

Qualcomm VisionX

Challenge 1: Removing Reflection from Images

Submission:

<https://github.com/shoryasethia/RobustSIRR>

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Introduction

Objective

- Detect and remove reflections from images captured through reflective surfaces.
- Preserve the clarity and details of the scene behind the reflection.

Applications

- Security camera footage enhancement.
- Improved personal photography.
- Enabling autonomous vehicles to see clearly through reflective surfaces.

Problem Statement

- Reflections blend the transmission and reflection layers, corrupting image quality.
- Existing challenges:
 - High variability in lighting and types of reflective surfaces.
 - Trade-offs between clarity and robustness against noise or attacks.

02

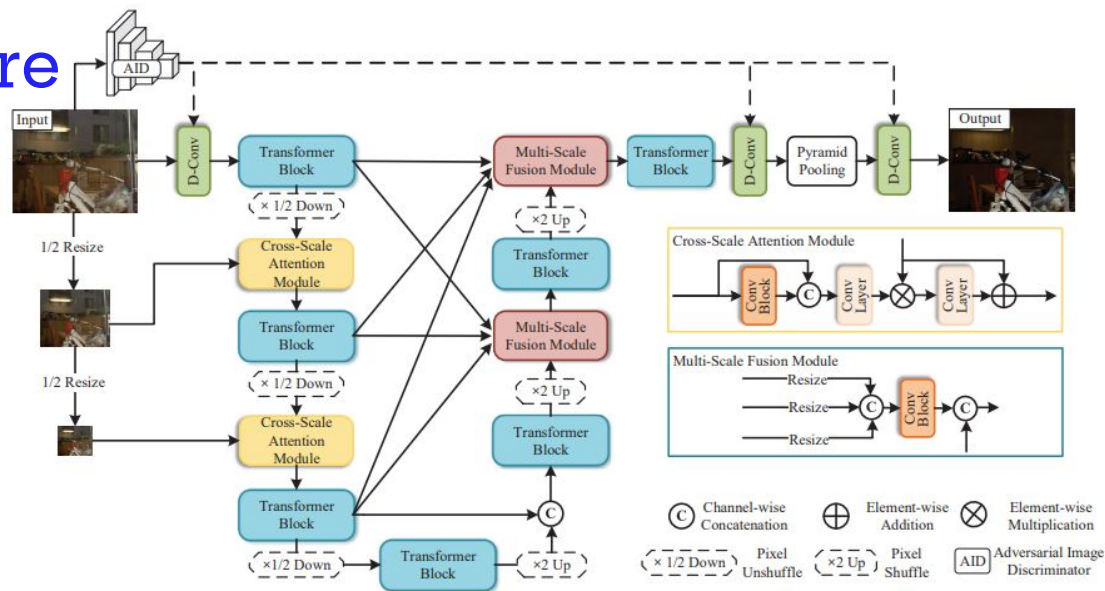
Proposed Solution and Architecture Overview

Proposed Solution Overview

- Robust SIRR against adversarial attacks (CVPR 2023 by Song et al.).
- Key techniques:
 - Cross-Scale Attention Module: Enhances feature robustness.
 - Multi-Scale Fusion Module: Aggregates multi-scale complementary information.
 - Adversarial Image Discriminator: Differentiates clean and corrupted inputs.

Model Architecture

- Key Components:
 - Multi-scale input encoding.
 - Transformer-based feature extraction.
 - Dynamic convolution layers.



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Training Strategy & Evaluation Metrics

Training Strategy

- Adversarial training approach:
 - Combines clean and adversarial samples.
- Loss functions used:
 - Adversarial image discriminator loss.
 - GAN loss for realism.
 - Perceptual loss for semantic preservation.

Evaluation Metrics

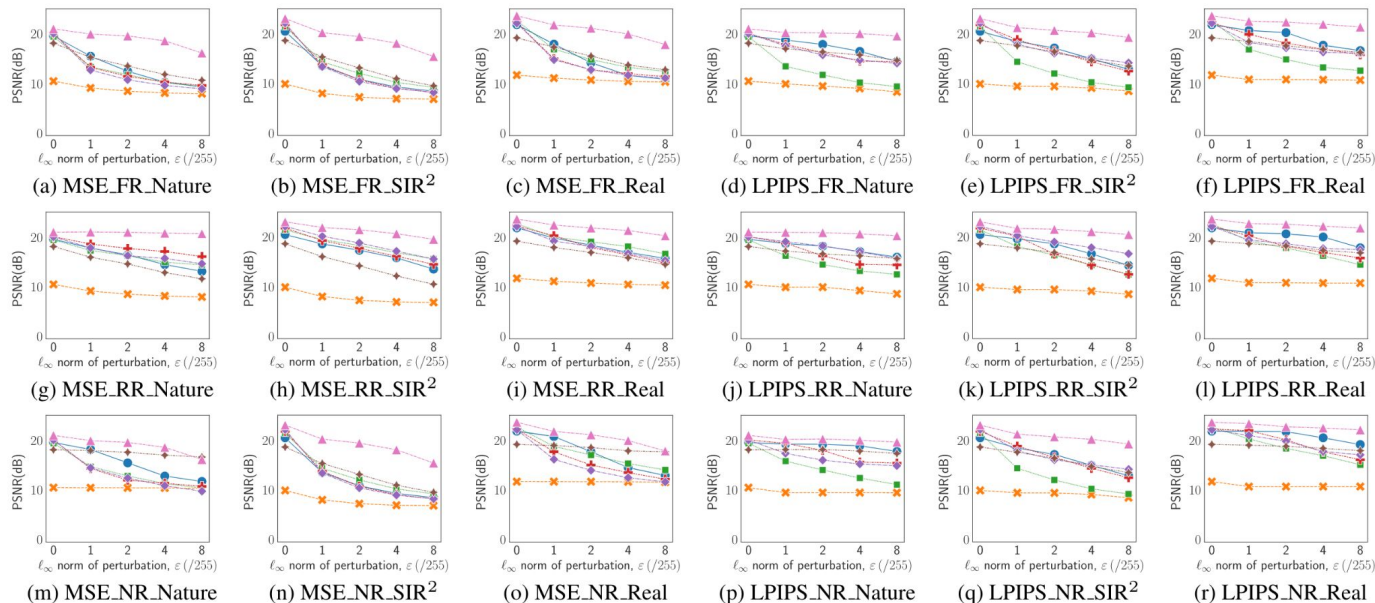
- Metrics used:
 - Peak Signal-to-Noise Ratio (PSNR).
 - Structural Similarity Index (SSIM).
- Evaluated under:
 - Clean images.
 - Adversarial perturbations.

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Results and Performance

Results and Performance

- Tabulate results (adapt from paper):
 - PSNR and SSIM for clean vs. adversarial images.
 - Highlight improvements with adversarial training.
- Include visual examples of before and after reflection removal.



Comparison of the PSNR values with respect to perturbation levels ϵ for different attacks on various datasets. 'MSE FR Nature' represents attacking on Full Region with MSE objective on the Nature dataset, and so the others.

Comparison of different training strategies on three benchmark datasets. ‘w/’ and ‘w/o adv.’ mean training with or without adversarial images. MSE and LPIPS denote corresponding attacks over Full regions. ↓ and ↑ represent the degradation and improvement performance compared to the original prediction inputting clean images.

		Nature		SIR ²		Real	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
WY19 [42] w/o adv.	Clean	19.54	0.738	20.45	0.853	21.82	0.812
	MSE	11.86↓7.68	0.361↓0.377	10.49↓9.97	0.410↓0.442	13.61↓8.21	0.388↓0.424
	LPIPS	16.85↓2.69	0.588↓0.149	15.81↓4.65	0.677↓0.176	18.79↓3.04	0.639↓0.173
WY19 [42] w/ adv.	Clean	17.28↓2.26	0.670↓0.067	17.97↓2.49	0.832↓0.021	19.23↓2.59	0.752↓0.060
	MSE	16.08↓3.46	0.613↓0.125	16.54↓3.92	0.769↓0.083	18.61↓3.21	0.718↓0.094
	LPIPS	17.01↓2.53	0.633↓0.105	17.49↓2.96	0.779↓0.074	16.64↓5.18	0.702↓0.110
Ours w/o adv.	Clean	20.33	0.758	23.43	0.894	22.26	0.826
	MSE	10.35↓9.98	0.264↓0.494	9.18↓14.24	0.317↓0.577	11.92↓10.34	0.274↓0.552
	LPIPS	15.15↓5.18	0.560↓0.198	14.84↓8.59	0.645↓0.250	16.38↓5.88	0.573↓0.253
Ours w/ adv.	Clean	20.97 ↑0.64	0.764 ↑0.006	23.02↓0.41	0.892↓0.002	23.61 ↑1.35	0.835 ↑0.009
	MSE	18.53↓1.79	0.726↓0.032	18.25↓5.17	0.821↓0.073	20.15↓2.11	0.752↓0.074
	LPIPS	19.98↓0.35	0.732↓0.026	20.31↓3.12	0.830↓0.064	22.02↓0.24	0.768↓0.058

Thank You!

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