COMPUTER VISION

TOPIC OF THE PROJECT – IMAGE DEFOGGING

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COMPARISION OF THE ADAPTIVE WEINER FILTER AND GUIDED FILTER FOR IMAGE DEFOGGING

***Abstract*—The goal of the paper is to do the image defogging using the locally adaptive wiener filter and the guided filter. Both these methods are capable of giving the appreciable results for defogging an image at the same making sure the foggy images retain their original details. But comparing these two techniques and finding which gives the better results definitely helps in understanding the concept of image defogging more. In this paper, we wish to give a detailed implementation of the two methods and there by compare the results by calculating the performance measure values.**

I. INTRODUCTION

Whenever there is some fog or haze is present in an image, it basically reduces the clarity of image . The process of Image Defogging typically involves the first step for analysing the image to estimate the distribution and density of fog particles. Once the fog or haze levels are estimated, algorithms can be applied to either directly remove the fog or to adjust the image to enhance contrast and clarity, effectively reducing the visibility of the fog.

To get a higher contrast image immediately, each image or frame (if it is a video stream that has to be enhanced) is needed to be enhanced in or near real time. One of the first and basic method which is used for this is the 'Histogram Equalization'. This is a statistical contrast enhancement method as it operates on the statistical data of the pixel values in an image . It uses the Probability distribution function and transforms it to be more uniform . Thus, the histogram equalization effectively enhances the image contrast by spreading out the intensity values across the entire image . But , the Histogram Equalization may not always produce visually pleasing results, especially if the image already has a relatively uniform histogram or if there are extreme local variations in contrast. So ,there are other methods which can be used for enhancing of the contrast, such as the Gray-Level-Grouping.

One of most important challenges while doing the enhancement of an image is , the amount of contrast degradation will be varying spatially. A reasonable approach to improving the spatially varying contrast is to design the contrast enhancement to be spatially varying as well. There are some methods proposed for overcoming this challenge such as the adaptive histogram equalization and contrast limited histogram equalization .

In this paper, we analyse the scenes that are affected by fog or haze which are needed to be enhanced in near-real time for the purpose of later stages in the respective scenarios. Two enhancement techniques are used in this paper , one of which is based on the physics model of the scene to obtain an arbitrary to scale image of scene depth and an enhanced image . The other is using a guidance image.

II. VEILING ESTIMATION

As mentioned in the introduction, contrast and fog/haze particles in an image have some connectivity between them. One of the methods which can be used for contrast enhancement if an image is "The atmospheric dichromatic model". It is a theoretical framework used to describe the degradation of colours and contrast in images due to atmospheric effects such as fog, haze, or mist. It provides a mathematical representation of how light interacts with atmospheric particles and the resulting impact on the observed image. This model actually gives a relation between the foggy image and defogged version of the image.

$$y_i = t_i x_i + (1-t_i)a,$$

In the above equation, pixel location which is represented by i,y_i ε R^3 and the "defogged" version which is represented as x_i ε R3 is related to the foggy image with the model . The right hand side of the above equation is considered the veiling

$$v = (1 - t_i)a$$

Our method is tailored specifically for scenes affected by fog or characterized by atmospheric scattering that remains consistent across wavelengths. This assumption simplifies the computation of transmission, allowing it to be treated as a scalar value, thereby validating our model. Within this framework, transmission is determined by a uniform factor and the scene's depth, expressed as

$$t_i = e^{-\beta r_i}$$

where *beta* denotes a constant coefficient.

With all pertinent parameters at our disposal, we can generate the defogged image using the following formula:

$$\hat{\mathbf{x}}_i = \frac{\mathbf{y}_i - \mathbf{a}}{\min(t_i, t_0)} + \mathbf{a},$$

Here, t_0 is selected for numerical stability and is typically set to 0.01.

In single image defogging methods, the primary task involves estimating the veiling, denoted as v which is composed of transmission t and airlight a.

If we make an assumption that one or more of the colour components of x is dark, then we may take the minimum of all of the colour components from y and measure the veiling with

$$\mathbf{v} = d_i \mathbf{a},$$
$$\text{and } d_i = \min_{c \in (r,g,b)} y_i(c),$$

where the cth color component of y is y(c). This method of measuring a "dark prior" or "whiteness" of the image, d, is commonly used in single image defogging methods as the first step in estimating the transmission (or veiling).

III. ADAPTIVE WEINER FILTER

The above observation which is used an estimate for veiling has many challenges. Estimating veiling, which represents the degradation caused by fog, is a challenging task due to several factors. One major challenge arises from the assumption that at least one colour component of an object in the scene is zero, which may not always hold true. This assumption can lead to ambiguity, especially in scenes where distinct objects blend together, such as a brightly coloured road merging with the horizon. Another challenge comes from the presence of texture in the scene, which interferes with the accurate estimation of veiling. Veiling is expected to represent scene depth, which typically exhibits smooth variations. However, the presence of texture introduces noise that needs to be addressed for accurate estimation.

Method for Veiling Estimation:

Existing methods utilize statistical smoothing operators and techniques like Spectral Matting to address the challenges of veiling estimation. These methods aim to smooth out the noise introduced by the aforementioned factors.

In this paper we used a Locally Adaptive Wiener Filter is proposed as a refinement technique for veiling estimation. This filter differs from previous approaches by directly refining the veiling estimate rather than applying it as a noise removal technique after enhancing the image. The Locally Adaptive Wiener Filter is chosen for its ability to adaptively filter noise while preserving image details. We focused on presenting only the essential terms necessary to describe the proposed method, rather than providing a comprehensive development of the filter.

The Locally Adaptive Wiener filter:

$$\hat{v}_i = \mu_{v,i} + \frac{\sigma_{v,i}^2 - \sigma_n^2}{\sigma_{v,i}^2}(d_i - \mu_{v,i})$$

The algorithm for the Adaptive Wiener Filter:

The strength in this approach is that although simple to implement, the filter can adapt for scene depth discontinuities. It applies a weight , where if the weight is low then the smoothed sample is chosen whereas if the weight is high then the original signal is preserved. This bilateral filtering technique is effective for our purpose in smoothing textures but preserving depth discontinuities.

A) Naive Estimation of Noise Variance:

In the initial stage of our proposed method for estimating the noise variance, we adopt a simplified approach by assuming v and n are uncorrelated and the mean of n is zero. This assumption allows us to express the variance of our observation di as the sum of the variances of v_i and n_i

$$\boxed{\mathrm{var}[d_i] = \sigma_{d,i}^2 = \sigma_{v,i}^2 + \sigma_n^2}$$

We assume that variance of v is very smaller compared to the variance of the n throughout the entire image and approximate the value of noise variance as follows

$$\hat{\sigma}_n^{2\,\prime} = \frac{1}{M} \sum_{j=0}^{M-1} \sigma_{d,j}^2,$$

Where M is the total number of pixels and estimation of variance is noted with a subscript.

B) Noise Estimation Correction

A correction would be required in the noise estimation, as the noise variance is dependent on the amount of fog. We proposed a method to estimate uncorrelated noise by analysing the non-foggy scene component, which is decomposed into low-resolution and high-resolution components. The low-resolution component represents the main scene content, while the high-resolution component includes texture and noise. The non-foggy scene component x_i is decomposed into $x_{L,I}$ and $x_{H,i}$, representing the low-resolution and high-resolution components, respectively.

$$\mathbf{x}_i = \mathbf{x}_{L,i} + \mathbf{x}_{H,i}.$$

IV. 1-STEP AND 2-STEP WEINER DEFOGGING

The proposed defogging methods, termed as the One-Step Wiener Defog and Two-Step Wiener Defog, are outlined in the paper. These methods, denoted as

$$\hat{\mathbf{x}}'_{w_1}, \hat{t}'_{w_1} \leftarrow \textbf{\textit{WienerDefog}}(\mathbf{y}, \Omega, t_0, w, 1)$$
$$\text{and } \hat{\mathbf{x}}_{w_2}, \hat{t}_{w_2} \leftarrow \textbf{\textit{WienerDefog}}(\mathbf{y}, \Omega, t_0, w, 2),$$

respectively, offer a solution for enhancing visibility in foggy scenes. The algorithms detailing the implementation of these methods are provided in Figure 2 of the paper. In terms of parameter settings, the experiments are conducted with w=0.9 and t_0=0.01, selected empirically for optimal performance. The choice between the One-Step and Two-Step methods depends on the characteristics of the foggy scene, with the former suitable for scenes with less severe depth discontinuities and the latter preferred when the defogged image exhibits "halos" or "burn-in" effects. Additionally, the estimation of local statistics for the Adaptive Wiener Filter necessitates a square-shaped moving sample window, with a suggested size for digital images. However, the paper highlights the importance of adjusting the sample window size for each image to improve subjective performance, with sizes varying . Overall, the proposed method offers flexibility and adaptability, underlining the significance of parameter tuning and window size adjustment for optimal defogging outcomes.

V. RESULTS AND CONCLUSIONS

Guided filter is a technique commonly used in image processing for tasks like image enhancement, dehazing, and denoising. The guided filter is particularly effective in preserving edges and fine details while performing smoothing or enhancement tasks.

1) Atmospheric light extraction

Is a crucial step in the image dehazing process, as it represents the ambient light in the atmosphere. Extracting the atmospheric light accurately helps in estimating the transmission map, which is essential for recovering the haze-free image. In this method atmospheric light extraction is achieved using the dark channel prior technique. The dark channel prior is a statistical property observed in outdoor haze-free images. It states that for most non-sky patches in an outdoor haze-free image, at least one colour channel contains some pixels whose intensities tend to be zero. The dark channel tends to be zero in areas with shadows, dark objects, or colourful objects.

The top brightest pixels are then selected from the dark channel. This selection is often based on a certain percentile of the brightest pixels, such as the top 0.1%.

Among these selected pixels, the pixel with the highest intensity in the original hazy image is chosen as the atmospheric light. The atmospheric light represents the global illumination present in the scene, which is partially obscured by haze. Estimating it accurately is crucial for correctly estimating the transmission map, which in turn helps in recovering the haze-free image.

Extracting the atmospheric light allows for a better understanding of the scattering and attenuation effects of the haze, aiding in the dehazing process.

2) Guided filter processing

Guided filter is a non-linear filter that operates on an input image (the "guide image") to produce an output image while preserving edges and fine details present in the guide image.

It achieves this by using the guide image to weigh the contributions of neighbouring pixels during filtering. Pixels that are similar to the corresponding pixels in the guide image are given higher weights, while dissimilar pixels are given lower weights.

The guided filter can be thought of as a refinement process that smooths the input image while retaining important details based on the information provided by the guide image. Hin general , the guided filter works by utilizing a reference image (often a hazy image) to guide the dehazing process. Here it uses a guidance image for the defogging process. The reference image serves as a guidance to the filter. It helps in preserving the structural details and edges during the dehazing process. In the absence of a reference image, the input hazy image itself can be used as the guidance. The guided filter performs a weighted average operation on the input image pixels, where the weights are determined based on the guidance image. This ensures that pixels with similar intensity or colour in the guidance image contribute more to the filtering process. The filtering process aims to reduce the haze while preserving important features. By utilizing the guidance provided by the reference image, the guided filter effectively removes haze from the input image while retaining sharp edges and fine details. This results in a clearer and more visually appealing image.

VI. PERFORMACE MEASURES AND COMPARISON

The two performance measures PSNR and SSIM are calculated for comparing the results.

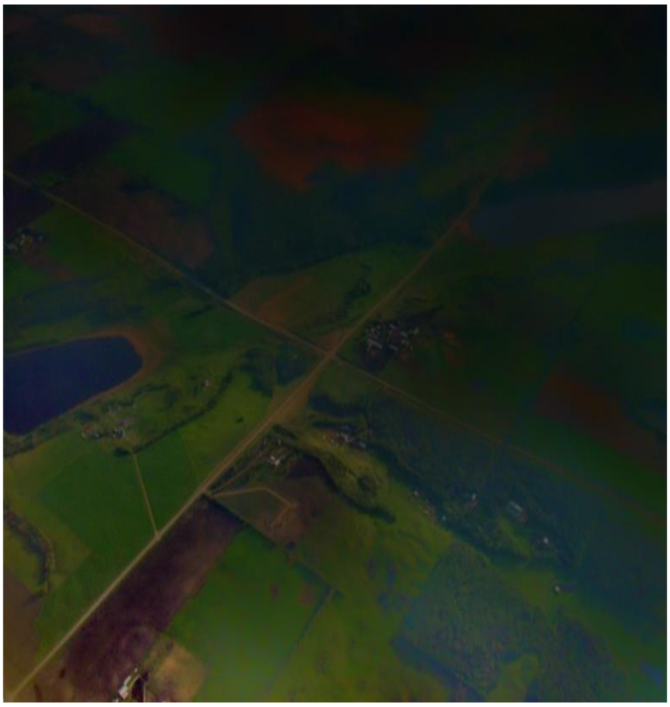
PSNR is a measure of the quality of a reconstructed signal compared to the original signal. It's often used in image and video compression to quantify the amount of distortion introduced by compression algorithms. PSNR is calculated as the ratio of the maximum possible power of a signal to the power of corrupted or noisy signal. The higher the PSNR, the closer the approximation of the original signal.

SSIM is a metric that quantifies the similarity between two images. It takes into account luminance, contrast, and structure, aiming to model human perception of image quality. Unlike PSNR, SSIM considers the structural information of the images being compared. SSIM ranges between -1 and 1, where 1 indicates perfect similarity between two images.

Input image -1

Input image -2

DEFOGGED IMAGE USING LAWF



DEFOGGED IMAGE USING GUIDED FILTER

The values of PSNR AND SSIM

PSNR_LWAF : 10.6432

SSIM_LWSAF : 0.8353

PSNR_GF: 14.3827

SSIM_GF: 0.8797

VII. PERFORMACE MEASURES AND COMPARISON

Based on the above values of the performance measures, we can say that guided filter will give better results than compared to the Adaptive Wiener filter. But the adaptive Wiener filter has more robustness because it can handle the varying characteristics of the image. At the same time adaptive Wiener filter is quite complex and very computationally intensive. But implementing the guided filter is simple. Overall, if we keep aside the point that, guided filter gives better outputs by smoothing, the two methods got their own advantages and disadvantage. Based on the density of fog present in the image and the availability of resources, the technique has to be chosen for dehazing the image.

VIII. REFERENCES

1)Research paper on image defogging by Kristofor B. Gibson and Truong Q. Nguyen

2)Research paper on image dehazing using the Guided Filter by Qiang Zhang, Xiaorun Li

3)ChatGPT and Google.