

Joint Image Demosaicing, Denoising and Super-Resolution Based on Deep Convolutional Neural Networks Supplementary Material

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1 Additional details of network structure

A summary of the $JD_N D_M SR$ network architecture is shown in Table 1.

Table 1: Summary of $JD_N D_M SR$ network architecture. The basic block is RCAB, the number of filters $C = 256$ and $W = 64$.

Stage	Layer	Output Shape
Input	Input (Bayer image)	$h \times w \times 1$
	Input (noise estimate)	$h/2 \times w/2 \times 1$
Color Extraction	Down-sampling Bayer input	$h/2 \times w/2 \times 4$
	Concatenate with noise input	$h/2 \times w/2 \times (4 + 1)$
	Conv	$h/2 \times w/2 \times C$
	Up-sampling	$h \times w \times W$
Feature Extraction	Basic block	$h \times w \times W$

	Basic block	$h \times w \times W$
	Conv	$h \times w \times W$
	Residual Add	$h \times w \times W$
Reconstruction	Up-sampling	$(sf \times h) \times (sf \times w) \times W$
	Conv	$(sf \times h) \times (sf \times w) \times 3$
Output	Output (color image)	$(sf \times h) \times (sf \times w) \times 3$

2 Image demosaicing and super-resolution: additional comparison of joint solutions

The noise-free version of the proposed $JD_N D_M SR$ is denoted as $JD_M SR$. A comparison of three solutions for joint demosaicing and super-resolution is shown

in Table 2. One can see from that table that the proposed combined solution $JD_M SR$ outperforms other two sequential solutions. The network $JD_N D_M SR^+$ is initialized by the learned parameters of this trained $JD_M SR$ model.

Table 2: Quantitative comparison of different solutions on the mixture problem of joint demosaicing and super-resolution using datasets Kodak and McMaster. The scale factor is set to 2. The best results are shown in bold.

Pipeline	McMaster		Kodak	
	cPSNR	SSIM	cPSNR	SSIM
DJDD \rightarrow VDSR	31.67	0.9590	31.08	0.9404
DJDD* \rightarrow VDSR*	31.37	0.9562	30.91	0.9395
$JD_M SR$	32.32	0.9632	31.36	0.9440

3 A comparison with the state-of-the-art: additional settings

For each training epoch, the mini-batch size is 16, and the patch size is 64×64 . For optimization of the network parameters, we use Adam with $\beta_1 = 0.9$, $\beta_2 = 0.999$ and the learning rate is initialized to 0.001. The training continues 250,000 iterations.

4 Additional ablation study

4.1 Long skip connection and transfer learning

Fig. 1 demonstrates that the additional LSC improves the performance of the network. In addition, we exploit the transfer learning, which transfers the well-learned parameters from the pre-trained noise-free model JD_{MSR} (Section 2). The curves (yellow and red lines) in Fig. ?? (b) prove that this kind of easy-to-hard transfer learning strategy not only improves the performance of network, but also supports a better starting point (at least 1.5 dB higher cPSNR).

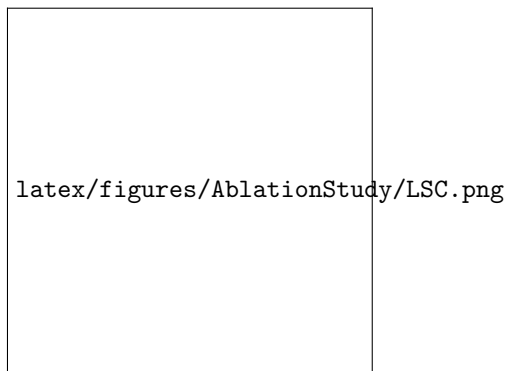


Figure 1: Ablation study of long skip connection and transfer learning.