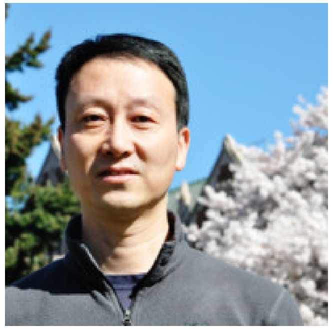
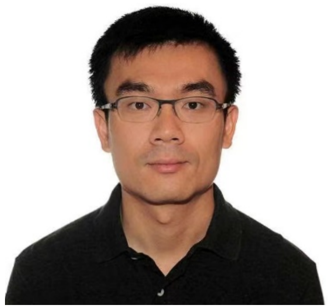
DeSRA: Detect and Delete the Artifacts of GAN-based Real-World Super-Resolution Models

Liangbin Xie*[1,2,3] Xintao Wang*[3] Xiangyu Chen*[1,2,5] Gen Li[4] Ying Shan[3] Jiantao Zhou[1] Chao Dong[2,5]

[1]University of Macau, [2]Shenzhen Institutes of Advanced Technology
[3]Applied Research Center (ARC), Tencent PCG, [4]Platform Technologies, Tencent Online Video
[5]Shanghai AI Lab

* Equal contributions

Background – GAN-SR Models in Real World Scene

- GAN-SR methods often generate perceptually unpleasant artifacts, which would seriously affect the user experience.

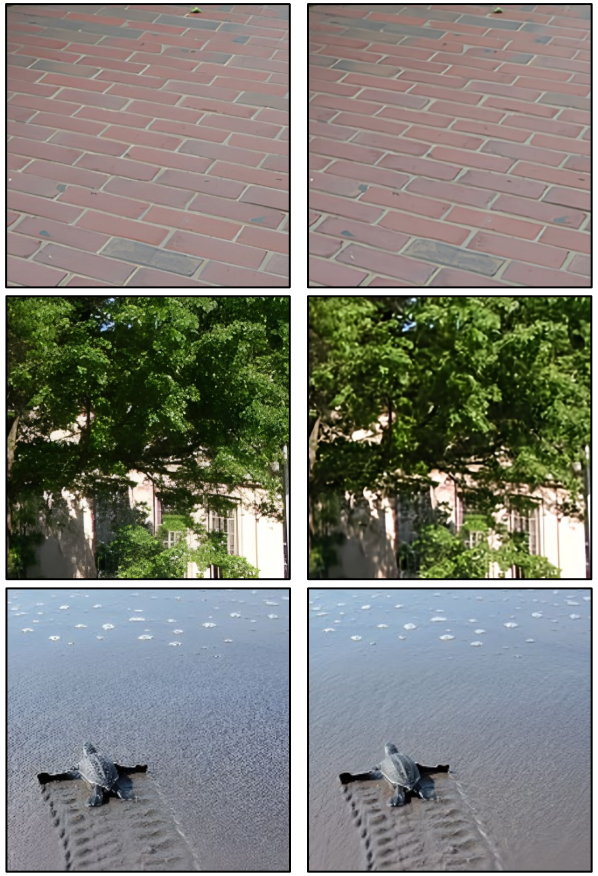
- These artifacts appear in the real-world unseen data during inference, which can be defined as GAN-inference artifacts. They are typically out of training distribution and do not appear in the training phase. **Solving GAN-inference artifacts has great practical value.**

In this paper, we deal with GAN-inference artifacts with two characteristics:

- The artifacts do not appear in the pretrained MSE-SR model.
- The artifacts are obvious and have a large area, which can be observed at the first glance.

Method – Detect GAN-inference Artifacts

- First step: we detect GAN-inference artifacts automatically.



GAN MSE

➢ We adopt the MSE-based results as the reference

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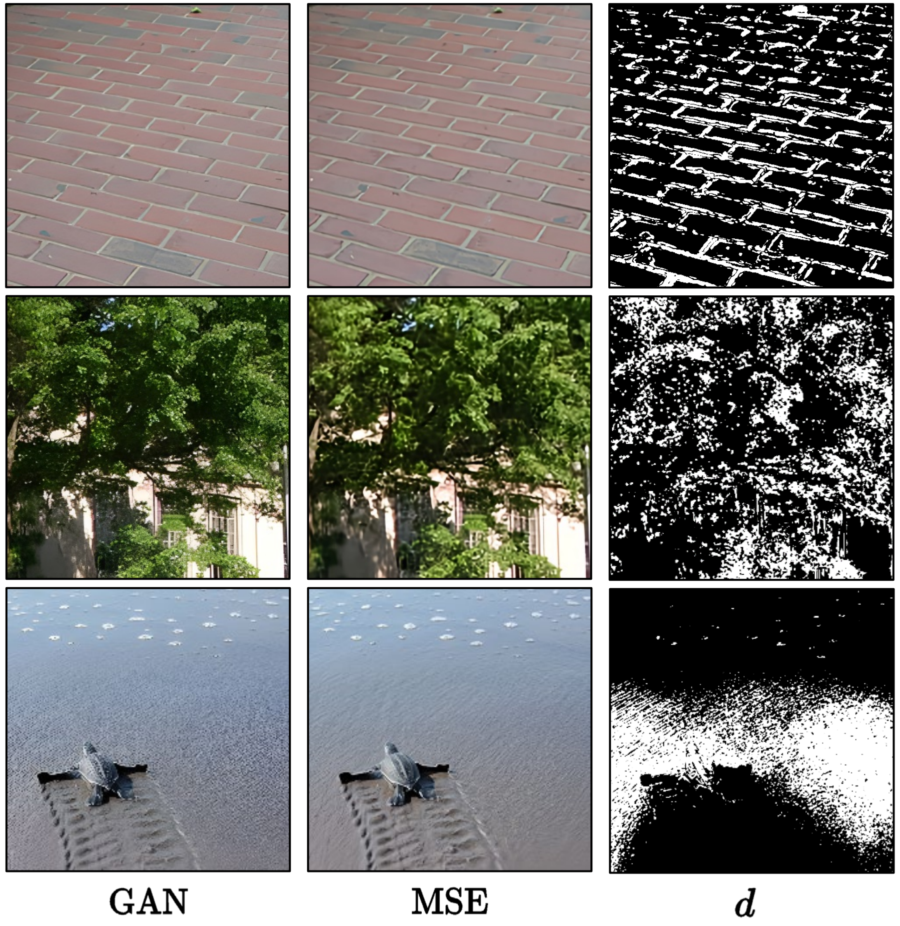

➢ We calculate the difference between standard deviations of GAN-SR patch and MSE-SR patch to measure the texture difference d as

$$d(x, y) = (\sigma_x - \sigma_y)^2$$

σ_x refers to the local standard deviation of GAN-SR patches;
σ_y refers to the local standard deviation of MSE-SR patches

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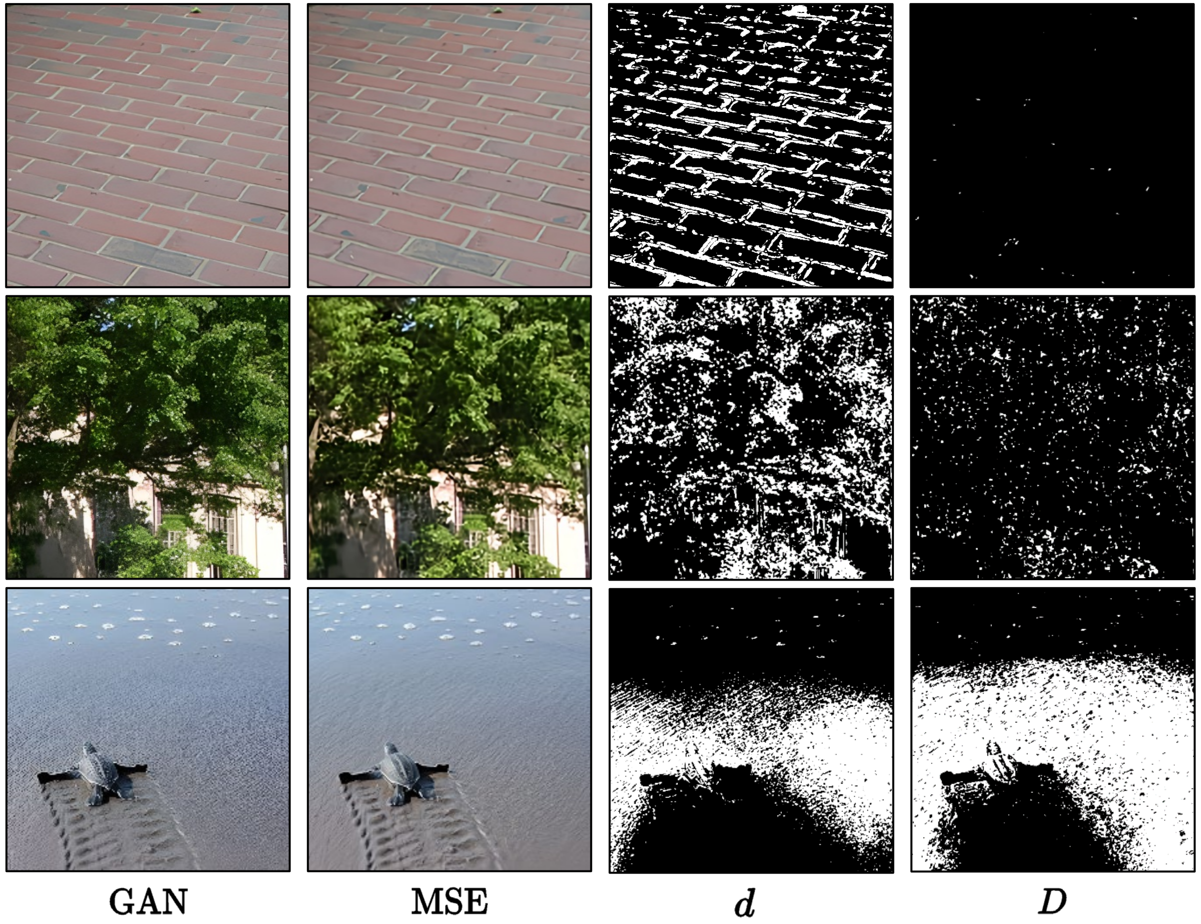

➢ We calculates the relative difference of local variance D between MSE-SR and GAN-SR patches

$$D = \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + C}$$

$\boldsymbol{\sigma_x}$ refers to the local standard deviation of GAN-SR patches;
$\boldsymbol{\sigma_y}$ refers to the local standard deviation of MSE-SR patches

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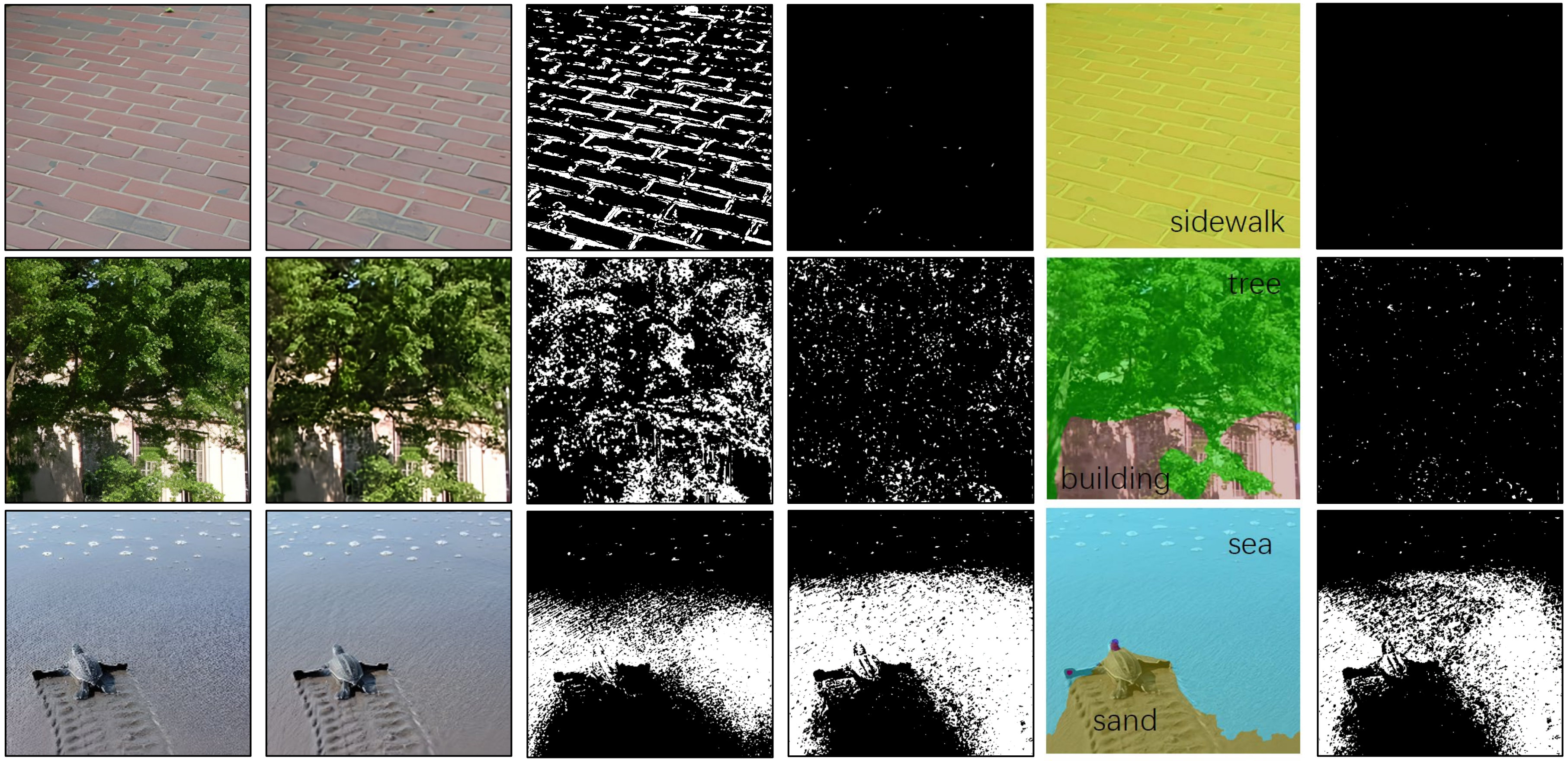

GAN | MSE | d | D | Segmentation | D_{refine} (semantic)

➢ We further introduce semantic-aware adjustment to enlarge the difference in perceptually artifact-sensitive regions (e.g., building, sea) while suppressing the difference in textured regions (e.g., foliage, animal fur).

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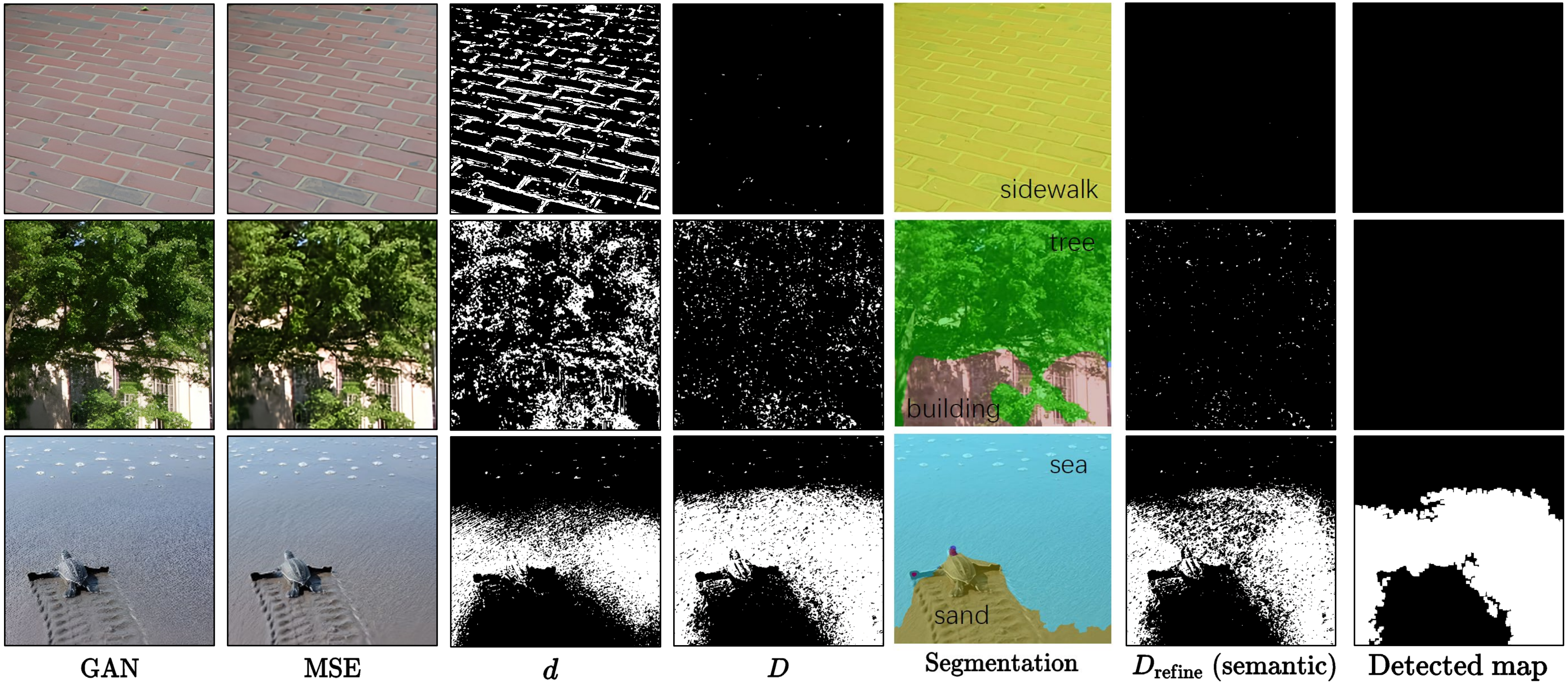
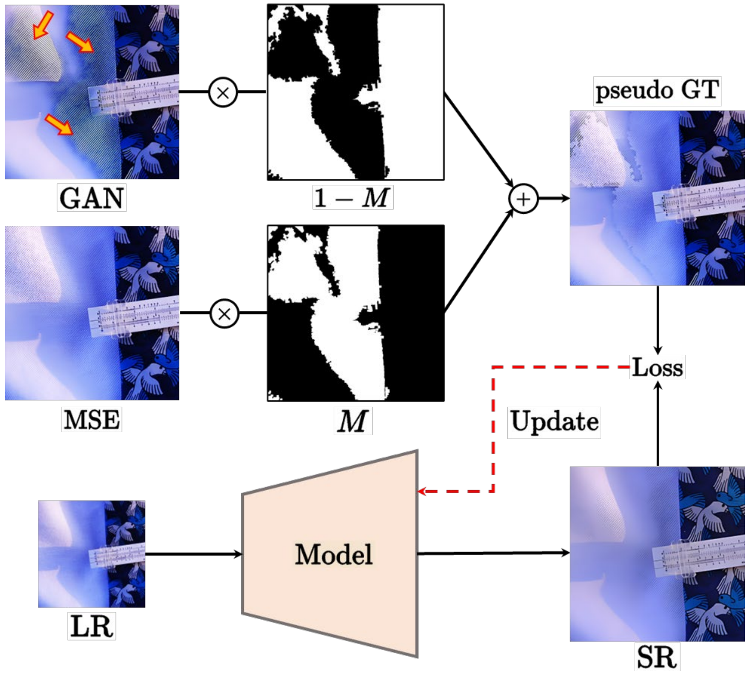


➢ We then filter out detection noises and perform morphological manipulations to generate the final artifact mask.

Method – Delete GAN-inference Artifacts

- Second step: we make the pseudo GT and finetune the GAN-SR model.



➢ We use MSE-SR results to replace the regions where artifacts were detected in GAN-SR results.

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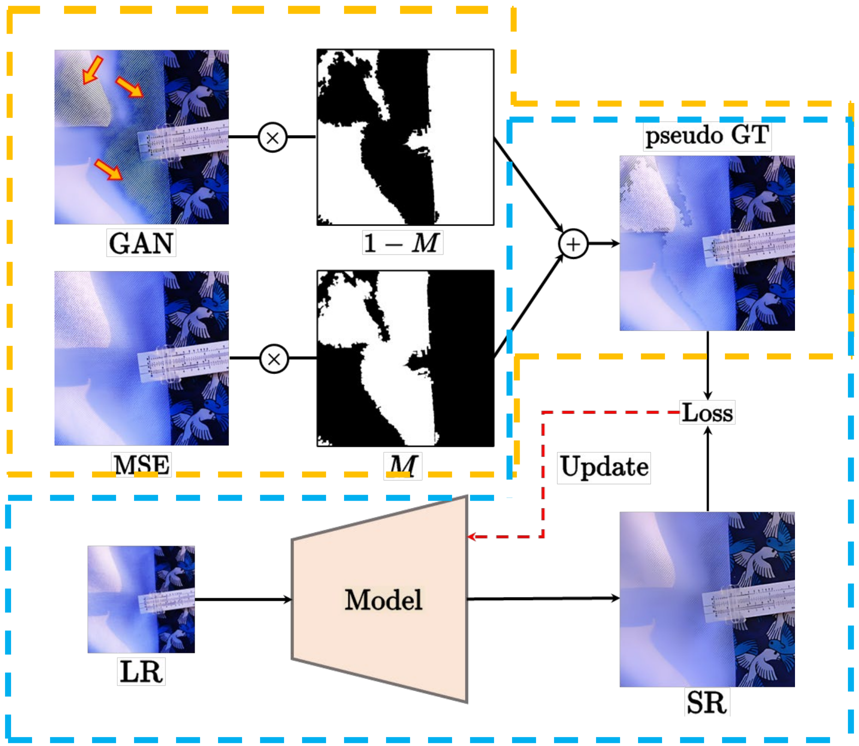

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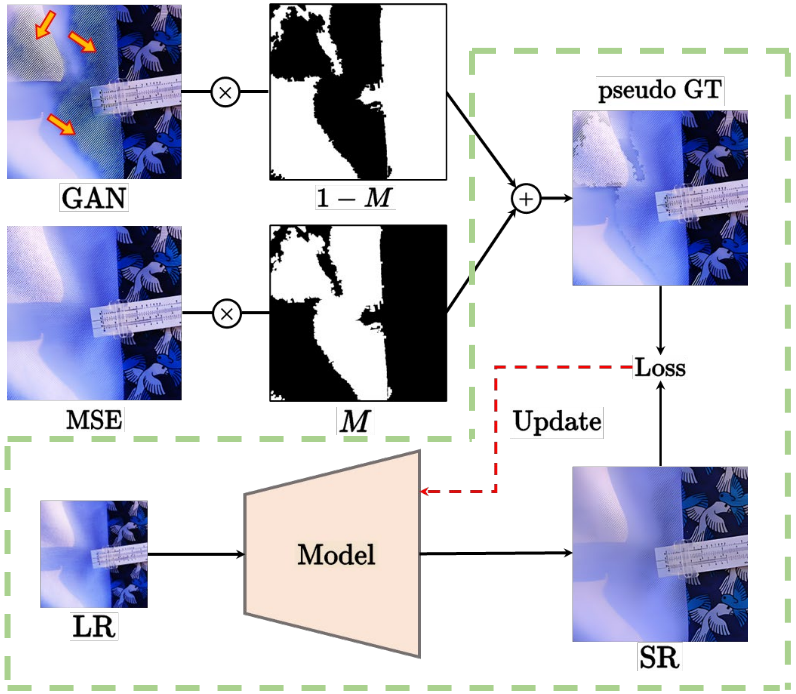


➢ We use MSE-SR results to replace the regions where artifacts were detected in GAN-SR results.

➢ We then use a small amount of data to generate the data pairs (LR & pseudo GT) from real data to finetune the model.

We only need to finetune the model for a few iterations (about 1K iterations) and the updated model would produce perceptually pleasant results without obvious artifacts. Moreover, it does not influence other fine details in regions without artifacts.

Experiments — Artifact Detection Results

Table 1. Artifact detection results based on Real-ESRGAN (Wang et al., 2021c). LDL* represents the modified detection method in LDL (Liang et al., 2022b).

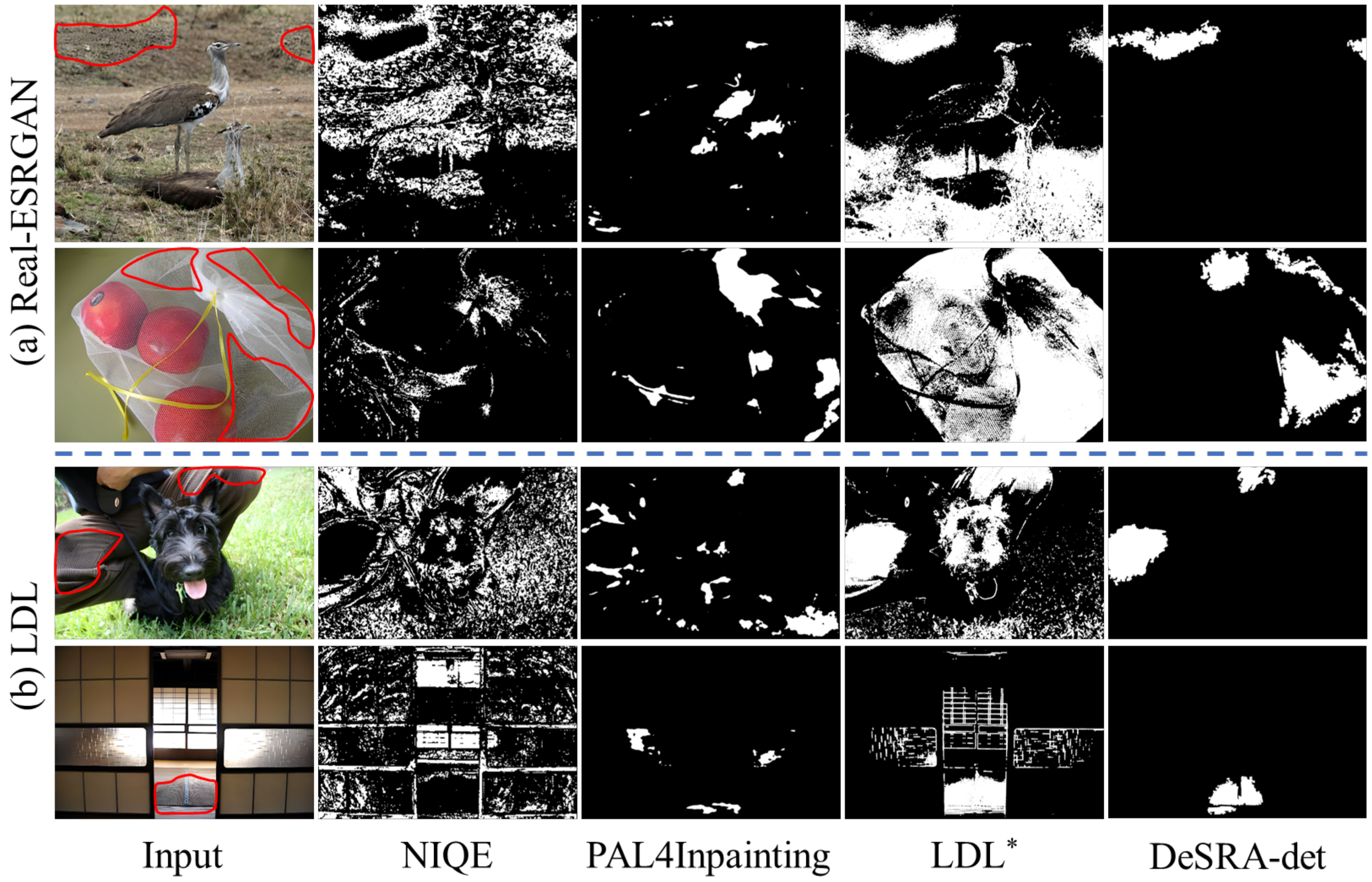
Method	IoU (↑)	Precision	Recall
NIQE	2.9	0.0494	0.1054
PAL4Inpainting	8.4	0.0855	0.0992
LDL*(threshold=0.01)	29.9	0.3504	0.3485
LDL*(threshold=0.005)	36.2	0.2618	0.5442
LDL*(threshold=0.001)	35.3	0.1410	**0.8391**
DeSRA-det (ours)	**51.1**	**0.7055**	0.6081

Table 2. Artifact detection results based on LDL (Liang et al., 2022b). LDL* represents the modified detection method in LDL (Liang et al., 2022b).

Method	IoU (↑)	Precision	Recall
NIQE	2.6	0.0236	0.1770
PAL4Inpainting	8.8	0.0699	0.1337
LDL*(threshold=0.01)	32.7	0.3070	0.4110
LDL*(threshold=0.005)	36.7	0.2100	0.5770
LDL*(threshold=0.001)	31.1	0.1003	**0.8659**
DeSRA-det(ours)	**44.5**	**0.6087**	0.5335

Our method obtains the best IoU and Precision that far outperform other schemes

Experiments — Artifact Detection Results



The detection results obtained by our approach have significantly higher accuracy than other schemes.

Experiments — Improved GAN-SR Results

Table 3. Artifact detection results of GAN-SR models with and without using DeSRA finetuning.

Method	IoU (↓)	Removal rate	Addition rate
Real-ESRGAN	51.1	-	-
Real-ESRGAN-DeSRA	**12.9**	75.43%	0%
LDL	44.5	-	-
LDL-DeSRA	**13.9**	74.97%	0%

Three-quarters of the artifacts on unseen test data can be completely removed after finetuning.

Experiments — Improved GAN-SR Results

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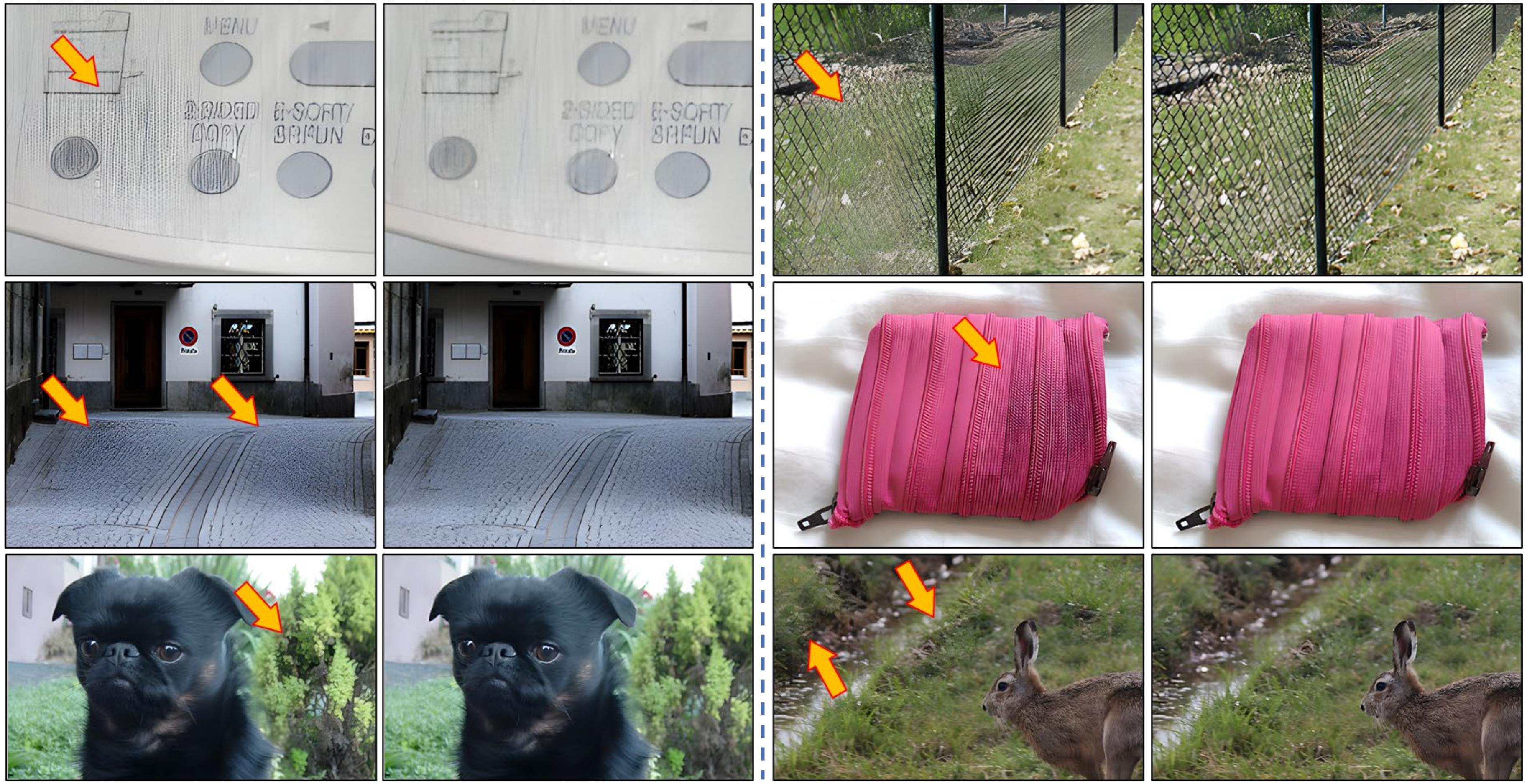
Our method does not introduce new additional artifacts, as the addition rate is 0.

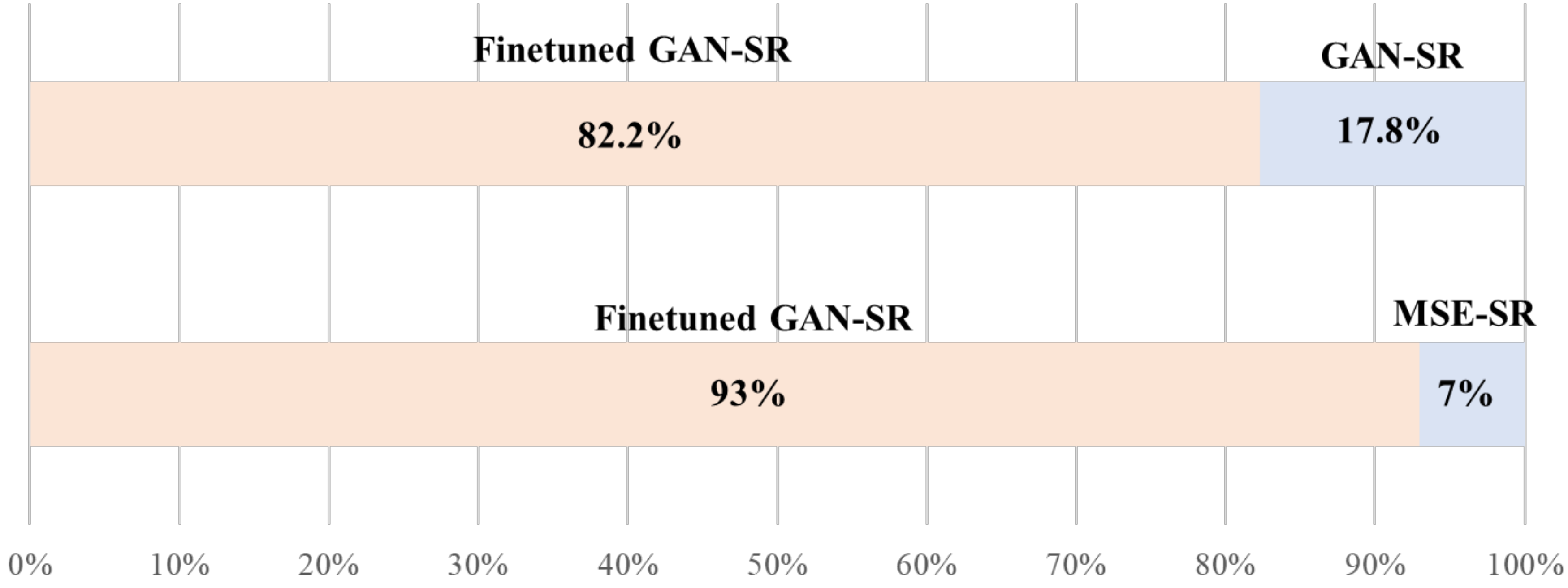
Experiments — Improved GAN-SR Results



RealESRGAN RealESRGAN-DeSRA LDL LDL-DeSRA

Artifacts are obviously alleviated for results produced by the improved GAN-SR models.

Experiments — User Study



- Our method largely removes the artifacts generated by the original model.
- The finetuned GAN-SR model generates more detailed results than the MSE-SR model.

Thanks for Watching

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40 Years

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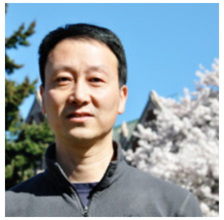
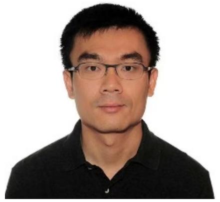

Ying Shan


Jiantao Zhou


Chao Dong

Codes