Residual Fractal Network for Single Image Super Resolution by Widening and Deepening

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Outline

- Introduction
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- Network
- Experiments

Introduction

Deep Network:

Extract and fuse multi-scale feature, such as RDN and MSRN

Zero-Shot Network:

Utilize the high similarity of texture feature in the images, such as ZSSR

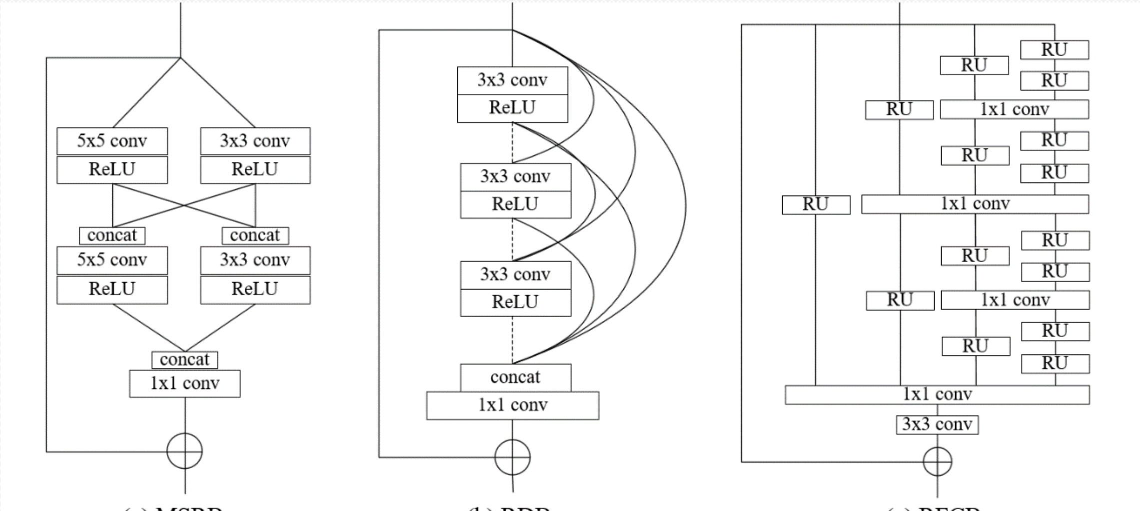
Related Work

MSRN and RDN obtained local multi-scale feature extracted by connected convolution module and fused all the feature through the gate unit. RCAN and SAN introduced attention mechanism to SISR to enhance the feature representation ability of network.

ZSSR first implemented an unsupervised method based on the patch recurrence and similarity between the multi-scale patches.

Network

To focus the network on the repetitive texture features in the images, we design residual fractal convolution block (RFCB) as shown below.



(a) MSRB (b) RDB (c) RFCB

MSRB and RDB are the convolution modules of MSRN and RDN respectively.

Network

Structure characteristics of RFCB

Multi-branch:

The number of convolutional layers of adjacent branches is doubled, which can effectively extract the multi-scale features of the image, and finally obtain the texture features that appear repeatedly at different scales.

Stage fusion:

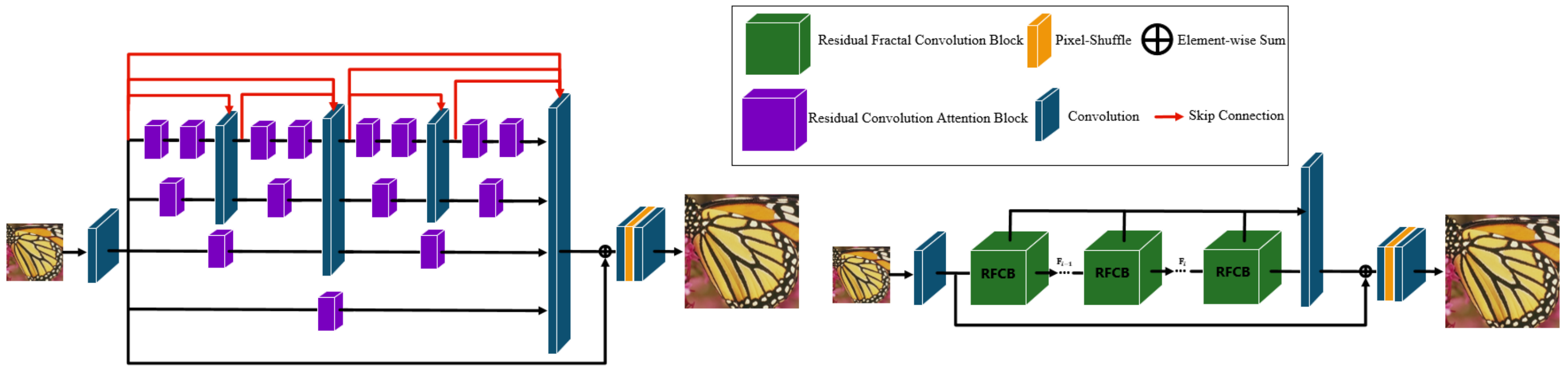
The stage output of adjacent branches is merged to enhance the proportion of repetitive features in the feature map.

Recursive properties:

RFCB can be easily extended to deeper and wider network structures using the recursive structure.

Network

We expanded the width of RFCB to obtain WRFN, and designed a network structure of module stacking to compare the effectiveness of the two in extracting multi-scale features. WRFN uses phase fusion and more branches to extract multi-scale features, while DRFN implements hierarchical feature fusion.



(a) WRFN

(b) DRFN

Experiments

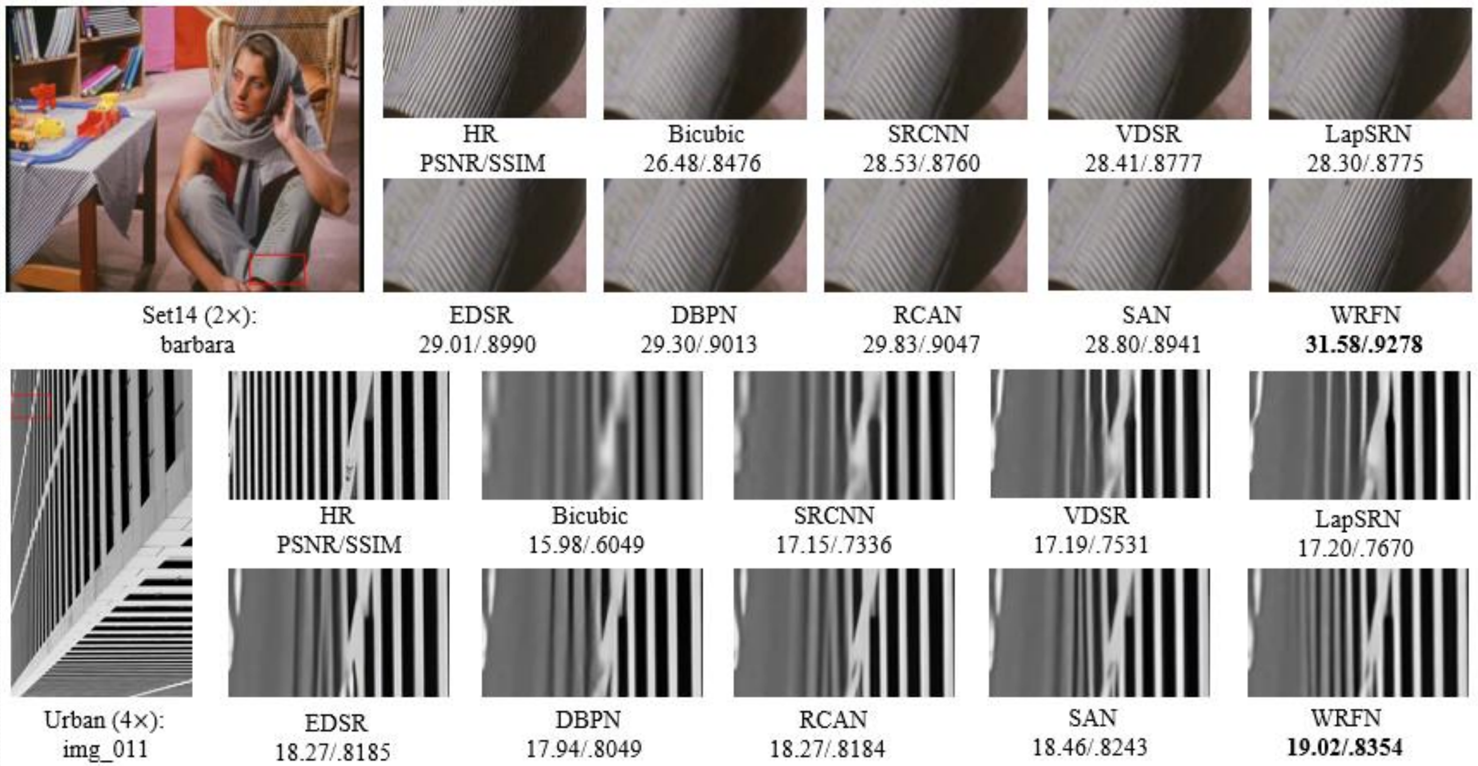
We compared the performance of RFCB with MSRB and RDB under the same parameter level. It can be seen that RFCB outperforms others.

TABLE I

EFFECTS OF DIFFERENT BLOCKS. WE OBSERVE THE BEST PSNR (DB) ON SEVERAL DATASETS ($2\times$) IN 5×10^4 ITERATIONS

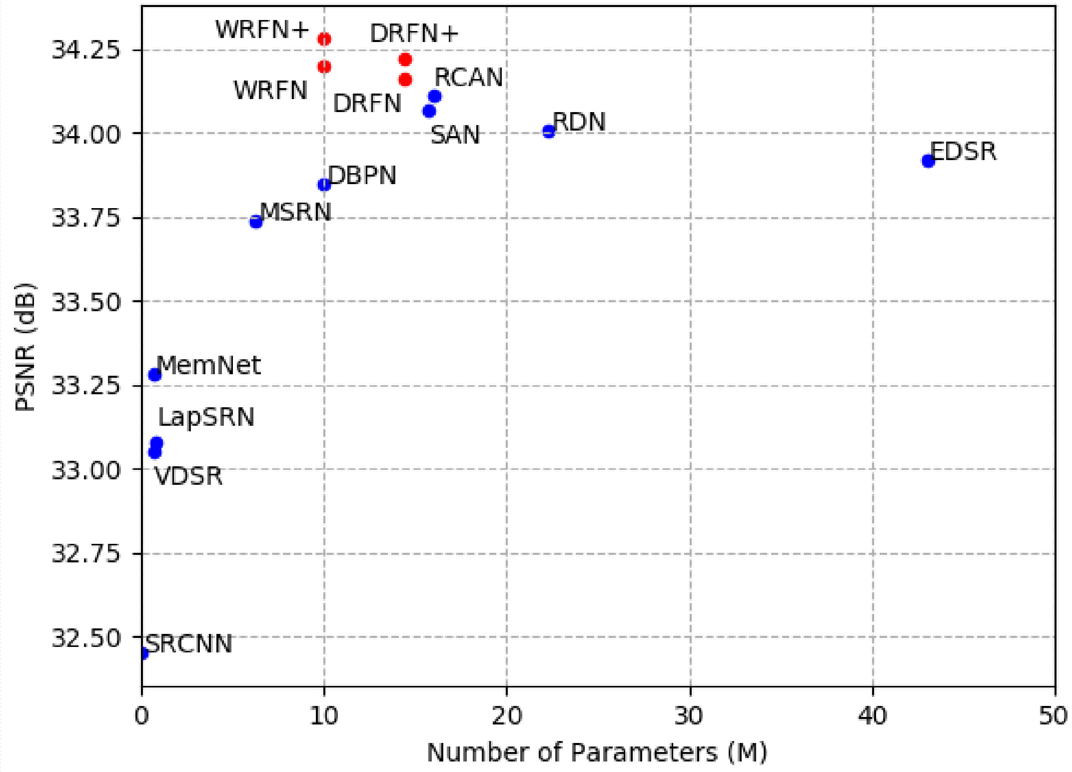
Stucture	Parameters	PSNR on several datasets ($2\times$)			
		DIV2K validation	Set5	Set14	B100
MSRB	712704	34.70	37.19	32.82	31.59
RDB(gr=5)	573440	34.90	37.35	32.93	31.71
RFCB(d=4)	573440	**35.00**	**37.45**	**33.03**	**31.77**

Experiments



Visual comparisons of WRFN and previous methods.

Experiments



Comparison of model size and performance. Results are evaluated on Set5 (2x)

Conclusion

Residual fractal convolution block is more efficient than other convolution modules. In addition, width and depth are both important factors to improve performance.

Acknowledgment

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