SINGLE IMAGE DEHAZING FROM REPEATED AVERAGING FILTERS WITH FEED FORWARD NEURAL NETWORK

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Abstract—**Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image. The image processing involves in the logical process in detecting, identifying, classifying, measuring and evaluating the significance of physical and cultural objects, their patterns and spatial relationship.**

This work present a method of Repeated Averaging Filters for estimating the atmospheric light from a single hazy image, which further contributes to better radiance recovery. Existing methods of dehazing are suffering from the problem of halo artifacts in the final output image after dehazing. For this purpose, an averaged channel is obtained from a single image by the repeated averaging filters via integral images with feed forward neural network which provides a faster and efficient way for removing halo artifacts. The proposed method of dehazing reveals competitive results in regards to quantitative and computational analysis and out-performs many previous states of the art techniques.

Index Terms—Image Dehazing; Averaging Filter; Integral Image; Gaussian smoothing, Feed Forward Neural Network

I. INTRODUCTION

Digital image is a numerical representation of an object. It is composed of picture elements called pixels. Each pixel has a particular location and value. Pixel represents the brightness at a point in the image. All the operations in image processing are applied on these pixels. Digital image processing is the use of computer algorithms to perform image processing on digital images to get an enhanced image or to extract some useful information from it. The advantage of digital image processing is its flexibility, adaptability and data storage and transmission. Hardware modifications are not required in the digital image processing and the data within the computer can be transmitted from one place to another. The limitations of digital image processing are memory and its processing speed. For processing digital images, we have to store them on a storage device so that we can also use it in future. There are several storages devices available for storing the image data. These storage devices include optical disk, magnetic disk, and floppy disk.

Removing haze from a single image or multiple images is a crucial and quite needed task in video processing, computer vision and digital photography [1] which benefits different objects visibility and color shift caused by air light. Another importance of haze removal is to provide aid to the computer vision algorithms for image analysis from a low level to high level and offers depth information [2].

Image dehazing can be classified into two categories: one is based on image enhancement and the other is on image restoration [3]. Image restoration based methods establish atmospheric scattering model and further use the inversing degradation process to overcome dehazing [4]. Further Image restoration based methods can be classified into two categories: first is to consider multiple images and second on the basis of the single image [5]. Similarly, some other techniques introduced such as Retinex [6], homomorphic [7] and wavelet transform [8].

Earlier proposed techniques evaluated their haze removal experimentation on multiple images. But multiple based images techniques have faced some problems in online imaging dehazing applications which requires an extraordinary sensor. Therefore, many researches focused on single image dehazing [2], [9], [10], [11].

Later on, for single image dehazing, the Dark Channel Prior [2] is proposed and much more attention driven towards dark channel prior based approaches. Extensive work has been performed by assuming the simple idea of dark channel prior methods [2, 9]. The dark channel prior method classifies single image dehazing in four steps, first; to estimate the air light (atmospheric light), secondly; transmission, third; refinement of the estimated transmission map the fourth and last one is the recovery of the scene radiance. Our proposed approach inspired by the dark channel prior (DCP) method and encounters the problems of DCP method such as removing the halo artifacts from the final recovered scene radiance map. Besides this, our approach provides an overall solution for outdoor single hazy image dehazing.

II. Literature Review

In the early development of image processing, linear filters were the primary tools for image enhancement and restoration. They have poor performance in the presence of non-additive noise and in situations where system nonlinearities or Gaussian statistics are encountered [19].

Now-a-days, images generated from any source will undergo certain degradation during transmission and manipulation process. Because of this degradation in the images, we cannot extract meaningful information from them. Therefore we identify the need of a technique that recovers the original image from a distorted one. That’s why; Image Restoration plays a very important role in the area of image processing. Image Restoration is used for restoring the image which contain unknown blur kernal and additive noise.

Image restoration and enhancement techniques are used to improve the appearance of the image or to extract the finer details in the degraded images. The purpose of image restoration and enhancement is to process an image so that the resulting image will be more suitable for a specific application than the original image. These techniques have a wide variety of applications such as computer vision, video surveillance, satellite and medical image processing and analysis etc. Image restoration is concerned with filtering the observed image to minimize the effect of degradations.

The images may be degraded in the form of sensor noise, random atmospheric turbulence, and so on. Images are often degraded by random noise. Noise can occur during image capture, transmission or processing, and may be dependent on or independent of image content. Noise is usually described by its probabilistic characteristics. The effectiveness of the image restoration filters depends on the extent and the accuracy of the knowledge of the degradation process as well as on the filter design criterion [Jain, 1989]. Conventional filters such as mean filter, median filter etc., are widely used for image restoration. But these conventional filters have their own disadvantages, which eventually led to the development of advanced filters such as decision-based median filters, switching median filters, wavelet filters, fuzzy filters etc [Gonzalez and Woods, 2008].

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers or to provide better input for other automated image processing techniques [Pratt, 2001]. Image enhancement transforms images to provide better representation of the subtle details. Image contrast enhancement is one type of image enhancement operation which involves transforming one image to another so that the look and feel of an image can be improved for machine analysis or visual perception of human beings [Acharya and Ray, 2005]. It is an indispensable tool for researchers in a wide variety of fields including medical imaging, forensics, atmospheric sciences etc.

Aghi and Ajami presented a novel approach in color image denoising based on artificial neural networks. The main objective of their work is to design an adaptive noise canceller using appropriate neural networks. A. De Stefano et al. presented an automatic technique for reducing the amount of grain on film images. This technique reduces the noise by thresholding the wavelet components of the image with parameterized family of functions. Volodymyr P and Francisco G. F presented the Vector Rank M-type K-Nearest Neighbor (VRMKNN) filter to remove impulsive noise from color static image and dynamic image sequences. This filter utilizes multichannel image processing by using the vector approach and rank M-type K-nearest neighbor algorithm.

Image segmentation is an important step for many image processing and computer vision applications. The interest is motivated by applications over a wide spectrum of topics. For example, analyzing different regions of an aerial photo helps to better understand the vegetation cover. Scene segmentation is helpful to retrieve images from large image databases for content-based image retrieval. Most of the segmentation methods require image features that characterize the regions to be segmented. In particular, texture and color have been independently and extensively used. The color information is a multi-dimensional vector and hence the segmentation techniques for gray images cannot be directly applied. The existing color image segmentation techniques can be broadly classified into eight approaches based on edge detection, region growing, clustering, neural network, fuzzy, tree/graph based approaches, probabilistic or Bayesian approaches and histogram thresholding.

Non-linear filters such as Adaptive Median Filter (AMF) [Hwang and Haddad, 1995] can be used for discriminating corrupted and uncorrupted pixels, and then apply the filtering technique. Noisy pixels will be replaced by the median value and uncorrupted pixels will be left unchanged. AMF performs well at low noise densities since the corrupted pixels which are replaced by the median values are very few. At higher noise densities, window size has to be increased to get better noise removal, which leads to less correlation between corrupted pixel values and replaced median pixel values. In decision-based or switching median filter the decision is based on a predefined threshold value. The major drawback of this method is that defining a robust decision measure is difficult. These filters will not take into account the local features, as a result of which, edge details may not be recovered satisfactorily, especially when the noise is high.

III. Image Restoration and Enhancement

Image dehazing can be classified into two categories: one is based on image enhancement and the other is on image restoration. Image restoration and enhancement is one of the leading research areas in the field of digital image processing. Image restoration attempts to reconstruct or recover an image that has been degraded by using a priori knowledge of the degradation phenomenon. On the other hand, image enhancement refers to accentuation or sharpening of image features such as edges, boundaries or contrast to make a graphic display more useful for display and analysis. Image restoration and enhancement techniques are widely used in the field of computer vision, video surveillance, medical and satellite image processing etc.

➢ Image Restoration

Images are often degraded by random noise which can occur during image acquisition, transmission or processing. The degradations may occur due to sensor noise, relative object-camera motion, random atmospheric turbulence, and so on. Noise may be either dependent or independent of image content, and is usually described by its probabilistic characteristics. During image transmission, noise which is usually independent of the image signal occurs. Gaussian noise is a very good approximation of noise that occurs in many practical cases. Image noise reduction has come to specifically mean a process of smoothing noise that has somehow corrupted the image. Image restoration is concerned with filtering the observed image to minimize the effect of degradations, where prior information of the degradation form is needed. The goal of image restoration is to recover an image that resembles the original image as closely as possible by reducing the noise.

Image restoration techniques are basically divided in two categories namely: Deterministic process and stochastic process. Deterministic processes are those processes in which there is a prior knowledge of degradation function or point spread function and stochastic processes are those processes in which there is no prior knowledge of degradation function or point spread function like blind de-convolution method. Deterministic methods are subsequently divided into two parts: Parametric and Nom-parametric. Linear Filters do not necessarily maintain image non-negativity or signal-dependent noise. This has led to the development of non-linear and iterative restoration algorithms. Image restoration is different from image enhancement in the way that the latter is designed to emphasize features of the image to make the image more pleasing to the observer, but not necessarily produce realistic data from a scientific point of view.

Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) use no a priori model of the process that created the image.

- **Image Enhancement**

Image enhancement includes sharpening, contrast manipulation, filtering, interpolation and magnification, pseudo coloring, and so on. The greatest difficulty in image enhancement is quantifying the criterion for enhancement. Therefore, a large number of image enhancement techniques are empirical and require interactive procedures to obtain satisfactory results. However, image enhancement remains very important because of its usefulness in virtually all image processing applications. Color image enhancement may require improvement of color balance or color contrast in a color image. Enhancement of color images becomes a more difficult task not only because of the added dimension of the data but also due to the added complexity of color perception [Gonzalez and Woods, 2008].
Image enhancement techniques are used to improve the appearance of the image or to extract the finer details in the degraded images. The principal objective of image enhancement is to process an image so that the result is more suitable than the original image for a specific application. A method that is quite useful for enhancing one category of images may not be necessarily be the best approach for enhancing other category of images. Color image enhancement using RGB color space is found to be inappropriate as it destroys the color composition in the original image. Due to this reason, most of the image enhancement techniques, especially contrast enhancement techniques, use HSV color space [Hanmandlu and Jha, 2006].
Image enhancement methods may be categorized into two broad classes: transform domain methods and spatial domain methods. The techniques in the first category are based on modifying the frequency transform of an image, whereas techniques in the second category directly operate on the pixels. However, computing a two dimensional (2-D) transform for a large array (image) is a very time consuming task even with fast transformation techniques and is not suitable for real time processing.
Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task.

IV. PERFORMANCE METRICS

It is a tedious task to assess the performance of haze image enhancement and restoration algorithms, as there are no ground truths available. To assess the enhanced visibility, we measure the performance of algorithms in two ways. First, we will assess the qualitative comparison of our method with other contemporary methods. This measure is subjective and hence proper quantification is not possible. Second approach is to follow quantitative comparison using the metrics which have been used by other researchers. Though, some researchers have used mean squared error (MSE) [19] and structural similarity index metric (SSIM) [20] they do not fit the test, particularly for the reason that these metrics need reference images for proper evaluation and specifically MSE is designed for applications such as image compression. For comparative evaluation with the existing methods, we have used it.
There are other techniques such as examining the number of visible edges before and after restoration, quantity of edges visible in output images to those not present in hazy images and mean ratio of the gradients at the visible edges. This metric was proposed Hautiere et al. in [60] and used for the purpose of visibility recovery assessment in [20]. To assess the quantitative comparison we have referred to blind contrast enhancement indicators to quantify the quality of the restoration.
The details of these metrics are explained in following sections, followed by a qualitative and quantitative comparison as applied to one of the haze image.

- **Peak signal to noise ratio (PSNR) and Mean Squared Error (MSE)**

The term peak signal-to-noise ratio (PSNR) is an expressed as the ratio of maximum possible value of a signal and the power of distorting noise that affects the quality of its representation. The dimensions of the two images must be the same. Mathematical representation of the PSNR is as follows:

$$PSNR = 20log_2\left(\frac{MAX_f}{\sqrt{MSE}}\right) \tag{1}$$

Where the MSE (Mean Squared Error) is:

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}|f(i,j) - g(i,j)|^2 \tag{2}$$

Where, f is the matrix data of the original image, g is the matrix data of processed image, m and n represents the numbers of rows and the columns of pixels of the images and i and j represents the index of row and the column respectively. MAX_f is the maximum signal in image f. The major shortcoming of PSNR metric is that it relies on numeric comparison and does not actually take into consideration the biological factors of the human vision system such as the structural similarity index (SSIM).

- **Structural similarity index (SSIM)**

Wang et al. proposed SSIM metric for assessing image quality. The structural similarity (SSIM) index computes the similarity index between two images. It is more consistent with human perception as opposed to conventional methods such as mean square error (MSE). As it is correlated to human visual perception, SSIM has become a universal quality metric for image and video applications for quantitative analysis. For input image O and R, let μ_O, σ_O and σ_{OR} denote the mean of O, the variance of O, and the covariance of O and R respectively, SSIM is mathematically given as

$$SSIM = \frac{(2\mu_O\mu_R + C_1)(2\sigma_{OR} + C_2)}{(\mu_O^2 + \mu_R^2 + C_1)(\mu_O^2 + \mu_R^2 + C_2)} \tag{3}$$

Where C_1 and C_2 are constants, this metric has been suggested for the haze environment for quantitative analysis in Lu et al.

V. Image Dehazing Methods and Models

Our work follows the restoration based image dehazing techniques which can be divided into single image and multiple based image dehazing methods. Multiple based images dehazing can be referred to as polarization methods [12], [13], [14]. The proposed method [12] considered the scene points and found the depth discontinuities by altering the intensities of scene structure under different weather conditions consideration. Similarly [13] proposed approach noted that only polarized filter is not enough to dehaze the haze image and used different orientations with polarization to get better estimations. Another regularization based approach [14] modeled inheriting body constraint and contextual regularization, which mutually estimated the scene transmission.

In [10] for a single image it is observed that a normal image without haze has higher contrast, while in the presence of haze and fog the contrast became lower. So for this purpose, a local contrast is maximized and gained better visibility, but the method remained suffered from halo artifacts in the final output map. The procedure in [11] targeted scene albedo and assumed that surface shading and transmission have no co-relations locally after transmission computation.

In recent past, the famous dark channel prior (DCP) [2] is introduced. Extensive experimentation on outdoor images have been performed, and found the dark pixels phenomena. The observations were based on dark pixels existence in natural outdoor images and observed that at least one color channel have lowest pixel intensities in an RGB image ignoring the sky region, which tends to a dark channel.

The DCP method put researchers on new directions. DCP method also had some limitations such as the use of soft matting to refine the transmission which is computationally an expensive task. Besides this, it is also inappropriate for the images which have brighter objects in, because it selects the highest pixel intensities which can cause trouble in final out map. For this purpose [9] advocated guided filters which preserved much of the edges and working as smooth operators.

Likewise [1] proposed an algorithm to overcome the halos in single image dehazing, for this purpose fixed points are computed by using the nearest neighbors (N-N) for recovering smooth transmission with feed forward neural. Aforementioned discussion gives us the motivation to propose a new procedure of repeated averaging filters, which encounters the mentioned.

➢ Haze Imaging Model

The haze imaging model in [4], [12] which shows a hazy image formation and widely used so far, is given as

$$I(x) = J(x)\, t(x) + A\,(1 - t(x)) \tag{4}$$

Where *I* is hazed image, *J* is the haze free image, *x* is a pixel location, *A* is the air light. *I*(*x*) and *J(x)* can be referred to as the intensities of the pixel location in *I*and *J* respectively, where *t*can be referred to as transmission coefficient which describes reflecting probability from an object not scattered and absorbed by air particles. The transmission map is given as

$$t(x) = e^{-\beta d(x)} \tag{5}$$

β is scattering coefficient and *d* is scene depth. The captured image in clear weather is $\beta \approx 0$ and hence $I \approx J$. But when has some value it results in a hazy image. In (4) the first component *J(x)t(x)* is the direct attenuation which is inversely proportional to the scene depth. The second component $A\,(1 - t(x))$ is the air light which is directly proportional to the scene depth. Thus dehazing is all about to recover *J* from *I* after estimation of *A* and *t* from *I*.

From haze imaging (1), transmission *t* is the ratio of two line segments which can be represented mathematically as:

$$t(x) = \frac{\|A - I(x)\|}{\|A - J(x)\|} = \frac{A^c - I^c(x)}{A^c - J^c(x)} \tag{6}$$

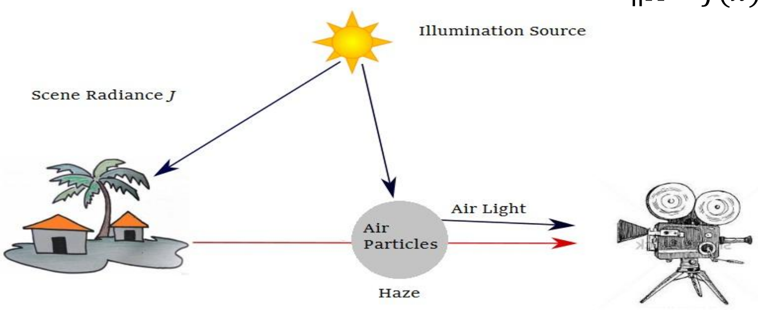


Fig 1: The Haze Imaging Model

➢ Dark Channel Theory

Dark Channel prior [2] suggests that most of the haze-free images have low pixels intensities in at least one color channel expect sky region due to three factors :1) Shadows of buildings, cars and cityscape images: 2) other objects in the image as for instance trees and plants :3) and some dark surfaces such as dark trunks of trees and stones. Noticing this phenomenon suggested that in the presence of haze, the dark pixels values altered by the air light by providing a direct contribution to its values. Therefore dark channels provide a direct clue for estimating the haze transmission. The dark channel is defined as

$$J^{dark}(x) = \min_{c\in\{r,g,b\}}\left(\min_{c\epsilon\Omega\{x\}}(J^c(y))\right) \tag{7}$$

Where $\Omega(x)$ is a local patch centering at x. $J^c$is a color channel of *J*. This scrutiny revealed that J^{dark}tends to low intensity such as zero, and hence $J^{dark}$is demonstrated as a dark channel of *J*. Summarizing our algorithm for recovering *J*, first a dark channel (J^{dark}) is derived from the hazy image, then we applied the repeated averaging filters to normalize the dark channel and estimated the better atmospheric light *A* on the basis of repeated averaging filters from the obtained dark channel. Finally got the haze free image as an output at low computational cost with high visual effects, estimated the dark channel from input image.

➢ Integration of DCP Theory with Repeated Averaged Channel Prior

A method in [16] approached approximations to the Gaussian filter. For computing Gaussian approximations a special averaging filter is required. The proposed technique was based to obtain the Gaussian approximations via integral images by combining both the repeated filtering and averaging filter with given sigma and *n* (where sigma is a standard deviation and n is the averaging). An averaging filter of width *w* is defined by the standard deviation, mathematical representation of the averaging filter as

$$\sigma av = \frac{\sqrt{W^2 - 1}}{12} \tag{8}$$

The ideal filter's width is defined for averaging filter as

$$Wideal = \frac{\sqrt{12\sigma^2 av}}{12} + 1 \tag{9}$$

After the derivation of (9) we applied this filter repeatedly to the estimated dark channel of the input image via integral images which out puts a new averaged channel. An integral image is used for fast computation. A sum area table (integral image) is a data structure for obtaining sum of values in a rectangular grid in a quick and efficient way. The mathematical representation for integral images is as follows:

$$\sum abcd = S(x_c, y_c) - S(x_b, y_b) - S(x_d, y_d) + S(x_a, y_a) \tag{10}$$

Where S refers to the sum of all pixels in an arbitrary rectangle with vertices a, b, c, and d, After getting the repeated averaged channel of the haze image we estimated the atmospheric light.

➢ Estimation of the Atmospheric Light from the Repeated Averaged Channel

Estimation of the atmospheric light, *A* can be considered an important task in image dehazing. Previous method [2] picked out the high intense values for estimating the atmospheric light from the dark channel. But the problem here arises due to selecting the high intensity pixels from the hazy image. Because the high intensity pixels can also be a part of some other brighter objects in the input image as car etc.
The proposed technique in [2] directly estimated the atmospheric light by selecting 0.1% highest intensity pixels from the dark channel. But still, this atmospheric light estimation method has some hallow artifacts in the final output image. On the other hand, we estimated the atmospheric light from the repeated averaged dark channel by selecting 0.2% highest intensity pixels and integrated it with the haze imaging (1) which has given the compromising results in the final output map.

➢ Transmission Estimation

We have estimated the air light *A* from the dark channel of the repeated averaged channel. For estimating the transmission it is assumed that a local patch and transmission in the given patch $\Omega(x)$ is constant which can be denoted as *t(x).* The minimum operation is applied to all three color channels of haze image. Therefore (4.1) becomes as

$$\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^C(y)}{A^C}\right)\right) = t(x)\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^C(y)}{A^C}\right)\right) + (1 - t(x)) \tag{11}$$

Radiance *J* tends to zero in the absence of haze on the assumption of dark channel and given as:

$$J^{dark}(x) = \min_c\left(\min_{y\in\Omega(x)}(J^C(y))\right) = 0 \tag{12}$$

Which leads to the following equation:

$$\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^C(y)}{A^C}\right)\right) = 0 \tag{13}$$

Now we can estimate the transmission t(x) by inserting (13) in (11) and final equation for transmission estimation will be written as follows:

$$t(x) = 1 - \omega\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^C(y)}{A^C}\right)\right) \tag{14}$$

$\omega$is the parameter to keep the naturalness of the image and to perceive the depth for the human eye.

VI. FEED-FORWARD NEURAL NETWORKS

Feedforward neural networks are artificial neural networks where the connections between units do not form a cycle. Feedforward neural networks were the first type of artificial neural network invented and are simpler than their counterpart, recurrent neural networks. They are called *feedforward* because information only travels forward in the network (no loops), first through the input nodes, then through the hidden nodes (if present), and finally through the output nodes.

Feed forward neural networks are primarily used for supervised learning in cases where the data to be learned is neither sequential nor time-dependent. That is, feedforward neural networks compute a function *f* on fixed size input *x* such that f(x) ≈ y for training pairs (x, y). On the other hand, recurrent neural networks learn sequential data, computing g on variable length input $X_k = \{x_1, x_2 \dots \dots . . x_k\}$such that g($X_k$) ≈ y_k for training pairs (X_n, Y_n) for the all $1 \leq k \leq n$.

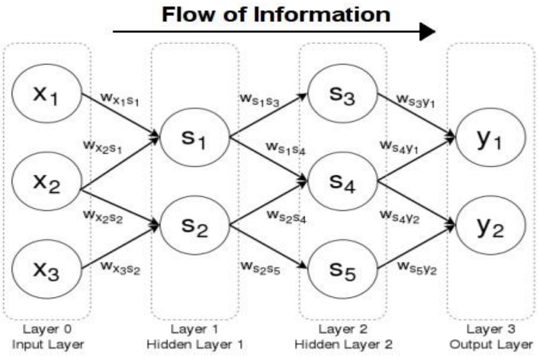


Fig 2: Feed-forward neural networks

VII. RESULT AND DISCUSSIONS

For our experimentation, the system specification is the ASUS machine with Intel Core i7-6700HQ 2.60 GHz CPU running with Installed memory (RAM) 8.00 GB, with MATLAB 2016b under windows 10. We performed our experiment on a general data set, a collection of outdoor hazy images used in previous literature such as cityscapes, aerial views, and landscapes. On the basis of our experimental results, it is showed that our approach is applicable to any scene or input image which is polluted by some fog, haze or dust.

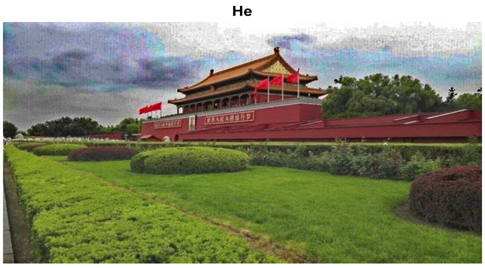
This performed algorithm evaluation in terms of qualitative analysis and quantitative analysis. The dark channel prior method had some drawbacks. For example, this could not be valuable to the images having bright objects with higher intensities. Because it selects the brightest pixels e.g. selecting pixels of a car from the input image as an atmospheric light and therefore can cause a bad transmission map.

Another limitation is, it uses the soft-matting procedure to refine the transmission map which is a time-consuming task. But our proposed method avoids these techniques previously adopted for transmission map refinement because our proposed method applies some amount of sigma with repeated averaging filters with feed-forward Neural Network. Therefore a smooth and filtered transmission map is recovered, free from halo artifacts risen in the DCP method.

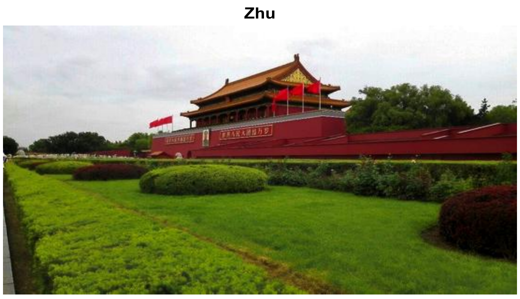
- **Qualitative Evaluation**

For qualitative evaluation we compared our results with [9], [14], [15] and [17] methods. Our proposed method dominates all the previous methods in terms of qualitative evaluation. The qualitative results of our proposed method are shown in Figure 3 with different data images.

(a) Input Data Image

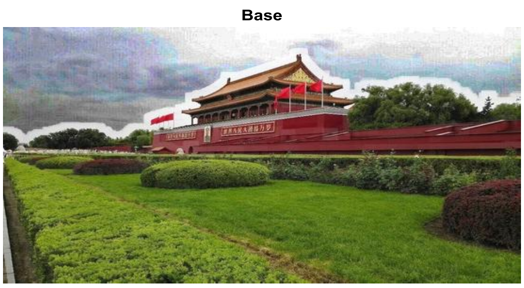


(b) By He [9]



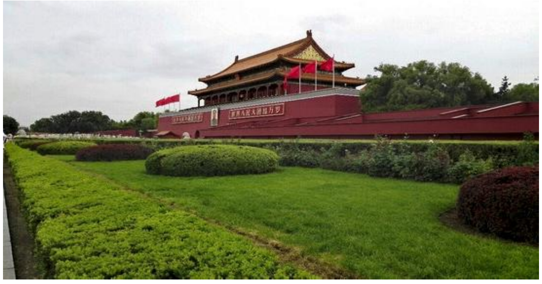
(c) By Zhu [14]

(d) By Zhu [15]



(e) By Base Paper [14]

Propose



(f) Proposed Algorithm Result

Fig 3: Qualatative Comparison of different data images

- **Quantitative Evaluation**

Table 1: Quantitative Comparison of different data images

Dataset	MSE Meng	SSIM Meng	MSE He	SSIM He	MSE Zhu	SSIM Zhu	MSE Base	SSIM Base	MSE Propose	SSIM Propose
1	3747.72	0.6485	3747.72	0.6485	3701.12	0.6354	3266.43	0.6312	2918.21	0.7235
2	1700.3	0.7506	1930.25	0.7881	1607.79	0.8143	4932.94	0.659	609.71	0.8941
3	2635.53	0.812	2635.53	0.812	4193.83	0.6199	2029.2	0.8465	1552.37	0.8617
4	1957.95	0.6282	1954.66	0.631	1765.88	0.7329	5868.32	0.6826	2605.06	0.7379
5	3067.3	0.8283	3560.02	0.8507	1121.69	0.9405	4034.36	0.7803	538.03	0.9325
Average	**2621.76**	**0.7335**	**2765.63**	**0.7461**	**2478.06**	**0.7486**	**4026.25**	**0.7199**	**1644.68**	**0.83**

For qualitative evaluation the SSIM and MSE measures are computed and compared with the methods [9], [14], [15] and [17].
*SSIM is Structural Similarity Index for measuring image quality
*MSE is Mean Square Error

VIII. CONCLUSION

In this work method encounters the operational complexity, successful dehazing of the dense haze image and applicable to the real-time systems. The operational complexity is solved by considering the use of integral image operations. Using the repeated averaging filters predicted better air light which further improves the recovered scene radiance. Our proposed method with the help of sigma amount refined the transmission map and removed the halo artifacts faced by the previous approaches.
The results have been evaluated using subjective visual analysis as well as quantitative approaches. To quantitatively evaluate the haze-free images, Mean Square Error (MSE) and structural similarity (SSIM) were used. These metrics quantify signal strength, the amount of feature preservation, and recovery of structural features obtained in the haze-free image.

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