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Single Image Haze Removal with Improved Atmospheric Light Estimation

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Abstract. A novel method for atmospheric light estimation has been proposed in this paper. The new estimation method, called Estimation Based on Patch Size Adjustment (PSA), firstly segments the sky region of dark channel through threshold segmentation method and then adaptively adjusts the patch for dark channel until the estimated atmospheric light is right in the segmented sky region. Experimental results show that this method is effective even when the intensity of some scene objects is inherently higher than the atmospheric light and no shadow is cast near them. However, PSA spends a lot of time on adjustment. In order to improve the time efficiency, another simplified method, called Estimation Based on Sky Region Segmentation (SRS), is proposed by directly estimating the atmospheric light in the segmented sky region. The test results show SRS is almost as good as PSA on haze removal effect. Both methods have advantages on improving visual effect and objective indicators of the haze-free images.

1. Introduction
The outdoor images are often affected by the haze in air and become fuzzy, which has a bad influence on everyday computer vision applications. With the increase of haze weather in the recent years, the research on single image haze removal is more urgent both for daily life and production.

In this paper, we conduct our research on atmospheric scattering model (firstly proposed in [1], then refined in [2-5]) and adopt the algorithm DCP (Dark Channel Prior, proposed in [6]) with guided image filtering [7] to remove the image haze generally. After a few more tests, we found the atmospheric light estimation in [6] is invalid when the intensity of some scene objects is inherently higher than the atmospheric light and no shadow is cast near them. And it falsely takes the pixel from small white buildings or bright light rather than the sky region as the atmospheric light estimation. For this limitation, we refine the algorithm by improving atmospheric light estimation to get haze-free images with better visual effect and higher quality. The improved atmospheric light estimation is based on sky region segmentation.

2. Related Work
In the field of single image haze removal, atmospheric scattering model is widely used to describe the formation of a haze image and has been defined as followed:

\[ I(x) = J(x)t(x) + A(1-t(x)) \] (1)

Where \( I \) is the haze image obtained by imaging equipment, \( J \) is the haze-free image that needs recovery, \( t(x) \) is the medium transmission describing the portion of the light that is not scattered and...
reaches the camera and $A$ is the atmospheric light. As we can see, only $I$ is known while $t(x)$ and $A$ are unknown. So it is necessary to estimate $t(x)$ and $A$ before we recover $J$. In this paper, $t(x)$ is estimated in the method proposed in [6] and further refined by guided image filtering proposed in [7]. The atmospheric light is estimated through the approach proposed later based on the estimation method in [6].

The atmospheric light is often estimated from the most haze-opaque pixel in the previous methods for single image haze removal. The brightest pixel is selected as the atmospheric light in [8] and is refined in [9]. Since the pixel with the highest intensity may be from a white building or bright vehicle light, these two methods are invalid sometimes. To break the limitation, a new method for atmospheric light estimation is proposed in [6].

According to [6], dark channel $J_{dark}$ has been defined as followed:

$$J_{dark}(x) = \min_{c \in \{r, g, b\}} \left( \min_{y \in \Omega(x)} (J^c(y)) \right)$$

(2)

Where $J^c(c \in \{r, g, b\})$ is a color channel of $J$ and $\Omega(x)$ is a local patch centered at $x$. According to the observation in [6], the intensity of $J_{dark}$ is low except for the sky region. So they first pick the top 0.1% brightest pixels in the dark channel, among which the pixel with highest intensity in the input image $I$ is picked as the atmospheric light. The method is effective in most cases. However, when there is no shadow cast near a white building or the vehicle light is too bright and the patch is not big enough (the patch is set to $15 \times 15$ for a $600 \times 400$ image, the same with [6]), the method turns out to be a wrong result, as shown in section 4.3.

3. Sky Region Segmentation

First of all, we get the dark channel of input image $I$ (see figure 1) according to equation (2), as shown in figure 2. Since only about the top 0.1% brightest pixels rather than all pixels in the sky region are needed for the estimation, we do not have to segment the sky region very precisely. So the only thing we have to do is get the rough sky region as fast as possible.

In most cases, the sky region is in the upper part of an image while the interfering bright pixel is usually in the lower part. Under this assumption, we can segment the sky region in a very simple way: (1) Calculate the average of the first row in the dark channel; (2) Compare every pixel with the average; (3) If the intensity of the pixel is lower than the average, we do not think it is from the sky region and put it zero; (4) Else we have to check adjacent pixels (the above pixel and the left pixel), if they are both zero, put it zero, else remain the same.

Here is the reason for step (4). Through step (4), we can get rid of the bright pixels that come from a white building and vehicle light, which always present themselves in isolated white patches in the dark channel. With the method above, we put a large amount of pixels zero, but it is fine because even in this way we also have enough pixels to meet the condition “the top 0.1% brightest pixels in the dark channel”.

Sometimes the sky region might be the upper left corner or the upper right corner rather than the entire upper part, we refine step (1) like this: we calculate and compare the averages of the left and right half of the first row and pick the higher one as final average for next steps. Until now, the entire steps for sky region segmentation have been introduced.

We firstly get the original dark channel (see figure 2) of the input haze image (see figure 1) according to equation (2), then we segment the rough sky region from dark channel through the approach above and the new dark channel is called improved dark channel, as shown in figure 3. As we can see, the sky region has been roughly segmented in the improved dark channel, meeting the needs of atmospheric light estimation.
4. Atmospheric Light Estimation

4.1. Estimation Based on Patch Size Adjustment (PSA)
We found the haze removal results are satisfactory when the patch size is set to 15 × 15 for a 600 × 400 image. However, when the intensity of some scene objects is inherently higher than the atmospheric light and no shadow is cast near them, the estimation in [6] turns out to be wrong because the bright objects still have high intensity in the dark channel and become the interference. After our research, we found that as the patch size is set bigger, the bright objects are dimmer in dark channel. When the patch size is set big enough, the bright objects are dim enough in dark channel, no longer being the interference. So the problem is to find the proper patch size.

With segmented sky region, it is easy to judge whether the atmospheric light is in the right place. So the improved estimation method PSA gets the right atmospheric light by adjusting the patch size automatically. What calls for special attention is that here we only adjust the patch size for dark channel, which only affects atmospheric light estimation but nothing else. So the improvement strategy has no negative impact on haze removal effect.

4.2. Estimation Based on Sky Region Segmentation (SRS)
PSA is valid even when the intensity of some scene objects is inherently higher than the atmospheric light and no shadow is cast near them. However, when the bright objects are too big or the shadow is too far, PSA takes a very long time to find the proper patch size. Therefore, PSA is not applicable for the applications that have critical real-time requirement. In order to improve the time efficiency, a simplified estimation method, called Estimation Based on Sky Region Segmentation (SRS) is proposed as followed.

With the segmented sky region above, we also can directly compare the intensity of pixels in the input image I that are nonzero in the improved dark channel and the pixel with the highest intensity is selected as the atmospheric light. We can also firstly pick the top 0.1% brightest pixels in the improved dark channel, among which the pixel with the highest intensity in I is selected as the atmospheric light. For a better comparison, we adopt the latter method in this paper.

4.3. Atmospheric Light Estimation Results
Figure 4 and figure 5 show the atmospheric light location in three different estimation methods.
As Figure 4 and Figure 5 show, although the locations of atmospheric light by using method PSA and SRS are different, both they are in the sky region, while the location of atmospheric light by using method in [6] is wrongly in the bright train light. Therefore, PSA and SRS are really the improvement for the estimation method in [6].

5. Haze Removal Results
With the estimated medium transmission \( t(x) \) and atmospheric light \( A \), we are able to recover the haze-free image as followed:

\[
J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A \tag{3}
\]

Where \( t_0 \) (in this paper, \( t_0 = 0.1 \)) is a threshold set to avoid great noise effect caused by the situation that \( A \) is too small. Figure 6 shows the results.
These haze-free images might seem dim because they are merely the results after haze removal without any enhancement. As haze-free images in Figure 6 show, the results by using PSA and SRS have a better visual effect (brighter, more colorful and more real), avoiding the obvious color distortion in the results by using method in [6]. Now let us have a look at their objective indicators, including average gray level, contrast and entropy.

According to [10], the average contrast of an image is measured by its variance (or standard deviation), which is given by

\[ \sigma^2(r) = \sum_{i=0}^{L-1} (r_i - m)^2 p(r_i) \]  

Where the \( m \) is the mean value of \( r \) (gray level):

\[ m = \sum_{i=0}^{L-1} r_i p(r_i) \]

Since the value of variance is too big, here we represent the contrast by calculating the standard deviation (square root of variance (\( \sigma^2 \))).

Entropy is a measure of image information and describes the degree of organization of the system. In [11], it is given by

\[ H_r = - \sum_{i=0}^{255} p_i \log p_i \]

Where \( p_i \) is the probability of the pixel \( i \).

Table 1, table 2 and table 3 show average gray level, contrast and entropy of the haze-free images after haze removal respectively.

### Table 1. Average gray level.

| Image (size) | train (600*400) | nyl (800*431) | hongkong (800*457) |
|--------------|-----------------|---------------|-------------------|
| method in[6] | 47.774          | 78.8635       | 87.9629           |
| method PSA   | 74.64           | 73.0636       | 93.431            |
| method SRS   | 64.966          | 73.0636       | 92.5878           |

### Table 2. Contrast.

| Image (size) | train (600*400) | nyl (800*431) | hongkong (800*457) |
|--------------|-----------------|---------------|-------------------|
| method in[6] | 24.298641       | 35.139465     | 50.215919         |
| method PSA   | 35.077812       | 36.158203     | 54.728184         |
| method SRS   | 33.23695        | 36.158203     | 55.164715         |

### Table 3. Entropy.

| Image (size) | train (600*400) | nyl (800*431) | hongkong (800*457) |
|--------------|-----------------|---------------|-------------------|
| method in[6] | 6.246151        | 7.104847      | 7.430906          |
| method PSA   | 6.994748        | 7.127379      | 7.597792          |
| method SRS   | 6.845019        | 7.127379      | 7.597830          |
As the results show, both PSA and SRS have improvement on image quality including contrast and entropy and that is why the images in figure 6 (b) (c) are more colourful and more real. In addition, the haze-free images recovered by PSA and SRS have almost the same average gray level, contrast, and entropy. So we can draw a conclusion that the haze removal results of PSA and SRS are almost the same.

6. Discussion and Conclusion

In this paper, we have presented a novel atmospheric light estimation method based on sky region segmentation. PSA is an improved strategy based on the estimation method proposed in [6] and solves the problem that sometimes the object in the scene is so bright that even in dark channel it is still very bright and becomes the wrong estimation. But the time efficiency of PSA is not so good sometimes. For this limitation, another method SRS has been proposed, improving the haze-free images both objectively and subjectively as well.

However, both PSA and SRS are invalid when the sky region is covered with leaves or something else so that some part of the sky region is really dark in dark channel. In this case, the sky region segmentation strategy might falsely put some sky region pixels (the right estimation might be one of them) zero by regarding them as bright interference pixels. We intend to work out a more effective method to break the limitation in the future.

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