Review on Comparative Evaluation of Traditional Methods for Image Defogging: Dark Channel Prior-Based Framework

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Abstract: *This paper shows a framework built on the Dark Channel Prior (DCP) method to address the persistent issue of image defogging in computer vision. We want to address the drawbacks of both the current deep-learning techniques and the restrictions of conventional methods with our suggested model., such as interpretability and overfitting. Specifically, we concentrate on reducing color differences within the DCP structure, eliminating contrast distortion, and enhancing fog rejection. Through a comprehensive comparison analysis that combines quantitative and qualitative methods, we evaluate the completion of our proposed model.metrics with the state-of-the-art deep learning methods. The paper provides a thorough evaluation of each method's effectiveness in a variety of defogging scenarios, showing both its benefits and drawbacks. According to our findings, the improved DCP-based model performs competitively while retaining simplicity and interpretability, indicating that it may be a feasible solution for image-defogging applications*[1]

Keywords: Image defogging, Dark Channel Prior, Competitive Performance, Practical Applications.

I. Introduction

Fog and haze significantly impair the vision of critical security and surveillance systems, hindering object identification and compromising their effectiveness. In order to guarantee precise monitoring and optimal performance, image quality degradation of this kind calls for the use of strong fog removal techniques. Fog's detrimental effects stem from two main mechanisms. In order to guarantee precise monitoring and optimal performance, image quality degradation of this kind calls for the use of strong fog removal techniques. Secondly, ambient light, such as sunlight, undergoes significant scattering, generating a luminous background that further reduces image clarity, resulting in a luminous background that further reduces visibility. Some computer vision programs that use photos taken in foggy settings may be severely hindered by these variables, which could result in poor performance or even operational mistakes Driven by its real-world significance, image defogging has become an active research area.[1] Utilizing the insight that certain image patches are not as intense in at least one colour channel, the Dark Channel Prior (DCP) algorithm has become a well-known method for dehazing single images. By exploiting this prior, DCP methods estimate fog transmission and subsequently recover fog-free images. While traditional DCP-based approaches have demonstrably worked well in many scenarios, they can struggle with complex fog distributions and diverse imaging conditions. This paper proposes an DCP-based defogging framework to address these limitations.Our approach builds upon the core principles of the DCP algorithm but incorporates key refinements to enhance its robustness and effectiveness:[2]

Adaptive Patch Size Estimation: Instead of relying on a fixed patch size, we dynamically adjust it based on local image characteristics. This enables better adaptation to varying fog densities and image textures.

Enhanced Transmission Refinement: We introduce a novel transmission refinement step utilizing guided filtering to leverage spatial coherence and refine the estimated transmission map, leading to more accurate fog removal.[2]

Color Consistency Improvement: To address potential color shifts that can occur during dehazing, we incorporate a color consistency correction step, ensuring color fidelity in the restored image.[2]

Adaptive patch size estimation for improved handling of diverse fog characteristics. Enhanced transmission refinement using guided filtering for more accurate fog removal. Color consistency correction to preserve color fidelity in the dehazed image.[3]

The balance of the paper is structured as follows:

Section 2: Delves into the details of our DCP-based defogging framework.

Section 3: Presents the experimental setup, results, and analysis contrasting our strategy with deep learning and DCP approaches currently in use.

Section 4: Provides concluding remarks and highlights potential future research directions.[3]

We believe that this improved DCP-based framework offers a robust and effective solution for image defogging, addressing the limitations of traditional methods and achieving competitive results compared to deep learning approaches while maintaining interpretability and computational efficiency

II Methodology

A. Dark Channel Prior

The following is the dark channel before based on observations of haze-free outdoor photographs:
The pixels with extremely low intensity have at least one colour channel in the majority of the non-sky regions. Put differently, there should be a very small minimum intensity in such a patch.[4, 5]
Formally, with an image J, we get

$$\mathrm{Jdark}(x) = \min c \in \{r, g, b\}\Big(\min y \in \Omega(x)\big(\mathrm{Jc}\,(y)\big)\Big) \quad (1)$$

where $\Omega(x)$ are local patch centered at x and Jc are colour channel of J.

$$t(x) = e^{-\beta d(x)} \quad (2)$$

$$I_{\mathrm{Dark}} = \min_{C\in\{R,G,B\}}\big(\min_{y\in\Omega(x)}(I^c)\big) \quad (3)$$

According to our observation, if J are unhazarded outdoor image, the intensity of Jdark is low and to be nil, with the exception of sky region. We refer to the aforementioned statistical finding or understanding as the Jdark or dark channel of J.

In dark channel, the primary cause of the low intensities is

Three things:
a) shadows. for instance, the shadows cast by vehicles, structures, and the shadows created by fallen leaves, trees, and rocks in photographs of land landscapes, or the interiors of windows in images of cities;

b) brightly coloured materials or items. For instance, low values will be found in dark channel for any object (such as green grass, trees, or plants, red and yellow flowers or leaves, blue water surfaces) that lacks colour in any colour channel;

c) Soothing surfaces or items. like the stone and black tree trunk. The black channels in these images are very dark because bright colors and lots of shadows are typical of natural outdoor photography.
We have built our dark channel prior on the well-known dark-object removal method from multi-spectral remote sensing. subtracts a fixed number equal to the object that is the darkest in the scene to eliminate spatially homogeneous haze. In order to dehaze natural photos, we provide a new prior.

Fog Removal using Dark Channel Prior
Let's assume ambient light A to start. We will provide an algorithmic approach to ambient light estimation in Section 4.4. In the regional patch $\Omega(x)$, we assume continuous transmission. The notation $\tilde{t}(x)$ represents the patch transmission. In the local patch of the haze imaging, we obtain: using the minimum operation.[6]

$$\min_{y\in\Omega(x)}\left(\frac{I(x)}{A}\right) = t(x)\min_{y\in\Omega(x)}\frac{J(x)}{A} + 1 - t(x) \quad (4)$$

The min operation applies to three color channels independently. This equation is equal:

$$\min_{C\in\{R,G,B\}}\Big(\min_{y\in\Omega(x)}\Big(\frac{I^c(x)}{A^c}\Big)\Big) = t(x)\min_{c\in\{R,G,B\}}\Big(\min_{y\in\Omega(x)}\frac{J^c(x)}{A^c}\Big) + 1 - t(x) \quad (5)$$

Then, we take the minimum operation among three color channels on the given equation and obtain:[5]

The haze-free radiation is predicted by the dark channel before J^{Dark} is zero.

$$\min_{c\in\{R,G,B\}}\Big(\min_{y\in\Omega(x)}\frac{J^c(x)}{A^c}\Big) \approx 0 \quad (6)$$

As A^c is positive, so this leads to:

$$t(x) = 1 - \min_{c\in\{R,G,B\}}\Big(\min_{y\in\Omega(x)}\frac{I^c(x)}{A^c}\Big) \quad (7)$$

In fact,

is the dark channel of the normalized haze image $\frac{I^c(x)}{A^c}$
As previously mentioned, the dark channel before is inappropriate for sky regions. The color of the sky in a foggy shot usually corresponds to the color of atmospheric light A, which produces:[7, 8]

$$\min_{c\in\{R,G,B\}}\Big(\min_{y\in\Omega(x)}\frac{I^c(x)}{A^c}\Big) \to 1, \text{and } t(x) \to 0 \quad (8)$$

in the sky regions. The endless sky has 0% transmission, making it suitable for both sky and non-sky environments. We don't need to divide the sky sections beforehand.

$$t(x) = 1 - \omega\min_{c\in\{R,G,B\}}\Big(\min_{y\in\Omega(x)}\frac{I^c(x)}{A^c}\Big) \quad (9)$$

The above equation shows the transmission map calculation process , After estimating A and calculating transmission map t(x), fog free image in reconstructed as,

$$J(x) = \frac{I-A}{t(x)} + A \quad (10)$$

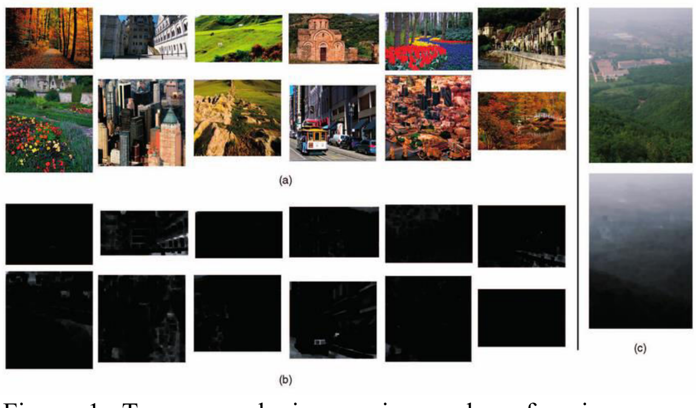

Figure 1. Top: example images in our haze-free image database.
Bottom: the corresponding dark channels.
Right: a haze image and its dark channel.[9]

B. Soft Matting

An iterative technique to maintain the bilateral filter for the edge. The filter replaces individual pixels with a weighted average of their neighbors.[10] The weight provided to each neighbor pixel decreases with distance in the image plane (Spatial domain) and intensity axis (Range domain). Using a Gaussian Gσ as a decreasing function and a grey-level picture I, the bilateral filter's result (b I) is defined.[11, 12]

$$I_p^b = \frac{1}{W_p^b}\sum G_\sigma(\|p-q\|)G_\sigma(|I_p - I_q|)I_q \qquad (11)$$

with

$$W_p^b = \sum_{q\in S} G_\sigma(\|p-q\|)G_\sigma(|I_p - I_q|) \qquad (12)$$

Where σ s control the size range of spatial filter ,σ r control the value of rights according the different gray pixels near the point, b Wp is standard measure which makes the weight norma-lizeation.[13, 14]

C. Atmospheric Light Estimation

In most previous single image techniques, the ambient light A is estimated using the most obscure pixel. On the other hand, a white building or car may have the brightest pixel in anactualshot[15]
You can improve the ambient light estimate by using the dark channel. We first choose pixels with a 0.1% brightness in the dark channel. The majority of these pixels lack clarity. The input image I's highest intensity pixels have been chosen to reflect the ambient light. These pixels are shown by the red rectangle.
This simple method based on the dark channel previously is more dependable than the "brightest pixel" approach. We use each image in the release to automatically assess[16, 17]

Figure 2. Single Image Haze Removal Dark channel prior The red rectangle in the right indicate where our method automatically obtain atmospheric light.[18, 19]

I. Experimental Result

Marcel van Herk's quick approach, whose complexity is linear with image size, is used to carry out the local minimum operator in our research. The patch size for a 600 × 400 photo is set to 15 x 15. We use the Preconditioned Conjugate Gradient (PCG) method as our soft matting solver. A 600 x 400 pixel image 1 is processed in around 10 to 20 seconds on a PC with a 3.0 GHz Intel Pentium 4 processor. The technique in Section C is automatically used to estimate the atmospheric lighting in the photos. The calculated depth maps are crisp and apply consistently with the input images, making them more dependable than the "brightest pixel". [20]

Figure 3. Image defogging Dark Channel Prior.[21]

II. Conclusion

To sum up, we have provided a thorough examination of the new DCP-based framework for the computer vision domain's use of image defogging in this review paper. The suggested approach resolves long-standing problems with both current deep learning techniques and classical methods. The proposed framework emphasizes interpretability, reduces color differences, eliminates contrast distortion, improves fog rejection, and more. A thorough comparative evaluation using qualitative and quantitative metrics compares the improved DCP model with existing deep learning methods in various defogging scenarios to demonstrate its performance. The results of the comparison demonstrate the competitive performance of the model while keeping it simple and interpretable. The improved DCP method not only advances image defogging but also contributes to a wider domain of the computer vision with promising approach that balances performance, simplicity, and interpretability in various practical situations. Further research should explore further optimization of the framework and extensions to address further challenges in real-world defogging scenarios to make it more practical and impactful.

III. References

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