AN EFFECTIVE SINGLE IMAGE DEHAZING METHOD TO ENHANCE IMAGE VISIBILITY

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Abstract. Foggy or hazy weather conditions, including distance, environmental particle density, wavelength, scattering, and attenuation of air particles, reduce contrast, brightness, and visibility, alter color, and produces unrealistic color grading, which causes issues with image quality. Low-quality image is a major issue in image processing and computer vision, compromising the detection of an object from images. So, image fog or haze removal is one of the most basic and important tasks in digital image processing. We aim to remove fog or haze from digital images. The study evaluated four methods, including the Dark Channel Prior Based method, which showed good results for gray and color images. However, it only processed dehaze images if some portion showed the sky region and had high time complexity. This study provided a method for dehazing and enhancing dehazed images to address these drawbacks. In The method, we first calculated the histogram equalized image, then the minimum channel image, then calculated the transmission map using fog level and, as post-processing, applied a guided filter and the PIL image improvement method, and finally, dehazed an image. It was created for RGB pictures without user input or prior knowledge and is faster and lightweight for real-time applications. The method produced enhanced images with higher contrast, brightness, and high-quality color grading, making it useful in traffic surveillance systems. The implementation was a procedural structured programming model, testing only one image at a time using a 0.9 airlight coefficient.

Keywords: Haze Removal, Histogram Equalization, Airlight Co-efficient Map.

1. Introduction

Haze is a natural occurrence that obscures and reduces visibility, affecting outdoor images due to haze, fog, and smog. When light encounters atmospheric particles, it scatters and absorbs, leading to reduced irradiance along the observer's line of sight. The presence of haze introduces challenges in image dehazing. In their paper 'Vision and the Atmosphere', Narasimhan and Nayar [1] discussed the impact of atmospheric conditions on visibility and highlight the problems faced in image processing and computer vision. Haze causes reduced contrast, low visibility range, color desaturation, and loss of fine details in captured images. These issues severely degrade image quality and hinder tasks such as object detection and scene understanding. Dealing with haze is fundamental, and efficient image dehazing methods are essential for enhancing visibility and improving image quality. If we cannot detect an object in an image, the image is rendered useless. As a result, image fog and haze removal are one of the most fundamental and important tasks in digital image processing.

Submitted: March 25, 2023
Accepted: June 21, 2023
https://doi.org/10.59185/6.12.01.1-12

1.1 Objective

The study explores and enhances image visibility through various individual picture reducing hazing methods. The goal is to select and improve a suitable individual picture reducing hazing technique. The proposed method is analyzed to remove fog or haze from digital images effectively. The suggested approach is contrasted with various dehazing techniques already in use. The evaluation includes qualitative and quantitative analysis of the proposed dehazing method. Our main aim is to advance the field of image dehazing by developing and evaluating innovative techniques to improve image visibility.

1.2 Threat Model

In computer vision applications, the single picture dehazing technique is crucial, for example, surveillance, object detection, and satellite image analysis. There are a lot of dehazing methods exist that have shown excellent results. Nevertheless, these methods have some limitations. Applications that operate in real time cannot be employed with all of these technologies. Our proposed method is much faster and very lightweight for real-time application use. Also, it can give an excellent enhanced image. Our proposed method can produce enhanced images with higher contrast, brightness, and high-quality color grading, which can be helpful in traffic surveillance systems. For single-colored fuzzy photos, the suggested technique produces superior results. However, our proposed method has some limitations. It cannot remove fog from dense foggy images. Also, the color contrast is different from the original image. If the image got a bright scene like the sky, then our proposed method cannot produce a good dehaze image.

2. Related Works

Many researchers have put their effort and time into producing single dehazed images. They have used many algorithms and methods to produce good results.

He et. al. [2] developed a straightforward yet efficient dark channel prior-based approach to eliminate haze from a single input image. It is based on an important finding: in haze-free outdoor photos, most local patch contains some pixels with extremely low intensity in at least one-color channel. Both grayscale and color images exhibit great results from the dark channel prior-based technique. However, unless a piece of the image can be made to display the sky region, this approach cannot process a dehaze image. Moreover, this method takes much time and cannot dehaze dark photos. Gaofeng Meng's Boundary constraint and contextual regularization approach [3] is another technique for reducing hazes from a single input image. Investigating the intrinsic boundary constraint of the transmission function is quite advantageous for this strategy. This constraint is an optimization problem with a weighted L1 norm-based contextual regularization to estimate the unknown scene transmission. The border constraint and contextual regularization method work well for dehazing natural color or grayscale photos. Nevertheless, this technique yields erroneous results for general image dehazing. Zhu et. al. [4] color attenuation prior-based method is simple but effective. By creating a linear model to represent the scene depth of the hazy image under this unique prior and learning the model's parameters using supervised learning, the depth information may be efficiently recovered. This method is speedy and efficient in single-image dehazing, which is critical in real-time computer vision applications. However, this method produces unrealistic color effects for single hazy images, and the color contrast is very low compared to other image dehazing algorithms.

Because there are inevitable uncertainties in assessing airlight color, Sami et. al. [5] presented a method employing haze levels to estimate the transmission map. Furthermore, they have proposed two metrics for evaluating haze removal algorithms based on natural outdoor image statistics. The benefit of this method is that it has better color contrast than the other existing dehazing methods and lower time complexity. However, this novel dehazing method produces high color contrast, which can sometimes be unusual and unnecessary

[6]. In conclusion, after explaining all these methods, we can see shaded channel earlier approach -based method and boundary constraint and contextual regularization method shows better results on dehazing a single image. However, these methods cannot produce a higher contrast image. So, these images suffer from low visibility. However, novel image dehazing methods produce better images with higher contrast and better visibility than other individual picture reducing hazing methods [7].

2.1 Overview

With the advancements in computer technology, numerous methods for single image dehazing have been proposed. These proposed method shows good results, but cannot produce satisfactory dehazing image [8]. The problem with some existing method is:

- The majority of existing methods produce high-quality images but have a high time complexity.
- These images suffer from low contrast and low visibility.
- Some method gives unrealistic color effect.

For further analysis we evaluated and improved the Dark Channel Prior Method for one-shot reducing hazing [9].

2.2 Dataset

The image dataset from Ancuti [10] was used. It is called NH-Haze image dataset. This dataset has lots of foggy images with ground truth of these images. This helps us to compare our output image data with the ground truth image. We have also used some local foggy image data for our research like fig. 2 and fig. 4. Its help us to analysis the images more efficiently and compare the output with ground truth of the image.

2.3 Methodology Design

Haze Image Formation

We can easily identify a quality image by seeing it and also can determined whether the image has haze or fog. But a computer system cannot understand an image like human. That’s why an image has to formulate with an equation. According to Saad Bin Sami [5], Image formation in haze/fog is modeled as follows:

$$I(x) = J(x)\, t(x) + K\,(1 - t(x)) \quad (1)$$

Here, I(x) = Observed hazy image. J(x) = Scene radiance / observed light scattering in the medium. t(x) = Observed light without scattering in the medium. K = Global atmospheric airlight coefficient / environmental illumination. So, if we want remove haze from the image, we can explore the haze image equation like, Haze free image restored as follows:

$$J(x) = (I(x)-K)/(t(x)) + K \quad (2)$$

Therefore, given a hazy image if we could estimate the observed light without scattering in the medium t(x) and global atmospheric airlight coefficient or environment illumination K, then we can remove haze and increase the contrast of the input haze image and obtain a haze free image.

3. Proposed Method

We've suggested a single-image removing hazing technique based on the novel image dehazing method [4] with pre-processing and post processing of the target image. We gave a small overview of the proposed method below and then in next section we will discuss this method overall.

A step wise overview of the proposed single image dehazing method given below:

a. First, we take the single hazy image as input.
b. Then we applied histogram equalization as pre-processing of the hazy image.
c. In this method observed light t(x) and airlight coefficient (K) is calculated without using dark channel. [Note: dark channel is combination of minimum pixel value of RGB channel and 15*15 filter]
d. Uses average filter for smoothing the image to reduce noise.
e. Apply guided filter for preserving the picture's edges.
f. Then restored the image with filtered image and original haze image.
g. Finally applied PIL image enhancer for the further enhancement as post processing.

Here, we showed the Block diagram of the proposed single image dehazing method. The block diagram is explained in fig. 1.

3.1 Methodology Steps

Pre-Processing

As a preprocessing step for a specific hazy image, we employed histogram equalization. The histogram serves as a graphical representation of the pixel intensity values in the image, containing the frequencies of each pixel intensity level. Histogram equalization is an image processing technique that enhances contrast by modifying the image's histogram. This adjustment involves expanding the intensity range or redistributing the most frequently occurring pixel intensity values to increase contrast. The objective is to enhance low-contrast areas of the image, resulting in improved contrast overall [10].

Image Model for Attenuation and Airlight

Before it reaches the camera, air particles scatter and absorb light that has been reflected from the scene, according to [4]. The size of the medium's particles and the degree of light scattering both affect how much the image degrades. The equation illustrates how light scattering grows as a function of scene depth:

$$E(d, \lambda) = E(0, \lambda)\, e^{-\beta(\lambda)d} \tag{3}$$

In the given equation, d denotes the scene depth, while β represents the total scattering coefficient, indicating how effectively a medium scatters light of a specific wavelength in all directions. E(d, λ) corresponds to the irradiance at x = 0, and E(d, λ) denotes the irradiance at the observer, specifically x = d. This irradiance accounts for the light that has undergone attenuation during its journey from the scene to the observer.

According to [4,] the color shift in the scene is caused by additive noise in the irradiance that the observer receives. It frequently turns the scene's colors grayish-whitish and makes the airborne particles act as sources of light. This is how it is written:

$$L(d, \lambda) = K(1 - e^{-\beta(\lambda)d}) \tag{4}$$

Where K is the proportionality constant, and the exact characteristics of the scattering function define its value. When the attenuation equation (1) and the airlight model equation (2) are combined, we get:

$$\text{Observed light} = \text{Attenuated light} + \text{Additive Airlight} \quad (5)$$

Let, E (d, λ) = I, $e^{-\beta(\lambda)d}$ = t and observed light = J, then our model can be written as::

$$I(x) = J(x)t(x) + K(x)(1 - t(x)) \quad (6)$$

Estimation of Transmission Map

Transmission estimation is crucial for fog thickness determination. The transmission map, denoted as t(x), represents the fraction of unscattered light reaching the observer. According to Sami et. al. [4], the transmission map is inferred to be small based on statistical analysis, as the product of the lowest channel of a haze-free image and its transmission map approximates zero. The transmission is initially calculated as follows:

$$I(x) = J(x)t(x) + K(x)(1 - t(x)) \quad (7)$$

Where, I(x) = Observed hazy image; J(x) = Scene radiance / observed light scattering in the medium; t(x) = Observed light without scattering in the medium; K = Global atmospheric airlight coefficient / environmental illumination.

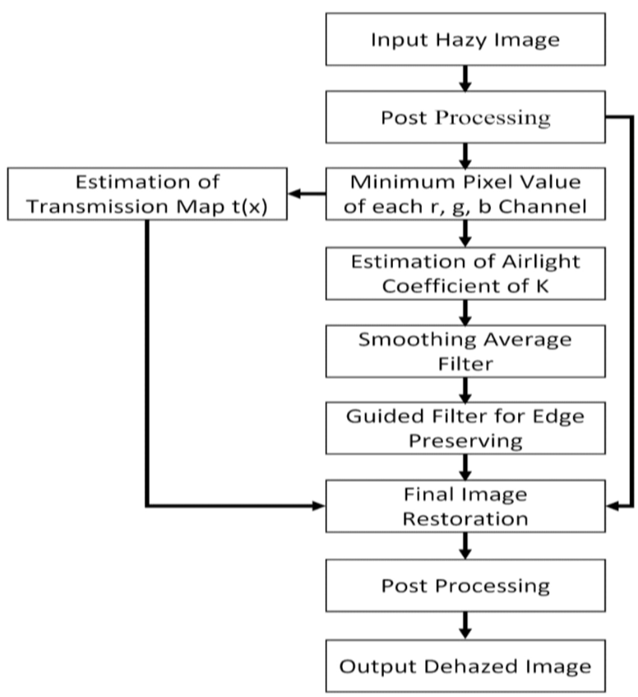

Fig. 1. Block diagram of proposed single image dehazing method

Taking the bare minimum of each channel,

$$\min_{c\in\{r,g,b\}}(I(x))= \min_{c\in\{r,g,b\}}\big(J(x)\big)t(x) + K(x)(1 - t(x)) \quad (8)$$

The term $\min_{c\in\{r,g,b\}}\big(J(x)\big)t(x)$ is negligible in this case due to the low values of the transmission map and the resulting minimum operation on each color vector. Hence, the above equation can be simplified to,

$$\min_{c\in\{r,g,b\}}(I(x)) = K(x)(1 - t(x)) \tag{9}$$

By solving the aforementioned equation, we obtain the value of t(x) as follows,

$$\check{t}(x) = 1 - \omega\,(\min_{c\in\{r,g,b\}}(\frac{I(y)}{K})) \tag{10}$$

Where ω is set to 0.95 to allow for some haze in order to preserve the natural look. Because this formula is derived by ignoring the lower value term $\min_{c\in\{r,g,b\}}\big(J(x)\big)t(x)$, the transmission estimation would be rough. As a result, normalizing it with a lower value will compensate. As a result, we employ:

$$\check{t}(x) = \frac{1 - \omega\,(\min_{c\in\{r,g,b\}}(\frac{I(y)}{K}))}{1-\beta} \tag{11}$$

Where, β is defined as :

$$\beta = \operatorname{mean}_{c\in\{r,g,b\}}(I) - \min_{c\in\{r,g,b\}}(I) \tag{12}$$

K = f (haze (depth))

The only unknowable variable in K is (8). Tests were conducted to estimate the unknown variable in K, revealing that its value varies geographically and with the quantity of haze. The value of K increases as haze or fog levels rise and also varies within homogenous zones and with scene depth. K represents the hazard level, while a local value of K (K = 0.5) suits the foreground region. However, the background area is undervalued, resulting in burnt pixels. Mathematically, this can be expressed as follows:

Estimating Airlight Coefficient K

The preceding discussion highlights the influence of scene depth on haze levels, indicating that haze persists locally within specific regions. Consequently, it becomes essential for the airlight coefficient, K, to possess a locally homogeneous value. To achieve this, we leverage a characteristic found in naturally captured outdoor photographs, where the grayscale representation of a hazy image exhibits higher values compared to its corresponding non-hazy image. Based on this observation, the calculation of K follows a specific procedure. To initiate the process, we determine the provided foggy image's grayscale value [11].

$$C(x) = \frac{Ir+Ig+Ib}{3} + \alpha \tag{13}$$

Where (r, g, b) denotes the red, blue, and green color channels of the input image I, and is the color distortion constant whose value is estimated as:

$$\alpha = \mu 1 - \mu mc \tag{14}$$

Where, μ1 is the mean of the input image I. It is the single value and μmc is the mean of minimum channel of I. Mathematically,

$$\mu 1 = \operatorname{mean}(\operatorname{mean}_{c\epsilon\{r,g,b\}}(Ic)) \tag{15}$$

Where, $\underset{c\epsilon\{r,g,b\}}{\text{mean}}(Ic)$ returns the mean of each channel and,

$$\mu mc = mean\ (\underset{c\epsilon\{r,g,b\}}{\text{mean}}(Ic)) \quad (16)$$

Given that the haze level remains constant locally, we employ an average filter to smooth C(x).

$$C(x)_{avg} = \underset{y\epsilon\Omega(x)}{\text{average}}(C(y)) \quad (17)$$

Where, Ω (x) is the filtering window centered at pixel x, and then and then apply the guided filter [7] to maintain edge-preserving properties.

$$K\ (x) = guidedfilter\ (I,\ p = C(x)_{avg}\ ) \quad (18)$$

To ensure that K does not become excessively low, we establish a lower bound for its value.

$$K\ (x) = \max\ (K\ (x),\ K_0) \quad (19)$$

In this case, K_0 is initially set as 0.75. However, its value can vary within the range of 0.75 to 0.95 to achieve optimal results.

Flaws in Airlight Estimation

Various methods exist to estimate A using a bright object in the scene. However, the dazzling white object does not reflect the skylight hue consistently. The original DCP approach initially selects the top 0.1 percent of dark channel pixels as indices. Based on these indices, the maximum intensity pixel in the hazy image is determined. The accuracy of A estimation is influenced by patch size, with larger patch sizes providing more accurate results but requiring more computational resources. The patch size should be large enough to encompass the entire brilliant object in the scene, which varies in size across images. In the absence of a sky region, a pixel from the foreground is chosen to approximate A, aiming for greater accuracy. The value of the airlight coefficient K is determined to eliminate any ambiguity [12].

Post-Processing

To enhance the output dehazed image, we employed the Python PIL image enhancer for post-processing. Adjustments were made to the image's contrast, brightness, and sharpness to achieve a desirable result. The post-processed image exhibits enhanced quality and is free from haze compared to the hazy input image. Several methods exist for calculating A using a bright object or scene point. However, it is not always the case that a dazzling white object accurately reflects the skylight hue. This discrepancy often leads to an overestimation of the global air light constant. Calculating the value of K becomes crucial in effectively removing haze from an image [13].

4. Results and Analysis

4.1 Overview

We have tested our dehaze method with various popular images used in other researchers' work. We also tested our method with a local area image captured in digital mobile cameras. Our implementation of the method is a procedural structured programming model, so we had to test only one image at a time. We have used 0.9 as the airlight coefficient. So, our image shows much contrast due to the higher airlight coefficient. Experimental Results are shown in the following part.

4.2 Qualitative result of different dehazing methods

Result from Image Dataset

In this section we showed input hazy image with the dehazed output image in fig. 2 and fig. 3 consecutively from the dataset that we used from [5].

Result of Local Image Dataset

In this section we showed input hazy image with the dehazed output image in fig. 4 and fig. 5 consecutively from the local dataset.

Fig. 2. Input dehaze image

Fig. 3. Output dehaze image

Fig. 4. Input dehaze image

Fig. 5. Output dehaze image

4.3 Comparison Result of Different Dehaze Method

Comparison results of Aerial hazy image

Through figs. 6, 7, 8, 9 we showed the difference between the different dehaze methods.

Comparison results of local hazy image

Fig. 6. Color Attenuation Prior Method

Fig. 7. Dark Channel Prior Method

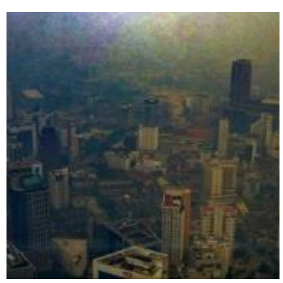

Fig. 8. Boundary Constraint And Regularization

Fig. 9. Proposed Method

Through fig. 10, 11, 12, 13 we showed the difference between the different dehaze methods.

Fig. 10. Color Attenuation Prior Method

Fig. 11. Dark Channel Prior Method

Fig. 12. Boundary Constraint And Regularization

Fig. 13. Proposed Method

4.4 Comparison of Different Image Histogram

Comparison of Normal Haze Image Histogram

Through fig. 14, 15, 16, 17 we compared the normal haze image histogram.

Comparison of Dense Haze Image Histogram

Through fig. 18, 19, 20, 21 we compared the normal haze image histogram.

Fig. 14. Input dehaze image

Fig. 15. Output dehaze image

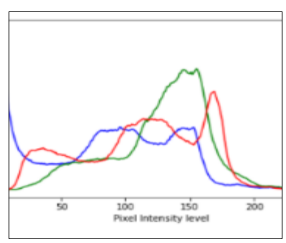

Fig. 16. Histogram of input image

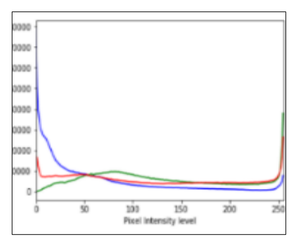

Fig. 17. Histogram of output image

Fig. 18. Input dehaze image

Fig. 19. Output dehaze image

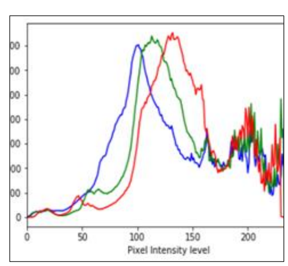

Fig. 20. Histogram of input image

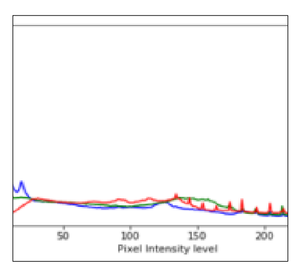

Fig. 21. Histogram of output image

4.5 Quantitative Result Based on Theory of Dark Channel

They proposed a metric based on dark channel theory in paper [2]. As a result, we computed the MSE (mean square error). In this method, the pixel values of corresponding pixels in both hazed and haze free images are compared. Using Python OpenCV, we input the original, foggy/hazy image and output the haze-free image to calculate the MSE. We can express it mathematically as [14]:

$$\alpha = \frac{\sum_{x=0}^{M-1} \sum_{Y=0}^{N-1} (D(x,y) - \widehat{D}(x,y))}{MN} \tag{20}$$

The dark channel is characterized by dimensions M and N. D represents the dark channel prior to haze removal, while $\widehat{D}$ represents the dark channel after haze removal [15]. While this metric provides an accurate measure of haze reduction, it can be misleading due to potential color distortion.

Table 1. Quantitative and Comparison of different dehaze method

Images	Boundary Constraint	Color attenuation	Dark channel	Proposed method
Aerial hazy city (Fig. 6)	0.1675444	0.049408	0.1685687	0.1014376
Dense foggy road (Fig. 10)	0.1431206	0.0205687	0.1420822	0.0822317

Various hazy images were analyzed using different dehaze methods, employing both qualitative and quantitative measurements. A comparison was made between the proposed method and another dehaze technique. The objective was to enhance color contrast while preserving the image's original quality. Brightening The color of the foggy image was attempted, and the condition of the output dehaze image was assessed. Our single-image dehaze method was tested on various hazy images. It performed well on a standard hazy image, but the sky region appeared slightly darker. However, it underperformed on dense foggy images, with abnormal scene depth color contrast. Overall, our method showed good performance compared to another dehazing method.

5. Conclusion and Future Work

5.1 Conclusion

In conclusion, this research estimates the airlight coefficient map for effective haze removal and color contrast improvement. The proposed method showed promising results. The results of the proposed method exhibited good visibility and brightness, and the evaluation metrics were based on haze theory, explicitly quantifying the amount of haze removed. This approach ensures that the assessment of haze removal algorithms aligns intending to reduce haze. The method employed histogram equalization as a pre-processing step, which enhanced the foggy image by increasing its contrast. This technique also highlighted dark regions while clearly distinguishing between dark and white pixels. Haze removal was then performed using the haze line method, then the final contrast of the dehazed output image was adjusted using the Python Imaging Library. The proposed approach demonstrated efficient fog removal by extracting more details in foggy regions compared to other methods. Even in dense fog images, nearby objects were clearly visible, although there were some color artifacts and blurring in distant objects. While the final output of the proposed method may not be as clear as the input hazy image, substantial efforts were made to remove as much haze as possible and enhance the image quality for potential computer vision applications. While using the proposed method on both standard hazy images and dense hazy local image datasets, the method worked well with normal haze images, producing dehazed results that appeared relatively normal, albeit slightly darker in the sky region. However, when applied to dense foggy images, the proposed method did not perform effectively and underperformed in terms of haze removal. Additionally, the color contrast of scene depth in the dehazed output did not look normal. Despite these limitations, the proposed method's overall performance was considered reasonable compared to other dehazing methods.

5.2 Future Work

Image dehazing improves the aesthetic quality, contrast, and image information quality in computer vision applications and data collection. In future this method can be improved more and used for Computer [16] Vision application like surveillance system, object detection and traffic system. Also, there is need to work on the color effect of this dehazing method for obtain realistic image.

References

1. S.G. Narasimhan and S.K. Nayar, "Vision and the Atmosphere," in International Journal of Computer Vision, vol. 48, pp. 233-254, 2002.
2. K. He, J. Sun, and X. Tang, "Single Image Haze Removal Using Dark Channel Prior," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 12, pp. 2341-2353, Dec. 2011.
3. G. Meng, Y. Wang, J. Duan, S. Xiang, and C. Pan, "Efficient image dehazing with boundary constraint and contextual regularization," in Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 617-624, 2013.
4. Q. Zhu, J. Zhang, M. Zhang, and L. Xu, "A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior," in IEEE Transactions on Image Processing, vol. 24, no. 11, pp. 3522-3533, Nov. 2015.
5. S. B. Sami, A. Moosa, D. J. Borikar, and H. T. Rauf, "A Novel Image Dehazing and Assessment Method," in Proceedings of the IEEE, pp. 72-77, 2019.
6. X. X. K. J. C. Q. a. D. T. B. Cai, "Dehazenet: An end-to-end system for single image haze removal," IEEE Trans. Image Process, vol. 25, no. 11, pp. 5187-5198, 2016.
7. M. N. D. a. J. W. Chen Chen, "Robust image and video dehazing with visual artifact suppression via gradient residual minimization," Proc. Eur. Conf. Computer Vision, pp. 576-591, 2016.
8. H. W. Y. L. Y. H. Y. L. Keyan Wang, "Quantitative Performance Evaluation for Dehazing Algorithms on Synthetic Outdoor Hazy Images," Access IEEE, vol. 6, pp. 20481-20496, 2018.
9. C. O. Ancuti and C. Ancuti, "NH-HAZE: An Image Dehazing Benchmark With Non-Homogeneous Hazy and Haze-Free Images," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, pp. 444-445, 2020.
10. A. Levin, "A closed form solution to natural image matting," Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), vol. 1, pp. 61-68, 2006.
11. S. Apurva Kumari, "Real Time Visibility Enhancement for Single Image Haze Removal," Procedia Computer Science , pp. 501-507, 2015.
12. R. Fattal, "Single Image Dehazing," SIGGRAPH, pp. 1-9, 2008.
13. K. S. W. W. H. F. M. M. R. N. N. K. Kenji Enomoto, "Filmy Cloud Removal on Satellite Imagery with Multispectral Conditional Generative Adversarial Nets," Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 1533-1541, 2017.
14. S. K. N. S. G. Narasimhan, "Chromatic Framewok for Vision in Bad Weather," CVPR, vol. 1, pp. 1-9, 2006.
15. J. Y. Shengdong Zhang, "Single Image Dehazing Using Fixed Points and Nearest-Neighbor Regularization," Asian Conference on Computer Vision, vol. 10116, pp. 18-33, 2017.
16. H. W. R. L. M. A. R. X. H. S. L. N. M. K. Shilong Liu, "Image De-hazing Based on Polynomial Estimation and Steepest Descent Concept," Vision Image and Signal Processing (ICVISP) 2017 International Conference on, pp. 63-70, 2017.