Evaluating Single Image Dehazing Methods Under Realistic Sunlight Haze

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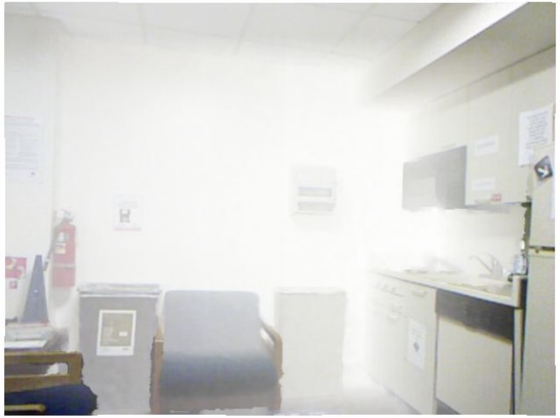
Single Image Dehazing Problem

- Haze degrades **visibility** and **image quality**
  - Degrades the performance of computer vision tasks, e.g., object detection
- **Goal**: Reconstruct haze-free image of a hazy image



Hazy

Haze-free/Ground truth

Motivation

- Current methods make assumptions that do not hold in reality
  - **Haze color:** Single color haze i.e grayish white
  - **Haze pattern/distribution:** homogeneous/uniformly distributed

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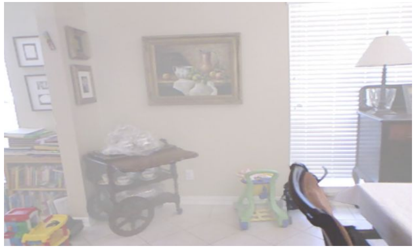


Sample images from NYU, SOTS and Middlebury synthetic hazy datasets

Goal

- Evaluating dehazing methods under realistic sunlight haze
    - Sun-light haze one of the most prevalent type of haze in the wild

Contributions

- We introduce a realistic sunlight haze, **Sun-Haze**
  - Containing 107 images
- We evaluate dehazing methods on the proposed dataset
- We present the limitations of current methods under realistic settings

Sun-Haze Dataset

- Having one ground truth for a hazy image is not practical
  - One hazy image could have a range of goud truth images with different lighting, contrast,..
  - One single image does not capture that
- Thus to be able to evalue dehazing methods in a more practical way, we need to have multiple ground truths
  - We build our dataset on top of MIT-fiveK
- MIT-fiveK includes:
  - 5,000 photos taken by photographers with SLR cameras.
  - These photos are captured from **different scenes**, **subjects**, and during **various lighting conditions**.
  - These photographs are retouched to obtain a visually pleasing renditions by **five photography experts** using **Adobe Lightroom**

Sun-Haze Dataset

- How we add haze?
  - We utilized **Adobe Photoshop** and **Luminar 4**
  - We use different parameters
    - **Intensity:** creates a thicker, more dense haze effect
    - **Penetration:** expands the sun haze effect to a broader region of the image
    - **Warmth:** creates a golden yellow sunhaze color, creates realistic sunlight color changes during the day
    - **Angle:** sunlight haze from different angles to further diversify our dataset
    - **Sunset/sunrise haze effect:** Using Adobe Photoshop we professionally added a gradient sunlight haze effect
    - **Number of Sun rays**

Sun-Haze Dataset

- Sun-haze contains 107 indoor and outdoor images along with six ground truth images:
  - One before retouch/original
  - Five ground truths retouched by five experts for MIT-fiveK dataset

Sun-Haze Dataset - Indoor sample

Hazy image

Original

Expert A

Expert B

Expert C

Expert D

Expert E

Sun-Haze Dataset - Outdoor sample

Hazy Image

Original

Expert A

Expert B

Expert C

Expert D

Expert E

Sun-Haze Dataset - Sunset sample

Hazy Image

Original

Expert A

Expert B

Expert C

Expert D

Expert E

Dehazing Methods

- We can categorize them into two categories:
  - Prior based
    - Mainly based on the parameter estimation of atmospheric scattering model
    - The physical scattering model consists of the transmission map and the atmospheric light:
      - $I(x) = J(x)\mathbf{t}(x) + \mathbf{A}(1 - \mathbf{t}(x))$
      - I(x) is the hazy image, J(x) is the haze-free image, t(x) is the medium transmission map, and A is the global atmospheric light on each x pixel coordinates
    - The solution of the haze-free image depends on the **estimation of the atmospheric light and the transmission map**

Dehazing Methods

- We can categorize them into two categories:
  - Prior based
  - Learning based/data-driven: Utilizes the deep convolutional neural networks or generative adversarial networks to estimate the transmission map indirectly
    - Takes advantage of the power of data
    - Paired vs unpaired supervision: Paired single image dehazing methods need the **haze-free/ground truth** of each hazy image for training, unpaired dehazing methods **do not require the haze-free pair** of the hazy images
  - combination methods:
    - Take advantage of deep CNNs/GANs and uses priors jointly

Dehazing Methods

Method	Paired vs. Unpaired	Prior-based	Learning-based	Adversarial-based
DCP [12]	NA	✓		
MSCNN [22]	Paired	✓	✓	
DehazeNet [10]	Paired	✓	✓	
AODNet [13]	Paired	✓	✓	
EPDN [19]	Paired		✓	✓
Dehaze-GLCGAN [6]	Unpaired		✓	✓
CycleDehaze [11]	Unpaired		✓	✓

Experiments

- Benchmark dataset: Sun-Haze
- Evaluated methods: DCP, MSCNN, DehazeNet, AOD-Net, Cycle-Dehaze, GLCGAN, EPDN
- Metrics:
  - Reference based:
    - PSNR
    - SSIM
    - CIEDE2000
  - No-reference based
    - PI
    - NIQE

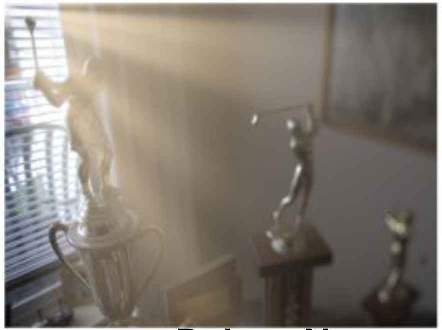
Quantitative Results on SUN-HAZE Dataset

Ground truth	Metric	DCP	MSCNN	Dehazenet	AOD-Net	EPDN	Dehaze-GLCGAN	CycleDehaze
Expert A	PSNR	11.01	**16.48**	15.62	14.83	15.88	14.38	15.53
	SSIM	0.641	0.773	0.733	0.698	0.784	**0.789**	0.778
	CIEDE	34.76	**23.46**	27.55	30.26	26.29	24.37	26.62
Expert B	PSNR	11.28	16.33	15.13	14.15	14.96	15.12	15.38
	SSIM	0.655	0.763	0.709	0.676	0.761	**0.801**	0.763
	CIEDE	32.66	25.43	30.90	34.33	31.64	**22.03**	26.49
Expert C	PSNR	11.32	**16.57**	15.49	14.49	15.44	14.74	15.23
	SSIM	0.643	0.746	0.703	0.670	0.756	**0.782**	0.737
	CIEDE	33.22	24.57	28.84	31.93	28.73	**23.98**	28.98
Expert D	PSNR	11.43	14.91	13.75	12.82	13.55	**14.93**	14.35
	SSIM	0.649	0.722	0.667	0.632	0.713	**0.781**	0.728
	CIEDE	30.87	29.10	34.76	38.87	36.28	**22.36**	28.67
Expert E	PSNR	11.32	15.27	13.86	12.99	13.56	**15.32**	14.84
	SSIM	0.640	0.719	0.660	0.626	0.704	**0.780**	0.733
	CIEDE	33.07	28.56	34.38	38.11	35.88	**22.30**	28.13
Original image	PSNR	11.40	**19.10**	17.78	16.89	17.96	14.57	16.39
	SSIM	0.686	**0.867**	0.814	0.782	0.857	0.810	0.834
	CIEDE	36.10	**18.44**	23.95	26.63	22.72	24.46	23.46
Average	PSNR	11.34	**17.51**	16.28	15.37	16.32	14.73	15.73
	SSIM	0.651	0.765	0.721	0.680	0.763	**0.799**	0.762
	CIEDE	33.45	24.93	30.06	33.36	30.26	**23.25**	27.06
No reference	NIQE	5.35	4.06	4.08	**3.93**	4.13	4.09	4.60
No reference	PI	3.71	3.25	3.25	3.02	3.04	**2.93**	4.08

Green: Best
Pink: Second best
Yellow: Third best

Qualitative Results on SUN-HAZE Dataset

Input: Hazy Image



AODNet

GLCGAN

DehazeNet

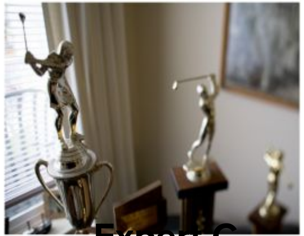
MSCNN

EPDN

Original

Expert A

Expert B



Expert C

Expert D

Expert E

Qualitative Results on SUN-HAZE Dataset

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Qualitative Results on SUN-HAZE Dataset

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Discussion and Conclusion

- The relatively low SSIM, PSNR and relatively high CIEDE2000, NIQE, and PI prove current dehazing methods are **unable to generalize well** to remove sunlight haze.
- The existing methods **performed even more poorly on varicolored haze**, .e.g., sunset hazy images
- **Our results question the underlying assumptions of these methods and their practicality in real-world scenarios.**
- Therefore, for dehazing methods to be practical they need to be trained and tested using more realistic and practical datasets which include a variety of realistic haze patterns and colors.

Thank You!

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