Spatial-Adaptive Network for Single Image Denoising Supplementary Material

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1   Visual results

More denoising results are present on both synthetic and real noisy images. In the comparisons of synthetic noisy images, we choose CBM3D [2] as representatives of the classical traditional methods as well as some state-of-the-art CNN-based methods, including DnCNN [4], FFDNet [5], RNAN [6], and RIDNet [1], for the comparisons. To conduct comparisons on real noisy images, we add some real noise removal methods including CBDNet [3] and PD [7] for the comparisons.

These results demonstrate that our SADNet can reduce noise and recover vivid details without introducing other artifacts.

References

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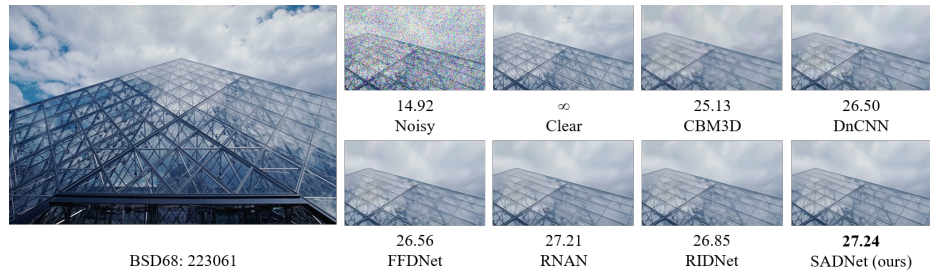
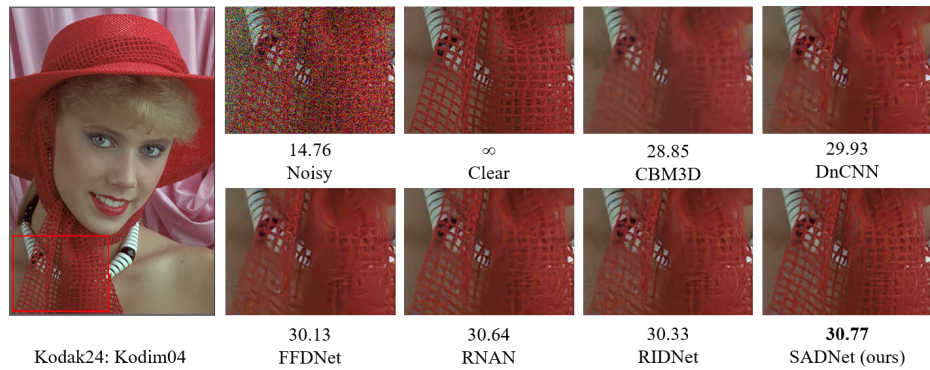**Fig. 1.** Synthetic image denoising results on BSD68 with noise level $\sigma = 50$.

Fig. 2. Synthetic image denoising results on Kodak24 with noise level $\sigma = 50$.
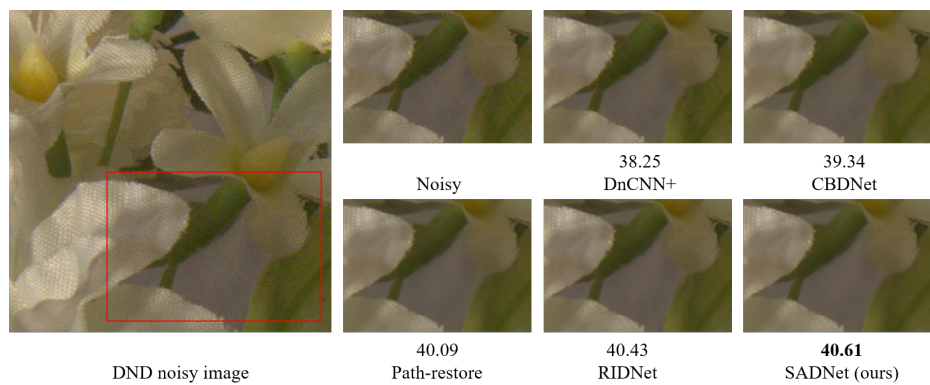

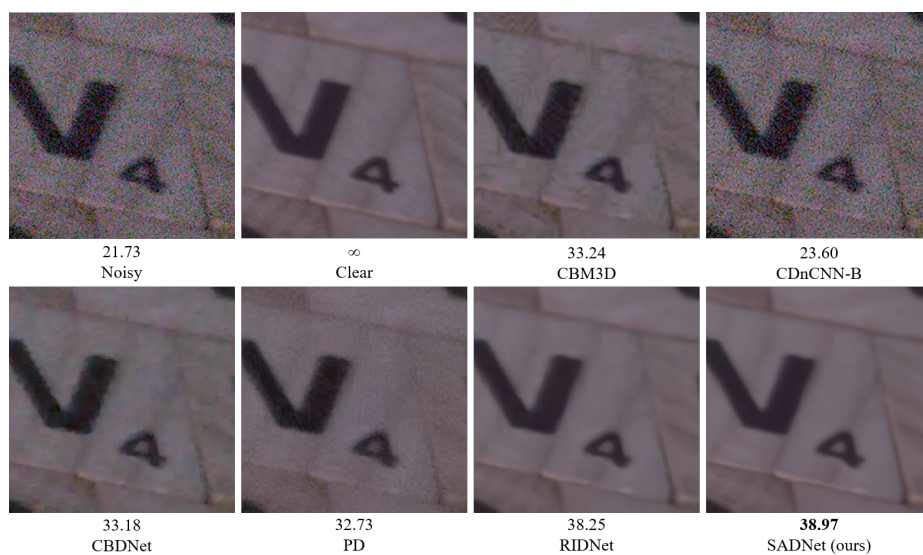**Fig. 3.** Real image denoising results on the DnD dataset.
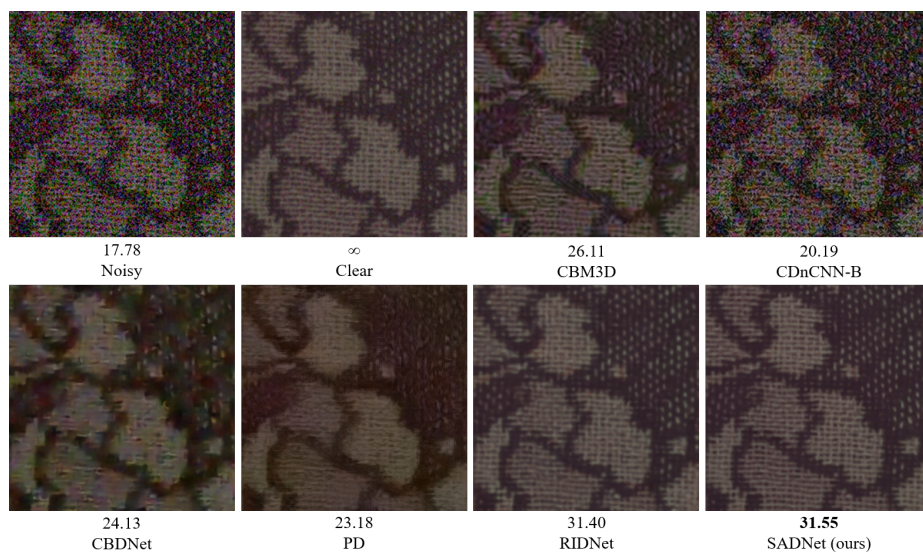
21.73	∞	33.24	23.60
Noisy	Clear	CBM3D	CDnCNN-B
33.18	32.73	38.25	**38.97**
CBDNet	PD	RIDNet	SADNet (ours)

Fig. 4. Real image denoising results on the SIDD dataset.

17.78	∞	26.11	20.19
Noisy	Clear	CBM3D	CDnCNN-B
24.13	23.18	31.40	**31.55**
CBDNet	PD	RIDNet	SADNet (ours)

Fig. 5. Real image denoising results on the SIDD dataset.

18.25	∞	28.28	20.76
Noisy	Clear	CBM3D	CDnCNN-B
31.23	30.16	35.66	**36.70**
CBDNet	PD	RIDNet	SADNet (ours)

Fig. 6. Real image denoising results on the SIDD dataset.

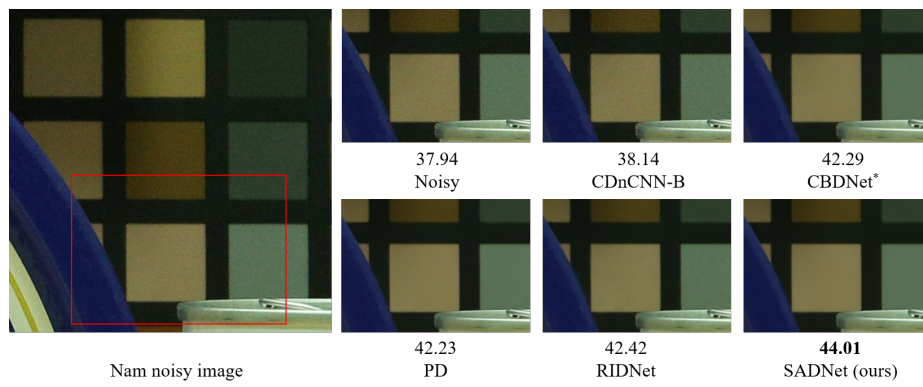|			
	37.94	38.14	42.29
	Noisy	CDnCNN-B	CBDNet*
Nam noisy image	42.23	42.42	**44.01**
	PD	RIDNet	SADNet (ours)
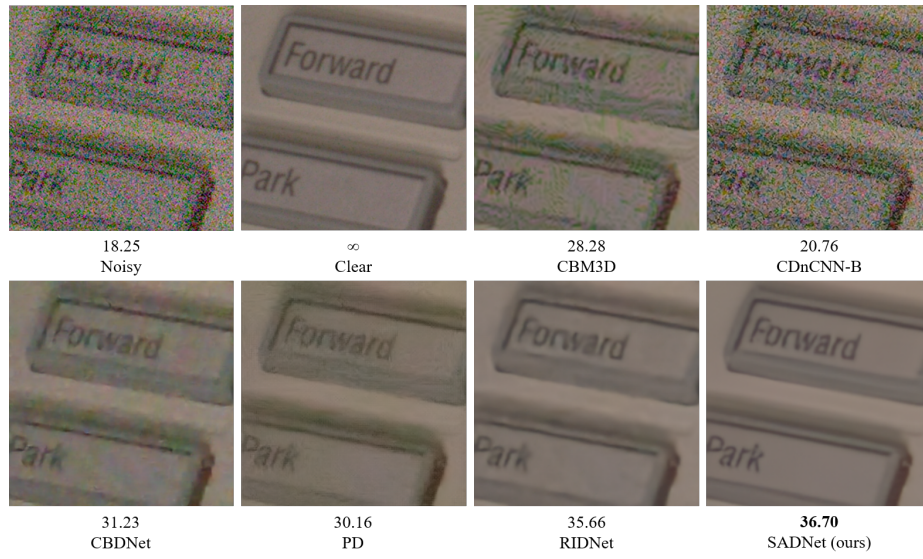
Fig. 7. Real image denoising results on the Nam dataset.