basic build module. RDN takes advantage of local and global feature fusion, obtaining very powerful representational ability. RDN uses less network parameters than residual network while achieves better performance than dense network, leading to a good trade-off between model size and performance. We apply the same RDN to handle three degradation models and real-world data in image SR. We further extend RDN to image denoising and compression artifact reduction. Extensive benchmark evaluations well demonstrate that our RDN achieves superiority over state-of-the-art methods. In the future works, our RDN may further benefit from adversarial training, which may help to alleviate the blurring artifacts. Moreover, more works deserve to be investigated to apply

RDN for other image restoration tasks, such as image demosaicing and deblurring. We also want to connect the low-level and high-level vision tasks with our RDN. When the inputs suffer from quality degradation, the performances in high-level vision tasks would be also decreased obviously. We plan to investigate how image restoration can alleviate such performance decrease.

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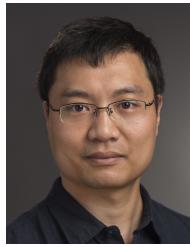
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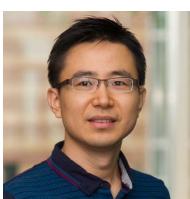
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