Fog and defogging

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Why we care

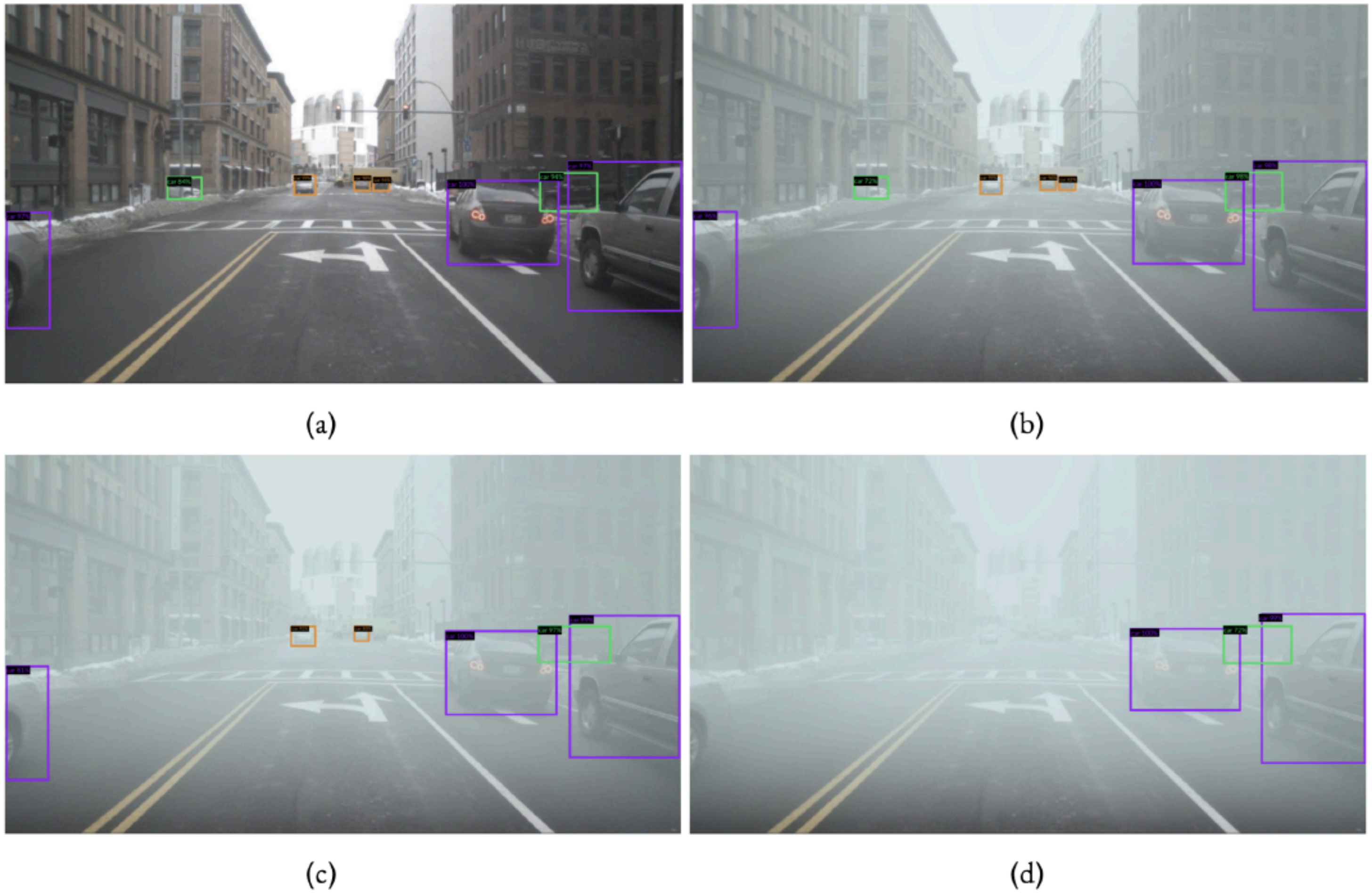


Figure 4.9: *(a) The output of Detectron2 on an image with no fog. All detected close-distance vehicles are outlined by a purple bounding box, all detected medium-distance vehicles are outlined by a green bounding box, and all detected far-distance vehicles are outlined by an orange bounding box. (b) The output of Detectron2 on a rendering of the same image with light fog synthetically added. (c) The output of Detectron2 on a rendering of the same image with medium-intensity fog synthetically added. (d) The output of Detectron2 on a rendering of the same image with heavy fog synthetically added.*

Kore, 23

Image interpretation strategies

- Dehaze (derain; denighttime; etc) image, then apply
  - detector, segmenter, etc
  - issues:
    - dehazing (etc.) may create signal problems
- Simulate haze (rain; night; etc) existing labelled data, then train
  - detector, segmenter, etc.
  - issues:
    - simulator may not be accurate
- Collect paired data (good conditions/bad conditions)
- Multi-sensor fusion
  - different sensors are affected in different ways, so….

There's a review in Hnewa, 21

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

Defogging by simple learning

- Idea:
  - Obtain (hazy image, clean image) pairs
  - Train network to recover clean from hazy
- Note:
  - given depth map, fog is easy to simulate quite well
    - good simulators take into account inhomogeneity in fog, etc.
  - so you could make pairs by simulation
    - strong evidence the depth map doesn't need to be consistent w/ image

Paired datasets

- Strategy:
  - 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
  - Take photos outdoors; introduce fog; repeat
    - NH-HAZE
      - https://data.vision.ee.ethz.ch/cvl/ntire20/nh-haze/

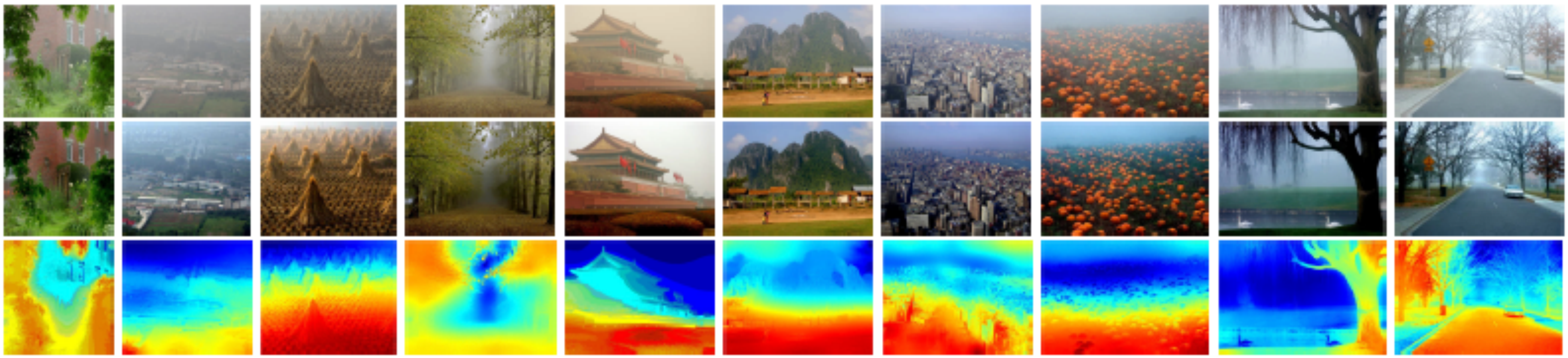


Fig. 11. The haze-free images and depth maps restored by DehazeNet

Cai et al 16 (DeHazeNet)

Single image dehazing

- Essentially
  - obtain images with/without haze (with haze by synthetic)
  - train network to reproduce without haze image from with haze

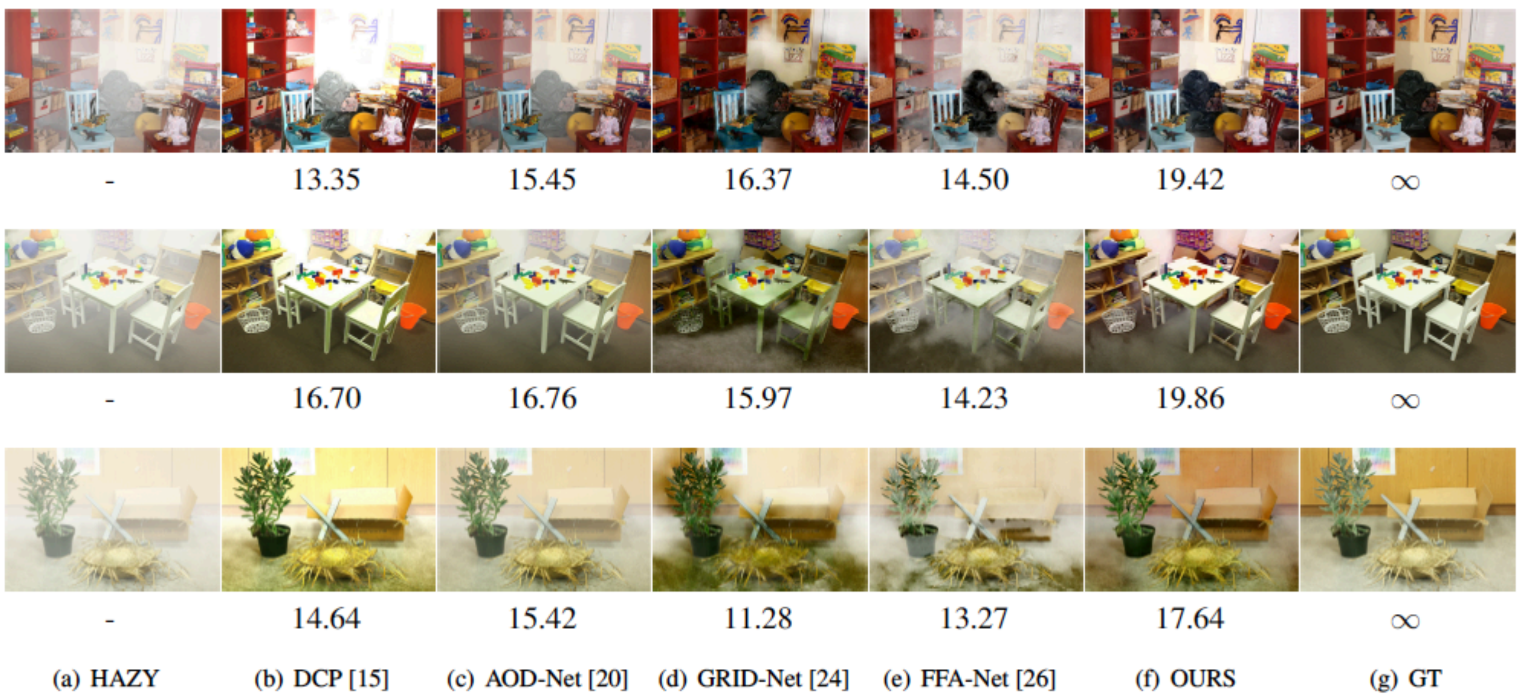
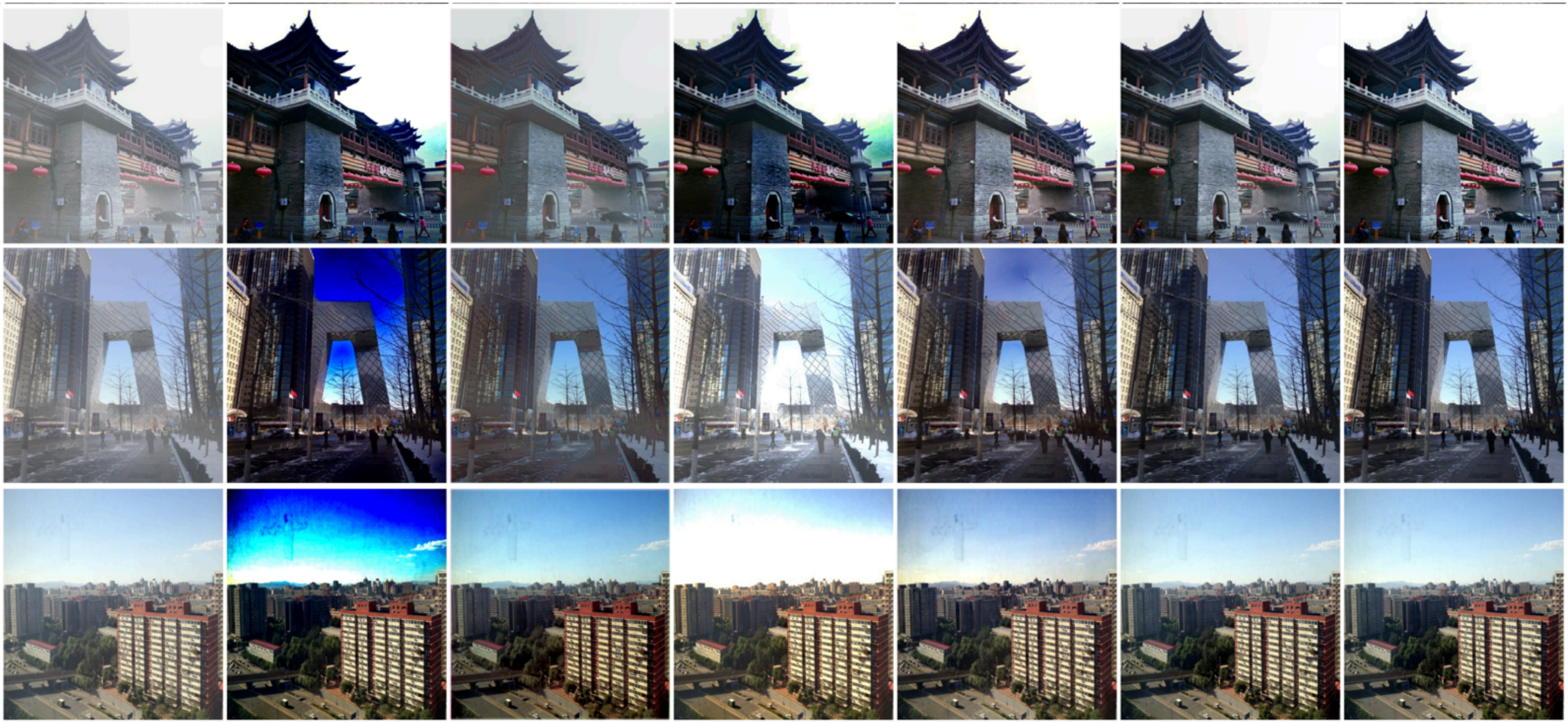


Figure 6. Qualitative comparisons with different state-of-the-art dehazing methods for indoor synthesis hazy images. The top two rows are from SOTS, the third row is from TestA dataset and the bottom three rows are from MiddleBury dehazing dataset. The numbers below image are PSNR (dB) value of each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

Shen et al 19

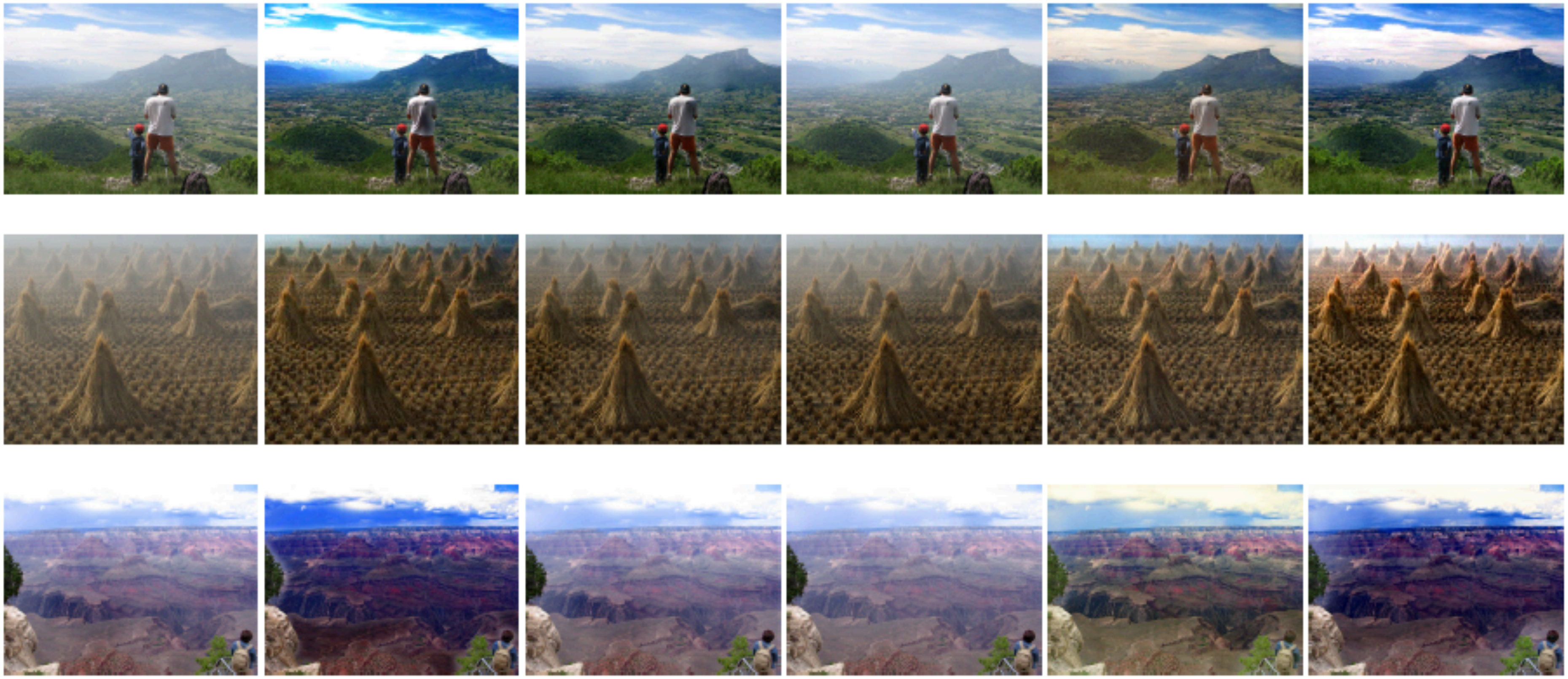


(a)Hazy inputs (b)DCP (c)AOD-Net (d)DehazeNet (e)GCANet (f)Ours (g) GT

Qin et al 19 - Use feature attention

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



(a) INPUT (b) DCP [15] (c) GRID-Net [24] (d) FFA-Net [26] (e) FD-GAN [11] (f) OURS

Figure 7. Qualitative comparisons with different dehazing state-of-the-art methods for real hazy images.

Shen et al 20 - Use sequence model (resnet as implicit euler method)

Challenges

- NTIRE workshops and challenges
  - https://data.vision.ee.ethz.ch/cvl/ntire21/
  - https://data.vision.ee.ethz.ch/cvl/ntire20/