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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	28.16	27.95	28.15	30.20
2	29.70	31.30	32.70	27.80	29.69	32.54	31.60	31.73	34.04
3	30.34	31.98	34.07	28.02	31.93	33.91	33.68	33.52	35.55
4	29.47	31.10	32.56	27.70	32.56	32.68	31.85	31.90	34.06
5	27.31	28.59	29.35	26.14	30.00	28.83	29.00	28.91	30.05
6	28.20	29.10	29.90	26.15	28.81	29.55	29.46	29.62	31.64
7	29.73	31.60	33.46	27.22	31.63	33.09	33.29	32.86	34.24
8	27.47	28.16	28.91	25.34	30.16	29.15	29.24	29.03	29.91
9	30.07	31.63	33.55	27.86	31.54	33.19	33.20	32.95	34.53
10	29.96	31.37	33.20	27.74	33.44	32.98	33.02	32.74	34.38
11	28.73	29.85	30.87	26.98	30.16	30.45	30.14	30.21	32.10
12	30.20	31.50	33.31	27.97	31.69	33.22	32.71	32.65	34.64
13	26.18	26.69	26.98	25.14	27.97	26.49	26.42	26.62	28.30
14	27.86	29.07	29.87	26.67	29.21	29.36	29.14	29.30	31.18
15	29.91	31.58	33.13	28.04	31.17	33.22	32.34	32.36	34.27
16	29.29	30.35	31.54	27.46	32.18	31.34	31.05	31.21	33.72
17	29.50	31.09	32.52	27.81	32.80	32.09	32.00	31.85	33.61
18	27.72	28.74	29.36	26.57	28.63	28.88	28.76	28.89	30.56
19	28.98	30.18	31.35	27.25	29.79	31.34	30.77	30.95	33.10
20	30.63	31.78	33.27	27.89	29.52	33.00	32.55	32.58	34.18
21	28.50	29.58	30.54	26.86	30.99	30.02	30.03	30.03	31.69
22	28.61	29.78	30.82	27.19	30.50	30.47	29.82	30.10	32.08
23	30.60	32.66	35.06	28.17	32.82	34.72	34.37	33.94	35.16
24	27.97	28.81	29.61	26.01	30.75	29.47	29.35	29.39	30.93
Average	28.92	30.19	31.44	27.04	30.73	31.17	30.91	30.89	32.67

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

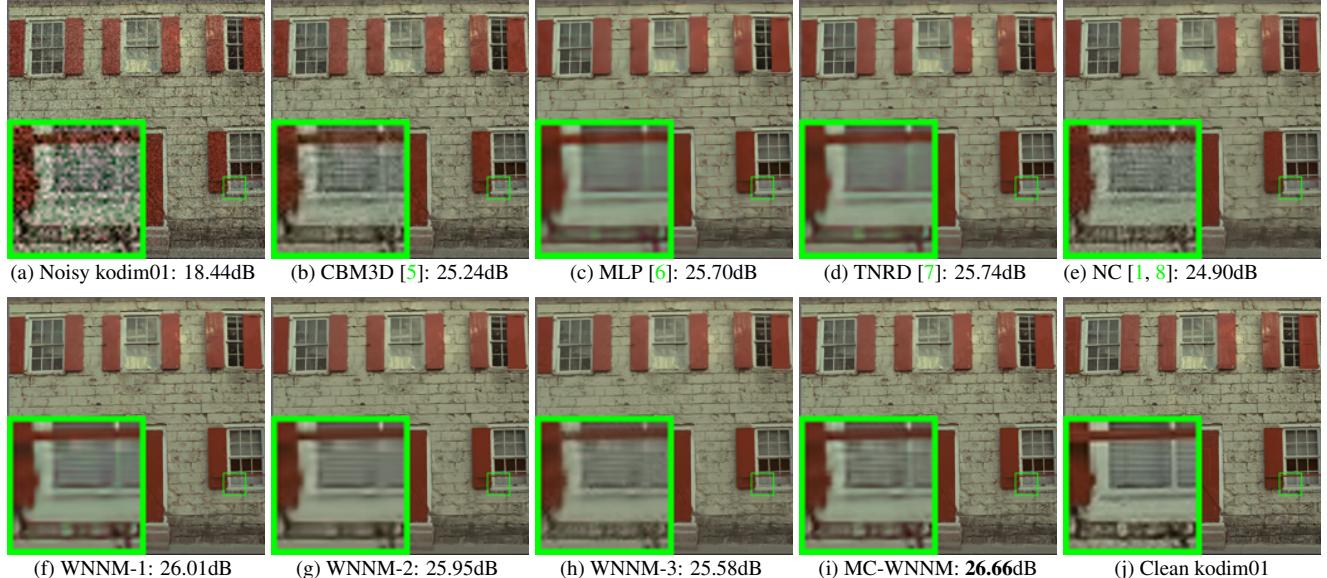
In the main paper, we have given the PSNR results of the competing methods on the 24 high quality images from the Kodak PhotoCD dataset when the standard deviations of the additive white Gaussian noise (AWGN) are $\sigma_r = 40, \sigma_g = 20, \sigma_b = 30$ for R, G, B channels, respectively. Here we 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 9-??, we give the visual comparisons of the denoised images by different methods.

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

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	24.76	27.81
2	25.19	30.94	30.90	26.82	27.79	30.89	29.75	29.21	30.96
3	25.39	32.03	32.09	27.52	27.41	32.20	31.17	30.39	32.89
4	24.96	30.55	30.47	27.34	27.00	30.74	29.71	29.10	31.19
5	23.29	26.65	26.73	25.72	26.67	26.74	25.98	24.68	27.60
6	24.09	27.76	27.70	26.10	26.12	27.85	26.96	26.01	29.15
7	24.89	30.70	30.72	27.17	28.07	30.91	29.94	28.87	31.37
8	23.30	26.12	26.27	25.59	26.11	26.87	26.33	24.74	27.44
9	25.20	31.35	31.31	27.74	28.33	31.30	30.45	29.44	32.08
10	25.13	31.01	31.05	27.60	28.53	31.12	30.17	29.21	31.83
11	24.54	28.79	28.82	26.72	24.40	28.73	27.79	26.94	29.60
12	25.43	31.60	31.60	27.82	29.01	31.59	30.62	29.91	32.11
13	22.50	24.71	24.73	24.96	23.36	24.70	23.85	22.86	25.96
14	23.91	27.69	27.72	26.26	23.08	27.62	26.81	25.91	28.57
15	25.45	31.09	31.05	27.36	28.49	31.29	30.21	29.46	31.39
16	24.89	29.79	29.73	27.35	27.10	29.84	28.85	28.13	31.10
17	25.12	30.26	30.24	27.15	27.54	30.11	29.35	28.43	31.08
18	23.83	27.26	27.26	26.05	26.15	27.32	26.18	25.28	28.32
19	24.63	29.40	29.39	27.06	27.41	29.78	28.87	28.05	30.53
20	26.43	31.16	31.27	26.43	26.92	31.25	30.43	29.41	31.55
21	24.24	28.26	28.27	26.66	27.18	28.22	27.45	26.40	29.29
22	24.51	29.03	29.06	26.83	27.64	29.02	27.81	27.18	29.57
23	25.55	32.87	32.75	27.60	23.75	32.58	31.46	30.50	32.34
24	23.85	27.06	27.13	25.86	27.05	27.50	26.63	25.55	28.32
Average	24.57	29.27	29.28	26.69	26.61	29.36	28.43	27.52	30.09

Figure 1. Denoised images of different methods on the image “kodim01” degraded by AWGN with different standard deviations 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.

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.

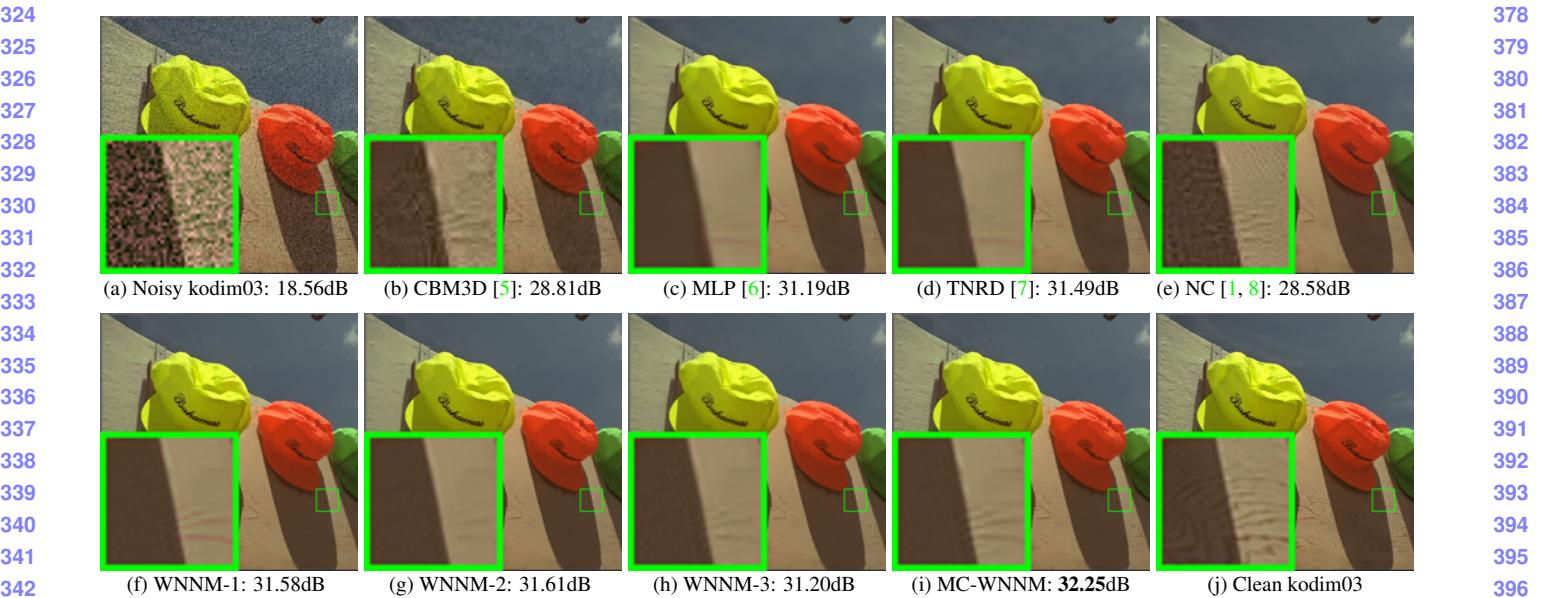


Figure 2. Denoised images of different methods on the image “kodim03” degraded by AWGN with different standard deviations of $\sigma_r = 40$, $\sigma_g = 20$, $\sigma_b = 30$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

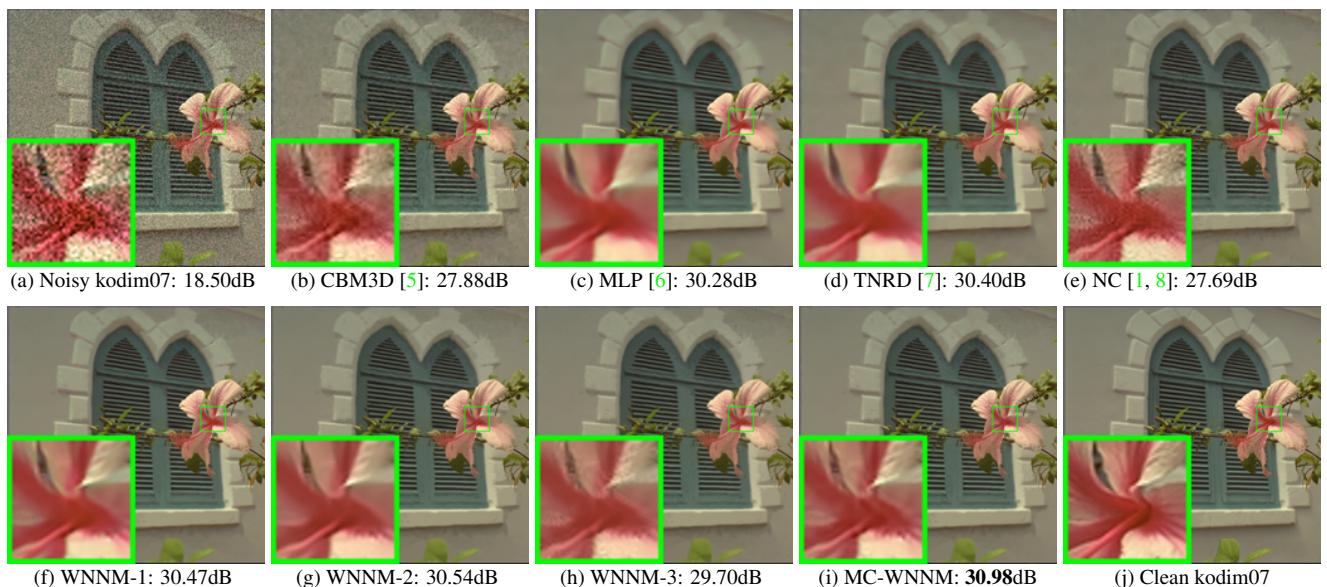


Figure 3. Denoised images of different methods on the image “kodim07” degraded by AWGN with different standard deviations of $\sigma_r = 40$, $\sigma_g = 20$, $\sigma_b = 30$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

As can be seen from Figures 16-??, 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.

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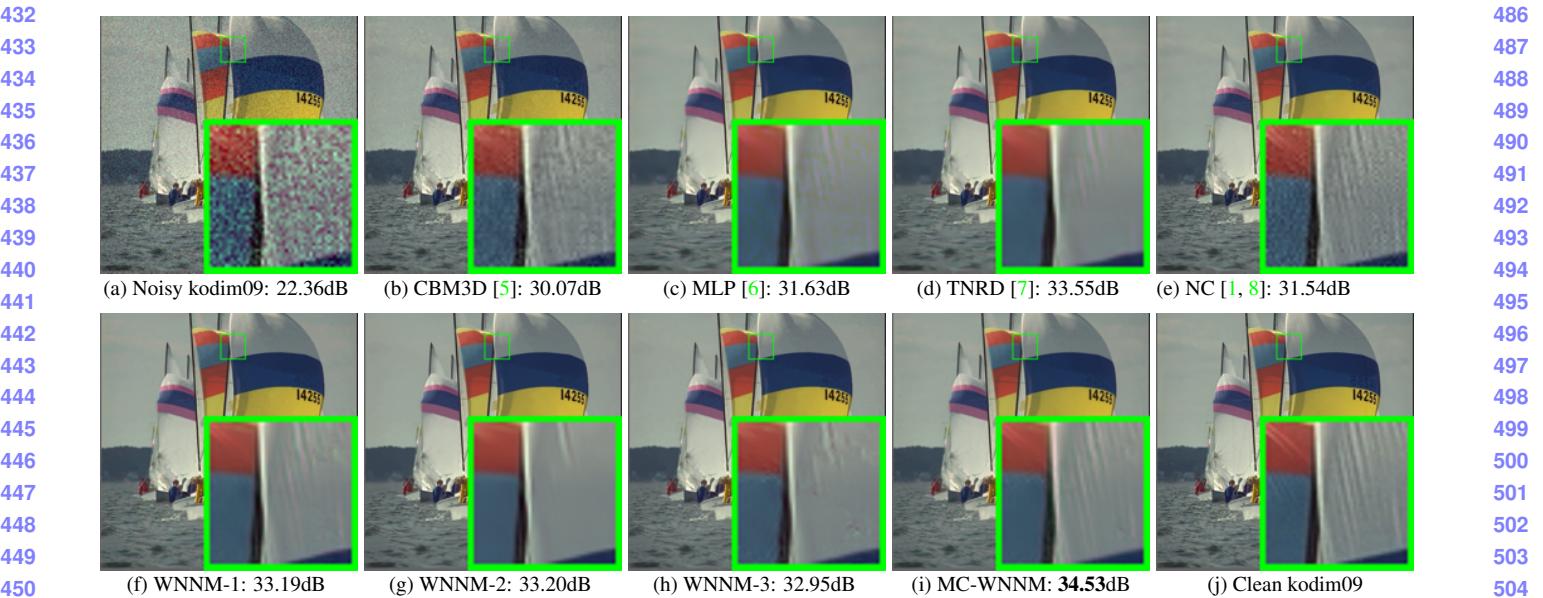


Figure 4. Denoised images of different methods on the image “kodim09” degraded by AWGN with different standard deviations of $\sigma_r = 5, \sigma_g = 30, \sigma_b = 15$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

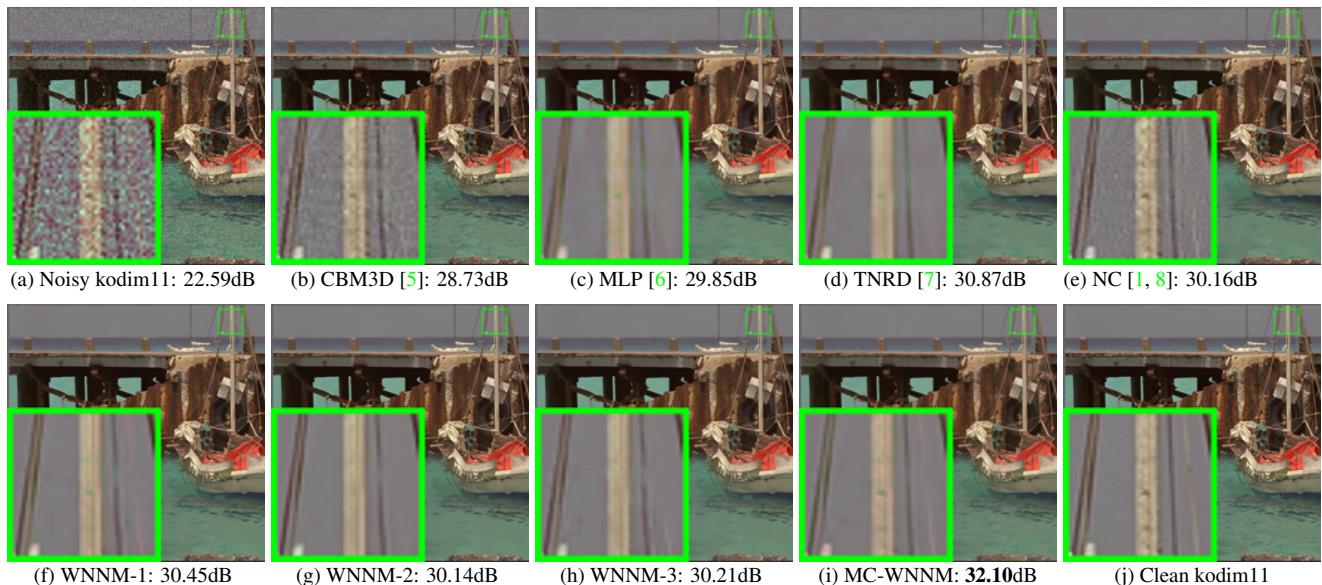


Figure 5. Denoised images of different methods on the image “kodim11” degraded by AWGN with different standard deviations of $\sigma_r = 5, \sigma_g = 30, \sigma_b = 15$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

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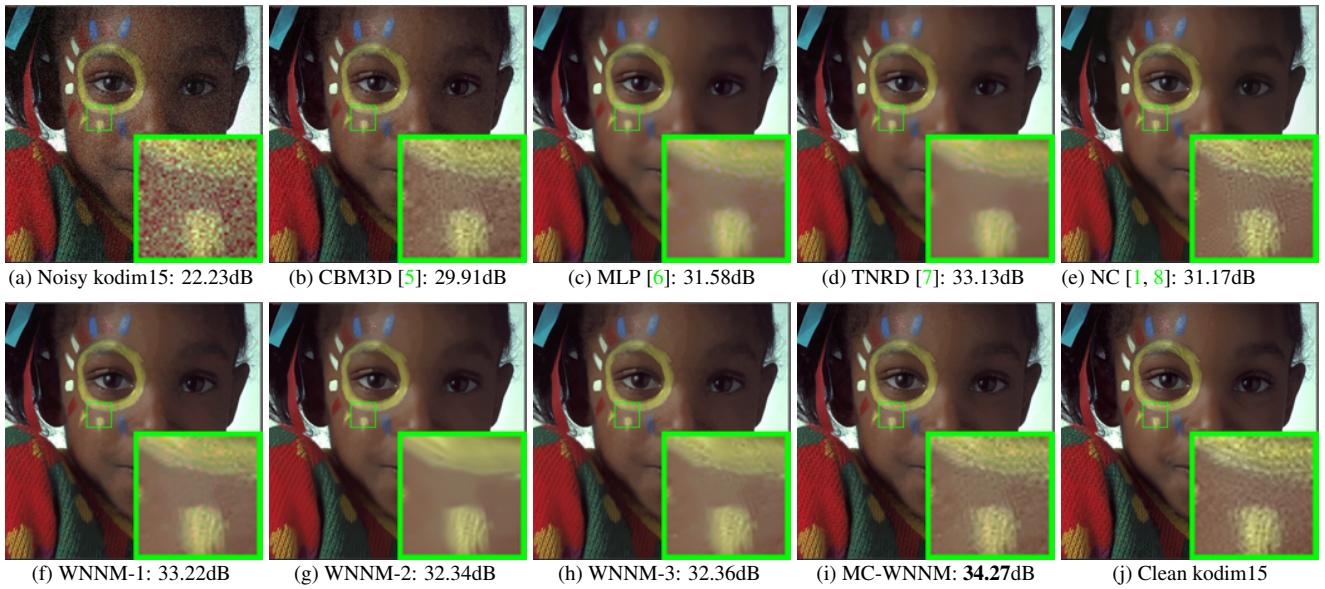


Figure 6. Denoised images of different methods on the image “kodim15” degraded by AWGN with different standard deviations of $\sigma_r = 5, \sigma_g = 30, \sigma_b = 15$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

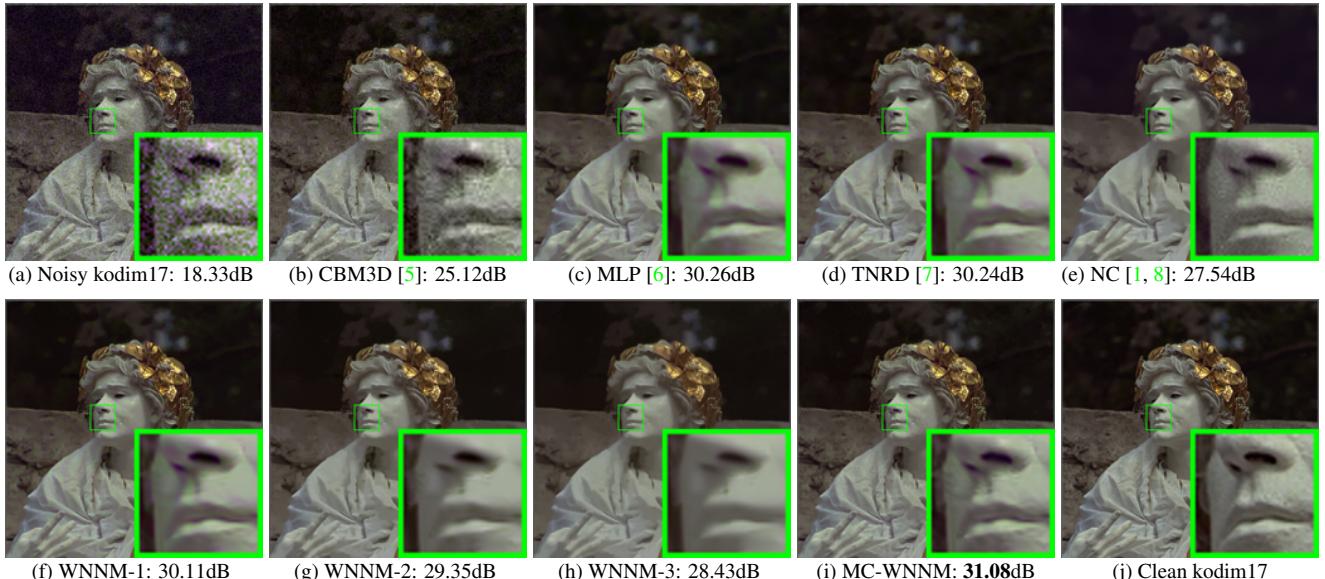
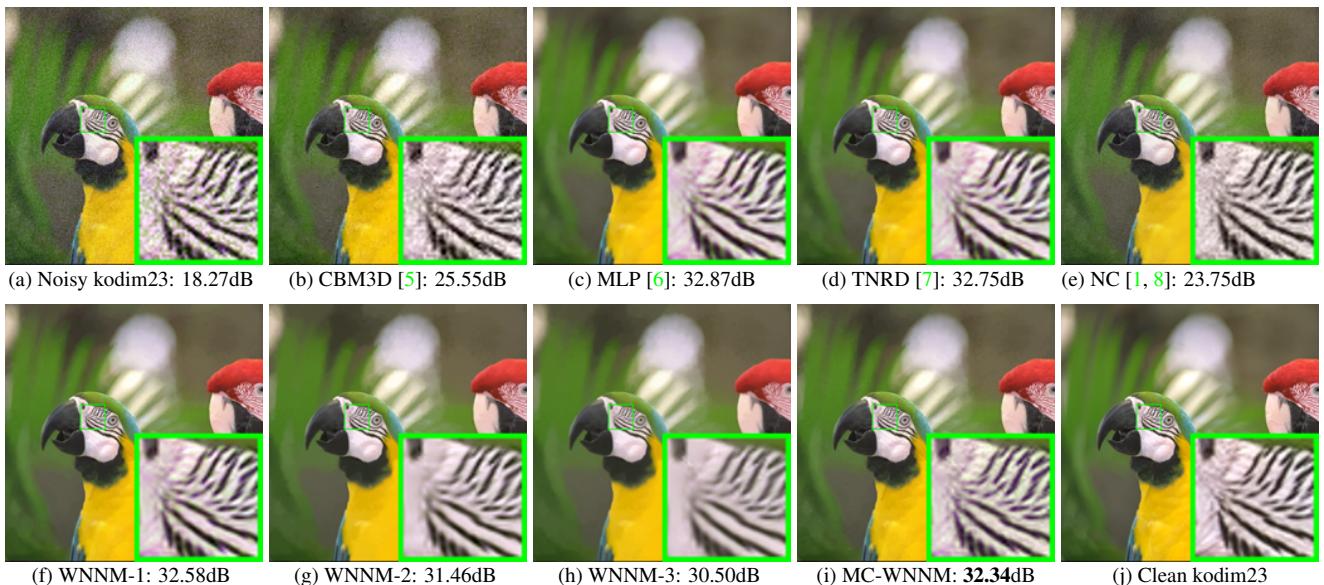
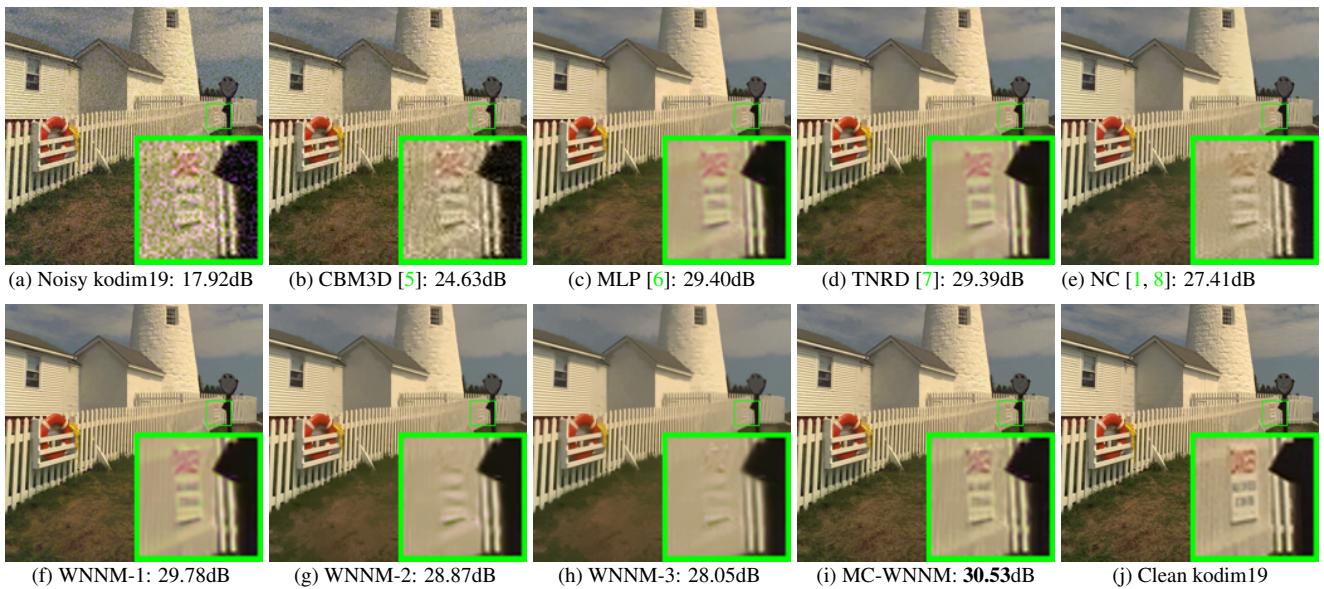


Figure 7. Denoised images of different methods on the image “kodim17” degraded by AWGN with different standard deviations of $\sigma_r = 30, \sigma_g = 10, \sigma_b = 50$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.

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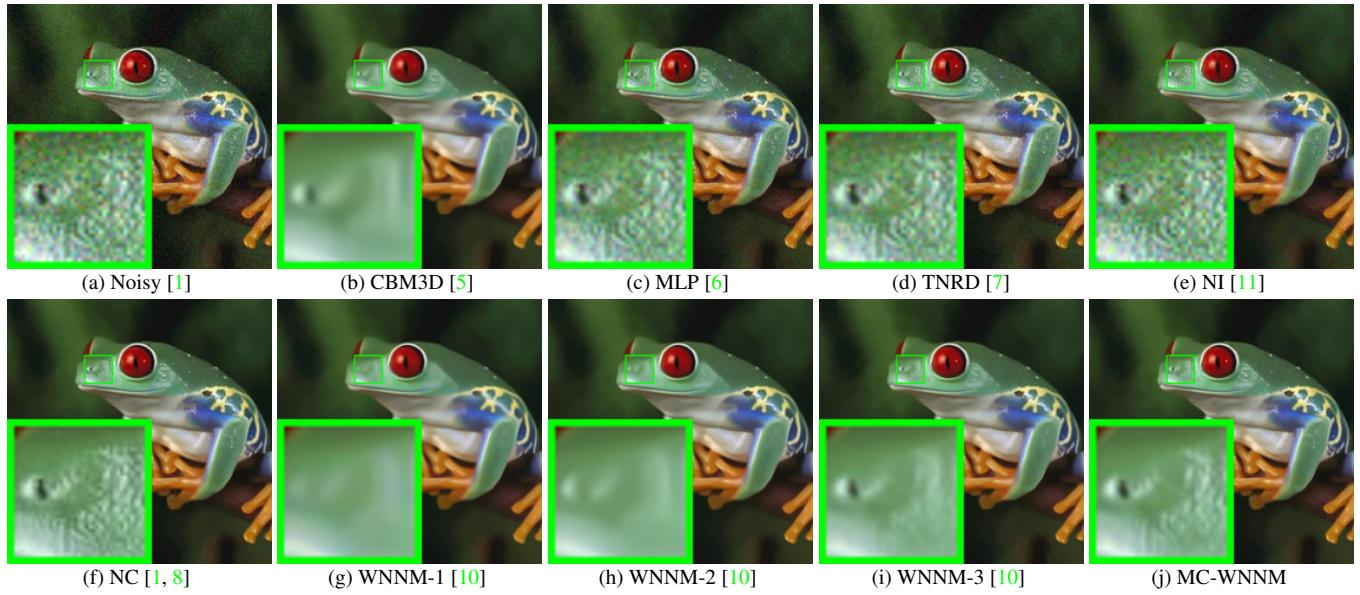


Figure 10. Denoised images of the real noisy image “Frog” [1] by different methods. The images are better to be zoomed in on screen.

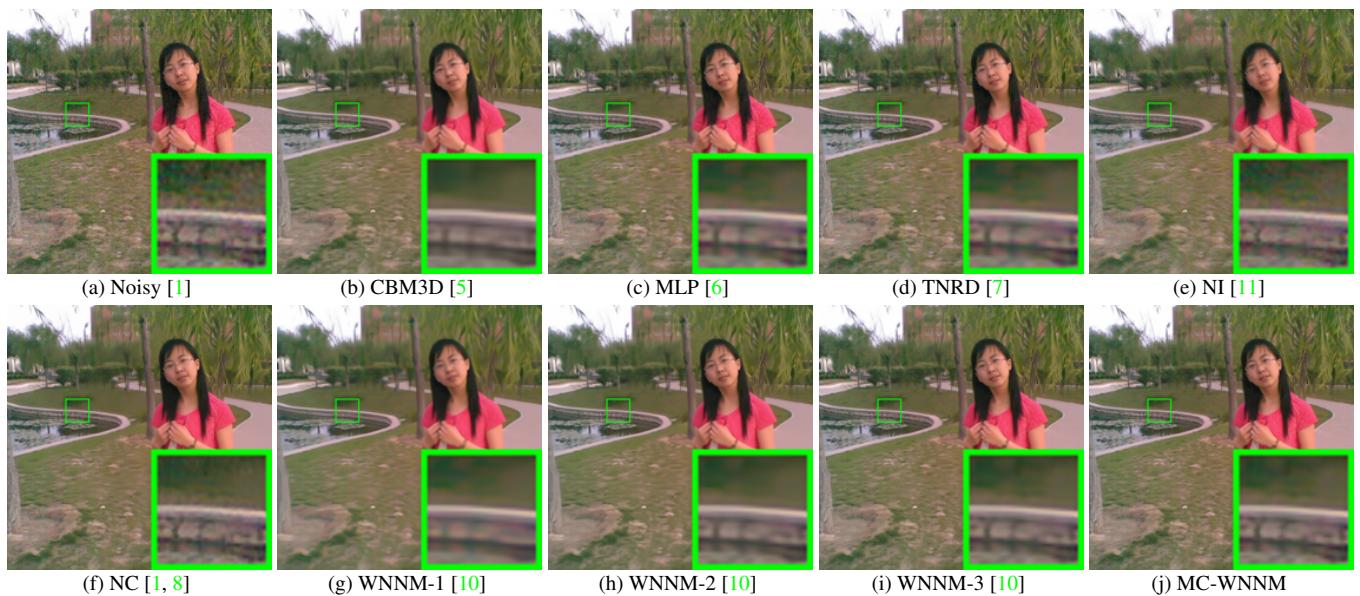


Figure 11. Denoised images of the real noisy image “Gril” [1] by different methods. The images are better to be zoomed in on screen.

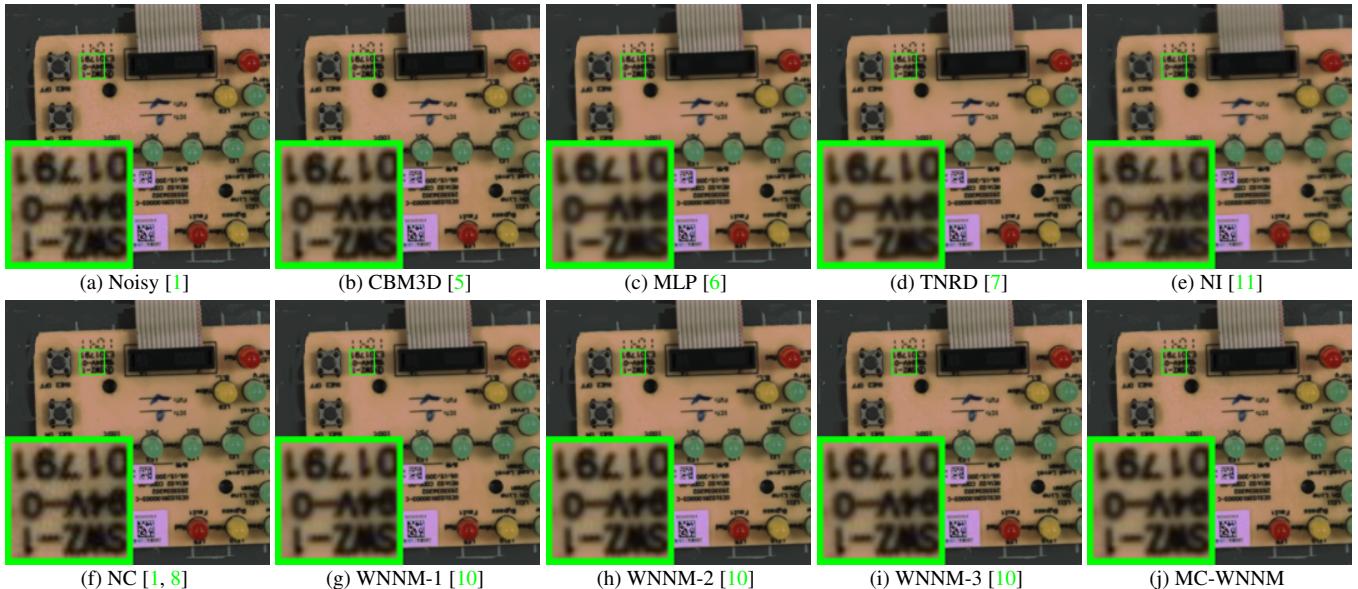


Figure 12. Denoised images of the real noisy image “Circuit” [1] by different methods. The images are better to be zoomed in on screen.

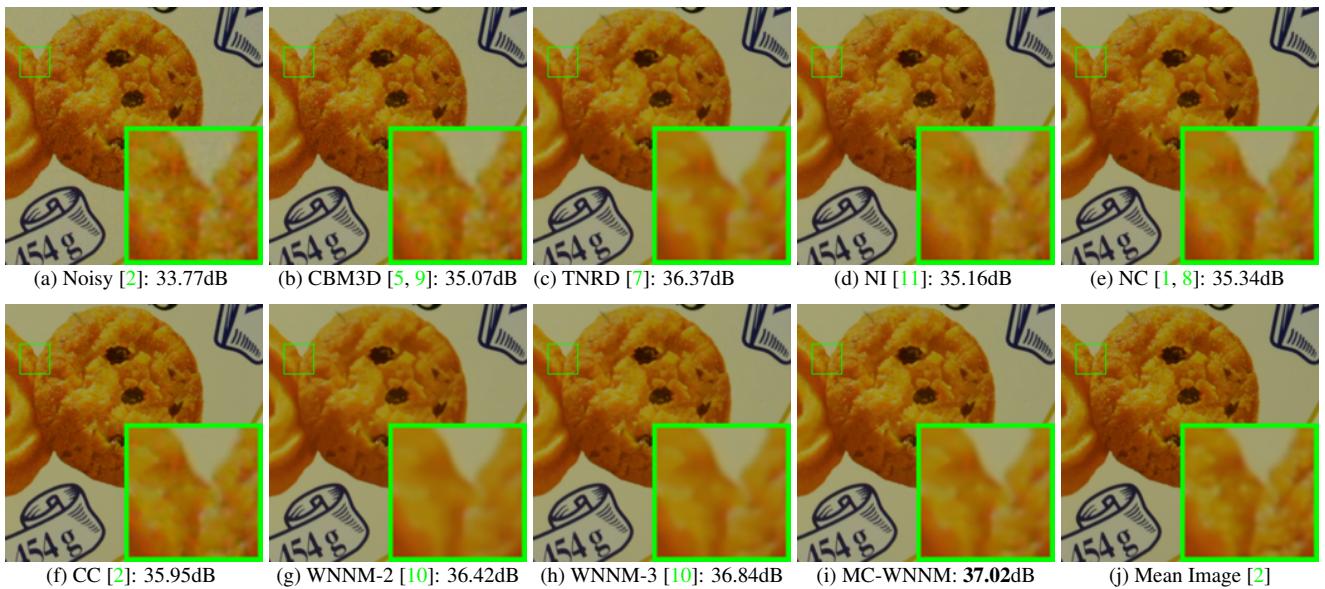


Figure 13. Denoised images of a region cropped from the real noisy image “Nikon D600 ISO 3200 2” [2] by different methods. The images are better to be zoomed in on screen.

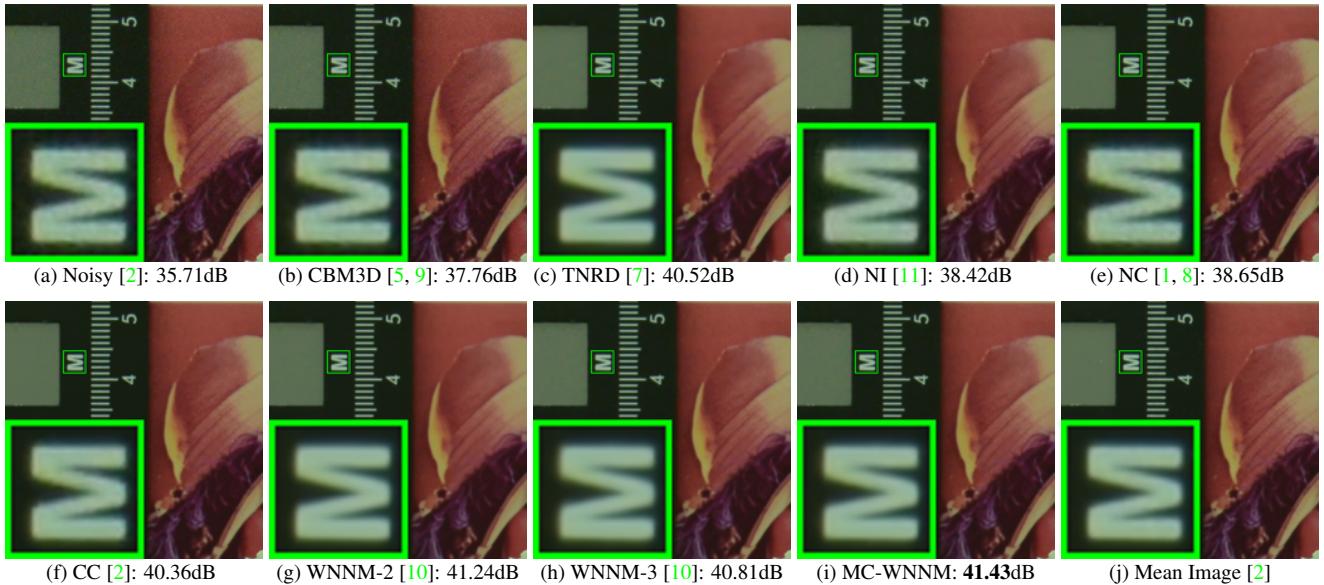


Figure 14. Denoised images of a region cropped from the real noisy image “Nikon D800 ISO 1600 2” [2] by different methods. The images are better to be zoomed in on screen.

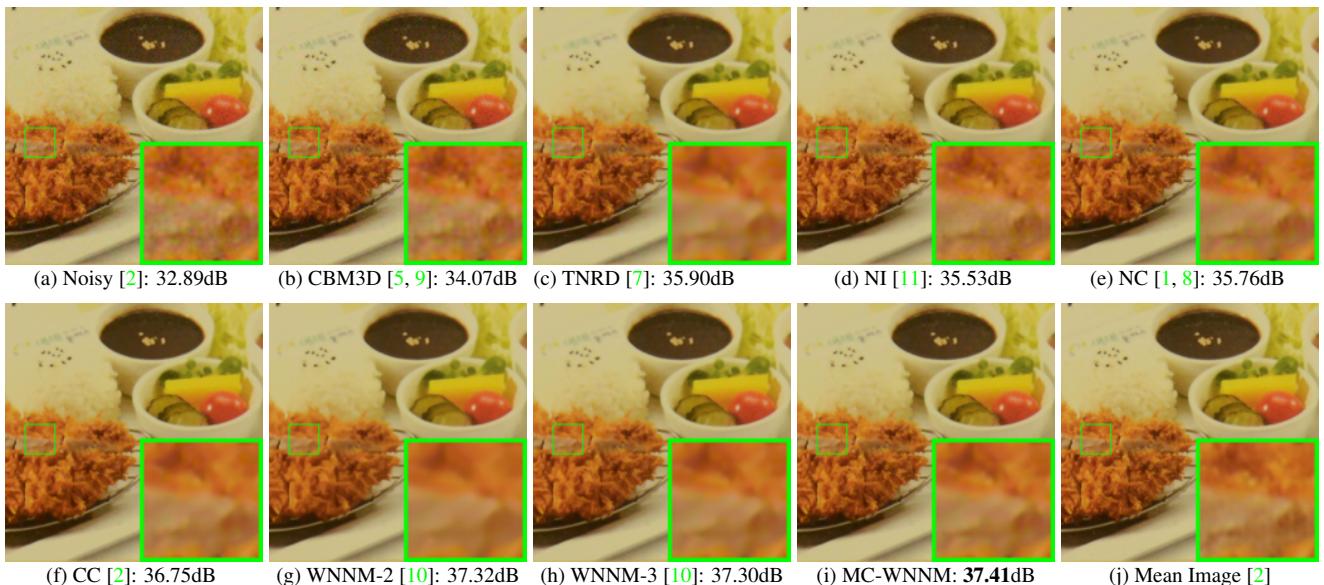


Figure 15. Denoised images of a region cropped from the real noisy image “Nikon D800 ISO 3200 2” [2] by different methods. The images are better to be zoomed in on screen.

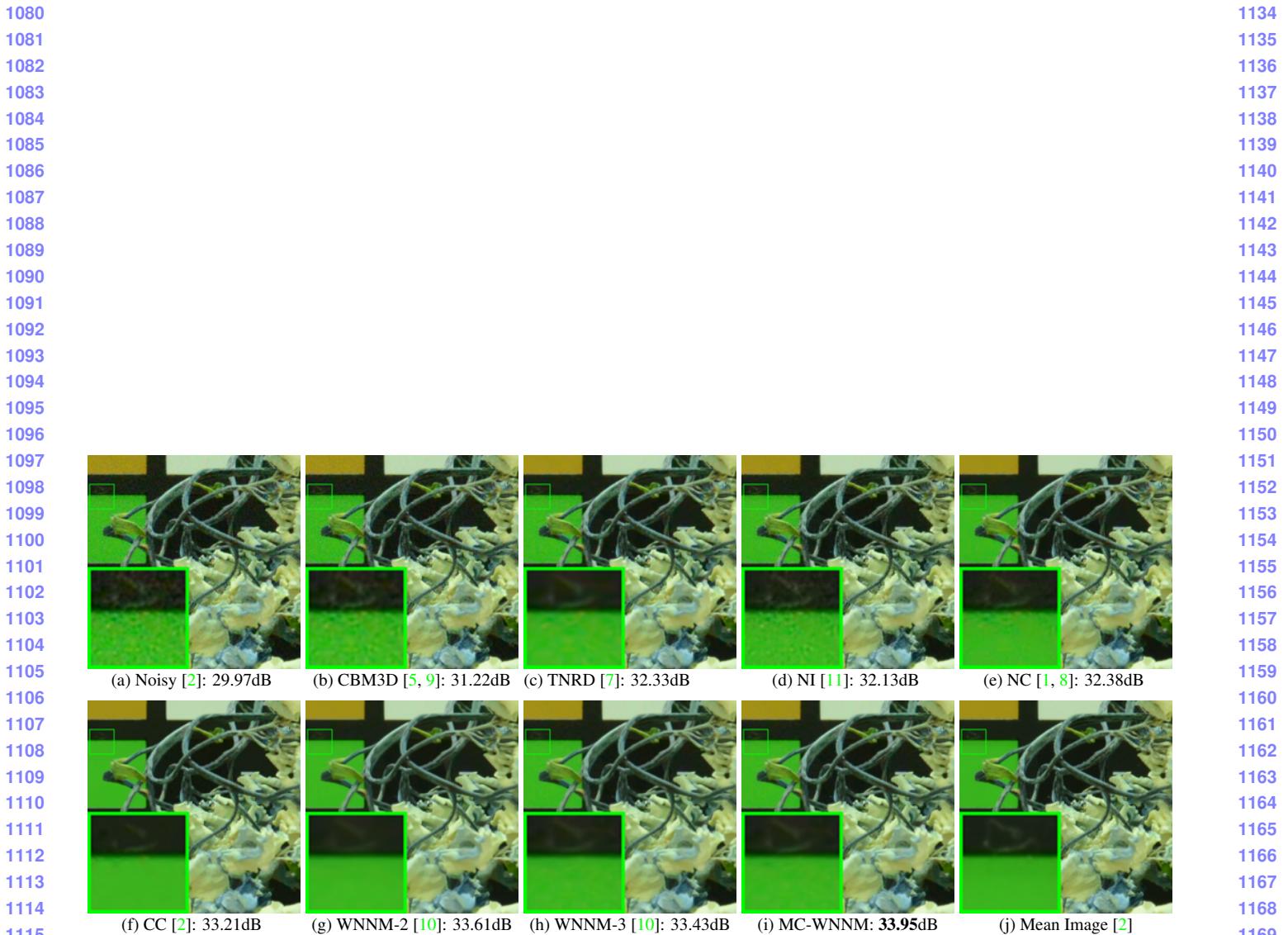


Figure 16. Denoised images of a region cropped from the real noisy image “Nikon D800 ISO 6400 2” [2] by different methods. The images are better to be zoomed in on screen.