Noise Dataset Synthesis Paper Survey

Presenter: Hao Wang

Advisor: Prof. Chia-Wen Lin

Outline

- LRD
  - ICCV 2023
- LRID
  - IEEE PAMI 2024

Towards General Low-Light Raw Noise Synthesis and Modeling

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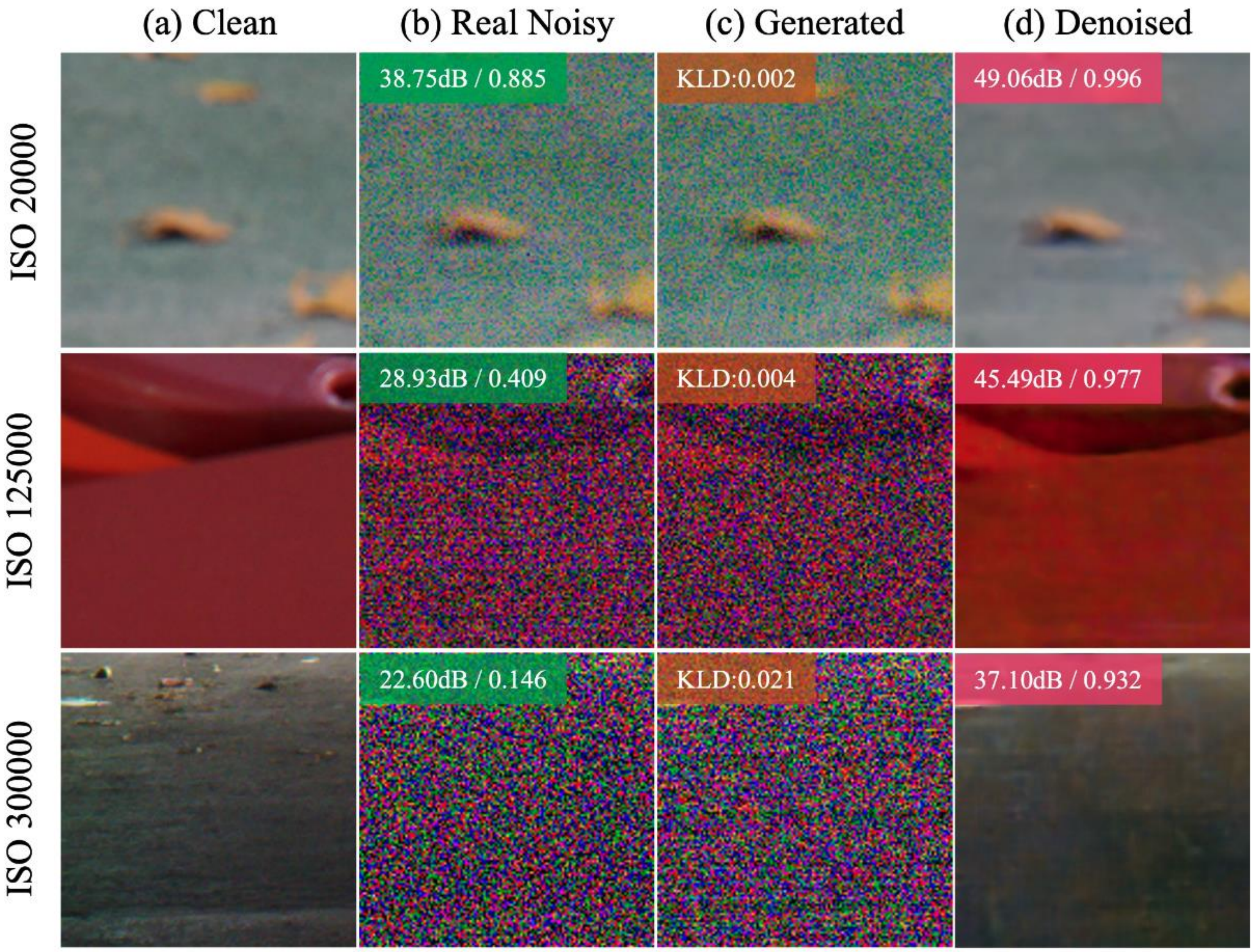
ICCV 2023

Presenter: Hao Wang

Advisor: Prof. Chia-Wen Lin

Introduction

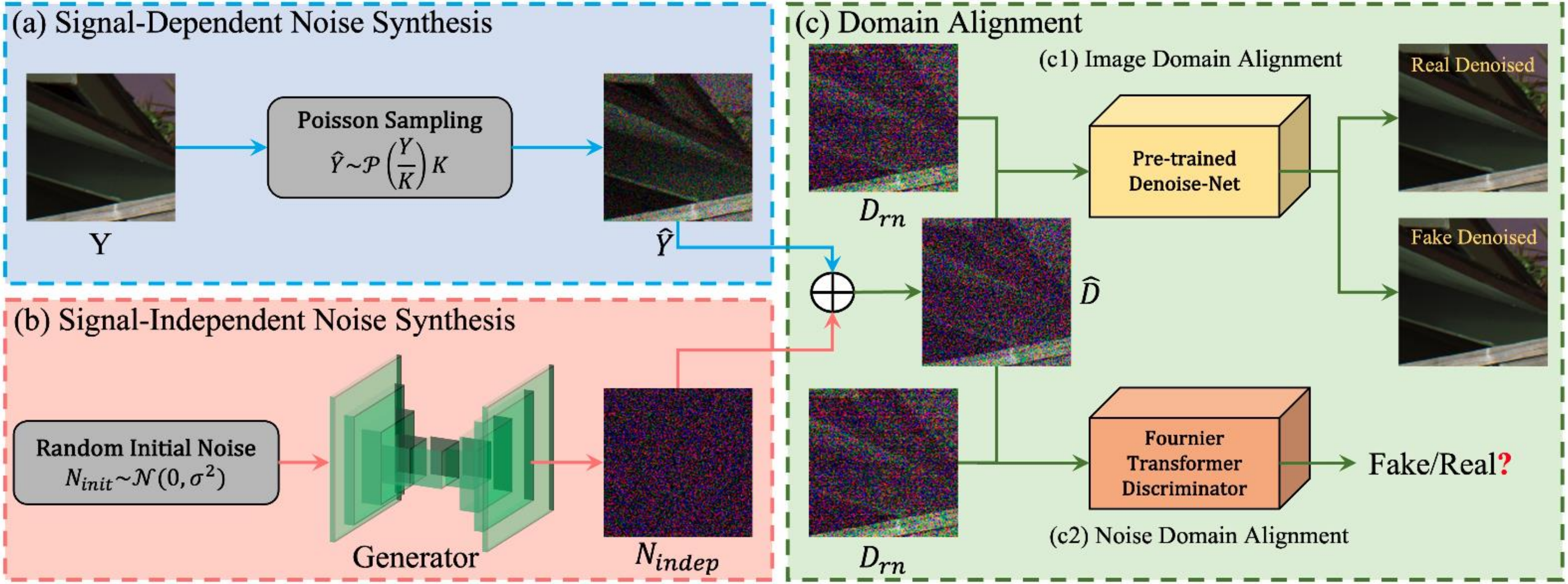
- Propose a general **noise model** to **imitate accurate low-light raw noise** on different sensors.
- Establish Fourier transformer **discriminator** (FTD), which encourages the generator to favor solutions.
- Collect a **new large-scale dataset**.



Framework

$$\mathcal{L}_1 = \| P(\hat{D}) - P(D_{rn}) \|_1,$$

$$\mathcal{L}_{per} = \| \phi(P(\hat{D}) - \phi(P(D_{rn}) \|_2^2,$$



ISO levels,
exposure times,
in-camera noise profiles

$$\mathcal{L}_{adv} = \mathop{\mathbb{E}}_{\hat{D} \sim \mathbb{P}_g}[D_F(\hat{D})] - \mathop{\mathbb{E}}_{D_{rn} \sim \mathbb{P}_r}[D_F(D_{rn})] + \lambda \mathop{\mathbb{E}}_{\tilde{x} \sim \mathbb{P}_{\tilde{x}}} [(\|\nabla_{\tilde{x}} D_F(\tilde{x})\|_2 - 1)^2],$$

Data collection

- Clean
  - long-exposure image at **ISO 100** to get a noise-free reference image

- Degraded
  - Total image:1800 pairs (**100 images × 6 ISO levels × 3 exposure value**)
  - different ISO levels and Evs
  - 6 different **ISO levels** ranging from **200 to 6400**

$$\mathrm{EV} = \log_2 \frac{N^2}{t}$$

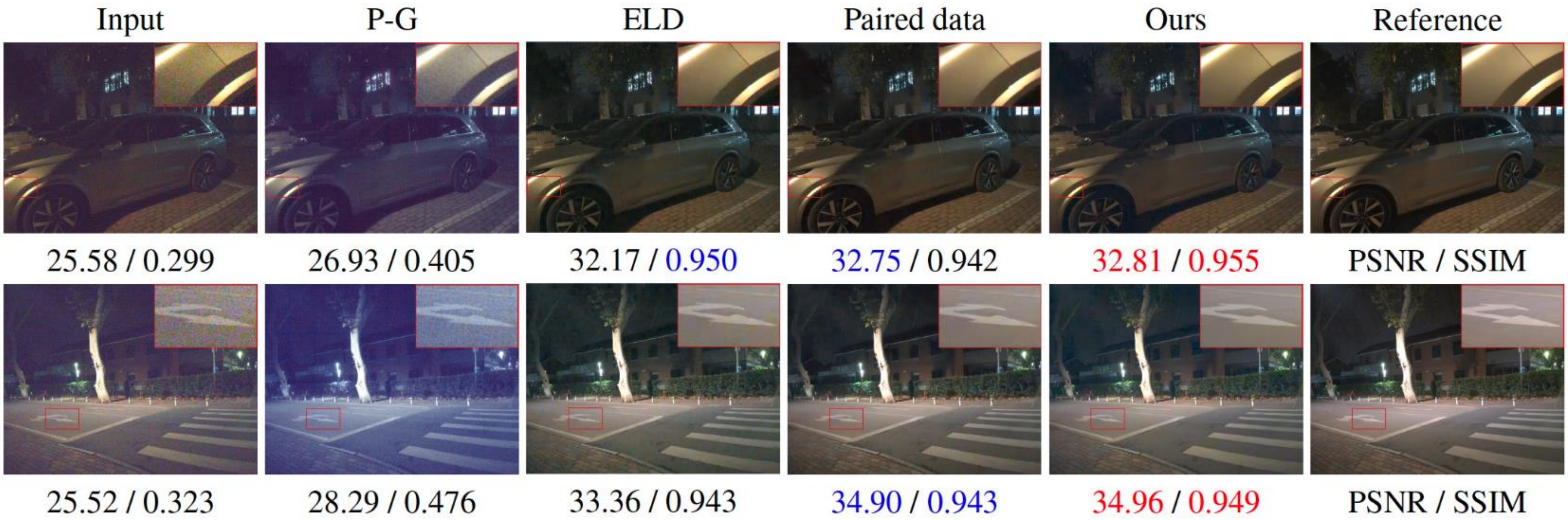
Data collection

Experiment

Dataset	Ratio	Physics-based		Real-noise-based	DNN-based	
		Poisson-Gaussian	ELD	Paired data	Noise Flow	Ours
		PSNR / SSIM	PSNR / SSIM	PSNR / SSIM	PSNR / SSIM	PSNR / SSIM
SID	×100	37.51 / 0.856	41.21 / 0.952	41.39 / 0.954	36.75 / 0.787	41.95 / 0.956
	×250	31.67 / 0.765	38.54 / 0.929	38.90 / 0.937	33.98 / 0.739	39.25 / 0.931
	×300	28.53 / 0.667	35.35 / 0.908	36.55 / 0.922	31.82 / 0.713	36.03 / 0.909
ELD	×100	39.46 / 0.785	45.06 / 0.975	43.80 / 0.963	38.68 / 0.793	44.95 / 0.979
	×200	33.81 / 0.615	43.21 / 0.954	41.54 / 0.918	36.30 / 0.713	43.32 / 0.966
LRD	-1EV	33.77 / 0.895	38.31 / 0.968	38.80 / 0.970	35.19 / 0.874	38.89 / 0.971
	-2EV	32.99 / 0.856	37.35 / 0.959	37.88 / 0.961	34.55 / 0.842	37.95 / 0.962
	-3EV	31.44 / 0.770	36.49 / 0.950	36.92 / 0.951	33.72 / 0.826	37.01 / 0.953

- Denoising models are optimized using the generated training pairs from the trained generator
- Even partially **outperforms** the denoiser trained with **real paired data**
    - the real image pairs still suffer from **luminance misalignment** and **pixel misalignment**

Experiment


Input
P-G
ELD
Paired data
Ours
Reference
25.58 / 0.299
26.93 / 0.405
32.17 / 0.950
32.75 / 0.942
32.81 / 0.955
PSNR / SSIM
25.52 / 0.323
28.29 / 0.476
33.36 / 0.943
34.90 / 0.943
34.96 / 0.949
PSNR / SSIM

Conclusion

- Synthesize the signal-dependent and signal-independent noise in a **physics- and learning-based manner.**

- **New low-light raw denoising (LRD) dataset** for training and benchmarking.

- Method is **general for different ISO levels** and **different camera sensors** and demonstrate the superiority of our method over state-of-the-art methods

Outline

- LRD
  - ICCV 2023
- LRID
  - IEEE PAMI 2024

Learnability Enhancement for Low-Light Raw Image Denoising: A Data Perspective

Hansen Feng, Lizhi Wang, *Member, IEEE*, Yuzhi Wang, Haoqiang Fan, and Hua Huang, *Senior Member, IEEE*

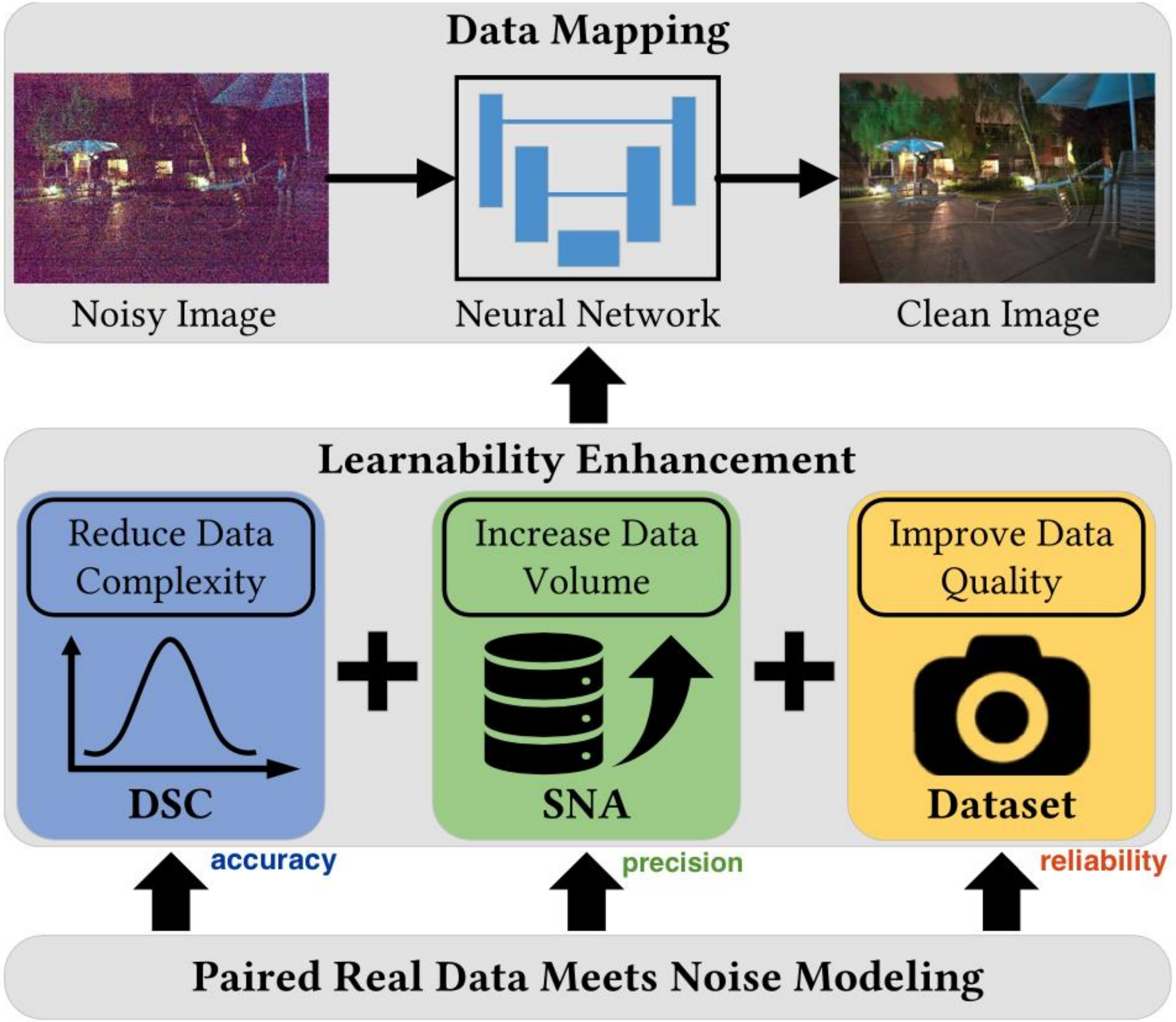
IEEE PAMI 2024

Presenter: Hao Wang

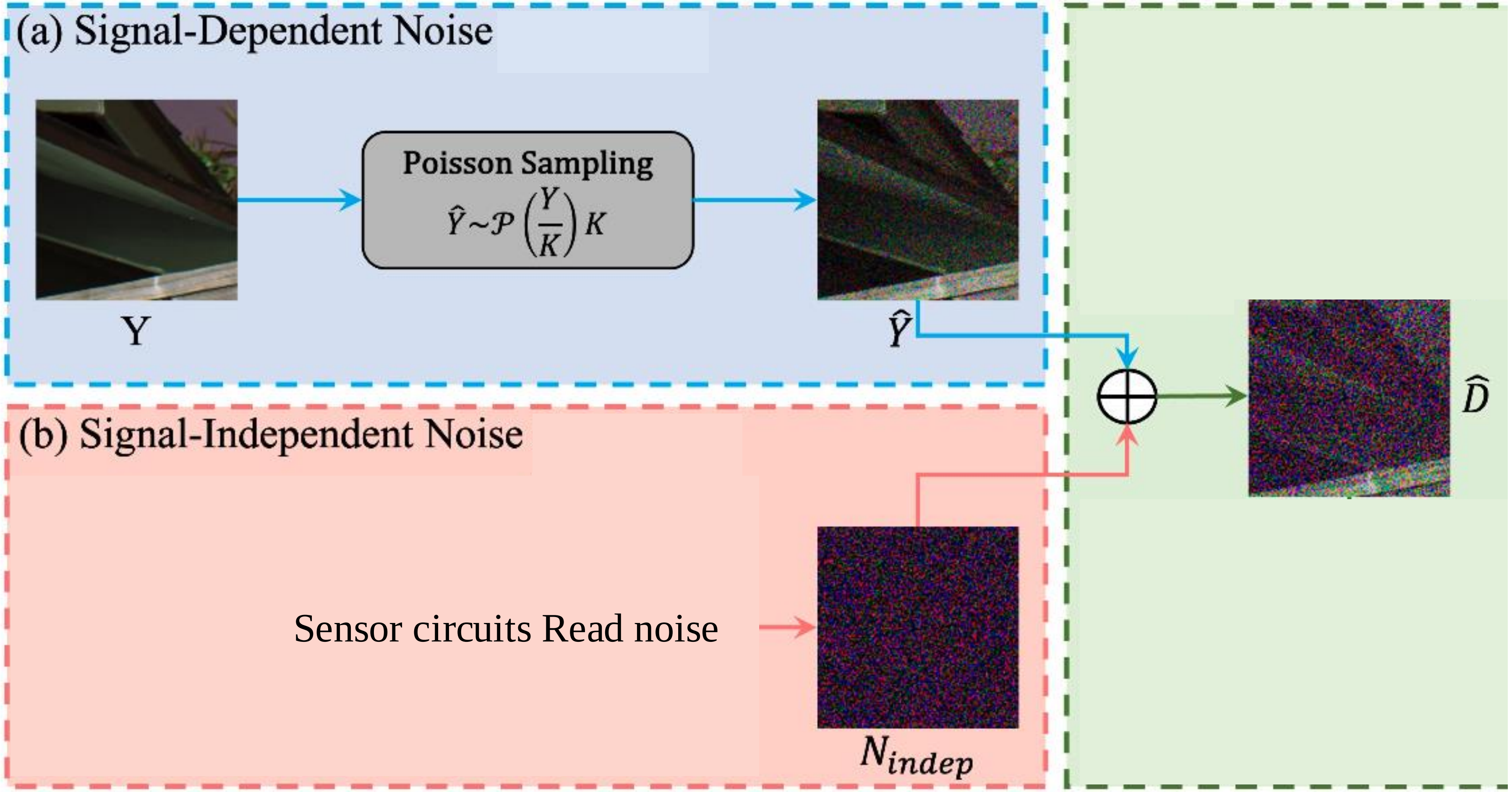
Advisor: Prof. Chia-Wen Lin

Introduction

- Introduce a learnability **enhancement strategy** for low-light raw image denoising by **reforming paired real data**.



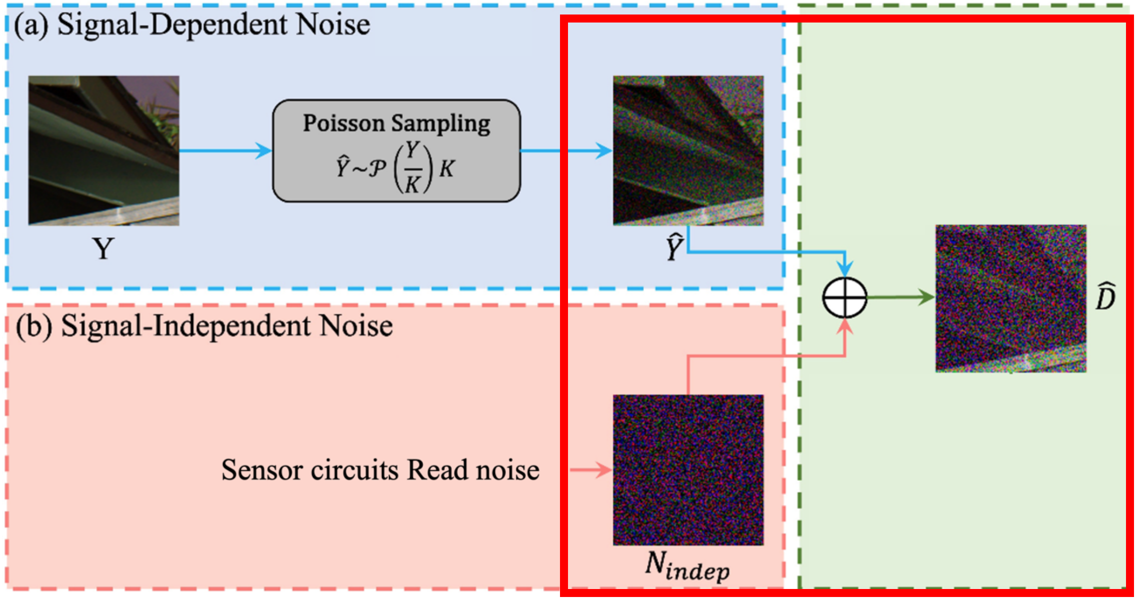
Preliminary

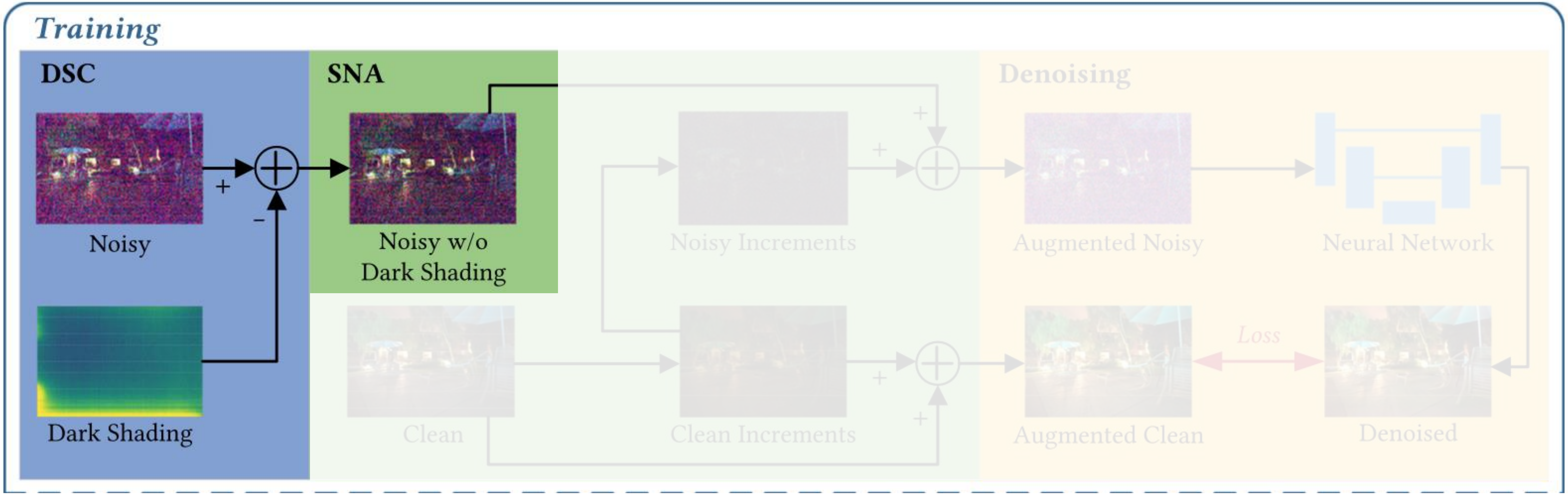


Towards General Low-Light Raw Noise Synthesis and Modeling (ICCV, 2023)

Framework

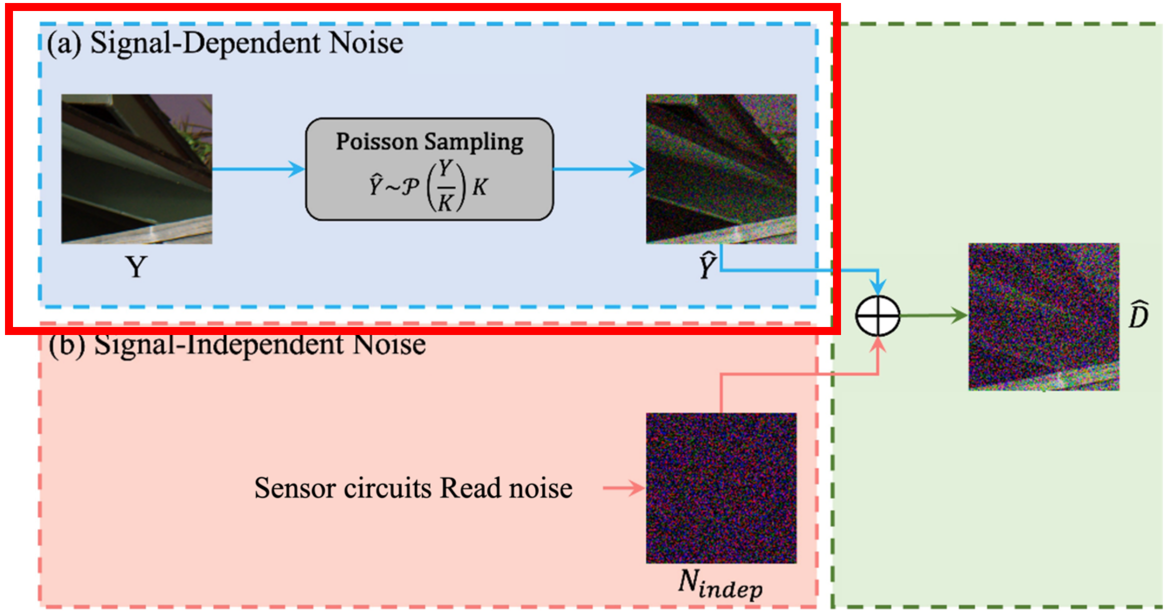
- **Dark Shading Correction**
- Shot Noise Augmentation

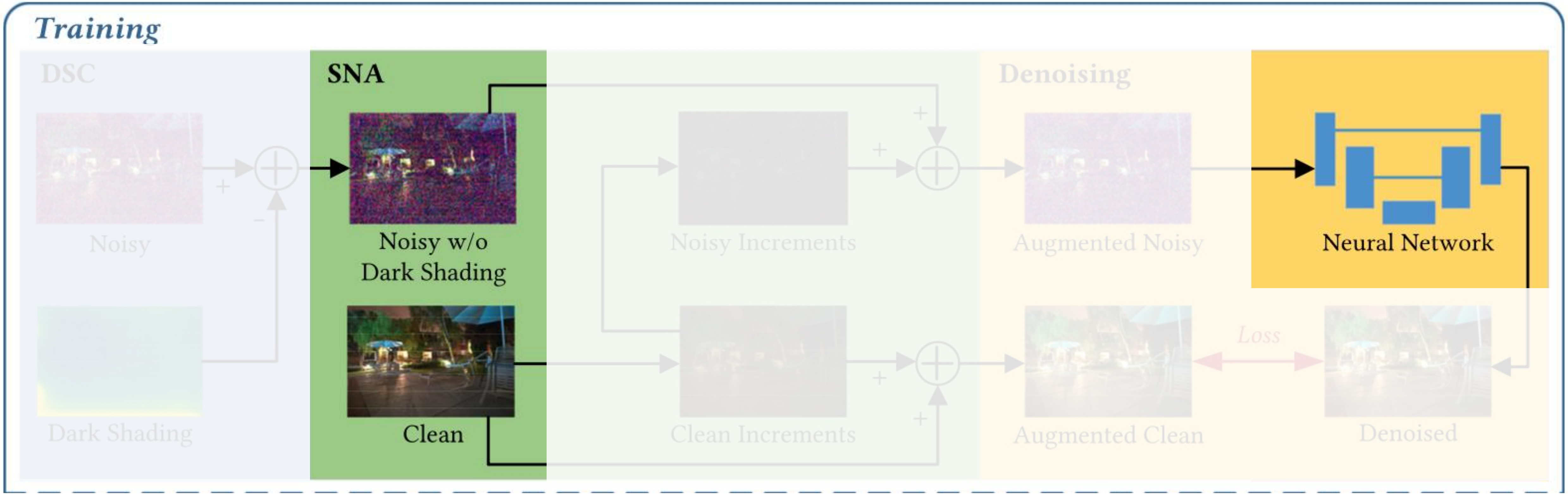




Framework

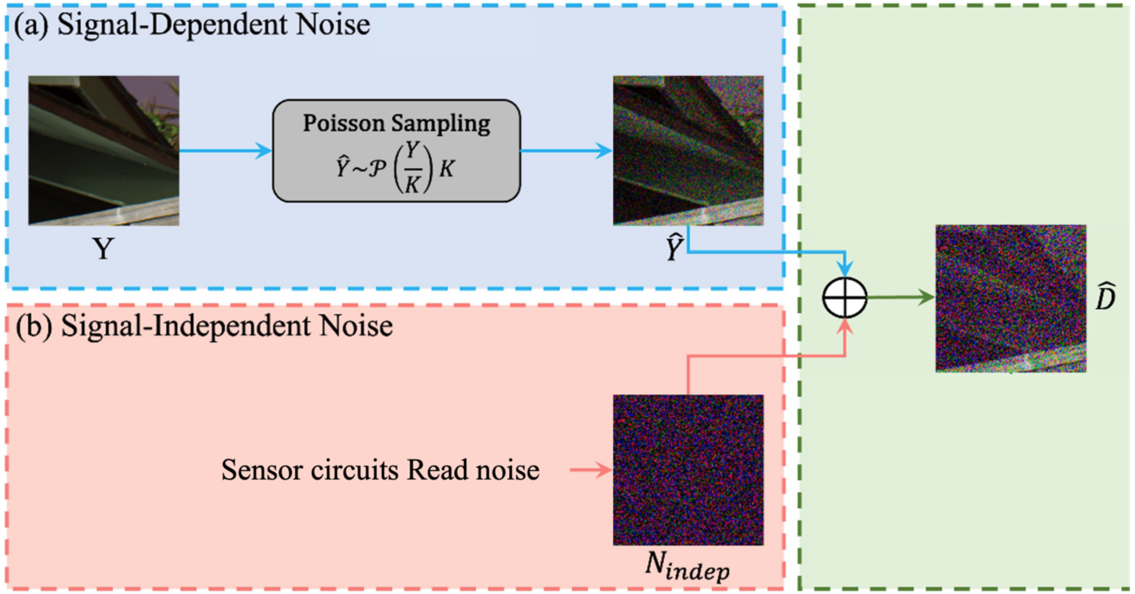
- Dark Shading Correction
- Shot Noise Augmentation

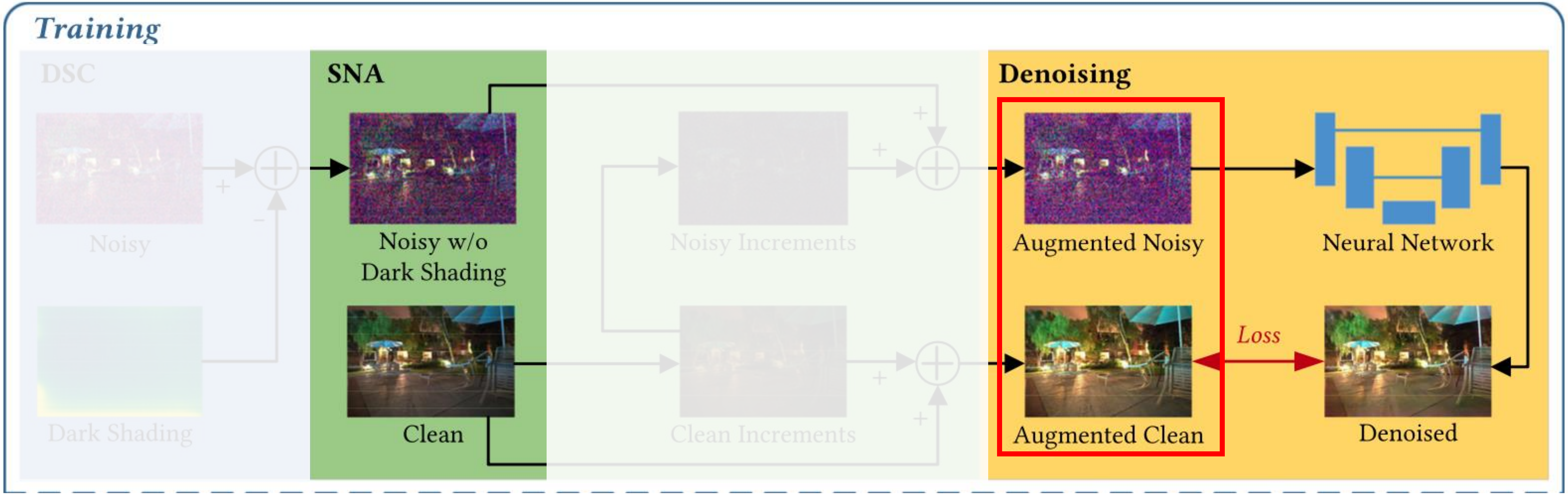




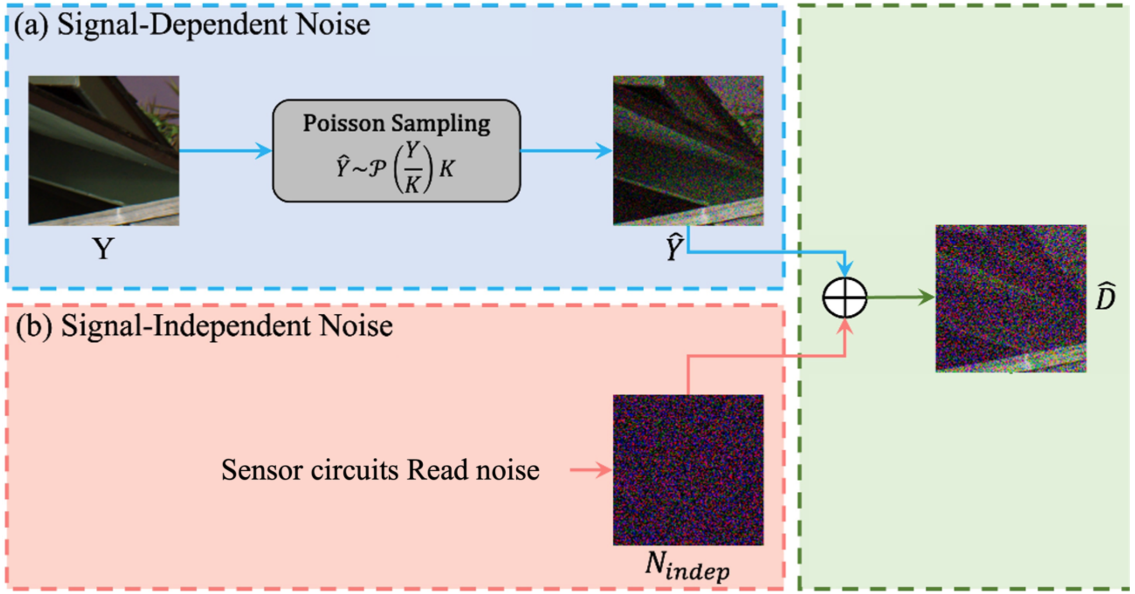
Framework

- Dark Shading Correction
- Shot Noise Augmentation

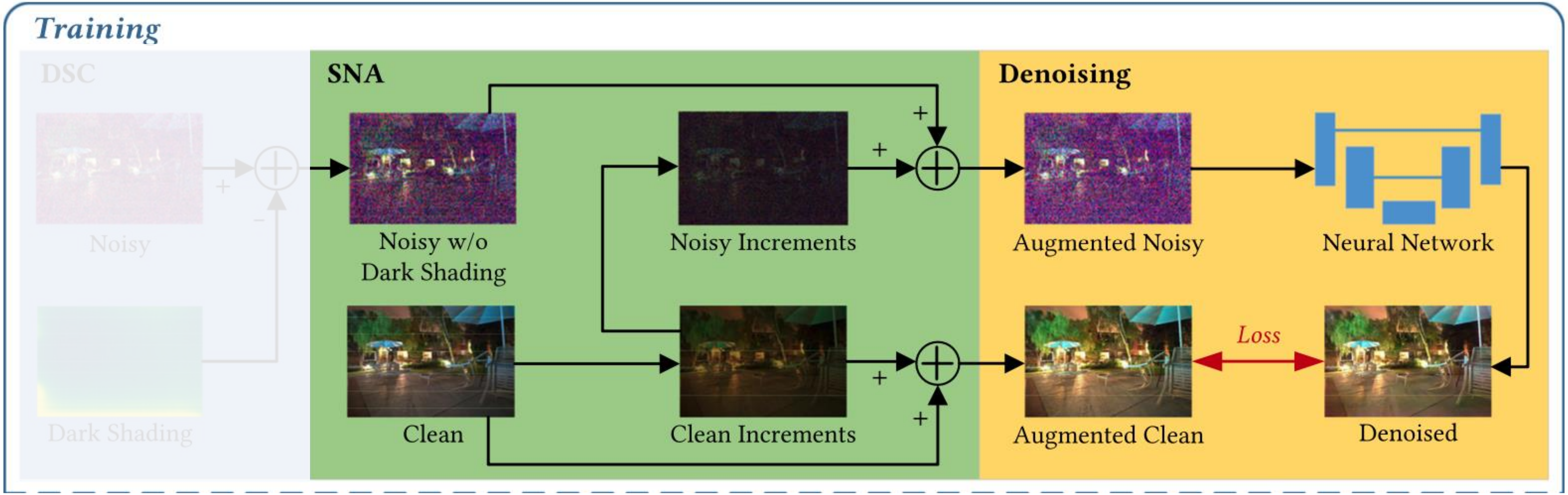




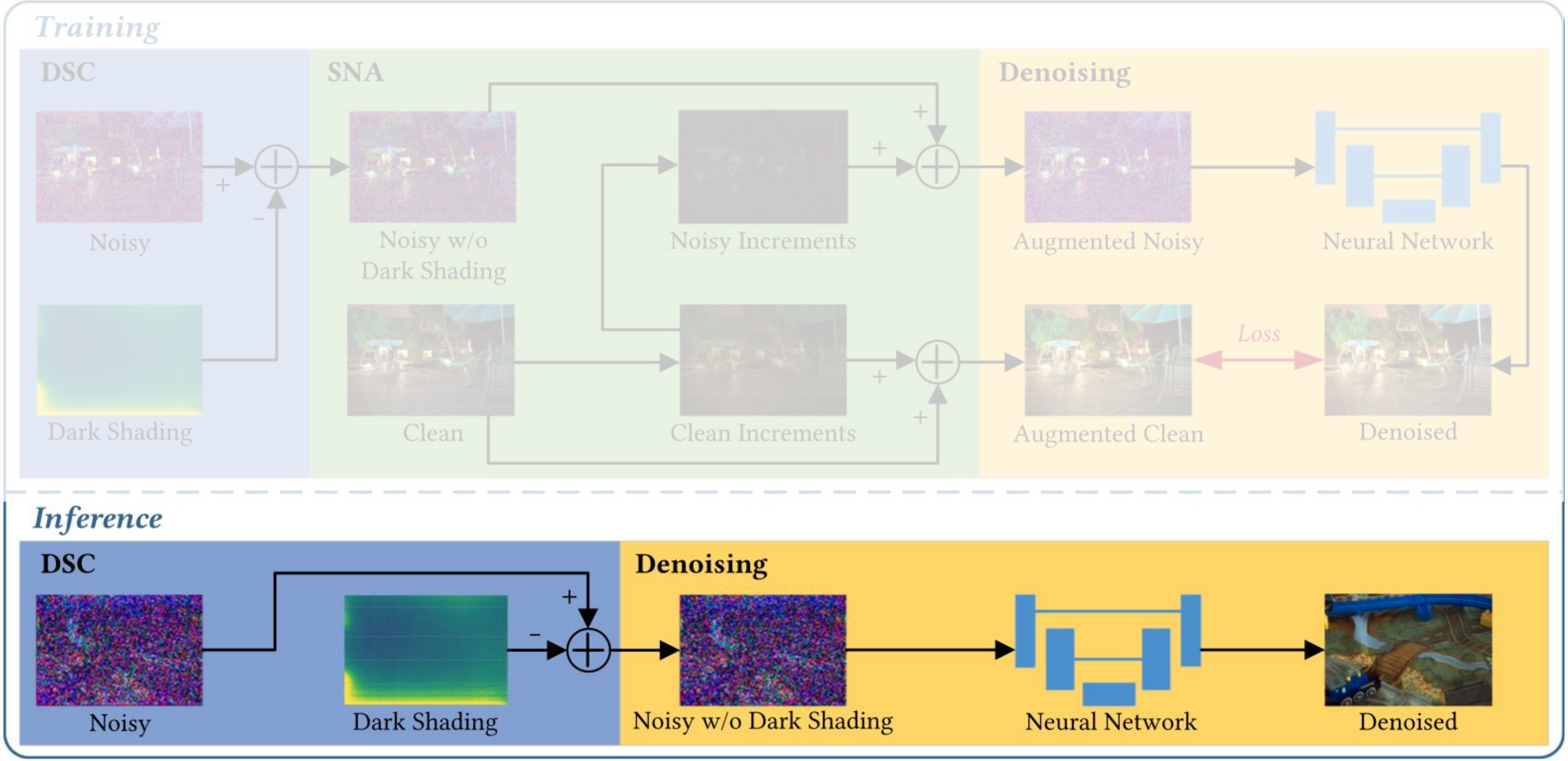
Framework



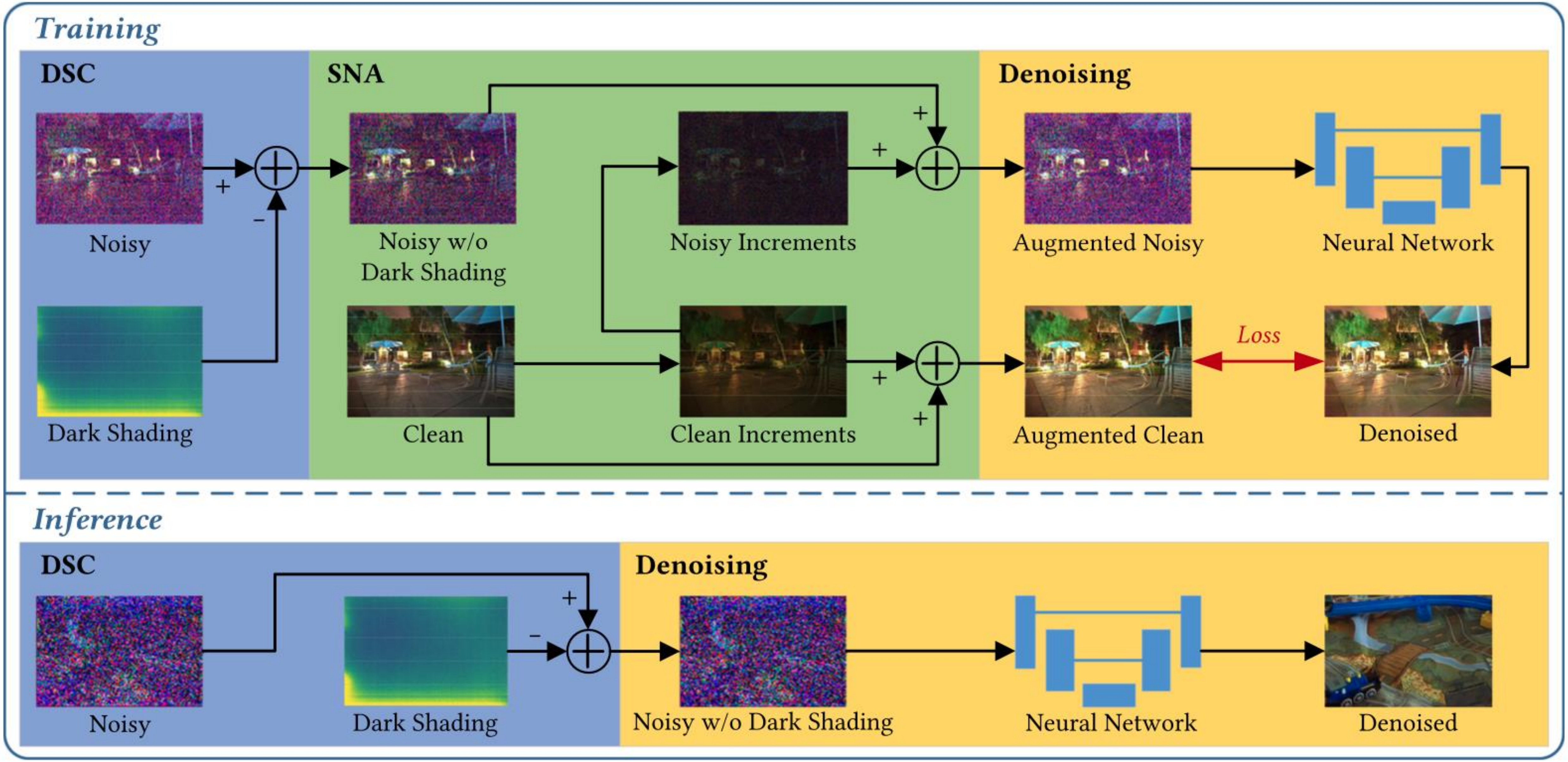
- Dark Shading Correction
- **Shot Noise Augmentation**



Framework

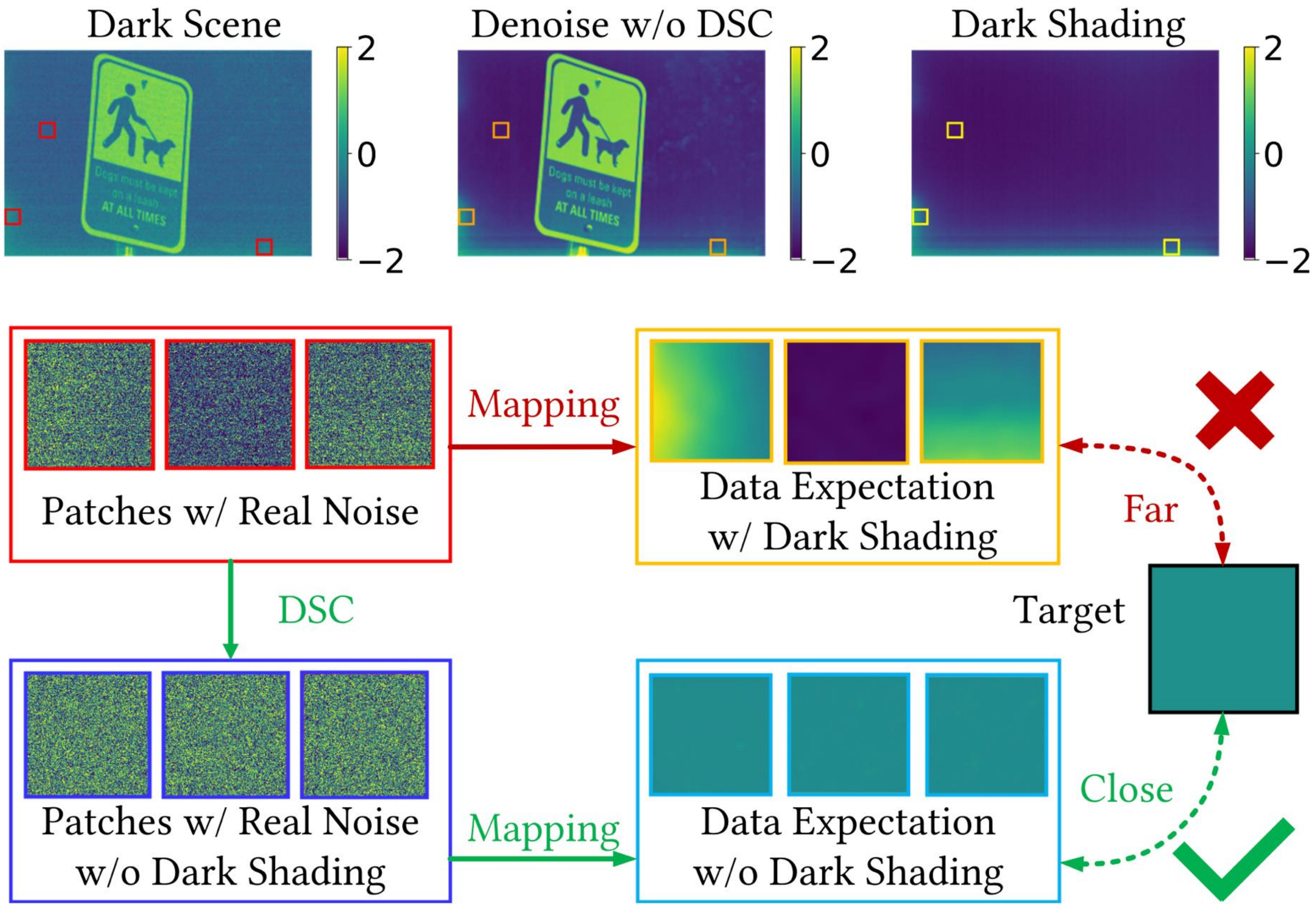

Training
DSC
SNA
Denoising
Noisy
Dark Shading
Noisy w/o
Dark Shading
Clean
Noisy Increments
Clean Increments
Augmented Noisy
Augmented Clean
Neural Network
Denoised
Loss
Inference
DSC
Denoising
Noisy
Dark Shading
Noisy w/o Dark Shading
Neural Network
Denoised

Framework



Training
DSC
SNA
Denoising
Noisy
Dark Shading
Noisy w/o Dark Shading
Clean
Noisy Increments
Clean Increments
Augmented Noisy
Augmented Clean
Neural Network
Denoised
Loss
Inference
DSC
Denoising
Noisy
Dark Shading
Noisy w/o Dark Shading
Neural Network
Denoised

Mapping dilemma



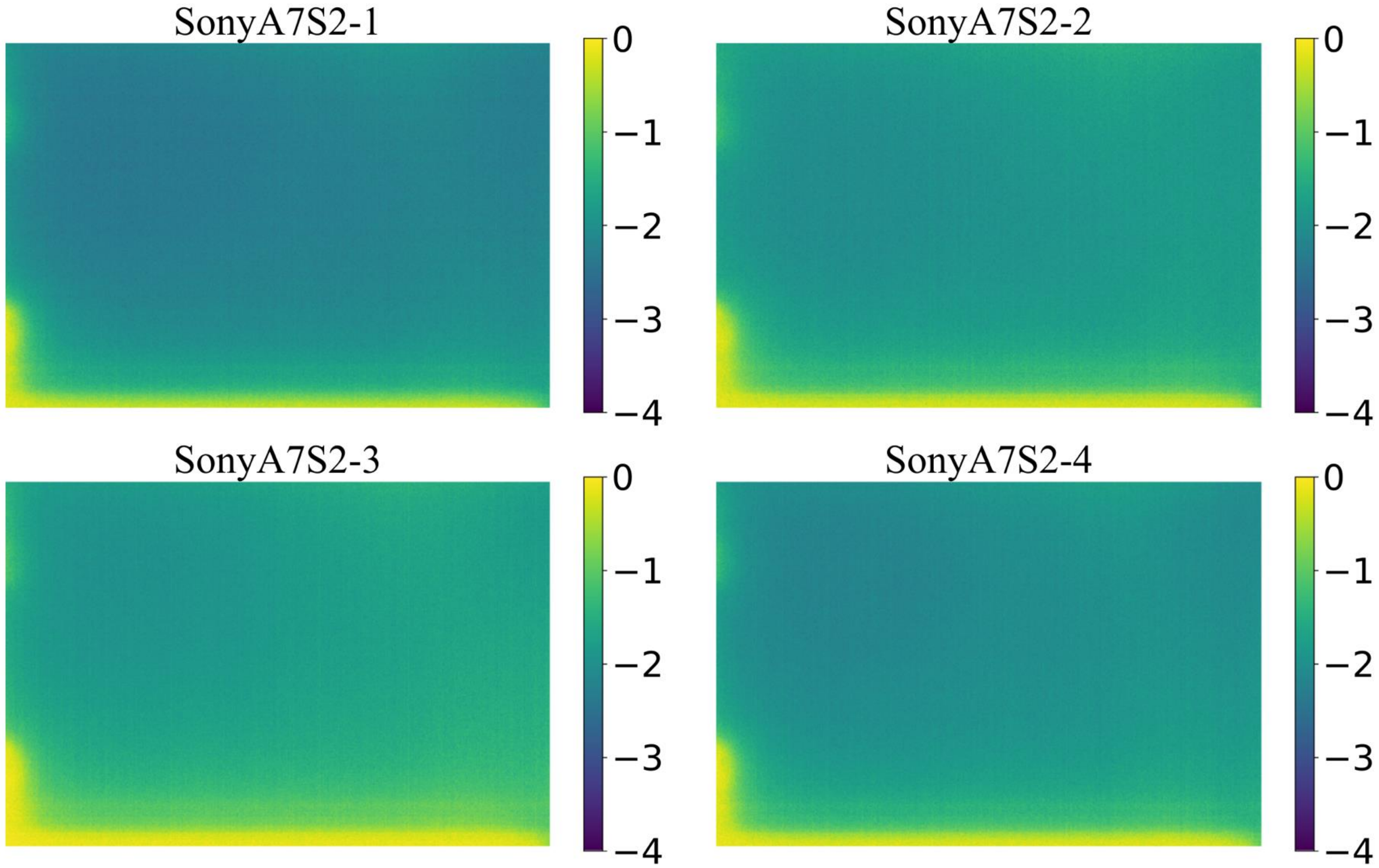
Dark shading correction

- **FPN (**fixed pattern noise)
  - FPN-k : iso-dependent
  - FPN-b : iso-independent
- **BLE** (black level error)

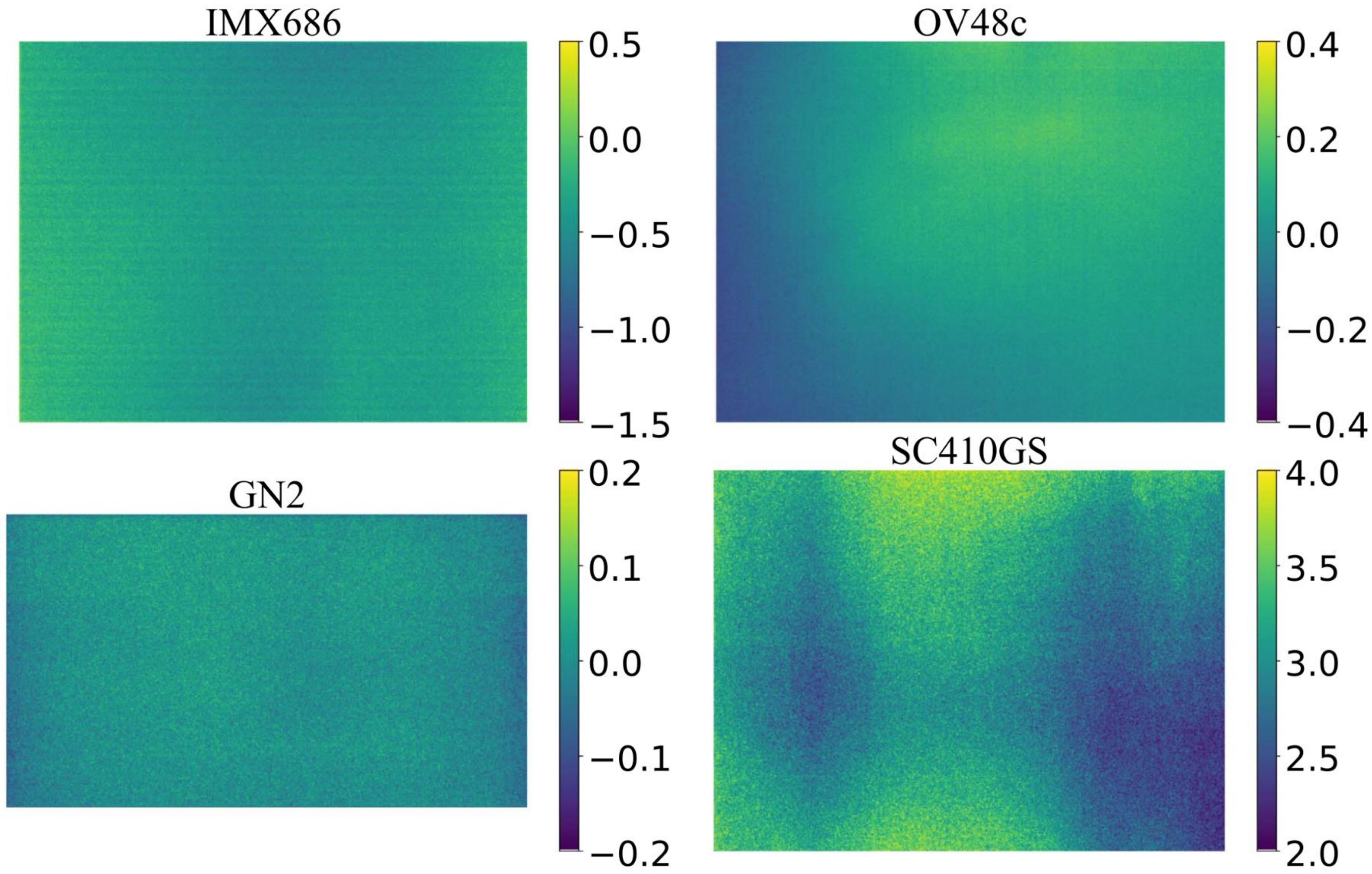
$$N_{ds} = N_{FPNk} \cdot \underline{iso} + N_{FPNb} + BLE(\underline{iso}, \underline{t}),$$

$$BLE(\underline{iso}, \underline{t}) = k_t(\underline{iso}) \cdot \underline{t} + b_t(\underline{iso}),$$

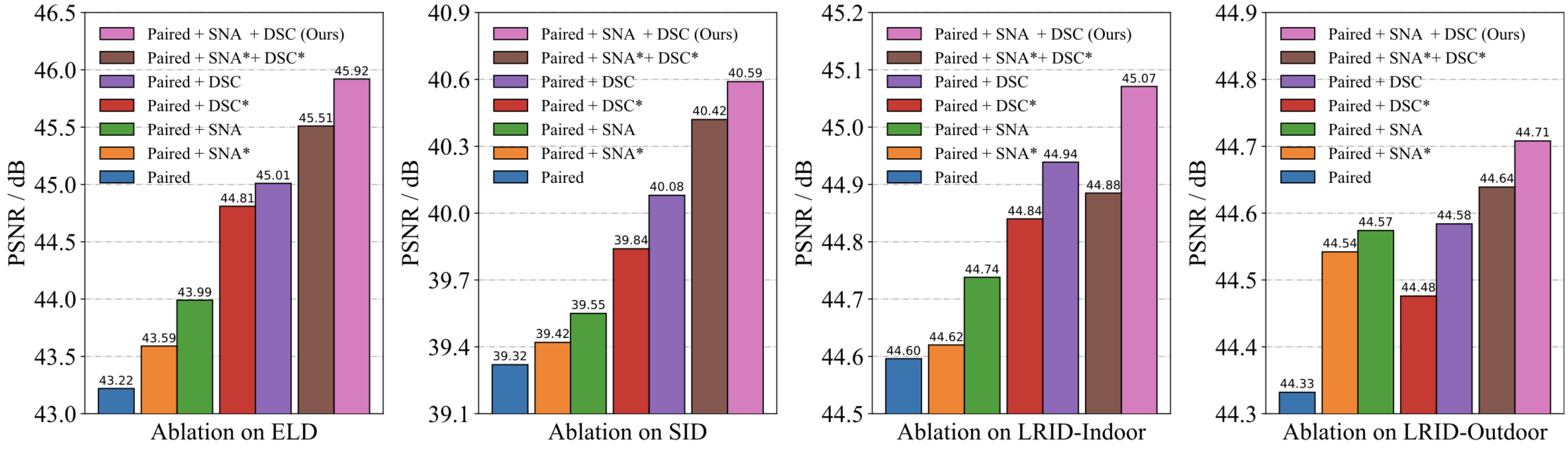
Different camera same sensor



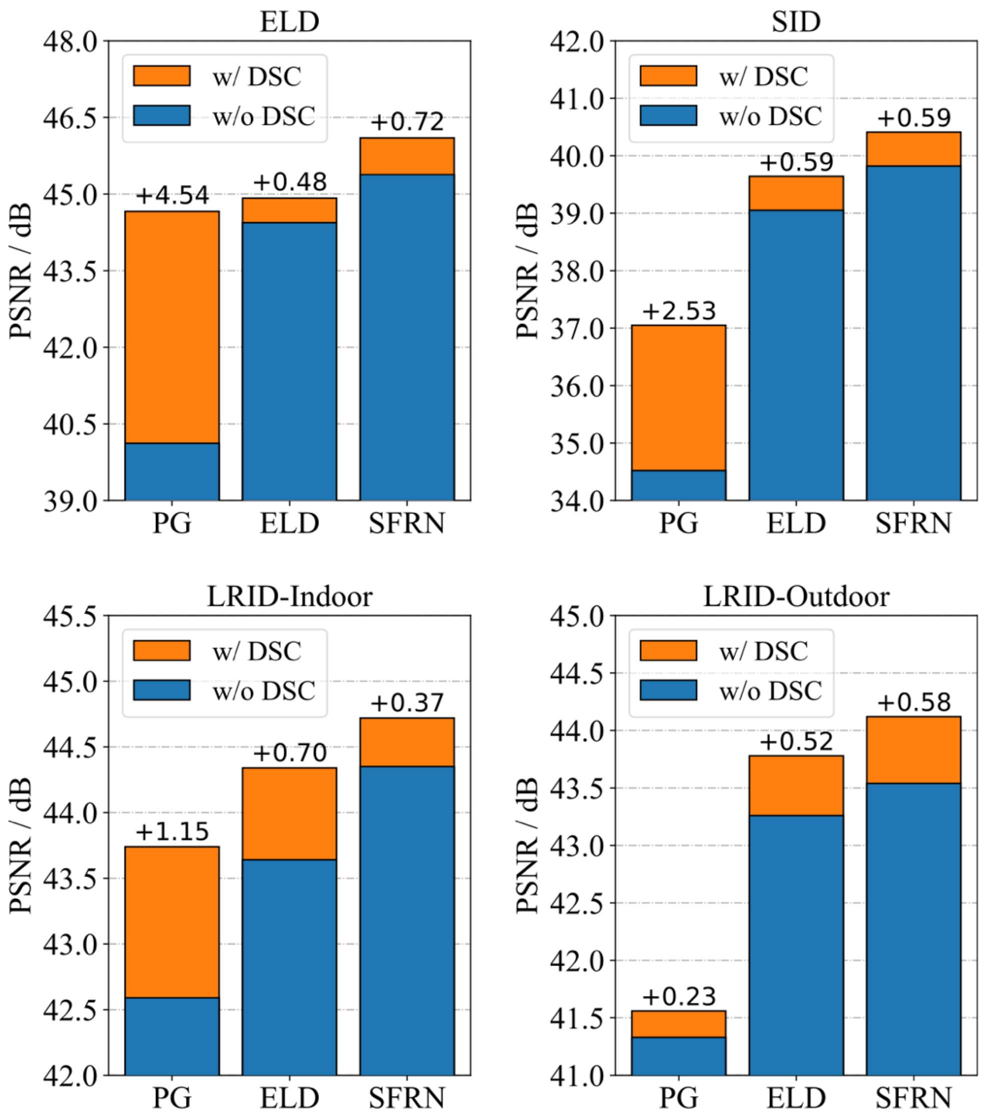
Different sensors

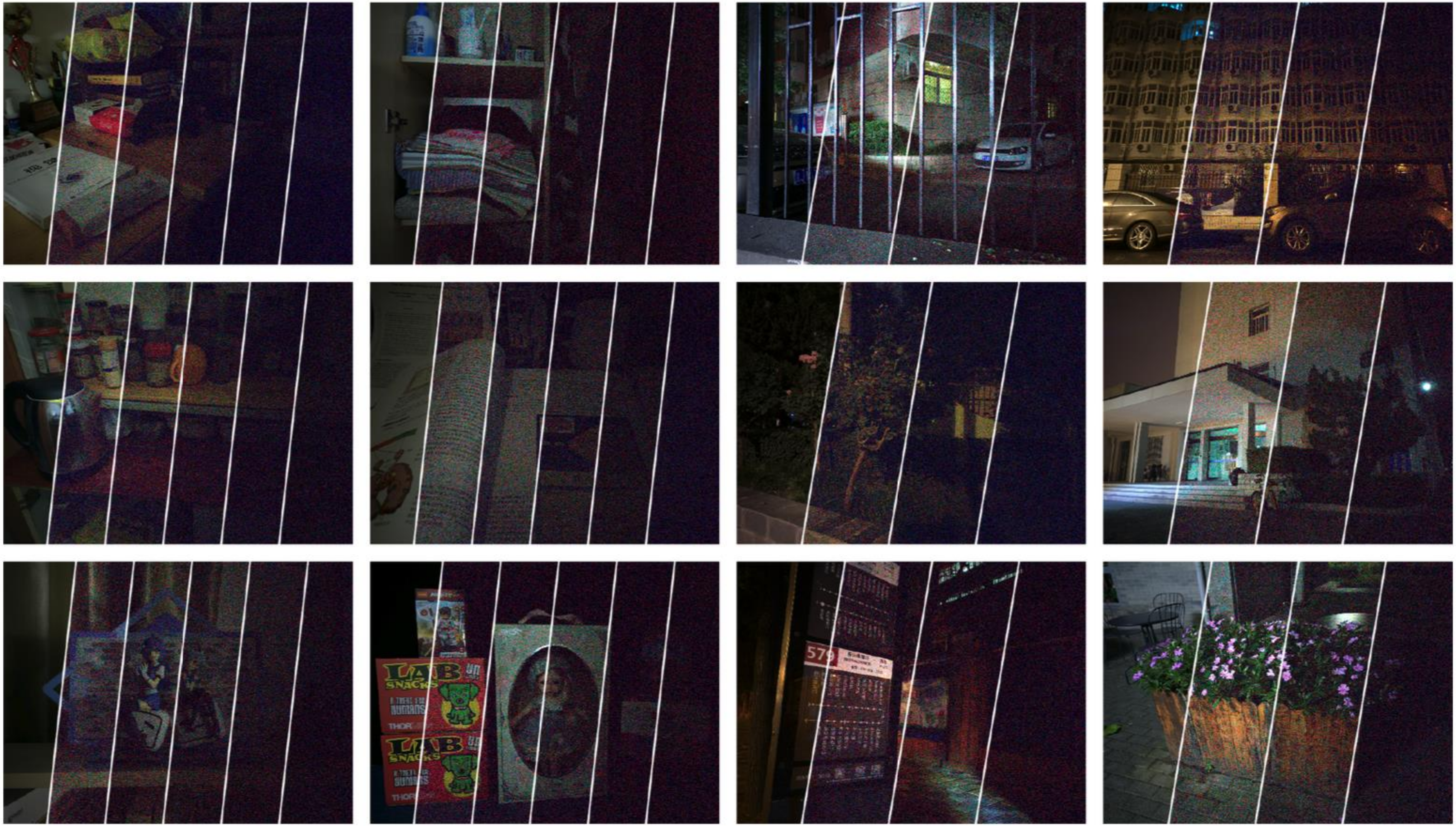


Ablation study



Noise models with and without DSC




LAB SNACKS
THOR
LAB SNACKS
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Experiment result

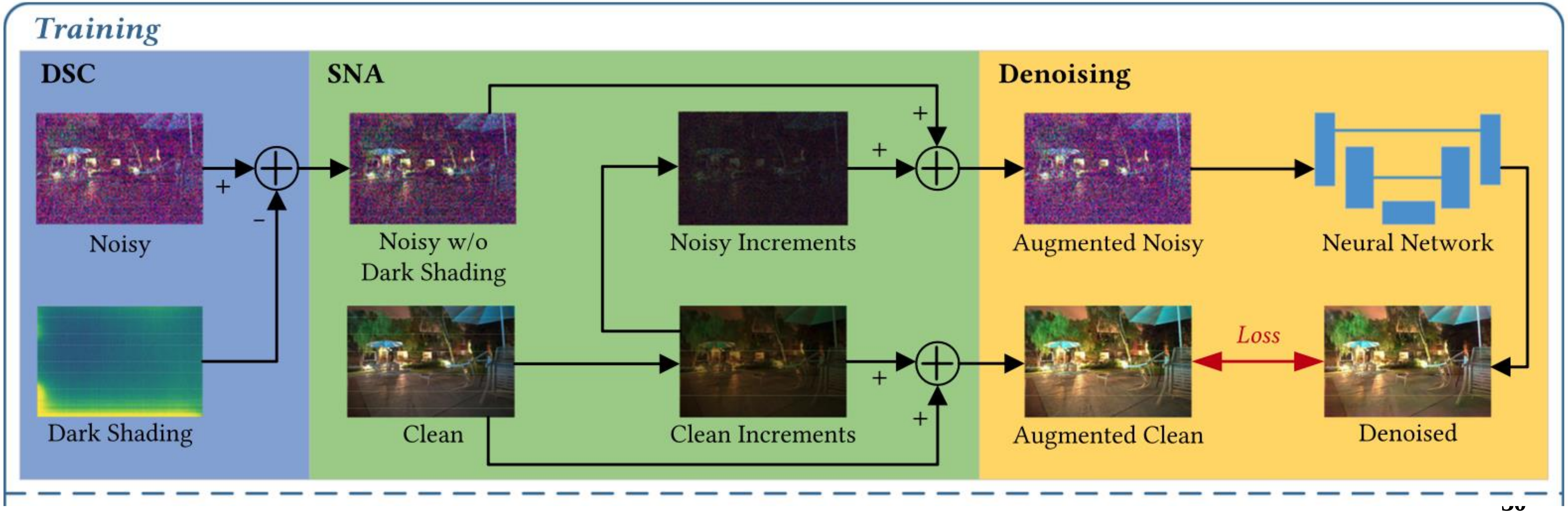
Dataset	Ratio	Input PSNR / SSIM	P-G [38] PSNR / SSIM	ELD [21] PSNR / SSIM	SFRN [46] PSNR / SSIM	Paired PSNR / SSIM	Ours PSNR / SSIM
ELD	×100	30.85 / 0.5045	42.05 / 0.8721	45.45 / 0.9754	46.38 / 0.9793	44.47 / 0.9676	46.99 / 0.9840
	×200	25.92 / 0.2607	38.18 / 0.7827	43.43 / 0.9544	44.38 / 0.9651	41.97 / 0.9282	44.85 / 0.9686
	Average	28.38 / 0.3826	40.12 / 0.8274	44.44 / 0.9649	45.38 / 0.9722	43.22 / 0.9479	45.92 / 0.9763
SID	×100	29.10 / 0.5266	39.44 / 0.8995	41.95 / 0.9530	42.81 / 0.9568	42.06 / 0.9548	43.47 / 0.9606
	×250	23.95 / 0.3595	34.32 / 0.7681	39.44 / 0.9307	40.18 / 0.9343	39.60 / 0.9380	41.04 / 0.9471
	×300	22.00 / 0.2752	30.66 / 0.6569	36.36 / 0.9114	37.09 / 0.9175	36.85 / 0.9227	37.87 / 0.9344
	Average	24.81 / 0.3793	34.52 / 0.7666	39.05 / 0.9303	39.82 / 0.9349	39.32 / 0.9374	40.59 / 0.9465
LRID-Indoor	×64	32.81 / 0.6728	46.14 / 0.9872	48.19 / 0.9898	47.94 / 0.9899	48.77 / 0.9906	49.24 / 0.9916
	×128	29.10 / 0.4621	44.98 / 0.9809	46.55 / 0.9836	46.52 / 0.9854	47.00 / 0.9860	47.47 / 0.9868
	×256	25.07 / 0.2380	43.31 / 0.9682	44.39 / 0.9730	44.74 / 0.9789	44.74 / 0.9786	45.36 / 0.9804
	×512	20.53 / 0.0872	40.80 / 0.9429	41.56 / 0.9452	42.46 / 0.9652	42.40 / 0.9647	43.09 / 0.9671
	×1024	15.43 / 0.0241	37.74 / 0.8905	37.50 / 0.8915	40.10 / 0.9453	40.07 / 0.9437	40.20 / 0.9453
	Average	24.59 / 0.2968	42.59 / 0.9539	43.64 / 0.9566	44.35 / 0.9729	44.60 / 0.9727	45.07 / 0.9743
LRID-Outdoor	×64	33.25 / 0.7255	42.16 / 0.9796	45.00 / 0.9841	45.05 / 0.9850	45.84 / 0.9876	46.27 / 0.9884
	×128	29.49 / 0.5100	41.48 / 0.9709	43.48 / 0.9734	43.67 / 0.9766	44.50 / 0.9821	44.86 / 0.9834
	×256	25.26 / 0.2557	40.36 / 0.9525	41.31 / 0.9450	41.89 / 0.9591	42.66 / 0.9709	42.99 / 0.9703
	Average	29.33 / 0.4971	41.33 / 0.9677	43.26 / 0.9675	43.54 / 0.9736	44.33 / 0.9802	44.71 / 0.9807

The red color indicates the best results and the blue color indicates the second-best results.

Input
P-G [38]
ELD [21]
SFRN [46]
Paired
Ours
Ground Truth
LRID-Indoor
25.82 / 0.2597
44.37 / 0.9721
45.27 / 0.9765
45.75 / 0.9810
45.49 / 0.9806
46.27 / 0.9837
PSNR / SSIM
21.34 / 0.0811
41.24 / 0.9060
42.26 / 0.9336
43.35 / 0.9639
43.13 / 0.9619
43.70 / 0.9678
PSNR / SSIM
LRID-Outdoor
26.25 / 0.2687
41.72 / 0.9662
43.53 / 0.9722
44.06 / 0.9811
44.52 / 0.9815
44.94 / 0.9824
PSNR / SSIM
25.55 / 0.2505
42.76 / 0.9468
41.19 / 0.9155
42.47 / 0.9367
44.73 / 0.9749
45.24 / 0.9783
PSNR / SSIM

Conclusion

- increases the data volume via SNA
- reduces the noise complexity via DSC
- improves the data quality via our image acquisition protocol



Key insight

- Both paper address noise separately according to signal dependent and independent.
- Not find out the way to handle noise pattern by fine-grain map.