A Survey on Single Image Dehazing Approaches

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Abstract - *Absorption, and scattering caused by particles suspended in the atmosphere results in low visibility. Image dehazing is the process of recovering a haze-free image from a hazy image. Single image dehazing, which aims to recover the clear image solely from an input hazy is a challenging ill-posed problem. Remarkable progress has been made in recent years on single image dehazing which has been an under-constrained challenge. This paper gives a brief review of the existing single image dehazing approaches.*

Key Words: **Image dehazing, Atmospheric Scattering Model (ASM), Image restoration, Dark Channel Prior (DCP), Image depth information, Airlight**

1. INTRODUCTION

Haze is an atmospheric phenomenon that occurs when suspended aerosols interact with light. It degrades the image quality by introducing blurring effect, reducing contrast, and creating false colors in the acquired image resulting in low visibility. Poor visibility in outdoor haze scenes generates significant problems for many applications of computer vision systems including surveillance, intelligent vehicles, object recognition, etc. Therefore, an effective haze removal method is necessary. The process of removing haze from a hazy image is referred to as dehazing and it is an area of active research and remarkable progress has been made in recent years on single image dehazing which has been under-constrained challenge.

2. ATMOSPHERIC SCATTERING MODEL

Image dehazing is an increasingly widespread approach to address the degradation of images of the natural environment by low-visibility weather, atmospheric particles, and other phenomena. Advancements in autonomous systems and platforms have increased the need for low-complexity, high-performing dehazing techniques.

An Atmospheric Scattering Model (ASM) to describe the formation of hazy images, shown in Fig 1, can be expressed as [1],[2],

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

where I is the hazy image, x is the pixel location of the image, t(x) is the medium transmission map, J is the dehazed image and A is the atmospheric light vector in RGB domain. If the atmosphere condition is assumed to be homogeneous, t(x) can be represented as

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

where β is the medium extinction coefficient, and d(x) is the depth between the objects and the camera. The value of β is assumed to be constant in every wavelength of light and hence, t(x) is considered the relative depth of the scene with a value between 0 and 1.

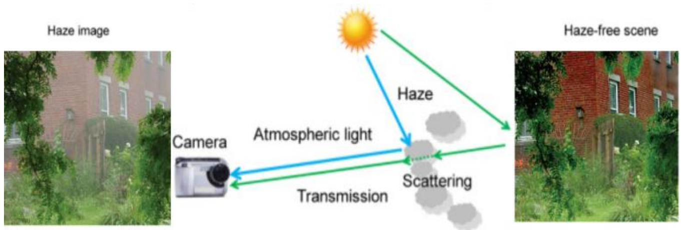

Fig -1: ASM for Hazy Image Formation

3. SINGLE IMAGE DEHAZING METHODS

Fattal proposed a method for estimating the optical transmission in hazy scenes given a single input image [3]. In this method, the image was first split into regions with constant albedo and the airlight-albedo ambiguity was removed by introducing a constant that requires the surface shading and medium transmission to be locally uncorrelated. The use of robust statistics helps to cope with complicated scenes containing different surface albedos and the use of an implicit graphical model makes it possible to extrapolate the solution to pixels where no reliable estimate is available. Based on the recovered transmission values the scene depths can be estimated. This method showed a significant reduction of the airlight and restored the contrasts of complex scenes. However, it does not assume the haze layer to be smooth i.e., it permits discontinuities in the scene depth and medium thickness.

Carr *et al.* proposed a single image dehazing method based on the assumption that the neighboring pixels in an image will have similar depths [4]. This method showed that a priori camera geometry can be exploited to improve the results of any statistical estimation technique. This can be implemented as a soft constraint within an energy minimization framework and it leads to a preference that pixels should get further away as one scans the image from bottom to top. This preference was fully compatible with the α-expansion algorithm; however, it does not always have to be true. The geometric model can be used for fog removal purposes and also can be incorporated with different depth estimation techniques.

Fang *et al.* proposed a single image dehazing method based on segmentation [5]. The image segmentation was used to calculate the dark channel instead of patch and then transmission maps prior were obtained according to the black body theory. Since the abrupt change of depth usually happens in the image edge regions, this method reduces the depth discontinuities within each patch and eliminates halo artifacts to a large extent. Also, this method overcomes the inherent deficiency of restoration model which can obtain better dehazed results. Since the errors in the dark channel prior remain, this method is limited to obtaining the haze-free result to some extent when color of the scene object is similar to the atmospheric light.

He *et al.* introduced a single image dehazing method based on Dark Channel Prior (DCP) [6] and it was based on the assumption that in most of the non-sky patches, at least one color channel has some pixels whose intensity is very low and close to zero and as a result, the minimum intensity in such a patch will be considered as zero. This method was very effective in recovering vivid colors and low contrast objects. However, if the haze is removed thoroughly, then the dehazed output loses the depth effect and it seems to be unnatural. Hence, a very small amount of haze has to be kept for distant objects. A major limitation of this method was that since the transmission map may not be always constant in a patch, it creates halos and block artifacts in the output. Thus soft matting technique was employed for better image restoration and the results of the restored images are impressive with visual contrast. However, this method was computationally complex because of the calculation of DCP. Also, as the haze imaging model assumes common transmission for all color channels, this method may fail to recover the true scene radiance of the distant objects and they remain bluish.

Kim *et al.* proposed a simple and adaptive single image dehazing algorithm based on contrast enhancement [7]. This method first estimates the airlight in a given hazy image based on the quad-tree subdivision and then estimates the optimal transmission to maximize the contrast. It provided good dehazing results at low computational complexity since the transmission was assumed to be a constant over an entire image. However, it may not produce faithful results when the depth differences between foreground objects and the background are very large. As a result, this method was also extended to estimate a space-varying transmission map to dehaze an image with a complicated depth structure more accurately. However, this optimization is less reliable since a smaller number of pixels were employed in the cost function formulation.

Ancuti *et al.* introduced a single image dehazing method using multi-scale fusion [8]. The fusion-based technique was based on the concept that two input images were derived from the original input to recover the visibility for each region of the scene in at least one of them. To blend the information of the derived inputs effectively, weight maps were used to filter the important features to preserve the regions with good visibility. Finally, the Laplacian of the inputs and Gaussian of the weights are blended in a multi-scale fashion to reduce the artifacts. Even though this method provided faster and more accurate results, it was limited only to homogeneous hazy images.

Zhu *et al.* proposed a color attenuation prior-based method for single image dehazing [9]. The color attenuation prior was based on the difference between the brightness and the saturation of the pixels within the hazy image. This simple and powerful prior can help to create a linear model for the scene depth of the hazy image. The bridge between the hazy image and its corresponding depth map was built effectively by learning the parameters of this linear model. With the recovered depth information, the haze can be removed from the hazy input image. This method provided much sharper and natural results free from halo effects. But, linear color attenuation prior was also based on statistics that were not sensitive to the scene objects with inherent white color.

Ren *et al.* introduced a multi-scale deep neural network for single-image dehazing by learning the mapping between hazy images and their corresponding transmission maps [10]. The scene transmission map was first estimated by a coarse-scale network and then refined by a fine-scale network. Even though this method was easy to implement and reproduce, it was less effective for nighttime hazy images.

Singh *et al.* designed Gradient profile prior (GPP) to evaluate depth map from hazy images [11]. The developed gradient-based profile prior was able to reduce the color and texture distortion issues. The transmission map was improved by utilizing guided anisotropic diffusion and an iterative learning-based image filter (GADILF). The restoration model was improved to reduce the effect of pixels saturation and color distortion from restored images. This method was able to suppress visual artifacts for hazy images and yield high-quality results with high computational speed. However, if the hazy image is removed completely, then the restored image looks like an artificial image.

Zhu *et al.* proposed a novel fast single image dehazing algorithm based on artificial multi-exposure image fusion to enhance the performance and robustness of image dehazing [12]. Based on a set of gamma-corrected underexposed images, pixel-wise weight maps were constructed by analyzing both global and local exposure to guide the fusion process. The spatial dependence of luminance of the fused image was reduced, and its color saturation was balanced in the dehazing process. However, it does not consider the saturation variation in a hazy image.

Zheng *et al.* proposed an adaptive multiple-exposure image fusion (AMEF) algorithm for single image dehazing [13]. An adaptive gamma transformation was utilized for each component (R, G, and B) of the color image, based on the mean and standard values of each component, that is, the global characteristics of the hazy image. A sequence of adaptive gamma corrections were employed to extract a collection of under-exposed multi-exposure image sequences from a haze image. Then, the Gaussian pyramid and Laplacian pyramid with the homomorphic filtering algorithm was utilized to address the exposed obtainable images, followed by a modified Laplacian filter for calculating the contrast of the exposed accessible images. This method provided higher contrast, richer details, and a better visual effect in the dehazed image. However, the linear adjustment of image saturation and the adaptive selection of image block size resulted in increased computational complexity.

Baiju *et al.* proposed an optimization framework using a low-rank approximation to efficiently estimate the scene transmission map for single image dehazing [14]. A low-rank approximation technique with weighted nuclear norm minimization was introduced to smoothen the coarse transmission map obtained from hazy data to remove the visual artifacts in the dehazed image. This efficient optimization model estimates scene transmission map for dehazed image using a single available hazy image and achieves fast dehazing. This method does not require any pre-trained model and was capable of retrieving good results in less execution time.

Sahu *et al.* proposed a single image dehazing method based on using a new color channel prior [15]. In this method, atmospheric light was estimated by dividing an image into blocks, then the score of each block was computed. The block having the highest score was further used for calculating the atmospheric light. A new color model was adopted to calculate the transmission map and it was further used for computing radiance. Although the results were acceptable for indoor images, further research needs to be performed to generate realistic and visually pleasing images.

Zhang *et al.* introduced a single image dehazing using a dual-path recurrent network (DPRN) [16]. The DPRN consists of a feature extraction block, a transmission map estimation block, a dual-path block with a parallel interaction function, and an image reconstruction block. Initially, the DPRN uses the feature extraction block and the transmission map estimation block to extract features from the hazy image. These features are then fed into the dual-path block, which utilizes two parallel branches to restore the basic content and details of the clear images. The dehazed result is obtained by processing the output features of the dual-path block by the image reconstruction block. Even though this method produces images with clear content and fine details, the model needs to be trained initially with different hazy images which is a time-consuming process.

3. CONCLUSION

Image has important applications in many fields such as marine surveillance, environment monitoring, and so on. The scattering effects of the atmospheric particles in the air play a main role, resulting in contrast reduction and color fading. As a result, the clear image is necessary. The main advantage of single image dehazing is that a haze-free image can be obtained from only a single available image. This work is a summary of different single image dehazing techniques with their advantages and limitations.

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