Image Dehazing using Contextual Regularisation and Boundary Constrains

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***Abstract*— Single image haze reduction presents an ill-posed challenge, making it extremely difficult to achieve. Perceptual picture quality and performance of computer vision algorithms such as tracking, surveillance, and navigation suffer from poor visibility. We present a simple but effective contextual regularization approach for removing haze from a single hazy input image in this work. The haze can be removed using filter banks and the Scale Invariant Feature Transform (SIFT) operator. We can simply estimate the boundary conditions manually as a result of this, which improves both efficiency and dehazing impact.**

Keywords—Image Dehazing, Contextual Regularization, PSNR, SSIM,

I. INTRODUCTION

Suspended air particles such as haze, fog, smoke, and mist typically degrade the visual quality of outdoor photographs. Visibility, contrast, and vividness have all been drastically decreased, making it hard to distinguish between objects. Defogging is a common deweathering issue that involves removing the weather effect generated by suspended aerosol and water drops. The goal of defogging is to increase the contrast of hazy photos and restore visibility to the scene. According to the atmospheric scattering model, the physical degradation process of a foggy image is a linear combination of two components: attenuated scene reflectance and intensified atmospheric luminance. The suspended particles that influence the transmission of scene reflectance and ambient brightness are known as the transmission medium. The albedo of the scene reflected by atmospheric brightness and attenuated by the transmission medium is known as scene reflectance. The transmission medium magnifies the atmospheric luminance, which is dispersed by suspended particles and perceived as ambient air light by the spectator. Due to the linear nature of light propagation, the two components are additive. Both visibilities and contrast are degraded as a result of this physical process

Attenuation and intensification are influenced by two key elements. The first is the atmospheric scattering coefficient of the transmission media, which is regarded as the polarization characteristics of the particles in a static scene and is commonly believed to be a constant. The distance between the scene and the observer is the second consideration. The farther the distance, the more attenuation and intensification occurs. The impact is stronger as the depth increases, and the hazy image loses more visibility and contrast. The two components are referred to as a depth map when they are combined.

II. PROPOSED METHOD

The atmospheric scattering model, a physical deterioration process, has been widely used in numerous dehaze projects. Contextual Regularization-based picture dehazing is employed in this way. Given a single photograph as input, this approach recovers a haze-free image. This approach uses an estimated transmission (depth) map to recover blurry pictures. There are three major contributions to this approach. The first is a new scene transmission constraint. This basic restriction, which has a clear geometric interpretation, is remarkably successful at dehazing images. The second addition is a novel contextual regularization that allows picture dehazing to include a filter bank.These filters aid in the reduction of picture noise as well as the enhancement of some fascinating visual features such as jump edges and corners. The last contribution is an efficient optimization approach that allows us to dehaze large-scale photos fast.

III. METHODOLOGY

The following linear interpolation model is widely used to explain the formation of a haze image,

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

where,

I(x) is the observed image,
J(x) is the scene radiance,
A is the global atmospheric light, and
t(x) is the scene transmission .

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{[\max(t(x), \epsilon)]^{\delta}} + \mathbf{A} \tag{2}$$

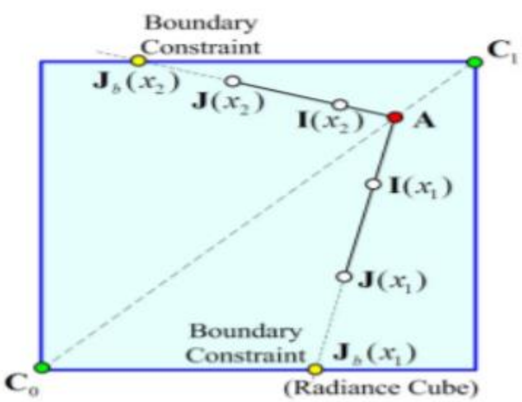
ε is a small constant (typically 0.0001) for avoiding division by zero, and the exponent δ, serving as the role of the medium extinction coefficient β

A. Estimate Global Airlight

The atmospheric luminance and the inverse of the depth map make up the airlight function. We assume that certain pixels in the picture are infinitely far away. The picture points corresponding to scene locations at infinity are treated as a collection of representative color vectors of atmospheric luminance, and the predicted color vector of atmospheric luminance is estimated using an average operation. Assuming an infinite distance, the white pixels in the fog picture with the highest intensity values are considered atmospheric luminance, as these pixels may indicate scene places with no reflection.

Estimating a suitable transmission function and the global atmospheric light A is required for dehazing a picture. We present a technique based on the image's dark channel for estimating atmospheric light. They start with the top 0.1 percent brightest pixels in the dark channel, then choose the one with the highest intensity as the A estimate. The approach starts by applying a minimum filter with a sliding window to each color channel of an input picture. The component of A is then estimated using the greatest value of each color channel

B. Calculating Patchwise Scene Transmission from Radiance Cube Boundary Constraint



A hazy pixel I(x) will be geometrically closer to the global atmospheric light, A. As a result, using a linear extrapolation from A to I, we may reverse this procedure and obtain the clean pixel J(x) (x). The amount of extrapolation required is determined by:

$$\frac{1}{t(x)} = \frac{||\mathbf{J}(x) - \mathbf{A}||}{||\mathbf{I}(x) - \mathbf{A}||} \tag{3}$$

Consider that the scene radiance of a given image is always bounded, that is,

$$\mathbf{C}_0 \leq \mathbf{J}(x) \leq \mathbf{C}_1, \forall x \in \Omega \tag{4}$$

where C0 and C1 are two relevant constant vectors for the given picture. As a result, a natural criterion for every x is that the extrapolation of J(x) be placed in the radiance cube bounded by C0 and C1, as shown in Figure 2. The boundary constraint on t(x) is imposed by the above requirement on J(x). Assume that A is the global atmospheric light. As a result, we may calculate the relevant boundary constraint point Jb(x) for each x. (see Figure 2). Then, using Eq. (3) and (4), a lower bound on t(x) may be found, yielding the following t(x) boundary constraint:
t(x): 0 ≤ tb(x) ≤ t(x) ≤ 1,

where tb(x) is the lower bound of t(x), given by

$$t_b(x) = \min\left\{\max_{c \in \{r,g,b\}}\left(\frac{A^c - I^c(x)}{A^c - C_0^c}, \frac{A^c - I^c(x)}{A^c - C_1^c}\right), 1\right\} \tag{5}$$

where I, Ac, Cc 0 and Cc 1 are the color channels of I, A, C0 and C1, respectively.

The patch-wise transmission is given as below:

$$\hat{t}(x) = \min_{y \in \omega_x} \max_{z \in \omega_y} t_b(z).$$

C. Weighted L1-norm based Contextual Regularization

To address the problem of having abrupt depth jumps in adjacent pixels in a local patch, which can cause halo effects, we apply a weighting function,

$$W(x,y)\,(t(y) - t(x)) \approx 0 \tag{7}$$

When the depth difference between two pixels is high, the applied weight is low and vice versa.
To calculate the weighting function, we use the squared difference of the color vectors between the neighbouring pixels.

$$W(x,y) = e^{-\|\mathbf{I}(x) - \mathbf{I}(y)\|^2 / 2\sigma^2} \tag{8}$$

We apply the integral of L1- norm for contextual regularization. L1-norm is used instead of L2-norm as L1-norm is more robust to outliers, which can be produced from incorrect values by Eq(7). Converting Eq(8) to discrete form and inserting differential operators, we can represent it as:

$$\sum_{j \in \omega} \|W_j \circ (D_j \otimes t)\|_1 \tag{9}$$

where ω is an index set, ∘ represents the element-wise multiplication operator, ⊗ stands for the convolution operator, Dj is a first-order differential operator, Wj (j ∈ ω) is a weighting matrix.. We use Kirsch and Laplacian operators to make a bank of high order differential filters to preserve the edges and corners of the image. Using these filters, we get Eq(8) as:

$$W_j(i) = e^{-\sum_{c\in\{r,g,b\}} \left|(D_j \otimes I^c)_i\right|^2 / 2\sigma^2} \tag{10}$$

D. Scene Transmission Estimation

After calculating patchwise scene transmission function and finding the weighting function, we use these to find the optimal scene transmission function by minimizing the following function:

$$\frac{\lambda}{2}\left\|t-\hat{t}\right\|_2^2 + \sum_{j\in\omega}\left\|W_j \circ (D_j \otimes t)\right\|_1 \tag{11}$$

Optimizing the above equation using variable splitting and applying 2D FFT, we get the optimal scene transmission function as,

$$t^* = \mathcal{F}^{-1}\left(\frac{\frac{\lambda}{\beta}\mathcal{F}(\hat{t}) + \sum_{j\in\omega}\overline{\mathcal{F}(D_j)}\circ\mathcal{F}(u_j)}{\frac{\lambda}{\beta} + \sum_{j\in\omega}\overline{\mathcal{F}(D_j)}\circ\mathcal{F}(D_j)}\right) \tag{12}$$

where F(·) is the Fourier transform and F−1(·) is its inverse transform, (·) represents the complex conjugate, and ◦ denotes the element-wise multiplication. The division is also performed in an element-wise manner.

IV. Evaluation Metrics

Many performance measures are available to compare the results of different compressed images and to measure the degree to which an image is compressed, such as:

1. Peak Signal to Noise Ratio(PSNR):

The Peak Signal to Noise Ratio (PSNR) is the proportion of highest signal power to noise power. The original image is referred to as the maximum signal power in image dehazing, and noise is added to dehaze it. This ratio is used to compare the quality of the original and the dehazed image. The greater the quality of the dehazed or reconstructed image, the higher the PSNR

$$\begin{aligned} PSNR &= 10\cdot\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20\cdot\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20\cdot\log_{10}(MAX_I) - 10\cdot\log_{10}(MSE) \end{aligned}$$

2. Structural Similarity Index Measure (SSIM):

The Structural Similarity Index (SSIM) is a perceptual metric that quantifies image quality degradation* caused by processing such as data compression or by losses in data transmission. It is a full reference metric that requires two images from the same image capture— a reference image and a processed image. It actually measures the perceptual difference between two similar images. Unlike PSNR (Peak Signal-to-Noise Ratio), SSIM is based on visible structures in the image.

V. Results and Discussions

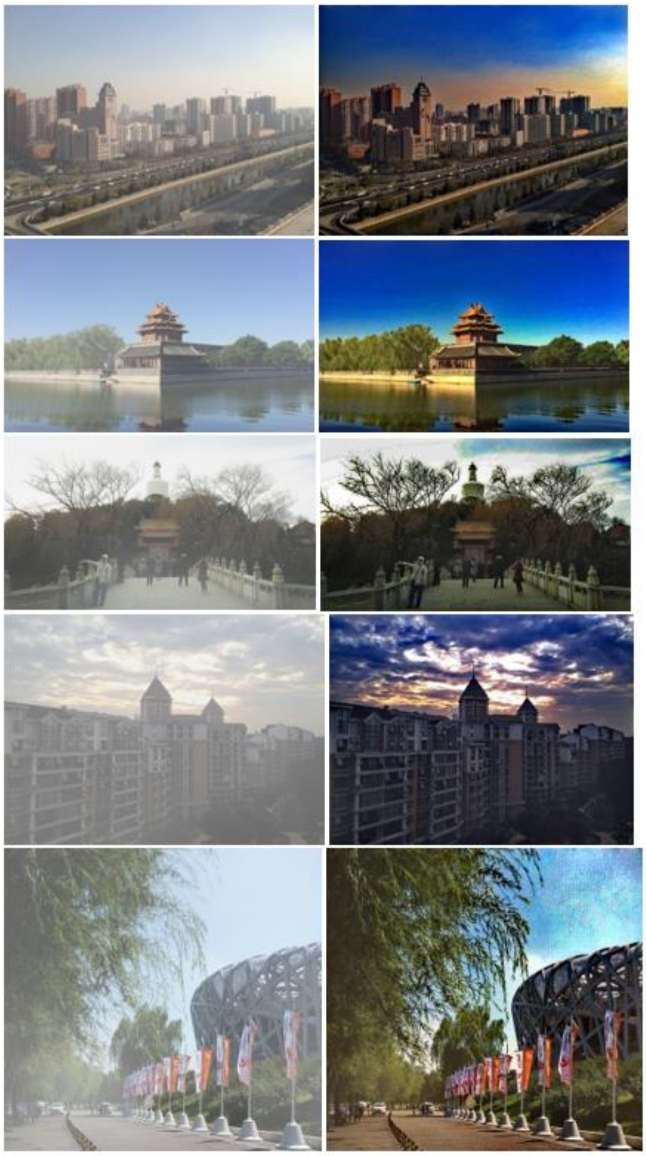


Image	PSNR (in dB)	SSIM
i	28.1209	0.7954
ii	27.9783	0.8017
iii	28.2006	0.7159
iv	28.1641	0.7936
v	28.0472	0.7712

The above images are taken for testing. It is observed that the PSNR value is around 28 while the SSIM score is around 0.8 for the dehazed images.

VI. CONCLUSION

We have presented an effective approach for removing hazes from a single picture in this study. An analysis of the transmission function's underlying boundary limitation enhances our strategy. To recover the unknown transmission, this limitation is combined with a weighted L1-norm based contextual regularization and characterized as an optimization problem. To tackle the optimization problem, an efficient approach based on variable splitting is presented. When compared to many other approaches, our approach produces more aesthetically appealing outcomes with more accurate color and finer picture features and structures.

REFERENCES

[1] P. Carr and R. Hartley. Improved single image dehazing using geometry. In Digital Image Computing: Techniques and Applications, pages 103–110, Dec. 2009.

[2] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski. Edgepreserving decompositions for multi-scale tone and detail manipulation. In ACM SIGGRAPH 2008, pages 67:1–67:10, 2008.

[3] R.T. Tan," Visibility in bad weather from a single image" in IEEE conference on computer vision and pattern recognition (2008),pages-1-8.

[4] Gaofeng MENG, Ying WANG, Jiangyong DUAN, Shiming XIANG, Chunhong PAN,*Efficient Image Dehazing with Boundary Constraint and Contextual Regularization*, in IEEE International Conference on Computer Vision (2013)