



Single Image Dehazing via Multi-Scale Convolutional Neural Networks

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Introduction



- ❑ Hazy images
 - ❑ Low visibility: distance between an object and the observer increases
 - ❑ Faint colors: atmosphere color replaces the color of the object



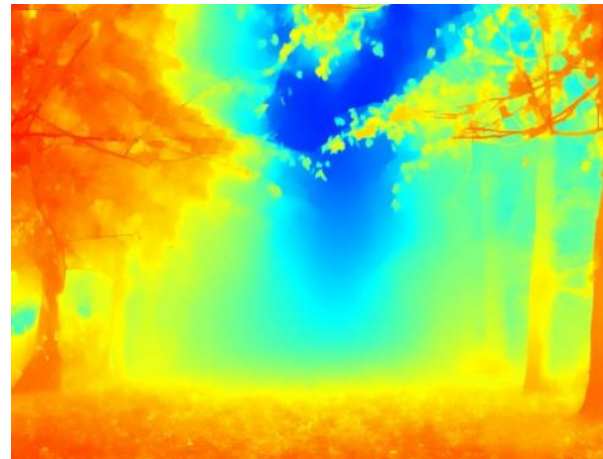
Introduction



- ❑ Goals of image dehazing
 - ❑ Transmission estimation
 - ❑ Scene recovering



Hazy image



Transmission



Scene

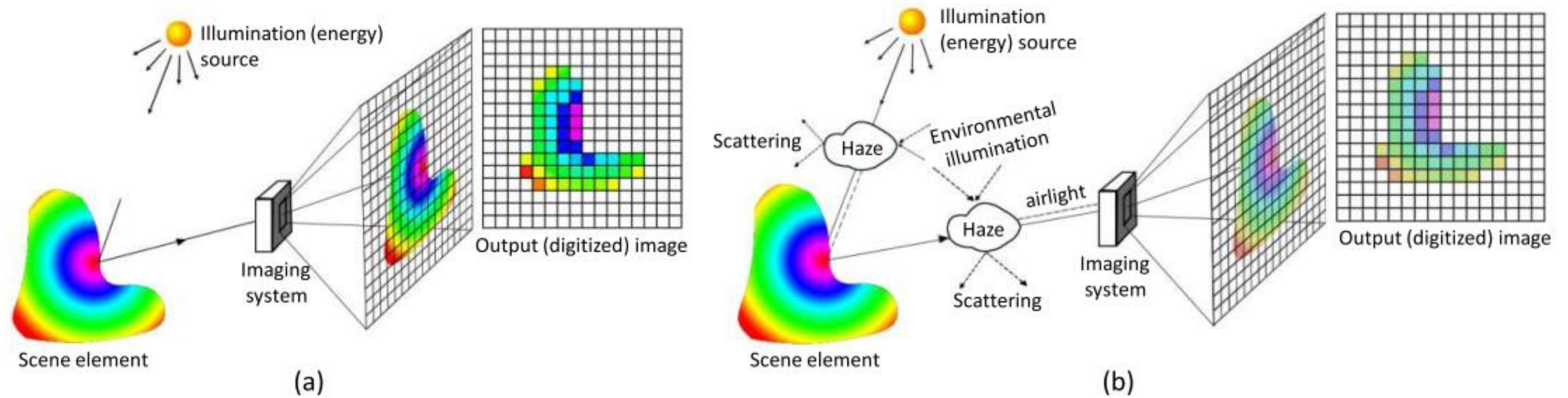


- ❑ Applications
 - ❑ CCTV surveillance (car plate or face)
 - ❑ Airborne surveillance
 - ❑ Unmanned drive

Introduction



□ Hazy imaging model



[1] A fast single image haze removal algorithm using color attenuation prior (Zhu et al. TIP 2015)

Introduction



- Hazy imaging model

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x))$$



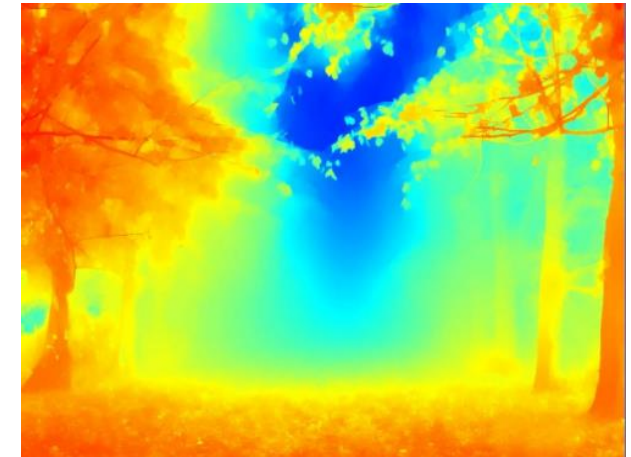
Atmospheric light



Hazy image



Scene

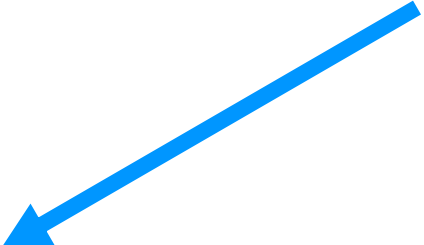


Transmission



□ Hazy imaging model

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x))$$

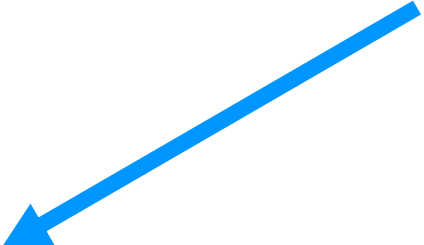

$$t(x) = e^{-\beta d(x)}$$

$t(x)$: Transmission
 $d(x)$: Scene depth
 β : medium extinction coefficient

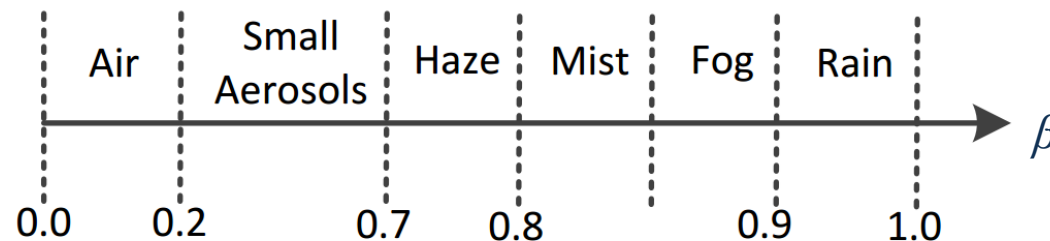


□ Hazy imaging model

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x))$$


$$t(x) = e^{-\beta d(x)}$$

$t(x)$: Transmission
 $d(x)$: Scene depth
 β : medium extinction coefficient



- ❑ Maximize local contrast



- Visibility in bad weather from a single image. Tan, CVPR 2008

❑ Dark channel prior



- Single Image Haze Removal Using Dark Channel Prior (He et al. CVPR 2009)



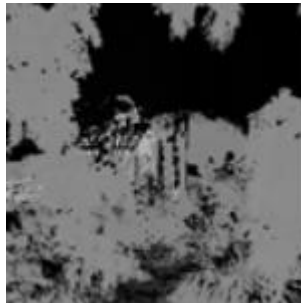
❑ Maximize local contrast



Hazy input



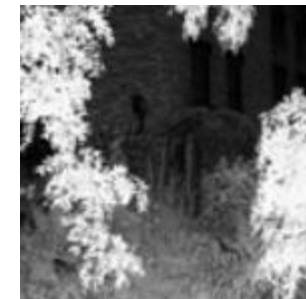
dark channel feature



hue disparity feature



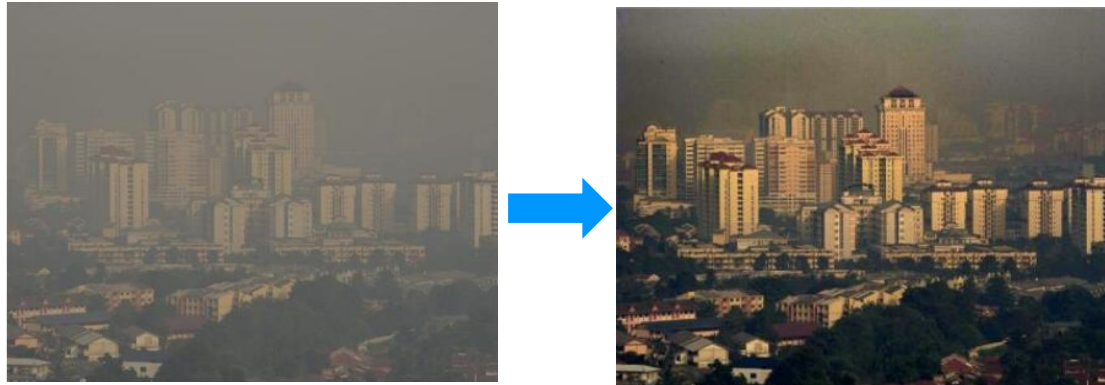
local max contrast feature



local max saturation feature

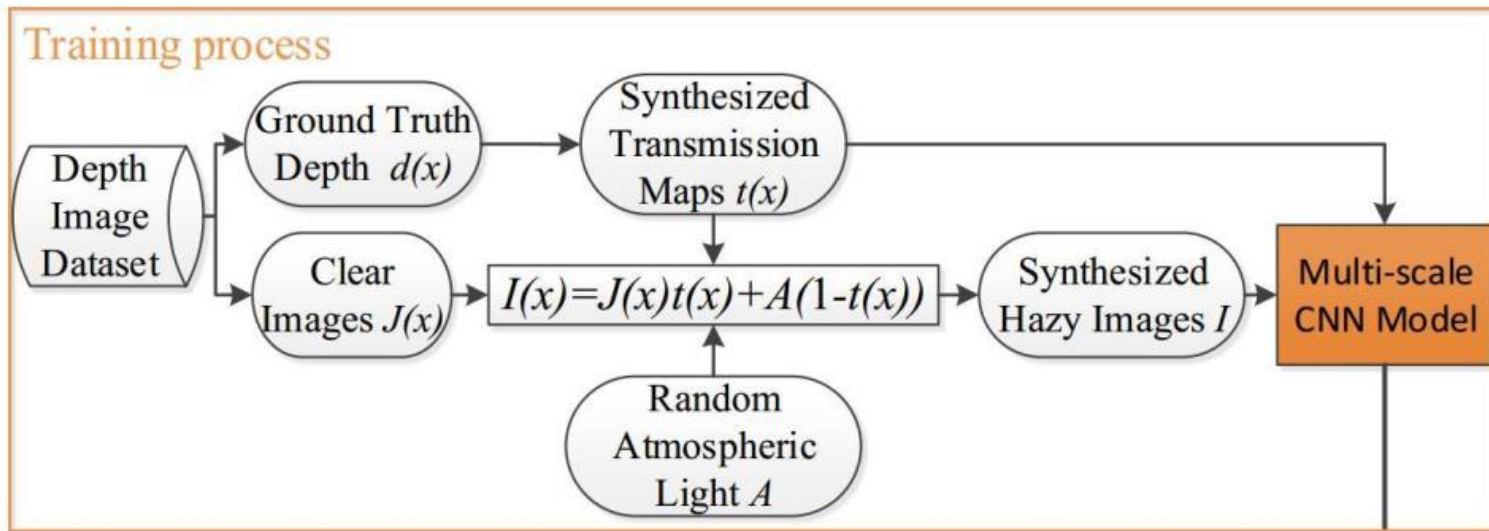
- Investigating Haze-relevant Features in A Learning Framework for Image Dehazing (Tang et al. CVPR 2014)

Contributions

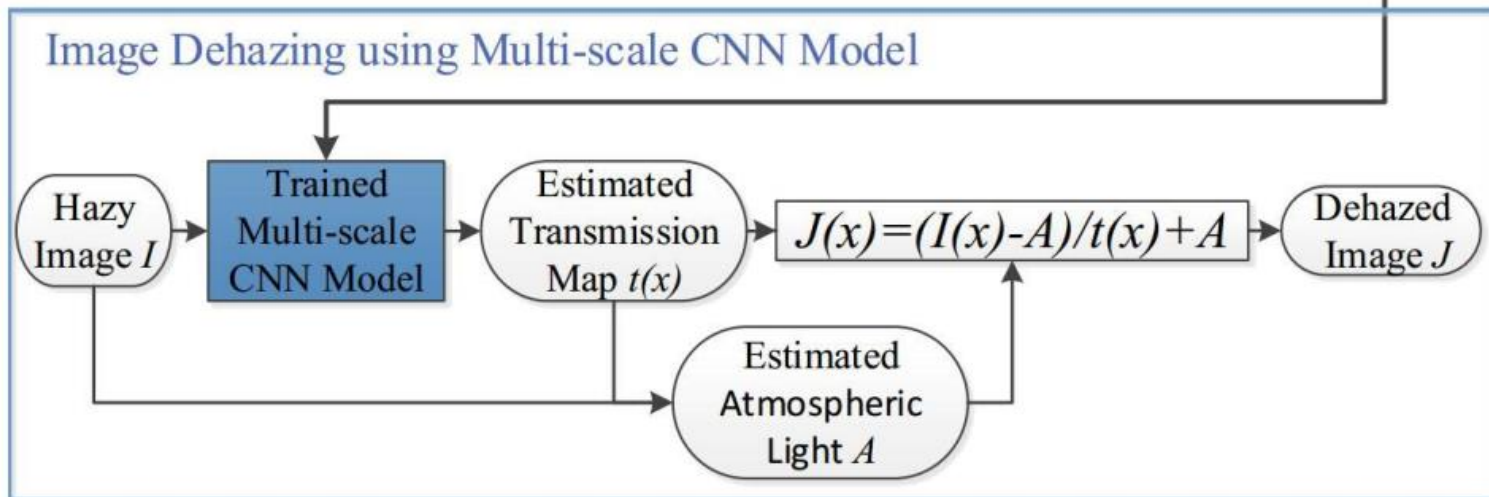


- A multi-scale convolutional neural network for transmission estimation
- Analyze the differences between traditional hand-crafted features and the features learned by the CNN
- Real-time on QVGA (320×240) images

Algorithmic Overview



We first train the multi-scale CNN based on synthesized dataset



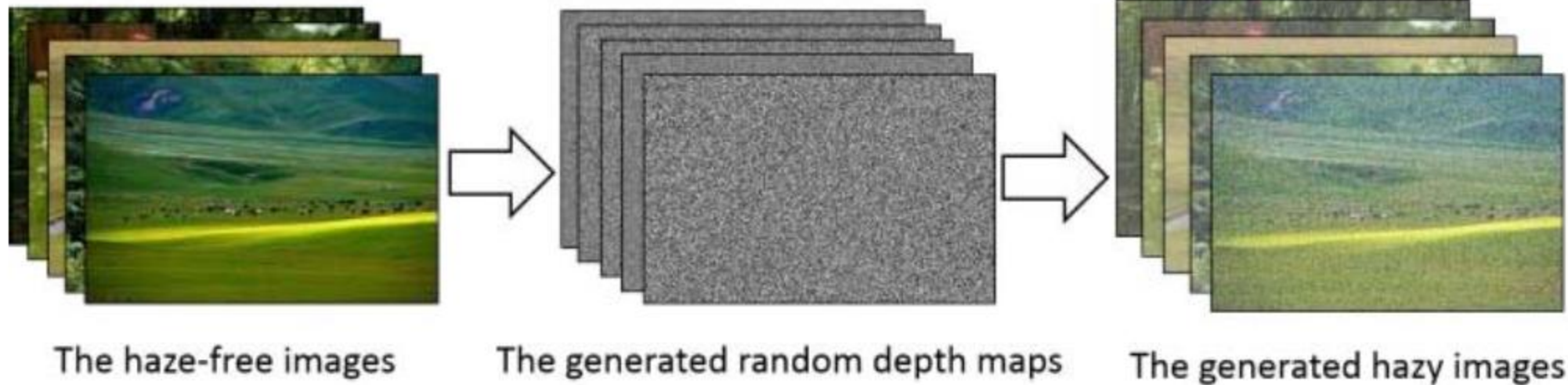
Then predict transmission based on the trained network

Training Data Synthesis



- Generate synthesized hazy images and transmission

$$I(x) = J(x)t(x) + A(1 - t(x))$$



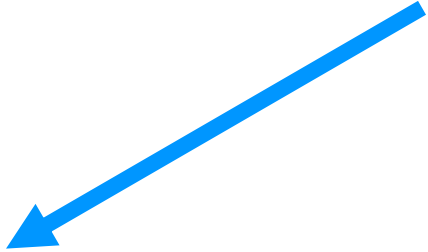
[1] A fast single image haze removal algorithm using color attenuation prior (Zhu et al. TIP 2015)

Training Data Synthesis



- ❑ Generate synthesized hazy images and transmission
 - ❑ NYU depth dataset: $J(x)$ and $d(x)$
 - ❑ Hazy imaging model

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x))$$

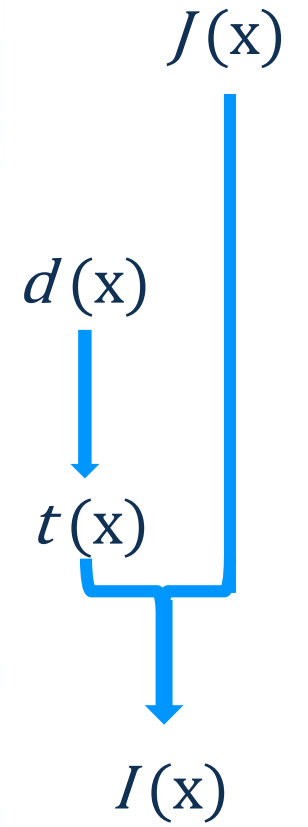
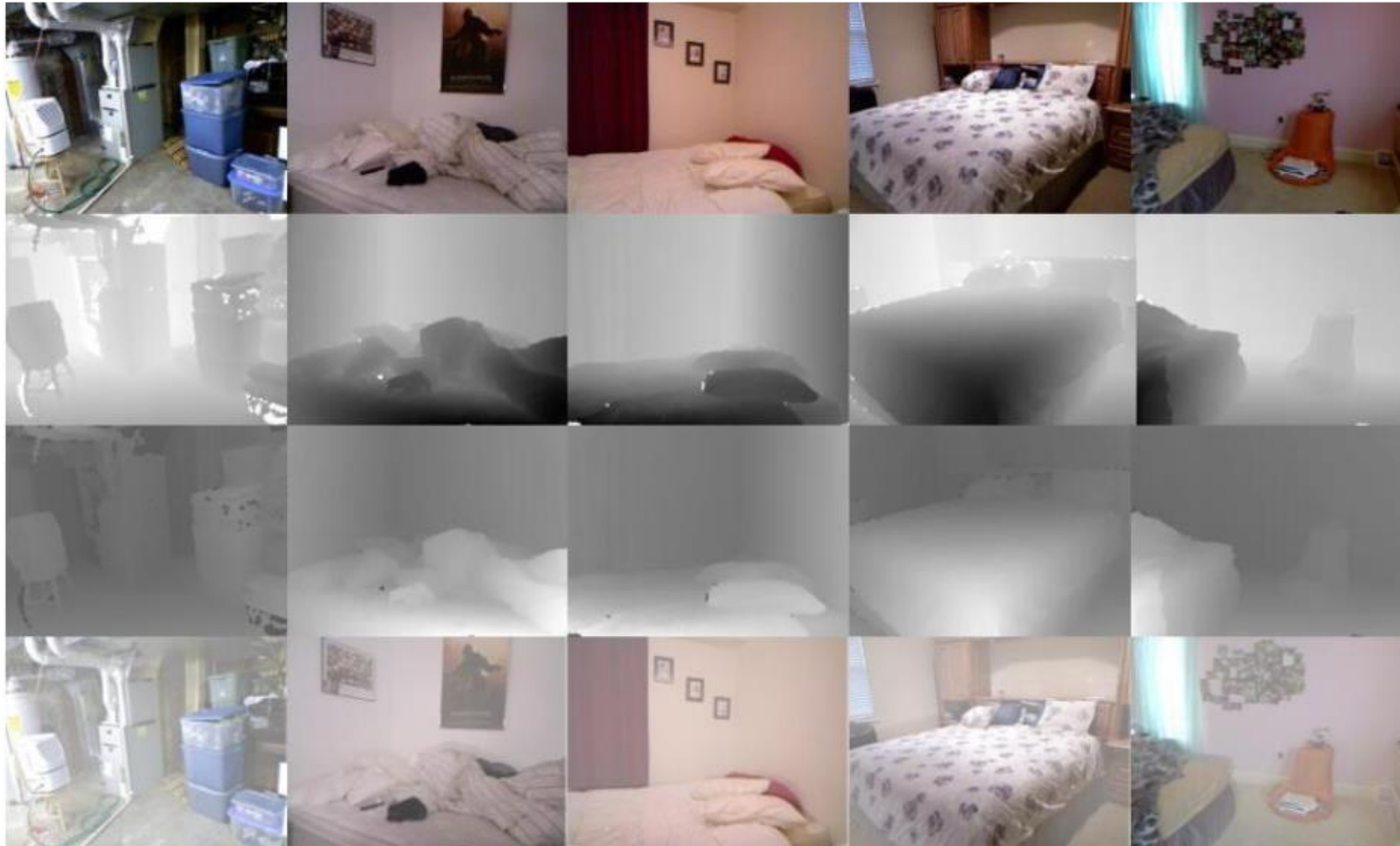

$$t(x) = e^{-\beta d(x)}$$

$t(x)$: Transmission
 $d(x)$: Scene depth
 β : medium extinction coefficient

Training Data Synthesis



Clear images
Depths
Transmissions
Hazy images



Training Data Synthesis



Clear image



Depth image

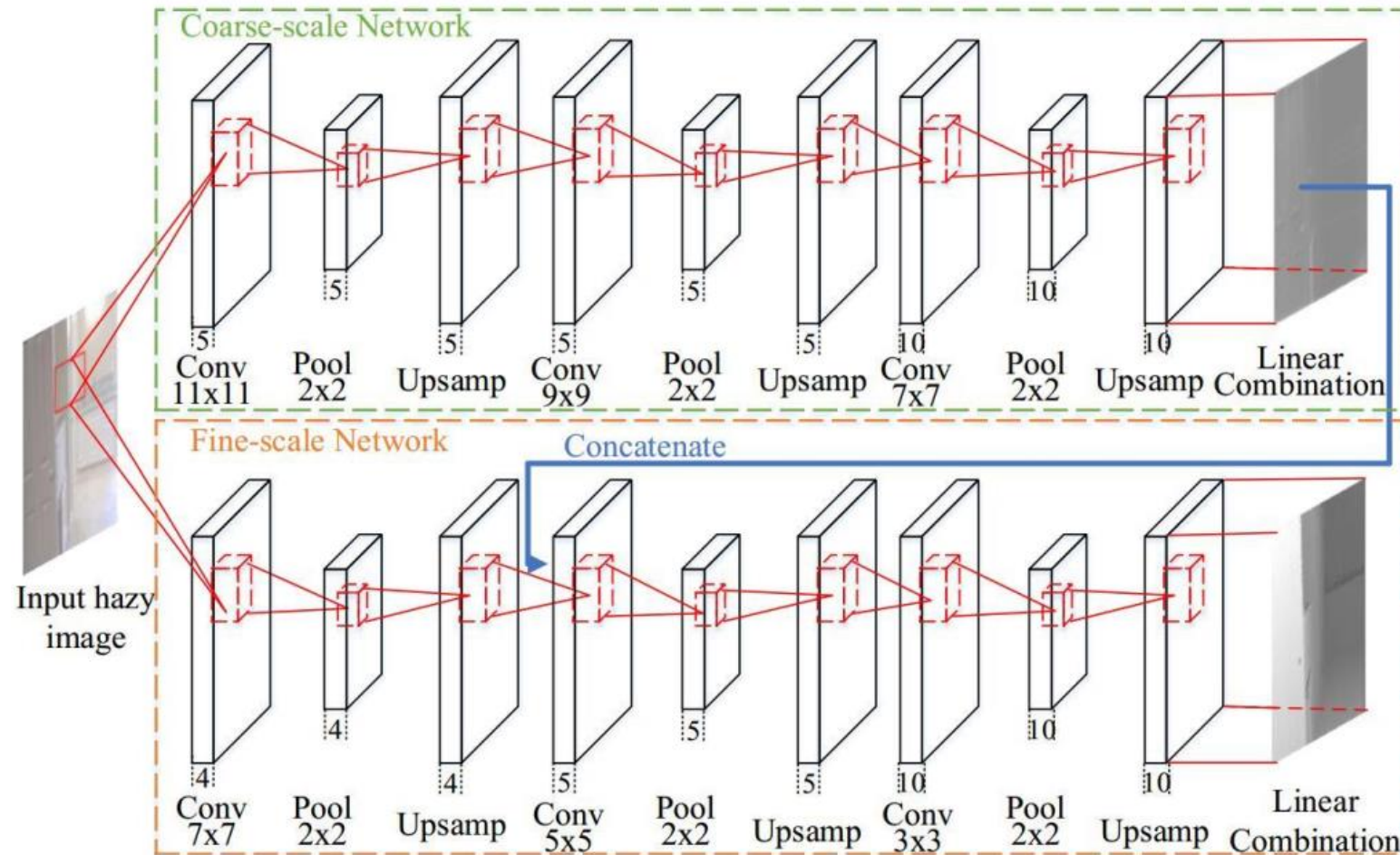


Hazy images with different β

Network Architecture



- The scene transmission map is first estimated by a **coarse-scale network** and then refined by a **fine-scale network**.



Network Architecture (Transmission Estimation)



- ❑ Training loss

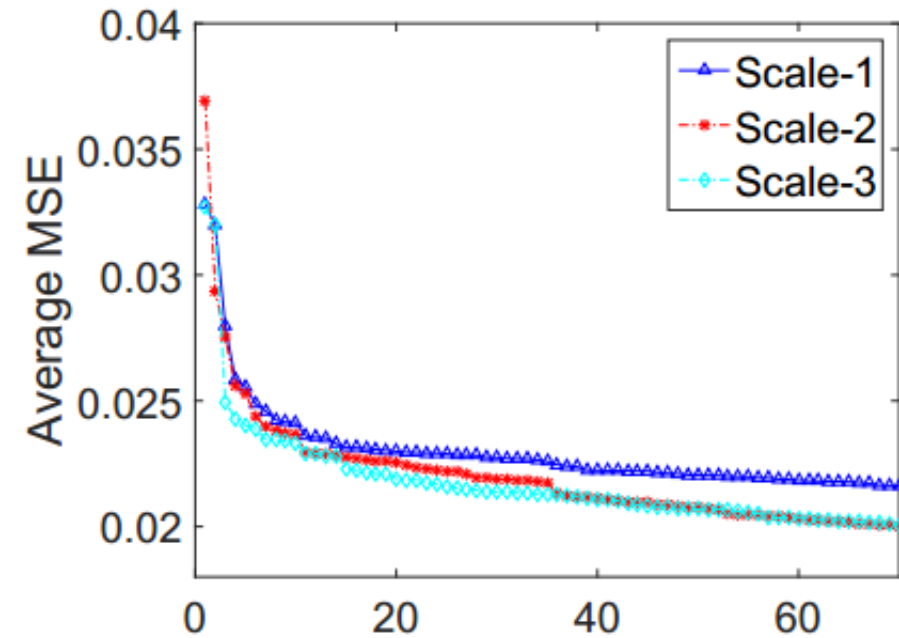
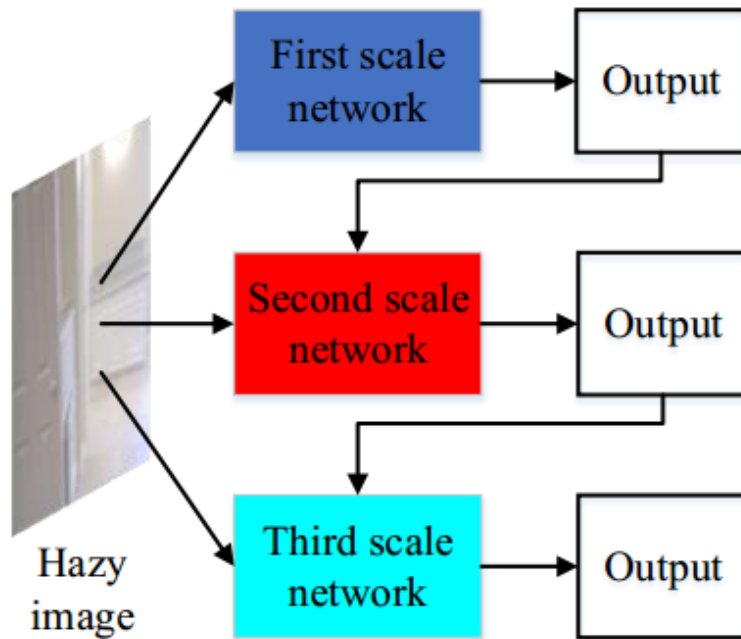
$$L(t_i(x), t_i^*(x)) = \frac{1}{q} \sum_{i=1}^q \|t_i(x) - t_i^*(x)\|^2$$

- ❑ The training loss is used in both coarse and fine-scale networks

Network Architecture



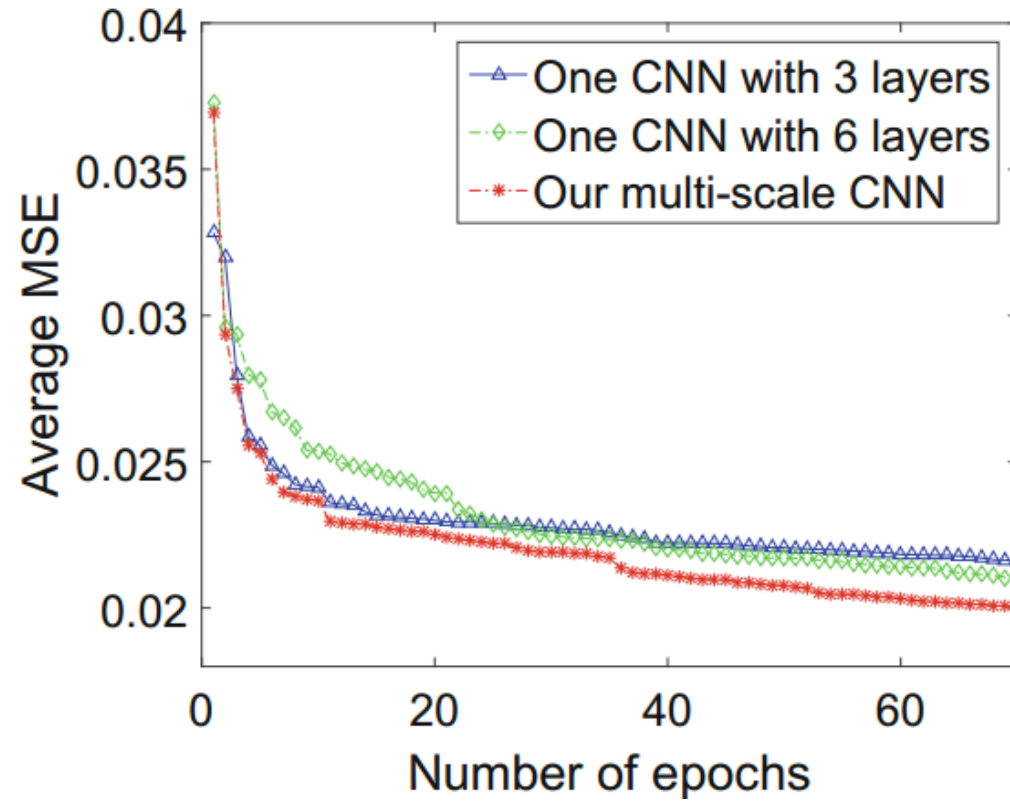
- ❑ Two-scale network is enough



Network Architecture



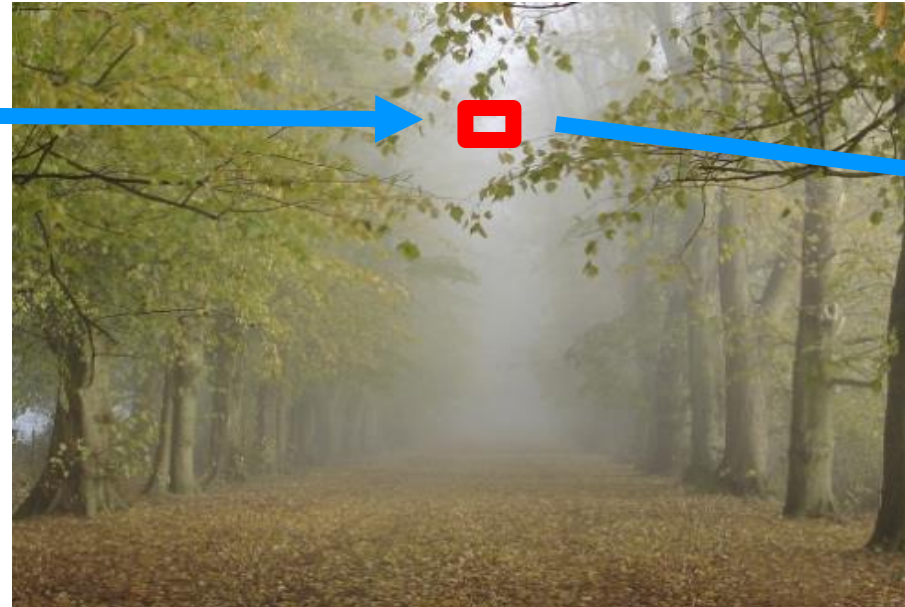
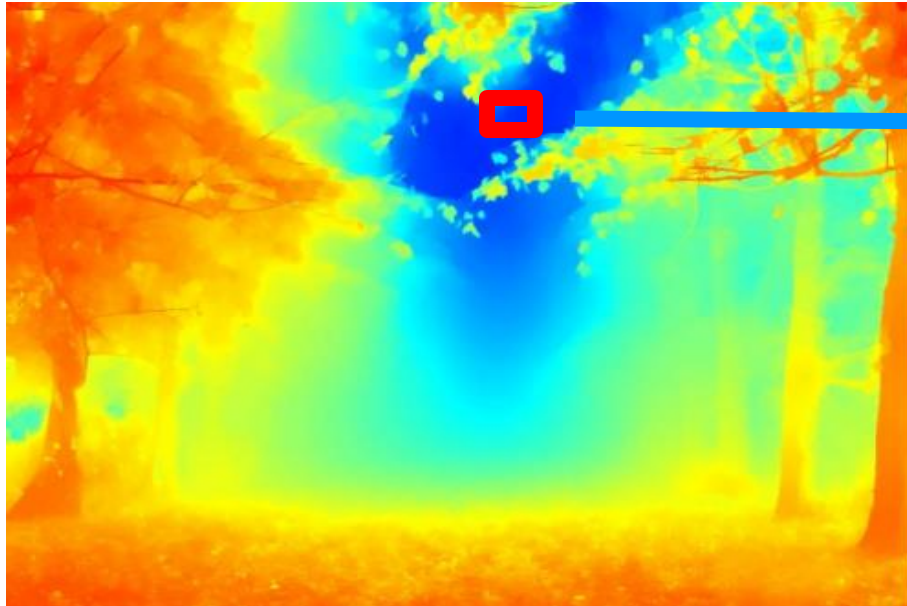
□ Depth vs Scale



Atmospheric Light Estimation



- ❑ Compute atmospheric light from the estimated transmission map



Atmospheric Light

Haze Removal

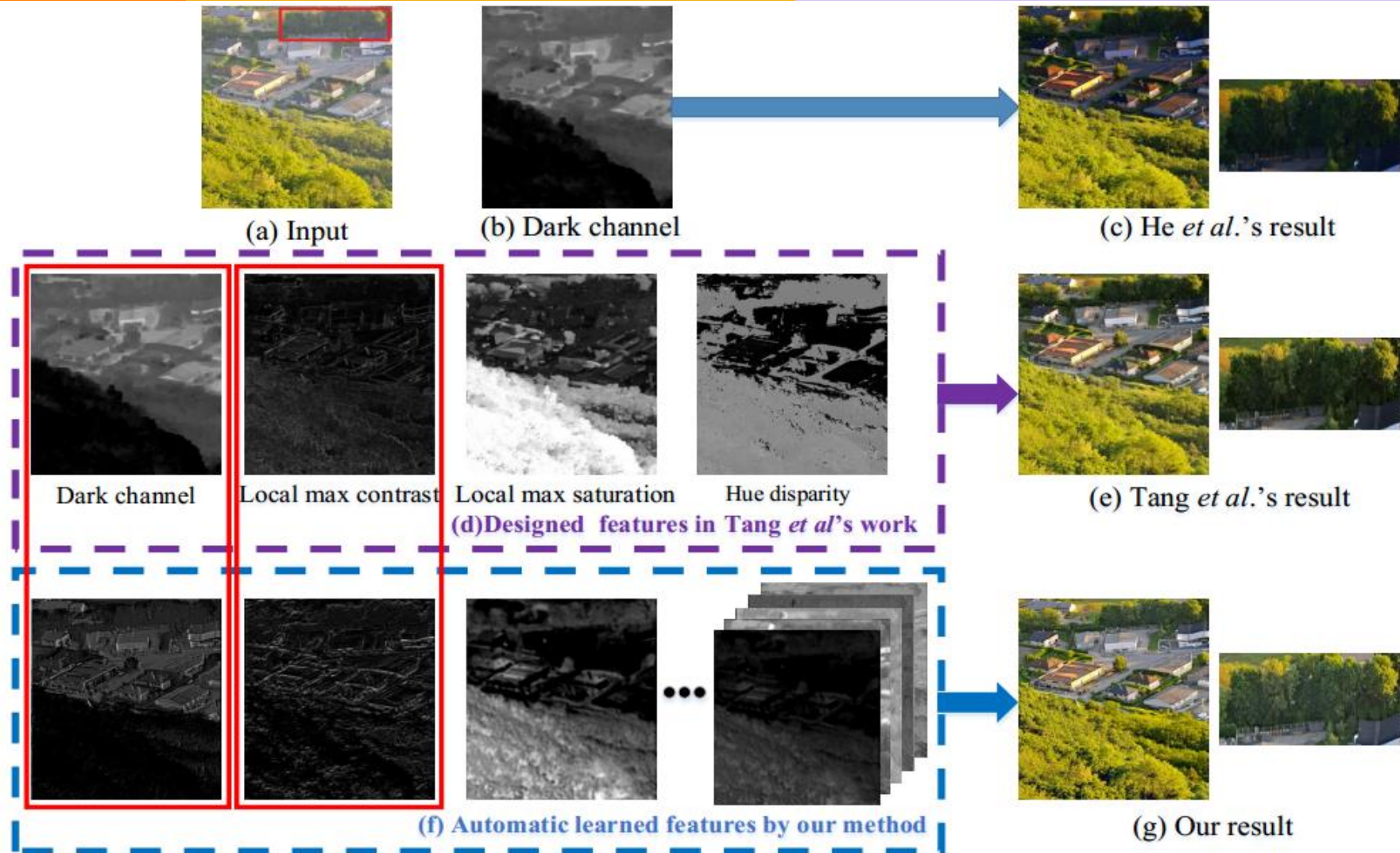


- Recover haze-free images After atmospheric light and transmission are estimated

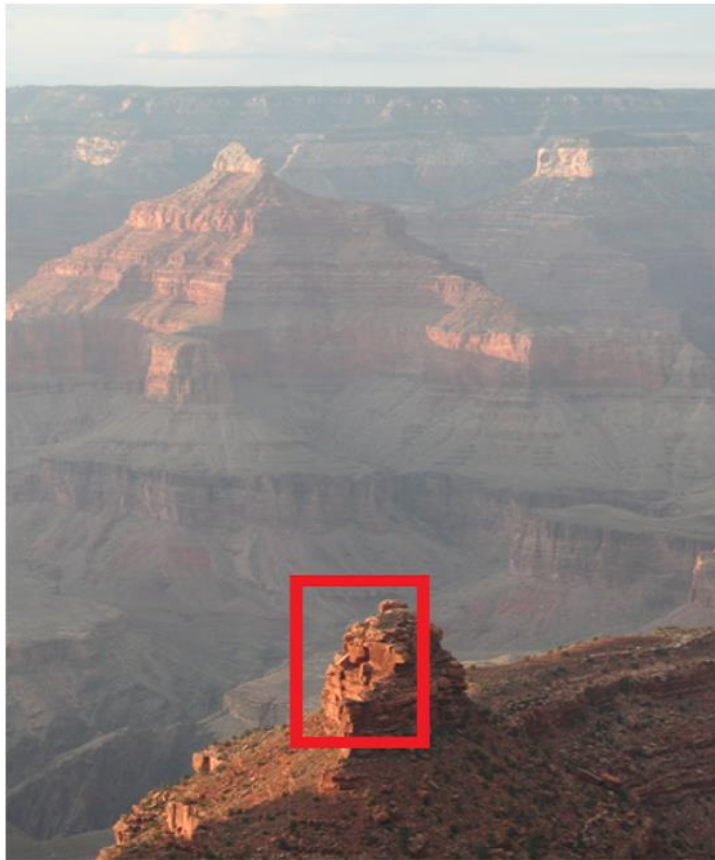
$$I(x) = J(x)t(x) + A(1 - t(x))$$

$$J(x) = \frac{I(x) - A}{t(x)} + A. \quad \longrightarrow \quad J(x) = \frac{I(x) - A}{\max\{0.1, t(x)\}} + A.$$

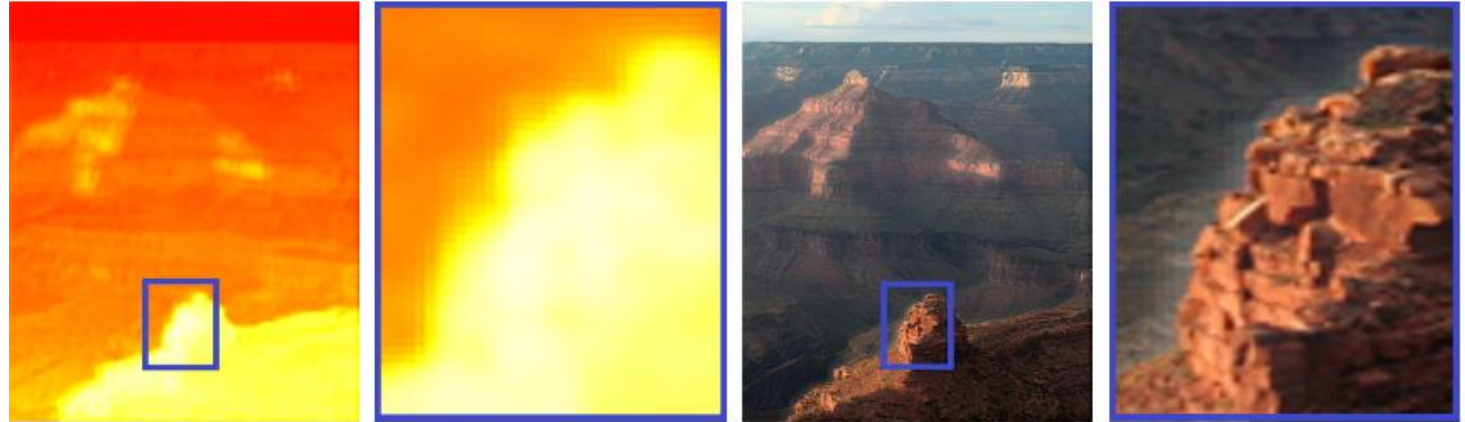
Feature Analysis



Effectiveness of Fine-scale Network



Hazy image



Without the fine-scale network



With the fine-scale network

Generalization Capability



- ❑ Our synthesized transmission maps cover the range of values in real transmission maps

Hazy images



Our results



Close shot

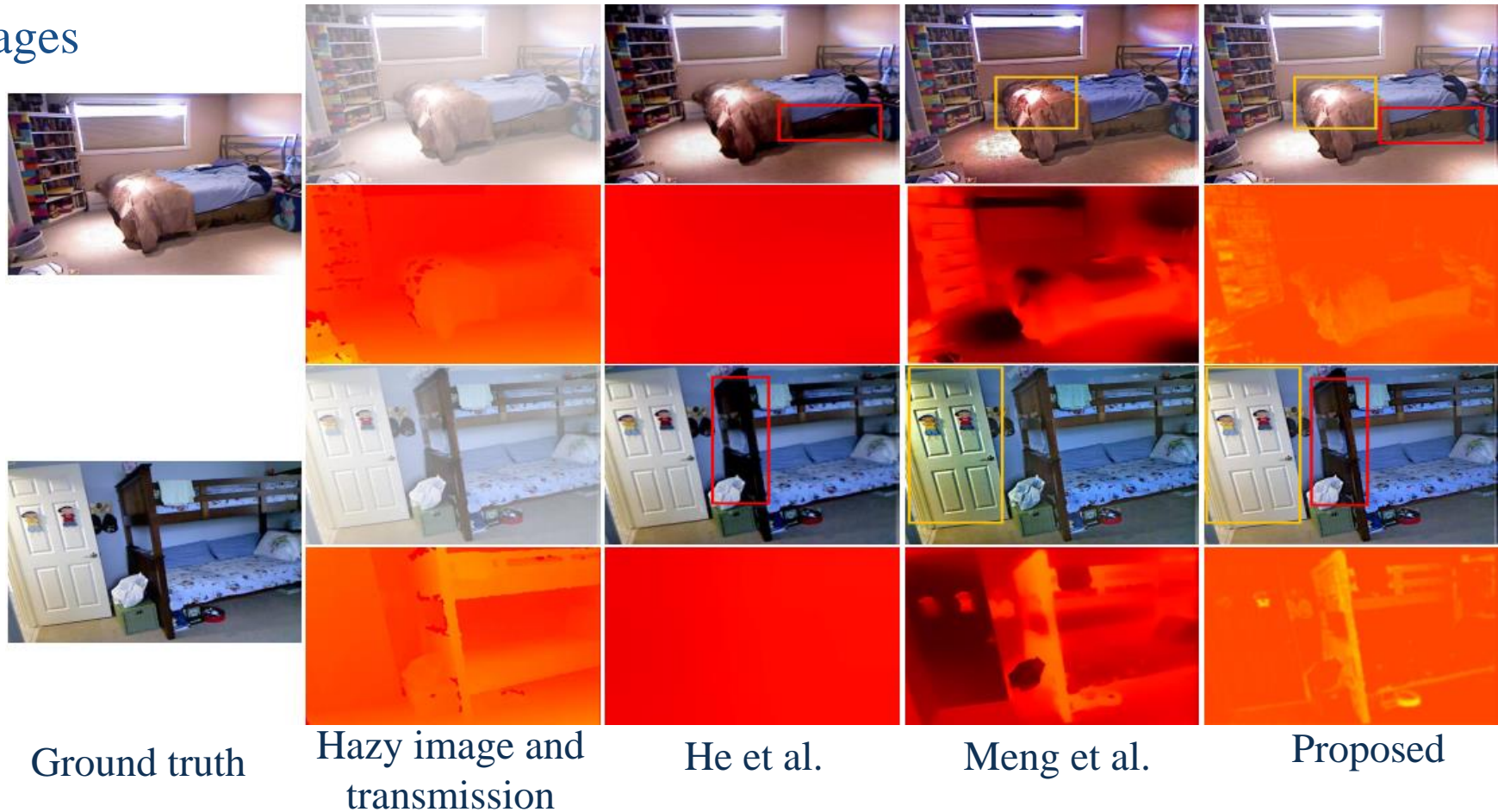
Medium shot

Long shot

Experimental Results



□ Synthesized images

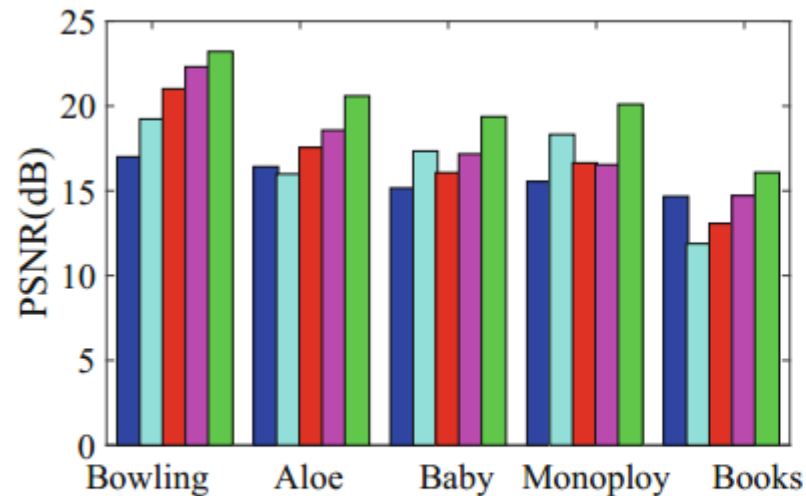


- Single Image Haze Removal Using Dark Channel Prior (He et al. CVPR 2009)
- Efficient Image Dehazing with Boundary Constraint and Contextual Regularization (Meng et al. ICCV 2013)

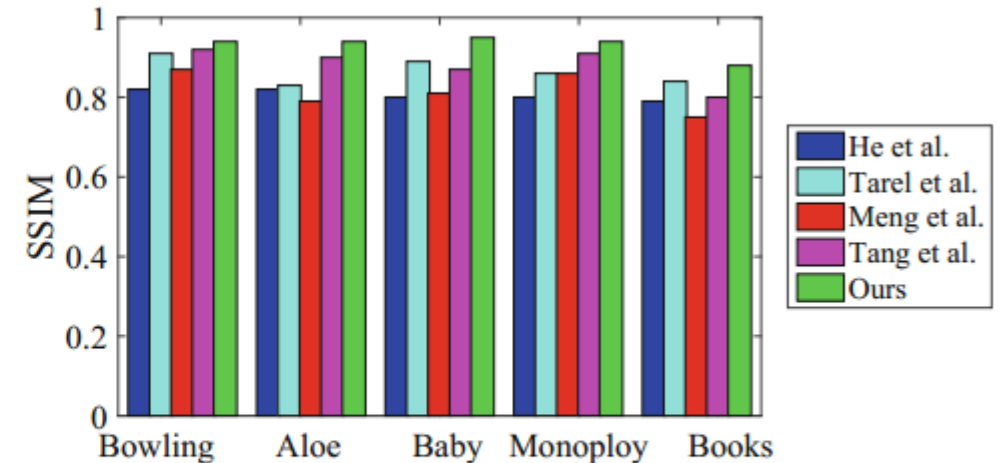
Experimental Results



☐ Synthesized images



(a) PSNR



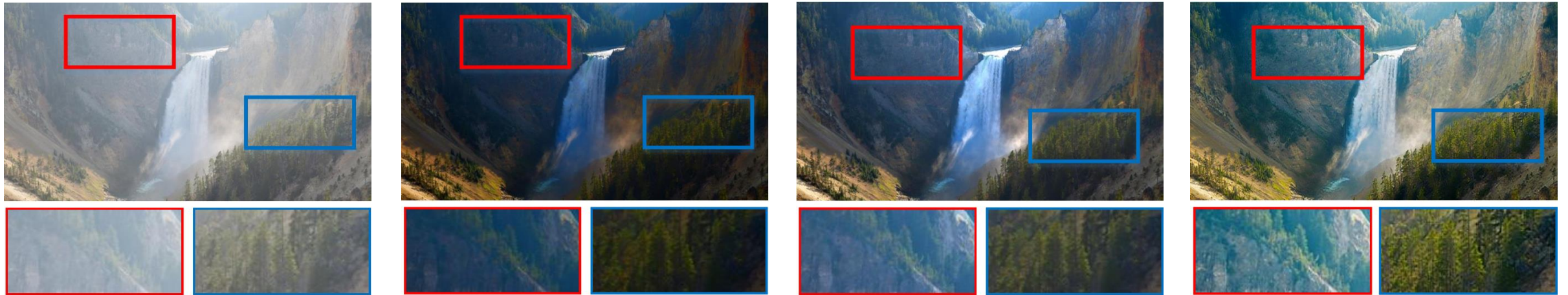
(b) SSIM

- Single Image Haze Removal Using Dark Channel Prior (He et al. CVPR 2009)
- Efficient Image Dehazing with Boundary Constraint and Contextual Regularization (Meng et al. ICCV 2013)
- Investigating Haze-relevant Features in A Learning Framework for Image Dehazing (Tang et al. CVPR 2014)

Experimental Results



Real-world images



Input

He et al

Tang et al

Proposed

- Investigating Haze-relevant Features in A Learning Framework for Image Dehazing (Tang et al. CVPR 2014)

Experimental Results



☐ Real-world images



Input



He et al



Meng et al



Proposed

Experimental Results



☐ Real-world images



Input



He et al



Tang et al



Proposed

Run Time



- ❑ Faster than other dehazing methods

Seconds	Fattal	He	Tarel	Meng	Zhu	Ours
427×370	25.68	13.15	2.02	2.29	1.13	0.36
640×480	63.09	26.90	7.02	3.23	2.51	0.61

- Single Image Dehazing (Fattal. Siggraph 2008)
- Vision enhancement in homogeneous and heterogeneous fog (Tarel et al. ITSM 2012)
- A fast single image haze removal algorithm using color attenuation prior (Zhu et al. TIP 2015): **Learning-based method**

Failure Case



❑ Failure case for nighttime hazy images

Nighttime hazy image model [1]: $I(x) = R(x)t(x) + L(x)(1 - t(x)) + L_a(x) * APSP$,



Input



Li et al



Proposed

- [1] **Nighttime haze** removal with glow and multiple light colors (Li et al. ICCV 2015)

Concluding Remarks



- ❑ Learning transmission map by a multi-scale neural network
 - ❑ Coarse-scale network predict holistic transmission
 - ❑ As an additional feature in Fine-scale network
- ❑ Achieve state-of-the-art dehazing results
 - ❑ Real time
 - ❑ Vivid color information

Code, model, and video dehazing example available at:
<https://sites.google.com/site/renwenqi888/research/dehazing>