Toward Convolutional Blind Denoising of Real Photographs: Supplementary material

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1. DND

We provide more results (i.e., Figs 3, 4, 5, 6, 7, 8, 9) containing fine textures on images from the DND dataset.

2. SIDD

Recently, a new dataset, Smartphone Image Denoising Dataset (SIDD) [1], is presented to evaluate the denoising performance for smart cameras. Since the online evaluation system is not available when we submit this paper, we only report several examples of denoising results for qualitative evaluation. The visual comparisons are shown in Figs 10, 11, 12, 13, 14, 15, 16. One can see that the performance of our CBDNet is preferable against other blind denoising algorithms.

3. More Ablation Studies

For better justification, we consider three CBDNet variants, (i) CBDNet(w/o E): remove noise estimation subnet and increase kernel size of the 1st layer to 5×5 to make the parameter numbers equal or greater than CBDNet, (ii) CBDNet(w/o A): set $\alpha = 0.5$ in asymmetric loss, (ii) CBDNet(w/o TV): remove TV loss. To assess the generalization ability, we adopt two types of noise, (a) Real noise including DND and realistic noise in Eqn.2 with $\text{Ind}_{crf} = 5$, pattern = 'gbrg', $\sigma_s = 0.04$ and $\sigma_c = 0.02$, (b) Salt & Pepper (SP) noise with noise density $d = 0.4, 0.8$. From Tab. 1, CBDNet slightly outperforms CBDNet(w/o E) for Eqn.2 noise containing in the training data, and is much better (> 1.0dB gain) for SP noise, indicating that noise estimation benefits generalization ability. The effect of TV and asymmetric losses is also given in Tab. 1.

To evaluate the accurate of estimated noise level, we test two realistic noise level defined in Eqn.2 with (i) $\text{Ind}_{crf} = 5$, pattern = 'gbrg', $\sigma_s = 0.08$, $\sigma_c = 0.03$ and (ii) $\text{Ind}_{crf} = 5$, pattern = 'gbrg', $\sigma_s = 0.10$, $\sigma_c = 0.05$ on CBSD68 dataset. Quantitative results of CBDNet and CBDNet(w/o TV) are given in Tab. 2. One can see that, comparing with CBDNet(w/o TV), CBDNet utilizing TV loss estimates more accurate noise level. Furthermore, we choose one image in CBSD68, synthesize the noisy image using the setting $\text{Ind}_{crf} = 5$, pattern = 'gbrg', $\sigma_s = 0.08$ and $\sigma_c = 0.03$ and show the visual results of estimated noise map. From Fig. 1, we can see that both CBDNet and CBDNet(w/o TV) can reasonably estimate noise level map, but CBDNet(w/o TV) suffers from relatively large fluctuations.

4. Effect of Perspective Loss

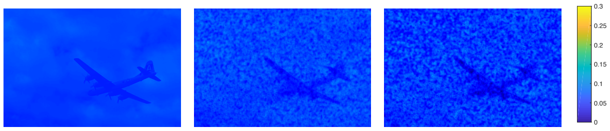
From Fig. 2, CBDNet w/o perceptual loss is effective in removing noise but may cause oversmoothing of structure and textures. Using perceptual loss benefits texture preserving and improves the visual quality of denoising result.

Table 1: The quantitative results on different kind of noise.

Dataset	Noise Type	Methods	PSNR(dB)
DND [5]	Real-world noise	CBDNet(w/o E)	37.41
		CBDNet	**37.57**
CBSD68	Ind_{crf}=5, pattern = 'gbrg' σ_s= 0.04,σ_c= 0.02(Equ.2)	CBDNet(w/o E)	30.13
		CBDNet(w/o TV)	30.07
		CBDNet(w/o A)	30.38
		CBDNet	30.39
		CBDNet(σ_{GT})	**31.69**
	Salt & Papper, $d = 0.4$	CBDNet(w/o E)	27.47
		CBDNet(w/o TV)	28.13
		CBDNet(w/o A)	28.23
		CBDNet	**28.46**
	Salt & Papper, $d = 0.8$	CBDNet(w/o E)	25.98
		CBDNet(w/o TV)	26.55
		CBDNet(w/o A)	26.82
		CBDNet	**27.12**

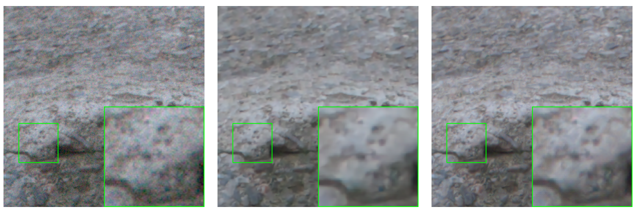
Table 2: The quantitative results on noise estimation.

	Methods	RMSE
Ind_{crf}=5, pattern = 'gbrg' σ_s = 0.08, σ_c = 0.03	CBDNet(w/o TV)	0.0153
	CBDNet	**0.0133**
Ind_{crf}=5, pattern = 'gbrg' σ_s = 0.10, σ_c = 0.05	CBDNet(w/o TV)	0.0205
	CBDNet	**0.0169**



(a) ground-truth (b) CBDNet (c) CBDNet(w/o TV)

Figure 1: Visual results of estimated noise map



(a) Noisy image (b) CBDNet(w/o Per) (c) CBDNet

Figure 2: Visual results of CBDNet with & without perceptual loss.

References

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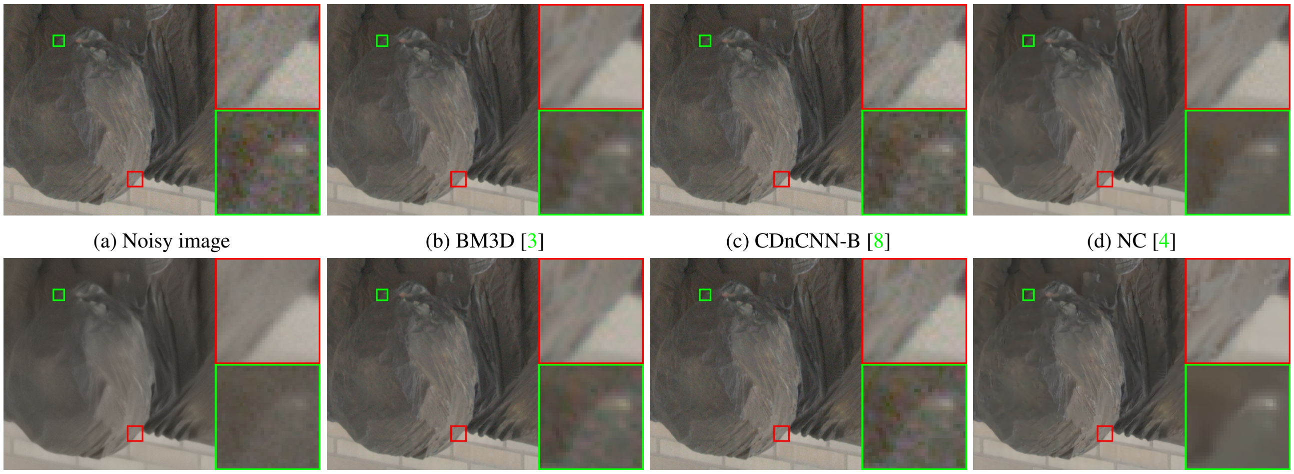
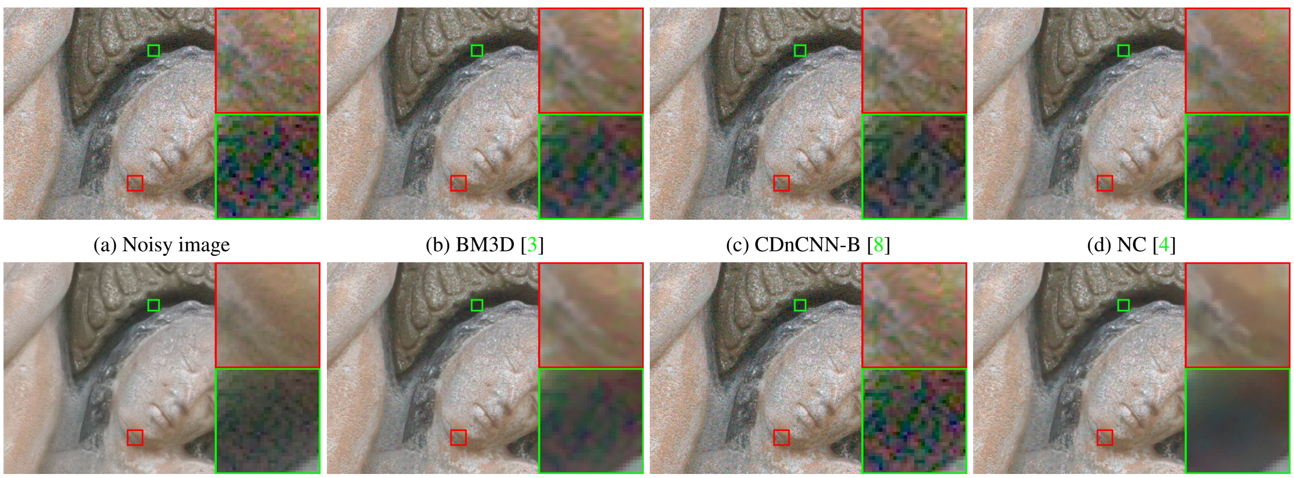


(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

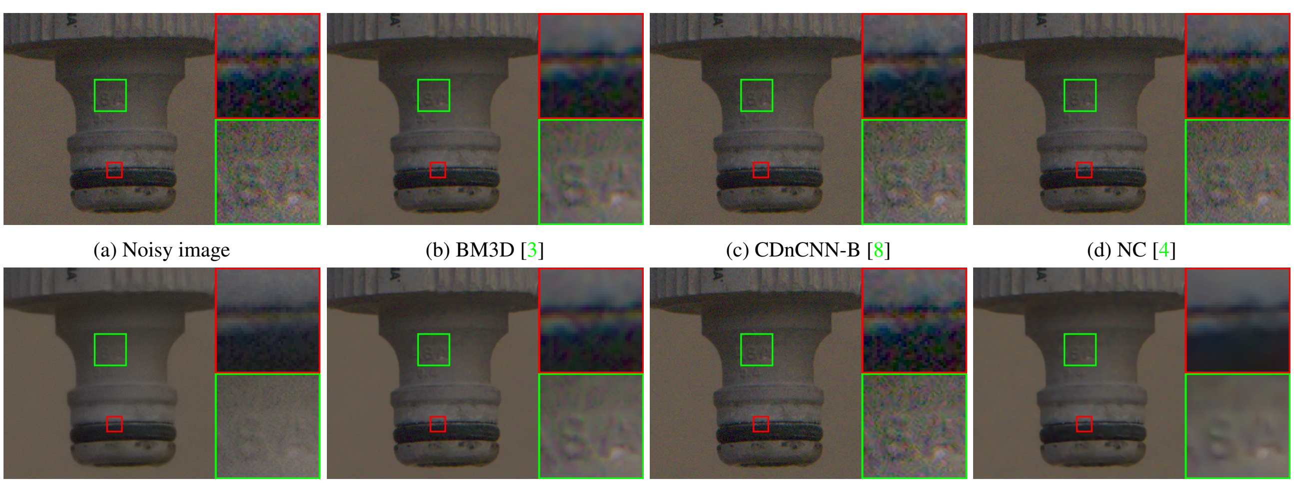
Figure 3: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

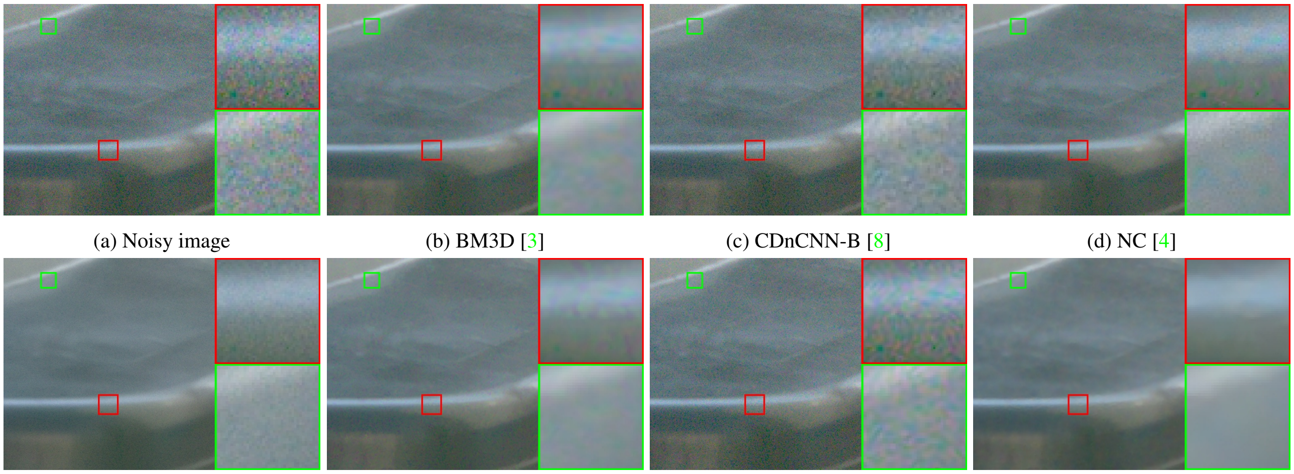
Figure 4: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

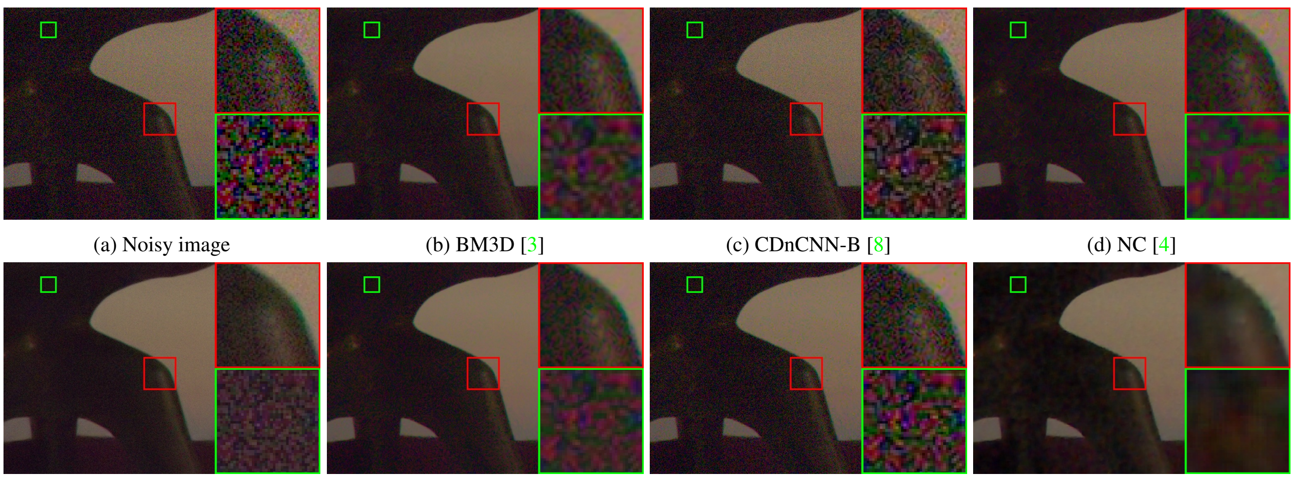
Figure 5: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

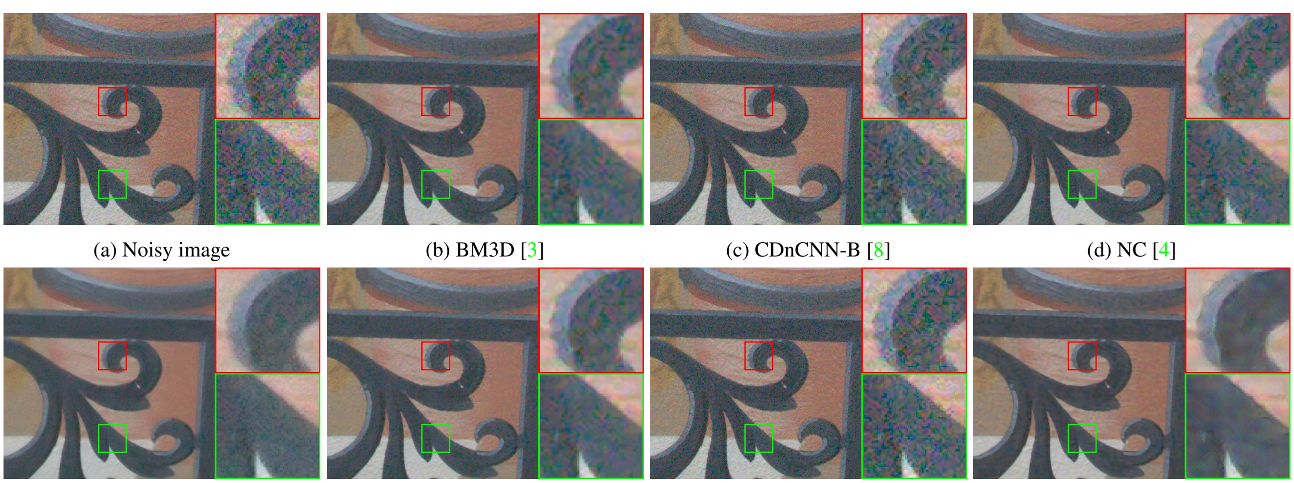
Figure 6: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

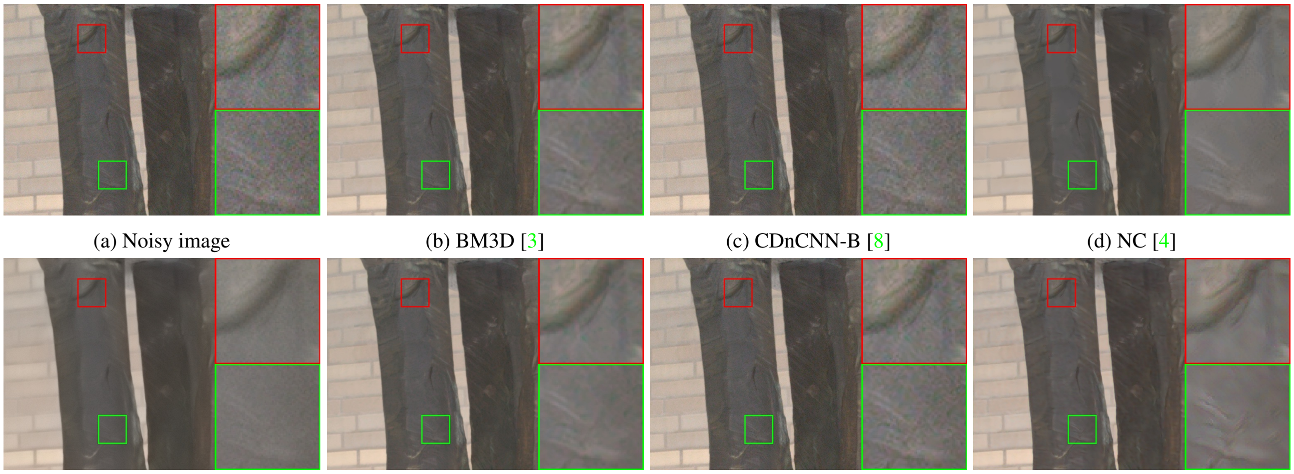
Figure 7: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

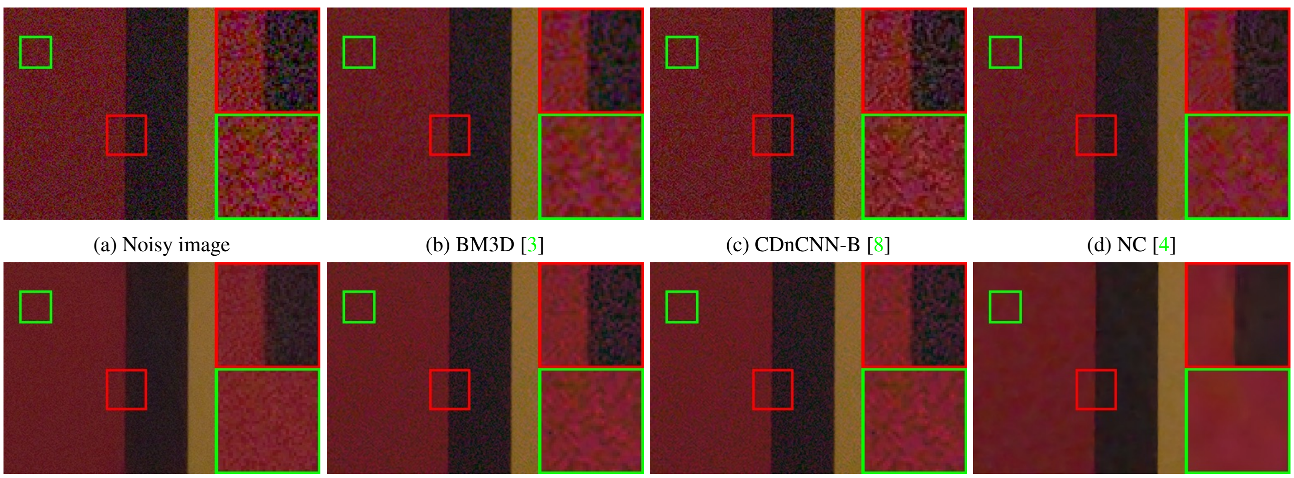
Figure 8: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

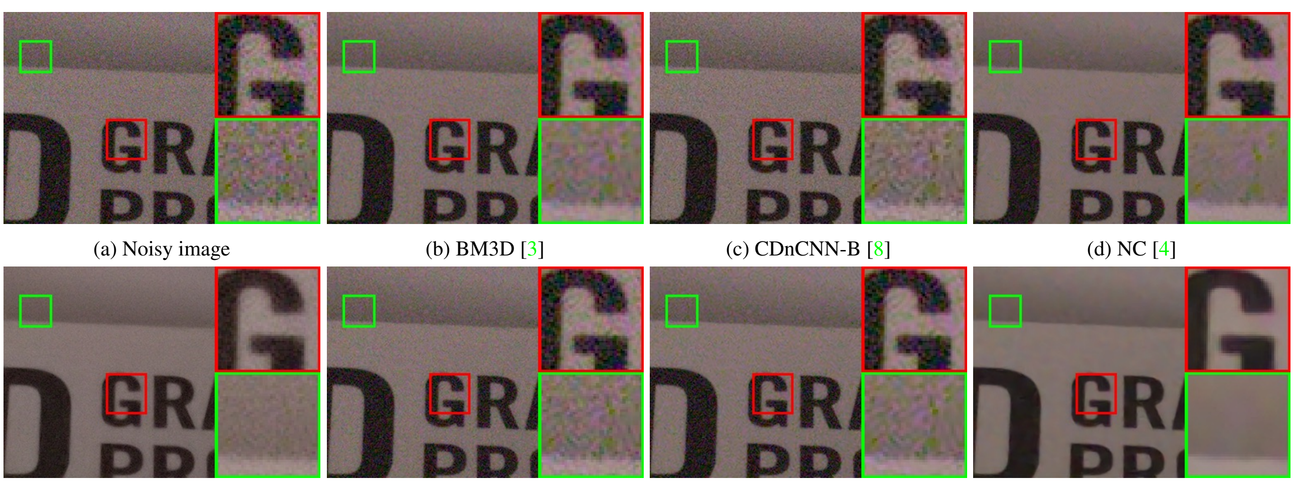
Figure 9: Denoising results of a DND image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

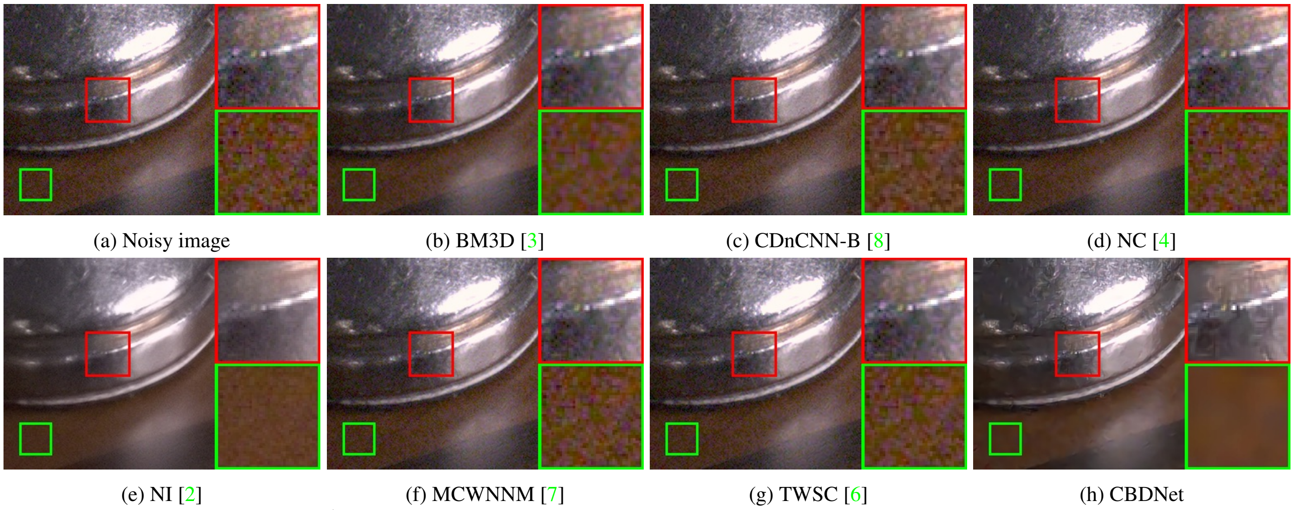
Figure 10: Denoising results of a SIDD image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

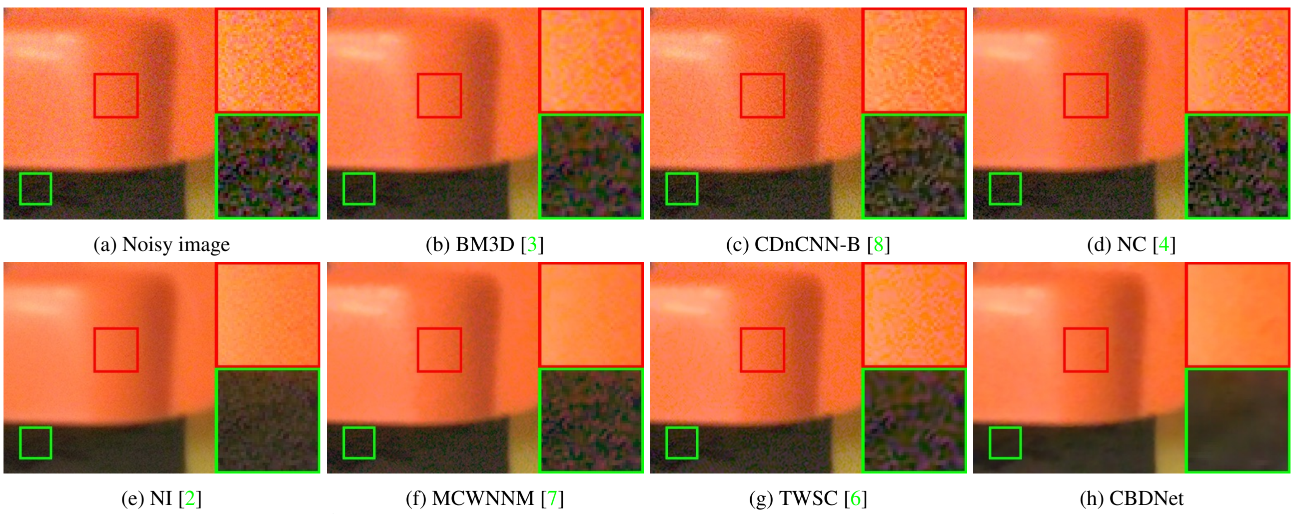
(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

Figure 11: Denoising results of a SIDD image by different methods.



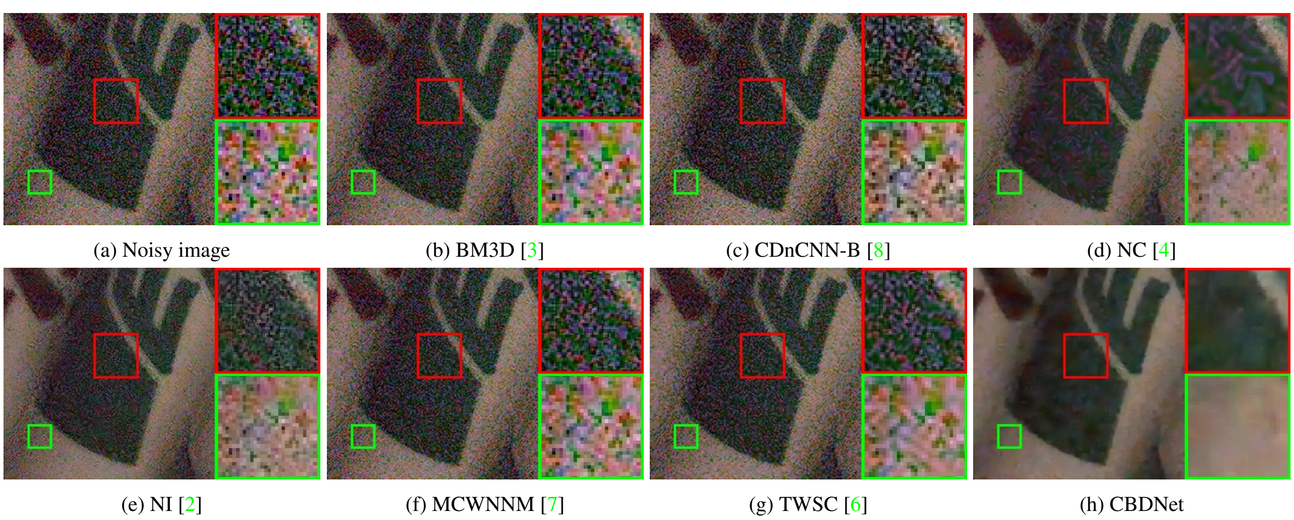
(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]
(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

Figure 12: Denoising results of a SIDD image by different methods.



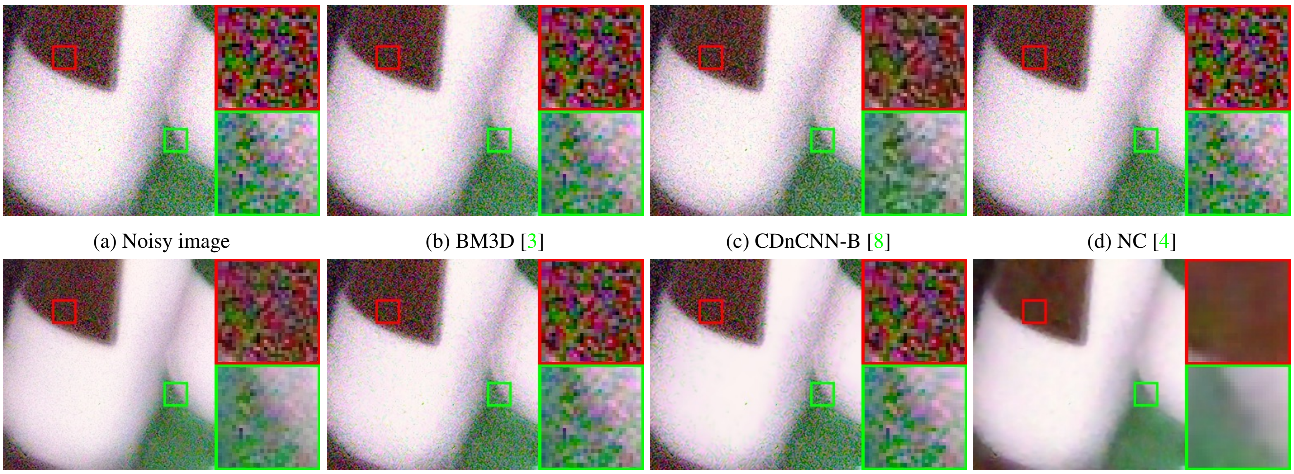
(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]
(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

Figure 13: Denoising results of a SIDD image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]
(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

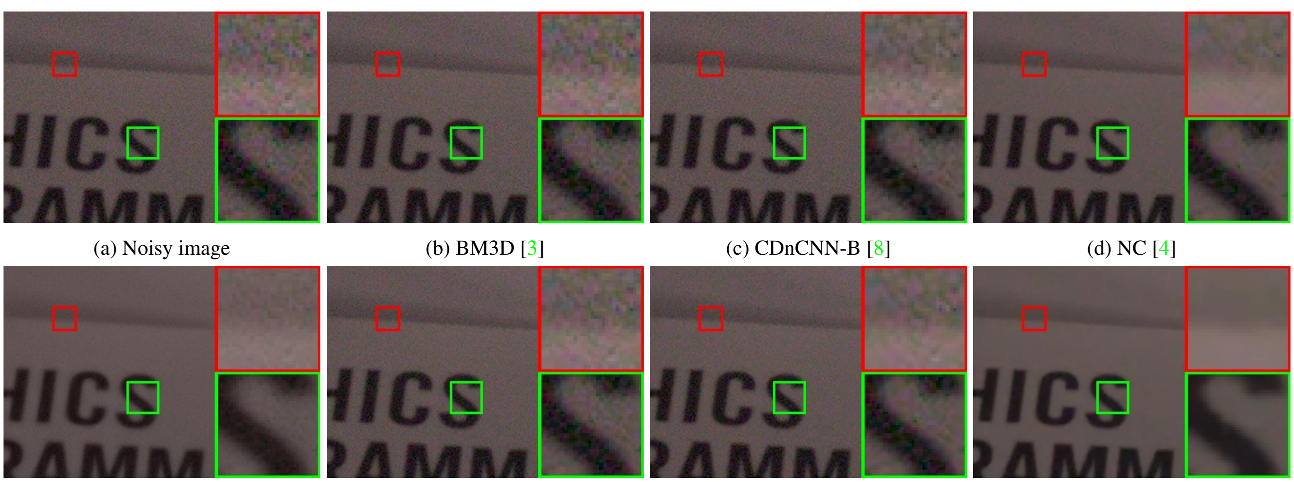
Figure 14: Denoising results of a SIDD image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

Figure 15: Denoising results of a SIDD image by different methods.



(a) Noisy image (b) BM3D [3] (c) CDnCNN-B [8] (d) NC [4]

(e) NI [2] (f) MCWNNM [7] (g) TWSC [6] (h) CBDNet

Figure 16: Denoising results of a SIDD image by different methods.