Image Dehazing

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Overview

1. Review of deblurring method
2. Introduction of dehazing method
3. Introduction of Convolutional Neural Network
4. Dehazing by Convolutional Neural Network

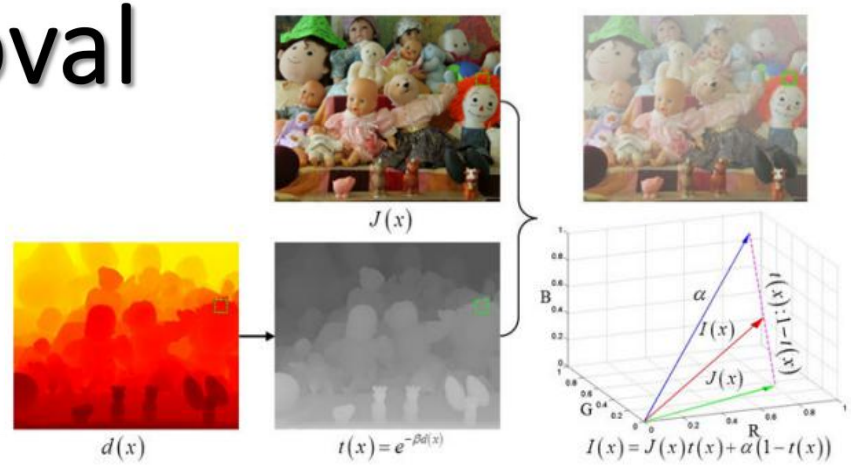
Dehaze Methods


- Dark Channel Prior
- Color Attenuation Prior
- DehazeNet
- MSCNN

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

- Bolun Cai, Xiangmin Xu, Member, IEEE, Kui Jia, Member, IEEE,
- Chunmei Qing, Member, IEEE, and Dacheng Tao, Fellow, IEEE

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



Estimation of a global atmospheric light

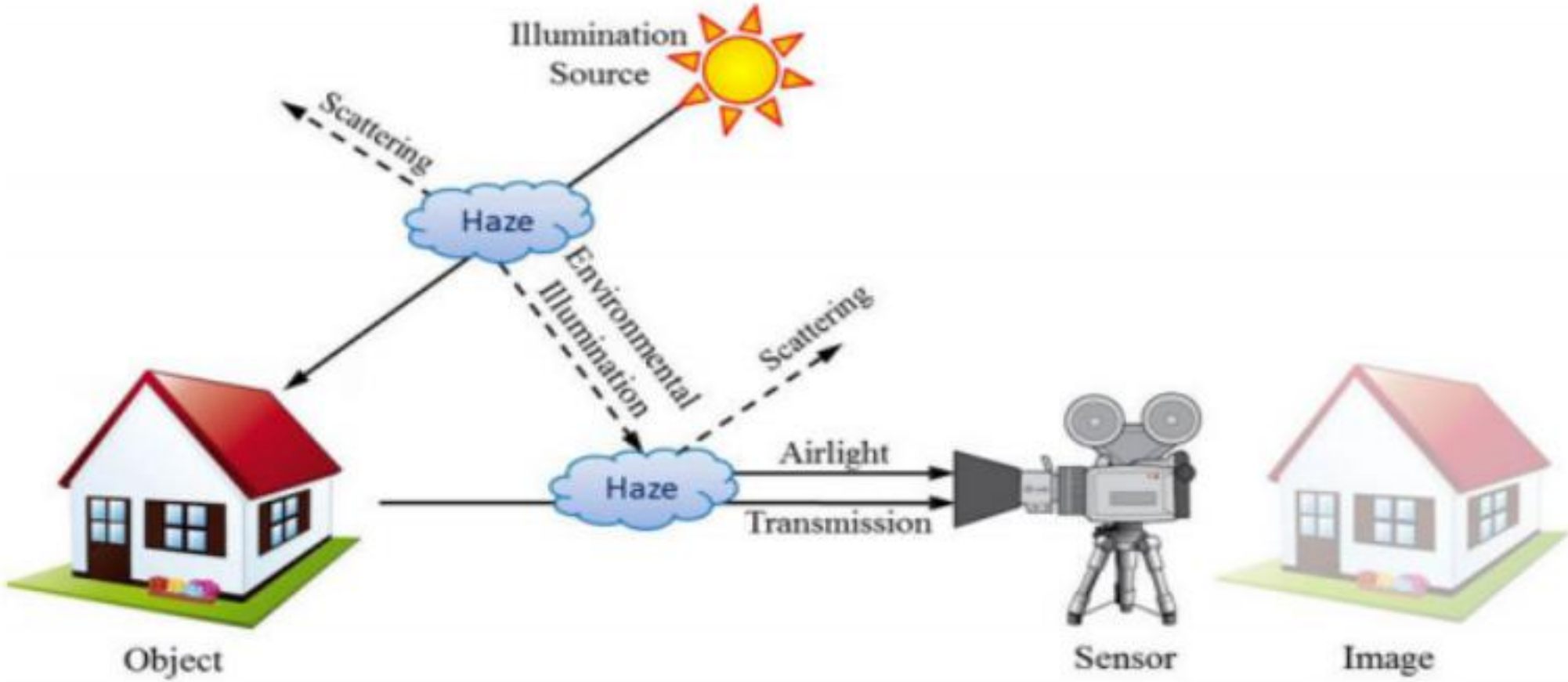
Recover an accurate medium transmission map

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

- Bolun Cai, Xiangmin Xu, Member, IEEE, Kui Jia, Member, IEEE,
- Chunmei Qing, Member, IEEE, and Dacheng Tao, Fellow, IEEE

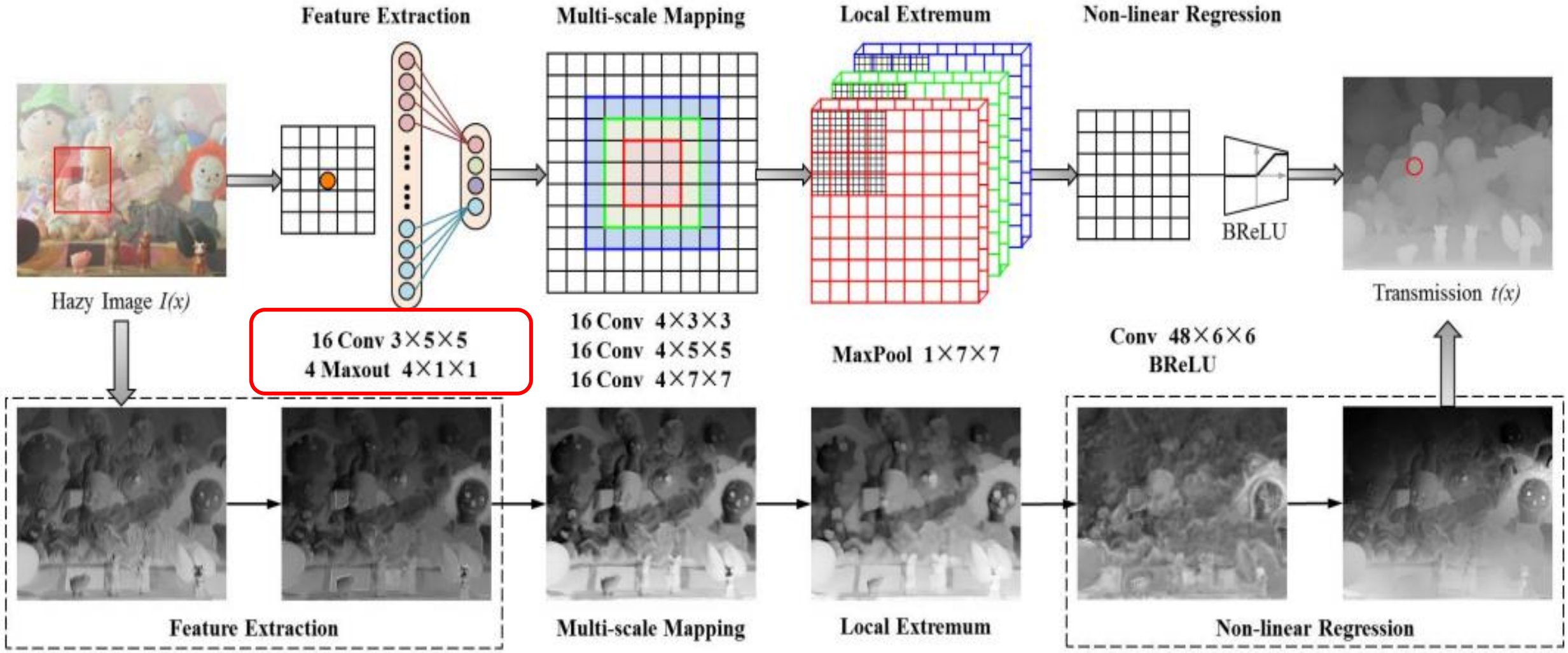
中国海洋大学

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



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

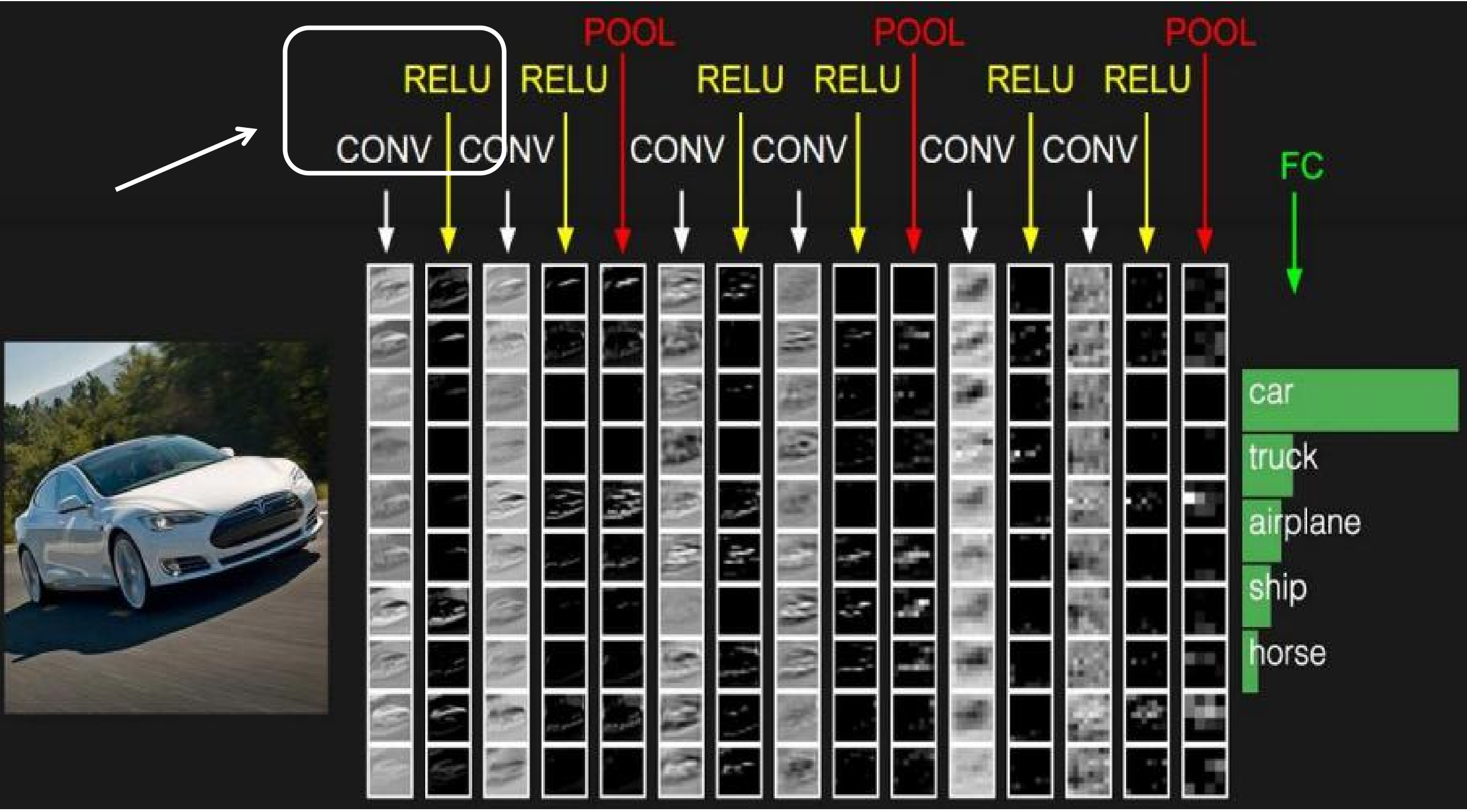
1. **Learn and estimate the mapping relations between hazy image patches and their medium transmissions.**
2. **Propose a novel nonlinear activation function in Net, called Bilateral Rectified Linear Unit(BReLU)**
3. **Establish connections between components of DehazeNet and priors used in existing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



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

The Structure in the CNN

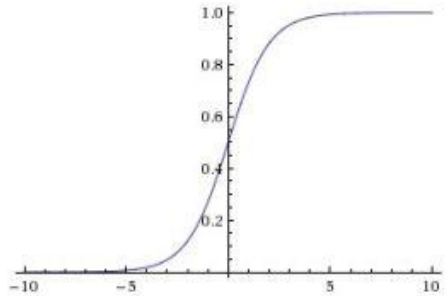
- Input
- [[Conv->ReLU]*N->Pool]*M
- [FC->ReLU]*K
- FC


POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

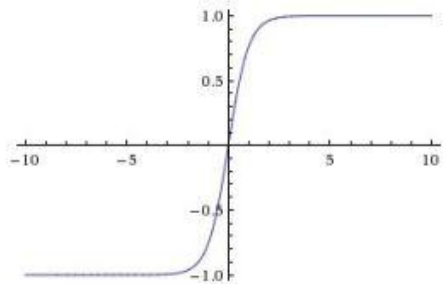
Activation Functions

Sigmoid

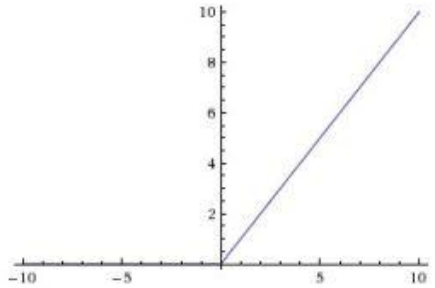
$$\sigma(x) = 1/(1 + e^{-x})$$



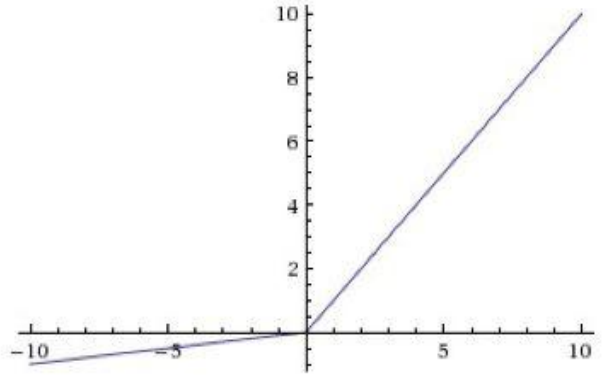
tanh tanh(x)



ReLU max(0,x)



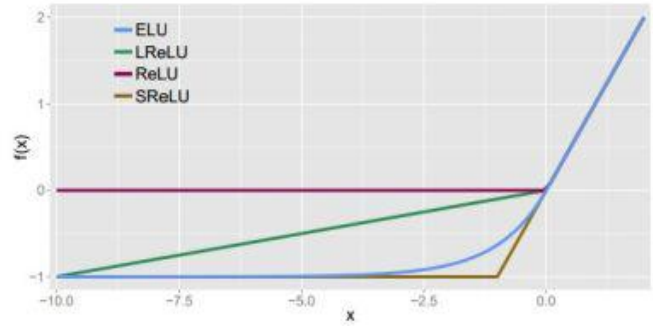
Leaky ReLU
max(0.1x, x)



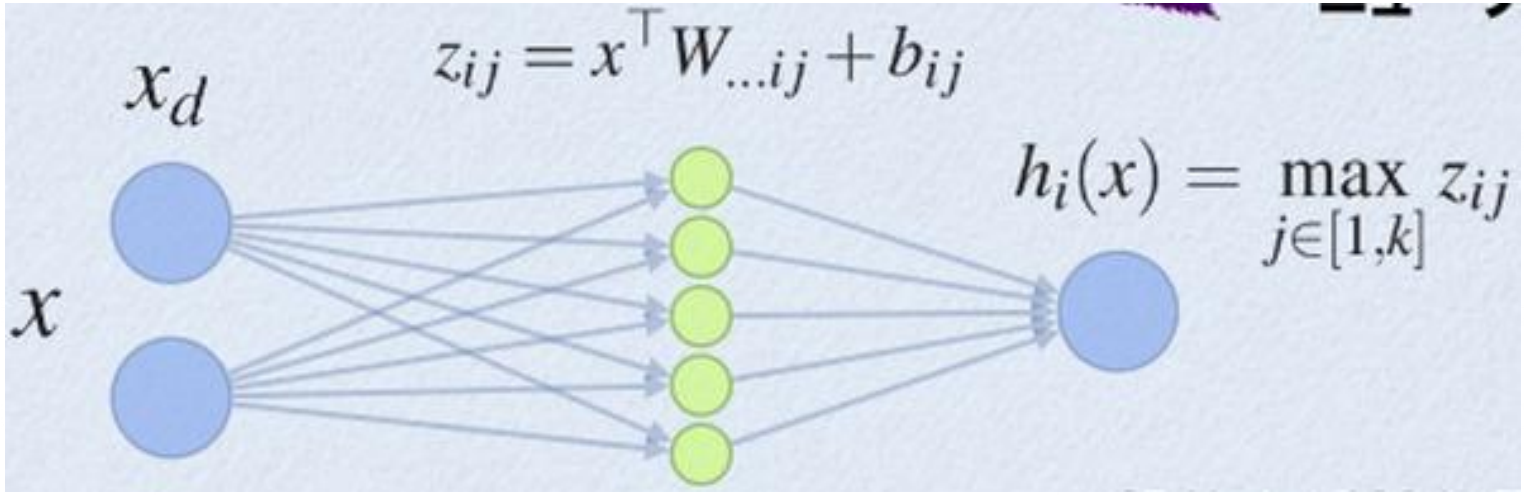
Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

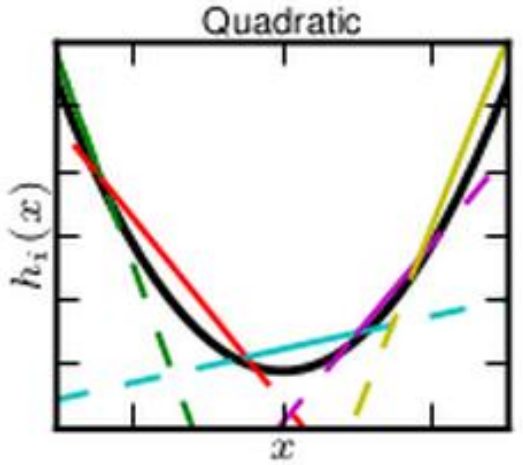
ELU

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$



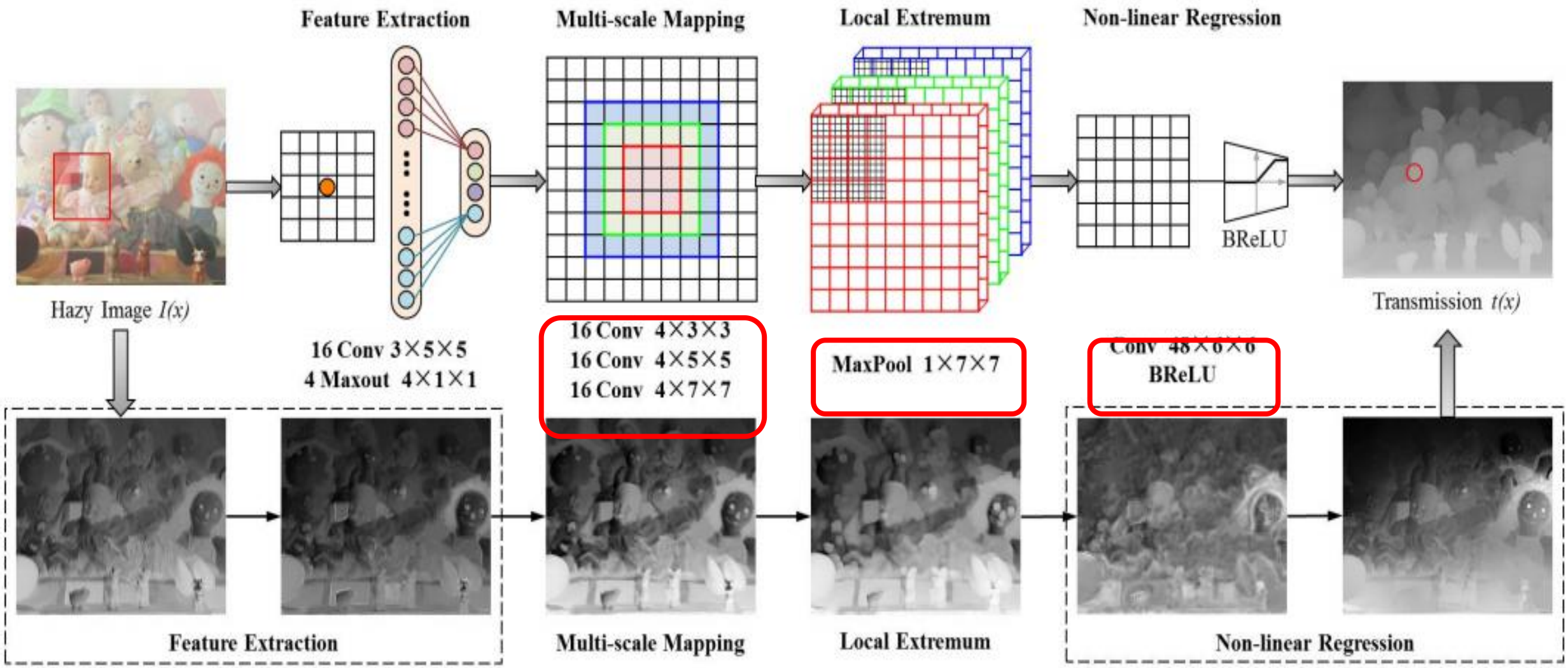
DehazeNet:An End-to-End System for Single Image Haze Removal





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

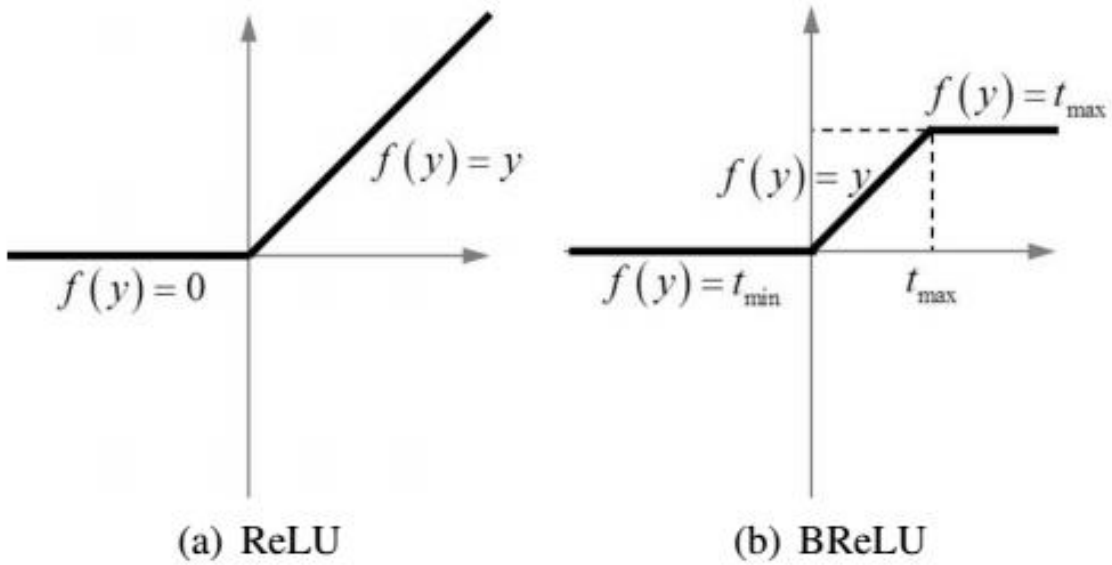
http://www.cnblogs.com/tornadomeet/p/3428843.html



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

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

- **Bilateral restraint:**
  - It applies a priori constraint (先验约束) to reduce the solution space scale.
- **Local linearity:**
  - It overcomes the gradient vanishing(梯度消失) to gain better precision.



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

1. **Layer Designs of DehazeNet**
2. **Multi-scale Mapping**
3. **Local Extremum**
4. **Non-linear Regression**

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

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

Training of DehazeNet

1.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)

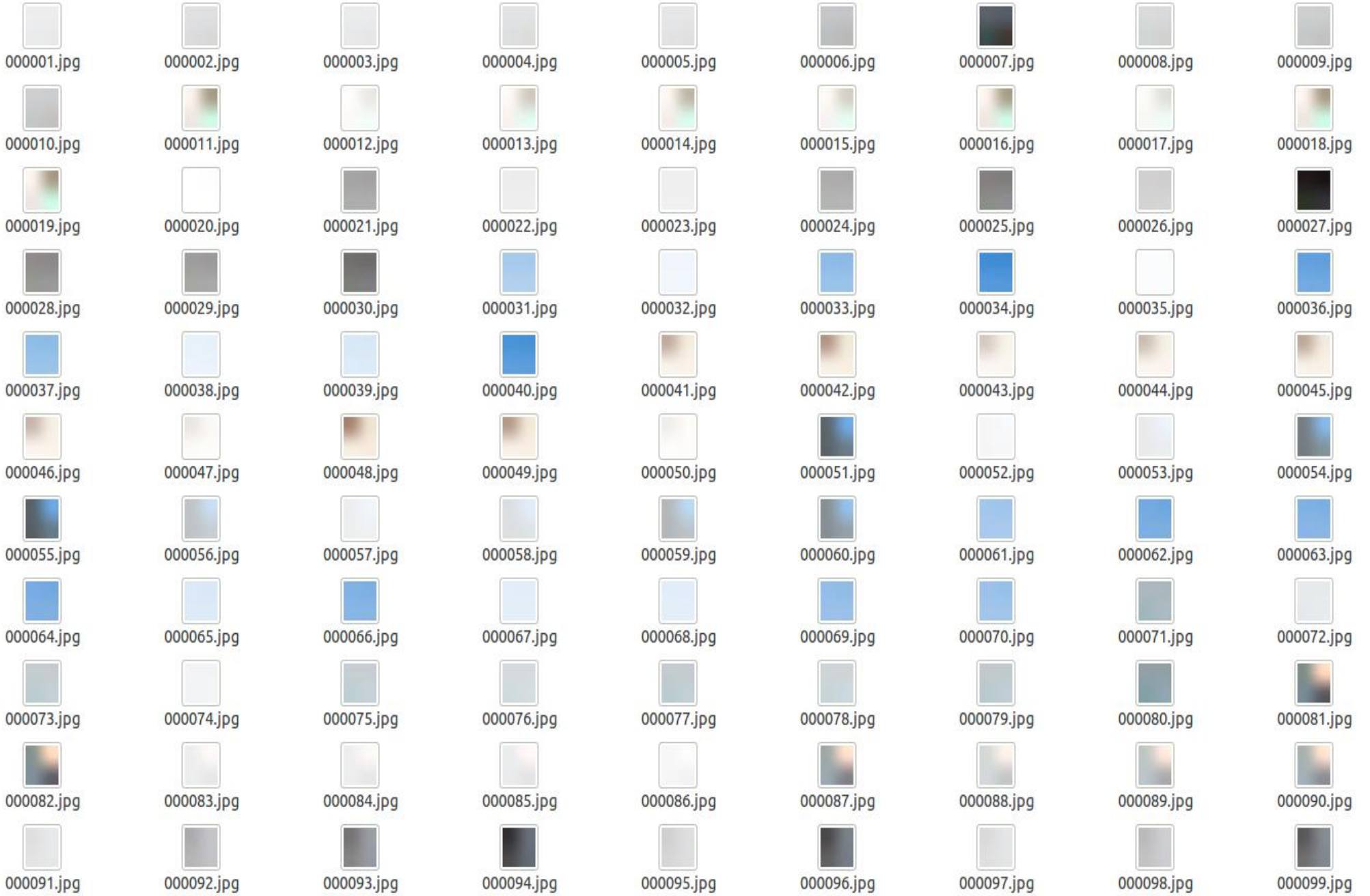
DehazeNet:An End-to-End System for Single Image Haze Removal

Training of DehazeNet

1.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
000020.jpg 0.01341821
000021.jpg 0.37994670
000022.jpg 0.07683825
000023.jpg 0.06725106
000024.jpg 0.34487915
000025.jpg 0.52858843
000026.jpg 0.19900572
000027.jpg 0.95942324
000028.jpg 0.48010922
000029.jpg 0.40867907
000030.jpg 0.60275455
000031.jpg 0.45066727
000032.jpg 0.07839893
000033.jpg 0.58494760
000034.jpg 0.98030893
000035.jpg 0.02719647
000036.jpg 0.81766764
000037.jpg 0.57564936
000038.jpg 0.11626336
000039.jpg 0.19522155
000040.jpg 0.93690418
000041.jpg 0.50169761
000042.jpg 0.63414945
000043.jpg 0.32533861
```

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

Training of DehazeNet

2.Training method:

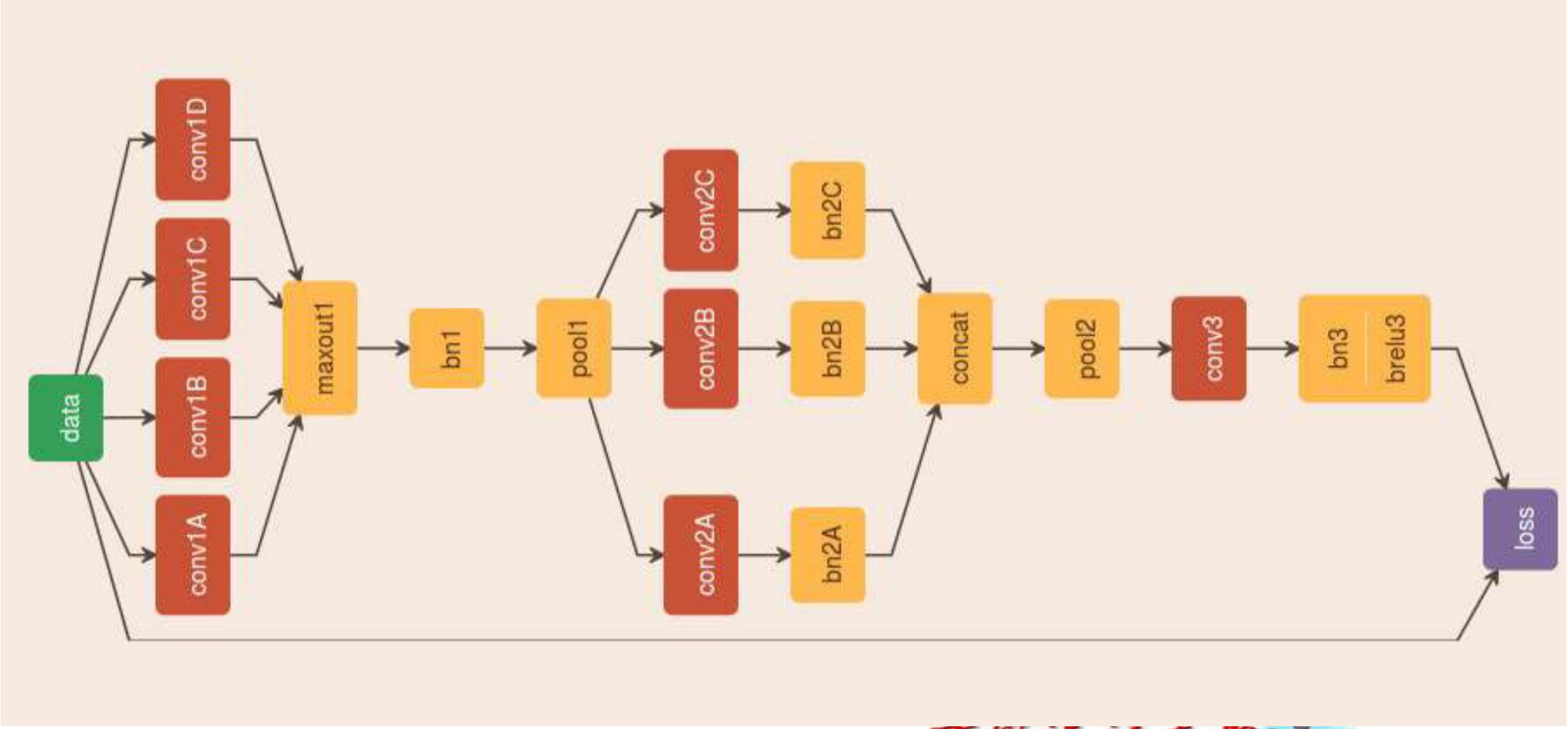
1) In the DehazeNet, supervised learning requires the mapping relationship F between RGB value and medium transmission.

2) Network parameters θ = {W,B} are achieved through minimizing the loss function between the training patch I(x) and the corresponding ground truth medium transmission t.

3) MSE(Mean Squared Error) as the loss function:

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

DehazeNet


data
conv1D
conv1C
conv1B
conv1A
maxout1
bn1
pool1
conv2C
conv2B
conv2A
bn2C
bn2B
bn2A
concat
pool2
conv3
bn3
brelu3
loss

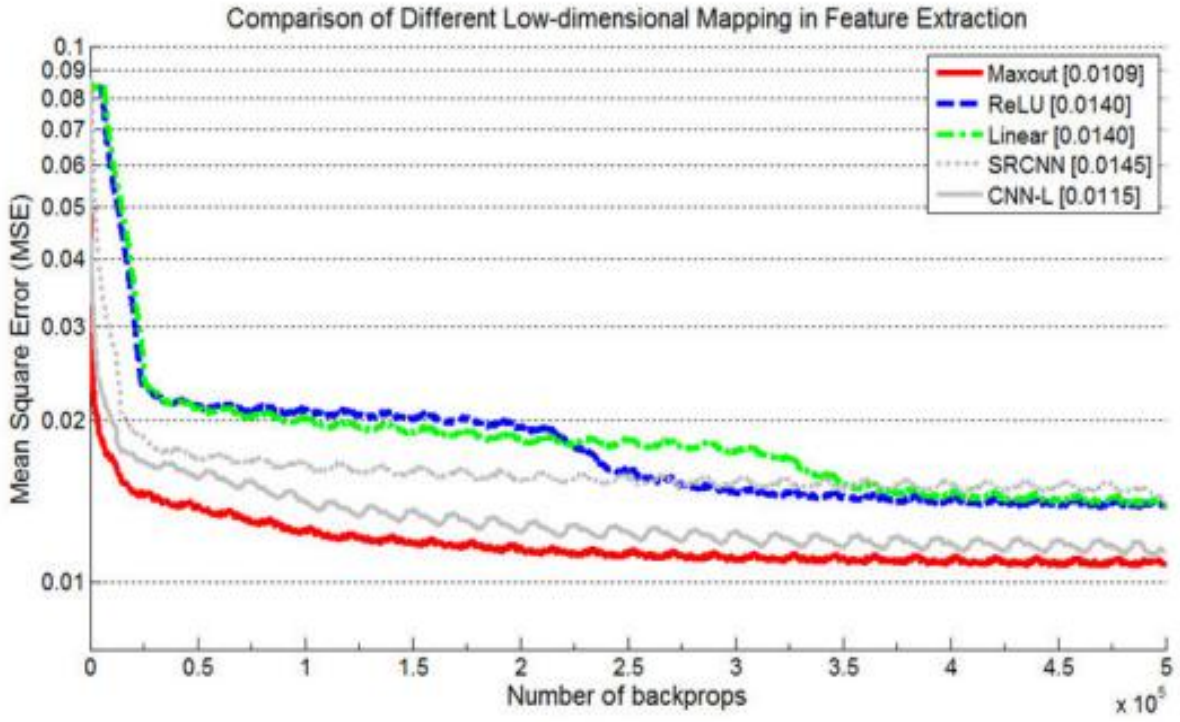


Fig. 6. The training process with different low-dimensional mapping in F_1

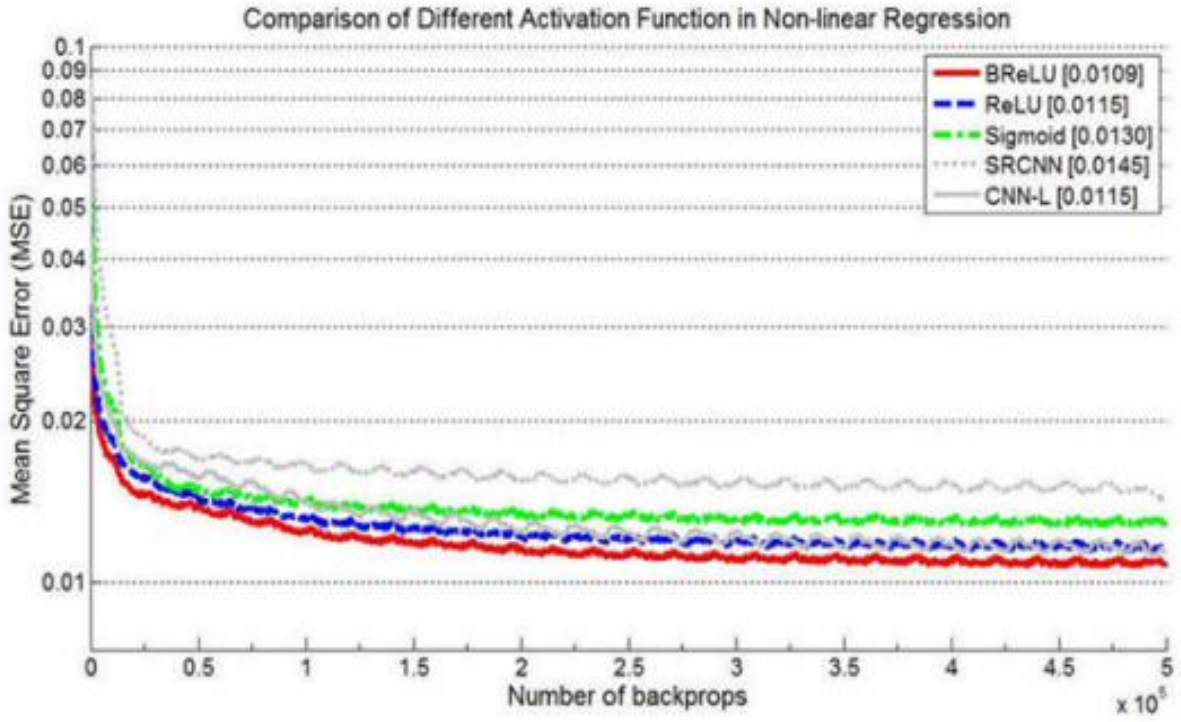
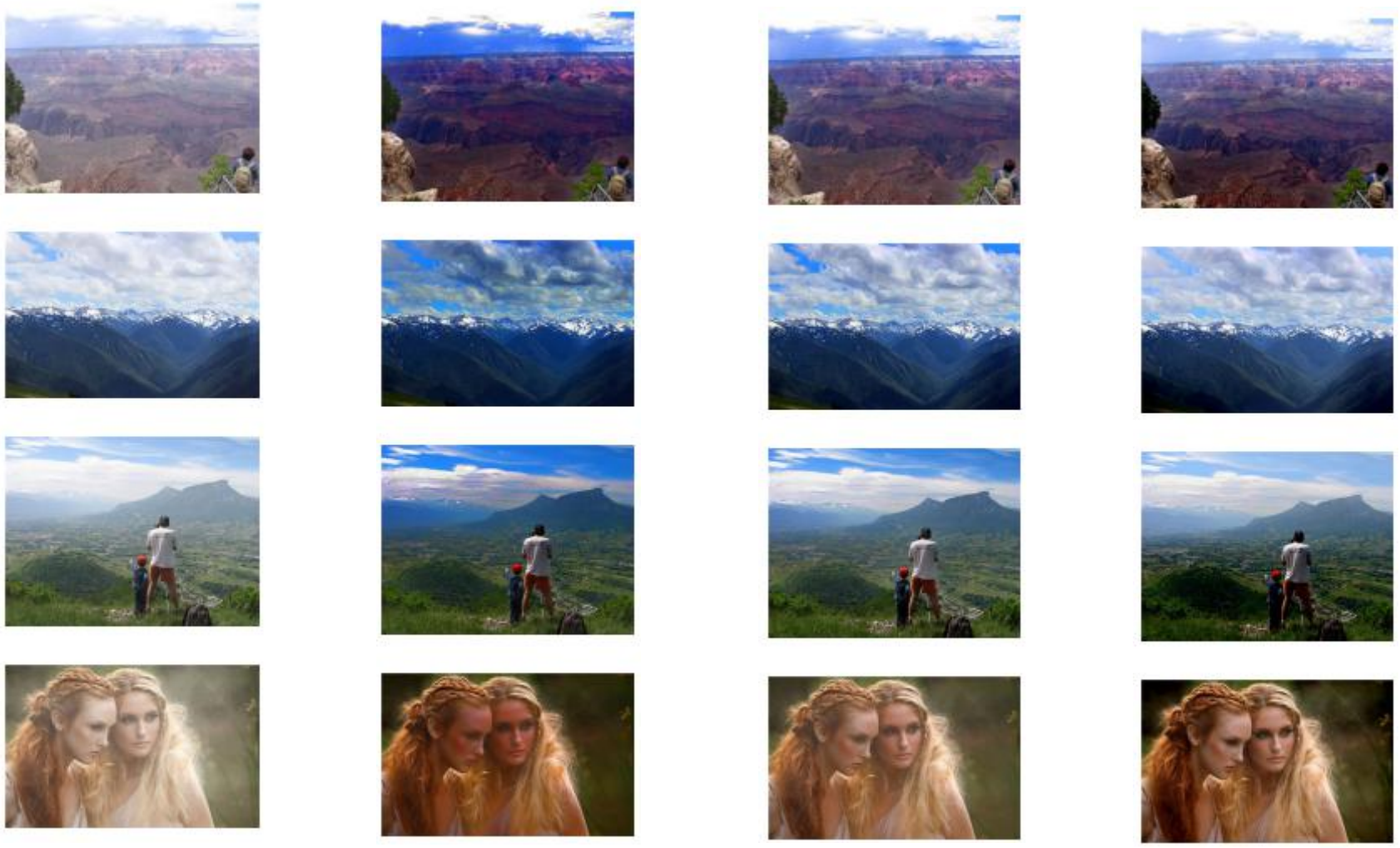


Fig. 7. The training process with different activation function in F_4

Results



Hazy image DCP CAP DehazeNet

Tools

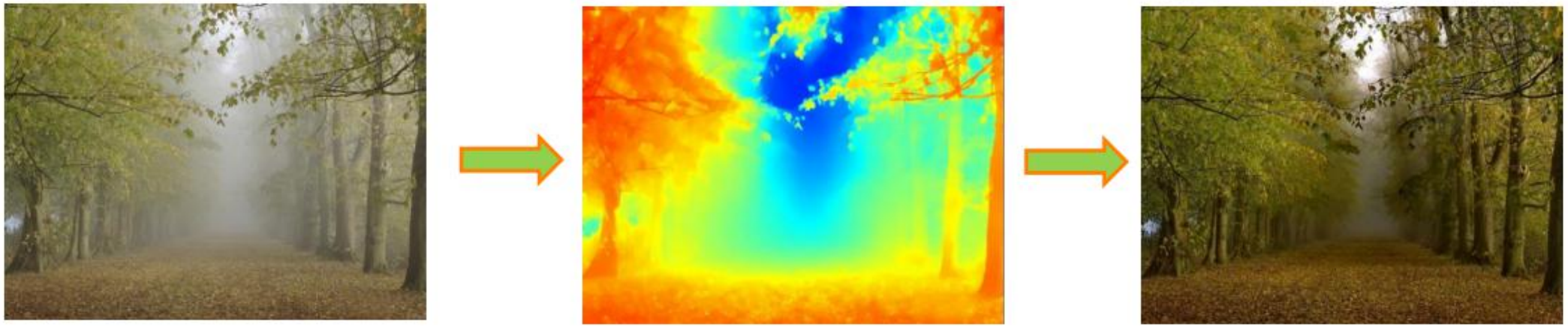
- Matlab
- Caffe（深度学习框架）

Dehaze Methods


- Dark Channel Prior
- Color Attenuation Prior
- DehazeNet
- MSCNN

Single Image Dehazing via Multi-Scale Convolutional Neural Network

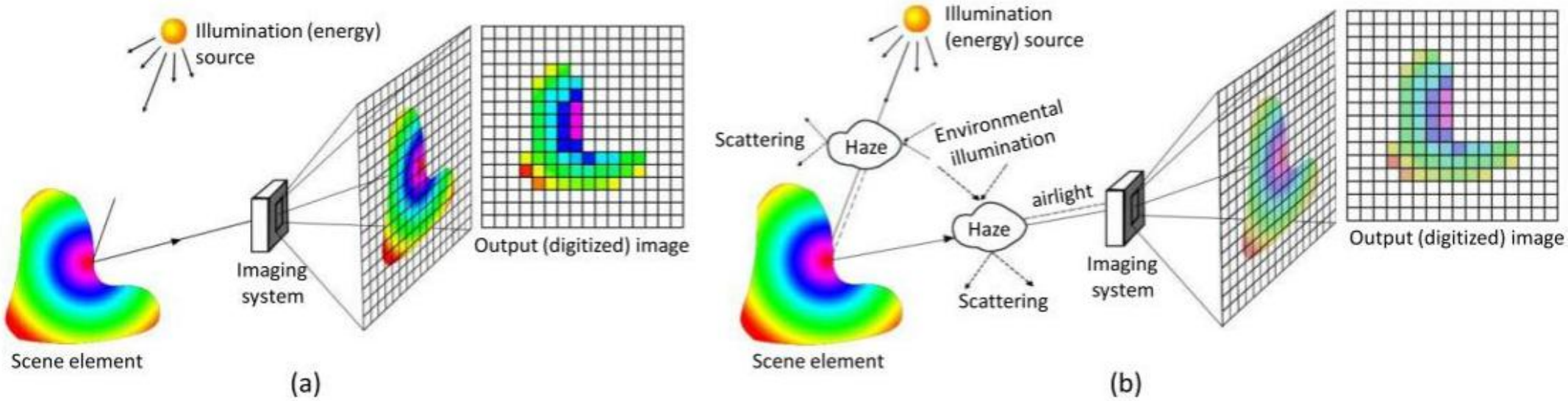
- Goals of image dehazing
  - Transmission estimation
  - Scene recovering



- Hazy image
- Transmission
- Scene

Single Image Dehazing via Multi-Scale Convolutional Neural Network

- Hazy imaging model



Single Image Dehazing via Multi-Scale Convolutional Neural Network

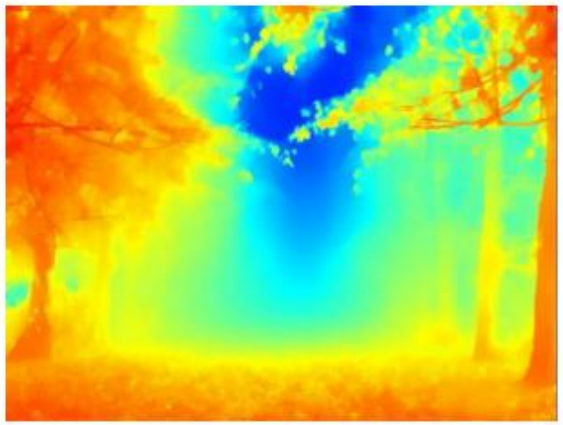
- Hazy imaging model

Atmospheric light

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

Haze image

Scene



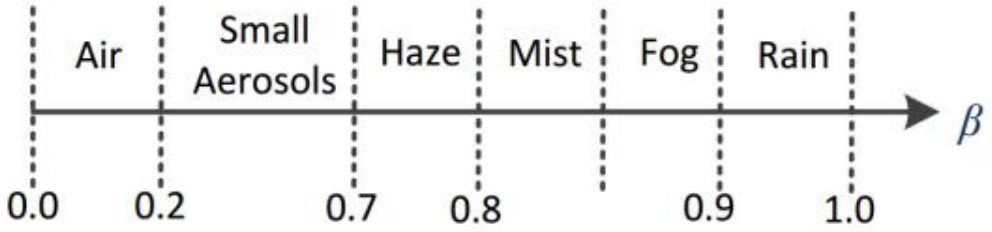
Transmission

Single Image Dehazing via Multi-Scale Convolutional Neural Network

- Hazy imaging model

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

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

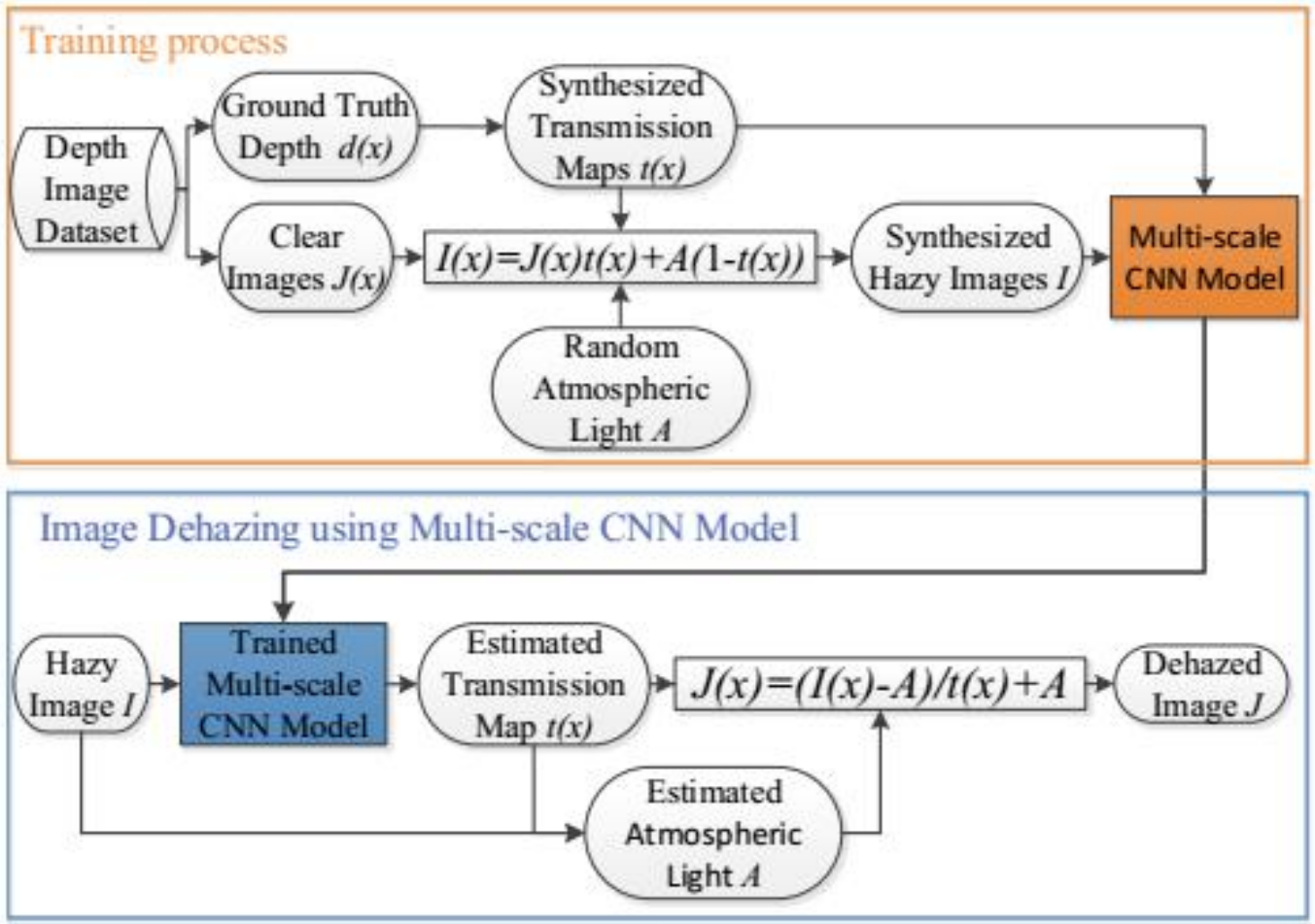


t(x): Transmission
d(x): Scene depth
β: medium extinction coefficient

Single Image Dehazing via Multi-Scale Convolutional Neural Network

- A multi-scale convolutional neural network for transmission estimation
- Analyze the differences between traditional hand-crafted features and the features learned by the CNN

Single Image Dehazing via Multi-Scale Convolutional Neural Network



(a)

- Train the multi-scale CNN based on synthesized dataset
- Predict transmission based on the trained network

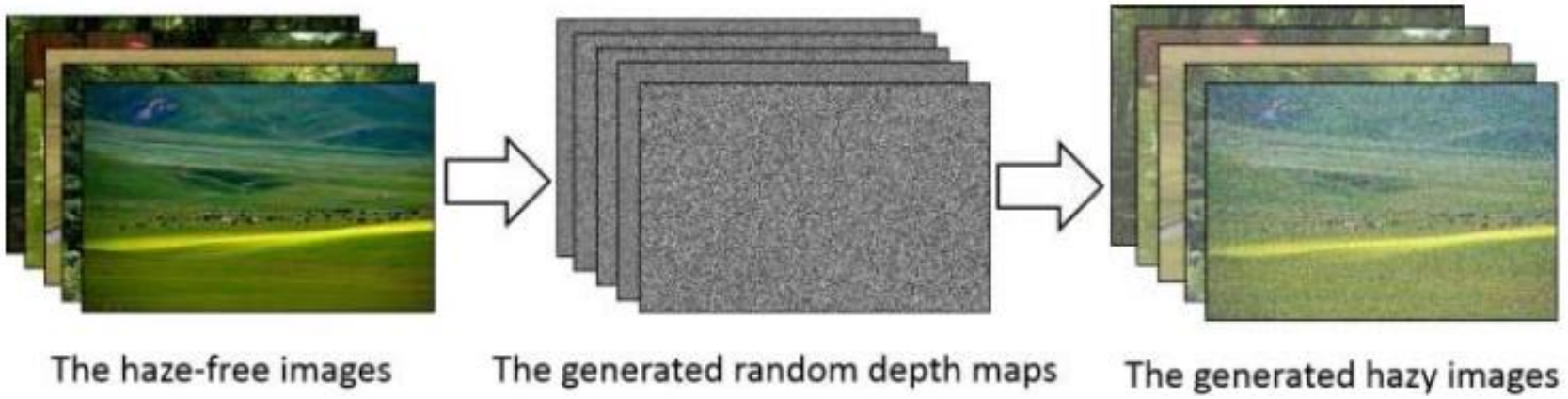
Single Image Dehazing via Multi-Scale Convolutional Neural Network

Scene depth recovery

1.Synthetic dataset

clear image + random depth maps + random global atmospheric light

=sample haze images



Single Image Dehazing via Multi-Scale Convolutional Neural Network

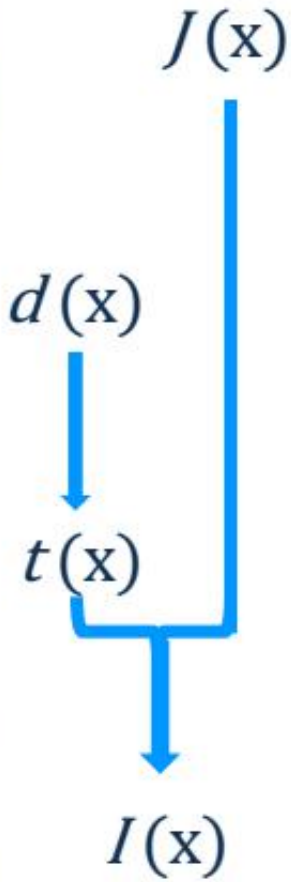
- Generate synthesized hazy images and transmission
  - NYU depth dataset: J(x) and d(x)
  - Hazy imaging model

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

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

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

Training Data Synthesis



Training Data Synthesis

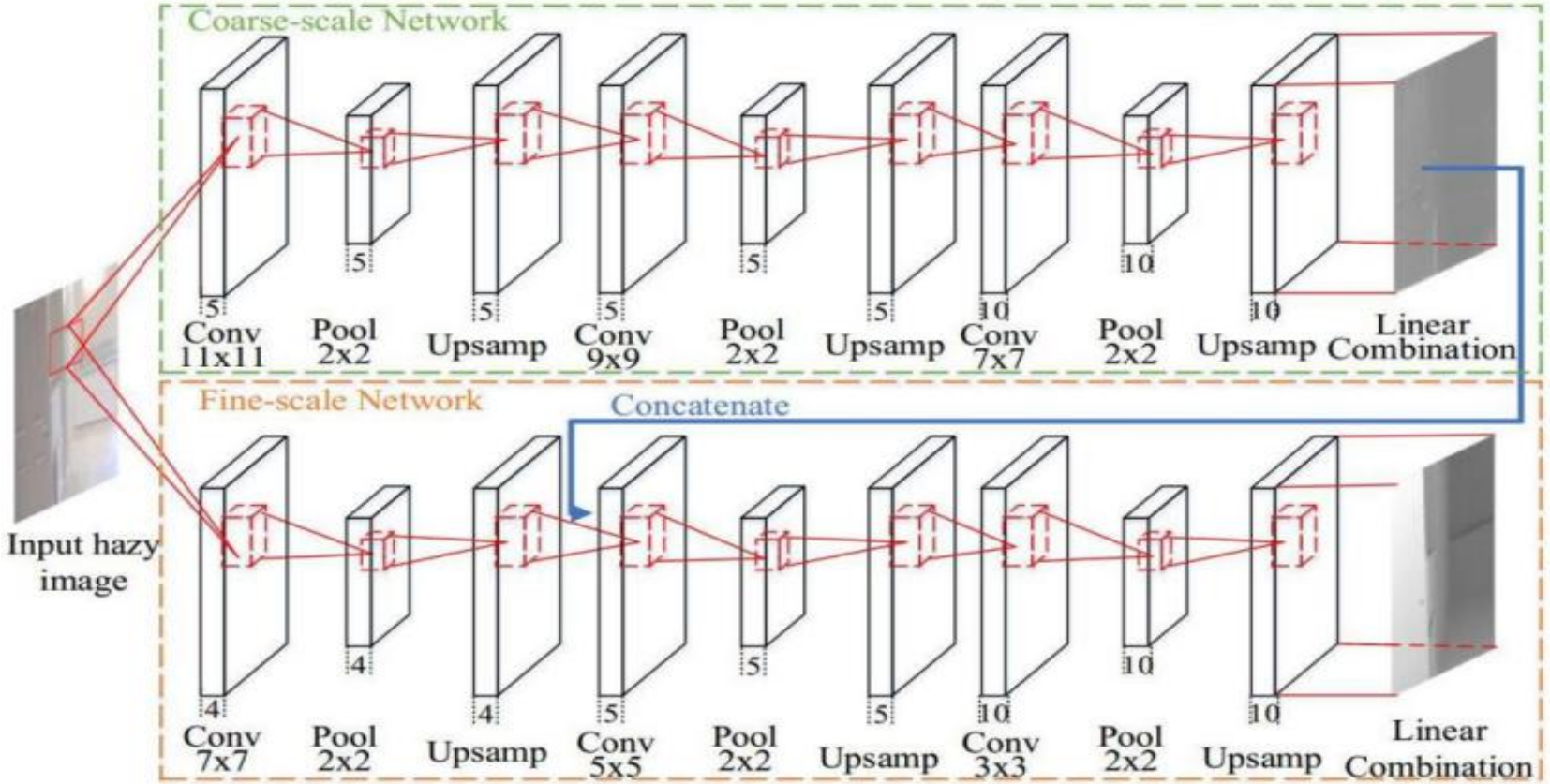
Clear image

Depth image

Hazy images with different β

Single Image Dehazing via Multi-Scale Convolutional Neural Network

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



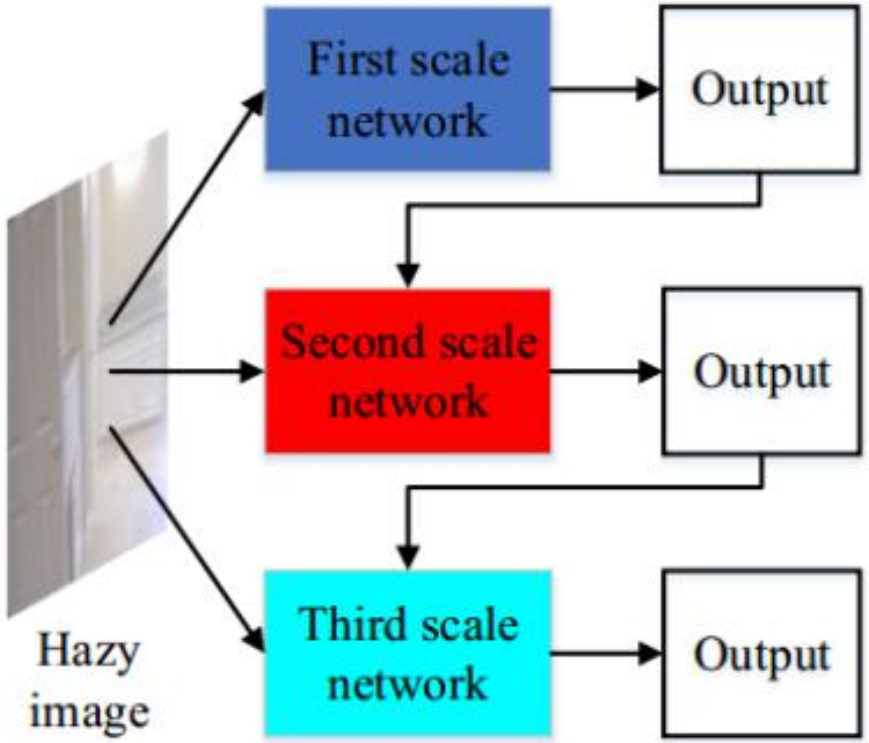
Single Image Dehazing via Multi-Scale Convolutional Neural Network

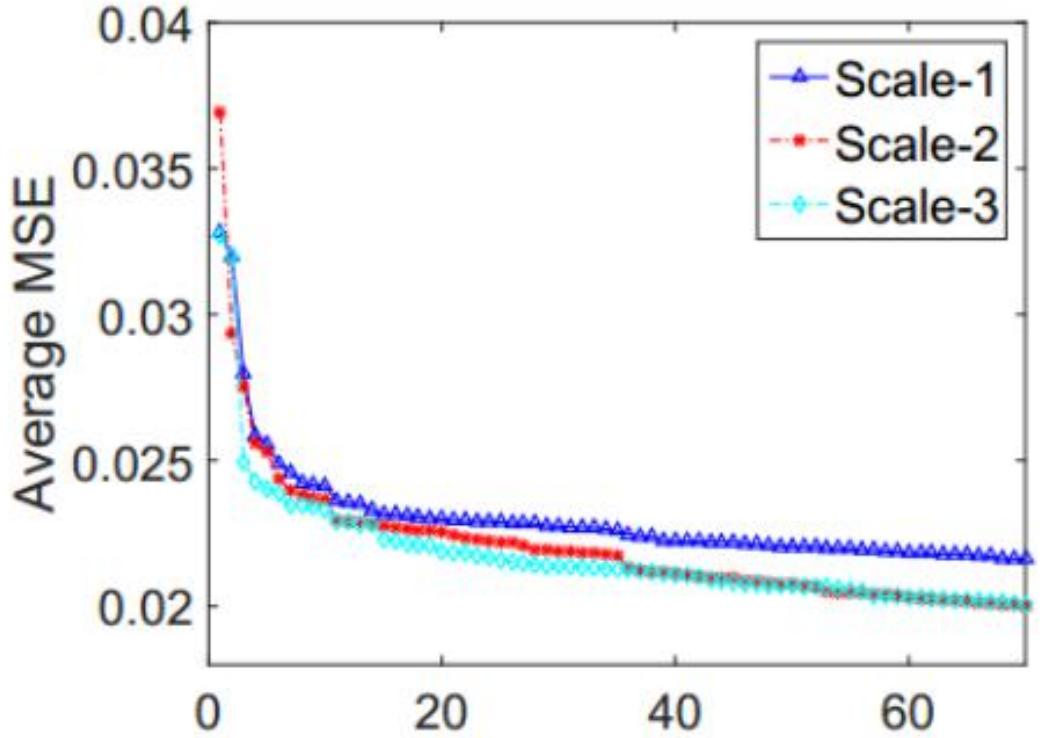
- Training loss

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

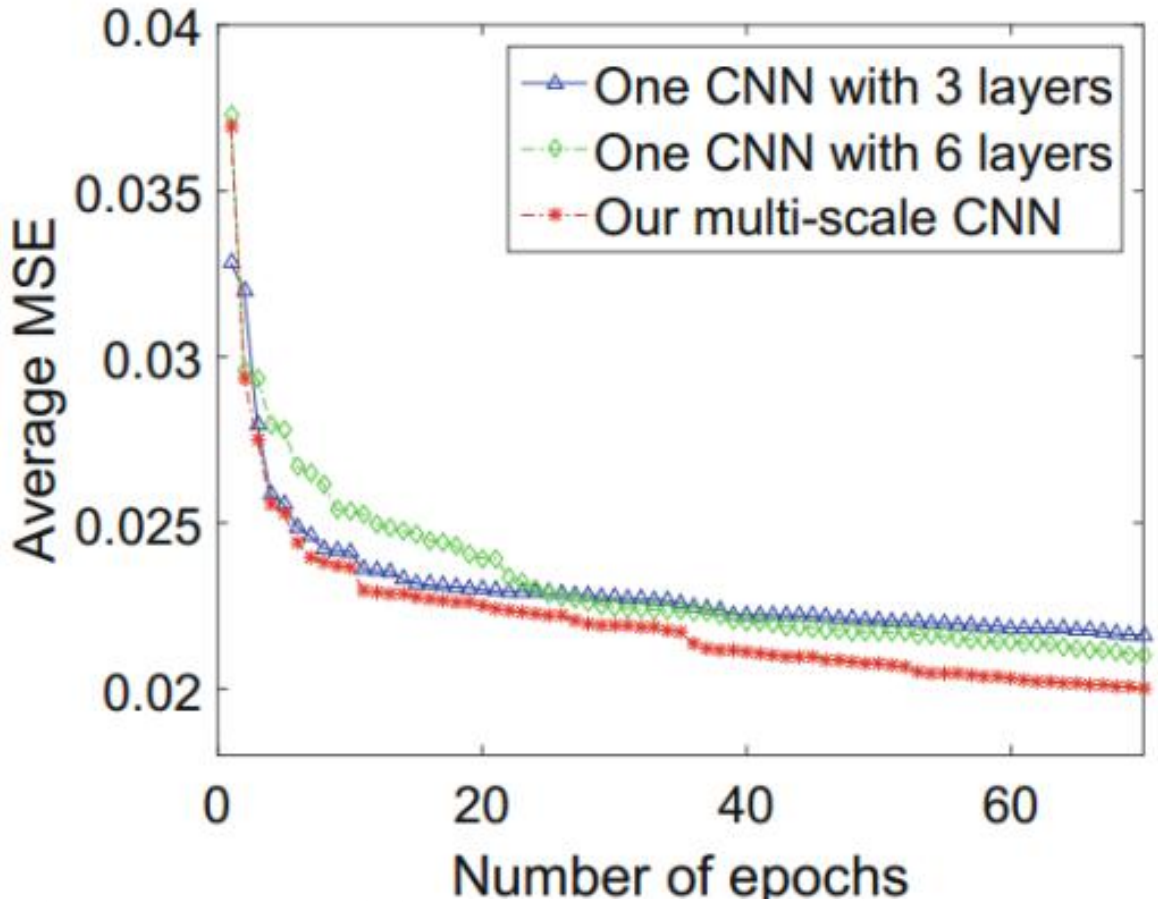
- The training loss is used in both coarse and fine-scale networks

Single Image Dehazing via Multi-Scale Convolutional Neural Network





Single Image Dehazing via Multi-Scale Convolutional Neural Network



Single Image Dehazing via Multi-Scale Convolutional Neural Network

- Compute atmospheric light from the estimated transmission map

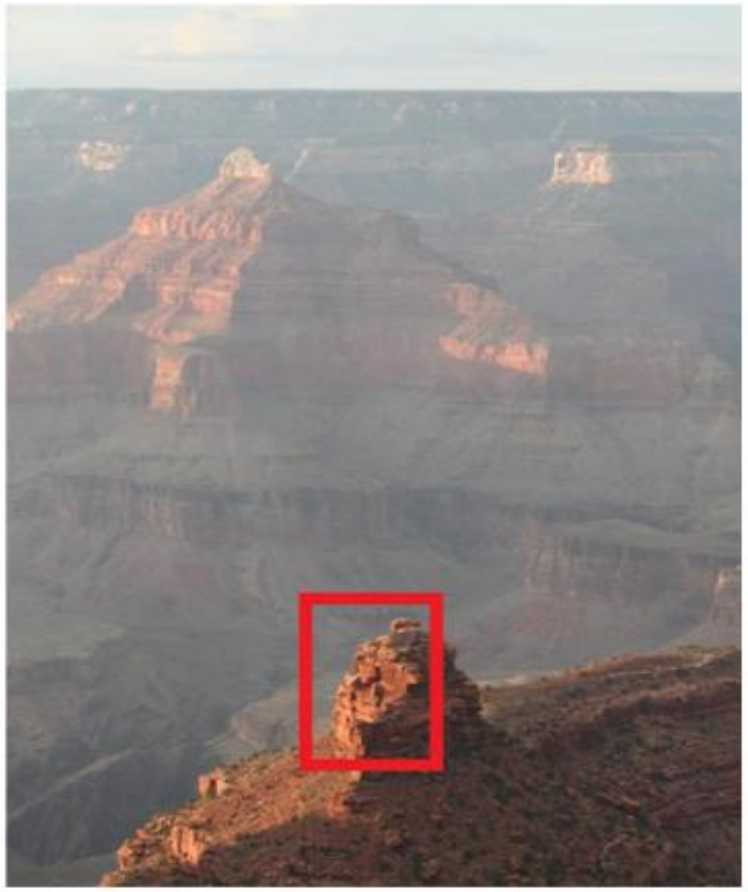
Single Image Dehazing via Multi-Scale Convolutional Neural Network

- Recover haze-free images after atmospheric light and transmission are estimated.

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

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

Effectiveness of Fine-scale Network



Hazy image

Without the fine-scale network

With the fine-scale network

Single Image Dehazing via Multi-Scale Convolutional Neural Network

Close shot Medium shot Long shot

Experimental Results

- Real-world images

- Input
- He et al
- Mai et al
- Proposed

Single Image Dehazing via Multi-Scale Convolutional Neural Network

- Failure case for nighttime haze images
- Nighttime hazy image model: $I(x) = J(x)t(x) + A(1\text{-}t(x)) + L_a(x) * APSF$

Input

Proposed

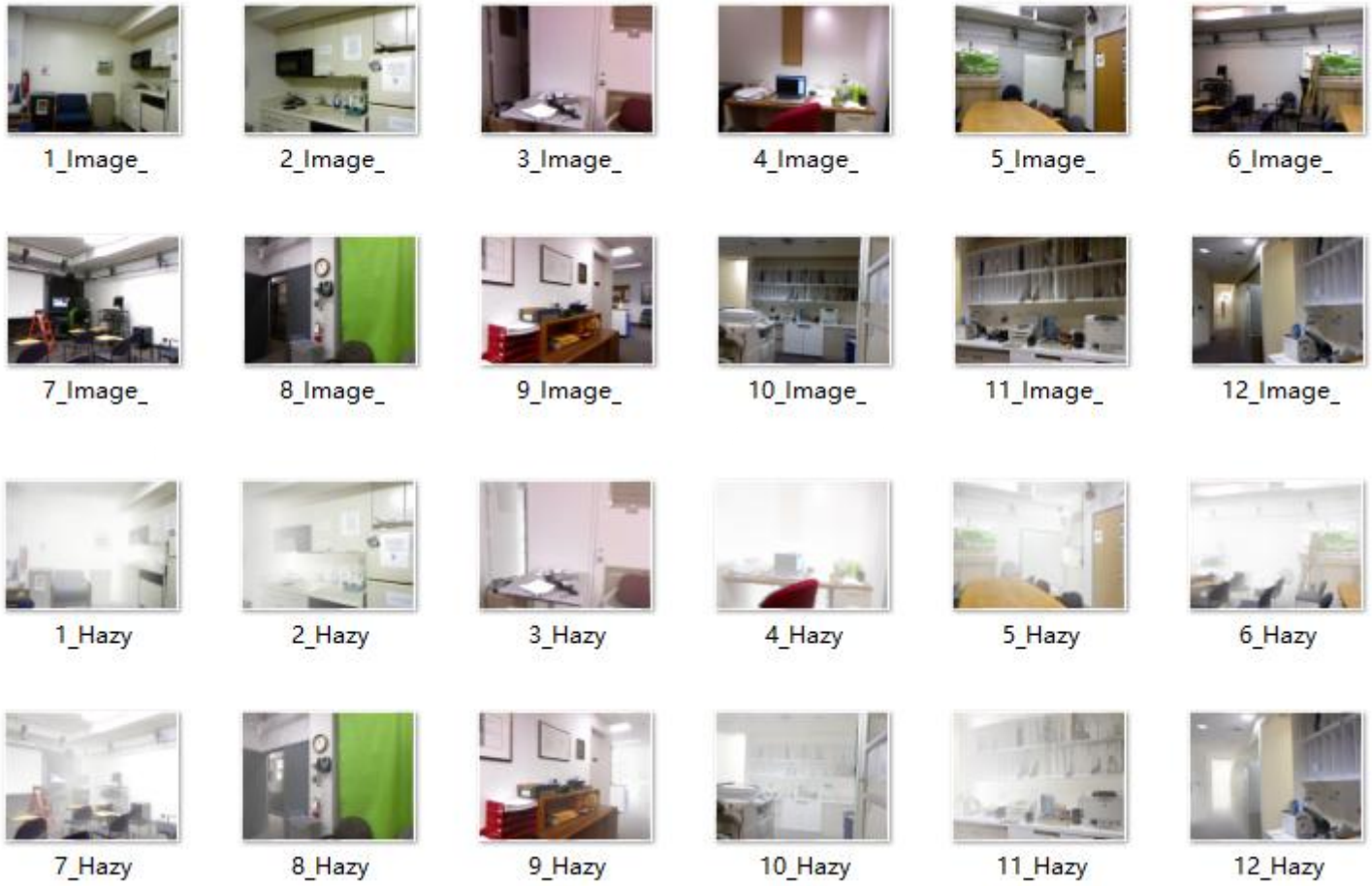
Li et al.“Nighttime haze removal with glow and multiple light colors”. ICCV. 2015

Review

1. Review of deblurring method
2. Introduction of dehazing method
3. Introduction of Convolutional Neural Network
4. Dehazing by Convolutional Neural Network

CV Assignment 3: Image Dehazing

- Dataset:
  - 50 clear images
  - 50 synthetic hazy images



Framework

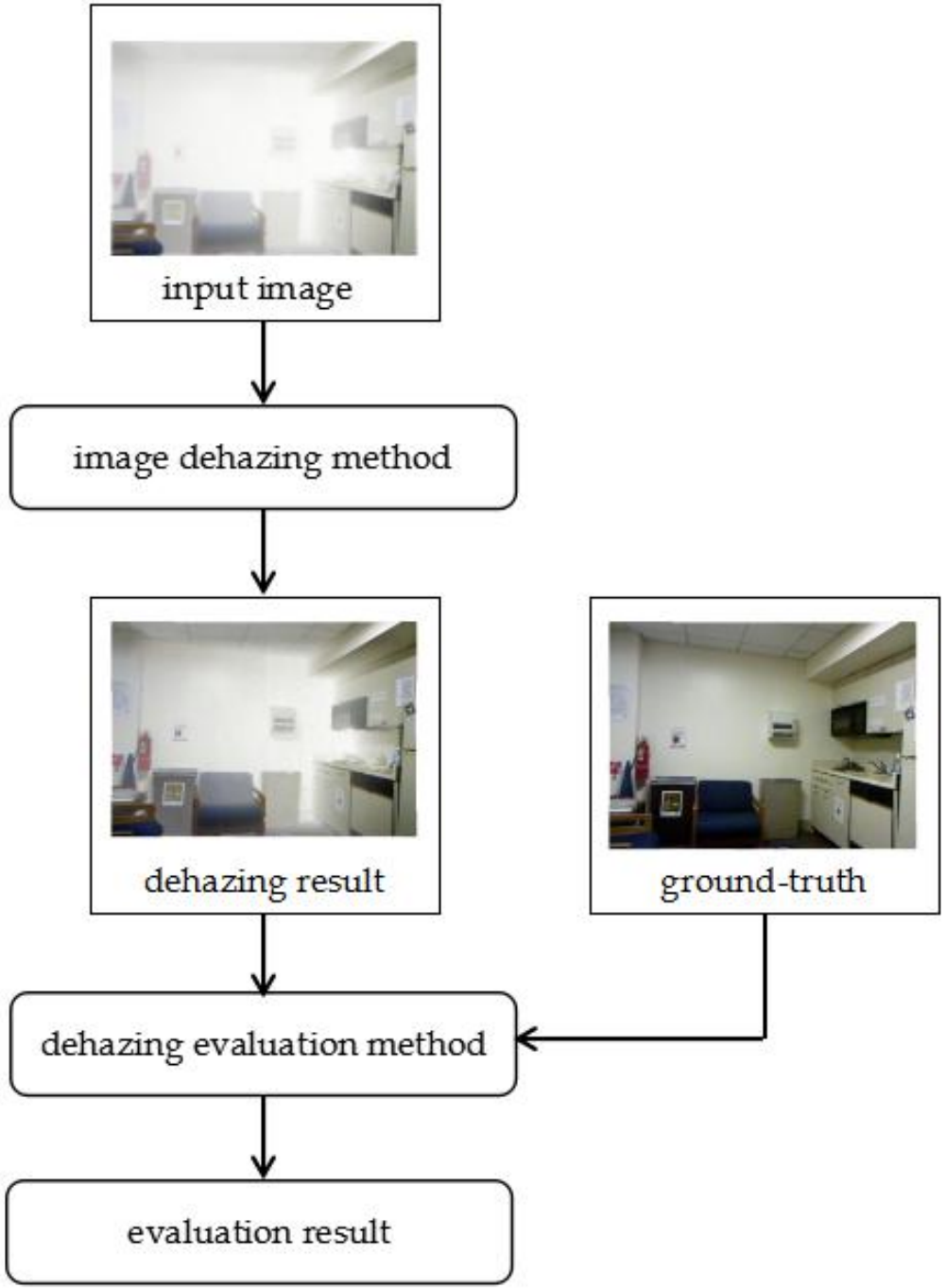

input image
image dehazing method
dehazing result
ground-truth
dehazing evaluation method
evaluation result

Image Dehazing Methods

- Implement at least three methods on all synthetic hazy images to get different dehazing results.

  - Dark Channel Prior
  - Color Attenuation Prior
  - DehazeNet
  - Single Image Dehazing via MSCNN
  - Non-Local Image Dehazing

Evaluation of Image Dehazing

- Compare the quality of algorithms using at least two evaluation measures.

  - Mean Squared Error (MSE)--------均方误差
  - Peak Signal to Noise Ratio (PSNR)--------峰值信噪比
  - Structural Similarity index (SSIM)--------结构相似性度量

Analysis of Image Dehazing Methods and Results

- Explain the principle of methods and analyze the results.

Submission

- 1.Your code.
- 2.Your results.
- 3.A report with methods and results of explanation and analysis.

THANKS