Supplementary File to "Unsupervised Boosting of Supervised Image Denoising Networks for Realistic Noise Removal"

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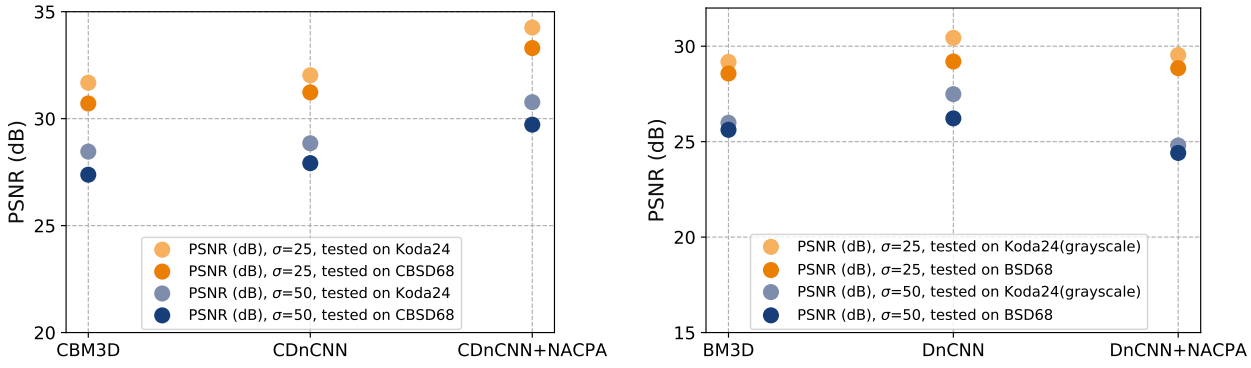
In this supplementary file, we provide:

- performance of different networks with our NACPA strategy under high level noises in §I.
- more comparison of denoising results by different methods applied with and without NACPA and tested on McMaster and Manga109 test sets in §II.
- more comparisons of visual results by different methods with or without our NACPA strategy for AWGN noise removal in §III.
- more comparisons of visual results by different methods with or without our NACPA strategy for realistic noise removal in §IV.

I. Performance Under High Level Noises

According to the proposed NACPA strategy is more suitable for the low-level noise denoising. So the experiments above were conducted under this setting. To further discover the proposed method, we also evaluated the proposed strategy under high-level of noises for RGB image and grayscale image here. In Fig. 1a, for RGB image denoising shows that the CDnCNN [12] applied with NACPA strategy still performs well under higher level of AWGN. While in Fig. 1b, for DnCNN [12] for grayscale image denoising, the performance drop quickly as the std. of the AWGN rises. Since color image has more correlated information between channels to help restore the information, so that the performance drop slower than the grayscale image denoising.



(a) RGB image denoising (b) Grayscale image denoising

Fig. 1: The average PSNR (dB) and SSIM [11] results of DnCNN [12] applied with and without NACPA strategy with high level AWGN for RGB and grayscale image denoising, for RGB image denoising tested on Koda24 [2] and CBSD68 [9] datasets, for grayscale image denoising tested on grayscale version of Koda24 and BSD68 datasets ,under noise levels $\sigma = \{25, 50\}$.

II. More denoising results comparison of different methods applied with and without NACPA and tested on McMaster and Manga109 test sets

In this section, more experiments conducted on more datasets are provided to demonstrate the effectiveness of the proposed NACPA strategy. Here we evaluated the performance of using different denoising models applied with and without the NACPA strategy and test on extra test sets of McMaster [14] and Manga109 [5]. As Table I shows that with NACPA strategy the

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supervised image denoising models are boosted and achieved a stable higher performance than the original supervised trained image denoising models. From Fig. 2 and Fig. 9 are two typical image from McMaster and MANGA109 datasets, the visual comparison of different denoising methods with or without NACPA strategy demonstrate that the denoising models with NACPA strategy achieve a better visual quality.

TABLE I: Average PSNR (dB) and SSIM [11] results of different denoising networks applied with and without NACPA strategy for color image denoising, trained on CBSD400 [9] dataset, tested on *McMaster* and *Manga109* datasets with AWGN levels $\sigma = \{5, 10, 15, 20\}$.

Test Set	Noise Level / Metric	$\sigma = 5$ PSNR↑	$\sigma = 5$ SSIM↑	$\sigma = 10$ PSNR↑	$\sigma = 10$ SSIM↑	$\sigma = 15$ PSNR↑	$\sigma = 15$ SSIM↑	$\sigma = 20$ PSNR↑	$\sigma = 20$ SSIM↑
McMaster	**CDnCNN**	39.19	0.9636	35.75	0.9342	33.91	0.9118	32.63	0.8920
	CDnCNN+NACPA	40.18	0.9701	37.36	0.9516	35.35	0.9304	34.26	0.9193
	RCAN*	35.52	0.9212	32.48	0.8585	30.13	0.7957	29.07	0.7452
	RCAN*+NACPA	39.64	0.9697	35.83	0.9260	33.30	0.8735	31.33	0.8140
	MemNet	35.86	0.9103	30.41	0.7655	28.58	0.7044	26.95	0.6260
	MemNet+NACPA	39.32	0.9643	35.13	0.9264	32.42	0.8703	29.26	0.8016
	RED	36.88	0.9387	33.82	0.9031	32.20	0.8680	30.52	0.8200
	RED+NACPA	39.83	0.9717	36.09	0.9329	33.23	0.8806	31.57	0.8303
Manga109	**CDnCNN**	40.33	0.9746	36.24	0.9442	34.60	0.9305	33.38	0.9155
	CDnCNN+NACPA	41.94	0.9815	38.48	0.9634	36.32	0.9446	35.29	0.9384
	RCAN*	35.59	0.9290	32.68	0.8708	30.38	0.8310	29.27	0.7751
	RCAN*+NACPA	39.68	0.9737	35.98	0.9316	33.31	0.8810	31.10	0.8191
	MemNet	35.73	0.9133	29.63	0.7273	28.63	0.7170	27.07	0.6538
	MemNet+NACPA	39.41	0.9764	35.20	0.9395	32.69	0.8875	29.25	0.8289
	RED	37.75	0.9509	34.43	0.9220	32.78	0.8932	30.90	0.8499
	RED+NACPA	40.54	0.9764	36.71	0.9371	33.47	0.8847	31.52	0.8311

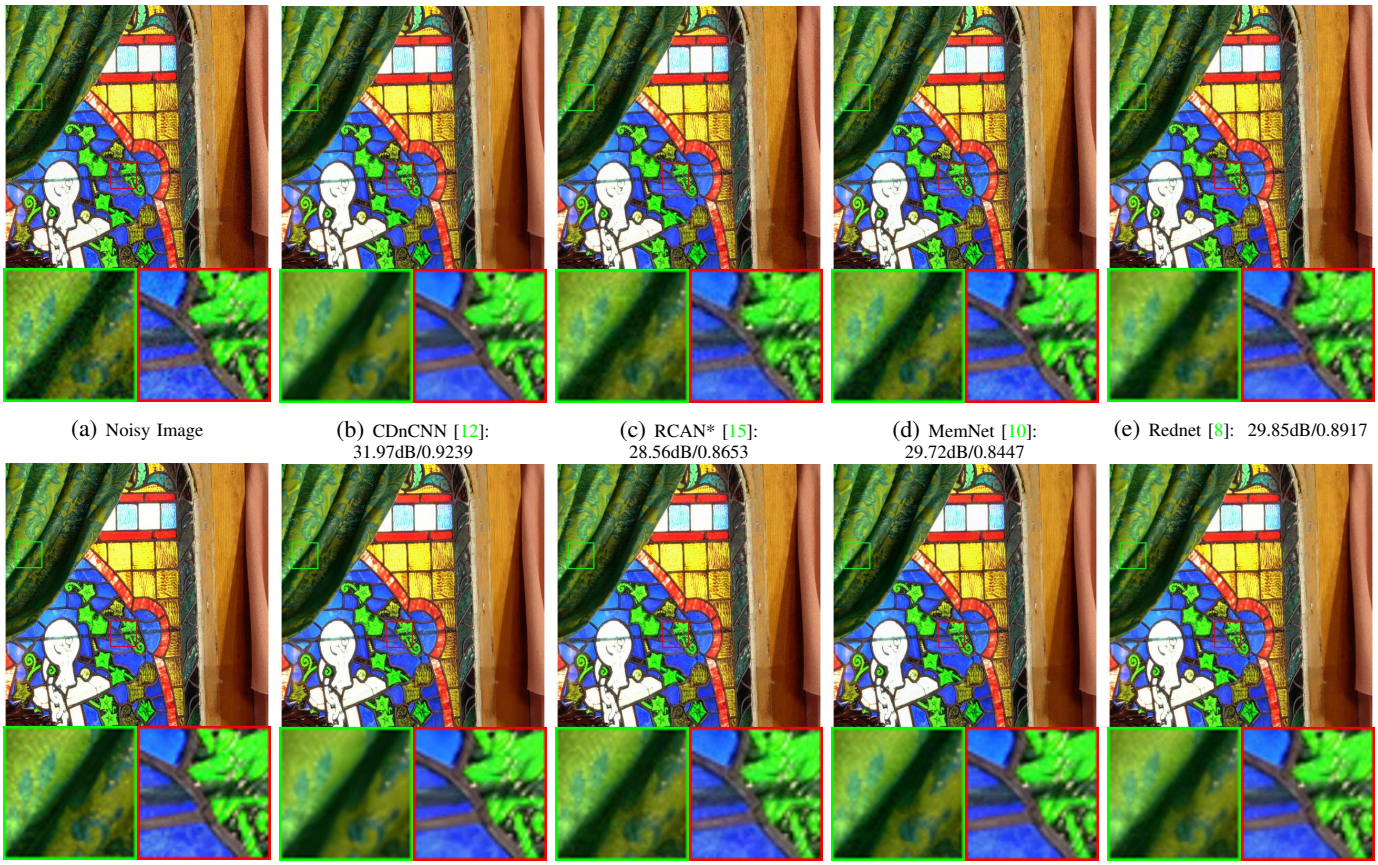
(a) Noisy Image (b) CDnCNN [12]: 37.94dB/0.9548 (c) RCAN* [15]: 35.02dB/0.9156 (d) MemNet [10]: 35.68dB/0.9688 (e) Rednet [8]: 36.20dB/0.9763

(f) Clean Image (g) CDnCNN [12]+NACPA: 38.43dB/0.9603 (h) RCAN* [15] + NACPA: 39.20dB/0.9697 (i) MemNet [10]+NACPA: 38.72dB/0.9828 (j) Rednet [8]+NACPA: 39.38dB/0.9889

Fig. 2: Denoising results of a typical images ("*2.tif*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 5$) on McMaster test set.

III. More denoising results comparisons on the visual quality of different denoising methods for AWGN applied with and without NACPA strategy

In this section, more visual comparison of different denoising models applied with and without NACPA strategy is provided. In our main paper, we have provided the PSNR and SSIM [11] results of the comparison methods on the *Koda24* [2],



(a) Noisy Image (b) CDnCNN [12]: 31.97dB/0.9239 (c) RCAN* [15]: 28.56dB/0.8653 (d) MemNet [10]: 29.72dB/0.8447 (e) Rednet [8]: 29.85dB/0.8917

(f) Clean Image (g) CDnCNN [12]+NACPA: 33.10dB/0.9386 (h) RCAN* [15] + NACPA: 32.44dB/0.9400 (i) MemNet [10]+NACPA: 33.12dB/0.9419 (j) Rednet [8]+NACPA: 30.44dB/0.8789

Fig. 3: Denoising results of a typical images ("*1.tif*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 10$) on McMaster test set.

CBSD68 [9] and *Urban100* [6] datasets when the standard deviations of the additive white Gaussian noise (AWGN) are $\sigma = 5, 10, 15, 20, 25$. In Figures 10-21, we provide the visual comparison of the denoised images by the competing methods. One can see that the denoising model applied with the proposed NACPA strategy produce better image quality than the comparison methods.

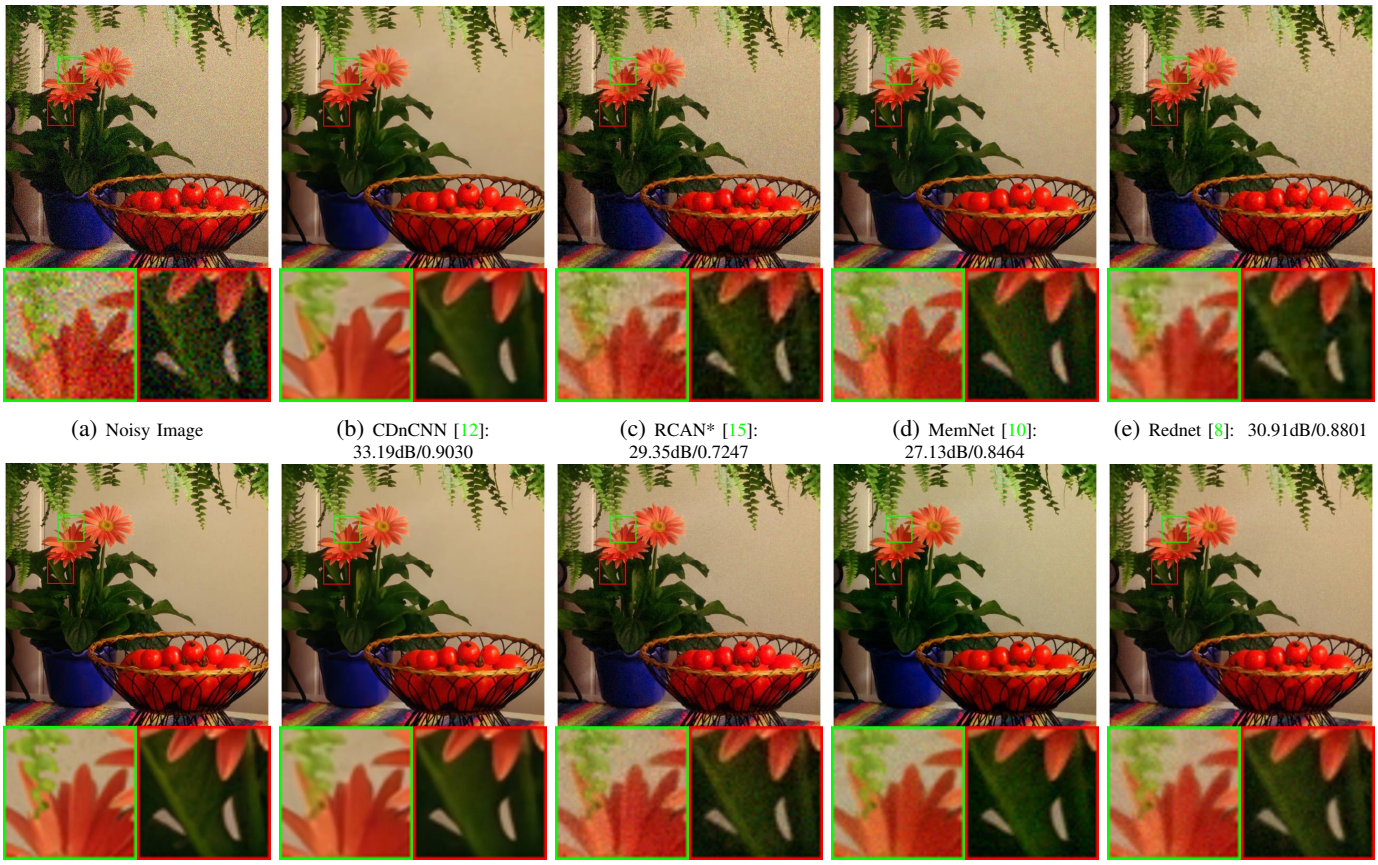
IV. More denoising results comparisons on the visual quality of different denoising methods for realistic noise removal

In this section, we compare the visual quality of the denoised images by different methods on realistic noise removal. From Figures 24-25, one can see that the unsupervised denoising networks trained by our NACPA scheme achieve better image quality than the original supervised denoising networks.

(a) Noisy Image (b) CDnCNN [12]: 32.23dB/0.9390 (c) RCAN* [15]: 29.26dB/0.8525 (d) MemNet [10]: 29.47dB/0.8545 (e) Rednet [8]: 30.77dB/0.8335

(f) Clean Image (g) CDnCNN [12]+NACPA: 33.94dB/0.9512 (h) RCAN* [15] + NACPA: 32.64dB/0.9097 (i) MemNet [10]+NACPA: 31.81dB/0.9261 (j) Rednet [8]+NACPA: 32.22dB/0.9350

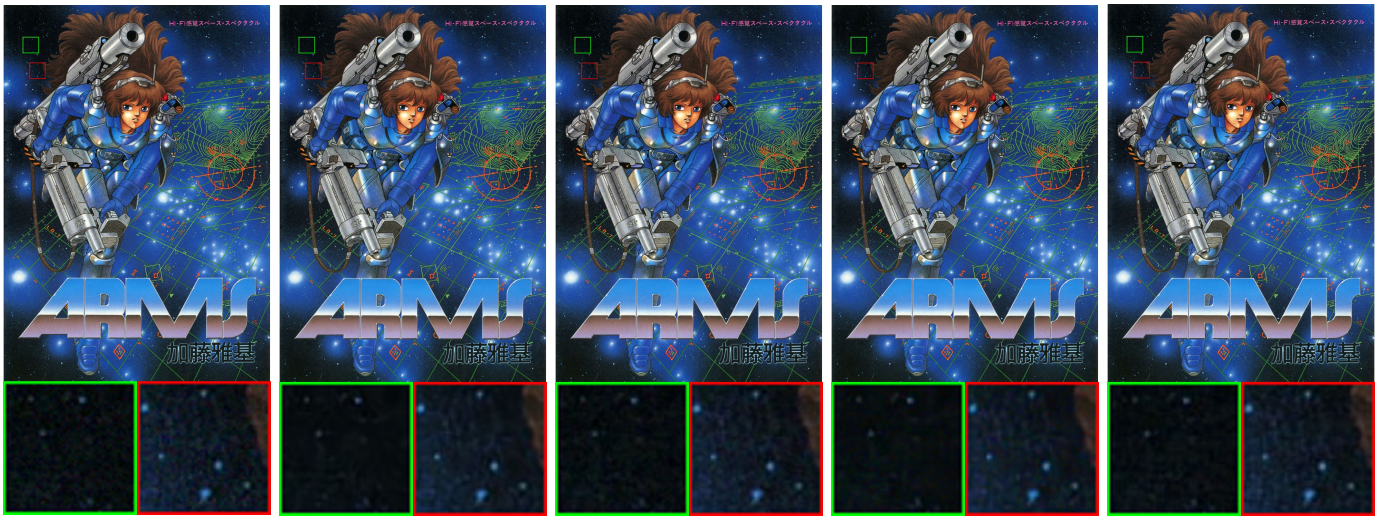
Fig. 4: Denoising results of a typical images ("*3.tif*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 15$) on McMaster test set.



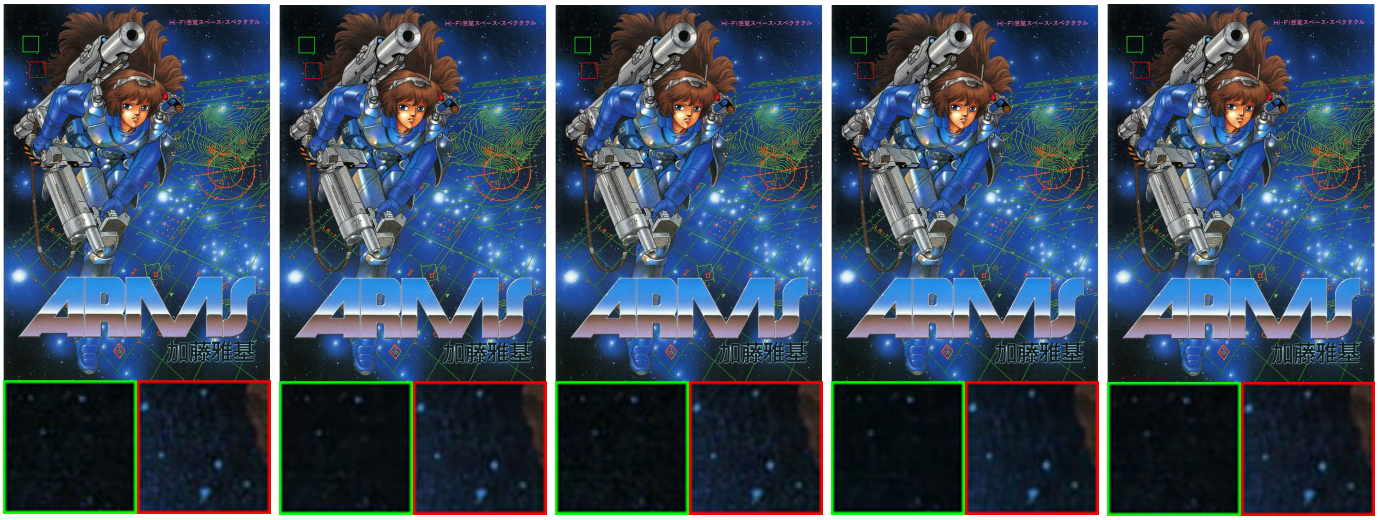
(a) Noisy Image (b) CDnCNN [12]: 33.19dB/0.9030 (c) RCAN* [15]: 29.35dB/0.7247 (d) MemNet [10]: 27.13dB/0.8464 (e) Rednet [8]: 30.91dB/0.8801

(f) Clean Image (g) CDnCNN [12]+NACPA: 34.73dB/0.9249 (h) RCAN* [15] + NACPA: 31.51dB/0.7933 (i) MemNet [10]+NACPA: 29.33dB/0.9280 (j) Rednet [8]+NACPA: 31.87dB/0.9630

Fig. 5: Denoising results of a typical images ("*9.tif*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 20$) on McMaster test set.



(a) Noisy Image (b) CDnCNN [12]: 38.60dB/0.9652 (c) RCAN* [15]: 34.39dB/0.9343 (d) MemNet [10]: 34.95dB/0.9719 (e) Rednet [8]: 36.43dB/0.9861



(f) Clean Image (g) CDnCNN [12]+NACPA: 40.13dB/0.9756 (h) RCAN* [15] + NACPA: 38.38dB/0.9753 (i) MemNet [10]+NACPA: 38.24dB/0.9898 (j) Rednet [8]+NACPA: 38.67dB/0.9922

Fig. 6: Denoising results of a typical images ("*ARMS.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 5$) on MANGA109 test set.

(a) Noisy Image (b) CDnCNN [12]: 38.40dB/0.9472 (c) RCAN* [15]: 34.43dB/0.8495 (d) MemNet [10]: 29.30dB/0.6455 (e) Rednet [8]: 36.62dB/0.9238

(f) Clean Image (g) CDnCNN [12]+NACPA: 39.98dB/0.9577 (h) RCAN* [15] + NACPA: 37.74dB/0.9192 (i) MemNet [10]+NACPA: 35.90dB/0.9286 (j) Rednet [8]+NACPA: 37.86dB/0.9265

Fig. 7: Denoising results of a typical images ("*Akuhamu.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 10$) on MANGA109 test set.

(a) Noisy Image (b) CDnCNN [12]: 34.07dB/0.9458 (c) RCAN* [15]: 30.05dB/0.8593 (d) MemNet [10]: 28.65dB/0.9186 (e) Rednet [8]: 32.32dB/0.9787

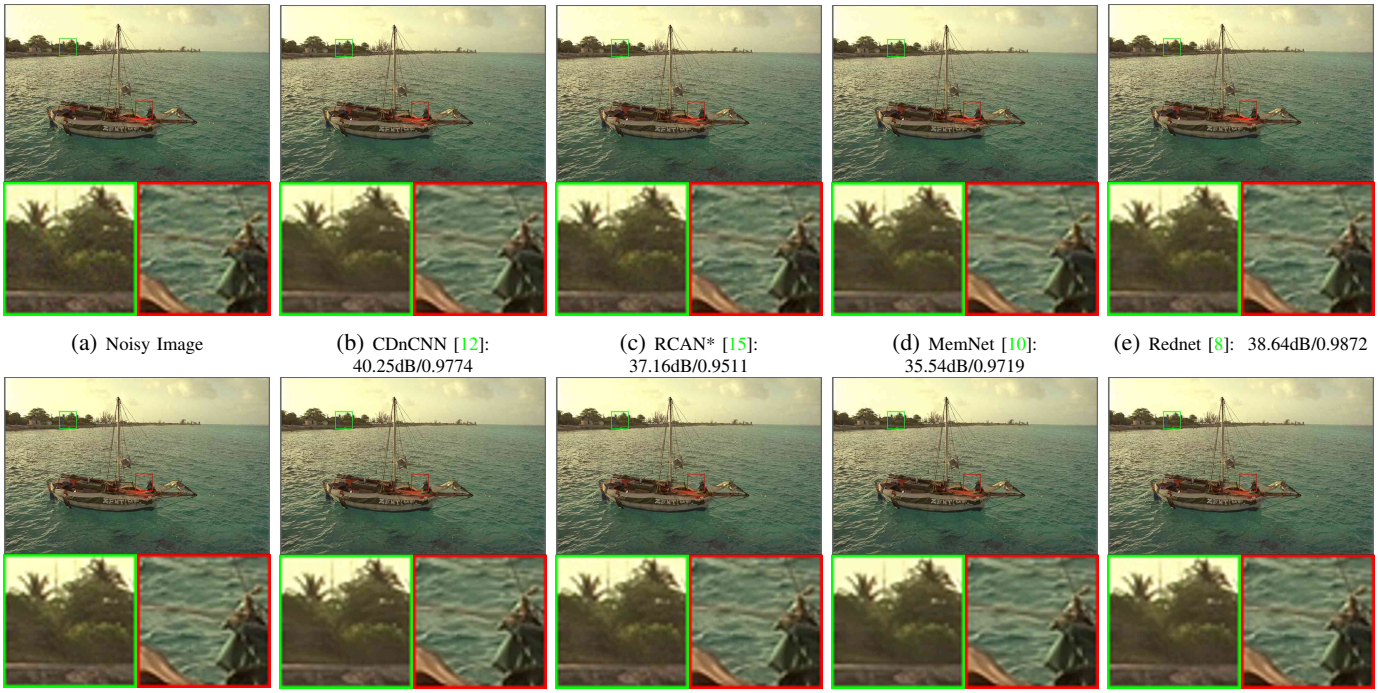
(f) Clean Image (g) CDnCNN [12]+NACPA: 35.40dB/0.9561 (h) RCAN* [15] + NACPA: 32.92dB/0.8933 (i) MemNet [10]+NACPA: 32.53dB/0.9656 (j) Rednet [8]+NACPA: 33.18dB/0.9750

Fig. 8: Denoising results of a typical images ("*YumeiroCooking.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 15$) on MANGA109 test set.

(a) Noisy Image (b) CDnCNN [12]: 33.35dB/0.9167 (c) RCAN* [15]: 29.40dB/0.7800 (d) MemNet [10]: 27.09dB/0.9296 (e) Rednet [8]: 31.06dB/0.9751

(f) Clean Image (g) CDnCNN [12]+NACPA: 35.30dB/0.9395 (h) RCAN* [15] + NACPA: 31.07dB/0.8220 (i) MemNet [10]+NACPA: 28.98dB/0.7516 (j) Rednet [8]+NACPA: 31.55dB/0.9711

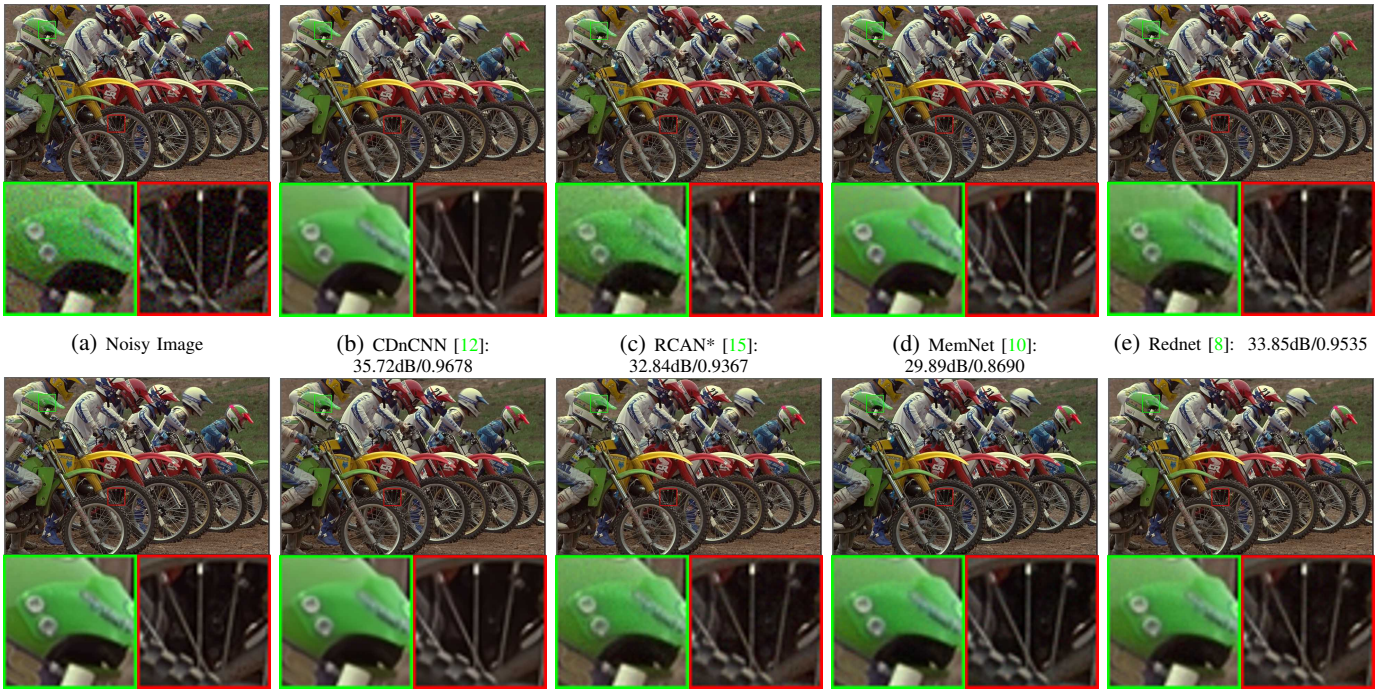
Fig. 9: Denoising results of a typical images ("*SonokiDeABC.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 20$) on MANGA109 test set.



(a) Noisy Image (b) CDnCNN [12]: 40.25dB/0.9774 (c) RCAN* [15]: 37.16dB/0.9511 (d) MemNet [10]: 35.54dB/0.9719 (e) Rednet [8]: 38.64dB/0.9872

(f) Clean Image (g) CDnCNN [12]+NACPA: 43.15dB/0.9859 (h) RCAN* [15] + NACPA: 41.24dB/0.9815 (i) MemNet [10]+NACPA: 39.90dB/0.9916 (j) Rednet [8]+NACPA: 41.53dB/0.9927

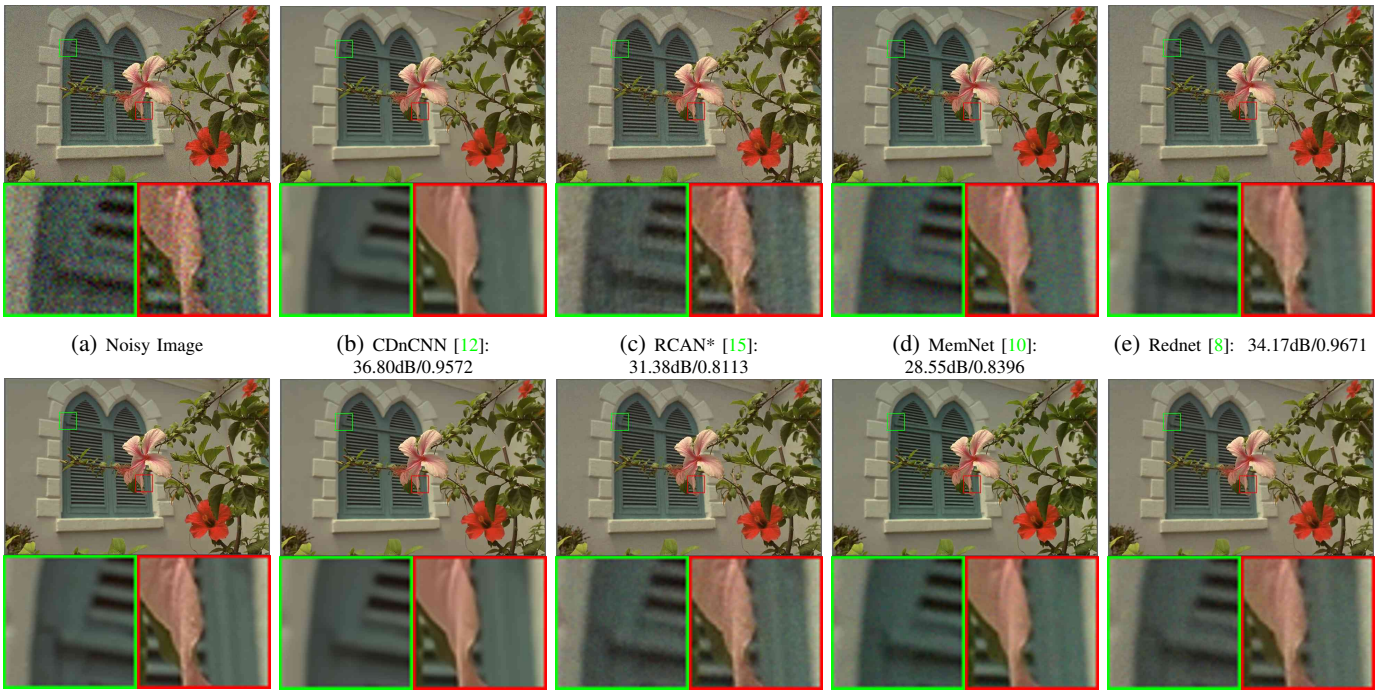
Fig. 10: Denoising results of a typical images ("*kodim06*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 5$) on Koda24 test set.



(a) Noisy Image (b) CDnCNN [12]: 35.72dB/0.9678 (c) RCAN* [15]: 32.84dB/0.9367 (d) MemNet [10]: 29.89dB/0.8690 (e) Rednet [8]: 33.85dB/0.9535

(f) Clean Image (g) CDnCNN [12]+NACPA: 39.45dB/0.9840 (h) RCAN* [15] + NACPA: 35.66dB/0.9648 (i) MemNet [10]+NACPA: 34.93dB/0.9655 (j) Rednet [8]+NACPA: 35.93dB/0.9627

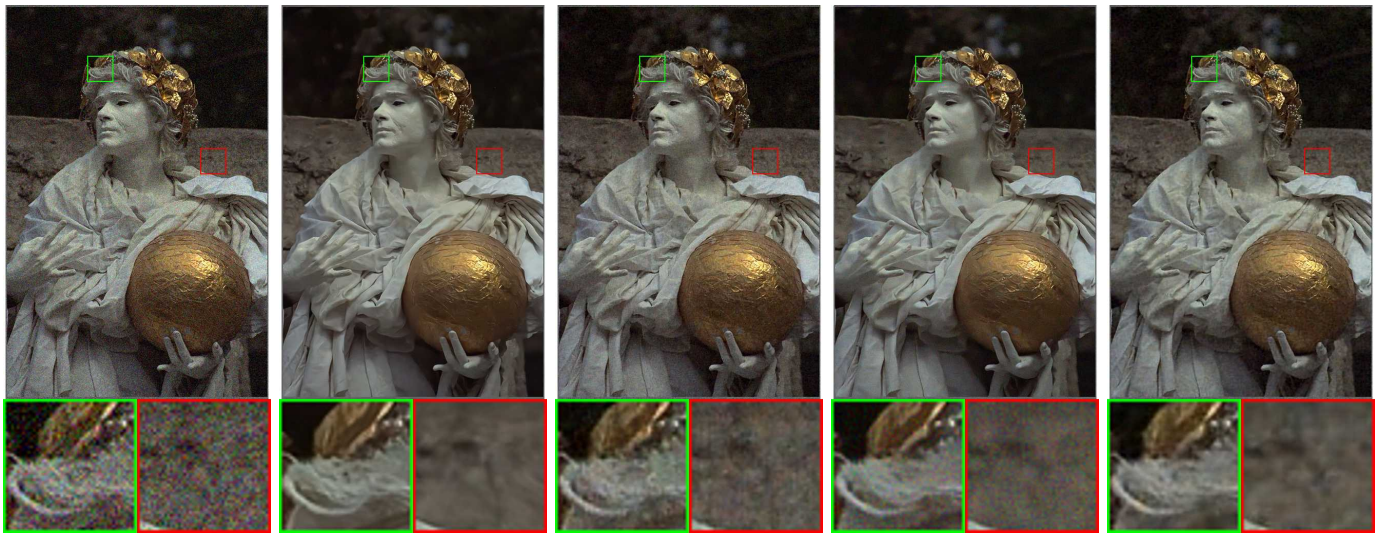
Fig. 11: Denoising results of a typical images ("*kodim05*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 10$) on Koda24 test set.



(a) Noisy Image (b) CDnCNN [12]: 36.80dB/0.9572 (c) RCAN* [15]: 31.38dB/0.8113 (d) MemNet [10]: 28.55dB/0.8396 (e) Rednet [8]: 34.17dB/0.9671

(f) Clean Image (g) CDnCNN [12]+NACPA: 39.08dB/0.9684 (h) RCAN* [15] + NACPA: 34.24dB/0.8736 (i) MemNet [10]+NACPA: 32.98dB/0.9483 (j) Rednet [8]+NACPA: 34.05dB/0.9568

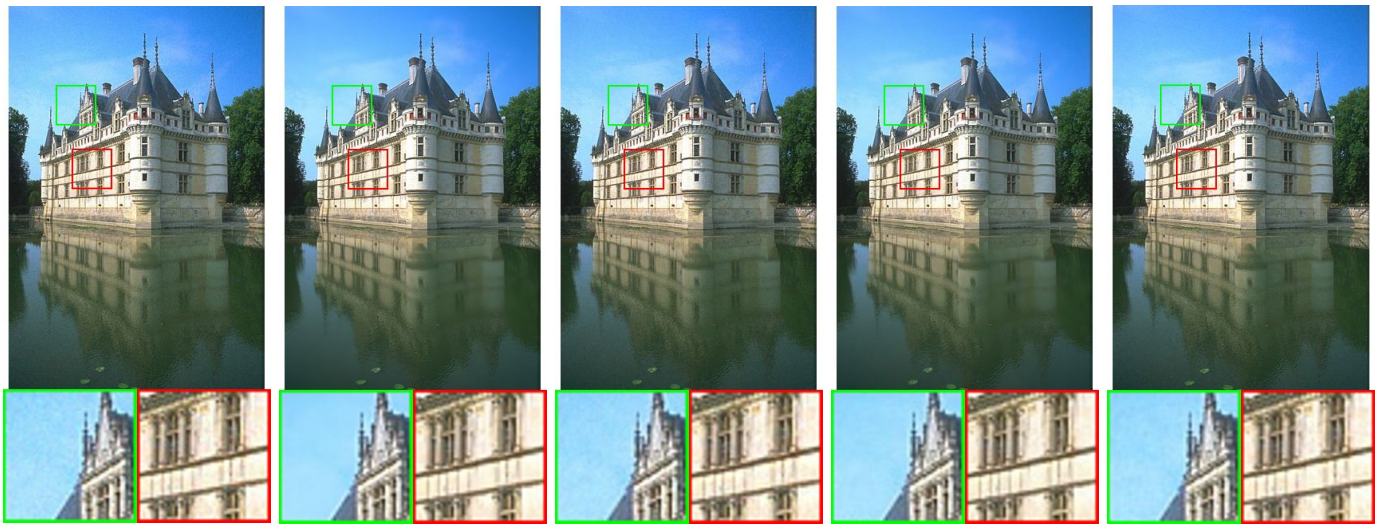
Fig. 12: Denoising results of a typical images ("*kodim07*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 15$) on Koda24 test set.



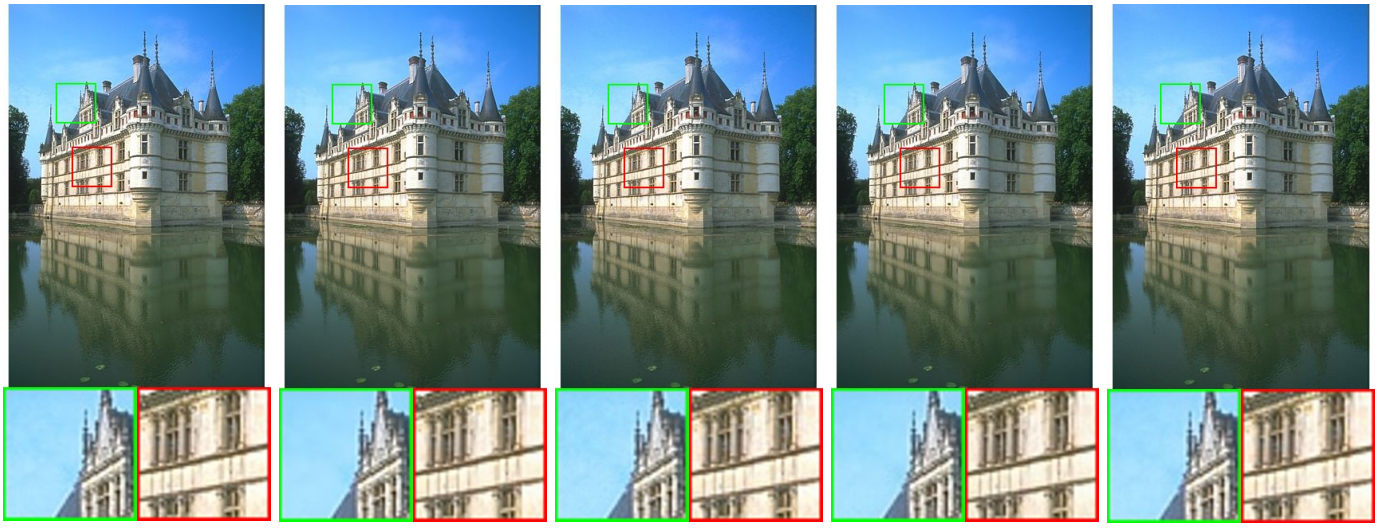
(a) Noisy Image (b) CDnCNN [12]: 34.36dB/0.9081 (c) RCAN* [15]: 30.39dB/0.7557 (d) MemNet [10]: 27.09dB/0.6358 (e) Rednet [8]: 31.93dB/0.8704

(f) Clean Image (g) CDnCNN [12]+NACPA: 37.30dB/0.9411 (h) RCAN* [15] + NACPA: 32.24dB/0.8075 (i) MemNet [10]+NACPA: 28.98dB/0.7443 (j) Rednet [8]+NACPA: 32.30dB/0.8564

Fig. 13: Denoising results of a typical images ("*kodim17*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 20$) on Koda24 test set.

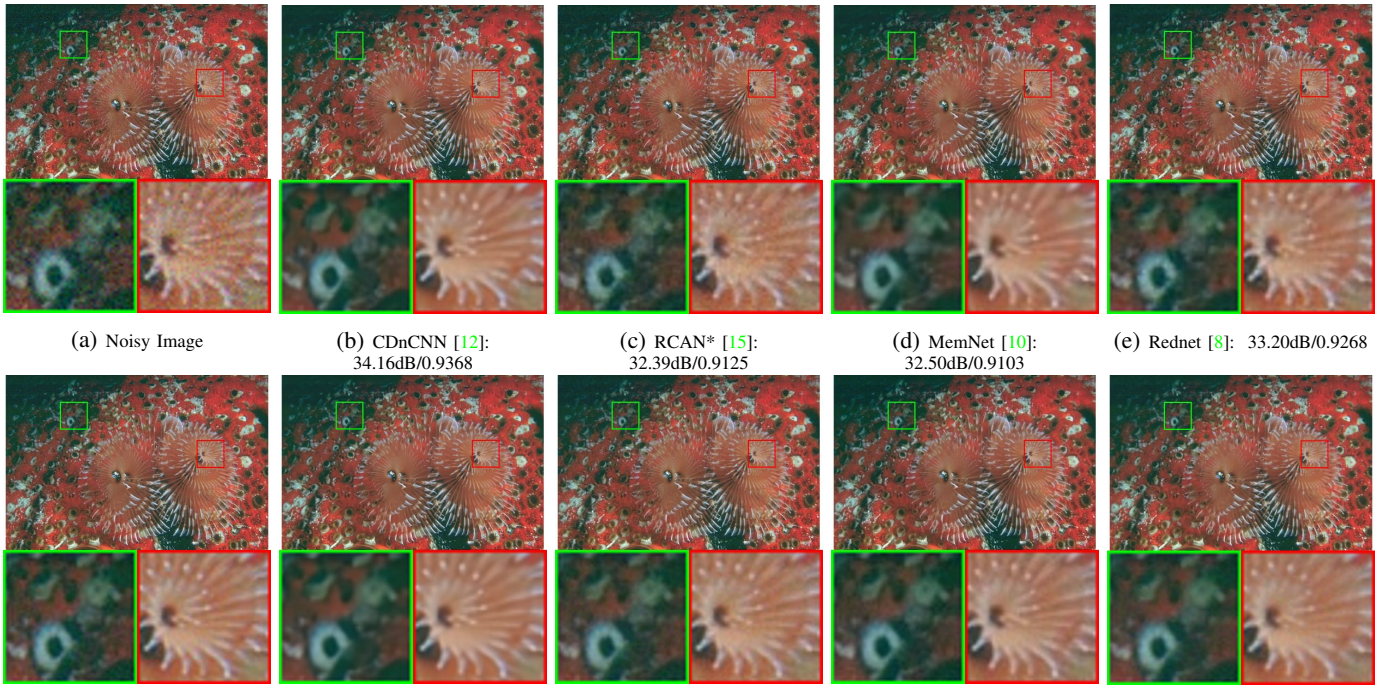


(a) Noisy Image (b) CDnCNN [12]: 40.83dB/0.9762 (c) RCAN* [15]: 37.11dB/0.9357 (d) MemNet [10]: 38.62dB/0.9845 (e) Rednet [8]: 38.95dB/0.9849



(f) Clean Image (g) CDnCNN [12]+NACPA: 43.52dB/0.9844 (h) RCAN* [15]+NACPA: 41.30dB/0.9756 (i) MemNet [10]+NACPA: 39.02dB/0.9875 (j) Rednet [8]+NACPA: 41.65dB/0.9941

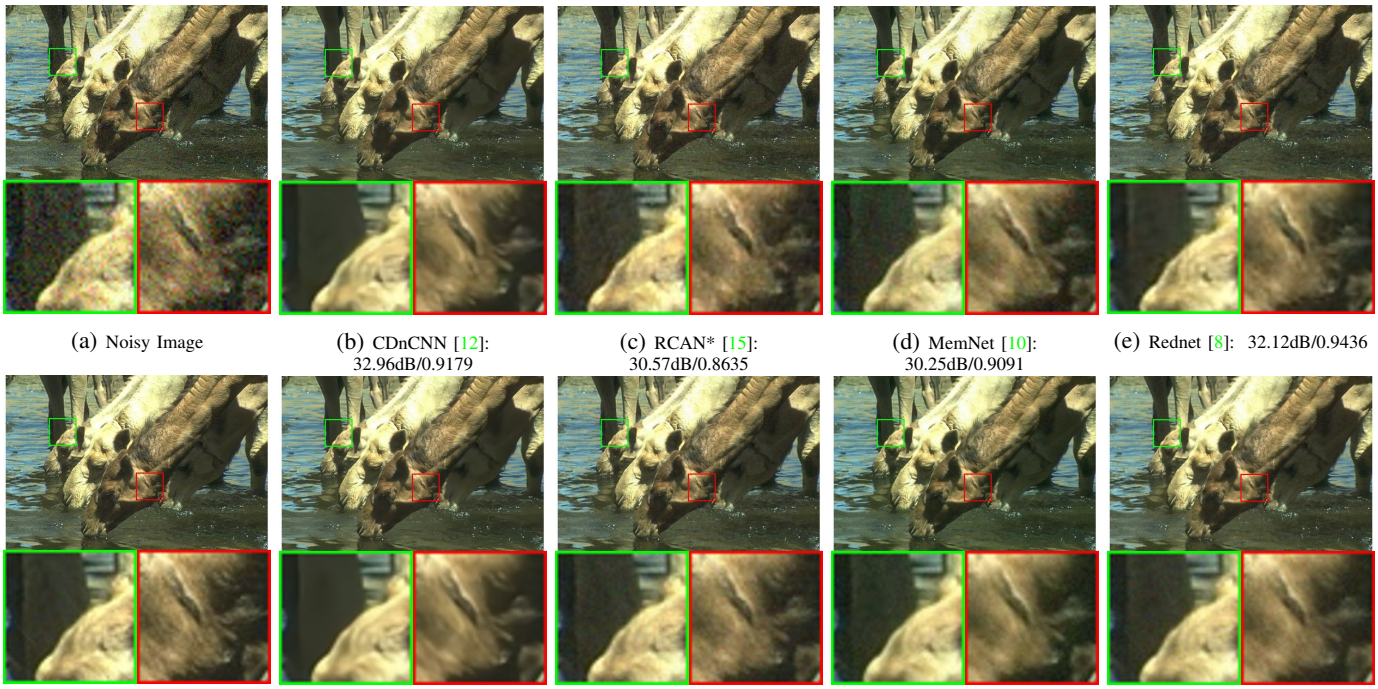
Fig. 14: Denoising results of a typical images ("*102061.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 5$) on CBSD68 test set.



(a) Noisy Image (b) CDnCNN [12]: 34.16dB/0.9368 (c) RCAN* [15]: 32.39dB/0.9125 (d) MemNet [10]: 32.50dB/0.9103 (e) Rednet [8]: 33.20dB/0.9268

(f) Clean Image (g) CDnCNN [12]+NACPA: 36.89dB/0.9596 (h) RCAN* [15]+NACPA: 35.54dB/0.9558 (i) MemNet [10]+NACPA: 34.08dB/0.9521 (j) Rednet [8]+NACPA: 35.24dB/0.9481

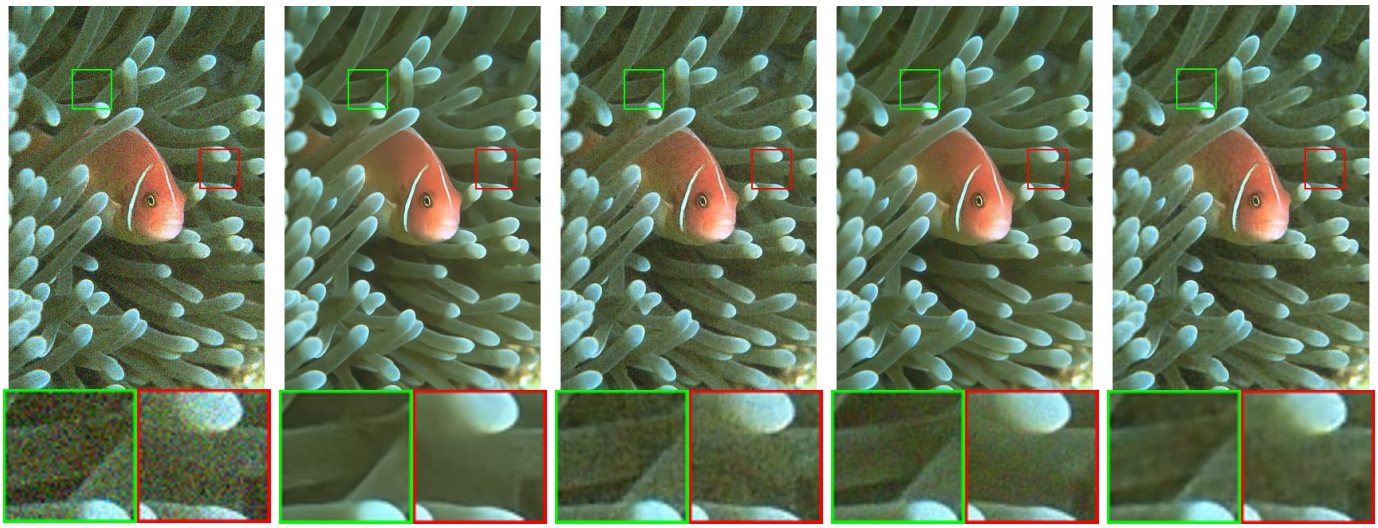
Fig. 15: Denoising results of a typical images ("*12084.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 10$) on CBSD68 test set.



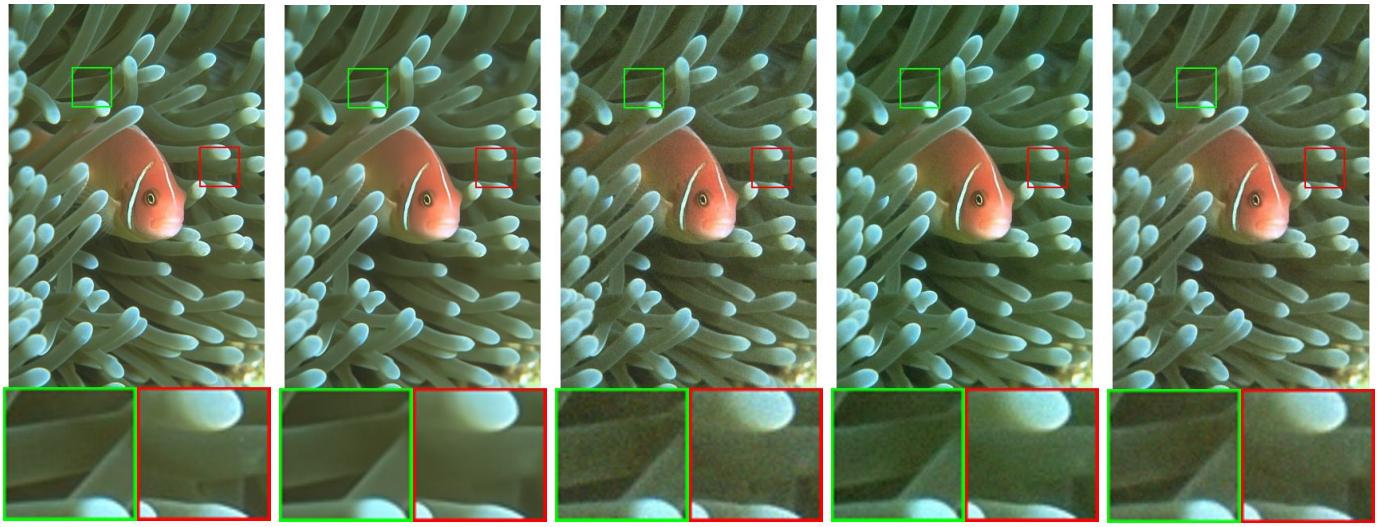
(a) Noisy Image (b) CDnCNN [12]: 32.96dB/0.9179 (c) RCAN* [15]: 30.57dB/0.8635 (d) MemNet [10]: 30.25dB/0.9091 (e) Rednet [8]: 32.12dB/0.9436

(f) Clean Image (g) CDnCNN [12]+NACPA: 34.91dB/0.9370 (h) RCAN* [15]+NACPA: 33.38dB/0.9090 (i) MemNet [10]+NACPA: 31.65dB/0.9435 (j) Rednet [8]+NACPA: 32.71dB/0.9453

Fig. 16: Denoising results of a typical images ("*16077.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 15$) on CBSD68 test set.

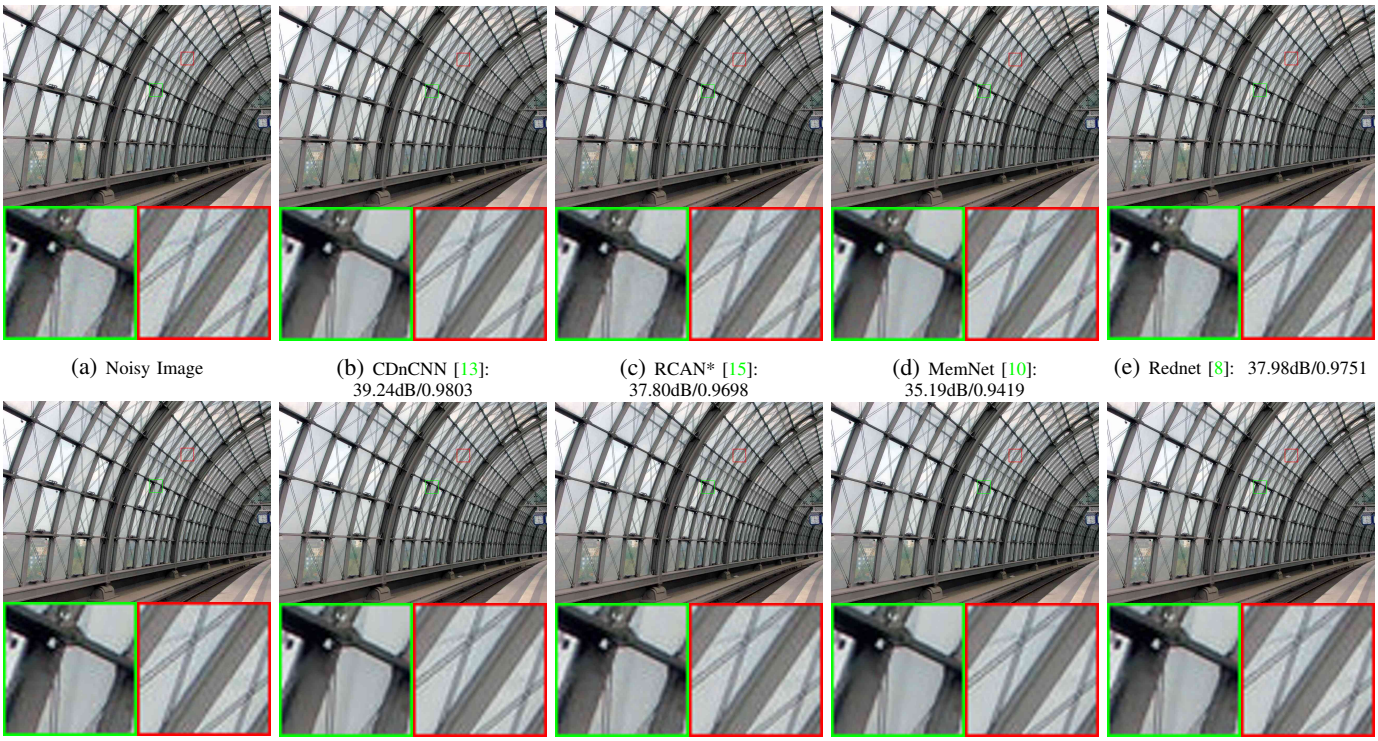


(a) Noisy Image (b) CDnCNN [12]: 34.85dB/0.9300 (c) RCAN* [15]: 29.94dB/0.7585 (d) MemNet [10]: 30.90dB/0.9288 (e) Rednet [8]: 32.44dB/0.9528



(f) Clean Image (g) CDnCNN [12]+NACPA: 37.53dB/0.9573 (h) RCAN* [15]+NACPA: 32.00dB/0.8210 (i) MemNet [10]+NACPA: 29.24dB/0.9332 (j) Rednet [8]+NACPA: 32.40dB/0.9411

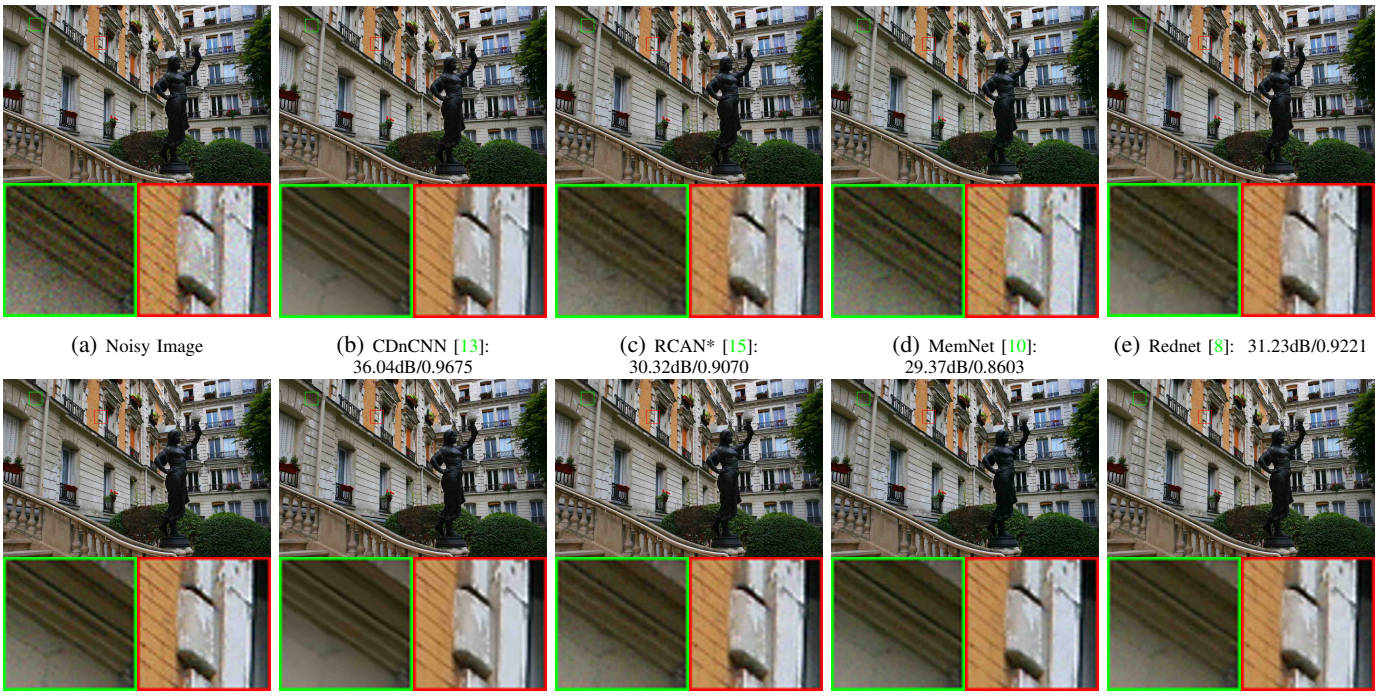
Fig. 17: Denoising results of a typical images ("*210088.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 20$) on CBSD68 test set.



(a) Noisy Image (b) CDnCNN [13]: 39.24dB/0.9803 (c) RCAN* [15]: 37.80dB/0.9698 (d) MemNet [10]: 35.19dB/0.9419 (e) Rednet [8]: 37.98dB/0.9751

(f) Clean Image (g) CDnCNN [12]+NACPA: 41.33dB/0.9859 (h) RCAN* [15]+NACPA: 40.65dB/0.9843 (i) MemNet [10]+NACPA: 39.15dB/0.9812 (j) Rednet [8]+NACPA: 41.13dB/0.9863

Fig. 18: Denoising results of a typical images ("*img _ 002.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 5$) on Urban100 test set.



(a) Noisy Image (b) CDnCNN [13]: 36.04dB/0.9675 (c) RCAN* [15]: 30.32dB/0.9070 (d) MemNet [10]: 29.37dB/0.8603 (e) Rednet [8]: 31.23dB/0.9221

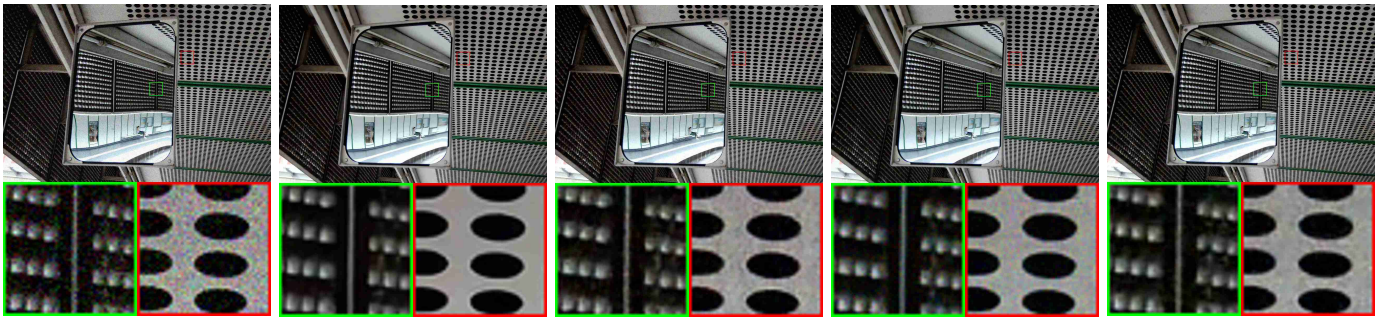
(f) Clean Image (g) CDnCNN [12]+NACPA: 33.73dB/0.9514 (h) RCAN* [15]+NACPA: 33.95dB/0.9557 (i) MemNet [10]+NACPA: 33.76dB/0.9504 (j) Rednet [8]+NACPA: 34.13dB/0.9535

Fig. 19: Denoising results of a typical images ("*img _ 003.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 10$) on Urban100 test set.

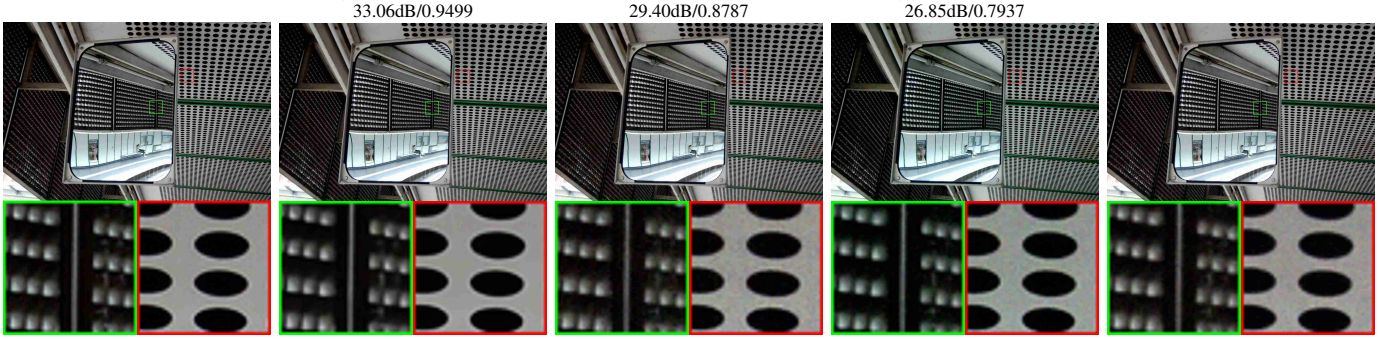
(a) Noisy Image (b) CDnCNN [13]: 34.05dB/0.9151 (c) RCAN* [15]: 28.96dB/0.7615 (d) MemNet [10]: 28.51dB/0.7632 (e) Rednet [8]: 31.86dB/0.8852

(f) Clean Image (g) CDnCNN [12]+NACPA: 35.69dB/0.9332 (h) RCAN* [15]+NACPA: 33.34dB/0.8928 (i) MemNet [10]+NACPA: 32.06dB/0.8888 (j) Rednet [8]+NACPA: 32.70dB/0.8980

Fig. 20: Denoising results of a typical images ("*img _ 001.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 15$) on Urban100 test set.

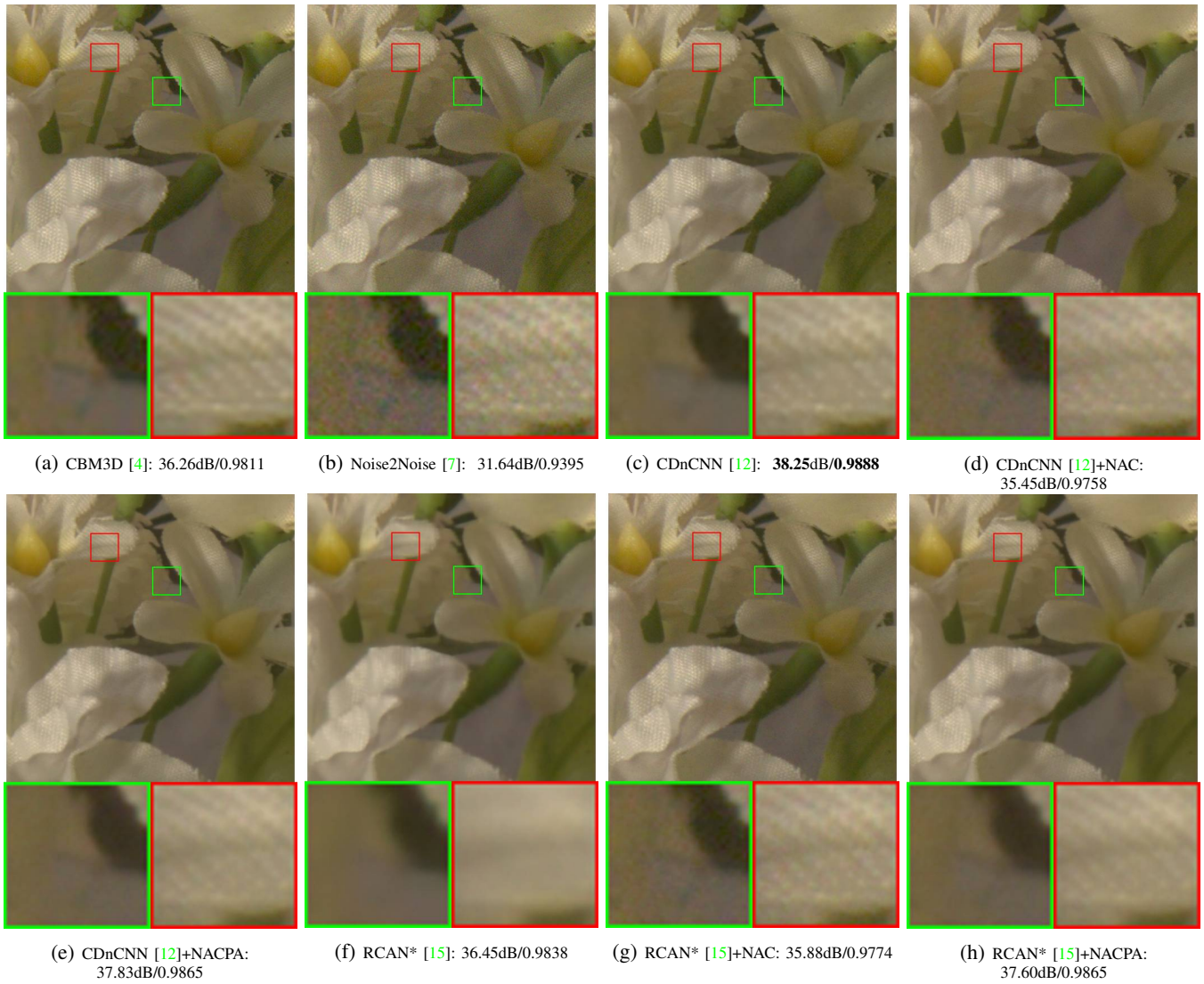


(a) Noisy Image (b) CDnCNN [13]: 33.06dB/0.9499 (c) RCAN* [15]: 29.40dB/0.8787 (d) MemNet [10]: 26.85dB/0.7937 (e) Rednet [8]: 30.26dB/0.9117



(f) Clean Image (g) CDnCNN [12]+NACPA: 35.63dB/0.9645 (h) RCAN* [15]+NACPA: 31.40dB/0.9059 (i) MemNet [10]+NACPA: 29.78dB/0.8795 (j) Rednet [8]+NACPA: 31.35dB/0.9086

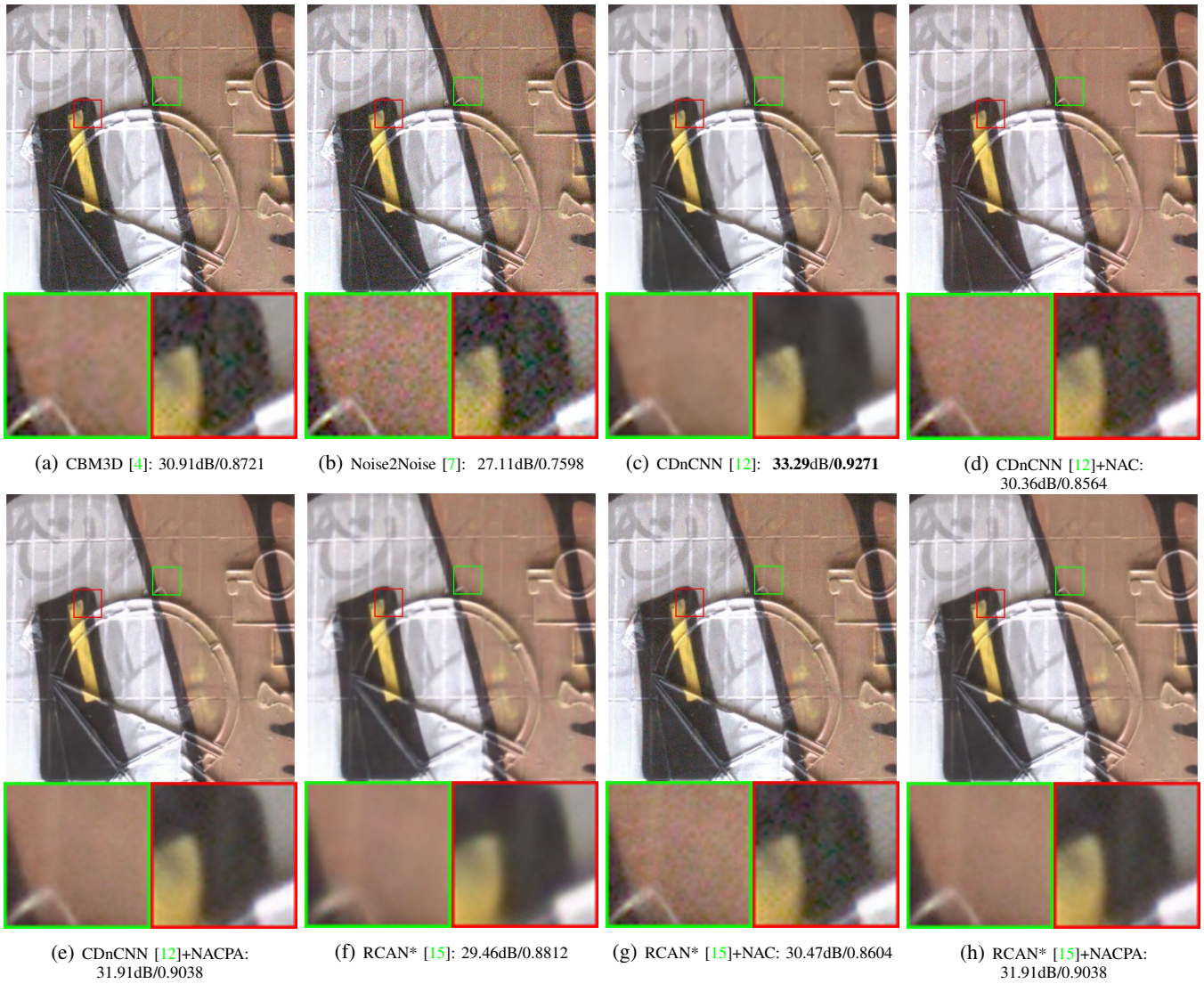
Fig. 21: Denoising results of a typical images ("*img _ 004.png*") of applied the proposed NACPA strategy on different denoising networks for AWGN denoising ($\sigma = 20$) on Urban100 test set.



(a) CBM3D [4]: 36.26dB/0.9811 (b) Noise2Noise [7]: 31.64dB/0.9395 (c) CDnCNN [12]: **38.25**dB/**0.9888** (d) CDnCNN [12]+NAC: 35.45dB/0.9758

(e) CDnCNN [12]+NACPA: 37.83dB/0.9865 (f) RCAN* [15]: 36.45dB/0.9838 (g) RCAN* [15]+NAC: 35.88dB/0.9774 (h) RCAN* [15]+NACPA: 37.60dB/0.9865

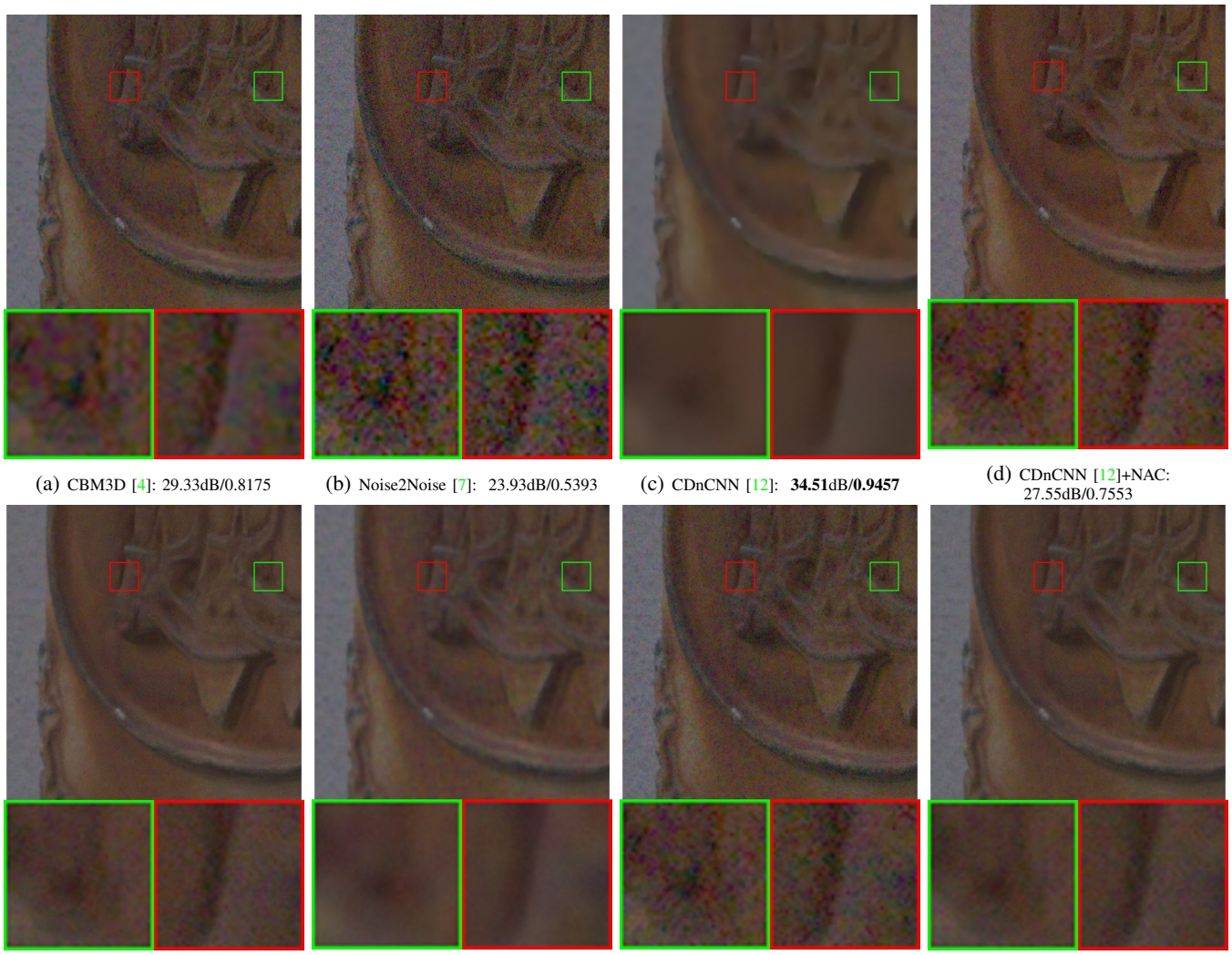
Fig. 22: Denoising results of image "*0017_3*" from DND [1] dataset of different methods. The ground-truth image is not released, but PSNR and SSIM [11] results are publicly provided on the *DND* Benchmark. The best PSNR and SSIM [11] results are highlighted in **bold**.



(a) CBM3D [4]: 30.91dB/0.8721 (b) Noise2Noise [7]: 27.11dB/0.7598 (c) CDnCNN [12]: **33.29**dB/**0.9271** (d) CDnCNN [12]+NAC: 30.36dB/0.8564

(e) CDnCNN [12]+NACPA: 31.91dB/0.9038 (f) RCAN* [15]: 29.46dB/0.8812 (g) RCAN* [15]+NAC: 30.47dB/0.8604 (h) RCAN* [15]+NACPA: 31.91dB/0.9038

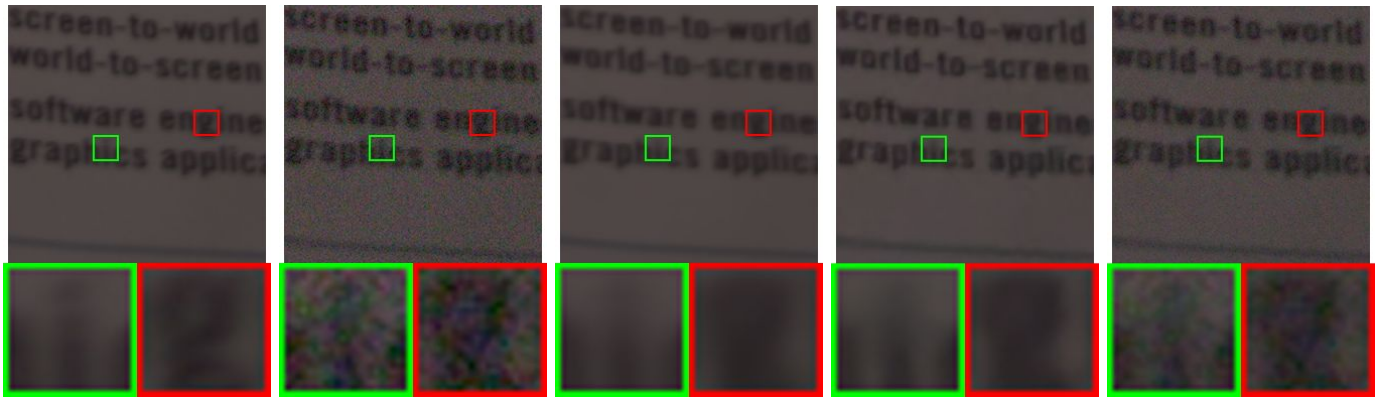
Fig. 23: Denoising results of image "*0002_19*" from DND [1] dataset of different methods. The ground-truth image is not released, but PSNR and SSIM [11] results are publicly provided on the *DND* Benchmark. The best PSNR and SSIM [11] results are highlighted in **bold**.



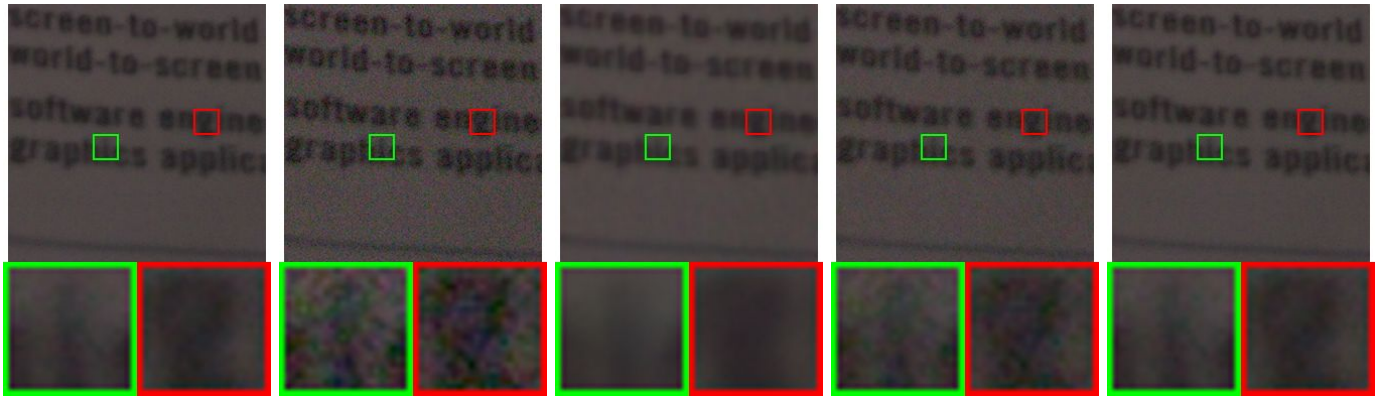
(a) CBM3D [4]: 29.33dB/0.8175 (b) Noise2Noise [7]: 23.93dB/0.5393 (c) CDnCNN [12]: **34.51**dB/**0.9457** (d) CDnCNN [12]+NAC: 27.55dB/0.7553

(e) CDnCNN [12]+NACPA: 32.67dB/0.8866 (f) RCAN* [15]: 35.20dB/0.9368 (g) RCAN* [15]+NAC: 28.71dB/0.7678 (h) RCAN* [15]+NACPA: 32.48dB/0.8913

Fig. 24: Denoising results of image "*0026_2*" from DND [1] dataset of different methods. The ground-truth image is not released, but PSNR and SSIM [11] results are publicly provided on the *DND* Benchmark. The best PSNR and SSIM [11] results are highlighted in **bold**.

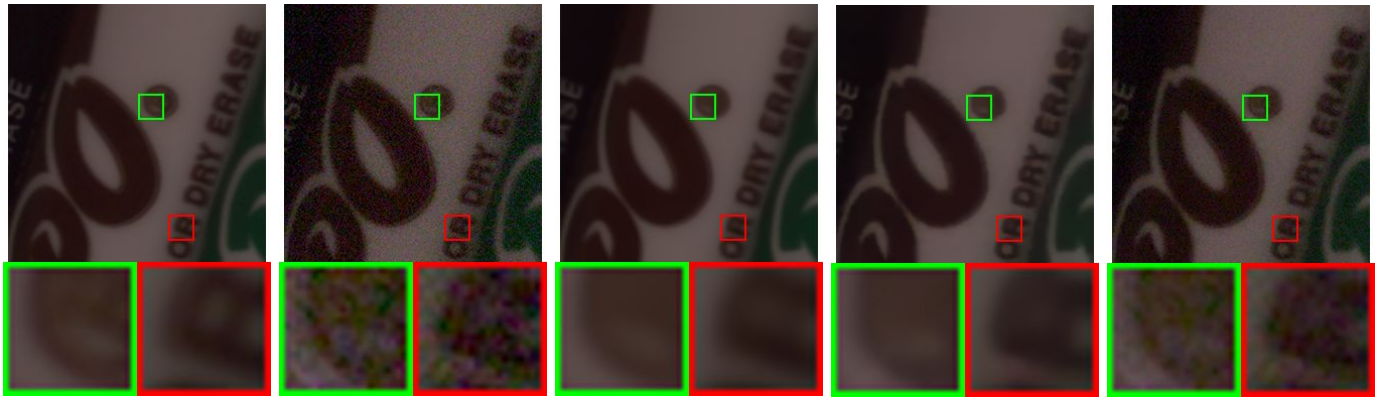


(a) Clean Image (b) Noisy Image (c) CBM3D [4]: 28.85dB/0.5386 (d) CDnCNN [12]: **42.50**dB/**0.9778** (e) CDnCNN [12] +NAC: 34.15dB/0.7972



(f) CDnCNN [12] + NACPA: 38.91dB/0.9257 (g) Noise2Noise [7]: 29.30dB/0.5723 (h) RCAN* [15]: 40.27dB/0.9595 (i) RCAN* [15]+NAC: 34.22dB/0.7959 (j) RCAN* [15]+NACPA: 38.48dB/0.9143

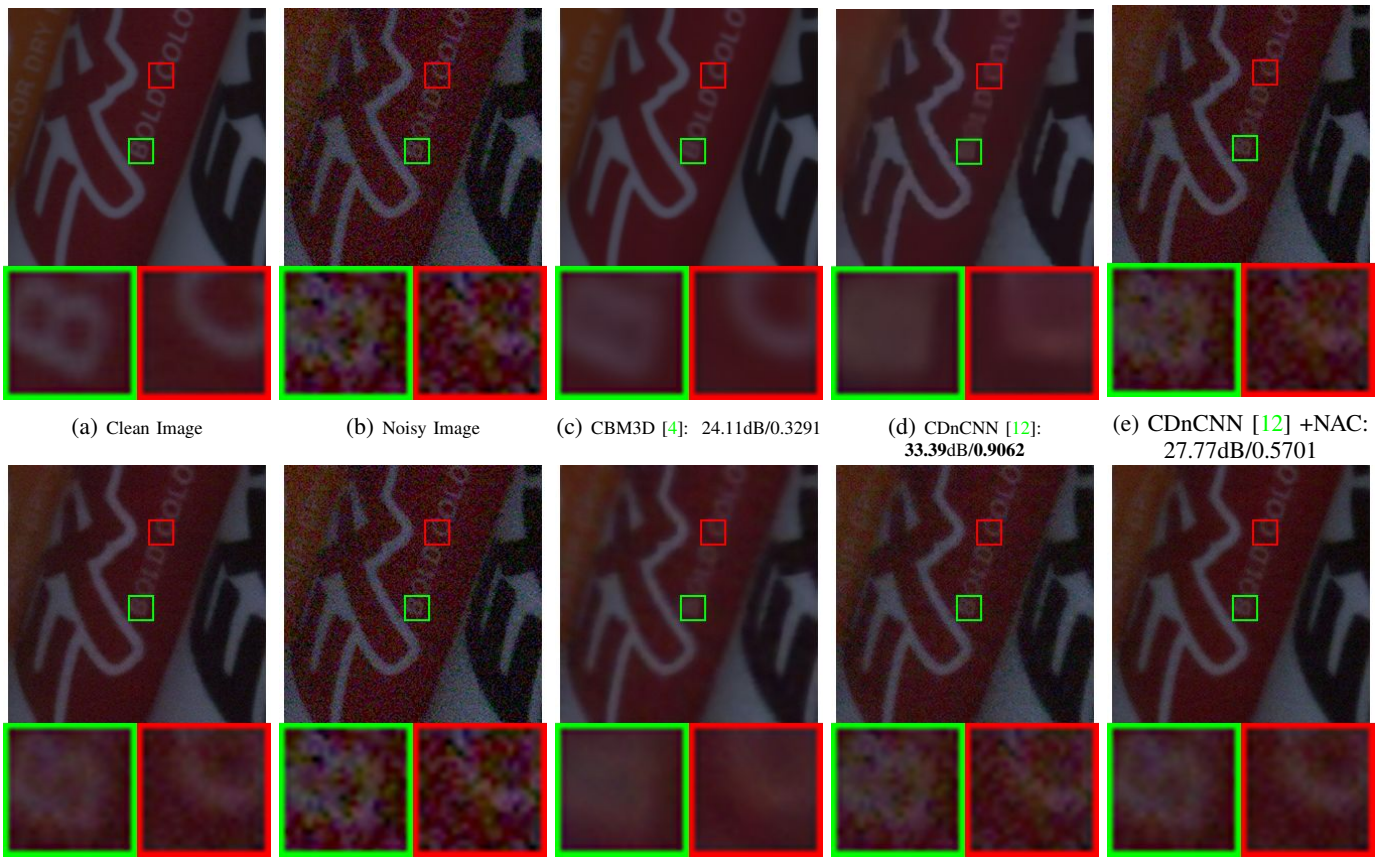
Fig. 25: Denoising results of image "*12_22*" from SIDD Validation set [3] of different methods. The best PSNR and SSIM [11] results are highlighted in **bold**.



(a) Clean Image (b) Noisy Image (c) CBM3D [4]: 27.59dB/0.5062 (d) CDnCNN [12]: **38.17**dB/**0.9653** (e) CDnCNN [12] +NAC: 32.01dB/0.7464

(f) CDnCNN [12] + NACPA: 36.90dB/0.9005 (g) Noise2Noise [7]: 27.91dB/0.5328 (h) RCAN* [15]: 36.98dB/0.9406 (i) RCAN* [15]+NAC: 32.78dB/0.7661 (j) RCAN* [15]+NACPA: 36.08dB/0.8809

Fig. 26: Denoising results of image "*8_23*" from SIDD Validation set [3] of different methods. The best PSNR and SSIM [11] results are highlighted in **bold**.



(a) Clean Image (b) Noisy Image (c) CBM3D [4]: 24.11dB/0.3291 (d) CDnCNN [12]: **33.39**dB/**0.9062** (e) CDnCNN [12] +NAC: 27.77dB/0.5701

(f) CDnCNN [12] + NACPA: 31.94dB/0.7907 (g) Noise2Noise [7]: 24.66dB/0.3746 (h) RCAN* [15]: 33.14dB/0.8760 (i) RCAN* [15]+NAC: 28.99dB/0.6105 (j) RCAN* [15]+NACPA: 31.37dB/0.7680

Fig. 27: Denoising results of image "*31_21*" from SIDD Validation set [3] of different methods. The best PSNR and SSIM [11] results are highlighted in **bold**.

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