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An Efficient Adaptive Denoising and Dehazing Technique

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Abstract: Image haze removal has become an important research direction in the field of computer vision because of the vast development and increasing demand of its applications. Outdoor images that are captured in bad weather are degraded due to factors like noise and haze. These factors seriously affect the visibility of the image. Images may contain impulse noise which is produced by the sensor and circuitry of image-capturing devices like cameras. Images may also contain haze, which is formed due to the combination of two fundamental phenomena namely, attenuation and the airlight. Attenuation reduces the image contrast and air light increases the whiteness in the image, thereby making the images unclear. This work presents a hybrid approach for denoising and dehazing a single noisy and hazy image. First, the input image is passed through an adaptive median filter to remove the impulse noise. Then the resultant image is dehazed using simple color attenuation prior. The experimental results show that the visual quality of the output images are much better than the original input images, which proves the efficiency of this method.

Keywords: Adaptive Median Filter ; Atmospheric Scattering Model ; Color attenuation prior ; Denoising ; Haze removal ; Impulse noise ;

I. INTRODUCTION

The outdoor images often contain haze, fog, or other kinds of atmospheric degradation caused by particles in the atmospheric medium. These particles absorb and scatter light as it travels from the source to the observer, resulting in an unclear or less visible image. Many computer vision algorithms rely on the assumption that the input image is haze-free. So when this assumption is violated, algorithmic errors can occur resulting in an undesired output.

When capturing an image of an object in the haze-free condition, the object to be captured reflects the energy from the illumination source (e.g., direct sunlight, diffuse skylight and light reflected by the ground) and only a little amount of energy is lost when it reaches the imaging system. The imaging system collects the incoming energy reflected from the object and focuses it onto the image plane. Hence, a clear image is obtained. Without the influence of the haze, outdoor images are usually with vivid color. But in hazy weather, the situation becomes more complex. There are two mechanisms in imaging under hazy weather, which causes the captured image to be unclear. First is the direct attenuation which is caused by the reduction in reflected energy. The other is the white or gray airlight, which is formed by the scattering of the environmental illumination. Since the haze concentration changes from place to place , it is difficult to detect haze in an image. The images captured under haze undergo degradation, loses fidelity and becomes less visible.

Among current haze removal scenarios, haze estimation methods can be broadly divided into two categories of either relying on additional data or using certain prior assumptions. The methods that rely on additional information include taking multiple images during different weather conditions, taking multiple images of the same scene using different degrees of polarization, and methods that require user supplied depth information or a 3D model. These methods achieved good results, but the extra information required is not available always.

II. RELATED WORKS

Significant progress in single image haze removal has been made in recent years. Reference [1] used an image dehazing method with the assumption that a haze-free image has a higher contrast than a hazy image. This method was able to obtain best results by maximizing the contrast in the local regions of the input image. But, the final results obtained by this approach were not based on a physical model and were often looking unnatural due to over-saturation. Reference [2] used a method for haze removal, by assuming that surface shading and transmission are locally uncorrelated and was able to obtain best results. With this assumption, the transmission map was obtained through Independent Components Analysis. Even though it was a physically reasonable approach, the method had trouble with dense haze regions where the different components are difficult to resolve. A simple but powerful approach was proposed by estimating the dark pixels in local windows, to obtain a coarse estimate of the transmission map followed by a refinement step using an image matting technique in [3]. The method obtained results which were much better than other state-of-the-art algorithms, and was even successful with every hazy image. Reference [4] uses a simple color attenuation prior for haze removal. By creating a linear model for modelling the scene depth of the hazy image, and learning the parameters of the model with a supervised learning method, the depth information was well recovered. This method provided better efficiency and dehazing effects compared to others and the obtained output images were not over enhanced.

Even when the concentration of haze is known, noise can be a major issue when dehazing images. The works mentioned above largely avoid the problem of noise, usually by assuming that the input image is noise-free. The existing methods that have addressed noise has taken two basic approaches: denoising during dehazing and denoising prior to dehazing. Reference [5] addressed the issue of noise through image fusion. By taking different images of the same hazy scene and using weighted averaging, they obtained a low noise, sharp, hazy image which was then dehazed using a variation of the dark channel prior method. Reference [6] used a polarization based method to estimate haze, and addressed noise by adding a local penalty term that is proportional to the transmission value as a regularization term in scene radiance recovery. Since the regularization was relatively simple, hazy regions were blurred while non-hazy regions were left sharp. A more sophisticated variant on this method was discussed in [7], which used a total variation method based on Beltrami flow for regularization. Although the method was effective, the use of complicated PDE methods, requiring minimization over the entire image, was a major drawback. Furthermore, all of the above mentioned works rely on multiple images.

This work addresses the problem of recovering and restoring the scene radiance of a single noisy, hazy image, with the main contributions as follows. First, the single input image is passed through an adaptive median filter to remove the impulse noises. Then, the resultant image is dehazed using simple and powerful color attenuation prior. A linear depth model is used to obtain the scene depth of the hazy image. With the depth map, we can easily estimate the airlight and transmission. Now the scene radiance can be restored via atmospheric scattering model to obtain the haze-free image .Thus, a dehazed and denoised image with enhanced visibility is obtained.

The rest of this paper is organized as follows: Section 2 briefly explains the essential background knowledge needed to understand the proposed work. Section 3 describes the proposed method in detail with a block diagram and an algorithm. The experimental results are mentioned in Section 4, followed by a brief conclusion in Section 5.

III. BACKGROUND DETAILS

Inorder to have a deep understanding of the proposed work, one needs to have some essential background knowledge. This section discusses some such background details.

A. *Adaptive Median Filter*

The adaptive median filter [8] performs spatial processing to preserve detail and to smoothen the non-impulsive noise. A prime benefit to this adaptive approach to median filtering is that repeated applications of this Adaptive Median Filter do not erode away edges or other small structure in the image. The basic operation of a median filter is as follows: at each pixel in a digital image, place a neighbourhood around that point, and analyze the values of all the pixels in the neighborhood according to some algorithm, and then replace the original value of the pixel with the one based on the analysis performed on the pixels in the neighborhood. The neighborhood then moves successively over every pixel in the image, repeating the process. But,the median filter can't distinguish fine detail and noise.

Therefore the adaptive median filtering has been applied widely as an advanced method compared to standard median filtering. The adaptive median filter performs spatial processing to determine which pixels in an image have been affected by impulse noise. It classifies pixels as noise by comparing each pixel in the image to its surrounding pixels in the neighbourhood. The size of the neighborhood is adjustable. A pixel that is different from a majority of its neighbours, or not being structurally aligned with those pixels to which it is similar, is called as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling test. The adaptive median filter preserves detail and smooth non-impulsive noise.

B. *Atmospheric Scattering Model*

The atmospheric scattering model [9] widely used to describe the formation of a hazy image **I**(x), where x is the pixel index, is shown as :

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

$$t(x) = e^{-\beta d(x)} \quad (2)$$

where **I** is the hazy image, **J** is the scene radiance representing the haze-free image, **A** is the atmospheric light (also called airlight), **t** is the medium transmission, **β** is the scattering coefficient of the atmosphere, **d** is the depth of scene and **t** is the medium transmission indicating the portion of the light that reaches the camera without getting scattered. The major goal of single image dehazing is to recover a haze-free image **J**, by estimating **A**, and **t** from the received input image **I**, which is an under-constrained problem. In this model, the term **J**(x).**t**(x) is called direct attenuation and the term **A**(1 - **t**(x)) is called airlight. The direct attenuation denotes the scene radiance and its decay in the medium while the airlight results from previously scattered light and leads to the shift of the scene colors. The direct attenuation is a multiplicative distortion of the scene radiance, while the airlight is an additive distortion. This haze optical model has been employed in most works of single image dehazing.

C. *Color Attenuation Prior*

The brightness and the saturation of pixels in a hazy image vary sharply along with the change of the haze concentration. The concentration of haze is positively correlated with the difference between brightness and saturation. In a dense-haze region, it is more difficult to recognize the inherent color of the scene, and the difference between brightness and saturation is very higher. In moderately hazy regions, the saturation decreases and the brightness increases at the same time producing the high value of the difference. In a haze-free region, the saturation of the scene is pretty high, the brightness is moderate and the difference between the brightness and the saturation is close to zero. Since the concentration of the haze increases along with the change of the scene depth in general, an assumption can be made that the depth of the scene is positively correlated with the concentration of the haze and we have:

$$d(x) \propto c(x) \propto v(x) - s(x) \quad (3)$$

where **d** is the scene depth, **c** is the concentration of the haze, **v** is the brightness of the scene and **s** is the saturation. This statistics is regarded as the color attenuation prior [4].

IV. PROPOSED METHOD

Noise and haze removal algorithms have become more and more of researcher's interest. Most of the image processing and computer vision applications use systems which assumes that the input images they are using are free of noise and haze. So, using a distorted and degraded input may affects the quality of the output produced by those systems. Here we propose an efficient and adaptive denoising and dehazing method. The block diagram of the denoising and dehazing model is shown in Figure 1. A noisy and hazy image is given as the input to the system. First, the image is passed through an adaptive median filter to filter the impulse noise present in the image. After obtaining the denoised image, depth map, transmission map and airlight is estimated from the resultant denoised, hazy image using a simple color attenuation prior. Finally, a hazy-free image is obtained from the atmospheric scattering model. Thus a denoised and dehazed image is obtained. Algorithm 1 presents the outline of the proposed method.

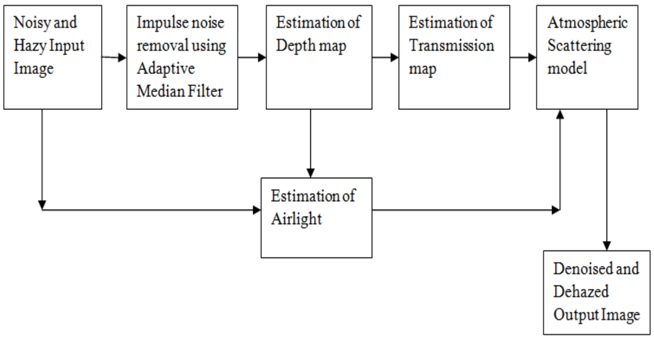

Figure 1. Block diagram of denoising and dehazing model

Algorithm 1: Outline of the proposed method
Input : Noisy and hazy image
Output: Denoised and dehazed image

1. Filter out noise from the input image using adaptive median filter.
2. Estimate depth map of the resultant image using color attenuation prior.
3. Estimate airlight.
4. Find transmission map and scene radiance using atmospheric scattering model.

The different modules of the proposed method are discussed in detail below.

A. *Noise Removal*

Image noise can be expressed as a random variation of brightness or color in the formation of images. Image noise is produced by the sensor and circuitry of image capturing devices such as a scanner or a digital camera. Image noise also originates from film grains. Image noise is an undesirable by-product of image capture that adds spurious information to images. The noise contained in the input image is removed using an adaptive median filter [8].The noise can be effectively removed by separating the RGB color image into red, green and blue channels. So the first step of noise removal is to divide the input image into red, green and blue components. Then, each of these components are separately input to the adaptive median filter to produce noise-free red, green and blue components. Finally all the three components are combined, so that the resultant image becomes noise free.

B. *Estimation of Depth map*

The depth map of the input image plays an important role in estimating the amount of haze present in the input images. A Depth map is an image or image channel that contains information relating to the distance of the surfaces of scene objects from a viewpoint. The depth map shows luminance in proportion to the distance from the camera. Nearer surfaces appear darker and farther surfaces appear lighter. Inorder to estimate the depth map, the RGB color image is first converted to HSV (hue, saturation, value) plane. Now, using the color attenuation prior [4], a linear model which defines depth map has been derived as :

$$d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + \varepsilon(x) \quad (4)$$

where **d** is the scene depth, **v** is the brightness component, **s** is the saturation component, $\theta_0, \theta_1, \theta_2$ are unknown linear coefficients, ε is the random error of the model. The values of $\theta_0, \theta_1, \theta_2$ are taken as 0.121779, 0.959710 and -0.780245 respectively [4].

To refine the depth map, a guided image filter [10] is used. The guided image filter is the fastest and efficient edge-preserving filter to smoothen the images. The blocking artifacts can also be effectively suppressed using this filter.

C. *Estimation of Airlight*

The airlight is a component which increases the whiteness in the captured images, making them unclear. Therefore the airlight need to be filtered out from the captured image to make the images clear. Bright regions in the depth map stand for distant places. The airlight [6] can be estimated by picking the top 0.1% brightest pixels in the depth map and selecting the pixel with highest intensity in the corresponding hazy input image among these brightest pixels.

D. *Transmission map estimation and Scene Radiance Recovery*

A Transmission map expresses the relative portion of light that manages to survive the entire path between the observer and a surface point in the scene without getting scattered. The estimation of transmission map, **t** and the scene radiance recovery is performed using the atmospheric scattering model. The haze-free image, J can be obtained by re-arranging the equation of atmospheric scattering model as:

$$J(x) = \left(\frac{(I(x) - A)}{t(x)}\right) + A \tag{5}$$

where **I** is the scene radiance representing the haze-free image, **A** is the atmospheric light, **t** is the medium transmission, **β** is the scattering coefficient of the atmosphere , **d** is the depth of scene.

V. EXPERIMENTAL RESULTS

A. Experimental Configuration

The proposed work is implemented in MATLAB 2015 environment. The sample input images were created by first taking a hazy image and then applying impulse noises to it using a impulse-noise-adding algorithm. After obtaining the denoised, dehazed image, the elapsed time for the entire process is calculated. The mean square error, peak signal to noise ratio and normalized correlation is also determined as a part of quantitative analysis.

B. Qualitative Analysis

Different noisy and hazy sample images were tested using the proposed method. Figure 2(a) shows four different sample input images used for testing the proposed method. Figure 2(b) shows the noise removal approach of the input images, which is performed by first separating the input image into three components (red, green and blue components) and then inputting these three components separately into the adaptive median filter. Figure 2(c) shows the depth map of the resultant image. The depth maps were obtained by first converting the RGB images to HSV plane. Then, a linear model of scene depth is used for estimating the scene depth. As the figure shows, nearer surfaces in depth map appear darker and farther surfaces appear lighter. Figure 2(d) gives the transmission map of the images. Transmission maps were obtained from the atmospheric scattering model, ie, by using (2). Figure 2(e) shows the estimation of airlight. The red colored dots in the images is the brightest pixels in the image, which are used for finding the airlight. Figure 2(f) gives the denoised and dehazed output image.

The output images obtained using the proposed method were able to filter out noise and haze completely. As the figure shows, there is a lot of difference between the input and output images. Noise and haze were removed and the outputs obtained are very clear as shown in Figure 2. Some state-of-the-art dehazing methods fail to distinguish between the white color objects and haze. For example, if the input image contains a white colored object such as swan or geese, some haze removal methods mistakenly consider these white objects as haze and therefore their outputs may give a wrong dehazing result. But our method was able to distinguish between white objects and haze due to the clear linear definition of the depth map. The outputs obtained were neither over-saturated nor over-enhanced.

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

Figure 2. Experimental results on various images.(a) Sample input images.(b) Noise removal.(c) Depth Map.(d) Transmission Map.(e) Airlight Estimation.(f) Denoised and Dehazed output.

Table I. Quantitative analysis of sample images

Sample Images	Time elapsed in obtaining output (in seconds)	MSE	PSNR	Normalized Cross-Correlation
Sample image 1	2.479746	0.0104	65.3042	1.1844
Sample image 2	2.743204	0.0063	70.1153	1.1219
Sample image 3	2.385306	0.0083	68.9232	1.1490
Sample image 4	2.373449	0.0186	65.4317	1.1606

C. *Quantitative Analysis*

In order to quantitatively assess and rate the proposed algorithm ,the total elapsed time, the mean square error (MSE) [11], peak signal to noise ration (PSNR) [12] and Normalized cross-correlation [13] of the results have been calculated. The four sample images shown in Figure 2 were used inorder to perform the qualitative analysis. Table 1 shows the results of the quantitative analysis for each sample image. From Table 1, it can be inferred that the values of MSE, PSNR and Normalized cross-correlation were desirable.

VI. CONCLUSION

Noise and haze removal has been gaining popularity in recent years as many computer vision applications' efficiency strongly relies on clarity the input images. Any error or unclear input would result in an undesirable output. The proposed work addresses the problem of recovering the underlying scene radiance of a single noisy, hazy image. First, the single input image is passed through an adaptive median filter to remove the impulse noise. Then, the resultant image is dehazed using a simple and powerful color attenuation prior. A linear depth model is used to obtain the scene depth of the hazy image. With the depth map, the airlight and transmission map can be estimated easily. Now the scene radiance can be restored using the atmospheric scattering model to obtain the haze-free image. Thus a denoised and dehazed image with enhanced visibility is obtained as output. Finally, the mean square error, peak signal to noise ratio and normalized cross-correlation is calculated as a part of quantitative analysis. Since the proposed method is based on a color attenuation prior, this method can be used to remove noise and haze from color images only. The denoising and dehazing of videos can be done as future work.

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