A survey on removing haze by discrete wavelet transform

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Paper Survey

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Outline

- Introduction
- Atmospheric Scattering Model
- U-Net
- Discrete Wavelet Transform
- WAVELET U-NET AND THE CHROMATIC ADAPTATION TRANSFORM FOR SINGLE IMAGE DEHAZING
- MULTI-SCALE FEATURE AGGREGATION NETWORK WITH WAVELET STRUCTURE SIMILARITY LOSS FUNCTION FOR SINGLE IMAGE DEHAZING
- Conclusion
- Reference

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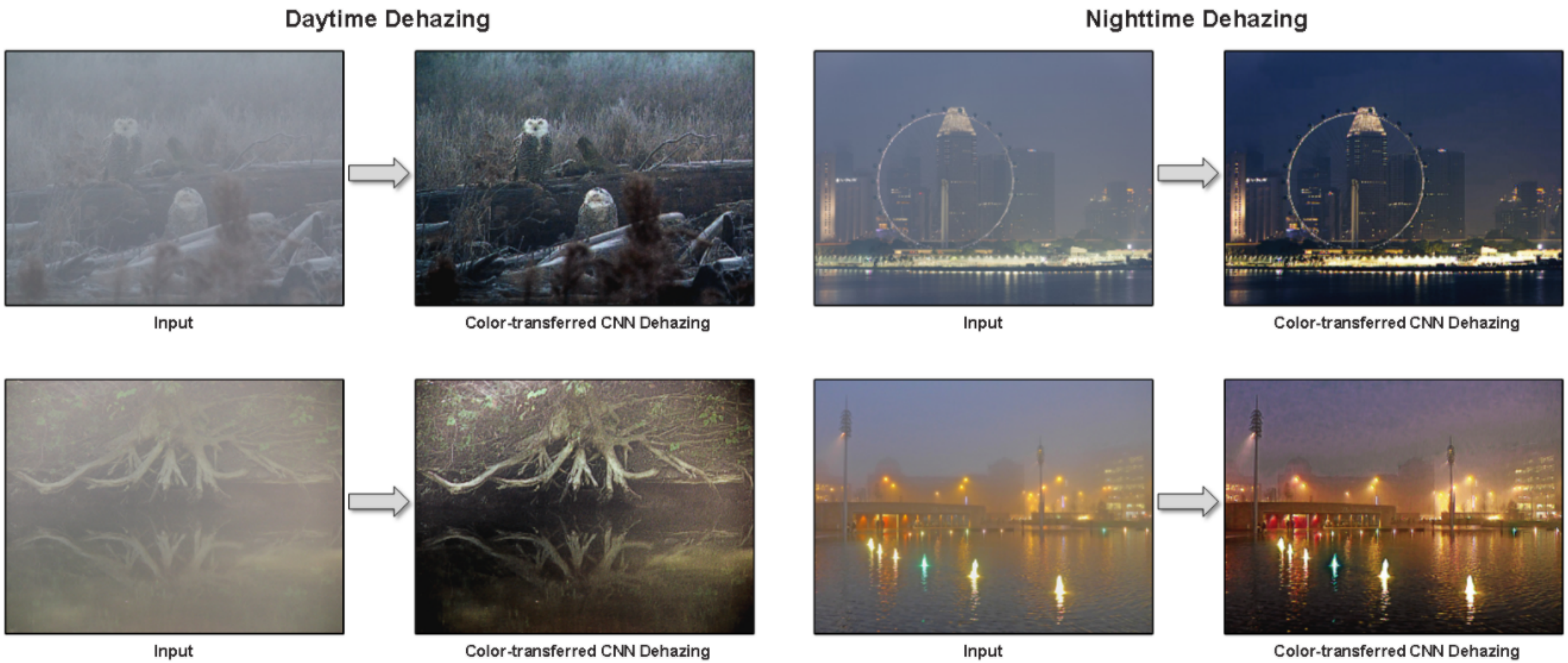
Introduction

- Issue: Make hazy images clean and find the best transmission matrix
- Related work: discrete wavelet transform, U-net, dehaze
- Challenge: low contrast, faint color and shifted luminance



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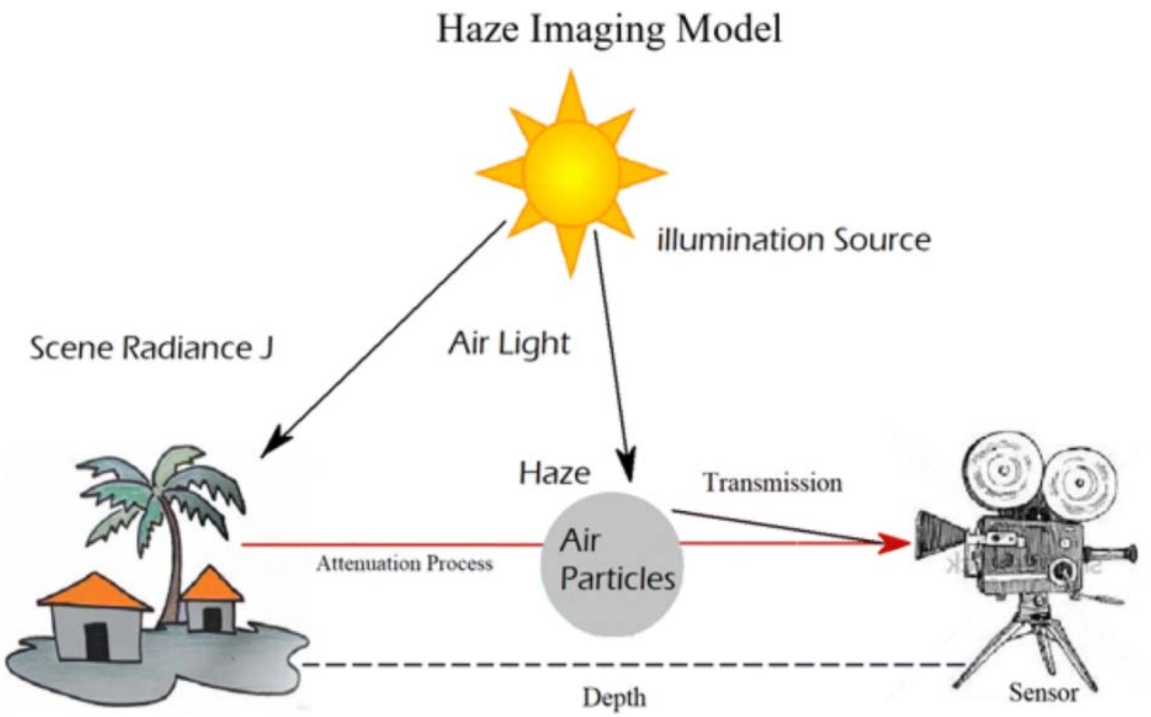
Atmospheric Scattering Model

- Image dehazing model : $I(x)=J(x)t(x)+A(1-t(x))$
- Transmission function : $t(x) = e^{-\beta d(x)}$



I(x) : observed image

J(x) : clear image

A : global atmospheric light

t(x) : medium transmission

β : scattering coefficient

d(x) : scene depth

ill-posed problem

- Image dehazing model : $I(x)=J(x)t(x)+A(1-t(x))$

I(x)

How to find A, t(x) ?

J(x)

- Prior-based：color attenuation prior, dark channel prior, etc.
- Learning-based：Lightweight model, multi-scale model, **U-Nets**, etc.

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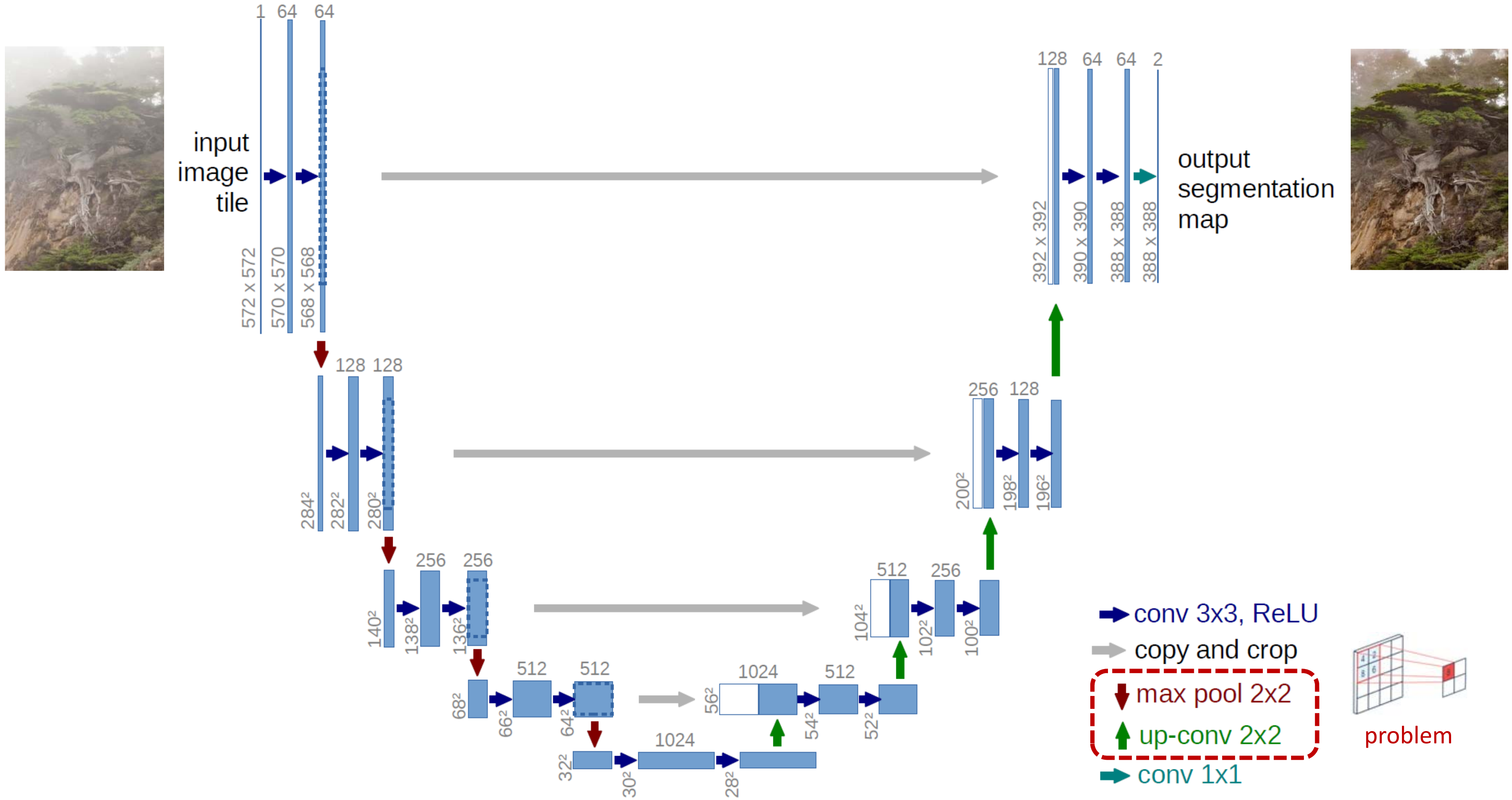
U-Net


input
image
tile
output
segmentation
map
1 64 64
572 x 572
570 x 570
568 x 568
128 128
284²
282²
280²
256 256
140²
138²
136²
512 512
68²
66²
64²
1024
32²
30²
28²
1024 512
56²
54²
52²
512 256
104²
102²
100²
256 128
200²
198²
196²
128 64 64 2
392 x 392
390 x 390
388 x 388
388 x 388
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1
problem

Bouns

In this class,

which method can be used for down-sampling and preserve high frequency information and low frequency information on images?

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Discrete Wavelet Transform

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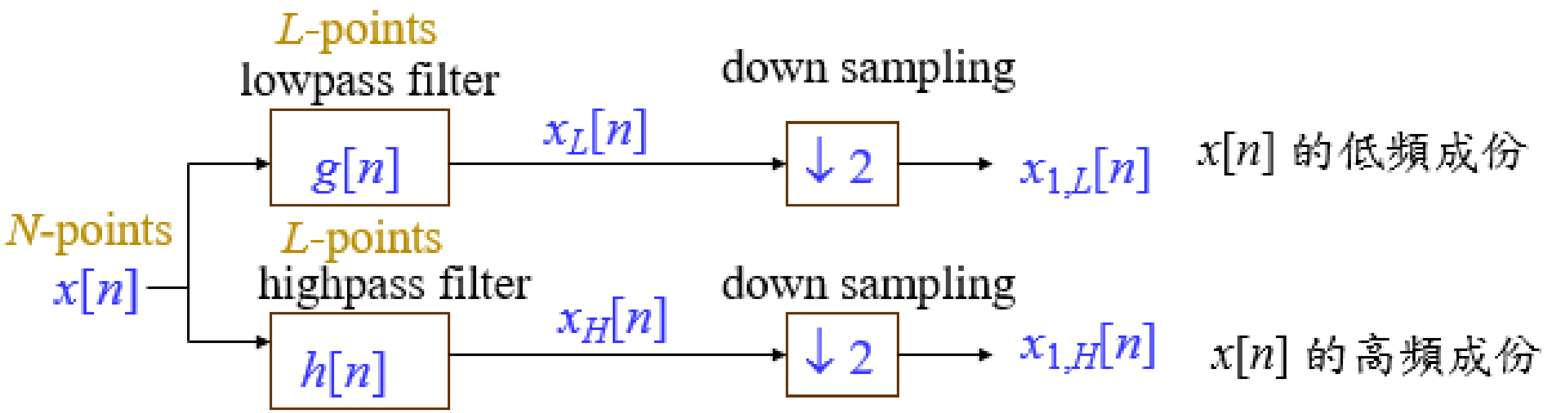
• Discrete Wavelet Transform (DWT)

The discrete wavelet transform is very different from the continuous wavelet transform. It is simpler and more useful than the continuous one.



(Scaling & Convolution)

$$x_L[n] = \sum_k x[n-k]\, g[k] \qquad x_{1,L}[n] = \sum_k x[2n-k]\, g[k]$$

$$x_H[n] = \sum_k x[n-k]\, h[k] \qquad x_{1,H}[n] = \sum_k x[2n-k]\, h[k]$$

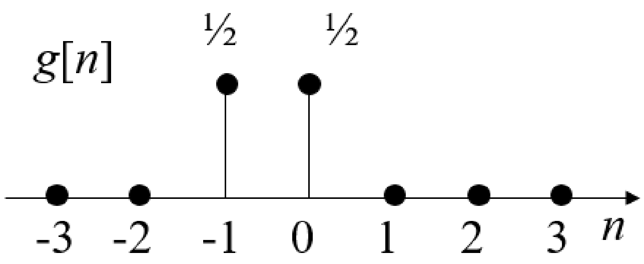
2-point Haar wavelet

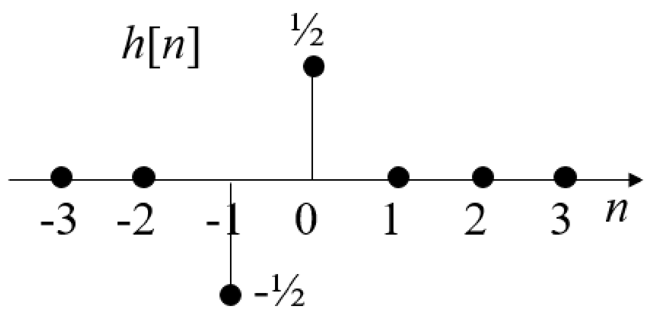
$$x_{1,L}[n]=\sum_k x[2n-k]\,g[k] \qquad x_{1,H}[n]=\sum_k x[2n-k]\,h[k]$$

例子：2-point Haar wavelet

$g[n] = 1/2$ for $n = -1, 0$ $\qquad h[0] = 1/2,\ \ h[-1] = -1/2,$

$g[n] = 0$ otherwise $\qquad h[n] = 0$ otherwise





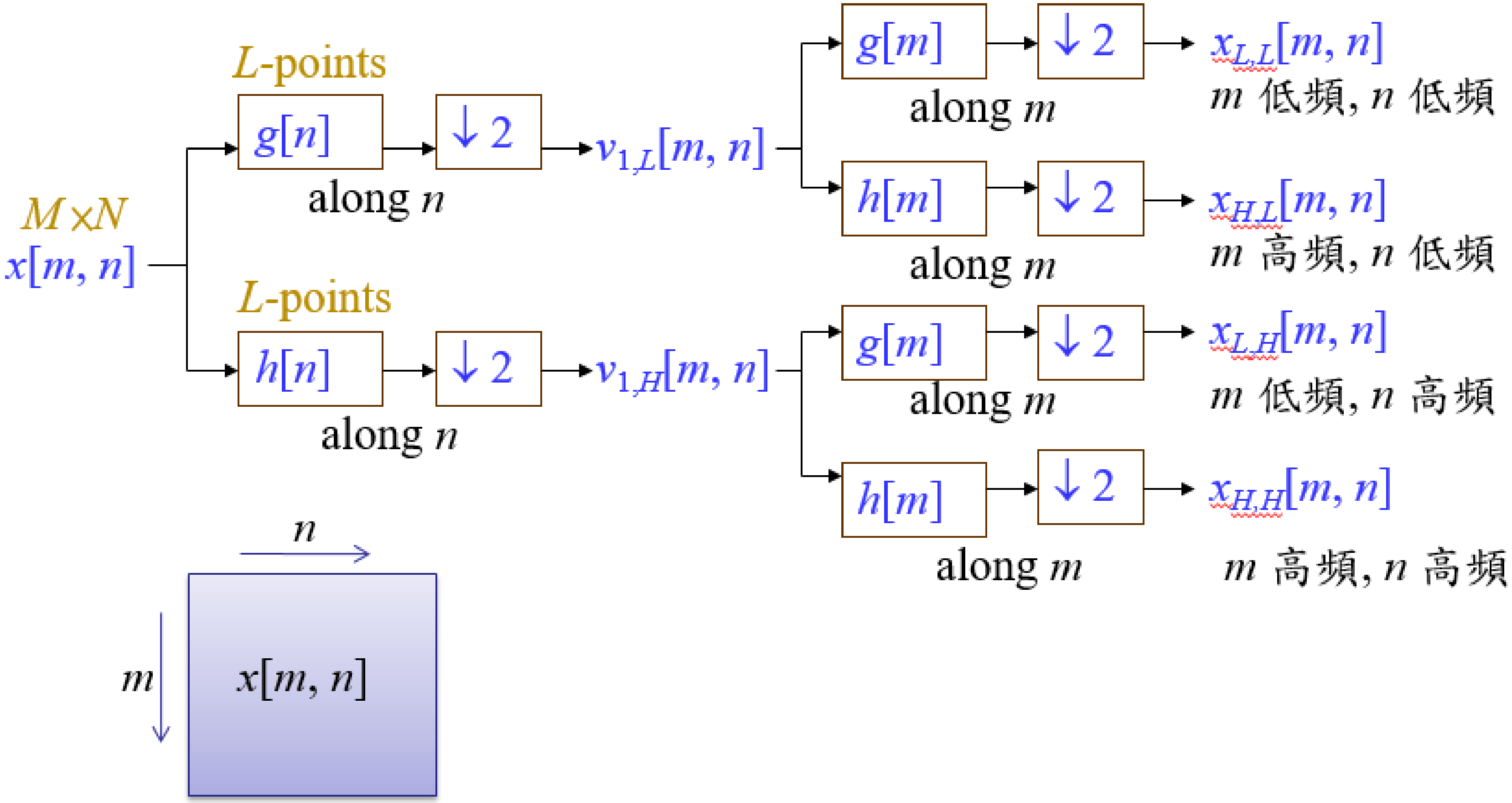
then

$$x_{1,L}[n]=\frac{x[2n]+x[2n+1]}{2} \qquad x_{1,H}[n]=\frac{x[2n]-x[2n+1]}{2}$$

（兩點平均） （兩點之差）

2D DWT

2-D 的情形

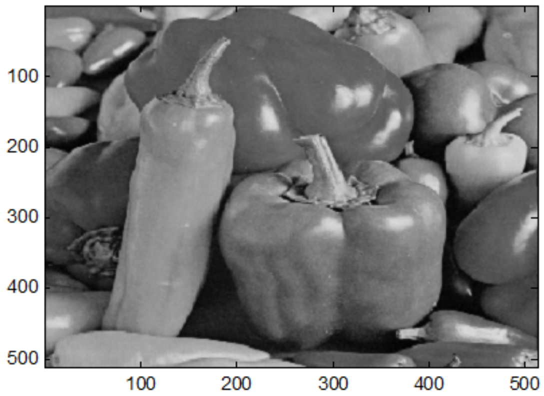


L-points
g[n]
↓2
along n
v1,L[m, n]
M×N
x[m, n]
L-points
h[n]
↓2
along n
v1,H[m, n]
g[m]
↓2
along m
xL,L[m, n]
m 低頻, n 低頻
h[m]
↓2
along m
xH,L[m, n]
m 高頻, n 低頻
g[m]
↓2
along m
xL,H[m, n]
m 低頻, n 高頻
h[m]
↓2
along m
xH,H[m, n]
m 高頻, n 高頻
n
m
x[m, n]

Sample

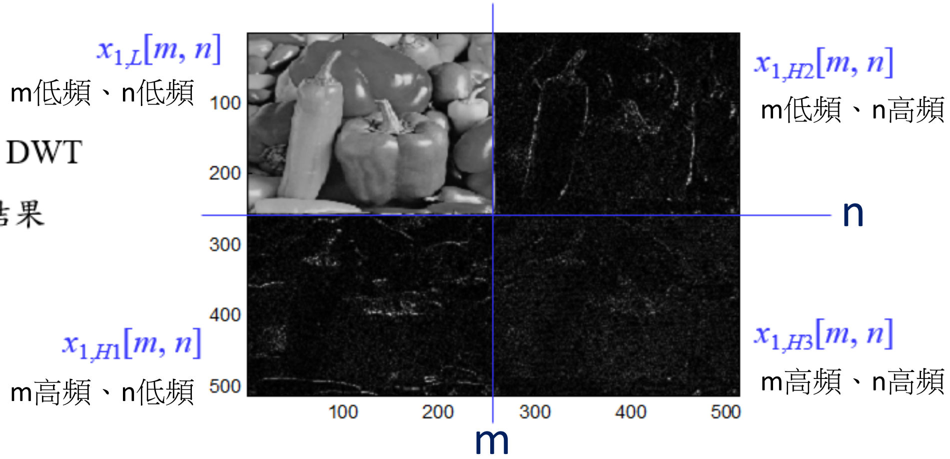
原影像

Pepper.bmp

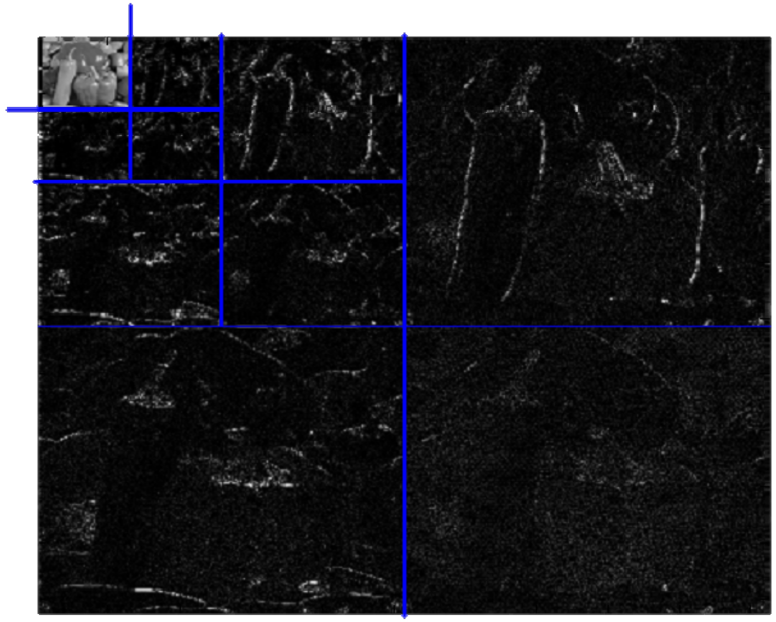


2-D DWT

的結果



3次 2-D DWT 的結果



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WAVELET U-NET AND THE CHROMATIC ADAPTATION TRANSFORM FOR SINGLE IMAGE DEHAZING

Hao-Hsiang Yang [1], Yanwei Fu [2]
1: Graduate Institute of Electrical Engineering, National Taiwan University, Taiwan
2: School of Data Science, Fudan University, Shanghai, China

IEEE International Conference on Image Processing (ICIP). IEEE, 2019

WAVELET U-NET AND THE CHROMATIC ADAPTATION TRANSFORM FOR SINGLE IMAGE DEHAZING

- Issue：edges and colors are two key factors to obtain better dehazed images, Clear edges and balanced color make the dehazed images look natural and detailed.
- Proposed：two-stage and end-to-end network.
  - Wavelet U-Net
    - Up-sampling：DWT
    - Down-sampling：IDWT
  - Chromatic adaptation transform
    - implemented by convolutional layers mathematically to enhance images

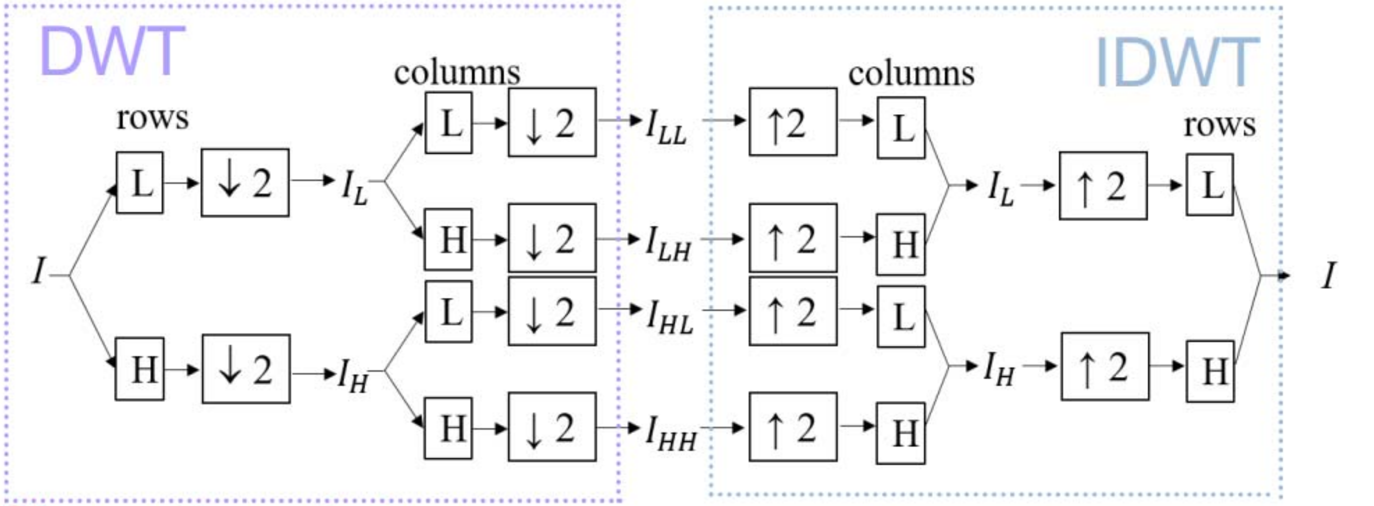
Wavelet U-Net

- **2D-DWT , 2D-IDWT**

$$\Phi_{LL}(x,y) = \phi(x)\phi(y)$$
$$\Psi_{LH}(x,y) = \phi(x)\psi(y)$$
$$\Psi_{HL}(x,y) = \psi(x)\phi(y)$$
$$\Psi_{HH}(x,y) = \psi(x)\psi(y)$$

$\phi(x)$ *means low − pass*
$\psi(x)$ *means high − pass*

ϕ_{LL}: *scaling*
$\psi_{LH}, \psi_{HL}, \psi_{HH}$: *wavelet*



※ 2D- Haar Wavelet

Fig. 1. The illustration of DWT and IDWT, where arrows mean down-sampling and up-sampling.

Wavelet U-Net

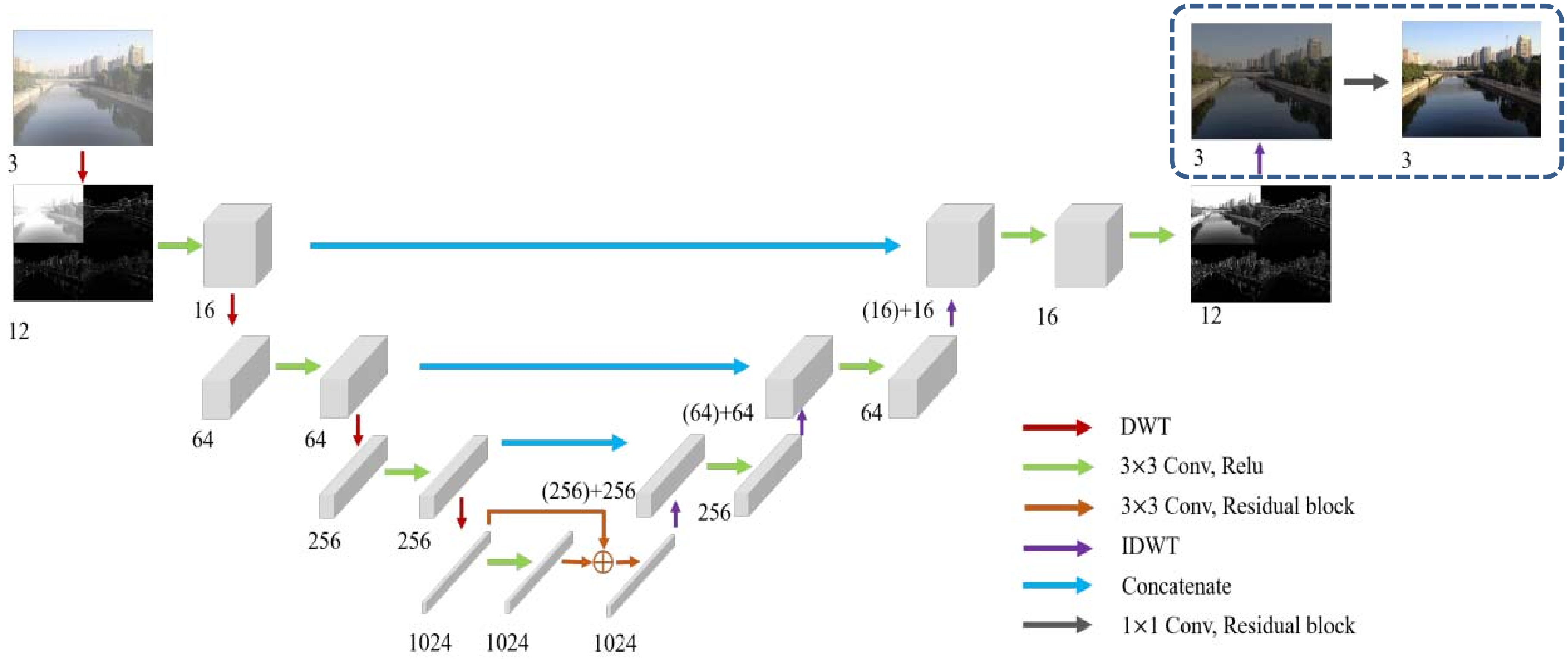


Fig. 2. Overview of the proposed wavelet-U-net with the chromatic adaption transform for single image dehazing. The digits under the blocks mean the numbers of channels and digits in parentheses mean concatenated layers.

Chromatic adaptation transform

- **Target : calibrate luminance and color**

- Color Corrected Mode

$$[R' \quad G' \quad B']^T = F\,[R \quad G \quad B]^T$$

$$F = \begin{bmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{bmatrix}$$ (light-weight matrix)

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$= \begin{bmatrix} \alpha - 1 & 0 & 0 \\ 0 & \beta - 1 & 0 \\ 0 & 0 & \gamma - 1 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$= F' \cdot [R \quad G \quad B]^T + [R \quad G \quad B]^T \quad = F' \cdot x + x$$ **(residual module)**

(F’ is 3x1x1 convolutional kernal)

Evaluation

- **PSNR**

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

- **SSIM**

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Table 1. Quantitative SSIM and PSNR on the synthetic RESIDE dataset.

	[2]	[10]	[13]	[4]	[14]	Ours
PSNR	16.58	17.72	18.55	21.42	18.41	**24.39**
SSIM	0.818	0.768	0.826	0.882	0.848	**0.901**

Qualitative dehazed results

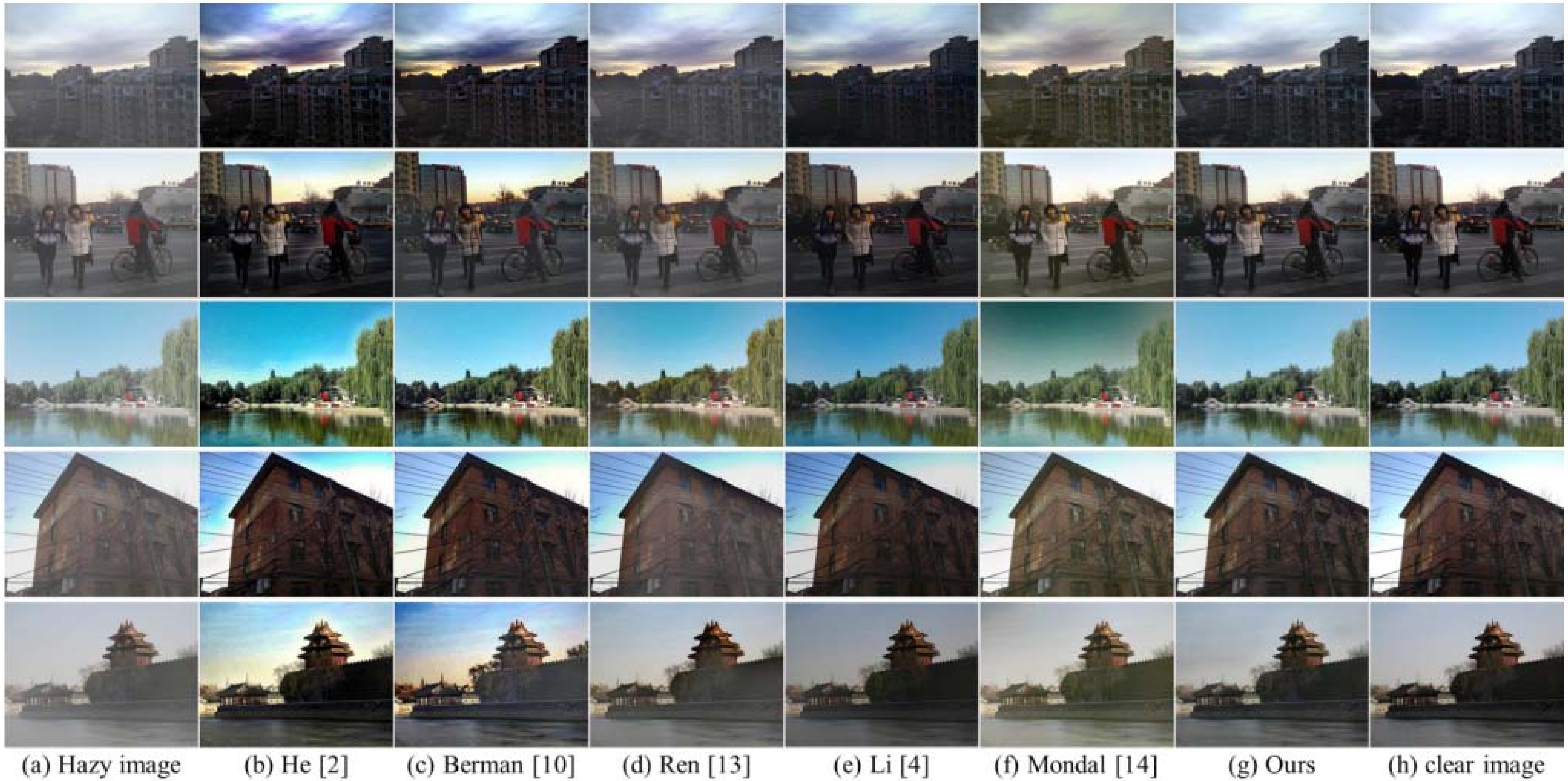


Fig. 3. Qualitative dehazed results on the synthetic dataset by comparing with state-of-the-art results.

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MULTI-SCALE FEATURE AGGREGATION NETWORK WITH WAVELET STRUCTURE SIMILARITY LOSS FUNCTION FOR SINGLE IMAGE DEHAZING

Hao-Hsiang Yang [1] ,Chao-Han Huck Yang [2] Yi-Chang James Tsai [2]
1: ASUS Intelligent Cloud Services, Taiwan
2: School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, USA

IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020

MULTI-SCALE FEATURE AGGREGATION NETWORK WITH WAVELET STRUCTURE SIMILARITY LOSS FUNCTION FOR SINGLE IMAGE DEHAZING

- Issue：Focus on multi-scaling and high frequency feature
- Proposed：Y-Net, W-SSIM
  - Y-Net
    - This network reconstructs clear images by aggregating multi-scale features maps
  - Wavelet Structure SIMilarity (WSSIM) loss function
    - DWT divide the image into differently sized patchs with different frequencies and scales
    - Accumulation of SSIM loss of various patches with respective ratios

Y-Net

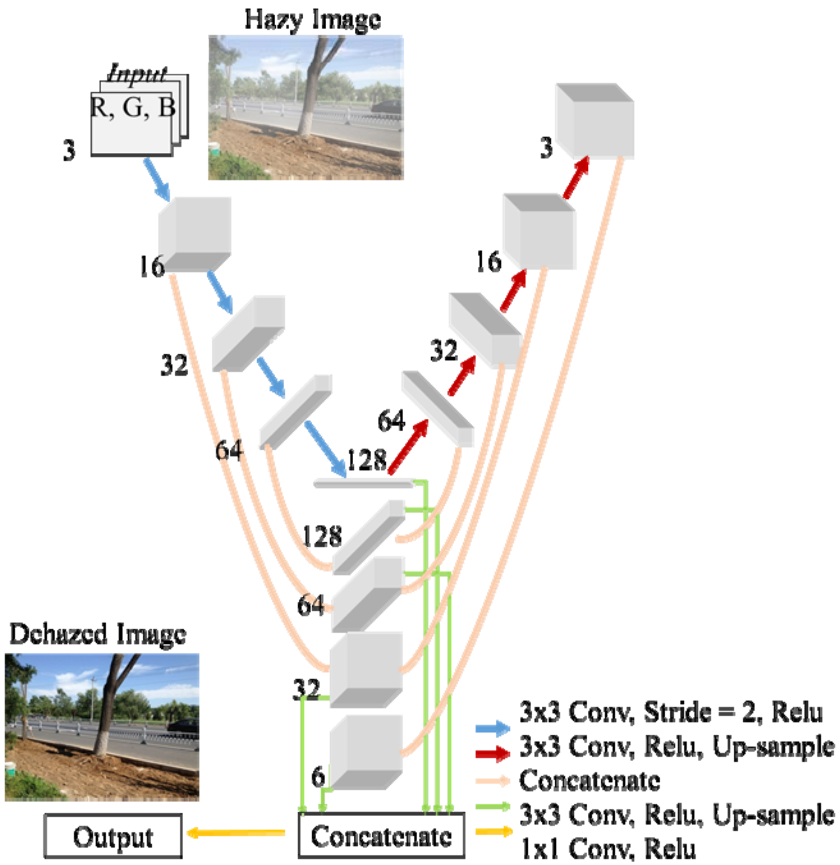

Fig. 1. The overview of our proposed Y-net. The clear image is composed of multi-scale feature maps from the hazy image. The digits under the blocks mean the numbers of channels.

Wavelet SSIM loss

- **Formulate :** $I^{LL}, I^{LH}, I^{HL}, I^{HH} = \mathrm{DWT}(I)$
- **Patch Weights :** r - low frequency patch, (1-r) – high frequency patch

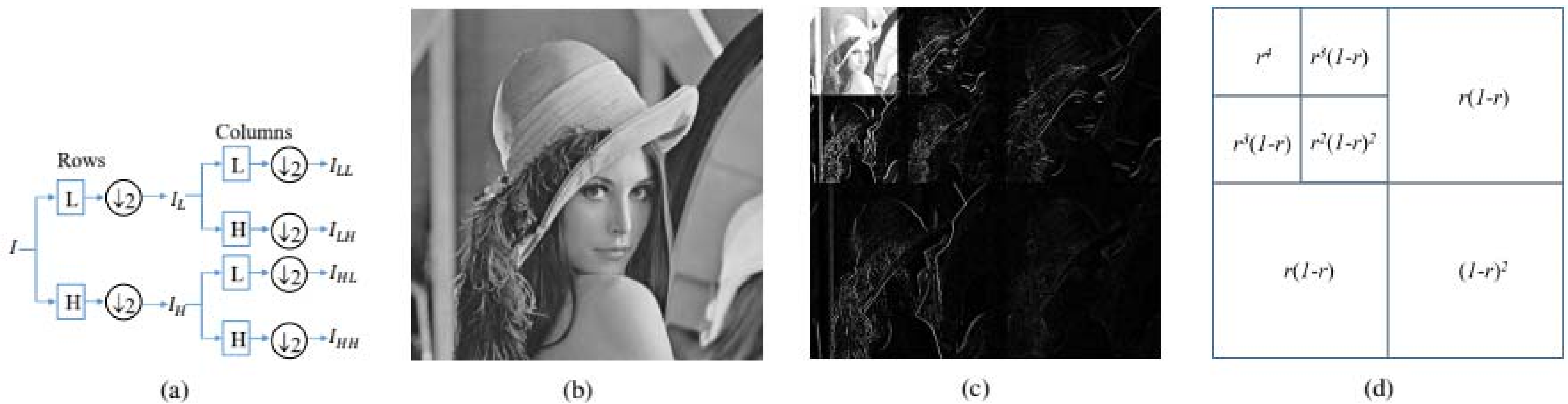

Fig. 2. The process of the DWT and the transformed example: (a) The process of the DWT, where downward arrows mean down-sampling. (b) The original image. (c) The result of the twp-times DWT. (d) The ratios for different patches.

Set : r=0.4

Wavelet SSIM loss

- **Algorithm :** $I_{i+1}^{LL}, I_{i+1}^{LH}, I_{i+1}^{HL}, I_{i+1}^{HH} = \mathrm{DWT}(I_i^{LL})$
- **SSIM :** $\mathrm{SSIM}(x,y) = \left[l(x,y)^{\alpha} \cdot c(x,y)^{\beta} \cdot s(x,y)^{\gamma} \right]$

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \Rightarrow \mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

(Luminance, Contrast and Structure Similarity)

$$\Rightarrow \quad L_{\mathrm{W-SSIM}}(x,y) = \sum_{0}^{i} r_i L_{\mathrm{SSIM}}(x_i^w, y_i^w),$$
$$w \in \{LL, HL, LH, HH\}$$

Wavelet SSIM loss

Input: Two images I, J, the ratio for multi-frequency r and iterative times n

Output: $loss = L_{\mathrm{W-SSIM}}(I, J)$

$I_0^{LL}, J_0^{LL} = I, J$;

Tensor $loss = 0$;

$x = r^2, y = r(1-r), z = (1-r)^2$ **for** $i = 1; i \leq n; i++$ **do**

  $I_i^{LL}, I_i^{LH}, I_i^{HL}, I_i^{HH} = \mathrm{DWT}(I_{i-1}^{LL})$

  $J_i^{LL}, J_i^{LH}, J_i^{HL}, J_i^{HH} = \mathrm{DWT}(J_{i-1}^{LL})$

  $loss+ = L_{SSIM}(I_i^{LH}, J_i^{LH}) \cdot y + L_{\mathrm{SSIM}}(I_i^{HL}, J_i^{HL}) \cdot y + L_{\mathrm{SSIM}}(I_i^{HH}, J_i^{HH}) \cdot z$

  $[x, y, z] = x \cdot [x, y, z]$

end

$loss+ = L_{\mathrm{SSIM}}(I_i^{LL}, J_i^{LL}) \cdot x$

return $loss$

Algorithm 1: W-SSIM Loss

Evaluation

- **PSNR**

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

- **SSIM**

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Table 1. Quantitative SSIM and PSNR on the synthetic RESIDE dataset.

	PSNR	SSIM
CAP [2] (prior-based)	23.02	0.865
AOD-Net [7] (learning-based)	23.92	0.875
MBE [5] (prior-based)	18.83	0.790
W U-net [11] (learning-based)	24.81	0.910
Ours	**26.61**	**0.947**

Evaluation

- **FADE : fog aware density evaluation**

Table 2. Quantitative FADE on restored images.

	River	People	Willow
CAP [2]	1.41	0.410	0.496
AOD-Net [7]	1.19	0.373	0.391
MBE [5]	0.440	0.184	0.184
W U-net [11]	1.51	0.647	0.562
Ours	**1.77**	**2.37**	**0.592**

- Ablation Study

Table 3. SSIM and PSNR results of all loss functions applied for the purposed network.

	L_2	L_{SSIM}	$L_{\text{W-SSIM}}$	$L_{\text{W-SSIM}} + L_2$
PSNR	26.31	26.27	26.50	**26.61**
SSIM	0.925	0.929	0.939	**0.947**

Qualitative dehazed results

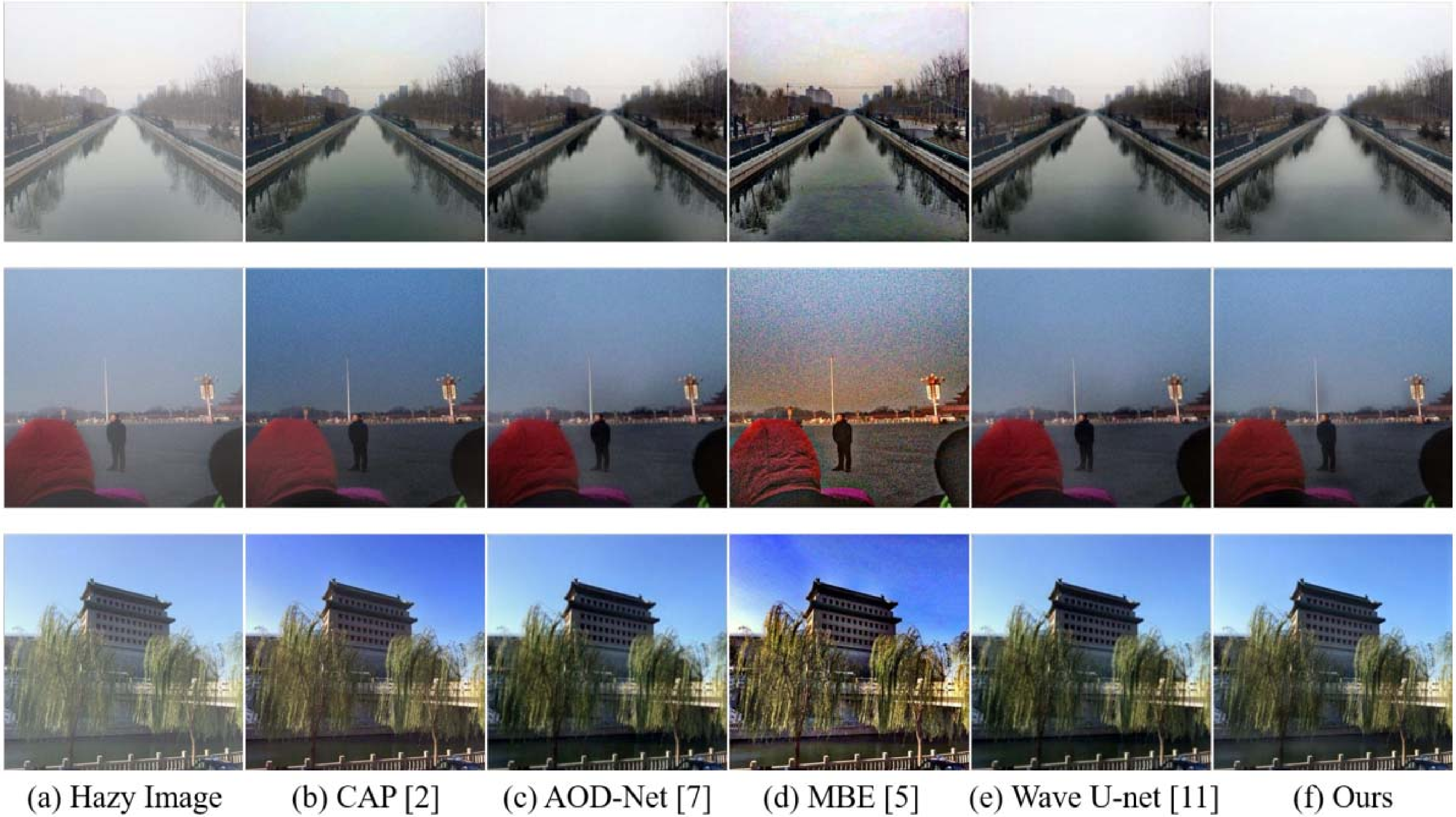

Fig. 3. Dehazed results in River, People and Willow.

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Conclusion

- W-UNet and chromatic adaptation transform helpful in improve constrast.

- Y-Net and W-SSIM make more edge detail with multi-scaling

- Discrete Wavelet Transform can perfectly replace down sampling and up sampling.

- Discrete Wavelet Transform can remain more high frequency feature whenever in loss-term or Network

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Thanks for your listening !