Single Image Dehazing without Paired Supervision

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Outline

1 Introduction

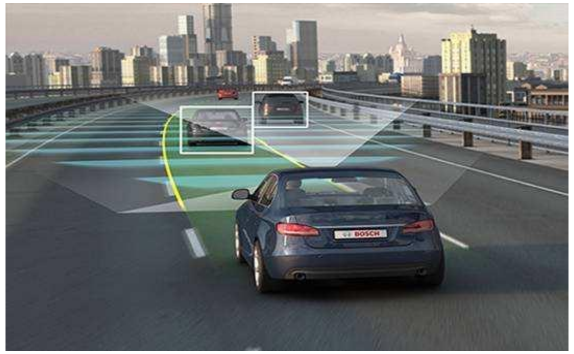
2 Related work

3 Our proposed method

4 Experiments

5 Conclusion

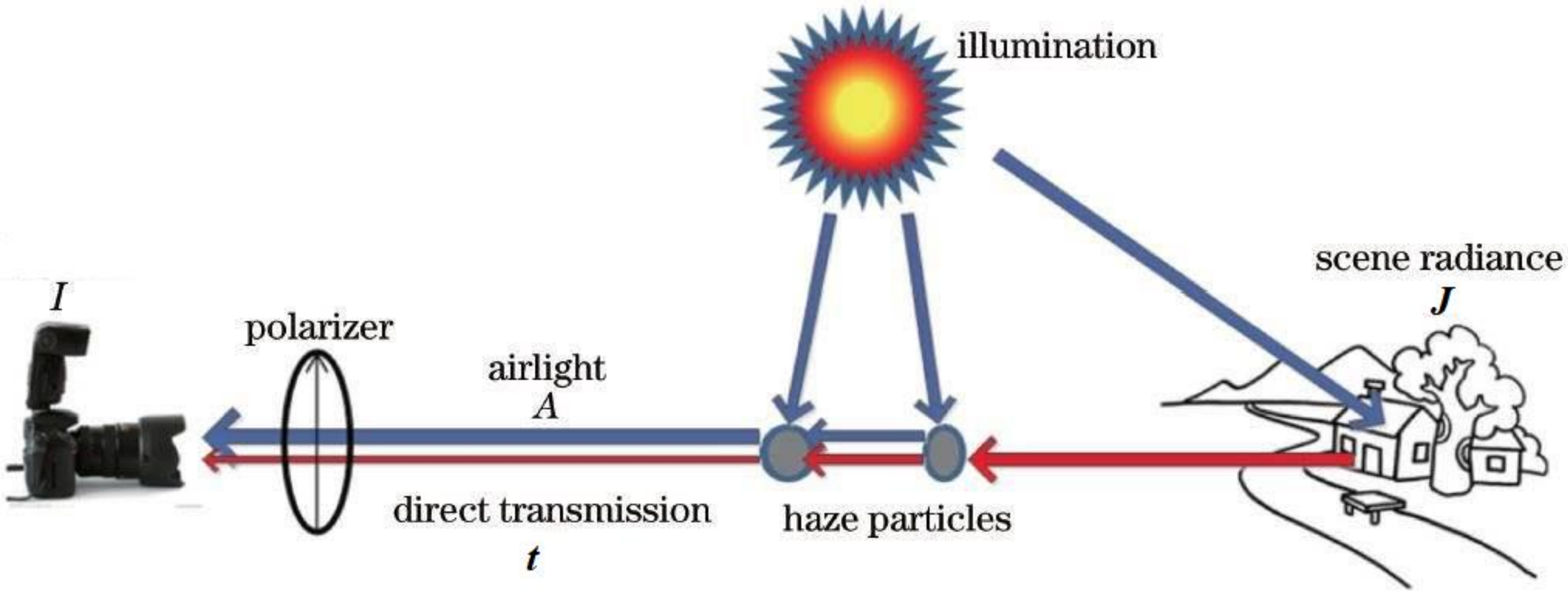
Background



Ideal image

Real image

- Classic dehazing model: $\boldsymbol{I} = \boldsymbol{J} * \boldsymbol{t}(\boldsymbol{x}) + \boldsymbol{A} * \left(\mathbf{1} - \boldsymbol{t}(\boldsymbol{x})\right)$



Contribution

- **An end-to-end network for single image dehazing**
  - Trained without paired Supervision.
  - surpassing existing methods.
- **A novel color-consistency loss**
  - Integrating DCP into deep learning-based dehazing methods.
- **A RealHaze Dataset**
  - Eliminating domain gap between real dataset and synthetic datasets.
  - 4,000 real hazy images and 4,000 haze-free outdoor images.

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Related work

- Prior-based methods
  - Dark channel prior (DCP)
  - Color attenuation prior (CAP)
  - Non-local dehazing
  - ……
- Limitation: Fitting for specific scenarios, but not robust for other conditions

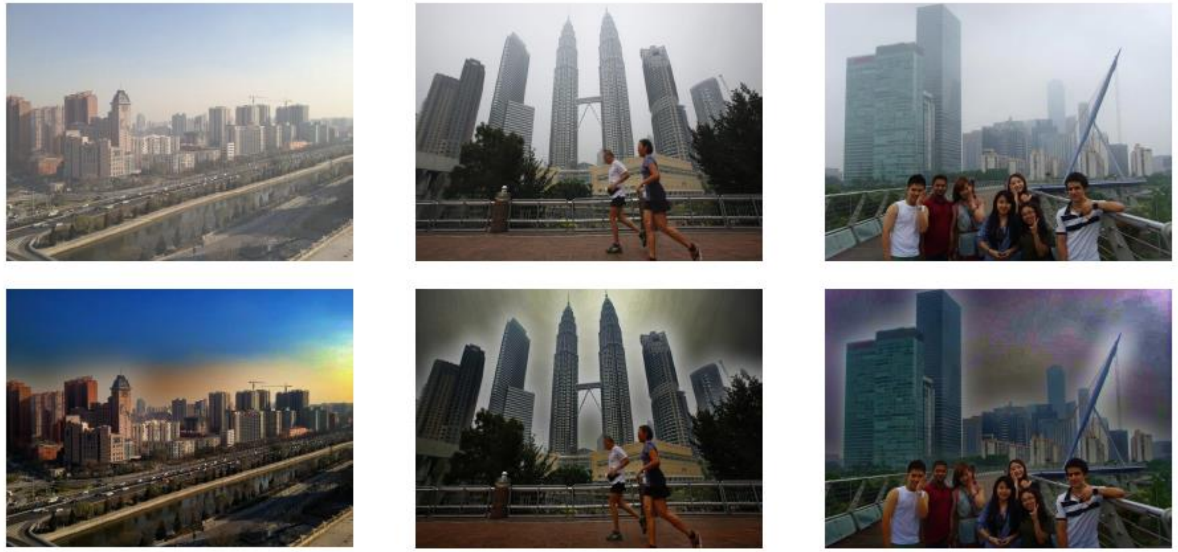

Fig. 3. Examples for DCP dehazing. First row: input haze image. Second row: DCP's result.

Related work

◆Learning-based methods

- DehazeNet
- MSCNN
- AOD-Net
- DCPDN
- ……

◆Limitation： Relying on paired datasets or synthetic datasets

Fig. 2. Examples and corresponding depth-map from NYU dataset[22] and Middelbury dataset[23]. Pay attention to the unprecise details and inconsistent edges.

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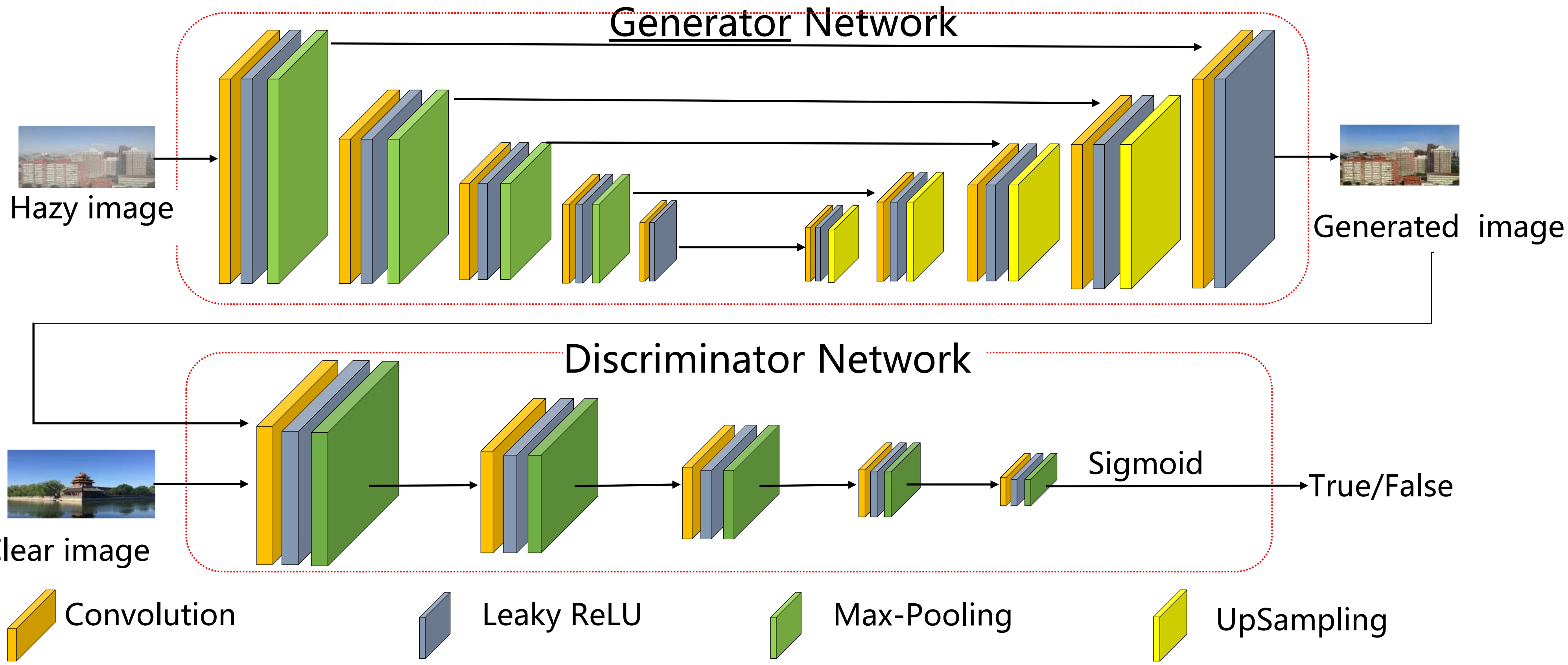
Network Architecture



- **Generator:**
  - Unet
  - Skip connections
- **Discriminator :**
  - relativistic discriminator

Loss Functions

- 1.Color-Consistency Loss
  - Dark Channel Prior(DCP):

$$J^{dark}(x) = \min_{c\in r,g,b\}} \left(\min_{y\in\Omega(x)} (J^c(y))\right) \approx 0$$

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

  - Gray-world assumption:

$$t^r(x) = t^g(x) = t^b(x)$$

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

  - Color-Consistency Loss

$$L_{color} = \frac{1}{WH} \sum_{1,1}^{W,H} \left[1 - CosSimilarity\left(J(x), I(x) - \min_{c} \min_{y\in\Omega(x)} \left(I^c(y)\right)\right)\right]$$

Loss Functions

◆ 2. Relativistic discriminator GAN Loss

$$L_D = -\mathbb{E}_{x_r}\left[log\left(D\left(x_r\right)\right)\right] - \mathbb{E}_{x_f}\left[log\left(1 - D\left(x_f\right)\right)\right]$$

$$L_G = -\mathbb{E}_{x_r}\left[log\left(1 - D\left(x_r\right)\right)\right] - \mathbb{E}_{x_f}\left[log\left(D\left(x_f\right)\right)\right]$$

◆ 3. Perceptual Loss

$$L_{perceptual} = \frac{1}{N}\sum_{i=1}^{N}\|\phi_i(I_i) - \phi_i(J_i)\|_2^2$$

◆ **Total Loss:**

$$Loss = L_G + L_D + \lambda_1 L_{color} + \lambda_2 L_{perceptual}$$

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Quantitative Comparison on Synthetic Datasets

- **Datasets**
  - **Training: RealHaze**
  - **Evaluating: RESIDE**
    - **HSTS**
    - **OTS**
- **Evaluation Metrics**
  - **PSNR**
  - **SSIM**

Dataset	**Metrics**	**Prior-Based Approaches**			**Learning-Based Approaches**		
		DCP[3]	***NLD[6]***	***CAP[5]***	***AODNet[11]***	***GCANet[8]***	***OURS***
HSTS	***PSNR***	14.61	17.74	19.88	19.75	23.06	**24.39**
	SSIM	0.882	0.860	0.885	0.903	0.936	**0.939**
OTS	***PSNR***	15.31	20.38	18.19	19.52	22.71	**23.79**
	SSIM	0.882	0.902	0.815	0.907	0.931	**0.936**

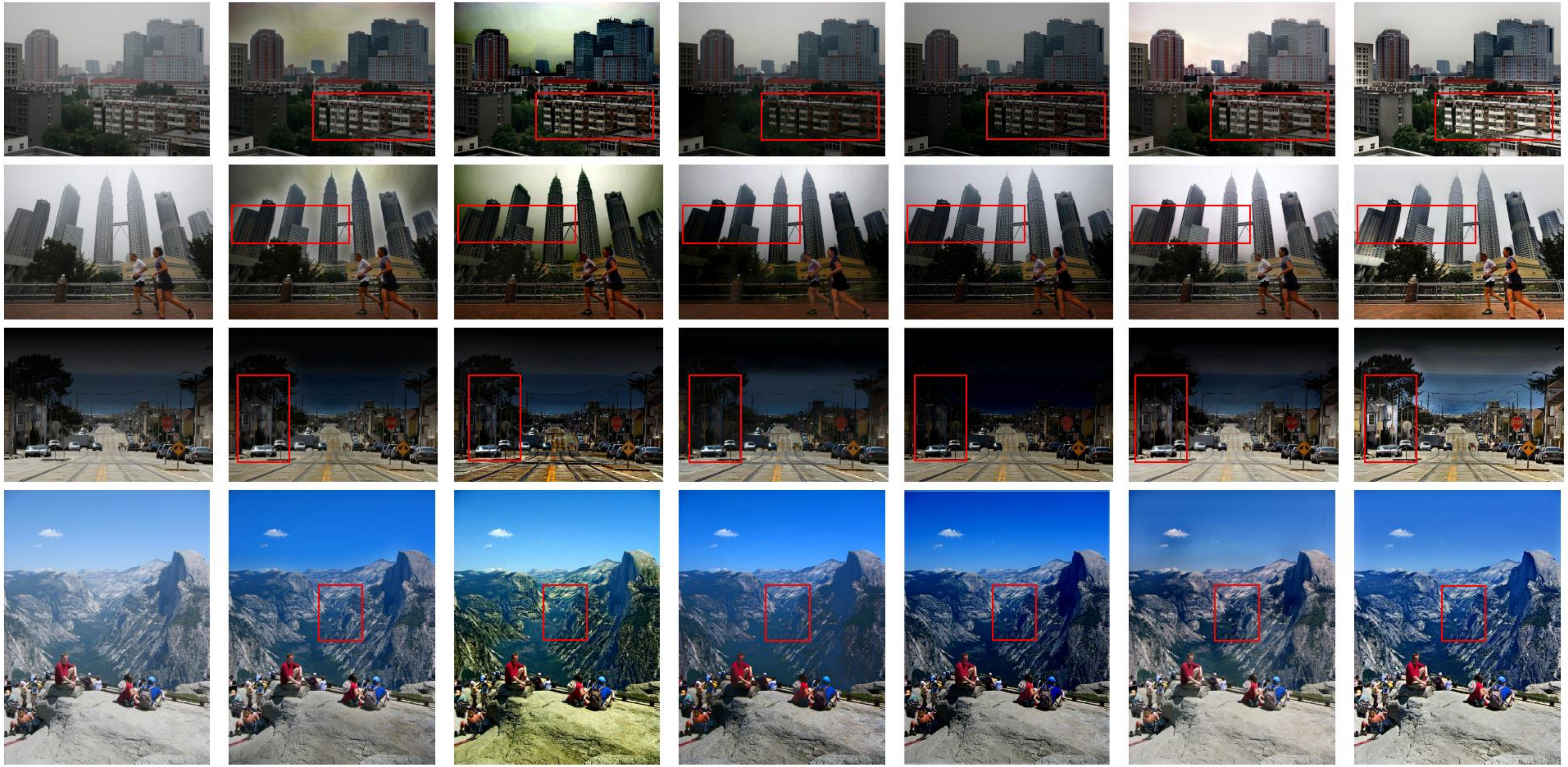
•Quantitative comparison on HSTS and OTS datasets (higher is better).

Qualitative Comparison on Synthetic Datasets

	(a) Haze Image	(b) DCP[3]	(c) NLD[6]	(d) CAP[5]	(e) AODNet[11]	(f) GCANet[8]	(g) Ours	(h) GT
PSNR		17.31	18.93	23.11	24.78	**25.60**	**26.30**	
SSIM		0.920	0.918	0.907	0.956	**0.961**	**0.971**	
PSNR		13.17	15.04	22.17	21.04	**24.70**	**24.98**	
SSIM		0.862	0.697	0.924	0.863	**0.929**	**0.970**	
PSNR		12.33	15.95	18.48	18.63	**22.46**	**26.26**	
SSIM		0.862	0.796	0.924	0.936	**0.957**	**0.974**	
PSNR		14.98	**24.57**	23.81	18.05	21.53	**24.73**	
SSIM		0.890	**0.964**	0.973	0.919	0.947	**0.963**	

Fig. 6. Qualitative comparison on HSTS dataset. Numbers in red and blue indicate the first and second best results, respectively.

Qualitative Comparison on Real Images



(a) Haze Image (b) DCP[3] (c) NLD[6] (d) CAP[5] (e) AODNet[11] (f) GCANet[8] (g) Ours

Fig. 8. Qualitative comparison on real outdoor images.

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Conclusions

- In this paper, we propose a single image dehazing network: SIDGAN

  - ✓ Trained with real outdoor images instead of paired synthetic datasets.
  - ✓ Integrate perceptual loss and color-consistency loss derived from DCP .
  - ✓ Achieve state-of-the-art results on both synthetic datasets and real datasets .

References

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Thank you!

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