03

Image Dehazing

Haze/Fog Weather



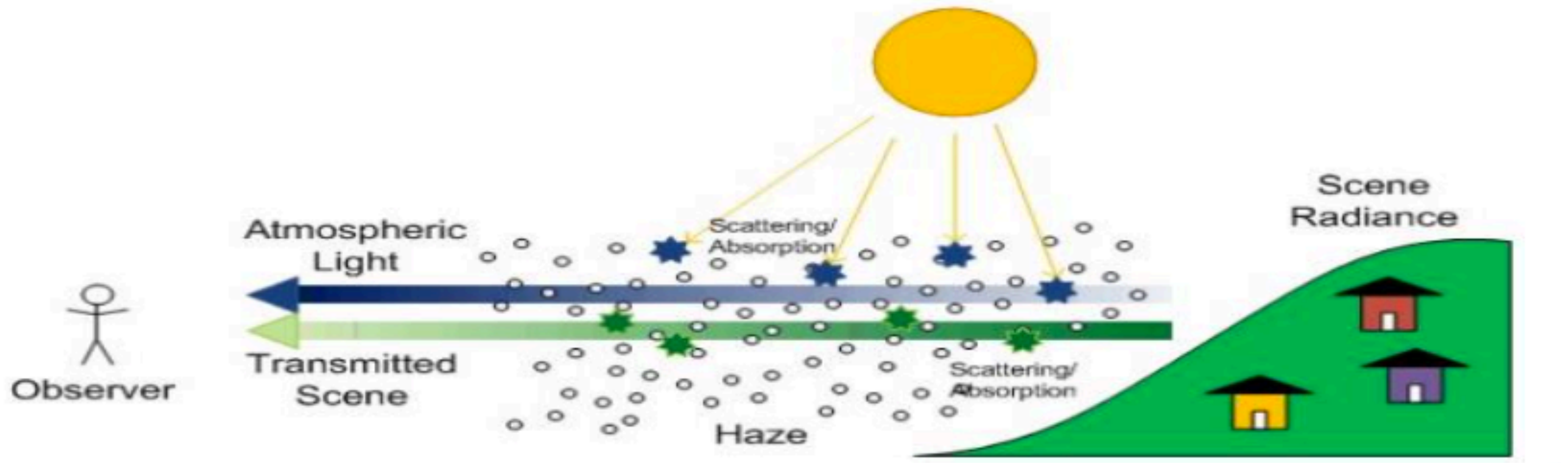

Haze

- **What is haze?**
  - The characteristics of atmosphere degradation
  - As distance between an object and the observer increases, atmosphere color replaces the color of the object.
  - Physical interactions of light with particles can be classified mainly as scattering and absorption.

https://github.com/zhenglab/2017SpringCV/tree/master/20170427-ImageDeblurringAndDehazing-LN

Haze

- **What is haze?**
  - Physical interactions of light with particles can be classified mainly as scattering and absorption.



https://github.com/zhenglab/2017SpringCV/tree/master/20170427-ImageDeblurringAndDehazing-LN

Application of Dehazing

- **Removing this degradation is useful in many applications:**
  - Autonomous vehicle navigation

https://baike.baidu.com/item/%E6%97%A0%E4%BA%BA%E9%A9%BE%E9%A9%B6%E6%B1%BD%E8%BD%A6/77997?fr=aladdin

Application of Dehazing

- **Removing this degradation is useful in many applications:**
  - Video surveillance systems

https://baike.baidu.com/item/%E8%A7%86%E9%A2%91%E7%9B%91%E6%8E%A7/9032286?fr=aladdin

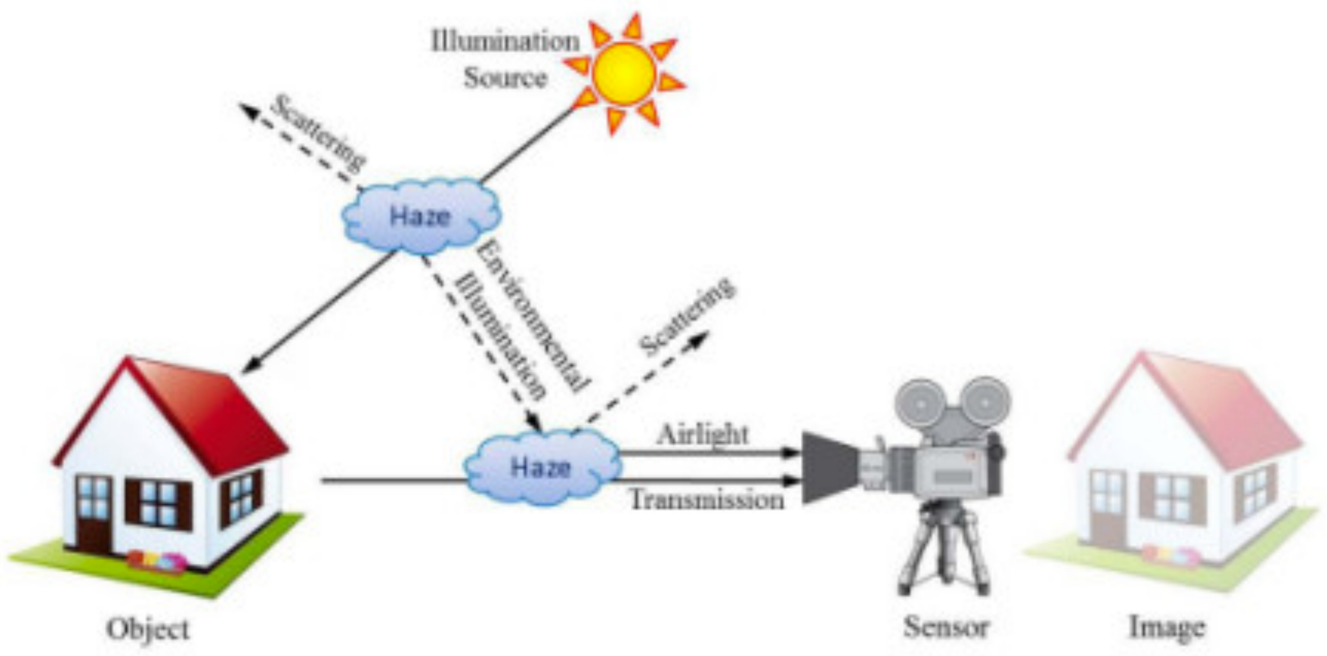
Application of Dehazing

- **Removing this degradation is useful in many applications:**
  - Aerial remote sensed images

https://baike.baidu.com/item/%E8%88%AA%E7%A9%BA%E9%81%A5%E6%84%9F/4326345?fr=aladdin

How to dehaze

- **Atmospheric scattering model**



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

B. Cai, X. Xu, K Jia, C. Qing, and D. Tao .DehazeNet: An End-to-End System for Single Image Haze Removal .IEEE Trans Image Process 2016

How to dehaze

- **Atmospheric scattering model**

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

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

$I(x)$ ---- *Haze image*

$J(x)$ ---- *Clear scene*

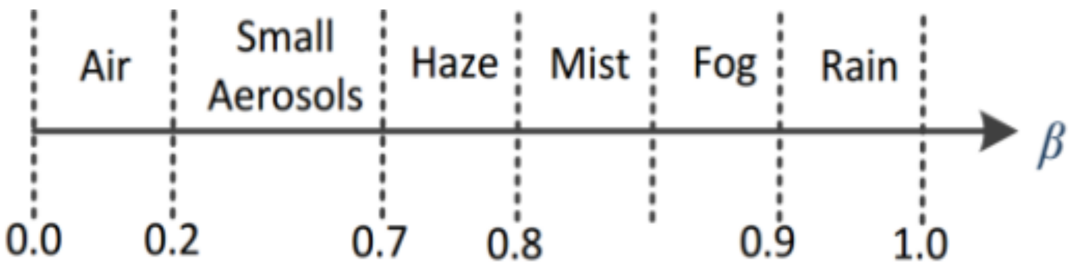
$t(x)$ ---- *Medium transmission*

A ---- *The global atmospheric light(Airlight)*

x ---- *Index pixels in the observed haze image*

$d(x)$ ---- *Depth map*

β ---- *Scattering cofficient of the atmosphere*



Srinivasa G. et al. Shedding Light on the Weather. CVPR 2003

How to dehaze

- **Atmospheric scattering model**

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

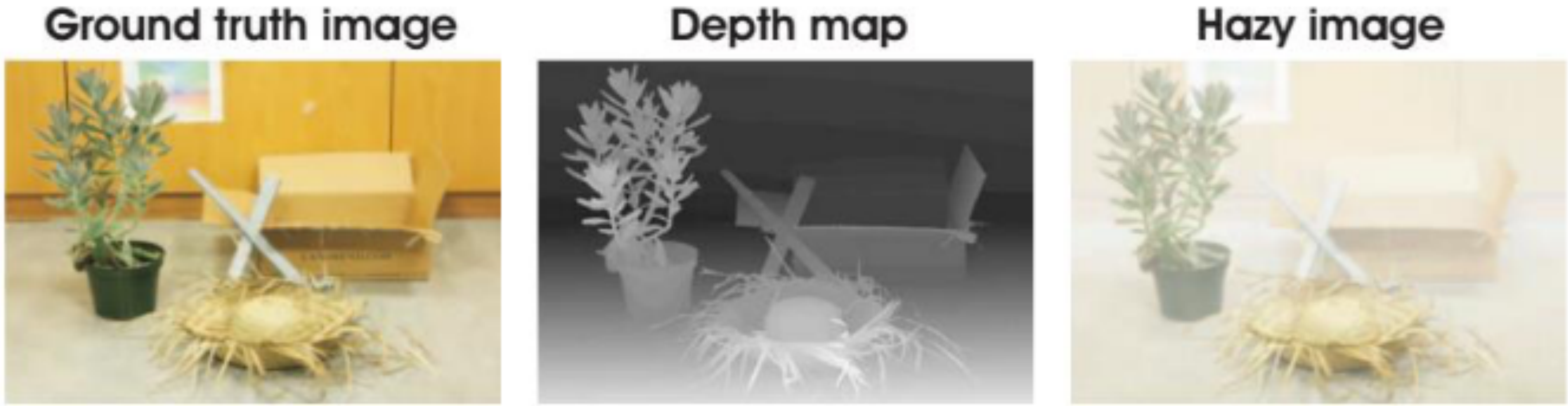
$$\Rightarrow \quad J(x) = \frac{I(x) - A\big(1 - t(x)\big)}{t(x)}$$

$$\Rightarrow \quad J(x) = \frac{I(x) - A + At(x)}{t(x)}$$

$$\Rightarrow \quad J(x) = \frac{I(x) - A}{t(x)} + A$$

Haze dataset

- **D-Hazy:**
  - The dataset that contains 1400+ pairs of images with ground truth reference images and hazy images of the same scene.



D-HAZY : A dataset to evaluate quantitatively dehazing algorithms.
C. Ancuti, C.Ancuti,C.D.Vleeschouwer. ICIP. 2016

Haze dataset

- **D-Hazy:**

  - The dataset is built on the Middelbury[1] and NYU[2] Depth datasets that provide images of various scenes and their correspond depth maps.

[1] http://vision.middlebury.edu/stereo/data/scenes2014/

[2] http://cs.nyu.edu/~silberman/datasets/nyu_depth_v2.html

Haze dataset

- **D-Hazy:**

- $\mathrm{t}(x) = e^{-\beta d(x)}$
- The transmission map is estimated based on equation using the depth d and the medium attenuation coefficient β.
- β=1
- A=[1,1,1]

Dehaze Methods

- **Single Image Haze Removal Using Dark Channel Pri**

  K. He, J.Sun, and X. Tang

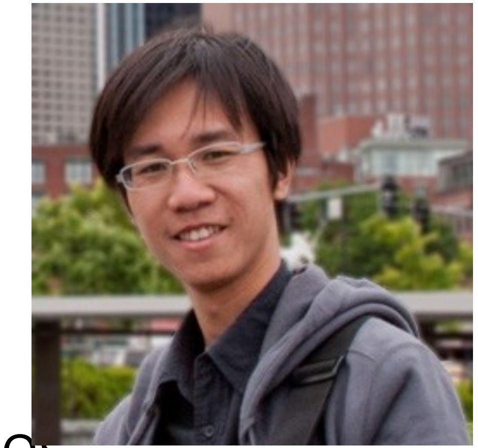
  CVPR2009

- **DehazeNet: An End-to-End System for Single Image Haze Removal**

  B. Cai, X. Xu, K Jia, C. Qing, and D. Tao

  IEEE Trans Image Process 2016

Single Image Haze Removal Using Dark Channel Prior



- **Dark channel prior**
  - It is a kind of statistics of the haze-free outdoor images.
  - It is based on a key observation —most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel.

Dark Channel

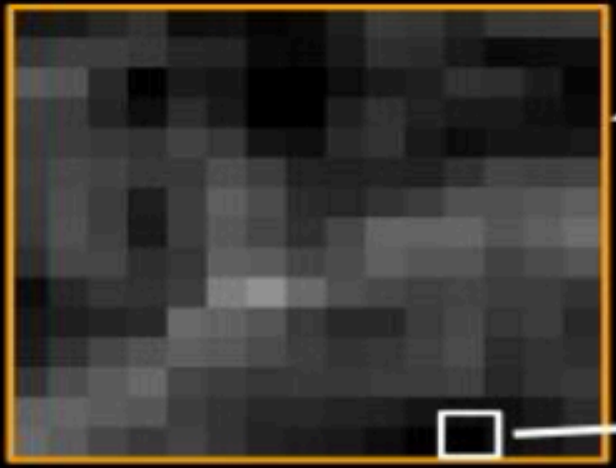
- min (rgb, local patch)
  - min (r, g, b)

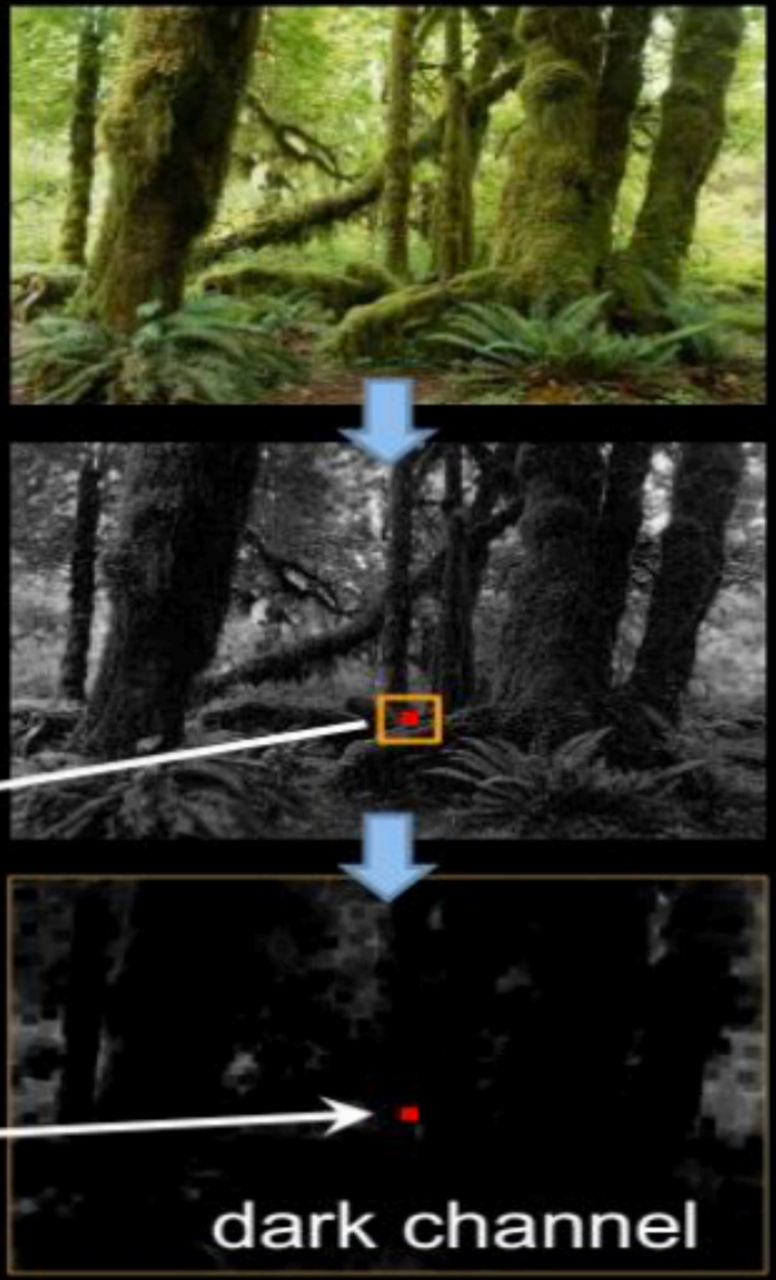
min (r, g, b)

*This slide is from Kaiming He's talking slides in CVPR'09.

Dark Channel

- min (rgb, local patch)
  - min (r, g, b)
  - min (local patch) = min filter





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Dark Channel

- min (rgb, local patch)
  - min (r, g, b)
  - min (local patch) = min filter

$$\boxed{J^{dark}(\mathbf{x}) = \min_{y \in \Omega(\mathbf{x})} \left(\min_{c \in \{r,g,b\}} J^c(\mathbf{y}) \right)}$$

  - J^c: color channel of $\mathbf{J}$
  - J^{dark}: dark channel of $\mathbf{J}$

*This slide is from Kaiming He's talking slides in CVPR'09.

Dark Channel

- min (rgb, local patch)
  - min (r, g, b)
  - min (local patch) = min filter

$$\boxed{J^{dark} = \min_{\Omega} \left(\min_{c} J^{c} \right)}$$

  - J^{c}: color channel of $\mathbf{J}$
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Dark channel prior

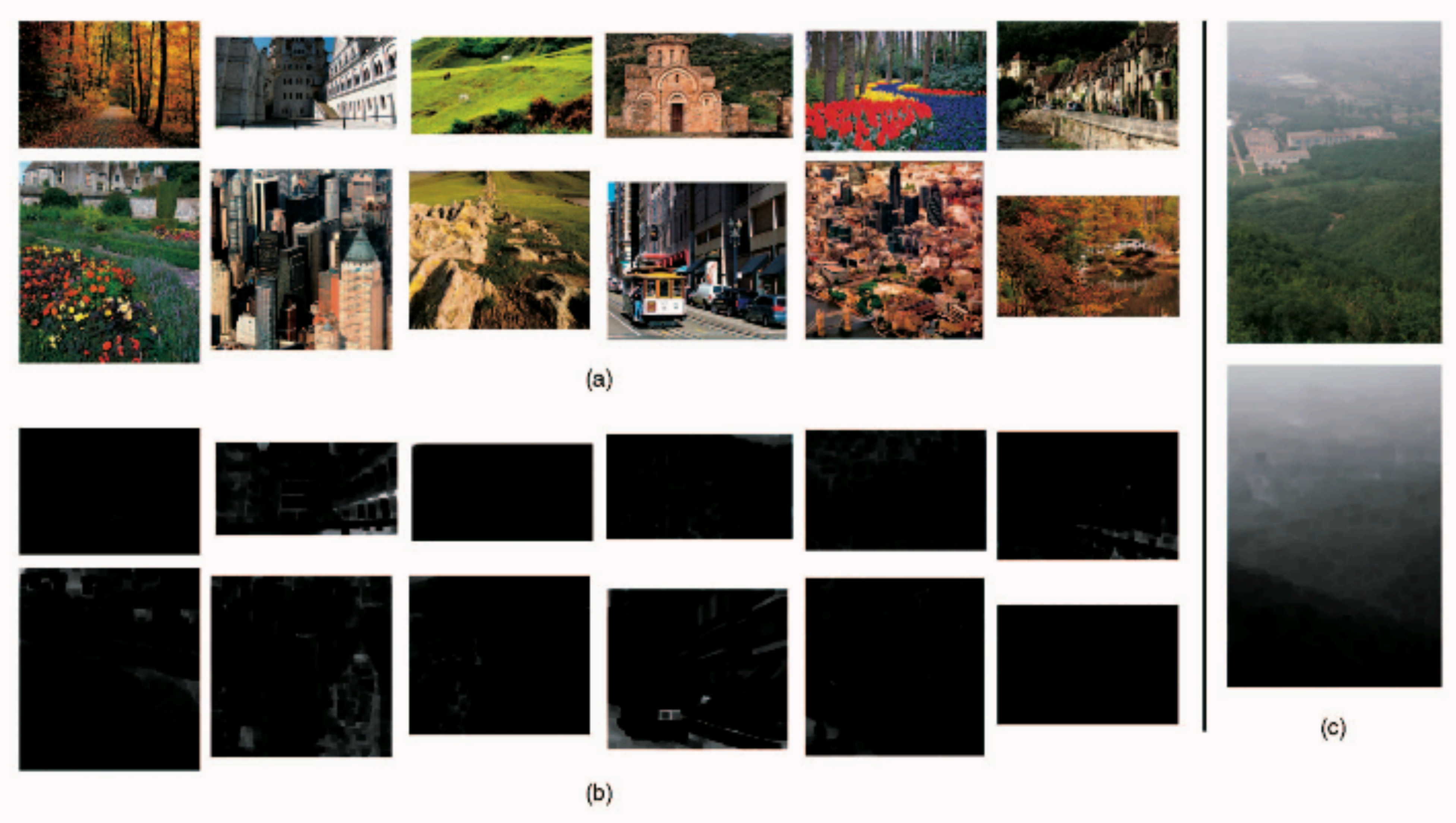


Fig. 4. (a) Example images in our haze-free image database. (b) The corresponding dark channels. (c) A hazy image and its dark channel.

Single Image Haze Removal Using Dark Channel Prior

- **Dark channel prior**

  - Image size: 500×500, patch size: 15×15
  - 75% dark channel values = 0
  - 86% dark channel values <16
  - 90% dark channel values <25

$$\Longrightarrow \quad J^{dark} \longrightarrow 0$$

- So: $\min\limits_{\Omega}\left(\min\limits_{c}(J^{c})\right) \longrightarrow 0$

Single Image Haze Removal Using Dark Channel Prior

- **Transmission Estimation**

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

$$\Rightarrow \min_{y\in\Omega(x)}\big(I^c(y)\big) = \tilde{t}(x)\min_{y\in\Omega(x)}\big(J^c(y)\big) + \big(1 - \tilde{t}(x)\big)A^c$$

$$\Rightarrow \min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right) = \tilde{t}(x)\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right) + \big(1 - \tilde{t}(x)\big)$$

$$\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right) = \tilde{t}(x)\min_{y\in\Omega(x)}\left(min\left(\frac{J^c(y)}{A^c}\right)\right) + \big(1 - \tilde{t}(x)\big)$$

- **Dark channel prior**

$$\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right) = \tilde{t}(x)\boxed{\min_{y\in\Omega(x)}\left(min\left(\frac{J^c(y)}{A^c}\right)\right)} + \left(1-\tilde{t}(x)\right)$$

$$J^{dark}(x) = \min_{y\in\Omega(x)}\left(\min_c\left(J^c(y)\right)\right) = 0\text{, and, } A^c > 0$$

$$\boxed{\min_{y\in\Omega(x)}\left(\min_c\left(\frac{J^c(y)}{A^c}\right)\right)} = 0$$

$$\min_{y\in\Omega(x)}\left(\min_c\left(\frac{I^c(y)}{A^c}\right)\right) = 1-\tilde{t}(x)$$

$$\tilde{t}(x) = 1-\omega\min_{y\in\Omega(x)}\left(\min_c\left(\frac{J^c(y)}{A^c}\right)\right)$$

Single Image Haze Removal Using Dark Channel Prior

- **He shows that the transmission can be estimated by calculating:**

$$\tilde{t}(x) = 1 - \omega \min_{y \in \Omega(x)} \left(\min_{c} \left(\frac{J^c(y)}{A^c} \right) \right)$$

ω=0.95

Single Image Haze Removal Using Dark Channel Prior

- **Atmospheric Light (A) Estimation:**
  - Airlight is estimated by picking up the pixels of the image corresponding to the 0.1% brightest pixels in the dark channel.
  - And then choosing the pixels with maximum intensity

K. He, J.Sun, and X. Tang Single Image Haze Removal Using Dark Channel Prior. CVPR2009

Single Image Haze Removal Using Dark Channel Prior

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

$$\Rightarrow \quad J(x) = \frac{I(x) - A\big(1 - t(x)\big)}{t(x)}$$

$$\Rightarrow \quad J(x) = \frac{I(x) - A + At(x)}{t(x)}$$

$$\Rightarrow \quad J(x) = \frac{I(x) - A}{t(x)} + A \quad \Rightarrow \quad J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A$$

Single Image Haze Removal Using Dark Channel Prior

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A$$

$$t_0 = 0.1$$

K. He, J.Sun, and X. Tang Single Image Haze Removal Using Dark Channel Prior. CVPR2009

Single Image Haze Removal Using Dark Channel Prior

- **Airlight and transmission are sufficient to invert the model and recover the original radiance of the scene**

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A$$

Single Image Haze Removal Using Dark Channel Prior

K. He, J.Sun, and X. Tang Single Image Haze Removal Using Dark Channel Prior. CVPR2009

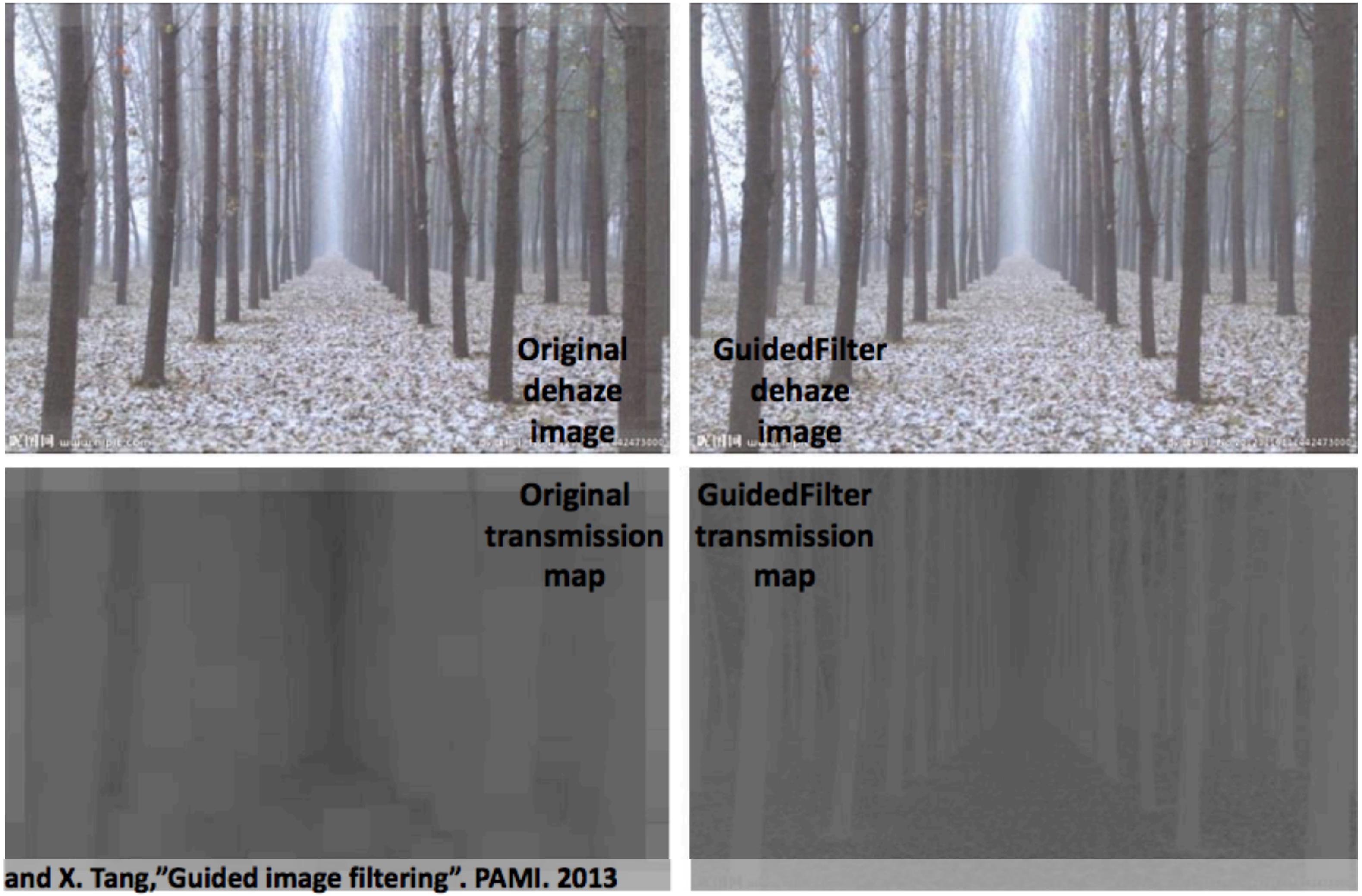
Single Image Haze Removal Using Dark Channel Prior

haze

dehaze

https://blog.csdn.net/songhhll/article/details/12612681

Single Image Haze Removal Using Dark Channel Prior



K. He, J.Sun, and X. Tang,"Guided image filtering". PAMI. 2013

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Single Image Haze Removal Using Dark Channel Prior

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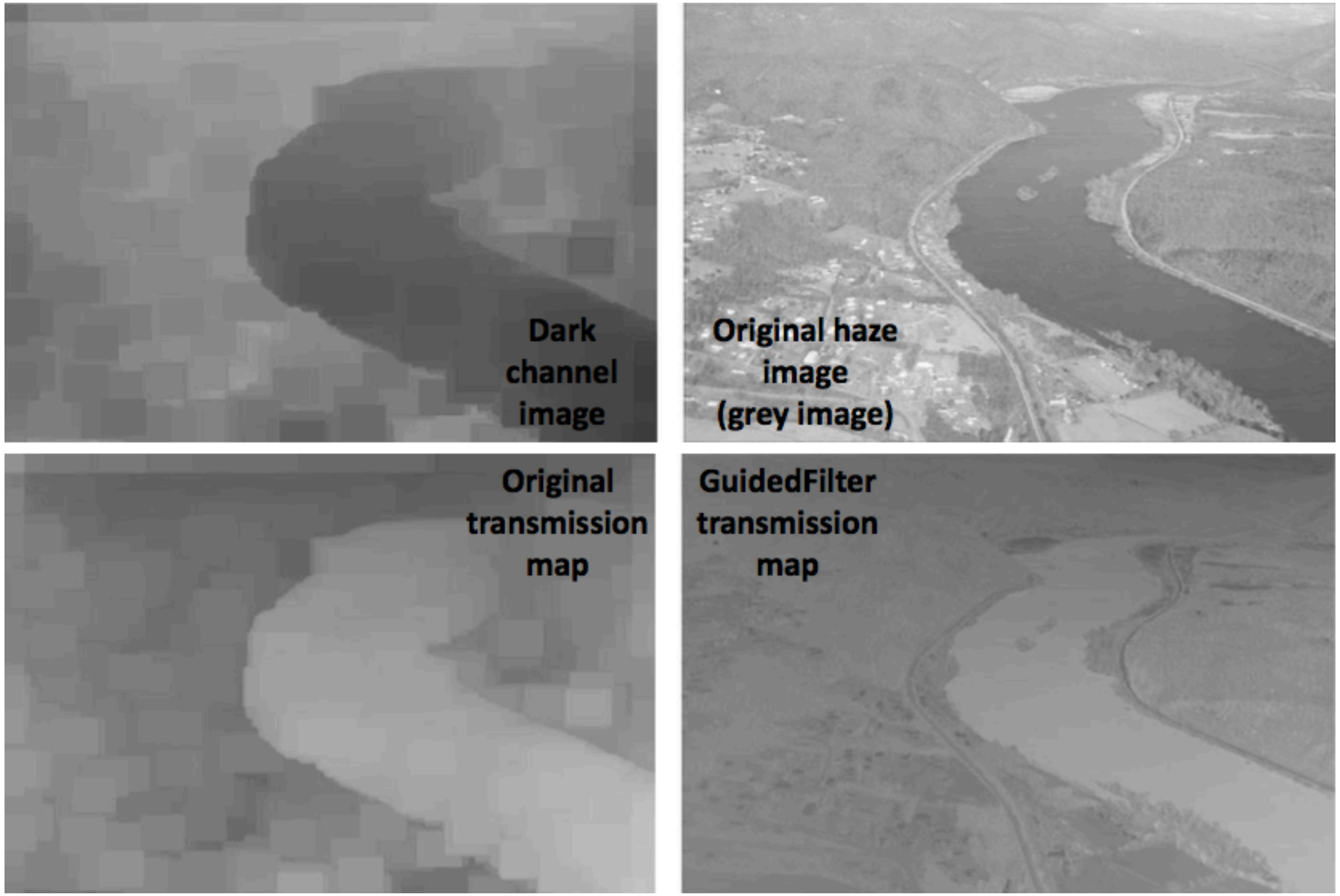

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https://blog.csdn.net/songhhll/article/details/12612681

Single Image Haze Removal Using Dark Channel Prior

- **Limitation**

It is known what are the consequences of a bad estimate for the transmission →

Haze is not completely removed, or it is removed where there is no haze (overboost contrast)

Single Image Haze Removal Using Dark Channel Prior

- **Limitation**

When the scene objects are similar to the atmospheric light and no shadow is cast on them, the dark channel prior is invalid.
The method will underestimate the transmission for these objects, such an the white marble in Figure.

Figure 13. Failure case. Left: input image. Middle: our result. Right: our transmission map. The transmission of the marble is underestimated.

K. He, J.Sun, and X. Tang Single Image Haze Removal Using Dark Channel Prior. CVPR2009

DehazeNet: An End-to-End System for Single Image Haze Removal

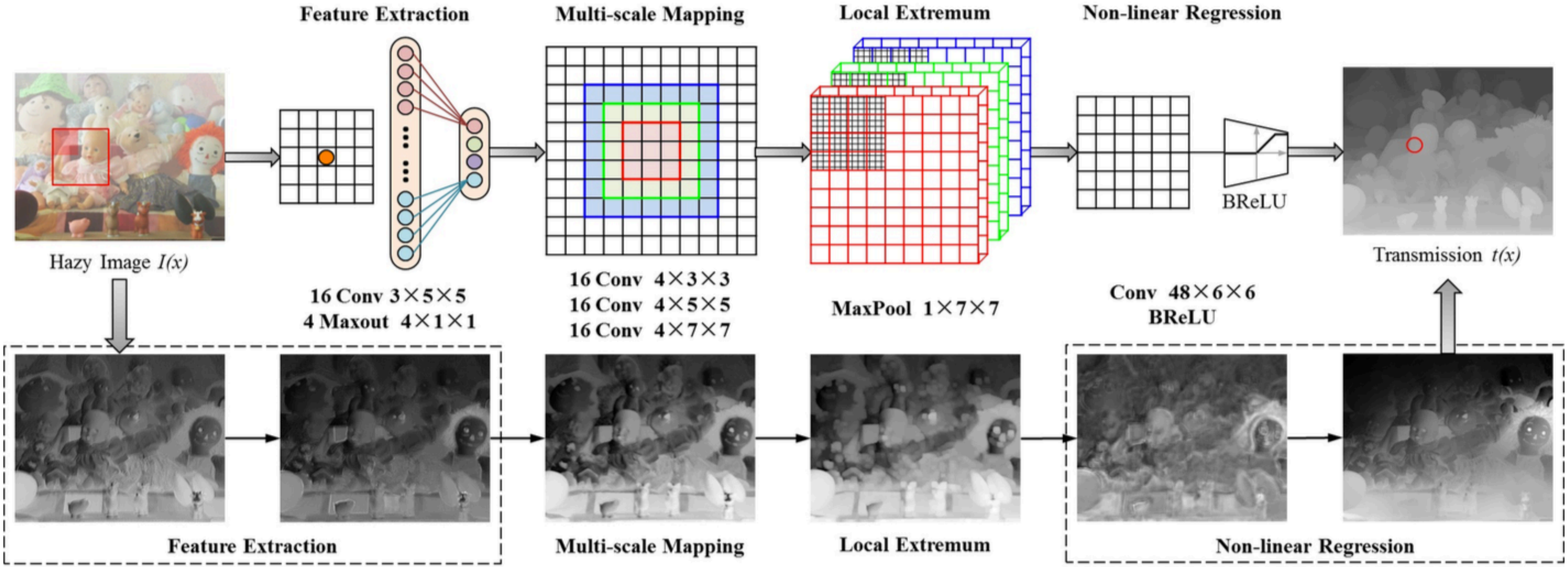
Estimation of a global atmospheric light

Recover an accurate medium transmission map

DehazeNet, a trainable CNN based end-to-end system for medium transmission estimation

DehazeNet: An End-to-End System for Single Image Haze Removal

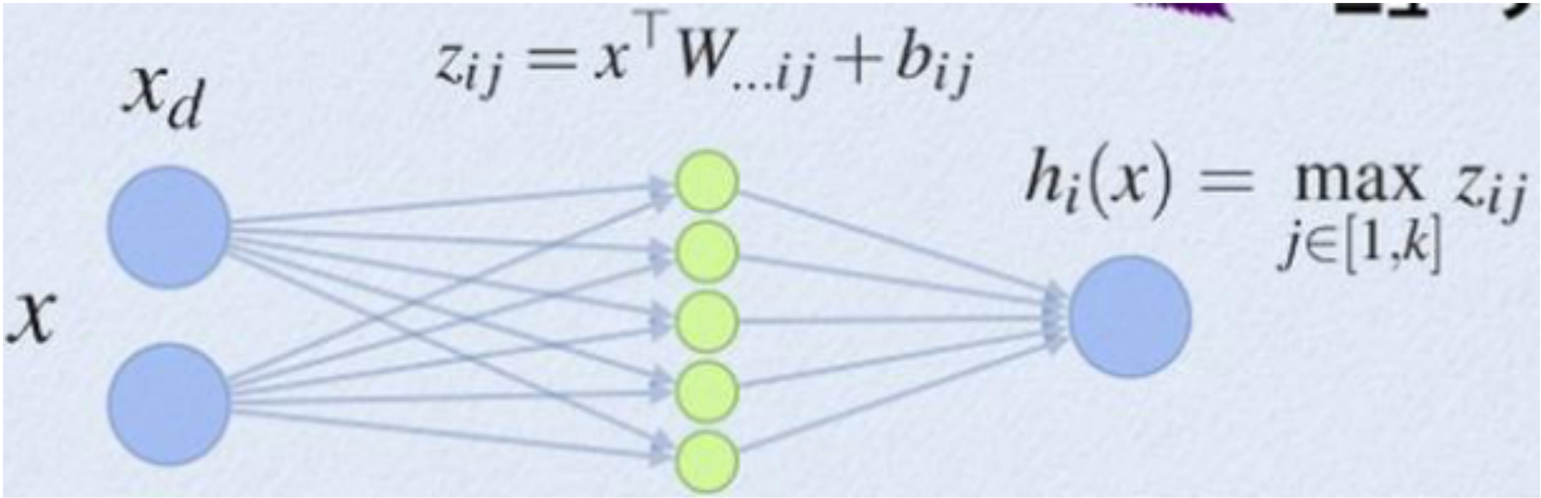
- Learn and estimate the mapping relations between haze image patches and their medium transmissions.
- Propose a novel nonlinear activation function in Net, called Bilateral Rectified Linear Unit(BReLU).
- Establish connections between components of DehazeNet and priors used in existing dehazing methods.

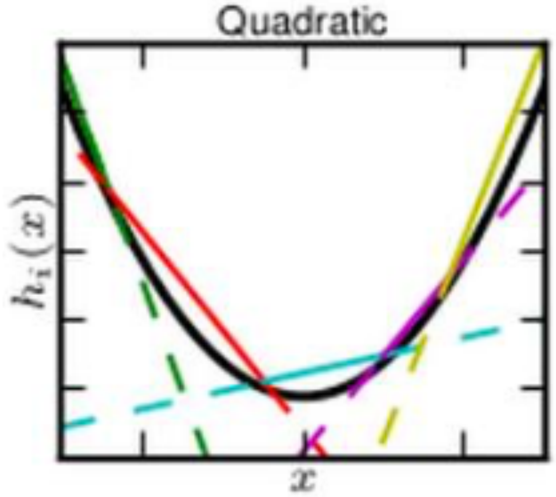


- DehazeNet conceptually consists of four sequential operations (feature extraction, multi-scale mapping, local extremum and non-linear regression which is constructed 3 convolution layers, a max-pooling, a Maxout unit an a BReLU activation function.

B. Cai, X. Xu, K Jia, C. Qing, and D. Tao .DehazeNet: An End-to-End System for Single Image Haze Removal .IEEE Trans Image Process 2016

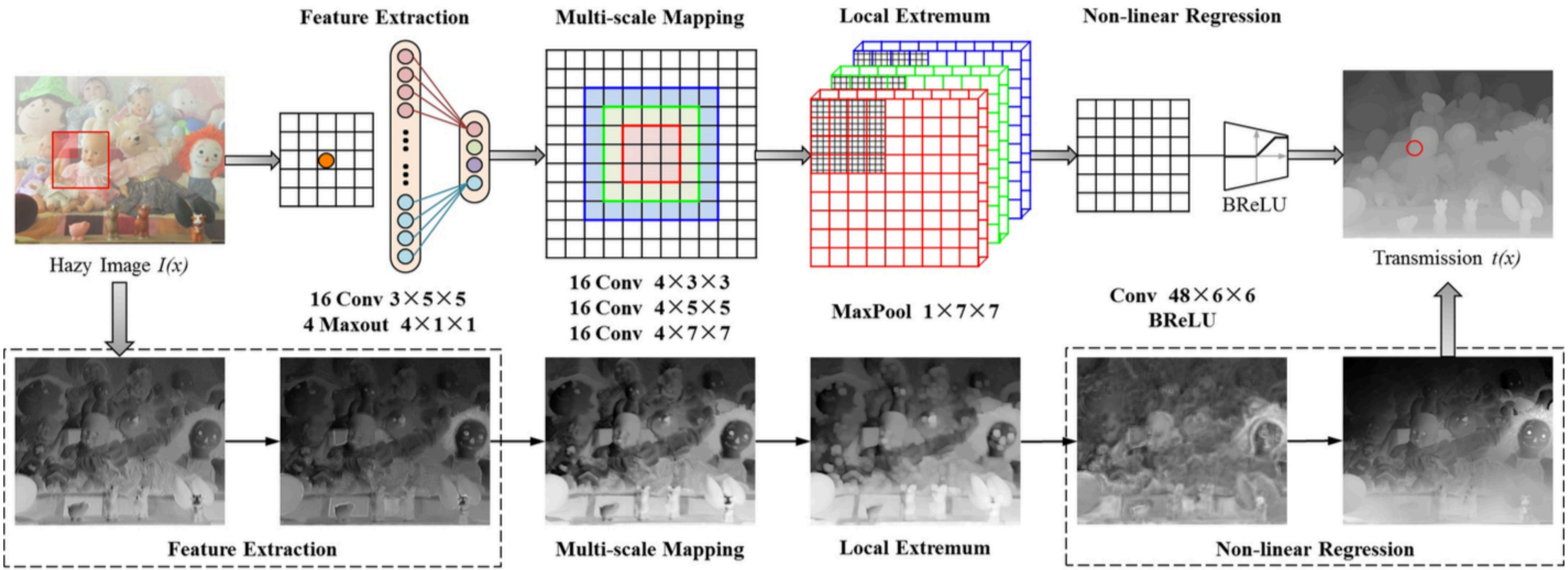
DehazeNet: An End-to-End System for Single Image Haze Removal





$$h_i(x) = \max_{j\in[1,k]} z_{ij} \quad z_{ij} = x^T W_{\dots ij} + b_{ij}, \text{ and } W \in R^{d*m*k}$$

http://www.cnblogs.com/tornadomeet/p/3428843.html



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DehazeNet: An End-to-End System for Single Image Haze Removal

- Layer Designs of DehazeNet
- Multi-scale Mapping
- Local Extremum
- Non-linear Regression

Formulation	Type	Input Size	Num n	Filter $f \times f$	Pad
Feature Extraction	Conv	$3 \times 16 \times 16$	16	5×5	0
	Maxout	$16 \times 12 \times 12$	4	–	0
Multi-scale Mapping	Conv	$4 \times 12 \times 12$	16	3×3	1
			16	5×5	2
			16	7×7	3
Local Extremum	Maxpool	$48 \times 10 \times 10$	48	7×7	0
Non-linear Regression	Conv	$48 \times 6 \times 6$	1	4×4	0
	BReLU	1×1	1	–	0

B. Cai, X. Xu, K Jia, C. Qing, and D. Tao .DehazeNet: An End-to-End System for Single Image Haze Removal .IEEE Trans Image Process 2016

DehazeNet: An End-to-End System for Single Image Haze Removal

- **Training of DehazeNet**
  - Training data

    Two assumptions:

    1) Image content is independent of medium transmission (the same image content can appear at any depths of scenes)

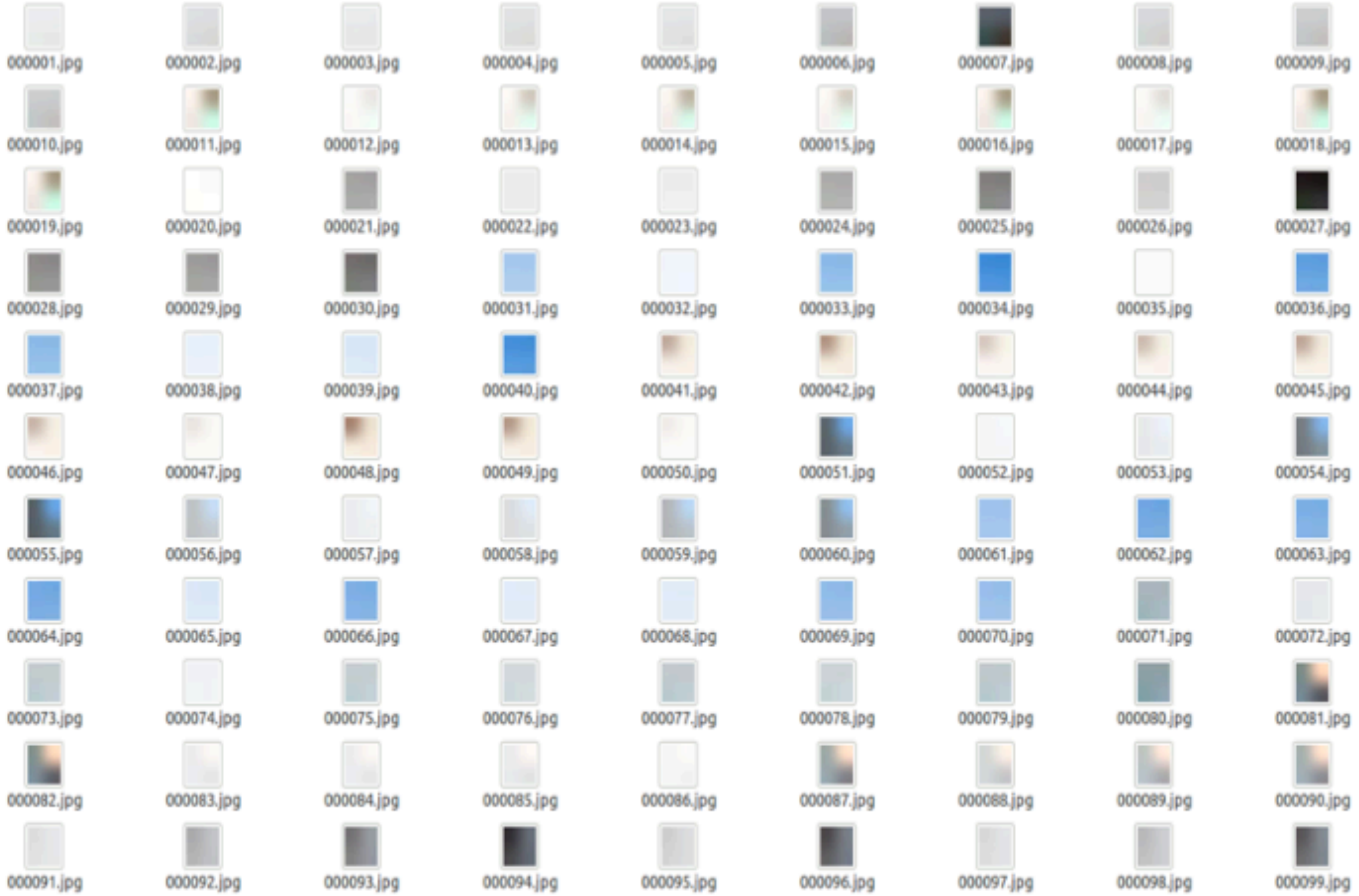
    2) Medium transmission is locally constant (image pixels in a small patch tend to haze similar depths)

DehazeNet: An End-to-End System for Single Image Haze Removal

- **Training of DehazeNet**
  - Training data

Assume an arbitrary(任意的) transmission for an individual image patch.

Given a haze-free patch J(x), the atmospheric light A, and random transmission t, a haze image is synthesized.




```
000001.jpg 0.10516242
000002.jpg 0.18558914
000003.jpg 0.11729032
000004.jpg 0.16907009
000005.jpg 0.14768056
000006.jpg 0.34322159
000007.jpg 0.96592681
000008.jpg 0.22404758
000009.jpg 0.29576940
000010.jpg 0.29701062
000011.jpg 0.76015258
000012.jpg 0.17341965
000013.jpg 0.40635436
000014.jpg 0.56143965
000015.jpg 0.37423851
000016.jpg 0.74566579
000017.jpg 0.25431978
000018.jpg 0.76111873
000019.jpg 0.77886669
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000025.jpg 0.52858843
000026.jpg 0.19900572
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000040.jpg 0.93690418
000041.jpg 0.50169761
```

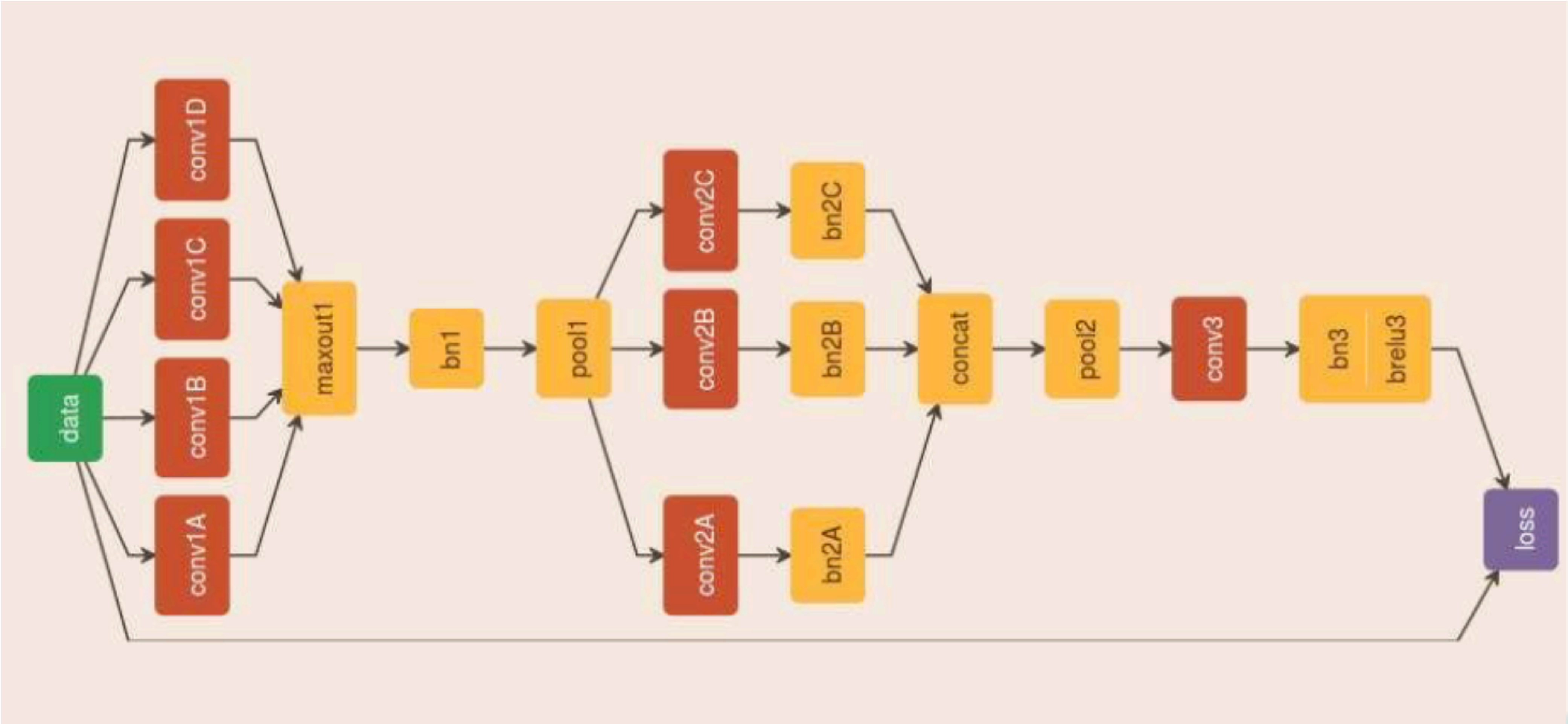
DehazeNet: An End-to-End System for Single Image Haze Removal

- **Training of DehazeNet**
  - Training method

1) In the DehazeNet, supervised learning requires the mapping relationship F between RGB value and medium transmission.
2) Network parameters $\Theta = \{W, B\}$ are achieved through minimizing the loss function between the training patch I(x) and the correspond ground truth medium transmission t.
3) MSE(Mean Squared Error) as the loss function:

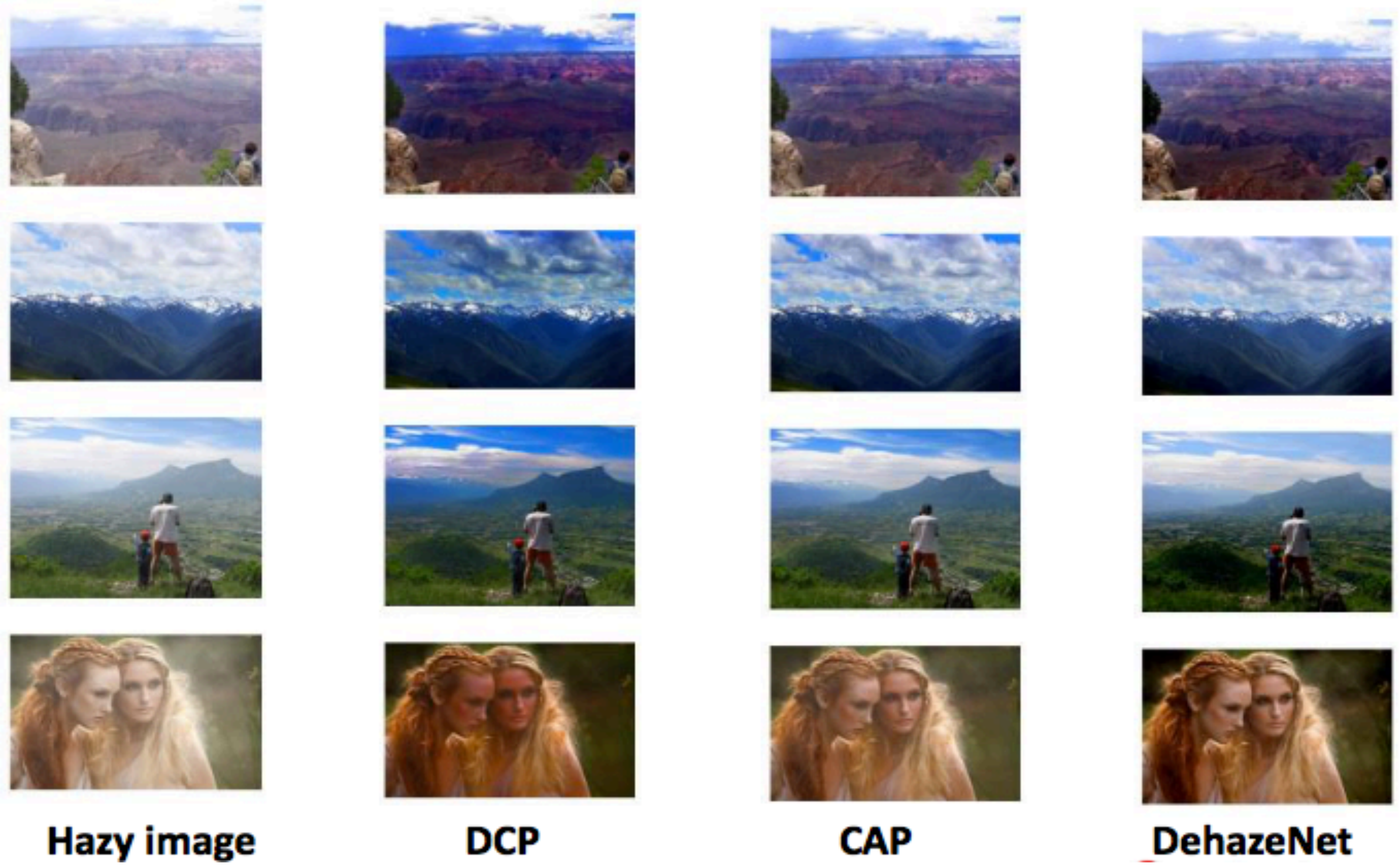
$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left\|F\left(I_i^P;\theta\right) - t_i\right\|^2$$

DehazeNet: An End-to-End System for Single Image Haze Removal



DehazeNet: An End-to-End System for Single Image Haze Removal

- **Results**



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