Unsupervised Deraining: Where Contrastive Learning Meets Self-similarity
Supplementary Material

In this supplementary, we fist show the real rain removal results of our methods NLCL in Section A. Then we generalize our methods to the haze removal task in Section B. Finally, in Section C, we visualize the results in ablation study to further illustrate the effectiveness of contrastive losses.

A. Visualization results in real rain removal

The real rain is more complex than the synthetic rain, which includes the veiling effects and rain streaks. We perform the real rain removal on the rainy images captured in the cities, as shown in Fig. 1 to Fig. 10. The compared methods include supervised method JORDER-E [4], semi-supervised methods SSIR [3], Syn2real [5] and unsupervised methods DSC [1], UDGNet [6] and CUT [2]. NLCL achieves better visual results with respect to both the image details preservation and rain streaks removal. We exploit not only the specific knowledge of rain or image layer via external datasets, but also the contrastive relationship between the layers, which takes the internal image information into consideration. Specifically, we model the exclusive dissimilarities between the image and rain, and the non-local self-similarities inside image or rain layers, which boosts the decoupling of image and real rain. It can be found from the visualization results that NLCL not only removes the rain streaks such as Fig. 1, Fig. 2, Fig. 3 and Fig. 4, and the veiling effects such as Fig. 5 and Fig. 6 , but also preserves the image structure better when compared with the competing methods, such as the words in Fig. 6 and Fig.7, texture of the trees in Fig. 8, Fig. 9 and Fig. 10.

B. Generalization in other low-level tasks

In this section, we generalize NLCL in another low-level artifacts removal task, the haze removal. In NLCL, our main motivation is not to learn the specific domain knowledge of rain, but to exploit the inter-layer dissimilarities and intra-layer self-similarities, which are the intrinsic properties existing in not only rainy images, but also the other degradations with distinct artifacts such as the hazy images. Therefore, we re-train and test the model in the real hazy images (with no ground truths) collected from Internet. The removal results in Fig. 11 and Fig. 12 show that we obtain a good performance in de-hazing task. Specifically, we remove the haze and restore the bright visually pleasing images with the details well preserved.

C. Ablations on losses

To illustrate the effectiveness of our proposed layer contrastive loss and location contrastive loss, we visualize the decomposed image and rain layers with and without the losses. Fig. 13 compares the decomposed results with and without the layer contrastive. It can be found that the rain streaks are left in the image, and contents are left in the rain layer when no layer contrastive is employed (shown in the left). The layer contrastive pushes residuals into the corresponding layer by the low similarity constraint across the layers (shown in the right). Fig. 14 illustrates the benefits of location contrastive, which aims to preserve the image content. Without the location contrastive, the structure of human body is destroyed when the rain is removed (shown in the left), while location contrastive preserves the structure under the high similarity constraint on the patches of corresponding location.

References

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Figure 1. Comparisons of deraining results in real scene. The example shows that NLCL successfully removes the real rain streaks. Moreover, the details such as the tree textures are well preserved by NLCL.

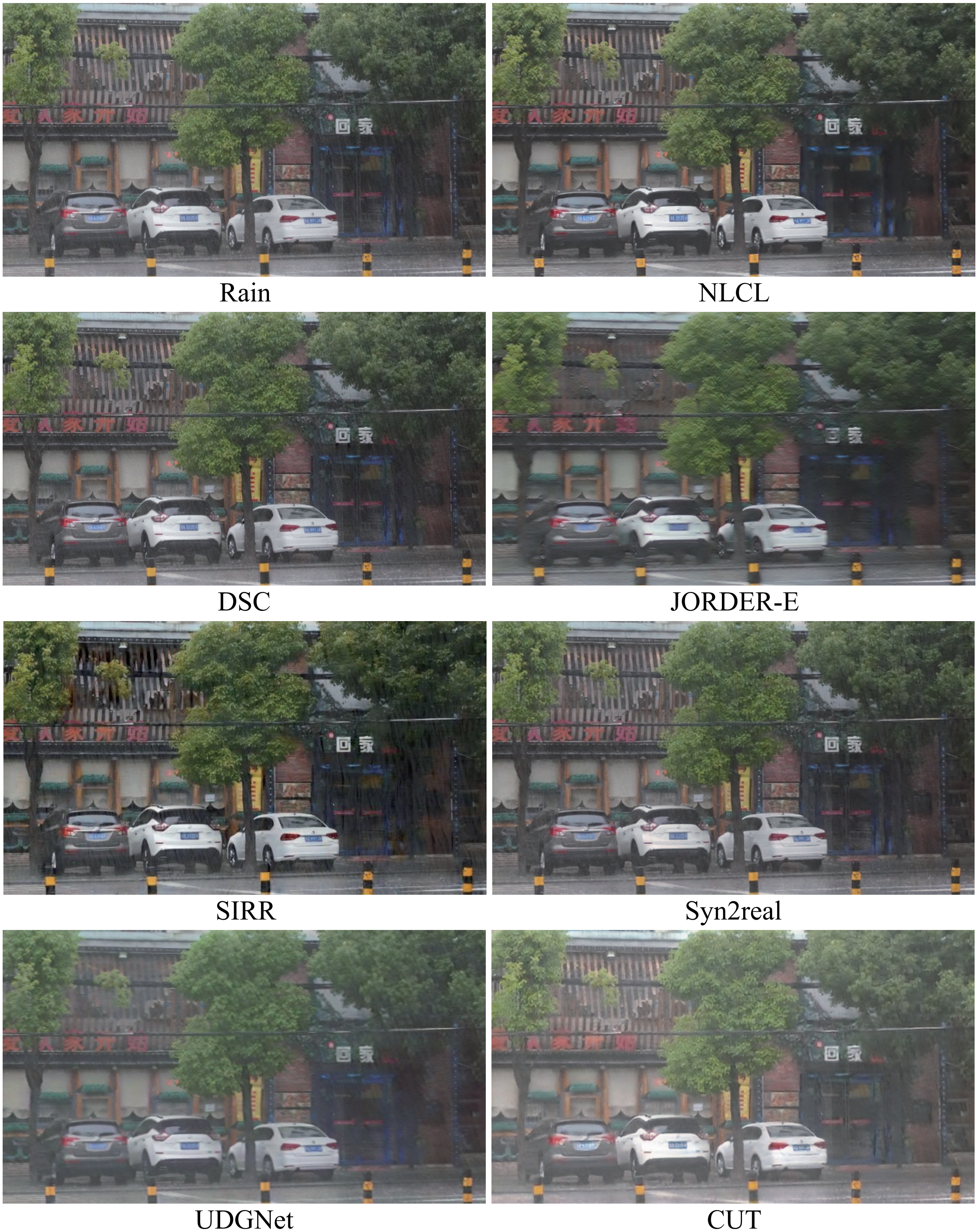

Figure 2. Comparisons of deraining results in real scene. The example shows that NLCL successfully removes the real rain streaks. Moreover, the details such as the words are well preserved by NLCL.

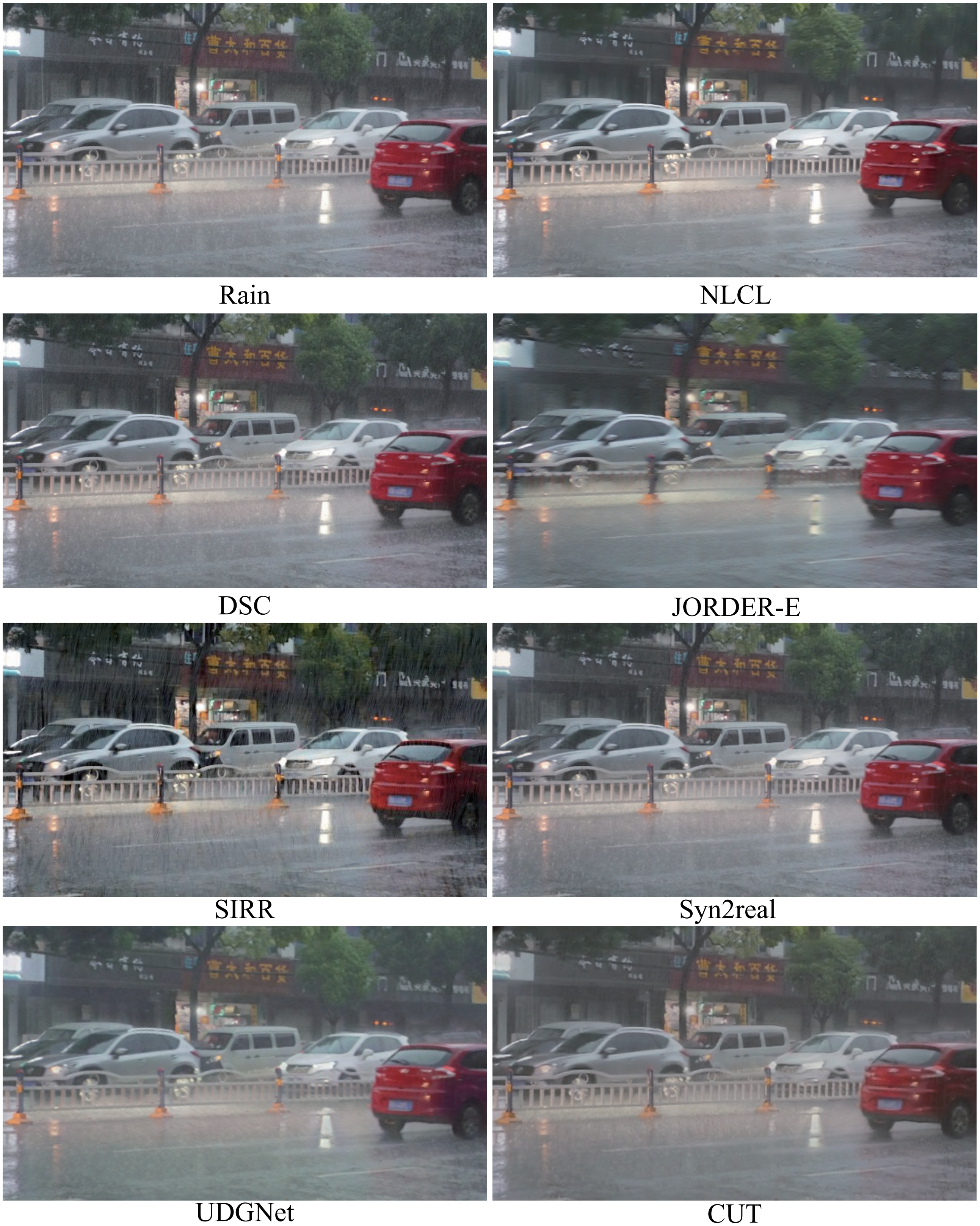

Figure 3. Comparisons of deraining results in real scene.

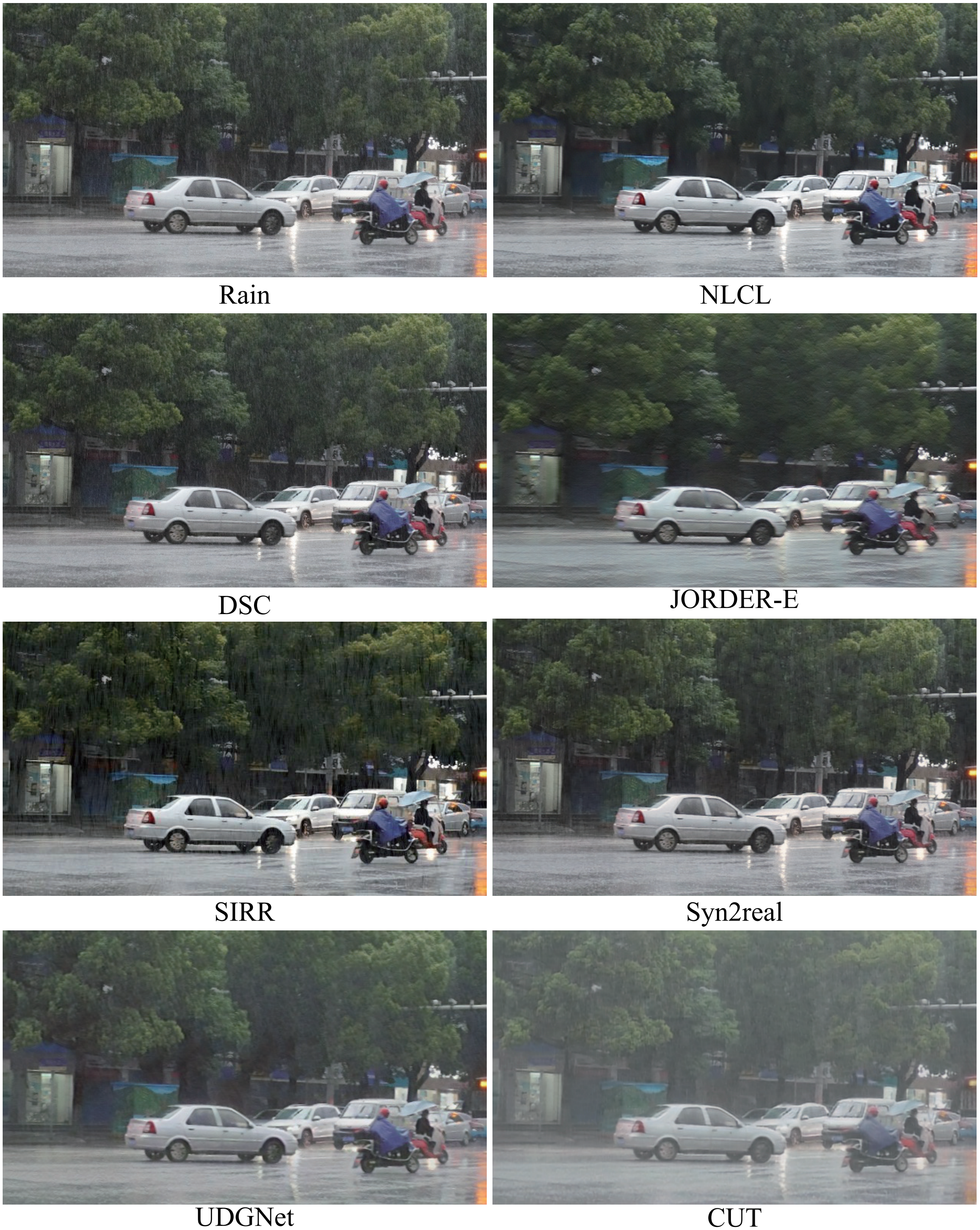

Figure 4. Comparisons of deraining results in real scene.

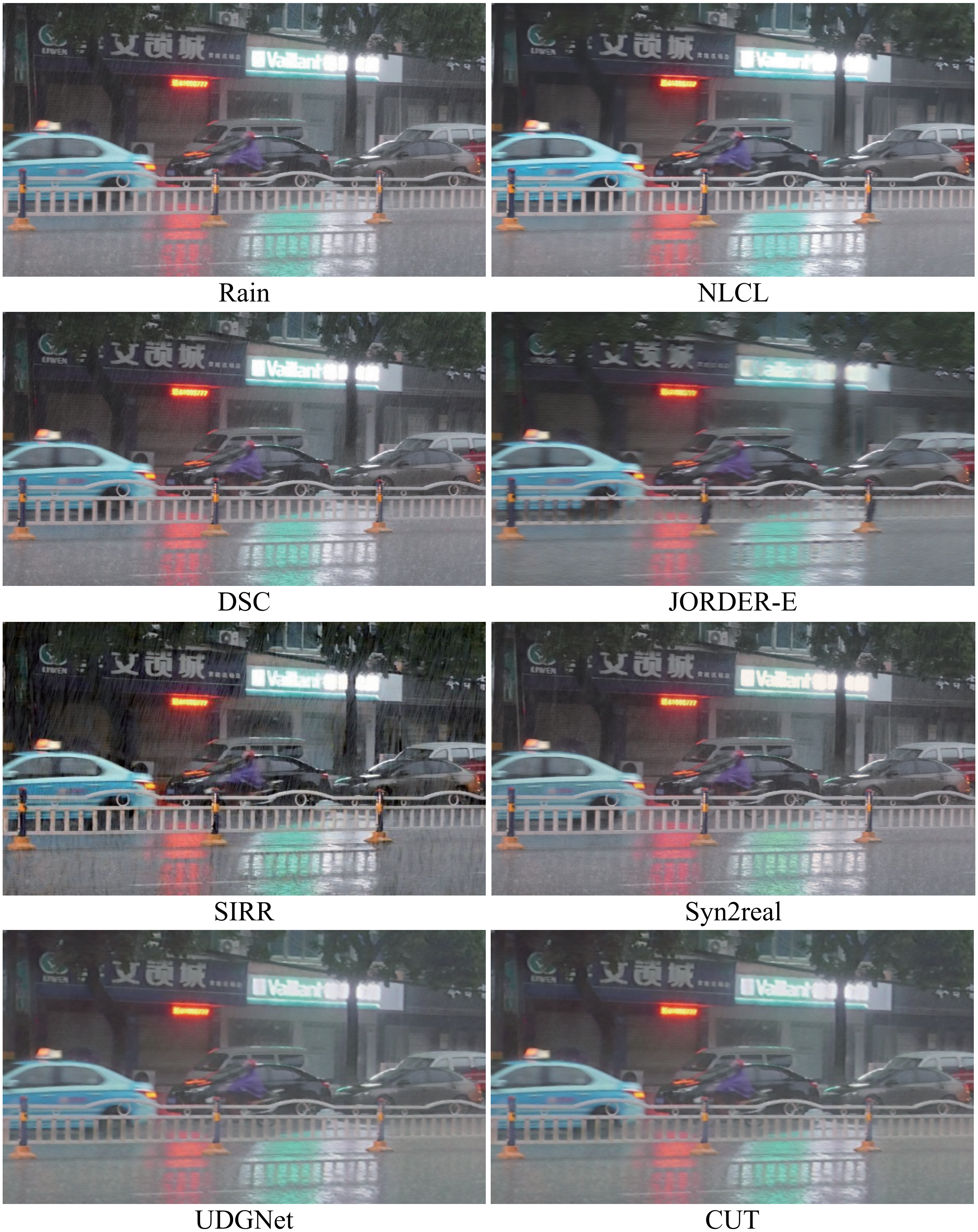

Figure 5. Comparisons of deraining results in real scene.

Figure 6. Comparisons of deraining results in real scene.

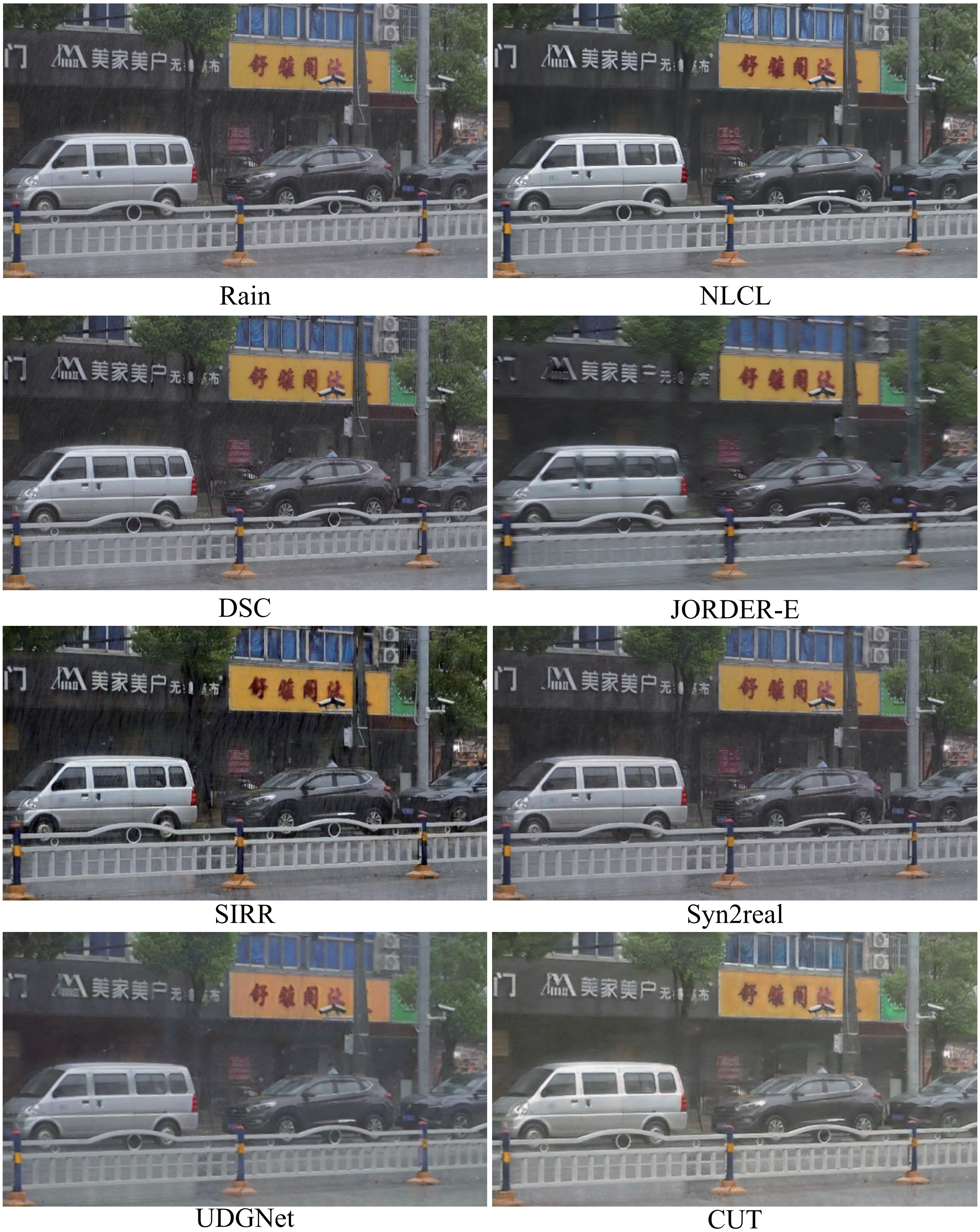

Figure 7. Comparisons of deraining results in real scene.

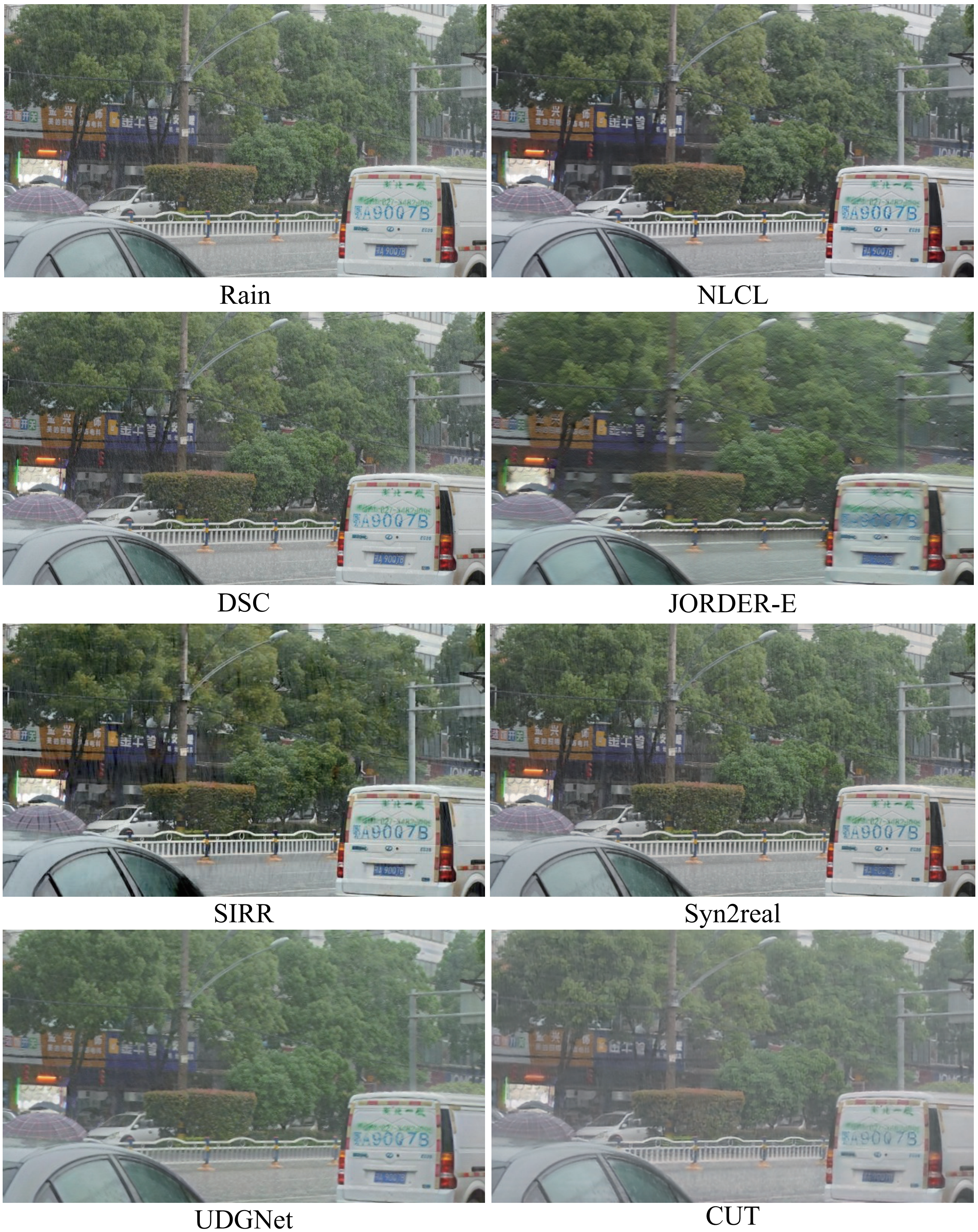

Figure 8. Comparisons of deraining results in real scene.

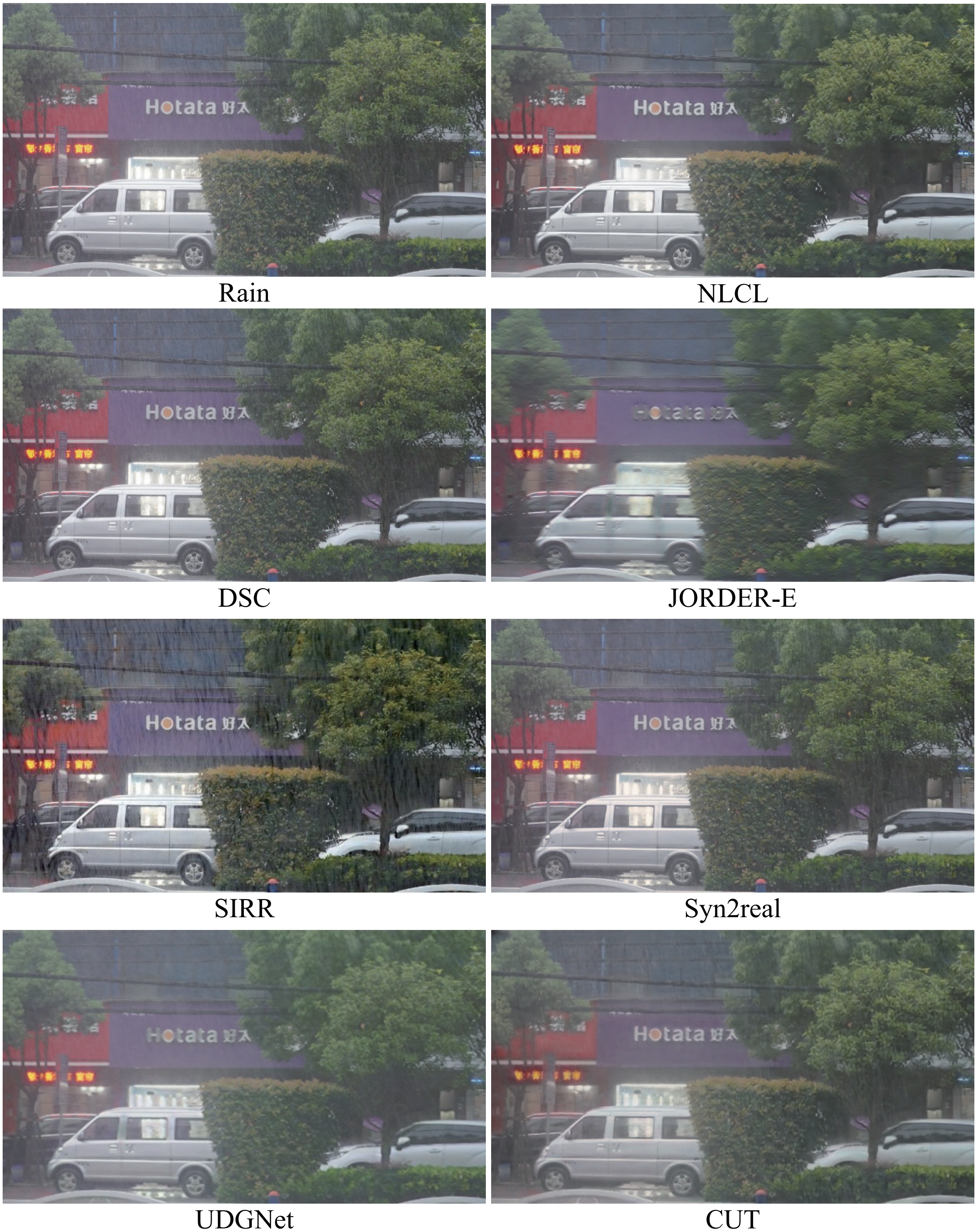

Figure 9. Comparisons of deraining results in real scene.

Figure 10. Comparisons of deraining results in real scene.

Haze NLCL

Figure 11. Generalization in real hazy removal. NLCL exploits the inter-layer dissimilarities between the degradations and images, and the intra-layer non-local self-similarities, which are the intrinsic properties widely exist in the low-level degradations. It can be found that NLCL generalizes well in haze removal, indicating that NLCL can handle not only the additional degradation (rain), but also the depth-related haze.

Figure 12. Generalization in real hazy removal. NLCL exploits the inter-layer dissimilarities between the degradations and images, and the intra-layer non-local self-similarities, which are the intrinsic properties widely exist in the low-level degradations. It can be found that NLCL generalizes well in haze removal, indicating that NLCL can handle not only the additional degradation (rain), but also the depth-related haze.

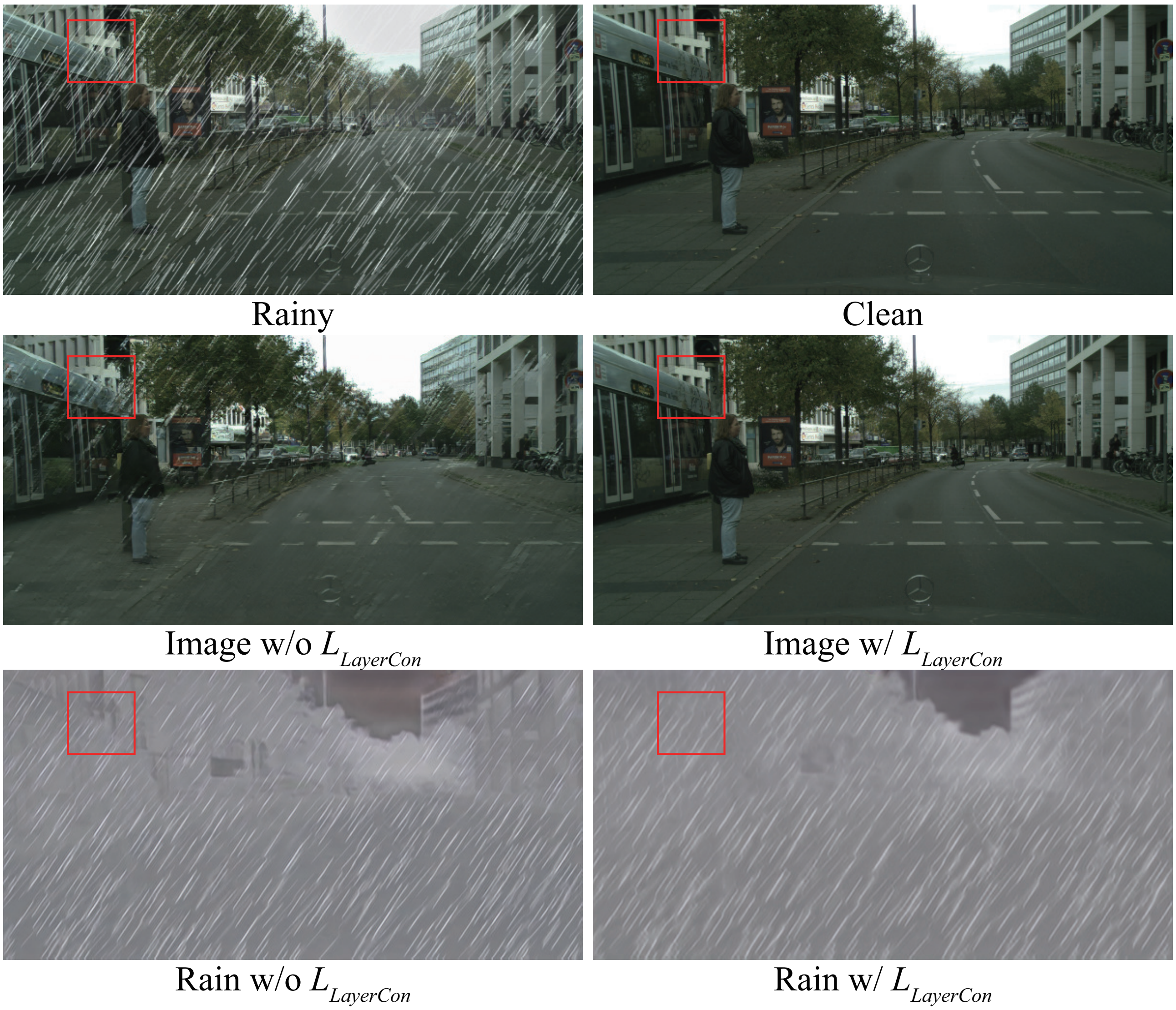

Figure 13. Comparison of image deraining with and without layer contrastive loss. Contrastive loss constrains the low similarity between the image and rain layers, which leads to better decomposition results.

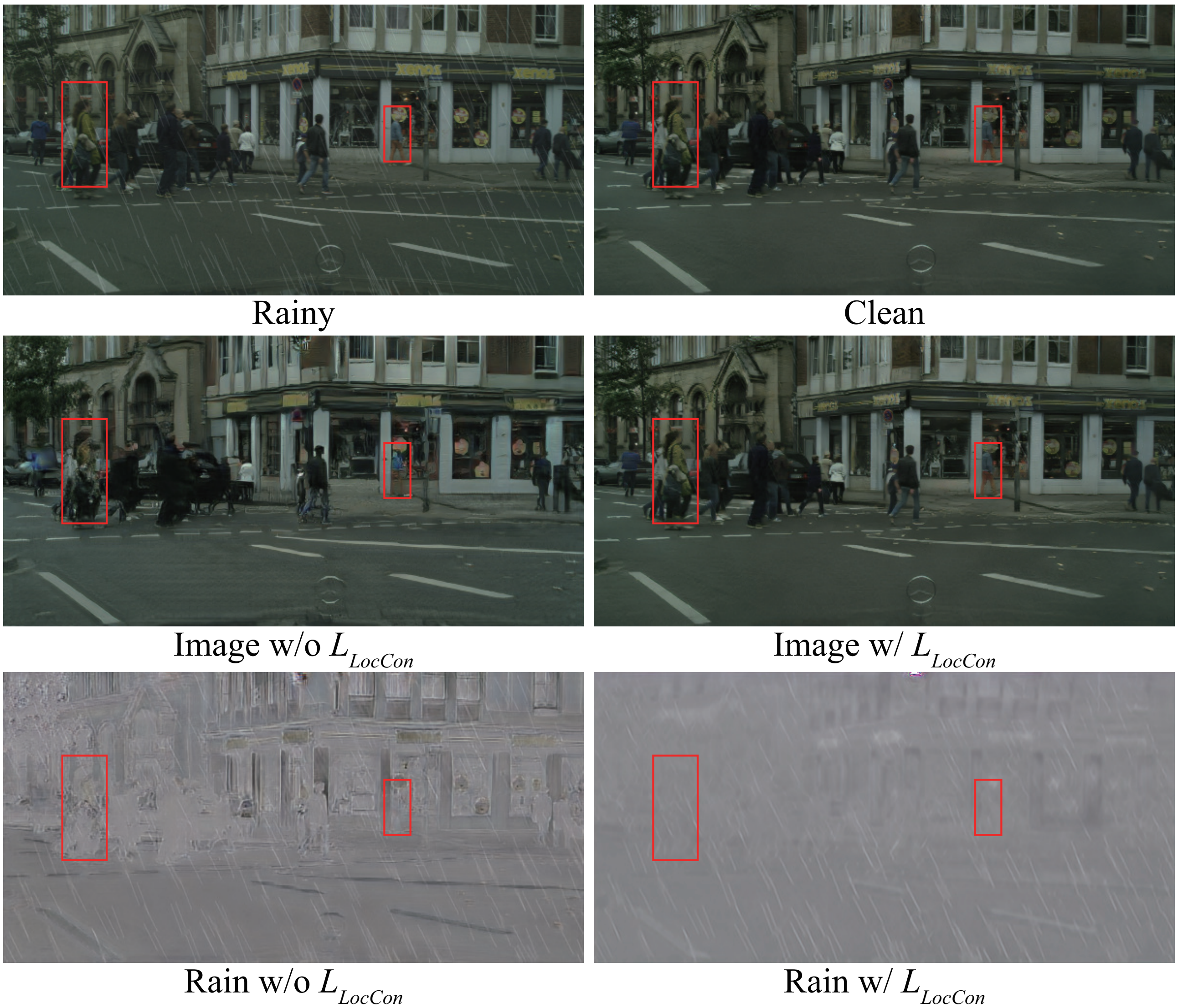

Figure 14. Comparison of image deraining with and without location contrastive loss. The location contrastive constrains the high similarity between the corresponding patches of rainy and de-rained images, which leads to better structure preservation.