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A Dehazing Benchmark with Real Hazy Outdoor Images

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ABSTRACT

A single image dehazing is one of the problemin image processing. The main aim of using this method is to obtain certain transmission map to abolish hazes from a single input image. An optical model is evaluated and the basic transmission map under an additional filter is modified. For better conservation of haze image, the globally guided image filtering can be applied to produce sharper images and preserves details in regions of fine structure visibly.

Keywords: *Globally guided image filtering (G-GIF); De-haze; Transfer filter and global edge-preserving smoothing filter.*

1.0 Introduction

Single image Dehazing has been a challenging problem due to its ill posed nature[6]. Bad weather conditions such as haziness, mist, foggy and smoky degradation in the quality of the outdoor scence.It is an annoying problem to photographers as it changes the colors and reduce the contrast of daily photos[8]. Effective haze removal is very widely demanded area in computer version and graphics applications. Haze is different from place to place quality of image in haze weather condition is reduced due to scattering of light .This may affect the normal working of outdoor recognition system[11] .Scattering of light is mainly due to two atmospheric phenomena air light and attenuation. Haze attenuate the reflector light from scene and some additive light from mixed light by using effective haze removal techniques stability and effectiveness of visual system can be improved[11].

Previous methods require more number of images to perform dehazing. For example, polarization-based methods use the polarization property of scattered light to restore the scene depth information from two or more images taken with different degrees of polarization. Similarly, in multiple images of the same scene are captured under different weather conditions[11] .The linear model was finally adopted to design a single image haze removal algorithm with the help of the guided image filtering.

Air light increase the whiteness and attenuation decreases the contrast in an image[9]. Haze removal method is divided into to two classifications: image enhancement and image restoration. The main objective of image enhancement[10] is to process a given image so that the result is more suitable than the original image. Image restoration is the process of taking dehazed image and evaluating the clean original image.

Haze removal needs depth map estimation, transmission map estimation, estimation of atmospheric light and transmission map refinement[2]. In haze removal image enhancement and restoration techniques are used[10].

2.0 Related Work

Meng et al[1] further exploits the advantages of the dark channel prior . The method applies a boundary constraint to the transmission estimate yielded by DCP. The boundary constraint is combined with a weighted L1 norm regularization. Overall, it mitigates the lack of resolution in DCP transmission map. This algorithm shows some improvement compared with the He et al. Technique

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reducing the level of the halo artifacts around sharp edges. It also better handles the appearance of the bright sky region.

Fattal [1]Introduces a method relying on the observation that the distributions of pixels in small natural image patches exhibit one-dimensional structures, named colorlines, in the RGB color space.

A first transmission estimation is computed from the detected color-lines offset to the origin, while a refined transmission is generated by a Markov random field model in charge of filtering the noise and removing other artifacts caused by scattering.

Cai et al[1] propose to adopt an end-to-end CNN deep model, trained to map hazy to haze-free patches. The algorithm is divided into four sequential steps: features extraction, multi-scale mapping, local extrema and finally non-linear regression. The training is based on synthesized hazy images.

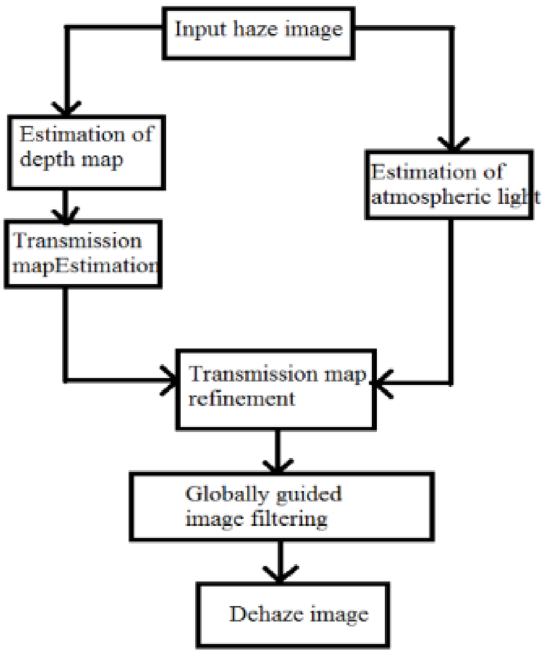
Ancuti et al[1]introduce a novel straightforward method for local airlight estimation, and take advantage of the multi-scale fusion strategy to fusion the multiple versions obtained from distinct definitions of the locality notion. Although the solution has been developed to solve the complex night-time dehazing challenge, including in presence of severe scattering or multiple sources of light, the approach is also suited to day-time hazy scene enhancement. Berman et al[1]Further exploits the color consistency observation , which considers that the color distribution in a haze-free images is well approximated by a discrete set of clusters in the RGB color space. They observe that, in general, the pixels in a given cluster are non-local and are spread over the entire image plane. The pixels in a cluster are thus affected differently by the haze. As a consequence, each cluster becomes a line in the hazy image, and the position of a pixel within the line reflects its transmission level. In other words, these haze-lines convey information about the transmission in different regions of the image, an dare used to estimate the transmission map.

Ren et al[1] develop a multi - scale CNN to estimate the transmission map directly from hazy images. The transmission map is first computed by a coarse-scale network, and is then refined by a fine-scale network. The training has been performed using synthetically generated hazy images, obtained from haze-free images and using their associated depth maps to apply a simplified light propagation model.

3.0 Proposed Method

The proposed filter is a globally guided image filtering and it is called the G-GIF. Inputs of the proposed G-GIF are an image to be filtered and a guidance vector field while inputs of the Previous techniques are an image to be filtered and a guidance image. The structure is defined by the guidance vector field. The proposed G-GIF is composed of a global structure transfer filter and a global edge-preserving smoothing filter. The function of the structure transfer filter is to transfer the predefined structure to the image to be filtered while the function of the smoothing filter is to smooth the transferred image so as to produce the output image. The proposed filter can be applied to produce sharper images.

Figure 1: Flow Chart



3.1 Dark Channel Prior

The channel is based upon the assumptions of dark pixels which have very low intensity in at least one color channel(R,G,B).We use min function in DCP[2] .It improves the quality of image Based on the observation ,a dark channel is defined as follows

$J^{dark}(x) = \left(J^c(y)\right)$

Where J^c is an intensity for a color channel $c\epsilon\{r,g,b\}$ of the RGB image and $\Omega(x)$ is a local patch centered at pixel x. According to the above equation the minimum valu among the three color channels and all pixels in $\Omega(x)$ is chosen as the dark channel $J^{dark}(x)$.The low intensities in the dark channel are due to the following colourful items or surfaces, dark objects and shadows.

3.2 Estimation of depth map

The scene objects with white color as being distant. This ends up in accurate estimation of the depth in some cases[7]. The minimum worth that is taken into account as depth of image.

$$d_r(x) = d(y)$$

Where r(x) is an r x r neighbourhood centerd at x and dr is the depth map with scale r.

3.3 Estimation of atmospheric light

The atmospheric light estimation method is used to identify dense haze regions. This method combines the color model and haze line model[7]. The magnitude of atmospheric light is estimated by balancing several intensities of different depth ranges. By using atmospheric light estimation we increase the brightness of the image the percentage value of brightness of image is 0.1%

$$A = I(X), X\epsilon\{X|\forall y: d(y) \leq d(X)\}$$

Where A is atmospheric light of the image and I(x) equal to A approximately .d(x) is the large enough in an image.

3.4 Transmission map estimation

The transmission map is estimated from the input hazy image and is concatenated with high dimensional feature map. The aim is to learn a pixel wise non-linear mapping from the given input image.

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

Where x is the position of the pixel within the image, t is the medium transmission,β is the scattering coefficient of the atmosphere and d is depth of scene.

3.5 Transmission map refinement

The refinement is used to supress small variations through adjacent pixels. We do refinement by combining original image and atmospheric light estimation image. In transmission map refinement we will get output which is inverted, by applying transpose we will get the exact image.

3.6 Globally guided image filtering

G-GIF is composed of global structure transfer filter and global edge preserving smoothing filter. The images which are obtained by using G-GIF are sharper than the images of existing GIF. The scene radiance Z(p) is recovered by using this filter

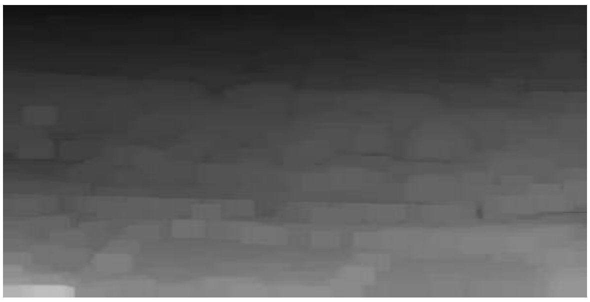
$$X_c(p)=Z_c(p)t(p) + A_c\big(1 - t(p)\big)$$

Where $c\epsilon$\{r, g, b\} is color channel index, $X_c$is a haze image and Z_c is a haze free image,A_c is the global atmospheric light, and t is the medium transmission describing the portion of the light that is not scattered and reaches the camera.

Figure 2: Results

Input image **Dark channel prior image**

Transmission map **Atmospheric light estimation**



Refinement image **Dehaze Output**

4.0 Visibility Metric Analysis

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codes (e.g., for image compression)[1]. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an *approximation* to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

PSNR is most easily defined via the mean squared error (*MSE*). Given a noise-free $m\times n$ monochrome image I and its noisy approximation K, *MSE* is defined as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i.j) - K(i,j)]^2$$

The PSNR (in dB) is defined as

$$PSNR = 10.log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$=20.log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

$$=20.log_{10}(MAX_I) - 10.log_{10}(MSE)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is 2^B-1. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three[1]. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space.

	Methods	PSNR	SNR
Existing	CNN	42.8	33.54
Proposed	G-GIF	47.56	38.94

5.0 Conclusions

Haze removals have become a need for various computer vision based applications. Different techniques are used to improve to remove the haze, which is caused due to light scattering particles. The proposed algorithm is based on different structure preservation prior which can estimate optimal transmission map and will restore original scene. The dark channel prior is based on the statistics of the outdoor images. Applying the prior into the haze imaging model, single image haze removal becomes simpler and more effective.To obtain transmission map we use sparse linear combination of elements from neighbourhood basis set to obtain accurate result.

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