FLUID: Few-Shot Self-Supervised Image Deraining (Supplementary Material)

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Data Augmentation	Parameters	1-shot	3-shot	5-shot
No Augmentation	-	23.6	19.4	17.2
Image Jitter	r1 = 0.8	41.3	37.52	28.9
Scale	r2 = [0.9, 1.1]	27.1	26.5	23.1
Translate	r3 = [-0.1, 0.1]	29.8	27.4	25.2
Rotation (R)	r4 = [-180°, 180°]	**17.8**	**14.8**	**12.1**
R + Image Jitter	r4 and r1	33.5	30.1	28.8
R + Scale	r4 and r2	20.3	19.1	18.5
R + Translate	r4 and r3	22.8	20.1	18.7

Table 1. Mean Absolute Error given by PEN trained on various data augmentation method in few shot setting. r1: probability with which a pixel could be jittered. r2: ratio range by which image is resized. r3: ratio range by which image can be translated left or right. r4: angle range by which image can be rotated with step size of 0.1°.

1. Effectiveness of Data Augmentation in PEN

We explore the effectiveness of various data augmentation methods while training PEN. Our choise of augmentations and its ranges are inspired from the SimCLR [1]. We train the PEN in few shot setting on Rain 100L. We use image jitter, scale, translate, rotation and its combination. We evaluate the performance of PEN on Mean Absolute Error (MAE) which is the mean absolute difference between predicted rain probability $\hat{p}$ and the ground truth rain probability I^L. The MAE equation is given by:

$$MAE = abs(\hat{p} - I^L) \tag{1}$$

From Table 1, we can observe that rotation as data augmentation method gives us the least MAE.

2. Additional Results

More results on object detection, semantic segmentation, as well as qualitative results in 1-shot, 3-shot and 5-shot settings on Rain 100L and DDN-SIRR datasets are provided below. The results show that our method provides significant improvement over the baseline methods across different backgrounds with just a few examples, highlighting the usefulness of the proposed methodology.

References

[1] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, pages 1597–1607. PMLR, 2020. 1

[2] Xun Huang, Ming-Yu Liu, Serge Belongie, and Jan Kautz. Multimodal unsupervised image-to-image translation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 172–189, 2018. 3

[3] Ming-Yu Liu, Xun Huang, Arun Mallya, Tero Karras, Timo Aila, Jaakko Lehtinen, and Jan Kautz. Few-Shot Unsupervised Image-to-Image Translation. In *ICCV*, 2019. 3

[4] Kuniaki Saito, Kate Saenko, and Ming-Yu Liu. Coco-funit: Few-shot unsupervised image translation with a content conditioned style encoder. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16*, pages 382–398. Springer, 2020. 3

[5] Wei Wei, Deyu Meng, Qian Zhao, Zongben Xu, and Ying Wu. Semi-supervised Transfer Learning for Image Rain Removal. In *CVPR*, 2019. 2

[6] Rajeev Yasarla, Vishwanath A Sindagi, and Vishal M Patel. Syn2real Transfer Learning for Image Deraining using Gaussian Processes. In *CVPR*, 2020. 2

[7] He Zhang, Vishwanath Sindagi, and Vishal M Patel. Image De-Raining Using a Conditional Generative Adversarial Network. *IEEE transactions on circuits and systems for video technology*, 2019. 2

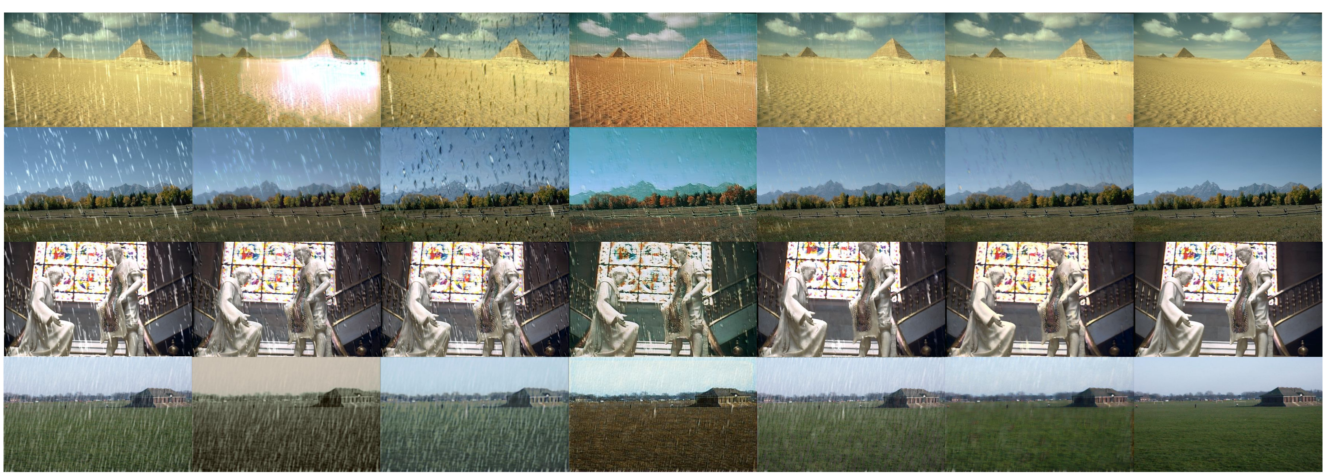
[8] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networkss. In *Computer Vision (ICCV), 2017 IEEE International Conference on*, 2017. 3

Input Rainy Image **ID-CGAN [7]** **Wei *et al*. [5]** **Yasarla *et al*. [6]** **Ours** **Rainy2Clean** **Ground Truth**

Figure 1. **Qualitative deraining results in 1-shot setting:** Qualitative results on Rain 100L and DDN-SIRR datasets

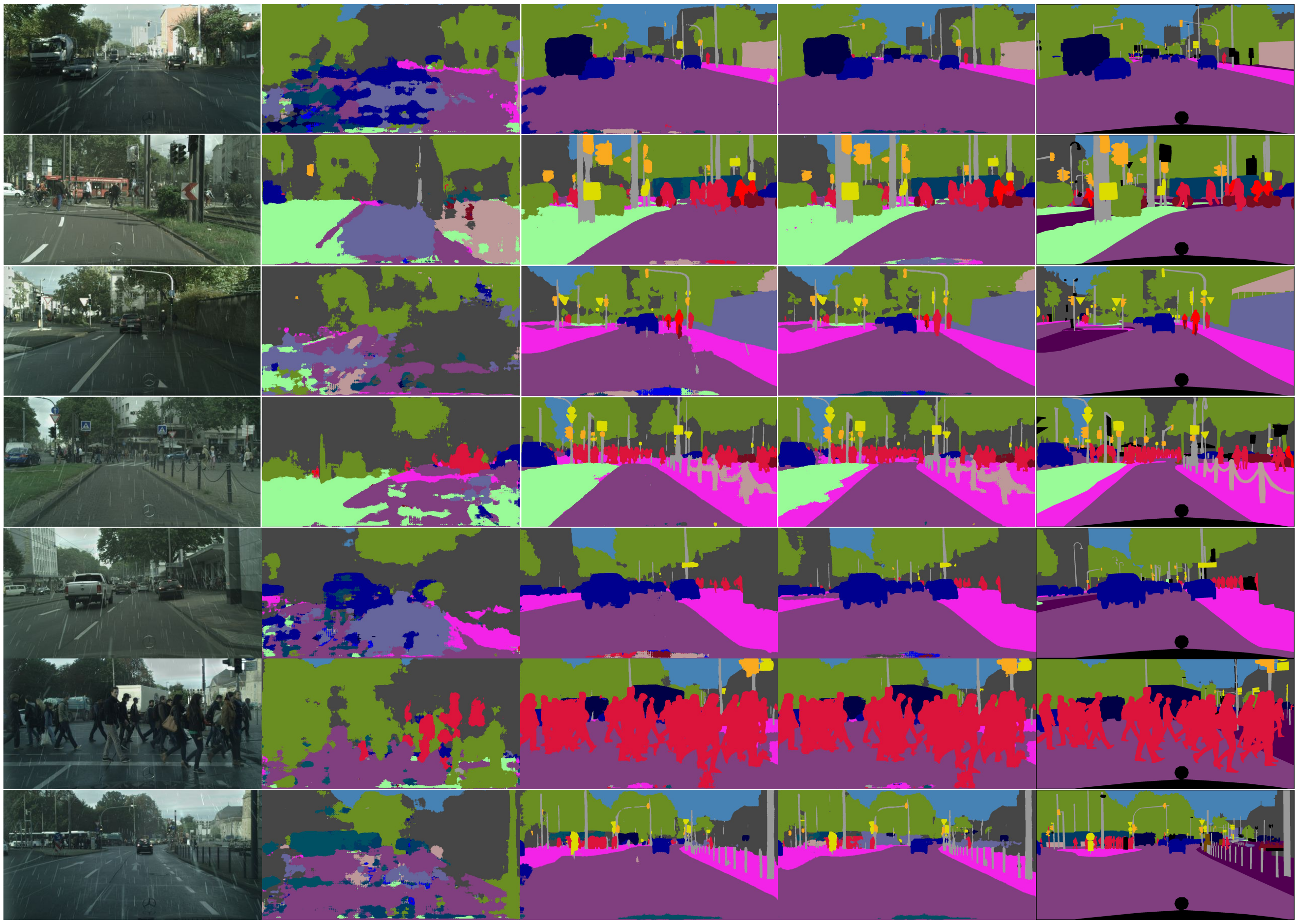
Input Rainy Image **ID-CGAN [7]** **Wei *et al*. [5]** **Yasarla *et al*. [6]** **Ours** **Rainy2Clean** **Ground Truth**

Figure 2. **Qualitative deraining results in 3-shot setting:** Qualitative results on Rain 100L and DDN-SIRR datasets



Input Rainy Image **ID-CGAN [7]** **Wei *et al*. [5]** **Yasarla *et al*. [6]** **Ours** **Rainy2Clean** **Ground Truth**

Figure 3. **Qualitative deraining results in 5-shot setting:** Qualitative results on Rain 100L and DDN-SIRR datasets

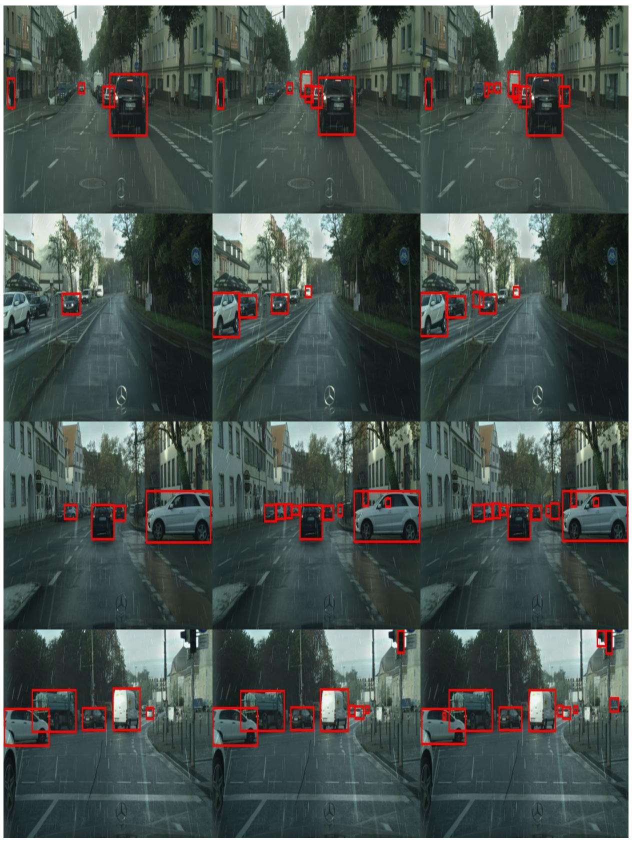


(a) Input Rainy Image (b) Yasarla *et al.* (c) Ours (d) Rainy2Clean (e) Ground Truth

Figure 4. **Additional Semantic Segmentation Results**

Input Rainy Image **Ground Truth** **FLUID (Ours)** **CycleGAN [8]** **MUNIT [2]** **FUNIT [3]** **COCO-FUNIT [4]**

Figure 5. **Additional comparison with image-to-image translation methods.**



(a) Yasarla et al. (b) Ours (c) Rainy2Clean

Figure 6. **Additional Object Detection Results**