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A SURVEY PAPER ON SINGLE IMAGE DEHAZING

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Abstract: Imaging in poor weather is often severely degraded by scattering due to suspended particles in the atmosphere such as haze, fog and mist. Poor visibility becomes a major problem for most outdoor vision applications. This paper discusses about various haze removal algorithms that provides better efficiency in order to retrieve the original image.

I. INTRODUCTION

In outdoor environments, light reflected from object surfaces is commonly scattered due to the impurities of the aerosol, or the presence of atmospheric phenomena such as fog and haze. Aside from scattering, the absorption coefficient presents another important factor that attenuates the reflected light of distant objects reaching the camera lens. As a result, images taken in bad weather conditions (or similarly, underwater and aerial photographs) are characterized by poor contrast, lower saturation and additional noise. When one takes a picture in foggy weather conditions, the obtained image often suffers from poor visibility. The distant objects in the fog lose the contrasts and get blurred with their surroundings. This is because the reflected light from these objects, before it reaches the camera, is attenuated in the air and further blended with the atmospheric light scattered by some aerosols. Also for this reason, the colors of these objects get faded and become much similar to the fog, the similarity of which depending on the distances of them to the camera. Early methods for haze removal mainly rely on additional depth information or multiple observations of the same scene. Single image dehazing, in contrast, is a more challenging problem, since fewer information about the scene structure is available. This paper is a survey on single image dehazing methods and gives a brief idea about several dehazing algorithms.

II. SINGLE IMAGE HAZE REMOVAL

A novel method is proposed to restore a single image degraded by atmospheric phenomena such as fog or haze. The algorithm allows for fast identification of hazy regions of an image, without making use of expensive optimization and refinement procedures. By applying a single per pixel operation on the original image a semi-inverse of the image is produced [1]. Based on the hue disparity between the original image and its semi-inverse, the hazy regions are identified on a per pixel basis. This enables for a simple estimation of the airlight constant and the transmission map. A direct haze detection algorithm that operates in a pixel-wise manner is designed and a semi-inversed image is created. This image can be obtained by replacing the RGB values of each pixel on a per channel basis by the maximum of the initial channel value and its inverse. The algorithm is initiated by creating several new images N, with $i \in [1, k]$ and k layers, in which a decreasingly growing portion of the airlight constant color $A\infty$ is removed from the initial hazy image I:

$$N = I - ci \cdot A\infty. \qquad (1)$$

With the iteratively increasing airlight contribution factor ci which is a scalar value in the range [0,1] and with its value depended by the number of layers. After applying the haze detection operation on Ii, only the pixels with a sufficiently low hue disparity are labeled as being part of layer Li. In the absence of the scene geometry, discretization of the image in k distinct layers enables us to estimate the values of ci that correspond to the most dominant depth layers of the scene. For instance, when the scene contains two objects located at diff erent depths, the transmission map will be characterized by two dominant values (as the airlight is correlated with the distance). Finally, these layers are blended into a single composite haze-free image.

The above mentioned method has inherent boundary constraint on the transmission function. This constraint, combined with a weighted L1−norm based contextual regularization, is modeled into an optimization problem to estimate the unknown scene transmission[2]. A quite efficient algorithm based on variable splitting is also presented to solve the problem. The proposed method requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine image details. This method benefits from two main contributions. The first is a new constraint on the scene transmission. This simple constraint, which has a clear geometric interpretation, shows to be surprisingly effective to image dehazing. The second contribution is a new contextual regularization that enables us to incorporate a filter bank into image dehazing. These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners.
It was difficult to obtain vivid color information even in very dense haze regions. For that a simple but effective dark channel prior technique is used to remove haze from a single input image [3]. The dark channel prior is a

kind of statistics of the haze-free outdoor images. It is based on a key observation most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel. Using this prior with the haze imaging model, the thickness of the haze can be directly estimated and recover a high quality haze-free image. Here, the atmospheric light A is assumed to be given with the transmission in a local patches $\Omega(x)$ to be a constant. The patch's transmission is denoted as T(x). Taking the min operation in the local patch on the haze imaging Equation

$$I(x) = J(x)\, t(x) + A\,(1-t(x)) \qquad (2)$$

According to the dark channel prior, the dark channel Jdark of the haze-free radiance J should tend to be zero. Then the value for transmission T is estimated after which a soft matting algorithm to refine the transmission is applied. The directly recovered scene radiance J is prone to noise. Therefore, the transmission t(x) is restricted to a lower bound t_0, which means that a small. Certain amount of haze is preserved in very dense haze regions. The final scene radiance J(x) is recovered by:

$$J(x) = A + (I(x) - A)/ \max(t(x), t_0) \qquad (3)$$

A typical value of t_0 is 0.1.Since the scene radiance is usually not as bright as the atmospheric light; the image after haze removal looks dim. So, the exposure of J(x) is increased for display. To find the value for atmospheric light, the top 0.1% brightest pixels in the dark channel is chosen. These pixels are most haze opaque. Among these pixels, the pixels with highest intensity in the input image I is selected as the atmospheric light.

A novel Bayesian probabilistic method that jointly estimates the scene albedo and depth from a single foggy image by fully leveraging their latent statistical structures is designed as a different approach in image dehazing techniques [4]. The key idea is to model the image with a factorial Markov random field in which the scene albedo and depth are two statistically independent latent layers and then to jointly estimate them. The natural image and depth statistics may get exploited as priors on these hidden layers and estimate the scene albedo and depth with a canonical expectation maximization algorithm with alternating minimization. Following the original inference algorithm for FMRF (Kim and Zabih, 2002), a joint energy minimization algorithm based on the expectation maximization principal to factorize the input image into the scene albedo layer C and scene depth layer D is derived. The algorithm alternates between the expectation step that computes the posterior probabilities of the latent layers, i.e., estimating the scene albedo and depth, and the maximization step that maximizes the expected log likelihood. In the expectation step, the posterior probabilities of the latent variables are computed and maximized assuming that the likelihood parameter, the noise variance σ2 (Equation 4), is known– they are set to the current estimates from the maximization step. The factorial Markov random field formulation provides a sound foundation for jointly estimating the scene albedo and depth from a single foggy image. Although this method provides a satisfactory efficiency, it is very complex. Thus, simple but powerful color attenuation prior for haze removal from a single input hazy image was the designers' next aim. By creating a linear model for modeling the scene depth of the hazy image under this novel prior and learning the parameters of the model as in equation (2) with a supervised learning method, the depth information can be well recovered. With the depth map of the hazy image, the transmission is estimated and the scene radiance is found via the atmospheric scattering model, and thus effectively removes the haze from a single image. Since the airlight plays a more important role in most cases, hazy regions in the image are characterized by high brightness and low saturation. What's more, the denser the haze is, the stronger the influence of the airlight would be. This allows us to utilize the difference between the brightness and the saturation to estimate the concentration of the haze. Since the concentration of the haze increases along with the change of the scene depth in general, the depth of the scene is positively correlated with the concentration of the haze and thus:

$$d(x) \propto c(x) \propto [v(x) - s(x)] \qquad (4)$$

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 is regarded as color attenuation prior. To find the depth, the equation is

$$d(x) = \theta_0 + \theta_1\, v(x) + \theta_2\, s(x) + \varepsilon(x) \qquad (5)$$

Where x is the position within the image, d is the scene depth, v is the brightness component of the hazy image, s is the saturation component, θ_0, θ_1, θ_2 are the unknown linear coefficients, ε(x) is a random variable representing the random error of the model, and ε can be regarded as a random image. The best learning result is that $\theta_0 = 0.121779$, $\theta_1 = 0.959710$, $\theta_2 = -0.780245$, $\sigma = 0.041337$. Once the values of the coefficients have been determined, they can be used for any single hazy image. These parameters will be used for restoring the scene depths of the hazy images in this paper. To find A, the top 0.1 percent brightest pixels in the depth map is picked, and the pixel with highest intensity in the corresponding hazy image I is selected among these brightest pixels as the atmospheric light A. Now that the depth of the scene d and the atmospheric light A are known, to estimate the medium transmission t and then the scene radiance J is recovered. For avoiding producing too much noise, the value of the transmission t(x) is restricted between0.1and 0.9. The scattering coefficient β, which can be regarded as a constant in homogeneous regions, represents the ability of a unit volume of atmosphere to scatter light in all directions. In other words, β determines the intensity of dehazing indirectly. As can be seen, on the one hand, a small β leads to small transmission, and the corresponding result remains still hazy in the distant. On the other hand, a too large β may result in overestimation of the transmission. Therefore, a moderate β is required when dealing with the images with dense-haze regions. In most cases, $\beta = 1.0$ is more than enough.

III. CONCLUSION

This paper discusses about various single image haze removal algorithms. Most of the algorithms make use of a linear model in order to design the algorithm. Finding out the value of atmospheric light is a major factor in determining the quality of the dehazed image. With the above mentioned methods dehazing has become a simple task.

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