Masked and Shuffled Blind Spot Denoising for Real-World Images (Supplementary Materials)

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1. Introduction

In this document, we provide more visual results on SIDD [1] and PolyU [3] datasets, that we could not include in the main paper. We also mention the implementation details of MASH and discuss the robustness of MASH to the choice of the hyperparameters.

2. Implementation details

The network architecture of MASH is the same as in Noise2Noise [2]. The denoising network is trained from scratch using the Adam optimizer with cosine annealing. The default hyperparameters that we use in our implementation are as follows: $\tau^{\text{high}} = 0.8$, $\tau^{\text{low}} = 0.2$ and $\tau^{\text{medium}} = 0.5$, $\varepsilon^{\text{low}} = 1.5$, $\varepsilon^{\text{high}} = 2.5$ and , $N = 800$.

3. Robustness to the choice of hyperparameters

Table 1 shows the performance of MASH when using different hyperparameters (ε^{low} and ε^{high}). MASH is robust to the choice of ε^{low} in the range $[1., 2.]$ and ε^{high} in the range $[2., 4.]$. Figure 1 shows some images where MASH fails to predict the optimal masking ratio on SIDD dataset. We note that most of these miss-classifications occur when ε is around the border regions (around ε^{low} or ε^{high}).

ε^{low}	ε^{high}	PSNR
1.	2.	33.73
1.	3.	33.71
1.5	2.5	33.66
2.	4.	33.87

Table 1. Robustness of MASH to the choice of the hyperparameters on FMDD dataset. .

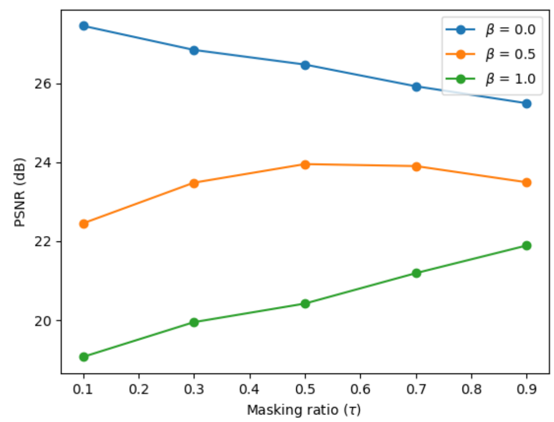


Figure 6. Impact of the masking ratio τ on the generalized BSD denoising performance (PSNR) when $\sigma = 40$. On the horizontal axis we consider several masking ratios τ and for each we train a BSD model on data with different levels of correlation β.

4. Additional Visual Results

We provide additional visual comparisons on SIDD and PolyU datasets in Figures 4, 2 respectively. MASH shows significant improvement over the baseline and competitive results compared to other self-supervised single-image denoising methods.

References

[1] Abdelrahman Abdelhamed, Stephen Lin, and Michael S. Brown. A high-quality denoising dataset for smartphone cameras. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. 1

[2] Munkberg J. Hasselgren J. Laine S. Karras T. Aittala M. Aila T. Lehtinen, J. Noise2noise: Learning image restoration without clean data. In *arXiv preprint arXiv:1803.04189*, 2018. 1

[3] Seonghyeon Nam, Youngbae Hwang, Yasuyuki Matsushita, and Seon Joo Kim. A holistic approach to cross-channel im-

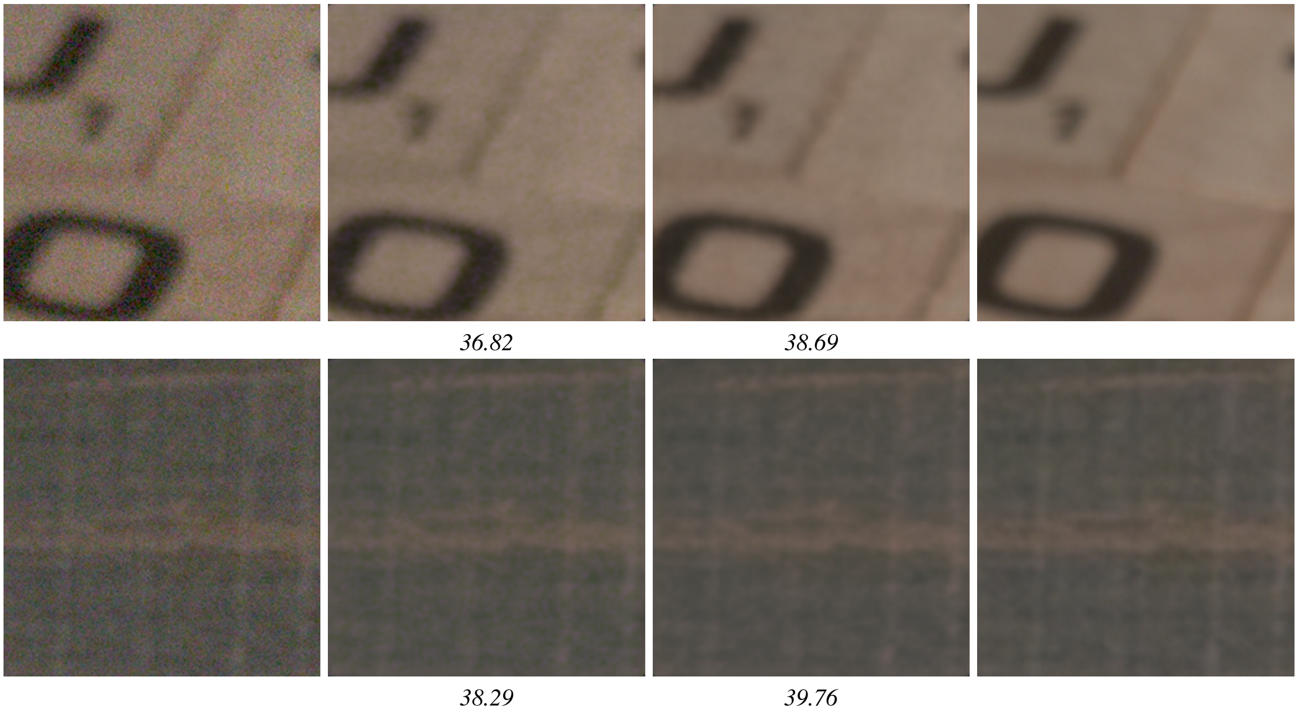


Figure 1. some images where MASH fails to predict the optimal masking ratio (when using $\varepsilon^{low} = 1.5$ and $\varepsilon^{high} = 2.5$) on SIDD dataset. From left to right: noisy input image, denoised image when using our adaptive masking scheme (PSNR is reported under the image), denoised image with the optimal masking ratio (PSNR is reported under the image), ground truth. First row: $\varepsilon = 1.32$, predicted masking ratio is τ^{low}, optimal masking ratio is τ^{medium}. Second row: $\varepsilon = 1.25$, predicted masking ratio is τ^{low}, optimal masking ratio is τ^{medium}.

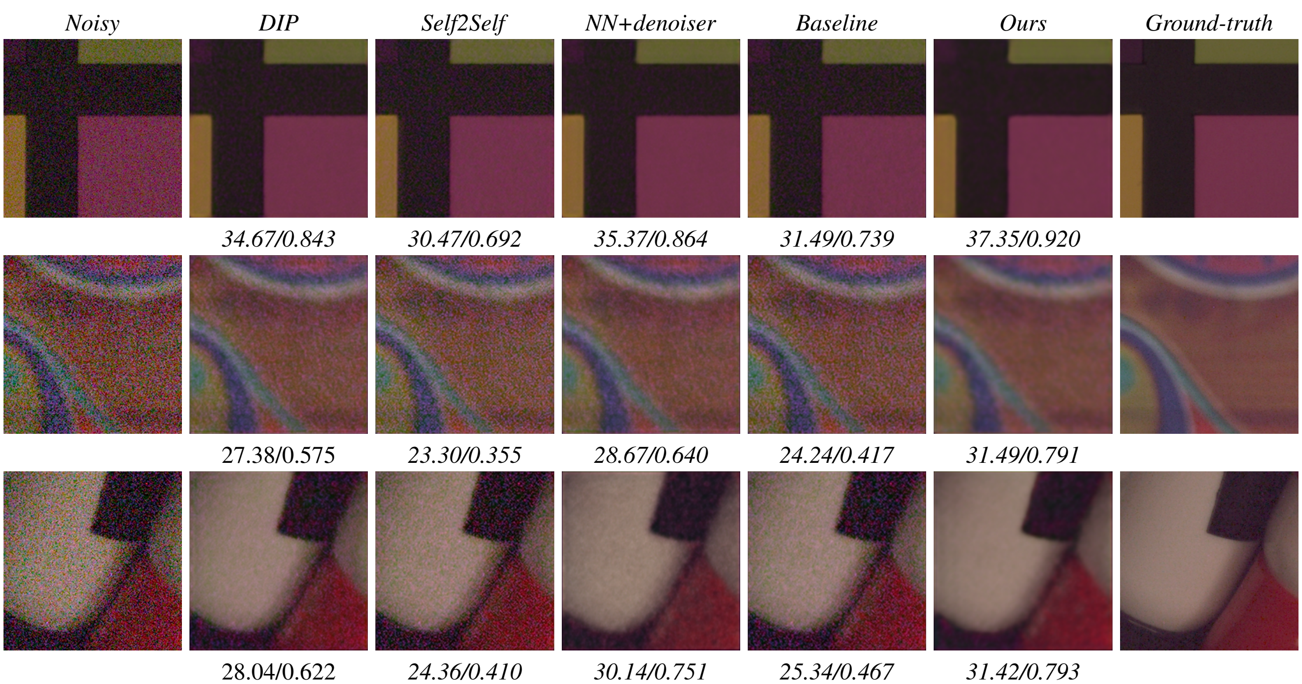


Figure 2. Visual comparison of our method against other single image-based denoising methods in SIDD validation. The PSNR/SSIM results are reported under each image.

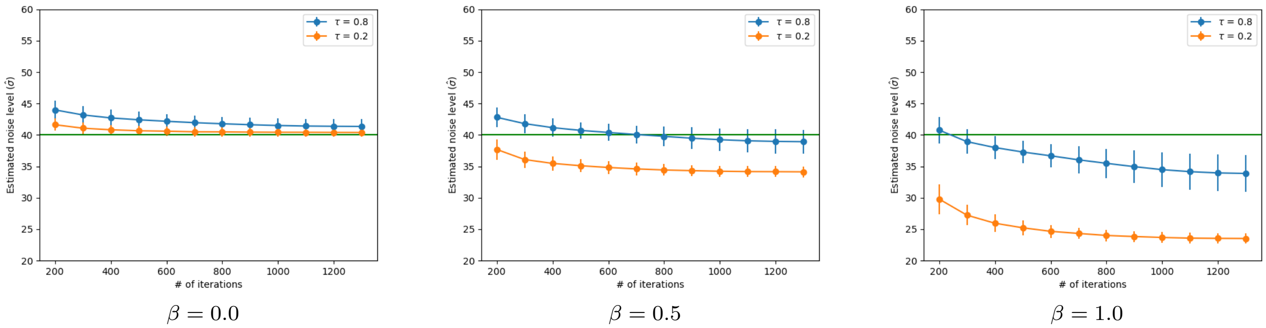


Figure 3. Estimated noise level based on different correlated noise magnitude and masking ratios when $\sigma = 40$.

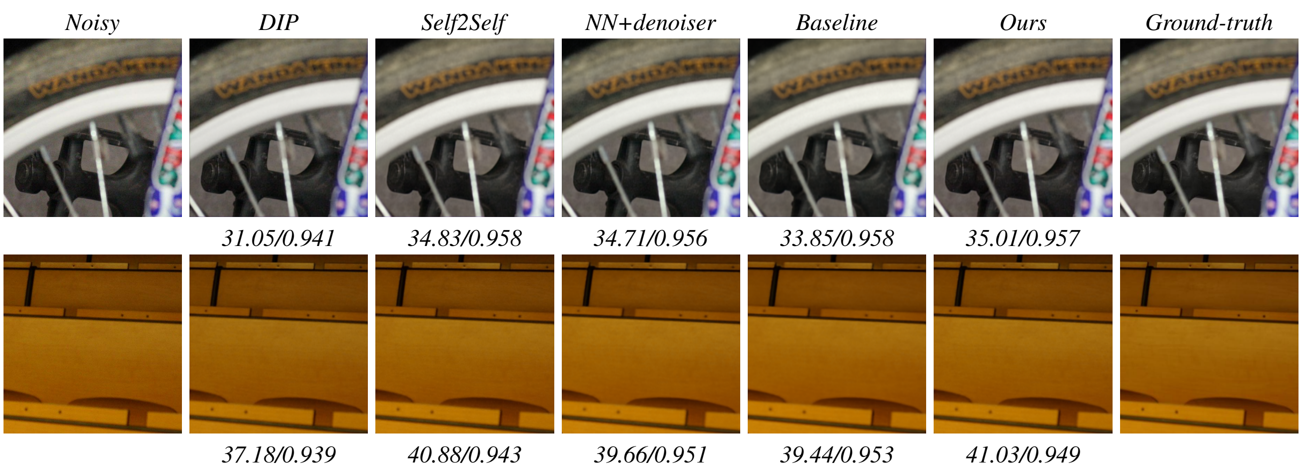
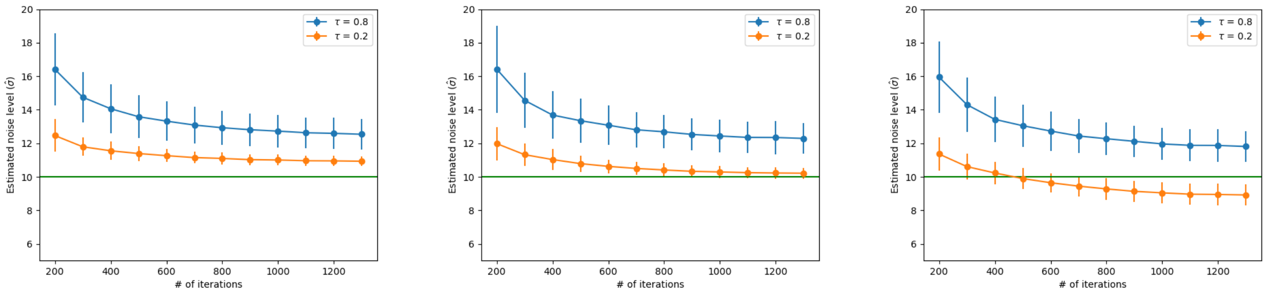


Figure 4. Visual comparison of our method against other single image-based denoising methods in PolyU dataset. The PSNR/SSIM results are reported under each image.

age noise modeling and its application to image denoising. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1683–1691, 2016. 1



$\beta = 0.0$ $\beta = 0.5$ $\beta = 1.0$

Figure 5. Estimated noise level based on different correlated noise magnitude and masking ratios when $\sigma = 10$.

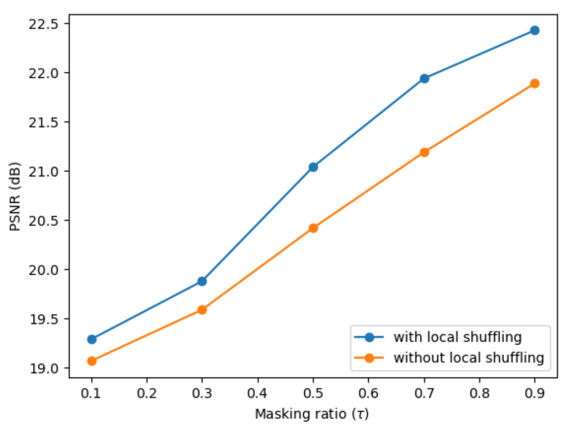


Figure 7. Impact of the local pixel shuffling on the denoising performance (PSNR) when noise is highly correlated when $\sigma = 40$