

000 054
 001 055
 002 056
 003 057
 004 058
 005 059
 006 060
 007 061
 008 062
 009 063
 010 064
 011 065
 012 066
 013 067
 014 068
 015 069
 016 070
 017 071
 018 072
 019 073
 020 074
 021 075
 022 076
 023 077
 024 078
 025 079
 026 080
 027 081
 028 082
 029 083
 030 084
 031 085
 032 086
 033 087
 034 088
 035 089
 036 090
 037 091
 038 092
 039 093
 040 094
 041 095
 042 096
 043 097
 044 098
 045 099
 046 100
 047 101
 048 102
 049 103
 050 104
 051 105
 052 106
 053 107

Supplementary File to “Multi-channel Weighted Nuclear Norm Minimization for Real Color Image Denoising”

Anonymous ICCV submission

Paper ID 572

In this supplementary file, we provide:

1. The proof of the Theorem 1 in the main paper.
2. More denoising results on the 24 high quality images from the Kodak PhotoCD dataset.
3. More visual comparisons of denoised images by different methods on the real noisy images of the dataset [1].
4. More visual comparisons of denoised images by different methods on the real noisy images of the dataset [2].

1. Proof of Theorem 1.

Theorem 1. Assume that the weights in w are in a non-descending order, the sequence $\{\mathbf{X}_k\}$, $\{\mathbf{Z}_k\}$, and $\{\mathbf{A}_k\}$ generated in Algorithm 1 satisfy:

$$(a) \lim_{k \rightarrow \infty} \|\mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F = 0; \quad (b) \lim_{k \rightarrow \infty} \|\mathbf{X}_{k+1} - \mathbf{X}_k\|_F = 0; \quad (c) \lim_{k \rightarrow \infty} \|\mathbf{Z}_{k+1} - \mathbf{Z}_k\|_F = 0. \quad (1)$$

Proof. 1. Firstly, we prove that the sequence $\{\mathbf{A}_k\}$ generated by Algorithm 1 is upper bounded. Let $\mathbf{X}_{k+1} + \rho_k^{-1} \mathbf{A}_k = \mathbf{U}_k \Sigma_k \mathbf{V}_k^\top$ be its singular value decomposition (SVD) [3] in the $(k+1)$ -th iteration. According to Corollary 1 of [4], we can have the SVD of \mathbf{Z}_{k+1} as $\mathbf{Z}_{k+1} = \mathbf{U}_k \hat{\Sigma}_k \mathbf{V}_k^\top = \mathbf{U}_k \mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k) \mathbf{V}_k^\top$. Then we have

$$\|\mathbf{A}_{k+1}\|_F = \|\mathbf{A}_k + \rho_k(\mathbf{X}_{k+1} - \mathbf{Z}_{k+1})\|_F = \rho_k \|\rho_k^{-1} \mathbf{A}_k + \mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F \quad (2)$$

$$= \rho_k \|\mathbf{U}_k \Sigma_k \mathbf{V}_k^\top - \mathbf{U}_k \mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k) \mathbf{V}_k^\top\|_F = \rho_k \|\Sigma_k - \mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k)\|_F \quad (3)$$

$$= \rho_k \sqrt{\sum_i (\Sigma_k^{ii} - \mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k^{ii}))^2} \leq \rho_k \sqrt{\sum_i \left(\frac{w_i}{\rho_k}\right)^2} = \sqrt{\sum_i w_i^2}. \quad (4)$$

The inequality in the second last step can be proved as follows: given the diagonal matrix Σ_k , we define Σ_k^{ii} as the i -th element of Σ_k^{ii} . If $\Sigma_k^{ii} \geq \frac{w_i}{\rho_k}$, we have $\mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k^{ii}) = \Sigma_k^{ii} - \frac{w_i}{\rho_k} \geq 0$. If $\Sigma_k^{ii} < \frac{w_i}{\rho_k}$, we have $\mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k^{ii}) = 0 < \Sigma_k^{ii} + \frac{w_i}{\rho_k}$. After all, we have $|\Sigma_k^{ii} - \mathcal{S}_{\frac{w}{\rho_k}}(\Sigma_k^{ii})| \leq \frac{w_i}{\rho_k}$ and hence the inequality holds true. Hence, the sequence $\{\mathbf{A}_k\}$ is upper bounded.

2. Secondly, we prove that the sequence of Lagrangian function $\{\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k)\}$ is also upper bounded. Since the global optimal solution of \mathbf{X} and \mathbf{Z} in corresponding subproblems, we always have $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k) \leq \mathcal{L}(\mathbf{X}_k, \mathbf{Z}_k, \mathbf{A}_k, \rho_k)$. Based on the updating rule that $\mathbf{A}_{k+1} = \mathbf{A}_k + \rho_k(\mathbf{X}_{k+1} - \mathbf{Z}_{k+1})$, we have $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_{k+1}, \rho_{k+1}) = \mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k) + \langle \mathbf{A}_{k+1} - \mathbf{A}_k, \mathbf{X}_{k+1} - \mathbf{Z}_{k+1} \rangle + \frac{\rho_{k+1} - \rho_k}{2} \|\mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F^2 = \mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k) + \frac{\rho_{k+1} + \rho_k}{2\rho_k^2} \|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F^2$. Since the sequence $\{\|\mathbf{A}_k\|_F\}$ is upper bounded, the sequence $\{\|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F\}$ is also upper bounded. Denote by a the upper bound of $\{\|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F\}$, we have $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_{k+1}, \rho_{k+1}) \leq \mathcal{L}(\mathbf{X}_1, \mathbf{Z}_1, \mathbf{A}_0, \rho_0) + a \sum_{k=0}^{\infty} \frac{\rho_{k+1} + \rho_k}{2\rho_k^2} = \mathcal{L}(\mathbf{X}_1, \mathbf{Z}_1, \mathbf{A}_0, \rho_0) + a \sum_{k=0}^{\infty} \frac{\mu+1}{2\mu^k \rho_0} \leq \mathcal{L}(\mathbf{X}_1, \mathbf{Z}_1, \mathbf{A}_0, \rho_0) + \frac{a}{\rho_0} \sum_{k=0}^{\infty} \frac{1}{\mu^{k-1}}$. The last inequality holds since $\mu+1 < 2\mu$. Since $\sum_{k=0}^{\infty} \frac{1}{\mu^{k-1}} < \infty$, the sequence of Lagrangian function $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_{k+1}, \rho_{k+1})$ is upper bound.

3. Thirdly, we prove that the sequences of $\{\mathbf{X}_k\}$ and $\{\mathbf{Z}_k\}$ are upper bounded. Since $\|\mathbf{W}(\mathbf{Y} - \mathbf{X})\|_F^2 + \|\mathbf{Z}\|_{w,*} = \mathcal{L}(\mathbf{X}_k, \mathbf{Z}_k, \mathbf{A}_{k-1}, \rho_{k-1}) - \langle \mathbf{A}_k, \mathbf{X}_k - \mathbf{Z}_k \rangle - \frac{\rho_k}{2} \|\mathbf{X}_k - \mathbf{Z}_k\|_F^2 = \mathcal{L}(\mathbf{X}_k, \mathbf{Z}_k, \mathbf{A}_{k-1}, \rho_{k-1}) + \frac{1}{2\rho_k} (\|\mathbf{A}_{k-1}\|_F^2 - \|\mathbf{A}_k\|_F^2)$. Thus $\{\mathbf{W}(\mathbf{Y} - \mathbf{X}_k)\}$ and $\{\mathbf{Z}_k\}$ are upper bounded, and hence the sequence $\{\mathbf{X}_k\}$ is bounded by the Cauchy-Schwarz inequality

Table 1. PSNR(dB) results of different denoising methods on 24 natural images.

Image#	$\sigma_r = 5, \sigma_g = 30, \sigma_b = 15$								
	CBM3D	MLP	TNRD	NI	NC	WNNM-1	WNNM-2	WNNM-3	MC-WNNM
1	27.25	28.06	28.62	25.00	29.55	28.91	27.95	28.15	
2	29.70	31.30	32.70	27.80	29.69	33.23	31.60	31.73	
3	30.34	31.98	34.07	28.02	31.93	34.60	33.68	33.52	
4	29.47	31.10	32.56	27.70	32.56	33.23	31.85	31.90	
5	27.31	28.59	29.35	26.14	30.00	29.70	29.00	28.91	
6	28.20	29.10	29.90	26.15	28.81	30.38	29.46	29.62	
7	29.73	31.60	33.46	27.22	31.63	33.85	33.29	32.86	
8	27.47	28.16	28.91	25.34	30.16	29.89	29.24	29.03	
9	30.07	31.63	33.55	27.86	31.54	33.88	33.20	32.95	
10	29.96	31.37	33.20	27.74	33.44	33.74	33.02	32.74	
11	28.73	29.85	30.87	26.98	30.16	31.22	30.14	30.21	
12	30.20	31.50	33.31	27.97	31.69	33.80	32.71	32.65	
13	26.18	26.69	26.98	25.14	27.97	27.27	26.42	26.62	
14	27.86	29.07	29.87	26.67	29.21	30.17	29.14	29.30	
15	29.91	31.58	33.13	28.04	31.17	33.71	32.34	32.36	
16	29.29	30.35	31.54	27.46	32.18	32.12	31.05	31.21	
17	29.50	31.09	32.52	27.81	32.80	32.77	32.00	31.85	
18	27.72	28.74	29.36	26.57	28.63	29.73	28.76	28.89	
19	28.98	30.18	31.35	27.25	29.79	31.98	30.77	30.95	
20	30.63	31.78	33.27	27.89	29.52	33.62	32.55	32.58	
21	28.50	29.58	30.54	26.86	31.71	30.80	30.03	30.03	
22	28.61	29.78	30.82	27.19	30.50	31.19	29.82	30.10	
23	30.60	32.66	35.06	28.17	32.82	35.23	34.37	33.94	
24	27.97	28.81	29.61	26.01	30.75	30.25	29.35	29.39	
Average	28.92	30.19	31.44	27.04	30.76	31.89	30.91	30.89	32.70

and triangle inequality. We can obtain that $\lim_{k \rightarrow \infty} \|\mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F = \lim_{k \rightarrow \infty} \rho_k^{-1} \|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F = 0$ and the equation (a) is proved.

4. Then we can prove that $\lim_{k \rightarrow \infty} \|\mathbf{X}_{k+1} - \mathbf{X}_k\|_F = \lim_{k \rightarrow \infty} \|(\mathbf{W}^\top \mathbf{W} + \frac{\rho_k}{2} \mathbf{I})^{-1} (\mathbf{W}^\top \mathbf{W} \mathbf{Y} - \mathbf{W}^\top \mathbf{W} \mathbf{Z}_k - \frac{1}{2} \mathbf{A}_k) - \rho_k^{-1} (\mathbf{A}_k - \mathbf{A}_{k-1})\|_F \leq \lim_{k \rightarrow \infty} \|(\mathbf{W}^\top \mathbf{W} + \frac{\rho_k}{2} \mathbf{I})^{-1} (\mathbf{W}^\top \mathbf{W} \mathbf{Y} - \mathbf{W}^\top \mathbf{W} \mathbf{Z}_k - \frac{1}{2} \mathbf{A}_k)\|_F + \rho_k^{-1} \|\mathbf{A}_k - \mathbf{A}_{k-1}\|_F = 0$ and hence (b) is proved.

5. Finally, (c) can be proved by checking that $\lim_{k \rightarrow \infty} \|\mathbf{Z}_{k+1} - \mathbf{Z}_k\|_F = \lim_{k \rightarrow \infty} \|\mathbf{X}_k + \rho_k^{-1} \mathbf{A}_{k-1} - \mathbf{Z}_k + \mathbf{X}_{k+1} - \mathbf{X}_k + \rho_k^{-1} \mathbf{A}_{k-1} + \rho_k^{-1} \mathbf{A}_k - \rho_k^{-1} \mathbf{A}_{k+1}\|_F \leq \lim_{k \rightarrow \infty} \|\Sigma_{k-1} - \mathcal{S}_{w/\rho_{k-1}}(\Sigma_{k-1})\|_F + \|\mathbf{X}_{k+1} - \mathbf{X}_k\|_F + \rho_k^{-1} \|\mathbf{A}_{k-1} + \mathbf{A}_{k+1} - \mathbf{A}_k\|_F = 0$, where $\mathbf{U}_{k-1} \Sigma_{k-1} \mathbf{V}_{k-1}^\top$ is the SVD of the matrix $\mathbf{X}_k + \rho_{k-1} \mathbf{A}_{k-1}$. \square

2. More denoising results on the 24 high quality images from the Kodak PhotoCD dataset

In the main paper, we have given the PSNR results of the competing methods on the 24 high quality images from the Kodak PhotoCD dataset when the noise standard deviations are $\sigma_r = 40, \sigma_g = 20, \sigma_b = 30$. Here we provide more denoising results on this dataset. In Tables ??-??, we give more PSNR results on these images when the noise standard deviations are $\sigma_r = 5, \sigma_g = 30, \sigma_b = 15$ in Table 1 and $\sigma_r = 30, \sigma_g = 10, \sigma_b = 50$ in Table 2, respectively. In Figures 1-??, we give the visual comparisons of the denoised images by different methods.

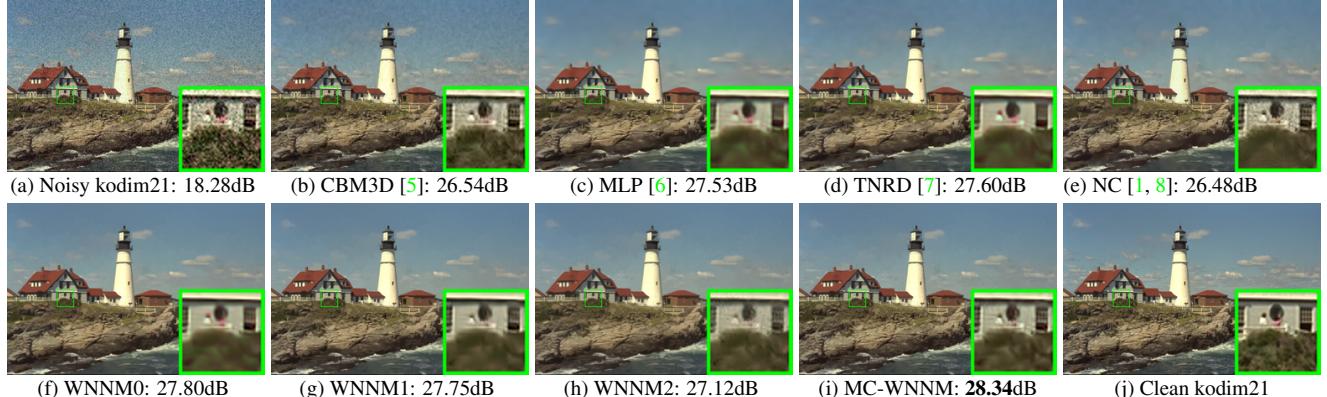
Fig. 1 shows a scene denoised by the compared methods. We can see that the methods of CBM3D and NC would remain some noise on the recovered images. The methods of MLP, TNRD, and “WNNM0”, which process separately the channels of color images, would over-smooth the images and generate false colors or artifacts. The method “WNNM1”, which process jointly the channels of color images, would not generate false colors, but still over-smooth the image. The “WNNM2”, which is the WNNM model solved by ADMM algorithm, would remain some noise on the image. By employing the proposed MC-WNNM model, our method preserves the structures (e.g., textures in windows and grass) better across the R, G, B channels and generate less artifacts than other denoising methods, leading to visually pleasant outputs.

3. More visual comparisons of denoised images by different methods on the real noisy images of the dataset [1]

In this section, we give more comparisons of the state-of-the-art denoising methods on the dataset [1]. The real noisy images in dataset [1] have no “ground truth” images and hence we only compare the visual quality of the denoised images

Table 2. PSNR(dB) results of different denoising methods on 24 natural images.

Image#	CBM3D	MLP	TNRD	NI	NC	WNNM-1	WNNM-2	WNNM-3	MC-WNNM
1	23.38	26.49	26.50	24.82	23.59	26.40	25.60		
2	25.19	30.94	30.90	26.82	27.79	30.89	29.75		
3	25.39	32.03	32.09	27.52	27.41	32.20	31.17		
4	24.96	30.55	30.47	27.34	27.00	30.74	29.71		
5	23.29	26.65	26.73	25.72	26.67	26.74	25.98		
6	24.09	27.76	27.70	26.10	26.12	27.85	26.96		
7	24.89	30.70	30.72	27.17	28.07	30.91	29.94		
8	23.30	26.12	26.27	25.59	26.11	26.87	26.33		
9	25.20	31.35	31.31	27.74	28.33	31.30	30.45		
10	25.13	31.01	31.05	27.60	28.53	31.12	30.17		
11	24.54	28.79	28.82	26.72	24.40	28.73	27.79		
12	25.43	31.60	31.60	27.82	29.01	31.59	30.62		
13	22.50	24.71	24.73	24.96	23.36	24.70	23.85		
14	23.91	27.69	27.72	26.26	23.08	27.62	26.81		
15	25.45	31.09	31.05	27.36	28.49	31.29	30.21		
16	24.89	29.79	29.73	27.35	27.10	29.84	28.85		
17	25.12	30.26	30.24	27.15	27.54	30.11	29.35		
18	23.83	27.26	27.26	26.05	26.15	27.32	26.18		
19	24.63	29.40	29.39	27.06	27.41	29.78	28.87		
20	26.43	31.16	31.27	26.43	26.92	31.25	30.43		
21	24.24	28.26	28.27	26.66	27.18	28.22	27.45		
22	24.51	29.03	29.06	26.83	27.64	29.02	27.81		
23	25.55	32.87	32.75	27.60	23.75	32.58	31.46		
24	23.85	27.06	27.13	25.86	27.05	27.50	26.63		
Average	24.57	29.27	29.28	26.69	26.61	29.36	28.43		29.90

Figure 1. Denoised images of different methods on the image “kodim21” degraded by AWGN with different standard derivations of $\sigma_r = 40, \sigma_g = 20, \sigma_b = 30$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

by different methods. As can be seen from Figures 2-5, our proposed method performs better than the competing methods.

4. More visual comparisons of denoised images by different methods on the real noisy images of the dataset [2]

In this section, we provide more comparisons of the proposed method with the state-of-the-art denoising methods on the 15 cropped real noisy images used in [2]. In this dataset, each scene was shot 500 times under the same camera and camera setting. The mean image of the 500 shots is roughly taken as the “ground truth”, with which the PSNR can be computed. As can be seen from Figures 6-10, in most cases, our proposed method achieves better performance than the the competing methods. This validates the effectiveness of our proposed external prior guided internal prior learning framework for real noisy image denoising.

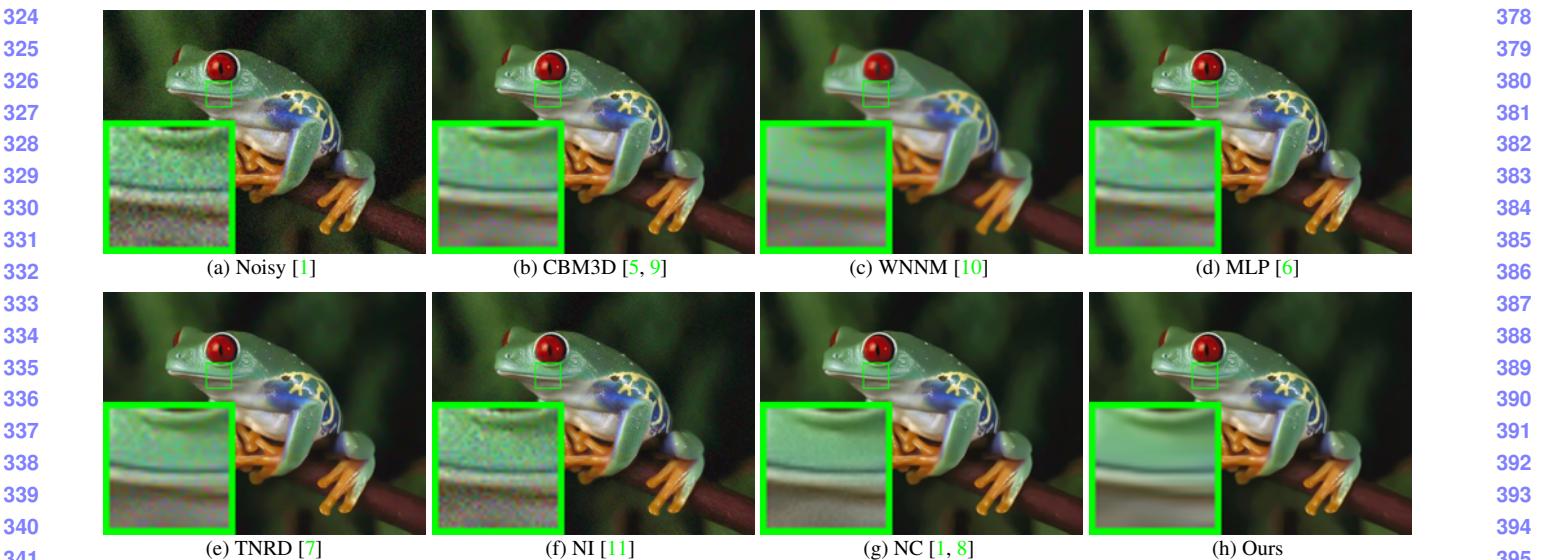


Figure 2. Denoised images of the real noisy image “Frog” [1] by different methods. The images are better to be zoomed in on screen.

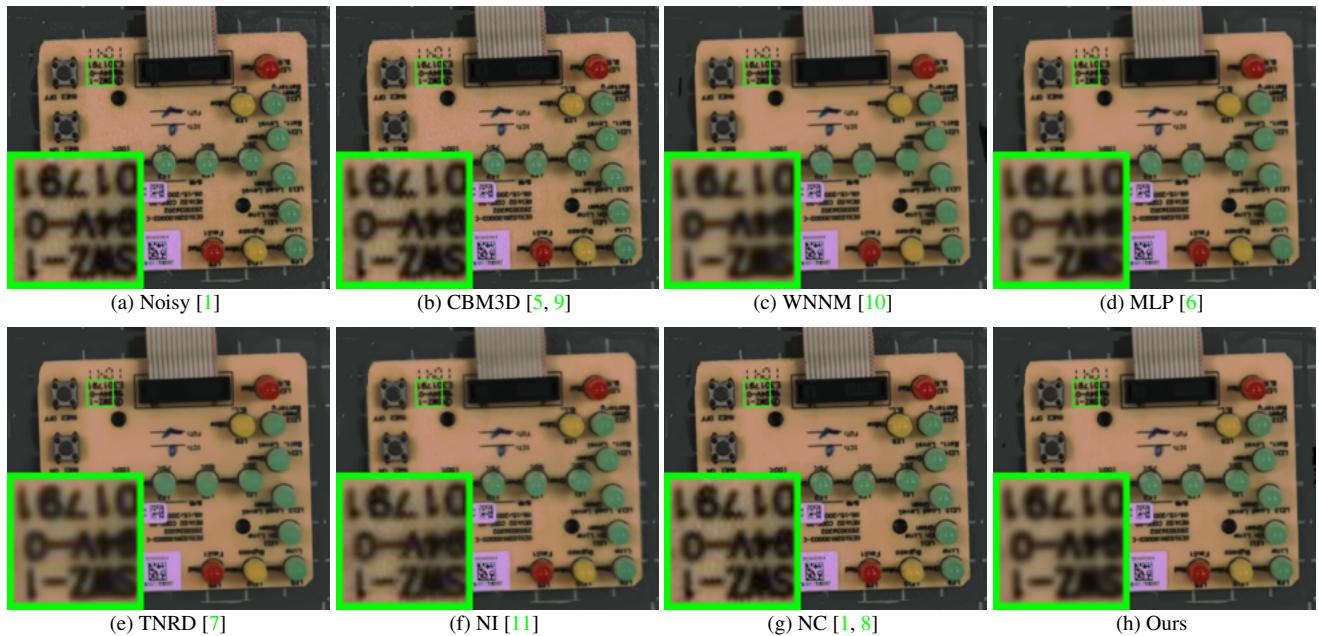


Figure 3. Denoised images of the real noisy image “Circuit” [1] by different methods. The images are better to be zoomed in on screen.

References

- [1] M. Lebrun, M. Colom, and J. M. Morel. The noise clinic: a blind image denoising algorithm. <http://www.ipol.im/pub/art/2015/125/>. Accessed 01 28, 2015. 1, 2, 3, 4, 5, 6, 7, 8
- [2] S. Nam, Y. Hwang, Y. Matsushita, and S. J. Kim. A holistic approach to cross-channel image noise modeling and its application to image denoising. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1683–1691, 2016. 1, 3, 6, 7, 8
- [3] C. Eckart and G. Young. The approximation of one matrix by another of lower rank. *Psychometrika*, 1(3):211–218, 1936. 1
- [4] S. Gu, Q. Xie, D. Meng, W. Zuo, X. Feng, and L. Zhang. Weighted nuclear norm minimization and its applications to low level vision. *International Journal of Computer Vision*, pages 1–26, 2016. 1
- [5] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian. Color image denoising via sparse 3D collaborative filtering with grouping

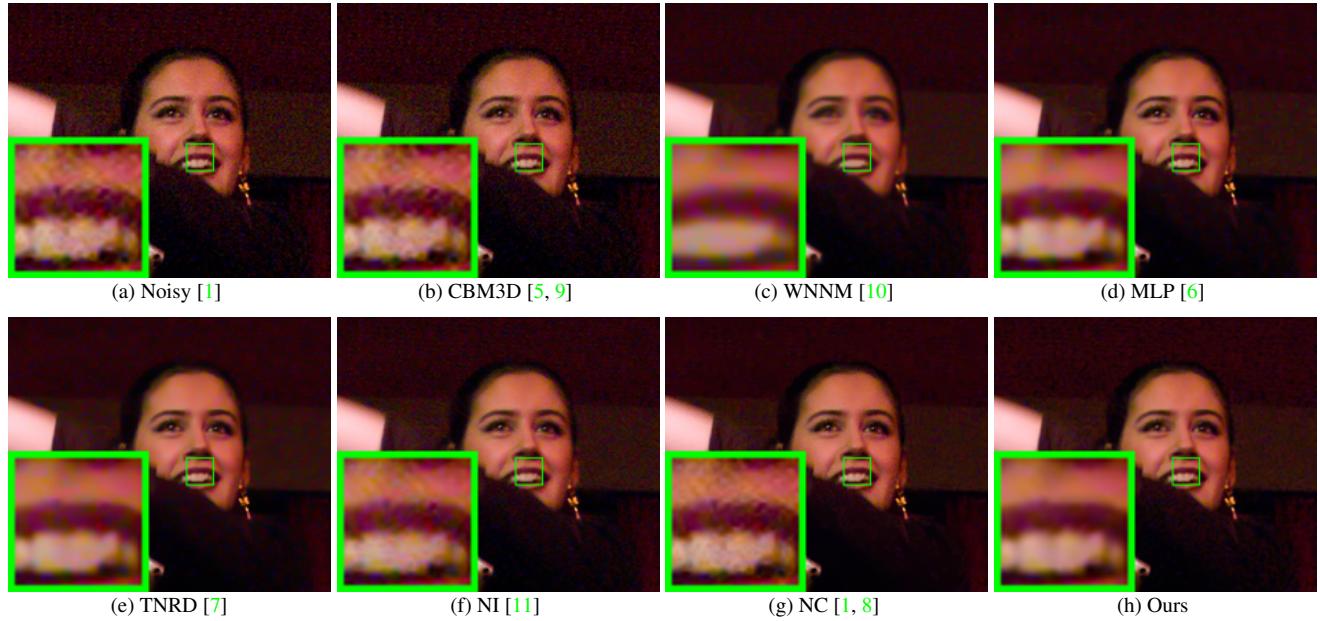
432
433
434
435
436
437
438
439
440
441

Figure 4. Denoised images of the real noisy image “Woman” [1] by different methods. The images are better to be zoomed in on screen.

452

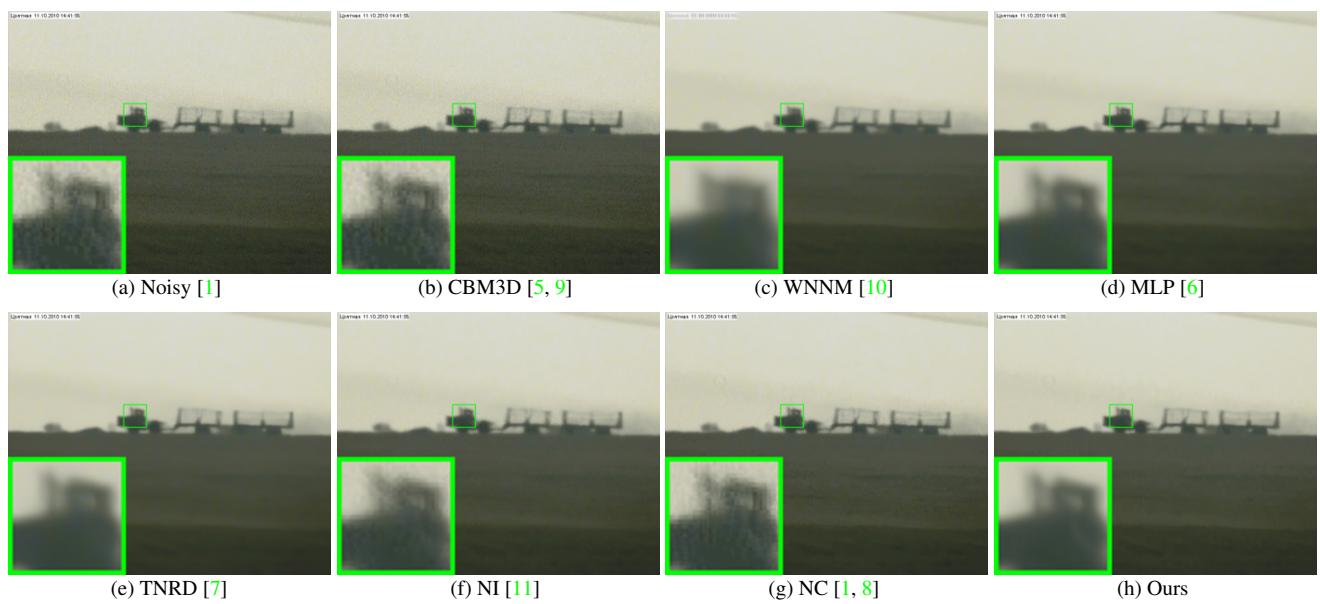


Figure 5. Denoised images of the real noisy image “Vehicle” [1] by different methods. The images are better to be zoomed in on screen.

474

constraint in luminance-chrominance space. *IEEE International Conference on Image Processing (ICIP)*, pages 313–316, 2007. 3, 4, 5, 6, 7, 8

479

[6] H. C. Burger, C. J. Schuler, and S. Harmeling. Image denoising: Can plain neural networks compete with BM3D? *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2392–2399, 2012. 3, 4, 5, 6, 7, 8

481

[7] Y. Chen, W. Yu, and T. Pock. On learning optimized reaction diffusion processes for effective image restoration. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5261–5269, 2015. 3, 4, 5, 6, 7, 8

483

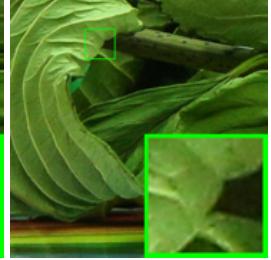
[8] M. Lebrun, M. Colom, and J.-M. Morel. Multiscale image blind denoising. *IEEE Transactions on Image Processing*, 24(10):3149–3161, 2015. 3, 4, 5, 6, 7, 8

486
487
488
489
490
491
492
493
494
495
496
497
498
499
500
501
502
503
504
505
506
507
508
509
510
511
512
513
514
515
516
517
518
519
520
521
522
523
524
525
526
527
528
529
530
531
532
533
534
535
536
537
538
539

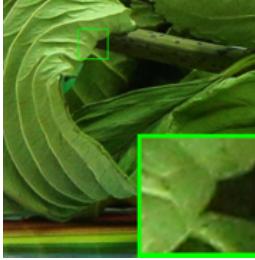
540



(a) Noisy [2]: 33.88dB



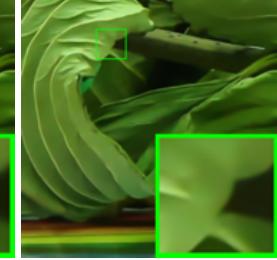
(b) CBM3D [5, 9]: 33.91dB



(c) WNNM [10]: 33.88dB



(d) MLP [6]: 33.23dB



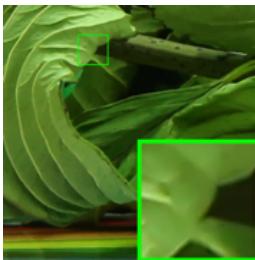
(e) TNRD [7]: 34.33dB



(f) NI [1]: 34.87dB



(g) NC [1, 8]: 35.69dB



(h) CC [2]: 35.37dB



(i) Ours: 37.05dB



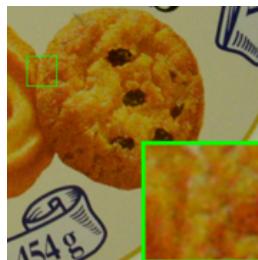
(j) Mean Image [2]

559

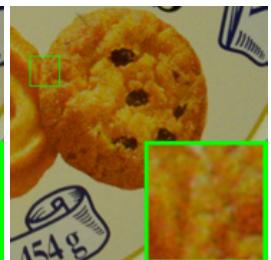
Figure 6. Denoised images of a region cropped from the real noisy image “Canon 5D Mark 3 ISO 3200 2” [2] by different methods. The images are better to be zoomed in on screen.

560

561



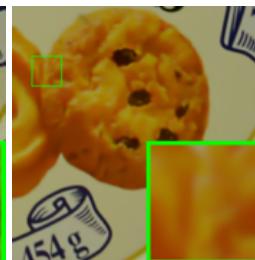
(a) Noisy [2]: 33.77dB



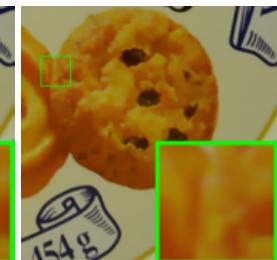
(b) CBM3D [5, 9]: 33.80dB



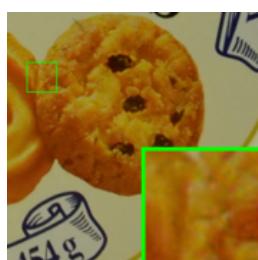
(c) WNNM [10]: 33.77dB



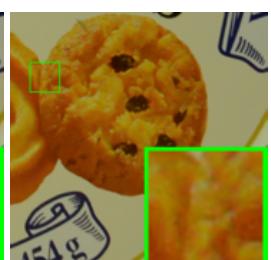
(d) MLP [6]: 34.13dB



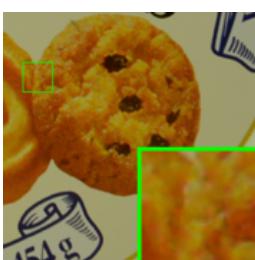
(e) TNRD [7]: 35.32dB



(f) NI [11]: 35.36dB



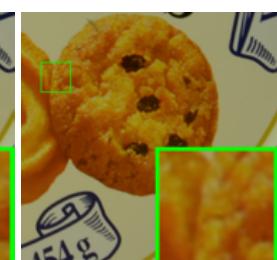
(g) NC [1, 8]: 36.70dB



(h) CC [2]: 35.95dB



(i) Ours: 36.31dB



(j) Mean Image [2]

581

Figure 7. Denoised images of a region cropped from the real noisy image “Nikon D600 ISO 3200 2” [2] by different methods. The images are better to be zoomed in on screen.

582

583

584

[9] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian. Image denoising by sparse 3-D transform-domain collaborative filtering. *IEEE Transactions on Image Processing*, 16(8):2080–2095, 2007. 4, 5, 6, 7, 8

585

586

587

588

589

590

591

592

593

594

595

596

597

598

599

600

601

602

603

604

605

606

607

608

609

610

611

612

613

614

615

616

617

618

619

620

621

622

623

624

625

626

627

628

629

630

631

632

633

634

635

636

637

638

639

640

641

642

643

644

645

646

647

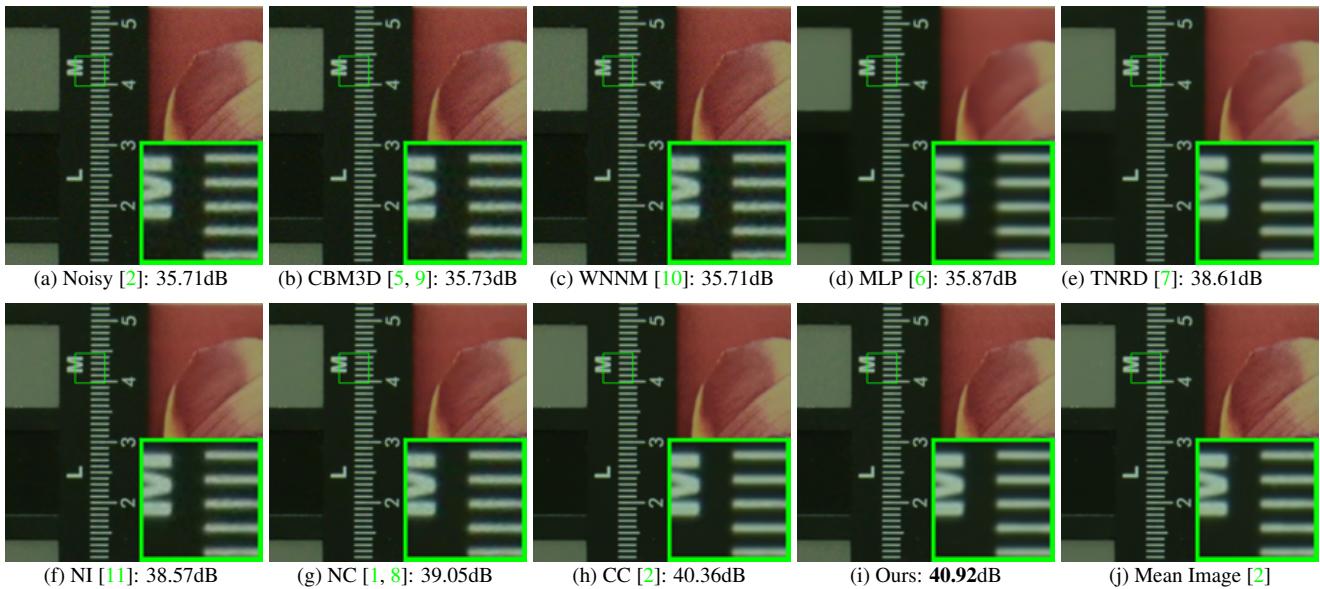


Figure 8. Denoised images of a region cropped from the real noisy image “Nikon D800 ISO 1600 2” [2] by different methods. The images are better to be zoomed in on screen.

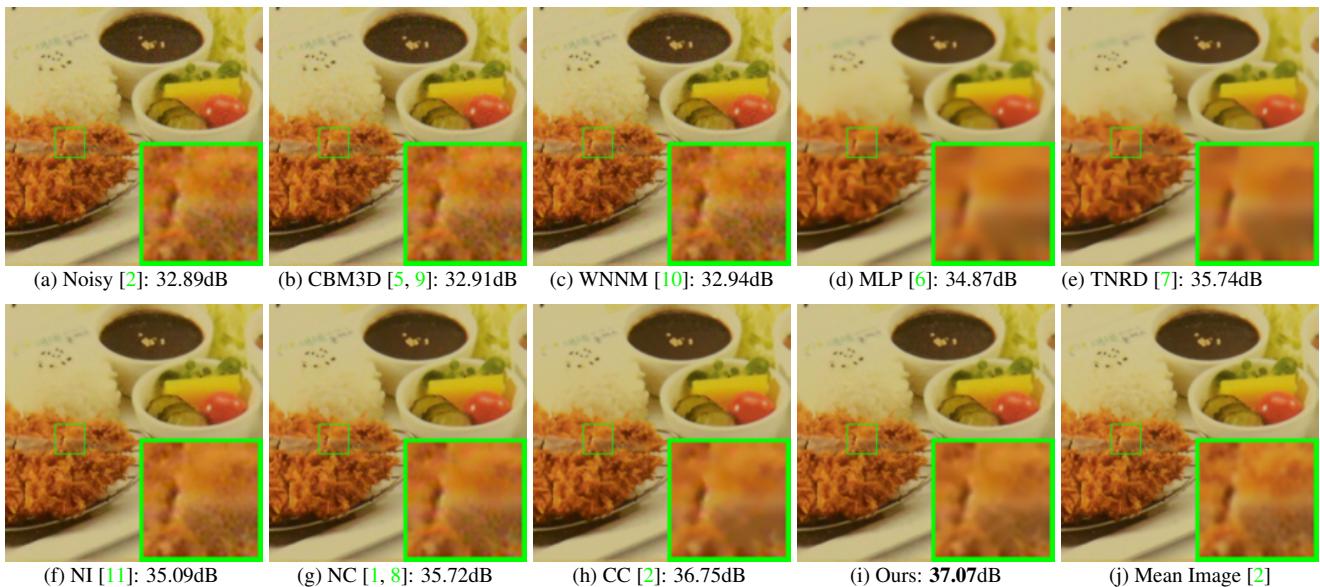


Figure 9. Denoised images of a region cropped from the real noisy image “Nikon D800 ISO 3200 2” [2] by different methods. The images are better to be zoomed in on screen.

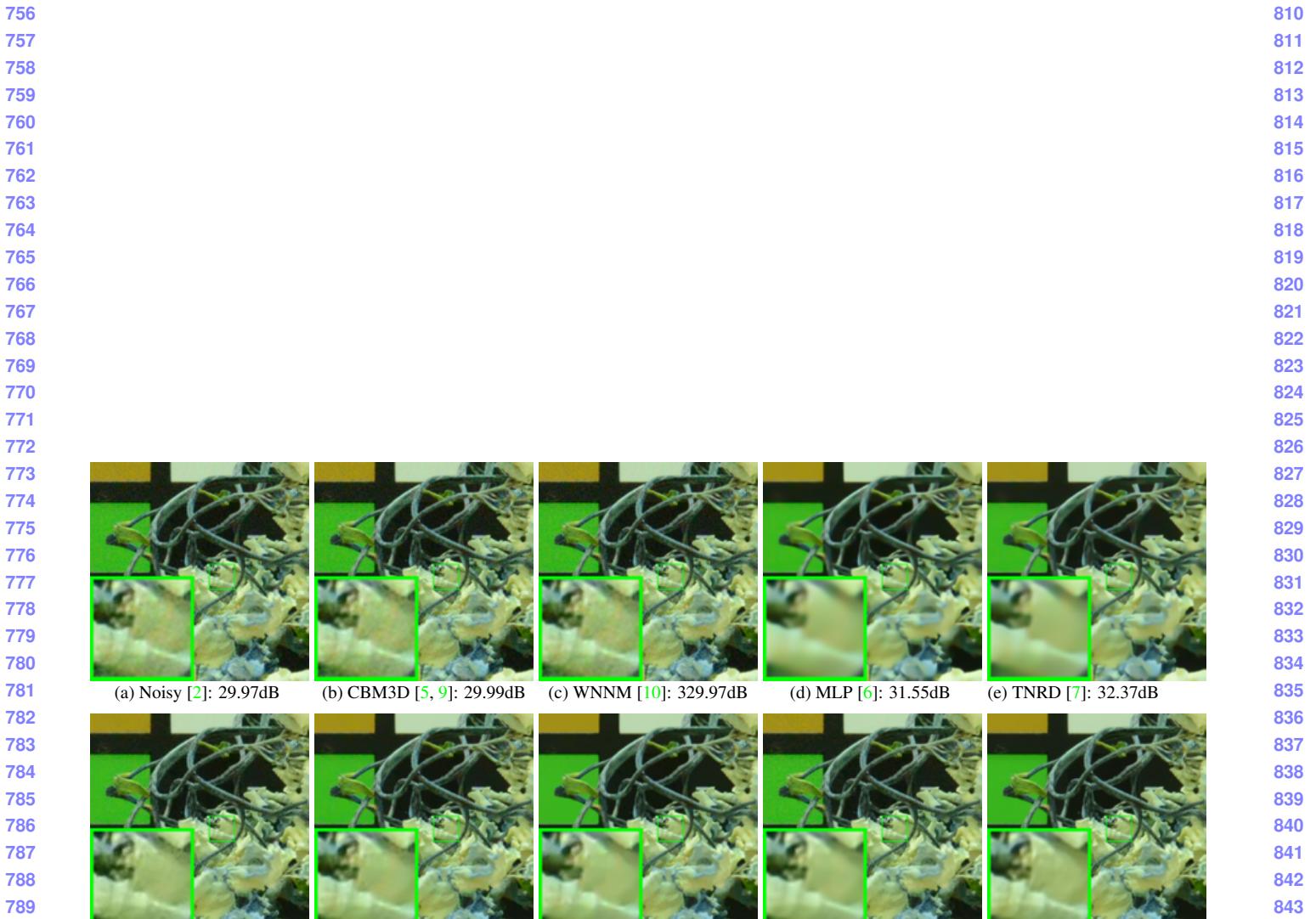


Figure 10. Denoised images of a region cropped from the real noisy image “Nikon D800 ISO 6400 2” [2] by different methods. The images are better to be zoomed in on screen.