Learning to Jointly Generate and Separate Reflections

Supplementary Material

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1 - Network Structure

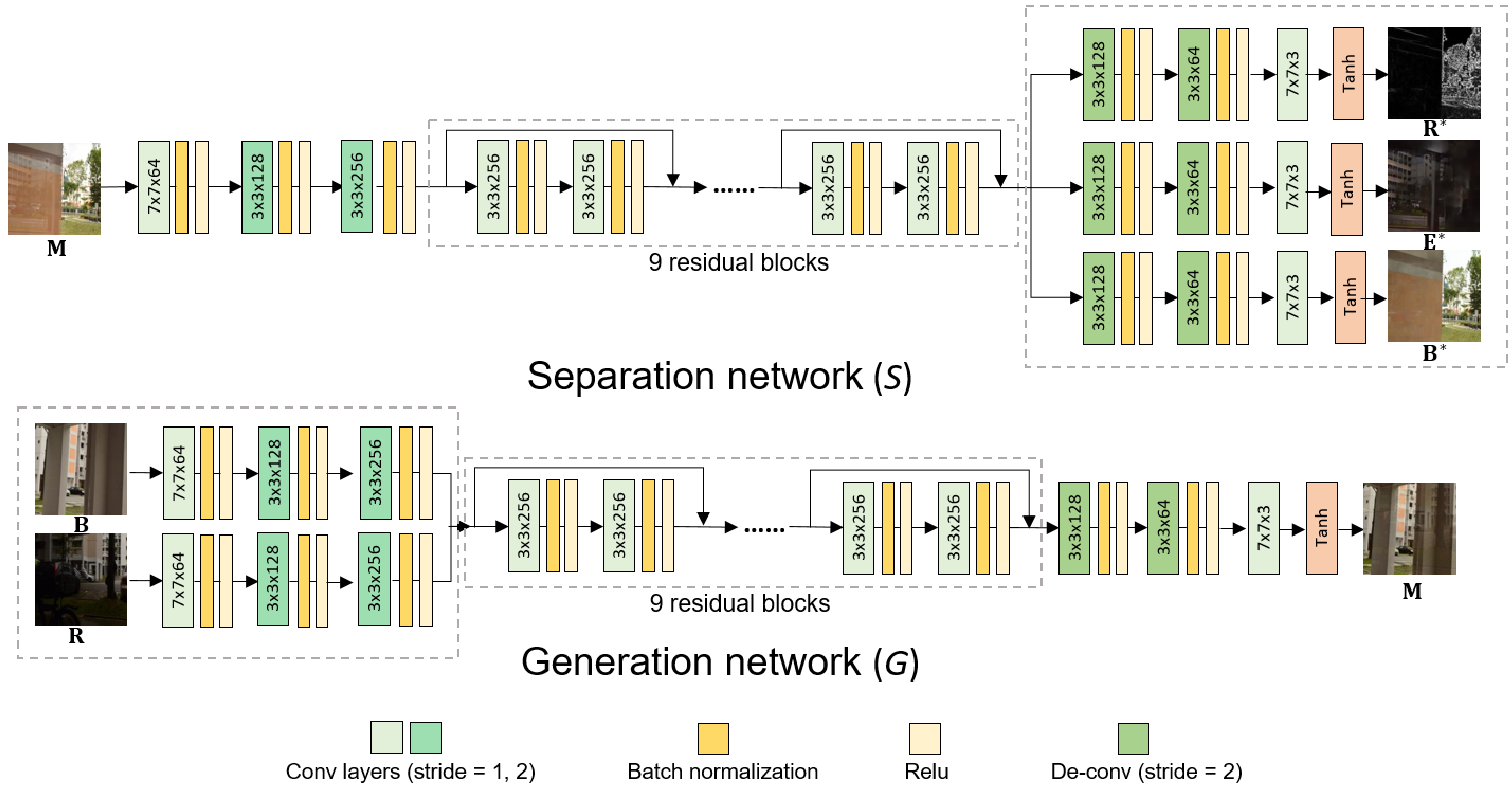
The comparisons between residual-blocks structure and U-Net structure

Architecture	$SSIM_r$	SSIM	PSNR
U-Net	0.851	0.886	24.35
Res-blocks	0.858	0.892	24.32

As shown above, the performance of these two structures are very close. We apply residual-blocks structure as the network architecture because it is more flexible to incorporate the entanglement and disentanglement mechanism.

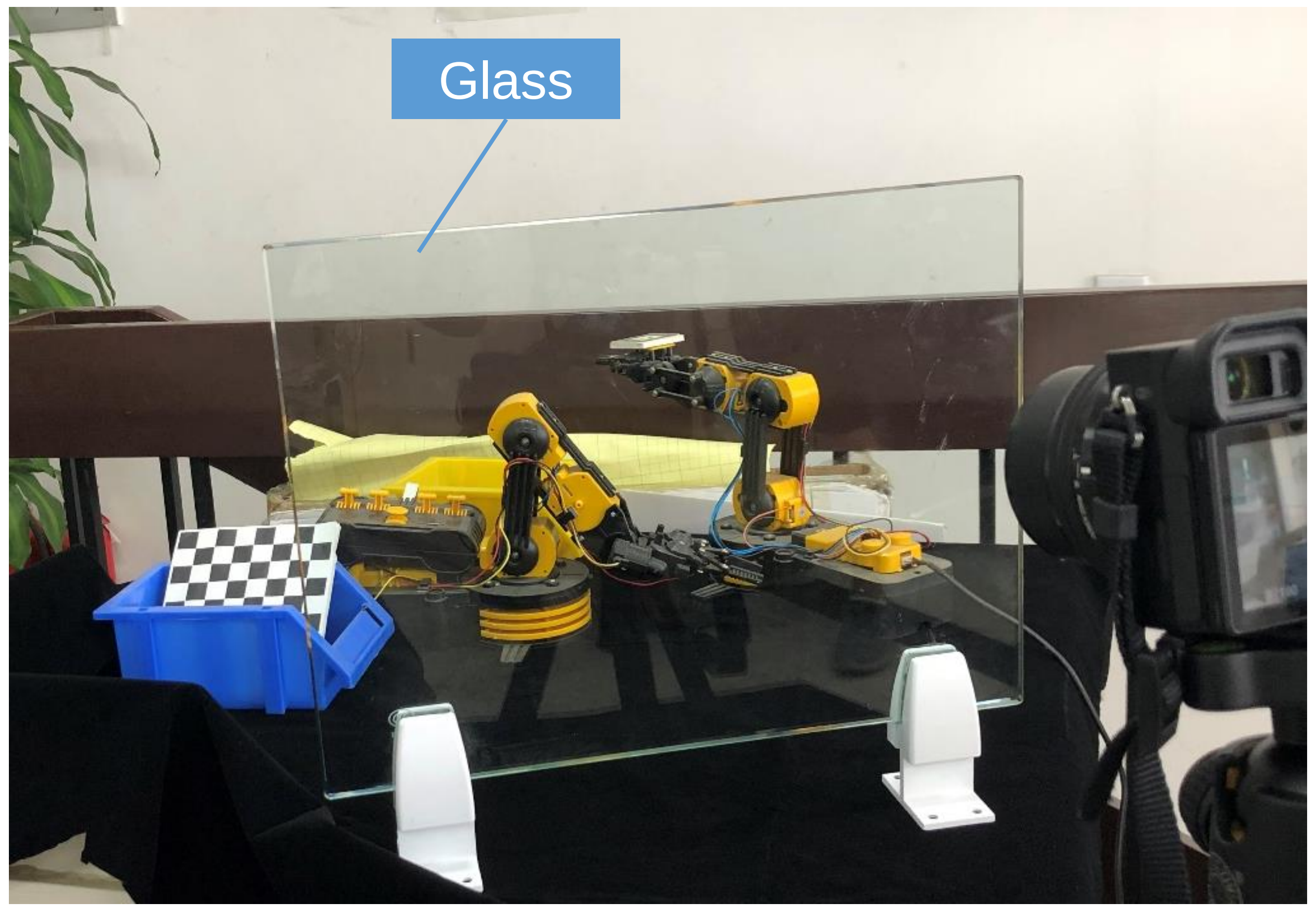
1 - Network Structure

The details of the separator and generator



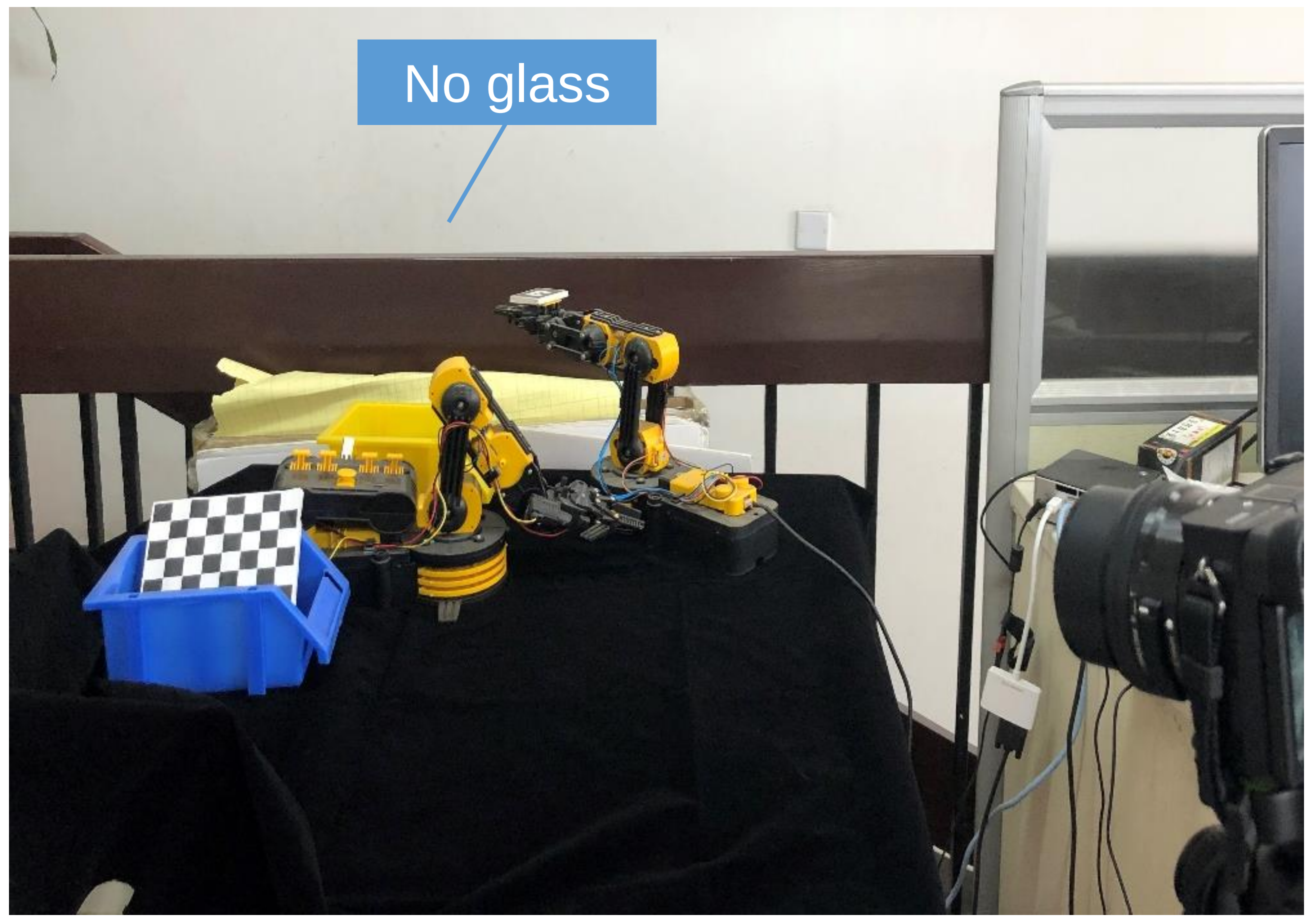
2 - Dataset Gap (Domain Gap)

The setup of data collection in our experiment.



Mixture image

Reflection image



Background image

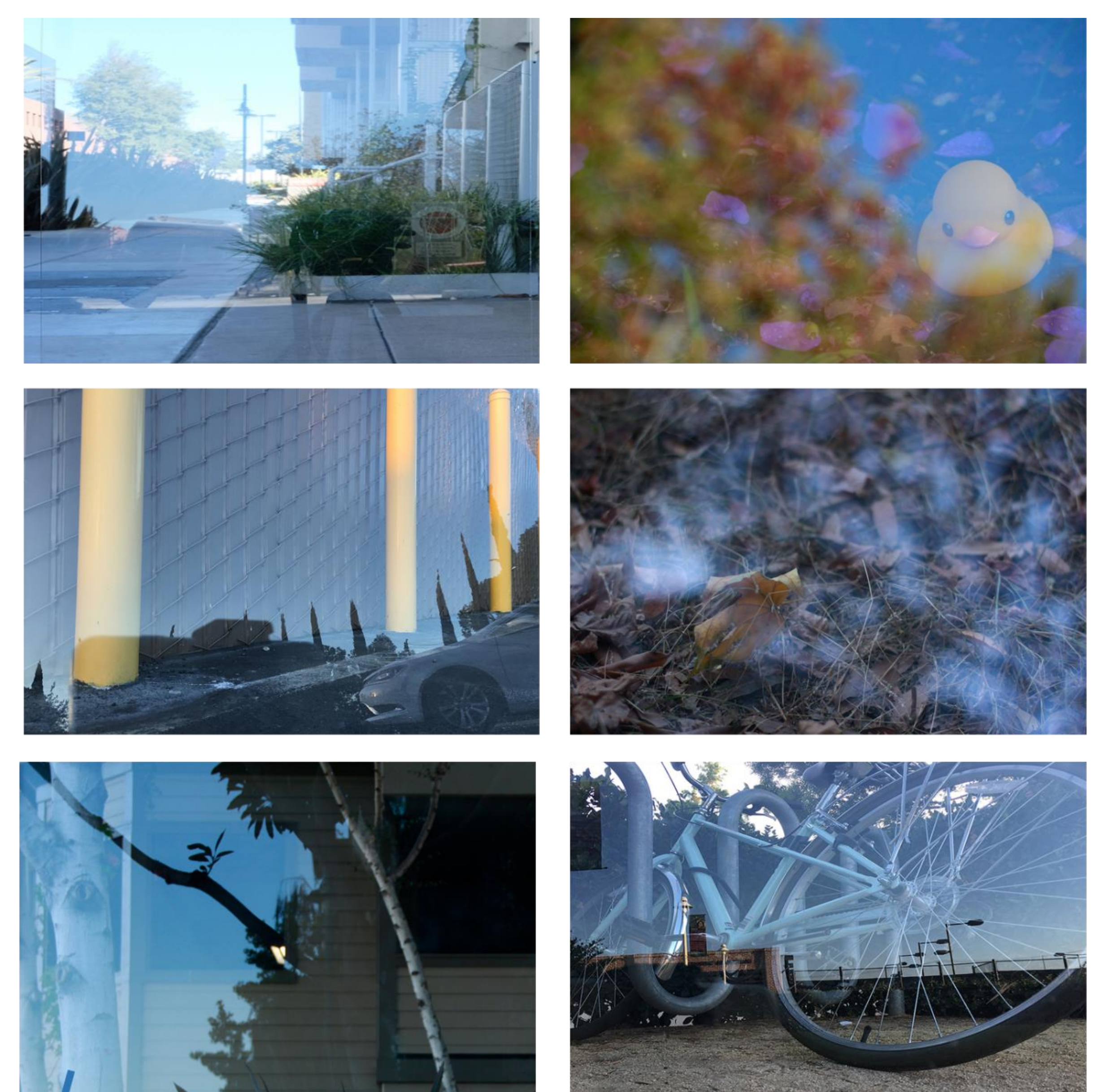
2 - Dataset Gap (Domain Gap)

We evaluate the generalization ability of each method to cross the domain gap.

The domain gap indicates the differences between datasets. It may cause noticeable performance drop when training and testing on datasets from different domains. For example, as shown in this page, the special glass coating in the dataset of Zhang18 [8] makes the behavior of their dataset fairly different from our proposed dataset and SIR^2 dataset [5]. A network model trained on the dataset suitable for Zhang18 may not generalize well on our proposed dataset.

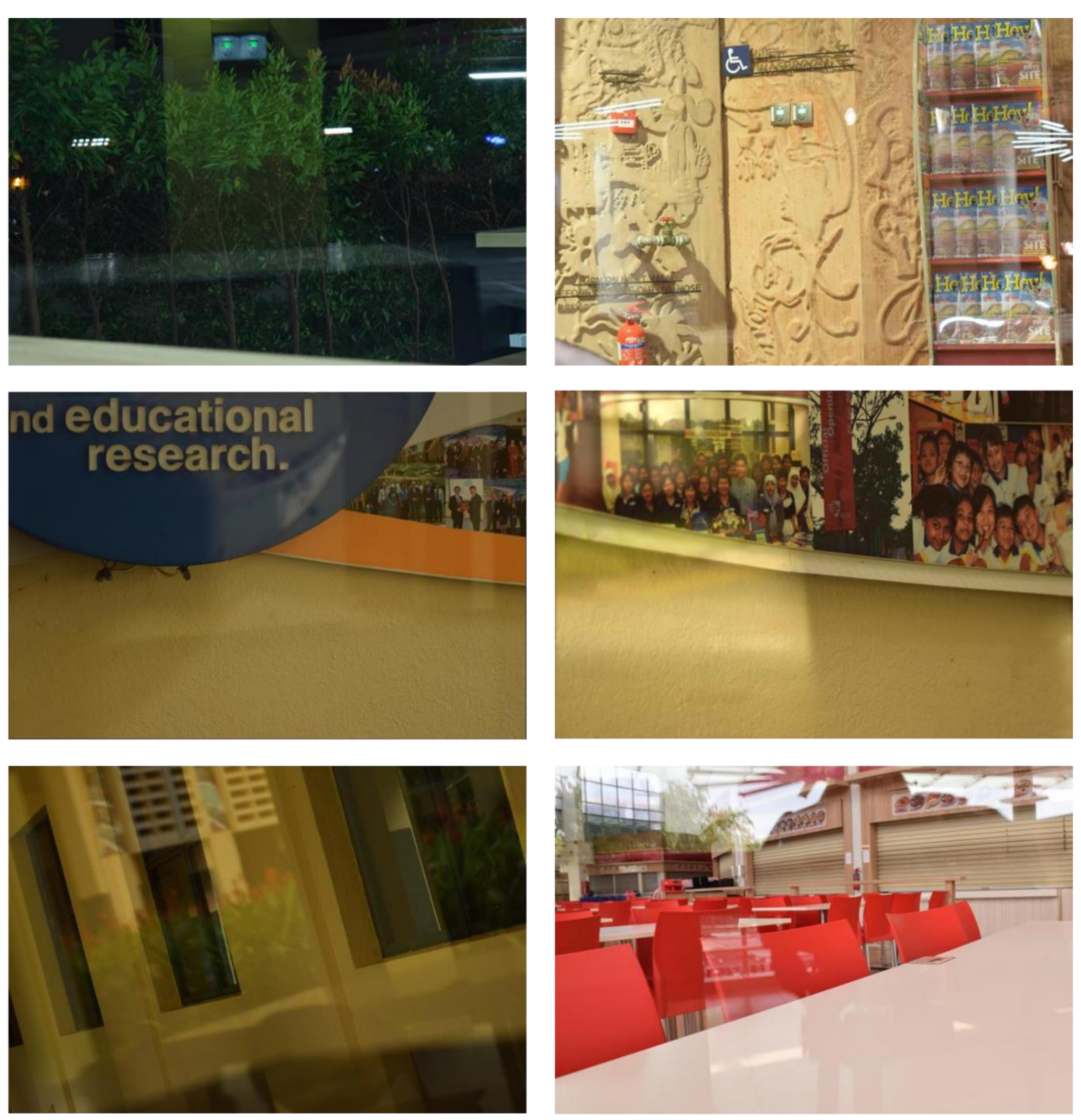
An overview of the existing datasets

Our proposed dataset



The dataset of Zhang18 [8]

Special glass coating



SIR^2 dataset [5]

2 - Dataset Gap (Domain Gap)

The performances of pre-trained models released by Zhang18 and Wan18 on SIR^2 and Zhang18 datasets

	SIR^2 dataset	Zhang18 dataset
Zhang18	0.860/23.13	0.821/21.30
Wan18	0.895/24.03	0.741/19.22

SSIM/PSNR

Pre-trained models provided by their authors

The variation of the performance

It is observed that both two models only perform well on one dataset but worse on the other dataset. The domain gap between these two datasets is obvious and we have observed similar phenomenon in the following experiment.

2 - Dataset Gap (Domain Gap)

The results of each method on the dataset of Zhang18 [8] (trained on our training dataset)

	SSIM	PSNR
LB14	0.752	19.05
WS16	0.640	17.92
NR17	0.650	18.41
FY17	0.757	19.10
CycleGAN	0.683	18.22
Zhang18	0.780	19.69
Wan18	0.784	19.54
Eq. (1)	0.765	19.48
Ours	0.791	19.92
Ours + Eq. (1)	**0.798**	**20.03**

(0.821 21.30)

Due to the lack of reflection images in the dataset of Zhang18 [8], it is difficult to train the methods like Wan18 [8] and our method on this dataset. For fair comparison, we train all the learning-based methods on our training dataset and evaluate their performances on the dataset of Zhang18 [8] to see whether they can generalize well on different datasets.

It is observed that our method can achieve consistent performances on the dataset of Zhang18 [8], but the performances of Zhang18 [8] trained on our training dataset are *lower than the performances* reported in their paper (SSIM:0.821, PSNR: 21.30). It shows that our method has better generalization ability to cross the domain gap. However, as we mentioned in the previous page, the dataset gap is a challenging yet important problem and we will continue working on this part to improve the generalization ability in our future work.

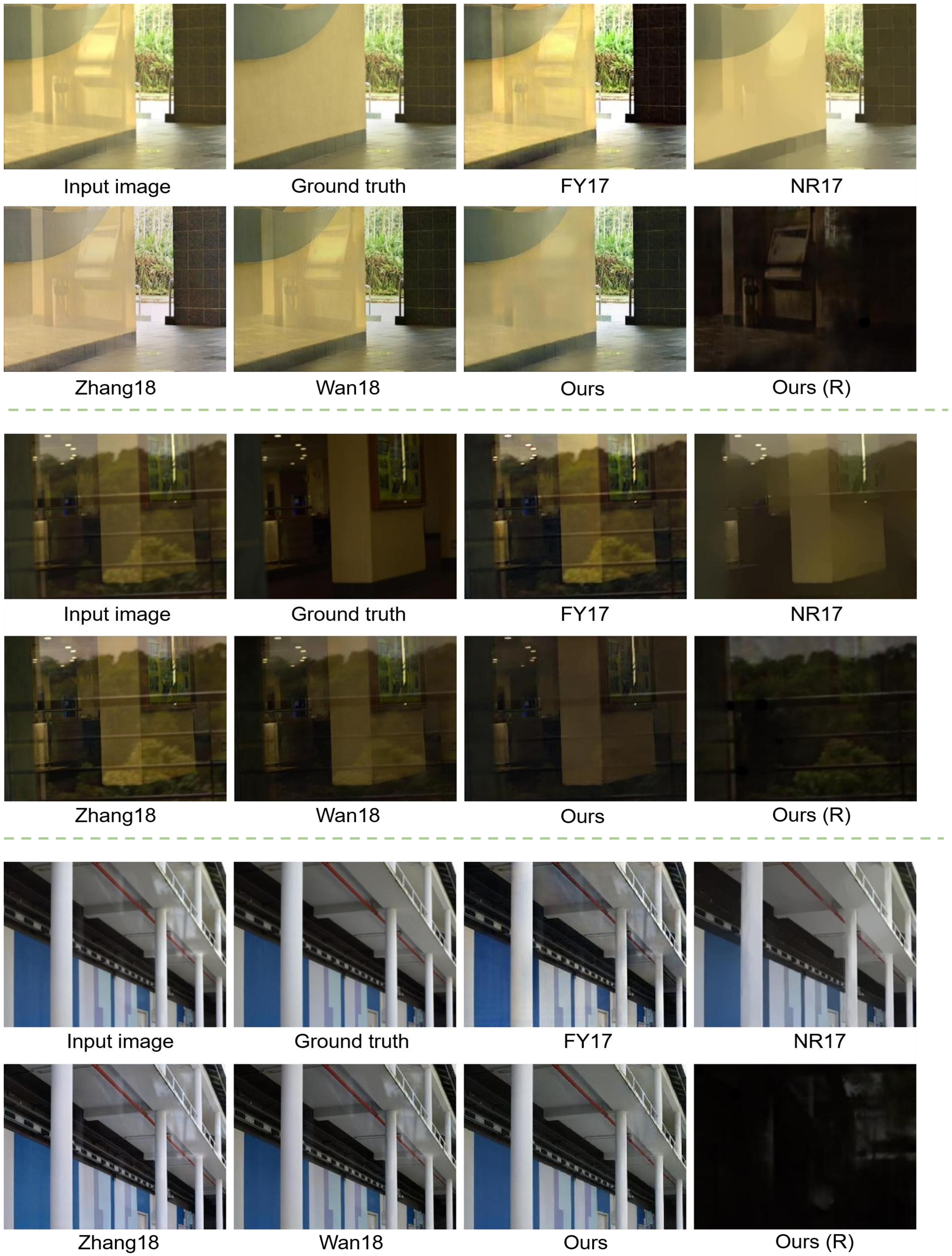
3 - Additional Results from the Generator

3 - Additional Results from the Generator

B | R | $I_{\emptyset_0}$ | $I_{\emptyset_1}$ | $I_{\emptyset_2}$ | Ours

Examples of mixture images compared with [10]

3 - Additional Results on SIR^2 dataset



3 - Additional Results on SIR^2 dataset

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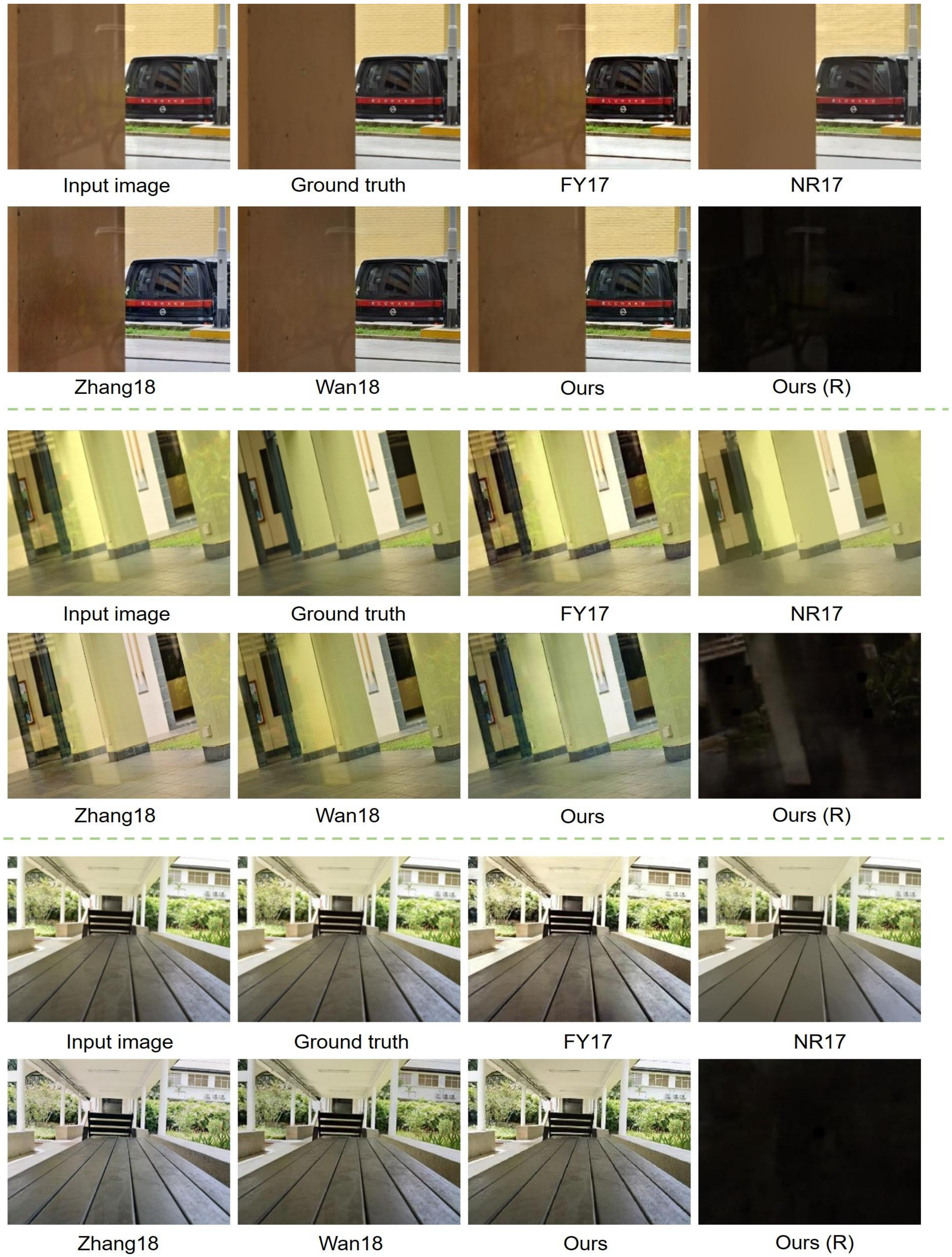
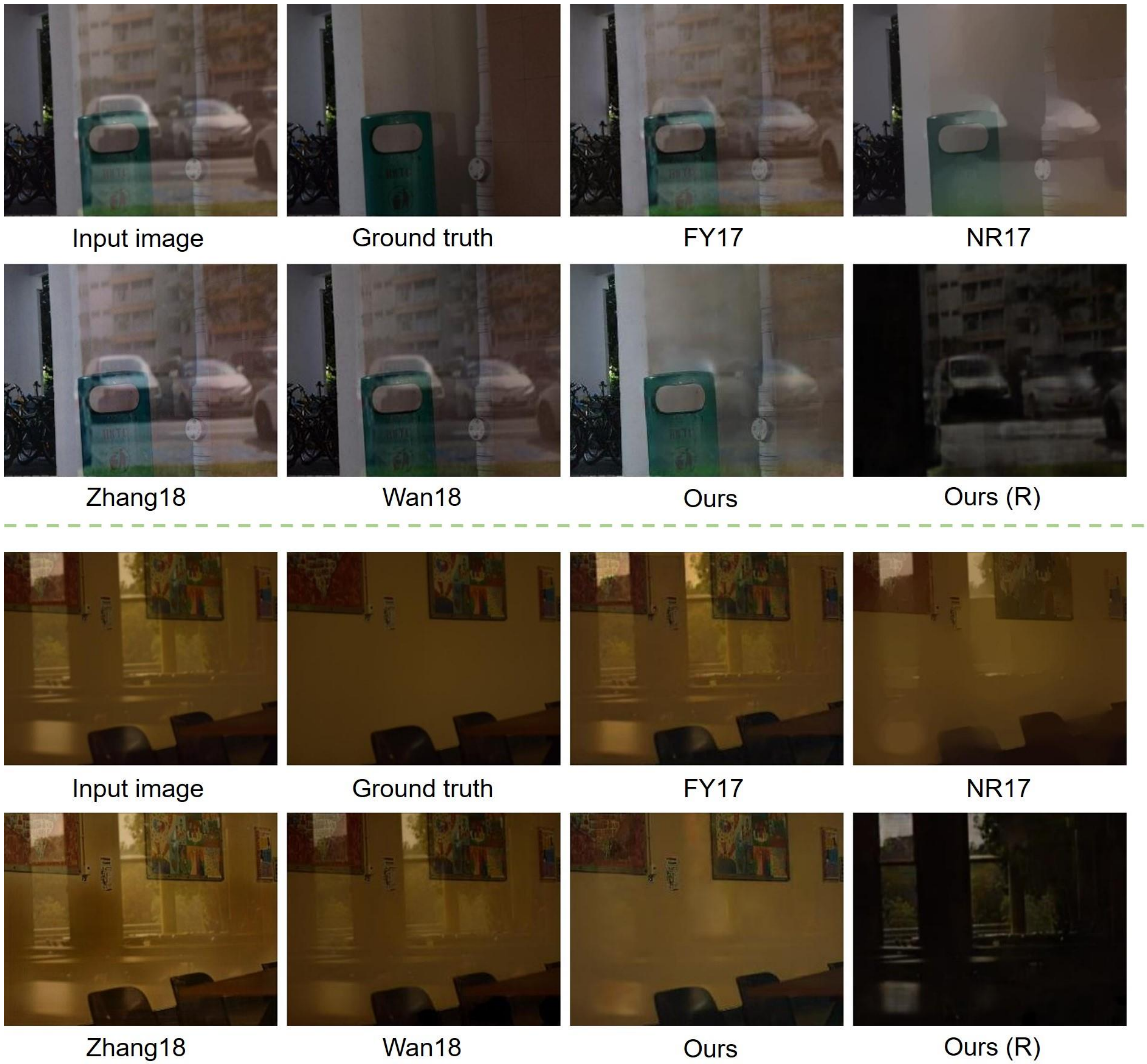


3 - Additional Results on SIR^2 dataset



3 - Additional Results on FY17 dataset


Input image

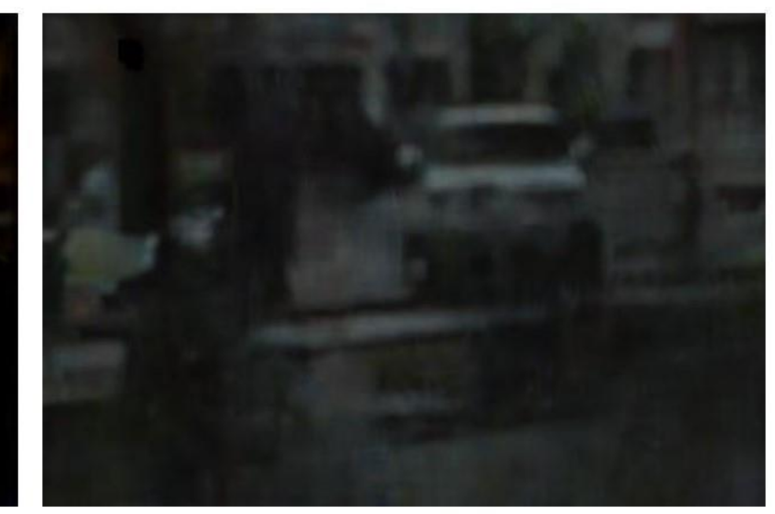

Wan18


FY17


Ours


Zhang18


FY17 (R)

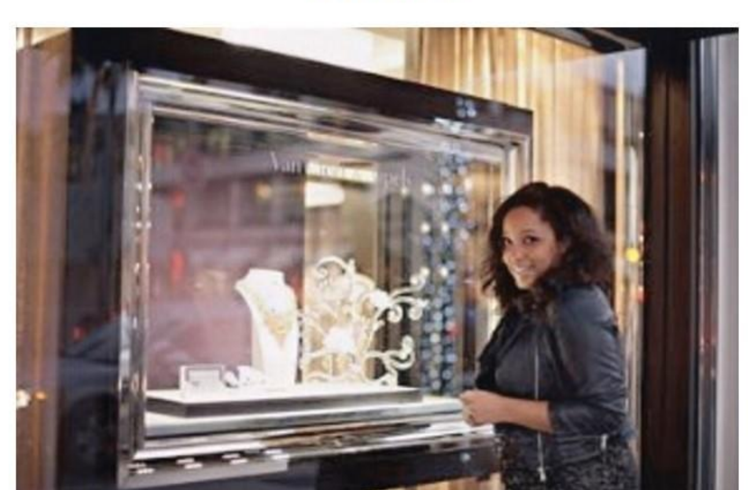

Ours (R)

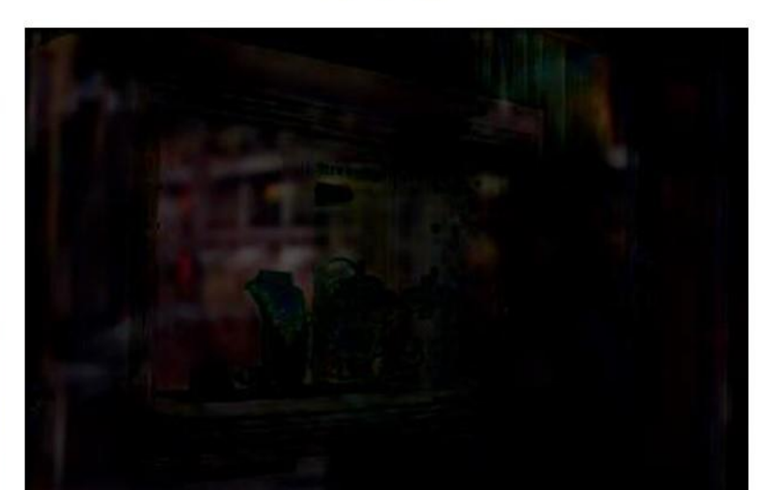

Input image

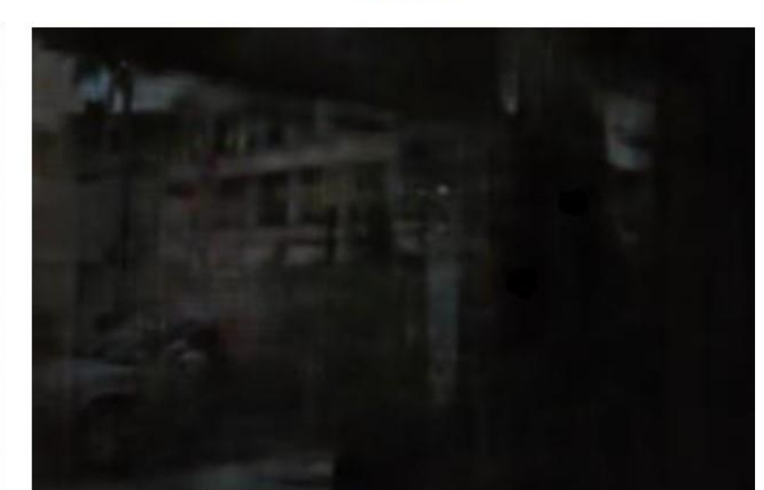

Wan18


FY17


Ours


Zhang18

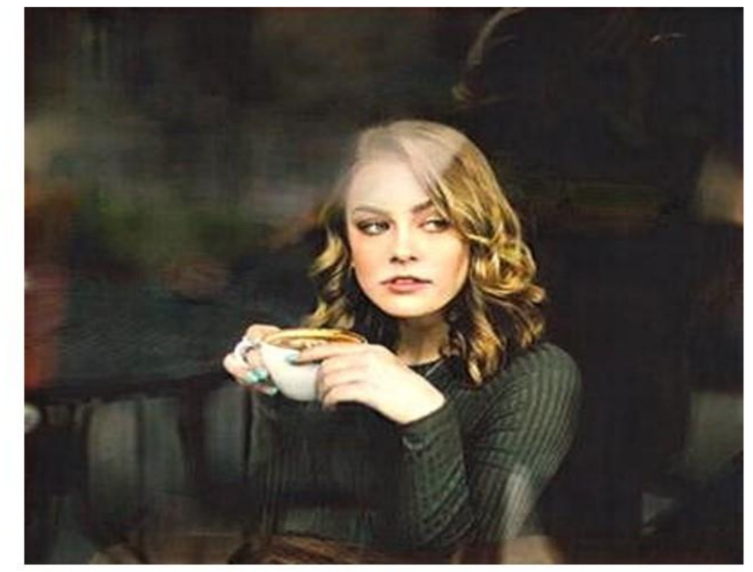

FY17 (R)


Ours (R)

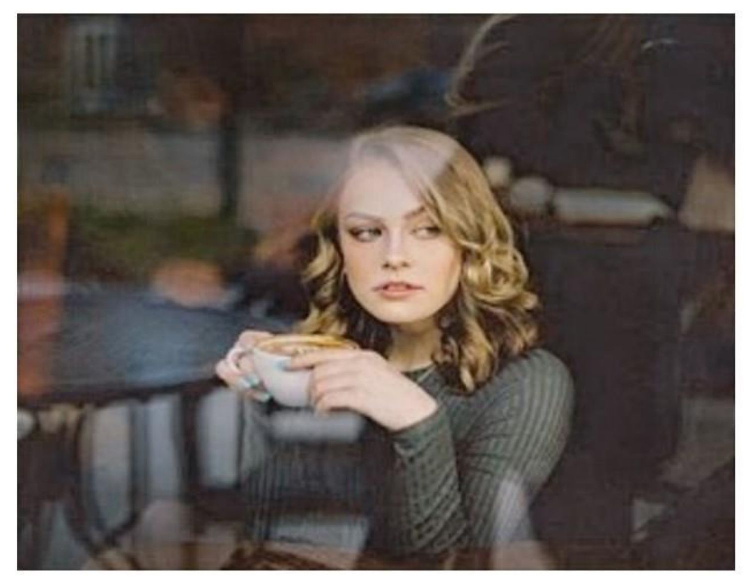
3 - Additional Results on FY17 dataset


Input image


Wan18

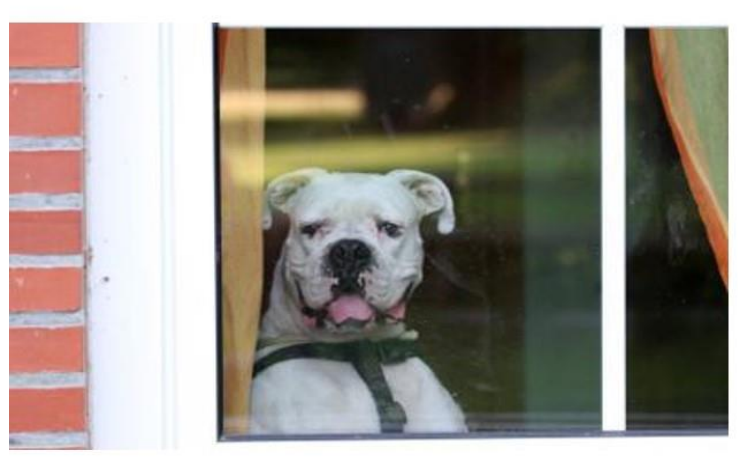

FY17


Ours


Zhang18

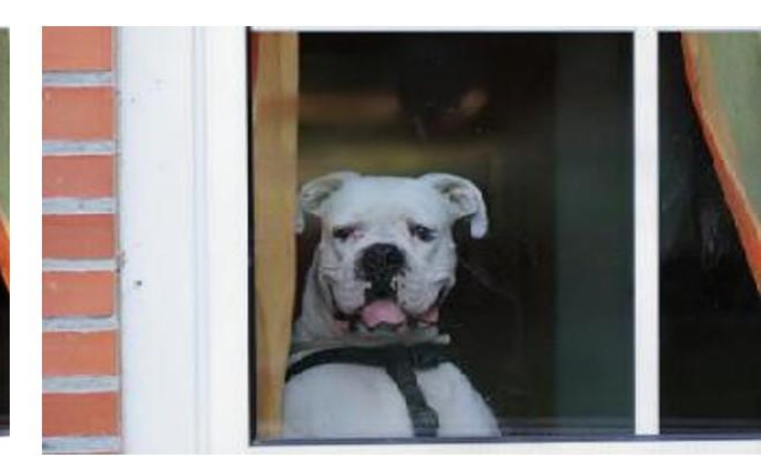

FY17 (R)


Ours (R)

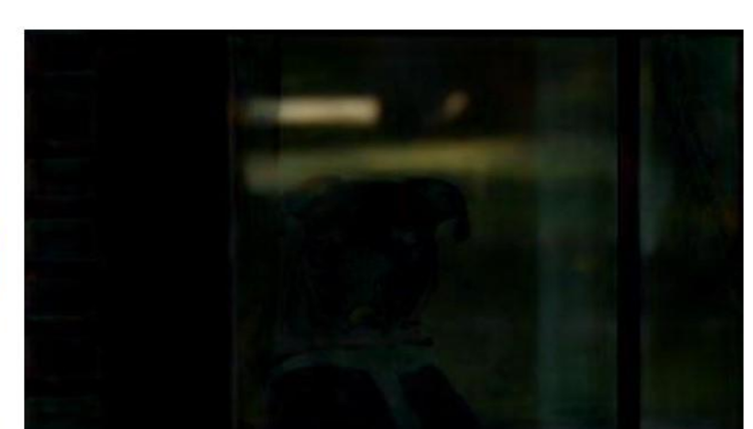

Input image


Wan18


FY17


Ours


Zhang18


FY17 (R)


Ours (R)

3 - Additional Results on Internet Images

Input

Zhang18

Wan18

Ours

3 - Additional Results on Internet Images

Input

Zhang18

Wan18

Ours

3 - Additional Results on the High-resolution Images

Input

1920x1080

3 - Additional Results on the High-resolution Images

Ours (R)

1920x1080

3 - Additional Results on the High-resolution Images

Ours (B)

1920x1080

Comparing the above result with the low-resolution result of Figure 9 in the main paper, we can find that though our method recovers the reflection part, the background is harder to recover clearly, which leaves more space for further exploration.

4 - Reference

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