

# SINGLE IMAGE DEHAZING USING AIR LIGHT REFINEMENT

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**Abstract**—Single image haze removal is important for many practical applications. But, dehazed results of the existing algorithm tend to be over smoothed with missing fine image details. This drawback is caused due to the following two factors: Inaccurate air light estimation and disregard of multiple scattering. In the proposed method, a dehazing algorithm which gives a detail preserving image is given based on two priors: depth edge aware prior and air light impact regularity prior. Based on the depth edge aware prior, an air light refinement algorithm is proposed. Here the gradient strength is employed to smoothen the channel. Based on air light impact regulatory prior, an adaptive sharpening model is established to enhance levels of detail. The proposed algorithm removes haze and enhances the level of detail in the image.

**Keywords**—De-hazing, airlight consistency, image sharpening, haze removal.

## I. INTRODUCTION

Haze forms due to the presence of suspended particles or water droplets in the atmosphere and it is a major cause of image quality decline. Moreover, haze renders video analysis more difficult to perform. Therefore, dehazing is critical but also a challenge for practical applications such as those related to surveillance. In conventional studies, image dehazing is described as a contrast enhancement problem. Histogram equalization models are typically utilized for image dehazing purposes. With the advances of cloud computing, an automatic image enhancement algorithm is devised based on the use of similar images stored in the cloud. In applying objective quality assessment algorithms, a novel reduced reference image metric is derived for automatic contrast enhancement. However, these algorithms disregard causes of degradation and fail to realize satisfactory perceived quality levels.

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reduced-reference image quality metric for automatic contrast enhancement has been devised. However, these algorithms disregard causes of degradation and fail to realize satisfactory perceived quality levels.

To ensure high levels of perceived quality, an imaging model is widely used to describe the formation of a hazy image. As the haze is dependent on the unknown depth information, degradation is a spatial variant. In order to extract depth information for image de-hazing, earlier image de-hazing algorithms mainly relied on the use of additional information or multiple images. Recently, various reasonable priors and assumptions have been proposed and single image de-hazing algorithms have attracted considerable attention.

For instance, visibility improvements of hazy images can be achieved by maximizing local contrast levels. Based on statistics of outdoor haze-free images, the Dark Channel Prior (DCP) for image de-hazing was first proposed. From low-intensity pixels of local patches, the air light can be directly estimated and then the levels of perceptual image quality can be improved by combining with the imaging model. Based on the generic regularity of natural images (pixels with small image patches typically present one-dimensional distribution in RGB color space), an airlight estimation strategy based on variations in color lines was proposed. Meanwhile, the color attenuation prior to calculate depth for transmittance was also proposed. Recently, based on the assumption that colors of a haze-free image are well approximated by a few hundred distinct colors, a non-local image dehazing algorithm has been developed. Although the above assumptions/priors may generate appropriate results, images processed from existing de-hazing algorithms are less detailed, resulting in pronounced blurring. While the haze has been removed, the de-hazed results are not easily observable. This loss of detail can be mainly attributed to the following two factors namely, airlight estimation and scattering.

On one hand, state-of-the-art de-hazing algorithms are typically based on statistical distributions and local operators. These algorithms tend to make coarse airlight/transmittance estimations. As a result, it is necessary to optimize the coarse estimation through a refining step. In He's algorithm, coarse estimations are refined by soft-

matting. To limit complexity levels, several fast edge-preserved filters are introduced. For example, when setting the hazy image and its dark channel as the guided image and the input image, respectively, the guided filter can transfer the neighbourhood pixels relationship of hazy images to facilitate airlight/transmittance smoothness. Fattal and Berman later developed an airlight/transmittance optimization algorithm based on the Gauss-Markov Random Field (GMRF) that smooths the airlight based on local standard deviations. However, the above algorithms refine the airlight/transmittance based on local image textures of hazy images. As the airlight is only related to depths but not to textures, the accuracy of the refined airlight is in turn compromised. These algorithms are prone to misjudging airlight edges. The final airlight of Gaussian Dark Channel Prior (GDCP) can include redundant details, and the GMRF can over-smooth the airlight. Therefore, details of the recovered image are not prominent. Following this idea, the study is begun by deriving a depth-edge aware prior to control airlight smoothness.

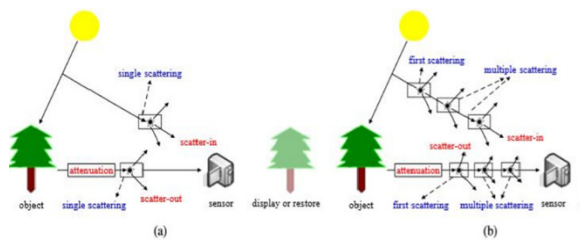


Fig. 1. Illustration of single and multiple scattering. (a) Illustration of single scattering. (b) Illustration of multiple scattering.

On the other hand, the model widely used to describe the formation of a hazy image is derived based on an assumption of single scattering by particles. However, the single scattering occurs only in ideal conditions. In reality, due to the complexities of the traversal of light rays, the multiple scattering is inevitable. Under inclement weather conditions, the effects of multiple scattering are significant. Therefore, Narasimhan and Nayar modelled the multiple scattering of light to better understand and exploit weather effects to improve the performance of outdoor vision systems. According to their theory, the multiple scattering causes images to blur easily. It is concluded that the multiple scattering has a convolution effect on hazy images and that the blurring degree is related to distance and visibility. Processes of the single scattering and the multiple scattering are illustrated in Fig.1.1.

Although some algorithms enhance hazy image details to eliminate convolution effects, most of these algorithms are only used as an independent post-processing solution without considering the depth. Therefore, these classic sharpening algorithms are ineffective. For example,

adaptive sharpening gains based on detail amplitudes were used to enhance hazy image detail levels.

However, this algorithm cannot address detail losses resulting from convolution effects in the distance. On the other hand, the sharpness weight was set as inversely proportional to the Laplacian magnitude. This strategy can result in the over-enhancement of proximal regions. Assuming that imaging systems are subject to isoplanatic conditions, a Wiener deconvolution algorithm to remove blurring was developed. This hypothesis cannot manage images of varying depth. Therefore, a detail-preserving single image de-hazing algorithm based on airlight refinement is proposed. The proposed algorithm can effectively address the problem of detail loss and the following main contributions called the depth-edge aware prior and the airlight impact regularity prior are developed. The former one is used to refine the airlight accurately. The latter one is used for image post-processing.

An airlight refinement algorithm is devised based on the proposed depth-edge aware prior that the locations of large gradients in the minimum channel typically correspond to depth edges. The inverse proportional function of the gradient strength of the minimum channel is used to calculate punishment weights of smoothing for the coarse airlight. Then, weights are used to control how many gradients are yielded to subject to the consistency of airlight by using joint weighted least squares framework.

An adaptive sharpening model is developed based on the proposed airlight impact regularity prior. In this model the sharpening strength is determined from visibility and airlight. Unlike the traditional sharpening strategy the proposed sharpening process is dependent and is inseparable from the airlight estimation process. Since inverting the physics-based model for multiple scattering is difficult, this study is taken on the basis of qualitative rather than quantitative conclusions.

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## II. OBSERVATIONS

The proposed single image haze removal algorithm is closely related to two important issues: the accurate airlight estimation and the convolution effect removal based on adaptive sharpening. Some works related to these issues are discussed in detail. Moreover, two important priors are identified based on the observation and the physics-based model for multiple scattering.

### A. Depth Edge Aware Prior

The depth-edge aware prior is based on the observation that the locations of large gradients in the minimum channel typically correspond to depth edges. To describe this observation, first the minimum channel is defined and then define the gradient significant degree.

This observation is validated based on the D-Hazy Dataset. This dataset is built on the Middlebury and NYU depth datasets, which store images of various scenes and corresponding depth maps. Because in a hazy image the scene radiance value is attenuated with distance, based on depth information and from the physical model of a hazy image, a corresponding hazy scene with high levels of fidelity is created. Finally, from the D-HAZY dataset, differences in gradient significant degree between the minimum channel and depth map are determined. It has been found that the difference of gradient significant degree between the minimum channel and depth map is small. This statistic strongly supports this observation. In a word, the gradient significant degree of the minimum channel is consistent with that of the depth/airlight map. Therefore, depth edge perceptions can be determined from the gradient of a minimum channel.

### B. Airlight Impact Regularity Prior

In the physics-based model for multiple scattering, the hazy image blurring resulting from multiple scattering is related to the atmospheric point spread function (APSF), which is dependent on two quantities: the optical thickness and the forward scattering parameter of weather conditions. The optical thickness is related to the visibility in the atmosphere and to the distance to the source. The value of the forward scattering parameter is constant for certain weather conditions. Since the solution of depth in a single image is ill-posed problem, the inverse solution is difficult. In previous literatures, it is concluded that the airlight value is a function of the depth. Therefore, we deduce that the hazy image blurring resulting from multiple scattering is related to the airlight and the visibility. In this paper, this

deduction is used as the airlight impact regularity prior to effectively render hazy images more detailed.

To prove the importance of the proposed prior, a group of images are processed using Unsharp Masking (UM), generalized un-sharp masking and unnatural L0 sparse representation de-blurring mechanism. These algorithms achieve satisfactory results in terms of motion deblurring and enhance image details based on distinct formulation and optimization steps. However, these algorithms are only based on the inherent details/visibility of images. Thus, sharpening results from the aforementioned algorithms can generate unsuccessfully or unnaturally enhanced results. As observed Generalized Unsharp Masking (GUM) and unnatural L0 sparse representation de-blurring algorithms cannot make good use of the relationship between detail losses resulting from convolution effects and depths, details shown in the distant region remain invisible. In contrast, UM enhances levels of detail from the same enhancement coefficient. Thus, some details may in turn be over-enhanced.

## III. PROPOSED METHOD

Based on the above analysis, a single image haze removal algorithm is designed to improve the accuracy of airlight estimation and to eliminate the multiple scattering blurring. First, based on the depth-edge aware prior, the gradient of the minimum channel to smooth the dark channel for airlight refinement is developed. Second, based on the airlight impact regularity prior, a sharpening model specifically designed for multiple scattering blurring is proposed. The airlight refinement and sharpening modules are inseparable. The block diagram of the proposed enhancement algorithm is shown in Fig2.

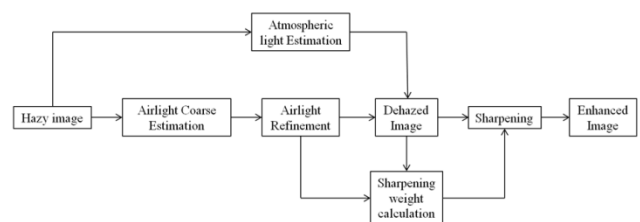


Fig 2. Block diagram of the proposed method

### A. Airlight Refinement Based On Gradient Constraint Of The Minimum Channel

In this section, the airlight is accurately estimated by refining the coarse airlight, which is derived from the dark channel prior. The dark channel is a statistical knowledge of haze-free outdoor images. Most local patches in a haze-free image include pixels that have low intensities in at least one color channel, which are mainly due to the

presence of the following three factors: shadows, colorful objects or surfaces (e.g., red or yellow flowers, blue water bodies and green plants) and dark objects or surfaces. As images captured from nature are always colorful and include numerous shadows, the dark channel is valid in most images.

Although the dark channel is effective at recovering vivid colors and at revealing low contrast objects, some halos and block artifacts are left because the airlight is not always constant in a given patch. Next, we propose an algorithm to refine the coarse airlight.

### *B. Airlight Refinement*

To refine the airlight, two observations can be considered. First, the final solution of the airlight must be as similar as possible to coarse airlight. Second, because the airlight at adjacent scene depths should have a similar value,  $S$  should be smooth except across different depths.

As the locations of large gradients in the minimum channel typically correspond to depth edges, punishment weights of airlight edges can be calculated based on the gradient of the minimum channel. In other words,  $S$  is sparse, and the gradient should be as small as possible in addition to significant edges. The smoothness requirement and edge recovery value are enforced in a spatially varying manner from smoothness weights which are based on the gradient of an image  $G$ .  $\lambda$  is the regularization parameter used to balance the two terms. A higher value of  $\lambda$  corresponds to a smoother final solution to the airlight  $S$ .

It is concluded that the depth edge perception can be determined from the gradient of the minimum channel. Thus, here  $G$  is the minimum channel.  $a_x(G)$  and  $a_y(G)$  can approximately describe the importance of each gradient in the whole image  $S$ . Note that when the window size is  $1 \times 1$ ,  $G$  and  $M$  are equal. However, because the dark channel of a small patch is not reliable,  $G$  cannot replace the coarse airlight  $M$ . Otherwise, the airlight would be seriously over-estimated.

In the proposed algorithm, we combine features of a minimum/dark channel pair: The minimum channel has complete edges but can over-estimate airlight. The dark channel is reliable airlight estimation with some halos and block artifacts. Because smoothness weights are inversely proportional to gradients of a minimum channel and depth edge perceptions can be determined from gradients of the minimum channel, the proposed algorithm can effectively maintain significant edges while eliminating tiny gradients to limit redundancy textures of the airlight. Moreover, halos often present pseudo edges in the coarse airlight. The minimum channel can identify these areas precisely and can

generate large smoothness weights. In turn, halos are simultaneously removed.

3-D illustrations of local airlight intensity values refined via the DCP, via GDCP and from the proposed algorithm are illustrated. The results show that as the distance increases (y direction), the airlight increases gradually. Moreover, no obvious change in intensity occurs in the x direction, suggesting that these pixels are of similar depths.

### *C. DETAIL ENHANCEMENT USING AIRLIGHT IMPACT REGULARITY PRIOR*

As detail losses resulting from convolution effects are not only related to detail/visibility levels but also to airlight/depth, eliminating detail losses resulting from multiple scattering involves considering airlight/depth and details/visibility levels. In this section, a detailed enhancement strategy based on the airlight impact regularity prior is proposed.

As discussed, adding high frequency information to the image itself as an equally scaled version can produce unnatural results. To address this problem, we calculate the sharpening coefficient based on the airlight impact regularity prior. Image objects are smoothed more severely by the haze in a local region where the airlight value is higher. Thus, sharpening coefficients are proportional to the airlight, which means that sharpening coefficients increase with an increase in the airlight value. Moreover, image objects are smoothed more when visibility levels are lower. Thus, the sharpening coefficient is inversely proportional to visibility levels, meaning that sharpening coefficients decrease as visibility levels increase.

### *D. Atmospheric Light Estimation And Haze Removal*

Based on the previous observation, airlight estimate optimization algorithm is introduced. However, to produce intermediate dehazing results, atmospheric light is another variable to be solved. Previous works show that the brightest pixel is the most haze-opaque and that it is theoretically approximately equal to atmospheric light. In considering sunlight and atmospheric light separately, the brightest pixel of an image can be brighter than atmospheric light. Thus, the authors proposed using the dark channel of a haze image to approximate the haze density value. From the top 0.1% of the brightest pixels in the dark channel, these pixels are mostly haze-opaque. From these pixels, the most intense pixel in the input image is selected as atmospheric light  $A$ . In consideration of both operational convenience and

performance, we select the top 0.1% of the brightest pixels and take their average as atmospheric light found in each color channel.

#### IV. CONCLUSION

The proposed method presents a single image haze removal algorithm based on the proposed depth-edge aware prior and airlight impact regularity prior. The proposed algorithm cannot only eliminate the additive influence of the airlight but can also eliminate convolution effects resulting from multiple scattering to enhance image details. The experimental results based on a wide variety of images demonstrate that the proposed algorithm can effectively remove haze while rendering dehazed images more detailed. Therefore, the proposed algorithm outperforms state-of-the-art algorithms. Moreover, de-hazed images obtained from the proposed algorithm are visually pleasing, are artifact free, and appear natural. The future work is to consider the illumination intensity levels of different scenes to further improve the performance of the proposed algorithm.

#### V. REFERENCES

- [1]. L. He, J. Zhao, et al., "Haze removal using the difference- structurepreservation prior," *IEEE Trans. Image Process.*, vol. 26, no. 3, pp. 1063-1075, 2017.
- [2]. D. Berman, T. Treibitz and S. Avidan, "Non-local image de-hazing," *CVPR*, 2016, pp. 1674-1682.
- [3]. R. Fattal, "Single image de-hazing," *ACM Trans. Graph.*, 2008, pp. 1-9.
- [4]. Y. Gao, H. Hu, et al., "A fast image de-hazing algorithm based on negative Correction" *Signal Processing*, vol. 103, no. 10, pp. 380-398, 2014.
- [5]. K. M. He, J. Sun and X. O. Tang, "Guided image filtering," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 6, pp. 1397-1409, 2013.
- [6]. Q. Yang, "Recursive bilateral filtering," *ECCV*, 2012, pp. 399-413.
- [7]. K. M. He, J. Sun and X. O. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341-2353, 2011.
- [8]. G. Deng, "A generalized unsharp masking algorithm," *IEEE Trans. Image Process.*, vol. 20, no. 5, pp. 1249-1261, 2011.
- [30]. J. Li, H. Zhang, et al., "Single image de-hazing using the change of detail prior," *Neurocomputing*, 2015, pp. 1-11.
- [9]. K. M. He, J. Sun and X. O. Tang, "Guided image filtering," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 6, pp. 1397-1409, 2013.
- [10]. J. P. Tarel, "Fast visibility restoration from a single color or gray level image," *ICCV*, 2010, pp. 2201-2208.
- [11]. J. Li, H. Zhang, et al., "Single image de-hazing using the change of detail prior," *Neurocomputing*, 2015, pp. 1-11.
- [12]. K. B. Gibson and T. Q. Nguyen, "An analysis and method for contrast enhancement turbulence mitigation," *IEEE Trans. Image Process.*, vol.23, no.7, pp.3179-3190, 2014.
- [13]. C. Ancuti, C. O. Ancuti and C. D. Vleeschouwer, "D-HAZY: A dataset to evaluate quantitatively de-hazing algorithms," *ICIP*, 2016, pp. 2226-2230.
- [14]. D. Scharstein, H. Hirschmiller, et al., "High-resolution stereo datasets with subpixel-accurate ground truth," *GCPR*, 2014, pp. 31-42.
- [15]. N. Silberman, D. Hoiem, et al., "Indoor segmentation and support inference from RGBD images," *ECCV*, 2012, pp. 746-760

