

FAST AND LIGHTWEIGHT IMAGE SUPER-RESOLUTION BASED ON DENSE RESIDUALS TWO-CHANNEL NETWORK Yonglian Shi, Sumei Li, Member, IEEE, Wen Li, Anqi Liu School of Electrical and Information Engineering, Tianjin University, Tianjin, China

Introduction

we propose a fast and lightweight two-channel end-to-end network with fewer parameters and low computational complexity in this paper. The main contributions are as follows:

- a) Speed: Our model not only has good reconstruction accuracy, but also provides fast processing speed.
- b) Computational complexity: The proposed FLSR and FLSR-G model have lower computational complexity and higher **c**) reconstruction accuracy compared.
- **Combination of dense and residual:** FLSR with dense and residual **c**) connection is chosen to weaken the gradient vanishing or exploding phenomenon, which shows excellent performance in SR task.

Our Algorithm

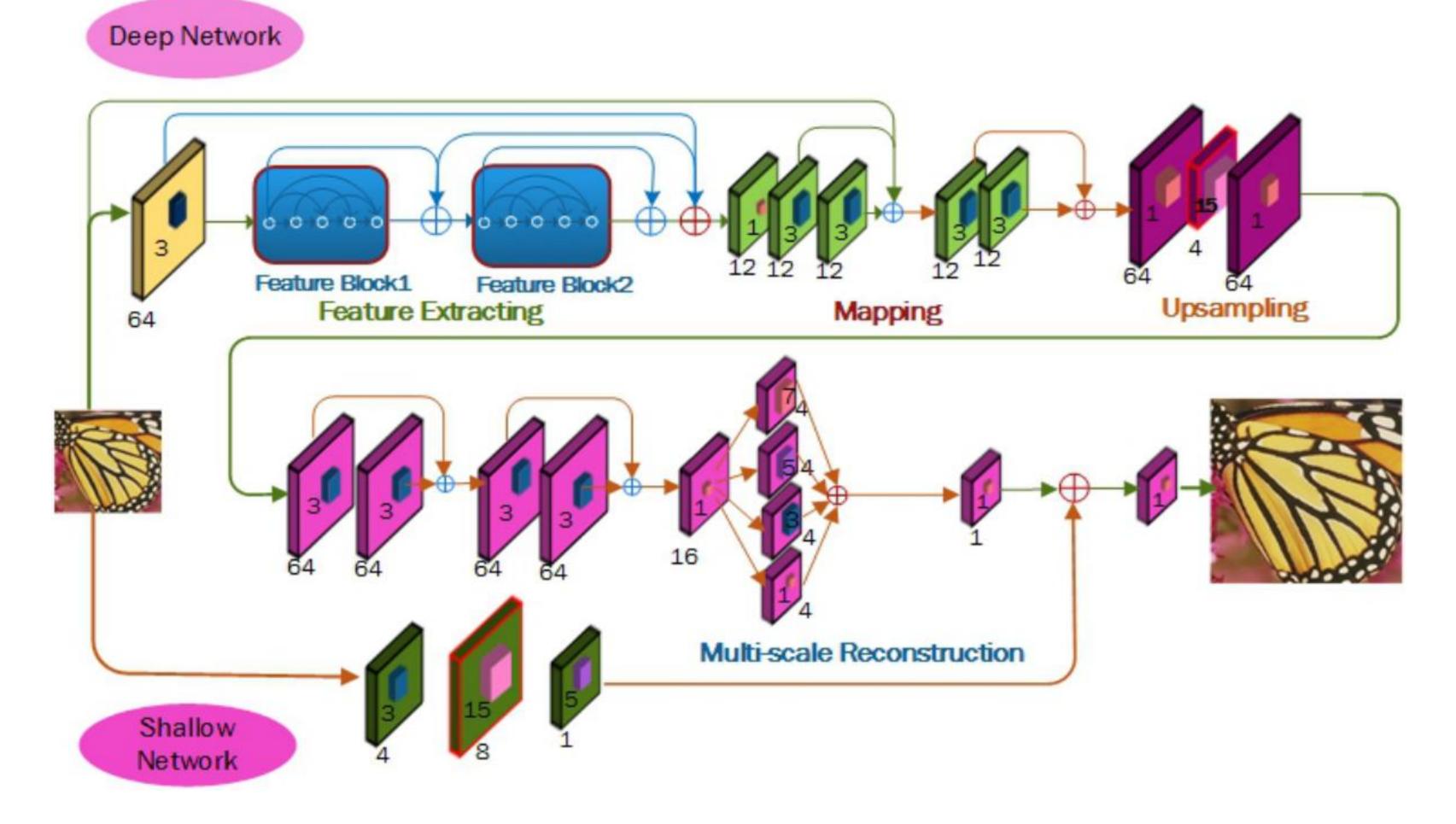


Fig.1 Architecture of the proposed network. The operations in network are element-wise addition for residual learning, and \bigoplus is densely skip connection. The small white circle is convolution operation.

- **a**) texture information.
- **b**) up the convergence of network.
- performance loss.



Fig.2 Speed and accuracy trade-off. The average PSNR and the average inference time for upscaling 2 on Urban100.

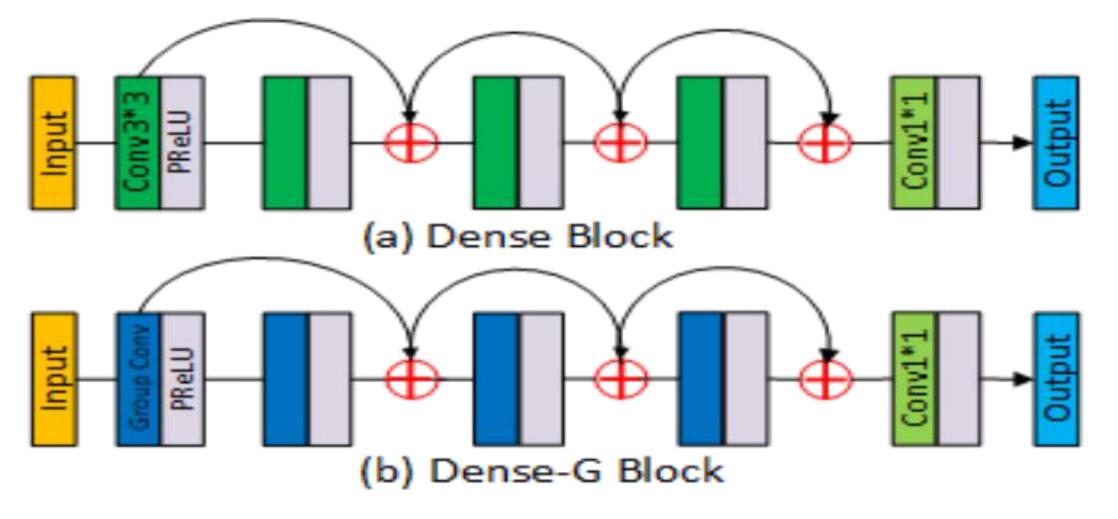


Fig.3 The structure of feature block. The half green rectangle represents convolutional layer, the half blue rectangle represents group convolution.

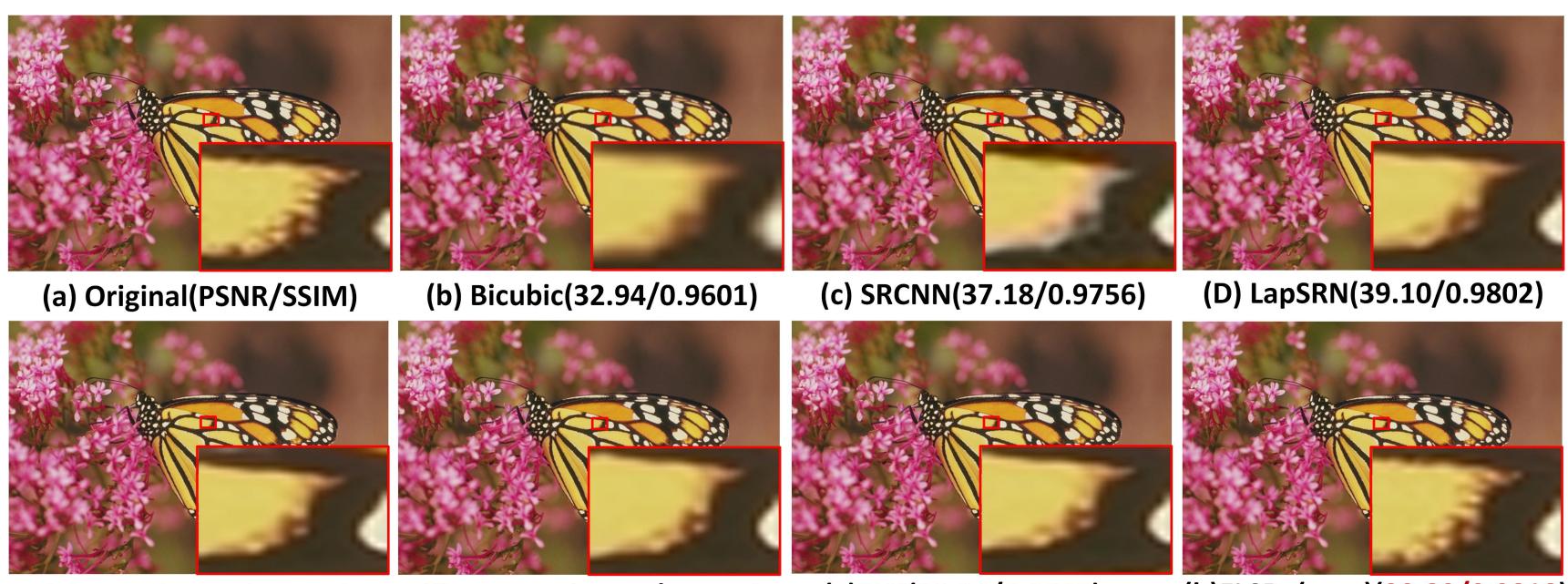
The shallow channel : mainly restores the general outline of the image, while the deep channel mainly learns the high-frequency

The deep channel : combines the dense block and residual connection. The dense block increases data flow of network, while the residual connection reduces the number of parameters and speeds

Enhanced network : uses group convolution, which significantly reduces the parameters and computational complexity with slight

					Set5	Set14	BSD100	Urban100			Set5	Set14	BSD100	Urban100			Set5	Set14	BSD100	Urban100
Model	Layer	Params	Scale	MultAdds	PSNR	PSNR	PSNR	R PSNR So	Scale N	MultAdds	PSNR	PSNR	PSNR	PSNR	Scale I	MultAdds	PSNR	PSNR	PSNR	PSNR
					(SSIM)	(SSIM)	(SSIM)	(SSIM)			(SSIM)	(SSIM)	(SSIM)	(SSIM)			(SSIM)	(SSIM)	(SSIM)	(SSIM)
SRCNN[1]	3	57k		52.7G	36.66	32.42	31.36	29.50		52.7G	32.75	29.28	28.41	26.24		52.7G	30.48	27.49	26.90	24.52
ononutil	Ŭ	OTK			(0.9542)	(0.9063)	(0.8879)	(0.8946)			(0.9090)	(0.8209)	(0.7863)	(0.7989)			(0.8628)	(0.7503)	(0.7101)	(0.7221)
VDSR[4]	20	665k		612.6G	37.53	33.03	31.90	30.76		612.6G	33.66	29.77	28.82	27.14		612.6G	31.35	28.01	27.29	25.18
					(0.9587)	(0.9124)	(0.8960)	(0.9140)			(0.9213)	(0.8314)	(0.7976)	(0.8279)			(0.8838)	(0.7674)	(0.7251)	
DRCN[3]	20	1774k		9788.7G	37.63	33.04	31.85	30.75	ç	9788.7G	33.82	29.76	28.80	27.15		9788.7G	31.53	28.02	27.23	25.14
					(0.9588)	(0.9118)	(0.8942)	(0.9133)			(0.9226)	(0.8311)	(0.7963)	(0.8276)			(0.8854)	(0.7670)	(0.7233)	
LapSRN[22]	27	813k		29.9G 6796.9G	37.52	33.08	31.80	30.41								149.4G	31.54	28.19	27.32	25.21
					(0.9590)	(0.9130)	(0.8950)	(0.9100)						07.50			(0.8850)	(0.7720)	1 .	1
DRRN[7]	52	297k			37.74	33.23	32.05	31.23		6796.9G	34.03	29.96	28.95	27.53		6796.9G	31.68	28.21	27.38	25.44
					(0.9591)	(0.9136)	(0.8930)	(0.9188)	-		(0.9244)	(0.8349)	(0.8004)	(0.8378)					-	
MemNet[21]	80	677K		623.9G	37.78	33.28	32.08	31.31		623.9G	34.09	30.00	28.96	27.56		623.9G	31.74	28.26	27.41	25.54
SRDenseNet			1.1.1.1 1.		(0.9597)	(0.9142)	(0.8980)	(0.9195)	Зх		(0.9248)	(0.8350)	(0.8001)	(0.8376)	4x		(0.8893) 32.02	(0.7723) 28.50	(0.7290) 27.53	(0.7666) 26.05
[24]			2x													389.9G	(0.8934)	(0.7782)	(0.7337)	(0.7819)
MS-LapSRN			1		37.62	33.13	31.93	30.82			33.88	29.89	28.87	27.23			31.62	28.16	27.36	25.32
-D5R2[23]	24	222k			(0.9600)	(0.9130)	(0.8970)	(0.9150)			(0.9230)	(0.8340)	(0.8000)	(0.8310)			(0.8870)	(0.7720)	(0.7290)	(0.7600)
	- 21	715.94		138.3G	37.83	33.30	32.08	31.27		30.8G	34.11	29.99	28.95	27.42		34.6 G	31.82	28.25	27.41	25.41
IDN[8]	31	715.3K			(0.9600)	(0.9148)	(0.8985)	(0.9196)		30.66	(0.9253)	(0.8354)	(0.8013)	(0.8359)			(0.8903)	(0.7730)	(0.7297)	(0.7632)
SDSR[6]	19	300.87k		175.5G	37.07	32.64	31.52		156	156.64G	33.42	29.47	28.65			149.68G	31.01	27.73	27.10	
SDSK[0]	19	300.07 K		175.56	(0.9564)	(0.9093)	(0.8911)			130.040	(0.9181)	(0.8288)	(0.7933)				(0.8744)	(0.7614)	(0.7186)	
FLSR	33	717.28K		271.35G	37.79	33.16	32.06	31.23		196.02G	34.02	29.76	28.89	27.31 (0.8314)		173.66G	31.41	27.98	27.30	25.33
(Ours)		THEOR		211.000	(0.9595)	(0.9143)	(0.8979)				(0.9229)	(0.8342)	(0.7991)				(0.8829)	(0.7688)	(0.7243)	(0.7574
FLSR-G+	33	330.21K		182.17G	37.73	33.17	31.99	31.07		157.01G	34.06	29.92	28.95	27.47		151.37G	31.62	28.24	27.39	25.26
(Ours)			na 1				(0.8971)	(0.9138)			(0.9247)		(0.8007)	(0.8352)	_		(0.8875)	-		
FLSR+	33	717.28K		271.35G	37.87	33.29	32.11	31.35		196.02G	34.14	29.94	28.97	27.47		173.66G	31.57	28.20	27.37	25.33
(Ours)					(0.9599)	(0.9152)	(0.8985)	(0.9196)			(0.9249)	(0.8353)	(0.8012)	(0.8359)			(0.8848)	(0.7713)	(0.7267)	(0.7574

Table 1. Average PSNR/SSIM for upscaling factors 2x, 3x and 4x on benchmark datasets.





(e)DRRN(39.73/0.9808)

Fig.4 The "monarch" image from the Set14 dataset with an upscaling factor 2. Red color indicates the best performance.

[8] Z. Hui, X. Wang, and X. Gao, "Fast and Accurate Single Image Super-Resolution via Information Distillation Network," IEEE Conference on Computer Vision and Pattern Recognition, pp. 723-731, 2018.

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Experiments

(g)IDN(39.84/0.9818)

(h)FLSR+(ours)(39.89/0.9818

References