RISPNet: A Network for Reversed Image Signal Processing

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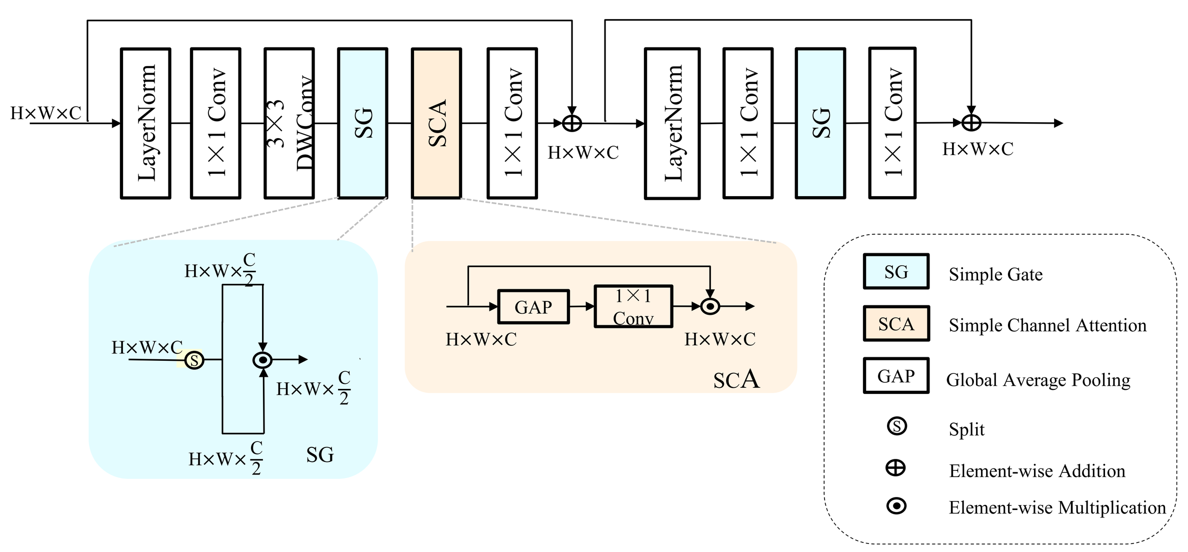
Contributions

- We develop a novel end-to-end learnable network to build the reversed ISP mapping from RGB to RAW images. Our RISPNet can generate accurate and realistic RAW data taking the RGB images as inputs, which is of great benefit to the downstream tasks.
- We explore the effectiveness of the simple activation gate module on the reversed ISP task by experiments. The SAG module will bring a performance gain of 0.03 dB to the NAFNet baseline.
- We design a third-order attention module to realize the complicated tradeoff between recovering spatial detail and high-level contextual information. This module can contribute to another performance gain of 0.13 dB on the basis of the SAG module.
- Extensive experiments show that our method achieving state-of-the-art performance for the reversed ISP task, which is promising for benefiting the down-stream tasks.

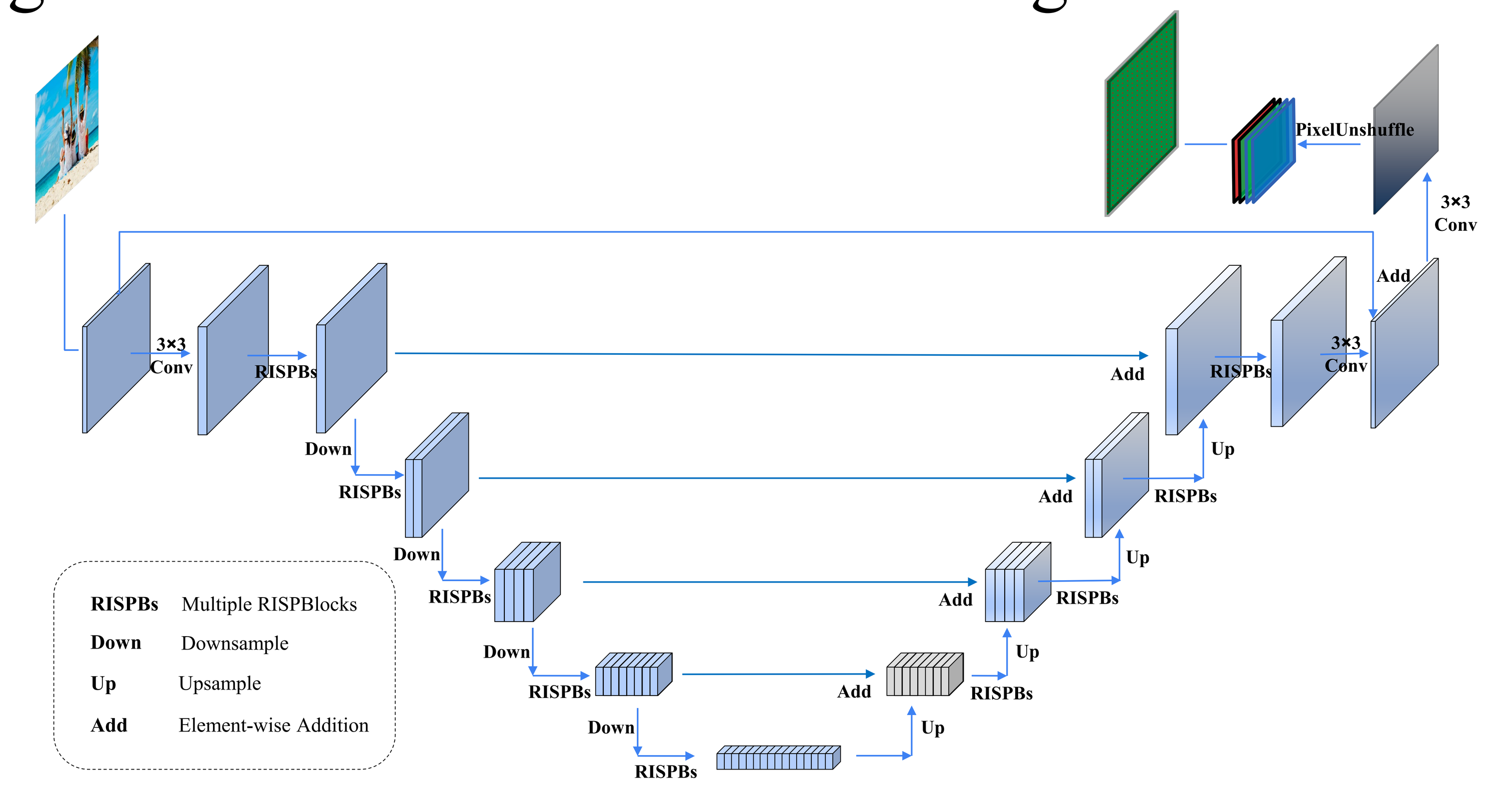
Related work

NAFNet achieved exciting results on the image deblurring task and the image denoising task, whose distinguished performance arouses our interest and is selected as our baseline.

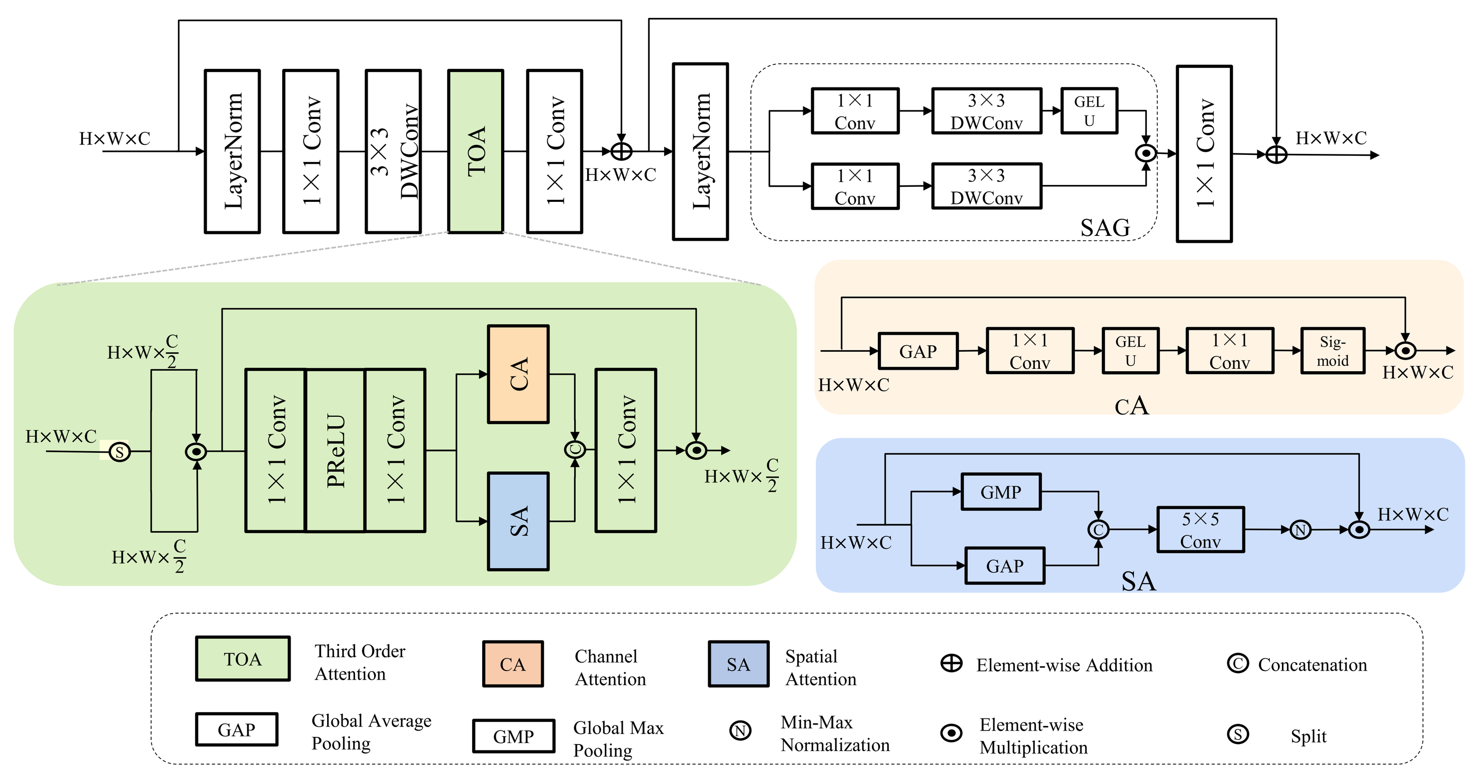


Method

RISPNet Similar to most image restoration methods, our RISPNet adopts an encoder-decoder based UNet architecture to learn the latent representation of RGB images and reconstruct the RAW images.



RISPBlock RISPBlock is the basic block of RISPNet, enabling the encoder, the decoder and the bottleneck layer described above to achieve efficient feature transformation by capturing both the long-range and local dependencies. Unlike the simple basic block in NAFNet, RISPBlock is improved by a third-order attention module (TOA) and a simple activation gate module (SAG).



Experiments

AIM 2022 Reversed ISP Challenge Results

Table 1. Quantitative results on the test sets of the AIM 2022 Reversed ISP Challenge Track P20 and Track S7. We won third place on both Track P20 and Track S7. Our results are in red.

Team name	Track 1 (Samsung S7) Test1 PSNR ↑	Track 1 Test1 SSIM ↑	Track 1 Test2 PSNR ↑	Track 1 Test2 SSIM ↑	Track 2 (Huawei P20) Test1 PSNR ↑	Track 2 Test1 SSIM ↑	Track 2 Test2 PSNR ↑	Track 2 Test2 SSIM ↑
NOAHTCV	31.86	0.83	32.69	0.88	38.38	0.93	35.77	0.92
MiAlgo	31.39	0.82	30.73	0.80	40.06	0.93	37.09	0.92
CASIA LCVG	30.19	0.81	31.47	0.86	37.58	0.93	33.99	0.92
HIT-IIL	29.12	0.80	29.98	0.87	36.53	0.91	34.07	0.90
CS^2U	29.13	0.79	29.95	0.84	-	-	-	-
SenseBrains	28.36	0.80	30.08	0.86	35.47	0.92	32.63	0.91
PixelJump	28.15	0.80	n/a	n/a	-	-	-	-
HiImage	27.96	0.79	n/a	n/a	34.40	0.94	32.13	0.90
0noise	27.67	0.79	29.81	0.87	33.68	0.90	31.83	0.89
OzU VGL	27.89	0.79	28.83	0.83	32.72	0.87	30.69	0.86
CVIP	27.85	0.80	29.50	0.86	-	-	-	-
CycleISP [31]	26.75	0.78	-	-	32.70	0.85	-	-
UPI [2]	26.90	0.78	-	-	-	-	-	-
U-Net Base	26.30	0.77	-	-	30.01	0.80	-	-

Ablation study

Table 2. Ablation study. Baseline, Baseline+SAG, Baseline+SAG+TOA, and RISPNet−SA denote the baseline, baseline applying SAG, baseline applying SAG and TOA (i.e., our RISPNet), and RISPNet without SA respectively. The star (*) on the right of the model name indicates that mix-up is employed when training. All models are tested on the validation set of Track P20. Note that here we don't use any ensemble strategy. Best results are in red.

Models	PSNR
Baseline	38.80
Baseline*	39.05
Baseline+SAG*	39.08
RISPNet−SA*	39.16
Baseline+SAG+TOA (RISPNet)*	39.21

As can be seen in the table, the SAG module could increase the recovery performance by 0.03 dB and the TOA module shall bring another 0.13 dB performance gain. which confirm the effectiveness of the two proposed modules. In addition, we also found that mix-up is an indispensable training strategy, without which, the recovery performance will drop.