IMAGE REFLECTION REMOVAL USING THE WASSERSTEIN GENERATIVE ADVASARIAL NETWORK

THE HONG KONG POLYTECHNIC UNIVERSITY 香港理工大學

Tingtian Li and Daniel P. K. Lun

The Hong Kong Polytechnic University

DEPARTMENT OF Electronic and Information Engineering

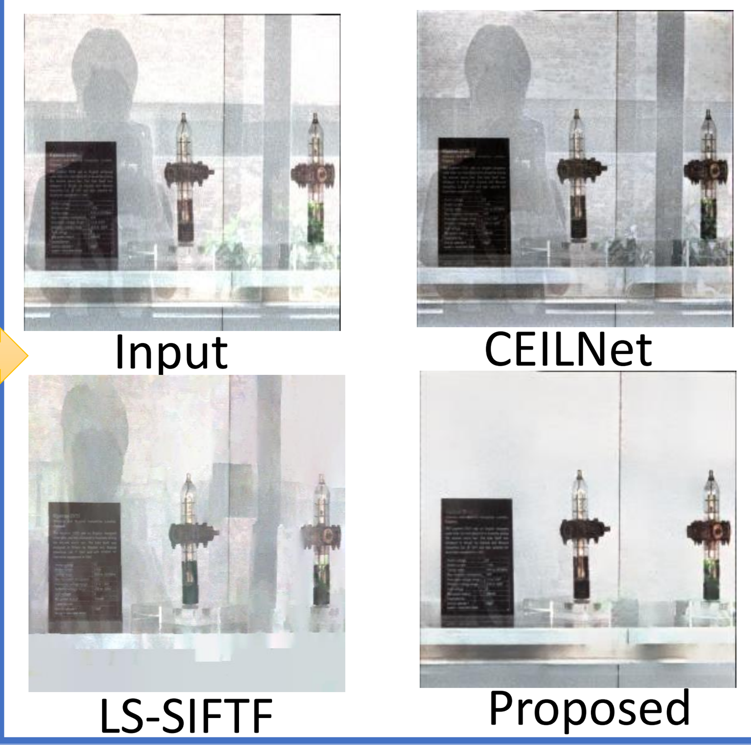
Objectives

1.Removing the reflection of image taken through semitransparent material, such as glass.

2.Improved over the existing CNN based methods in terms of robustness.

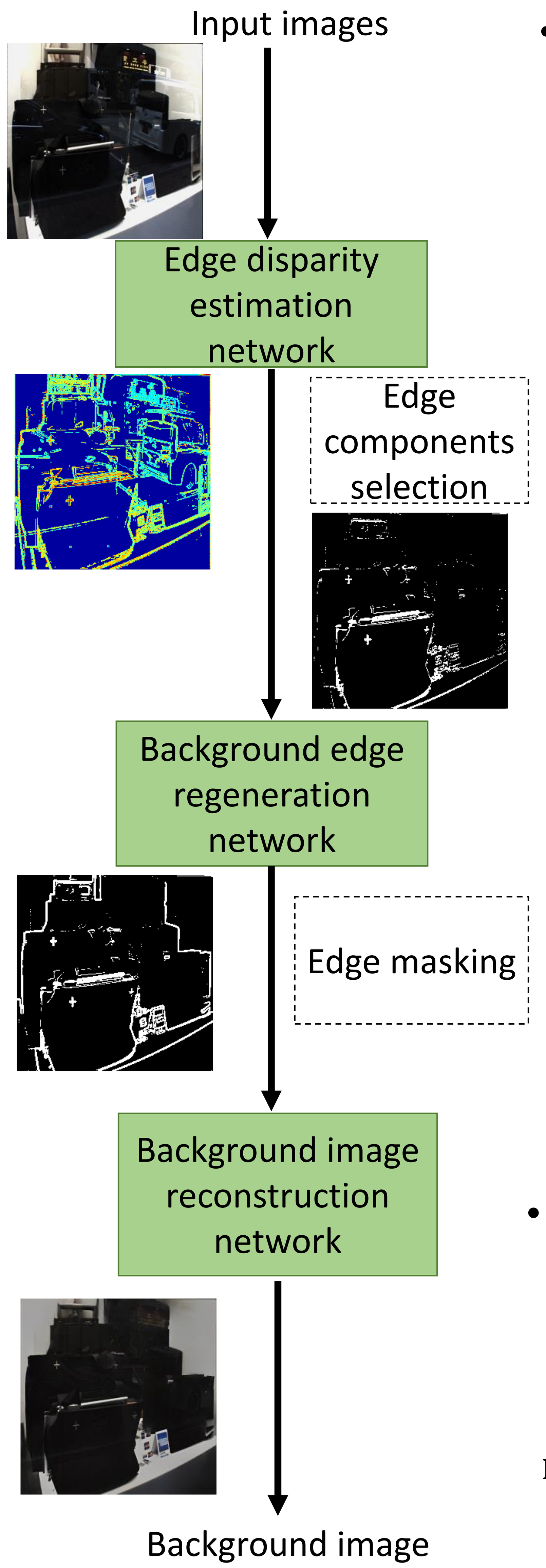
3.Improved over the existing optimization based methods in terms of efficiency.

Shortcomings of the current methods



- Single-image reflection removal algorithms (such as CEILNet):
  - They require the reflection must be blurry for identifying reflection components.
  - Therefore, they cannot remove sharp reflection components.
- Multiple-image reflection removal algorithms (such as LS-SIFTF):
  - They need to estimate the different motions of the background and reflection
  - However, the motions become ambiguous after two images are superimposed.

The novel framework

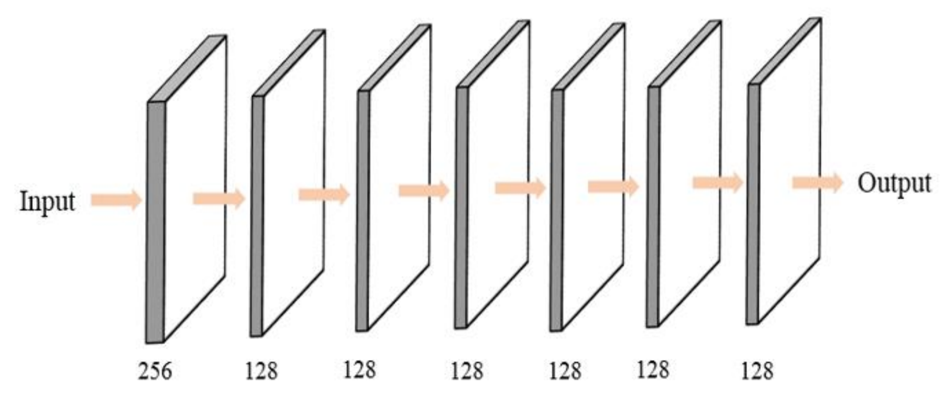


- **The network for unambiguous edge disparity estimation:**

Motivation: The background and reflection images usually have different disparity ranges, which can help us sperate the background and reflection images.

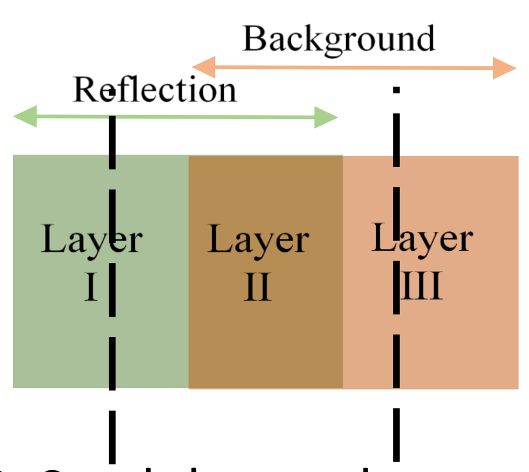
Problem: The image disparity values are ambiguous after two images are superimposed.

Solution: 1. The edges of two images are seldomly overlapped. Thus, the disparities on edges should be independent and unambiguous.
2. We use an edge emphasized disparity estimation network for estimating disparity values on image edges.



Disparity network

- **The WGAN trained for background edge regeneration:**



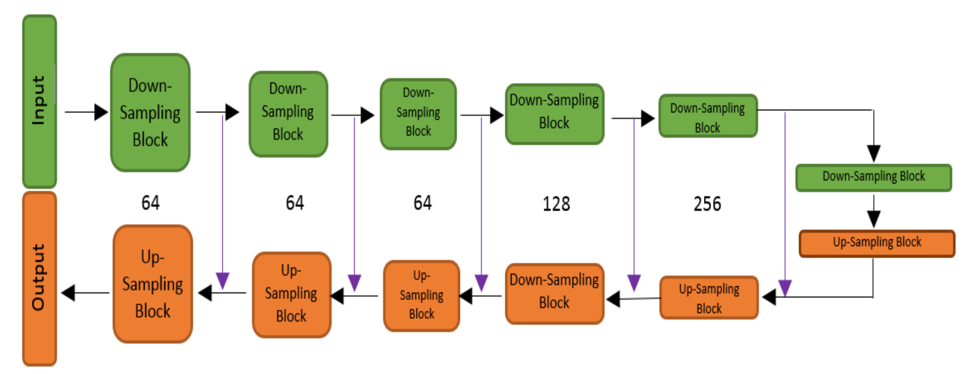
Problem: The disparity ranges of background and reflection may be partially overlapped

Solution:
1. Only extract edges with large and small disparity values. Those edges tend to only belong to one image layer.

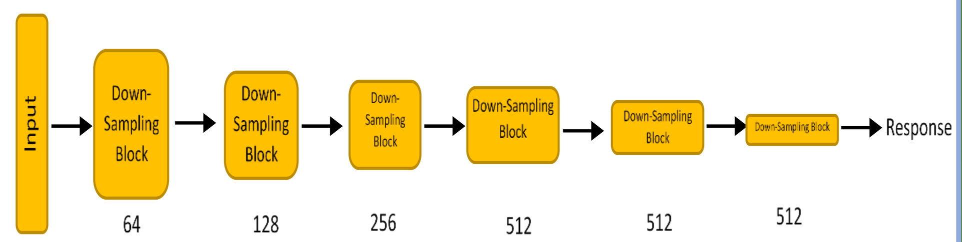
2. Send those edges to a WGAN for regenerating complete background edges.

$$\min_{G}\max_{D_1,D_2} \mathcal{L}_{rec}^{E} + \lambda_1\left(\mathcal{L}_{adv_1}^{E} + \mathcal{L}_{adv_2}^{E}\right)$$

3. The adversarial terms $\mathcal{L}_{adv_1}^{E}$ and $\mathcal{L}_{adv_2}^{E}$ for background and reflection edges respectively in the WGAN can force the estimated edges to better follow distributions of natural image edges.



Generator



Discriminator

- **Another WGAN trained for background image reconstruction:**

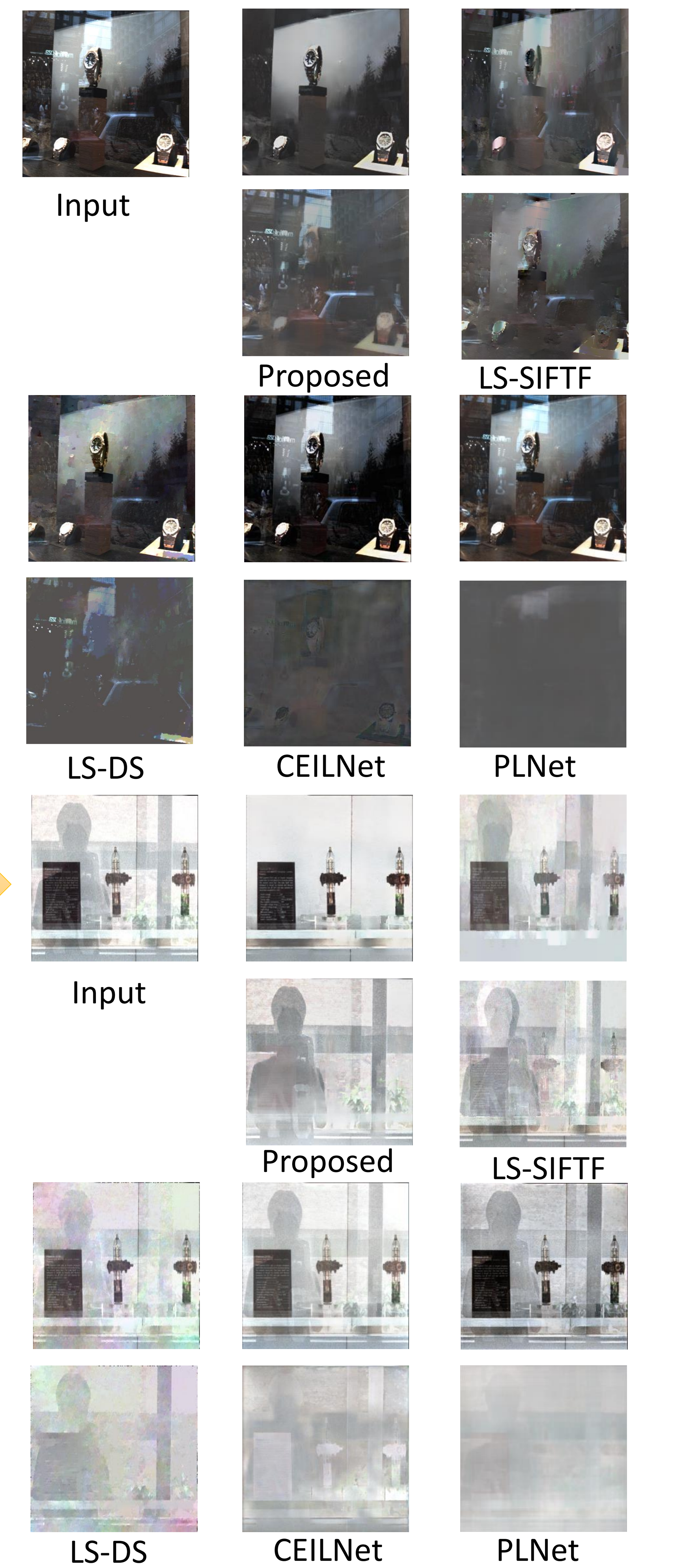
Motivation: 1. Improving the speed over traditional optimization-based approaches.
2. Obtaining better performance via exploiting the strong prediction ability of DNN. However, a normal L2 norm pixel loss term may lead to a blurry result.

$$\min_{G}\max_{D_1,D_2} \mathcal{L}_{rec}^{B} + \lambda_2\mathcal{L}_{p}^{B} + \lambda_3\left(\mathcal{L}_{adv_1}^{B} + \mathcal{L}_{adv_2}^{B}\right)$$

Solution: 1. Use a VGG perceptual feature term $\mathcal{L}_{p}^{B}$ to improve the perceptual similarity between the background result and ground truth.

2. Use the adversarial terms $\mathcal{L}_{adv_1}^{B}$ and $\mathcal{L}_{adv_2}^{B}$ to guide the background result to better follow natural image distributions.

Comparisons and evaluations



Method	PSNR values of Background results	Ave. Time
Original images	13.09	NA
LS-LFGS	21.71	69.51s
LS-SIFTF	18.91	130.59s
LS-DS	18.85	17.01s
CEILNet	17.71	0.82s
PLNet	19.09	1.15s
Proposed	**24.22**	**1.08s**