Self-Supervised Image Restoration with Blurry and Noisy Pairs

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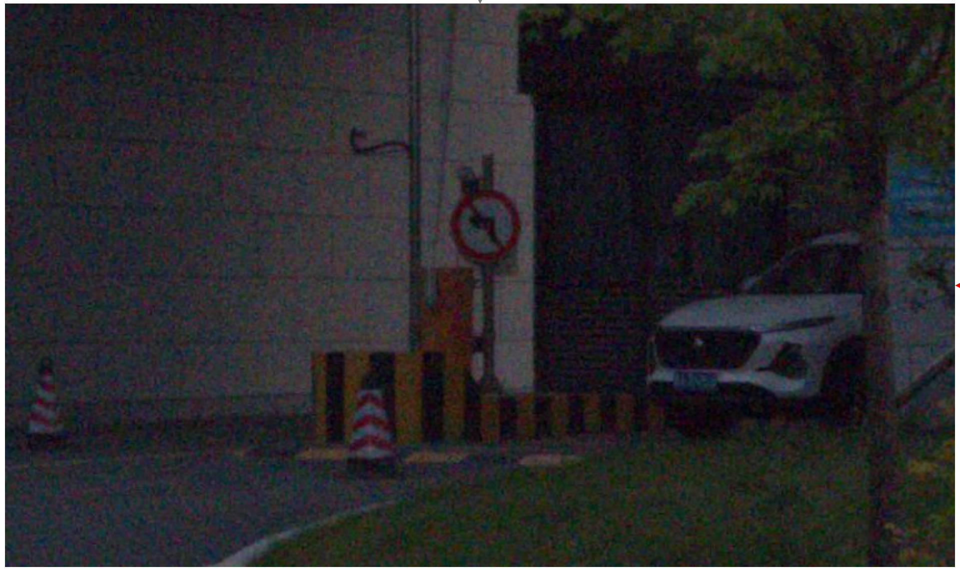
NEURAL INFORMATION PROCESSING SYSTEMS

Motivation

Low light photography with smartphones

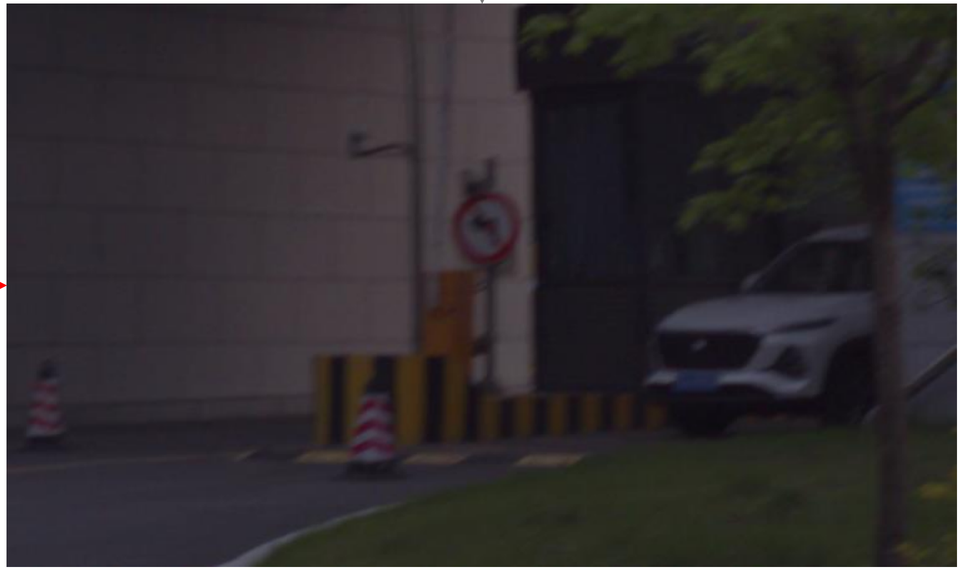
Short-exposure and high ISO



Noisy
but hardly blurry

Complementary

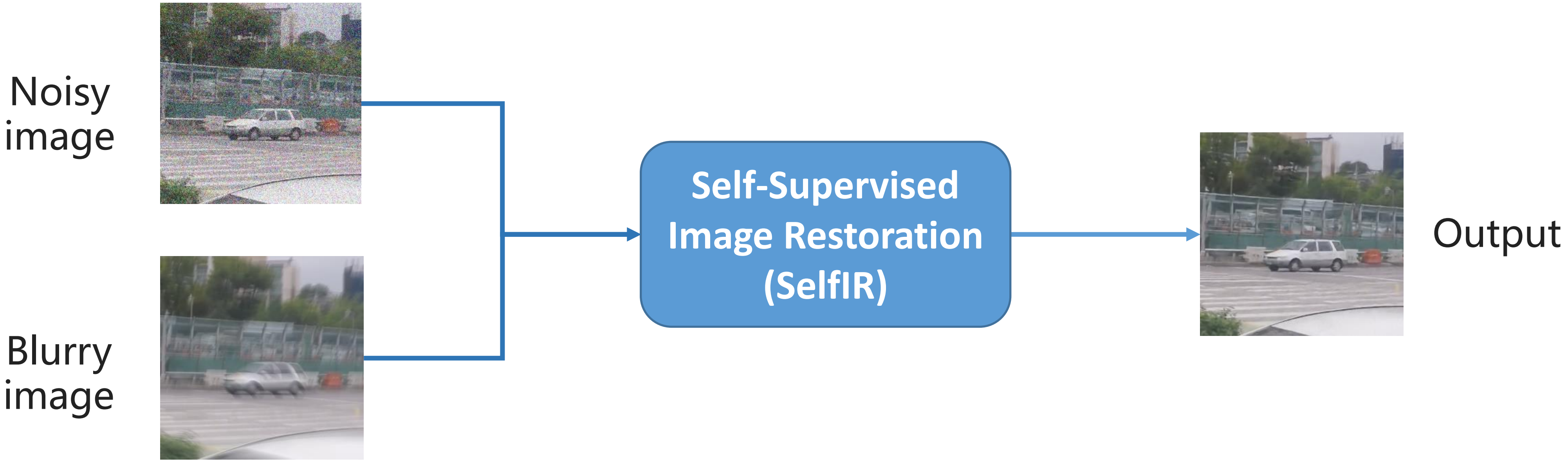
Long-exposure and low ISO



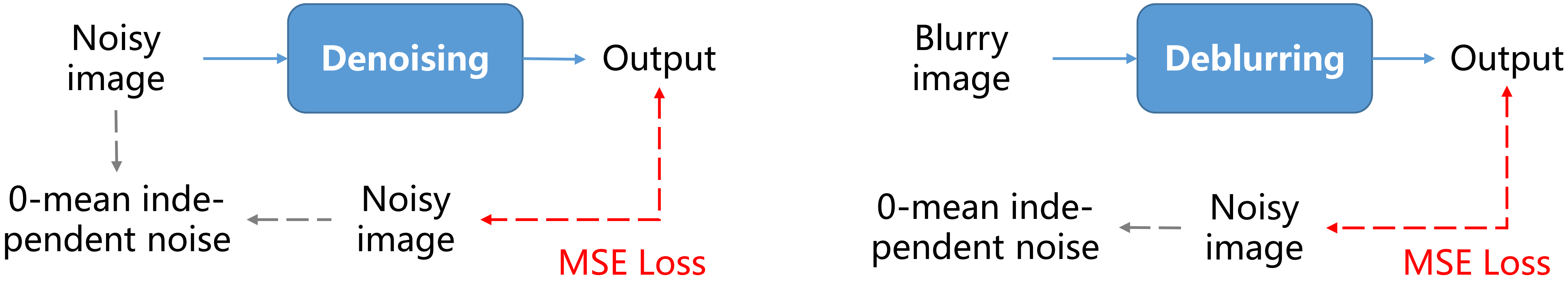
Blurry
but near noise-free

Self-Supervised Image Restoration (SelfIR)

- The complementary information between short-exposure and long-exposure images
  - Be beneficial to improve restoration performance
  - Make self-supervised image restoration possible



Deblurring with Noisy Images



(a) Noise2Noise [1]

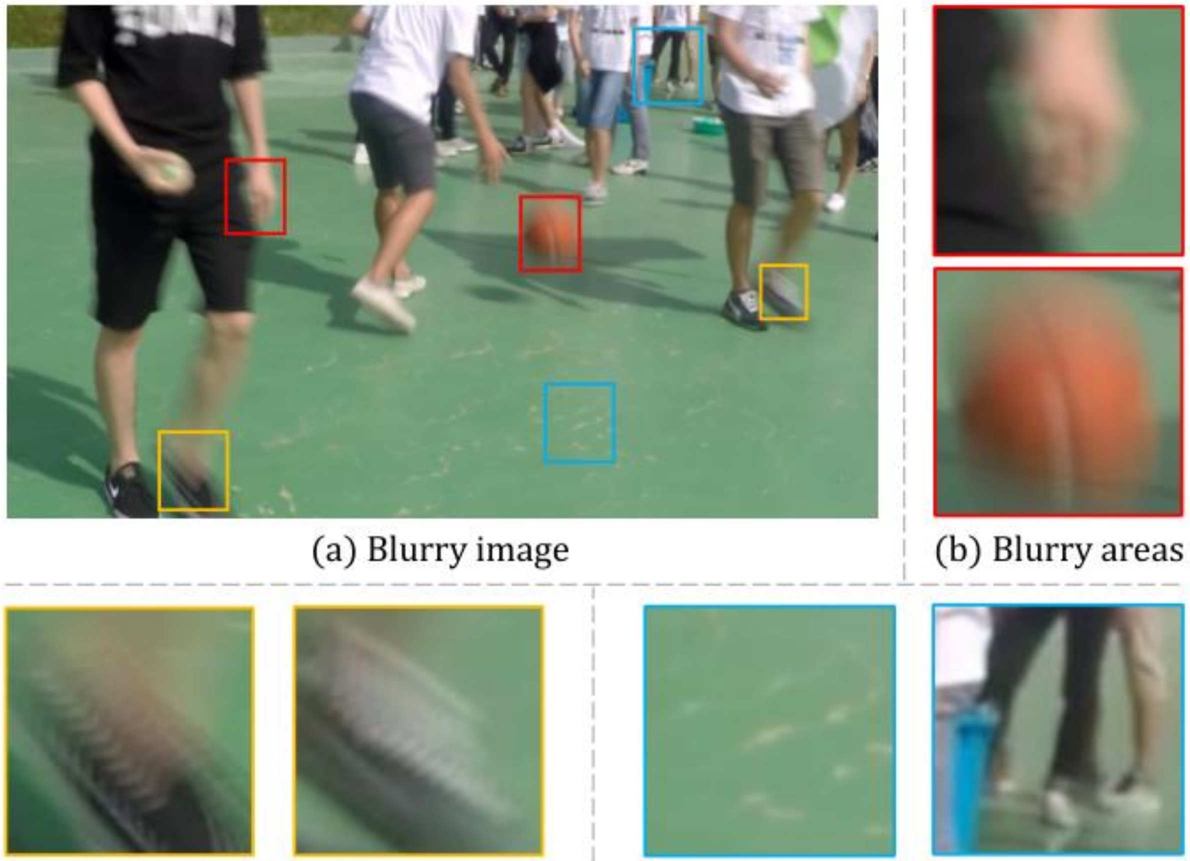
(b) Ours

Table 3: Results of deblurring with clear images and noisy images as the supervision.

Supervision Information	Gaussian $\sigma \in [5/255, 50/255]$ PSNR↑ / SSIM↑ / LPIPS↓	Poisson $\lambda \in [5, 50]$ PSNR↑ / SSIM↑ / LPIPS↓	Sensor Noise [3] PSNR↑ / SSIM↑ / LPIPS↓
Clear Images	28.24 / 0.8561 / 0.191	28.24 / 0.8561 / 0.191	28.14 / 0.8547 / 0.162
Noisy Images	28.29 / 0.8578 / 0.190	28.23 / 0.8563 / 0.191	28.16 / 0.8545 / 0.164

[1] Lehtinen J, Munkberg J, et al. Noise2Noise: Learning image restoration without clean data. ICML 2018.

Improve Denoising with Blurry Images



(a) Blurry image (b) Blurry areas (c) Blurry areas with ringing artifacts (d) Approximately sharp areas

- Detect sharp areas

$$m^n = \mathtt{sgn}(\mathtt{max}(0, s(\mathbf{I}^n_{\mathcal{B}}, \tilde{\mathbf{I}}^n_{\mathcal{N}}) - \epsilon_s)) * \mathtt{sgn}(\mathtt{max}(0, \mathtt{var}(\mathbf{I}^n_{\mathcal{B}}) - \mathtt{var}(\tilde{\mathbf{I}}^n_{\mathcal{N}}) - \epsilon_v)).$$

- Auxiliary loss

$$\mathcal{L}_{aux}(\hat{\mathbf{I}}, \mathbf{I}_{\mathcal{B}}) = \sum\nolimits_{n=1}^{N} m^n \|\hat{\mathbf{I}}^n - \mathbf{I}^n_{\mathcal{B}}\|_2^2.$$

$\mathbf{I}_{\mathcal{B}}$ — Blurry image

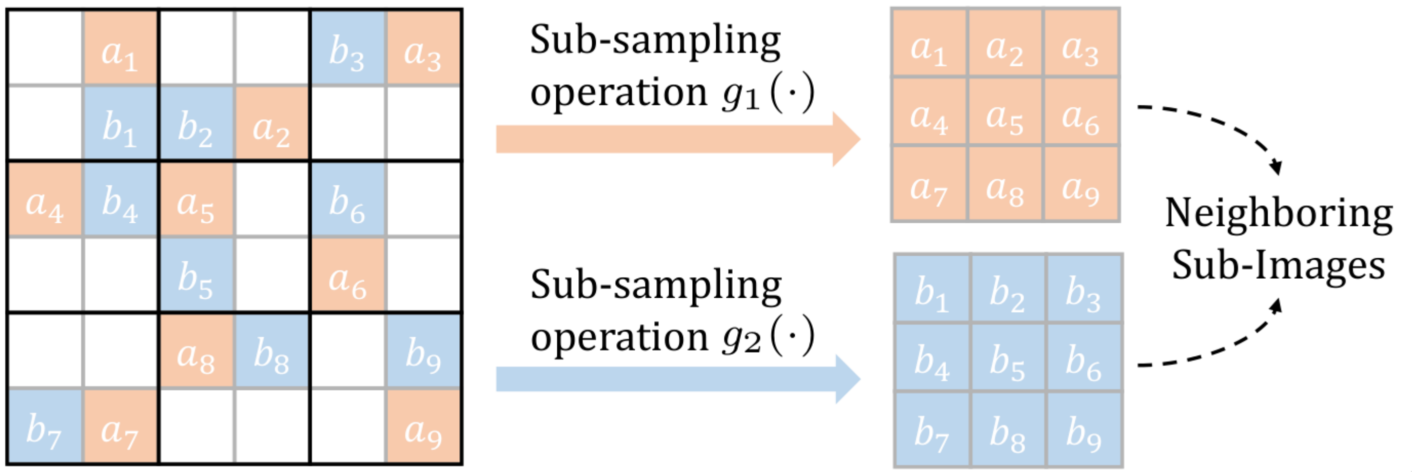
$\mathbf{I}_{\mathcal{N}}$ — Noisy image

$\tilde{\mathbf{I}}_{\mathcal{N}}$ — Denoising result by self-supervised denoising model

$\hat{\mathbf{I}}$ — Restoration result by SelfIR

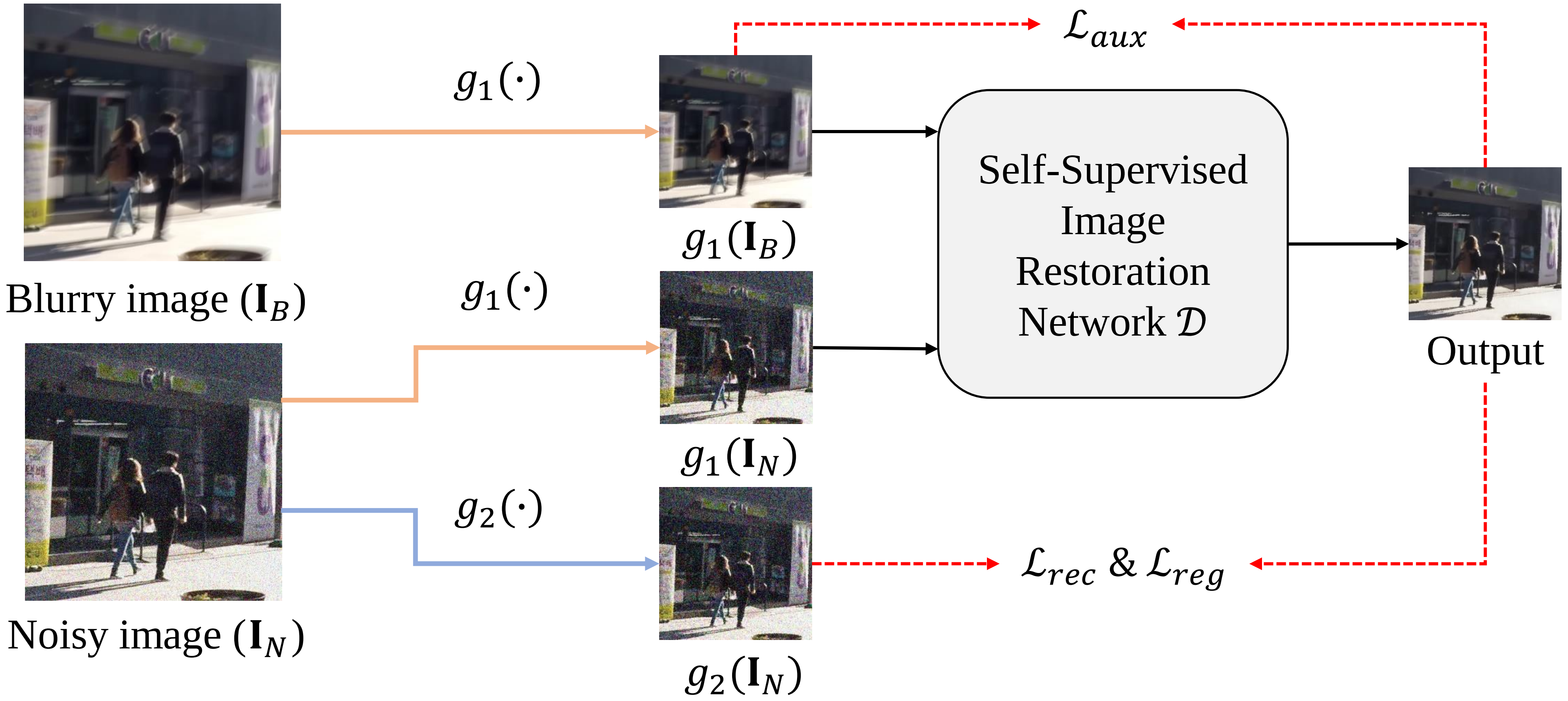
Training of SelfIR

- SelfIR should learn from both deblurring and denoising tasks.
- However, it is required to avoid the trivial solution when taking both blurry and noisy images as the input.
- Fortunately, Neighbor2Neighbor shows that noises in two sub-sampled images are almost independent. [2]



[2] Huang T, Li S, Jia X, et al. Neighbor2Neighbor: Self-supervised denoising from single noisy images. CVPR 2021.

Training of SelfIR



Reconstruction loss: $\mathcal{L}_{rec} = \|\mathcal{D}(g_1(\mathbf{I}_{\mathcal{B}}), g_1(\mathbf{I}_{\mathcal{N}})) - g_2(\mathbf{I}_{\mathcal{N}})\|_2^2$

Regularization loss: $\mathcal{L}_{reg} = \|\mathcal{D}(g_1(\mathbf{I}_{\mathcal{B}}), g_1(\mathbf{I}_{\mathcal{N}})) - g_2(\mathbf{I}_{\mathcal{N}}) - (g_1(\hat{\mathcal{D}}(\mathbf{I}_{\mathcal{B}}, \mathbf{I}_{\mathcal{N}})) - g_2(\hat{\mathcal{D}}(\mathbf{I}_{\mathcal{B}}, \mathbf{I}_{\mathcal{N}})))\|_2^2$

Results on Synthetic sRGB Images

	Method	Gaussian $\sigma \in [5/255, 50/255]$ PSNR↑ / SSIM↑ / LPIPS↓	Poisson $\lambda \in [5, 50]$ PSNR↑ / SSIM↑ / LPIPS↓
Supervised Deblurring	Baseline$_{\mathcal{B}}$	28.24 / 0.8561 / 0.191	
	DeepDeblur [21]	30.04 / 0.9015 / 0.133	
Supervised Denoising	Baseline$_{\mathcal{N}}$	34.91 / 0.9360 / 0.098	33.15 / 0.9225 / 0.126
	DnCNN [46]	34.63 / 0.9308 / 0.121	32.45 / 0.9084 / 0.128
Supervised IR	Baseline$_{\mathcal{R}}$	36.15 / 0.9534 / 0.070	34.74 / 0.9454 / 0.084
Self-Supervised Denoising	N2N [15]	34.88 / 0.9354 / 0.100	33.09 / 0.9216 / 0.129
	N2V [11]	33.09 / 0.9180 / 0.115	31.81 / 0.8999 / 0.137
	Laine19-mu [13]	33.61 / 0.9227 / 0.104	32.29 / 0.9091 / 0.131
	Laine19-pme [13]	34.76 / 0.9322 / 0.086	32.77 / 0.9147 / 0.116
	DBSN [38]	33.72 / 0.9224 / 0.111	31.46 / 0.8883 / 0.144
	R2R [23]	33.74 / 0.9223 / 0.100	30.05 / 0.7649 / 0.230
	Neighbor2Neighbor [9]	34.29 / 0.9271 / 0.085	32.68 / 0.9160 / 0.111
	Blind2Unblind [37]	34.69 / 0.9353 / 0.107	33.09 / 0.9216 / 0.132
Ours	SelfIR	35.74 / 0.9499 / 0.076	34.27 / 0.9404 / 0.092

Results on Synthetic and Real-World raw-RGB Images

	Method	Sensor Noise [3] PSNR↑ / SSIM↑ / LPIPS↓	Real-World Images NIQE↓ / NRQM↑ / PI↓
Supervised Deblurring	Baseline$_{\mathcal{B}}$	28.14 / 0.8547 / 0.162	6.26 / 5.04 / 5.62
	DeepDeblur [21]	29.75 / 0.8881 / 0.115	6.76 / 4.78 / 6.00
Supervised Denoising	Baseline$_{\mathcal{N}}$	34.52 / 0.9461 / 0.053	5.69 / 4.85 / 5.43
	DnCNN [46]	33.81 / 0.9325 / 0.076	6.05 / 5.10 / 5.48
Supervised IR	Baseline$_{\mathcal{R}}$	36.10 / 0.9574 / 0.035	5.54 / 5.14 / 5.18
Self-Supervised Denoising	N2N [15]	34.67 / 0.9472 / 0.053	6.10 / 4.93 / 5.59
	N2V [11]	31.39 / 0.9227 / 0.076	5.82 / 5.52 / 5.17
	Laine19-mu [13]	32.74 / 0.9304 / 0.073	5.87 / 5.67 / 5.10
	Laine19-pme [13]	33.28 / 0.9119 / 0.095	7.26 / 6.03 / 5.62
	DBSN [38]	33.59 / 0.9389 / 0.060	6.57 / 5.48 / 5.54
	R2R [23]	32.21 / 0.8807 / 0.117	5.63 / 5.63 / 4.99
	Neighbor2Neighbor [9]	32.82 / 0.9275 / 0.087	6.47 / 5.86 / 5.33
	Blind2Unblind [37]	33.30 / 0.9380 / 0.061	5.28 / 5.22 / 5.04
Ours	SelfIR	34.51 / 0.9440 / 0.053	5.48 / 5.83 / 4.86

Results on Gaussian Noise

Noisy Image | Baseline$_{\mathcal{N}}$ | N2V [11] | Laine19-pme [13] | DBSN [38] | R2R [23]

Blurry Image | Baseline$_{\mathcal{B}}$ | Neighbor2Neighbor [9] | Blind2Unblind [37] | SelfIR (Ours) | Baseline$_{\mathcal{R}}$

Results on Real-World Images


Noisy Image

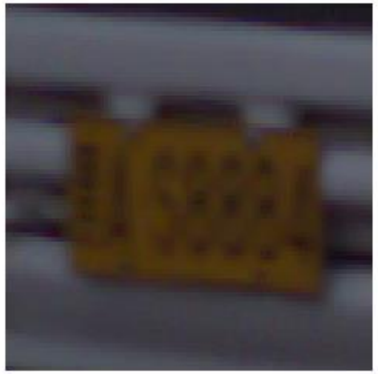

Baseline$_{\mathcal{N}}$


N2V [4]


Laine19-pme [5]


DBSN [10]


R2R [7]


Blurry Image


Baseline$_{\mathcal{B}}$


Neighbor2Neighbor [3]


Blind2Unblind [9]


SelfIR (Ours)


Baseline$_{\mathcal{R}}$

Thanks for Watching!