Hazy images dataset with localized light sources for experimental evaluation of dehazing methods

Andrei Filin[a,*], **Andrei Kopylov**[a], **Oleg Seredin**[a] **and Inessa Gracheva**[a]

[a] *Laboratory of Cognitive Technologies and Simulation Systems, Tula State University, 92, Lenin ave., Tula, 300012, Russia*

E-mail: andrewifilin@gmai.com, andkopylov@gmail.com

Image haze removal methods have taken increasing attention of researchers. At the same time, an objective comparison of haze removal methods struggles because of the lack of real data. Capturing pairs of images of the same scene with presence/absence of haze in real environment is a very complicated task. Therefore, the most of modern image haze removal datasets contain artificial images, generated by some model of atmospheric scattering and known scene depth. Among the few real datasets, there are almost no datasets consisting of images obtained in low light conditions with artificial light sources, which allows evaluating the effectiveness of nighttime haze removal methods. In this paper, we present such dataset, consisting of images of 2 scenes at 4 lighting levels and 4 levels of haze density. The scenes has varying "complexity" – the first scene consists of objects with a simpler texture and shape (smooth, rectangular and round objects); the second scene is more complex – it consists of objects with small details, protruding parts and localized light sources. All images were taken indoors in a controlled environment. An experimental evaluation of state-of-the-art haze removal methods was carried out on the collected dataset.

The 6th International Workshop on Deep Learning in Computational Physics (DLCP2022)
6-8 July 2022
JINR, Dubna, Russia

*Speaker

https://pos.sissa.it/

PoS(DLCP2022)019

1. Introduction

In the past two decades, image haze removal methods have improved significantly. Existing solutions demonstrate the high quality of dehazing in standard scenes. The majority of current efforts are focused on improving image restoration results in increasingly challenging scenes.

The development of image haze removal methods in this direction is hampered by the lack of data that could be used for objective evaluation and comparison of the proposed solutions. Most of publicly available large-scale datasets either have artificially generated hazy images [1, 2, 3] or contain images with natural haze, without corresponding reference haze-free images. There are a limited number of datasets where both hazy and haze-free images are real [4, 5, 6, 7, 8], but the number of such pairs of images in this datasets is much less than in the datasets where hazy images were generated.

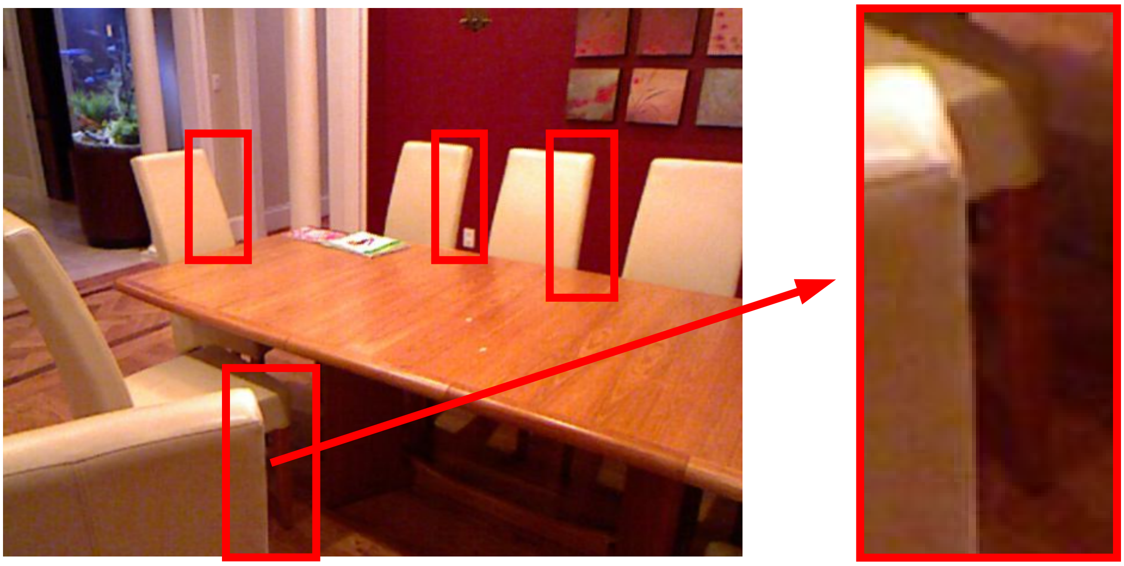
The use of datasets with generated haze and non-reference images without ground truth does not allow to objectively evaluate haze removal methods. In the first case, there is an original haze-free image, and the corresponding hazy image is obtained using an optical model and a known depth map [1, 2, 3]. The images obtained in this way have noticeable distortions associated with low accuracy of the depth map, as well as an insufficiently detailed atmospheric scattering model (Fig. 1). In the second case, it is impossible to use quantitative quality metrics based on a comparison of dehazed and haze-free (ground truth) images – such estimates are usually more objective and predictable than those that can be obtained without ground truth.

In addition, an important fact is that we have not found any publicly available dataset, which consist of pairs of real hazy and haze-free images, obtained in low light conditions and the presence of localized light sources. Since, in real world applications, in most cases it is assumed that haze removal methods can receive images obtained under varying environment, including nighttime. The evaluation of methods using datasets, that do not contain ground truth images, distorts the results of assessing the quality of image restoration.

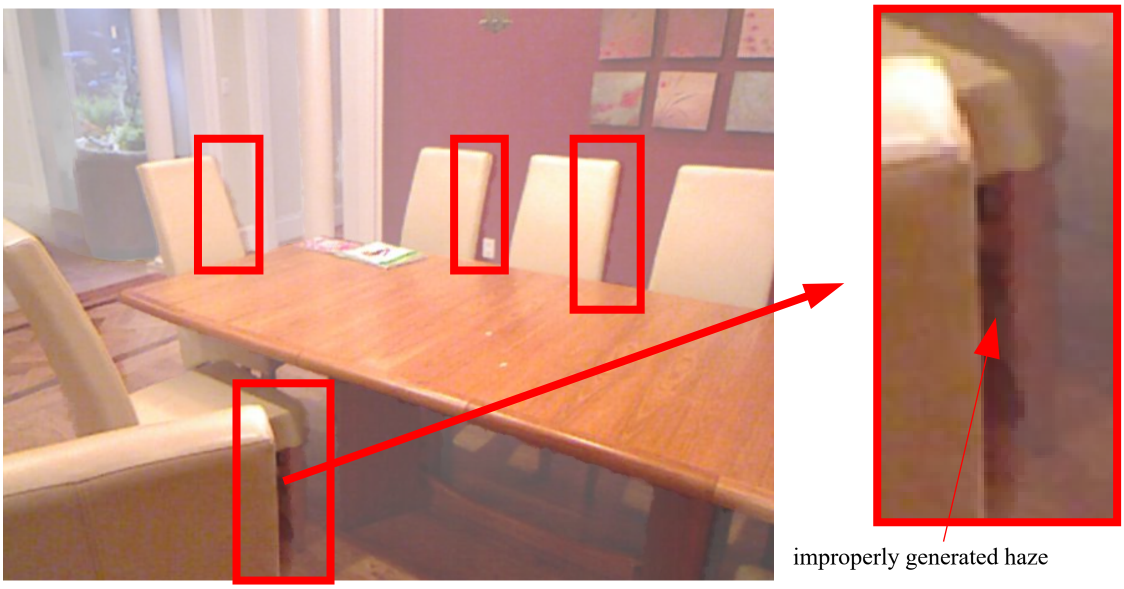
Among the publicly available image haze removal datasets consisting entirely of pairs of real hazy and haze-free images, we managed to find several. The dataset [4] consists of 30 pairs of images of indoor scenes, the haze is distributed homogeneously. The dataset [8] was obtained similarly, but have different levels of haze density for single scene, and consists of 27 pairs of images. The dataset [5] consists of 45 pairs of images of street scenes. The authors tried to obtain the most homogeneous haze distribution, which was not achieved sufficiently in this work but succeeded in the next one [7]. This dataset consists of 33 pairs of images of street scenes, where a denser and more homogeneous haze was obtained. In another paper [6], the authors aimed to obtain non-homogeneous haze, because it is more common in the real world. As the result, 55 pairs of such images were collected.

As we can see, the found datasets, firstly, contain a small number of images (190 in total), and secondly, they do not contain images taken in low light and with the localized light sources. This is critical for developing methods that will work, among others conditions, in the nighttime. For this reasons, we have decided to collect a new dataset, free from the described disadvantages.

PoS(DLCP2022)019



(a)



(b)

Figure 1: An example of an image with haze generated using the known depth map (SOTS dataset [2]). (a) – haze-free (ground truth) image (1446.png); (b) image with generated haze (1446_10.png). An unrealistic haze can be seen near the back of the chairs and on the leg of the left chair due to an inaccurate depth map

In Section 1, we analyze methods for collecting known datasets consisting of pairs of real images, and also draw up a Night-haze acquisition plan and describe the resulting dataset.

Section 2 presented the experimental results of applying well-known haze removal methods to the collected, and also other two datasets, which contain real images [4, 5]; the description of the methods used, as well as metrics for evaluating the quality of haze removal, is given.

In section 3, conclusions about the collected dataset and the experimental results are drawn, and the directions of future research are described.

2. Night-haze dataset acquisition

The goal of this work is to obtain a dataset consisting of pairs of real hazy and haze-free images, obtained in low light conditions and with the presence of localized light sources. The resulting Night-haze dataset, described in the paper, consists of 32 images of 2 scenes of varying complexity. For each scene, images were captured at 4 lightning levels and 4 haze density levels.

In preparing the Night-haze collection plan, we analyzed papers that described ways to obtain image dehazing datasets, that consist entirely of real images [4, 5, 6, 7, 8]. As the result, the following main points were discovered:

- It is convenient to obtain haze using a fog machine – since it has a high speed of generation and produces particles close to those in atmospheric haze (with a diameter size of 1-10 micrometers). In addition, the generated haze does not damage the equipment.
- For image post-processing and comparison, it is necessary to place calibration devices (such as Datacolor SpyderCheckr) in the frame, as well as control such camera settings as aperture, shutter speed, and ISO.

For data collection, 2 indoor scenes of varying complexity were prepared (Fig. 2). The first scene contained a small number of objects with simple texture and shape. The second scene contains objects of more challenging texture and shape, as well as localized (point-light) sources (garland lights). In addition, the following devices were placed in the frame:

- Datacolor SpyderLensCal – to focus the camera;
- Datacolor SpyderCheckr 48 – for color calibration;
- Datacolor SpyderCUBE – to adjust the white balance;
- Test chart according to ISO 12233.

To generate haze, a JINWEIGE FM900-C fog generator was used. The pictures were taken on a Canon 2000d camera in raw and jpg formats. Images resolution – 6000x4000; color depth – 24 bit. Additionally, depth maps were obtained for each scene using Microsoft Kinnect v2 and Intel RealSence d435i. To obtain a homogeneous haze, the fan was running during its injection. The pictures were taken remotely from the next room using the mobile application to control the camera; switching on/off the fog generator and the fan was done manually. The intensity of lighting for each scene was also changed remotely by changing the number of lamps turned on – from the imitation of twilight (one switched-on portable lamp) to bright ("daylight") lighting (all 4 lamp sources were turned on). Only lamps, which regulated the intensity of illumination, served as light sources in the dark room.

The objects that make up the scene were placed on the table. The cameras position was in front of the scene on the tripod at such a distance that the scene size of at least 1x1 meters fit in the frame, and the colors on the ColorCheckr were distinguishable and were on the same axis as the sensor. In our case, the distance from the lens to the ColorCheckr was 2 meters. The average performance of the fog generator and the maximum fan speed was set; camera aperture and ISO settings were fixed for all photos: aperture F=5, ISO=100; shutter speed varied depending on the lighting: 5" for minimum illumination and 1/4 for the rest. White balance was set for each scene using a Datacolor SpyderCUBE.

After placing the objects on the scene and preparing the equipment, ground truth images with all illumination levels were taken. Then the ventilation openings of the room were sealed, the fog generator and the fan were turned on, and every 5 minutes a series of 4 shots was taken with different illumination – thus, images with different haze densities and lighting were obtained.

Since both illumination and haze densities were varied in 4 levels, for each of 2 scenes, 16 images were obtained – 32 images in total. The resulting dataset has the characteristics described above – it consists of hazy and corresponding haze-free images with natural haze of different densities and illumination levels and with the presence of point light sources in the frame, which makes it possible to benchmark haze removal methods in the environment, closer to the real world than in other datasets.

Figure 2: Examples of images of 2 scenes with different degrees of illumination and haze density from the presented dataset

3. Experimental research

The experimental evaluation of state-of-the-art haze removal methods was performed on the resulting dataset. Most of them use the classic atmospheric scattering model proposed in [9] and based on the optical model [10]. The variety of image haze removal methods consists of different heuristics, used for the estimation of the scattering map or atmospheric light [11, 12, 13, 14]. Another approach utilizes machine learning methods to obtain hidden patterns in pairs of hazy and haze-free images of the same scene. The corresponding research areas addresses building a regression model of the scatter map, as well as direct restoration of the haze-free image. The method proposed by Qin [15] was chosen as an example of this approach. This is the evolution of the attention-based deep neural network architecture that improves the feature attention module to provide low-level features to deeper layers, allowing the core network to find more patterns from the combination of high-level and low-level features.

In addition to the proposed dataset, experiments research was also performed on the i-haze and o-haze datasets. Peak signal-to-noise ration (PSNR) [16] and structural similarity index (SSIM) [17] were used as metrics for quantitative evaluation of the haze removal quality.

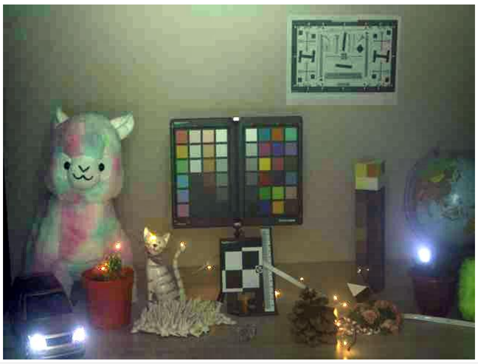
Table 1 shows results of the experiments. Figure 3 demonstrates examples of haze removal by different methods on images from i-haze and the proposed dataset (night-haze).

Table 1: Experimental results of haze removal on the proposed set (night-haze), i-haze, and o-haze datasets. For i-haze and o-haze average results are shown for two sets

Method	Average PSNR over all images from both i-haze and o-haze	Average PSNR for the proposed dataset (night-haze)	Average SSIM over all images from both i-haze and o-haze	Average SSIM over the proposed set (night-haze)
Berman et al. [11]	15.76	15.76	**0.74**	0.73
Dhara et al. [12]	14.85	**18.59**	0.67	**0.71**
He et al. [14]	13.51	**17.42**	**0.62**	0.49
Qin et al. [15]	15.16	**19.37**	0.65	**0.74**
Zhu et al. [13]	16.58	**17.65**	**0.70**	0.62

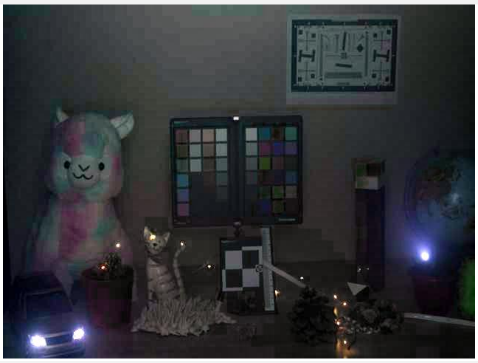
(a)

(h)



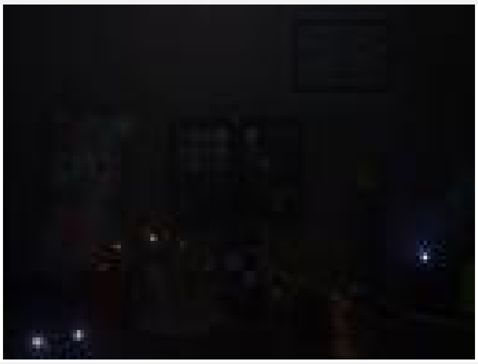
(b)

(i)



(c)

(j)



(d)

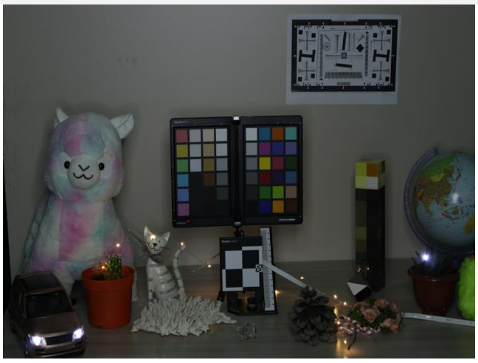
(k)

(e)

(l)

(f)

(m)



(g)

(n)

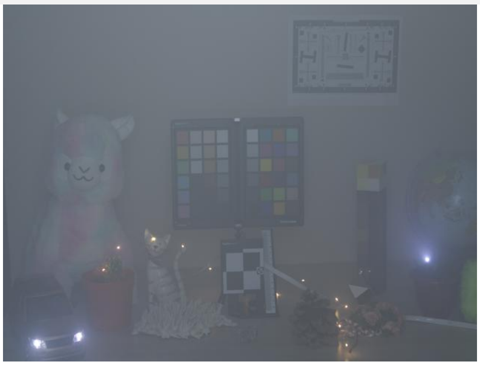


Figure 3: Results of haze removal from images (g) (file 34_indoor_hazy.jpg from the i-haze dataset) and (n) (file stage-2_frame-24_light-2_h3.jpg from the night-haze dataset). Images (a)-(e) correspond to the results of processing (g) by Berman methods et all, Dhara et all, He et all, Qin et all, Zhu et all; (h)-(l) correspond to similar results of image processing (n); (f) – ground truth for image (g); (m) – ground truth for the image (n)

4. Conclusion

The dataset presented in this paper, in comparison with similar datasets, has specific features that make it possible to achieve a more objective quality assessment of the haze removal methods in terms of usage in the real world environment:

1. It contains images taken in low light conditions.
2. There are localized light sources in the frame.

The experimental results demonstrate that the average PSNR on the presented night-haze dataset is better than on the i-haze and o-haze datasets for all methods. This fact can be explained in that it is difficult to estimate the depth map on the images from the night-haze dataset correctly because the difference in the scatter map for neighboring objects turns out to be small due to the small depth of the scene. In addition, the PSNR and SSIM metrics do not seem to give sufficiently correct values when assessing the quality of haze removal in images taken in low light conditions. Further research is aimed at eliminating these shortcomings.

Acknowledgements

This research is funded by Russian Fund for Basic Research, grants 20-07-00441, 20-07-00055.

References

[1] C. Ancuti, C. O. Ancuti, C. De Vleeschouwer, *D-HAZY: A dataset to evaluate quantitatively dehazing algorithms*, in *Proceedings - International Conference on Image Processing, ICIP*, 2016, vol. 2016-Augus, pp. 2226–2230.

[2] B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, Z.Wang, *Benchmarking single-image dehazing and beyond*, in *IEEE Trans. Image Process.*, vol. 28, no. 1, pp. 492–505, 2018.

[3] K. Ma, W. Liu, Z. Wang, *Perceptual evaluation of single image dehazing algorithms*, in *2015 IEEE International Conference on Image Processing (ICIP)*, 2015, pp. 3600–3604.

[4] C. Ancuti, C. O. Ancuti, R. Timofte, C. De Vleeschouwer, *I-HAZE: A Dehazing Benchmark with Real Hazy and Haze-Free Indoor Images*, in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2018, vol. 11182 LNCS, pp. 620–631.

[5] C. O. Ancuti, C. Ancuti, R. Timofte, C. De Vleeschouwer, *O-HAZE: A dehazing benchmark with real hazy and haze-free outdoor images*, in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 2018, vol. 2018-June, pp. 867–875.

[6] C. O. Ancuti, C. Ancuti, R. Timofte, *NH-HAZE: An image dehazing benchmark with non-homogeneous hazy and haze-free images*, in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 2020, vol. 2020-June, pp. 1798–1805.

[7] C. O. Ancuti, C. Ancuti, M. Sbert, R. Timofte, *Dense-haze: A benchmark for image dehazing with dense-haze and haze-free images*, in *2019 IEEE international conference on image processing (ICIP)*, 2019, pp. 1014–1018.

[8] J. El Khoury, J. Thomas, A. Mansouri, *A Database with Reference for Image Dehazing Evaluation*, jbthomas.org, vol. 62, no. 1, pp. 10503–10504, 2018.

[9] F. Cozman, E. Krotkov, *Depth from scattering*, in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1997, pp. 801–806.

[10] H. Koschmieder, *Theorie der horizontalen Sichtweite*, *Beitr. Phys. freie Atmos.*, vol. 12, pp. 33–55, 1924.

[11] D. Berman, S. Avidan, T. Treibitz, *Non-local image dehazing*, in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 1674–1682.

[12] S. K. Dhara, M. Roy, D. Sen, P. K. Biswas, *Color Cast Dependent Image Dehazing via Adaptive Airlight Refinement and Non-linear Color Balancing*, in *IEEE Trans. Circuits Syst. Video Technol.*, vol. 8215, no. c, pp. 1–1, 2020.

[13] Q. Zhu, J. Mai, L. Shao, *A fast single image haze removal algorithm using color attenuation prior*, in *IEEE Trans. image Process.*, vol. 24, no. 11, pp. 3522–3533, 2015.

[14] K. He, J. Sun, X. Tang, *Single image haze removal using dark channel prior*, in *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, 2011.

[15] X. Qin, Z. Wang, Y. Bai, X. Xie, H. Jia, *FFA-Net: Feature fusion attention network for single image dehazing*, in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2020, vol. 34, no. 07, pp. 11908–11915.

[16] R. Kreis, *Issues of spectral quality in clinical 1H-magnetic resonance spectroscopy and a gallery of artifacts*, in *NMR Biomed.*, vol. 17, no. 6, pp. 361–381, 2004.

[17] J. E. Farrell, *Image quality evaluation*, in *Colour imaging Vision and Technology*, pp. 285–313, 1999.

PoS(DLCP2022)019