Single Image Dehazing

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August 16, 2021

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References

- [1] Gui, J., et al. **A Comprehensive Survey on Image Dehazing Based on Deep Learning**. 2021. arXiv:2106.03323.
- [2] K. He, J. Sun and X. Tang, "**Single Image Haze Removal Using Dark Channel Prior**," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 12, pp. 2341-2353, Dec. 2011, doi: 10.1109/TPAMI.2010.168.
- [3] M. Ju, C. Ding, W. Ren, Y. Yang, D. Zhang and Y. J. Guo, "**IDE: Image Dehazing and Exposure Using an Enhanced Atmospheric Scattering Model**," in IEEE Transactions on Image Processing, vol. 30, pp. 2180-2192, 2021, doi: 10.1109/TIP.2021.3050643.
- [4] B. Li, X. Pengand Z. Wang, and J. Xuand D. Feng. " **Aod-net: All-in-one dehazing network** ," In IEEE International Conference on Computer Vision, pages 4780–4788, Los Alamitos, CA, USA, oct 2017. IEEE Computer Society
- [5] Liu, Z., et al. **Generic Model-Agnostic Convolutional Neural Network for Single Image Dehazing**. 2018. arXiv:1810.02862.
- [6] A. Mehra, M. Mandal, P. Narang and V. Chamola, "**ReViewNet: A Fast and Resource Optimized Network for Enabling Safe Autonomous Driving in Hazy Weather Conditions**," in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 7, pp. 4256-4266, July 2021, doi: 10.1109/TITS.2020.3013099.
- [7] Oktay, O., et al. **Attention U-Net: Learning Where to Look for the Pancreas**. 2018. arXiv:1804.03999.
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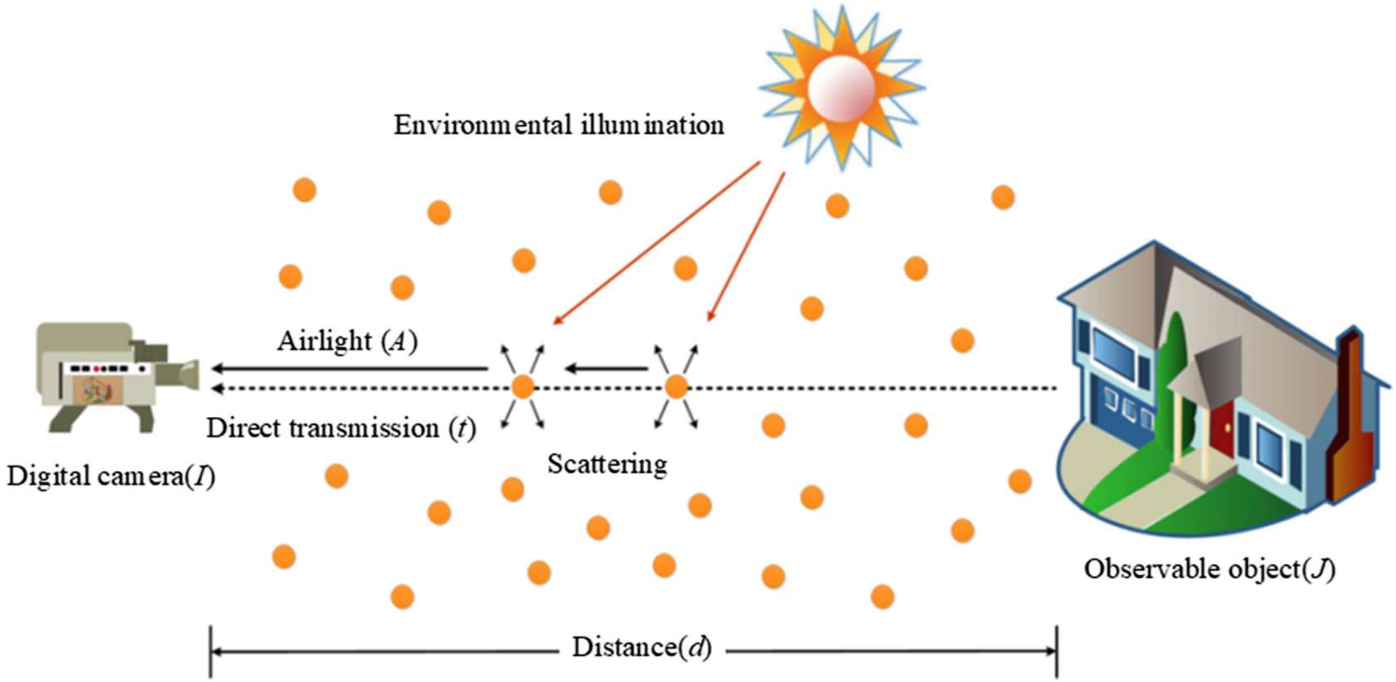
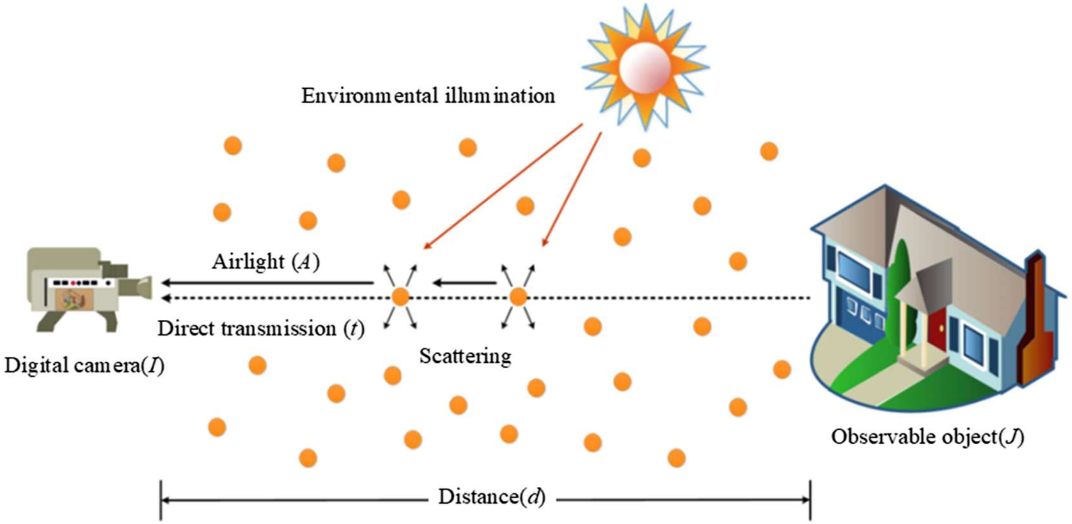
Dehazing Based on the ASM (Atmospheric Scattering Model) [1]

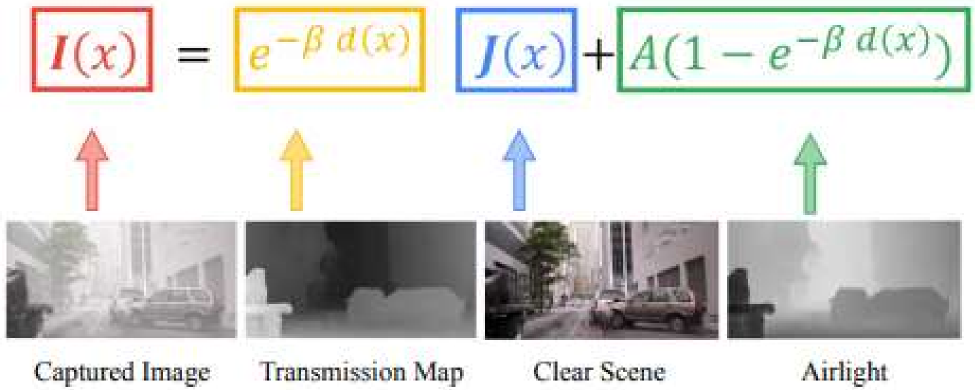


Atmospheric Scattering Model



The formula of ASM is as following:

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

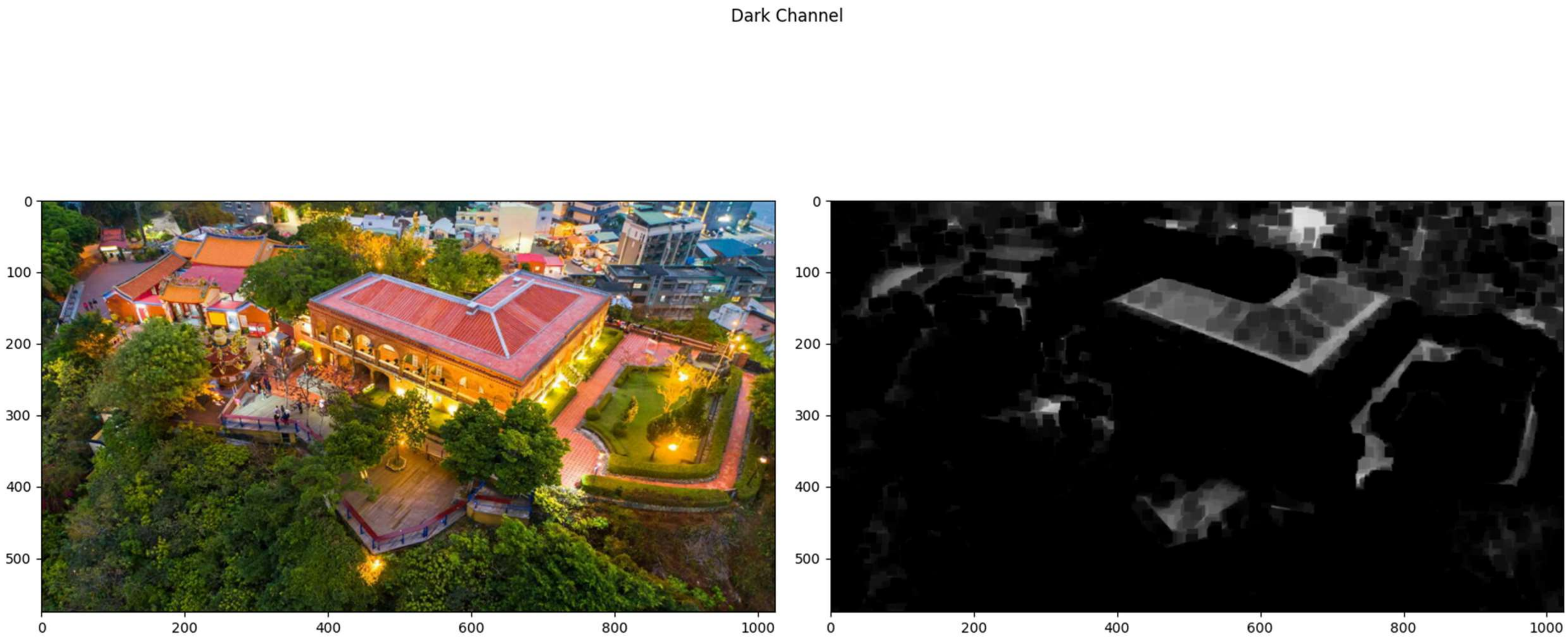


(a) Formula of illumination components

dehazing image $J(x)$ is

$$J(x) = \frac{I(x) - A(1 - t(x))}{t(x)}. \tag{3}$$

Dark Channel Prior [2]



Dark Channel Prior [2]

- Assume that A is known and the transmission in a local window is constant

$$\mathbf{I}(x) = J(x)t(x) + \mathbf{A}(1 - t(x)) \qquad t(x) = e^{-\beta d(x)}$$

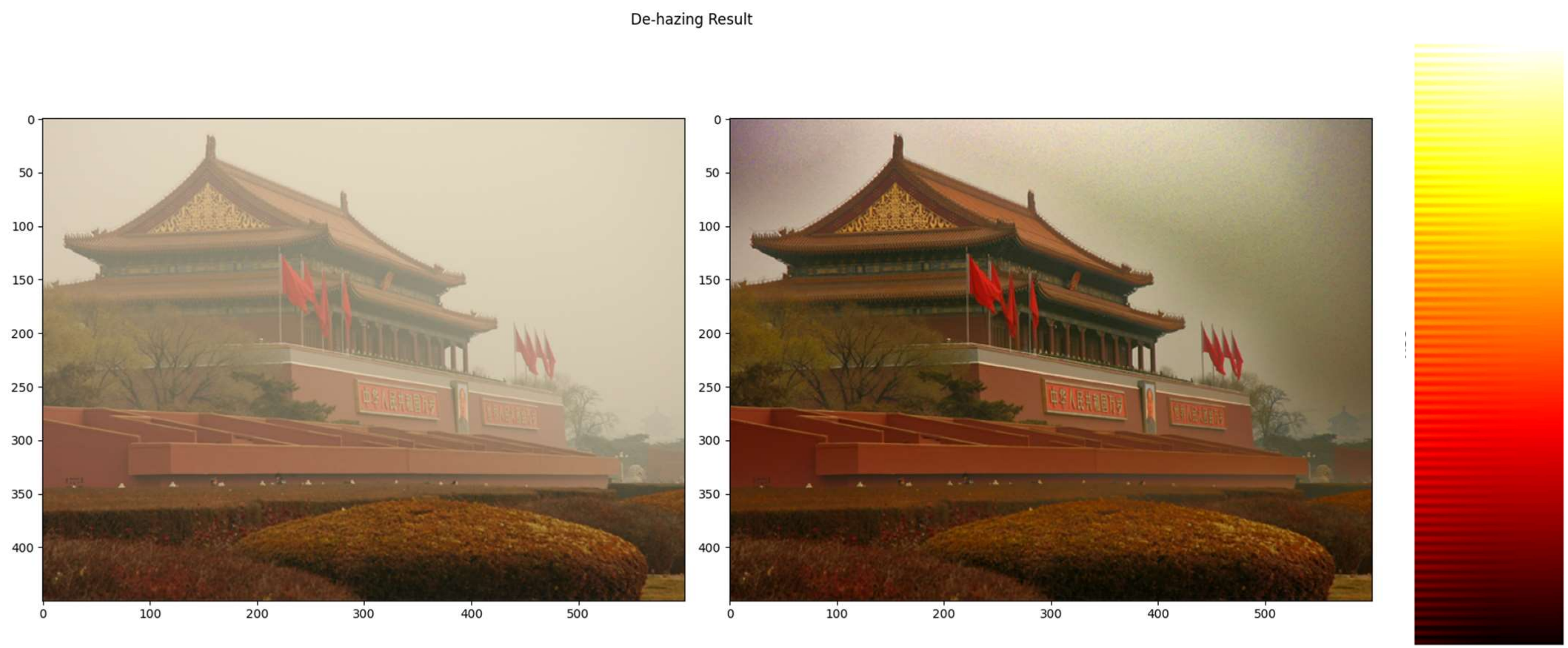
$$J^{dark}(x) = \min_{c \in \{r,g,b\}} \left(\min_{y \in \Omega(x)} J^{c}(y) \right)$$

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

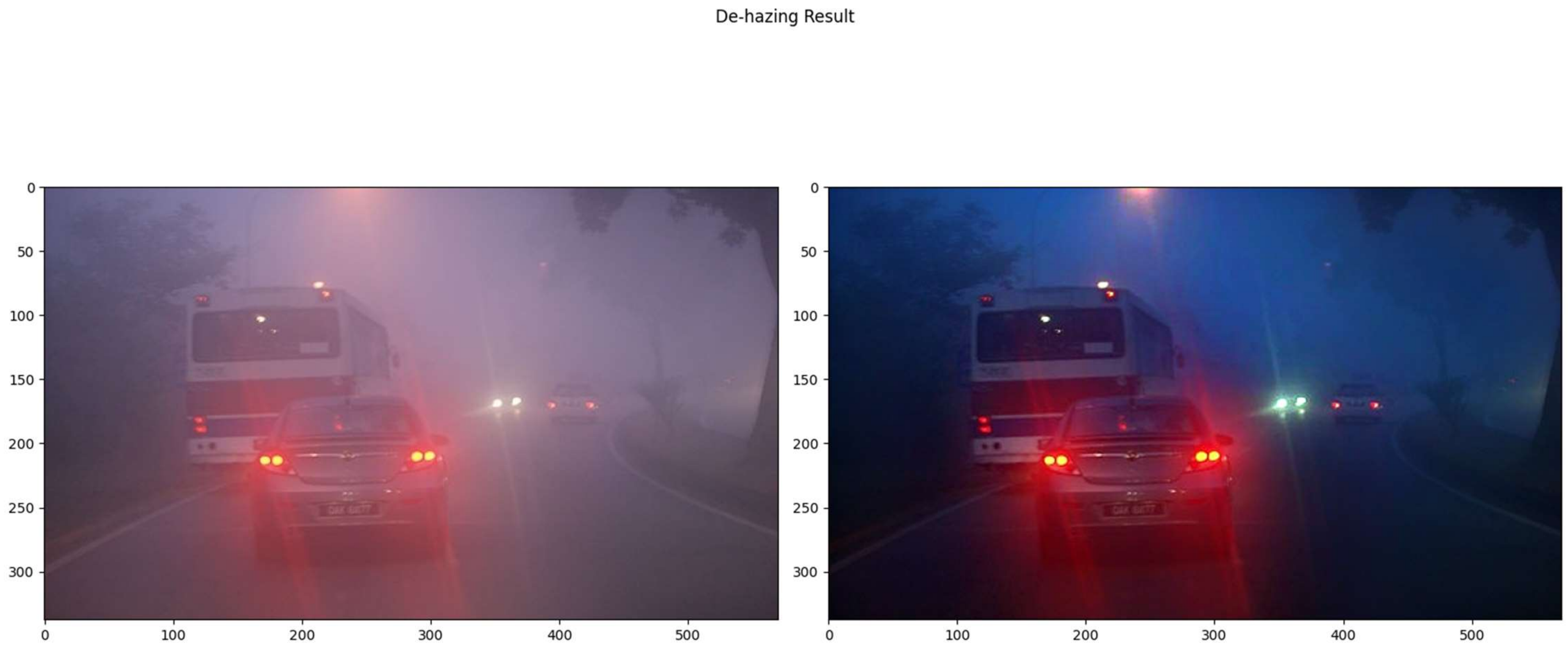
$$\tilde{t}(x) = 1 - \omega \min_{c} \left(\min_{y \in \Omega(x)} \left(\frac{I^{c}(y)}{A^{c}} \right) \right)$$

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

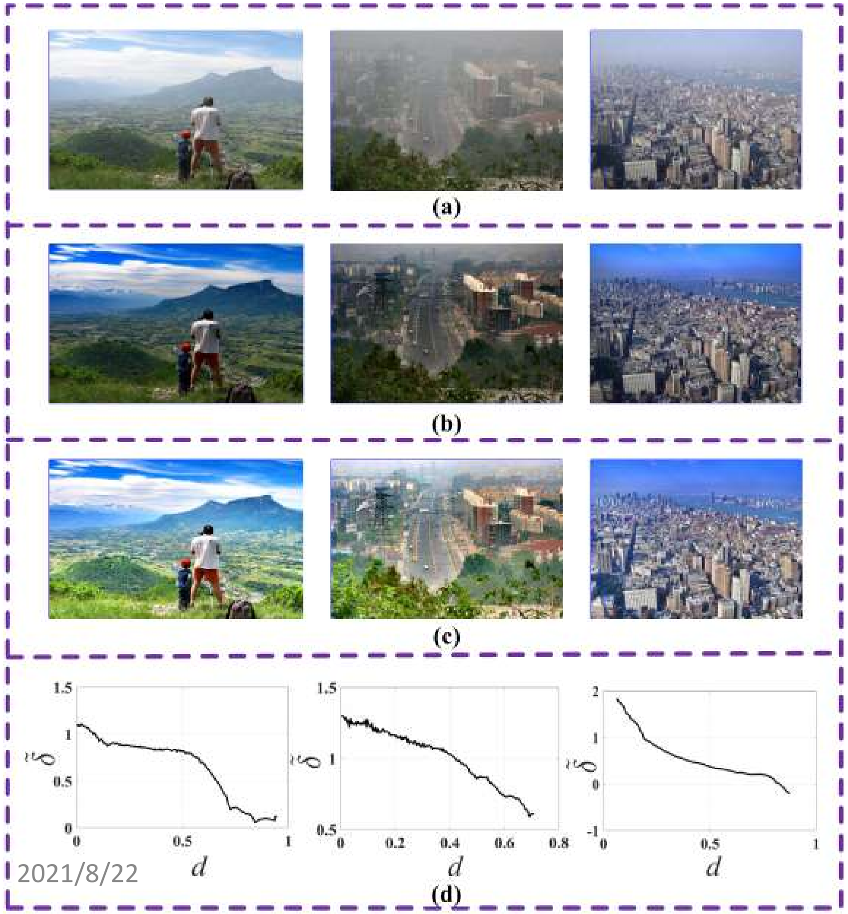
Dark Channel Prior [2]



Dark Channel Prior [2]



Enhanced ASM (EASM) [3]



$$\boldsymbol{I}(x, y) = \boldsymbol{A} \cdot \boldsymbol{\rho}(x, y) \cdot t(x, y) + \boldsymbol{A} \cdot (1 - t(x, y)),$$

$$\hat{\delta} = \frac{\boldsymbol{\rho}_{real} - \boldsymbol{\rho}_{ASM}}{\boldsymbol{\rho}_{ASM}}$$

To eliminate this limitation of ASM, the light absorption coefficient $\alpha \in (0, 1]$ is introduced into ASM. The enhanced ASM can be expressed as

$$\begin{aligned} \boldsymbol{I}(x, y) = \boldsymbol{A} \cdot (1 - \alpha(x, y)) \cdot \boldsymbol{\rho}(x, y) \cdot t(x, y) \\ + \boldsymbol{A} \cdot (1 - t(x, y)). \end{aligned} \tag{4}$$

Enhanced ASM (EASM) [3]

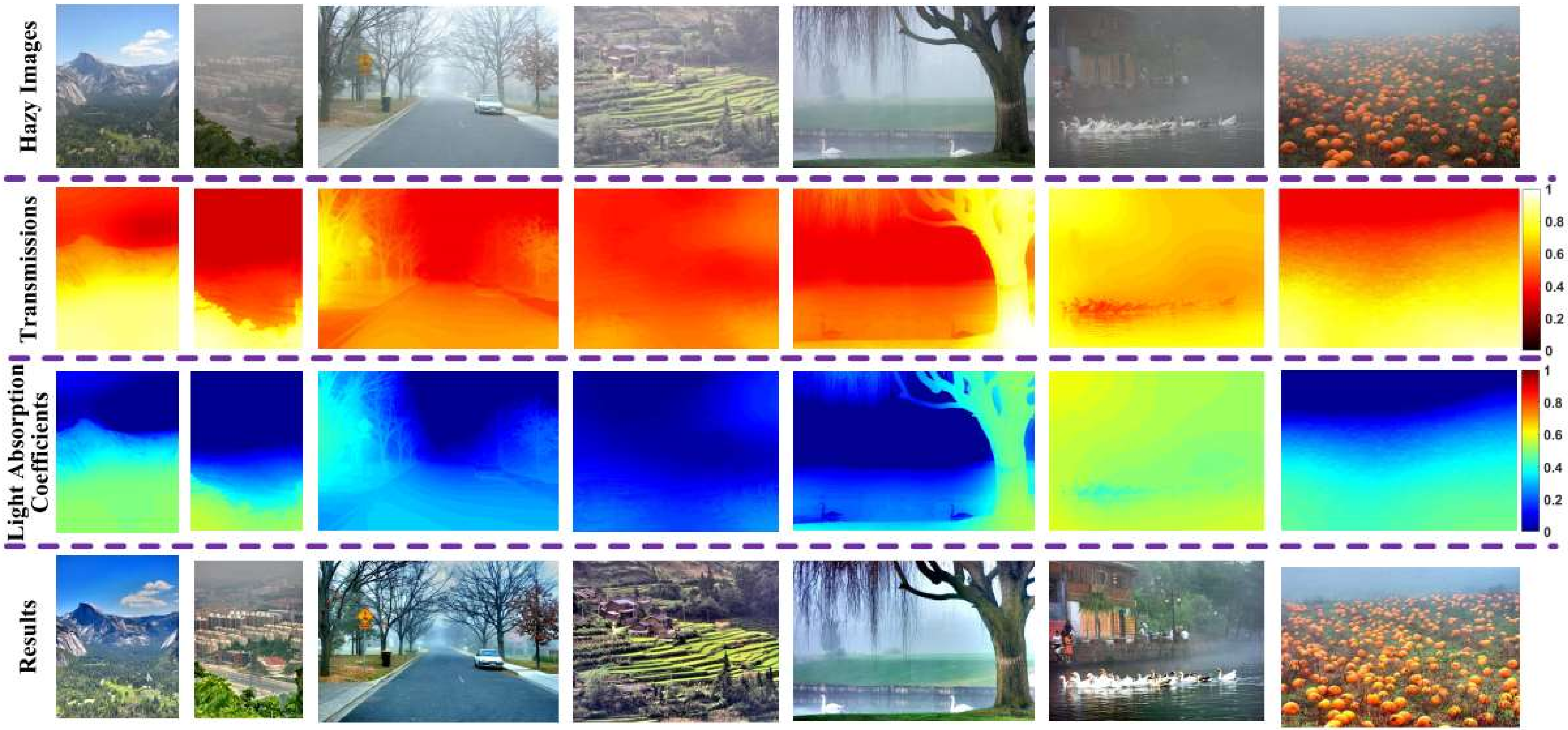


Fig. 7. Recovery results of IDE on different types of outdoor hazy images.

Enhanced ASM (EASM) [3]

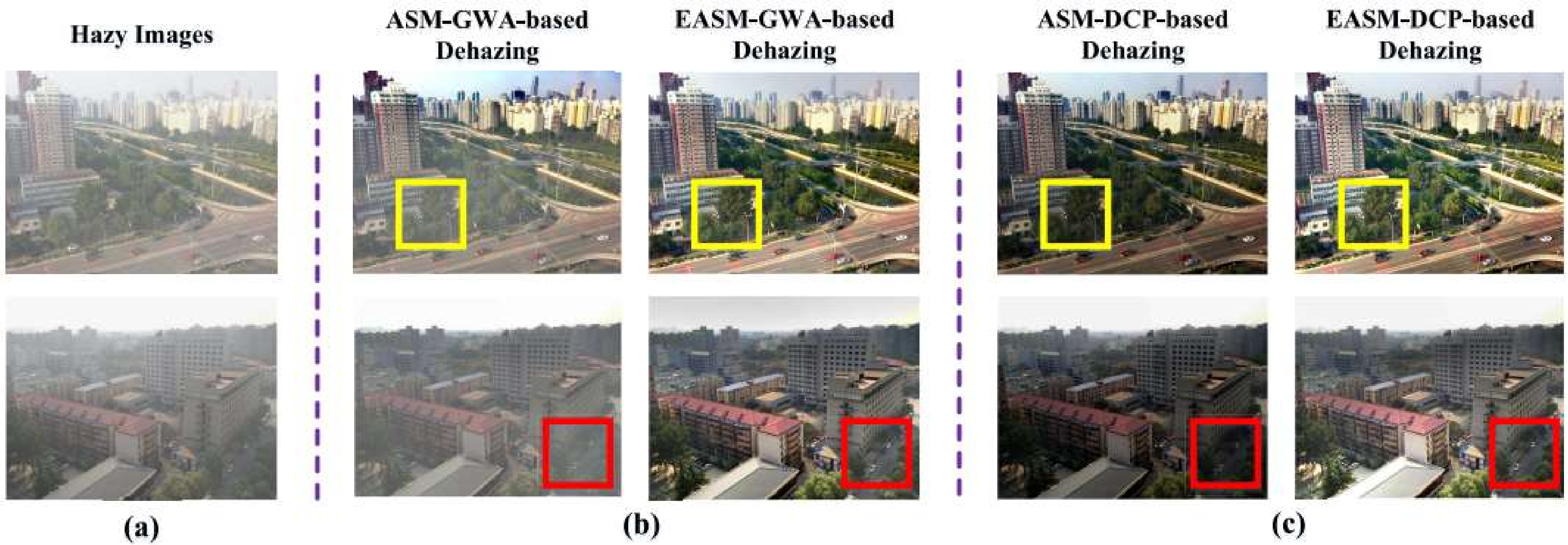


Fig. 6. Robustness test on ASM and EASM. (**a**): Hazy images. (**b**): Results comparisons between ASM-GWA-based dehazing and EASM-GWA-based dehazing. (**c**): Results comparisons between ASM-DCP-based dehazing and EASM-DCP-based dehazing. In this test, GSS is employed to search the minimum transmission in EASM.

AOD-net [4]

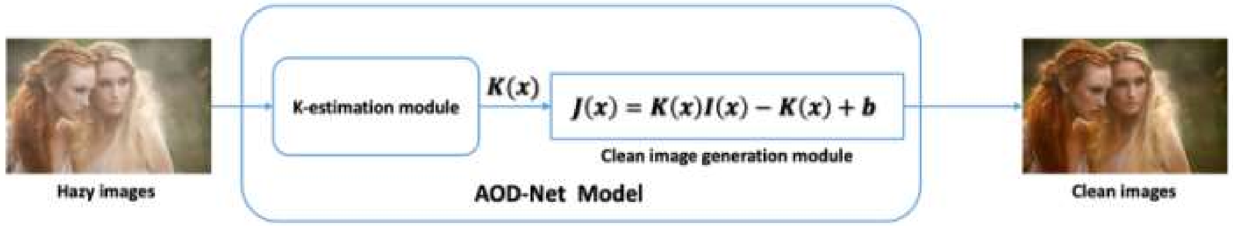
$$J(x) = \frac{1}{t(x)} I(x) - A \frac{1}{t(x)} + A.$$

In order to avoid the estimation of $t(x)$ in the ASM, AOD-Net proposed the $K(x)$, an intermediate parameter without physical meaning:

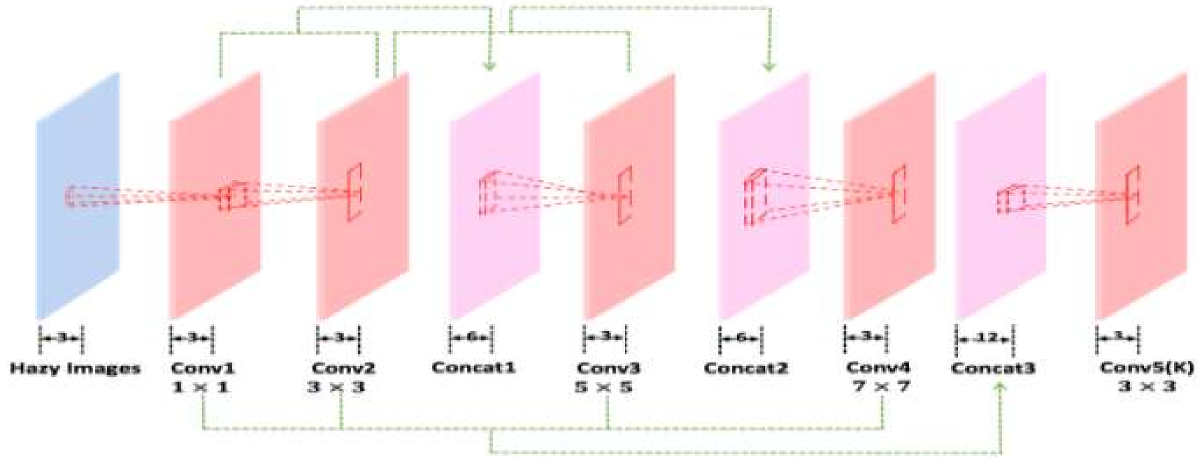
$$K(x) = \frac{\frac{1}{t(x)}(I(x) - A) + (A - b)}{I(x) - 1}. \quad (10)$$

Next, the acquisition of the clear image $J(x)$ only requires a single parameter $K(x)$:

$$J(x) = K(x)I(x) - K(x) + 1. \quad (11)$$



(a) The diagram of AOD-Net



(b) K-estimation module of AOD-Net

GMAN (Generic Model-Agnostic Convolutional Neural Network for Single Image Dehazing) [5]

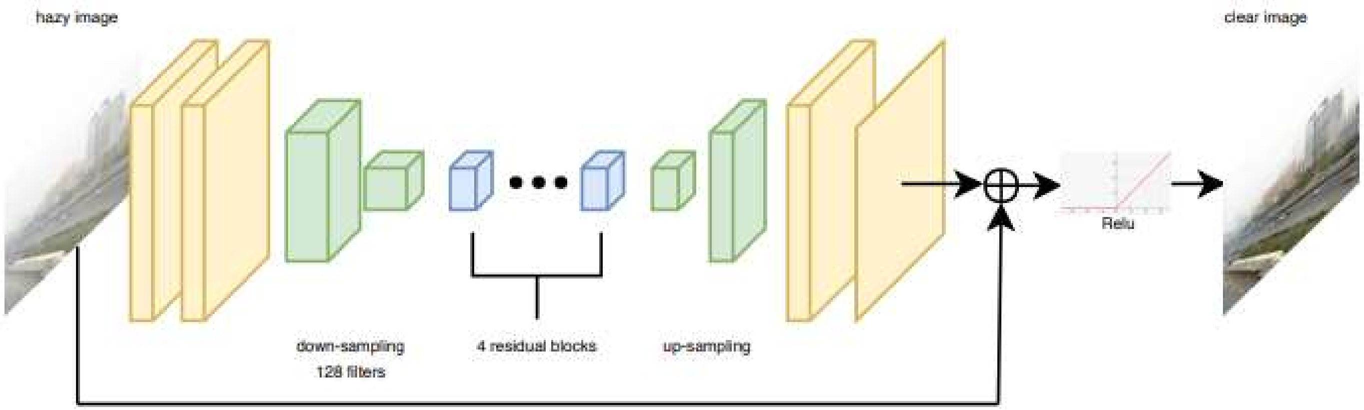
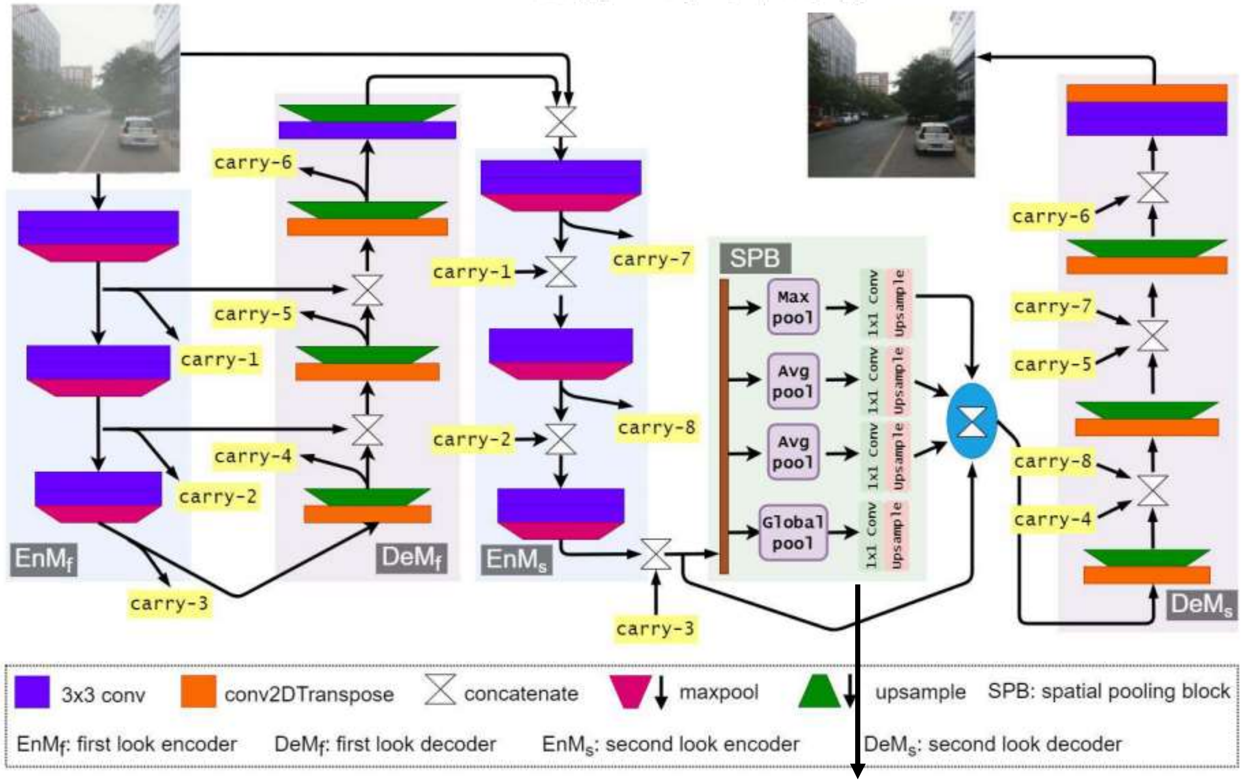


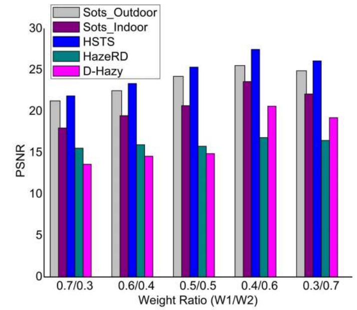
Fig. 2: Structure and details of GMAN. The yellow blocks are convolutional layers, the green blocks are down-sampling layers and deconvolutional layers. We cascade 4 residual blocks shown as blue blocks, and the number of convolutional layers inside are 2, 2, 3, 4.

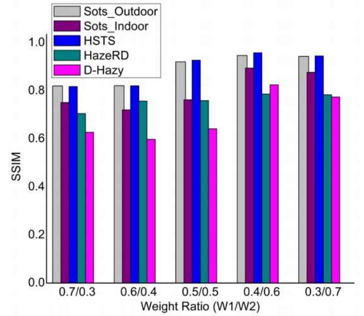
ReViewNet [6]

$$I_{12} = [R_{m,n,1}, G_{m,n,1}, B_{m,n,1}, H_{m,n,1}, S_{m,n,1}, V_{m,n,1}, Y_{m,n,1}, Cb_{m,n,1}, Cr_{m,n,1}, L_{m,n,1}, a_{m,n,1}, b_{m,n,1}]$$

$$Loss_{net} = W_1 L_1 + W_2 L_2$$







SPB leverages the spatial dimensions of the feature vector after the encoding process.

ReViewNet [6]

TABLE I

DESCRIPTION OF THE TRAINING AND TESTING DATASETS (NUMBER OF IMAGES CONTRIBUTED IN EACH CATEGORY)

Dataset	Training Outdoor	Training Indoor	Testing Outdoor	Testing Indoor
RESIDE β OTS	72,135	—	—	—
RESIDE Std ITS	—	13,990	—	—
RESIDE HSTS	—	—	10	—
RESIDE SOTS	—	—	500	500
HazeRD	—	—	75	—
D-HAZY	—	1,249	—	200

D-Hazy (Indoor Dataset)

TABLE VI

COMPARATIVE RESULTS OVER D-HAZY [53] DATASET

Method	SSIM (% inc)	PSNR (% inc)
CycleGAN[42]	0.6490 (26.95)	13.69 (50.77)
CycleDehaze [17]	0.6746 (22.13)	12.54 (64.59)
DCP[18]	0.7060 (16.70)	11.59 (78.08)
$C^2 MSNet$[45]	0.7201 (14.41)	12.71 (62.39)
DehazeNet[23]	0.7270 (13.33)	13.40 (54.03)
CAP[48]	0.7231 (13.94)	13.19 (56.48)
MSCNN[27]	0.7231 (13.94)	12.82 (61.00)
DDN[47]	0.7383 (11.59)	10.96 (88.32)
CDNet[31]	0.7411 (11.17)	13.84 (49.13)
RI-GAN[32]	0.8179 (0.73)	18.82 (9.67)
RYF-Net [50]	0.8230 (0.11)	17.56 (17.54)
ReViewNet	**0.8239 (best)**	**20.64 (best)**
TheiaNetv1	**0.7336 (1.5)**	**15.39 (5.7)**
TheiaNetv2	**0.7451 (best)**	**16.28 (best)**

Hazy Image

Ground Truth Image

Dataset	Type	Number	I/O
D-Hazy [Ancuti *et al.*, 2016]	Syn	1400+	I
HazeRD [Zhang *et al.*, 2017]	Syn	15	O
I-HAZE [Ancuti *et al.*, 2018c]	HG	35	I
O-HAZE [Ancuti *et al.*, 2018a]	HG	45	O
RESIDE [Li *et al.*, 2019]	S&R	10000+	I&O
Dense-HAZE [Ancuti *et al.*, 2019]	HG	33	O
NH-HAZE [Ancuti *et al.*, 2020a]	HG	55	O
MRFID [Liu *et al.*, 2020]	Real	200	O
BeDDE [Zhao *et al.*, 2020]	Real	200+	O

Table 2: Datasets for ID tasks. Syn means synthetic hazy images. HG stands for the hazy images generated from haze generator. Real represents real world scenes. S&R denote Syn&Real. I/O denote indoor/outdoor.

PSNR : Peak Signal-to-Noise Ratio
SSIM : Structural SIMilarity

Journal of Visual Communication and Image Representation
Volume 77, May 2021, 103137

Full length article

TheiaNet: Towards fast and inexpensive CNN design choices for image dehazing ☆

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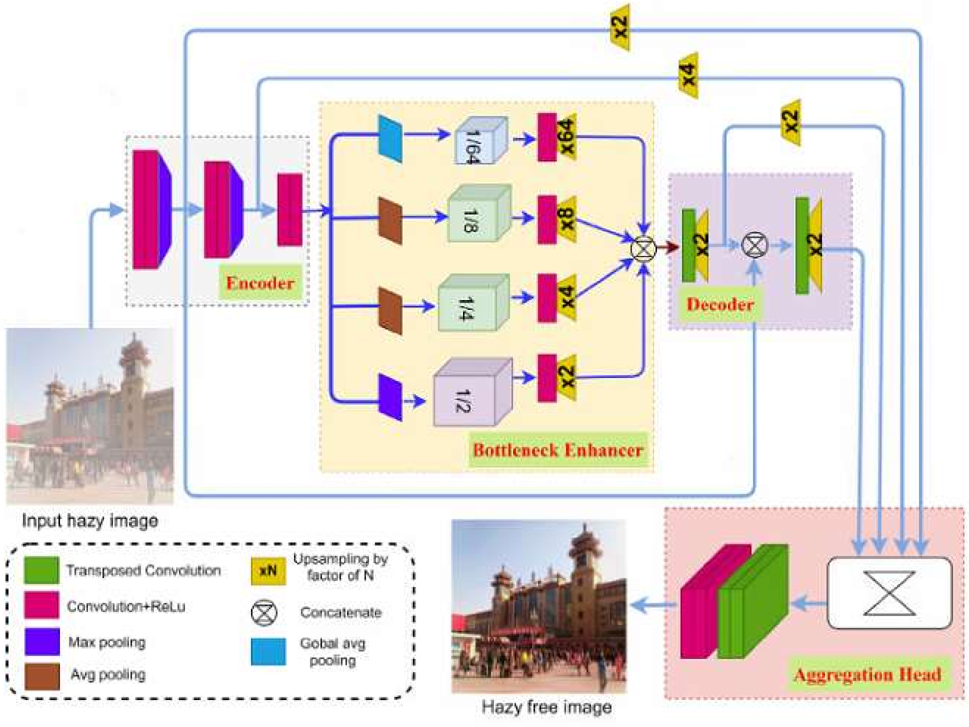
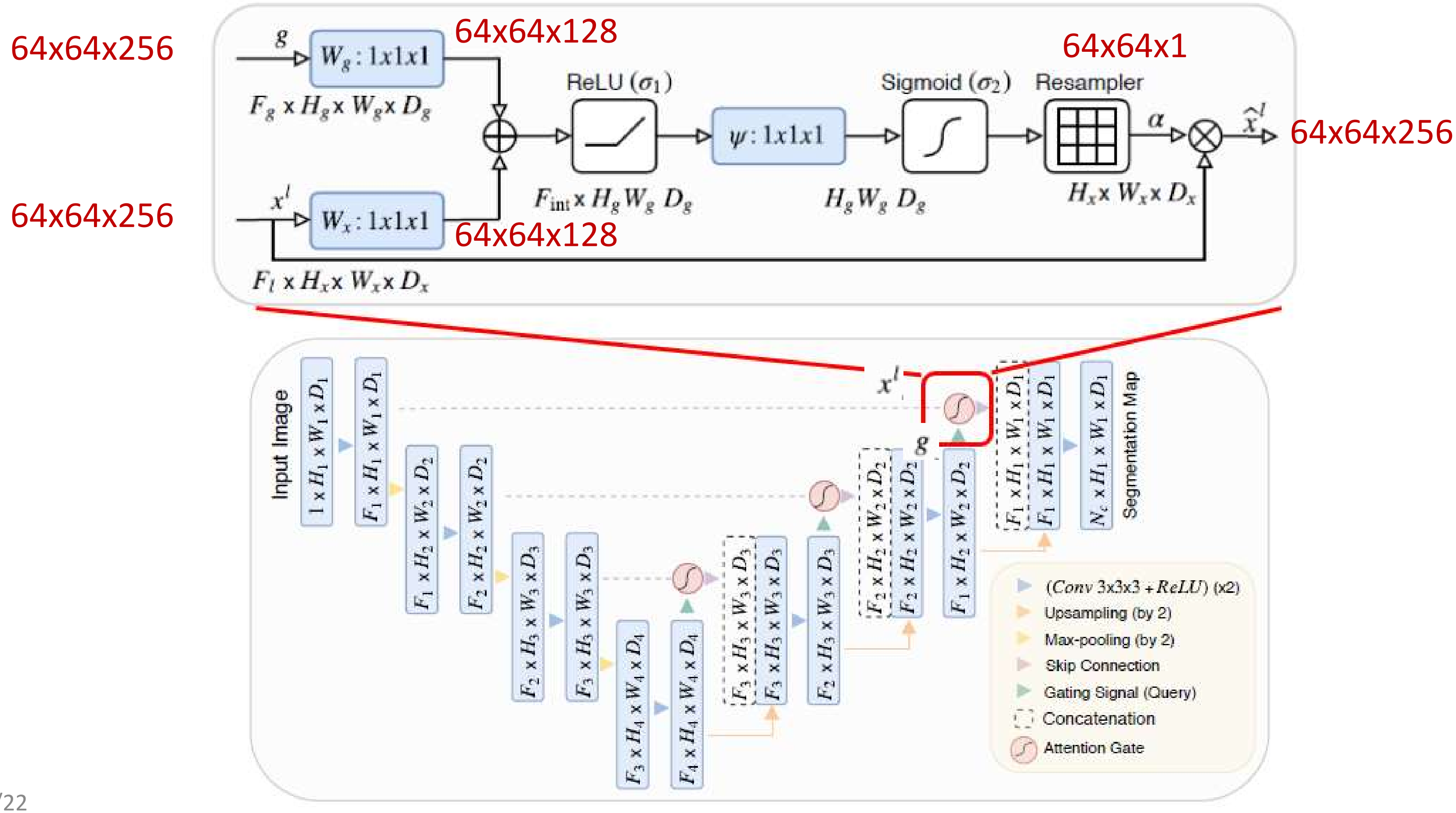
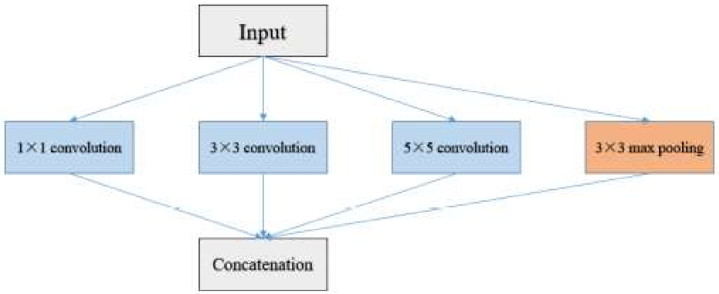


Fig. 2. TheiaNet architecture.

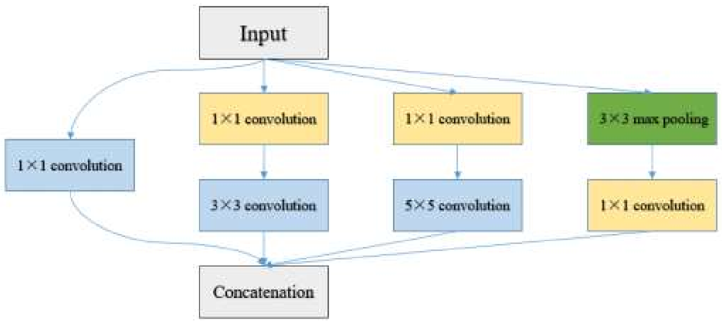
Attention U-net [7]



Dual channel U-net [8]

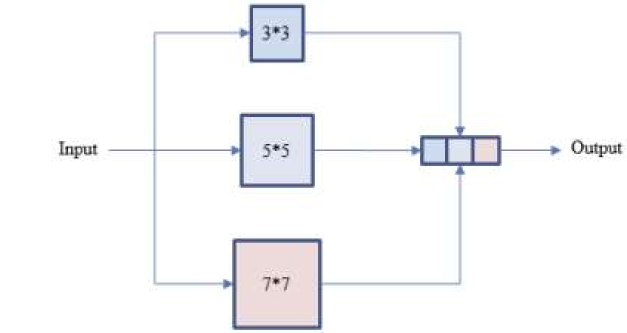


(a) Inception block, naïve version

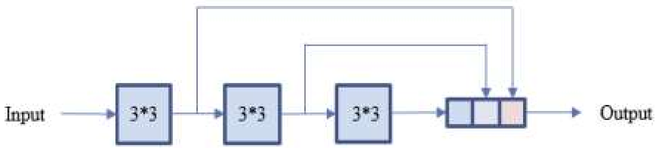


(b) Inception block with dimensionality reduction

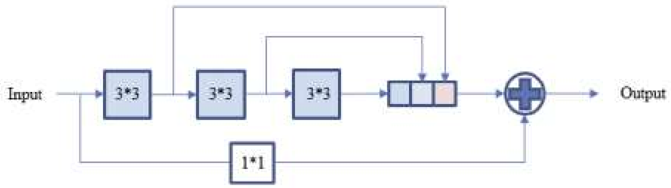
Fig. 2. Inception block



(a)



(b)



(c)

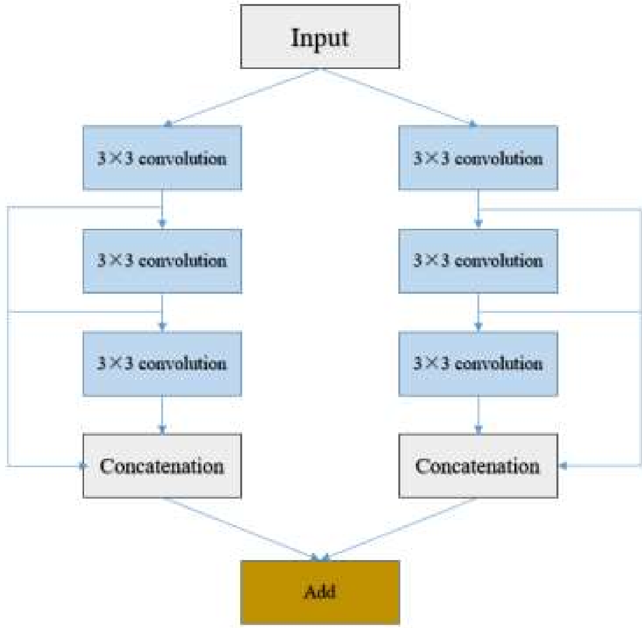
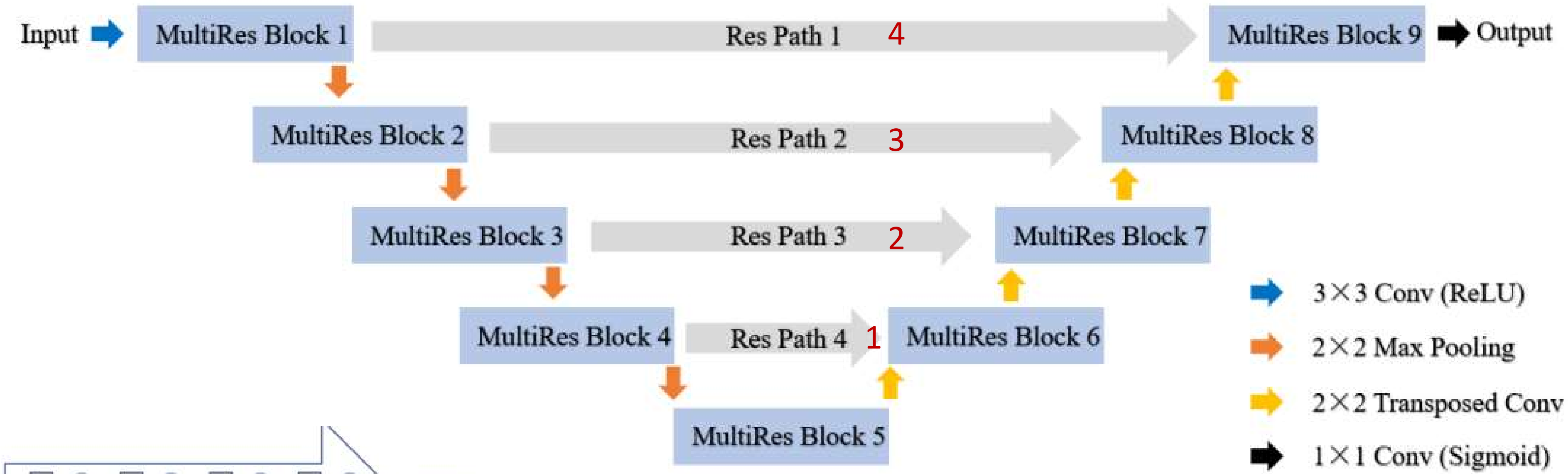


Fig. 7. Dual-Channel block

Dual channel U-net [8]



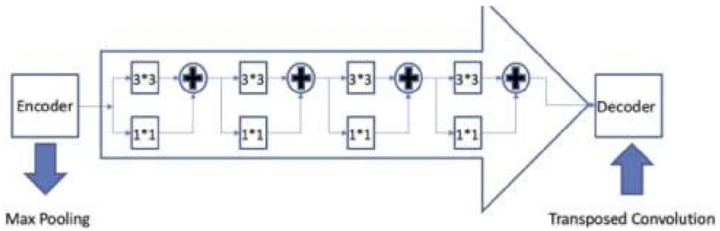


Fig. 6. Architecture of MultiResUNet

Dual channel U-net [8]

(a)

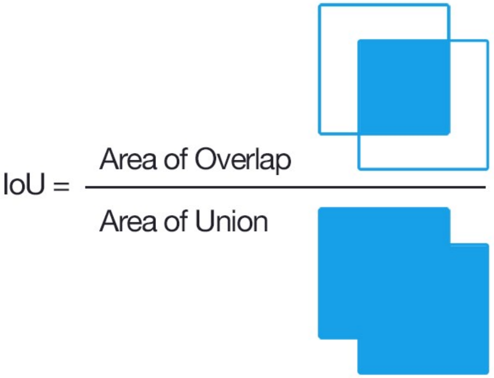
(b)

(c)

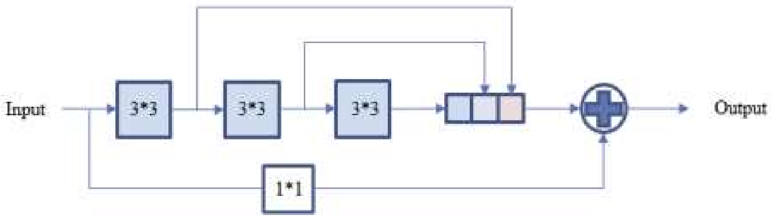
(d)

(e)

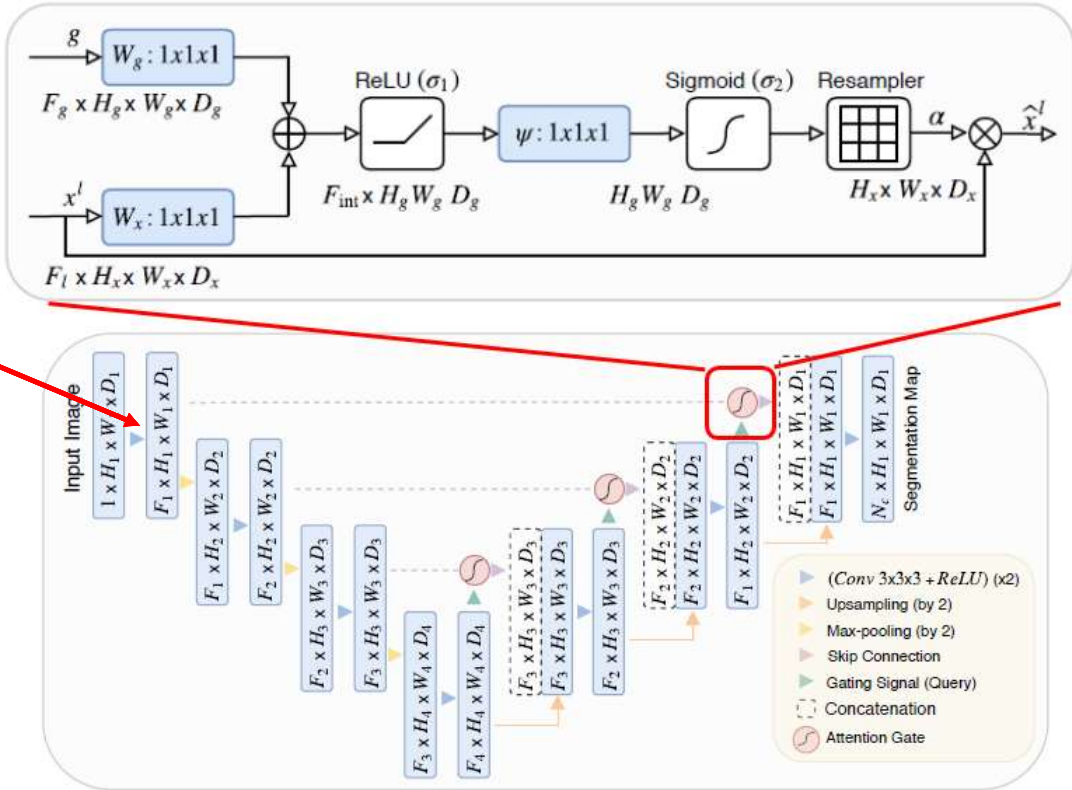
Fig. 19. Segment images with vague boundaries. (a) Original image (b) Ground truth (c) U-Net (72.25%) (d) MultiResUNet (73.04%) (e) DC-UNet (96.45%)



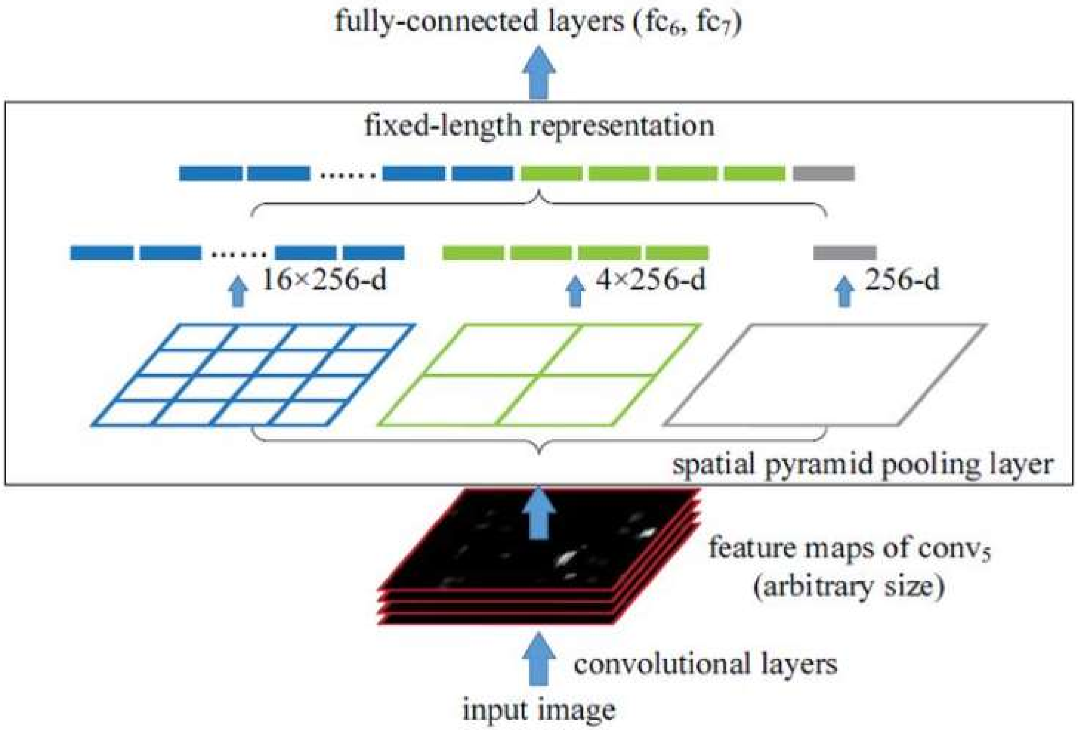
Attention U-net with Inception-like block



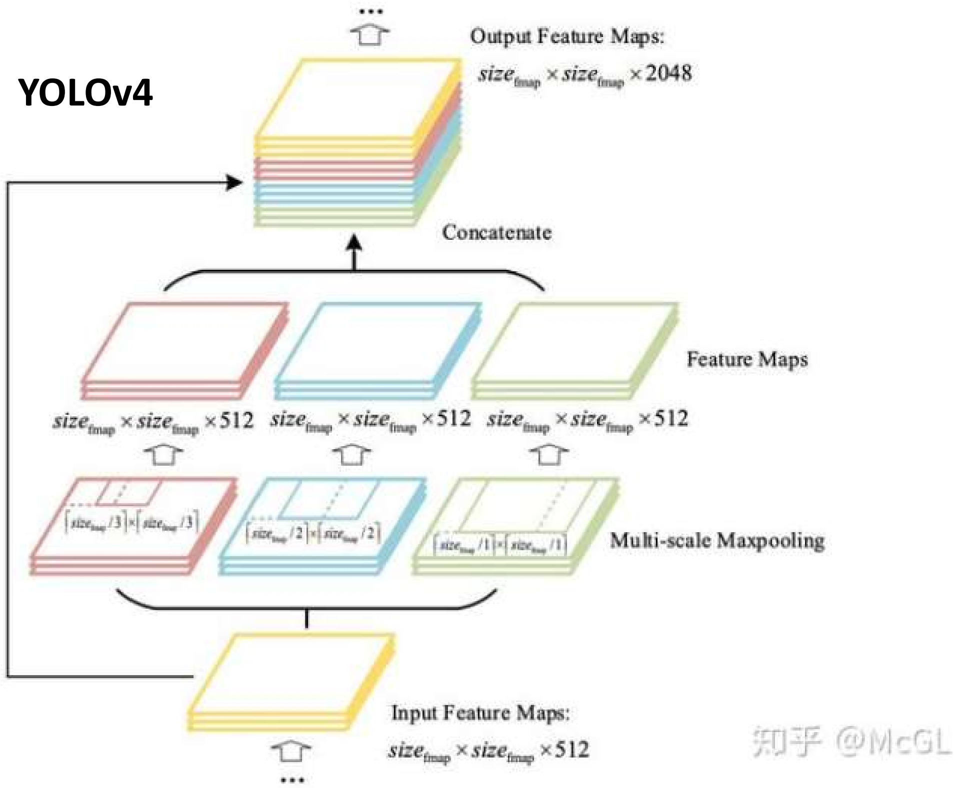
(c)



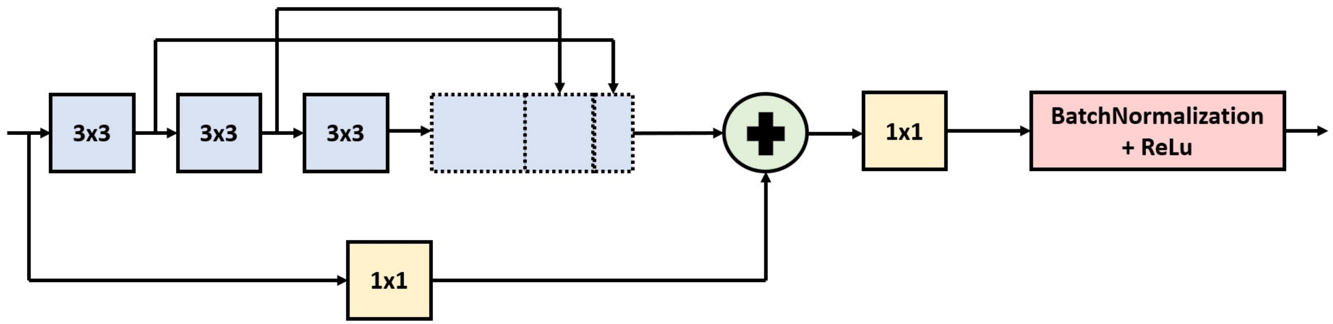
SPP-Net



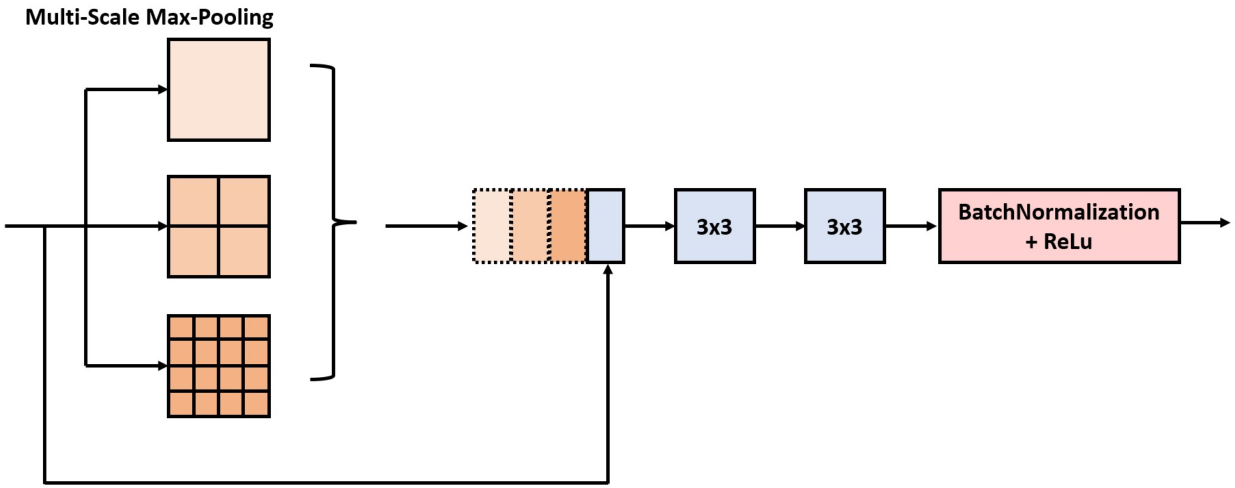
YOLOv4



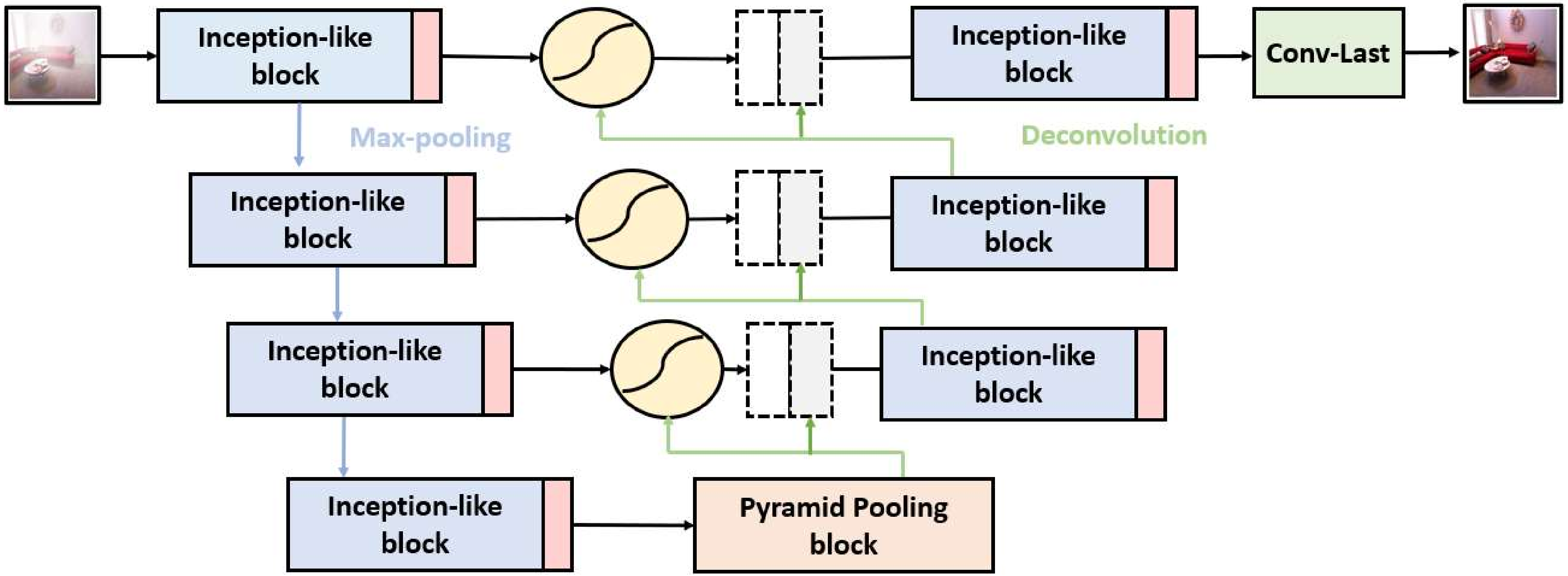
Inception-like block

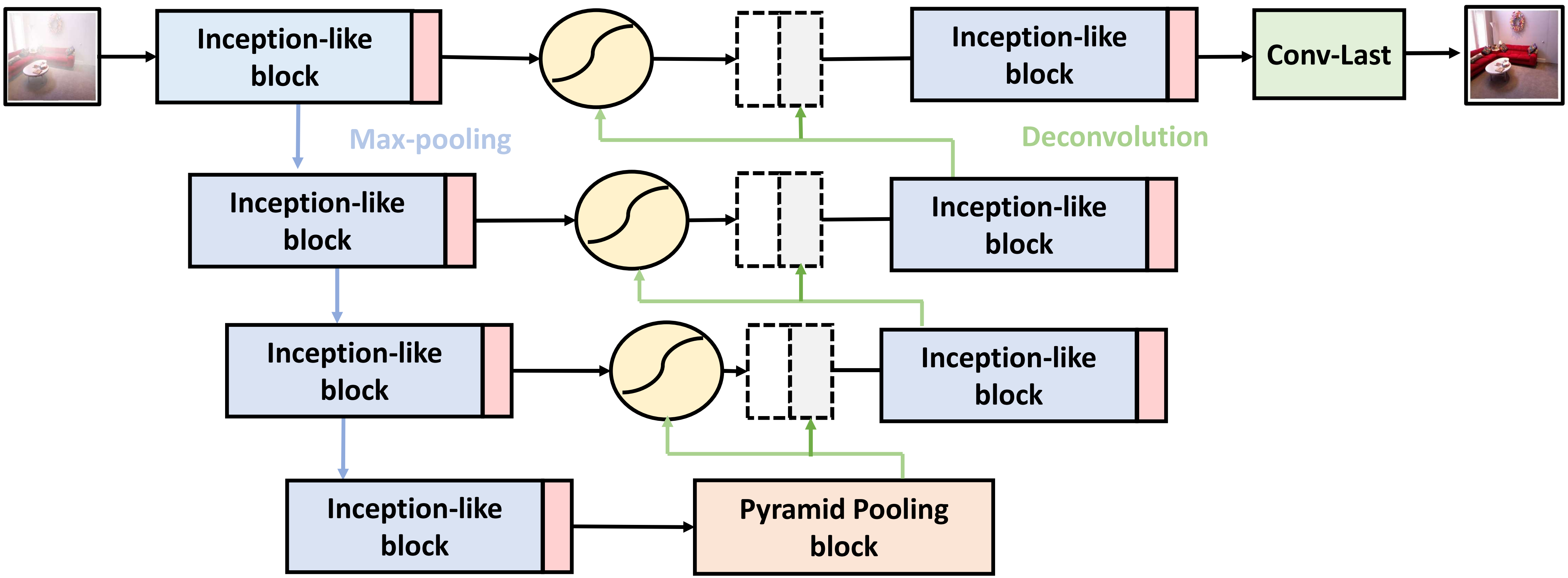


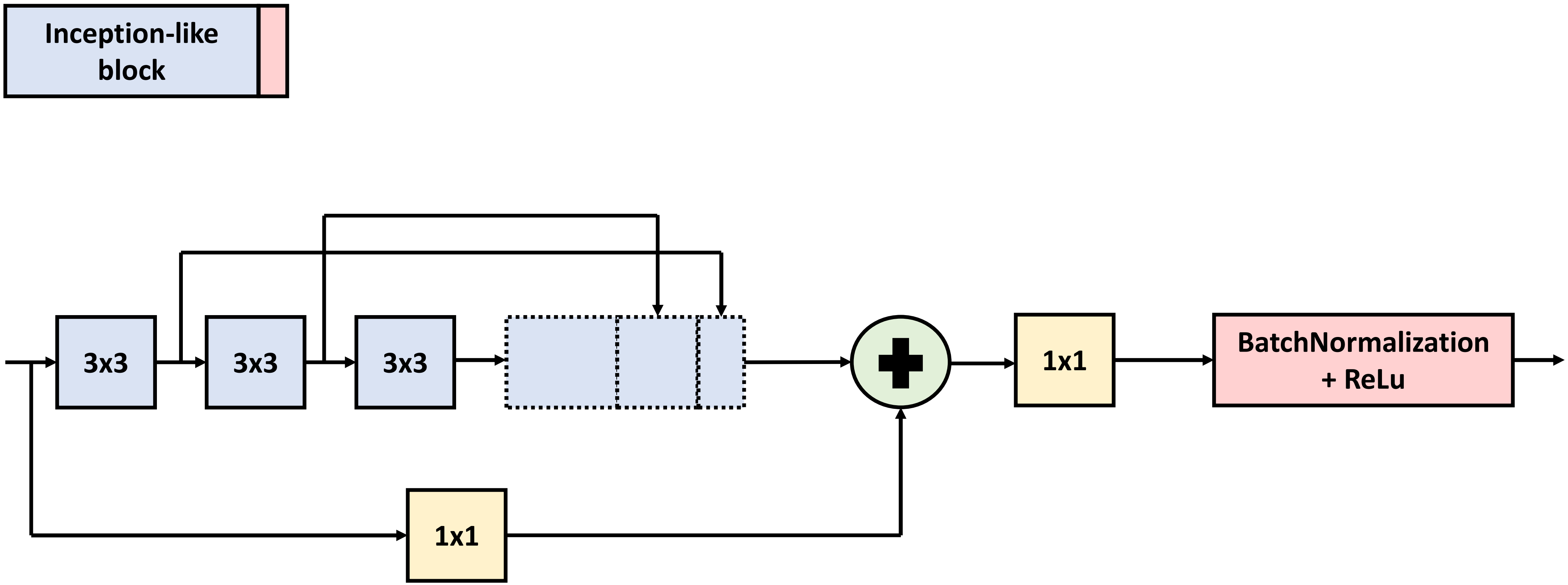
Pyramid Pooling block



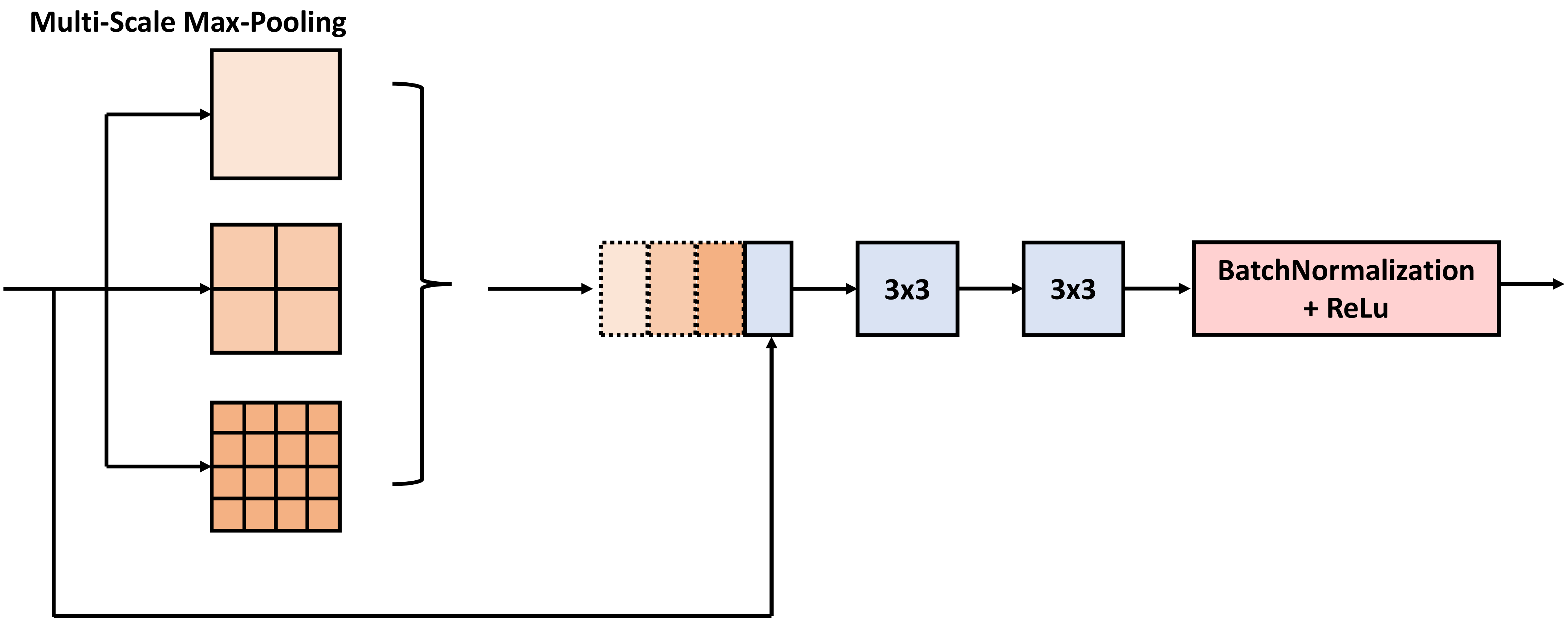
API : Attention Gate based Model with Pyramid Pooling and Inception-like block for Image Dehazing



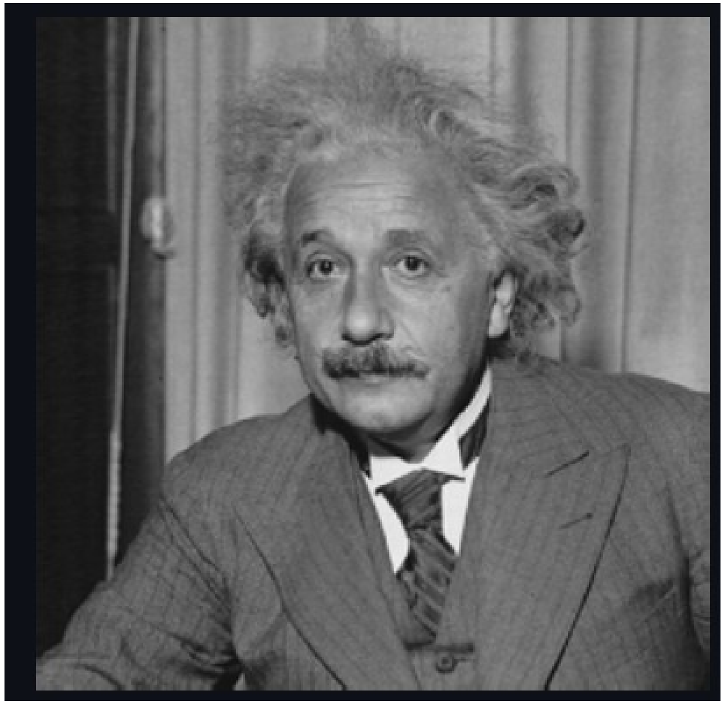

Inception-like block
Inception-like block
Conv-Last
Max-pooling
Deconvolution
Inception-like block
Inception-like block
Inception-like block
Inception-like block
Inception-like block
Pyramid Pooling block

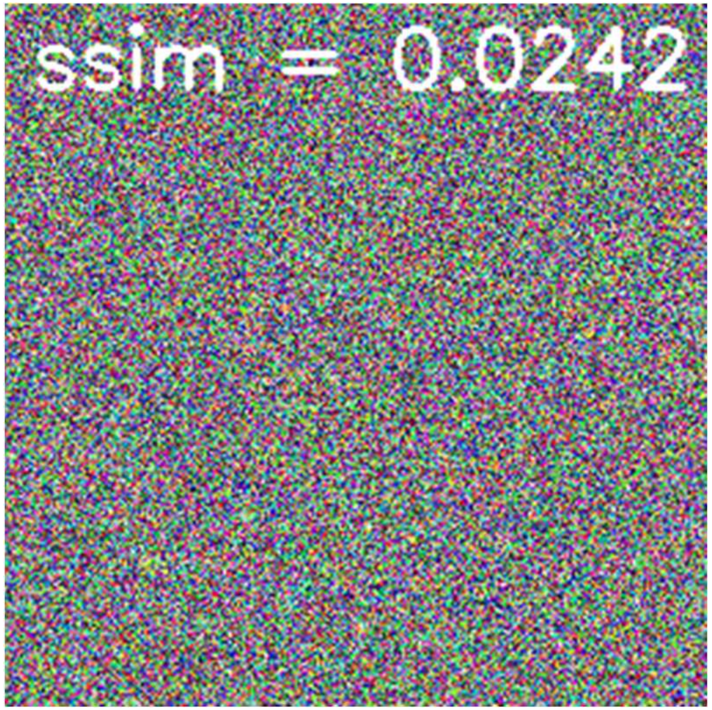

Inception-like block
3x3
3x3
3x3
1x1
1x1
BatchNormalization
+ ReLu

Pyramid Pooling block



Loss Function





Experimental Result

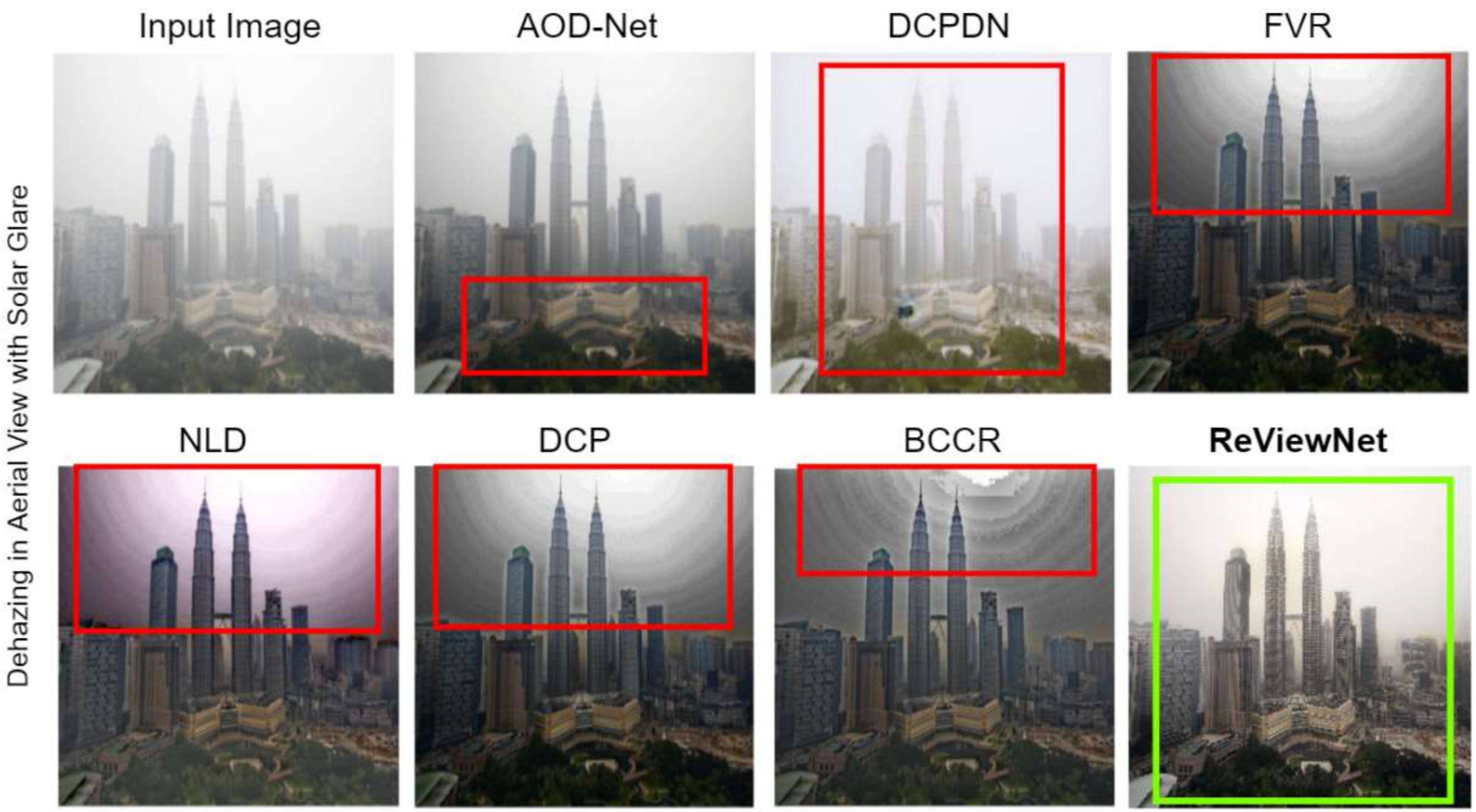
```
visual_range = [0.05,0.1,0.2,0.5,1];
% visual range in km
```

HazeRD (Outdoor)

Experimental Result

RESIDE-Standard SOTS Outdoor Dataset

Experimental Result



Quantitative Analysis

TABLE I: Comparative results over D-Hazy Dataset

Method	SSIM	PSNR
RYF-Net	0.8230	17.56
ReViewNet	0.8239	20.64
API	0.8607	19.32

TABLE II: Comparative Results Over RESIDE-Standard SOTS Indoor Dataset

Method	SSIM	PSNR
CDNet	0.8852	21.30
ReViewNet	0.8946	23.61
API	0.9337	22.73

Quantitative Analysis

TABLE III: Comparative Results Over RESIDE-Standard SOTS Outdoor Dataset

Method	**SSIM**	**PSNR**
MADN	0.9137	23.64
ReViewNet	0.9468	25.55
API	0.9597	25.39

TABLE IV: Comparative Results Over HSTS Dataset

Method	**SSIM**	**PSNR**
Deep DCP	0.9330	24.44
ReViewNet	0.9582	27.50
API	0.9562	26.40

Quantitative Analysis

TABLE V: Comparative Results Over HazeRD Dataset

Method	SSIM	PSNR
RYF-Net	0.6525	16.82
ReViewNet	0.7868	16.84
API	0.8387	17.35

TABLE VI: Average Per Image GPU Running Time (in seconds) Comparison Of Various Methods

Method	AOD-Net	DehazeNet	ReviewNet	API
Run-time	0.08	0.30	0.025	0.0062

Conclusion and Future Work

- 1. Modify Atmospheric Scattering Model
- 2. Supervised (Improve U-net ?) vs. Unsupervised (GAN)
- 3. Consider other family of color spaces (ex : YCbCr, RSV, etc.)
- 4. Combine other Loss Function (ex : MSE + Perceptual loss) $L_{per}(x,y) = \sum_{i=1}^{n} ||\psi(x) - \psi(y)||^2.$
- 5. Deal with Nighttime Image Dehazing