A. Additional Material for Experiments

We provide the code to generate the weather augmentations and run all adversarial weather attacks at https://github.com/cv-stuttgart/DistractingDownpour. The tested optical flow networks utilize the respective author-provided PyTorch implementations with Sintel-checkpoints for FlowFormer [2], GMA [10], RAFT [10] and FlowNetCRobust [9]. For FlowNet2 [3] and SpyNet [6] we use the implementations from [7] and [5], respectively.

A.1. Weather augmentations: Configurations

In Tab. A.1 we give a full list of parameter configurations for the particle effects from Main Tab. 2. In addition to the weather visualizations in Main Fig. 4, we visualize all Size-variations for particles in Fig. A.1 and all Particle count, Motion blur and color variations in Fig. A.2. From these figures it becomes clear that the configurations size: small, motion blur: 0.0 and color: white all visually correspond to snow. Therefore, they were not chosen as four main weather effects. Instead, we selected configurations that lead to more diverse visual appearance, even though these configurations were not necessarily the most effective ones to perturb the optical flow output in Main Tab. 2.

A.2. Adversarial weather attacks

A.2.1 Attack Configurations

With the provided code and the network implementations above, Tab. A.2 lists the configurations for all weather attacks that were used to create Tables 4, 5 and 6 from the Main paper. To compare to PCFA [8] and I-FGSM [9], we use the implementation from [8] and the author-provided configurations for PCFA with $\varepsilon_2 = 5e-3$, AEE loss, COV constraint and disjoint, non-universal perturbations. For I-FGSM we use a perturbation bound of $\varepsilon_\infty = 5e-3$ and 25 optimization steps. Both attacks are run on Sintel train.

A.2.2 Additional configurations for training with snow

Regarding the configurations for the snow-augmented training in Sec. 4.3, Main Tab. 7 uses snow, rain, sparks and fog augmentations as specified in Tab. A.1 and the respective attack configurations that were used for Main Tab. 5, which are listed in Tab. A.2.

A.2.3 Additional visualizations for weather attacks

Finally, in Figures A.3, A.4, A.5 and A.6 we provide additional visualizations for attacks with snow, rain, sparks and fog. They complement Main Fig. 6, and provide visualizations for sample images from the attack runs in Main Tab. 5.

References

<table>
<thead>
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<th>Weather</th>
<th>Particle base properties</th>
<th>Color properties</th>
<th>Motion properties</th>
<th>Motion blur</th>
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<tr>
<td>Count</td>
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<td>d-decay</td>
<td>Templates</td>
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<td>71</td>
<td>9</td>
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Table A.1. Particle configurations for Sintel train dataset augmentations from Main Tab. 2. It additionally lists the grey particle configuration used in Main Tab. 4. d-Decay is a depth-decay parameter that affects the size, δH, δL and δS are random color variations in the HLS space around the initial RGB color configurations. While all effects use a depth-dependent transparency scaling, fog has a depth-constant transparency of 0.3. The motion m is always along the y-axis (vertically, m = m2 = 0), and may vary by a random angle δ∥ or be scaled by a random factor that scales with a fraction of ∥m∥. All configurations were created with 8 GPUs and a random seed of 0. To train RAFT on another snow dataset than the test set (Main Tab. 7), the training set uses a random seed of 1234.

Table A.2. Weather attack configurations for the experiments from Main Tables 4, 5 and 6. Augment specifies the augmentation, cf. Tab. A.1. LR denotes the optimizer learning rate and the optimization variables δp1, δp2, δγ, and δθ indicate which of them were optimized. Optimization with 750 steps of Adam using weights α1 = α2 = 1000 for the loss function.


Figure A.2. Augmentations for different particle count, motion blur and color from Main Tab. 2. on exemplary Sintel [1] frames. Augmentations for particle sizes are shown in Fig. A.1; augmentation parameters are listed in Tab. A.1.


Figure A.3. Snow. Qualitative results for 3000 snowflakes on images from the Sintel final dataset with random initialization and adversarial optimization with optical flow predictions for FlowNet2 [3], FlowNetCRobust [9], SpyNet [6], RAFT [10], GMA [4] and FlowFormer [2], as extension to Main Fig. 6. See also Figs. A.4, A.5 and A.6.
Figure A.4. Rain. Qualitative results for 3000 rain streaks on images from the Sintel final dataset with random initialization and adversarial optimization with optical flow predictions for FlowNet2 [3], FlowNetC Robust [9], SpyNet [6], RAFT [10], GMA [4] and FlowFormer [2] as extension to Main Fig. 6. See also Figs. A.3, A.5 and A.6.
Figure A.5. Sparks. Qualitative results for 3000 fire sparks on images from the Sintel final dataset with random initialization and adversarial optimization with optical flow predictions for FlowNet2 [3], FlowNetCRobust [9], SpyNet [6], RAFT [10], GMA [4] and FlowFormer [2] as extension to Main Fig. 6 and visualization of exemplary results from Main Tab. 5. See also Figs. A.3 and A.6.
Figure A.6. Fog. Qualitative results for 60 fog clouds on images from the Sintel final dataset with random initialization and adversarial optimization with optical flow predictions for FlowNet2 [3], FlowNetCRobust [9], SpyNet [6], RAFT [10], GMA [4] and FlowFormer [2], as extension to Main Fig. 6. See also Figs. A.3, A.4 and A.5.