Image Super-Resolution Using Deep Convolutional Networks

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Outline

1. Introduction
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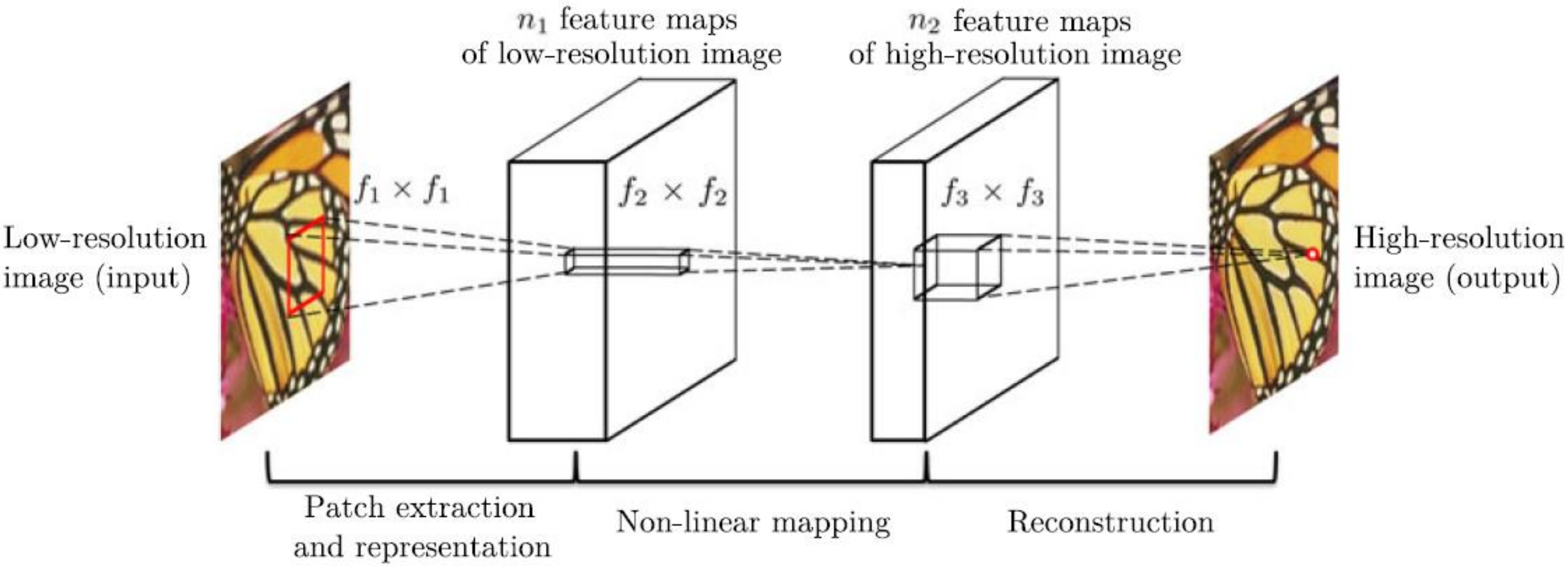
1. Introduction

- We present a fully convolutional neural network for image super-resolution.

- We establish a relationship between our deep-learning-based SR method and the traditional sparse-coding-based SR methods.

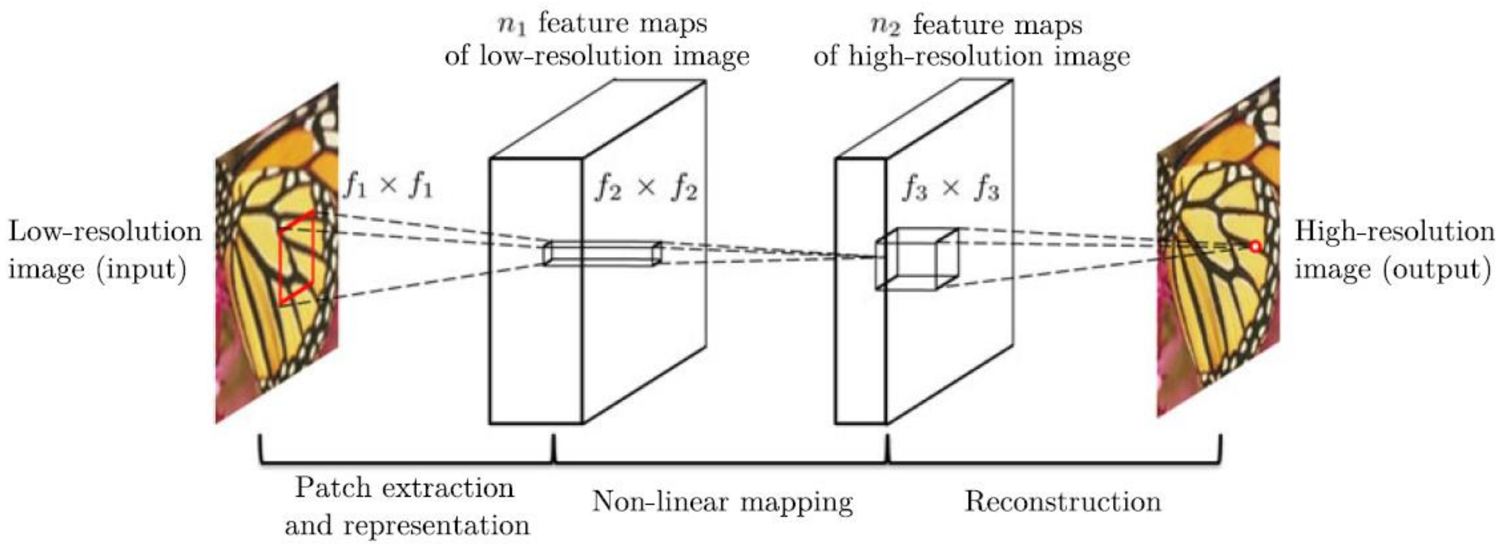
- We demonstrate that deep learning is useful in the classical computer vision problem of super-resolution, and can achieve good quality and speed.

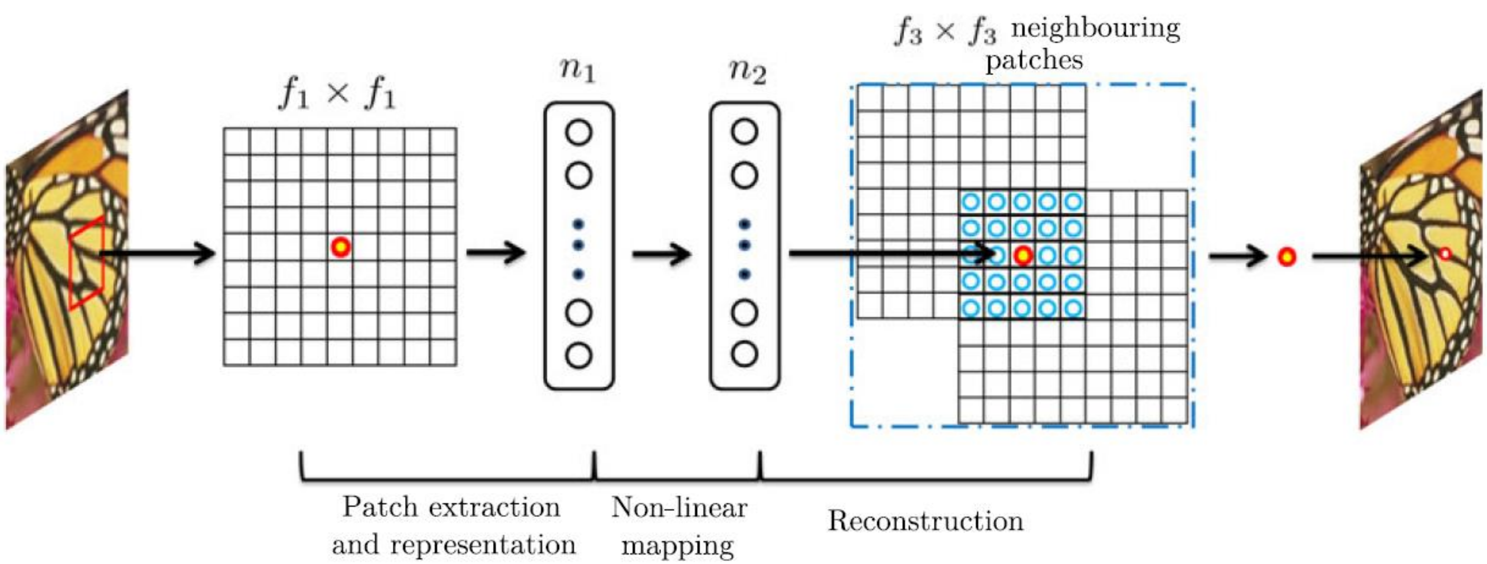
2. Method



- First convolutional layer: $F_1(Y) = \max(0, W_1 * Y + B_1)$
- Second convolutional layer: $F_2(Y) = \max(0, W_2 * F_1(Y) + B_2)$
- Third convolutional layer: $F\ (Y) = \max(0, W_3 * F_2(Y) + B_3)$

- An illustration of sparse-coding-based methods in the view of a convolutional neural network.





3. Experiment

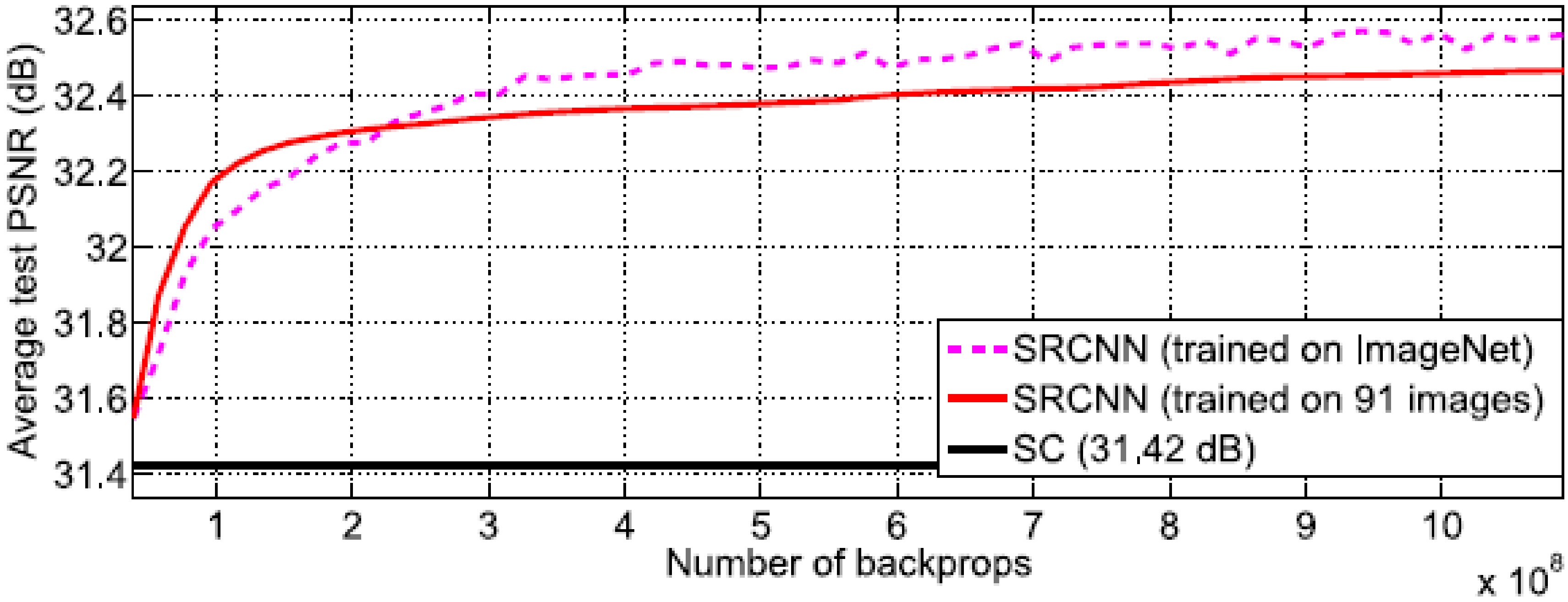
- Investigate the impact of using different datasets on the model performance

- Examine the filters learned by our approach.

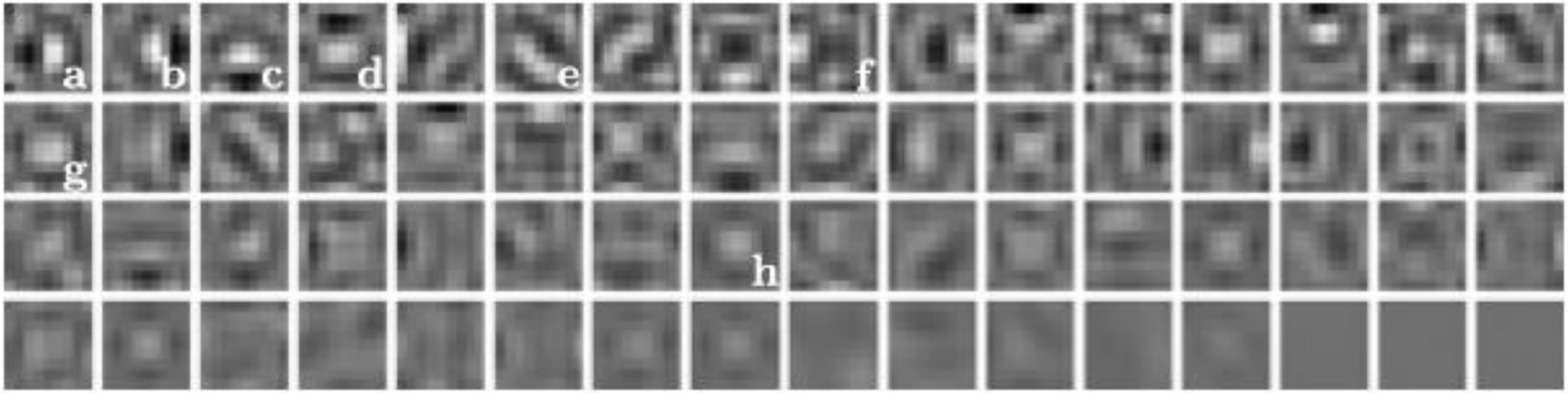
- Explore different architecture designs of the network, like depth, number of filters, and filter sizes.

- Compare our method with recent state-of-the-arts

- Training with the much larger ImageNet dataset improves the performance over the use of 91 images.



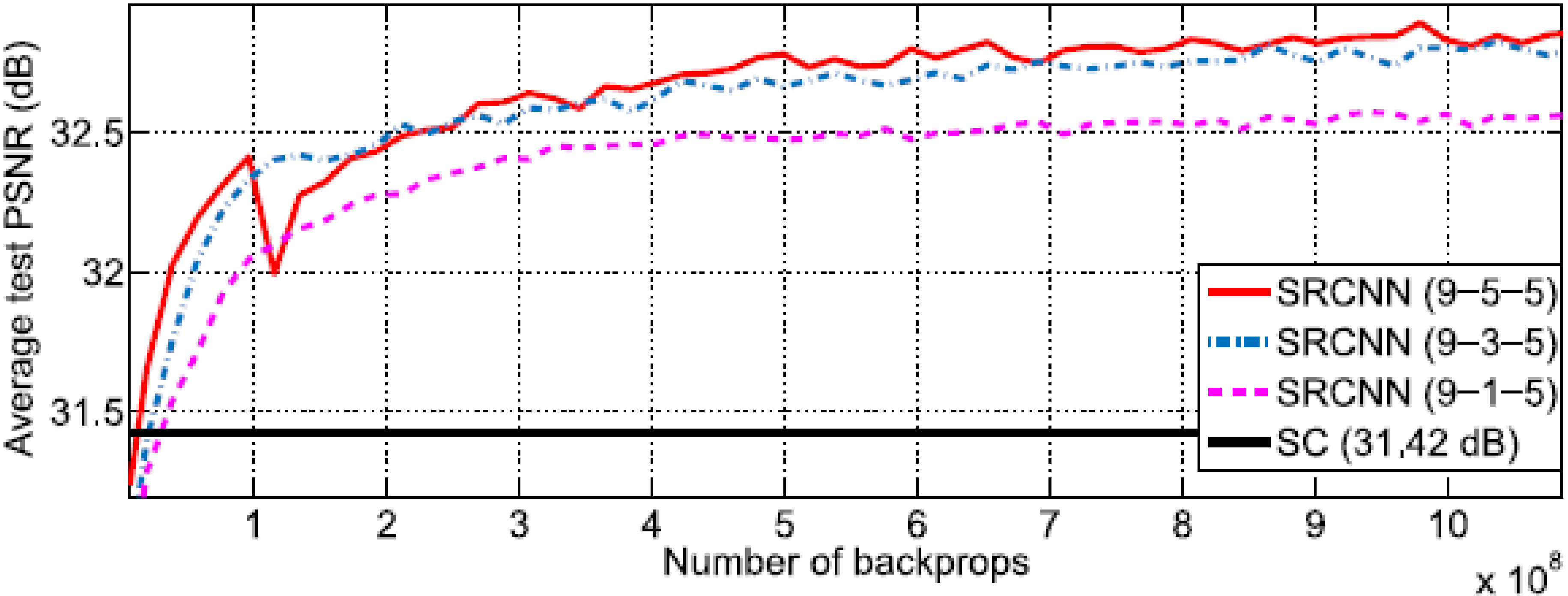
- The filters g and h are like Laplacian/Gaussian filters.
- The filters a - e are like edge detectors at different directions.
- The filter f is like a texture extractor.



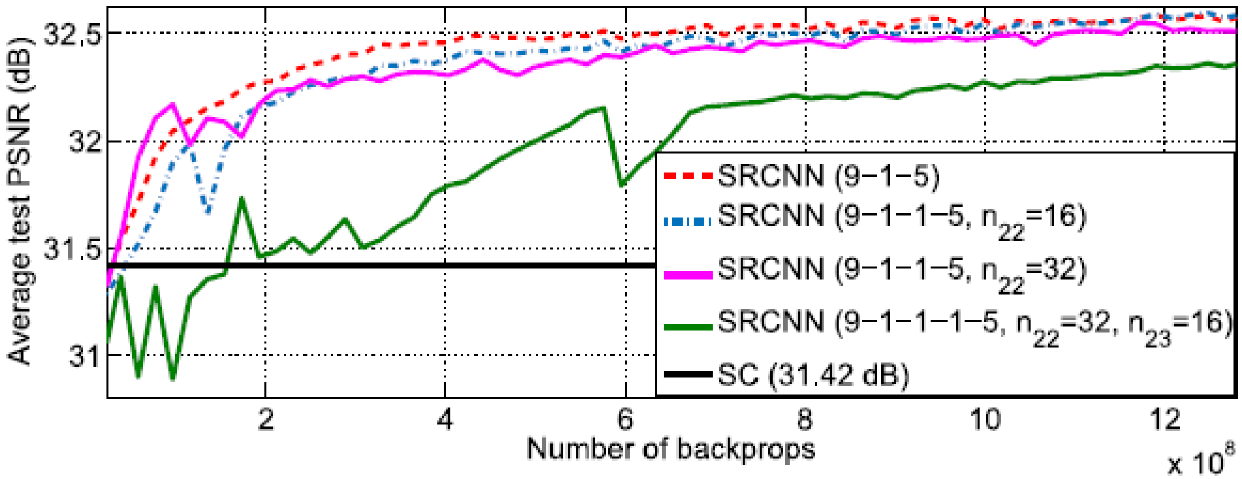
- The Results of Using Different Filter Numbers in SRCNN

$n_1 = 128$, $n_2 = 64$		$n_1 = 64$, $n_2 = 32$		$n_1 = 32$, $n_2 = 16$	
PSNR	Time (sec)	PSNR	Time (sec)	PSNR	Time (sec)
32.60	0.60	32.52	0.18	32.26	0.05

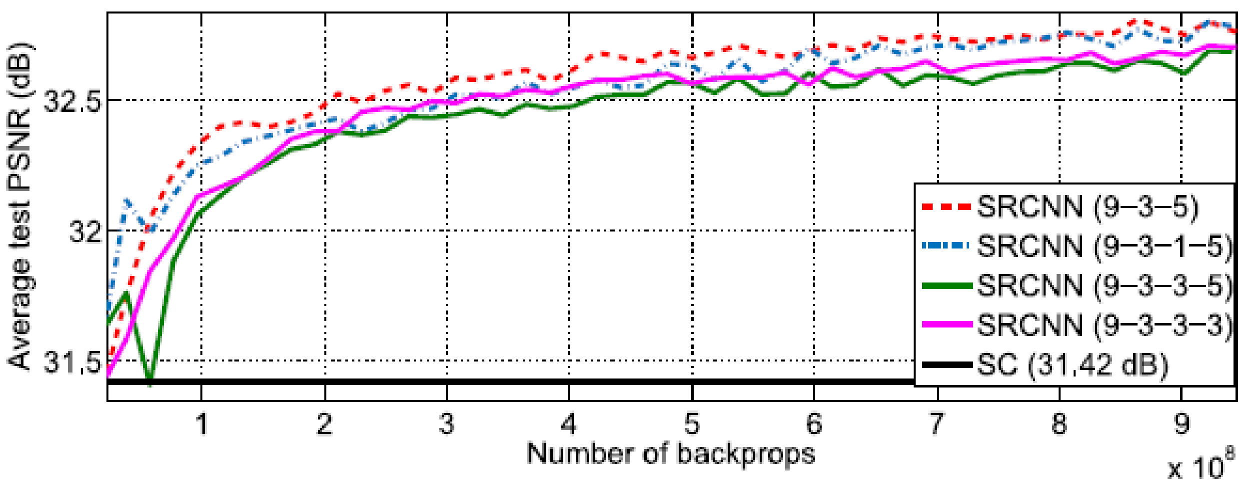
- A larger filter size leads to better results.



- Deeper structure does not always lead to better results.

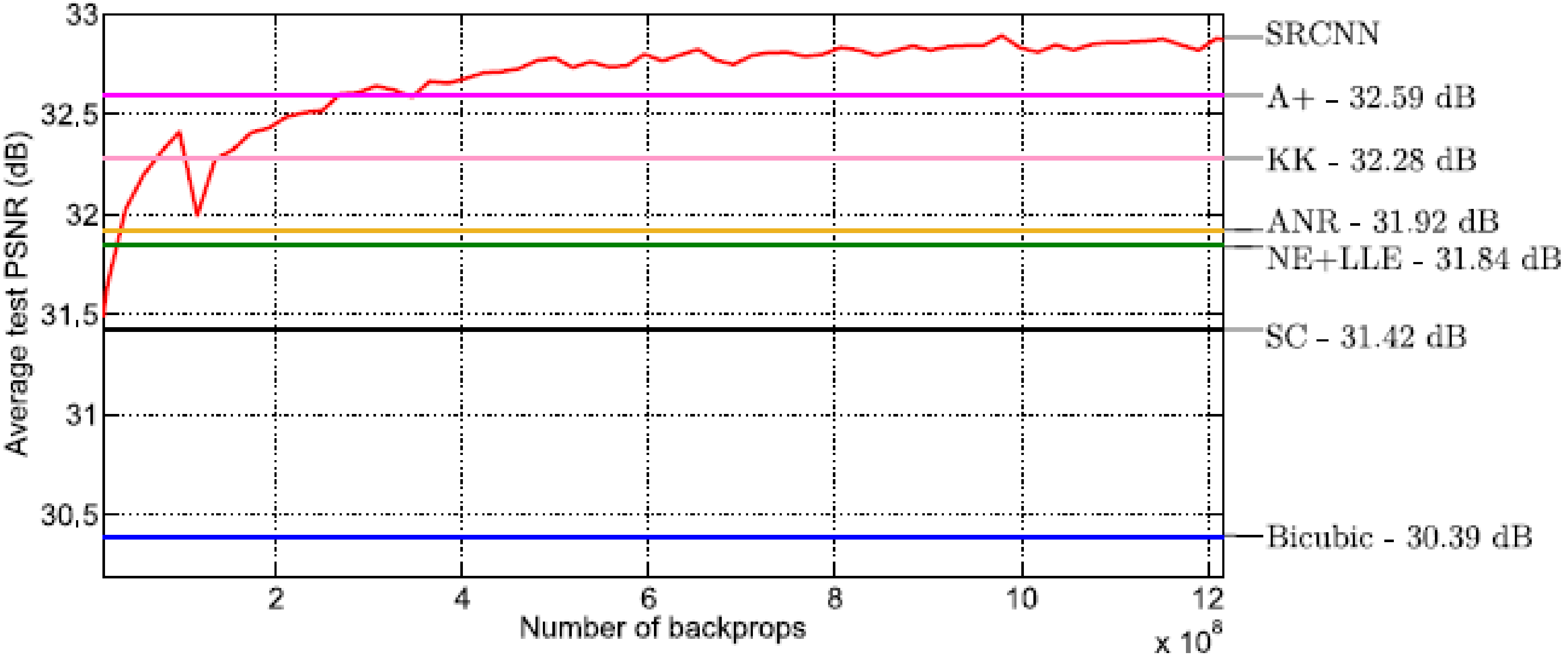


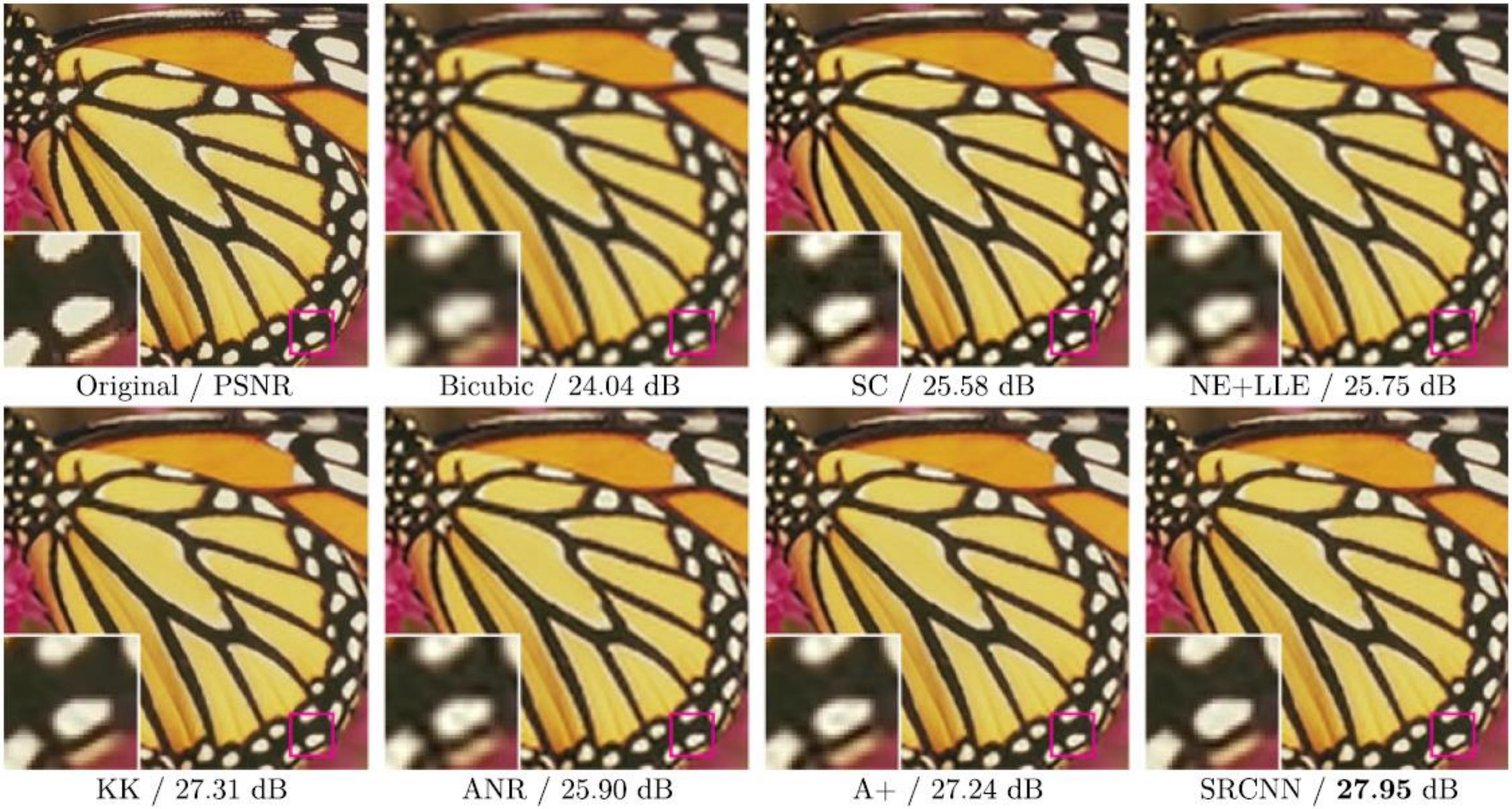
(a) 9-1-1-5 ($n_{22} = 32$) and 9-1-1-1-5 ($n_{22} = 32, n_{23} = 16$)

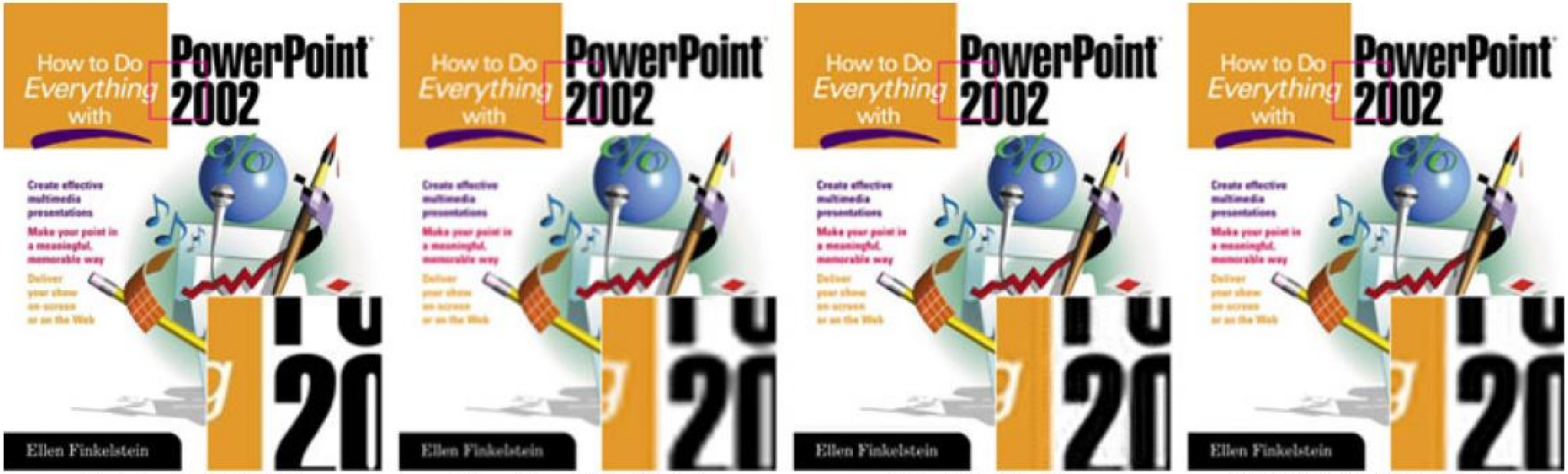


(b) 9-3-3-5 and 9-3-3-3

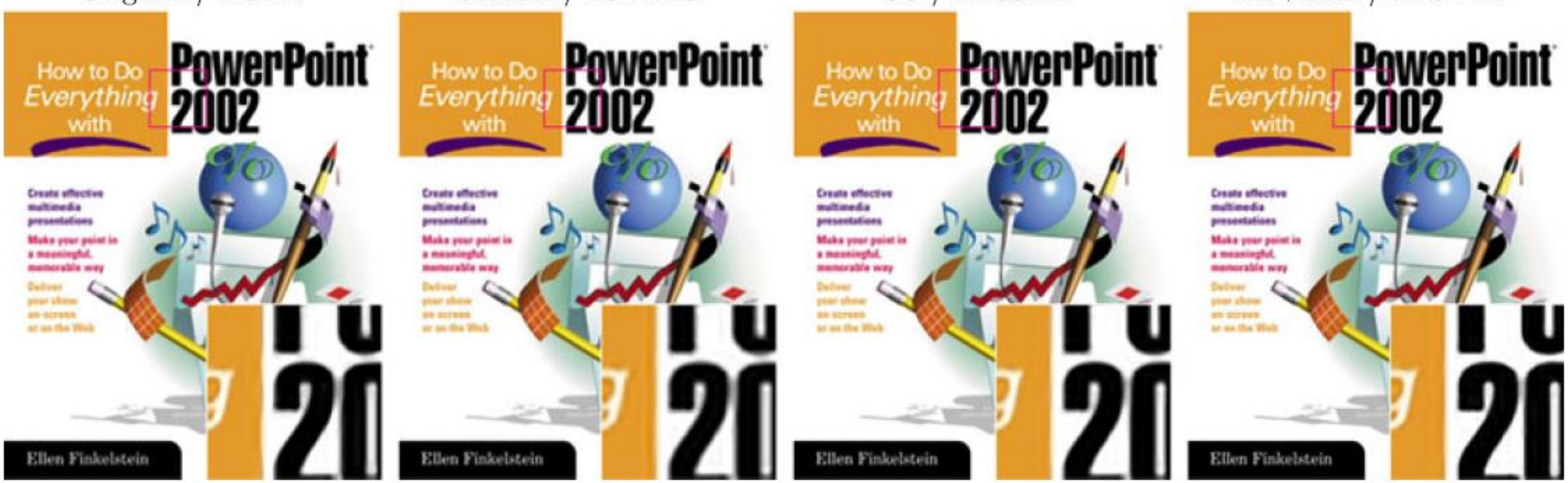
- Compare our method with recent state-of-the-arts



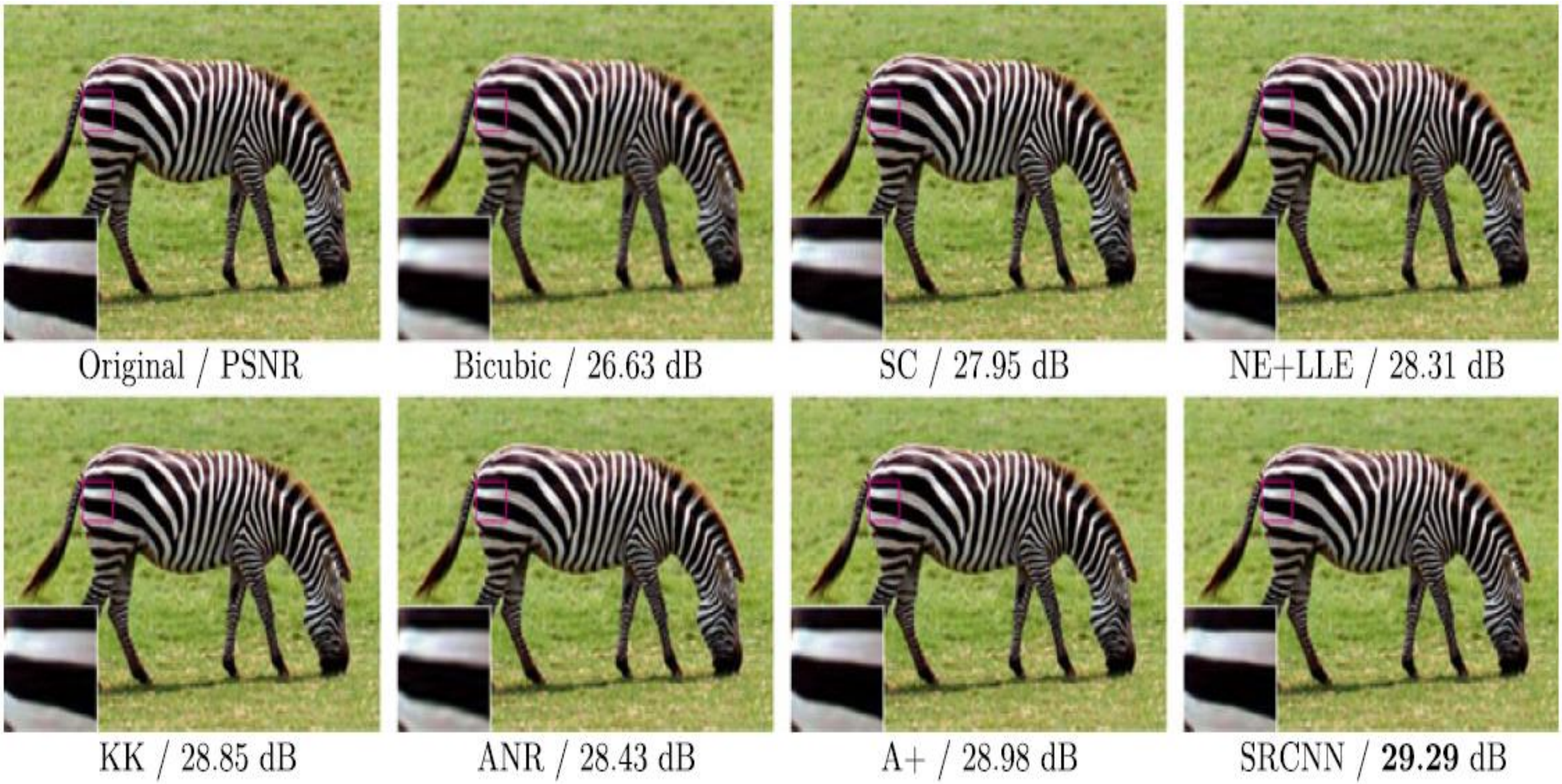

Original / PSNR
Bicubic / 24.04 dB
SC / 25.58 dB
NE+LLE / 25.75 dB
KK / 27.31 dB
ANR / 25.90 dB
A+ / 27.24 dB
SRCNN / **27.95** dB



Original / PSNR | Bicubic / 23.71 dB | SC / 24.98 dB | NE+LLE / 24.94 dB



KK / 25.60 dB | ANR / 25.03 dB | A+ / 26.09 dB | SRCNN / **27.04** dB


Original / PSNR
Bicubic / 26.63 dB
SC / 27.95 dB
NE+LLE / 28.31 dB
KK / 28.85 dB
ANR / 28.43 dB
A+ / 28.98 dB
SRCNN / **29.29** dB

4. Conclusion

- We show that conventional sparse-coding-based SR methods can be reformulated into a deep convolutional neural network.

- Besides, the proposed structure, with its advantages of simplicity and robustness, could be applied to other low-level vision problems, such as image deblurring or simultaneous SR+denoising