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_ND_MSR network architecture is shown in Table 1.

Table 1: Summary of JD_ND_MSR 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_ND_MSR is denoted as JD_MSR. 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_MSR outperforms other two sequential solutions. The network $JD_ND_MSR^+$ is initialized by the learned parameters of this trained JD_MSR 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→VDSR	31.67	0.9590	31.08	0.9404
DJDD* →VDSR*	31.37	0.9562	30.91	0.9395
JD_MSR	**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).

`latex/figures/AblationStudy/LSC.png`

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