中國海洋大學
OCEAN UNIVERSITY OF CHINA

RSAN: Residual Subtraction and Attention Network for Single Image Super-Resolution

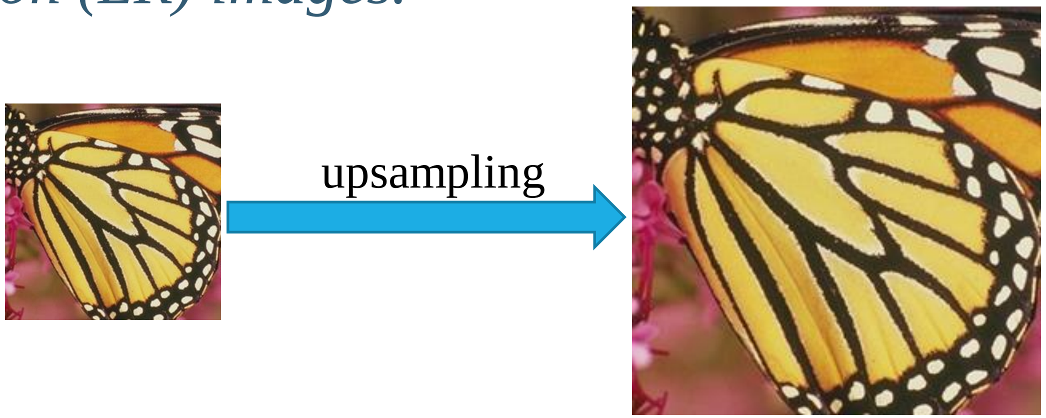
Shuo Wei, Xin Sun, Haoran Zhao, Junyu Dong
Ocean University of China

Outline

- Introduction
- Related work
- Proposed Method
- Experiments
- Conclusion

Introduction

– *Image super-resolution is a popular research direction in the computer vision area that generates high-resolution (HR) images from the low-resolution (LR) images.*



Learning-based methods performances are still limited by two problems:

- ➢ most of the SISR methods neglect the importance among the feature map channels.
- ➢ they can not eliminate the redundant noises, making the output image be blurred.

Related work

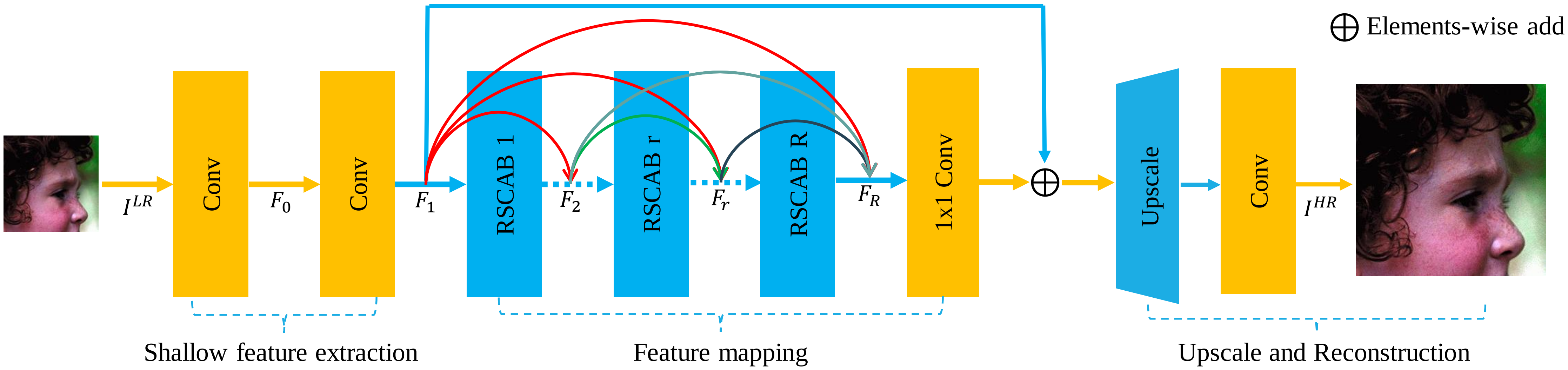
- Deep CNN for SR:

Single image super-resolution(SISR) tend to build end-to-end CNNs models, and learn the mapping function from LR to HR images. Such as SRCNN, VDSR, MemNet, EDSR, and etc.

- Attention in Deep Neural Networks

It has become a trend to apply attention mechanism to solve various computer tasks. There is a lot of work applying attention to convolutional neural networks. Such as SE, RCAN, SAN, and etc.

Proposed Method

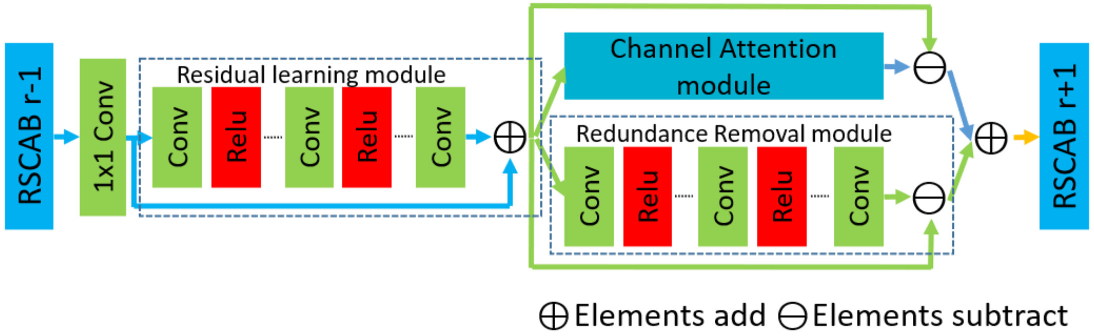


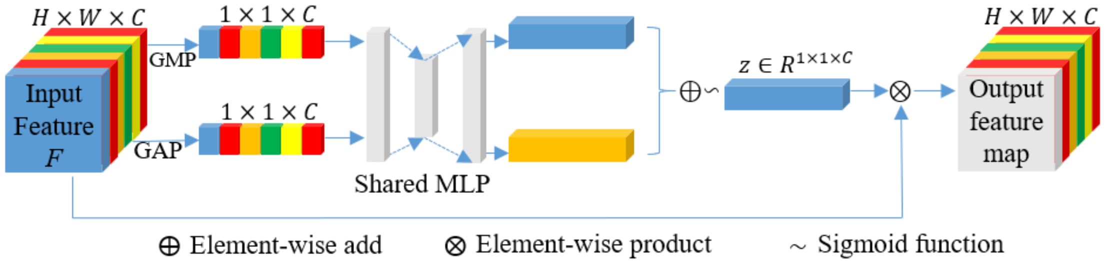
Residual Subtraction and Attention Network (RSAN) can be divided into four parts: shallow feature extraction, feature mapping, upscale and image reconstruction

Proposed Method

- Residual Subtraction and Channel Attention Block

  RSCAB has three module: residual learning module, channel attention module and redundance removal module.





- Redundance Removal Module

  The proposed redundance removal module is similar to residual learning module. The difference is that we use elements-wise subtraction to remove noise information.

- Channel Attention Module

  As shown in channel attention module, we first use global avg-pooling and max-pooling operations to generate avg-pooling and max-pooling features respectively. Then, we use multi-layer perceptron (MLP) to share weight. At last, we merge the output feature vectors via element-wise summation and product with input feature.

Experiments

- Datasets
  - *Set5*  ……
  - *Set14*  ……
  - *B100*  ……
  - *Urban100*  ……

Experiments

- Experimental results

TABLE I: Average PSNR/SSIM for scale factor x2 on datasets Set5, Set14, B100 and Urban100.

Datasets		Set5		Set14		B100		Urban100	
Method	scale	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	X2	33.66	0.9299	30.24	0.8688	29.56	0.8431	26.88	0.8403
SRCNN	X2	36.66	0.9542	32.45	0.9067	31.36	0.8879	29.50	0.8946
FSRCNN	X2	37.05	0.9560	32.66	0.9090	31.53	0.8920	29.88	0.9020
VDSR	X2	37.53	0.9590	33.05	0.9130	31.90	0.8960	30.77	0.9140
LapSRN	X2	37.52	0.9591	33.08	0.9130	31.08	0.8950	30.41	0.9101
DRRN	X2	37.74	0.9591	33.23	0.9136	32.05	0.8973	31.23	0.9188
RSAN(ours)	X2	38.20	0.9612	33.86	0.9201	32.28	0.9007	32.68	0.9333
RSAN*(ours)	X2	**38.25**	**0.9614**	**34.00**	**0.9214**	**32.32**	**0.9013**	**32.84**	**0.9363**

TABLE II: Average PSNR/SSIM for scale factor x3 on datasets Set5, Set14, B100 and Urban100.

Datasets		Set5		Set14		B100		Urban100	
Method	scale	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	X3	30.39	0.8682	27.55	0.7742	27.21	0.7385	24.46	0.7349
SRCNN	X3	32.75	0.9090	29.30	0.8215	28.41	0.7863	26.24	0.7989
FSRCNN	X3	33.18	0.9140	29.37	0.8240	28.53	0.7910	26.43	0.8080
VDSR	X3	33.67	0.9210	29.78	0.8320	28.83	0.7990	27.14	0.8290
DRRN	X3	34.03	0.9244	29.96	0.8349	28.95	0.8004	27.53	0.8378
LapSRN	X3	33.82	0.9227	29.79	0.8320	28.82	0.7973	27.07	0.8272
RSAN(ours)	X3	34.68	0.9292	30.38	0.8449	29.21	0.8086	28.60	0.8613
RSAN*(ours)	X3	**34.77**	**0.9300**	**30.50**	**0.8467**	**29.28**	**0.8099**	**28.85**	**0.8650**

TABLE III: Average PSNR/SSIM for scale factor x4 on datasets Set5, Set14, B100 and Urban100.

Datasets		Set5		Set14		B100		Urban100	
Method	scale	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	X4	28.42	0.8104	26.00	0.7027	25.96	0.6675	23.14	0.6577
SRCNN	X4	30.48	0.8628	27.50	0.7513	26.90	0.7101	24.52	0.7221
FSRCNN	X4	30.72	0.8660	27.61	0.7550	26.98	0.7150	24.62	0.7280
VDSR	X4	31.35	0.8830	28.01	0.7680	27.29	0.7251	25.18	0.7540
DRRN	X4	31.68	0.8888	28.21	0.7721	27.38	0.7284	25.44	0.7638
LapSRN	X4	31.54	0.8855	28.19	0.7720	27.32	0.7280	25.21	0.7553
RSAN(ours)	X4	32.44	0.8981	28.66	0.7867	27.70	0.7410	26.49	0.7993
RSAN*(ours)	X4	**32.56**	**0.8995**	**28.76**	**0.7888**	**27.77**	**0.7425**	**26.72**	**0.8039**

Conclusion

- We propose a residual subtraction and attention network for highly accurate SISR. Extensive experiments on benchmarks demonstrate its superiority over previous methods in terms of both quantitive and visual quality.
- We propose redundance removal module to subtract the noises in feature maps in order to enhance feature extraction capability.
- We introduce attention mechanism to identify the importance of different channels. It can amplify high-frequency information and avoid effectless channels.

Thank you for your attention!