Weather, Regression and Speculation

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Key points

- Weather effects cause detectors to work poorly
  - We can collect weathered data
  - OR unweather using regression procedures
  - OR we can train on artificially weathered data
- Lighting also causes methods to work poorly
  - we can relight images (hard!)

How weather affects images

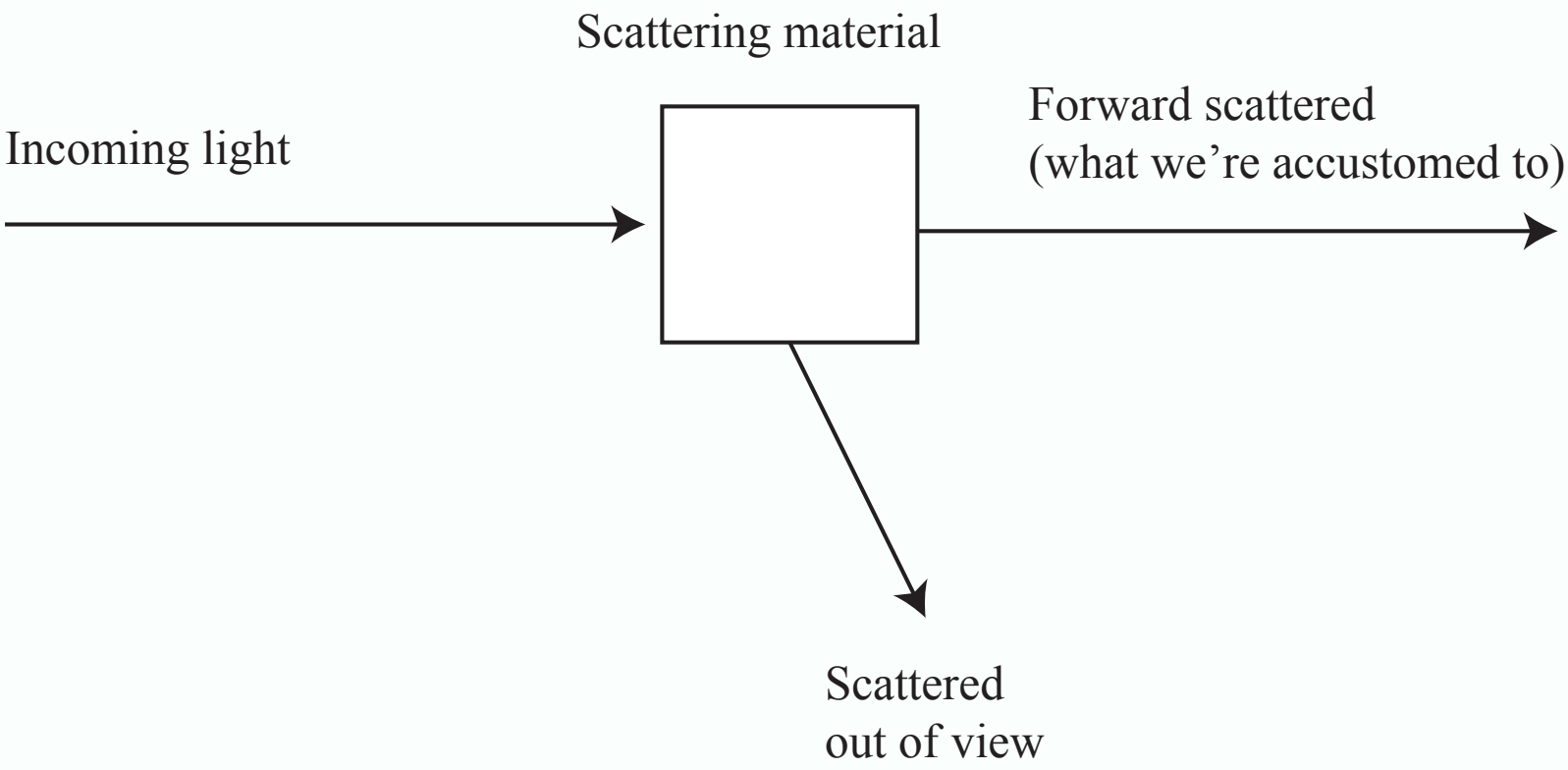
Scattering

- Fundamental mechanism of light/matter interactions
- Visually important for
  - slightly translucent materials (skin, milk, marble, etc.)
  - participating media

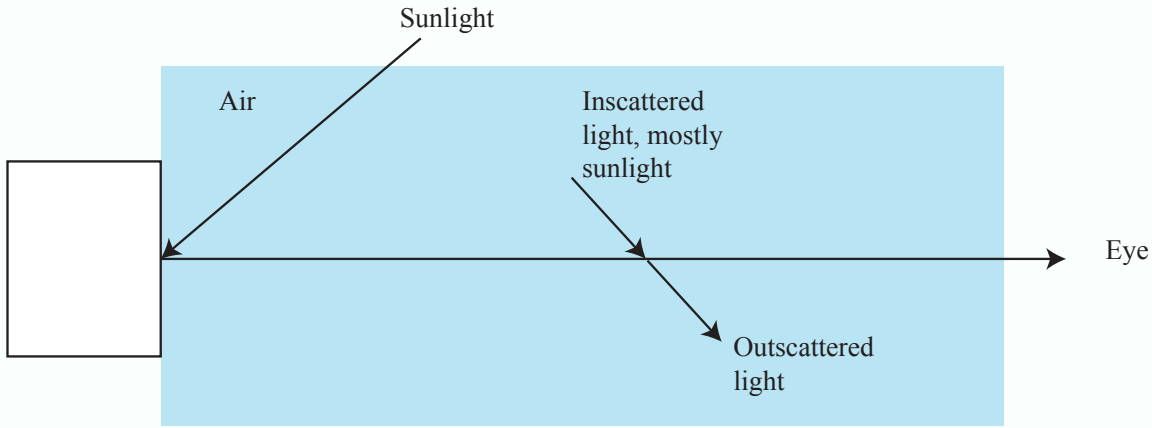
Participating media

- for example,
  - smoke,
  - wet air (mist, fog)
  - rain
  - dusty air
  - air at long scales
- Light leaves/enters a ray travelling through space
  - leaves because it is scattered out
  - enters because it is scattered in
- New visual effects

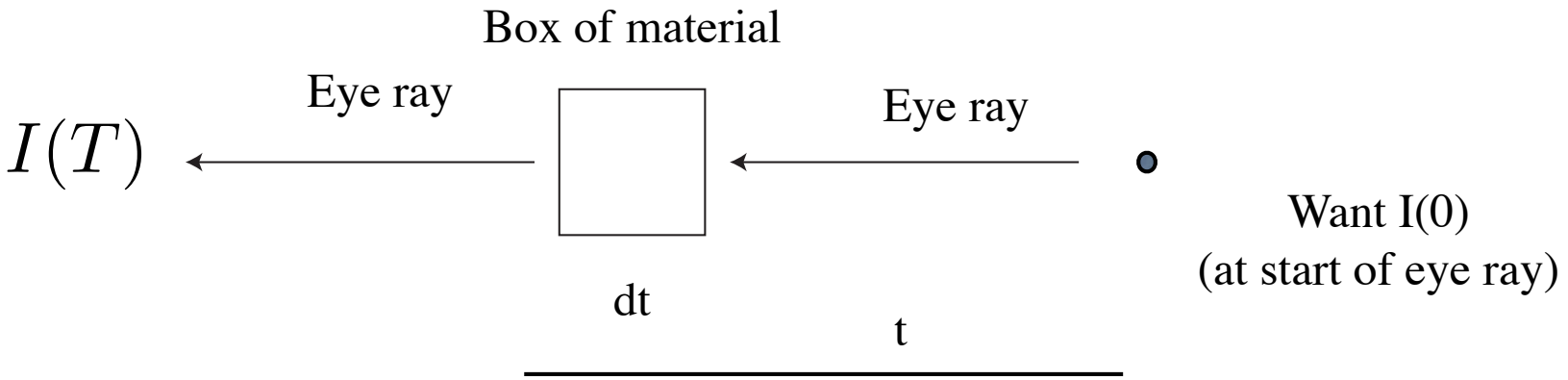
Light hits a small box of material



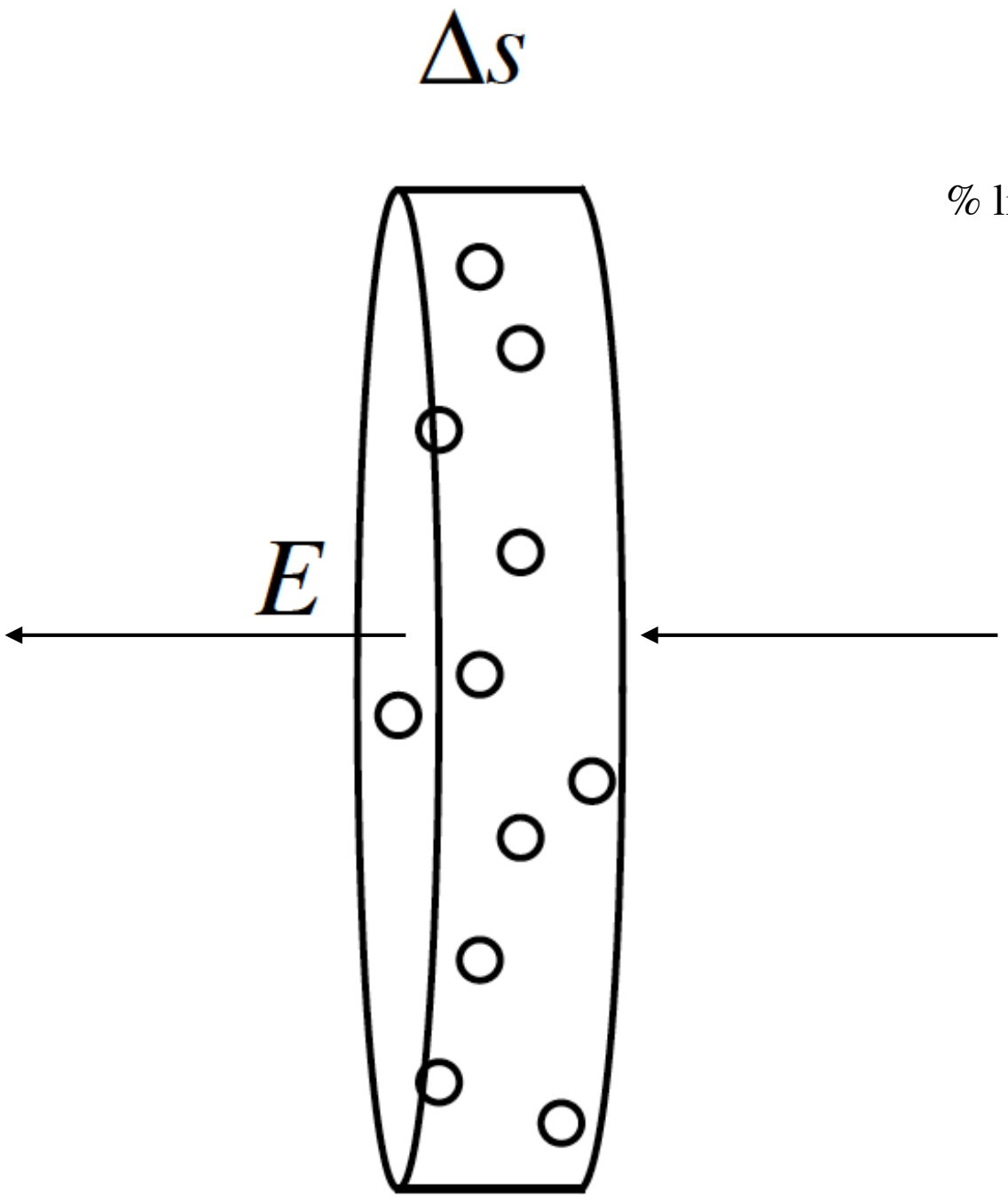
Airlight as a scattering effect



Absorption



- Ignore in-scattering
  - only account for forward scattering
- Assume there is a source at t=T
  - of intensity I(T)
  - what do we see at t=0?



Cross sectional area of "slab" is E
Contains particles, radius r, density rho

Too few to overlap when projected

% light absorbed = (area of projected particles)/ (area of slab)

This is:

$$\frac{(\rho E \Delta s)\pi r^2}{E} = \sigma(s)\Delta s$$

$$I(0) = I(T)e^{-\int_0^T \sigma(t)dt}$$

Eye is at 0 Intensity at T

From Lynch and Livingstone, Color and Light in Nature

This sort of thing affects detectors, etc.

- Fairly clear (more later)
- What to do:
  - Train detectors on real weather images
    - hard - collect and mark them up; rich collection of effects
    - mostly, this won't work out
  - Remove weather effects, then apply detector
    - Q: Remove how?
      - Simple physics
      - Regression (next)
  - Take training images, synthesize weather on top
    - Q: How?
      - complicated mixture of physics and advanced regression tricks

Paired data

- Collect data on good days, bad days
  - along the same routes, w/ GPS
  - use dynamic programming, GPS to compute alignment at the image level
- Now label
  - annotator labels bad image round 1
  - compares to good image; fixes labelling round 2

(a) Input image I (b) Stage 1 annotation (draft) (c) Corresponding image I' (d) Stage 2 annotation (GT) (e) Invalid mask J

Figure 2. **Illustration of annotation protocol for ACDC.** The color coding of the semantic classes matches Fig. 1. All annotations in (b), (d) and (e) pertain to the input image I in (a). A white color in (b) and (d) denotes unlabeled pixels.

Sakaridis et al, 21

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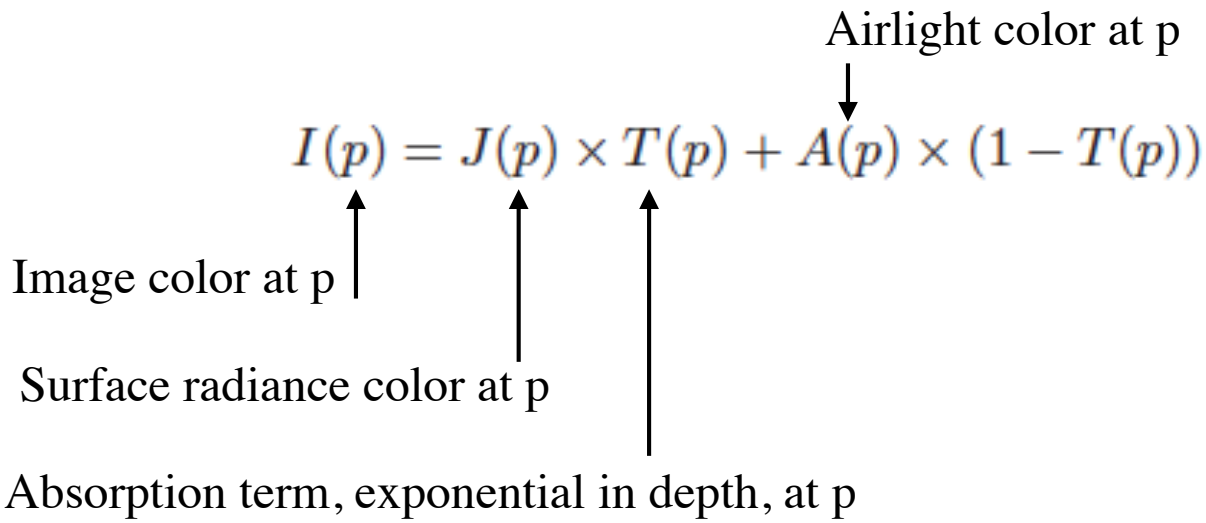
Removing haze by physical reasoning



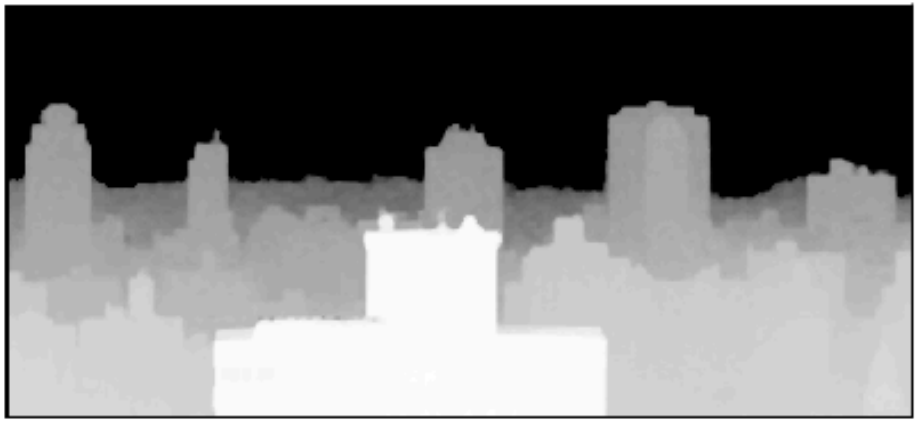
- Consequences
  - Brightness is a depth cue
  - Reasoning about airlight color yields dehazed image

Airlight yields a depth cue

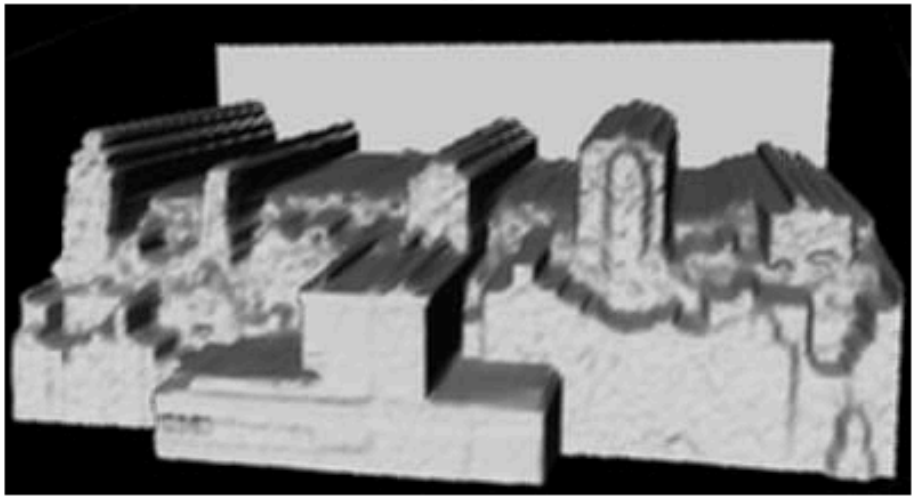
$$I(p) = J(p) \times T(p) + A(p) \times (1 - T(p))$$

- Assume that airlight is dominant
  - (i.e. most of light arriving at camera is airlight)
  - then you can recover depth from a single image
- Disadvantages
  - requires significant fog (but not too much) or large scales

(a)



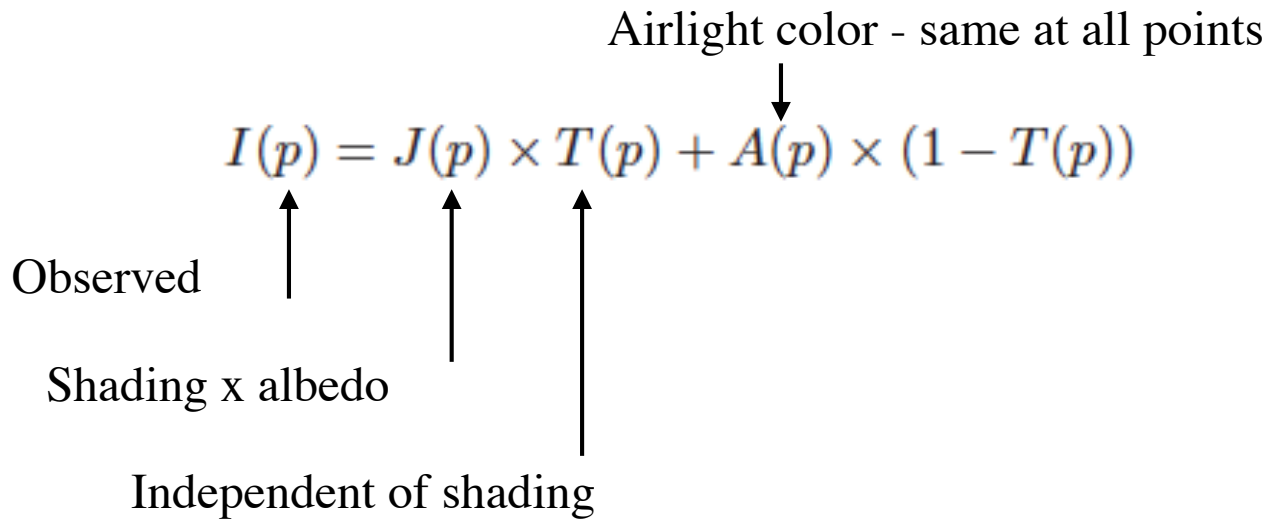
(b)



(c)

Nayar and Narasimhan, 1999

Model



- With work, this yields
  - neighboring pixels with same albedo yield
    - constraints on shading and T
  - assume shading and T independent
    - estimate A to yield “most independent” shading and T
  - result: J(p)

Figure 1: Dehazing based on a single input image and the corresponding depth estimate.

Fattal, 08 - note depth map AND dehaze; note also slightly odd colors

Improved estimation by cleaner model

Fig. 1. Old Town of Lviv. Input image on the left, our result on the right.

Fattal, 08 - note depth map AND dehaze; note also slightly odd colors

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Image regression

- Take an image, predict something “like” an image
  - Underlying technology is straightforward, significant tricks
- Cases
  - train with real paired data eg (image, foggy version of image)
  - train with fake paired data eg (image, simulated foggy version of image)
  - train with unpaired data; important, we’ll ignore
- Motivating problems
  - image -> depth
    - also, image pair -> optic flow; low res image-> high res image
  - image -> foggy image; image -> rainy image
- Mechanics sketched yesterday

Paired datasets

- Obtain pairs (hazy image, clear image)
- Real data:
  - Take photos outdoors; introduce fog; repeat
    - NH-HAZE
      - https://data.vision.ee.ethz.ch/cvl/ntire20/nh-haze/
- Synthesized data:
  - Fake fog model on real image
    - Foggy cityscapes
      - https://people.ee.ethz.ch/~csakarid/SFSU_synthetic/
  - Render synthetic images fog/no-fog
    - RESIDE
      - https://arxiv.org/pdf/1712.04143.pdf

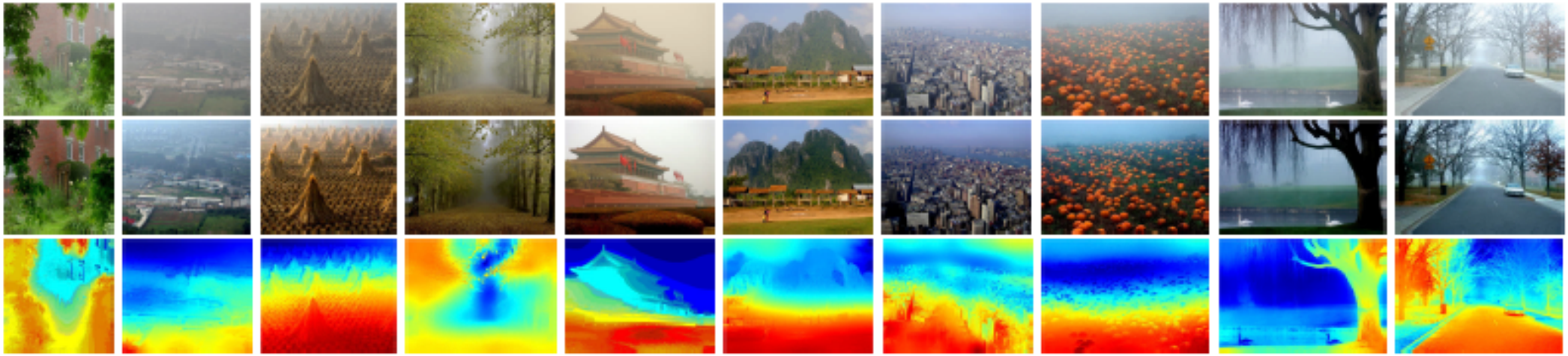


Fig. 11. The haze-free images and depth maps restored by DehazeNet

Cai et al 16 (DeHazeNet)

Single image dehazing

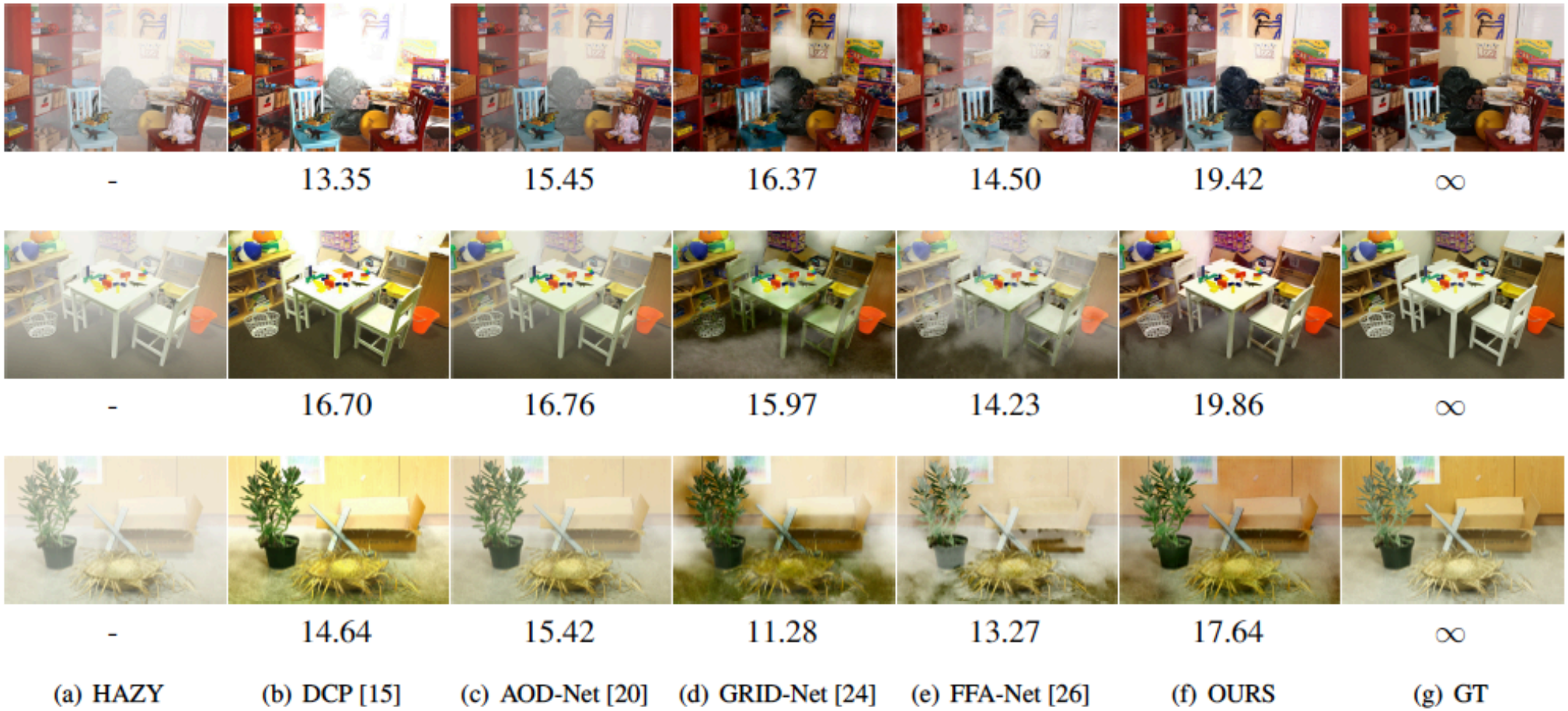
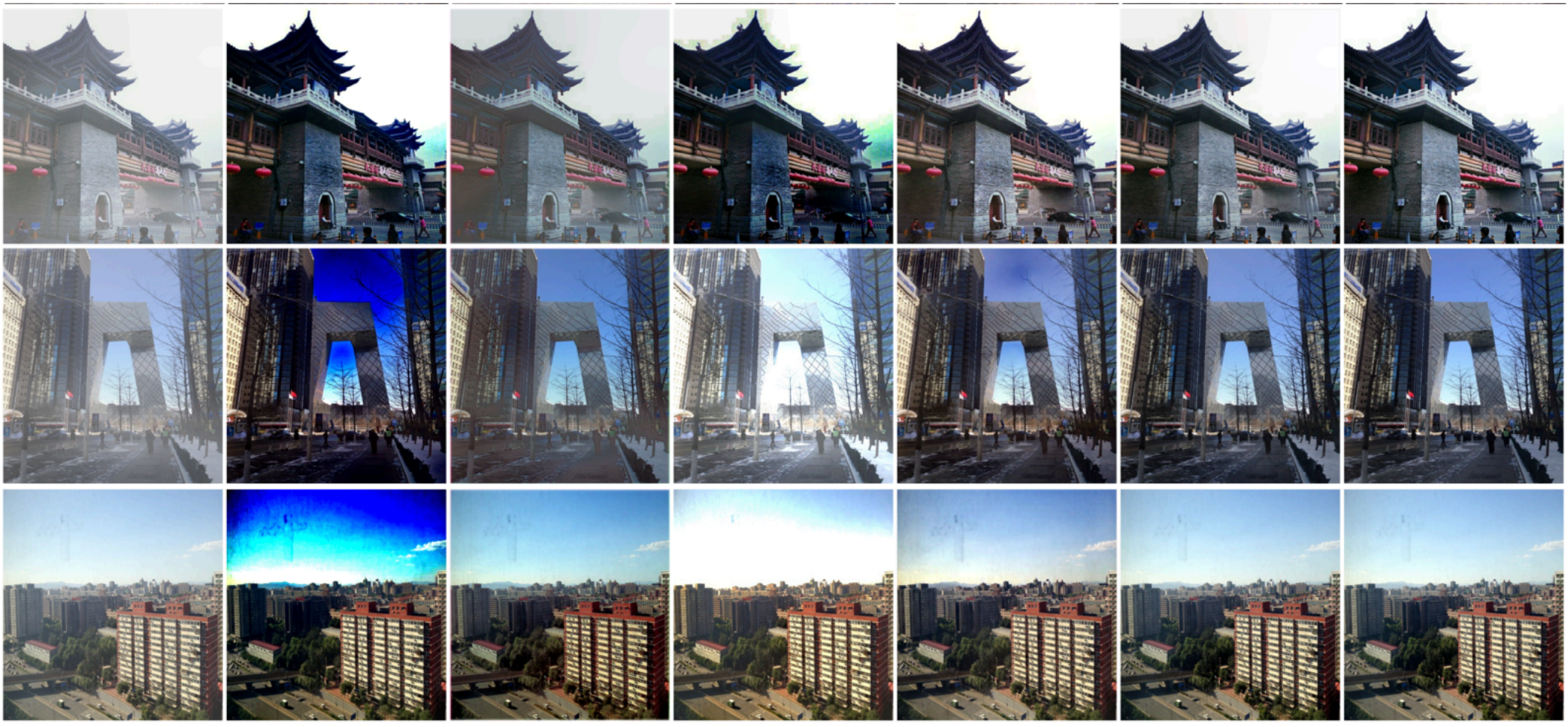


Figure 6. Qualitative comparisons with different state-of-the-art dehazing methods for indoor synthesis hazy images. The top two rows are from SOTS, the third row is from TestA dataset and the bottom three rows are from MiddleBury dehazing dataset. The numbers below image are PSNR (dB) value of each image.

Shen et al 19



(a)Hazy inputs (b)DCP (c)AOD-Net (d)DehazeNet (e)GCANet (f)Ours (g) GT

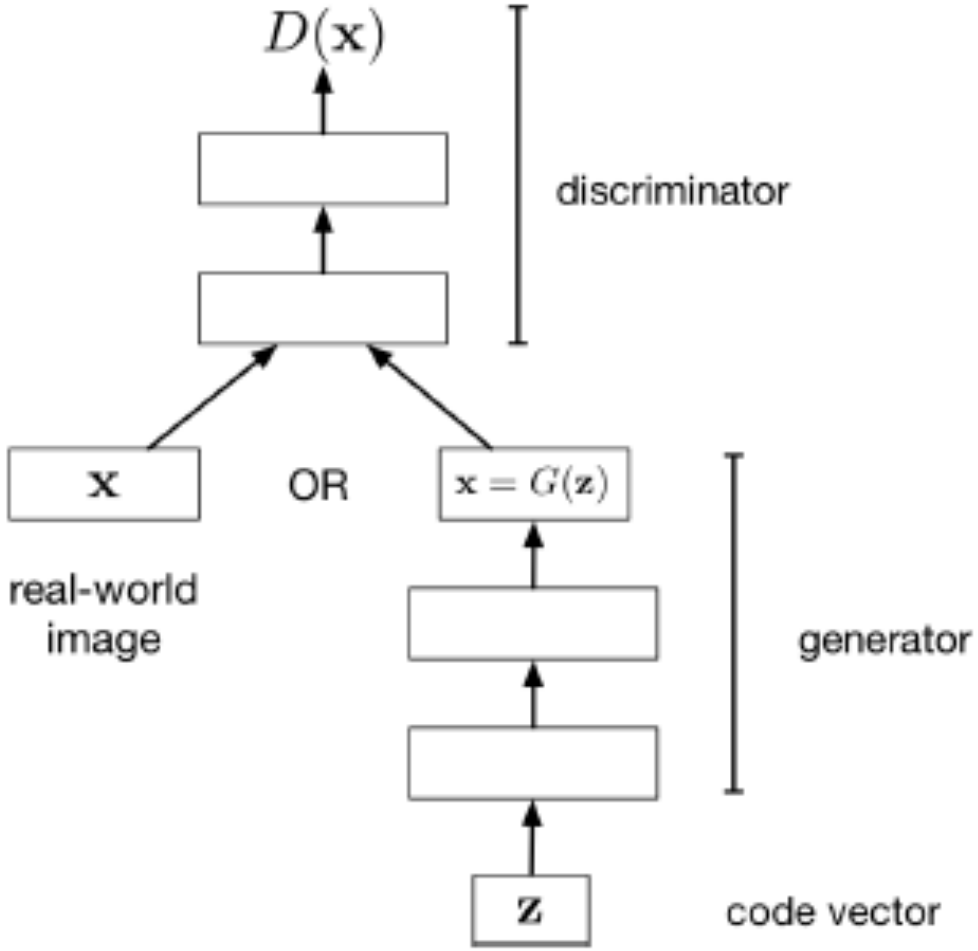
Qin et al 19 - Use feature attention

Side topic - Adversarial losses

- Issue:
  - we are making pictures that should have a strong structure
    - eg - it should be “like” a true image
    - but we don’t know how to write a loss that imposes that structure
- Strategy:
  - build a classifier that tries to tell the difference between
    - true examples
    - examples we made
  - use that classifier as a loss

A GAN

Generative Adversarial Network



Grosse slides

- Let D denote the discriminator's predicted probability of being data
- Discriminator's cost function: cross-entropy loss for task of classifying real vs. fake images

$$\mathcal{J}_D = \mathbb{E}_{\mathbf{x}\sim\mathcal{D}}[-\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}}[-\log(1 - D(G(\mathbf{z})))]$$

Notice: we want the discriminator to make a 1 for real data, 0 for fake data

- One possible cost function for the generator: the opposite of the discriminator's

$$\begin{aligned}\mathcal{J}_G &= -\mathcal{J}_D \\ &= \text{const} + \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]\end{aligned}$$

- This is called the minimax formulation, since the generator and discriminator are playing a zero-sum game against each other:

$$\max_G \min_D \mathcal{J}_D$$

Solution (if exists, which is uncertain; and if can be found, ditto) is known as a saddle point. It has strong properties, but not much worth talking about, as we don't know if it is there or whether we have found it.

Grosse slides

Quote from the original paper on GANs:

> *"The generative model can be thought of as analogous to a team of counterfeiters, trying to produce fake currency and use it without detection, while the discriminative model is analogous to the police, trying to detect the counterfeit currency. Competition in this game drives both teams to improve their methods until the counterfeits are indistinguishable from the genuine articles."*

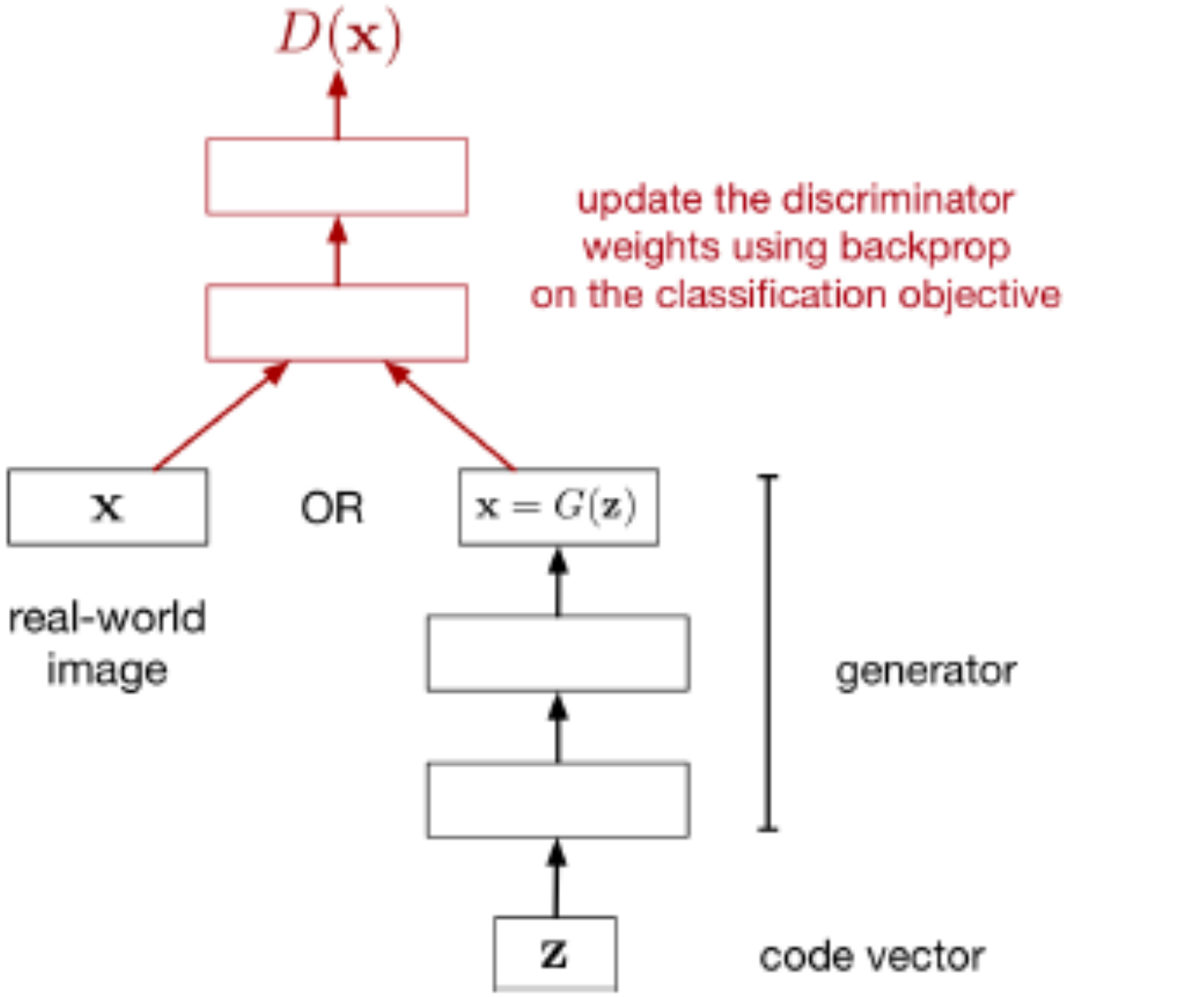
-Goodfellow et. al., "Generative Adversarial Networks" (2014)

Thakar slides

Important, general issue

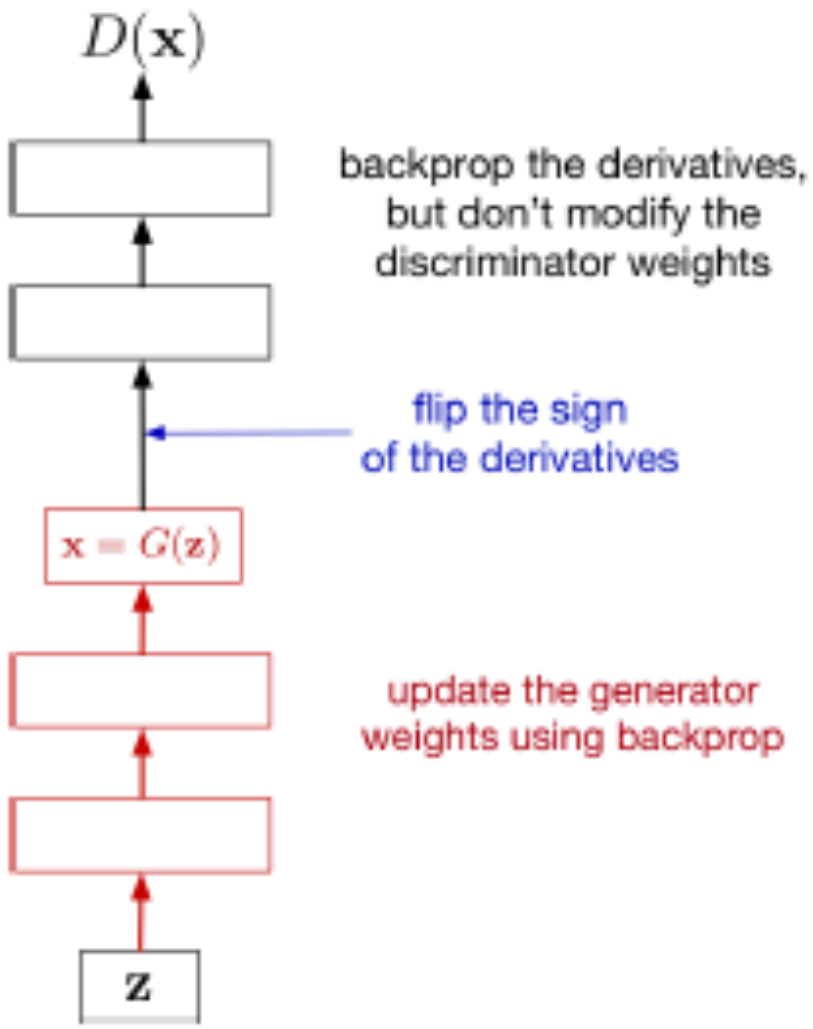
- If either generator or discriminator “wins” -> problem
- Discriminator “wins”
  - it may not be able to tell the generator how to fix examples
  - discriminators classify, rather than supply gradient
- Generator “wins”
  - likely the discriminator is too stupid to be useful
- Very little theory to guide on this point

Updating the discriminator:



Grosse slides

Updating the generator:



Grosse slides

One must be careful about losses…

- We introduced the minimax cost function for the generator:

$$\mathcal{J}_G = \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]$$

- One problem with this is saturation.
- Recall from our lecture on classification: when the prediction is really wrong,
  - "Logistic + squared error" gets a weak gradient signal
  - "Logistic + cross-entropy" gets a strong gradient signal
- Here, if the generated sample is really bad, the discriminator's prediction is close to 0, and the generator's cost is flat.

Grosse slides

One must be careful about losses…

- Original minimax cost:

$$\mathcal{J}_G = \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]$$

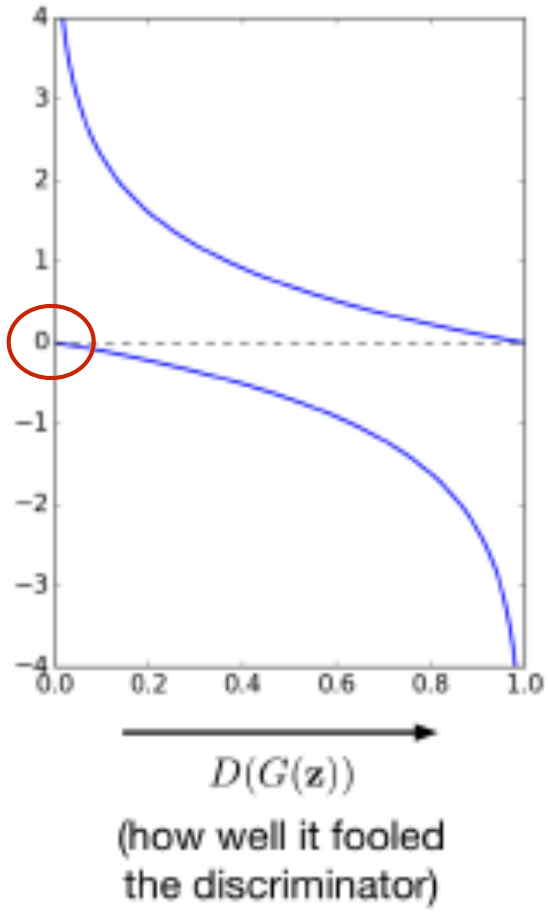
- Modified generator cost:

$$\mathcal{J}_G = \mathbb{E}_{\mathbf{z}}[-\log D(G(\mathbf{z}))]$$

- This fixes the saturation problem.

modified cost

minimax cost



Grosse slides

Alternative losses

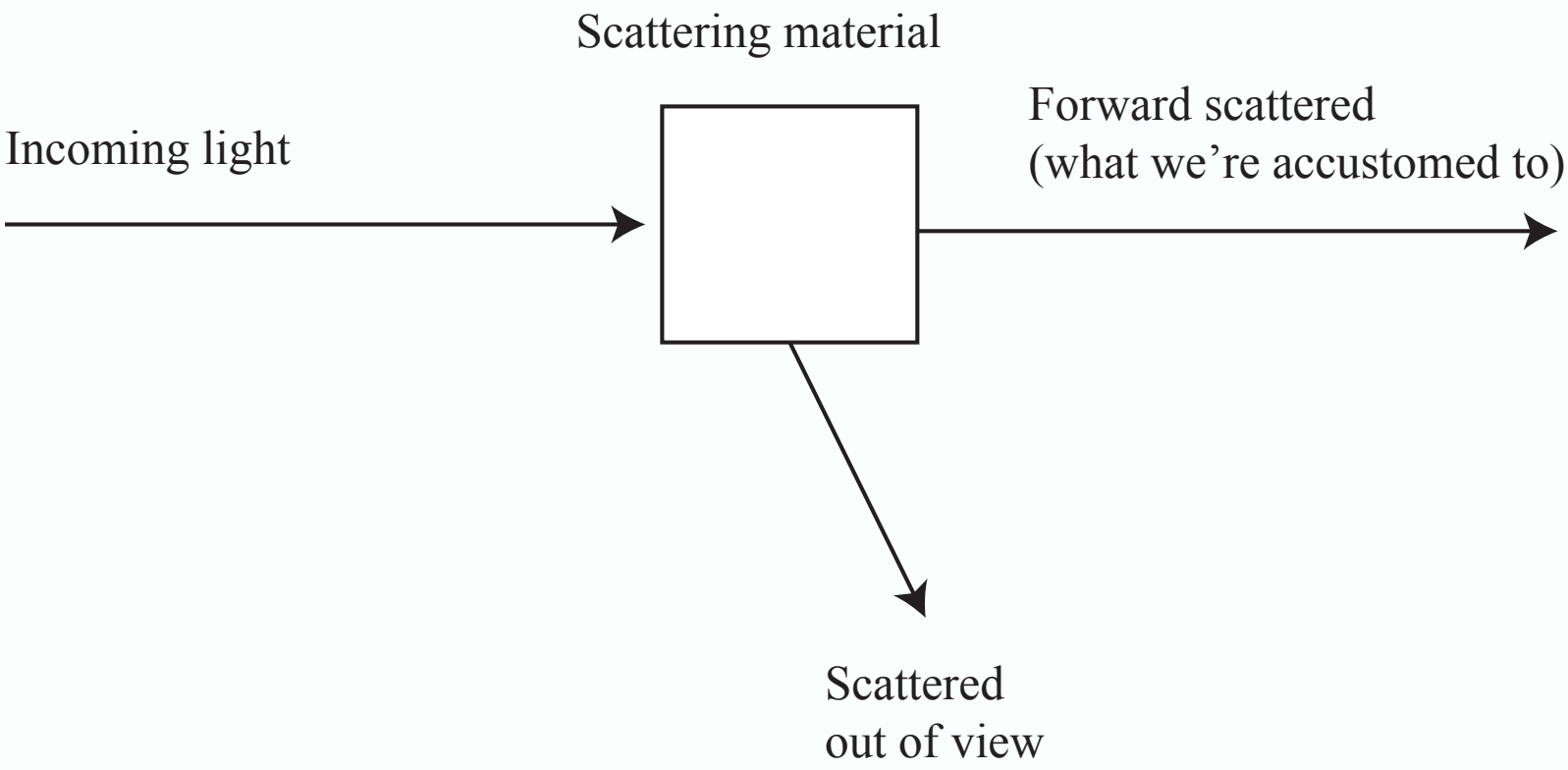
- Hinge:
  - Discriminator makes D(im)
    - want
      - real images -> -1
      - fake -> 1
  - Discriminator loss: $$\sum_{\text{fakes and real}} \max(0, 1 - y_i D(I_i))$$
    - where y_i=-1 for real, y_i=1 for fake
  - Generator loss:
    - $$\sum_{\text{fakes}} D(I_i)$$

Figure 5: Visual comparisons on real-world hazy images. Our model can generate more natural and visual pleasing dehazed results with less color distortion. Please see the details in red rectangles. Zoom in for best view.

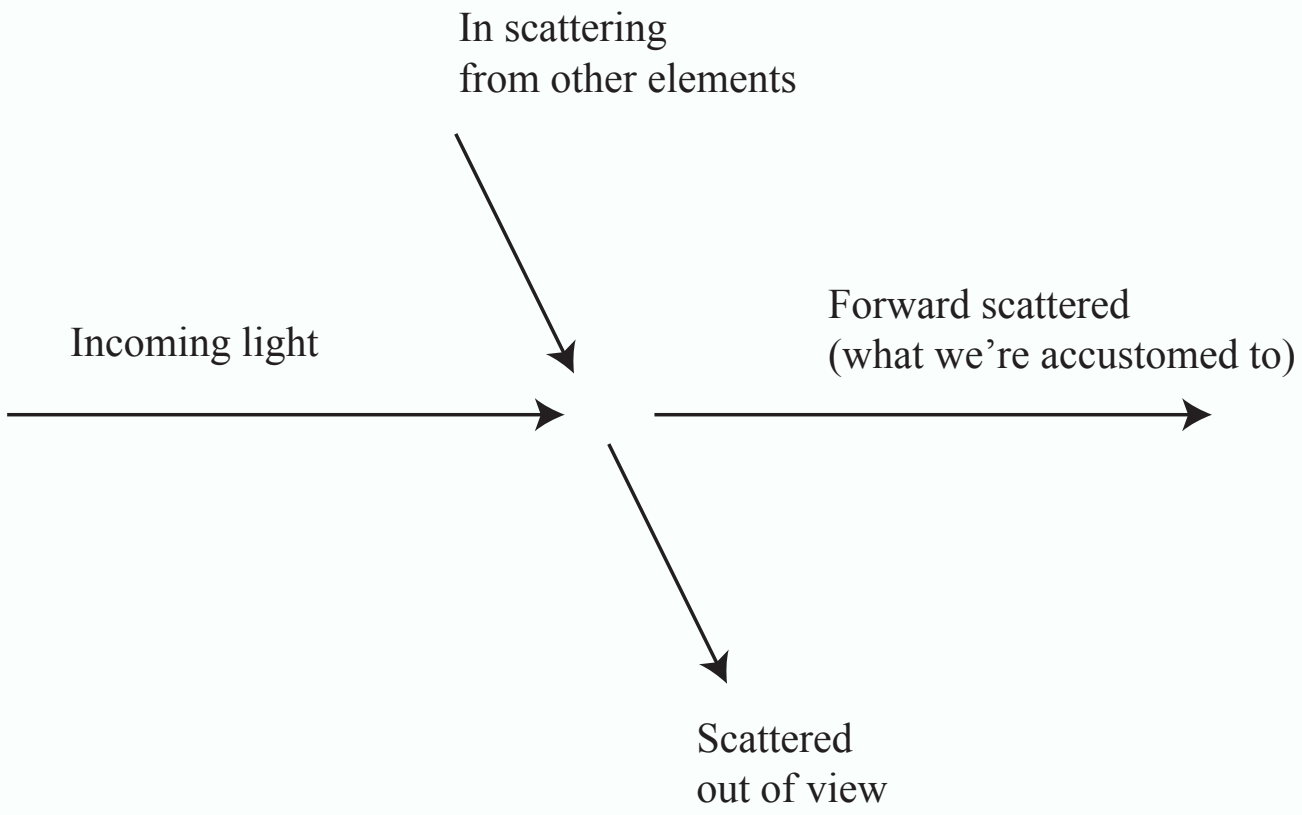
Dong et al 21 - Use an adversarial loss

More complicated weather effects

Light hits a small box of material

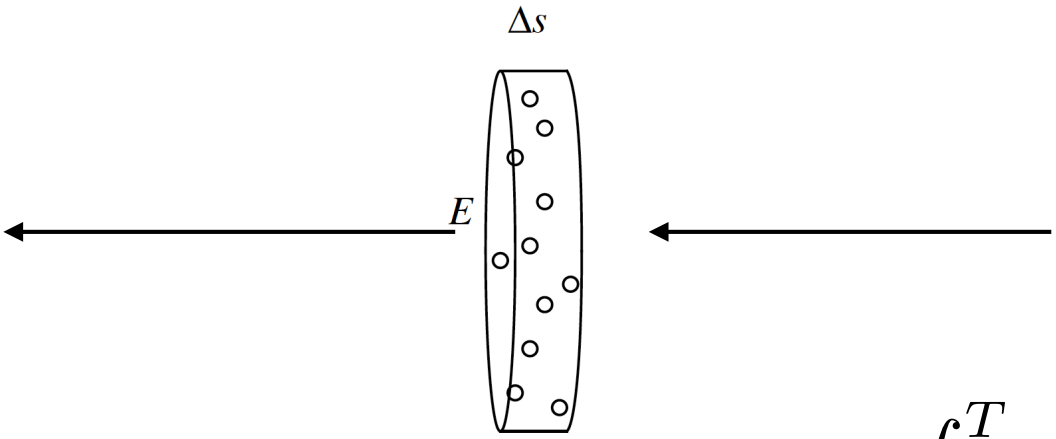


A ray passing through scattering material



More interesting…

- Intensity is "created along the ray"
  - by (say) airlight
  - Model - the particles glow with intensity C(x)



Cross sectional area of "slab" is E
Contains particles, radius r, density rho

Too few to overlap when projected

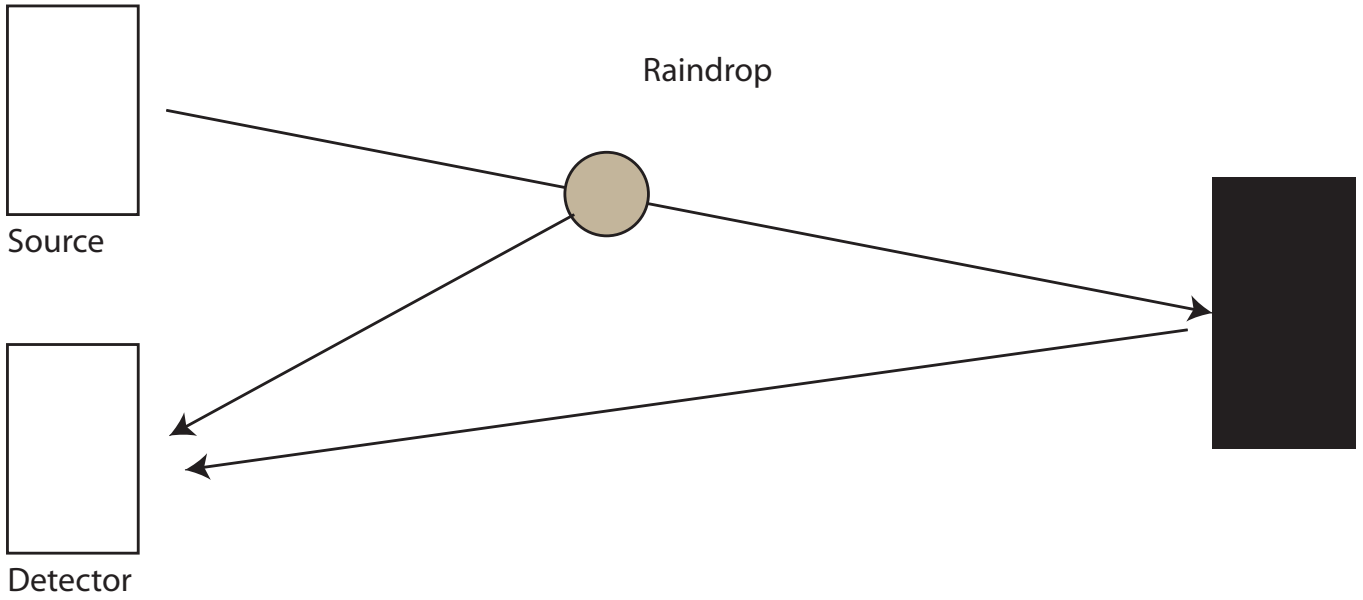
Light out = Light in -
Light absorbed+
Light generated

Light generated: C x (area fraction of proj. particles)

which is

$$I(0) = \int_0^T \mathbf{c}(\mathbf{x}(s))\sigma(s)e^{-\int_0^s \sigma(u)du} ds$$

Raindrop scatter



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

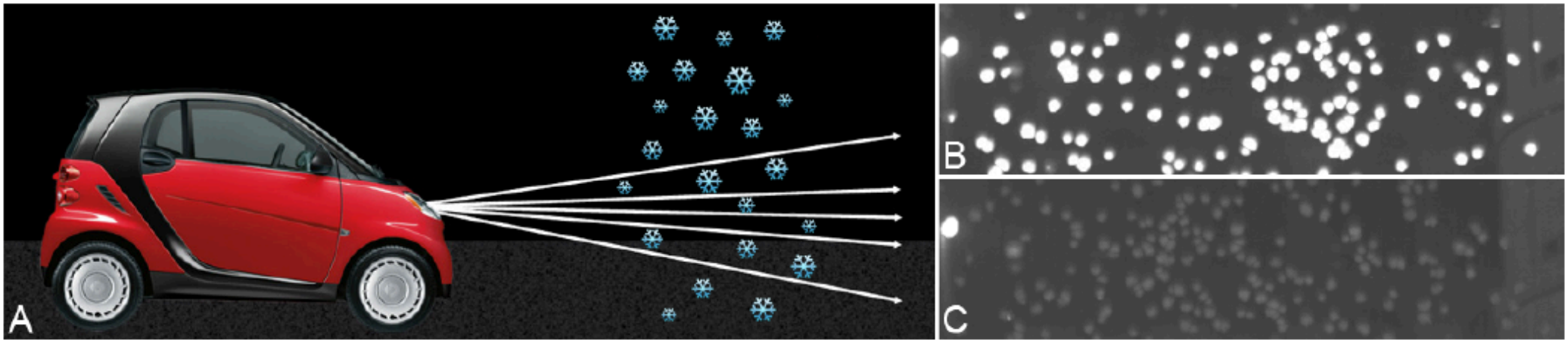
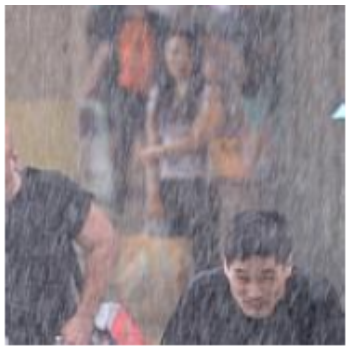


Fig. 7. A: Our headlight has unprecedented resolution over space and time so that beams of light may be sent in between the falling snow. Illustration adapted from [11]. B: Artificial snowflakes brightly illuminated by standard headlight. C: Our system avoids illuminating snowflakes making them much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

Rain has multiple interesting effects

Blur from wet air

Puddles



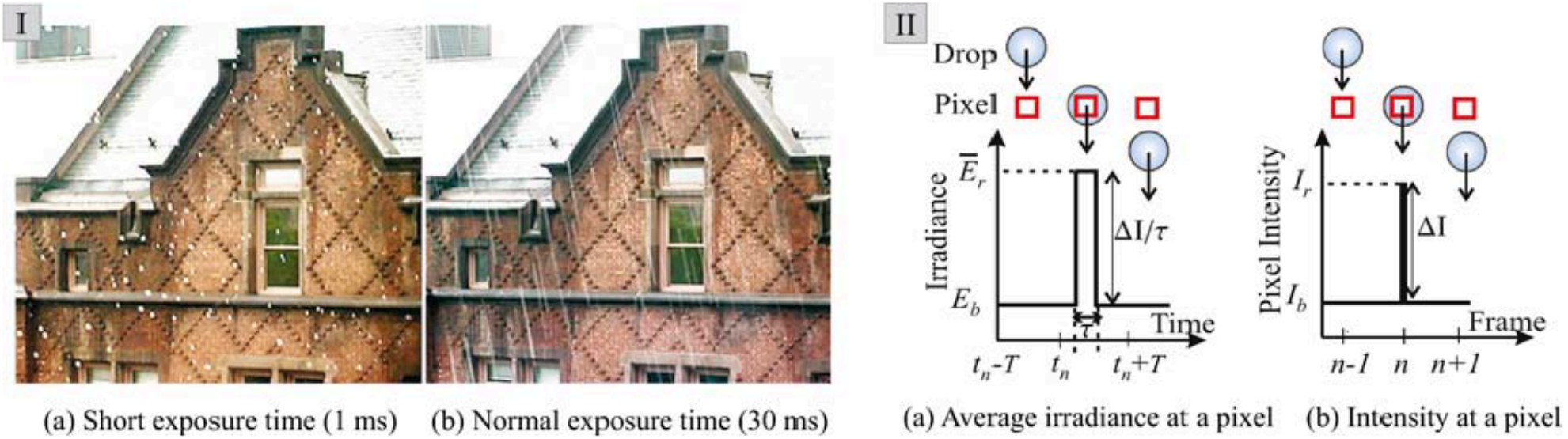
Color shifts

Streaks

These are often quite strongly coupled to scene geometry

Rain - phenomena

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



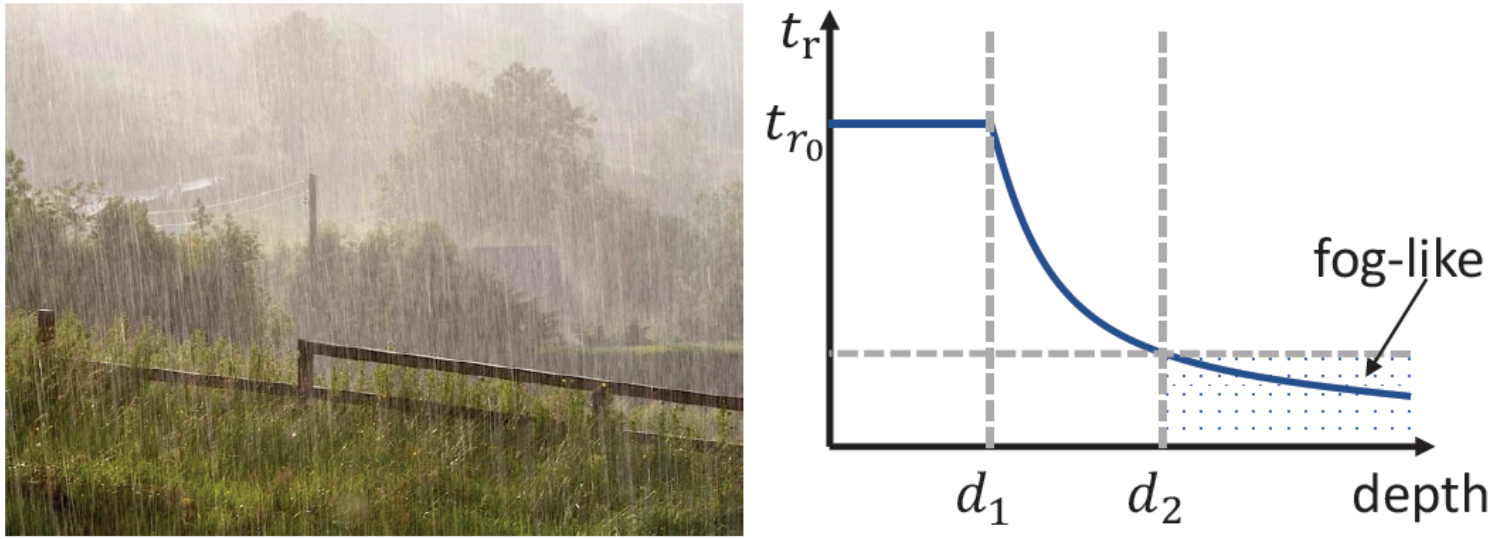
(a) Short exposure time (1 ms) (b) Normal exposure time (30 ms) (a) Average irradiance at a pixel (b) Intensity at a pixel

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.

Garg and Nayar 07

Rain - phenomena

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



(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].

Hu et al 19

Rain mangles detection

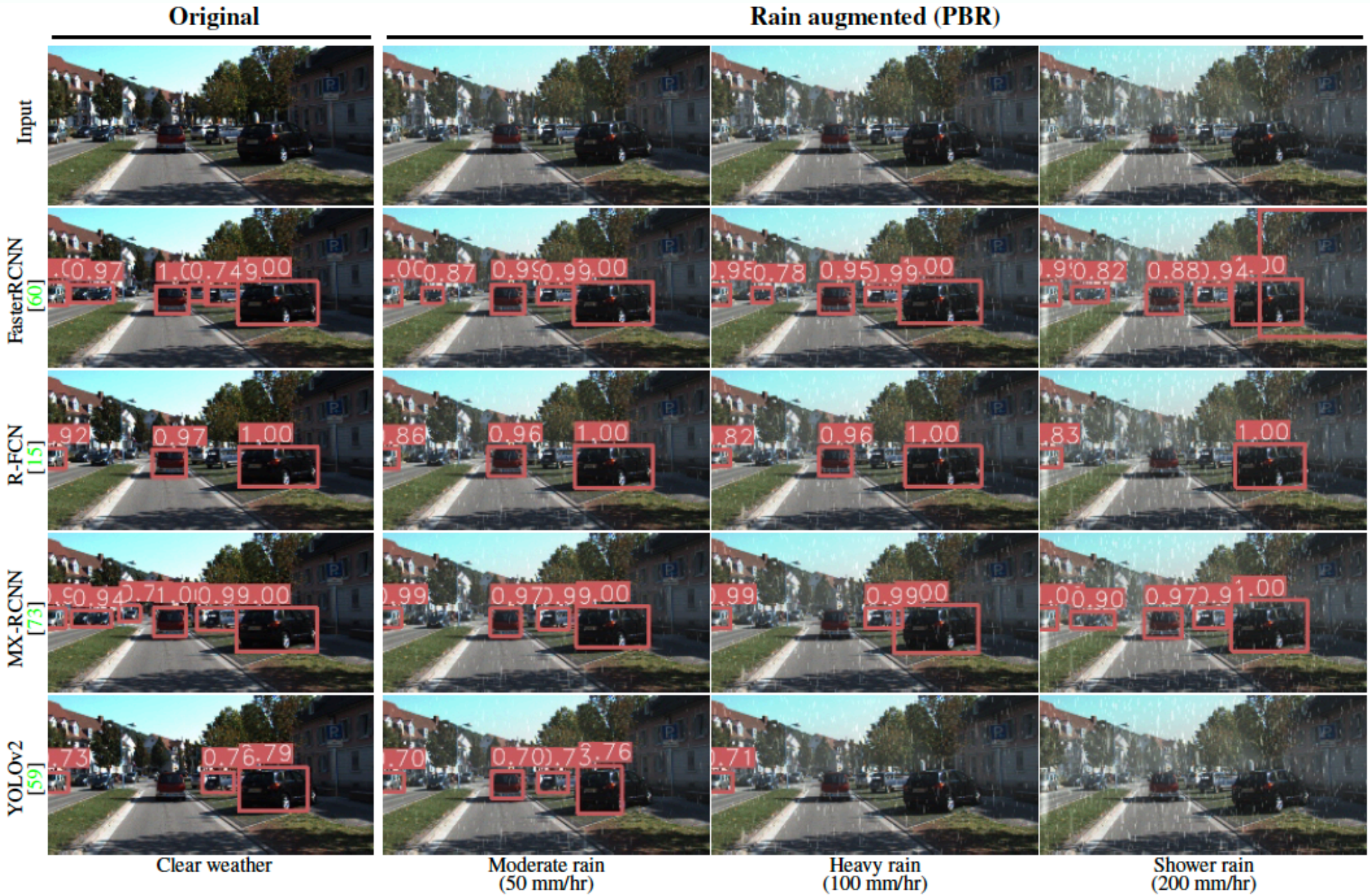


Fig. 11 Object detection on PBR rain augmentation of KITTI. From left to right, the original image (clear) and three PBR augmentations with varying rainfall rates. Images are cropped for visualization.

Tremblay et al 20

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

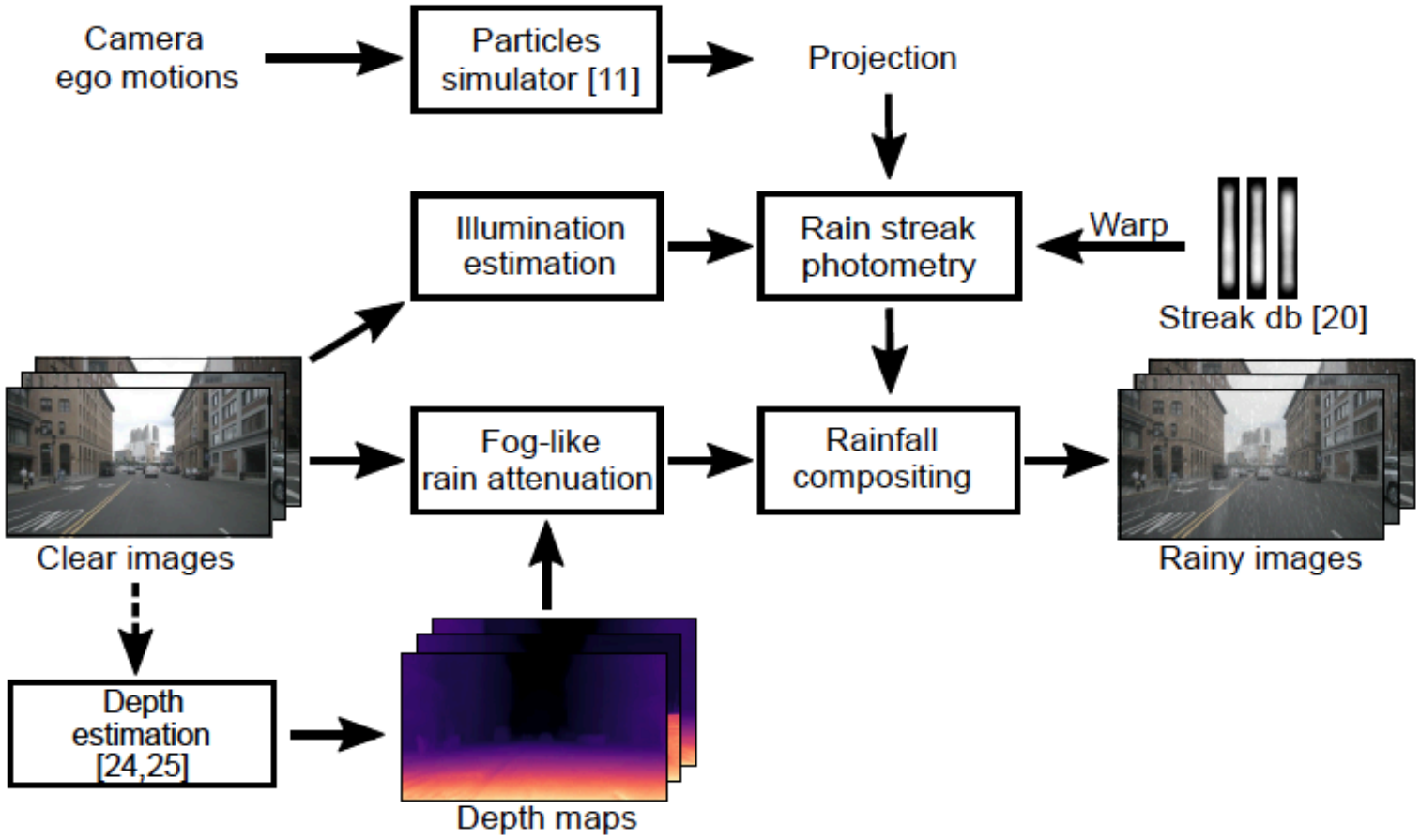


Fig. 2 Physics-Based Rendering for rain augmentation. We use particles simulation together with depth and illumination estimation to render arbitrarily controlled rainfall on clear images.

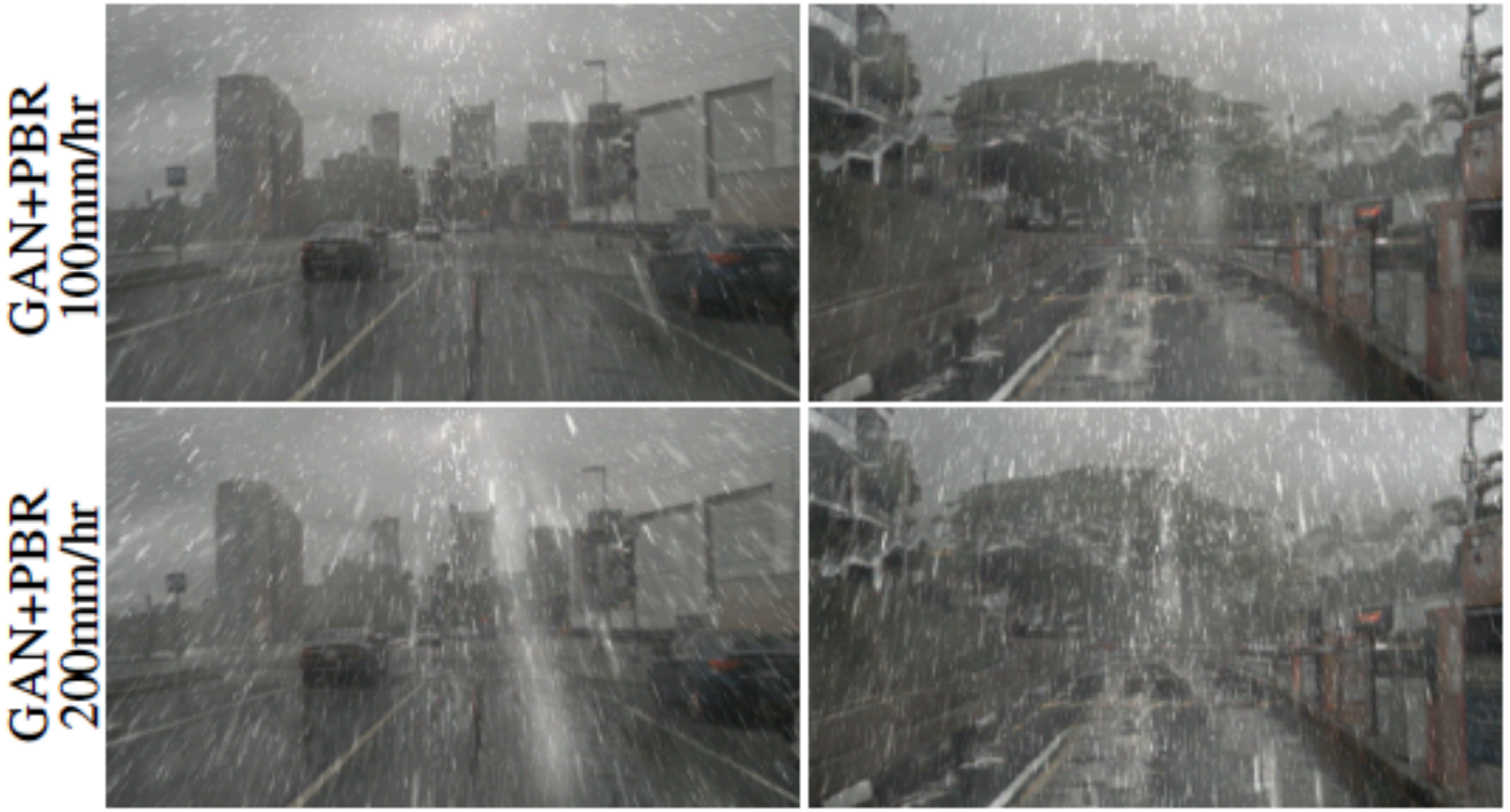
Tremblay et al 20

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).

Tremblay et al 20



Tremblay et al 20

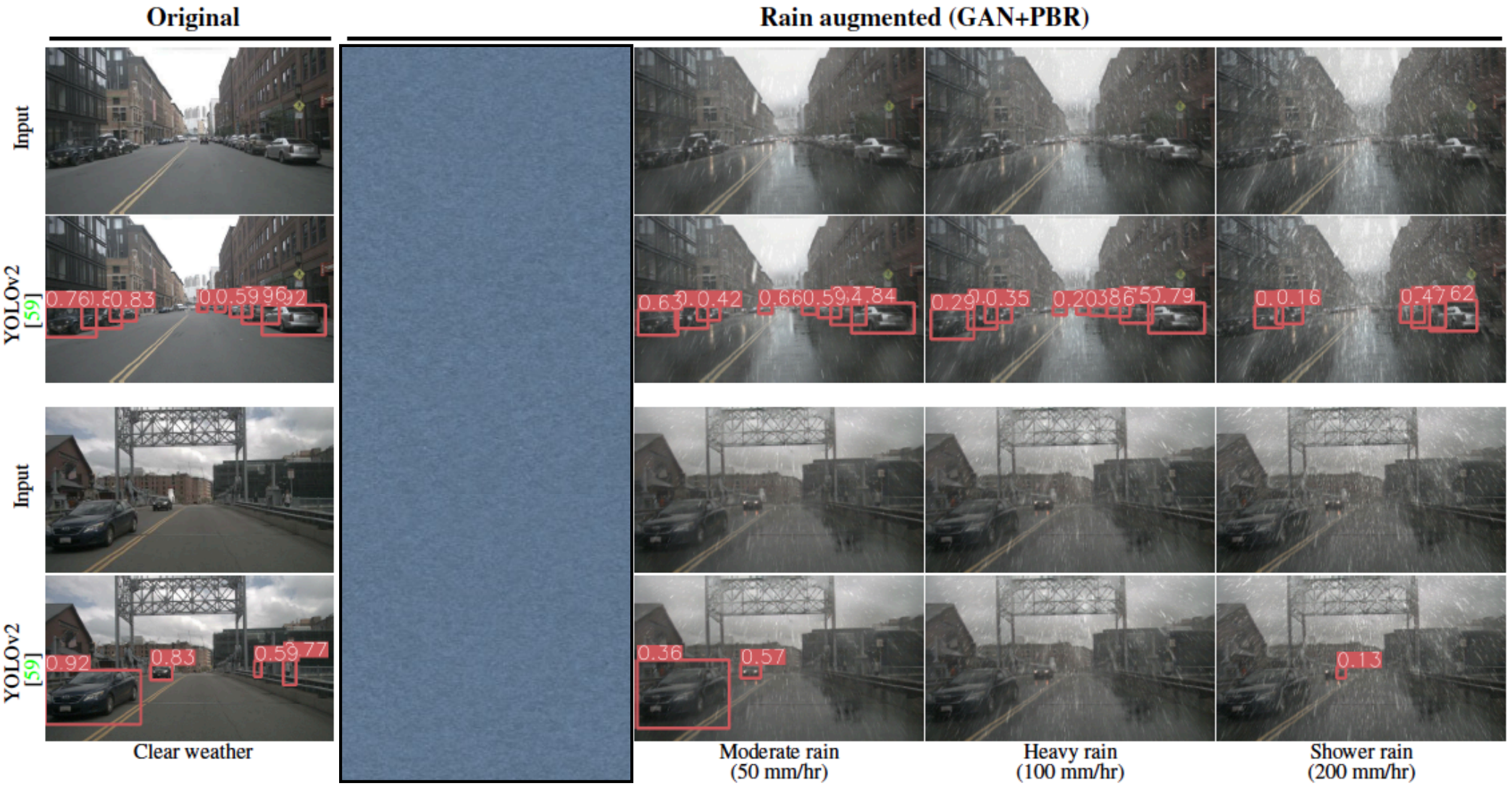
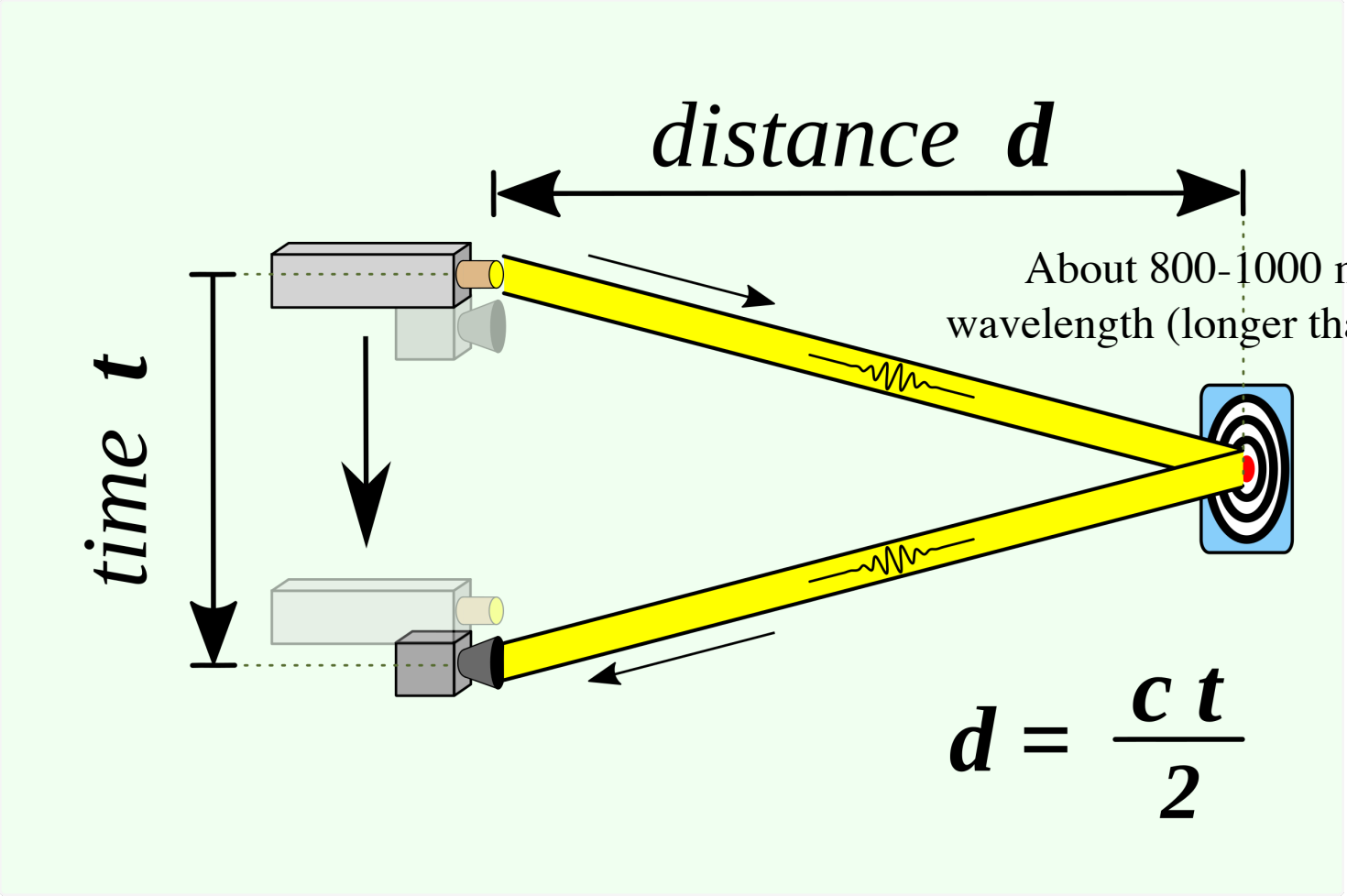


Fig. 15 Object detection on our GAN+PBR augmented nuScenes. From left to right, the original image (clear), the GAN augmented image and three GAN+PBR images.

Tremblay et al 20

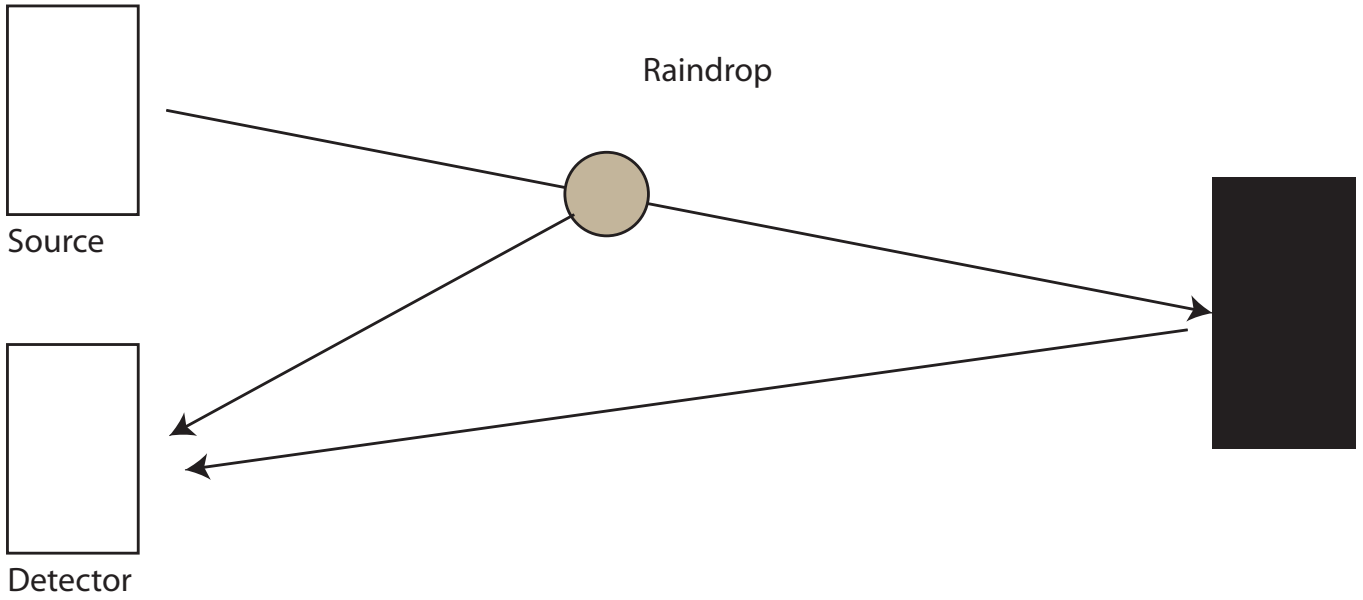
Fog and rain affect LIDAR

Fog and Lidar: Lidar

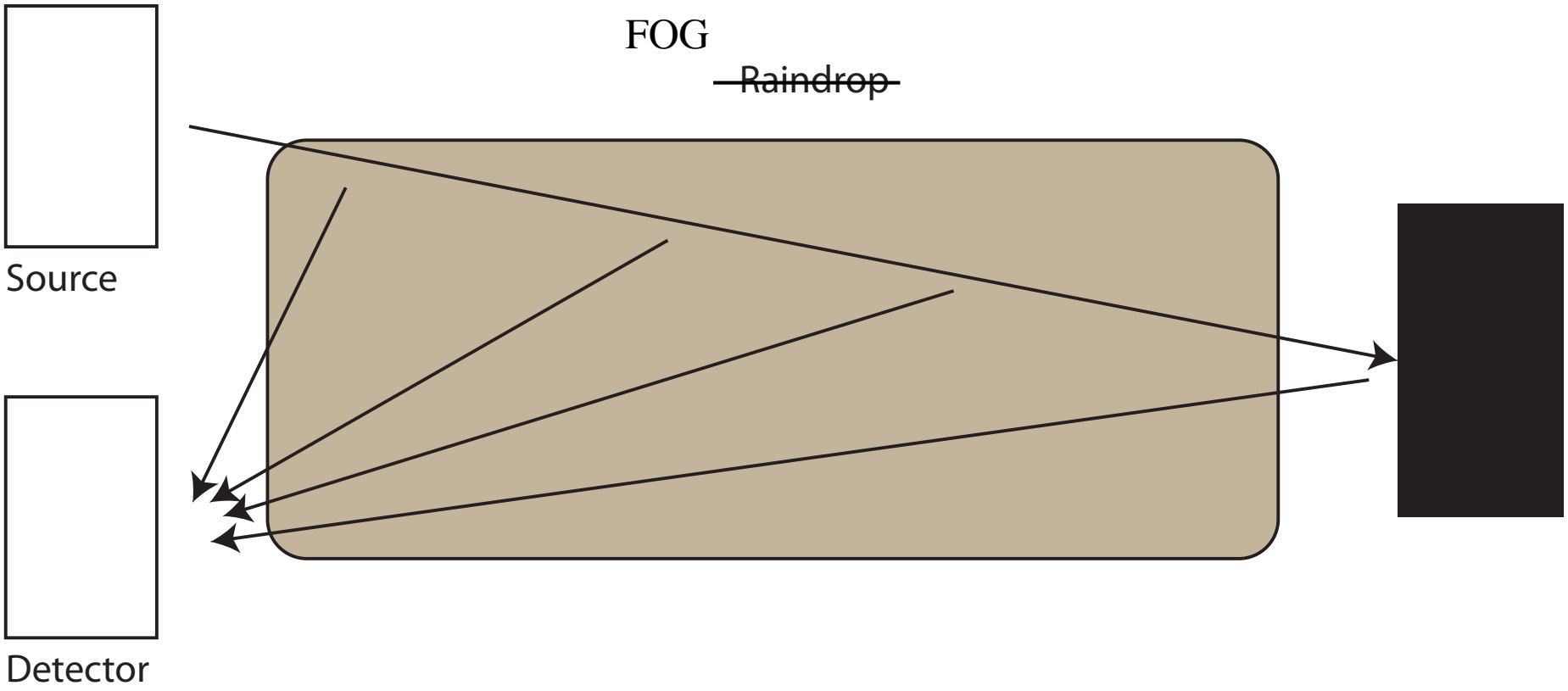


Wikipedia

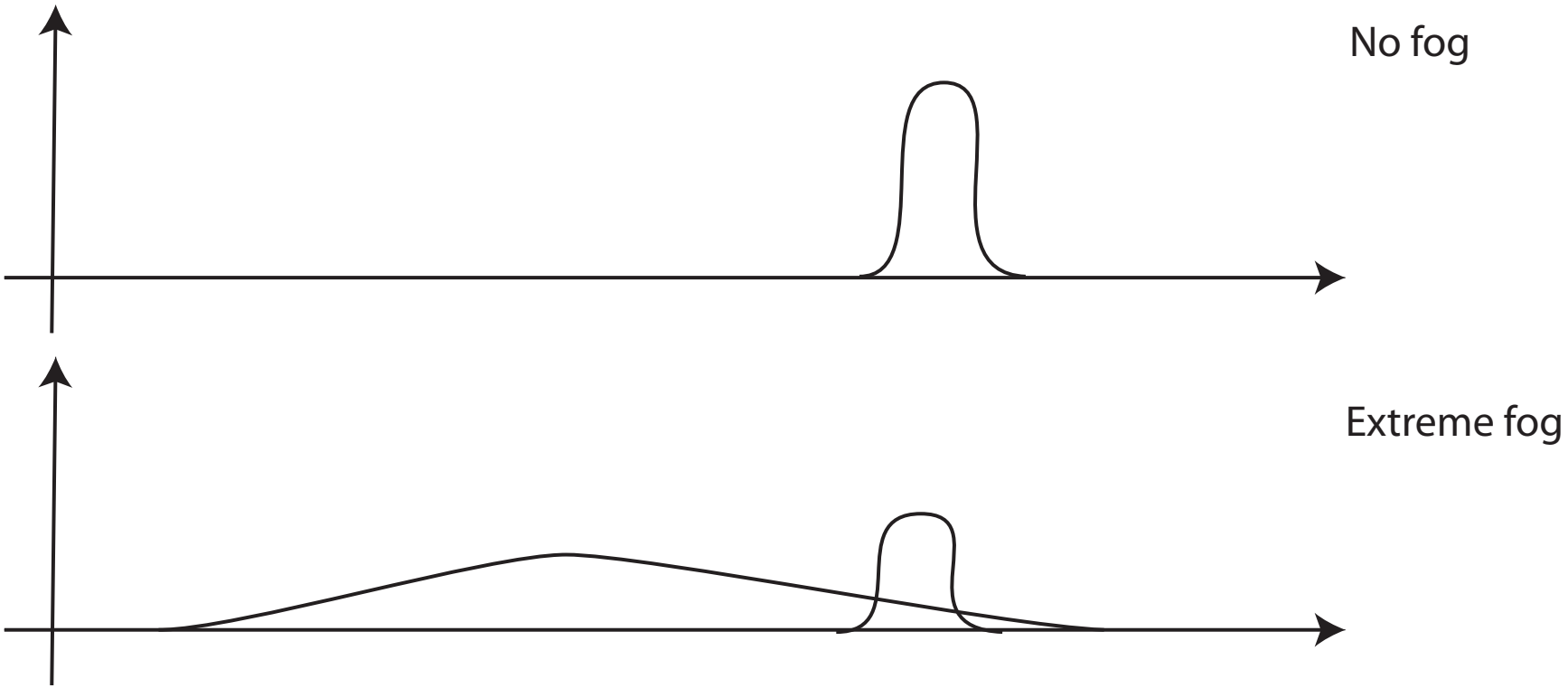
Raindrop scatter



Fog scattering



What the sensor sees…



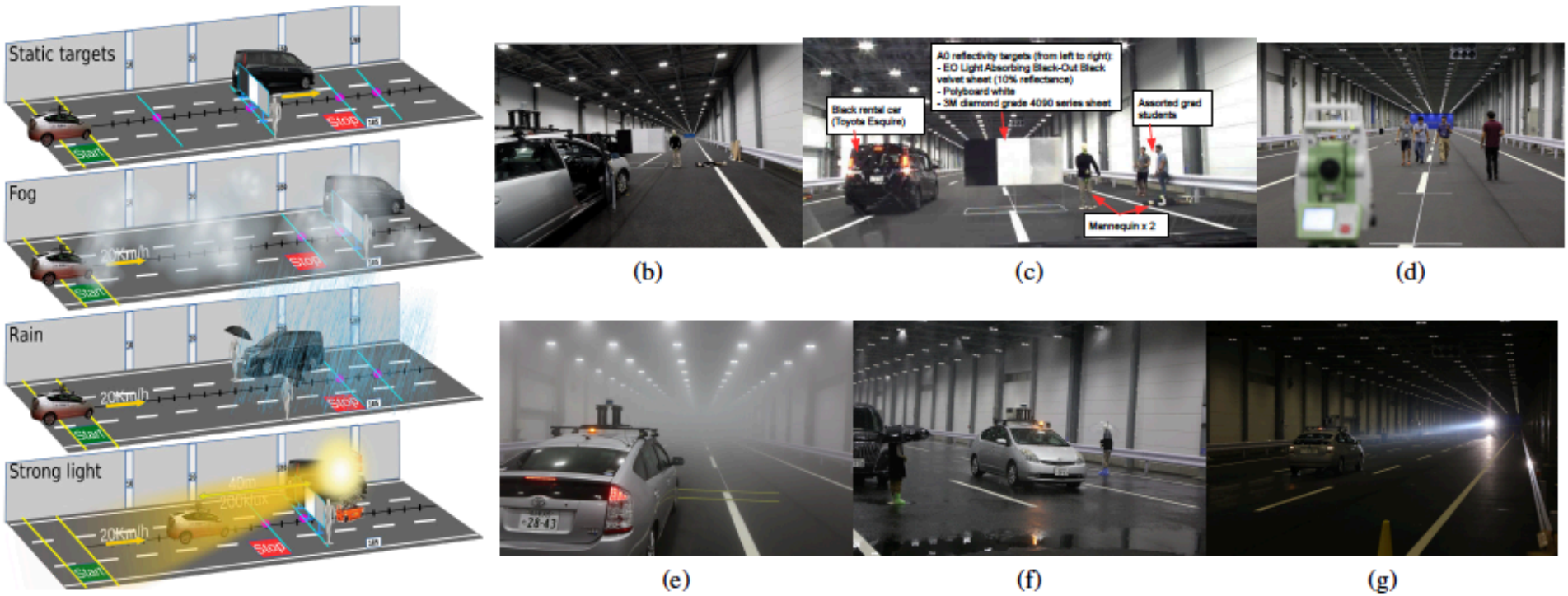
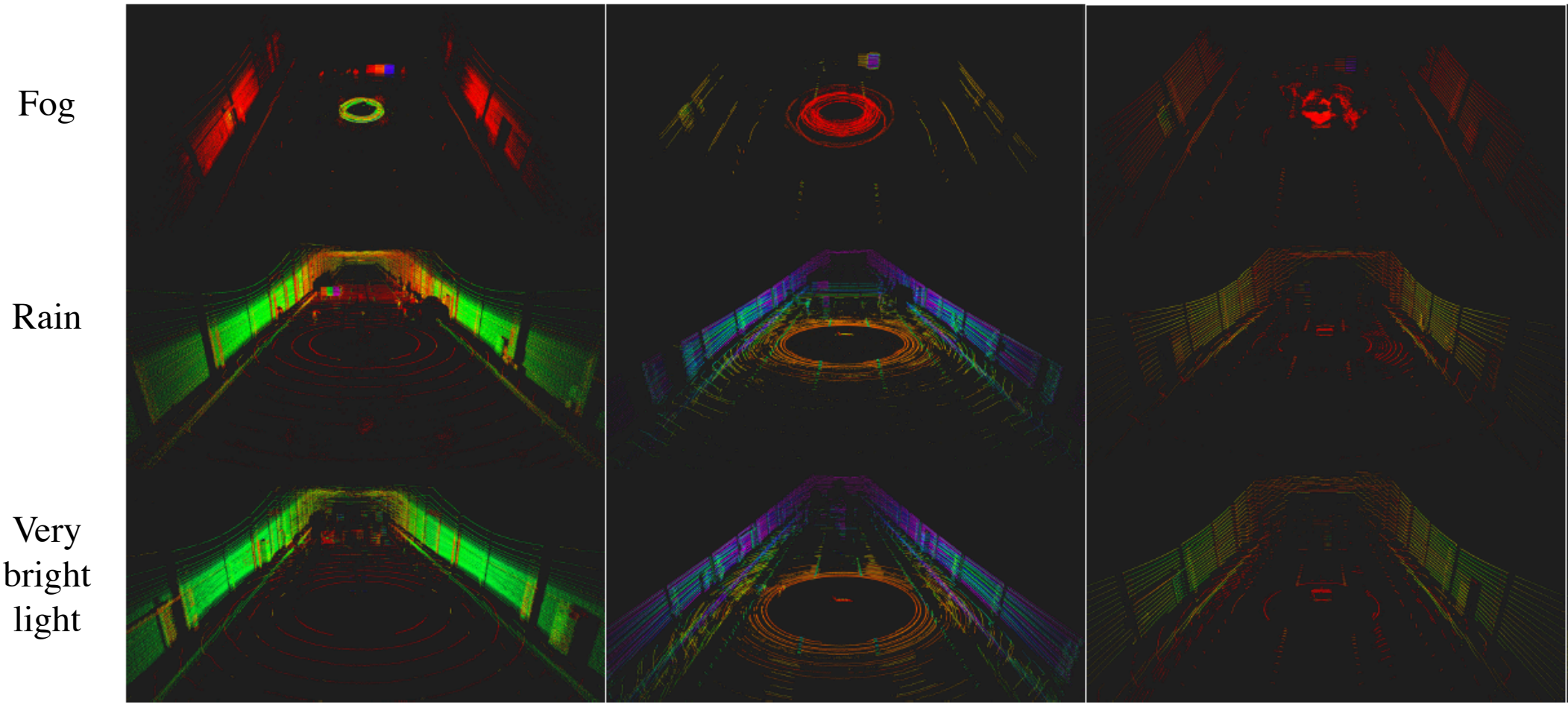


Fig. 5: Static targets and adverse weather experiments at JARI's weather chamber: (a) configuration of the different scenarios, (b) and (c) measurement, (e) to (g) sample adverse weather scenes, (d) setting up ground truth.



(a) VLS-128 (b) HDL-64S2 (c) HDL-32E

Carballo, 20

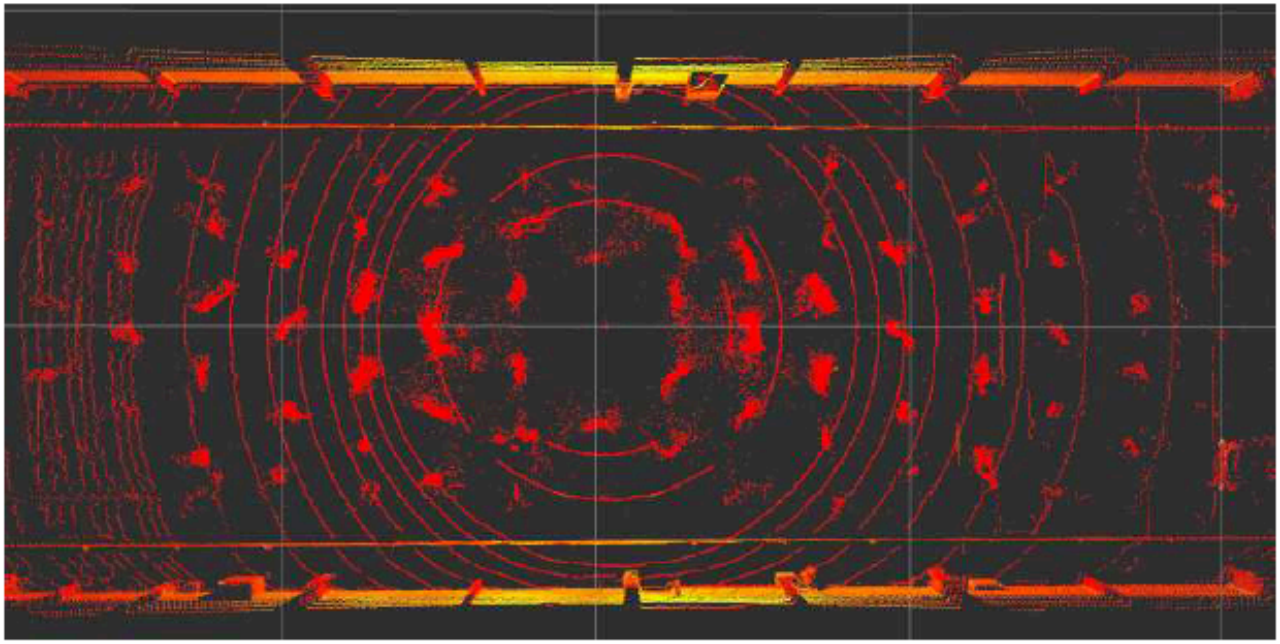


Fig. 9: “Rain pillars” as detected by a LiDAR.

- Qualitative effects
  - lost returns
  - fog torus
  - early returns
  - rain pillars
  - noise

Radar is unaffected

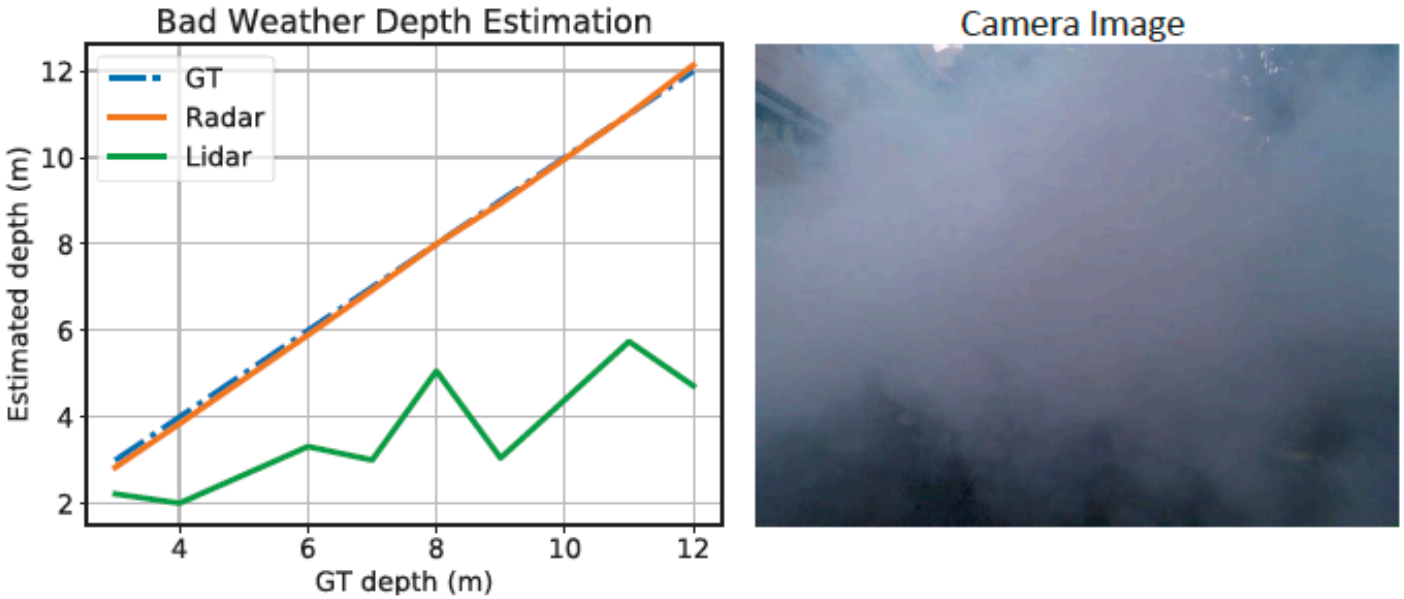
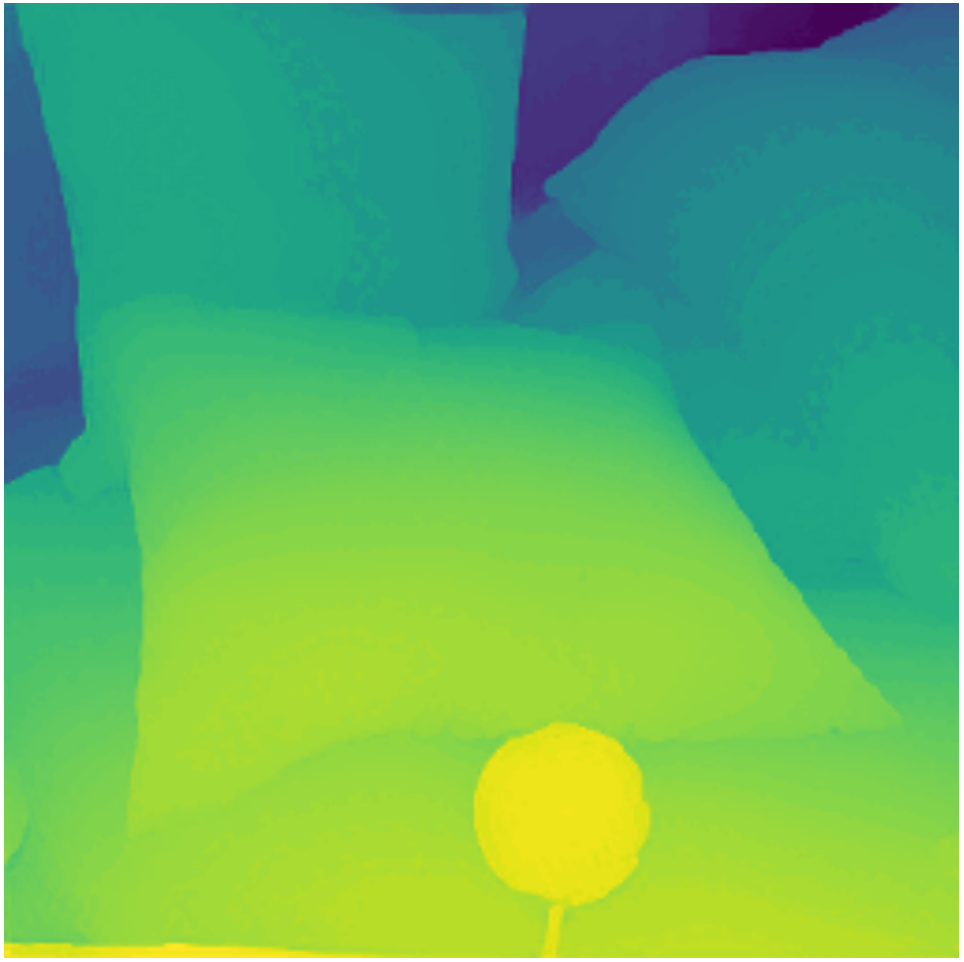


Figure 16: *Performance comparison of different sensors in the presence of adverse conditions. The left plot shows the depth estimation performance of Radar and LiDAR for an object directly in front of the sensor in the presence of fog. The right figure shows the camera image for the experiment.*

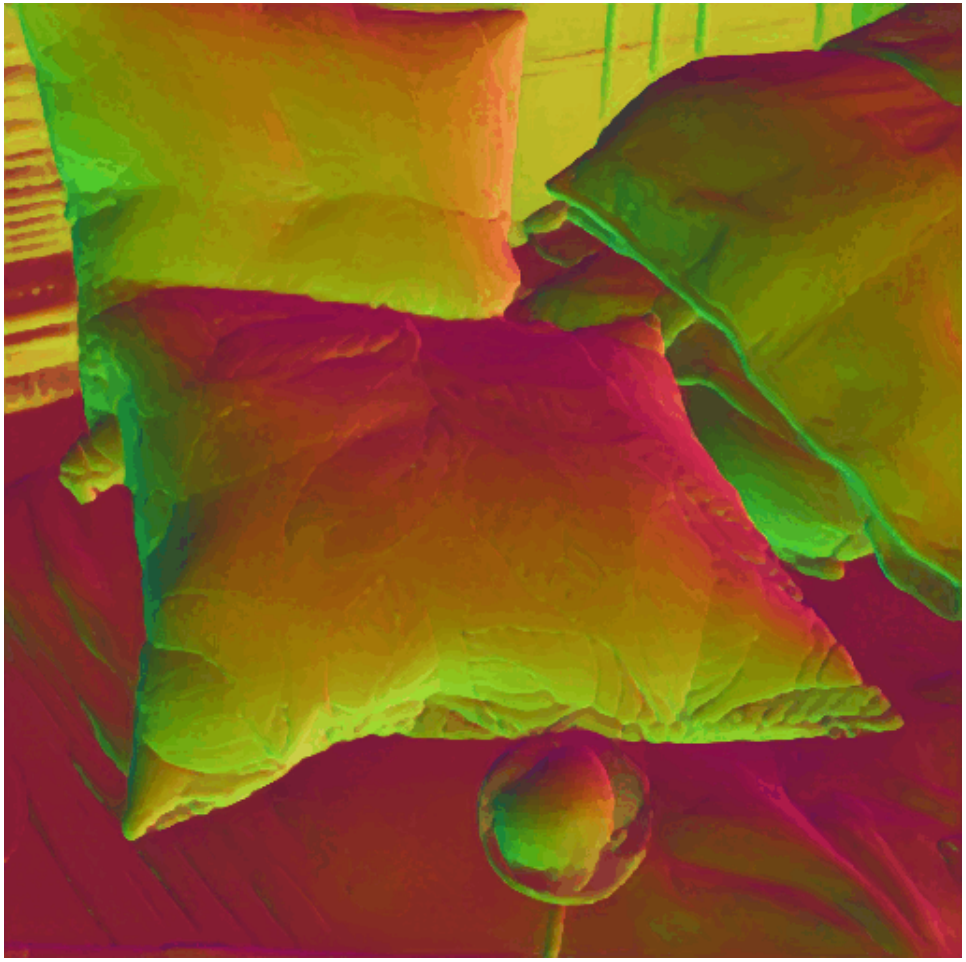
Bansal et al 20

Lighting affects methods, too

Depth (omnimap, current best depth est)



Normal (omnimap, current best normal est)



What to do?

- Maybe:
  - generate multiple lightings of the same image
    - analogy with rain
  - force method to produce same result for each

- Q: How to generate multiple lightings of the same image?

Hijacking knowledge

- StyleGAN2 is a network that
  - accepts random vectors
  - produces very convincing face images (and some others; churches, etc)
  - is trained by adversarial procedures
- This process can be “inverted”
  - GAN-inversion: given face, what random number made it?
- Pretrained models like StyleGAN2 “know” a lot
  - established literature around the idea that StyleGAN2 outputs are faces
    - pretty much whatever you do to the input

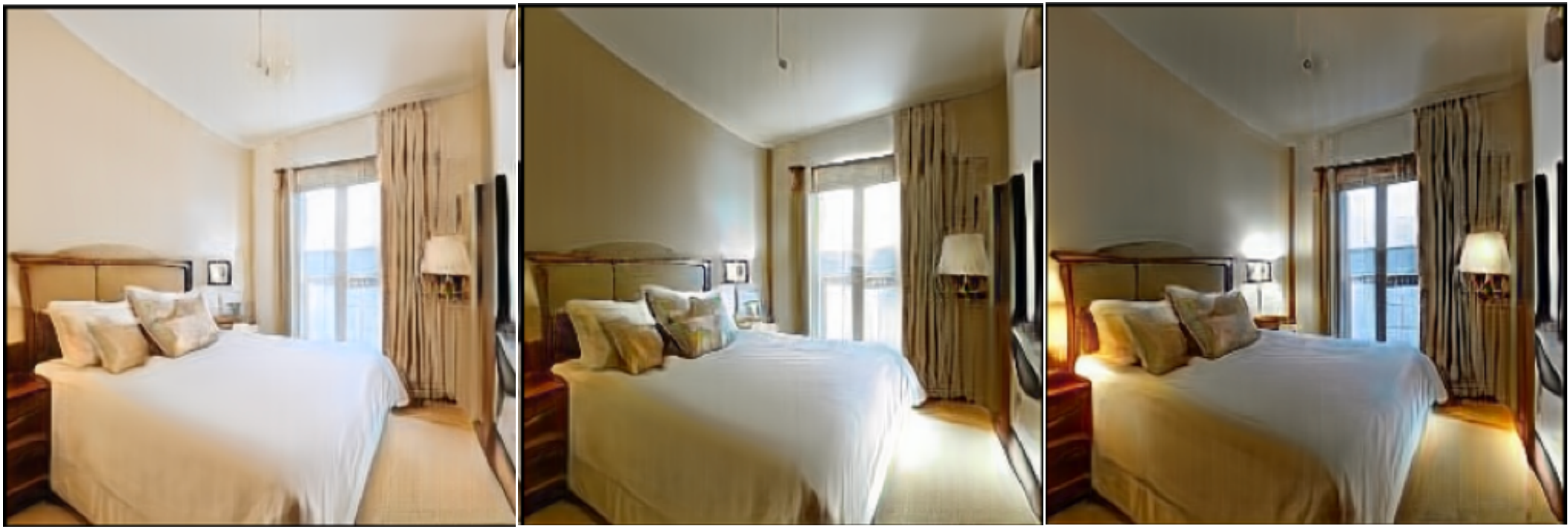
Relighting synthetic scenes

- Significant literature based on “inverse graphics”
  - Impute: geometry, albedo, luminaires; change luminaires; render
  - Zhengqin Li thesis, 2022
  - But this involves CGI,
    - which we don’t trust and
    - may not be available
- StyleGAN Judo
  - Search latent space of a generative model to find directions that
    - change image
    - don’t change computed albedo
  - for free, resurfacing
    - change image
    - don’t change shading

Luminaire aware

Bhattad et al, 23

Luminaire aware



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Real Images

- Problem:
  - who cares about normals/depth/albedo of generated images?
- Idea
  - apply GAN inversion to real image
  - then fiddle with lighting
  - THIS DOESN”T WORK
    - GAN inversion doesn’t actually get you the image you started with

Make it so - inversion

Bhattad et al, 23

Make it so: Flawless Inversion

Method	LSUN Bedroom		CelebA-HQ Faces	
	MSE	LPIPS	MSE	LPIPS
ALAE	0.330	0.65	0.150	0.32
IDInvert	0.113	0.41	0.061	0.22
Psp	0.099	0.34	0.034	0.16
GHFeat (CVPR 2022)	0.068	NA	0.046	NA
PadInv (ECCV 2022)	0.054	0.21	0.021	0.10
StyleGAN2 Optim	0.17	0.42	0.020	0.009
Make it So – Simple (ours)	0.002	0.05	NA	NA
Make it So – Final (ours)	0.002	0.03	NA	NA

Bhattad et al, 23

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Image

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Invert

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Relights

Bhattad et al, 23

Key points

- Weather effects cause detectors to work poorly
  - We can collect weathered data
  - OR unweather using regression procedures
  - OR we can train on artificially weathered data
- Lighting also causes methods to work poorly
  - we can relight images (hard!)