Accelerating the Super-Resolution Convolutional Neural Network

[illegible], [illegible] (✉), [illegible]

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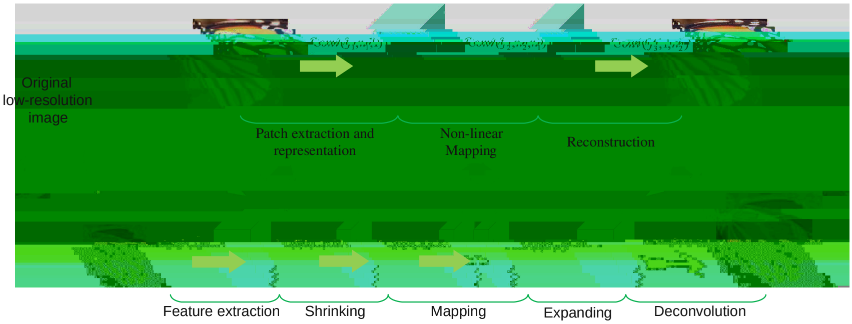
Abstract. As a successful deep model applied in image super-resolution

two inherent limitations

n,


Original
low-resolution
image
Patch extraction and
representation
Non-linear
Mapping
Reconstruction
Feature extraction
Shrinking
Mapping
Expanding
Deconvolution

Fea e E ac : ff

Y_s. B

(1-)

f, n, c

9.

Y. A Y Y_s, 5×5

Y_s 9×9 Y.

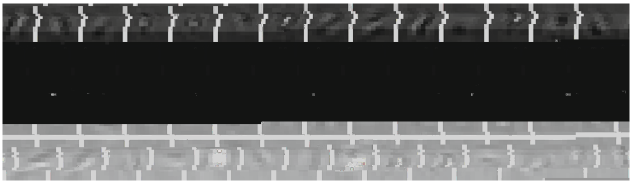
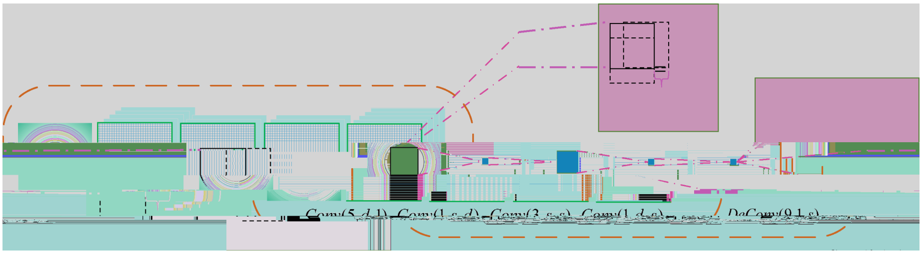


Fig. 3. The learned deconvolution layer (56 channels) for the upscaling factor 3.

a_i … [11] … ff …

O e a S c e: … $Con\ (5, d, 1) - PReLU - Con\ (1, \ , d) - PReLU - m \times Con\ (3, \ , \ ) - PReLU - Con\ (1, d, \ ) - PReLU - DeCon\ (9, 1, d)$. … , … $(i.e.,$ … d, … $m)$ …

] .] $n = 3.$.] . ,]


Conv(5, d, 1)
Conv(1, s, d)
Conv(3, s, s)
Conv(1, d, s)
DeConv(9, 1, s)

, 91- -100 91- [8]. (1) 0.9, 0.8, 0.7 0.6. (2) 90, 180 270. $5 \times 4 - 1 = 19$.

T e a d Va da Da a e. 5 [15], 14 [9] B 200 [25]. A 20 B 500.

T a g Sa e. n $f_{sub} \times f_{sub}$ k. ((nfn

Table 2. The comparison of PSNR (Set5) and parameters of di erent settings.

Settings	$m = 2$	$m = 3$	$m = 4$
$d = 48, s = 12$	32.87 (8832)	32.88 (10128)	33.08 (11424)
$d = 56, s = 12$	33.00 (9872)	32.97 (11168)	33.16 (12464)
$d = 48, s = 16$	32.95 (11232)	33.10 (13536)	33.18 (15840)
$d = 56, s = 16$	33.01 (12336)	33.12 (14640)	33.17 (16944)

$d = 48, 56$, $= 12, 16$ $m = 2, 3, 4$, $2 \times 2 \times 3 = 12$ ff 5 2. , *i.e.*, d, m. $m = 4$ $m = 2$ $m = 3$. 5( ). , m d , (*e.g.*, d), 5( ), , ff (56,12,4), (48,12,2) 32.87 B, (32.75 B) 2[. (48,12,2) 8,832 , $57184/8832 \times 9 = 58.3$

4.3 T a d Rea -T e SR h FSRCNN

(24). A ,

760×760 1.32 3,

8032 1 2,

$8032 \times 1.32/$

(56,12,4)),
(32,5,1)).
++ 7 4.0
3.
40
3),
(>24)
×2 ×3.

Table 4. The results of PSNR (dB) on three test datasets. We present the best results reported in the corresponding paper. The proposed FSCNN and FSRCNN-s are trained on both 91-image and General-100 dataset. More comparisons with other methods on PSNR, SSIM and IFC [29] can be found in the supplementary file.

Test dataset	Upscaling factor	Bicubic	KK [28]	A+ [5]	SRF [7]	SRCNN [1]	SRCNN-Ex [2]	SCN [8]	FSRCNN-s	FSRCNN
		PSNR	PSNR	PSNR	PSNR	PSNR	PSNR	PSNR	PSNR	PSNR
Set5	2	33.66	36.20	36.55	36.89	36.34	36.66	36.93	36.58	**3[illegible].00**
Set14	2	30.23	32.11	32.28	32.52	32.18	32.45	32.56	32.28	**32.63**
BSD200	2	29.70	31.30	31.44	31.66	31.38	31.63	31.63	31.48	**31.[illegible]0**
Set5	3	30.39	32.28	32.59	32.72	32.39	32.75	33.10	32.61	**33.16**
Set14	3	27.54	28.94	29.13	29.23	29.00	29.30	29.41	29.13	**2[illegible].43**
BSD200	3	27.26	28.19	28.36	28.45	28.28	28.48	28.54	28.32	**2[illegible].60**
Set5	4	28.42	30.03	30.28	30.35	30.09	30.49	**30.[illegible]6**	30.11	30.71
Set14	4	26.00	27.14	27.32	27.41	27.20	27.50	**2[illegible].64**	27.19	27.59
BSD200	4	25.97	26.68	26.83	26.89	26.73	26.92	**2[illegible].02**	26.75	26.98

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