Rain and deraining for images

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Why we care

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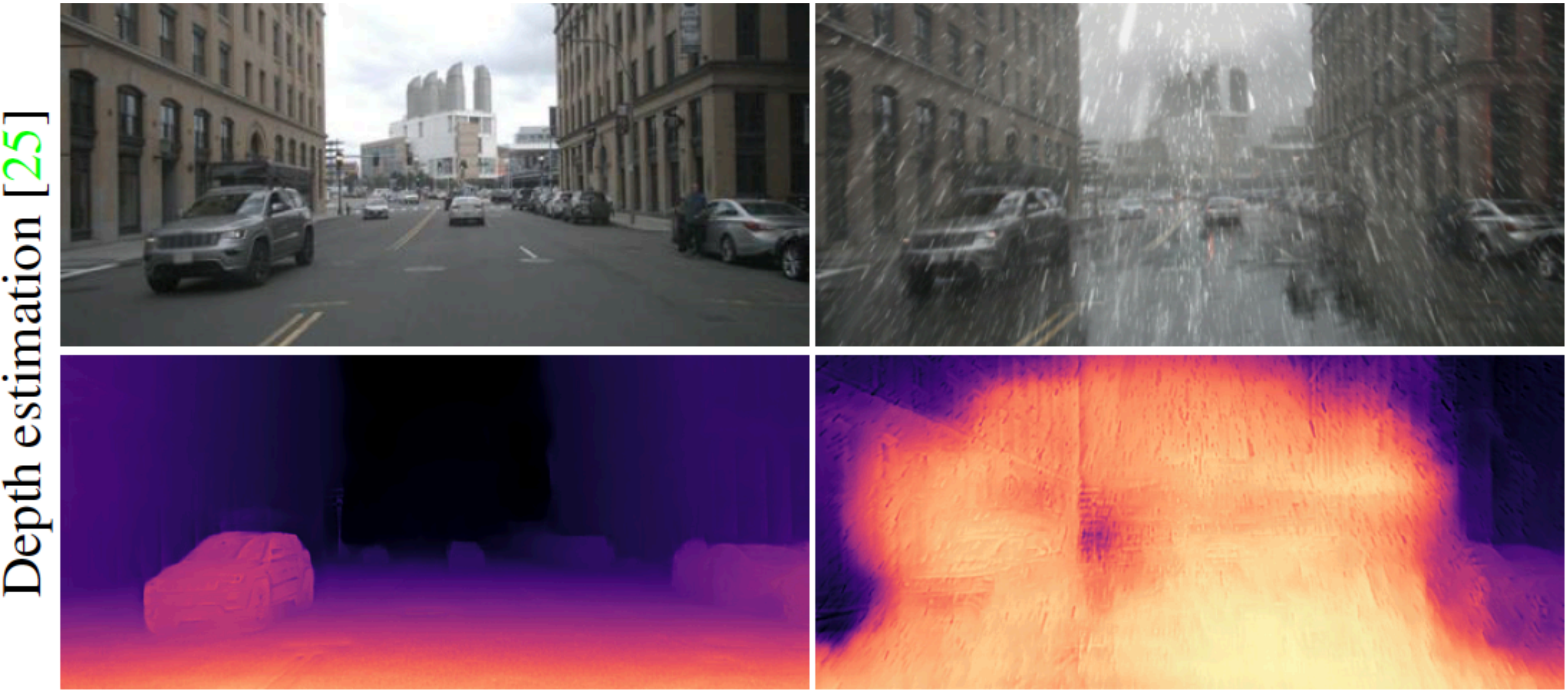
Why we care



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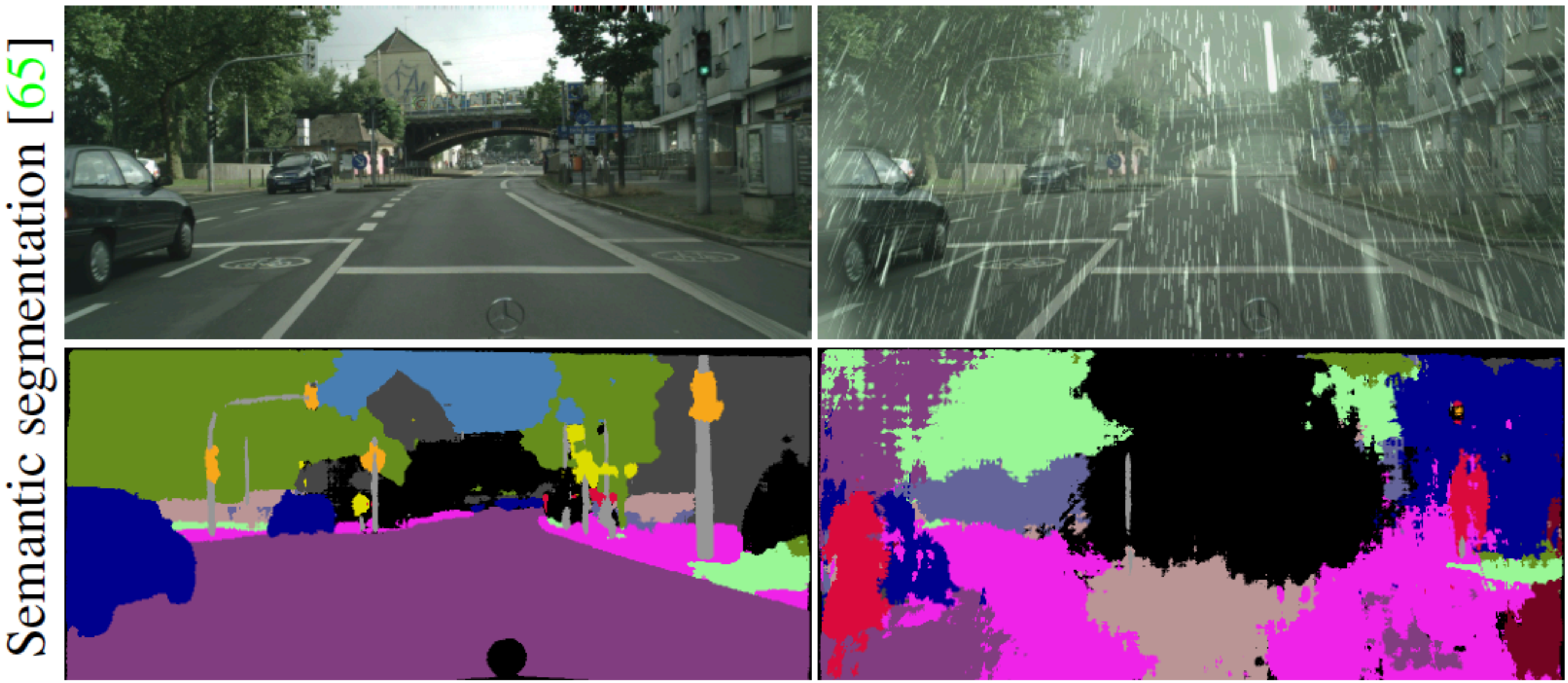
Why we care



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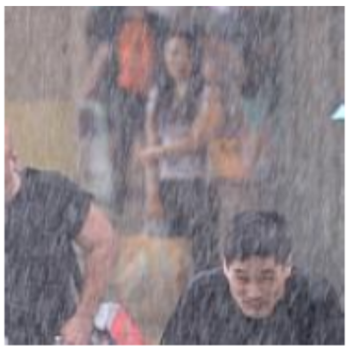
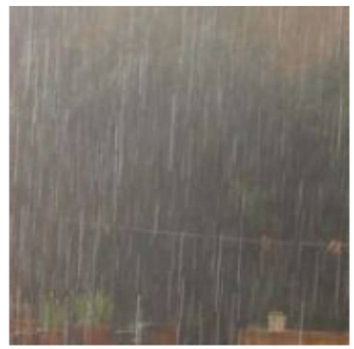
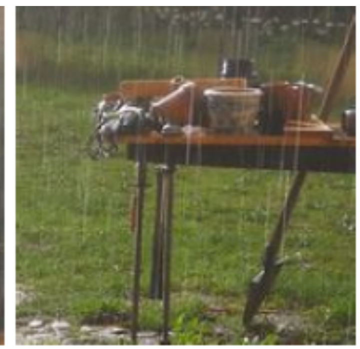
Rain has multiple interesting effects

Blur from wet air

Puddles


Color shifts

Streaks

These are often quite strongly coupled to scene geometry

Rain - multiple extrinsic phenomena,
including smoothing, raindrops, loss of saturation,
glossy/wet surfaces, etc. etc.

Rain - phenomena

Refraction causes each drop to contain a tiny image

(a) An image of a drop hanging from a pipette (b) Perspective views created from (a)

Figure 7. Looking at the world through a raindrop. (a) An image of a drop hanging from a pipette and a magnified version. (b) Near-perspective views computed using the geometric mapping due to refraction. Note that, in the perspective views, straight lines in the scene are mapped to straight lines in the image.

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Backscatter

- Refraction in drops causes backscatter of headlight light
  - makes driving in rain at night harder
- Neat trick
  - (Tamburo et al 14)
  - Do not illuminate raindrops by
    - having headlights that are highly steerable (multiple micro mirrors)
    - very fast exposure with usual illumination identifies raindrops
      - too fast for driver to resolve
    - now direct light between drops

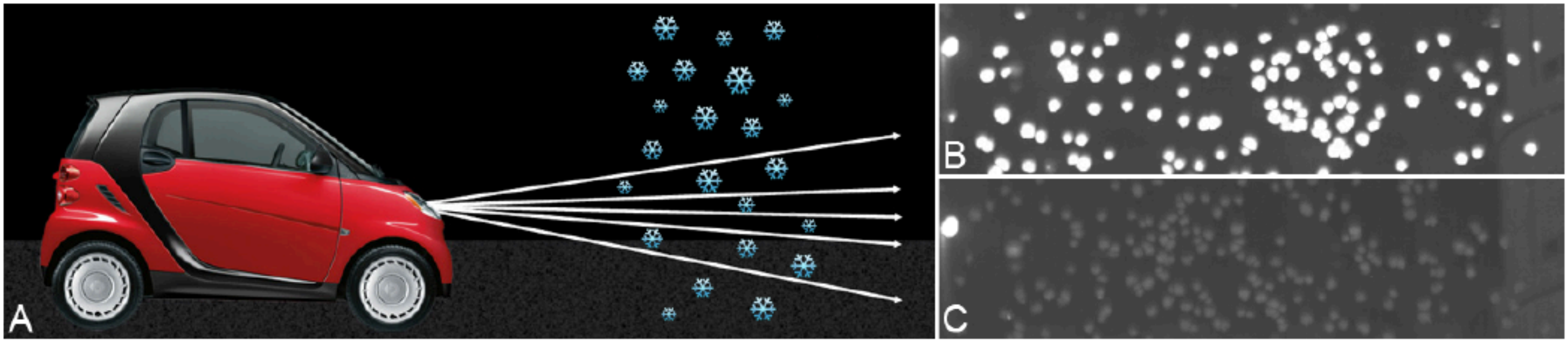
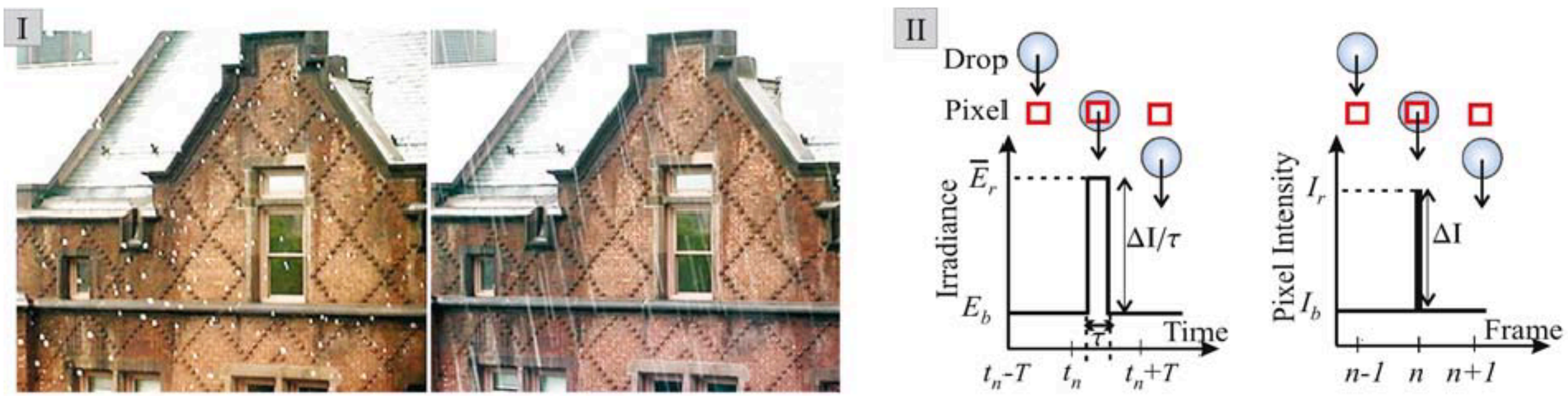


Fig. 7. A: Our headlight has unprecedented resolution over space and time so that beams of light may be sent in between the falling snow. Illustration adapted from [11]. B: Artificial snowflakes brightly illuminated by standard headlight. C: Our system avoids illuminating snowflakes making them much less visible.

Rain - phenomena

Drops move fast, and so create motion blur (streaks)



(a) Short exposure time (1 ms) (b) Normal exposure time (30 ms) (a) Average irradiance at a pixel (b) Intensity at a pixel

Figure 9. (I) Raindrops and motion-blur. An image of a scene taken in rain with (a) a short exposure time of 1 ms and (b) with typical exposure time of a camera (30 ms). (II) The intensities produced by motion-blurred raindrops. II (a) The average irradiance at the pixel due to the raindrop is $\bar{E}_r$ and that due to the background scene is E_b. Note that $\bar{E}_r > E_b$. The drop projects onto a pixel for time $\tau < 1.18$ ms, which is far less than the typical exposure time T of a camera. (b) Intensities of a pixel in three frames. A drop stays over the pixel in only a single frame and produces a positive intensity fluctuation of unit frame width.

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Rain - phenomena

Shallow free space - individual rain streaks
Deep free space - more bulk, fog-like effects

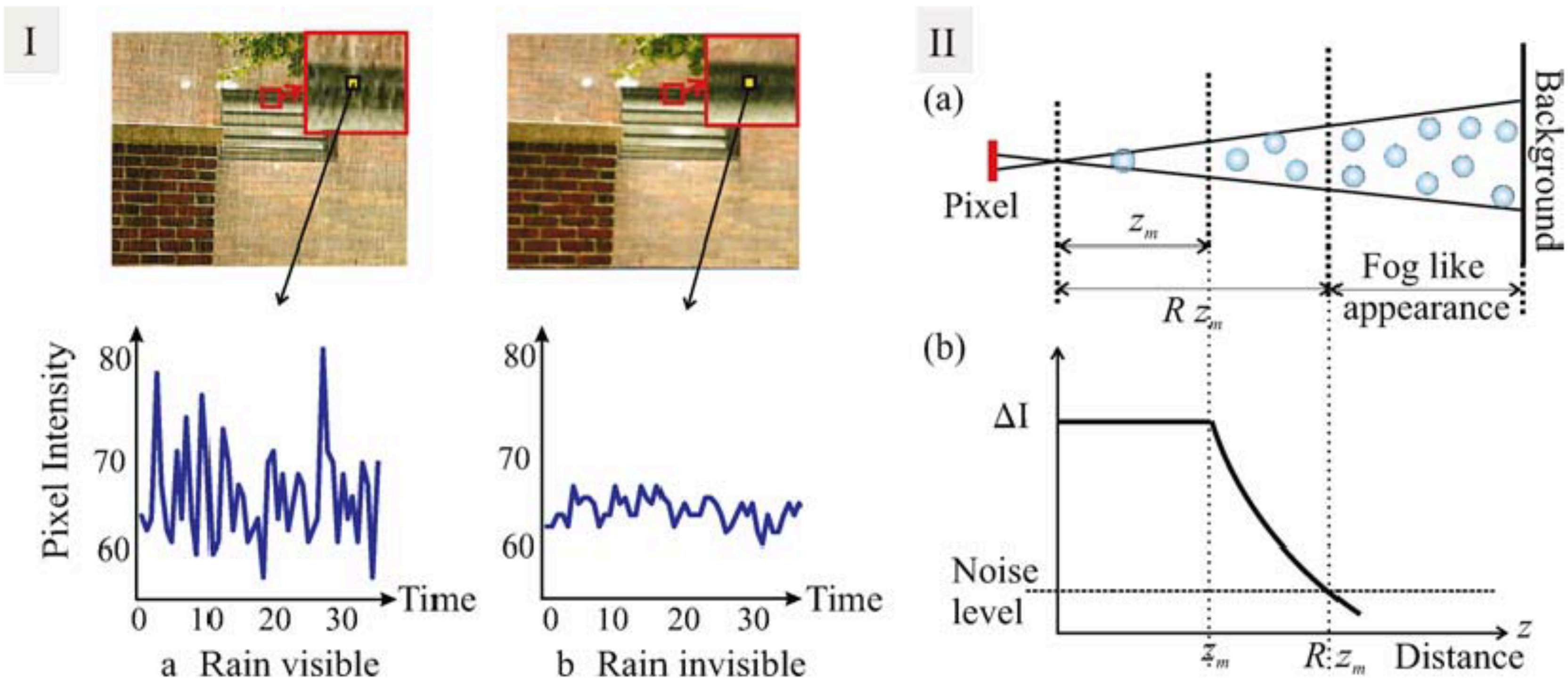

Figure 13. Dynamic weather and visibility: (I)(a) Frame from a video of a scene where rain is visible. The intensity variation due to rain is high. (b) Frame from a video of the same scene taken with camera parameters to reduce the visibility due to rain. The intensity at the same pixel shows low variance over time. (II) The change in intensity produced by a falling raindrop as a function of the drop's distance z from the camera. The change in intensity ΔI does not depend on z for drops that are close to the camera ($z < z_m$). While for raindrops far from the camera ($z > z_m$), ΔI decreases as $1/z$ and for distances greater than $R\,z_m$, ΔI is too small to be detected by the camera. Therefore, the visual effects of rain are only due to raindrops that lie close to the camera ($z < Rz_m$) which we refer to as the *rain visible region*.

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Rain - phenomena

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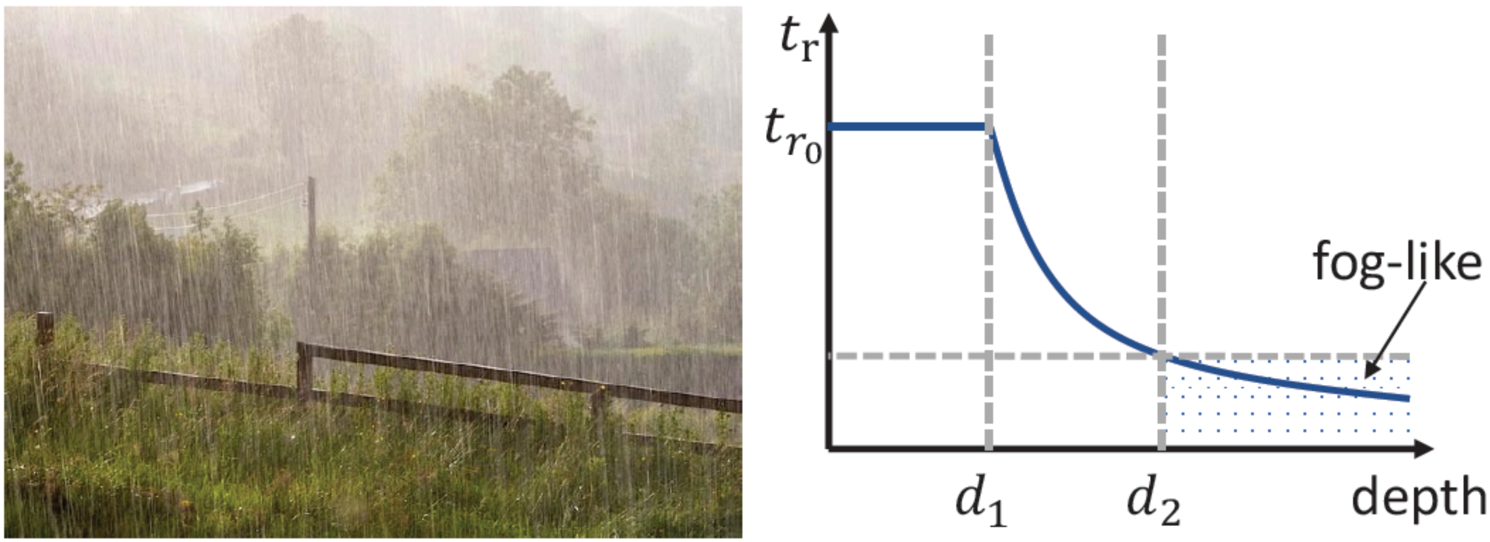

(a) input real photo (b) rain visibility & depth

Figure 1: (a) An example real photo that demonstrates the scene visibility variation with depth, and the presence of rain streaks and fog; and (b) a plot of rain streak intensity (t_r) against scene depth (d) based on the model in [13].

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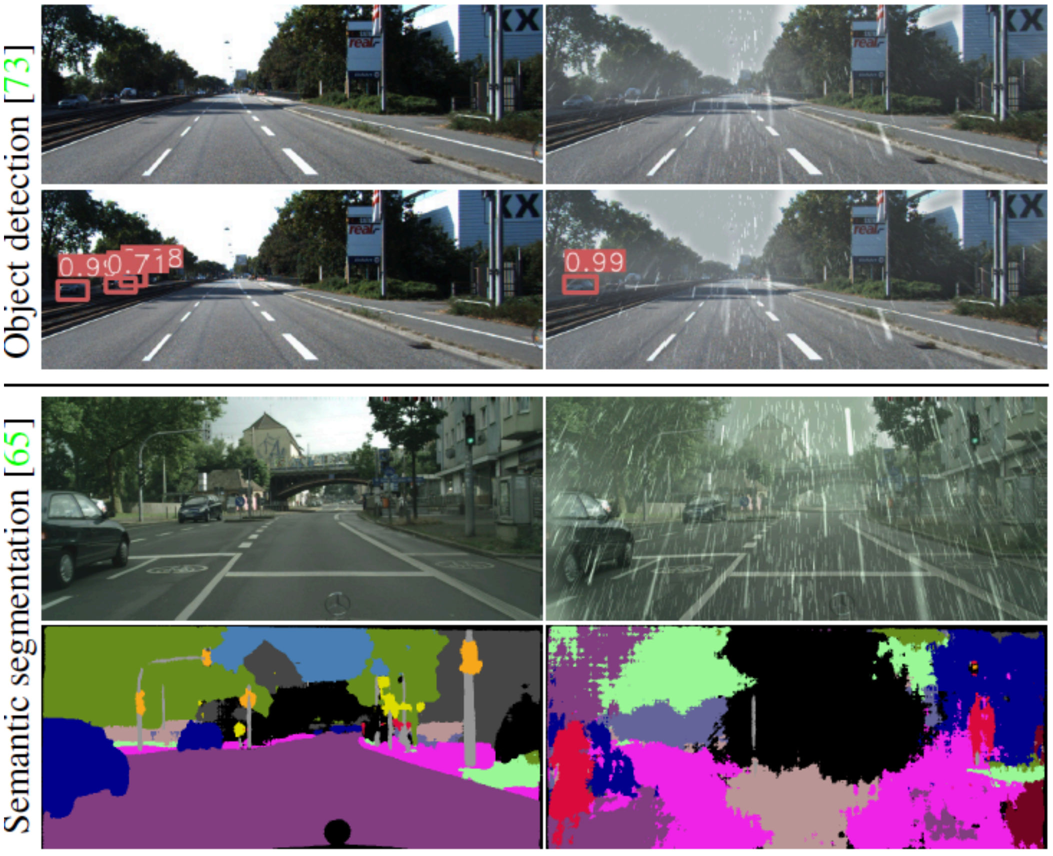
Strategies

- Train on rainy data
  - tough to get more labels in sufficient quantity
  - BUT
    - you could drive the same road many times, as above
      - and fix labels
- Simulate rain and fine-tune methods
  - labels remain the same
- Derain images

Simulating rain



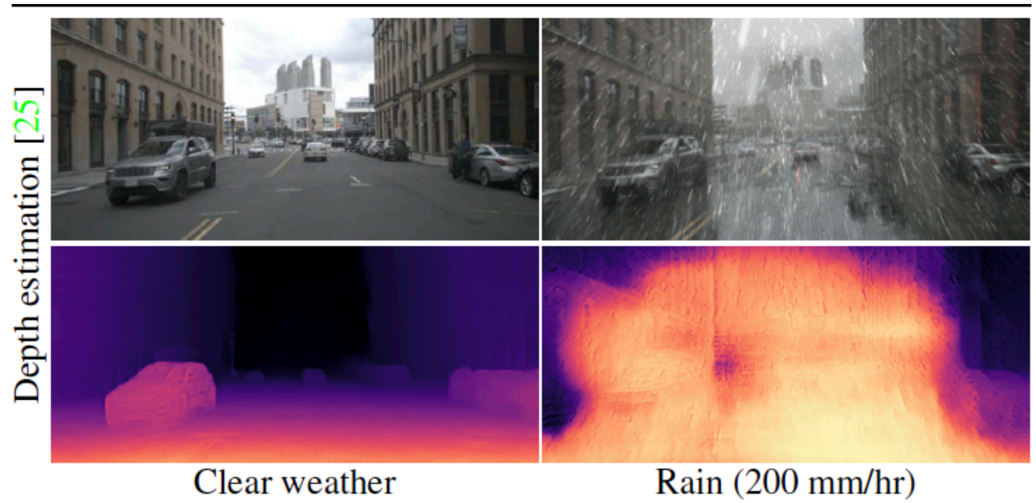


Fig. 1 Vision tasks in clear and rain-augmented images. Our synthetic rain rendering framework allows for the evaluation of computer vision algorithms in challenging bad weather scenarios. We render physically-based, realistic rain on images from the KITTI [23] (rows 1-2) and Cityscapes [13] (rows 3-4) datasets with object detection from mx-RCNN [73] (row 2), semantic segmentation from ESPNet [65] (row 4). We also present a combined data-driven and physic-based rain rendering approach which we apply to the nuScenes [9] (rows 5-6) dataset with depth estimation from Monodepth2 [25] (row 6). All algorithms are quite significantly affected by rainy conditions.

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Simulating rain - issues

- Near field:
  - drops are bright, discrete, likely ballistic motion
    - how bright?
    - where?
    - how moving?
  - likely air is “wet”
    - so some fogging, depending on depth
- Far field:
  - fog like effects
- So we need to know
  - depth, environment map, falling drops, camera movement

Simulating rain

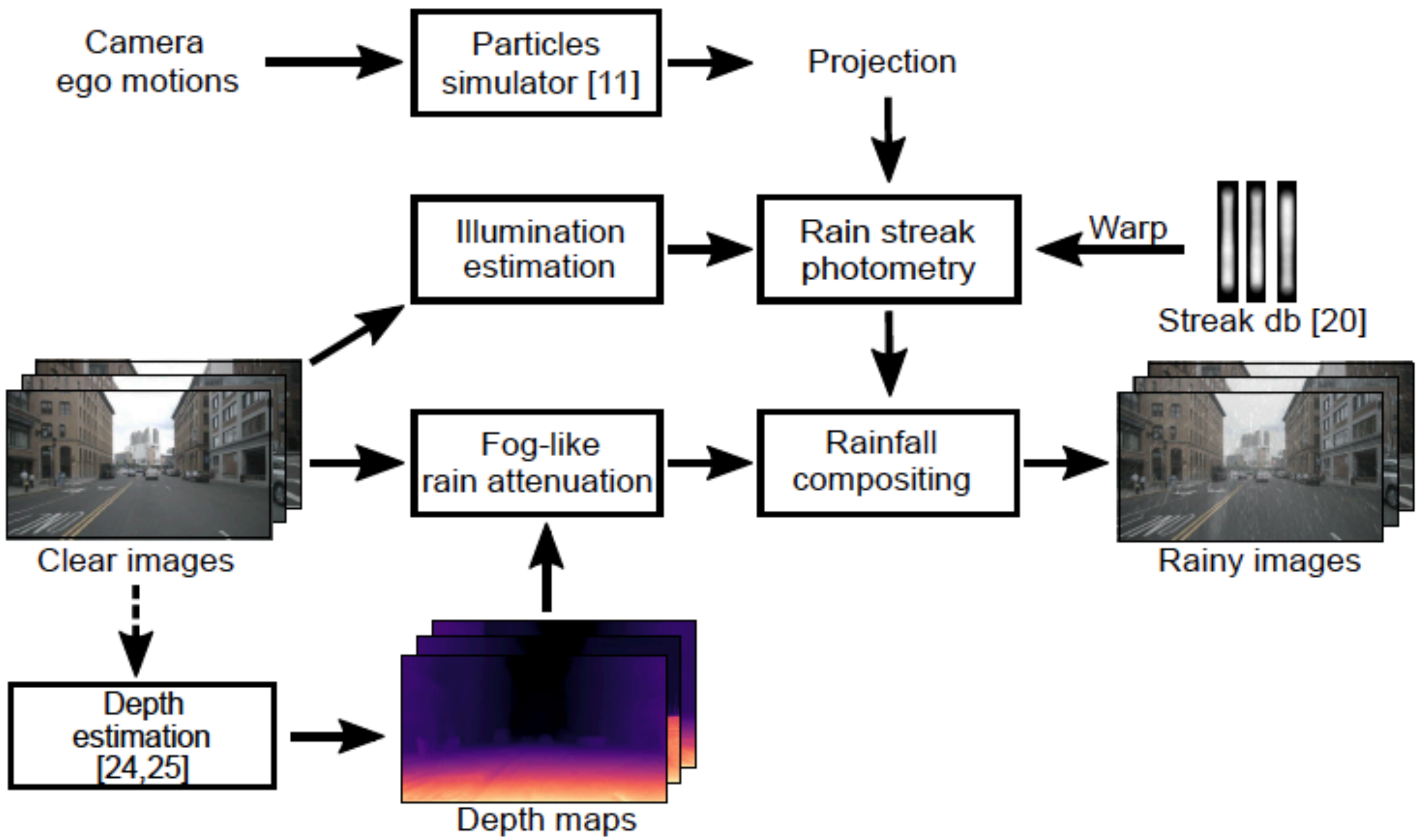

Fig. 2 Physics-Based Rendering for rain augmentation. We use particles simulation together with depth and illumination estimation to render arbitrarily controlled rainfall on clear images.

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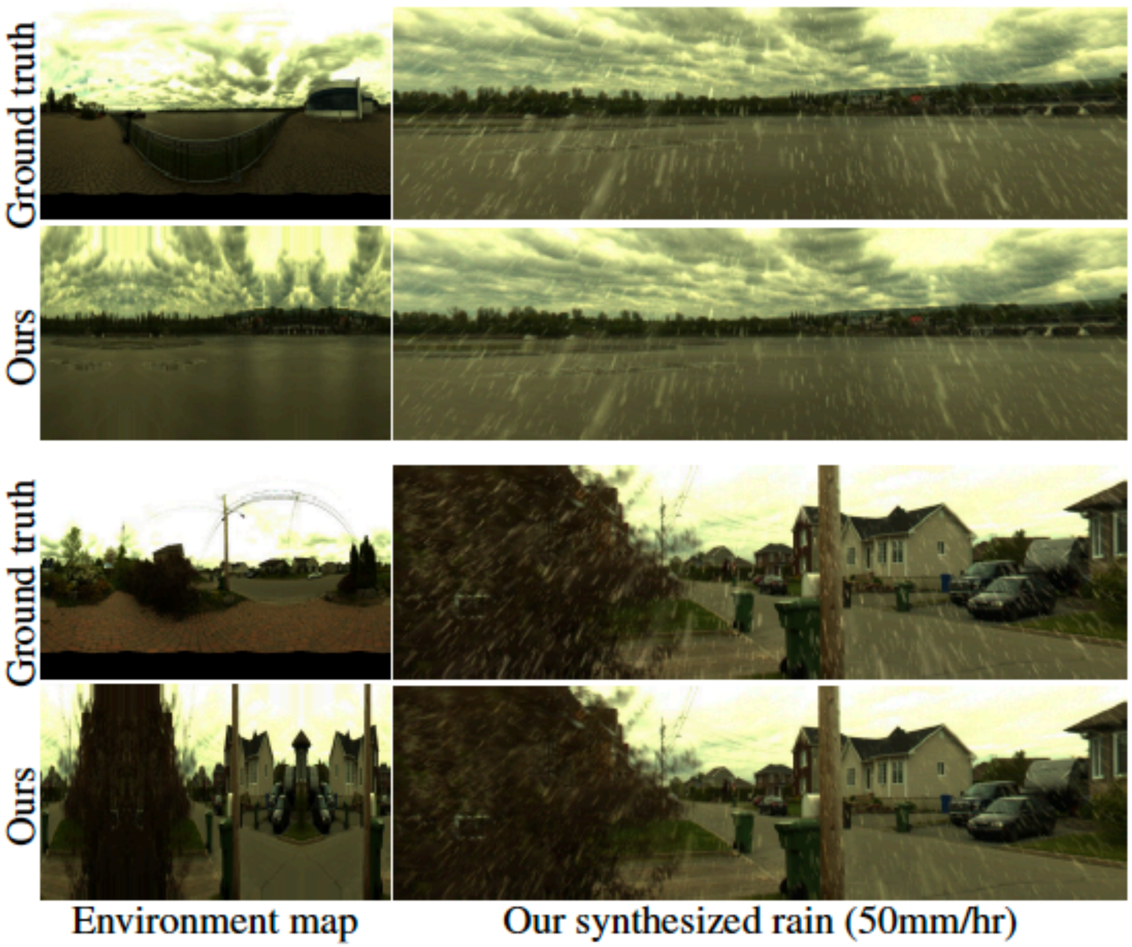
Simulating rain



Minor errors in environment map have no real effect on rain appearance

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Simulating rain

- Trick:
    - rain causes color effects, specular effects etc.
        - CycleGAN is good at this, but bad at streaks
        - Physics based simulation is bad at this but good at streaks

Fig. 5 GAN+PBR rain-augmentation architecture. In this hybrid approach, clear images are first translated into rain with CycleGAN [83] and subsequently augmented with rain streaks with our PBR pipeline (see fig. 2).

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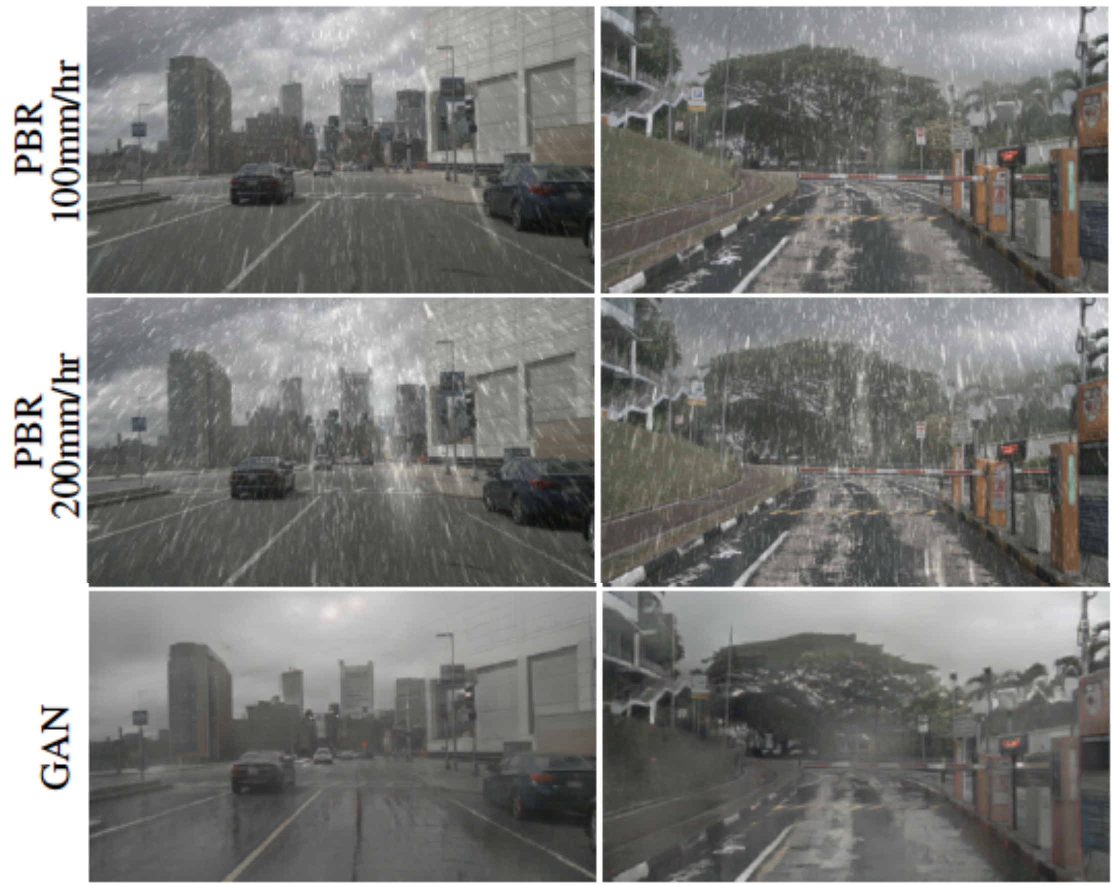
Rain photographs



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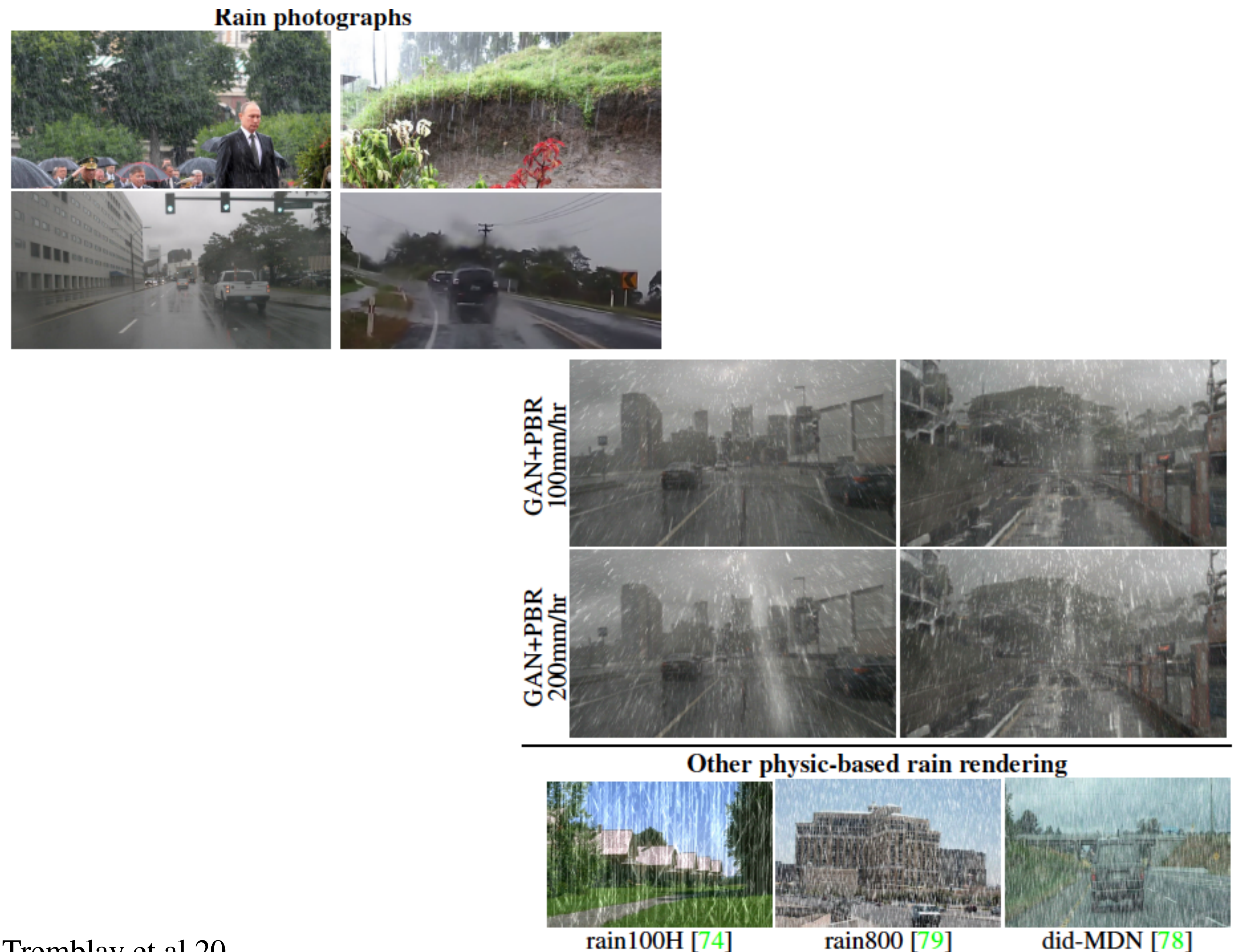

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Improvements on simulated data

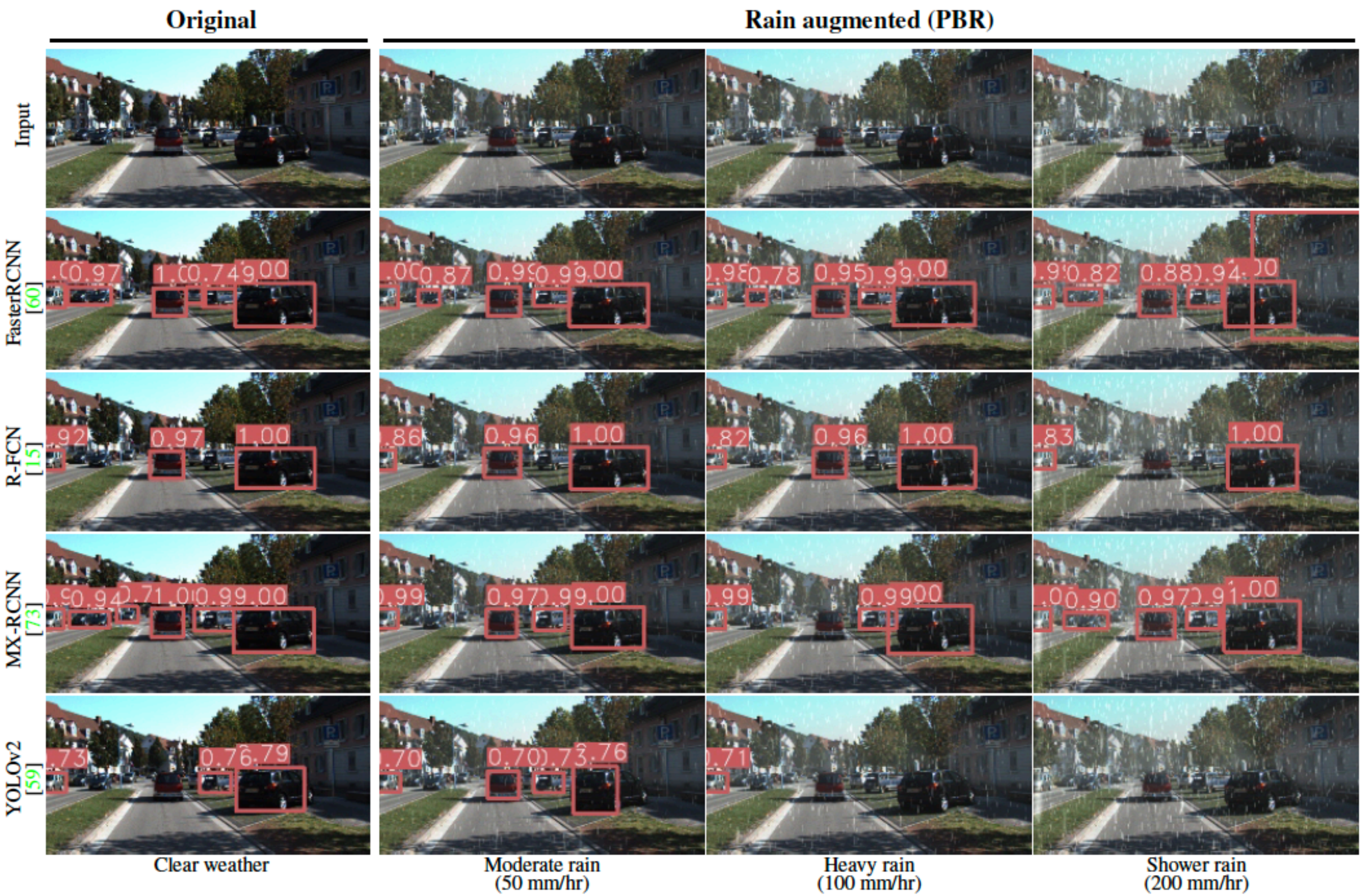

Fig. 11 Object detection on PBR rain augmentation of KITTI. From left to right, the original image (clear) and three PBR augmentations with varying rainfall rates. Images are cropped for visualization.

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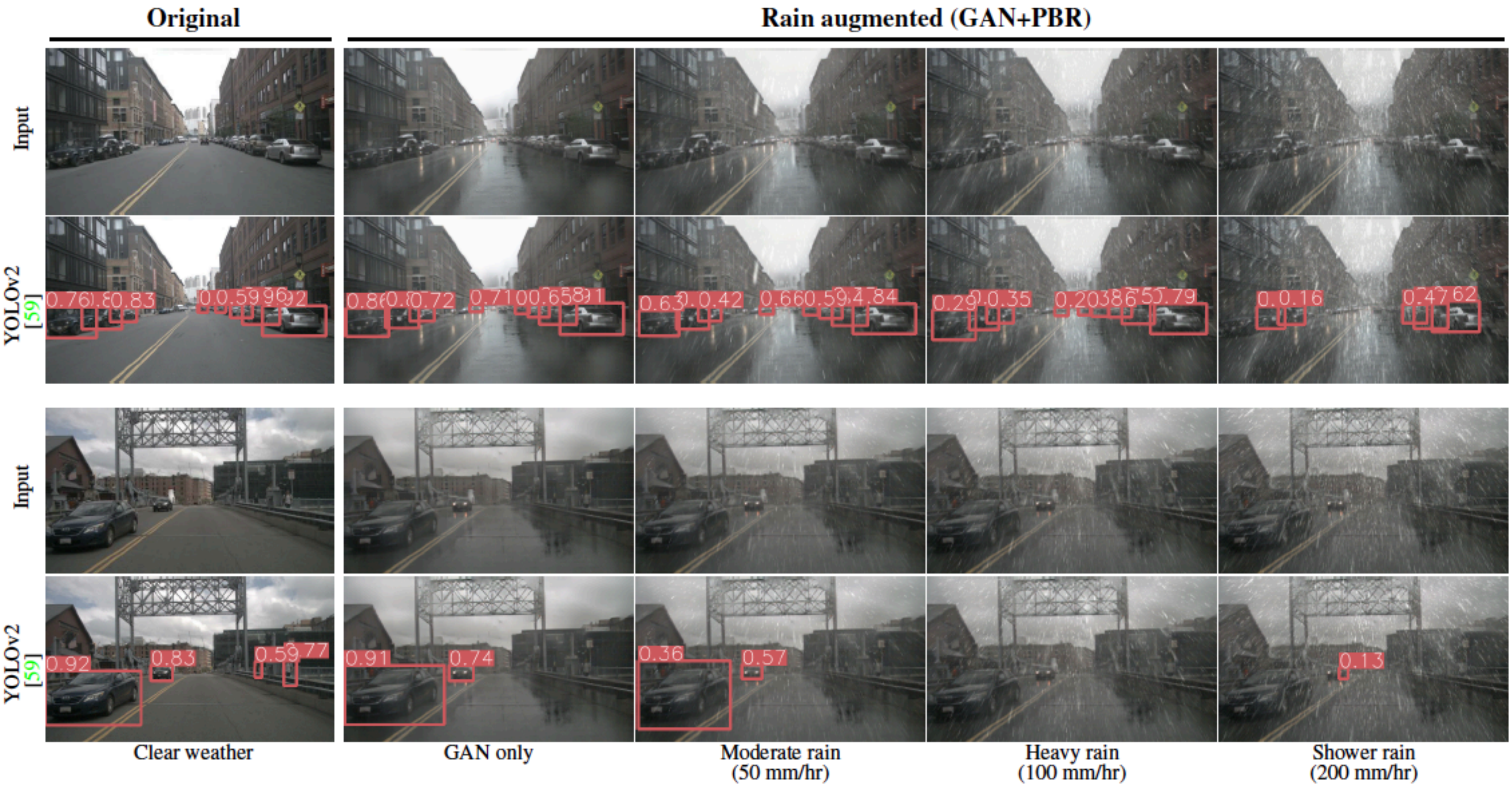

Fig. 15 Object detection on our GAN+PBR augmented nuScenes. From left to right, the original image (clear), the GAN augmented image and three GAN+PBR images.

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Improvements

	Object det. [59] mAP (%) ↑		Semantic seg. [82] AP (%) ↑		Depth est. [25] Sq. err. (%) ↓	
	Clear	Rain	Clear	Rain	Clear	Rain
Untuned	32.53	16.30	**40.8**	18.7	2.96	3.53
Finetuned (PBR)	**33.51**	19.68	39.0	**25.6**	3.15	3.54
Finetuned (GAN)	32.26	18.07	*	*	**2.89**	3.40
Finetuned (GAN+PBR)	30.59	**19.73**	*	*	3.01	**3.29**
De-rained DualResNet	32.60	18.30	*	*	2.25	3.09

* Not evaluated due to lack of semantic labels for GAN training.

Table 2 Improving performance of computer vision tasks on real nuScenes [9] images. These tasks are object detection (YOLOv2 [59]), semantic segmentation (PSPNet [82]), and depth estimation (Monodepth2 [25]). The last line shows performance with the untuned models after the de-raining [50] process.

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Deraining - strategies

- Essentially
  - obtain images with/without rain (with rain by synthetic)
  - train network to reproduce without rain image from with rain
  - starts with Eigen et al 13

Figure 1. A photograph taken through a glass pane covered in rain, along with the output of our neural network model, trained to remove this type of corruption. The irregular size and appearance of the rain makes it difficult to remove with existing methods. This figure is best viewed in electronic form.

From Eigen et al. 13

Rainy windows

From Eigen et al. 13

Rain streaks

Figure 7: Visual comparison of different rain streak removal methods on real example images.

Li et al 16

Streaks

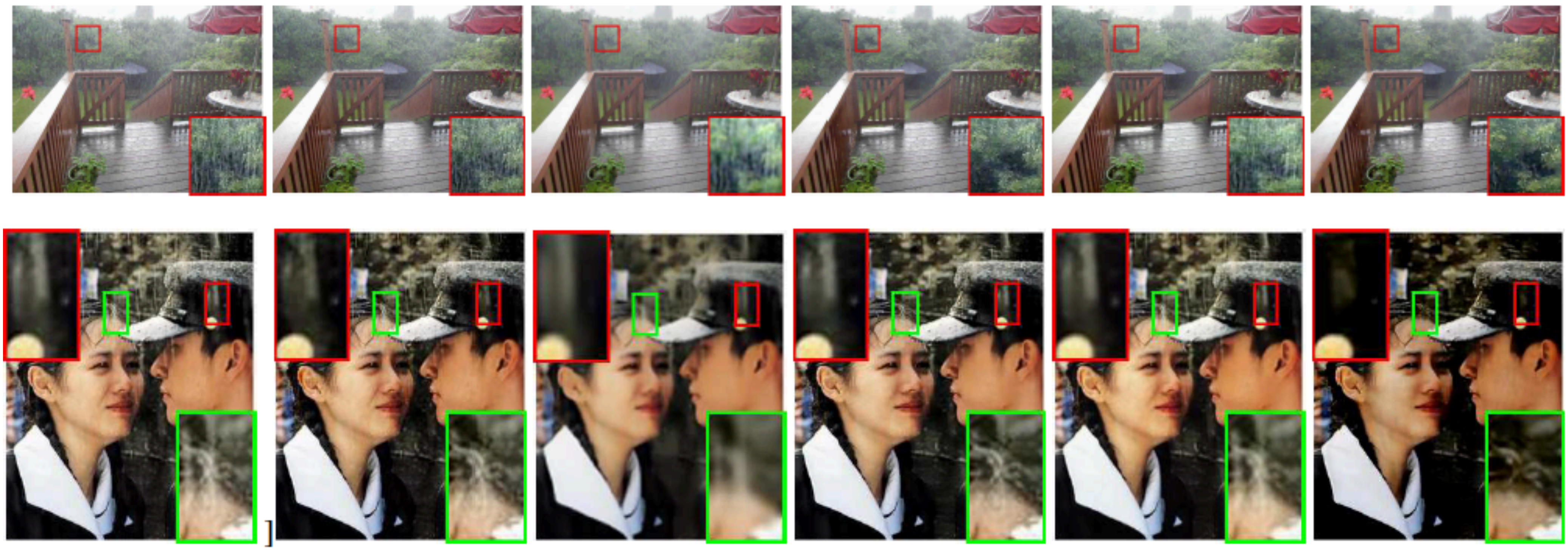

Figure 6: Real rain streaks removal experiments under different scenarios. From left to right are input image, results of DSC[26], LP [24], CNN [10], DID-MDN[31] and ours. Demarcated areas in each image are amplified at a 3 time larger scale.

Wei et al 19

Both rain streaks and haze

Figure 7. Examples of JORDER-R-DEVEIL on heavy rain (left two images) and mist images (right two images).

Yang et al 17