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Nighttime Dehazing with a Synthetic Benchmark

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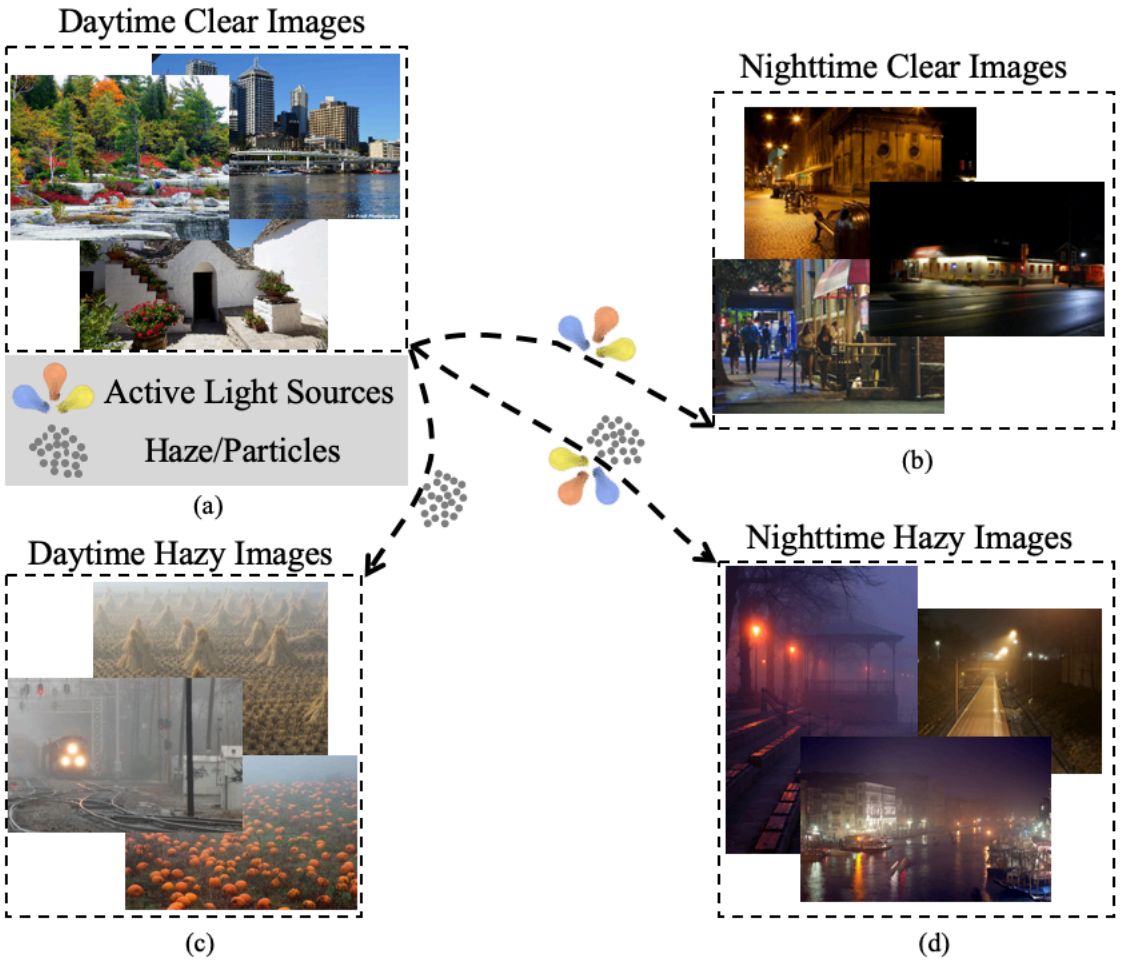
Background

Nighttime Dehazing with a Synthetic Benchmark (2/12)

Jing Zhang,
Yang Cao
Zheng-Jun Zha,
Dacheng Tao

Background
Related work
Method
Experiments
Conclusion



- **Artificial light sources** lead to a low-visibility image with uneven illumination and color cast
- **Haze** degrades image contrast due to absorption and scattering effects

Background

Nighttime Dehazing with a Synthetic Benchmark (3/12)

Jing Zhang, Yang Cao Zheng-Jun Zha, Dacheng Tao

Background
Related work
Method
Experiments
Conclusion

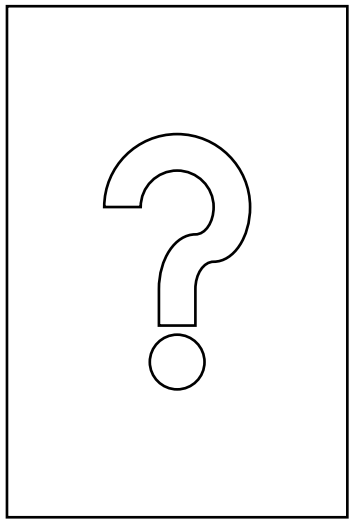
Imaging Model [39]:

Nighttime Hazy Image — Reflectance — Transmission — Illuminance — Color Cast

$$\mathbf{I}(\mathbf{x}) = L(\mathbf{x})\boldsymbol{\eta}(\mathbf{x})\mathbf{R}(\mathbf{x})t(\mathbf{x}) + L(\mathbf{x})\boldsymbol{\eta}(\mathbf{x})(1 - t(\mathbf{x}))$$
$$\triangleq \mathbf{J}(\mathbf{x})\boldsymbol{\eta}(\mathbf{x})\,t(\mathbf{x}) + L(\mathbf{x})\,\boldsymbol{\eta}(\mathbf{x})\,(1 - t(\mathbf{x}))\,,$$

Clear Image

$$\mathbf{I}(\mathbf{x}) \longrightarrow \mathbf{J}(\mathbf{x})$$



It is challenging due to the **ill-posed** nature.

Related Work

Nighttime Dehazing with a Synthetic Benchmark (4/12)

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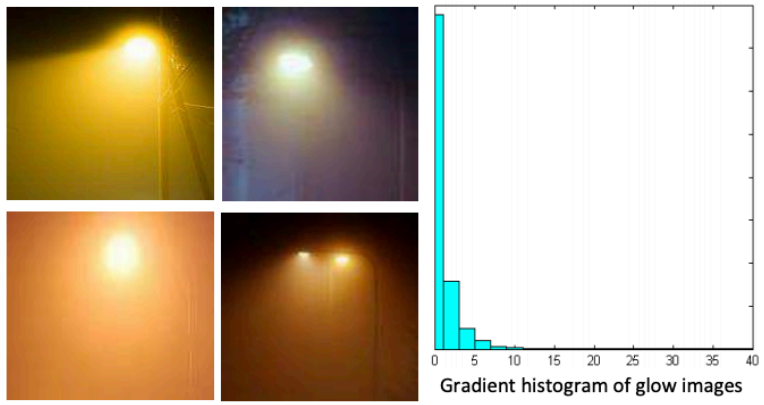
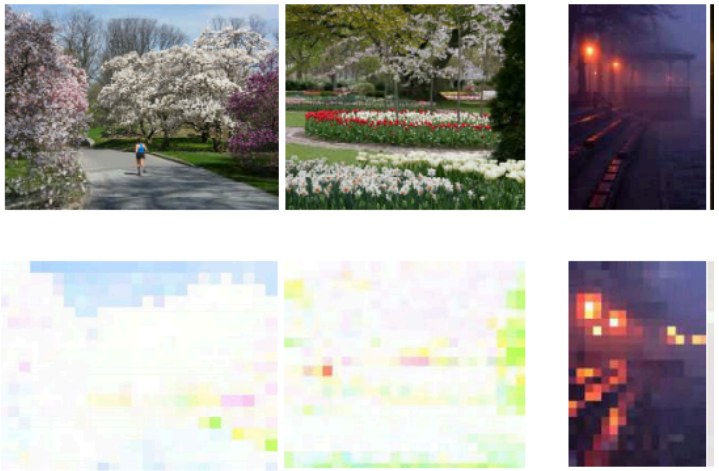
Background
Related work
Method
Experiments
Conclusion

- Prior-based Method

Dark Channel Prior [15]



Glow Separation [23]



Maximum Reflectance Prior [39]

Method

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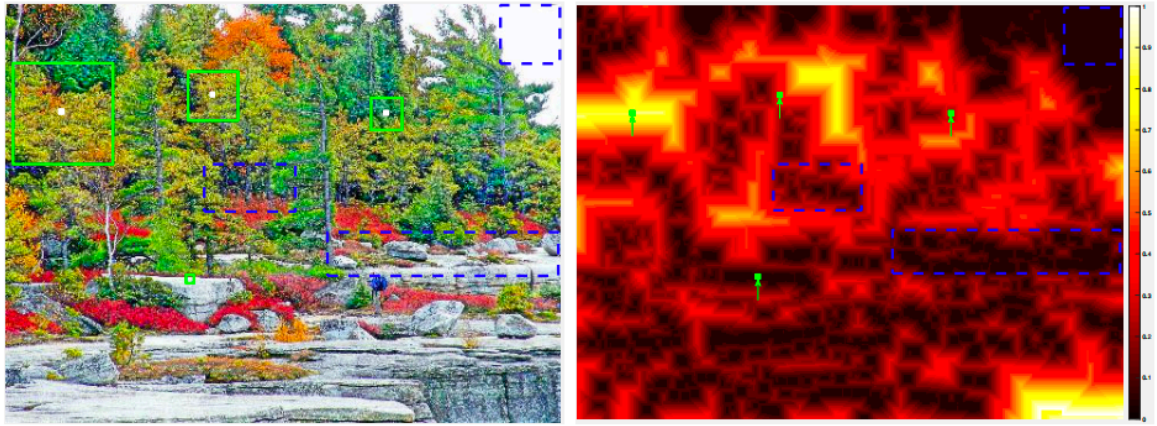
Background
Related work
Method
Experiments
Conclusion

- OS-MRP for nighttime dehazing
  - Optimal-scale maximum reflectance prior

Optimal scale:
a sufficiently large scale but not necessary to be larger to obtain the highest maximum reflectance probability.

OS-MRP:
the maximum reflectance is always close to 1 within each local patch at its optimal scale.



(a) (b)

Figure 4: (a) A clear image. (b) The optimal scale map. Hot colors represent large scales. Please refer to Section 4.1.

Method

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Jing Zhang, Yang Cao Zheng-Jun Zha, Dacheng Tao

Background
Related work
Method
Experiments
Conclusion

- OS-MRP for nighttime dehazing
  - Nighttime dehazing

1) **Initial multiscale fusion**
   1) Color cast estimation at each scale
   2) Multiscale fusion
   3) Color cast correction
   4) Dehazing

2) **OSFD: Optimal-scale fusion-based dehazing**
   1) Calculation of optimal scale at each pixel
   2) Optimal-scale fusion of color cast
   3) Color cast correction
   4) Dehazing

- A CNN baseline for nighttitme dehazing
  - Network structure
    - Encoder
      - MobileNet-v2 backbone
    - Decoder:
      - five conv blocks
      - a conv prediction layer
      - U-Net like shortcuts
  - Training objectives
    - L2 loss
    - Perceptual loss

Method

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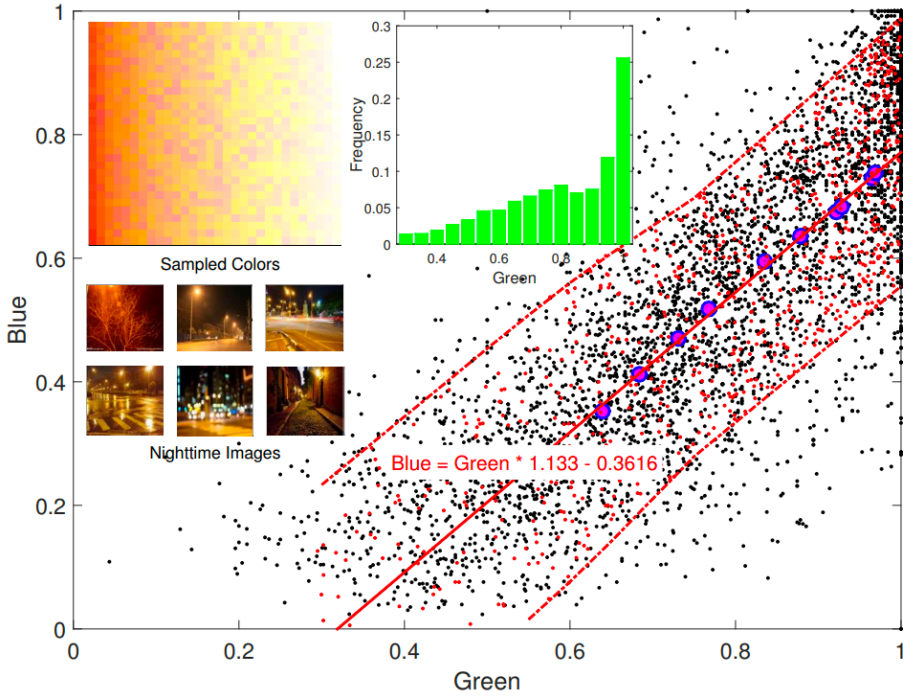
Background
Related work
Method
Experiments
Conclusion

- Synthetic nighttime hazy images
  - Empirical study on real-world light colors



- A novel synthetic method: 3R
  - Scene **R**econstruction
  - **R**ay simulation
  - **R**endering

Algorithm 1: Synthesizing Images via 3R

Input: $\mathbf{R}$, C, D, β_l, β_t, $\{\boldsymbol{\eta}_\mathbf{k}\}_{k=1}^{K}$
Output: $\mathbf{I}$

Scene Reconstruction:
  Segment C into super-pixels $\{\mathbf{z_1}, ...\}$;
  Calculate the world coordinates $\mathbf{x_i}$ of pixels on $\mathbf{z}$;
  Calculate the normal vector $\mathbf{v}$ according to Eq. (4);
Ray Simulation:
  Calculate the illuminance $\mathbf{L_k}$ according to Eq. (5);
  Aggregate the illuminance $\mathbf{L_k}$ according to Eq. (6);
  Calculate the transmission t according to Eq. (7);
Rendering:
  Synthesize $\mathbf{I}$ according to Eq. (1).

Method

Nighttime Dehazing with a Synthetic Benchmark (8/12)

Jing Zhang, Yang Cao Zheng-Jun Zha, Dacheng Tao

Background
Related work
Method
Experiments
Conclusion

- Synthetic ighttime hazy images
  - A novel synthetic benchmark
    - Cityscapes dataset
    - Middlebury dataset
    - RESIDE dataset

Dataset	Haze Density	Number	Synthetic	Tasks
NHC-L	Light	2,750	✓	ND+CR
NHC-M	Medium	2,750	✓	ND
NHC-D	Dense	2,750	✓	ND
NHM	All	350	✓	ND
NHR	All	8,970	✓	ND
NHRW	All	150	x	ND
DCRW	x	1500	x	CR

ND: Nighttime Dehazing; CR: Color Removal

Experiments

Nighttime Dehazing with a Synthetic Benchmark (9/12)

Jing Zhang, Yang Cao Zheng-Jun Zha, Dacheng Tao

Background
Related work
Method
Experiments
Conclusion

- Main Results

Table 2: Dehazing results on the NHC dataset.

Method	PSNR (↑)	SSIM (↑)	CIEDE2000 (↓)
	NHC-L		
NDIM [41]	11.12	0.2867	21.77
GS [23]	18.84	0.5537	10.12
MRPF [39]	19.17	0.5831	9.42
MRP [39]	23.02	0.6855	8.12
OSFD	**23.10**	**0.7376**	**7.48**
ND-Net	**26.12**	**0.8519**	**6.16**
	NHC-M		
NDIM [41]	10.93	0.2959	22.31
GS [23]	15.88	0.4654	12.81
MRPF [39]	16.40	0.5093	11.71
MRP [39]	20.61	0.6238	9.12
OSFD	**21.15**	**0.6782**	**8.56**
ND-Net	**22.72**	**0.7899**	**7.31**
	NHC-D		
NDIM [41]	10.66	0.3077	23.25
GS [23]	12.70	0.3690	17.72
MRPF [39]	13.48	0.4289	15.71
MRP [39]	17.62	0.5483	11.24
OSFD	**18.41**	**0.6002**	**10.66**
ND-Net	**18.90**	**0.7010**	**9.58**

Table 3: Dehazing results on the NHM and NHR datasets.

	NHM			NHR		
Method	PSNR (↑)	SSIM (↑)	CIEDE2000 (↓)	PSNR (↑)	SSIM (↑)	CIEDE2000 (↓)
NDIM [41]	14.58	0.5630	19.23	14.31	0.5256	18.15
GS [23]	16.84	0.6932	15.84	17.32	0.6285	12.32
MRPF [39]	13.85	0.6056	19.20	16.95	0.6674	12.32
MRP [39]	17.74	0.7105	15.23	19.93	0.7772	10.01
OSFD	**19.75**	**0.7649**	**12.23**	**21.32**	**0.8035**	**8.67**
ND-Net	**21.55**	**0.9074**	**9.11**	**28.74**	**0.9465**	**4.02**

Table 4: Color cast removal results on the NHC-L and DCRW datasets.

Method	PSNR (↑)	SSIM (↑)	CIEDE2000 (↓)
	NHC-L		
GS [23]	27.92	0.6454	5.735
MRP [39]	30.80	0.7525	5.100
OSFD	**30.91**	**0.7586**	**4.879**
	DCRW		
GS [23]	12.56	0.6313	19.02
MRP [39]	20.29	0.7923	10.18
OSFD	**22.89**	**0.8711**	**7.659**

1) **OSFD** outperforms other prior-based methods
2) **ND-Net** achieves the best performance

Experiments

Nighttime Dehazing with a Synthetic Benchmark (10/12)

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Background
Related work
Method
Experiments
Conclusion

- Main Results

Figure 1: (a) Nighttime hazy images. (b) NDIM [41]. (c) GS [23]. (d) MRP [39]. (e) Our OSFD. (f) Our ND-Net.

1) Many **color artifacts** in the results of **NDIM** and **GS**, e.g., light source areas
2) **Whitish artifacts** in large monochromatic areas of **MRP's** results, e.g., light sources, lawn
3) **OS-MRP based OSFD** is better than MRP while **ND-Net** is more natural

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Conclusion

Nighttime Dehazing with a Synthetic Benchmark (11/12)

Jing Zhang, Yang Cao Zheng-Jun Zha, Dacheng Tao

Background
Related work
Method
Experiments
Conclusion

- The proposed **3R synthetic method** can generate realistic nighttime hazy images; Based on 3R, we propose **a large-scale synthetic benchmark** including several datasets for nighttime dehazing
- Our **OS-MRP is more effective than MRP**, especially in large monochromatic areas
- **OSFD** based on OS-MRP **achieves better dehazing and color removal performance** than previous prior-based methods
- Our **ND-Net can serve as a strong baseline** for nighttime dehazing

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Nighttime Dehazing with a Synthetic Benchmark (12/12)

Jing Zhang,
Yang Cao
Zheng-Jun Zha,
Dacheng Tao

Background
Related work
Method
Experiments
Conclusion

Thank you!