Learning Degradation Representation for Image Deblurring

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Github: https://github.com/dasongli1/Learning_degradation

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Motivation & Contributions

Blur in Dynamic Scenes: 1) Camera Shake 2) Scene Motion 3) Depth defocus 4) lens imperfection.
Conventional methods: Insufficient in describing the clean images and blur kernels.

$$(k, x) = \arg\max \mathbb{P}(y|x,k)\mathbb{P}(x)\mathbb{P}(k).$$

Kernel-based Deblurring: 1) Not practical in real-world. 2) incorrect kernels -> artifacts. 3) Huge computation.
Kernel-free Deblurring: 1) Learning the mapping from blur to sharp. 2) Not consider prior of blur kernel. 3) limited in extreme blur (unknown blurring patterns).
→ We incorporate degradation prior into deblurring.

Our contributions:

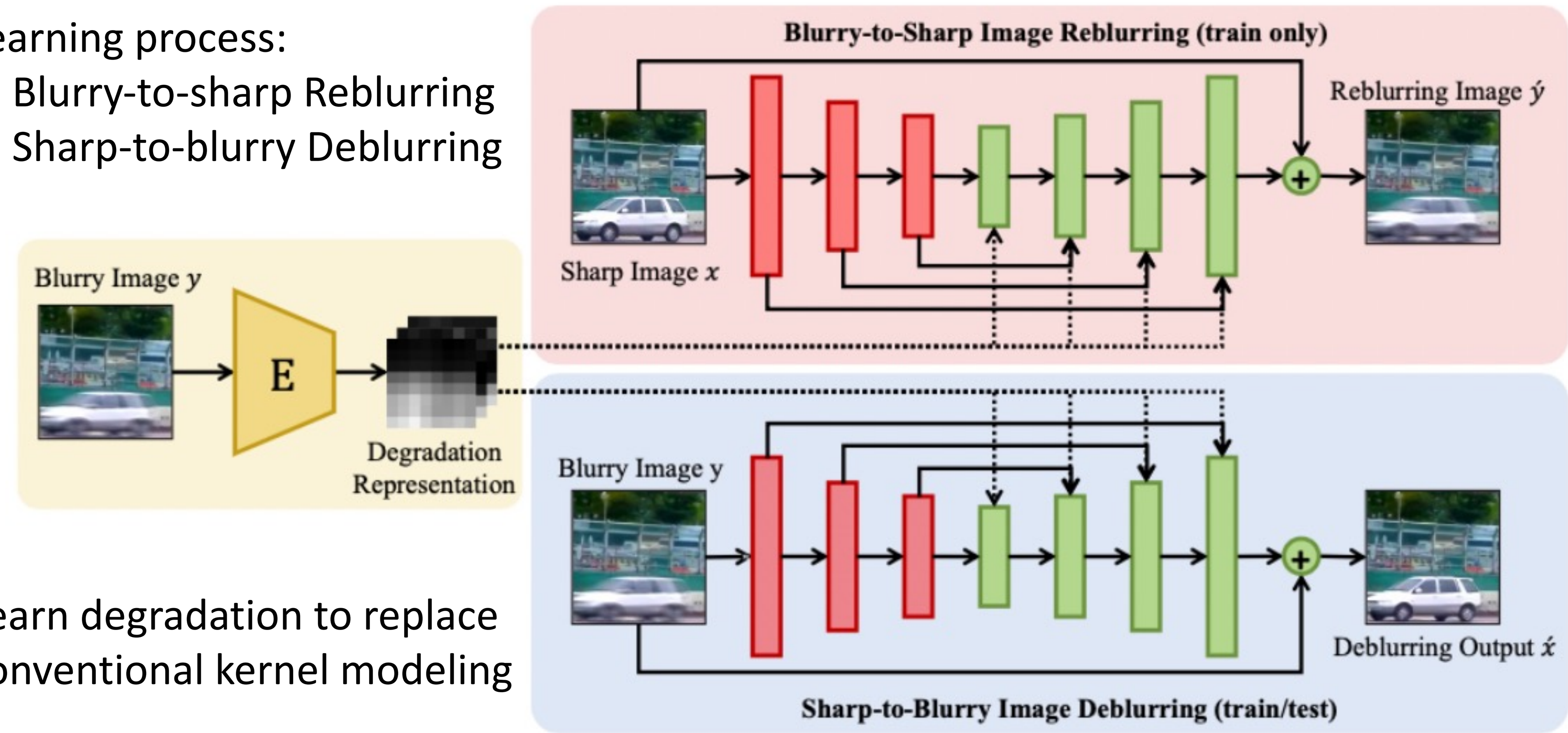
- A novel framework for reblurring and deblurring to adaptive encode spatially varying degradations, which benefits the deblurring performance.
- Our framework achieves SOTA performance on widely used GOPRO and RealBLur datasets.

Framework Overview

Learning Degradation Representations: We Learn explicit representations with a joint sharp-to-blurry reblurring and blurry-to-sharp deblurring. Adversarial training is applied to help reblurring process and improve the expressiveness of degradation representations.

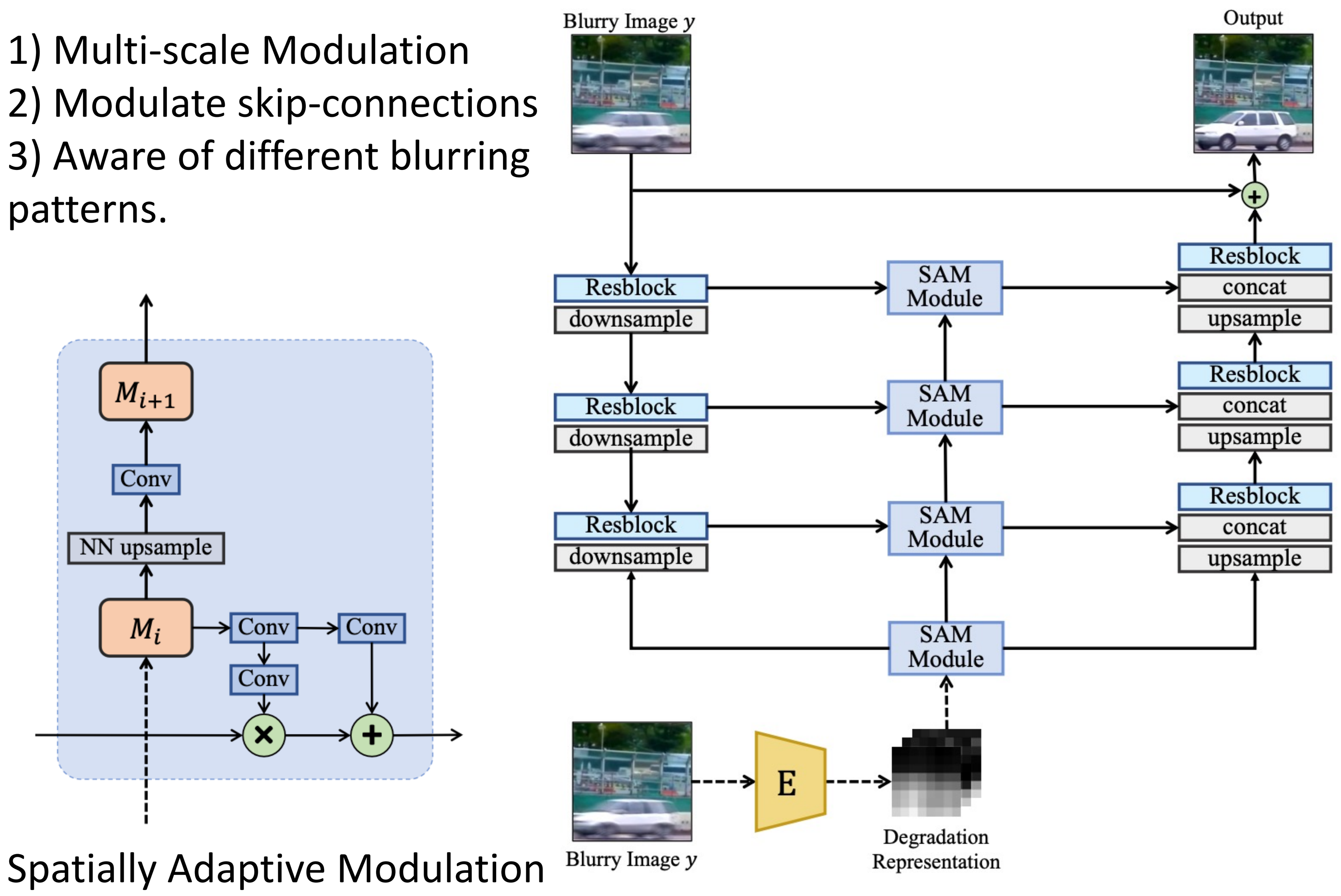
Learning process:
1) Blurry-to-sharp Reblurring
2) Sharp-to-blurry Deblurring

Learn degradation to replace conventional kernel modeling



Multi-scale Degradation Injection Network:

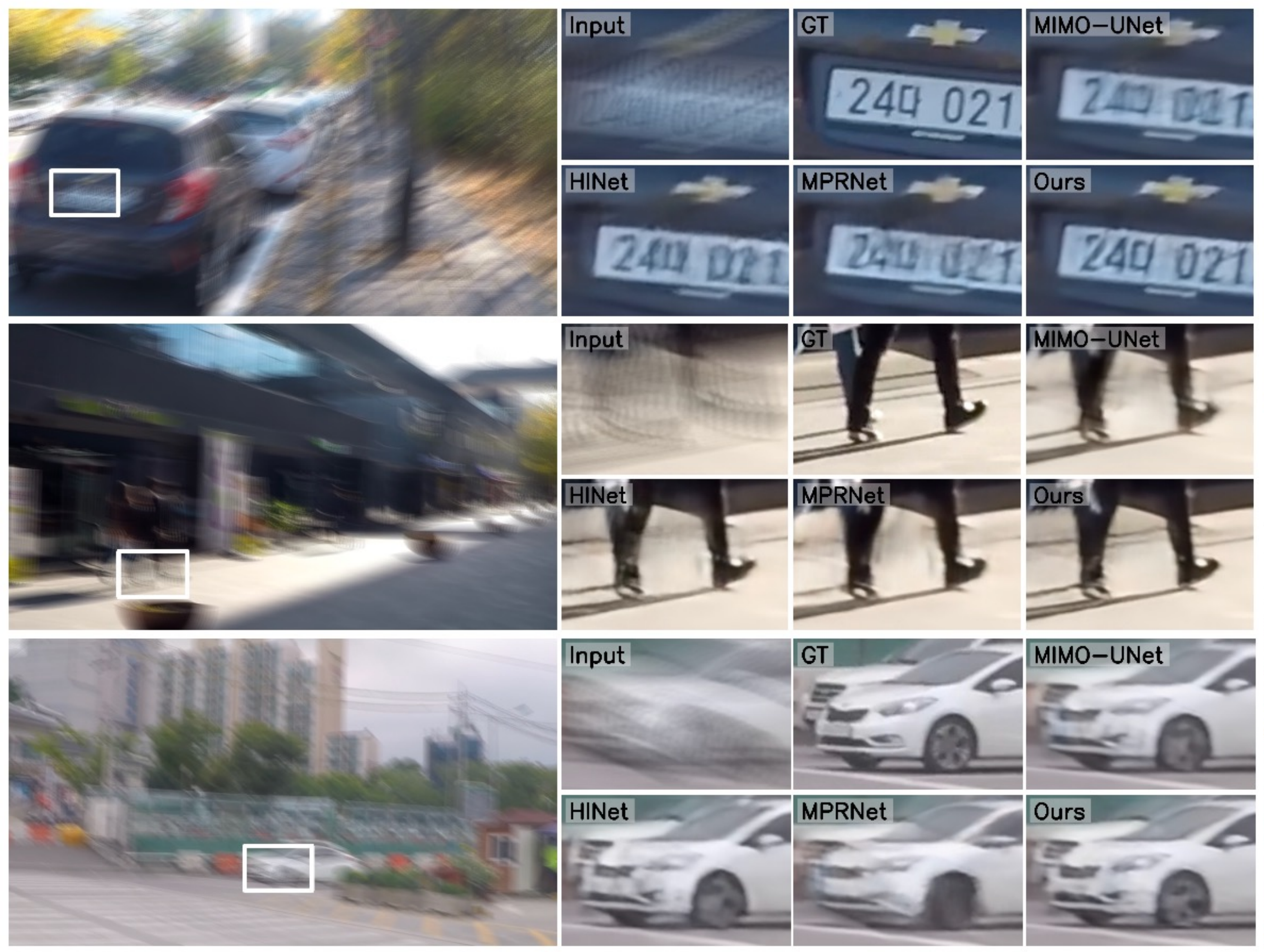
1) Multi-scale Modulation
2) Modulate skip-connections
3) Aware of different blurring patterns.



Spatially Adaptive Modulation

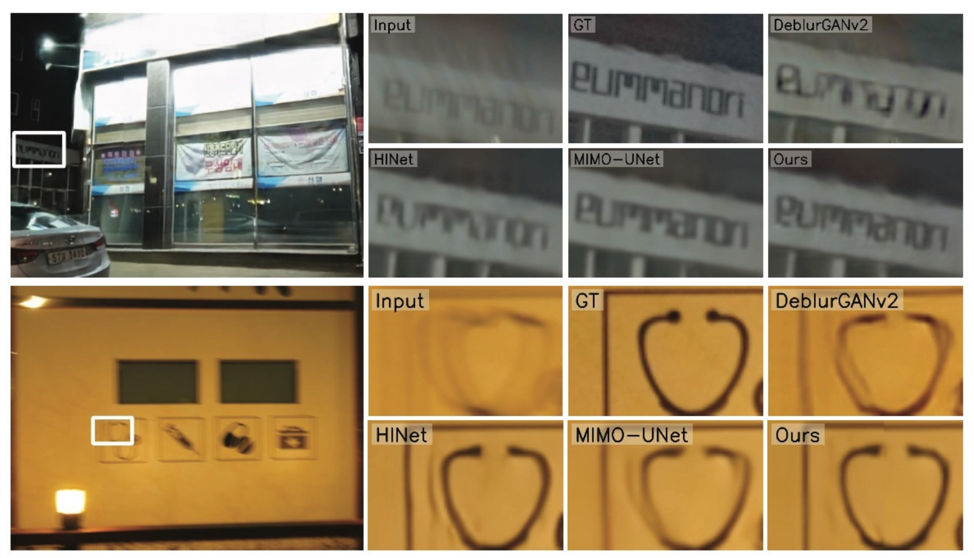
Properties : 1) Aware of spatially varying degradations. 2) Interpolating blurry images with controllable levels. 3) Decoupleness: content-independent representation.

Qualitative Comparison



Visual Comparisons on GOPRO dataset

Interpolation: generating blurry images with controllable blurry levels



Visual Comparisons on RealBlur dataset

Decoupleness

Quantitative Comparison

Method	PSNR	SSIM
DeblurGAN	28.70	0.858
DeblurGAN-v2	29.55	0.934
SRN	30.26	0.934
Gao et al.	30.90	0.935
DBGAN	31.10	0.942
MT-RNN	31.15	0.945
DMPHN	31.20	0.940
Suin et al.	31.85	0.948
MIMO-UNet	32.45	0.957
MPRNet	32.66	0.959
HINet	32.71	0.959
MPRNet-patch256	32.96	0.961
Ours	**33.28**	**0.964**

Results on GoPro dataset

Method	PSNR	SSIM
DeblurGAN-v2	29.69	0.870
SRN	31.38	0.909
MPRNet	31.76	0.922
MIMO-UNet	32.05	0.921
HINet	32.12	0.921
Ours	**32.35**	**0.923**

Results on RealBlur dataset

Model	PSNR
Ours w/o degradation	32.81
Ours w/o reblurring	33.09
Ours	**33.28**

Ablation on Degradation

Model	Blurriest 10%	Sharpest 10%	All	MACs (G)
MPRNet-patch256 [47]	29.31	35.52	32.96	760.11
Ours	**29.65**	**35.58**	**33.28**	336.43

Detailed Comparison with MPRNet