Identifying Recurring Patterns with Deep Neural Networks for Natural Image Denoising
Supplementary Material

Zhihao Xia Ayan Chakrabarti
Washington University in St. Louis
{zhihao.xia,ayan}@wustl.edu

A. Separate Evaluation of Matching Network

While our main evaluation considers the performance of our overall method, below we separately evaluate the performance of just our matching network and compare it to other "internal statistics"-based methods. Our matching network is trained with the objective of maximizing denoising quality when using its outputs as weights for averaging patches. Therefore, as evaluation, we include average PSNR and SSIM values on all datasets of the *initial* estimates of our method: based on averaging using predicted matching scores (but without the second regression step). For comparison, we also include the results of the other internal statistics-based methods from Table 1: CBM3D which is based on sum-of-squares distance (SSD) matching, and the neural network-based methods CBM3D-Net and CNL-Net.

We find that even our matching network by itself outperforms past self similarity-based methods (while our full method achieves state-of-the-art performance as demonstrated in the main paper).

	Method	σ=75		σ=50		σ=35		σ=25	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Urban-100	CBM3D	25.97	0.784	27.94	0.843	29.27	0.875	**31.38**	0.912
	Ours: Match-average Only	**26.15**	**0.793**	**28.12**	**0.850**	**29.76**	**0.886**	31.34	**0.913**
Kodak-24	CBM3D	26.82	0.714	28.45	0.775	29.90	0.821	31.67	0.868
	Ours: Match-average Only	**27.27**	**0.735**	**28.98**	**0.796**	**30.53**	**0.843**	**32.06**	**0.880**
CBSD-68	CBM3D	25.75	0.698	27.38	0.767	28.89	0.821	30.71	0.872
	CBM3D-Net	-	-	27.48	-	-	-	30.91	-
	CNL-Net	-	-	27.64	-	-	-	30.96	-
	Ours: Match-average Only	**26.15**	**0.723**	**27.83**	**0.791**	**29.40**	**0.843**	**31.00**	**0.884**
McMaster	CBM3D	26.80	0.735	28.52	0.794	29.92	0.833	31.66	0.874
	Ours: Match-average Only	**27.18**	**0.757**	**28.92**	**0.812**	**30.39**	**0.850**	**31.81**	**0.882**

B. Additional Examples

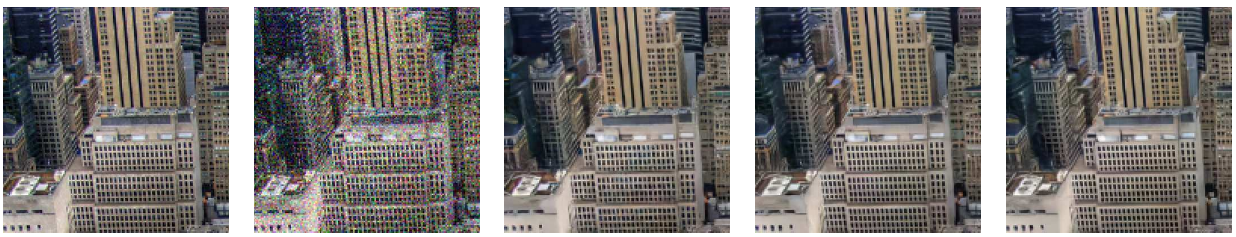
B.1. Comparisons to FFDNet

We begin by showing more visual results comparing our performance to the state-of-the-art method. Here, we include denoising estimates with both the "blind" and noise-specific versions of our model.

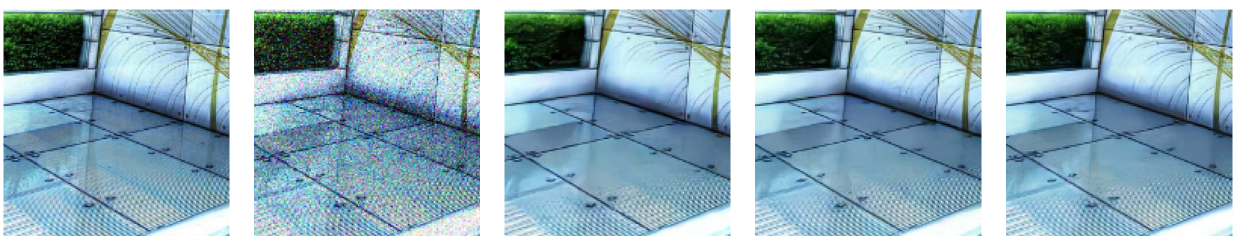
GT Noisy FFDNet (31.34dB) Ours-Blind (31.69dB) Ours (31.72dB)

GT | Noisy | FFDNet (25.84dB) | Ours-Blind (26.21dB) | Ours (26.25dB)

GT | Noisy | FFDNet (25.90dB) | Ours-Blind (26.51dB) | Ours (26.51dB)

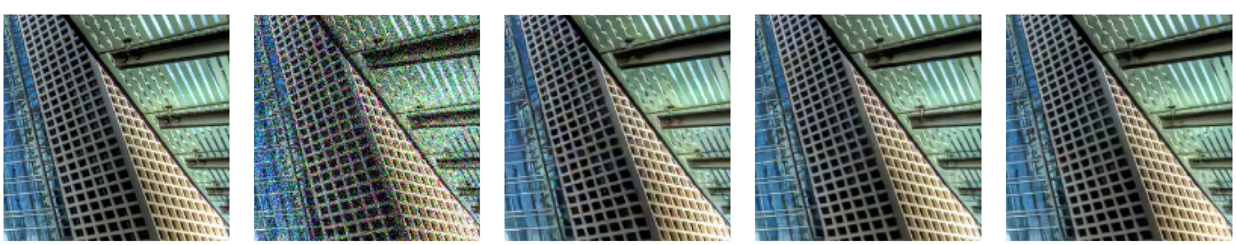


GT | Noisy | FFDNet (25.86dB) | Ours-Blind (26.40dB) | Ours (26.42dB)

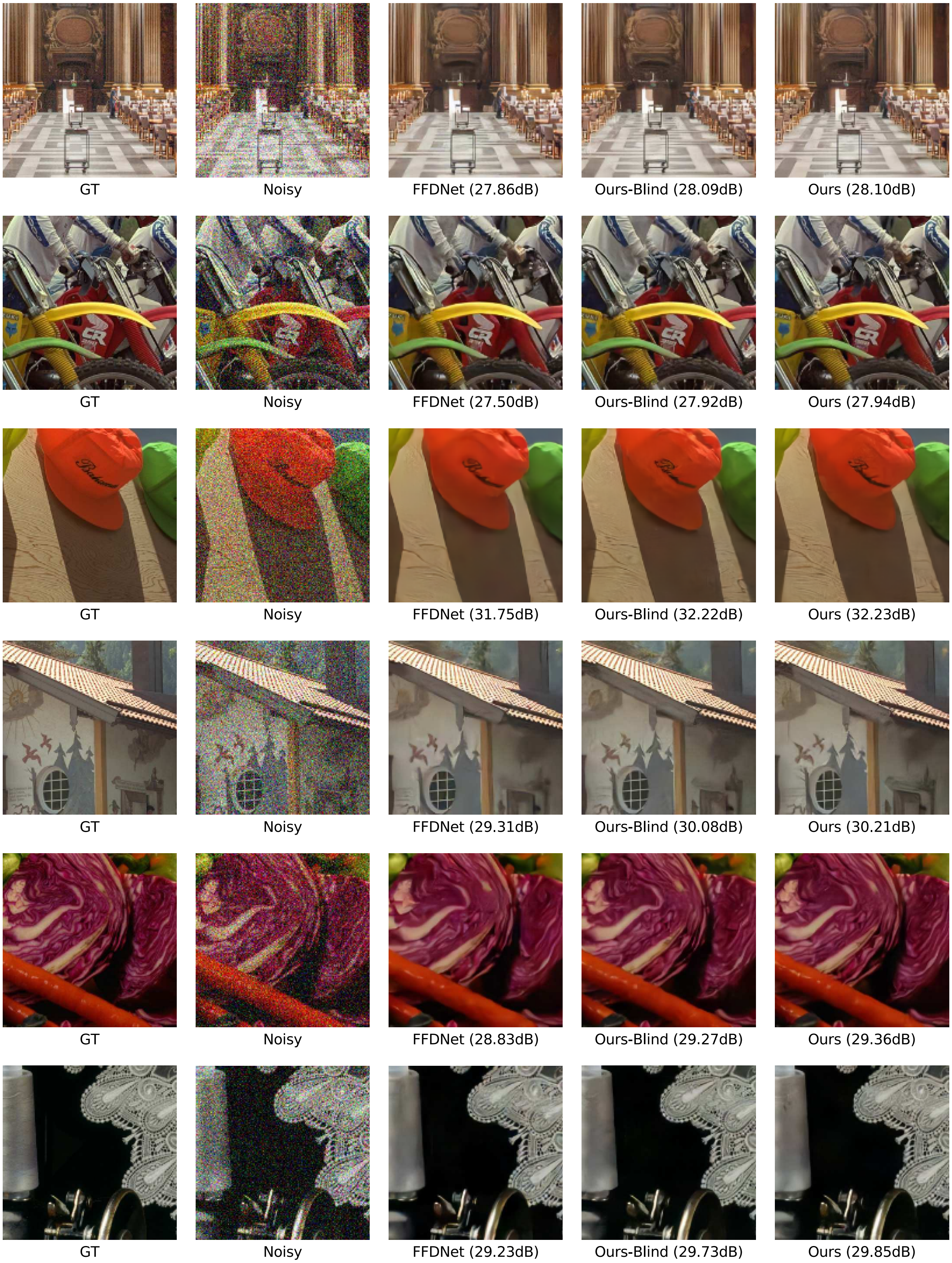


GT | Noisy | FFDNet (27.36dB) | Ours-Blind (27.97dB) | Ours (28.00dB)

GT | Noisy | FFDNet (26.42dB) | Ours-Blind (26.62dB) | Ours (26.73dB)



GT | Noisy | FFDNet (26.20dB) | Ours-Blind (27.30dB) | Ours (27.28dB)


GT
Noisy
FFDNet (27.86dB)
Ours-Blind (28.09dB)
Ours (28.10dB)
GT
Noisy
FFDNet (27.50dB)
Ours-Blind (27.92dB)
Ours (27.94dB)
GT
Noisy
FFDNet (31.75dB)
Ours-Blind (32.22dB)
Ours (32.23dB)
GT
Noisy
FFDNet (29.31dB)
Ours-Blind (30.08dB)
Ours (30.21dB)
GT
Noisy
FFDNet (28.83dB)
Ours-Blind (29.27dB)
Ours (29.36dB)
GT
Noisy
FFDNet (29.23dB)
Ours-Blind (29.73dB)
Ours (29.85dB)

B.2. Failure Cases

Next, we show some of the examples of image regions where our denoised estimates have low accuracy.

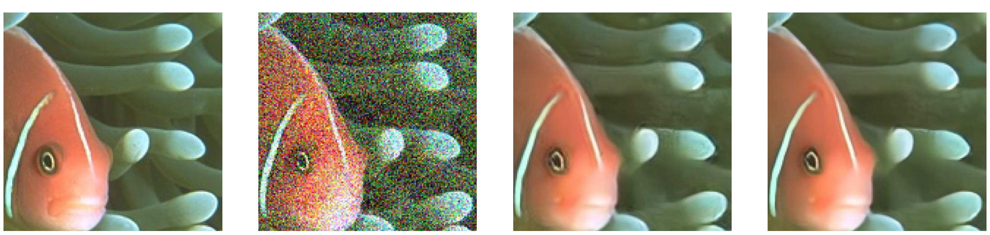
GT | Noisy | FFDNet (37.69dB) | Ours-Blind (37.44dB) | Ours (37.44dB)

GT | Noisy | FFDNet (35.12dB) | Ours-Blind (34.65dB) | Ours (34.77dB)

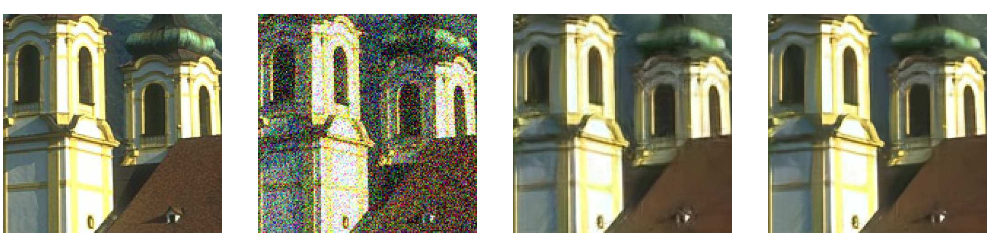
GT | Noisy | FFDNet (29.51dB) | Ours-Blind (29.22dB) | Ours (29.26dB)

B.3. Initial vs Final Estimates

Finally, we include examples of the intermediate output of our method—our initial estimates formed only by averaging based on scores from the matching network—and compare it to the final output after processing by the regression network. The match-average estimates are of reasonably high quality, and the regression network improves these results by varying amounts in different images (by removing subtle "ringing-like" artifacts).



GT | Noisy | Ours (w/o regression) (29.97dB) | Ours (Final) (30.61dB)



GT | Noisy | Ours (w/o regression) (26.55dB) | Ours (Final) (27.36dB)


GT
Noisy
Ours (w/o regression) (30.35dB)
Ours (Final) (30.37dB)
GT
Noisy
Ours (w/o regression) (29.76dB)
Ours (Final) (29.78dB)