

## Overview

This paper presents a novel adversarial scheme to perform image denoising for the tasks of rain streak removal and re-flection removal, *i.e.*, jointly learn the prior/gradient image and noise-free image based on an adversarial scheme. More specifically, the inferred noise-free image guided by an estimated gradient (**fake gradient**) is regarded as a **negative sample**, while the noise-free image guided by the ground truth of a gradient (**real gradient**) is taken as a **positive sample**. With the **anchor** defined by the ground truth of noise-free image, we play a min-max game to jointly train two optimizers for the estimation of the gradient and the inference of noise-free images. State-of-the-art performance is achieved on two public benchmark datasets.

## Min-Max Optimization

Optimize an  $h$  to distinguish whether a sample is inferred guiding by a **fake** or **real** gradient. Optimize a  $g$  to fool the  $h$ .

### Differences from GAN:

1. Focus on the output of  $h$  **vs.** focus on the output of  $g$
2. Minimize the difference between  $\mathbf{G}_f$  and  $\mathbf{G}_r$  **vs.** minimize KL-divergence

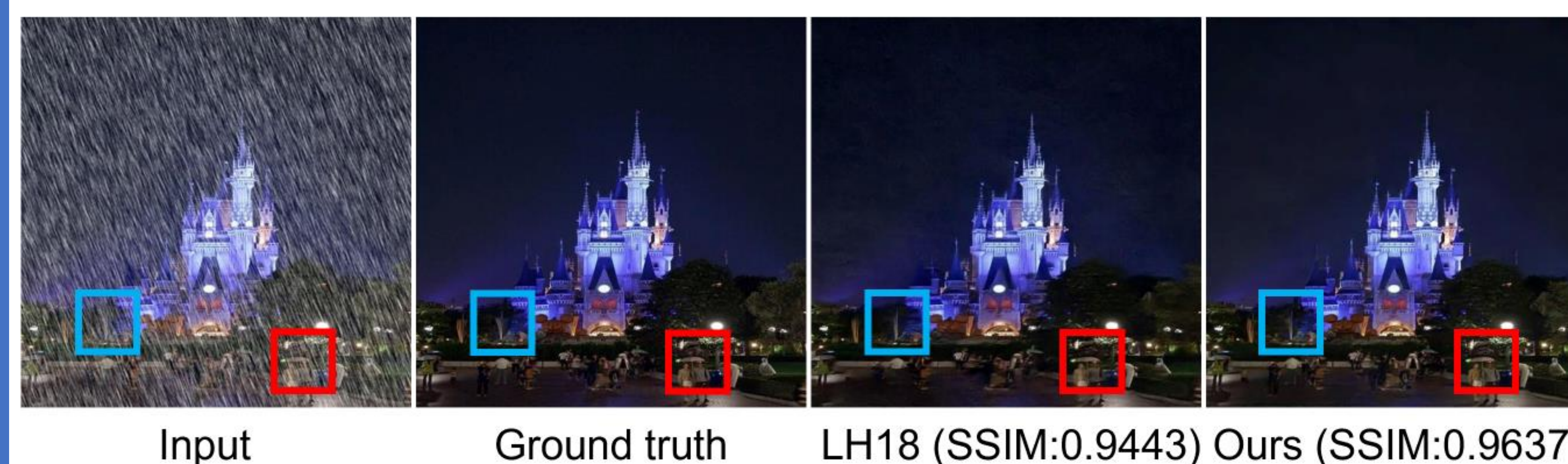
$$\min_g \max_h d(\mathbf{B}_a, \mathbf{B}_n) - d(\mathbf{B}_a, \mathbf{B}_p)$$

$$\approx \min_g d(\mathbf{B}_p, \mathbf{B}_n) = \min_g d(h(\mathbf{M}, \mathbf{G}_r), h(\mathbf{M}, \mathbf{G}_f))$$

## Performance

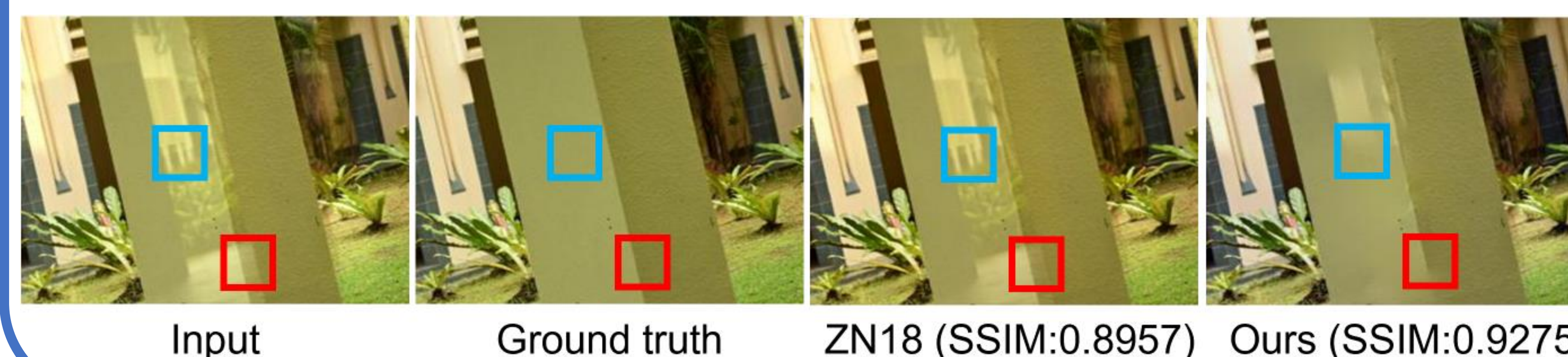
Results of rain removal on DIDMDN-DATA [ZP18]

Metric	FH17	YT17	ZP18	LH18	Ours
SSIM	0.7057	0.8763	0.8707	0.9192	<b>0.9331</b>
PSNR	23.53	30.35	28.30	33.16	<b>33.43</b>

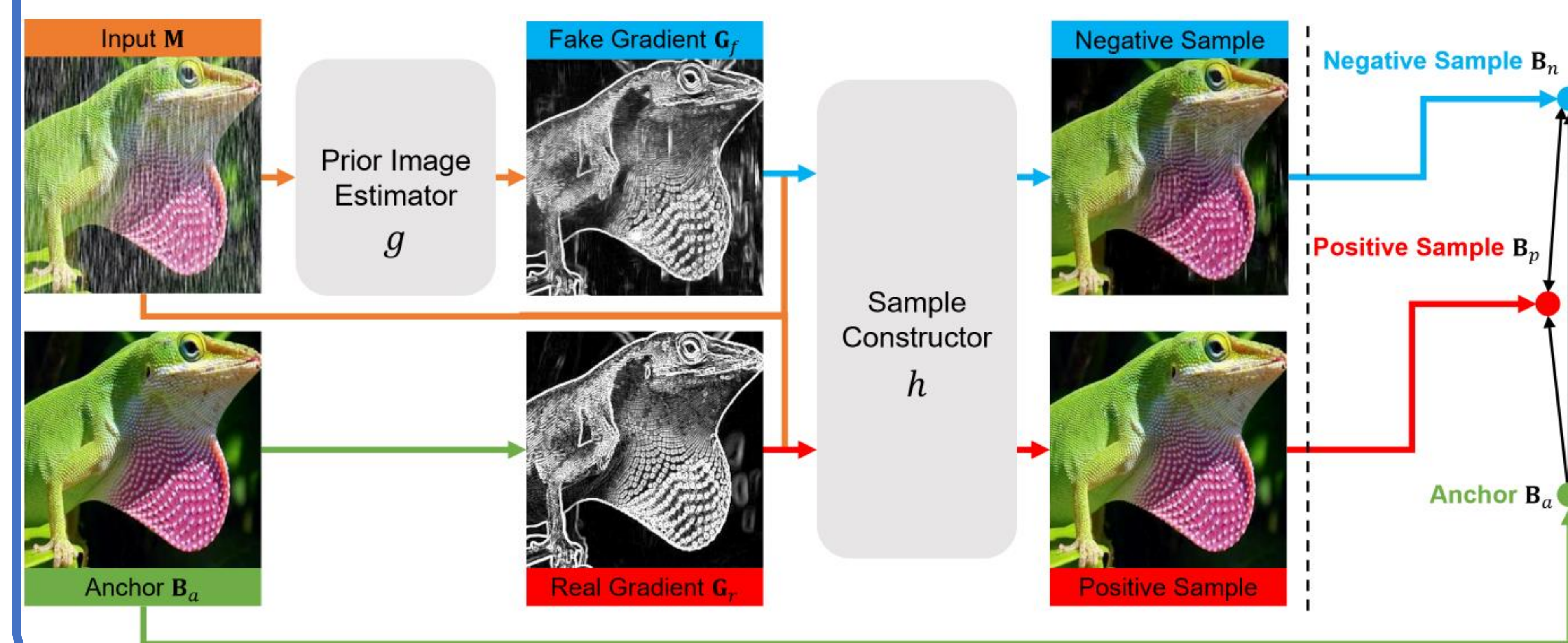


Results of reflection removal on SIR<sup>2</sup> [WS17]

Metric	AA17	FY17	WS18	ZN18	Ours
SSIM	0.8614	0.8649	0.8907	0.8981	<b>0.9022</b>
SI	0.8979	0.8896	0.9160	0.9150	<b>0.9229</b>



## Framework



## Objective Function

$$\min_g \max_h d(\mathbf{B}_a, \mathbf{B}_n) - d(\mathbf{B}_a, \mathbf{B}_p), \quad \text{s.t.} \quad d(\mathbf{B}_a, \mathbf{B}_p) < \delta$$

$$\mathbf{B}_n = h(\mathbf{M}, \mathbf{G}_f) = h(\mathbf{M}, g(\mathbf{M})), \quad \mathbf{B}_p = h(\mathbf{M}, \mathbf{G}_r)$$

## Implementation Details

Loose constraint  $d(\mathbf{B}_a, \mathbf{B}_p) < \delta$  and reformulate objective function as

$$\min_g \max_h d(\mathbf{B}_a, \mathbf{B}_n) - \alpha d(\mathbf{B}_a, \mathbf{B}_p)$$

### Algorithm:

**for** number of training iterations **do**  
**for** 5 steps **do**

sample minibatch of  $m$  data pairs from training data:  
 $\{(\mathbf{M}^{(1)}, \mathbf{B}_a^{(1)}), \dots, (\mathbf{M}^{(m)}, \mathbf{B}_a^{(m)})\}$

update  $h$  by ascending its stochastic gradient:

$$\nabla_{\theta_h} \frac{1}{m} \sum_{i=1}^m (d(\mathbf{B}_a, \mathbf{B}_n) - \alpha d(\mathbf{B}_a, \mathbf{B}_p))$$

**end for**

update  $g$  by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^m d(\mathbf{B}_a, \mathbf{B}_n)$$

**end for**

## References

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- [YT17] W Yang, R T Tan, and et al. Deep joint rain detection and removal from a single image. CVPR, 2017
- [LH18] G Li, X He, and et al. Non-locally enhanced encoder-decoder network for single image de-raining. ACM Multimedia, 2018
- [AA17] N Arvanitopoulos, R Achanta, and et al. Single image reflection suppression. CVPR, 2017
- [FY17] Q Fan, J Yang, and et al. A generic deep architecture for single image reflection removal and image smoothing. ICCV, 2017
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