

Learning Rain Location Prior for Nighttime Deraining (Supplementary Material)

Fan Zhang¹ Shaodi You² Yu Li³ Ying Fu^{1*}

¹Beijing Institute of Technology ²University of Amsterdam

³International Digital Economy Academy

In this supplementary material, we first present the results of investigations on regularization imposed on RLP during training. Then we provide the quantitative results on GT-Rain dataset [1]. Finally, we provide more qualitative results on both synthetic data and real night rainy images.

1. Regularization on RLP

Here we explain the reason why we do not impose additional constraints on the RLP during training. We adopted the common practice in raindrop removal [3, 4, 10] to guide the training of RLP using binary masks obtained by subtracting the rainy image from the clean ground truth. However, we found that this did not lead to any improvement in performance, as shown in Table 1. Instead, we find that models get comparable PSNR no matter whether the RPIM module exists or not when additional supervision is imposed on RLP. It means that the performance of the model may be limited by the preciseness of the rain mask and we suspect hard masks may limit the adaptive learning of RLP. Therefore, for simplicity, we did not impose any additional constraints on the RLP during training.

2. Quantitative Results on GT-Rain Dataset

We conducted experiments on the real daytime dataset GT-Rain [1] to further show the generalization of our method on daytime data. Experimental results are listed in Table 2. Despite the original goal of nighttime deraining, our method still gets comparable performance to state-of-the-art methods. Experimental results of other methods are reported from the dataset paper [1].

3. Qualitative Results on GTAV-NightRain

More quantitative results on synthetic data are illustrated in Figures 1, 2, 3 and 4. Compared methods include PReNet [5], SPANet [7], DRDNet [2], RCDNet [6], SPDNet [9], MPRNet [11], U-Net [4] and Uformer [8].

Table 1: Experimental results on whether or not to impose regularization on RLP during training. Rain mask as guidance brings no improvement in performance, thus we do not impose regularization terms on RLP for simplicity.

Modules	RLP	RPIM	SS on RLP	PSNR	SSIM
U-Net	✓	-	-	35.63	0.9609
U-Net	✓	-	✓	35.32	0.9599
U-Net	✓	✓	-	35.85	0.9617
U-Net	✓	✓	✓	35.28	0.9604

We can find that all compared methods can only remove part of rain streaks from rainy images, while our method can improve the deraining performance in night scenes and Ours (Uformer) outperforms them in most cases. As shown in Figure 1, when rain streaks fall in different directions due to the wind (*e.g.* the first image), compared methods cannot handle them properly. Many rain streaks still stay on the image for visual results of SPANet [7], DRDNet [2], RCDNet [6] and SPDNet [9]. PReNet [5], U-Net [4] and Uformer [8] can remove more rain streaks than the former five methods while our method outperforms them. For the second image, when rain streaks with different scales occur, most methods fail to remove thick rain streaks, while Ours (Uformer) can nicely handle them. For the third image where bright and dark rain streaks occur simultaneously, all compared methods ignore the dark rain streaks while Ours (Uformer) removes all the rain streaks. For the last image in Figure 1, many methods mistake the glare as rain streak and remove it, *e.g.* the area emphasized in the blue box in the result of PReNet [5], RCDNet [6], SPDNet [9], MPRNet [11], U-Net [4], Uformer [8] and even Ours (U-Net). However, Ours (Uformer) can well handle the case and keep the glare unchanged. Similar results can also be found in Figures 2, 3 and 4, corresponding to the quantitative results.

4. Qualitative Results on Real Data

We present the qualitative results on real night rainy images in Figures 5, 6, 7 and 8. These images are collected from the Internet and existing datasets.

We can find that previous methods including PReNet [5],

*Corresponding author: fuying@bit.edu.cn

Table 2: Experimental results on GT-Rain dataset [1]. Despite our goal of nighttime deraining, our method is comparable to state-of-the-art methods on daytime data. DRS and DRA denote for *Dense Rain Streaks* and *Dense Rain Accumulation*, respectively.

Data Split	Metrics	Input	RCDNet	EDR	MPRNet	GT-Rain	Ours
DRS	PSNR	18.46	19.6	19.95	20.19	20.84	20.35
	SSIM	0.6284	0.6492	0.6436	0.6542	0.6573	0.6545
DRA	PSNR	20.87	22.74	23.42	23.38	24.78	23.58
	SSIM	0.7706	0.7891	0.7994	0.8009	0.8279	0.8037
Overall	PSNR	19.49	20.94	21.44	21.56	22.53	21.73
	SSIM	0.6893	0.7091	0.7104	0.7171	0.7304	0.7184

SPANet [7], DRDNet [2], RCDNet [6], SPDNet [9], MPRNet [11], U-Net [4] and Uformer [8] can only remove some rain streaks in real night rainy images and many rain streaks still stay on these images. However, our method can outperform all compared methods for most tested real images, removing most of the rain streaks and keeping the background tidy. For example, in the first image of Figure 5, the rain in the results of SPANet [7], RCDNet [6], MPRNet [11], U-Net [4] and Uformer [8] is less than in the original rainy image. But we can find artifacts in that of RCDNet [6] and U-Net [4]. Our method removes the most rain streaks and the visual result looks pleasing. Similar results can also be found in other images.

References

- [1] Yunhao Ba, Howard Zhang, Ethan Yang, Akira Suzuki, Arnold Pfahnl, Chethan Chinder Chandrappa, Celso M de Melo, Suya You, Stefano Soatto, Alex Wong, et al. Not just streaks: Towards ground truth for single image deraining. In *ECCV*, 2022. 1, 2
- [2] Sen Deng, Mingqiang Wei, Jun Wang, Yidan Feng, Luming Liang, Haoran Xie, Fu Lee Wang, and Meng Wang. Detail-recovery image deraining via context aggregation networks. In *CVPR*, 2020. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
- [3] Zhixiang Hao, Shaodi You, Yu Li, Kunming Li, and Feng Lu. Learning from synthetic photorealistic raindrop for single image raindrop removal. In *ICCVW*, 2019. 1
- [4] Rui Qian, Robby T Tan, Wenhan Yang, Jiajun Su, and Jiaying Liu. Attentive generative adversarial network for raindrop removal from a single image. In *CVPR*, 2018. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
- [5] Dongwei Ren, Wangmeng Zuo, Qinghua Hu, Pengfei Zhu, and Deyu Meng. Progressive image deraining networks: A better and simpler baseline. In *CVPR*, 2019. 1, 3, 4, 5, 6, 7, 8, 9, 10
- [6] Hong Wang, Qi Xie, Qian Zhao, and Deyu Meng. A model-driven deep neural network for single image rain removal. In *CVPR*, 2020. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
- [7] Tianyu Wang, Xin Yang, Ke Xu, Shaozhe Chen, Qiang Zhang, and Rynson WH Lau. Spatial attentive single-image

- deraining with a high quality real rain dataset. In *CVPR*, 2019. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
- [8] Zhendong Wang, Xiaodong Cun, Jianmin Bao, Wengang Zhou, Jianzhuang Liu, and Houqiang Li. Uformer: A general u-shaped transformer for image restoration. In *CVPR*, 2022. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
- [9] Qiaosi Yi, Juncheng Li, Qinyan Dai, Faming Fang, Guixu Zhang, and Tiejong Zeng. Structure-preserving deraining with residue channel prior guidance. In *ICCV*, 2021. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
- [10] Shaodi You, Robby T Tan, Rei Kawakami, Yasuhiro Mukaigawa, and Katsushi Ikeuchi. Raindrop detection and removal from long range trajectories. In *ACCV*, 2014. 1
- [11] Syed Waqas Zamir, Aditya Arora, Salman Khan, Munawar Hayat, Fahad Shahbaz Khan, Ming-Hsuan Yang, and Ling Shao. Multi-stage progressive image restoration. In *CVPR*, 2021. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10

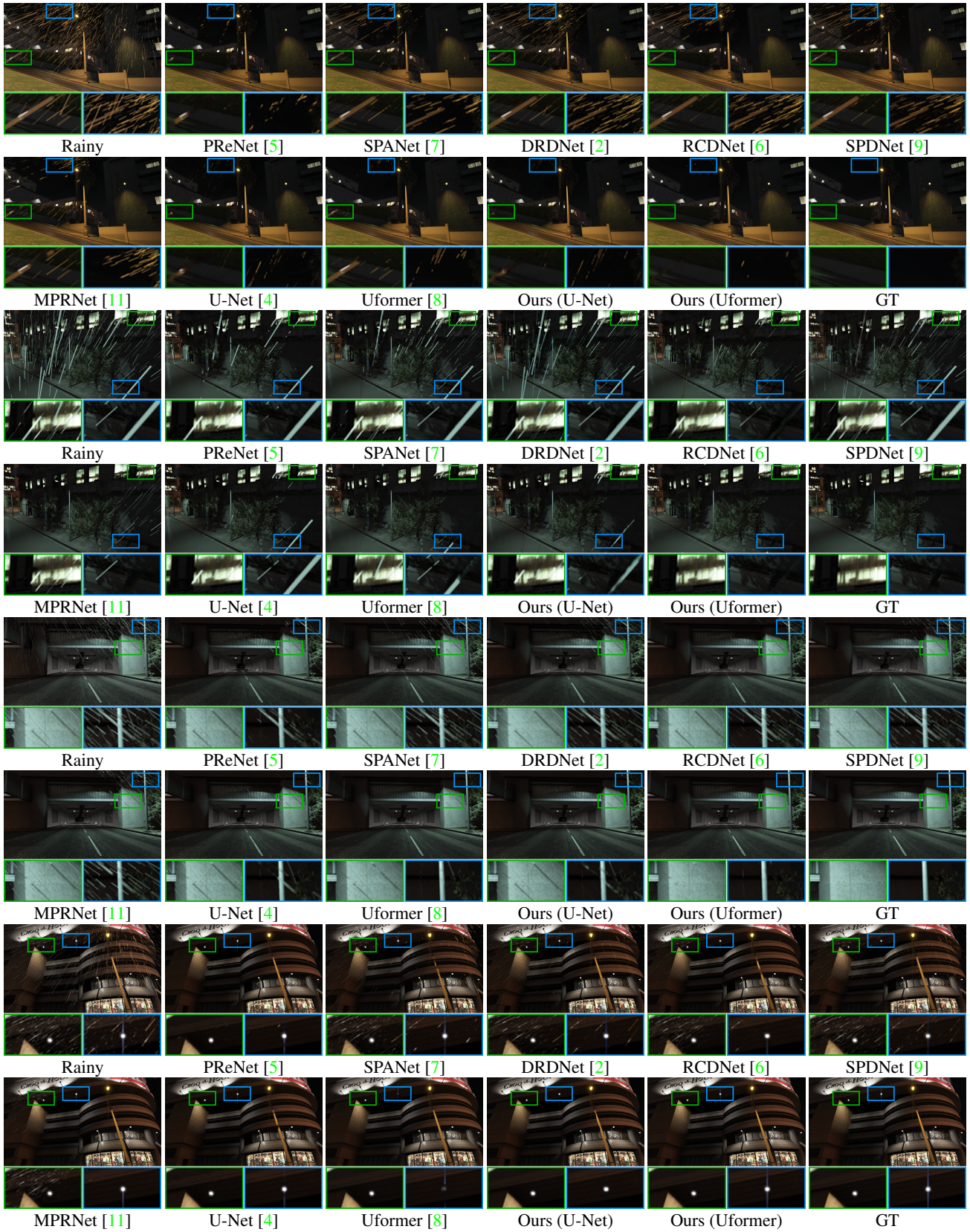


Figure 1: Qualitative results on synthetic data, brightness is adjusted for better visualization. Please zoom in for more details.

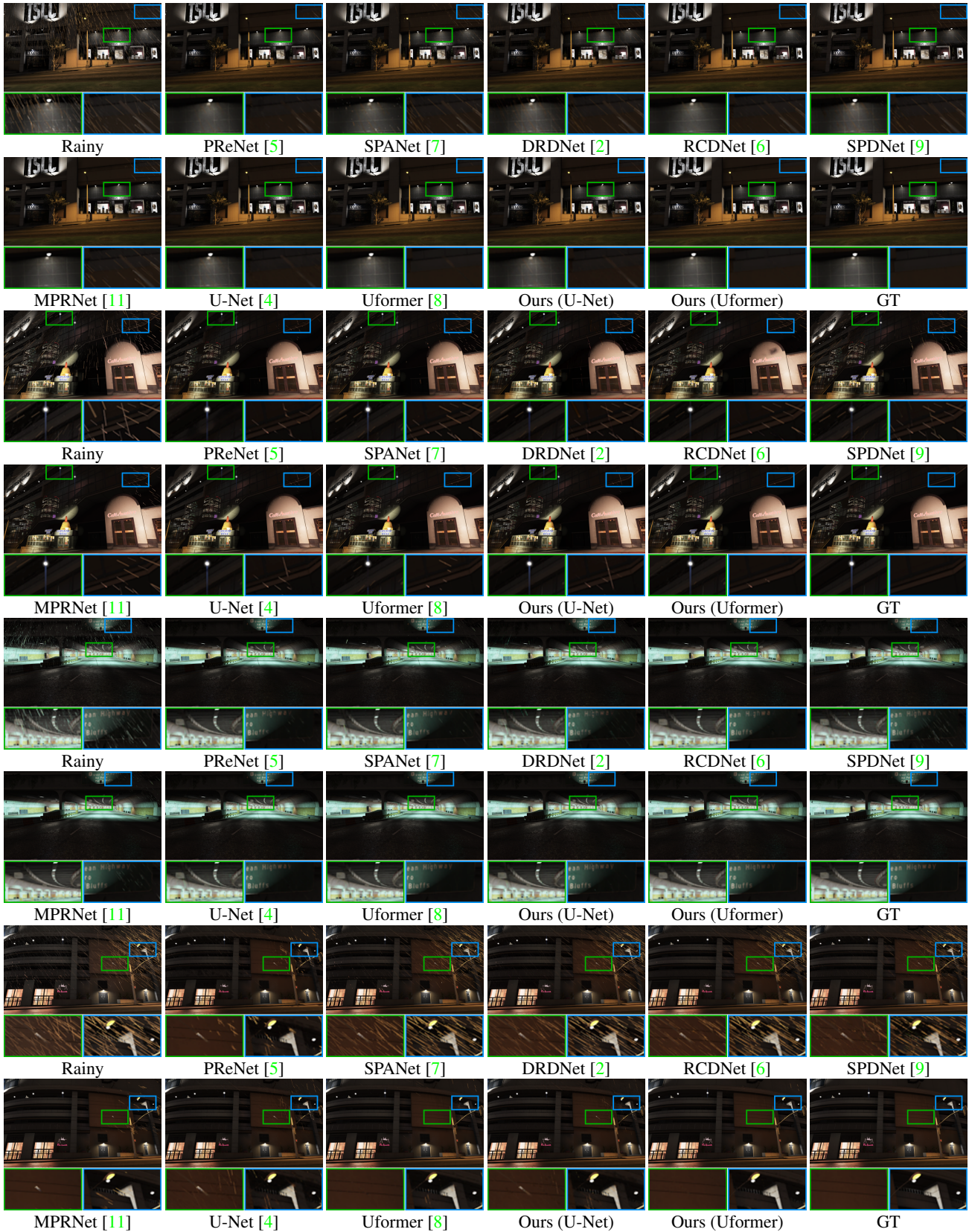


Figure 2: Qualitative results on synthetic data, brightness is adjusted for better visualization. Please zoom in for more details.

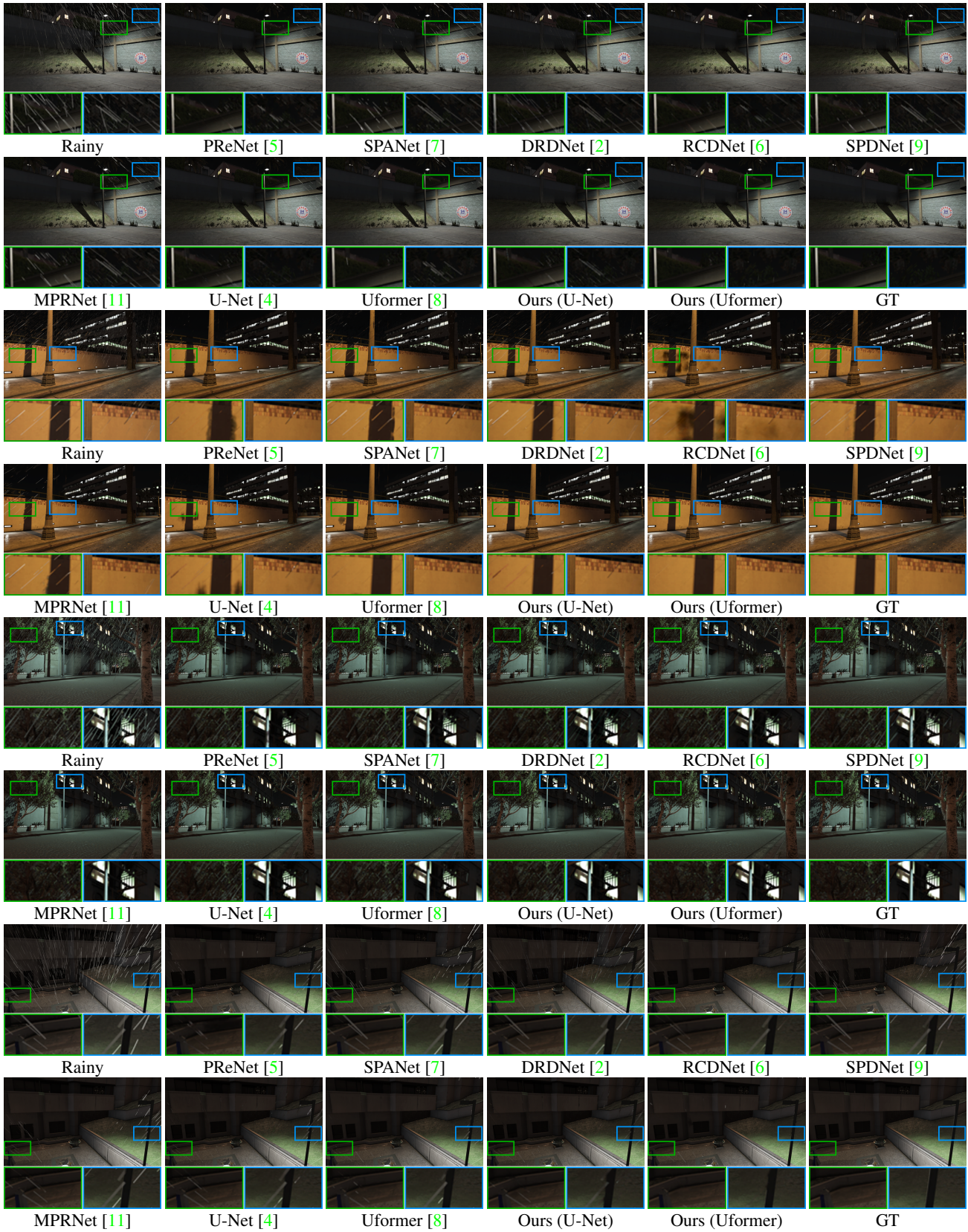


Figure 3: Qualitative results on synthetic data, brightness is adjusted for better visualization. Please zoom in for more details.



Figure 4: Qualitative results on synthetic data, brightness is adjusted for better visualization. Please zoom in for more details.

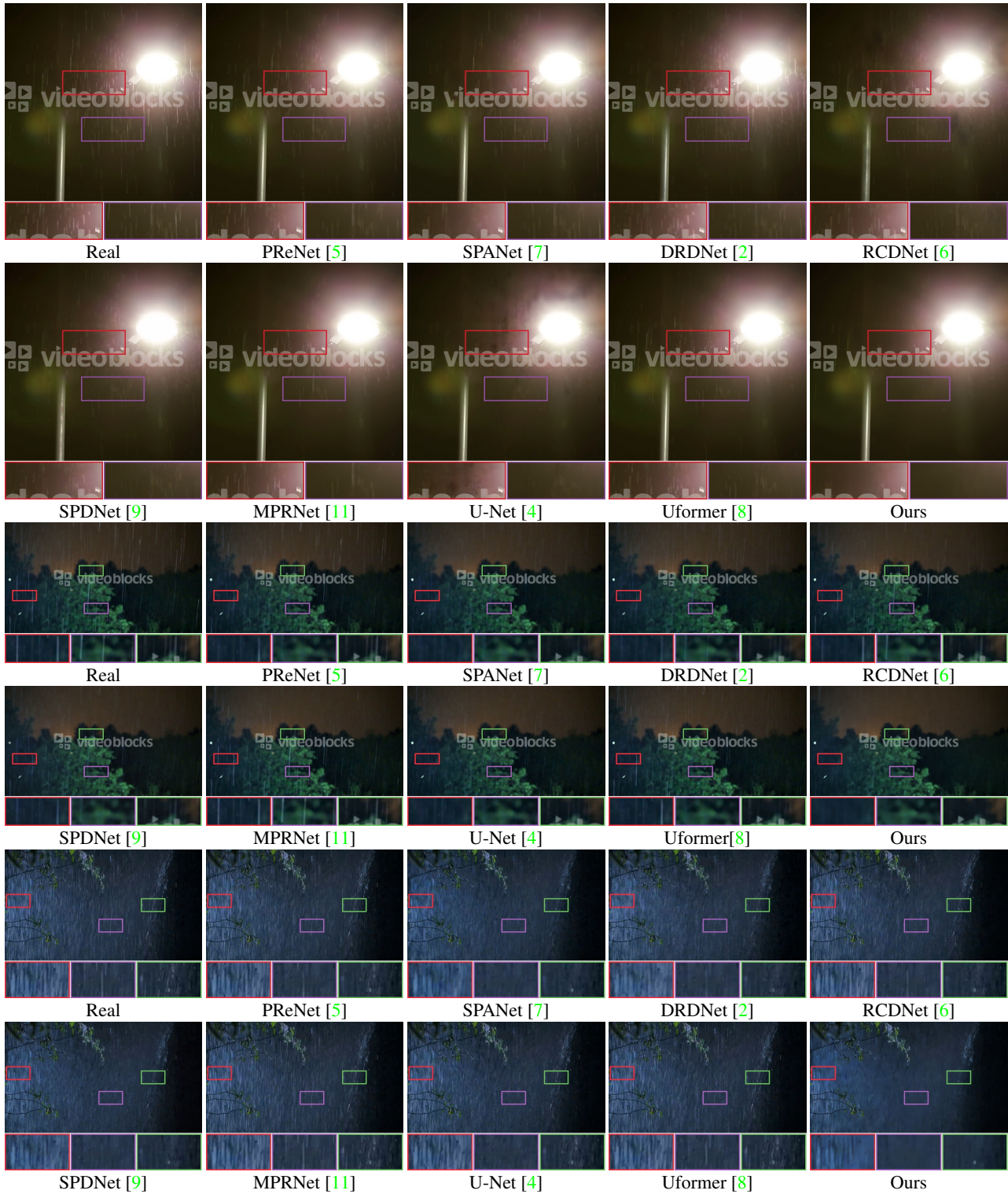


Figure 5: Qualitative results on real night rainy images. Please zoom in for details.

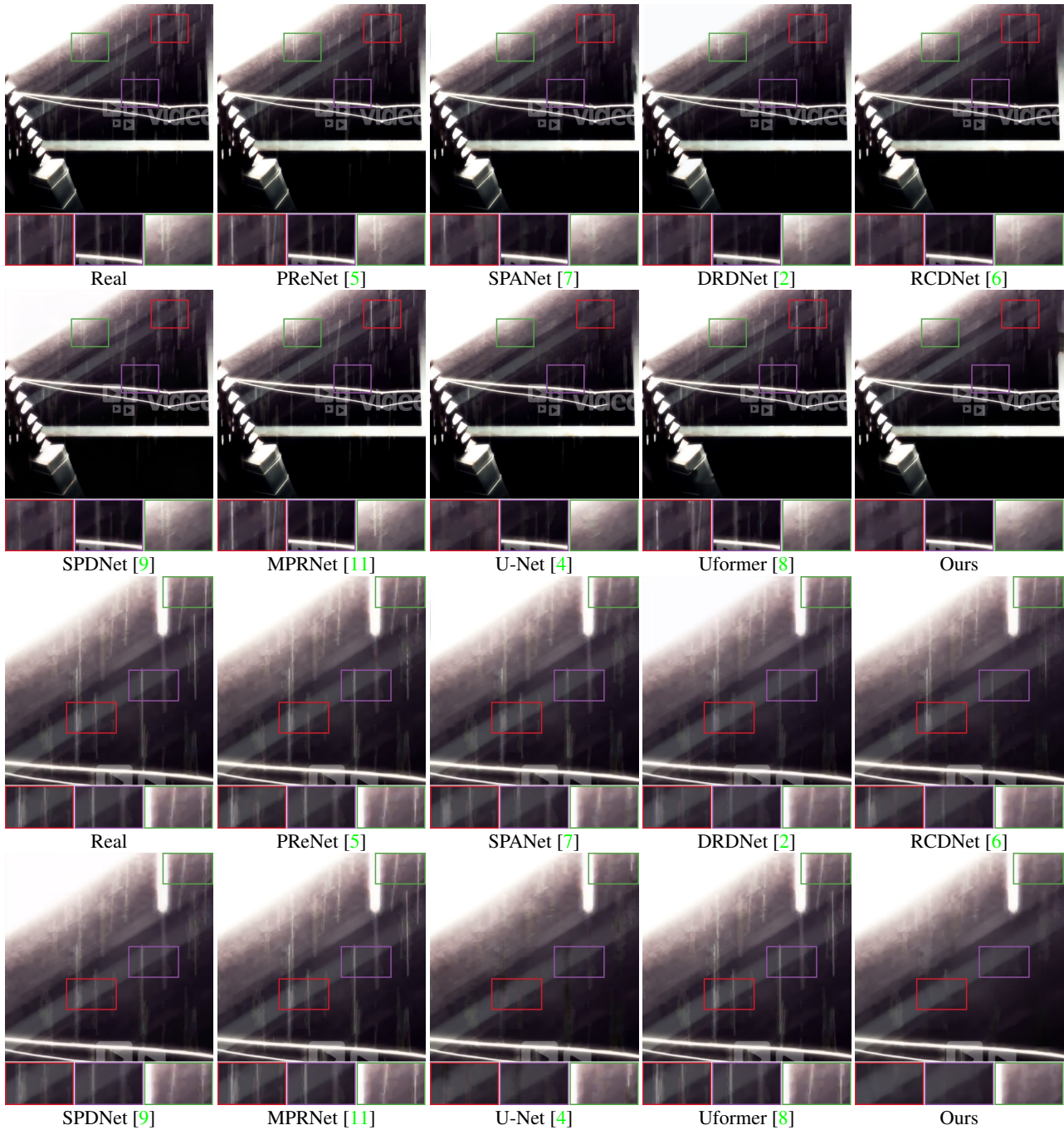


Figure 6: Qualitative results on real night rainy images. Please zoom in for details.

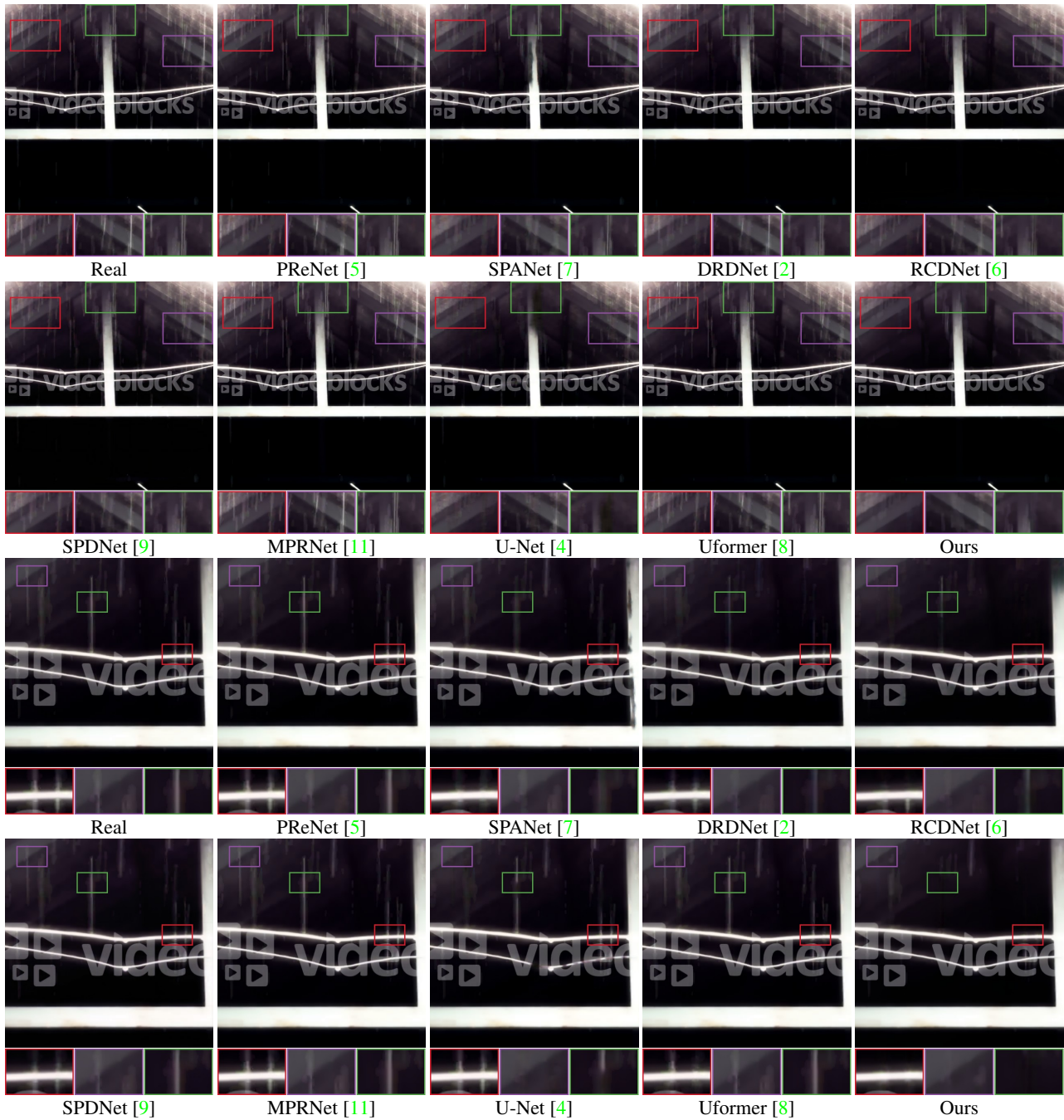


Figure 7: Qualitative results on real night rainy images. Please zoom in for details.

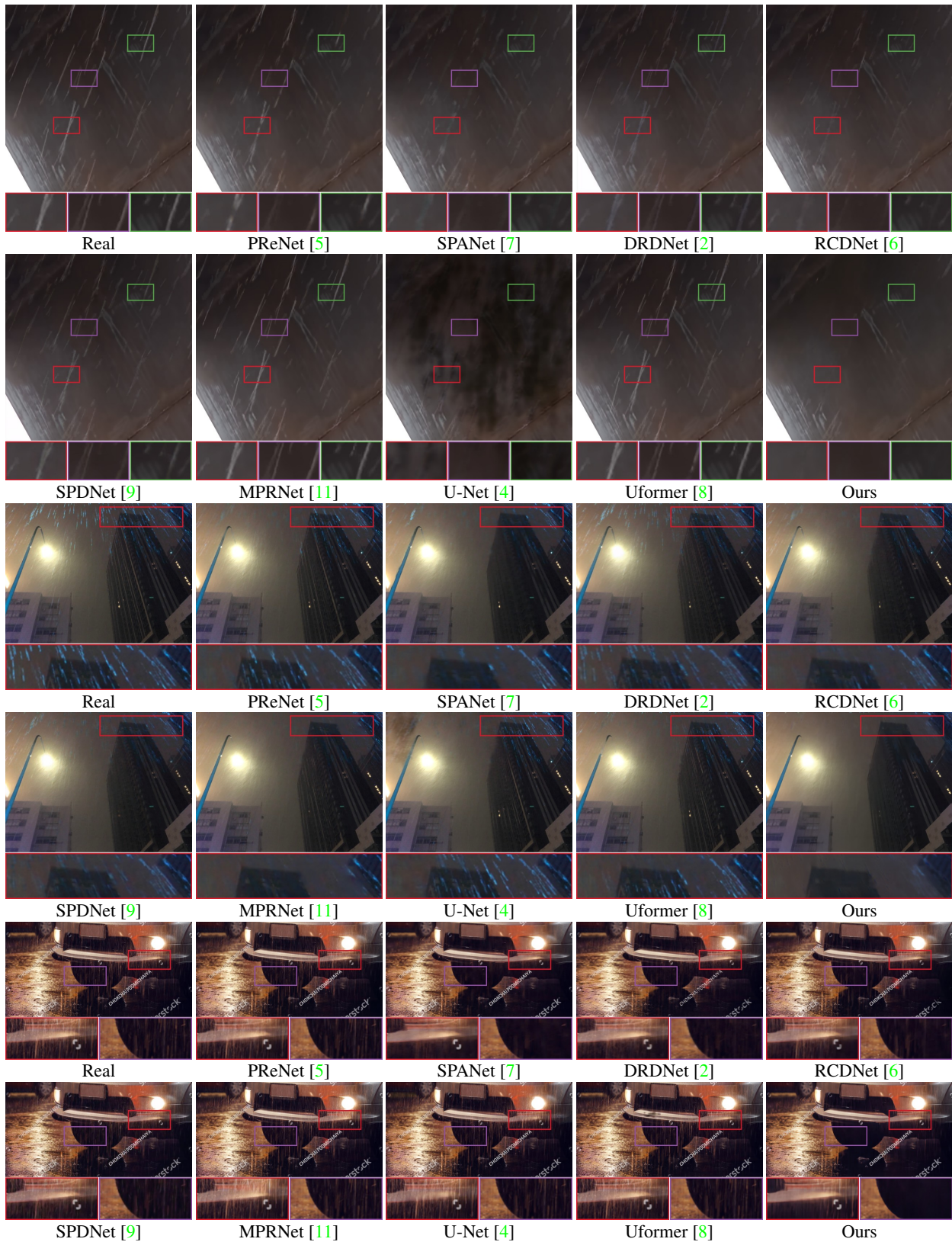


Figure 8: Qualitative results on real night rainy images. Please zoom in for details.