Supplementary

This supplementary aims to show more (visual) results which cannot be included in the paper. In the paper, the proposed GCBD is evaluated with both synthetic and real-world data. Specifically, four parts of experiments are carried out: Gaussian blind denoising tasks to indicate the accuracy of noise modeling through using GAN (refer to the first part of section 4.2 in the paper), mixture noise blind denoising tasks to demonstrate the superiority of GCBD when dealing with more complex unknown noises (refer to the second part of section 4.2), real-world noise denoising tasks to show the applicability of GCBD to solve realistic blind denoising problems (refer to section 4.3). Experimental details can be found in the paper.

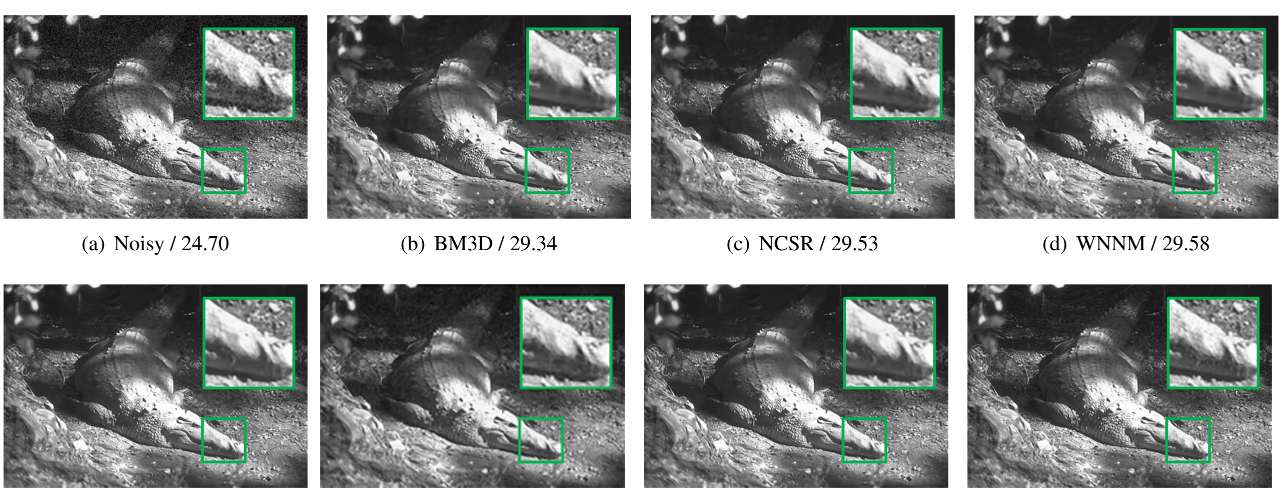
Gaussian noise blind denoising Fig. 1 and Fig. 2 show some results in this tasks. Though no noise information is provided, GCBD still outperforms BM3D, EPLL, WNNM and Multiscale. Particularly, GCBD achieves comparable results with DnCNN-B. This is impressive because DnCNN-B is trained with accurate data while GCBD is trained with approximate data generated by GAN. This experiment demonstrates the accuracy of noise modeling through using GAN.

Mixture noise blind denoising Besides Gaussian noise, we further evaluate the performance of all the competing methods in complex tasks. The mixture noise adopted in the experiments consists of uniform noise $[-s, s]$ and Gaussian noise. Fig. 3 and Fig. 4 show some results in this tasks. GCBD also performs much better than BM3D, EPLL, WNNM and Multiscale, which further shows the superiority of GCBD when dealing with unknown noises. Particularly, DnCNN-B cannot work well because the paired training dataset is unavailable. On the contrary, the proposed GCBD exploits GAN to estimate the noise distribution of noisy images and addresses the problem of lack of training data, which achieves remarkable denoising results.

Real-world noise blind denoising The experiments in this part are conducted on dataset NIGHT, which is divided into 20 images (denoted as NIGHT-A) and the other 5 images (denoted as NIGHT-B). For the proposed GCBD, only NIGHT-A is used during training. Fig. 5 shows some results on NIGHT-A. As we can see, all the methods except GCBD still keep noise textures more or less. By comparison, GCBD does a pretty good job at retaining details while removing the noises, which demonstrates the applicability of GCBD to solve realistic blind denoising problems. Fig. 6 shows some results on NIGHT-B. GCBD also produces more visually pleasing denoised images over the other methods, which demonstrates that GCBD can be employed to handle noisy images taken under similar conditions.

Extensive experiments demonstrate the superiority of the proposed GCBD in image blind denoising problems.

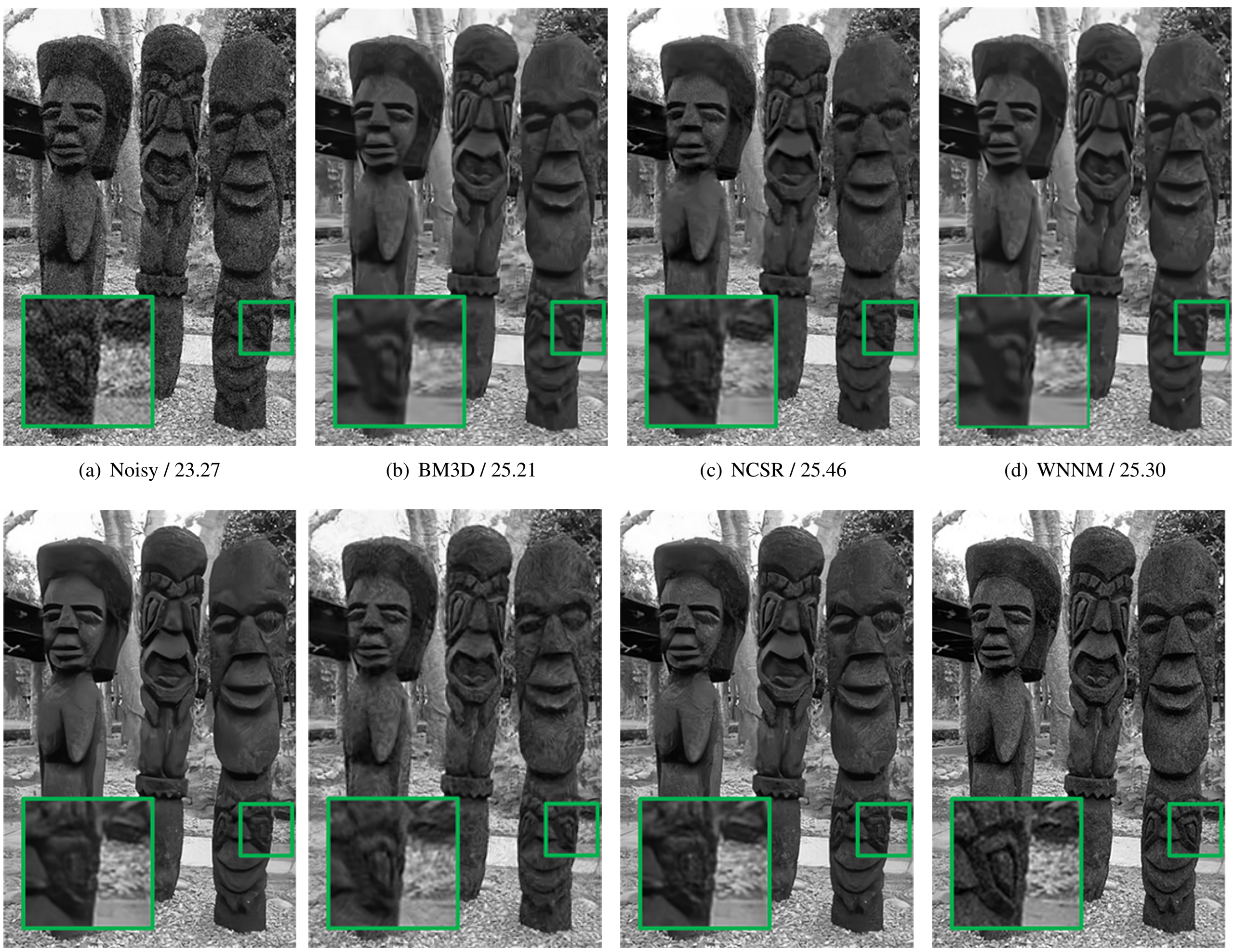
Figure 1. Comparison (PSNR/dB) on BSD68 in the evaluation of **Gaussian noise denoising** with $\sigma = 15$. Zoom in for better view.



(a) Noisy / 24.70 (b) BM3D / 29.34 (c) NCSR / 29.53 (d) WNNM / 29.58

(e) DnCNN-B / 29.90 (f) Multiscale / 29.46 (g) GCBD (ours) / 29.91 (h) Ground truth

Figure 2. Comparison (PSNR/dB) on BSD68 in the evaluation of **Gaussian noise denoising** with $\sigma = 25$. Zoom in for better view.



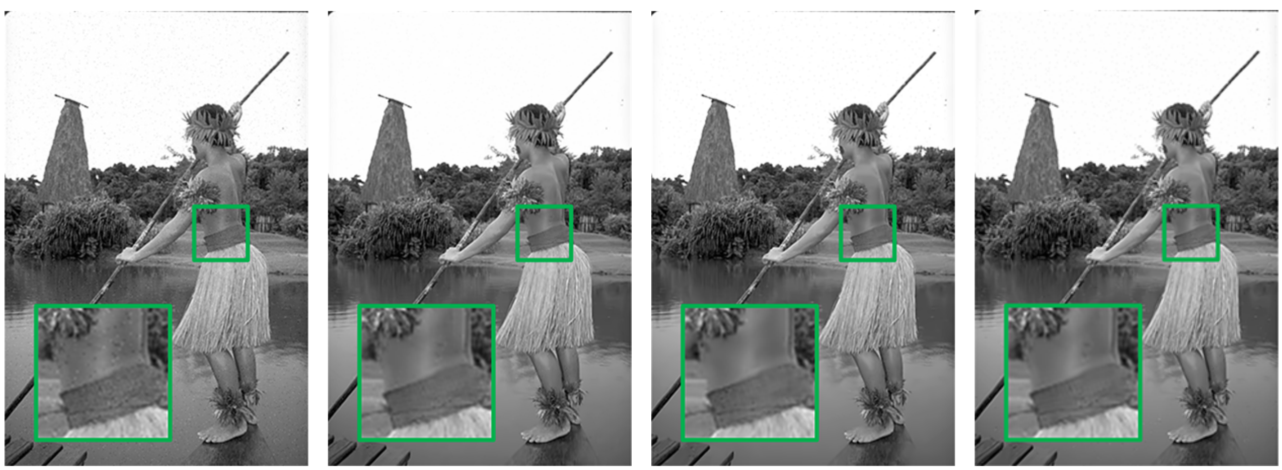
(a) Noisy / 23.27 (b) BM3D / 25.21 (c) NCSR / 25.46 (d) WNNM / 25.30

(e) DnCNN-B / 25.87 (f) Multiscale / 25.32 (g) GCBD (ours) / 25.93 (h) Ground truth

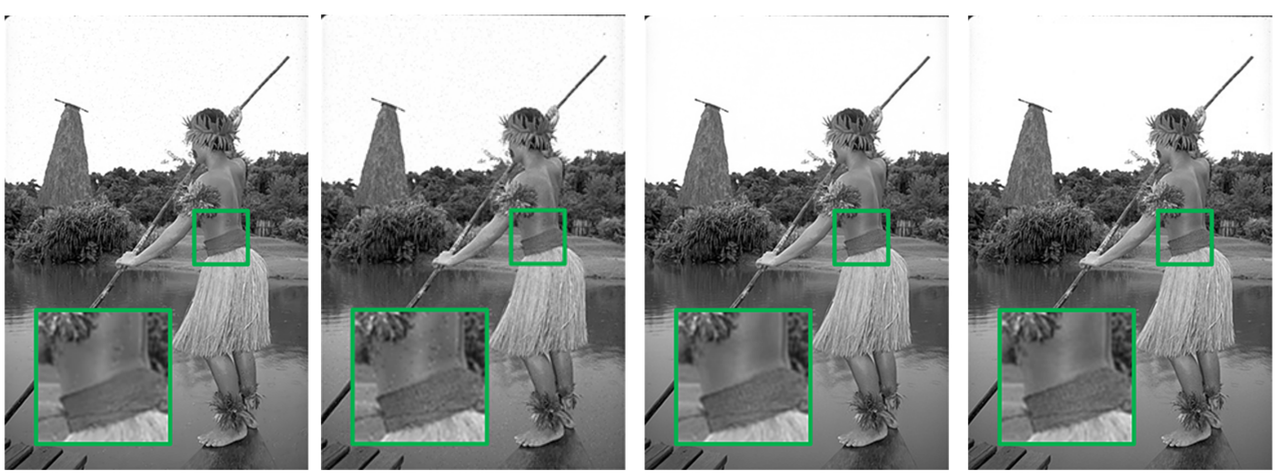
Figure 3. Comparison (PSNR/dB) on BSD68 in the evaluation of **mixture noise denoising** with $s = 25$ (10% uniform noise). Zoom in for better view.

(a) Noisy / 34.85 (b) BM3D / 37.50 (c) NCSR / 37.71 (d) WNNM / 37.59

(e) DnCNN-B / 37.31 (f) Multiscale / 28.02 (g) GCBD (ours) / 40.67 (h) Ground truth

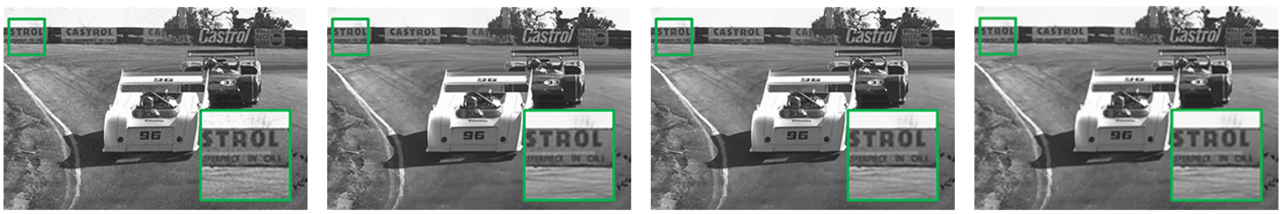


(i) Noisy / 35.47 (j) BM3D / 38.82 (k) NCSR / 38.77 (l) WNNM / 38.36

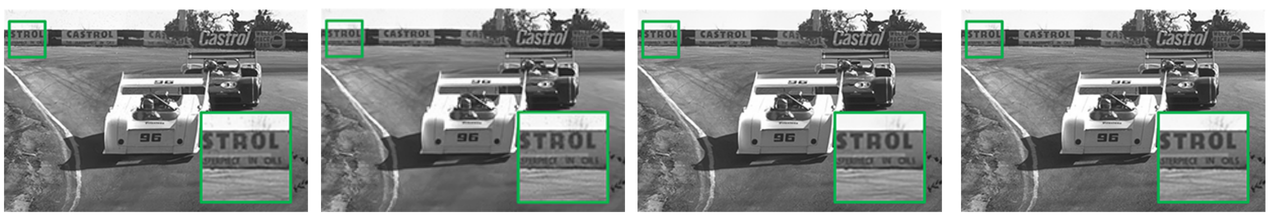


(m) DnCNN-B / 38.03 (n) Multiscale / 35.83 (o) GCBD (ours) / 40.56 (p) Ground truth

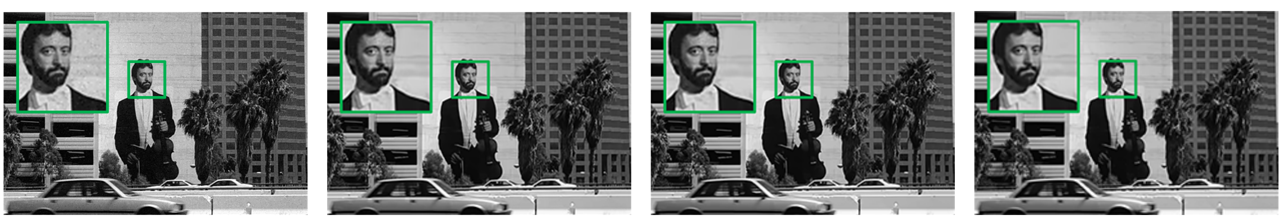
Figure 4. Comparison (PSNR/dB) on BSD68 in the evaluation of **mixture noise denoising** with $s = 25$ (20% uniform noise). Zoom in for better view.



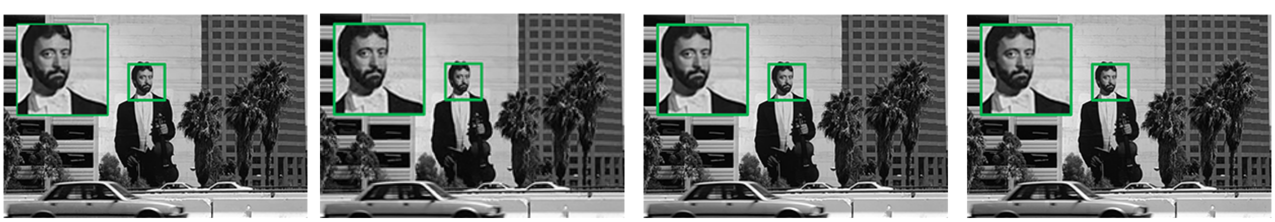
(a) Noisy / 32.06 (b) BM3D / 35.07 (c) NCSR / 35.13 (d) WNNM / 35.16



(e) DnCNN-B / 35.15 (f) Multiscale / 34.15 (g) GCBD (ours) / 36.48 (h) Ground truth

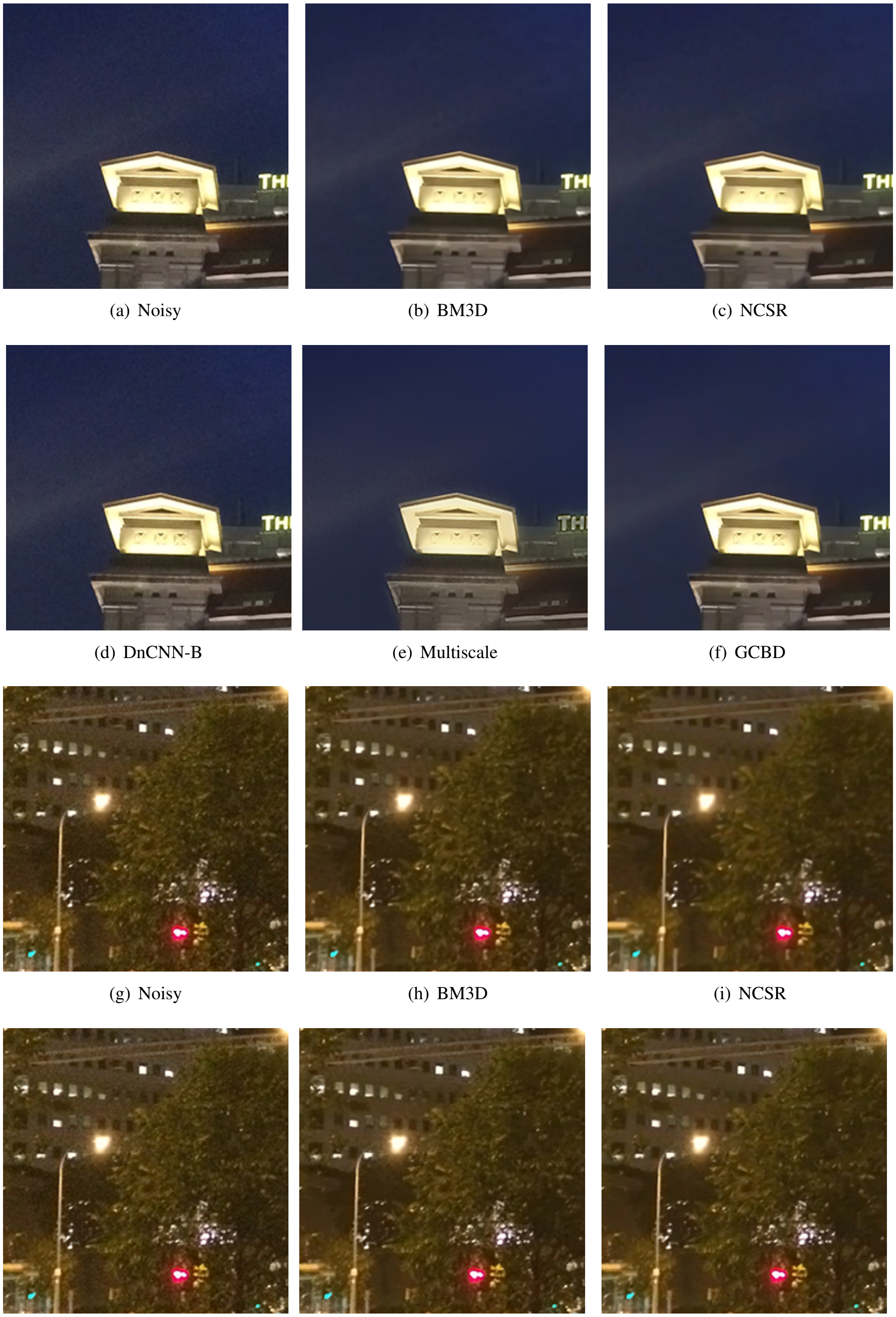


(i) Noisy / 32.09 (j) BM3D / 36.19 (k) NCSR / 36.25 (l) WNNM / 36.40



(m) DnCNN-B / 35.90 (n) Multiscale / 34.58 (o) GCBD (ours) / 37.42 (p) Ground truth

Figure 5. Comparison on **NIGHT-A** in the evaluation of real-world noise denoising. Zoom in for better view.



(a) Noisy (b) BM3D (c) NCSR

(d) DnCNN-B (e) Multiscale (f) GCBD

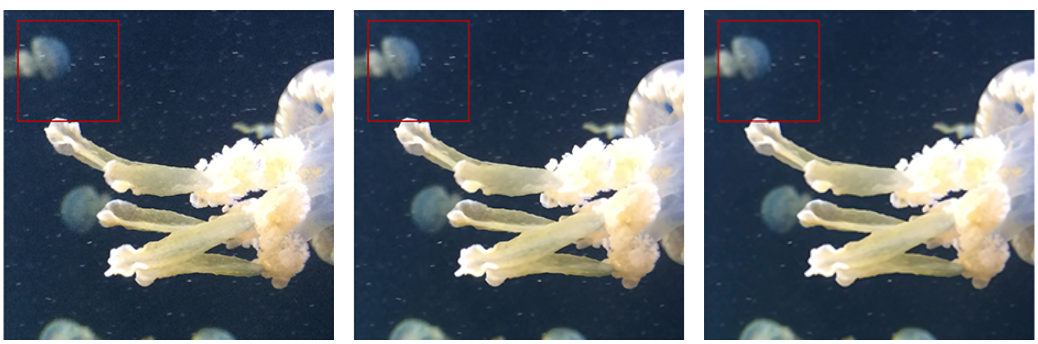
(g) Noisy (h) BM3D (i) NCSR

(j) DnCNN-B (k) Multiscale (l) GCBD

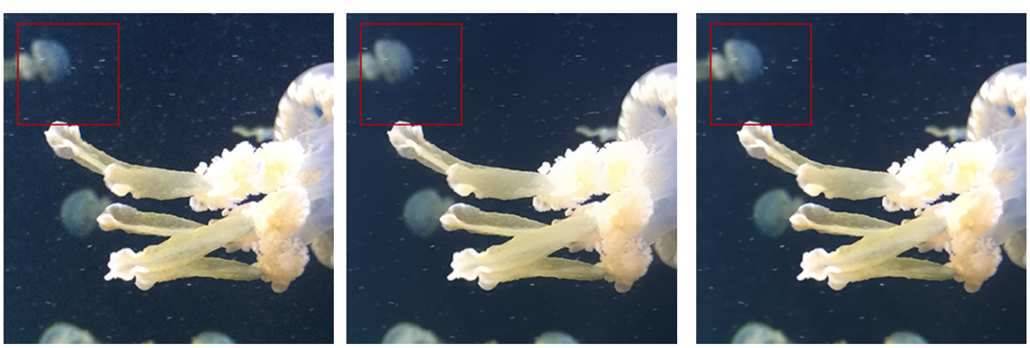
Figure 6. Comparison on **NIGHT-B** in the evaluation of real-world noise denoising. Zoom in for better view.

(a) Noisy (b) BM3D (c) NCSR

(d) DnCNN-B (e) Multiscale (f) GCBD



(g) Noisy (h) BM3D (i) NCSR



(j) DnCNN-B (k) Multiscale (l) GCBD