

Motivation



Fig.1: a real photo

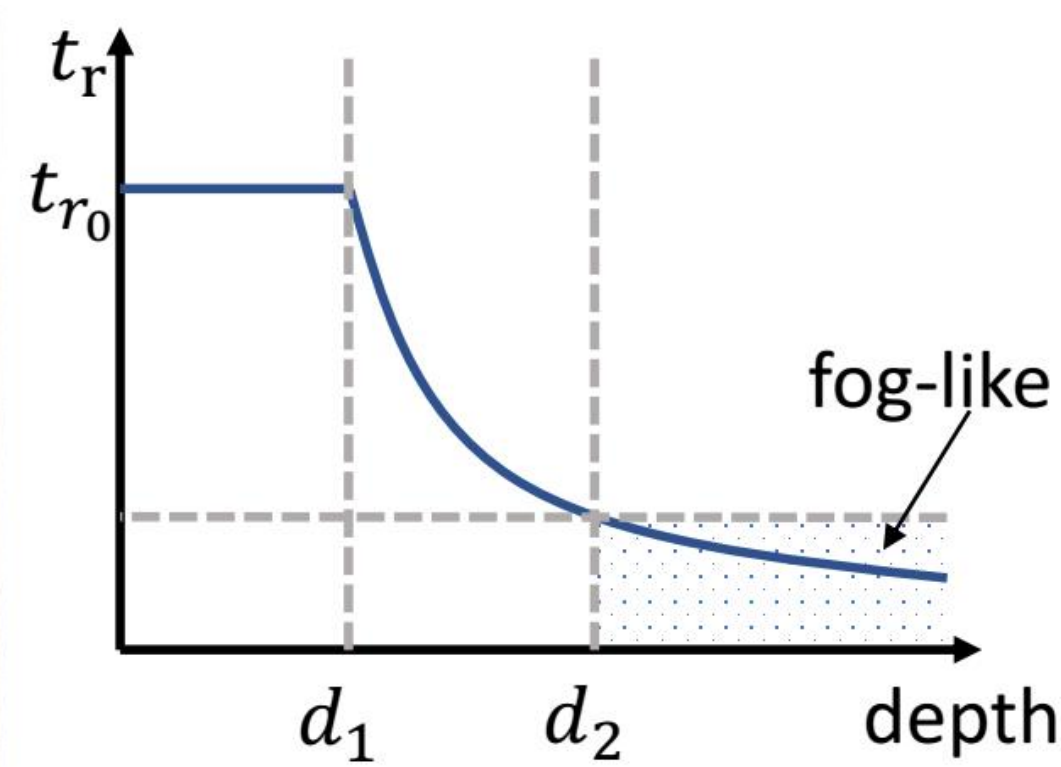


Fig.2: rain streak intensity (t_r) vs. scene depth (d)

Rain model:

- Rain often comes with fog (Fig.1).
- Object visibility varies with depth from the camera.
- Objects closer to the camera are covered mainly by the rain streaks, while objects far away are covered more heavily by the fog (Fig.1).
- Fig.2 plots the rain streak intensity (t_r) against the scene depth (d) based on the rain model in [1].

Problems:

- Existing methods focus mainly on removing rain streaks and ignore the physical properties of rain.
- Existing datasets for rain removal contain only rain streaks, while some of the images are even indoor.

Contribution #1: Rain Image Formulation

An observed rain image $O(x)$ is a composition of a rain-free image $I(x)$, a rain layer $R(x)$, and a fog layer $A(x)$ (see the examples in Fig.3):

$$O(x) = I(x) (1 - R(x) - A(x)) + R(x) + A_0 A(x),$$

where

- $R(x) = R_{\text{pattern}}(x) * t_r(x)$, $t_r(x) = e^{-\alpha \max(d_1, d(x))}$,

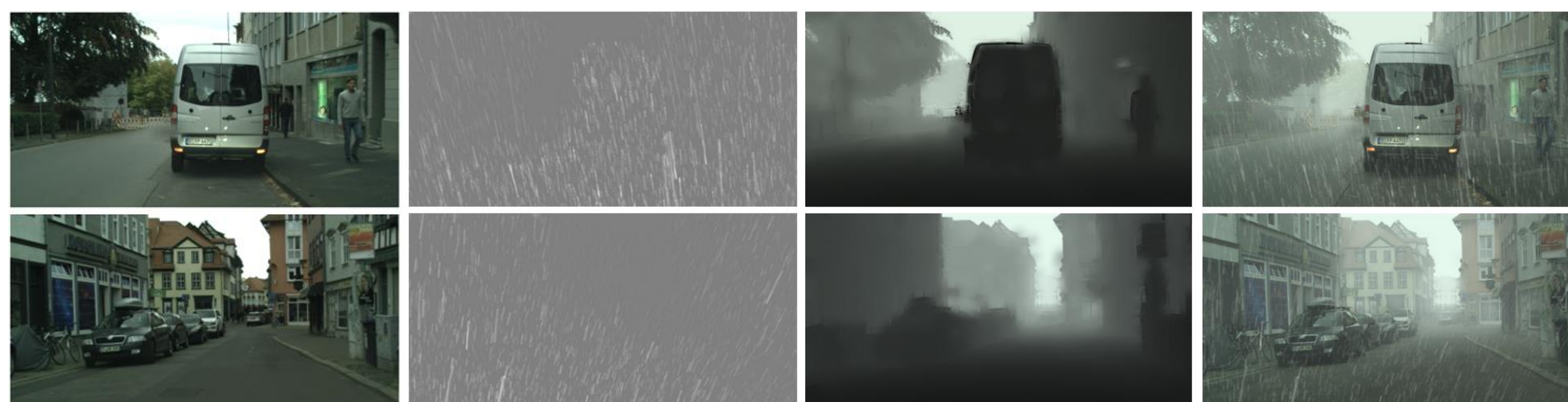
where $R_{\text{pattern}}(x)$ is an intensity image of rain streaks from [2]; $t_r(x)$ is the rain streak intensity map (Fig.2); and α is an attenuation coefficient that controls the rain streak intensity.

- $A(x) = 1 - e^{-\beta d(x)}$,

where β is an attenuation coefficient that controls the fog thickness.

- A_0 is the atmospheric light, assumed to be a global constant.

Contribution #2: RainCityscapes Dataset

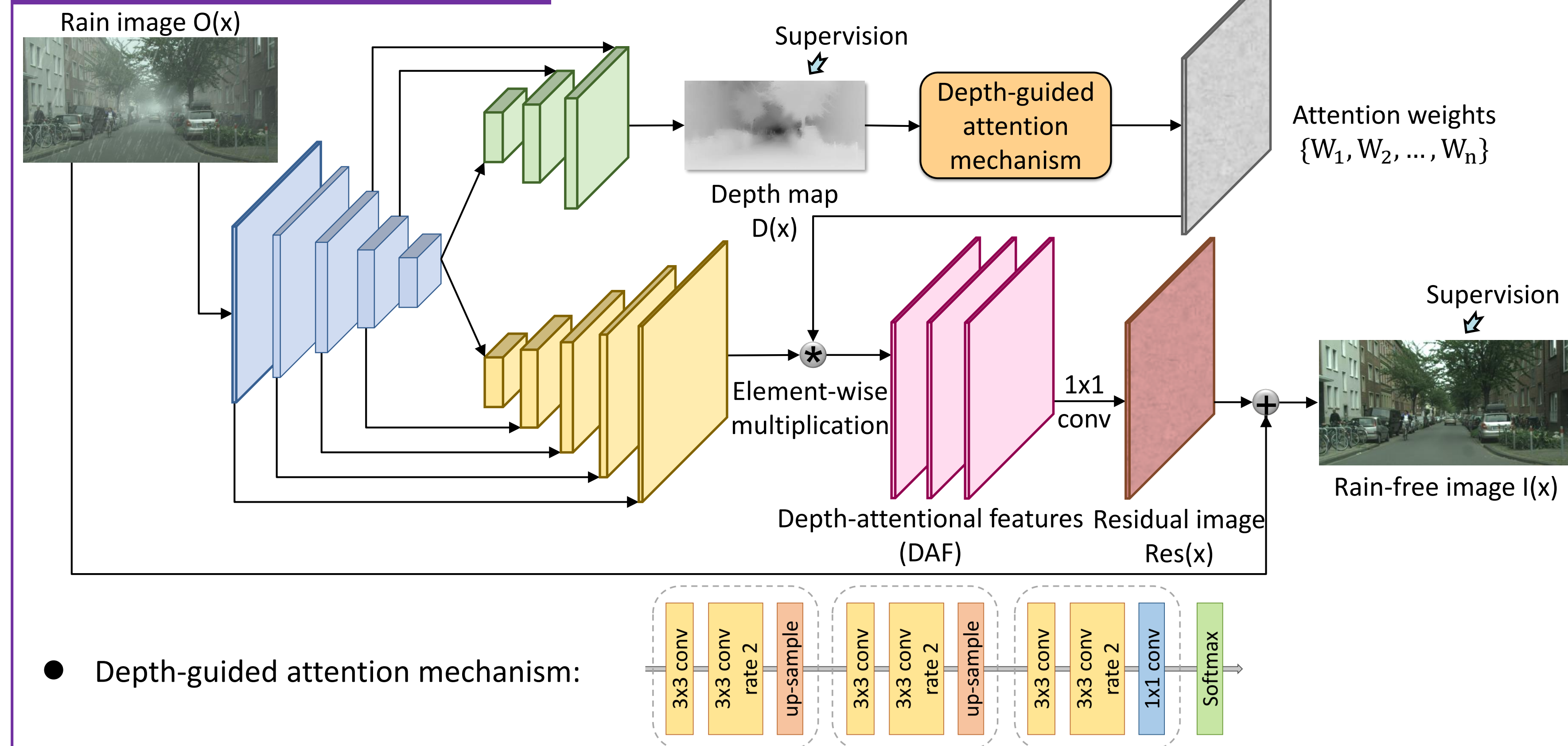


(a) rain-free image $I(x)$ (b) rain layer $R(x)$ (c) fog layer $A(x)$ (d) rain image $O(x)$

Fig.3: two sets of example images in our dataset RainCityscapes

- We prepared this dataset by first picking 262 training images and 33 testing images from the training and validation sets of the Cityscapes dataset [3] as our rain-free images, where the weather is overcast without obvious shadow and the depth map is plausible. Then, we used different parameters to simulate different degrees of rain and fog; see paper for details.
- Altogether, our RainCityscapes dataset has 9,432 training images and 1,188 testing images.

Contribution #3: DAF-Net



Experimental Results



(a) input real photo (b) DID-MDN (c) RESCAN (d) RES'+DCPDN (e) our results

- Compare different methods on RainCityscapes

method		PSNR	SSIM
DAF-Net (ours)		30.06	0.9530
rain removal	DID-MDN [CVPR18']	28.43	0.9349
	RESCAN [ECCV18']	24.49	0.8852
	JOB [ICCV17']	15.10	0.7592
	GMMLP [CVPR16']	17.80	0.8169
	DSC [ICCV15']	16.25	0.7746
haze removal	DCPDN [CVPR18']	28.52	0.9277
	AOD-Net [ICCV17']	20.40	0.8243

- User study: mean ratings from 1 (fake) to 10 (real)

dataset	rating (mean & standard dev.)
real rain photo	8.93 ± 1.66
RainCityscapes (ours)	6.38 ± 2.52
Rain800 [arXiv17']	3.69 ± 2.58
DID-MDN [CVPR18']	2.90 ± 2.39
Rain100H [CVPR17']	1.46 ± 1.18

Application: Vehicle Detection

The presence of rain affects the vehicle detection performance. We used SINet [4] (trained on Cityscapes) to detect vehicles in various kinds of images; see average precision reported below.

various kinds of images	car	bus
rain images	43.89%	56.63%
rain-free images (ours)	63.99%	78.95%
rain-free images (ground truth)	74.29%	84.34%



References

[1] K. Garg and S. K. Nayar. "Vision and rain." *IJCV*, 75(1):3-27, 2007.
 [2] Y. Li, et al. "Rain streak removal using layer priors." In *CVPR*, 2016.
 [3] M. Cordts, et al. "The cityscapes dataset for semantic urban scene understanding." In *CVPR*, 2016.
 [4] X. Hu, et al. "SINet: A scale-insensitive convolutional neural network for fast vehicle detection." *IEEE TITS*, 20(3):1010-1019, 2019.