Low-light Images Haze Removal

Ye Chen

Abstract—This paper proposes a new post-processing pipeline focusing on the haze removal of images captured under low-light condition. Most of the existing haze removal methods are either developed on statistical observation of the daytime hazy images or trained on daytime hazy image datasets, and therefore perform poorly on the low-light hazy images. We introduce an end-to-end system to perform both the low-light image enhancement and haze removal using the input image to obtain a visually brighter and clearer image. This dehazing pipeline can also serve as a pre-processing for object detection and classification algorithms in advanced driver assistant systems and surveillance systems.

Index Terms—Image Dehazing, Visibility Enhancement, Low-light Image, Dark Channel Prior, Convolutional Neural Network

1 Introduction

DRIVING in foggy or rainy night can be a challenging task not only for drivers, but also for car dashboard camera to record a clear view of a vehicle's front screen. In the scene of road accident under the presence of adverse weather, good image quality of dashboard cameras is essential for determining accident liability and for tracking down hit-and-run drivers.

Image dehazing has been an ill-posed inverse problem that draws attention for research. The main cause of the low visibility of hazy images is the absorption and scattering of light by suspended particles in the atmosphere. Drawbacks of foggy scenes include lower contrast in the captured image and a smaller field of view.

The atmospheric scattering model was proposed by McCartney in 1976 that widely used to describe the formation of image in hazy scenes [6]:

$$I(x) = J(x)t(x) + A(1 - t(x)),$$

where I is the observed intensity of the hazy image, J represents the real scene radiance, t represents the medium transmission, A represents the global atmospheric light, and x is the pixel index in the image.

At the condition where fog or haze presented, the visibility of image captured degrades and thus the need of algorithms to recover the image $J'(x)$, which is the estimation of the scene radiance J, with better visibility from the observed hazy image I emerges.

However, most of the existing image dehazing models are either based on statistically observed and computed features or trained on daytime hazy scene datasets. The main challenge posed for this problem is that for daytime, the light source of the scene is usually uniform and not visible in the scene, while in low-light conditions, other non-uniformly distributed light sources can often be introduced into the dashboard camera such as street lights or car lights to create glow in image [1]. Therefore, the daytime dehazing method does not perform equally well on images captured in low-light conditions.

To solve the challenge posed above, this paper studies the existing implementations for low-light image quality adjustment and day-time image dehazing to propose a new image post-processing pipeline, improving the visibility and quality of images captured under low-light hazy scenes.

2 Related Work

In recent years, extensive research have been conducted on image dehazing and different models were leveraged to bring a huge performance boost on this topic.

For day-time image haze removal, the traditional method uses various image prior to retrieve a natural transmission map $t(x)$ and real scene radiance $J(x)$ from the observed image $I(x)$. in 2008, Fattal presented a single image dehazing method to estimate the optical transmission in hazy scenes and then to remove haze by eliminating the measured scatter light [2]. In 2009, He et al. proposed a image prior: dark channel prior based on statistical observation of the haze-free images for effective image haze removal [3]. In 2014, Tang et al proposed a random forest regression model to combine various prior features explored previously to complementarily generate the transmission map.

Besides, machine learning technique has also been applied for day-time image dehazing. In 2016, an end-to-end system for haze removal, DehazeNet, was proposed by Cai et al [4]. It trained a convolutional network network (CNN) to estimate the transmission map. In 2021, Chen et al introduced Principled Synthetic-to-real Dehazing (PSD) framework that pre-trained deep learning-based model on synthetic hazy images and fine-tuned on real hazy images with physical priors.

For low-light image, works have been done on mostly night-time image. In 2015, Li et al. introduced a method for night-time image dehazing that focusing on reducing the effect of light glow on image [1], whose model takes the non-uniform light source presented in the nighttime hazy images into account. In 2016, another method proposed by Zhang et al focused on remove the non-uniform illumination of

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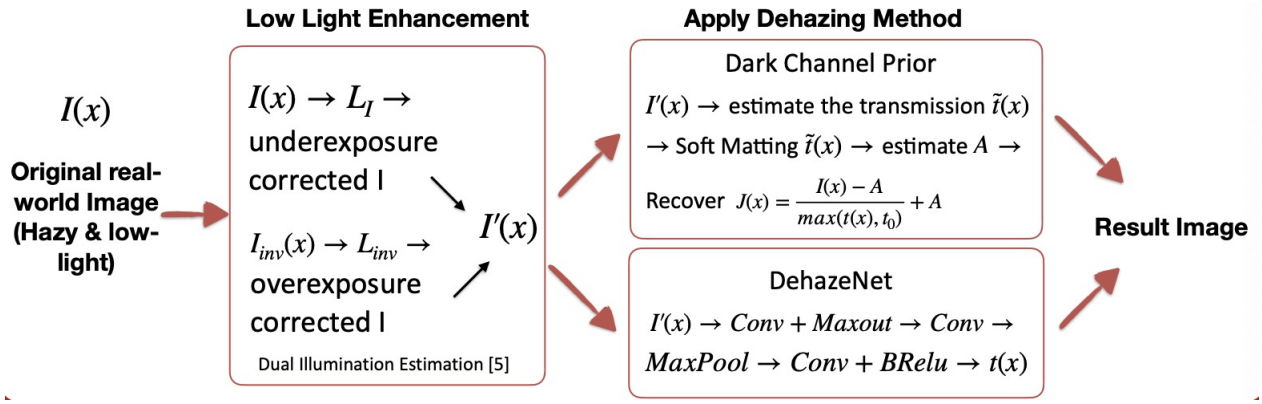

Fig. 1. Processing Pipeline Overview

nighttime image and then dehazed the image with dark channel prior [11].

Our approach uses the day-time image haze removal method using dark channel prior and DehazeNet as the dehazing part of the pipeline, and also implements pre-processing of the low-light image for the day-time haze removal method to generate better results.

3 Proposed Method

We propose a low-light hazy image post-processing pipeline to achieve the objective. The pipeline is divided into the following two parts: the low-light image enhancement and the image dehazing, as shown in Figure 1.

3.1 Low-light Image Enhancement

In observation of the hazy image captured under low-light condition, we discover that the low-light hazy image can not only have under-exposed area caused by dark scene, but also have over-exposed area given the presence of non-uniform light sources in the low-light hazy image, such as the street lights and car lights. Therefore, for enhancing the visibility of low-light image, instead of simply increasing the image brightness, we adopt the dual illumination estimation method proposed in 2019 by Zhang et al [5], which takes both the under-exposure and over-exposure into account for image quality enhancement.

This approach firstly obtain the dual illumination images, which are the forward illumination of input image and the reverse illumination of the inverted input image. The forward illumination image is used to recover the intermediate underexposed corrected image of the input image, while the reverse illumination is for overexposed corrected image. Finally, we apply the multi-exposure image fusion to synthesize the visually clearer exposed output image.

The enhanced example image is displayed in the lower left of Figure 2. This dual illumination enhancement method brings major visual improvement for under-exposed area of the example image.

3.2 Image Dehazing

We experiment with two different types of existing daytime image dehazing model: Dark Channel Prior and DehazeNet. Both methods achieve a plausible haze removal result on daytime image examples by estimating the medium transmission map $t(x)$ of the input hazy image $I(x)$, either using prior or convolutional neural network.

We feed the low-light enhanced image into two different daytime dehazing models to evaluate the output results for low-light images.

3.2.1 Dark Channel Prior

Dark channel prior is one of the most popular image dehazing prior firstly proposed by He et al [1] in 2009. It is a prior based on statistical observation that the haze-free outdoor images contain some pixels that have low light intensities in at least one color channel. This characteristic is then used with the formation of hazy image model to estimate thickness of haze in image and to recover estimation of the haze-free images $J(x)$.

In this pipeline, we adopt the dark channel prior equation of estimating the haze-free image $J(x) = \frac{I(x)-A}{max(t(x),t_0)} + A$ with the enhanced image.

The dark channel prior dehazed images are displayed in the middle of Figure 2. The low-light enhanced, dark channel prior dehazed image is visually clearer than the image without enhancement. However, both images contain color artifacts after processing with dark channel prior dehazing.

3.2.2 DehazeNet

DehazeNet is an end-to-end system with convolutional neural netwprk architecture for estimation of medium transmission $t(x)$ firstly proposed in 2016 by Cai. et al [4].

In this pipeline, we obtain the same architecture of DehazeNet. The architecture has only four layers of convolutional neural networks. The first layer is to use the conv layer followed by the Maxout unit for feature extraction. The second layer is the multi-scale mapping layer, which uses convolution kernels of different sizes in parallel. The third layer is the local extremum achieved by Maxpooling. The final layer uses the conv layer with the Bilateral ReLu activation function to serve as the non-linear regression to obtain the final transmission map. The loss function used for training is the mean square error.

The images processed by DehazeNet are displayed in the right of Figure 2. The low-light enhanced, CNN dehazed image is visually clearer. Also, the CNN-based method does

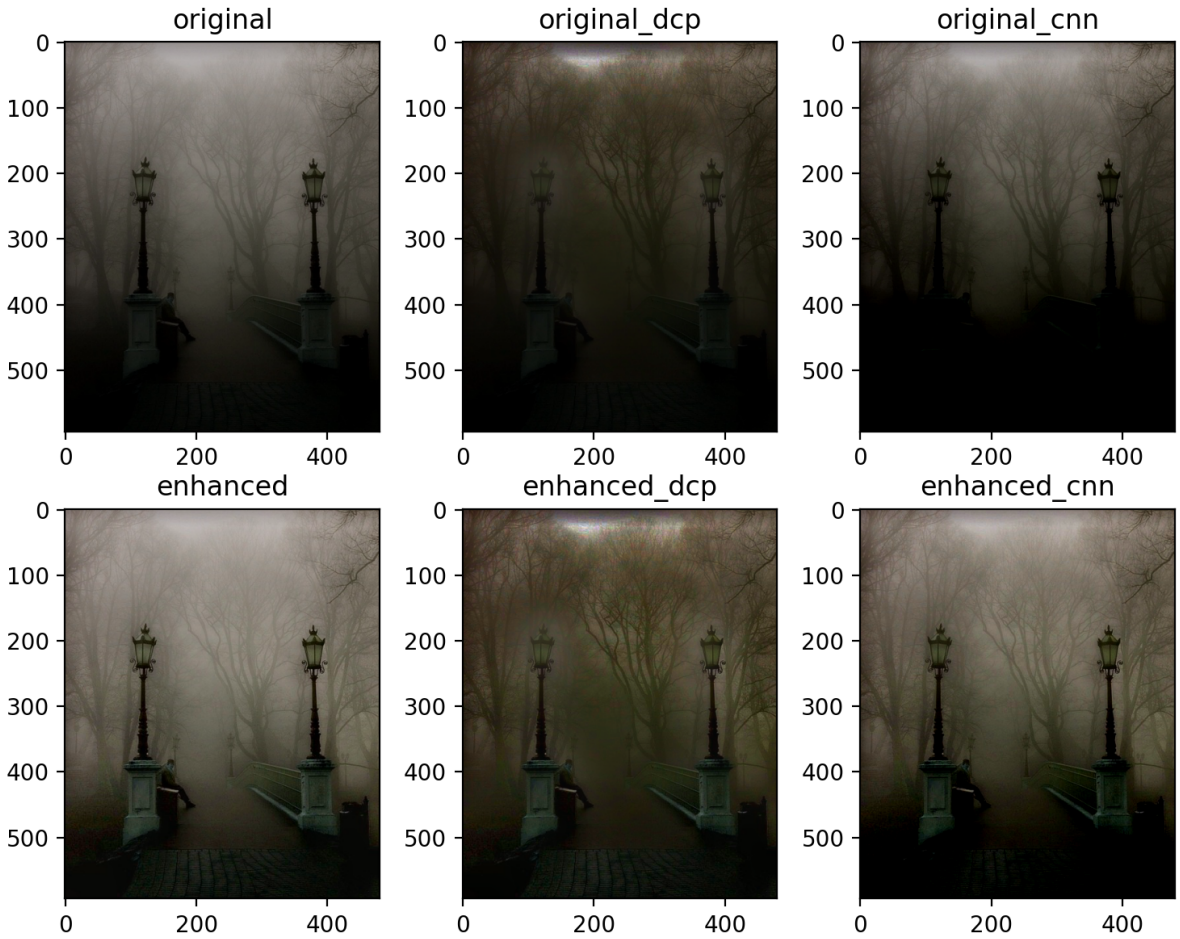

Fig. 2. Example of Processed Image in Pipeline

not introduce new color artifacts to the image while visually increasing the visibility of the image.

4 Experimental Results

We measure the performance of our proposed pipeline with qualitative and quantitative evaluations. Experiments have been conducted on both the Dark Channel Prior (DCP) dehazing model and the DehazeNet Convolutional Neural Network (CNN) model.

4.1 Qualitative Results

While there exists research projects that evaluate the dehazing result using synthesized hazy image, we evaluate the performance of the pipeline using solely real-world low-light hazy images.

All the test images are adopted from real-world nightime hazy image from 3R dataset [8] and ExDark dataset [9].

The results are displayed in Figure 2. We select two real-world hazy images for comparison between different methods.

For the upper image, He et al's method using only dark channel prior does remove haze. However, the visibility of the object in the middle of the image also decreases. Similarly for Li et al's method that separate glows in image. The proposed result with dark channel prior and CNN dehazing did visually remove the haze while keeping the object in the middle recognizable.

For the lower image, similarly, He et al. and Li et al's method both remove the haze while decreasing the visibility of objects in image as it also lower the brightness of the original image. Our method to remove the haze performs visually better in increasing the visibility for objects in image, especially in retrieving the corrected exposure of vehicles in lower right corner of the image.

4.2 Quantitative Results

Given the difficulty of capturing ground truth image for real-life low-light foggy image, we evaluated the performance of this processing pipeline with two reference-less evaluation metric.

The first evaluator we used is the Fog Aware Density Evaluator (FADE) [3], which is a reference-less model to predict the perceptual fog density of a single image based on statistical features of fog. Lower FADE scores represent clearer image. As shown in Table 1, our proposed pipeline with convolutional neural network yield the best FADE score.

The second reference-less evaluator we used is the dubbed blind/referenceless image spatial quality evaluator (BRISQUE) [7]. It is a statistical model used to assess

Fig. 3. The Qualitative Comparisons of original hazy image, He et al's method [1], Li et al's method [2], our proposed DCP method, our proposed CNN method using two different low-light images

the image quality and the "naturalness" of image. Lower BRISQUE score represents better image quality and more natural image. As shown in Table 1, our proposed pipeline with Dark Channel Prior yield the best BRISQUE score.

5 Conclusion

In summary, our approach for low light image haze removal does generate a visually and quantitatively better result than the existing commonly used approach for day-time and night-time image dehazing. One advantage of this pipeline is that it enhances both the under-exposed area and the over-

TABLE 1
The Quantitative Comparison of Image Quality between Different Methods

	FADE ↓	BRISQUE↓
Original Image	0.7479	36.7298
He et al.	0.6591	35.8072
Li et al.	0.2752	28.1834
Proposed (DCP)	0.5406	**22.7432**
Proposed (CNN)	**0.2681**	46.1784

exposed area of the low-light image prior to the dehazing step, which takes the over-exposed part of image caused by non-uniform light source into account to generate results with better visibility.

The limitations of this approach are mainly as the follows: 1. there is a gamma correction step in low-light image enhancement that the parameter is currently manually adjusted based on the input image, and thus this pipeline is not completely automatic; 2. the performance of this pipeline drops when there exists a strong non-uniform light source, e.g. car headlight, in the input image. The model has not yet included a method to account for the glow in image and Tyndall effect.

More evaluation works can be done on further evaluating this pipeline with synthesized image to compute peak signal to noise ratio. Moreover, this model can potentially be further improved with glow part detection and removal, given that we do not specifically handle the glow and illumination caused by non-uniform light source in this pipeline.

6 Project Source Code

The project source code can be found in the link below: https://github.com/cynthiayechen/EE367FinalProjectCode

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References

[1] Kaiming He, Jian Sun and Xiaoou Tang, "Single image haze removal using dark channel prior," 2009 IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 1956-1963, doi: 10.1109/CVPR.2009.5206515.

[2] Y. Li, R. T. Tan and M. S. Brown, "Nighttime Haze Removal with Glow and Multiple Light Colors," 2015 IEEE International Conference on Computer Vision (ICCV), 2015, pp. 226-234, doi: 10.1109/ICCV.2015.34.

[3] L. K. Choi, J. You and A. C. Bovik, "Referenceless Prediction of Perceptual Fog Density and Perceptual Image Defogging," in IEEE Transactions on Image Processing, vol. 24, no. 11, pp. 3888-3901, Nov. 2015, doi: 10.1109/TIP.2015.2456502.

[4] Cai, Bolun Xu, Xiangmin Jia, Kui Qing, Chunmei Tao, Dacheng. (2016). DehazeNet: An End-to-End System for Single Image Haze Removal. IEEE Transactions on Image Processing. 25. 10.1109/TIP.2016.2598681.

[5] Zhang, Qing Nie, Yongwei Zheng, Wei-Shi. (2019). Dual Illumination Estimation for Robust Exposure Correction. Computer Graphics Forum. 38. 243-252. 10.1111/cgf.13833.

[6] E. J. McCartney, "Optics of the atmosphere: scattering by molecules and particles," New York, John Wiley and Sons, Inc., vol. 1, 1976.

[7] A. Mittal, A. K. Moorthy and A. C. Bovik, "No-Reference Image Quality Assessment in the Spatial Domain," in IEEE Transactions on Image Processing, vol. 21, no. 12, pp. 4695-4708, Dec. 2012, doi: 10.1109/TIP.2012.2214050.

[8] Jing Zhang, Yang Cao, Zheng-Jun Zha, and Dacheng Tao. 2020. Nighttime Dehazing with a Synthetic Benchmark. Proceedings of the 28th ACM International Conference on Multimedia. Association for Computing Machinery, New York, NY, USA, 2355–2363. DOI:https://doi.org/10.1145/3394171.3413763

[9] Loh, Yuen Peng Chan, Chee Seng. (2018). Getting to know low-light images with the Exclusively Dark dataset. Computer Vision and Image Understanding. 178. 10.1016/j.cviu.2018.10.010.

[10] K. Tang, J. Yang and J. Wang, "Investigating Haze-Relevant Features in a Learning Framework for Image Dehazing," 2014 IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 2995-3002, doi: 10.1109/CVPR.2014.383.

[11] Zhang, Jing Cao, Yang Wang, Zengfu. (2016). Nighttime Haze Removal with Illumination Correction.

[12] Souhaib Attaiki, Low-light-Image-Enhancement, (2019), GitHub repository, https://github.com/pvnieo/Low-light-Image-Enhancement

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