A Comprehensive Study of Different Methods for Single Image and Video Dehazing Based on Machine Learning

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Abstract: The presence of haze in the atmosphere often results in low contrast and limited visibility in images and videos taken in hazy weather. Environments that are not favourable to photographs, such as fog, ice fog, steam fog, smoke, volcanic ash, dust, and snow further degrade and degrade the color and contrast of photographs. Due to degraded images, many computer vision applications fail to work effectively. Various computer vision applications, such as photometric analysis, object recognition, and target tracking, are unavoidably degraded by hazy images and videos with biased colour contrasts and poor visibility. By using image haze removal techniques to remove those deficiencies, computer applications can be used for both image comprehension and classification. In the field of image dehazing, deep learning methods are now being applied. There have been many studies done on removing haze. Reviewing works on dehazing daytime and night-time images, this paper discusses several approaches for removing haze and describes them all in detail. A statistical method or a network-based method refines an image by using statistical observations of the scene. In order to compare their dehazing potential, these algorithms were assessed quantitatively and visually. This paper presents a comparison of the various methods for image and video dehazing that use different methods for estimating transmission and atmospheric light. Signal-to-noise ratio (SNR) and structural index similarity (SSIM) are two of the tools used to assess image quality. In our study we will consider database such as RESIDE, SceneNet, I-HAZE, O-HAZE, D-HAZY, Middlebury, NYU Depth Dataset V2.

Keywords: Machine Learning, Dehazing Method, Dehazing Images, Video Dehazing Atmospheric scattering model

I. Introduction

Haze is an atmospheric phenomenon caused by dust, smoke, and dry particles in the atmosphere that obscures the sky's clarity. There are numbers of activities that contribute to the creation of polluted air such as farming, vehicle traffic, and wildfires. There are several types of atmospheric obscuration that are categorized by the World Meteorological Organization (WMO)[1]. Haze, fog, ice fog, steam fog, smoke, volcanic ash, dust, and snow comprise these types of conditions. Dehaze research aims to improve visibility as well as color recovery, as if imaging were being conducted under clear conditions. These improved images can then be processed for a wide range of applications like long-range surveillance by computer vision. Due to the fact that particles are always present in the atmosphere, image enhancement is necessary. In pure air, regardless of curvature of the earth's surface, the visual range varies from 277km to 348km. In reality, the range is considerably shorter than these figures. In exceptional clear air, visibility ranges from under 50 feet to over 50 kilometres in the international visibility code. As part of the daily work of meteorologists, these codes reflect a convenient visual scale. The WMO hazy image range is shown in Table 1.1.

Table 1.1 Range of Hazy Image [2]

Weather Condition	Meteorological Range
Dense fog	50m
Thick fog	50m-200m
Moderate fog	200m-500m
Light fog	500m-1000m
Thin fog	1km-2km
Haze	2km-4km
Light haze	4km-10km
Clear	10km-20km
Very clear	20km-50km

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Exceptionally clear	>50km
Pure air	277km

There are many reasons why images can appear hazy. Conditions such as air pollution, fog, or conditions in the atmosphere could be a factor. When the image has a lot of background haze, dehazing is used to restore detail to the image[3].

"The Dehaze technology is based on a physical model of how light is transmitted, and it tries to estimate light that is lost due to absorption and scattering through the atmosphere."

Meteorology, optical physics, and computer vision and graphics are all involved in image dehazing, a highly interdisciplinary field. In the atmosphere, fog, haze, and clouds limit the scope of visual observation and have a considerable impact on the contrast in scenes[4][5]. This is where visibility is the main objective. The color recovery is similar to when imaging is done under clear conditions. Various applications, like long range surveillance, can then take advantage of such improved images. It has become increasingly popular to use satellite imagery to create accurate maps of the earth, among other tasks. A satellite image's resolution must be high enough for small details to be discernible [6]. Since the light must pass through particles in the atmosphere which will scatter and absorb the light, taking images from outside of the atmosphere has a great disadvantage because the result will be distorted. If the distortions are not corrected, the resulting images will be less useful. The removal of these undesirable effects from remote sensing is important since these effects are unavoidable [7]. Figure 1.1 shows the hazy image of road and accident situation due to this.

Figure 1.1 Hazed Image

Generally, video dehazing and image dehazing are done separately. This is because pictures or videos of outdoor scenes frequently contain atmospheric haze or fog. The quality of images and videos can be severely affected by haze, raindrops and rain streaks. Furthermore, unlike other opaque objects, haze does not affect human recognition in general, but rather interferes with computer vision systems. Therefore, dehazing system has attracted attention from a wide range of researchers [8][9]. As many classifications of haze removal technologies are available, they are becoming more popular. Dehaze images constructed using these methods will have high quality and be noise free. Classification can be divided into two main types: image segmentation and image restoration. A low-quality image of an outdoor scene may be captured due to the presence of fog, mist, or haze in the atmosphere. The removal of haze is a vital component of surveillance and transportation areas. By analysing the scene, obtaining useful information, and detecting the image, this system is able to determine the image. During bad weather conditions, light is often absorbed by other particles and scattered by falling raindrops. As part of this prototype, a variety of haze removal techniques have been implemented [10].

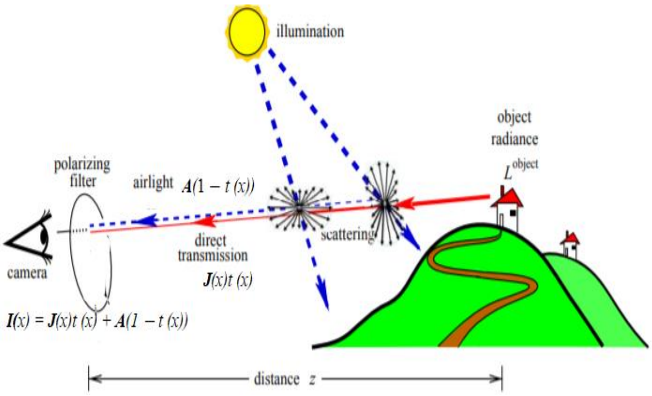

Figure: 1.2 Atmospheric light and object

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

The hazy image is represented by I(x) and the clear image by J(x), respectively. A describes the atmospheric light, and t (x) is the transmission of the scene, which is the light that is not scattered and reaches the camera[11][12].

II. Review of Image and Video Dehazing

Image dehazing

Image dehazing aims to restore visibility of the image by regulating the contrast and sharpening the details.

Schechner et al. propose taking two images of a scene with polarizers at different orientations in order to remove haze [13][14][15]. A dehazing technique developed by Narasimhan and Nayar uses multiple images taken of the same scene under various weather conditions [16][17][18]. Despite their effectiveness in removing haze, these algorithms require multiple images of the same scene with differing conditions, and thus their application to actual cases was limited. While other approaches [19][20] do not require multiple images, they do require three-dimensional rough geometric information, which limits their application. Several techniques were developed to dehaze images, including the use of near-infrared light systems due to their penetration capability [21][22]. However, this technique requires a special camera and cannot be applied to existing digital images. Since these methods require additional information, their applications are limited. The success of these methods may be attributed to strong a priori assumptions. A new method was developed that eliminates the additional information required. He et al. developed the Dark Channel Prior (DCP) method, which is considered the most successful of these methods. [23]. According to He et al., the image's dark channel can be used to approximate the light transmission function. After that, the light transmission function was refined using the Matting method He et al. modified their algorithm by implementing a Guided filter instead of a Matting technique [24].

In spite of the simple and robust dehazing theory of the DCP method, the approximate transmission function was estimated through low efficient pixel computation and over-correction. Many studies have further developed and improved the DCP method [25][26][27][28], but these methods suffer from the same drawbacks as DCP [low efficiency and overcorrection]. Another widely used method for dehazing single images is Markov Random Fields (MRFs), which have made major strides in recent years [29][30][31][32][33][34]. Physical phenomenon are dependent on spatial and contextual parameters according to the MRF approach[35]. When an image needs to be dehazed, the MRF method is used to model the hazy scene. The cost function was developed by Tan [30] within the framework of MRF to increase the colour contrast of the hazed image, with the assumption that the local contrast of the haze-free image would be much higher than that of hazed image in general. However, Tan's algorithm produced halo artifacts and over-saturation, even though its algorithms recovered details and structures in the hazy image. A dehazing algorithm was proposed by Fattal [31] based on the assumption that light transmission function and surface shading are uncorrelated fields. Bringing the transmission function into smooth harmony required an additional Gaussian-MRF technique. A hazy scene was modeled by Katz et al. with a multi-factorial MRF where depth and albedo are assumed to be independently dependent. Next, the scene albedo and depth were jointly estimated using an expectation maximum algorithm. In spite of their relatively compelling results, their method caused significant halos and distortions in the colors.

Cataffa et al. proposed an MRF model [32] to improve the results of road images with the assumption of flat roads. Wang et al. [33] combined MRF with a fusion technique to produce sharp details at finer granularity, but the application of the low-efficient alternative optimization algorithm resulted in a low time efficiency; in addition, the results did not appear satisfactory visually. Despite their ability to produce compelling results in some cases, some of these methods suffer from considerable computational burden; some methods created distorted colours and obvious halos due to their defective MRF models. However, certain methods of dehazing images restore visibility purely by manipulating the image's colour contrast, ignoring the conditions that caused the haze. These methods include ones which utilized the histogram equalization, Retinex [36][36][37] or image fusion technique [38][39]. A color contrast enhancement technique was implemented by Liu et al. in. In spite of the fact that the histogram equalization technique enhanced the colour contrast to some extent, mainly unchanged, it is not suitable for dehazing problems as it does not affect the additive airlight component. The variable filter Retinex algorithm[36] was proposed by Yang et al. to restore hazed images. They found that their results had increased contrast, but also lost color fidelity. A white-balanced image and a colour-corrected image were used by Ancuti et al. in their improvement of image visibility using a Laplacian pyramid fusion-based method. After that, a fusion algorithm was applied to arrive at the final result. Their results showed however that the process of exposure shifted the colours of the images.

Recent research has focused on fast dehazing of images. There are some algorithms[40][41] [42] that apply the DCP technique, in which inefficient pixel-operations are necessary, making them unequal to the task of fast dehazing. In some cases, Tarel et al.'s method[43], which relies on the median filter, does not work well because such strong assumptions are violated. Moreover, images with large dimensions require a lot of computing power. Additionally, the approach is not adaptive as it requires too many parameters to be controlled. Zhang et al. [44][45] have proposed a fast dehazing algorithm that uses an automatic algorithm to teach the parameters of a linear model for modeling scene depth and the depth of the hazed image.

The transmission function can be calculated with the depth information. Next, a haze model was used to estimate radiance of the scene. Although this linear model provides depth information for white objects, further refinement is needed through patch-based minimization and guided filtering [24]. Further, the haze cannot be completely removed by their method in areas with heavy haze. These fast dehazing methods decrease the quality of dehazing while increasing calculation speed. The algorithm of Zhu et al. [44] provides the fastest performance of all codes currently available.

Video Dehazing

An image frame represents a digital video, and it is most often characterized by strong temporal coherence between the frames. There has also been significant progress in the field of dehazing video. Dehazing methods for images were naturally applied to videos, and the frames of hazed videos were processed independently [46][42][47]. Yeh et al. estimated the light transmission function with DCP pixels and bilateral filters. However, due to its computational complexity, they were unable to do so in real-time. Kumari et al.'s method for removing haze from videos increased processing speed but incorrectly corrected the results. It rendered the dehazing useless. As a consequence, the video dehazing methods have broken the coherence of the time when they dehaze every frame of the video separately. Human visual systems (HVS) are extremely sensitive to temporal inconsistencies in video sequences. If the video sequence is not coherent, flickering artifacts are experienced. The algorithms used to dehaze videos later considered the temporal coherence between adjacent image frames. Kim et al. [48] proposed a real-time video dehazing method based on the assumption that the adjacent image frames are temporally coherent when their transmission function values are similar. According to Zhang et al. [40], a MRF model was constructed to measure the light transmission function of adjacent frames and improve spatial and temporal coherence. However, their algorithm required a lot of computation since it used three frames of information to estimate a frame's transmission map, so it couldn't be used for real-time video dehazing. According to Shin et al.'s work [49], flickering artifacts are caused not only by changing transmission maps, but also by changes in atmospheric light values as a result of frame-by-frame video frame changes. For this reason, they proposed a technique for calculating the atmospheric light values that employed adaptive temporal averaging. By fixing the atmospheric light value throughout the video sequence, these other video dehazing methods prevent changes in light values from occurring [50]. The environment illumination can change radically, however, causing colour shifts/distortions.

III. Overview of dehazing method

Dehazing images involves removing haze, improving vision, and enhancing overall visual impact. This is the greatest challenge of mathematical ambiguity. During the haze elimination process, the objective is to expose the desired light (i.e., the scene colors) from the mixed light. In computer vision, dehazing images is critical. Therefore, most researchers have proposed a variety of dehazing algorithms to address these challenging tasks. There are two types of dehazing methods: single image haze removal, which takes a single image as input, and multiple image haze removal, which takes multiple images of the same scene, two, three or more of them. Figure 2.1 shows further categories of image dehazing. [51], [52], [53], [54],[55].

Multiple Image Dehazing: The depth of a photograph could be approximated by using multiple images. In order to aid recovery, 1) a polarizing filter may have to be in good condition, and 2) the weather may be favourable.[56]

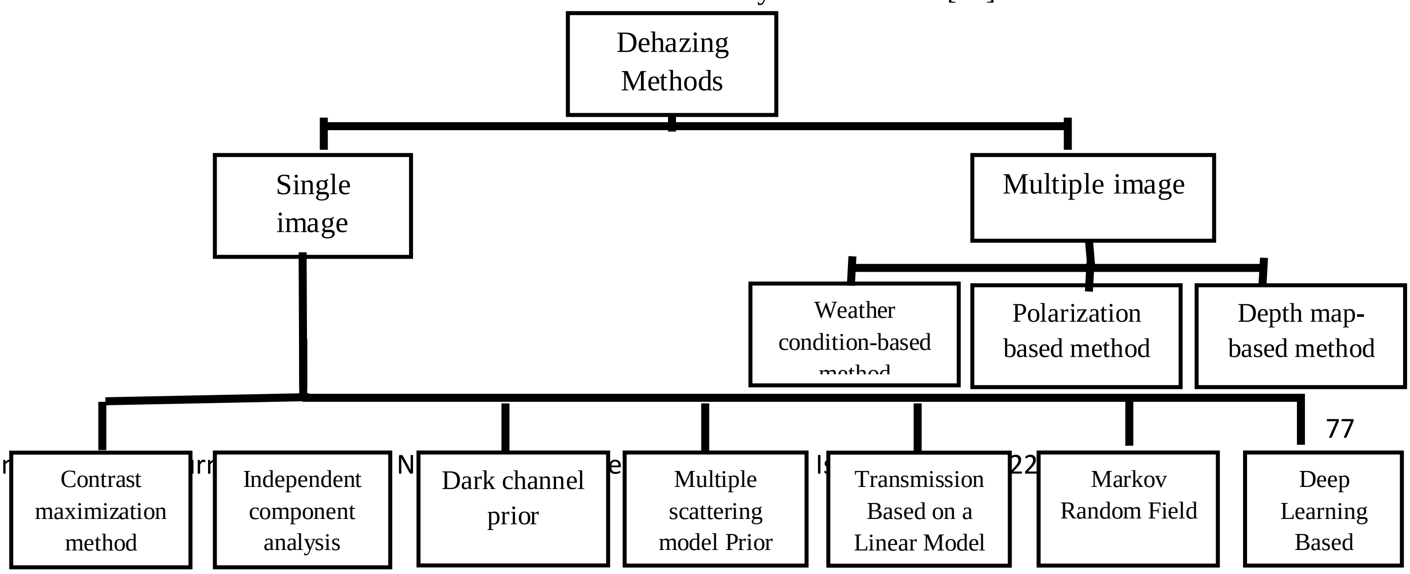

Figure 2.1: Image Dehazing Methods Diagram

i. Weather condition-based method: This technique employs variations of two or more images of the same scene. These images are distinct in their characteristics because it on one hand enhances visibility, and on the other, it makes users wait to see the changes in the medium. The results of this technique are not immediately seen. Dynamic scenes also cannot be handled using this method [16][57].

ii. Polarization Based Method: In this method, a camera rotates a polarizing filter attached to the lens to acquire shots of the same scene through multiple polarization filters. Using this method, dynamic scenes with rapid changes cannot be compared with filters rotating at the same speed [58]. According to a light polarizing study by [45], skylights exhibit polarization properties when they scatter light. In addition, a study concluded that the polarization properties of targets are not determined by light reflections. Using the skylight's properties, the researchers succeeded in reducing haze through computing polarization degrees by retrieving several images of a scene point on the distinct angle of polarization. Using two polarization images reduced the noise in image restoration, as Treibitz et al. compared the effect of one or two polarization images [59]. When polarization filters with different orientations are used on the same scene, they provide polarization images of different brightnesses. For such a method, a pair of identical images must be collected before restoring the image using inverse projection. First, Schechner and colleagues described an algorithm for restoring the image by using two polarization images [58]. Parallel and perpendicular rotations are used to capture the two polarization images, respectively[60].

iii. **Depth Map-Based Method:** In this method, the scene is modelled in 3D and the texture is applied. An accurate result can be obtained using this 3D model, which aligns blurry images and provides depth to the scene. This method does not require special equipment [61].
Depth map-based methods are based on the assumption that Google has indexed the scene's construction and single image [18], and the scene's texture (terrestrial imagery) is ready for retrieval. A haze-filled image's depth is evaluated according to a manual intervention by the user [62]. As a result, no additional tooling was needed for this work, which produced great accuracy. In this method, however, haze removal is highly dependent on the user's manipulation of parameters in the image restoration process. In addition, the lack of other information obtainable makes the method challenging to implement[63].

Single Image Dehazing Methods In this method, only one image is used as the input, and it relies on the particular scene and statistical assumptions[64].

i. **Contrast Maximization Method**: The contrast maximization method reduces the brightness and does not increase the depth of the image. As a result, the saturation values are high [65]. A light source causes the picture to crumble and original differentiation to move radically. When histograms extend before dehazing, picture pixels will fill the entire intensity spectrum, presenting a picture with high complexity. Before shifting the RGB standardized picture back to RGB, the S and V channels were additionally connected to the histogram. The variance enhancement technique was proposed by Robert T. Tan [66] to maximize the regional contrast of the hazy picture. It is principally based upon an appreciation of air-light. By expanding the contrast in the hazy picture with different colors, we can select the brightest pixels. Utilizing algorithm represented as:

$$\text{Contrast}(\hat{R}(x)) = \sum^{S}{}_{x,c} \mid \nabla \hat{R}_{c(x)} \mid,$$

This window has a size of 5x5 and S is its size. The connection and contrast in this problem can be cast into a Markov Random Field because of how evenly spread they are. It is capable of handling both grayscale and color images well, including handling haze depth well.

ii. Independent component analysis: The hypothesis is that surface shading in local patches is uncorrelated statistically. Although this method produces a better result, the disadvantage is that dense fog and haze cannot be removed effectively.For the estimation of surface shading, Fattal has used independent component analysis and Markov random fields. In this strategy, we assume that surface and transmission grayscales are independent of each other. Despite poor performance in conditions of heavy haze, the strategy can still yield superior results. In addition, the statistical assessment of transmissions and shadings could provide optimization opportunities. In addition, color lines have been considered in some recent work [67]. Image regions are assumed to exhibit a consistent colored surface with a constant depth that can only be separated by shadings. Typical hazy images look as follows:

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

where $l(x)$ is the shading.

iii. **Dark channel prior**: To dehaze the hazy image, dark channel priors are effective. They are the minimum intensity value with the lowest haze. A method of removing the haze in an image starts with calculating the atmospheric light and transmission [68].

Based on observations on images taken outdoors with no haze, the dark channel prior is derived from the following observation: At least one color channel has at least one pixel that is very low in intensity. This patch has a minimum intensity close to zero, i.e. it is near the bottom. This observation can be described formally by defining the concept of a dark channel. In any image J, it's dark channel is given by J dark

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

A local patch cantered at x is referred to as Ώ(x) and Jc is a colour channel of J. If J is a haze-free image taken outside, except for the sky region, then we find that the intensity of J's dark channel is very low or often zero[69].

iv. Multiple Scattering Model: An MSM is a technique for removing haze from a single image by utilizing information from the DCP (also known as the point spread function, SPF). According to [66] in performing estimations of SPF in transmission maps, a global Gaussian assumption was undertaken instead of MSM. By examining haze removal visually and numerically, this strategy is considered accurate. Accordingly, this strategy is comprehensive as it both analyzes the subjective aspect of images as well as assessing their numerical structure (quantitative), resulting in promising results compared to existing techniques.

v. **Transmission Based on a Linear Model**: There have previously been a number of methods for removing haze, thereby improving the general quality of computer vision applications.

When searching for haze areas, quadtree can be used effectively to represent airlight conditions. In the presence of sunrays, the quadtree is particularly useful as the algorithm combines spatial requirements with topical inclination and brightness, leading to superior results in identifying sky regions[70]

vi. Markov Random Field: This concept refers to a graph in which nodes, or random variables, are the nodes, and edges, or local interactions, are the edges. This concept leverages the connectivity of a graph to propagate local influences globally. According to Robert T. Tan [67], Markov Random Fields (MRF) have been used to enhance brightness in images. Using the joint probability distribution, nodes in the graph denote random variables and undirected graphs represent probability distributions. Two conclusions can be drawn. First, the contrast between fine and poor weather is greater when the weather is poor. Second, airtight magnitude is a function of distance from the camera to the scene point.

vii. Deep Learning-Based: A variety of deep learning algorithms have been described in literature for dealing with haze images. The use of shallow learning algorithms is lower in comparison to deep neural networks, also known as deep learning or feature learning [71]. Several researchers have used deep learning for image classification and other high-level tasks in computer vision [72], [73]. The tracking of moving objects is being proposed by an object-tracking CNN with pre-trained convolutional layers. The work of [74] was also able to identify end-to-end mapping between low-pixel and high-pixel pictures by using CNN. Additionally, researchers have used CNNs to estimate hazeladen pictures' transmission maps [45], [75],[71],[76],[77]. Even though deep learning strategies have a wide range of applications, it is difficult to apply them to a single image due to difficulties retrieving poor weather images that could be related to poor weather images of the same scene. Because deep learning cannot be applied to identical scenes with poor weather, results will be poor. Table 2.1 show the comparison of all dehazing methods

Table 2.1: Comparison Of Single Image De-Hazing Method Based On Strategies

Method	Technique	Author	Year	Strategy	pros	con
Dark Chanel Prior (DCP)	DCP	He et al.	2011	Dark pixels are exploited Discounting sky region from the scene point	Preserves effectively A natural characterization of an image.	As a result, it would be less effective An estimation of transmission that is hollow within a patch. In order to use an additional boundary, the original transmission map must be recast.
	Improved DCP	Ullah et al.	2013	To define the dark channel, rely on the DCP to theorize both chromatic and chromatic aspects of an image	A better quality of services restored haze-free images with the dark channel/shadow completely redone. The restored images have an improved considerable disparity.	eliminate tools for quantifying the color vibrancy by quantifying quantitative measures
	Dark Channel Prior and Energy Minimizat i on	Zhu et al.	2017	Piecewise smoothness and a DCP were combined to reduce the energy function.	An outstanding performance Removing the unwanted artifacts, as opposed to traditional DCP.	In terms of hollow transmissions, it cannot determine the number of hollow transmissions of smaller radii than the patch radius
Multiple Scattering Model	atmosphere point spread function (APSF)	Wang et al.	2016	DCP can be used to eliminate haze on a single image	A measurement of conveyance in regions of the sky and out of the sky. Provide relief around	Natural recovery should be balanced with both efficiency and effectiveness through learning adaptation
Transmission Function Based on a Linear Model	based on a linear model	Wencheng Wang et al.	2016	Based Quadtree to search for the optimal area where the air-light scatters, and compute the efficiency	Improving efficiency by 30% is, in fact, twice as significant at large and medium sizes.	By identifying a workable way to identify a workable parameter, lose to identify the effects of modifications in user-specified parameters.
Contrast Enhancement	Markov Rando m Field (MRF)	Tan	2008	Air-lighting and enhanced visibility	We solve many of the problems with the previous approaches that were difficult to fulfill, with polarizations of varying degrees or various aerial states. The effect can be applied to color as well as grayscale images	Several small auras line a deep cutout. The image is fenced with them. - Since the data cost optimization algorithm does not know the existing data value, the output has greater saturation (does not know the existing values)

	Color-Lines based Markov Random Field	Fattal	2014	Using estimation of optical transmission to eliminate scattered light and restore haze-free scene disparities	Based on the offset of color lines in hazy images, the method describes color lines in hazy images. Generic regularity of pixels within small image patches, called color lines, in RGB color space, leading to the appearance of small image patches with a regular distribution of pixels	Brightness is poor. No refinement was possible for greyscale images. The resolution of monochromatic images in which the color lines do not match fails. A classification based on this list cannot be guaranteed
Independent Component Analysis (ICA)	estimating the optical transmissio n	Fattal	2008	To improve visibility and remove scattered light based on estimating optical transmission	Produce a refined image formation model that incorporates the transmission function and surface shading	The fog cannot be removed Halo artifacts cannot be removed efficiently by this method.
Deep Neural Network	DehazeNet based on CNN	Cai et al.	2016	A haze-free image is achieved using a trainable end-to-end DehazeNet system	Produces outstanding dehazing results and a dramatic increase in efficiency. For the purposes of learning atmospheric scattering models, this provides a suitable platform	There is no global constant for light at the atmosphere. Through one network, learning would occur in addition to communication
	(Ranking-CNN)	Song et al.	2017	An end-to-end trainable system that generates effective features was proposed as a ranking network.	Massive patch datasets can be used to learn haze-relevant features. Haze-related features can be automatically gathered.	Hazy images may not be captured fully by it. In image retrieval applications, it has poor performance.
	DNN	Huang et al.	2017	Deep neural network dehazing method is proposed for restoring hazy images.	Halo effect is reduced better with this method than with others. The program restores color to input images quite well. Faster process, finally. Restore and dehize colors effectively	The quality of contrast is negatively affected by poor weather conditions. The result of an insufficient understanding of how hazy images form. This method ignores important information. MSE can be larger than other comparable methods in some cases

	multi-channel multi-scale convolutional neural network (C2MSNet)	Dudhane et al.	2018	Based on Cardinal color fusion, we propose using McMs-CNN for dehazing, and DCP for estimating scene transmission maps.	- Do away with customization of haze deactivation features.	When images are captured in poor illumination conditions (gloomy surroundings), color distortion occurs in the final image output.

IV. Recent Related Works

Geet Sahu et al. describe an algorithm that dehazes single images in a relatively new color channel using atmospheric light, radiance, transmission map, and radiance map calculations. It is capable of restoring scene visibility[7]. A new dehazing algorithm has been developed by Jinsheng Xiao et al based-on layers of haze. Through an end-to-end mapping from the original hazy images, the residual images between the hazy and clear images will first be obtained by applying haze layers. Convolutional neural networks may be used to remove residual images from hazy images to recover dehazed images [78]. The back-projected pyramid network (BPPNet) is a generational adversarial network proposed by Singh et al., which is capable of handling challenging haze conditions such as dense haze and heterogeneous haze. By incorporating iterative blocks of UNets and pyramidal convolution blocks, the architecture incorporates multiple levels of complexity while keeping spatial context. The generator consists of these blocks, which are able to be learned via projection[79] DRHNet (Deep Residual Haze Network) imaging dehazing method (end-to-end resolution dehazing) was developed by Chuansheng Wang and colleagues, which subtracts the negative residual map from the hazy images to restore the haze-free image. In particular, DRHNet proposes a module for extracting contextual information in a contextually appropriate way. In addition, RPReLU (Reverse Parametric Rectied Linear Unit) is proposed as a new nonlinear activation function for improving representation and acceleration. Both quantitatively and qualitatively, DRHNet performs better than state-of-the-art methods [6]. Wenqi Ren et al. proposed the use of deep neural networks to dehaze single images. They learned the transmission maps from the hazy images. Using a coarse-scale net, the proposed algorithm predicts a holistic transmission map of an image, while a fine-scale net dehazes the image locally[71]. A simple method for removing haze from a single satellite image was proposed by Ni et al. With the help of local property analysis(LPA) and linear intensity transformation(LIT), this method is developed. Analyzing differences between effects of depth information on hazy natural image and hazy satellite image. They first employ a classical degradation model to demonstrate the rationale of using LIT, and then propose that local image properties such as luminance, color, and texture can be analyzed to adaptively estimate LIT parameters. An experimental study is provided[80]. In this study, Shuai Shao and team developed an algorithm to improve the visibility of a single multispectral hazy image. Their algorithm is based on a learning framework. In this study, haze features from regression models and haze-specific features were aligned. This model was then learned by the gradient descent method. Then, the linear model coefficients are learned to obtain an accurate transmission map of a hazy image [81]. Using incremental transmission learning and spatial-temporally coherent regularization, Shu-Juan Peng and colleagues proposed a dehazing method for real-time video, while explicitly suppressing the possible visual artifacts. A boundary constrained open dark channel model is proposed as an initialization strategy for the transmission map. They derive an incremental transmission adjusting term to adapt the abrupt depth changes between adjacent frames as a result of the highly correlated transmission values between adjacent frames and an imposed temporally coherent term to maintain the temporal consistency[82]. Researchers Zhong Luan and colleagues presented a fast and accurate video dehazing method that reduced computational complexity and maintained video quality. Pixels are assigned a minimum channel and corresponding transmission maps are estimated. The transmission map is adjusted to reduce color distortion in the sky area using an adjustment parameter. To estimate atmospheric light, the authors propose a new quad-tree model. A simple yet highly efficient parameter, describing the similarity of the interframe image content, keeps the atmospheric light unchanged when dehazing a video. The method does not produce unexpected flickers[83]. According to Emberton et.al., they devised a method for detecting and segmenting water-only image regions in order to improve visibility in images and videos. As a result of the process of dehazing, these areas, called pure haze regions, have a similar appearance to the haze that is removed. The authors propose, as well, a semantic white balancing approach for illuminate estimation that takes into account the dominant colour of the water to mitigate the spectral distortion that occurs in scenes underwater [84]. A key problem in computer vision is the dehazing of videos, because turbid images can significantly hamper their performance. Wang et al. proposed a high-speed development of automated driving and video monitoring systems. Presently, convolutional neural networks are being used in video dehazing as one of the remarkable techniques. Deep learning is the inspiration behind this [85]. Video-based approaches can utilize a wealth of information that exists between neighbouring frames, as demonstrated by Wenqi Ren, et al. They develop a deep learning solution for video dehazing that uses a CNN trained end-to-end to learn how to accumulate information across video frames for transmission estimation, on the assumption that a given scene point yields highly correlated transmission values between adjacent video frames. Following the estimation of the transmission map, the atmospheric scattering model is used to recover a haze-free frame [10]. Table 2.1 show the comparative analysis of various recent technique and result.

Table: 3.1 Comparative Analysis

Author Name	Title	Technique Used	Dataset Used	Parameter	Result
Geet Sahu Et Al. 2021.[7]	“Single Image Dehazing Using A New Color Channel”	“Dark Channel , New Color Model”	“I HAZE, O-HAZE, BSDS500, RESIDE, FRIDA, And Google Dataset”	Atmospheric Light, Transmission Map, Radiance, And Enhancement Of The Dehazed	Good And Acceptable
Jinsheng Xiao Et Al. 2020 [78]	“Single Image Dehazing Based On Learning Of Haze Layers”	“Convolutional Neural Network”	“Middlebury Stereo Datasets, NYU Depth Datasets, Hazerd Datasets And RESIDE Datasets”	Feature Extraction, Multi-Convolutional Layers , Reconstruction Decon V	Better Than DCP, SCDCP, And CAP; Ground Truth, Dehazenet, MSCNN,
Ayush Singh ,Et Al. 2020.[79]	“Single Image Dehazing For A Variety Of Haze Scenarios Using Back Projected Pyramid Network”	“Genera-Tive Adversarial Network Architecture”	“I-Haze And O-Haze Datasets Of NTIRE 2018, NTIRE 2019, NTIRE 2020”	Atmospheric Light, Transmission Map,	Average Running Time Of 0.0311 S I.E. 31.1 Ms Per Image. SSIM: 0.8994 PSNR: 22.56
Chuansheng Wang,Et Al. 2020. [6]	“Deep Residual Haze Network For Image Dehazing And Deraining”	“Drhnet (Deep Residual Haze Network), Reverse Parametric Rectied Linear Unit”	“New Dataset Containing Images With Rain-Density Labels Is Created And Used To Train The Proposed Density-Aware Network”	Atmospheric Light, Transmission Map,	7 Layer Transformation Component Is The Best Choice For The Proposed Drhnet.
Wenqi Ren,Et Al. 2019.[71]	“Single Image Dehazing Via Multi-Scale Convolutional Neural Networks With Holistic Edges”	“Multi-Scale Deep Neural Network”	“NYU Depth Dataset”	Atmospheric Light, Transmission Map,	PSNR: 21.27 SSIM: 0.85
Shuai Shao,Et Al. 2019.[81]	“Single Remote Sensing Multispectral Image Dehazing Based On A Learning Framework”	“Novel And Effective Algorithm Based On A Learning Framework”	“Google Earth And NASA Earth Observatory Website”	Atmospheric Light, Transmission Map,	PSNR : 27.28 SSIM: 0.812 MSE: 2.137 FADE: 0.761

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Shu-Juan Peng Et Al. 2020 [82]	"Real-Time Video Dehazing Via Incremental Transmission Learning And Spatial-Temporally Coherent Regularization"	"Transmission Map Frame-By-Frame By A Boundary Constrained Open Dark Channel Model"	"Five Real-World Video Sequences, I.E., 'Hazeroad', 'Bali', 'Playground', 'City1' And 'City2'"	Visible Edge Ratio E And The Average Gradient Ratio R	E : 0.73 R: 2.39
Zhong Luan Et.Al, 2018 [83]	"Fast Video Dehazing Using Per-Pixel Minimum Adjustment"	"New Quad-Tree Method To Estimate The Atmospheric Light"	"NYU Depth V2 Dataset"	Atmospheric Light, Transmission Map,	Result (ε = 0.95,K = 35, μ = 0.9, Andδ = 15)
Simon Emberton Et.Al. 2017 [84]	"Underwater Image And Video Dehazing With Pure Haze Region Segmentation"	"Novel Dehazing Method That Improves Visibility In Images And Videos By Detecting And Segmenting Image Regions That Contain Only Water"	"PKU-EAQA Dataset"	White Balancing	Subjective Evaluation (SE% 43.67
Wang Ziyan Et. Al. 2020 [85]	"Video Dehazing Based On Convolutional Neural Network Driven Using Our Collected Dataset"	"Convolutional Neural Networks"	"NYU Depth V2 Dataset"	Atmospheric Light, Transmission Map,	PSNR :20.4987 SSIM : 0.9683
Wenqi Ren, Et.Al. 2018. [10]	"Deep Video Dehazing"	"Deep Learning"	"NYU Depth V2 Dataset"	Atmospheric Light, Transmission Map,	PSNR: 22.32 SSIM :0.83

V. Research Gap

Dehazing poses the challenge of recognizing scenery objects that are inherently similar to atmospheric light, which is one of the key problems of image dehazing. It would be better to refine the methods for removing haze of course. There is still a distortion problem, especially in those cases where there is a lot of haze. Dehazing is a process that aims to recover dehazed images from hazed images according to the appearance of the scene objects. By recovering the original appearance of the scene objects, we can now highlight the features of the scenes. As a result, outdoor images often appear fuzzy, have reduced contrast, and are affected by color shift and hazy weather. For example, hazy weather will obscure the vision of on-board cameras and create confusing reflections and glare, leaving state-of-the-art self-driving cars in struggle, Outdoor surveillance and Object detection.

VI. Conclusion & Future Work

Literature reviewed shows that the concentration of haze at different locations makes it difficult to recognize haze. To calculate the distribution of transmission maps, a rough estimate can be computed for the dark constituent in native windows pixels, then refined using an image matting technique. Using their method, they achieved much better results than existing state-of-the-art algorithms, and their method worked with every hazy image. It is not uncommon for hazy images to be corrupted due to noise, even when there is known haze concentration. The most efficient method of dehazing can be analyzed in this area in the future. Our main contribution to proposed work is based on an observation that the difference of the maximum and minimum color channel of the hazy image is negatively correlated with depth. If during training proper attention is given to the sub-pixels and blocks where such Contrast exists, progressive deep learning can able to recover the details from hazy image in the form of structure, edges, corners, colors and visibility. We propose a novel Attention Mechanism to effectively generate high quality haze-free images by the application of Contrasting Attention Mechanism over sub-pixels and blocks Also a Variational auto-encoder based dehazing network can be used for training, As an autoencoder accepts input images compresses it and then tries to recreate the original image. This may require estimation of hundreds of parameters which may have impacted the image. However in a variational autoencoder the hazy input images are provided unknown probability distribution (lets say Gaussian) directly and the VAE attempts to estimates the parameters of the distribution The proposed Contrastive Attention Mechanism with existing regularizations and Variational auto-encoder can further improve the performance of various state-of-the-art dehazing networks. The accuracy and robustness of the proposed method will be proved by comparing the results with known dehazing methods based on qualitative and quantitative analysis using RESIDE dataset. RESIDE is a widely used dataset, which consists of subsets of synthetic and real world samples of single image dehazing each serving different training or evaluation purposes.

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