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Image Defogging and Quality Assesment

Yarlagadda Vyshnavi, Inapanurthi Swarupa, Yalamarthi. Sireesha, Mupparaju. Venkata Aparna
Department of Information Technology
VR Siddhartha Engineering College,
Vijayawada, India
188w1a12b6@vrsiddhartha.ac.in, 188w1a1276@vrsiddhartha.ac.in, 198w5a1214@vrsiddhartha.ac.in, 198w5a1213@vrsiddhartha.ac.in

Abstract- Images captured in foggy weather conditions often suffer from bad visibility. Under bad weather conditions is prone to yield image with low contrast, faded color, and overall poor visibility. Dehazing can significantly improve contrast, correct distortion, remove unwanted visual effects/ and therefore enhance the image quality.

Keywords- Visual Quality, Fog Density, Accurately, Image Dehazing, Dark Channel Prior, Image Quality Assesment.

I. INTRODUCTION

Images captured using camera in poor weather conditions such as fog or haze gets degraded in terms of low contrast and faded colors. The solution to this problem is to develop an algorithm for removing fog from these images. The existing methods focus on over all contrast enhancements of images and even removal of fog without quality contrast enhancement. Here we propose a method which initially removes the fog and then the haze free image is given as input to the contrast enhancement algorithm so that we get a better quality image with effective fog removal and contrast enhancement. Quality of image in haze weather condition is reduced due to scattering of light. This may affect the normal working of many systems like automatic monitoring systems, transportation systems, outdoor recognition systems and tracking systems.

Images acquired by a visual system are seriously degraded under hazy and foggy weather, which will affect the detection, tracking, and recognition of targets. The degraded images have reduced contrast and the local information is lost. Thus, restoring the true scene from such a foggy image is of significance. The paper focuses on enhancing the contrast and visibility of the foggy image by using various enhancement techniques.

Dehazing can significantly improve contrast, correct distortion, remove unwanted visual effects/ and therefore enhance the image quality.

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II. RELATED RESEARCH WORK

Haze removal is a difficult problem due the inherent ambiguity between the haze and the underlying scene. Furthermore, all images contain some noise due to sensor (measurement) error that can be amplified in the haze removal process if ignored.

III. LITERATURE REVIEW

There are only a few projects that deal with Image Defogging that too maximum they are done by the foreigners.Although we have some projects,some of them suffer with time complexity and some of them with accurate results and some with oldest technologies and other with custom photo size .Our Project will overcome all these problems and it will be a user friendly one.

In some existing single image defogging algorithms, some parameters are required to be set manually which is unrealistic in real time applications. A fast, efficient and useful algorithm is the need of the hour.

IV. PROPOSED ARCHITECTURE

The proposed image defogging and contrast enhancement will be explained in detail in this section. First the model that is used for the formulation of the hazy image to get the dehazed image is explained. After this the overall description of the proposed method will be briefly explained.

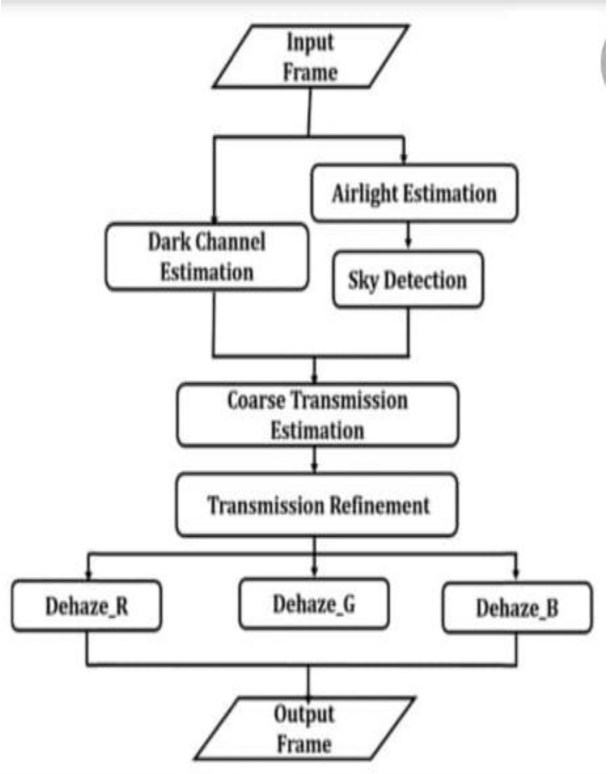

Fig 1. Proposed Architecture.

1. The Haze Image Model:
The 'haze image model' (Equation 1) has been widely used to describe haze formation in computer vision [11, 12].

$$I(x)=u(x)t(x)+Air(1-t(x)), \qquad (1)$$

Where I is the observed hazy image, u is the real scene radiance, A ir is the global airlight, and t is the medium transmission coefficient (standing for the amount of light that is not scattered and arrives at the imaging instrument). The term A ir (1 - t(x)) is therefore called the local atmospheric light, and the first term u(x)t(x) on the right-hand side is called the direct attenuation.

2. The Dark Channel Prior Method:
In terms of a solution for the haze image model (Equation 1), the dark channel prior method [11, 12] has been the state of the art until now. A brief review is presented next.

Outdoor haze-free images often contain colorful objects or surfaces, dark objects or surfaces, and shadows. Consequently, in most of the patches, at least one of the color channels (red, green, blue (RGB)) will contain one or more low-intensity pixels and may even be close to zero. Based on the above idea, the concept of the dark channel [11, 12] was proposed, which is defined as follows:

$$udark(x)=miny\in\Omega(x)(minc\in\{r,g,b\}uc(y)), \ (2)$$

Where Ω(x) is a local neighbor centered at pixel x, and u c is one of the color channels (RGB). For a haze-free image, the dark channel tends to zero (Equation 3), which is called the dark channel prior.

$$udark\rightarrow 0, \ (3)$$

However, the formation of hazy images is affected by atmospheric light (see Equation 1). According to Equation 1 and the dark channel prior, the dark channel of the hazy image yields:

$$Idark(x) \rightarrow miny\in\Omega(x)(minc\in\{r,g,b\}Acir(1-t(y))), \qquad (4)$$

The global airlight A ir can be estimated by detecting the region with the deepest haze using the dark channel. The top 0.1% brightest pixels in the dark channel are picked out. Corresponding to these pixels, the highest intensities in the input hazy image are taken as the airlight. Primarily, the transmission t(x) is assumed as a constant in the local neighbor Ω(x).

Therefore, the transmission t(x) can be coarsely estimated as follows:

$$\tilde{t}(x)=1-wminc\in\{r,g,b\}(miny\in\Omega(x)(Ic(y)Acir)), \qquad (5)$$

In order to retain a small quantity of haze in a distant object, an adjustable parameter w $(0 < w \leq 1)$ is selected in Equation 5. The transmission is then refined using a soft matting framework [23]. Finally, the transmission and the atmospheric light are estimated.

A haze-free image u is restored, according to Equation 1, yielding:

$$u(x)=I(x)-Airmax(t(x),t0)+Air, \qquad (6)$$

Where a typical value of t 0 is 0.1

3. Calculating Boundary Constraints:
After estimating the airlight values we calculate the boundary constraints using dilationmethod in dilation method it produce contrasting results when applied to either gray-scale or binary images.duringdilationIt increases the size of the imageIt fills the holes and broken areas. It connects the areas that are separated by space smaller than structuring element. It increases the brightness of the image

Fig 2. Example for dilation.

The above figure is an example of dilation it finds the brokenparts and Shows the images as large.

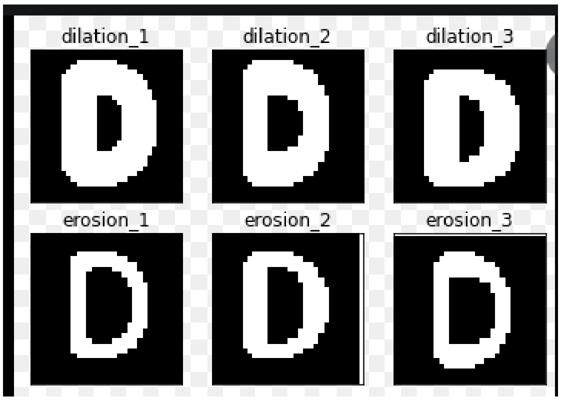

Fig 3. Comparision between erosion and dilation.

Here we see that the above example for comparision between erosion and dilation dilation identifies the brokenparts in the image and erosion removes the noise data and decreases the size of objects.

However, dehazing from a single image is highly underconstrained, since the number of unknowns is much greater than the number of available equations. Thus, we have to first exploit more constraints on the unknowns.

1 t(x) = ||J(x) − A|| ||I(x) − A|| (7)

(4) Consider that the scene radiance of a given image is always bounded, that is, C0 ≤ J(x) ≤ C1, ∀x ∈ Ω, (5) where C0 and C1 are two constant vectors that are relevant to the given image. Consequently, for any x, a natural requirement is that the extrapolation of J(x) must be located in the radiance cube bounded by C0 and C1, as illustrated in Figure 2. The above requirement on J(x), in turn, imposes a boundary constraint on t(x). Suppose that the global atmospheric light A is given. Thus, for each x, we can compute the corresponding boundary constraint point Jb(x) (see Figure 2).

Then, a lower bound of t(x) can be determined by using Eq.(4) and Eq.(5), leading to the following boundary constraint on t(x):

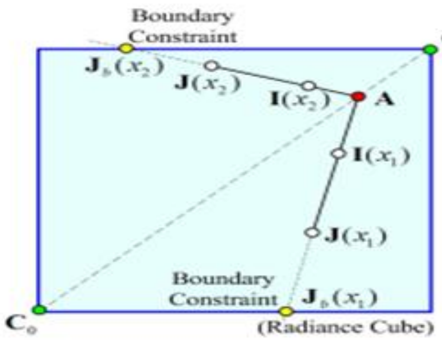

Fig 4. Boundary Constraint.

where tb(x) is the lower bound of t(x), given by tb(x) = min max c∈{r,g,b} Ac − Ic(x) Ac − Cc 0 , Ac − Ic(x) Ac − Cc 1 , 1 , (7) where Ic, Ac, Cc 0 and Cc 1 are the color channels of I, A, C0 and C1, respectively. The boundary constraint of t(x) provides a new geometric perspective to the famous dark channel prior [5]. Let C0 = 0 and suppose the global atmospheric light A is brighter than any pixel in the haze image.

One can directly compute tb(x) from Eq.(1) by assuming the pixel-wise dark channel of J(x) to be zero. Similarly, assuming that the transmission in a local image patch is constant, one can quickly derive the patch-wise transmission t ˜(x) in He et al.'s method [5] by applying a maximum filtering on tb(x), i.e.,

t ˜(x) = max y∈ωxtb(y), (8)

Where ωx is a local patch centered at x. It is worth noting that the boundary constraint is more fundamental. In most cases, the optimal global atmospheric light is a little darker than the brightest pixels in the image. Those brighter pixels often come from some light sources in the scene, e.g., the bright sky or the headlights of cars. In these cases, the dark channel prior will fail to those pixels, while the proposed boundary constraint still holds.

-3	-3	-3	-3	-3	-3	-3	-3	-3
-3	0	5	-3	0	-3	5	0	-3
-3	5	5	5	5	5	5	5	-3
-3	-3	5	-1	-1	-1	5	-3	-3
-3	0	5	-1	8	-1	5	0	-3
-3	-3	5	-1	-1	-1	5	-3	-3
-3	5	5	5	5	5	5	5	-3
-3	0	5	-3	0	-3	5	0	-3
-3	-3	-3	-3	-3	-3	-3	-3	-3

Fig 5. Radiance Cube Boundary Constraint.

4. Transmission function:

After calculating the bpundaryconstraintsApplying the transmission function.this function is used to find the depth of the image because camera cannot capture the entire image.

Fig: These are some Hogh-order filters used in our study.Dehazing an image by Eq. (3) requires to estimate an appropriate transmission function t(x) and the global atmospheric light A. To estimate the atmospheric light, He et al. [5] propose a method based on image's dark channel. They first pick up the top 0.1% brightest pixels in the dark channel, and then select the one with the highest intensity as the estimate of A. In this study, we propose a modified Figure 4. A bank of high-order filters used in our study. It consists of eight Kirsch operators and a Laplacian operator

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for preserving image edges and corners. Version of He et al.'s method. This method produces a similar result but performs more efficiently. The method begins with filtering each color channel of an input image by a minimum filter with a moving window. Then the maximum value of each color channel is taken as the estimate of the component of A. We find an optimal transmission function t(x) by minimizing the following objective function:

$$\lambda\ 2\ t - t\ \hat{}\ 2\ 2 + j \in \omega W j \circ (D j \otimes t) 1, (9)$$

Where the first part is the data term, which measures the fidelity of t(x) to the patch-wise transmission t ˆ(x) derived from the boundary constraint map, the second part models the contextual constraints of t(x), and λ is the regularization parameter for balancing the two terms. To optimize (19), an efficient method based on variable splitting is employed. The basic idea of this method is to introduce several auxiliary variables and construct a sequence of simple sub-problems, the solutions of which finally converge to the optimal solution of the original problem. More specifically, we introduce the following auxiliary variables, denoted by uj (j ∈ ω) and convert (19) to a new cost function as below:

$$t - t\ \hat{}\ 2\ 2 + j \in \omega W j \circ u j 1 + \frac{\lambda\ 2}{\beta\ 2} \left(j \in \omega u j - D j \otimes t\ 2\ 2 \right), (10)$$

Where β is a weight. Obviously, as β → ∞, the solution of (20) will converge to that of (19). Minimizing (20) for a fixed β can be performed by an alternating optimization with respect to uj and t. That is, we first solve for each optimal uj by fixing t, and then solve for an optimal t by fixing uj . This process is repeated until convergence. Fortunately, the sub-problems of this process have close-form solutions that can be solved quite efficiently. 6

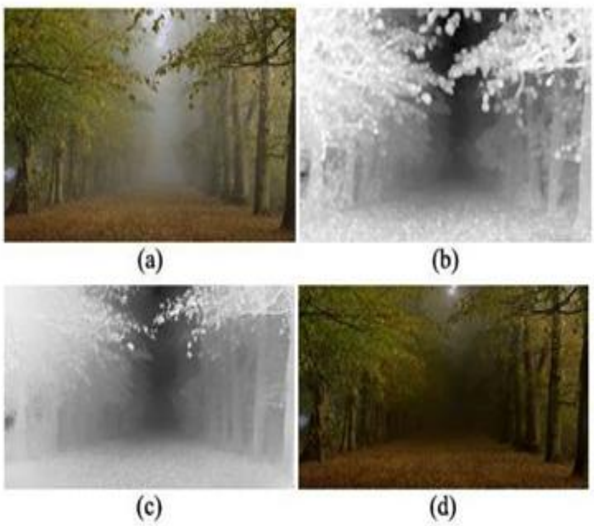

Fig 6. Example of Scene Transmission Estimation

5. Fog Quality Assessment:
BRISQUE is a model that only uses the image pixels to calculate features (other methods are based on image transformation to other spaces like wavelet or DCT). It is demonstrated to be highly efficient as it does not need any transformation to calculate its features.

BRISQUE relies on spatial Natural Scene Statistics (NSS) model of locally normalized luminance coefficients in the spatial domain, as well as the model for pairwise products of these coefficients.

6. Natural Scene Statistics in the Spatial Domain:
Given an image, we need to compute the locally normalized luminescence via local mean subtraction and divide it by the local deviation. A constant is added to avoid zero divisions.

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C}$$

If I(i, j) domain is [0, 255] then C=1 if the domain is [0, 1] then C=1/255.

To calculate the locally normalized luminescence, also known as mean subtracted contrast normalized (MSCN) coefficients, we have to calculate the local mean. Here, w is a Gaussian kernel of size (K, L).

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j)\ ;$$

Then, we calculate the local deviation

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} (I_{k,l}(i,j) - \mu(i,j))}$$

Finally, we calculate theMSCN coefficients

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C}$$

The MSCN coefficients are distributed as a Generalized Gaussian Distribution (GGD) for a broader spectrum of the distorted image.

V. IMPLEMENTATION

The Implementation part of the Project Management method puts the project into action. It is the most important phase as all the main tasks including the execution of the project are done here. Some of the software and frameworks which we used for the implementation of various steps of the project are:

1. Visual Code Studio:
Visual Studio Code is a streamlined code editor with support for development operations like debugging, task running, and version control. It aims to provide just the tools a developer needs for a quick code-build-debug cycle and leaves more complex workflows to fuller featured IDEs, such as Visual Studio IDE.It is a Built on open source. Runs everywhere. By using VS Code, you agree to its license and privacy statement.

2. Django-framework:
Djangois a high-level Python web framework that enables rapid development of secure and maintainable websites. Built by experienced developers, Django takes care of much of the hassle of web development, so you can focus on writing your app without needing to reinvent the wheel.Django is a collection of Python libs allowing you to quickly and efficiently create a quality Web application, and is suitable for both frontend and backend.

3. OpenCv:
OpenCV-Python is a library of Python bindings designed to solve computer vision problems. cv2. imread() method loads an image from the specified file. If the image cannot be read (because of missing file, improper permissions, unsupported or invalid format) then this method returns an empty matrix.cv2. erode() method is used to perform erosion on the image. ... A pixel in the original image (either 1 or 0) will be considered 1 only if all the pixels under the kernel is 1, otherwise it is eroded (made to zero).We are using this openc package for image reading and writing.we have also used erosion method on image for boundaries.

4. Numpy:
NumPy is the fundamental package for scientific computing in Python. ... NumPy arrays facilitate advanced mathematical and other types of operations on large numbers of data. Typically, such operations are executed more efficiently and with less code than is possible using Python's built-in sequences.We are using numpy for calculations/operations on array.we are converting the input image into binary format using with numpypackage,we are calculating the noisy data of the image.

5. Brisque:
BRISQUE is a model that only uses the image pixels to calculate features (other methods are based on image transformation to other spaces like wavelet or DCT). It is demonstrated to be highly efficient as it does not need any transformation to calculate its features.score = brisque(A) calculates the no-reference image quality score for image A using the Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE). brisque compare A to a default model computed from images of natural scenes with similar distortions. A smaller score indicates better perceptual quality.

VI. RESULTS

These are the results of our project the left side is a foggy image that is the input and it gives output as foff-freeimage and our project also gives the ranking.

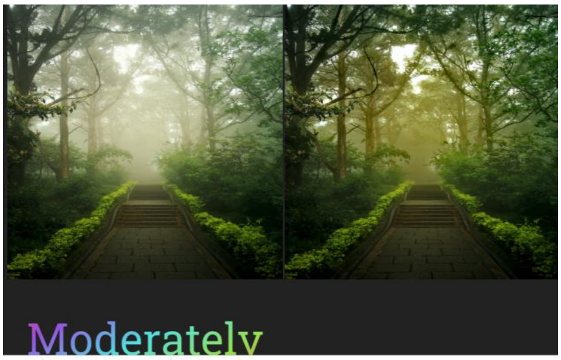

Fig 7. **Text Here Your Fig Title.**

Fig 8. **Text Here Your Fig Title.**

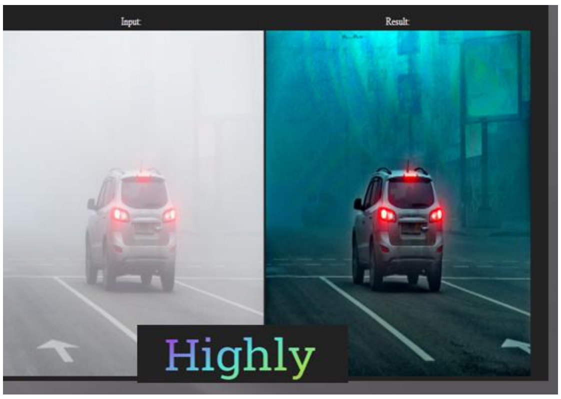

Fig 9. **Text Here Your Fig Title.**

We are giving these ranking based on the scores for scores we are using a package called brisque.

VII. CONCLUSION AND FUTURE WORK

To conclude, the above results are sample results Our Project will plays a key role in Fraud detecting like identifying the vehicle numbers in the number plate in foggy climate,Which will be more useful for traffic police.It will be useful for military and navy so they can clearly visualize the attackers in the foggy climate. hence the overall contrast of the entire image increases. As we can see the development of Technology with great Innovations every time in day to day of our life.Right now we are planning for the fog percentage at different places which will helps in urban traffic monitoring which decreases the accidents rate in foggy climate by suggesting the less foggy roots for the people.

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