

# Learning to Generate Realistic Noisy Images via Pixel-level Noise-aware Adversarial Training

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# Overview

- Introduction
- Method
- Experiments

# Introduction

# Introduction

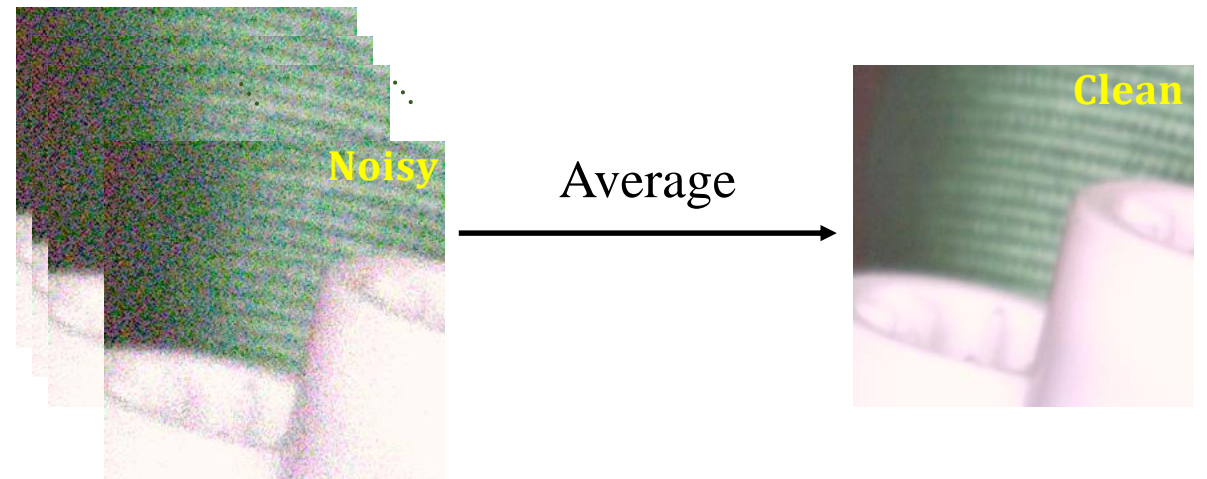
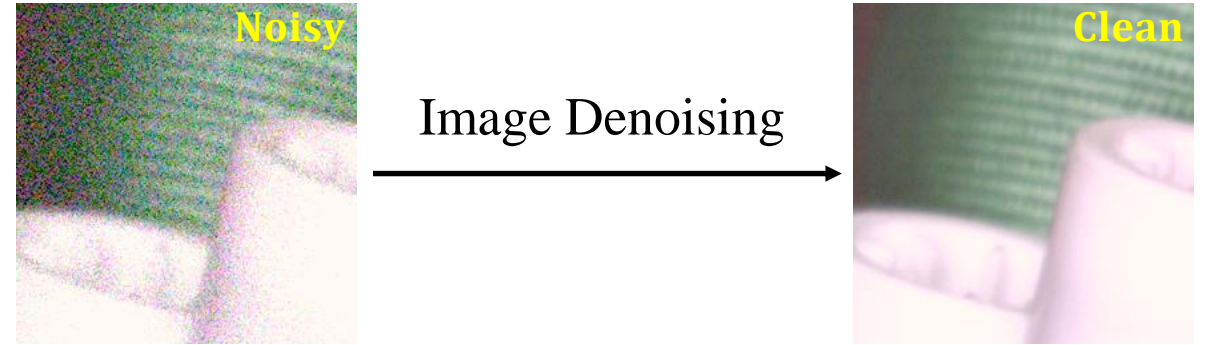
- Image Denoising

- Traditional methods

Based on hand-crafted assumptions or models, poor representing capacity

- Deep learning methods

Powerful learning models – CNN.  
Collecting image pairs is tedious and labor-intensive. DL methods face a severe data-hungry situation.



# Introduction

- Noise Generation

- Gaussian Distribution

Fundamentally different from real noise. Dramatic performance drop.

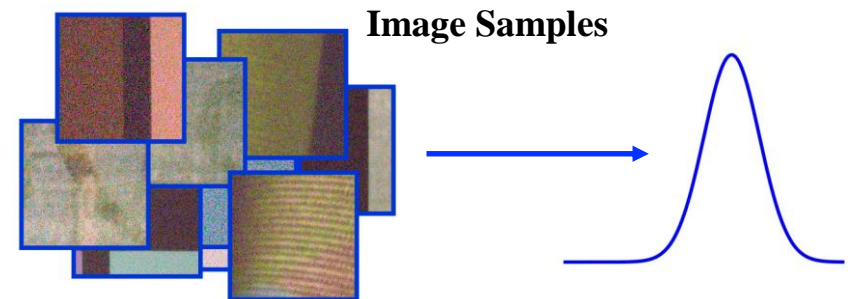
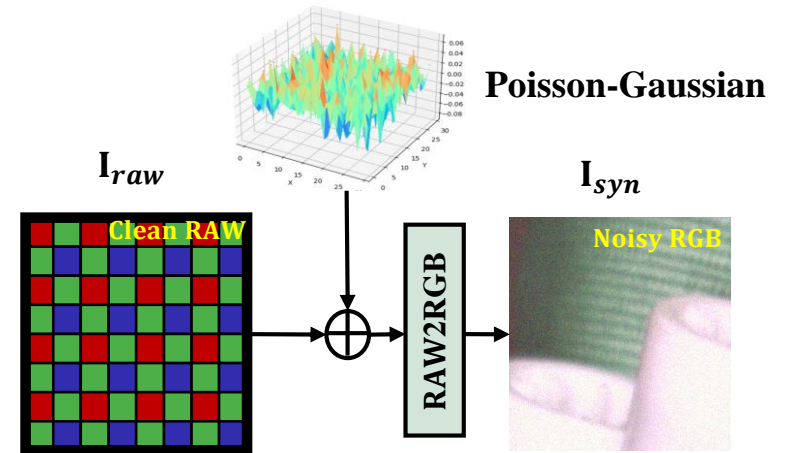
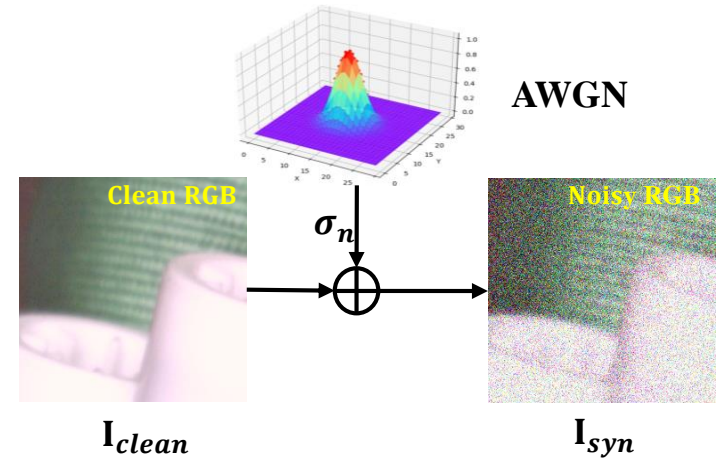
- Pseudo ISP

Cannot ensure the mapping from Poisson-Gaussian noisy RAW image to real-camera noisy RGB image.

- GAN-based

Treat images as samples, coarse learning

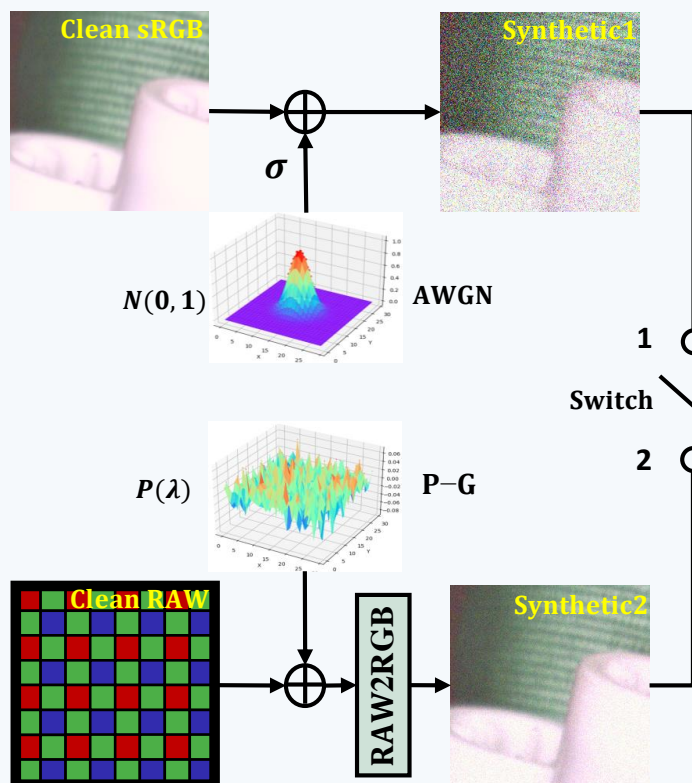
There still remains a domain discrepancy



# Method

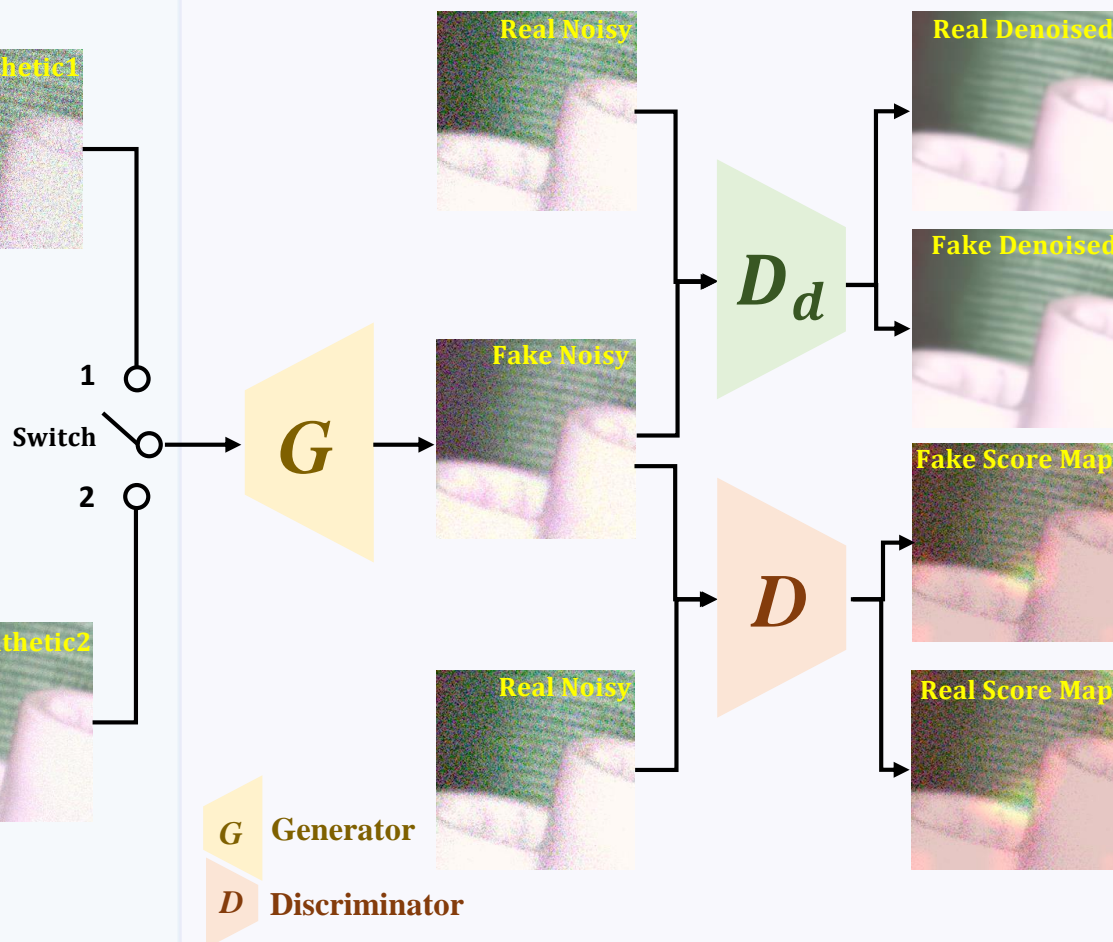
## (a) Synthesizing Phase

### (a1) Synthetic Setting1



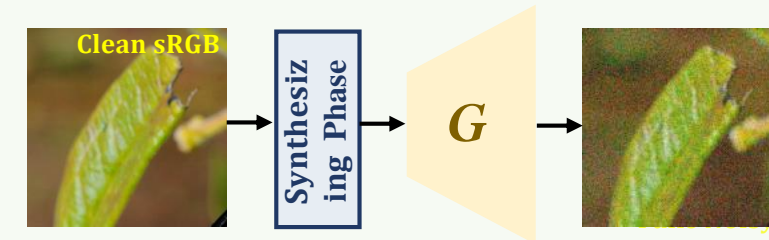
### (a2) Synthetic Setting2

## (b) Training Phase

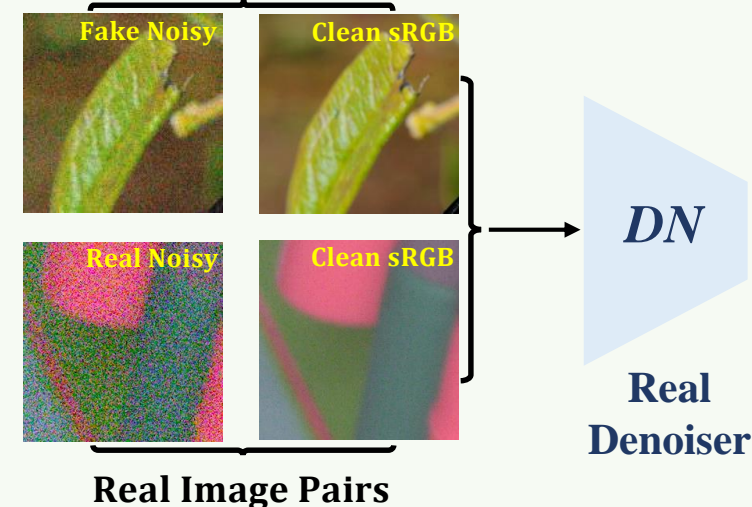


## (c) Finetuning Phase

### (c1) Fake Image Pairs Generating



### Fake Image Pairs



### Real Image Pairs

### (c2) Real Denoiser Finetuning

Setting1 : Gaussian Distribution

Setting2 : Poisson-Gaussian

Distribution + Pseudo ISP

$G$  : Noise Generator

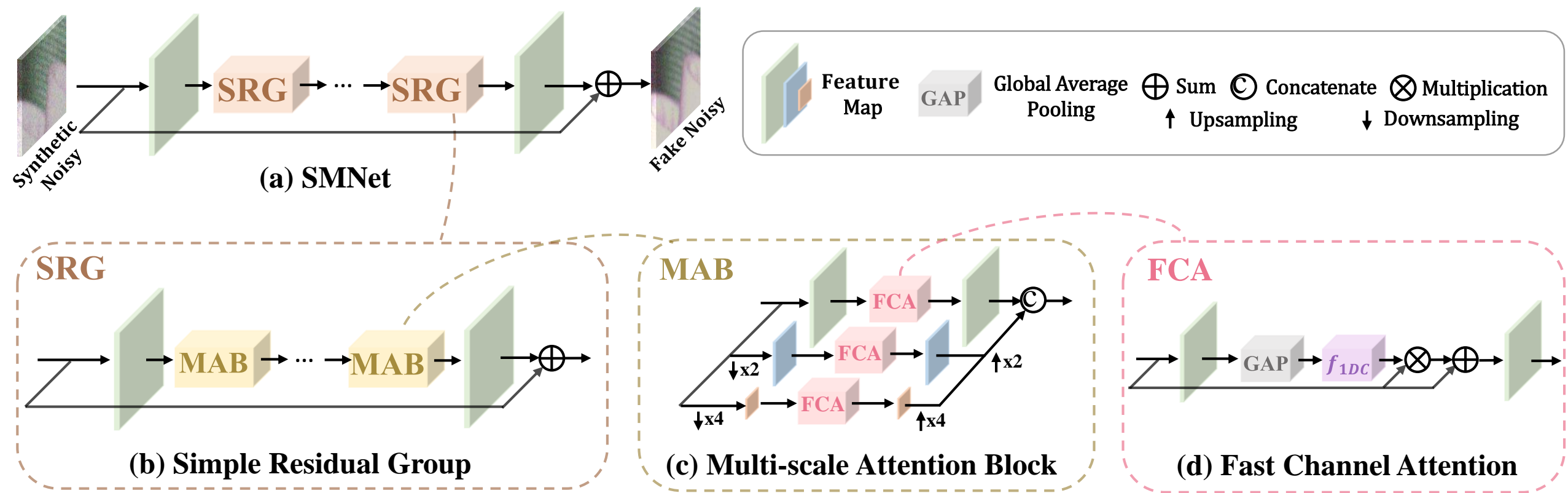
$D$  : Pixel-level Discriminator

$D_d$  : Pre-trained Denoiser

Use  $G$  to generate image pairs

Add image pairs to the data

pool of any real denoiser  $DN$



## The Architecture of the Generator

- Simple Multi-scale Network (SMNet) is cascaded by Simple Residual Groups (SRG)
- SRG is built by Multi-scale Attention Blocks (MAB)
- MAB exploits Fast Channel Attention (FCA) mechanism
- FCA uses 1D convolution to cut down Params and FLOPS, and promote its efficiency



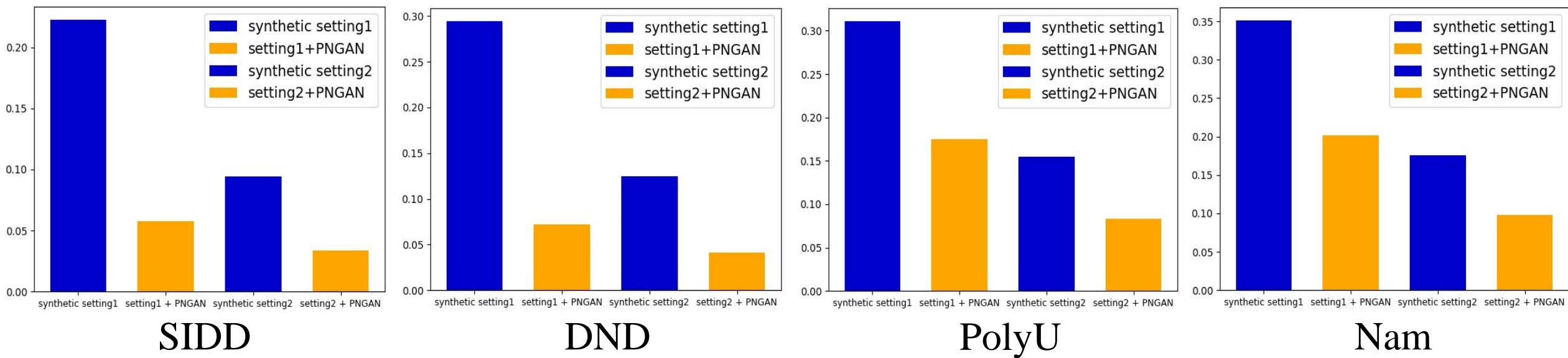
# Experiments

# Experiments

- Datasets
  - Real Noisy Image Pairs
    - SIDD : 320 image pairs for training, 1280 patch pairs for validation
    - DND : 50 image pairs, 1000 patch pairs cropped at size  $512 \times 512$
    - PolyU : 40 real camera noisy-clean image pairs
    - Nam : real noisy image pairs of 11 static scenes
  - HD Clean Image
    - DIV2K, Flickr2K, BSD68, Kodak24, and Urban100

# Experiments

- MMD - Maximum Mean Discrepancy



- SIDD : Setting1 (74% ↓), Setting2 (64% ↓)
- DND : Setting1 (75% ↓), Setting2 (67% ↓)
- PolyU : Setting1 (44% ↓), Setting2 (46% ↓)
- Nam : Setting1 (43% ↓), Setting2 (44% ↓)

# Experiments

- Comparisons with SOTA Methods

Methods	SIDD [43]		DND [44]		Methods	PolyU [37]		Nam [45]	
	PSNR $\uparrow$	SSIM $\uparrow$	PSNR $\uparrow$	SSIM $\uparrow$		PSNR $\uparrow$	SSIM $\uparrow$	PSNR $\uparrow$	SSIM $\uparrow$
DnCNN-B [10]	23.66	0.583	32.43	0.790	RDN [12]	37.94	0.946	38.16	0.956
CBDNet [46]	33.28	0.868	38.06	0.942	FFDNet+ [17]	38.17	0.951	38.81	0.957
RIDNet [40]	38.71	0.914	39.26	0.953	TWSC [47]	38.68	0.958	38.96	0.962
AINDNet [48]	39.15	0.955	39.53	0.956	CBDNet [46]	38.74	0.961	39.08	0.969
VDN [49]	39.23	0.955	39.38	0.952	RIDNet [40]	38.86	0.962	39.20	0.973
CycleISP [20]	39.52	0.957	39.56	0.956	VDN [49]	39.04	0.965	39.68	0.976
MPRNet [50]	39.71	0.958	39.80	0.954	MPRNet [50]	39.07	0.969	39.41	0.974
MIRNet [51]	39.72	0.959	39.88	0.956	MIRNet [51]	39.18	0.973	39.57	0.979
<b>RIDNet* (Ours)</b>	<b>39.25</b>	<b>0.956</b>	<b>39.55</b>	<b>0.955</b>	<b>RIDNet* (Ours)</b>	<b>39.54</b>	<b>0.971</b>	<b>39.69</b>	<b>0.975</b>
<b>MPRNet* (Ours)</b>	<b>40.06</b>	<b>0.960</b>	<b>40.18</b>	<b>0.961</b>	<b>MPRNet* (Ours)</b>	<b>40.48</b>	<b>0.982</b>	<b>40.72</b>	<b>0.984</b>
<b>MIRNet* (Ours)</b>	<b>40.07</b>	<b>0.960</b>	<b>40.25</b>	<b>0.962</b>	<b>MIRNet* (Ours)</b>	<b>40.55</b>	<b>0.983</b>	<b>40.78</b>	<b>0.986</b>

- Improvements Achieved by Denoisers Finetuned with Fake Image Pairs

SIDD (0.35 dB  $\uparrow$ )

DND (0.37 dB  $\uparrow$ )

PolyU (1.37 dB  $\uparrow$ )

Nam (1.10 dB  $\uparrow$ )

# Experiments

- Improvements of PNGAN on Different Datasets

Methods	SIDDD [43]						DF2K [53, 54]						
	S1	S1 + PNGAN	S2	S2+PNGAN	Real		S1	S1 + PNGAN	S2	S2+PNGAN			
RIDNet	22.55	<b>37.92</b>	(+15.37)	36.13	<b>38.71</b>	(+2.58)	38.69	22.55	<b>32.10</b>	(+9.55)	33.98	<b>38.14</b>	(+4.16)
MPRNet	22.86	<b>38.52</b>	(+15.66)	36.52	<b>39.53</b>	(+3.01)	39.45	22.85	<b>32.82</b>	(+9.97)	34.19	<b>38.61</b>	(+4.42)
MIRNet	22.83	<b>38.76</b>	(+15.93)	36.55	<b>39.57</b>	(+3.02)	39.58	23.08	<b>32.34</b>	(+9.26)	34.26	<b>38.72</b>	(+4.46)

We use the fake noisy images generated from clean SIDDD train and DF2K (DIV2K+Flicker2K) respectively to train denoisers from scratch.

SIDDD : Setting1 ( $\sim 15.65$  dB  $\uparrow$ ), Setting2 ( $\sim 2.87$  dB  $\uparrow$ )

DF2K : Setting1 ( $\sim 9.59$  dB  $\uparrow$ ), Setting2 ( $\sim 4.35$  dB  $\uparrow$ )

# Experiments

- Ablation Study

Methods	PNGAN Component							Generator Architecture						
	Baseline1	+ $D_d$		+ $D$		+ $\mathcal{L}_p$		Baseline2	+ Multi-scale		+ SID		+ FCA	
RIDNet	14.54	35.37	(+20.83)	37.49	(+2.12)	37.92	(+0.43)	35.62	37.01	(+1.39)	37.23	(+0.22)	37.92	(+0.69)
MPRNet	14.25	36.26	(+22.01)	38.27	(+2.01)	38.52	(+0.25)	36.28	37.47	(+1.19)	37.86	(+0.39)	38.52	(+0.66)
MIRNet	13.57	36.15	(+22.58)	38.28	(+2.13)	38.76	(+0.48)	36.39	37.66	(+1.27)	37.89	(+0.23)	38.76	(+0.87)

## Ablation Study of PNGAN Components

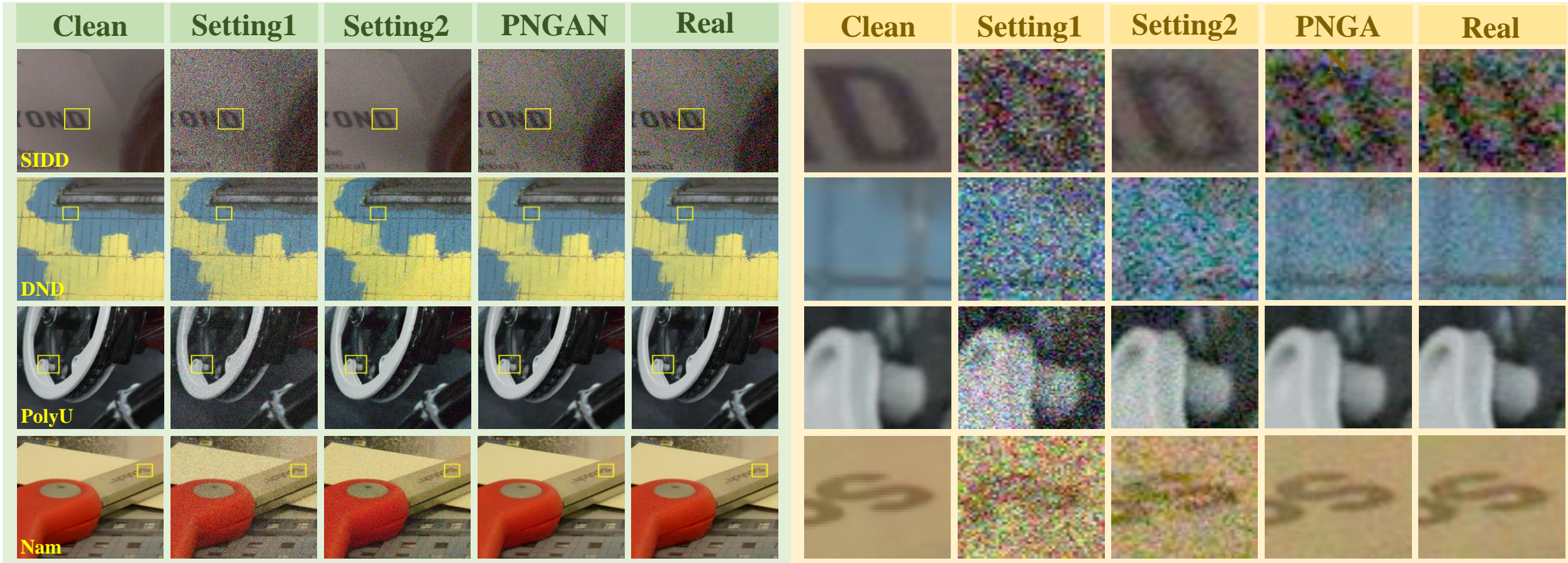
+  $D_d$  : ( $\sim 21.81$  dB  $\uparrow$ ),    +  $D$  : ( $\sim 2.09$  dB  $\uparrow$ ),    +  $L_p$  : ( $\sim 0.39$  dB  $\uparrow$ )

## Ablation Study of Generator Architecture

+ Multi-scale : ( $\sim 1.28$  dB  $\uparrow$ ),    + SID : ( $\sim 0.28$  dB  $\uparrow$ ),    + FCA: ( $\sim 0.74$  dB  $\uparrow$ )

# Experiments

- Visual Examinations of Noisy Images



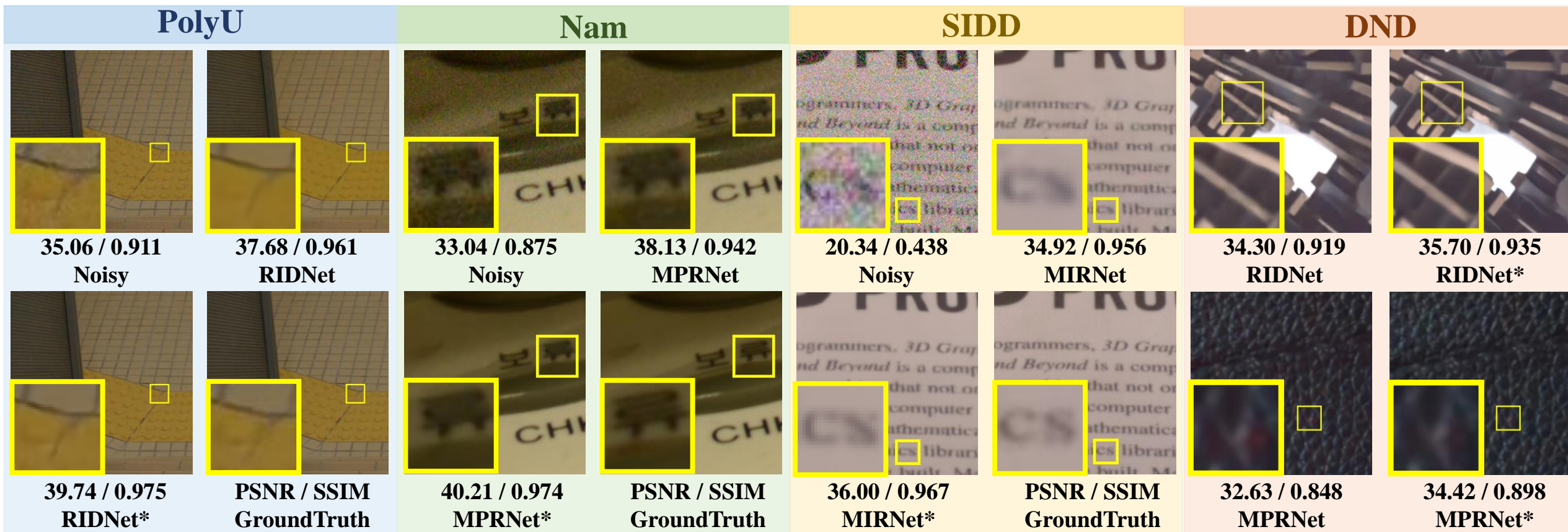
Setting1 : Gaussian Noise, fundamentally different from real noise

Setting2 : Poisson-Gaussian + Pseudo ISP, different in intensity and distribution

PNGAN : Can model spatio-chromatically correlated and non-Gaussian noise

# Experiments

- Visual Comparisons of Denoised Images



- Models finetuned with the generated data are capable of preserving the structural content, textural details, and spatial smoothness of the homogeneous regions.
- In contrast, original models either yield over-smooth images sacrificing fine textural details and structural content or introduce redundant blotchy texture and chroma artifacts.

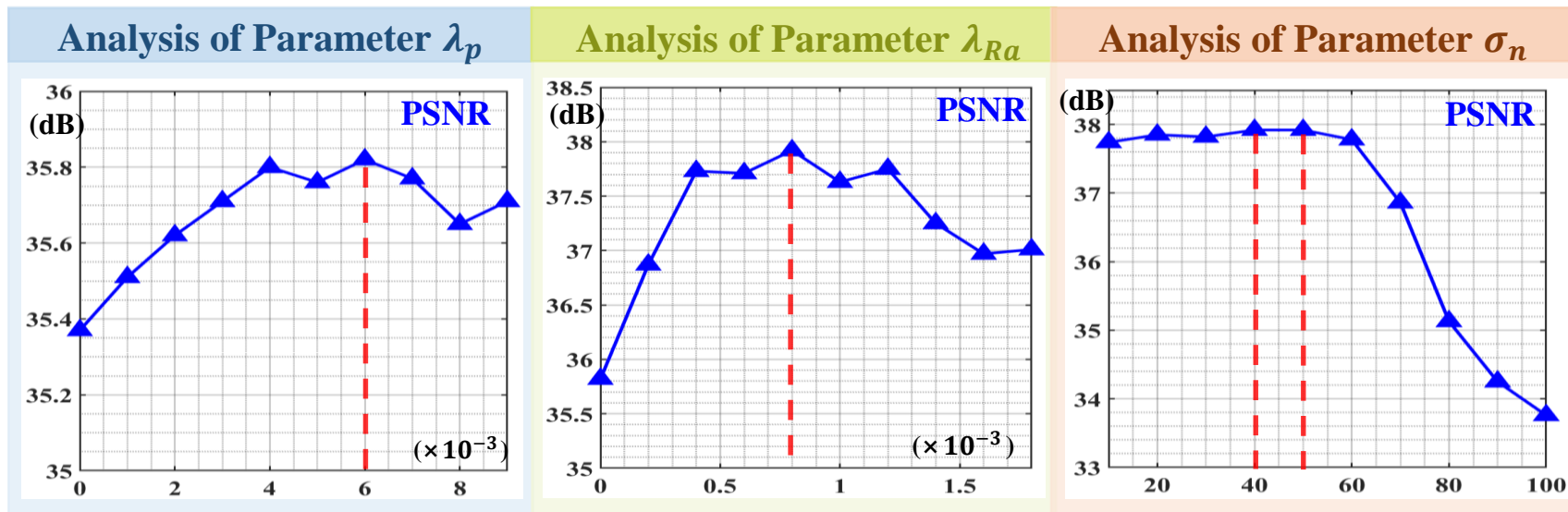


# Experiments

- Parameter Analysis

The optimal setting:

- $\lambda_p = 6 \times 10^{-3}$
- $\lambda_{Ra} = 8 \times 10^{-4}$
- $\sigma_n = 40$  or  $50$



- $q = 60\%$

$q$	SIDD [43]		PolyU [37]		Nam [45]		Total	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
None	38.71	0.914	38.86	0.962	39.20	0.973	38.76	0.929
0	<b>39.32</b>	<b>0.957</b>	38.01	0.949	38.34	0.958	38.92	0.955
20%	39.29	<b>0.957</b>	38.45	0.959	38.87	0.970	39.03	0.958
40%	39.28	0.956	39.02	0.966	39.26	0.973	39.20	0.959
60%	39.26	0.956	39.54	0.971	39.69	0.975	<b>39.35</b>	<b>0.961</b>
80%	39.23	0.955	39.56	<b>0.972</b>	39.72	<b>0.976</b>	39.33	0.960
100%	39.21	0.955	<b>39.57</b>	<b>0.972</b>	<b>39.73</b>	<b>0.976</b>	39.33	0.960

Thanks