Dual-Branch Feature Fusion Network for Single Image Super-Resolution

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Abstract. Recently, the research of single image super-resolution (SISR) based on deep learning has made great progress. However, most of the methods of super-resolution (SR) study use a simple chain structure to obtain higher super-resolution performance. Additionally, most methods do not fully utilize the hierarchical features generated in the middle of the network, thereby cannot achieve relatively high performance. In this paper, we propose a novel dual-branch feature fusion network (DBFFN) to address this two problems in image SR. The backbone of DBFFN is composed of multiple dual-branch feature fusion block (DBFFB) cascaded. The DBFFB has a dual-branch structure which mainly contains two parallel sub-networks, one extracts image fine features via densely connected convolution layers, the other one sub-network extracts image more contextual features by stacking dilated convolution layers. The features extracted from each hierarchical of the DBFFB are cascaded, and then feature fusion is performed. A skip connection is introduced to learn residual between input and output of the DBFFB. Especially, we use the deconvolution layer at the end of the network to enlarge the image. The results of the experiment are exciting, when the scale factor is 3, the performance of our network has 0.56dB, 0.6dB, and 0.79dB improvement on the set5, set14, and urban100 benchmark datasets compared with RDN.

1. Introduction
Limited by the physical characteristics and physical structure of the optical sensor, we cannot get the high-resolution images we want in many cases. Single image super-resolution (SISR) technology can help us to solve this issue, it means that reconstruct a high-resolution (HR) image from the corresponding low-resolution (LR) image. The practical application of SISR is very extensive, such as surveillance, medicine, remote sensing and face recognition.

Recently, deep learning has made breakthroughs in SISR as reviewed in[1]. Dong et al. first introduced the convolutional neural network (CNN) to SISR in SR CNN[2]. Inspired by the success of SRCNN, many deeper and more complex network structures based on convolutional neural networks are proposed for SISR. Kim et al. proposed VDSR[3] which increased the network depth to 20. By deepening the network, the performance is greatly improved compared with SRCNN[2]. Both of two methods input the interpolated version of the LR image into the network, which increases the computational load. To solve this problem, Shi et al. proposed ESPCN[4], the network using sub-pixel convolution operation to enlarge the image from low-resolution space to high-resolution space in the last layer. Similarly, Dong et al. adopted deconvolution layer with small convolutional kernel size named FSRCNN[5] to enlarge the image. Lim et al. proposed EDSR[6] by using ResNet[7] and removing some unnecessary component to speed up the SISR process and improve the performance.
These convolutional neural networks mentioned above for SISR have two common disadvantages: one is that they use chain structure in their network, the other disadvantage is that their models do not make full use of hierarchical features generated in the middle of the network.

To handle the above disadvantages, we design a dual-branch feature fusion network. In summary, our main contributions are two-fold:

- We propose a novel dual-branch feature fusion network (DBFFN) for high-performance image SR with bicubic degradation model. The network is a dual branch network, it makes full use of all the hierarchical features from the whole life cycle of network. And the network achieves high performance under medium parameters.
- We propose dual-branch feature fusion block (DBFFB), multiple DBFFB cascaded forms main body of DBFFN. DBFFB can not only extract the shallow and deep features of the image, but also get the texture information and structure information of the image. Specifically, through a skip connection of the DBFFB to learn residual mapping which can ease the training.

2. Related work

2.1. Densely connected network

Recently, Huang et al. [8] proposed densely convolutional networks. Dense connections and skip connections are introduced in this network, these designs can not only enhance feature propagation, but also encourage feature reuse, which promote the network to have higher performance.

2.2. Dual branch network

Chen et al. [9] proposed a dual path network (DPN). The backbone of the network is composed of two parallel sub-networks, one draws on the design idea of the ResNet [7], and the other draws on the design idea of the DenseNet [8]. It has achieved better performance than traditional single-branch networks.

2.3. Dilated network

Dilated convolution is also known as hole convolution or atrous convolution, which inject holes into the standard convolution. Compared with the original normal convolution operation, the dilated convolution increases the receptive field of the network without increasing parameters.

3. Network structure

3.1. Dual-branch feature fusion network (DBFFN)

As shown in Figure 1, our DBFFN mainly consists four parts: shallow feature extraction by SF module, deep feature extraction by DBFFBS module (multiple DBFFBs cascaded), upscale module, reconstruction module. Let’s denote $I_{LR}$ and $I_{SR}$ as the input and output of DBFFN. we use only one convolutional layer to extract the shallow feature $F_0$ from the $I_{LR}$

\[
F_0 = H_{SF}(I_{LR})
\]  

(1)

where $H_{SF}(\cdot)$ denotes the SF module operation. $F_0$ is pass to DBFFBS module for deep feature extraction. We can further have

\[
\begin{align*}
F_{DF,\alpha} &= H_{DBFFB,\alpha}(H_{DBFFB,\alpha-1}(\cdots H_{DBFFB,1}(F_0))) \\
F_{DF} &= Concat(F_{DF,1}, F_{DF,2}, \ldots, F_{DF,D})
\end{align*}
\]  

(2)
Figure 1. The architecture of our proposed dual-branch feature fusion network (DBFFN)

Figure 2. The architecture of our proposed dual-branch feature fusion block (DBFFB)

$H_{DBFFB,d}$ represents the d-th DBFB in DBFFN. $F_{DF,d}$ represents the features extracted by the network from the d-th DBFFB. D represents the number of DBFFB of our DBFFN. $Concat(\cdot)$ represents feature concatenation operation. Then upscaled via a upscale module

$$F_{UP} = H_{UP}(F_{DF})$$

(3)

where $H_{UP}(\cdot)$ and $F_{UP}$ denote the upscale module and upscaled feature respectively. We choose deconvolution layer[5] to enlarge our network. The upscaled feature is then reconstructed by the reconstruction module

$$I_{SR} = H_{REC}(F_{UP}) = H_{DBFFN}(I_{LR})$$

(4)

where $H_{REC}(\cdot)$ and $H_{DBFFN}(\cdot)$ denote the reconstruction module and the function of our DBFFN respectively.

3.2. Dual-branch feature fusion block (DBFFB)

As depicted in Figure 2, our dual-branch feature fusion block (DBFFB) is constructed by dual branch module, feature concatenate and fusion module and skip connection.
3.2.1. Dual branch module

The dual branch module contains two sub-networks, one is constructed by densely connected convolutional (include convolution layer and activation layer). The number of output channels of this sub-network can be manually set to 64 based on our experience. The main idea of this branch is to extract the hierarchical features from each convolution operation. This process can be described as

\[ X_{i,t} = \omega_i [X_1, X_2, \ldots, X_{i-1}] + b_i , \quad 1 \leq i \leq 5 \]

\[ X_i = \text{LReLU}(X_{i,t}) = \max(X_{i,t}, 0) + 0.01 \times \min(X_{i,t}, 0) , \quad 1 \leq i \leq 5 \]

(5)

\( X_i \) represents the output of the i-th convolutional layer of the densely connected sub-network. Where \([X_1, X_2, \ldots, X_{i-1}]\) represents the concatenation of the feature maps generated in the preceding convolution layers 1,2,...,i-1. \( \omega_i \) and \( b_i \) are the weights and bias parameters of the i-th layer, “∗” represents the convolution operation. We use Leaky ReLU (LReLU) as the activation function.

The other one sub-network is consists of a series of dilated convolutions

\[ Y_{j,t} = \omega_j [Y_{j-1}] + b_j , \quad 1 \leq j \leq 5 \]

\[ Y_j = \text{LReLU}(Y_{j,t}) = \max(Y_{j,t}, 0) + 0.01 \times \min(Y_{j,t}, 0) , \quad 1 \leq j \leq 5 \]

(6)

In order to increase the receptive field as much as possible and alleviate the "gridding" effect, the dilation rate of each layer is set to a specific order (e.g., 1, 2, 3, 2, 1, respectively).

3.2.2. Feature concatenate and fusion module

DBFFFB extracts rich hierarchical features and contextual features from the two sub-networks, we need to efficiently integrate these two features. Based on the idea of DenseNet[8], we cascade these two sub-network’s features in the direction of the channel. We then use a convolution to perform feature fusion operation. The process can be described by the following formula

\[ F_d = \text{Conv}_f (\text{Concat}(X_1, X_2, \ldots, X_5, Y_1, Y_2, \ldots Y_5)) \]

(7)

\( X_i \) and \( Y_j \) represents the output of the i-th convolutional layer (include convolution layer and activation layer) of two sub-network respectively. \( \text{Concat}(\cdot) \) represents feature cascade operation. \( \text{Conv}_f (\cdot) \) represents feature fusion operation. \( F_d \) represents the output after feature fusion operation.

3.2.3. Skip connection

As illustrated at the bottom of Figure 2, a skip connection is introduced in the DBFFB. This process can be expressed as

\[ F_d = F_{d-1} + F_d \]

(8)

4. Experiments

4.1. Settings

The loss function of our DBFFN is L1. Following [6][10], we use DIV2K dataset[11] training images as training set. We use five standard benchmark datasets: Set5[12], Set14[13], B100[14], Urban100[15], and Manga109[16] as testing set. Our low-resolution image is obtained by the bicubic interpolation method. The SR results are evaluated with PSNR and SSIM [17] on Y channel of transformed YCbCr space. We use PyTorch to implement our models with a NVIDIA 2070 SUPER GPU. We set the number of DBFFB as D=11 in the DBFFN. We set 3×3 as the size of all convolutional layers except for that in
the upscale module, whose kernel size is 9×9. The number of output channels of DBFFB is 128. The number of output channels of SF module and DBFFBS module is 128 and 1408 respectively.

4.2. Ablation investigation

In order to prove the effectiveness of the DBFFB of our network, we designed three other comparison networks. Training 310 epochs, the scale factor is 3, and the test data set is set14[13]. We term the original network model as DBFFB_Dense1_Dil1_Res1. In the DBFFB_Dense0_Dil1_Res1, we removed all dense connections in all DBFFBs, changed them to ordinary connections. In the DBFFB_Dense1_Dil0_Res1, we removed all the dilated convolutions in all DBFFBs, and replaced them with ordinary convolutions. In the DBFFB_Dense1_Dil1_Res0, we removed all the skip connection structures in all DBFFBs. The experimental process record is shown in Figure 3.

4.3. Results with bicubic degradation model

Table 1 shows quantitative comparisons for ×2, ×3 and ×4 SR. When compared with other state-of-the-art methods, our DBFFN performs the best on all the datasets with ×3 scaling factor. Figure 4 show the qualitative comparison with some state-of-the-art methods. We found that the image details recovered by our network are more realistic and closer to real high-resolution images compared with other methods.

| Method          | Scale | Set5       | Set14       | BSD100      | Urban100     | Manga109     |
|-----------------|-------|------------|------------|-------------|--------------|--------------|
|                 |       | PSNR/SSIM  | PSNR/SSIM  | PSNR/SSIM   | PSNR/SSIM   | PSNR/SSIM   |
| Bicubic         | X2    | 33.86/0.9299 | 30.24/0.8688 | 29.56/0.8431 | 26.88/0.8403 | 30.80/0.9359 |
| SRCNN[2]        |      | 36.66/0.9542 | 32.45/0.9067 | 31.36/0.8879 | 29.50/0.8946 | 35.60/0.9663 |
| FSRCNN[5]       |      | 37.06/0.9558 | 32.63/0.9088 | 31.53/0.8920 | 29.88/0.9020 | 36.67/0.9710 |
| VDSR[3]         |      | 37.53/0.9587 | 33.03/0.9124 | 31.90/0.8960 | 30.76/0.9140 | 37.22/0.9750 |
| DBFFB(ours)     |      | 37.74/0.9591 | 33.23/0.9136 | 32.05/0.8973 | 31.23/0.9188 | 37.88/0.9740 |
| EDR-p baseline(6) |      | 37.99/0.9604 | 33.57/0.9175 | 32.16/0.9054 | 31.90/0.9272 | 38.54/0.9769 |
| RDN[10]         |      | 38.24/0.9614 | 34.01/0.9212 | 32.34/0.9017 | 32.89/0.9363 | 39.18/0.9780 |
| DBFFB(ours)     | X3    | 38.16/0.9611 | 33.89/0.9198 | 34.16/0.9269 | 32.43/0.9311 | 39.37/0.9802 |
| Bicubic         |      | 30.39/0.8682 | 27.50/0.7742 | 27.21/0.7385 | 24.46/0.7490 | 26.95/0.8556 |
| SRCNN[2]        |      | 32.75/0.9009 | 29.30/0.8215 | 28.41/0.7863 | 26.24/0.7899 | 30.48/0.9117 |
| FSRCNN[5]       |      | 33.18/0.9149 | 29.37/0.8240 | 28.53/0.7910 | 26.63/0.8080 | 31.10/0.9210 |
| VDSR[3]         |      | 33.68/0.8213 | 29.71/0.8114 | 28.82/0.7916 | 27.14/0.8279 | 32.01/0.9348 |
| DBFFB(ours)     |      | 34.03/0.9244 | 29.96/0.8349 | 28.95/0.8094 | 27.53/0.8318 | 32.11/0.9319 |
| EDR-p baseline(6) |      | 34.37/0.9270 | 30.28/0.8417 | 29.09/0.8052 | 28.15/0.8527 | 33.45/0.9439 |
| RDN[10]         |      | 34.71/0.9296 | 30.57/0.8468 | 29.26/0.8093 | 28.80/0.8653 | 34.13/0.9481 |
| DBFFB(ours)     | X4    | 35.27/0.9418 | 31.17/0.8606 | 29.73/0.8212 | 29.59/0.8787 | 34.17/0.9501 |
| Bicubic         |      | 28.42/0.8104 | 26.00/0.7027 | 25.96/0.6675 | 23.14/0.6577 | 24.89/0.7866 |
| SRCNN[2]        |      | 30.48/0.8628 | 27.50/0.7513 | 26.90/0.7191 | 24.52/0.7221 | 27.58/0.8555 |
5. Conclusion
We propose dual-branch feature fusion network (DBFFN) for highly accurate image SR. The DBFFN is composed of multiple cascaded dual-branch feature fusion blocks (DBFFBs) for extracting hierarchical features. Specifically, the DBFFB structure allows network to reach very depth and width by dual-branch module, feature concatenate and fusion module and skip connection. Meanwhile, there are dense connections and a skip connection in the DBFFB structure, so it prevents gradient vanishing effectively. Especially, the dual-branch network structure of DBFFB makes network have a larger receptive field. Furthermore, in order to improve performance of the network and ease the training, we use as similar as FSRCNN method to upscale image. Our network DBFFN achieving comparable even better results in terms of accuracy and visual quality compared with state-of-the-art methods.

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