Supplementary Material for "RainFlow: Optical Flow under Rain Streaks and Rain Veiling Effect"*

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1. Data Scheduling

In our experiments, we also compare the effects of using different data scheduling to train our network. We train our network using the dataset scheduling schemes suggested by [1, 3] (FlyingChair → FlyingThings) with long learning rate schedule S_{long}. Our network presented in the main paper is trained on a mix of the FlyingChair and FlyingThings datasets (ChairThings dataset). As shown in Table 1, we find that sequentially training on *FlyingChair+FlyingThings3D* (rendered with rain) does not perform as good as mixing the two datasets randomly at the beginning of every training epoch. For training our method on mixed FlyingChair and FlyingThings, our cropped image size is set to 256×448 instead of 320×448 described in [3]. As one can see from the table, training our method on the mixed data has significant improvement on the performance on Sintel dataset.

Table 1: Performance comparison of different training schedule.

Schedule Condition	Sintel		VKITTI	
	clean	rain	clean	rain
FlyingChair → FlyingThings	3.84	4.88	8.52	8.62
Mixed	2.61	4.59	6.90	8.27

2. More Results

We demonstrate more qualitative results of our algorithm compared with the state of the art optical flow methods on VKITTI, Sintel, FVR-660 and real world rain data. Fig. 1 and Fig. 2 show the results on the rain sequences of VKITTi dataset. One can find that our algorithm is able to predict the correct objects boundaries on the background trees and buildings. However, PWC-Net [3] trained on rain images tends to blur out the background images. RobustFlow does not perform well on large displacement regions. In addition, the road and background color of VKITTI data is close to achromatic color, therefore the residue channel of [2] may have significant information loss. As a result, the predictions on these areas are also poor.

Fig. 3 and Fig. 4 show the results of our method and baseline methods tested on the sintel data rendered with rain streaks [2]. The RobustFlow [2] does not perform well on the dark and achromatic background in Fig. 3 because of the insufficient performance of residue channel. One can see that the shape of the humans in the image is not affected by the rain streaks as severe as PWC-rain [3] .

Fig. 5 shows the results of our method and baseline methods tested on the FVR-660 data. From the figure, although RobustFlow [2] produces sharp boundaries for the moving objects in the rainy scenes, it also creates halo effects around the object boundaries due to the decomposition schema introduced in its objective function.

Finally, we also test our algorithm by comparing with baselines on the real world rain data as shown in Fig. 6. RobustFlow [2] creates more halo effects on the boundaries of the moving vehicles. It may be caused by the gray color road and the reflection of the headlight. The PWC-Net [3] trained under rain images does not work well on the real rain sequences, producing many spurious flow estimates due to the presence of dense rain streaks. However, our network is designed to handle rain streak and rain accumulation, hence is able to produce clean motion of the moving vehicles in the rainy scenes.

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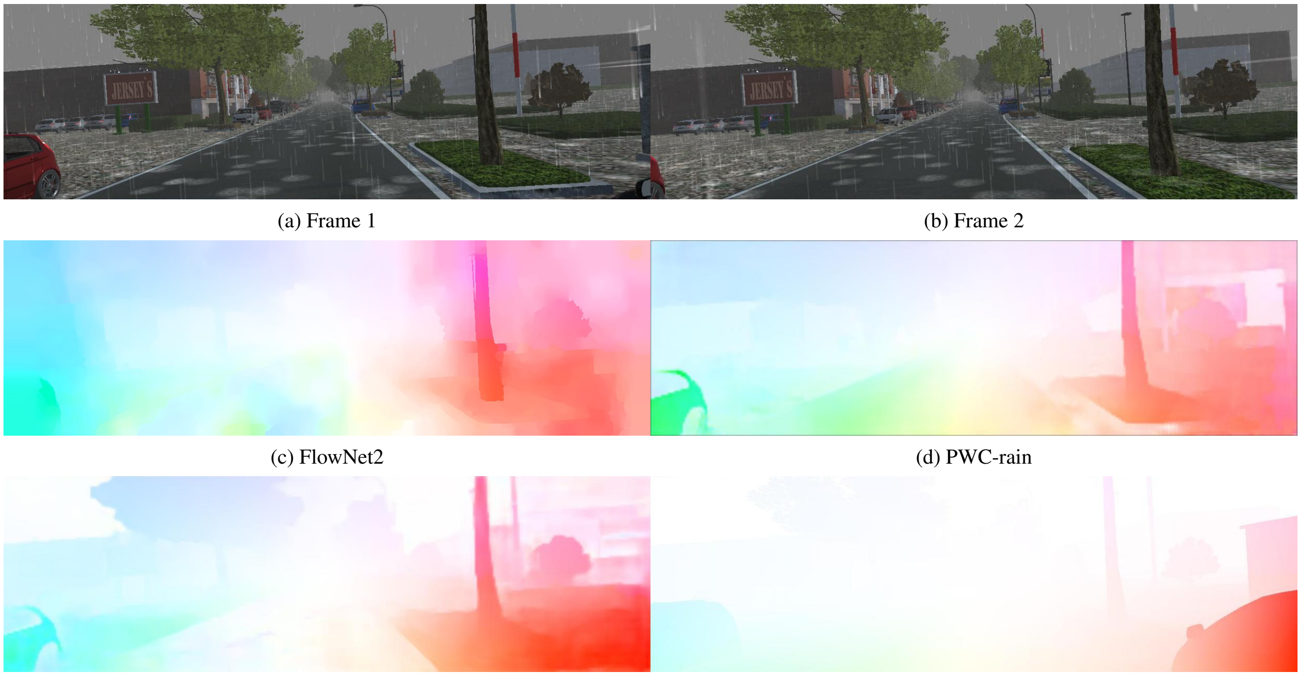


(a) Frame 1 (b) Frame 2

(c) FlowNet2 (d) PWC-rain

(e) Ours (f) Ground Truth

Figure 1: Qualitative comparison between our method and baseline methods on VKITTI dataset.

References

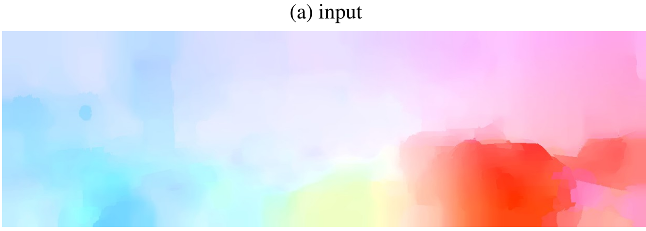
[1] A. Dosovitskiy, P. Fischer, E. Ilg, , V. Golkov, P. Häusser, C. Hazırbaş, V. Golkov, P. Smagt, D. Cremers, , and T. Brox. Flownet: Learning optical flow with convolutional networks. In *IEEE International Conference on Computer Vision (ICCV)*, 2015.

[2] R. Li, R. T. Tan, and L.-F. Cheong. Robust optical flow in rainy scenes. In *The European Conference on Computer Vision (ECCV)*, September 2018.

[3] D. Sun, X. Yang, M.-Y. Liu, and J. Kautz. PWC-Net: CNNs for optical flow using pyramid, warping, and cost volume. In *CVPR*, 2018.

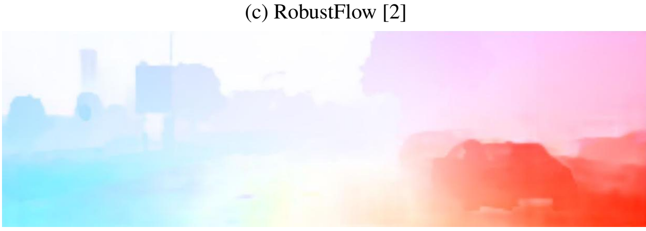
(a) input

(b) Red Feature @ Level 2

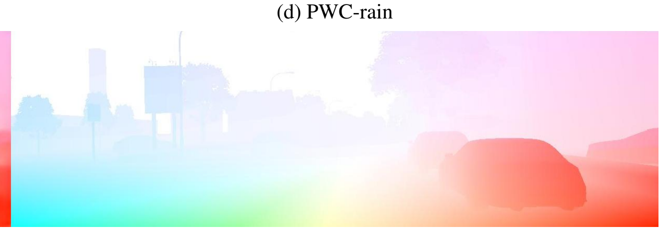


(c) RobustFlow [2]

(d) PWC-rain

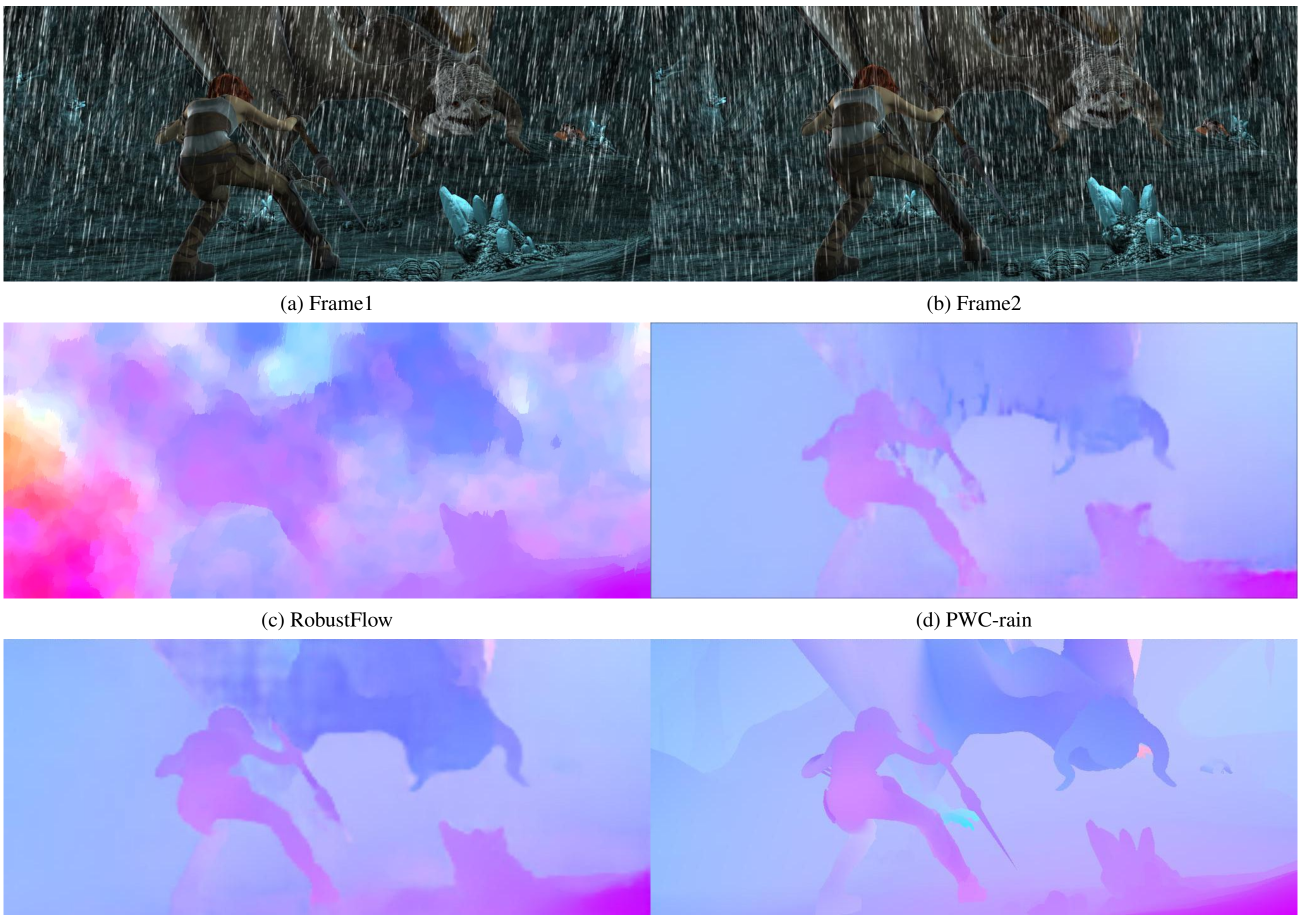


(e) Green Feature @ Level 2



(f) Ground Truth

Figure 2: Qualitative comparison between our method and baseline methods on VKITTI dataset.

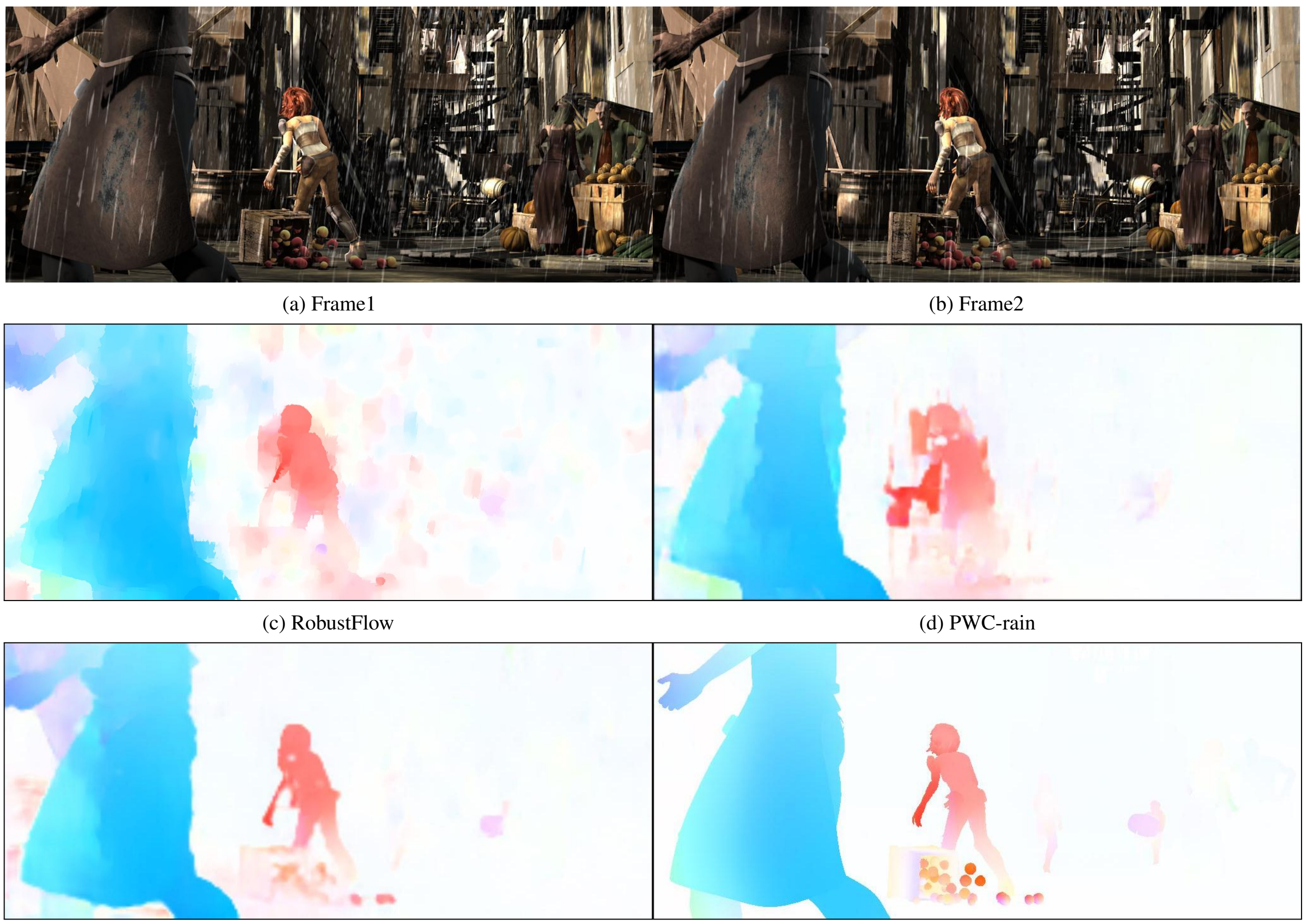


(a) Frame1 (b) Frame2

(c) RobustFlow (d) PWC-rain

(e) ours (f) Ground Truth

Figure 3: Qualitative comparison between our method and baseline methods on Sintel dataset.



(a) Frame1 (b) Frame2

(c) RobustFlow (d) PWC-rain

(e) ours (f) Ground Truth

Figure 4: Qualitative comparison between our method and baseline methods on Sintel dataset.

(a) Frame1 (b) Frame2

(c) RobustFlow (d) PWC-rain

(e) ours (f) Ground Truth

Figure 5: Qualitative comparison between our method and baseline methods on FVR dataset.


(a) Frame1


(b) Frame2


(c) RobustFlow


(d) PWC-rain


(e) ours

Figure 6: Qualitative comparison between our method and baseline methods on real world rain data.