# REFERENCE IMAGE BASED METHOD OF REGION OF INTEREST ENHANCEMENT FOR HAZE IMAGE

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## ABSTRACT

Different from general algorithms of haze removal and low lighting image enhancement, which only use the information of image to process, this paper adds a reference image to get more information for the algorithm and focuses on enhancing region of interest of an image based on the reference one. With the reference image, the haze one can be divided into Region of Interest (RoI) and Region of no Interest (non-RoI). Furthermore, the reference image can provide more useful information for computing the transmission map and atmospheric light. For the non-RoI region, a more robust transmission map and minimizing reconstruction error cost function based method to estimate atmospheric light has been proposed. Because the atmospheric light is a global variable, the optimized one is also suitable for the RoI region. With the global optimized atmospheric light, an optimized transmission map can be got for the RoI region. The RoI region can be enhanced via the optimal transmission map and atmosphere light. Theoretical analysis gives eloquent proof proving that the proposed method is definitely better than the traditional dark-channel-prior-based methods due to our better transmission map and atmosphere light. Extensive experiments also show the expected results.

***Index Terms*—**Region of interest, dark channel prior, image enhancement, dehazing

## 1. INTRODUCTION

Enhancing the perceptual quality of haze image or low lighting ones is a hot and challenging research topic in computer vision community due to its wide applications in video surveillance, forensics, filmmaking and so on. Removing haze can significantly increase the visibility of the scene and correct the color shift caused by the airlight and help the haze-free-based computer vision algorithms to work well. Many methods[1,2,3] have been proposed to remove the haze. For example, Fattal [1] estimates the albedo of the scene and then infers the medium transmission, under the assumption that the transmission and surface shading are locally uncorrelated. Tan [2] observes that that the haze-free image must have higher contrast compared the input haze image and he removes the haze by maximizing the local contrast of the restored image. Among various haze removal methods, the Dark Channel Prior (DCP) based method proposed by He (Kaiming He) et al. [3] has a good dehazing performance. However, the above mentioned methods [1,2,3] can't always get the global optimal solution. And sometimes we will have the Region of Interest (RoI) in an image especially for the forensics. So this paper just focuses on enhancing the region of interest to improve the dehazing result.

(a) Haze image (b) Haze-free image

Fig. 1. Schematic plot of RoI. (a) is haze image with a region of interest, and the RoI has been marked in a red box. (b) is the reference image.

The dark channel prior was first proposed in [3] for single image haze removal. After some statistical analysis of haze-free outdoor images, the authors found that in most of the local regions which do not cover the sky, it is very often that some pixels (called "dark pixels") have very low intensity in at least one of the color (RGB) channels. With this prior, it is easy to estimate the haze's transmission and recover the haze-free image. Furthermore, Dong et al. [4] expanded the DCP to low lighting image enhancement. One of the biggest advantages of DCP-based methods is that it is very simple and makes algorithms real-time. However, there are too many assumptions to make a rough estimate on the transmission map and atmospheric light. For example, the atmospheric light just uses the brightest pixel to estimate. It turns out to get the unsatisfied enhanced result.

Different from no reference image enhancement methods, which only use the information of image to process, the reference image based methods always get more useful information and perform better. Schaul et al. [5] proposed fusing a visible and a near-infrared image of the same scene for the color image dehazing. However, it is hard to collect the near-infrared image. It is a good idea to make use of the information of a clear reference image. Especially, it always exists some clear reference images to use in surveillance. For example, Fig. 1 extracts two frames of a surveillance video in the same scene. Image (a) is a haze image and image (b) is a haze-free one as reference. The haze image is easy to divide the RoI and non-RoI region compare to the reference image. The RoI has been marked in a red box in Fig. 1(a).

In this paper, we focus on enhancing the region of interest based on dark channel prior. Three main contributions of this paper can be conclude as: introducing a reference image to divide the haze image into RoI and non-RoI region; presenting a new and more accurate estimate formula for transmission map for the non-RoI region; getting the optimal global atmospheric light; getting the optimal transmission map for the RoI region. Extensive experimental results show that the proposed method with optimal transmission map and atmospheric light performs better than the traditional haze removal methods.

The outline of the paper is as follows. The dark channel prior based haze removal method was first outlined in Section 2. The referenced image based method of region of interest enhancement was proposed in Section 3. Experimental results and some discussion were shown in Section 4. Finally, we conclude our paper in Section 5.

## 2. HAZE REMOVAL USING DCP

For a haze image *I*, it can be described by the atmospheric scattering light physical model [6,7]:

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

where *J* is the haze-free image to recover, *A* is the global atmospheric light, *t* is the medium transmission describing the portion of the light that is not scattered and reaches the camera, and *x* is the pixel's index. The first term $J(x)t(x)$ describes the result of direct attenuation from the scene [2]. The second term $A(1-t(x))$ describes the impact of airlight to haze image [8].

After estimating the transmission map *t* and atmospheric light *A*, we can get the haze-free image *J* from the equation (1) as follows:

$$J(x)=\frac{I(x)-A}{\max(t(x),t_0)}+A \tag{2}$$

where $t_0$ is used to avoid $t(x)$ too small.

In [3], the authors proposed the dark channel prior that estimates the transmission map *t* and atmospheric light *A*. The DCP can be formulized as:

$$J^{dark}(x)=\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) \tag{3}$$

where $J^c$ is a color channel of *J* and $\Omega(x)$ is a local patch centered at *x*. Statistical analysis shows that the dark channel prior of haze-free image *J* tends to be zero.

Taking the min operation among three color channels in the local patch $\Omega(x)$ and obtaining:

$$\begin{aligned}&\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right)\\&=t_e(x)\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right)+(1-t_e(x))\end{aligned} \tag{4}$$

Since DCP of haze-free image tends to be zero, we can estimate the transmission $t_e$ simply by:

$$t_e=1-\omega\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right) \tag{5}$$

where $\omega$ is a tunable parameter.

To estimate the global atmosphere light *A*, we first select the top 0.1% brightest pixels in the dark channel. Then, the highest intensity pixel is selected as atmospheric light *A* among these pixels with the same indexes in the image *I*.

The DCP-based method has made great progress in haze removal, and many methods have been proposed to extend it to other applications including dehazing and low lighting image enhancement [4]. However, some problems still need to be solved. It is too coarse to estimate the atmospheric light by a brightest pixel. And the coarse atmospheric light will make the DCP in Eq. (3) inaccuracy. Furthermore, although the DCP is low, let it equals to zero will introduce error into the transmission map.

## 3. REGION OF INTEREST ENHANCEMENT

In this section, we introduce how to enhance the RoI for the haze image. As show in Fig.1, we not only want to remove the haze from the haze image, but also to significantly increase the visibility of the RoI or recognize what is the target in the RoI. In this paper, the information of the reference image (b) is taken into account to enhance the RoI for the haze image (a).

With the reference image, the haze image can be divided into RoI region and non-RoI one. Then, the atmospheric scattering light physical model in Eq. (1) is divided into two corresponding ones:

$$I_{RoI}(x)=J_{RoI}(x)t_{RoI}(x)+A(1-t_{RoI}(x)) \tag{6}$$

$$I_{non-RoI}(x)=J_{non-RoI}(x)t_{non-RoI}(x)+A(1-t_{non-RoI}(x)) \tag{7}$$

### 3.1 New transmission map estimation

As analysis in [3], if $J$ is a natural haze-free outdoor image, the intensity of DCP image $J^{dark}$ is low and tends to be zero except for the sky. And the original authors simply set the DCP image $J^{dark}$ in eq. (4) to zero and get a coarse estimation $t_e$ (eq. (5)). Of course, it is adjudged wise to approximate it if we just have the haze image. But it is inappropriate to estimate the transmission map of the region of sky or the image with too much white pixels such as the surveillance video in snowy day (Fig. 1).

Just like forensic analysis, if we get an unclear image of the scene of crime, we can take a clear background photograph auxiliary our analysis afterwards. With the clear haze-free reference image $J_{ref}$, the DCP image $J^{dark}$ in eq. (4) no longer equals to zero in spite that most of the intensity is very low. Derived from eq. (4), we get a more acute transmission map for the haze image except the RoI:

$$t_{non-RoI}(x) = \frac{1-\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^c_{non-RoI}(y)}{A^c}\right)\right)}{1-\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c_{ref}(y)}{A^c}\right)\right)} \tag{8}$$

### 3.2 Global atmospheric light estimation

To the atmospheric light, He (Kaiming He) [3] et al. use the brightest pixel to estimate it. Some people proposed computing the weighted average of some top brightest pixels to optimize it. But it is still hard to ascertain the atmospheric light estimation is the globally optimal solution. In this paper, we iteratively compute the global atmospheric light.

With the new transmission map $t_{ref}$ and global atmospheric light $A_{ref}$, we can get the optimized haze-free image $J_{non-RoI}$:

$$J_{non-RoI}(x) = \frac{I_{non-RoI}(x) - A_{ref}}{\max\left(t_{non-RoI}(x), t_0\right)} + A_{ref} \tag{9}$$

We can use different kinds of evaluation criterion of reconstructed images, such as Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR), to test the dehazing result. The MSE and PSNR between the reconstructed image $J_{non-RoI}$ and reference image $J_{ref}$ can be formula as:

$$MSE = \frac{1}{N}\left\| J_{ref} - J_{non-RoI} \right\|_2^2 \tag{10}$$

$$PSNR = 10\cdot\log_{10}\frac{255^2}{MSE} \tag{11}$$

where $N = m\times n$ is the size of image $J_{non-RoI}$ and $J_{ref}$.

In this paper we use the PSNR to evaluate it. Putting Eq. (9) and (10) into Eq. (11), the cost function can be formulated as

$$A_{ref} = \arg\min_A 10\cdot\log_{10}\frac{255^2}{\frac{1}{N}\left\| J_{ref} - \left(\frac{I_{non-RoI} - A}{\max\left(t_{non-RoI}, t_0\right)} + A\right)\right\|_2^2} \tag{12}$$

### 3.3 Optimized transmission map for RoI

**Algorithm 1:** Enhance RoI for haze image

**Input:** the haze image $I$ and haze-free image $J_{ref}$

**Initialize:** parameter $\omega$, atmospheric light $A_{ref}$

For non-RoI region

1. $A$ equals to the value of the highest intensity pixel
2. $I^{dark}_{non-RoI}(x) = \min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^c_{non-RoI}(y)}{A^c}\right)\right)$

   $J^{dark}_{ref}(x) = \min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c_{ref}(y)}{A^c}\right)\right)$
3. $t_{non-RoI}(x) = \frac{1-\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^c_{non-RoI}(y)}{A^c}\right)\right)}{1-\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c_{ref}(y)}{A^c}\right)\right)}$
4. $J_{non-RoI}(x) = \frac{I_{non-RoI}(x) - A}{\max\left(t_{non-RoI}(x), t_0\right)} + A$
5. $MSE = \frac{1}{N}\left\| J_{ref} - J_{non-RoI} \right\|_2^2$
6. $A_{ref} = \arg\min_A 10\cdot\log_{10}\frac{255^2}{\frac{1}{N}\left\| J_{ref} - \left(\frac{I_{non-RoI} - A}{\max\left(t_{non-RoI}, t_0\right)} + A\right)\right\|_2^2}$

For RoI region

7. $t_{RoI}(x) = 1-\omega\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I^c_{RoI}(y)}{A^c_{ref}}\right)\right)$
8. $J_{RoI}(x) = \frac{I_{RoI}(x) - A_{ref}}{\max\left(t_{RoI}(x), t_0\right)} + A_{ref}$

**Output:** haze-free image with enhanced RoI.

Now, we have got the optimized global atmospheric light and transmission map for the image except RoI. Because the RoI is very different with the reference background image, we can't use the Eq. (6) to estimate it. Then, based on Eq. (4) and (10), we get the optimized transmission map for RoI,

$$t_{RoI}(x) = 1 - \omega \min_{c}\left(\min_{y\in\Omega(x)}\left(\frac{I_{RoI}^{c}(y)}{A_{ref}^{c}}\right)\right) \tag{13}$$

After getting the optimal transmission map $t_{RoI}$ and atmospheric light $A_{ref}$, the enhanced RoI can be formulized as:

$$J_{RoI}(x) = \frac{I_{RoI}(x) - A_{ref}}{\max\left(t_{RoI}(x), t_0\right)} + A_{ref} \tag{14}$$

The Algorithms 1 summarize the process of the RoI enhancement.

## 4. EXPERIMENTAL RESULTS AND DISCUSSIONS

In order to verify the robustness of our algorithm, we compare it with the classical DCP-based method [3]. Similar to other methods, we evaluate the quality of the enhanced images by qualitative analysis and report two experimental results in this paper (Fig. 2 and 3).

Both in Fig. 2 and 3, image (a) is the haze image with a target of interest, which is marked in a red box. Image (b) is the reference background image. Image (c) is the dehazing result using He's method. Image (d) is the enhancing result using our proposed method.

In Fig. 2, He's method just makes the umbrella of RoI a little bit clear. For our proposed method, we can recognize that a man with a red umbrella is riding a vintage bicycle. In Fig. 3, the haze is too heavy making He's method work poorly. We can't know what vehicle the man is riding. But in our proposed method, we can basically recognize that the man is riding an electric car. The reason for our better performance is that we get an optimized transmission map and atmospheric light.

## 5. CONCLUSIONS & FUTURE WORK

The dark channel prior information has been successfully used in signal image haze removal and low lighting image enhancement. In this paper, we introduce how to optimize the transmission map and atmospheric light using a reference image based on DCP. First, with the reference image we derived a new novel and robust transmission map $t$ for the haze image except for the region of interest. Second, by minimizing reconstruction error we get the optimal atmosphere light $A$. Third, train the optimal transmission map $t$ based on the new atmosphere light for the region of interest. Then, we enhance the region of interest using the optimal transmission map and atmosphere light. Experimental results show that the proposed method performs better than state-of-the-art one.

There are many interesting ways to extend this work in the future. First, the reference image we used here is a haze-free clear image, and could be replaced with author haze image. Furthermore, it is alternative method to automatically detect the target of interest by the transmission maps. Finally, it would be interesting to extend this framework to recognize what the target is in the RoI.

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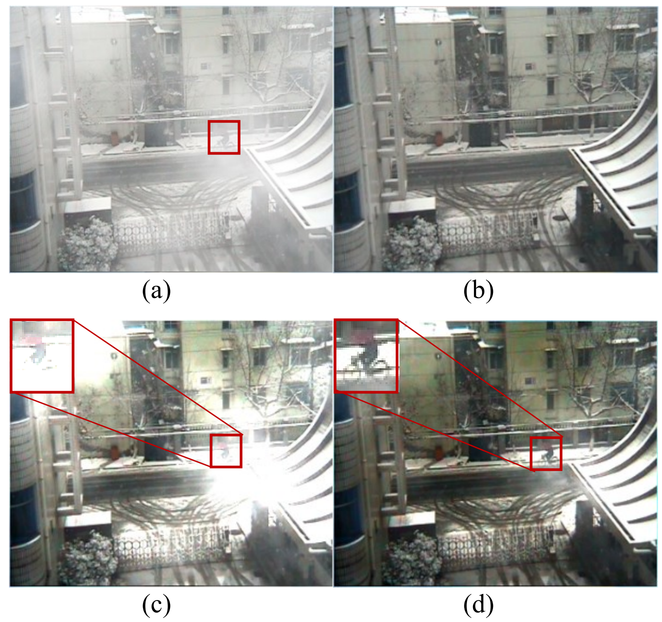


Fig. 2. Comparison of enhancing results of RoI. (a) Haze image, (b) Haze-free image, (c) He's method's result, (d) Proposed method's result.

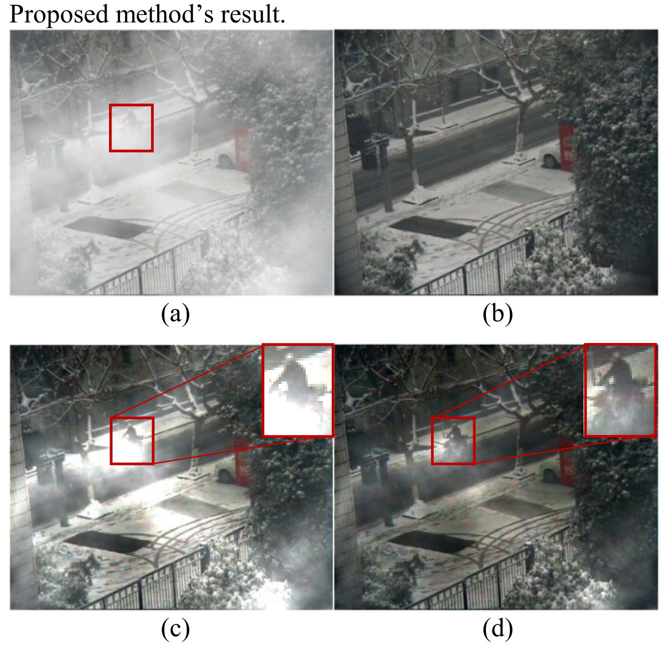


Fig. 3. Comparison of enhancing results of RoI. (a) Haze image, (b) Haze-free image, (c) He's method's result, (d) Proposed method's result.

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