Simple Baselines for Image Restoration

> conference: ECCV2022
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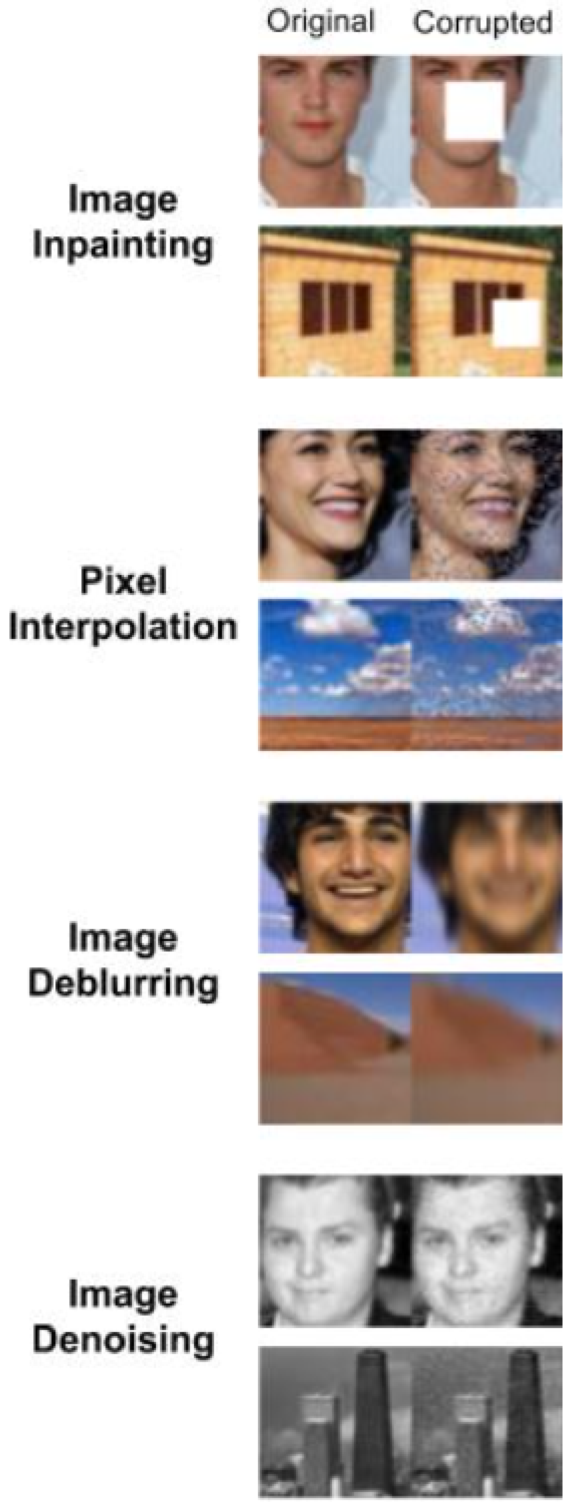
> github: https://github.com/megvii-research/NAFNet
> reference: https://arxiv.org/abs/2204.0467

Image Restoration

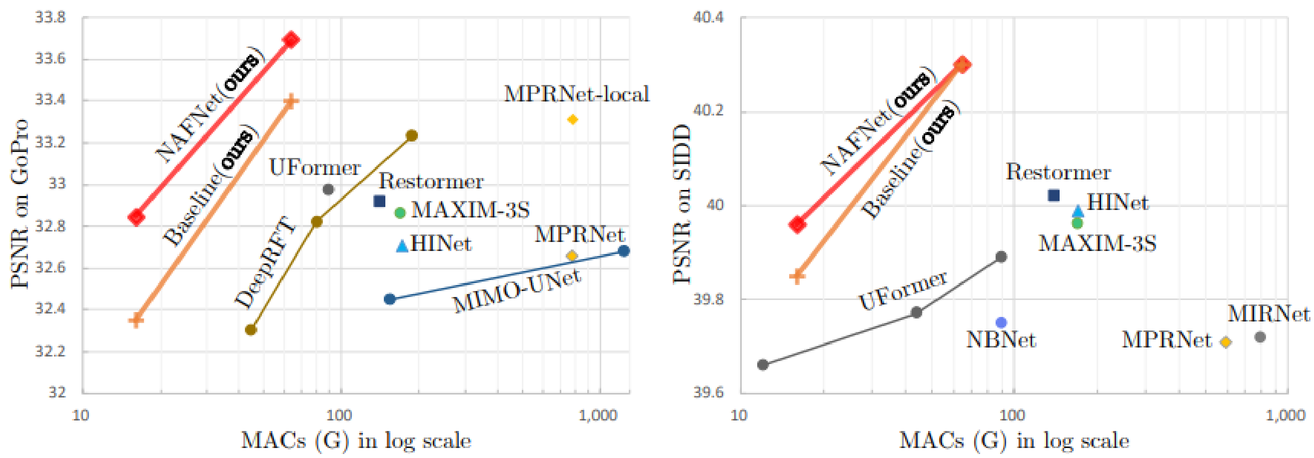
> Image Restoration is a family of inverse problems for obtaining a high quality image from a corrupted input image. Corruption may occur due to the image-capture process (e.g., noise, lens blur), post-processing (e.g., JPEG compression), or photography in non-ideal conditions (e.g., haze, motion blur).
> Examples of Image Restoration:



Abstract

- Although there have been significant advances in the field of image restoration recently, the **system complexity** of the SOTA methods is increasing as well, which may hinder the convenient analysis and comparison of methods.
- In this paper, we propose a **simple baseline** that exceeds the SOTA methods and is computationally efficient.

- We derive a Nonlinear Activation Free Network, namely **NAFNet**, from the baseline.

> 
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>
> Fig. 1: PSNR vs. computational cost on Image Deblurring (left) and Image Denoising (right) tasks.
> (Peak signal-to-noise ratio, PSNR)
> (Giga Multiply Add Caculation per Second, MACs)

Build A Simple Baseline

Architecture

- Inter-block Complexity are multi-stage networks, i.e. the latter stage refine the results of the previous stage, and each stage is a U-shaped architecture.
- To reduce the inter-block complexity, we adopt the classic single-stage U-shaped architecture with skip-connections, as shown in Figure 2c, following **Restformer** and **Uformer**.

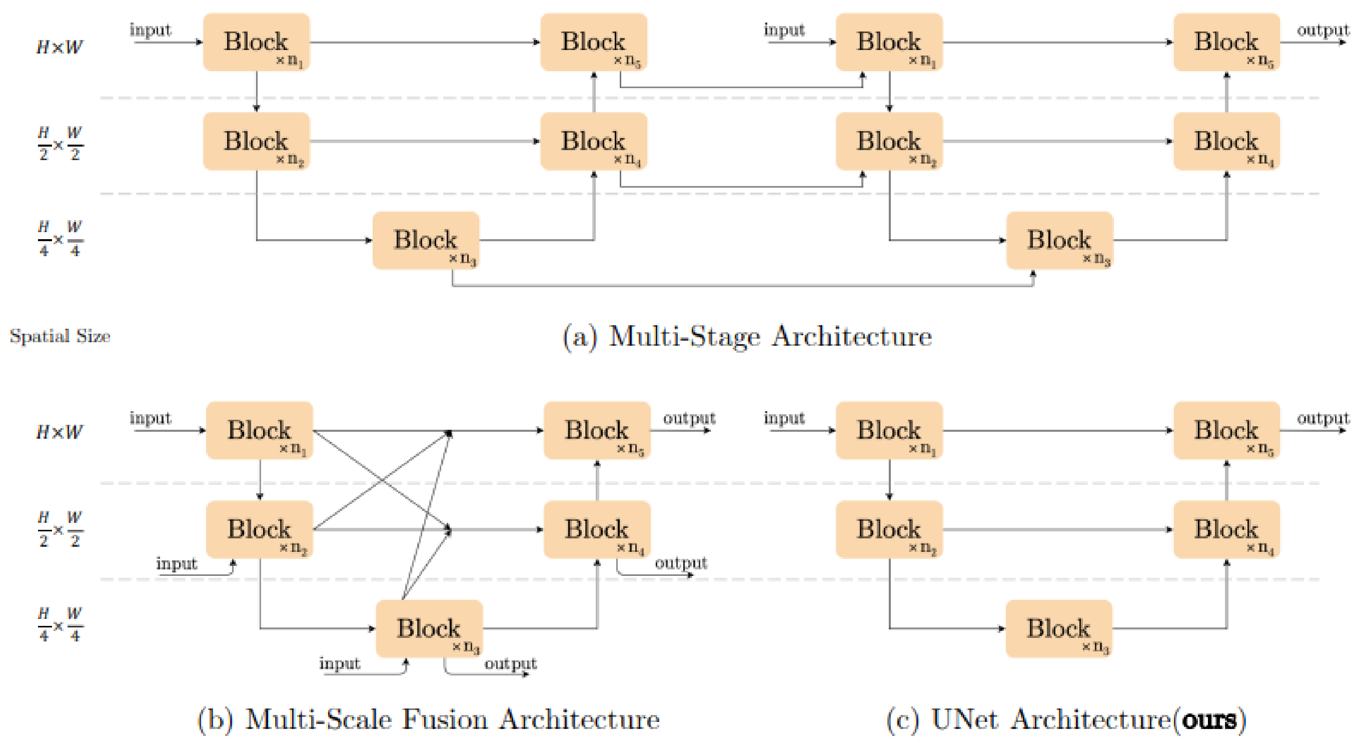


Fig. 2: Comparison of architectures of image restoration models. Dashes to distinguish features of different sizes.

(a) The multi-stage architecture[4,35] stacks UNet architecture serially.

(b) The multi-scale fusion architecture[24,6] fusions the features in different scales.

(c) UNet architecture, which is adopted by some SOTA methods[37,34]. We use it as our architecture.

Layer Normalization

- Although abandoned ~~**Batch Normalization**~~ as the small batch size may bring the unstable statistics, re-introduce the Instance Normalization and avoids the small batch size issue.
- However, **Hinet** shows that adding instance normalization does not always bring performance gains and requires manual tuning.
- Based on these facts we conjecture **Layer Normalization** may be crucial to SOTA restorers, thus we add Layer Normalization to the plain block described above.

Activation

- The activation function in the plain block, ~~**Rectified Linear Unit (ReLU)**~~, is extensively used in computer vision. However, there is a tendency to replace ReLU with GELU in SOTA methods [22,37,30,21,11].
- We replace ReLU with **GELU** in the plain block, because it keeps the performance of image denoising while bringing non-trivial gain on **image deblurring**.

Attention

- Inspired by **Restormer**, we realize the vanilla channel attention meets the requirements: computational efficiency and brings global information to the feature map.
- In addition, the effectiveness of channel attention has been verified in the image restoration task, thus we add the **channel attention** to the plain block.

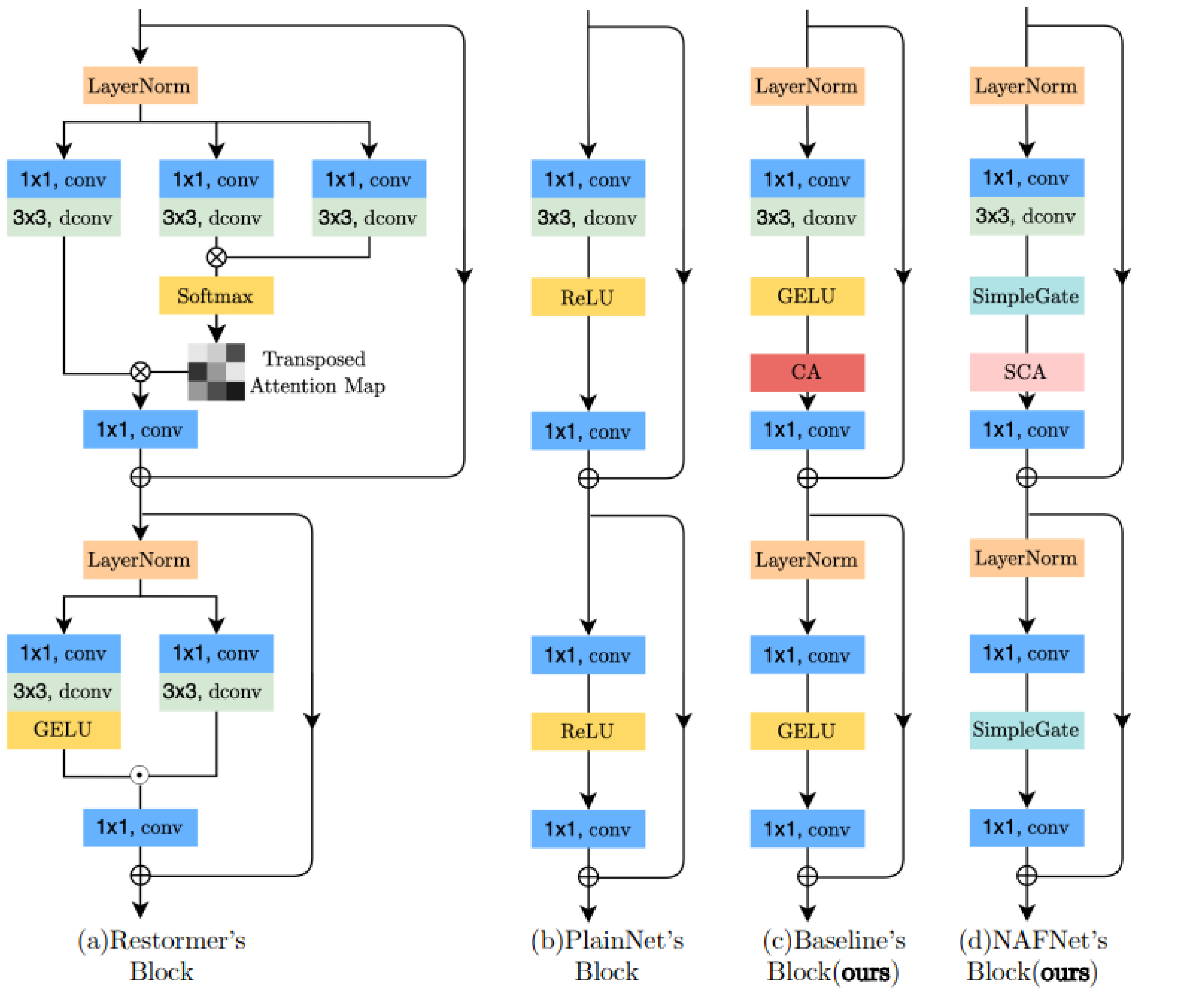
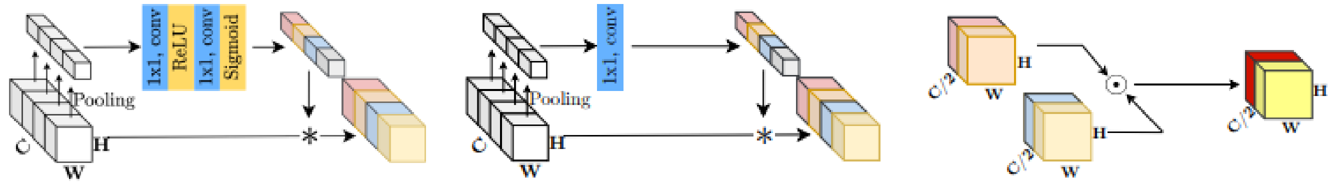


Fig. 3: Intra-block structure comparison. ⊗:matrix multiplication, ⊙/⊕:elementwise multiplication/addition. dconv: Depthwise convolution. Nonlinear activation functions are represented by yellow boxes.

Nonlinear Activation Free Network (NAFNet)

- The baseline described above is simple and competitive, but is it possible to further improve performance while ensuring simplicity?



(a)Channel Attention (b)Simplified Channel Attention (c)Simple Gate

> Fig. 4: Illustration of (a) Channel Attention[15] (CA), (b) Simplified Channel Attention (SCA), and (c) Simple Gate (SG). $\odot$/$*$: element-wise/channel-wise multiplication.

Simple Gate Unit

- Based on these, we propose a simple GLU variant: directly divide the feature map into two parts in the channel dimension and multiply them, as we shown in Figure 4c, noted as SimpleGate.
- The results demonstrate that GELU could be replaced by our proposed SimpleGate.

$$SimpleGate(\mathbf{X}, \mathbf{Y}) = \mathbf{X} \odot \mathbf{Y}, \tag{4}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are feature maps of the same size.

> GAUSSIAN ERROR LINEAR UNITS (GELUS):
>
> $$\text{GELU}(x) = xP(X \le x) = x\Phi(x) = x \cdot \frac{1}{2}\left[1 + \text{erf}(x/\sqrt{2})\right].$$
>
> where Φ indicates the cumulative distribution function of the standard normal distribution. And based on [14], GELU could be approximated and implemented by:
>
> $$0.5x(1 + tanh[\sqrt{2/\pi}(x + 0.044715x^3)]). \tag{3}$$

Simplified Channel Attention

- Channel Attention: it squeezes the spatial information into channels first and then a multilayer perceptual applies to it to calculate the channel attention, which will be used to weight the feature map.
- This inspires us to consider channel attention as a special case of GLU, which can be simplified like GLU in the previous subsection.

Experiments

The ablation studys are conducted on image denoising (SIDD) and deblurring (GoPro) tasks. We limit our computational budget to 16 GMACs (when input size is 256 × 256) in experiments if not specified, following.

> Using metrics:
> (Peak signal-to-noise ratio, PSNR)
> (Structural SIMilarity, SSIM)
> (Giga Multiply AddCaculation per Second, MACs)

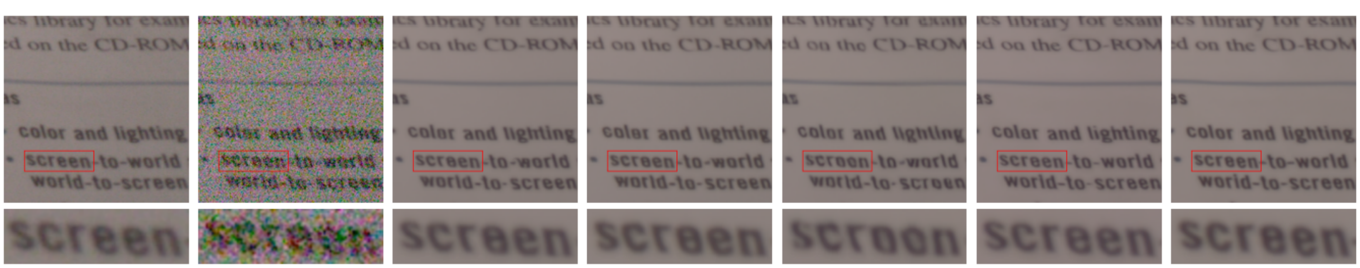
	lr	LN	ReLU→GELU	CA	SIDD PSNR	SIDD SSIM	GoPro PSNR	GoPro SSIM
PlainNet	$1e^{-4}$				39.29	0.956	28.51	0.907
PlainNet*	$1e^{-3}$				-	-	-	-
	$1e^{-3}$	✓			39.73	0.959	31.90	0.952
	$1e^{-3}$	✓	✓		39.71	0.958	32.11	0.954
Baseline	$1e^{-3}$	✓	✓	✓	39.85	0.959	32.35	0.956

Table 1: Build a simple baseline from PlainNet. The effectiveness of Layer Normalization (LN), GELU, and Channel Attention (CA) have been verified. $*$ indicates that the training is unstable due to the large learning rate (lr)

	GELU→SG	CA→SCA	SIDD PSNR	SIDD SSIM	GoPro PSNR	GoPro SSIM
Baseline			39.85	0.959	32.35	0.956
	✓		39.93	0.960	32.76	0.960
		✓	39.95	0.960	32.54	0.958
NAFNet	✓	✓	39.96	0.960	32.85	0.960

Table 2: NAFNet is derived from the simplification of baseline, i.e. replacing GELU to SimpleGate (SG), and replacing Channel Attention (CA) to Simplified Channel Attention (SCA)

RGB Image Denoising



PSNR Reference | 19.01 dB Noisy | 35.21 dB HINet[4] | 35.01 dB Restormer[37] | 34.96 dB MPRNet[35] | 35.97 dB Baseline(**ours**) | 35.77 dB NAFNet(**ours**)

Fig. 5: Qualitative comparison of image denoising methods on SIDD.

Method	MPRNet [35]	MIRNet [38]	NBNet [5]	UFormer [34]	MAXIM [30]	HINet [4]	Restormer [37]	Baseline **ours**	NAFNet **ours**
PSNR	39.71	39.72	39.75	39.89	39.96	39.99	40.02	40.30	40.30
SSIM	0.958	0.959	0.959	0.960	0.960	0.958	0.960	0.962	0.962
MACs(G)	588	786	88.8	89.5	169.5	170.7	140	65	65

Table 5: Image Denoising Results on SIDD.

Image Deblurring

Method	MIMO-UNet [6]	HINet [4]	MAXIM [30]	Restormer [37]	UFormer [34]	DeepRFT [24]	MPRNet -local[7]	Baseline **ours**	NAFNet **ours**
PSNR	32.68	32.71	32.86	32.92	32.97	33.23	33.31	33.40	33.69
SSIM	0.959	0.959	0.961	0.961	0.967	0.963	0.964	0.965	0.967
MACs(G)	1235	170.7	169.5	140	89.5	187	778.2	65	65

Table 6: Image Deblurring Results on GoPro[25].

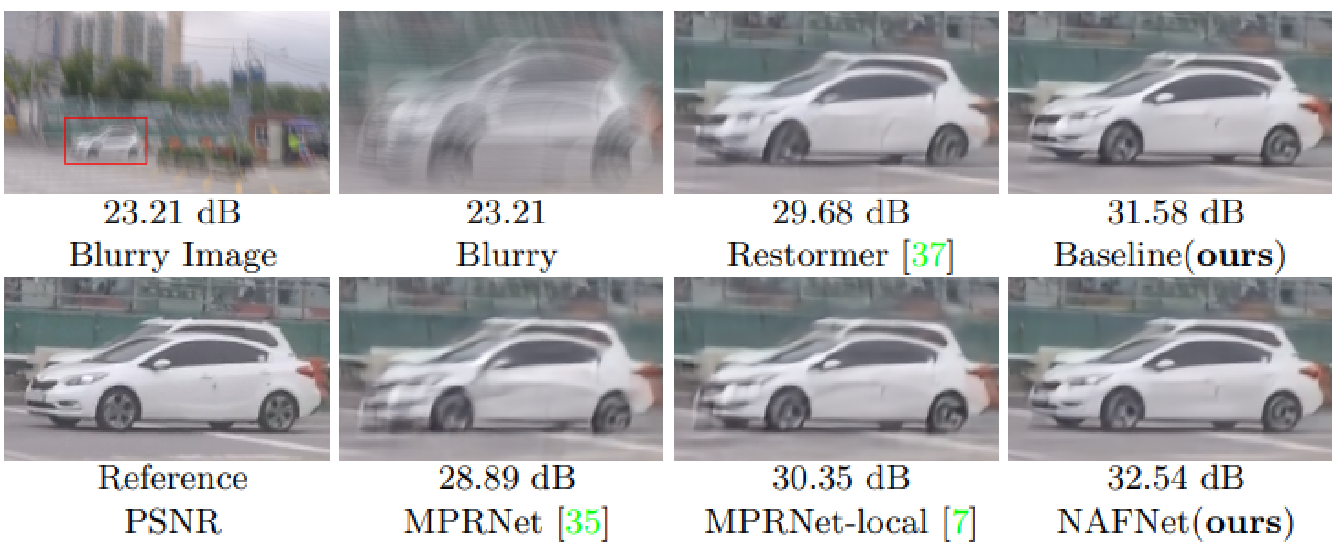


Fig. 6: Qualitative comparison of image deblurring methods on GoPro[25].

Raw Image Denoising

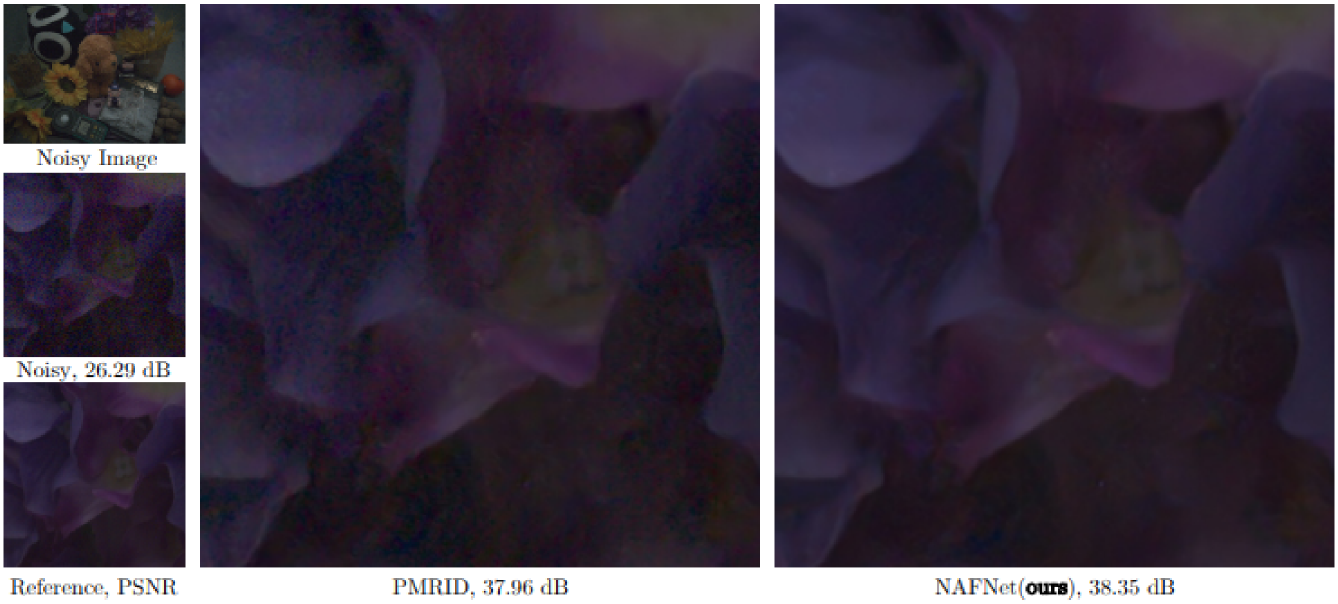


Fig. 7: Qualitatively compare the noise reduction effects of PMRID[33] and our porposed NAFNet. Zoom in to see details.

Method	PSNR	SSIM	MACs(G)
PMRID[33]	39.76	0.975	1.2
NAFNet(**ours**)	40.05	0.977	1.1

Table 7: Raw image denoising results on 4Scenes[33]