Dehazing Foggy Images Using Dark Channel Prior Method

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Abstract—This paper addresses atmospheric haze's impact on visible camera sensor image quality. It introduces the Darka Chennel prior (DCP) as a novel solution to the Dehazingproblem. DCP exploits natural outside image characteristics, when near zero intensity of single color within local window indicates significant reduction of reference in the images segment.

The four steps are included in dehazing process based on DCP includes Atmospheric light estimate, transmission map computation, Transmission map refinement, and Image restoration. This systematic approach offers a stepwise solution to the complex inverse problems. The paper provides a detailed survey and experimental analysis of DCP-based methods,highlighting their effectiveness in image dehazing steps. The insights gained aimed to provide the development of advanced image dehazing algorithms.

Keywords: Dark Channel Prior, ImageRestoration.

1. INTRODUCTION

Image dehazing has been a focal point of research for over a decade. Typically, the challenge of haze or mist arises from unfavorable weather conditions, contingent on particle characteristics, dimensions, and concentration. Unfavorable weather conditions induce shifts in color and diminish image or video contrast. Alterations in color or contrast significantly impact objects or surveillance systems.

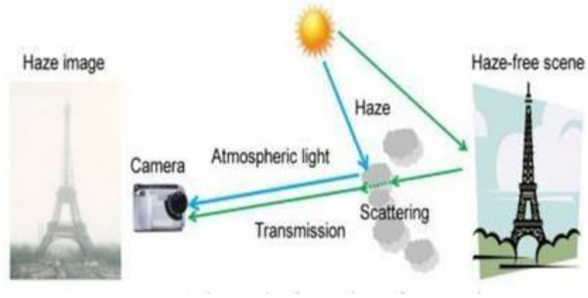

Figure 1: Creation of a Hazy image

This above figure shows the formation of haze image. The light from the object is get attenuated and scattered by the atmospheric particles like fog, haze, mist etc. This is known as attenuation. A little amount of light from the source also get scattered and go towards the camera is called the airlight. This Model is used find the Transmission Map and Atmospheric light. Airlight and attenuation which will affects the clarity of the image.

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

Where, J(x) = clear scene,

A = Atmospheric light,

t(x) = transmission value

I(x) = observed hazy scene,

Transmission map value is given by:

t(x) = $e -\beta(\lambda)d$

Where β is scattering coefficient, d is scene depth.

There are mainly two distinct image dehazing process types: Diurnal and nocturnal dehazing.

Diverse dehazing techniques are available for daytime scenarios. The daytime haze model is encapsulated by a linear equation, comprising a transmission map and the atmospheric light. Successful daytime dehazing image generation hinges on the accurate estimation of the corresponding transmission map and airlight. Beyond daytime dehazing, addressing nocturnal dehazing is a noteworthy endeavor.

In nocturnal conditions, dehazing poses a formidable challenge, as atmospheric light varies across the entire image. Unlike daytime dehazing, this is primarily cause due to the influence of various light sources like street lights and vehicle lights. Consequently, the block effect is introduced to the image under these circumstances.

2. LITERATURE SURVEY

Codruta Orniana Ancuti proposed a Multi - scale image fusion methodology as a singular approach to image dehazing. This fusion-based technique incorporates inputs and weights derived from the hazy image. To generate two inputs, White balancing and Contrast Enhancement are applied on the original hazy image. While executing contrast enhancement, some image details may be sacrificed. To address this, appropriate weight maps are introduced. All weight maps are then applied to both inputs. Subsequently, the weight maps for both inputs undergo normalization. The final step involves weighting the inputs using specific weight maps to preserve the most crucial detected features.

For the normalized weight map, a Gaussian pyramid is computed. A Laplacian pyramid is then formed from the Gaussian pyramid, obtained by subtracting the extended Gaussian pyramid from the levels in the Gaussian pyramid. Atlast, all the levels are compressed in a bottom-up way.[1].

Metwaly, K., Li, X., Guo, T., & Monga, V. (2020). In this proposed deep learning network design, that directly find the haze free image or haze model parameter such as atmospheric light or transmission map. It takes the help of inverse haze model which uses DenseNet encoder and four distinct decoder to estimates the transmission map along with given atmospheric value. The main advantage is that uses for non-homogenous image dehazing. The main disadvantage is that cannot be applied for dense haze [2].

Park, J., Han, D. K., & Ko, H. (2020). Proposed heterogeneous adversarial network fusion for outdoor dataset. This technique consists of fusion of cycle generative adversarial network (GAN) and conditional GAN. Cycle GAN train outdoor dataset and gives clear output while conditional GAN preserve texture detail. This techniques work well for both synthetic and real world in future need to work for dark images [3].

Ren, W., PanCao, X., & Yang, M. H. , J., Zhang, H., (2020). Proposed the image dehazing problem via multi scale deep network which learns effective feature to learn scene transmission better as compared to traditional for a single hazy image. In multi scale model, a holistic computation of the scene transmission is learned by using the scale network and then to refineit use a fine scale network using the local scale information from the outcome of the -scale network.

In addition, used holistic edge guided network to assure that the objects should have the same transmission value for same depth. The outcome shows that this method will not work good for thick haze and night time hazy image in future better prediction of Atmospheric light is needed [4]

Liu, X.., Shi, Z., Ma, Y., & Chen, J. GridDehazeNet uses three steps ie. Pre-processing, backbone andpost-processing. The post processing uses CNN which train and generate learned input. The backbonemodule on a grid network implements a novel attention based multi scale estimation. The post processing module decreases the artifact in the final output. The main disadvantage is that not used for non- homogenous haze [5].

Yang, X., Li, H., Fan, Y. L., Li, H., & Chen, R. (2019). A region detection network is to learn in a patch wise manner relationship between input foggy image and medium transmission map. The Transmission map is then used to remove haze from image by the work of an atmospheric scattering model to enhance the detail of de-hazed images. CNN consists of two types of network units which can be trained in an end to end manner. One networkunit is module with the residual structure that facilitates the learning process of deep network. The another is a novel module cascaded cross channel pool, fuses multilevel haze relevant features and boosts the abstraction ability of the model on a non linear manifold. Moreover, an evolutionary based enhancement method is developed to make better the level of over smoothed results. In some case visual artifact may occur during image dehazing process [6]

Yang, Y., Bian, K.., Hu, Z., & Song, L. (2019, April). An Image sensingNet technique is used for predict and monitoring of air quality which utilizes UAV camera. It uses deep CNN and haze features for direct learning between hase images and corresponding air quality index. Image SensingNet has been deployed on two university campuses for daily monitoring and forecasting. The main advantage of this method is provide a good inference accuracy [8].

Yibo Tan : Image dehazing process is a challenging task for the current dehazing techniques for removing the block effect and also working according with object that is also same to light. For finding a solution to this problem, a single image dehazing process based the on superpixels and markov random field (MRF). This markov random field improves the clarity of the hazy image. Estimation of Transmission map is using the superpixels and MRF. The propoesd technique protect the edge details of the original image successfully. The segmentation is applied on the superpixels using simple linear iterative clustering method where the artifacts are found. For extract the halo effect correspondence between component pixels and super pixel are choosen. For detecting the super pixels multivariate gaussian distribution function is used. Super pixels that are not at the structural boundaries have similer scene depths and transmission. The adopted transmission map is measured by using the minimizing energy function. The three terms are being used for calculating energy function. First the dataterm indicates supe rpixel is having the Transmission map. Secondly neighbor term denotes the intensity between the supe rpixels.

Ultimately, the smooth term indicates the probability of neighbor pixels have same transmission map. Data term resolves the incorrectly calculated transmission map. The Markov random field method not build block effect on the edges. MRF preserves the boundary efficiently.[9]

3. PROPOSED SYSTEM

The proposed dehazing system uses the Dark Channel Prior (DCP) algorithm to enhance visibility in foggy images. The algorithm calculates the dark channel for the input foggy image, estimates atmospheric light, and computes a transmission map. Leveraging this map, the system then performs image dehazing, attenuating the haze and producing a clearer output. The approach is computationally efficient and cost-effective, offering improved visibility and detail in foggy conditions. However, the method's efficacy may vary based on input characteristics, and it may not handle extreme scenarios and more advanced image dehazing techniques.

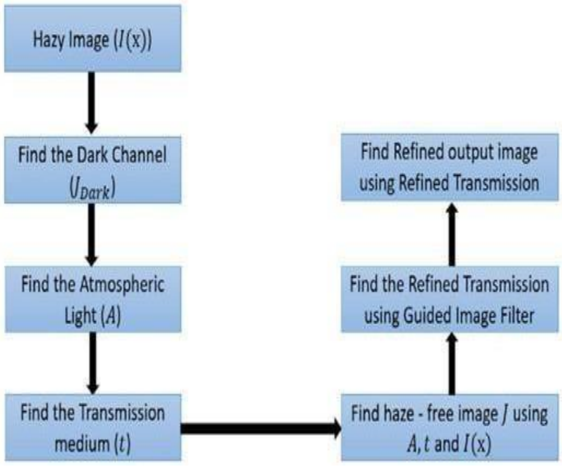

Figure 2: Architecture diagram

Input Foggy Image: The system takes a hazy image as the input, which is characterized by reduced contrast, color distortion, and limited visibility of distant objects.

1. **Dark Channel Prior Algorithm:** The system takes a hazy image as input, which is characterized by reduced contrast, color distortion, and limited visibility of distant objects.

2. **Dark Channel Prior Algorithm:** The objective of the proposed system lies in the application of the Dark Channel Prior method. This algorithm exploits the statistical regularity that dark channels in haze-free images are often very poor in intensity.

3. **Dark Channel Computation:** The Dark channel of the input foggy image is computed by finding the minimum intensity value in a local window for each pixel. This dark channel represents the transmission of the hazy image and provides insights into the percentage of haze in different regions.

4. **Estimation of Atmospheric Light:** The next step involves estimating the atmospheric light, which be light scattered by the haze in the image. This is typically achieved by analyzing the intensity values of the dark pixels in the dark channel.

5. **Transmission Map Calculation:** Using the dark channel and the atmosphere light estimation, the system calculates the transmission map. The Transmission map describes how much light is transmitted through the haze in different parts of the hazy image.

6. **Image Dehazing:** The transmission map is then applied to perform image dehazing. The haze is attenuated based on the estimated transmission values, resulting in an enhanced, haze-free image.

7. **Post-Processing (Optional):** Additional post-processing techniques may be applied to further improve the quality and clarity of the dehazed image. This can include color correction, contrast adjustment, or other enhancement methods.

8. **Output Dehazed Image:** The final outcome of the system is a dehazed image that exhibits improved visibility, reduced haze, and enhanced details. This image is ready for analysis, interpretation, or further processing as needed.

4. TRAINING MODEL

Creating a model for dehazing foggy or hazy images using Dark Channel Prior (DCP) involves several key steps. Initially, a dataset comprising foggy and haze-free image pairs is compiled, and some preprocessing techniques are used for consistency. The model, often a Convolutional Neural Network (CNN), is designed to learn the mapping from foggy to haze-free images. A loss function, like Mean Squared Error, guides the model's training. The dataset is split into training, validation, and testing sets, facilitating effective training and evaluation. The model undergoes optimization, with regular monitoring to prevent overfitting. Post-training, it is tested on unseen foggy images, and refinement may be carried out based on performance. Ultimately, the deployed model offers a practical solution for enhancing visibility by dehazing foggy images across diverse real-world scenarios.

5. MODEL PERFORMANCE

Model performance in dehazing images using Dark Channel Prior is assessed through various metrics such as Mean square error (MSE), Structural Similarity Index (SSI), and Peak Signal- to-Noise Ratio (PSNR). Lower MSE and higher SSI and PSNR values give better reconstruction accuracyand image quality. Additionally, qualitative assessments by human evaluators are crucial for gauging perceptual quality, considering factors like clarity and color fidelity.

Ongoing refinement and validation against various datasets are usefull for enhancing and ensuring the robustness of the model's performance.

6. IMPLEMENTATION

In computer the atmospheric scattering model is commonly used to explain fundamental framework for understanding how haze or fog affects input image formation. This model is divided into a foggy image into two main components: the directreflection of light from objects attenued by the fog and the reflection from the fog particles themselves within that medium.

$$I(x) = J(x)t(x) + A(1-t(x)). \quad (1)$$

In equation (1), 'I' represents the how much intensity of the hazy image, 'J' stands for dehazed image (which is also the clear, haze-free image), 'A' denotes the atmospheric light, and 't' stands for the transmission map of the medium. Haze removal aims to give 'J,' 'A,' and 't' from 'I.' The term 'J(x)t(x)' in equation (1) refers to the direct attenuation, representing the scene radiance of the hazy image. The second term 'A(1−t(x))' is known as the airlight, which is from previously scattered light and influencing the change in image color. The transmission 't' is defined as a measure how much light is able to move through the medium, affecting the overall visibility of the image.

$$t(x)=e-\beta d. \quad (2)$$

Equation (2) says β as the atmospheric scattering coefficient and d as the scene depth, indicating that scene radiance 'J'. He et al. introduced the dark channel prior method, noting that haze-free outdoor images often feature local patches with low-intensity pixels, and darker elements.

6.1 Dark Channel Prior Calculation

The dark channel prior is a fundamental concept in haze removal algorithms. It exploits the statistical regularity that in most local patches of an outdoor image, there exists atleast one color channel with lower intensity. This low-intensity channel tends to correspond to the presence of haze.

The Dark channel prior is computed as

Dark(I)=min(min(R,G),B) (3)

where R, G, and B are the red, green, and blue channels of the image I, respectively.

6.2 Atmosperic Light Estimation

The atmospheric light serves as a measure of the overall illumination intensity across the scene. It's estimated by identifying the brightest pixels within the dark channel, assumed to represent haze-free regions or highly reflective objects. Averaging these bright pixels provides an approximation of the atmospheric light. Initially, a dark channel is calculated using Eq. (1), followed by applying a minimum filter with a window size of 31x31 to generate the dark channel. Hazy images, together with their respective dark channels.

$$I_{\mathrm{DCP}} = \min_{x \in w(k)} \left(\min_{y \in \{R,G,B\}} I(y) \right) \tag{4}$$

After computing the dark channel, the atmospheric light is determined as a 3 × 1 vector, extracting the highest intensity values from the top 0.1% brightest pixels within the dark channel. The algorithm's pseudo code outlines this process, where the input hazy image (I), dark channel prior (DCP), and a threshold value (N) for selecting the brightest pixels are utilized. By comparing DCP with the maximum value of N, pixels corresponding to the N pixel locations in the input image are designated as the atmospheric light.

6.3 Transmission map estimation and refinement

The atmospheric light is employed in calculating the transmission map, which is computed individually for each RGB color channel by dividing the input hazy image by its corresponding color channel atmospheric light, as described in equation (2).

$$T(x) = 1 - \zeta \left[\frac{I(x)}{A} \right] \tag{5}$$

In this context, the value of ζ relies on the fog density of the hazy input image, which is determined using the Fog Density Estimation (FADE) method. FADE utilizes fixed parameters fFD1 and fFD2, set to 2.5 and 1 respectively, to balance between avoiding over-saturation and completely removing fog from the input image. These values were chosen after cross-validation on the RESIDE dataset to ensure optimal model performance. Algorithm 2 outlines the pseudo code for estimating and refining the transmission map. Following transmission map calculation, refinement becomes necessary to preserve gradient information. Our methodology employs the Guided Image Filter (GIF) for this task, utilizing the input image itself as a guidance image for edge preservation and smoothing. GIF offers computational efficiency compared to other refinement filters, reducing the overall complexity of the defogging algorithm. Therefore,

$$T_{\mathrm{refined}}(x) = a_k T_k + b_k \quad \forall k \in W_k \tag{6}$$

After refining the transmission map, the defogged image is reconstructed using the refined transmission map (T_refined). This refined map undergoes a linear transformation within a window of size W, with constant coefficients a and b in each window (W_k), ensuring consistent defogging across the image. using:

$$R(x) = \frac{I(x) - A}{T_{\mathrm{refined}} + \epsilon} + A \tag{7}$$

Here, 'e' represents a constant with a negligible value, preventing division by zero. Towards the conclusion of the defogging algorithm, gamma correction is applied to enhance the overall brightness of the reconstructed image.

6.4 Gaussian filter

The transmission map to be refined, denoted as ~t, is transformed into the Gaussian filtered transmission map, represented as ^t.

$$\hat{t}(x) = \frac{1}{\sum_{y\in\Omega(x)} G_{\sigma_s}(\|x-y\|)} \cdot \sum_{y\in\Omega(x)} G_{\sigma_s}(\|x-y\|)\hat{t}(y), \quad (8)$$

Refining the transmission map ~t includes changing it into the Gaussian sifted transmission map ^t, using the 2-D Gaussian capability Gσs with the standard deviation σs. While the Gaussian channel isn't especially viable in honing a foggy transmission map because of its low-pass trademark, it demonstrates useful in dispensing with variety surfaces that might persevere in the transmission map. At the point when transmission maps are gotten from little neighborhood patches, they frequently display variety surfaces, making the Gaussian channel important for improving their precision. In any case, unreasonable use of the Gaussian channel can superfluously obscure the transmission map when there are no hazardous variety surfaces present. Quantitative quality assessment results uncover that the Gaussian channel's adequacy shifts with the size of the neighborhood fix utilized for transmission map age. Cautious thought of variety surfaces inside the murky picture is fundamental for reasonable utilization of the Gaussian channel in refinement.

7 Results and discussion

To lay out an exhibition benchmark for the proposed strategy, an examination was led against four cutting edge procedures. These incorporated the old style Dim Channel Earlier (DCP) technique with a delicate matting refinement stage, a strategy utilizing a middle channel for transmission refinement, an original methodology coordinating a straight variety constriction earlier, and a technique utilizing a profound brain organization. Assessment was directed on 22 pictures obtained from two normally utilized datasets, with mimicked dimness impacts utilizing irregular upsides of transmission (t) and environmental light (A). Quantitative examination was performed utilizing the Pinnacle Signal-to-Commotion Proportion (PSNR) and the Underlying Comparability File (SSIM). PSNR measures the rebuilding quality between the reestablished picture J and the objective picture K, characterized as:

$$\mathrm{PSNR} = 10.log_{10}\left(\frac{max_I^2}{\frac{1}{n}\sum_{(x,y)}(J(x,y)-K(x,y))^2}\right) \quad (9)$$

(x, y) denotes pixel coordinates, n represents the number of pixels in images J and K, and max2I is the maximum possible value for the images (typically 255). The Structural Similarity (SSIM) Index, based on a perception model, encompasses three key aspects of comparison.

Table 1 displays the comparison in terms of PSNR across 100 synthetic images with varying resolutions

Resolution	Original	320 × 240	600 × 400	800 × 600	1280 × 960
PSNR(Db)	19.21	19.01	19.24	19.05	19.19
Time (s)	9.3	1.2	2.1	4.0	10.2

SSIM = [l, c, s]

SSIM components: l (luminance), c (contrast), s (structure). Tests ran on a Core i5-2400 processor at 3.10 GHz with 12 GB RAM using Matlab 2018a. Figure 2 shows dataset and results; proposedmethod offers higher contrast and brightness than others

(a) (b) (c) (d) (e) (f)

Fig. 2: Haze removal results for synthetic images.

a) Input images.b) Results by He et al. c) Results by Gibson et al. d) Results by Zhu et al. e) Results by Ren et al.f) Our method.

Table 2: Comparative analysis using the Peak Signal-to-Noise Ratio (PSNR) (in dB).

Image	He et al.	Gibson et al.	Zhu et al.	Ren et al.	Proposed
Aloe	12.02	13.40	14.72	13.86	13.19
Baby1	21.79	21.71	19.27	22.56	21.56
Books	20.49	23.08	17.14	20.51	23.46
Bowling1	15.53	16.29	26.13	28.02	21.44
Cones	26.79	19.99	16.67	22.63	21.05
Dolls1	14.03	10.71	9.46	12.22	12.23
Moebius1	22.89	23.64	18.97	21.91	24.20
Monopoly	16.09	18.74	21.25	21.37	19.12
Reindeer	17.38	12.44	10.34	12.49	15.47
Bikes1	20.68	15.47	12.68	14.36	17.97
Church	12.90	14.00	13.77	15.01	13.17
Couch	18.89	17.41	18.90	19.24	18.21
Dolls	19.09	17.85	16.92	18.93	18.59
Flower1	19.92	20.77	18.80	11.30	19.93
Flower2	18.67	18.62	21.45	13.27	18.42
Mansion	20.11	16.98	18.10	17.86	19.60
Moebius	14.76	15.44	18.54	17.16	15.35
Raindeer	18.73	19.12	20.47	17.45	19.22
Roofs2	21.87	17.51	15.40	13.95	19.49
Trees2	19.57	16.60	13.23	14.29	18.33
Average	18.61	17.49	17.11	17.42	18.50

6. CONCLUSION

The Dark Channel Prior (DCP) calculation for dehazing hazy pictures offers a promising methodology, showing both quantitative and subjective benefits. By leading orderly model preparation and assessment, measurements like Mean Squared Blunder (MSE), Primary Comparability Record (SSI), and Pinnacle Signal-to-Commotion Proportion (PSNR) attest the model's adequacy in cloudiness decrease and picture quality improvement. Also, focusing on perceptual quality appraisals, including visual lucidity and variety devotion, features the useful importance of the dehazing model. Persistent refinement and approval against assorted datasets are basic to guarantee the model's heartiness and versatility across different true situations.

7. REFERENCES

1. Cordruta Orniana Ancuti Cosmin Ancuti and Philippe Bekaert, "Effective Single Image Dehazing by Fussion", IEE 17th International Conference on Image Proccesing.(ICIP)Sept 2010, pp.3541-35.
2. Metwaly, K., Li, X., Guo, T., & Monga, V. (2020). Nonlocal channel attention for non homogeneous image dehazing. Image Procceeding of the IEEE/CVF Conferrence on Computer Recognition Workshops.
3. Park, J., Han, D. K., & Ko, H. (2020). Fussion of the heterogeneous adversiial networks for single image dehazing.IEEE Transaction on Image Processing, 29, 4721-4732.
4. Ren, W., Pan, J., Zhang, H., Cao, X., & Yang, M. H. (2020). Single image dehazing via multi-scale convolutional neural networks with holistic edges. International Journal of Computer Vision, 128(1), 240-259.In European conference on computer vision (pp. 154- 169). Springer, Cham.
5. Liu, X., Ma, Y., Shi, Z., & Chen, J. (2019). Griddehazenet: Attention-based multi-scale network for image dehazing. In Procceedings on Computer Vision. for image dehazing. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 7314-7323).
6. Yang, Y., Hu, Z., Bian, K., & Song, L. (2019, April). Imgsensingnet: Uav vision guided aerial-ground air quality sensing system. In IEEE NFOCOM 2019-IEEE Conference on Computer Communications (pp. 1207-1215). IEEE.
7. Yang, X., Li, H., Fan, Y. L., & Chen, R. (2019). Single image haze removal via region detection network. IEEE Transactions on Multimedia, 21(10), 2545-2560
8. Yibo Tan, Guoyu Wang. "Image haze removal based on superpixels and markov random field." Transactions on IEEE Access, 8(4):60728– 60736, March 2020.
9. Jeong, C.Y., Moon, K. & Kim, M. An end-to-end deep, learning approach for real time single image dehazing. J Real-Time Image Proc 20, 12 (2023)
10. Shaojin Ma ,1 Weiguo Pan , 1 Hongzhe Liu ,1 Songyin Dai, 1 Bingxin Xu,1 ChengXu , Xuewei Li,2 and Huaiguang Guan Image Dehazing Based on Improved Color Channel Transfer
11. A. S. Parihar and G. Gupta, "Prior based using Decision Image.", 2020 4th International Confference on Electronics Communication and Aerospace Technology (ICECA), pp. 960-965, 2020.
12. H. Khan, M. Sharif, N. Bibi, M. Usman, S. A. Haider, S. Zainab, J. H. Shah,Y. Bashir, and N. Muhammad, ''Localization of radiance transformation for image dehazing in wavelet domain,'' Neurocomputing, vol. 381, pp. 141–151, Mar. 2020.