Generalized Real-World Super-Resolution through Adversarial Robustness


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Overview

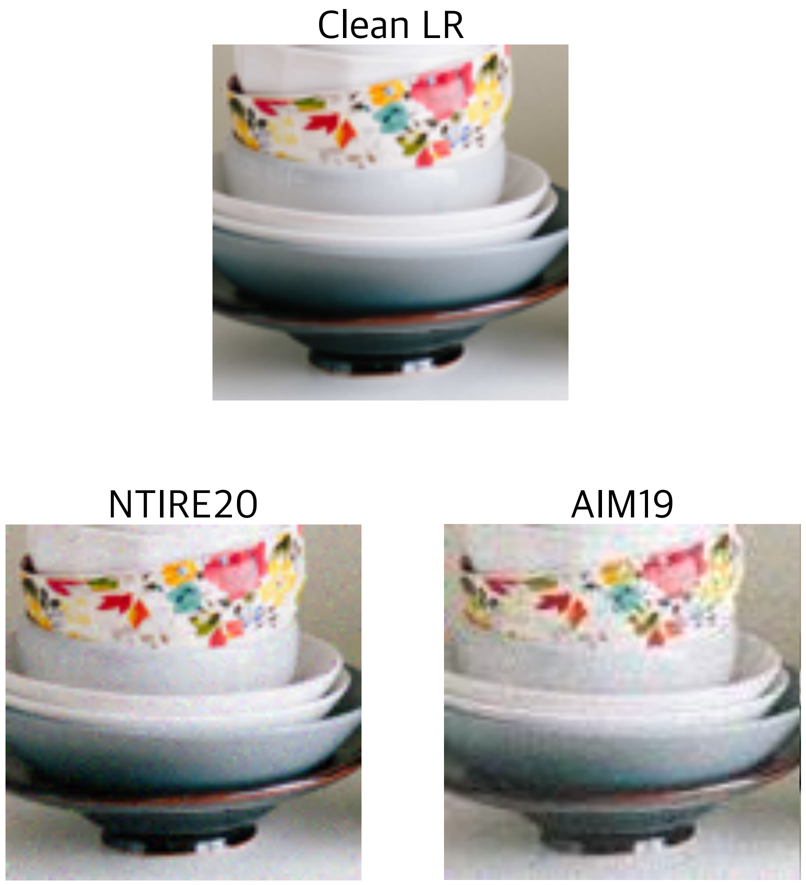
1. **Motivation**
2. Related-work
3. Robust Super-Resolution
4. Results
   4.1 Synthetic datasets
   4.2 Real-world datasets
5. Contributions

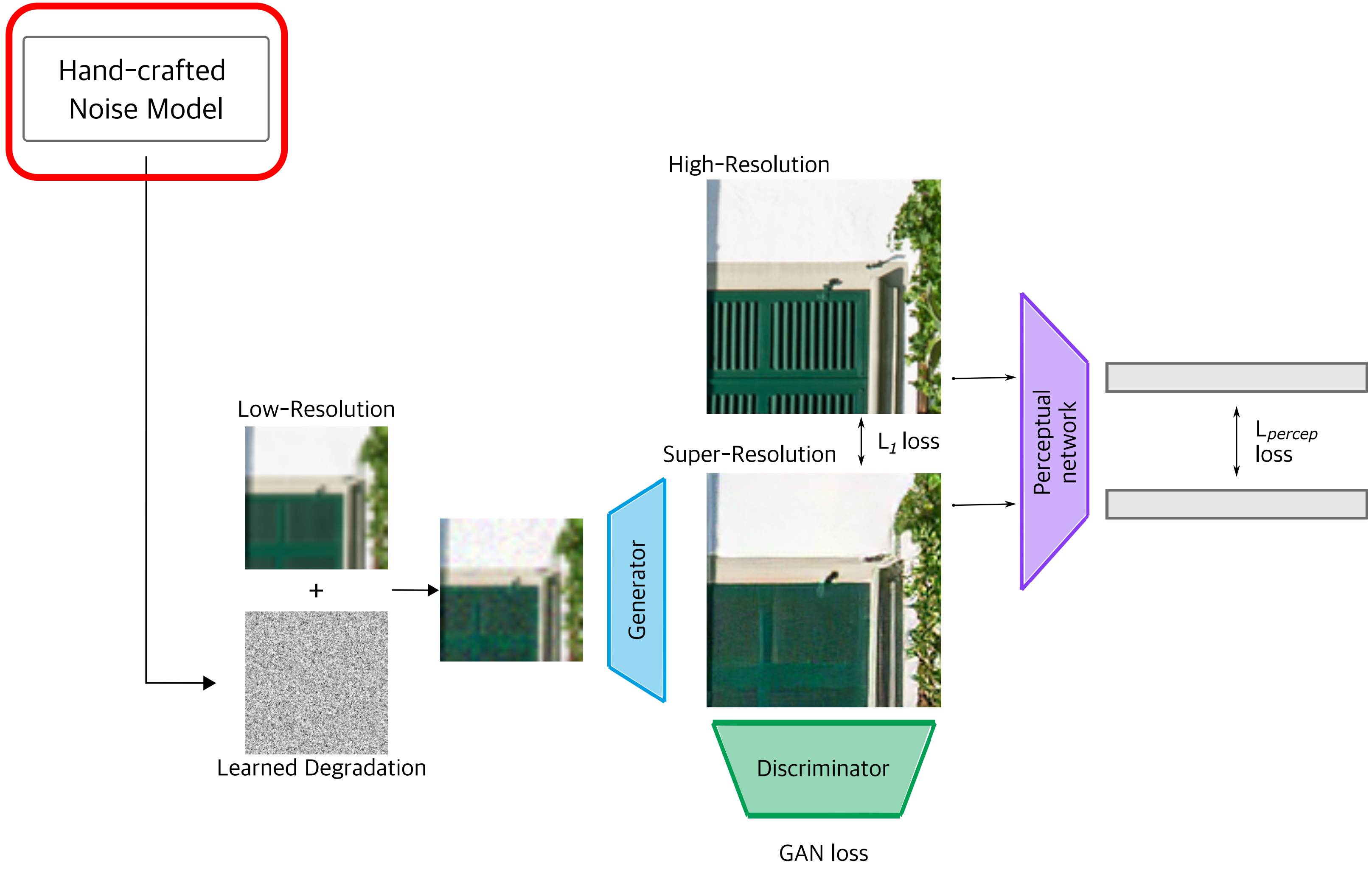
Motivation

Super-Resolution methods for clean images underperform on corrupted input images.

Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Yu Qiao, and Chen Change Loy. Esrgan: En- hanced super-resolution generative adversarial networks. (ECCVW), pages 0–0, 2018.

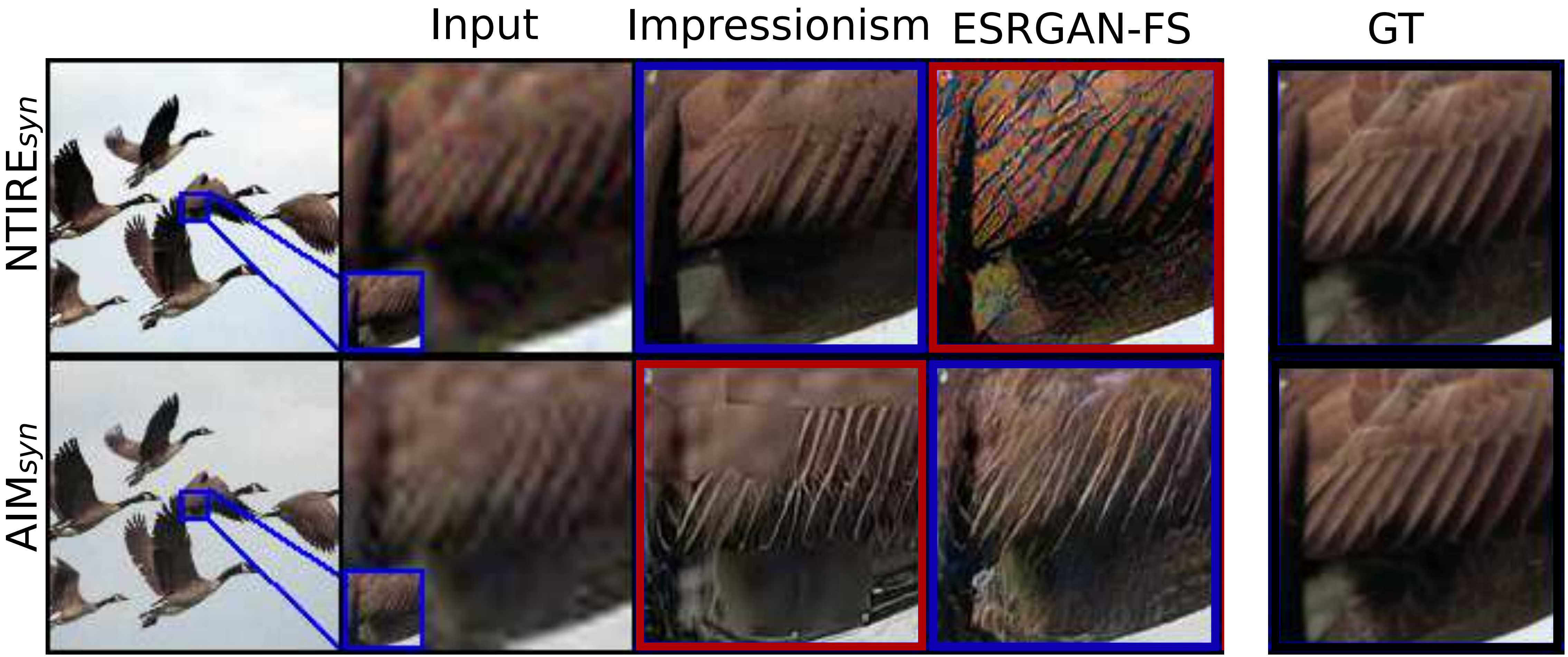
Motivation





Andreas Lugmayr, Martin Danelljan, and Radu Timofte. Ntire 2020 challenge on real-world image super-resolution: Methods and results. CVPRW, pages 494–495, 2020.
Andreas Lugmayr, et al. Aim 2019 challenge on real-world image super-resolution: Methods and results. In *(ICCVW)*, pages 3575–3583. IEEE, 2019.
Eirikur Agustsson and Radu Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. (CVPRW), pages 126–135, 2017

Motivation



Xiaozhong Ji, Yun Cao, Ying Tai, Chengjie Wang, Jilin Li, and Feiyue Huang. Real-world super-resolution via kernel estimation and noise injection. (CVPRW), pages 466–467, 2020
Manuel Fritsche, Shuhang Gu, and Radu Timofte. Fre- quency separation for real-world super-resolution. (ICCVW), pages 3599–3608. IEEE, 2019.

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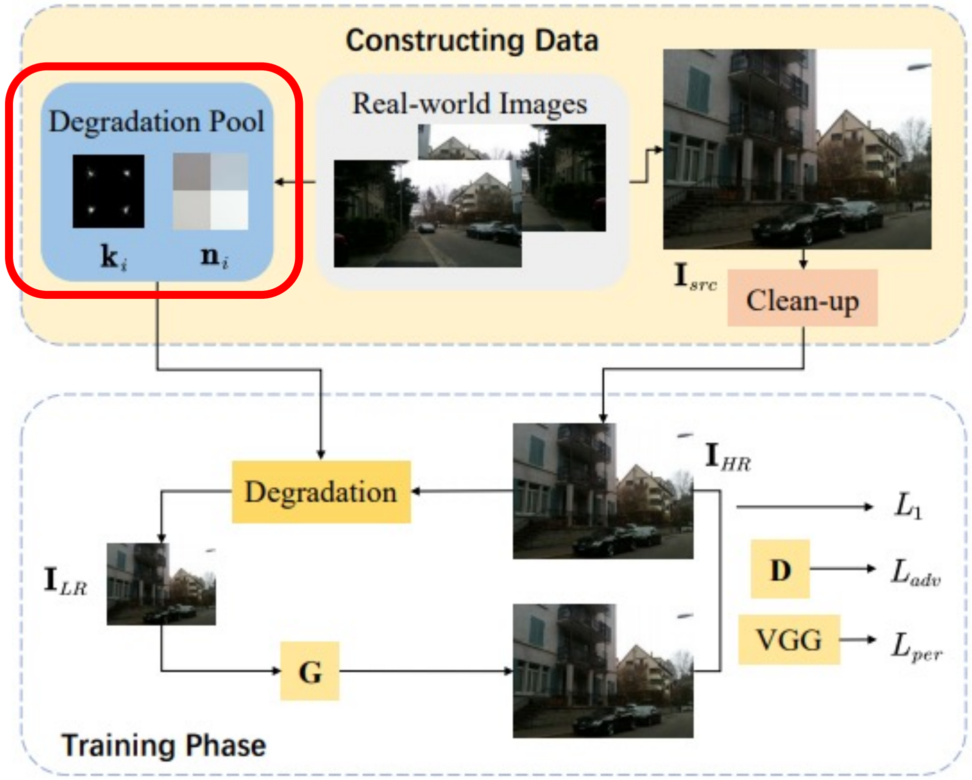
Related-work

REAL-WORLD SUPER-RESOLUTION METHODS

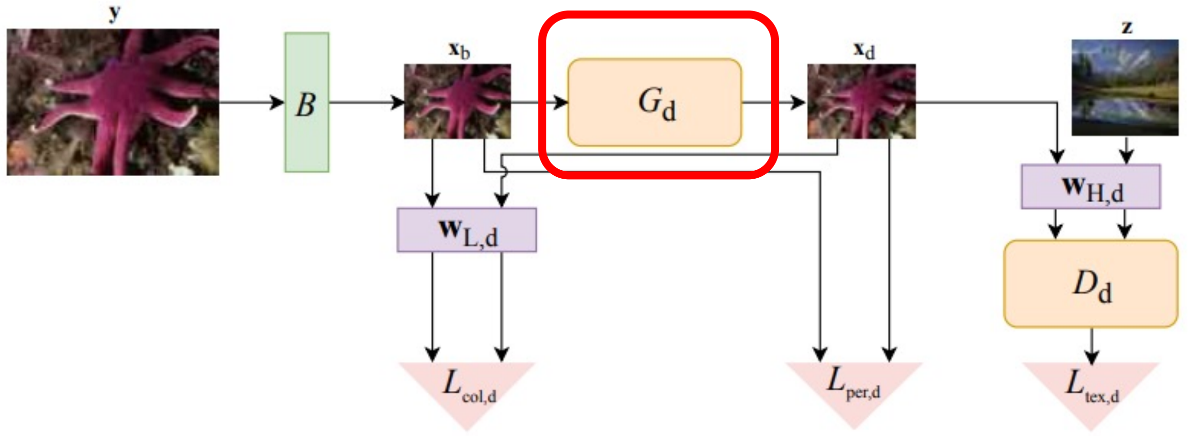
Real-World Super-Resolution via Kernel Estimation and Noise Injection

Xiaozhong Ji[1,2] Yun Cao[2] Ying Tai[2*] Chengjie Wang[2] Jilin Li[2] Feiyue Huang[2]
[1]Nanjing University, [2]Tencent Youtu Lab



Frequency Separation for Real-World Super-Resolution

Manuel Fritsche Shuhang Gu Radu Timofte
Computer Vision Lab, ETH Zürich, Switzerland



Xiaozhong Ji, Yun Cao, Ying Tai, Chengjie Wang, Jilin Li, and Feiyue Huang. Real-world super-resolution via kernel estimation and noise injection. CVPRW pages 466–467, 2020.
Manuel Fritsche, Shuhang Gu, and Radu Timofte. Frequency separation for real-world super-resolution. *ICCVW* pages 3599–3608. IEEE, 2019.

Related-work

ROBUST TRAINING

$\boldsymbol{x}$

"panda"
57.7% confidence

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. ICLR 2015.

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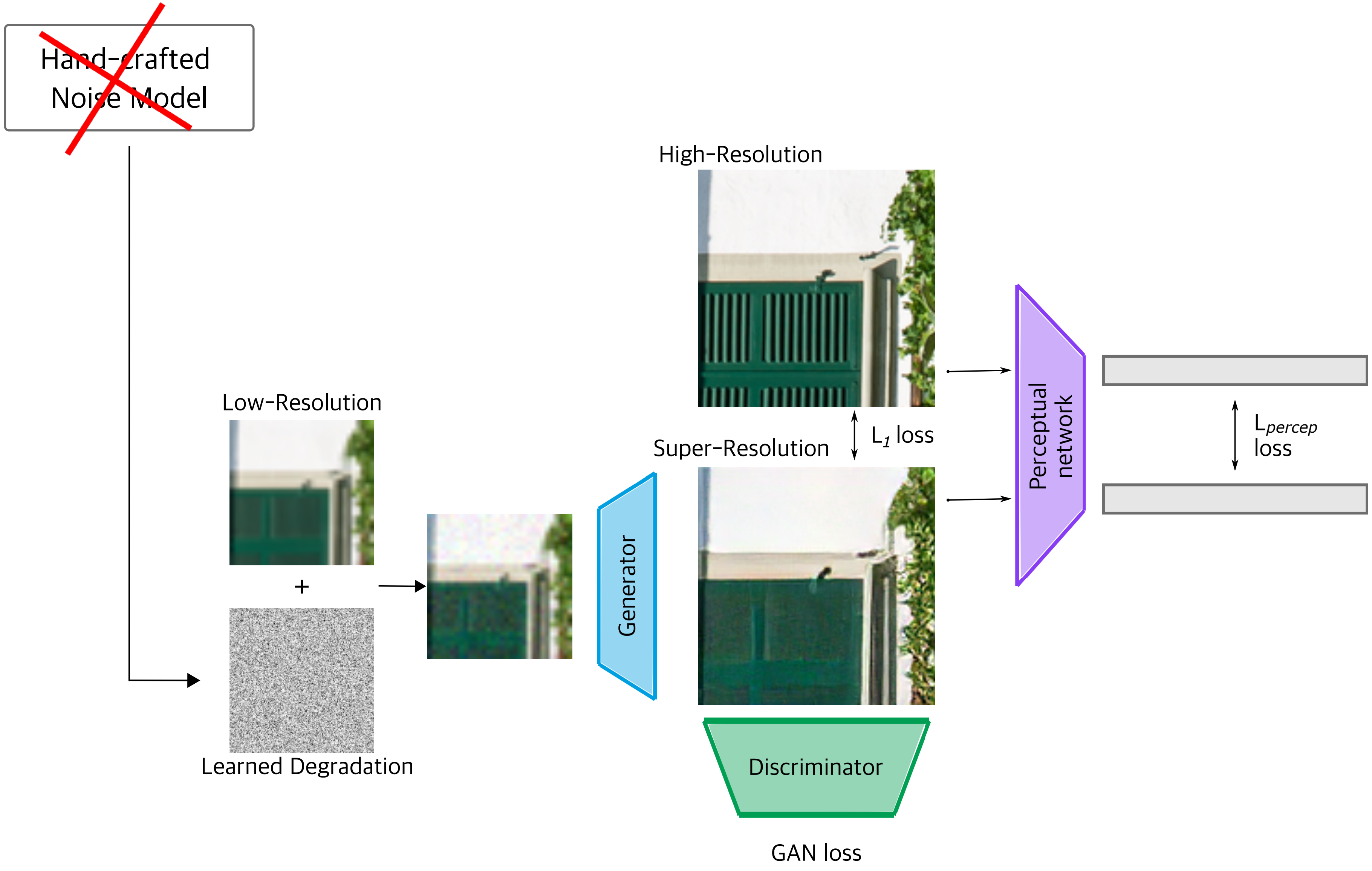
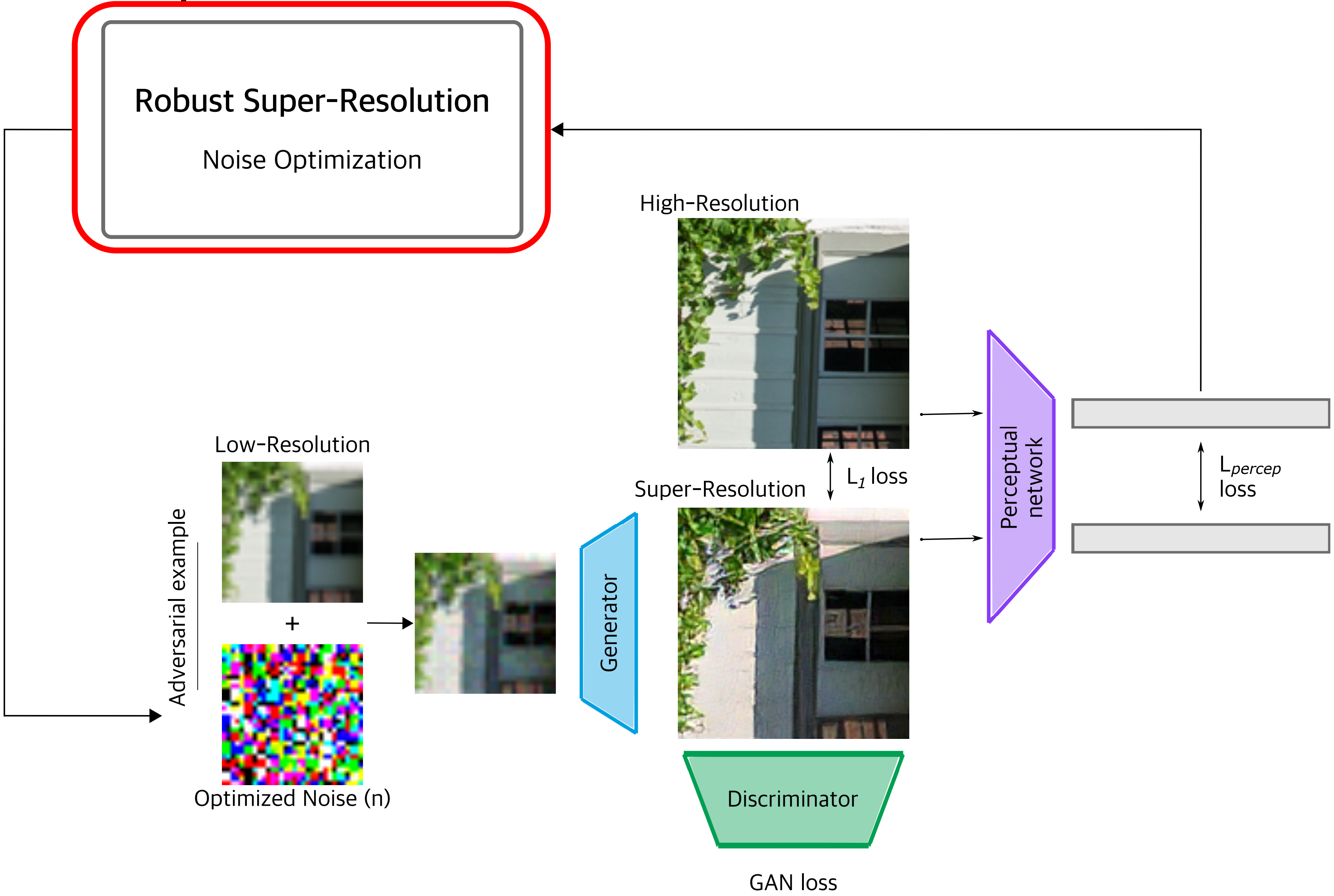
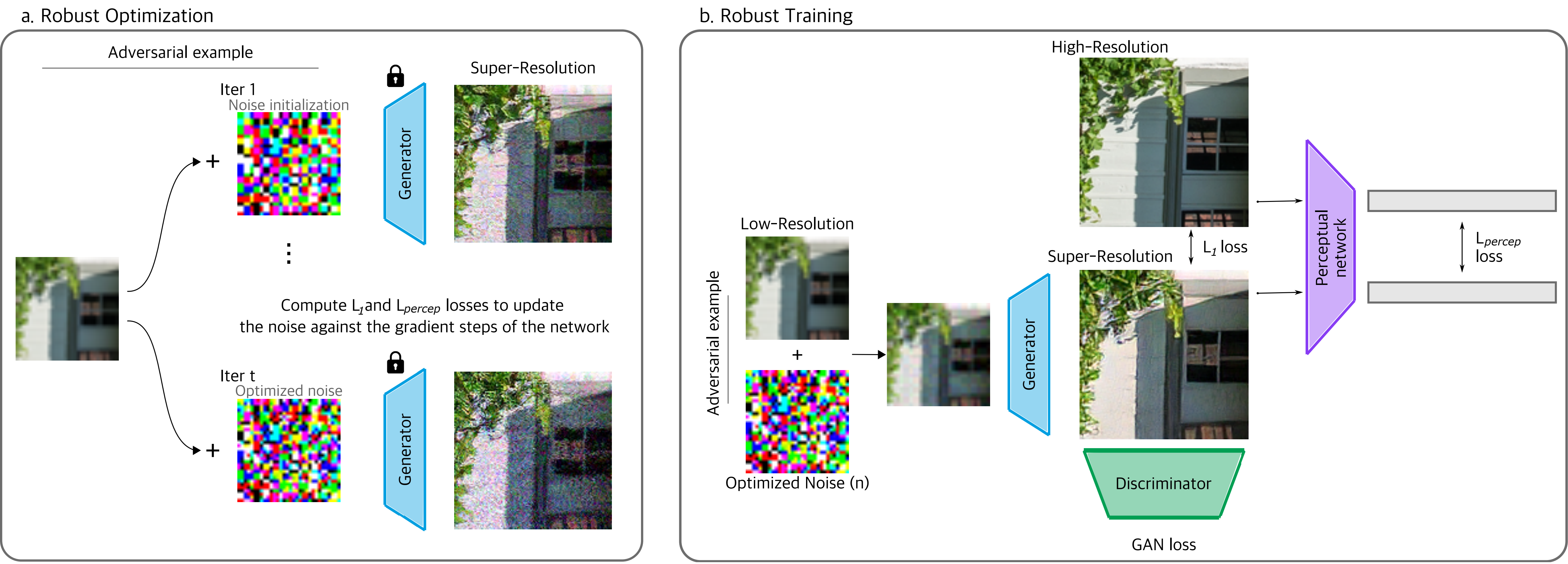
Robust Super-Resolution



Robust Super-Resolution



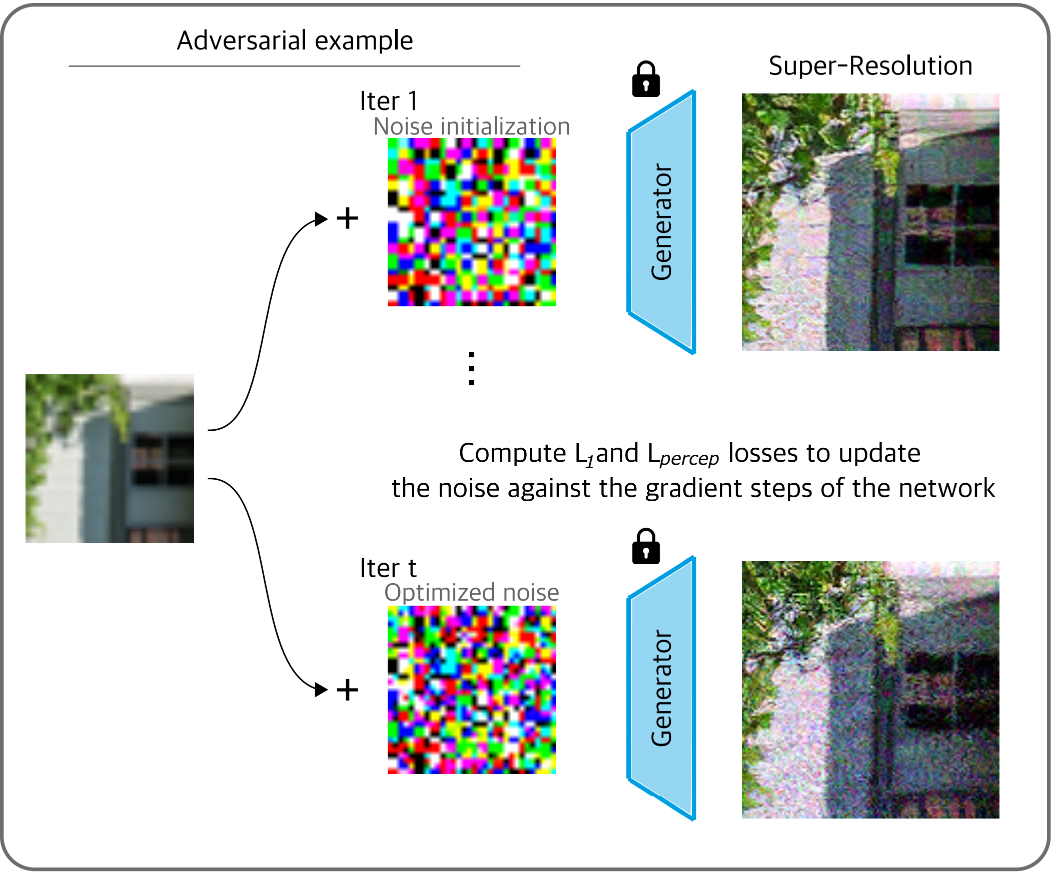
Robust Super-Resolution



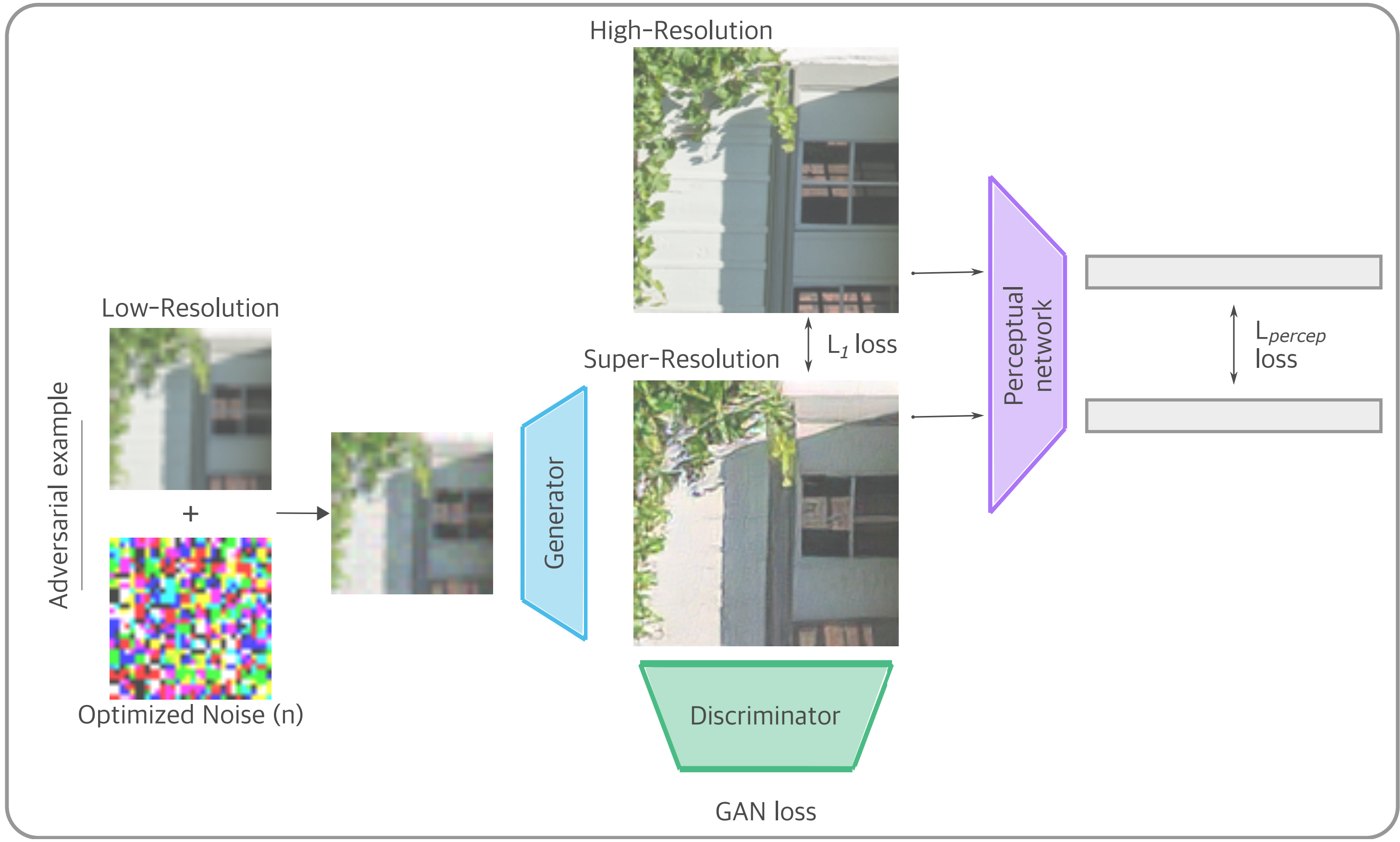
Robust Super-Resolution

ROBUST OPTIMIZATION

a. Robust Optimization

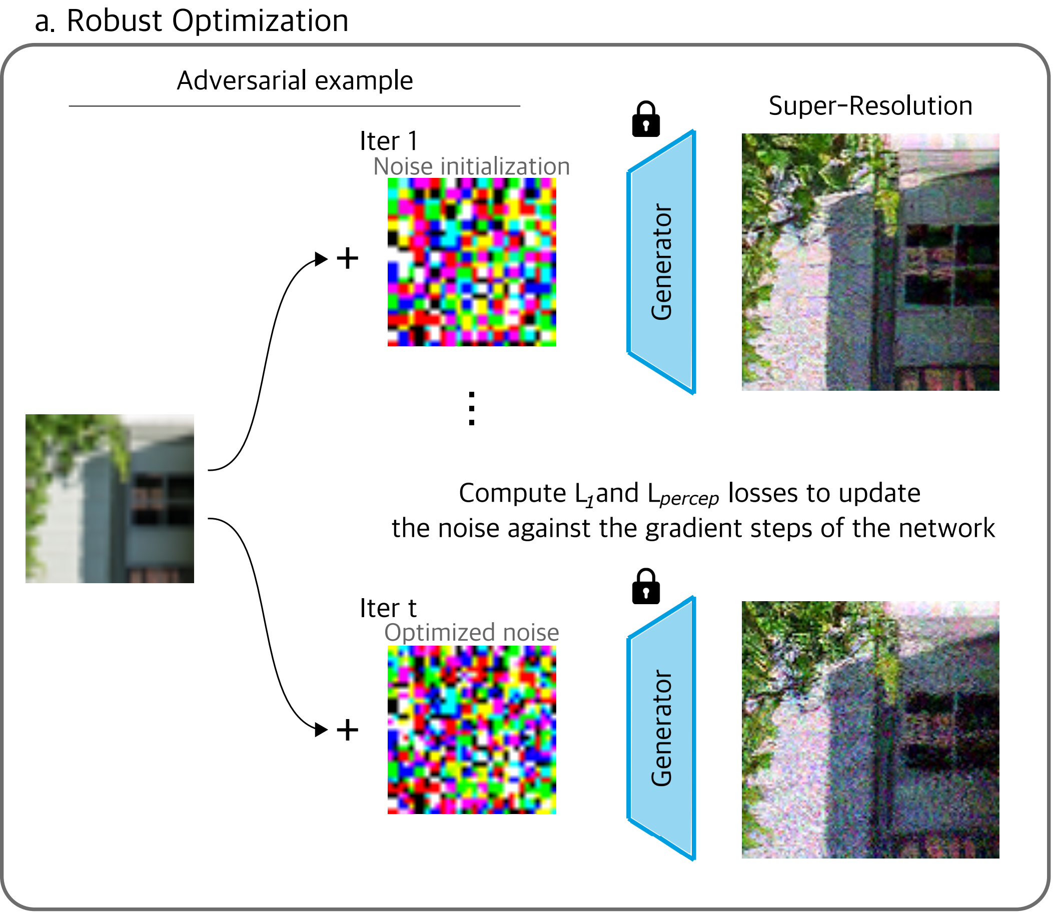


b. Robust Training



Robust Super-Resolution

ROBUST OPTIMIZATION



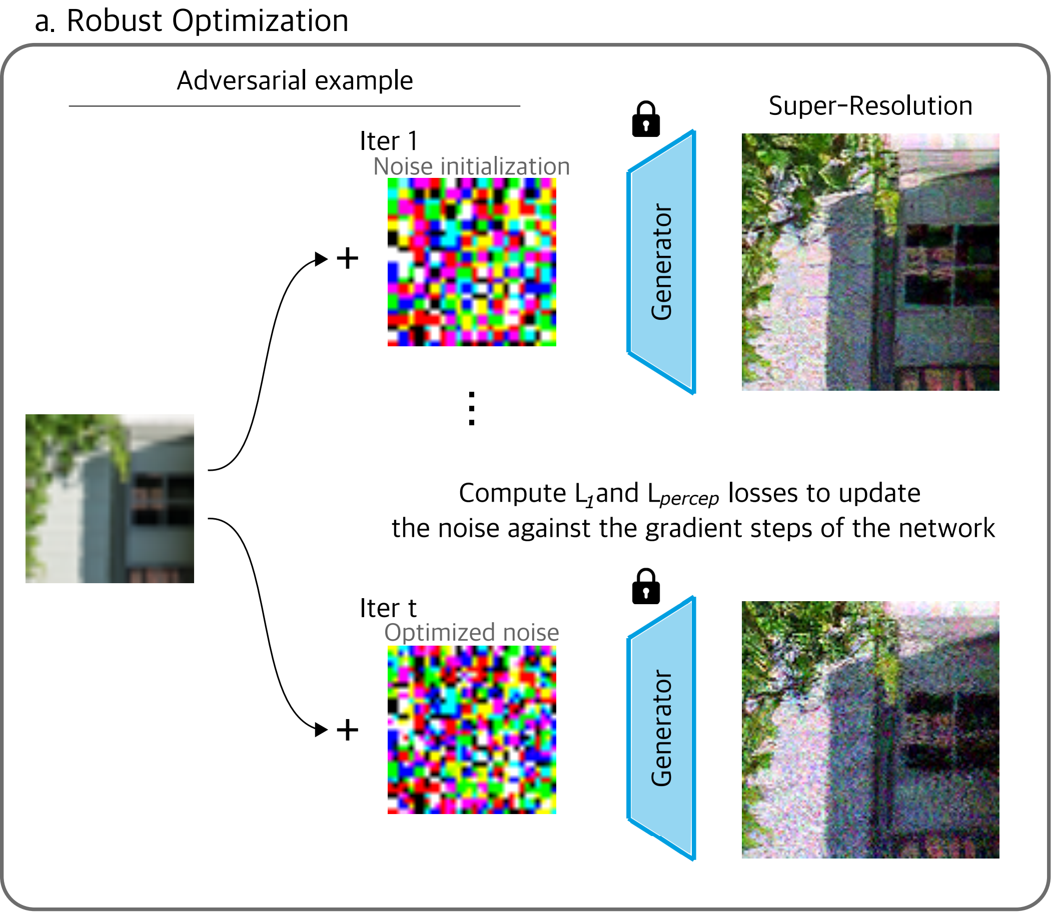
We produce adversarial examples that are generated on-the-fly via the Projected Gradient Descend (PGD) method.

We focus in particular on ℓ_∞-bounded examples, computed as repeated iterations of

$$x_{t+1}^{adv} = \prod_X x_t + \alpha \, sign\left(\nabla_{x_t} L(x_t, y)\right)$$

Robust Super-Resolution

ROBUST OPTIMIZATION

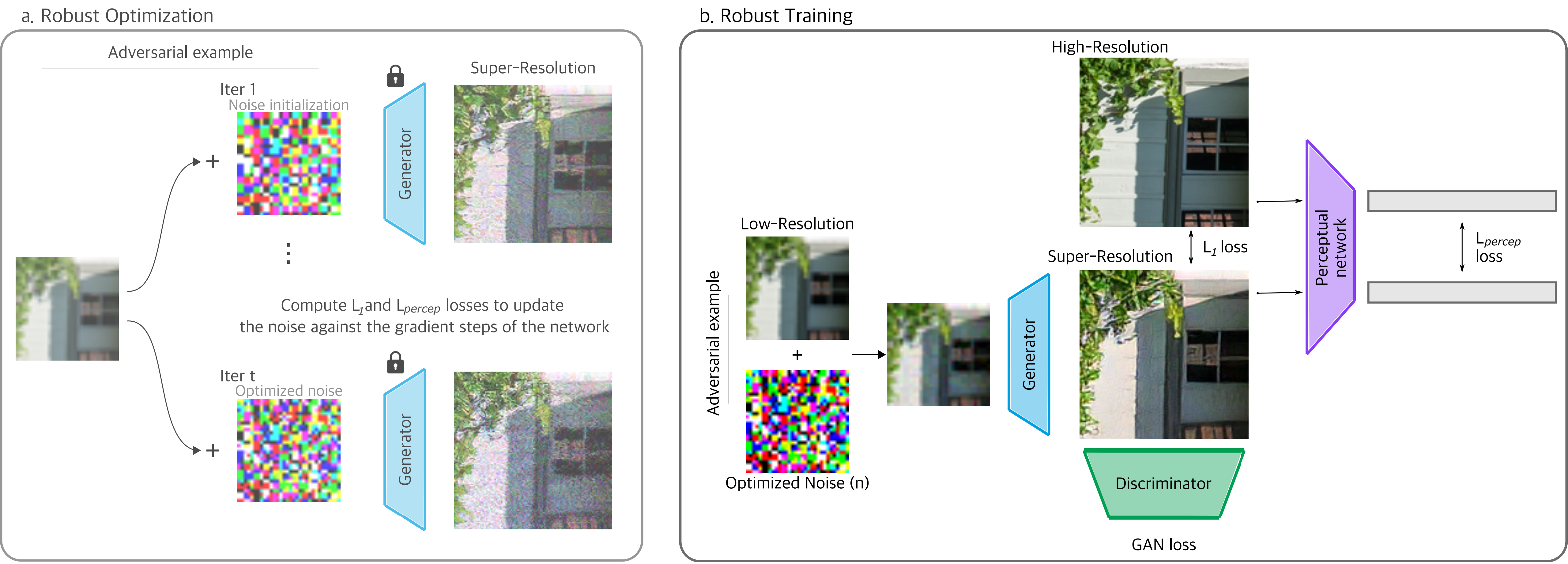


We change the input scale when creating the noise.

Jeremy Cohen, Elan Rosenfeld, and Zico Kolter. Certified adversarial robustness via randomized smoothing. In *International Conference on Machine Learning*, pages 1310– 1320. PMLR, 2019.

Robust Super-Resolution

GAN TRAINING



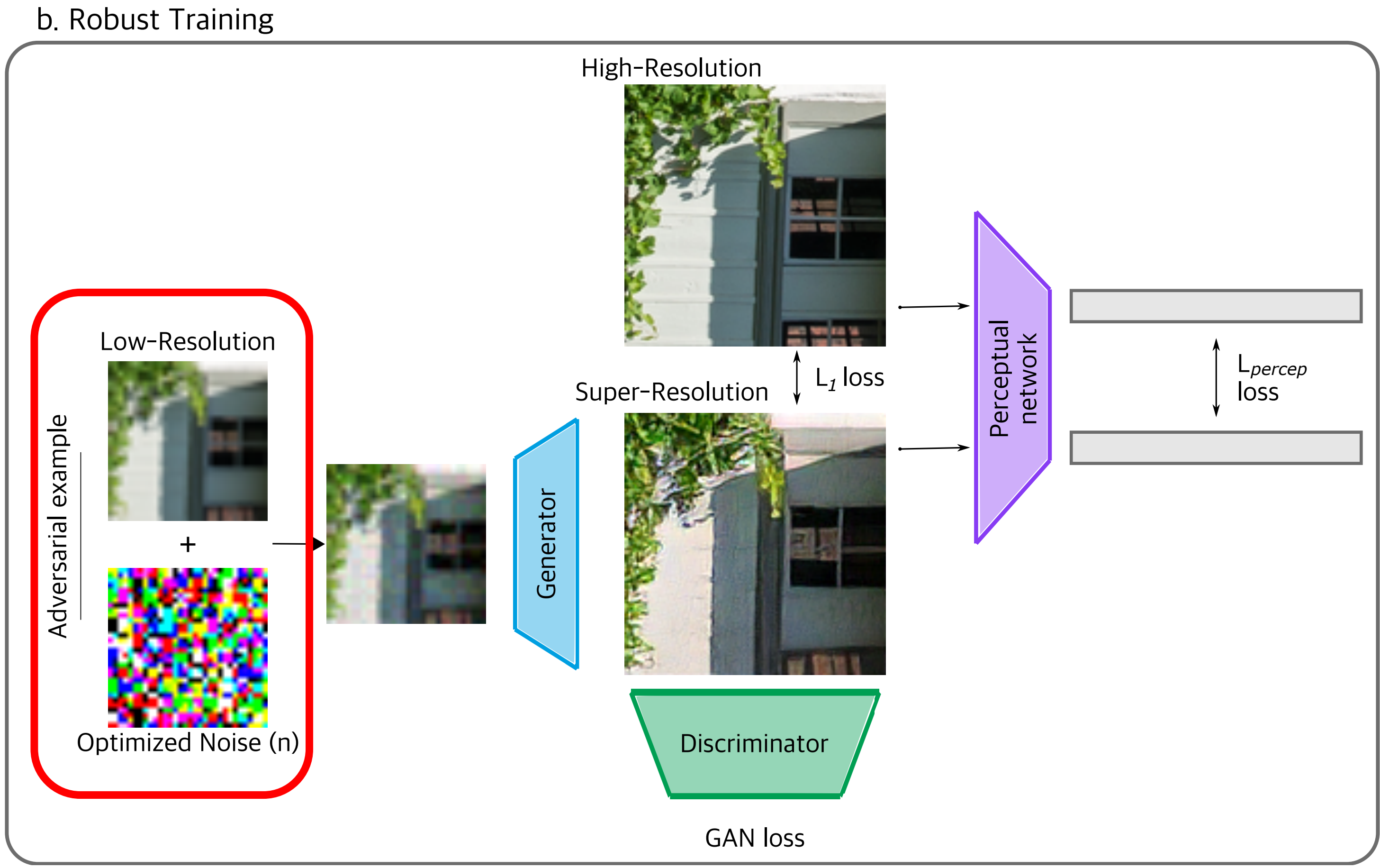
Robust Super-Resolution

GAN TRAINING

We add the updated noise to the LR input image and perform the common min-max optimization process with the generator and the discriminator, to train the GAN robustly.

The objective function of the generator is:

$$L_G = L_1 + L_{percep} + L_G^{GAN}$$



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Experimental Setup

SYNTHETIC DATASETS

- Training images from DIV2K (Clean images)
- Validation images with synthetic corruptions

GT **DIV2K** **NTIREsyn** **AIMsyn**

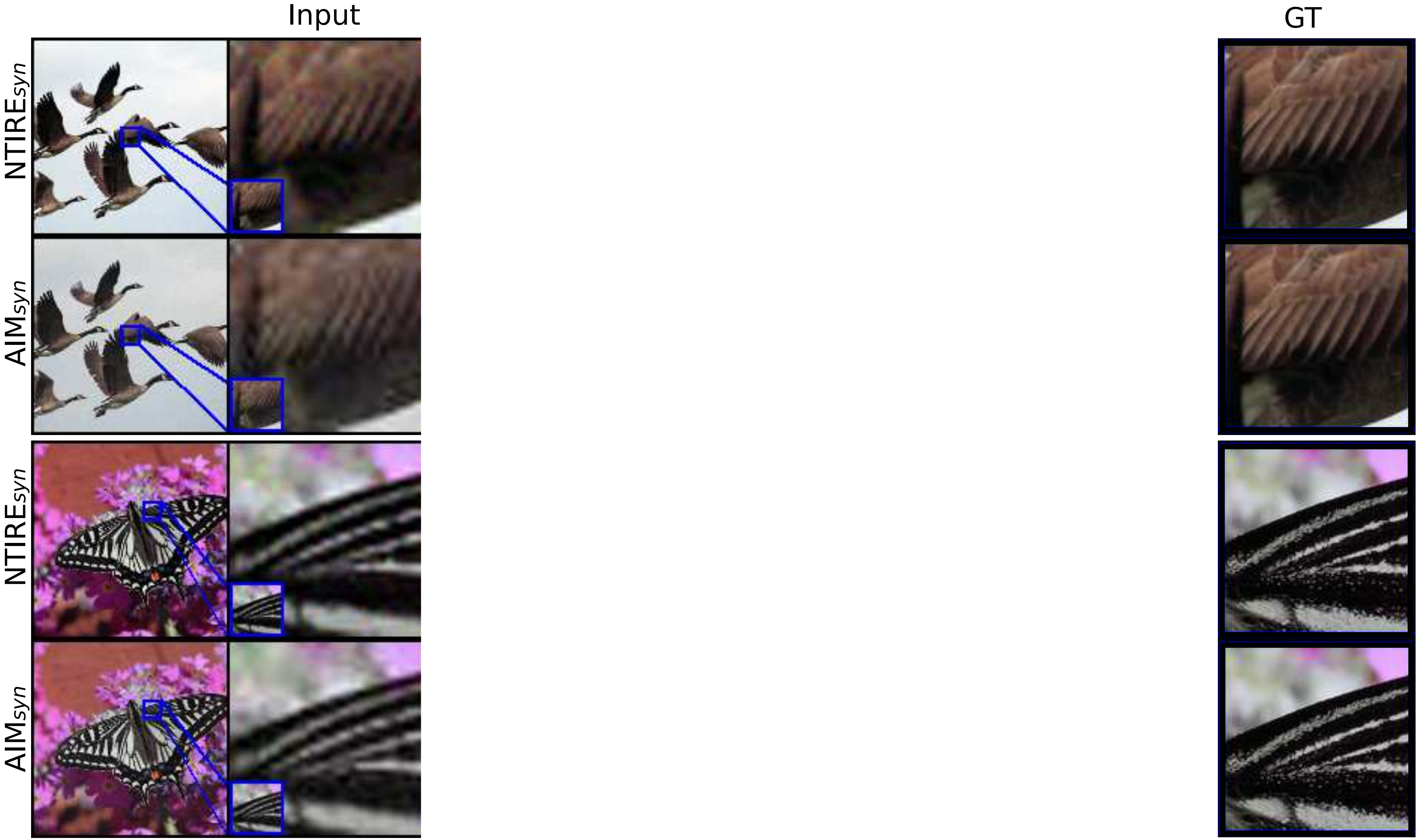
Results

STATE-OF-THE-ART COMPARISON

Method	Training Dataset	PSNR↑			SSIM↑			LPIPS↓		
		NTIRE_{syn}	AIM_{syn}	*Avg*	NTIRE_{syn}	AIM_{syn}	*Avg*	NTIRE_{syn}	AIM_{syn}	*Avg*
Bicubic	-	25.51	22.35	23.93	0.67	0.62	0.65	0.63	0.68	0.66
Impressionism	NTIRE_{syn}	24.82	21.47	23.15	0.66	0.54	0.60	0.23	0.52	0.37
	AIM_{syn}	19.65	21.89	20.77	0.29	0.60	0.45	0.67	0.41	0.54
	DPED_{rw}	17.53	18.84	18.18	0.34	0.49	0.41	0.60	0.47	0.53
ESRGAN-FS	NTIRE_{syn}	24.59	22.07	23.33	0.69	0.63	0.66	0.25	0.47	0.36
	AIM_{syn}	19.56	20.82	20.19	0.31	0.51	0.41	0.56	0.39	0.48
	DPED_{rw}	17.79	20.15	18.97	0.34	0.53	0.43	0.51	0.47	0.49
ESRGAN	DIV2K	20.59	21.48	21.03	0.43	0.56	0.49	0.68	0.53	0.60
RSR (Ours)	DIV2K	24.31	21.99	23.15	0.65	0.60	0.62	**0.23**	**0.37**	**0.30**

Results

SYNTHETIC DATASETS



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REAL-WORLD DATASETS

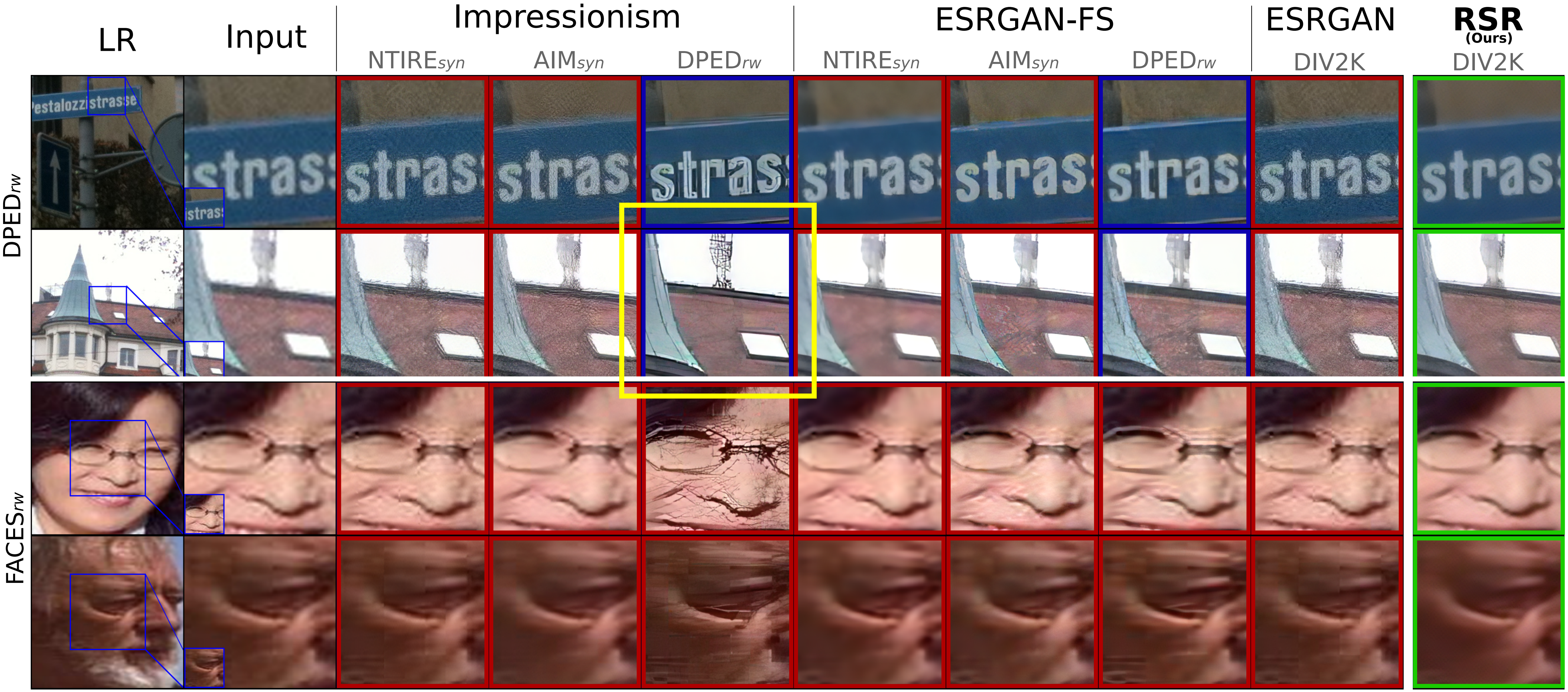
DPEDrw

FACESrw

Andrey Ignatov, Nikolay Kobyshev, Radu Timofte, Kenneth Vanhoey, and Luc Van Gool. Dslr-quality photos on mobile devices with deep convolutional networks. ICCV pages 3277–3285, 2017.
Shuo Yang, Ping Luo, Chen Change Loy, and Xiaoou Tang. Wider face: A face detection benchmark. *(CVPR)*, 2016.

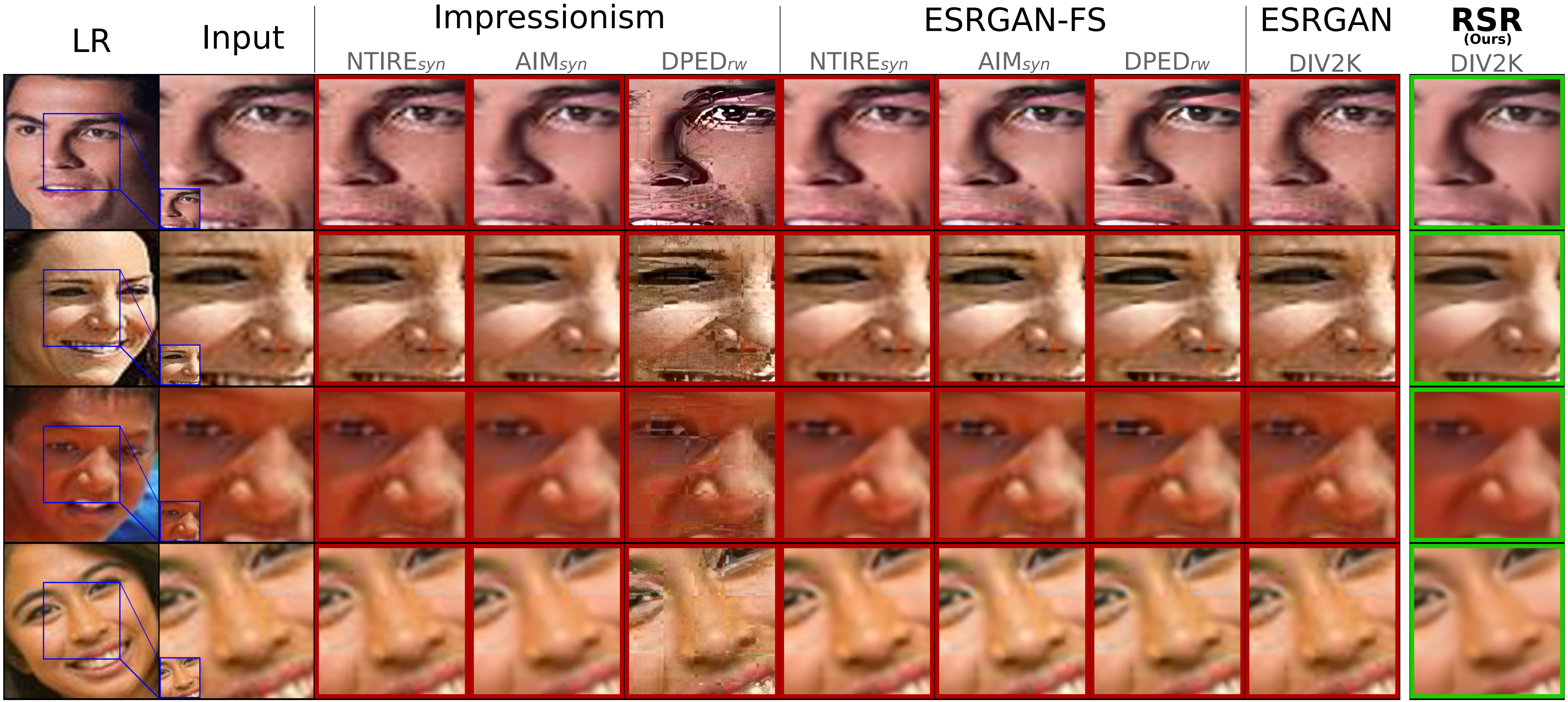
Results

REAL-WORLD DATASETS



Results

REAL-WORLD DATASETS



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Contributions

- We propose a novel use of adversarial attacks in real-world super-resolution.
- We create a generalized real-world SR model that achieves state-of-the-art results without training or fine-tuning on corrupt real-world datasets.

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For more information

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Project webpage:

Code:

2021 ICCV OCTOBER 11-17 VIRTUAL