

GLOBALLY GUIDED IMAGE FILTERING METHOD FOR SINGLE IMAGE HAZE REMOVAL USING AN TRANSMISSION MAP

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Abstract—Due to ill-posed nature single image haze removal has been a great challenge. The goal of using this method is to obtain an optimal transmission map to remove hazes from a single input image. An optical model is analyzed and the initial transmission map under an additional filter is recasted. For a better preservation of haze image, the globally guided image filtering could be used such that the local consistency features of the transmission map are well preserved after coefficient shrinkage. Finally, it preserves the natural appearance of the image.

Index terms—Single image dehazing, Globally guided image filtering, structure transfer, edge-preserving smoothing.

I. INTRODUCTION

The light received by a sensor from scene points is often absorbed and scattered by a complex medium (e.g., dust, mist, fog, or fumes). Therefore images of outdoor scenes are often degraded, with fog, mist, or haze. The scene contents in such degraded images will not be easily visible. However, most of the outdoor computer vision systems, such as those used in surveillance and transportation, need to carry our meaningful scene analysis, extract useful information, and detect image features. It is imperative to remove the effects of bad weather from these images. The amount of irradiance scattering and haze depends on the unknown scene depth, which makes haze removal complicated. Most haze removal methods require multiple images or additional prior information. The method used to remove haze using single image under different degrees of polarization. It is necessary to recover the original scene to improve human identification ability. In general, dehazing is a special case of image restoration. According to Koschmiedar's law, a hazy image is normally modeled by:

$$I^c(x) = J^c(x)t(x) + A^c(1-t(x))$$

Our goal is to recover the underlying scene radiance, where $c \in \{r, g, b\}$, $I^c(x) \in R^C$ is the observed intensity at pixel x , $J^c(x)$ is the scene radiance or haze-free image, A^c is the sky brightness for the whole image, and $t(x)$ is the scene transmission, which is correlated with the scene depth. The approach of measurements assumes that the natural image belongs to a continuous function space, and can define a norm or semi-norm to measure the global regularity. Due to the strict mathematical theory, it has received widespread attention. However, a natural image is complex and mutative, so it is difficult to decide which smooth space an image is embedded into. In addition, the global regularity prior only focuses on the whole image property rather than the local structures, so it may lead to deviations in describing the details of the image.

A typical dehazing algorithm uses total variation minimization. The purpose of the other group of methods is to determine the specific characteristics based on the statistical distribution prior. Based on observations that the color of the scene fades under the influence of the haze and the brightness increases at the same time producing the high value of the difference, a simple color attenuation prior was proposed, and a linear model was then built up to represent the relationship between the depth and the brightness as well as the saturation using the prior. The linear model was finally adopted to design a single image haze removal algorithm with the help of the guided image filtering (GIF)

Image restoration aims to recover a degraded image using a model of the degradation and of the original image formation; it is essentially an inverse problem. These methods are rigorous but they

require many model parameters (like attenuation and diffusion coefficients that characterize the water turbidity) which are only scarcely known in tables and can be extremely variable. Another important parameter required is the depth estimation of a given object in the scene.

Image enhancement is a technique of improving the quality of image by improving its feature and its RGB values. A major difficulty to process underwater images comes from light attenuation; it limits the visibility distance, at about twenty meters in clear water and five meters or less in muddy water. The light reduction process is caused by the absorption (which removes light energy) and spreading which changes the direction of light wave path). Absorption of light and its scattering effects are because of the water itself and to other components such as dissolved organic matter or small observable floating particles. Due to this difficulty, underwater imaging suffers too many problems.

HAZE REMOVAL TECHNIQUES

Dark Channel Prior

The dark channel prior is based on the following observation on haze-free outdoor images: in most of the non-sky patches, at least one color channel has very low intensity at some pixels. In other words, the minimum intensity in such a patch should have a very low value. Formally, for an image \mathbf{J} , we define

$$\mathbf{J}_{\text{dark}}(\mathbf{x}) = \min_{c \in \{r, g, b\}} (\min_{\mathbf{y} \in \Omega(\mathbf{x})} (\mathbf{J}_c(\mathbf{y})))$$

Where \mathbf{J}_c is a color channel of \mathbf{J} and $\Omega(\mathbf{x})$ is a local patch centered at \mathbf{x} . Our observation says that except for the sky region, the intensity of \mathbf{J}_{dark} is low and tends to be zero, if \mathbf{J} is a haze-free outdoor image. We call \mathbf{J}_{dark} the dark channel of \mathbf{J} , and we call the above statistical observation or knowledge the dark channel prior.

The low intensities in the dark channel are mainly due to three factors: a) shadows. e.g., the shadows of cars, buildings and the inside of windows in cityscape images, or the shadows of leaves, trees and rocks in landscape images; b) colorful objects or surfaces. e.g., any object (for example, green grass/tree/plant, red or yellow flower/leaf, and blue water surface) lacking color in any color channel will result in low values in the dark channel; c) dark objects or surfaces. e.g., dark tree trunk and stone. As the natural outdoor images are usually full of shadows and colorful, the dark channels of these images are really dark.

Geometric Bounds on Transmission

He's algorithm encounters the problems described above due to the assumption of a local dark channel prior. To solve these problems, we make assumptions on two basic geometric properties in the haze model to obtain the optimal parameter $\mathbf{t}(\mathbf{x})$

- 1) The scene radiance $\mathbf{J}^e(\mathbf{x})$ is nonnegative and it is related to the neighboring pixels.
- 2) Pixels in a local patch have similar depth values and consistent transmission maps.

To view the whole image, the scene radiance $\mathbf{J}^e(\mathbf{x})$ is a collection of all the clean pixels, and it is pushed towards the global atmospheric light \mathbf{A}^e by the fog and haze. As a result, $\mathbf{J}^e(\mathbf{x}_1), \mathbf{J}^e(\mathbf{x}_2), \mathbf{A}^e$ and can be seen as having a linear relationship on each black dotted line. From the local patch perspective and following the above assumptions, all of the pixels in a local patch Ω share the same transmission map, as illustrated by the points on the blue and dotted blue lines.

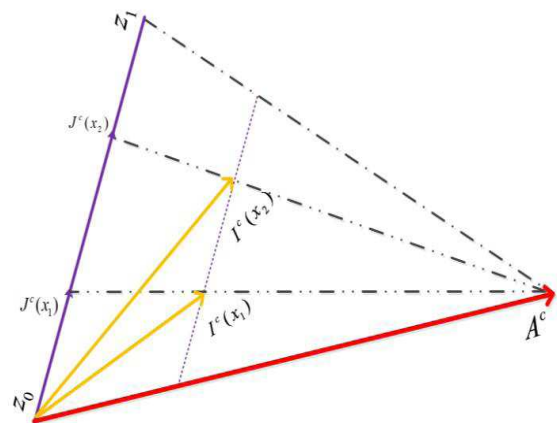


Fig 1. The boundary constraint of Real Radiance.

II PROPOSED WORK

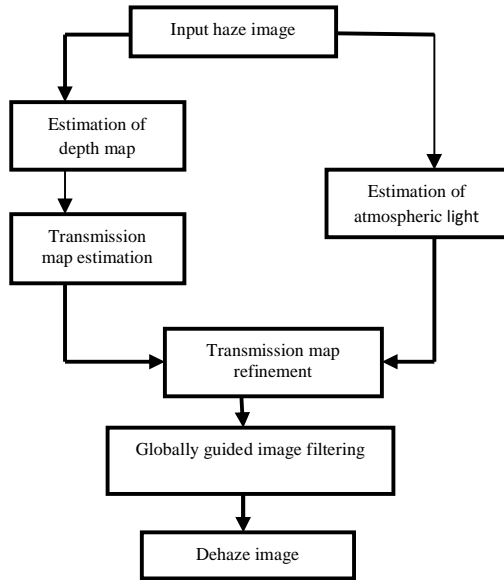
Estimation of Depth Map

The model tends to consider the scene objects with white color as being distant. Unfortunately, this misclassification will result in inaccurate estimation of the depth in some cases. For this consider each pixel in the neighbourhood. Based on the assumption that the scene depth is locally constant, the raw depth map by:

$$d_r(\mathbf{x}) = \min_{\mathbf{y} \in \Omega_r(\mathbf{x})} d(\mathbf{y})$$

Where, $r(\mathbf{x})$ is an $r \times r$ neighbourhood centered at \mathbf{x} , and d is the depth map with scale r .

Fig 2. Haze removal technique



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Restoration of Transmission Map

The restoration of transmission map for a single input haze image can be estimated by the equation given below,

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

Where, \mathbf{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 the depth of scene.

Refine Transmission Map

It is evident to suppress small variations through adjacent pixels. However, one may still obtain an inconsistent scene transmission for objects with large structural regions. To overcome this limitation and get a better transmission map, for this follow the idea described earlier of minimizing the cost function to obtain the refined $t(\mathbf{x})$.

$$\inf_{t \in \mathbb{R}} = \alpha \| \hat{t} - t \|^2 + \mathcal{R}(t)$$

Where the first term is the data-fidelity term, which represents the fidelity between the observed degraded images and the restored image, $\mathcal{R}(t)$ is the regularization, which gives a prior model of the image, and α is the regularization parameter, which controls the trade-off between the data-fidelity and prior items. Normally, images consist of various patterns and it is difficult to describe an image by one

distribution. Fortunately, structural similarities are prevalent in natural images, which will be fully exploited to build the regularization $\mathcal{R}(\mathbf{x})$.

Estimation of Atmospheric Light

As the depth map of the input hazy image has been recovered, the distribution of the scene depth is known. The Bright regions in the map stand for distant places. According to Equation below,

$$A = \mathbf{I}(\mathbf{x}), \mathbf{x} \in \{\mathbf{x} | \forall \mathbf{y}: d(\mathbf{y}) \leq d(\mathbf{x})\}$$

The intensity of the pixel, which makes the depth tend to infinity, can stand for the value of the atmospheric light A . If $d(\mathbf{x})$ is large enough, $t(\mathbf{x})$ tends to be very small and $\mathbf{I}(\mathbf{x})$ equals to A approximately.

It is necessary to pick the top 0.1 percent brightest pixels in the depth map, and select the pixel with highest intensity in the corresponding hazy image \mathbf{I} among these brightest pixels as the atmospheric light A .

Globally guided image filtering

To measure the local depth consistency, use the locally consistent depth as a regularizer, Assume that a local patch can be approximated by a sparse linear combination of elements from a neighbor basis set. A simple single image haze removal algorithm is introduced by using the proposed G-GIF and the Koschmiedar's law. The global atmospheric light $A_c (c \in \{r, g, b\})$ is empirically determined by using a hierarchical searching method based on the quad-tree subdivision. The value of the transmission map $t(p)$ is then estimated by using the proposed G-GIF. Finally, the scene radiance $Z(p)$ is recovered.

According to the Koschmiedar's law, a haze image is generally modeled by

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

where $c \in \{r, g, b\}$ is a color channel index, X_c is a haze image, 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.

Unlike the decomposition model is assumed that the values of A_r , A_g and A_b are estimated before the simplified dark channel is computed. Fortunately, this is not problem by using the method to estimate the values of A_r , A_g and A_b . It should be pointed out that the methods are not applicable because the global atmospheric light is needed to estimate before the dark channel is computed.

A simple haze image model is derived by using the simplified dark channels of the normalized haze image X/A and the normalized haze-free image Z/A . Through the selection of parameters, an optimal transmission can be proposed and the complete calculation process is summarized.

From a statistical point of view, if the two samples are very close or similar, i.e., the distance between them is small or the similarity is high, they provide little information; on the contrary, the difference information should be great. In this way, there is a matrix for each initial transmission patch x_i . Although there are many neighboring patches, it may lead to inaccurate estimation vector x_i and then produce misty results with high residual fog because sub-patches may not have the same depth

Spatially Consistent Depth

The depth edge consistency is decided using neighboring pixels. Hence, whether pixels lie on the same depth is decided only by the locations of the pixels. Following this idea, then a pixel is modeled and its nearest neighbors as a vector variable to measure the depth information.. To determine whether there are other pixels at the same depth, one must need a set of neighboring training sample patches so that the transformation matrix can be calculated.

For this purpose and following the LPG-PCA, then set $N \times N$ window centered at the pixel in the initial transmission map t . In addition, let C_i be the matrix of ones, and assume that,

$$C_i t = [c_1 \cdot t_2 \dots c_s]$$

Where s is the number of pixels in the image. The vector contains all the components within the window $N \times N$. Then, use a $L \times L$ ($L > N$) training block to find the training samples.

Although there are many neighboring patches, it may lead to inaccurate estimation vector x_i and then produce misty results with high residual fog because sub-patches may not have the same depth. If these patches have the same structure, they may be successful in preserving a consistent transmission over the same object and can better reflect the structure of the image.

Inspired by the GIF and WGIF the gradient domain image processing algorithms in the WLS filter and the quadratic optimization problem a new type of GIFs is proposed in this section. Unlike the GIF and the WGIF, the proposed filter is a global filter and it is thus 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 GIF and WGIF 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 structure transfer filter is inspired by the GIF in the WGIF and the gradient domain image processing algorithms. The inputs of the structure transfer filter are an image to be filtered and a guidance vector field. The structure to be transferred is defined by the guidance vector field. The objective of the structure transfer filter is to transfer the structure to the image to be filtered. The structure transfer filter is formulated as a global optimization problem. The cost function is composed of two terms. One term is in image domain and it measures the fidelity of the output image to the image to be filtered. The other is in gradient domain and it specifies the structure of the output image. The former is defined as

$$E_1(O, X) = (O(p) - X(p))^2$$

Where X is an image to be filtered. The term $E_1(O, X)$ implies that the output image O is required to approximate the image to be filtered as much as possible.

The structure transfer filter is applied to estimate the transmission map of a haze image. The structure of the haze image is indeed transferred to the simplified dark channel by the structure transfer filter. Even though the structure of the vector field V is transferred into the output image O^* by the structure transfer filter, the output image O^* sometimes needs to be smoothed.

Scene Radiance Recovery

The depth of the scene d and the atmospheric light A are known, and hence one can estimate the medium transmission t easily and recover the scene radiance J in Equation below,

$$J(x) = \frac{I(x) - A}{t(x)} + A = \frac{I(x) - A}{e^{-\beta d(x)}} + A$$

For avoiding producing too much noise, it is necessary to restrict the value of the transmission $t(x)$ between 0.1 and 0.9. So the final function used for restoring the scene radiance J in the proposed method can be expressed by:

$$J(x) = \frac{f(x) - A}{\min(\max\{\frac{f(x) - A}{0.1}, 0.9\}, 0.9)} + A$$

The adaptive domain selection strategy can be organized to code each patch, which is called the difference-structure-preservation dictionary. Based on the initial dictionary, using the cross-interactivemethod and setting the time to 5, dictionary D_i and codes a_i can be obtained. It should be noted that this approach learns the dictionary on the set of overlapping patches so that sparse image models can handle such situations by exploiting the redundancy between overlapping patches.

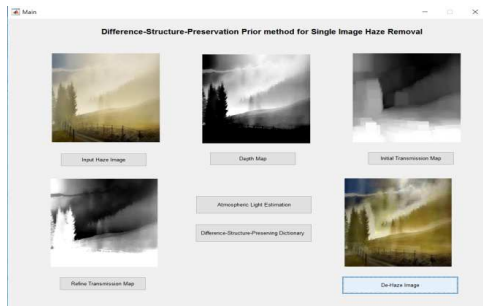


Fig 3. Dehazing Process using MATLAB

III CONCLUSION

This project proposed a dehazing algorithm based on the difference-structure-preservation prior, which can estimate the optimal transmission map and restore the actual scene. To obtain the rough transmission map, two basic properties is used in the haze model to resolve the optimal parameter at the same depth. Afterwards, an image patch can be approximated by a sparse linear combination of elements from a neighbor basis set to obtain a more accurate transmission map that can better preserve

the structures of images. Experimental test results were also used to verify that the method effectively achieves accurate and true representation]

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