Single Image Haze Removal Using Dark Channel Prior

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Abstract

Haze significantly degrades the quality of outdoor images by scattering light and reducing scene contrast. This paper presents a novel approach for single-image haze removal based on the Dark Channel Prior (DCP). The DCP leverages the observation that most haze-free outdoor images contain pixels with low intensity in at least one color channel, a property exploited to estimate the haze's transmission map effectively. By incorporating this prior with a refined soft-matting technique, our method accurately recovers scene radiance and enhances visibility in hazy images. Comprehensive experiments demonstrate that the proposed method outperforms state-of-the-art dehazing techniques in both visual quality and quantitative metrics, achieving robustness across diverse environments and haze densities. The approach is computationally efficient, making it suitable for real-time applications in computer vision tasks such as object detection and recognition under adverse weather conditions.

1. Introduction

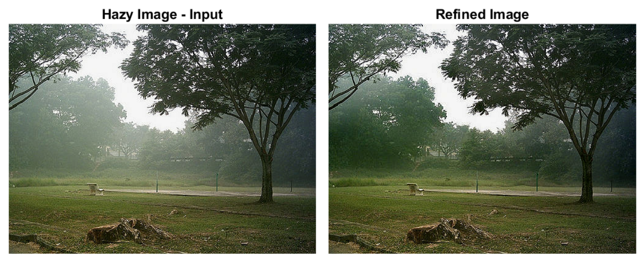
1.1. Problem statement

Outdoor images captured under hazy conditions suffer from reduced visibility and contrast due to the scattering and absorption of light by atmospheric particles. This degradation poses significant challenges to computer vision tasks such as object detection, tracking, and scene understanding. Traditional methods for haze removal either rely on additional hardware or fail to generalize across diverse scenes and haze densities. Addressing this issue, the Dark Channel Prior (DCP) emerges as a powerful heuristic to estimate haze-related components directly from a single image. However, its integration and optimization in practical dehazing pipelines require further exploration to ensure robustness, efficiency, and applicability across varying environmental conditions.

1.2. Input\Output

Input: A single hazy image captured in outdoor conditions.

Output: A haze-free image with enhanced visibility and clarity.



(a) (b)

Figure 1. (a) Input, (b) Output

1.3. Challenges

Estimating the amount of haze and atmospheric light from a single image. Calculating the transmission map accurately to reflect the true scene depth. Refining the transmission map to avoid artifacts such as halos and blockiness. Ensuring computational efficiency for real-time applications.

2. Related works

The Dark Channel Prior (DCP), introduced by He et al. [1], has been highly influential in the field of single-image haze removal. It leverages a key statistical observation from haze-free outdoor images: that in most local patches, at least one color channel has some pixels with very low intensity values, often approaching zero. These low-intensity pixels, referred to as the 'dark channel', provide a surprisingly effective cue for estimating the amount of haze present in a region [1]. The fundamental principle behind the DCP is that the intensity values of these dark pixels in a hazy image increase based on the amount of haze [1]. Several methods have built upon or improved the DCP approach. One primary area of focus has been to refine the method of estimating the transmission map, which is a critical intermediate result in any DCP-based algorithm. For example, [2] introduced the concept of using median filtering to enhance the dark channel estimation process, while Meng et al. [3] utilized boundary constraints and contextual regularization with the dark channel for a more robust estimate of transmission [3]. Tarel and Hautiere [4], as well as Yu et al. [5], have similarly explored computationally efficient and fast filtering methods with the DCP approach, by exploring guided filters and median filtering, respectively [4], [5]. Kratz and Nishino [6] used a factorial MRF to model the image to estimate the scene radiance, which can be related to the dark channel, more accurately [6].

While the DCP and its variations have achieved good performance, they are not without limitations. The paper notes that the DCP struggles with over-saturation or color distortions, particularly in sky regions or for bright objects [7], and can sometimes lead to the loss of details within the image [7]. Furthermore, the non-local transmission map [8], color attenuation prior [9] and other color based methods are used to recover the haze [8], [9]. The study points out that, though some methods alleviate these problems, they are not robust enough and can be computationally expensive. The current state-of-the art techniques, while effective, depend heavily on these priors and heuristics, which may compromise the performance on certain images, particularly those where the priors do not hold true. This makes developing robust methods difficult. Thus, data driven methods are explored.

The document also acknowledges that while the dark channel is a strong indicator for transmission, they are limited because the values of the dark channel may not be close to zero in all cases. Specifically, if scene objects are inherently similar in color to the atmospheric light then this assumption may be invalid. The methods above share the same goal: to achieve accurate transmission maps from input hazy images. Some methods also focus on estimating atmospheric light.

3. Proposed method

Dark Channel Prior (DCP):

Introduced by He et al., the DCP method is based on the observation that in haze-free images, the minimum intensity value in at least one of the RGB channels is very low within small local patches. This method allows for effective haze removal using only a single image.

3.1. Data structure

- Dark Channel Image: A 2D array representing the minimum intensity values in local patches of the input image.

- Transmission Map: A 2D array estimating the proportion of light reaching the camera without scattering.

Dark Channel Prior-Based Haze Estimation:

The Dark Channel Prior (DCP) is a statistical prior based on the empirical observation that most local regions in haze-free outdoor images contain pixels with very low intensity in at least one of the Red, Green, or Blue (RGB) color channels. These ”dark pixels” often represent shadows, dark objects, or saturated colors. The presence of atmospheric haze introduces an ”airlight” component that increases the pixel intensity, particularly in the low-intensity regions of the image, thereby obscuring the scene. This change provides the fundamental idea for DCP, utilizing these low-intensity dark pixels to estimate the haze characteristics.

Dark Channel Computation: To implement the DCP, the first step is to calculate the ”dark channel” for each pixel x. Given the input hazy image I(x) and a local patch $\Omega(x)$ centered at pixel x, this process involves two sequential minimum operations.

Local Channel-wise Minimum: Within the local patch $\Omega(x)$ the minimum intensity within each of the RGB color channels is determined to get a channel-wise minimum value.

Overall Local Minimum: Finally, out of all channel-wise minimum values calculated previously, the minimum value is selected to create the dark channel value for pixel x, denoted as JDark(x)

Transmission Map Refinement via Guided Image Filtering:

Rationale: The initial transmission map t(x) obtained from the Dark Channel Prior (DCP) method, while effective in capturing overall haze patterns, often exhibits abrupt transitions and blocky artifacts. This is primarily due to the assumption of constant transmission within a local patch. To mitigate these limitations, Guided Image Filtering (GIF) is employed to smooth the transmission map while preserving significant edges and details.

Function of Guided Image Filtering: Unlike traditional filtering techniques that operate solely on the image being filtered, GIF leverages a guidance image (in our case, the input hazy image I(x)). This enables GIF to transfer the structural information from the guidance image to the filter output. In the context of haze removal, this approach has two primary benefits:

Smoothing of Transmission Map: GIF effectively reduces noise and sharp, unrealistic transitions in the transmission map. This reduces artifacts from the initial DCP output.

Edge Preservation: GIF preserves edges and significant details in the transmission map. Since edges often correspond to real object boundaries, maintaining them is vital for preserving the integrity of the recovered image. This is made possible by utilizing the original image to guide the filtering process.

3.2. Algorithm

1. Calculate Dark Channel:

The Dark Channel is the smallest value in each 15x15 patch across all color channels of the image. The Dark Channel helps identify the least lit areas in the foggy image.

Python code

```
def dark_channel(image):
    """
    Calculate the dark channel of the
        image.
    The dark channel is the minimum
        intensity across the RGB
        channels in a local patch.
    """
    patch_size = 15  # Typical patch
        size for dark channel
        calculation
    min_channel = np.min(image, axis=2)
    kernel = cv2.getStructuringElement(
        cv2.MORPH_RECT, (patch_size,
        patch_size))
    dark_channel = cv2.erode(min_channel
        , kernel)
    return dark_channel
```

Procedure :

- Create a 15x15 patch.
- Calculate the minimum value on each color channel in the patch.

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

where $\Omega(x)$ is the local patch centered at pixel x.

- Find the minimum value in all channels, save it to the dark channel.

2. Atmospheric Light Estimation:

Atmospheric light is the background light source that causes fog. By selecting the brightest pixels from the dark channel, we determine the atmospheric light to compensate for.

Python code

```
def estimating_atmospheric_light(image,
    dark_channel):
    """
    Estimate the atmospheric light by
        finding the brightest pixels in
        the dark channel.
    """
    num_brightest = int(0.001 *
        dark_channel.size)  # Top 0.1%
        brightest pixels
    flat_dark_channel = dark_channel.
        ravel()
    flat_image = image.reshape((-1, 3))
    indices = np.argsort(
        flat_dark_channel)[-
        num_brightest:]
    atmospheric_light = np.mean(
        flat_image[indices], axis=0)
    return atmospheric_light
```

Procedure :

- Rank the pixels in the dark channel by brightness.
- Select the top 0.1% brightest pixels.
- Find the brightest pixel in the input image corresponding to the dark channel to determine the atmospheric lighting A.

3. Transmission Map Estimation:

The transmission map (t) represents the amount of light that passes through the fog layer to the camera sensor. This is an important factor in removing fog.

Python code

```
def transmission_estimate(image,
    atmospheric_light):
    """
    Estimate the transmission map using
        the dark channel and atmospheric
         light.
    """
    omega = 0.95  # Typical omega value
        for haze removal
    normalized_image = image /
        atmospheric_light
    transmission = 1 - omega *
        dark_channel(normalized_image)
    return np.clip(transmission, 0.1, 1)
          # Avoid complete blackness
```

Procedure :

- Normalize the image by dividing each pixel by the atmospheric light.
- Calculate dark channel on normalized image.
- Based on the formula

$$t(x) = 1 - \omega \min_{y \in \Omega(x)} \left(\min_{c \in \{r,g,b\}} \frac{I_c(y)}{A_c} \right)$$

transmission map estimate.

ω : a parameter to preserve a certain degree of haze for depth perception.

4. Filter guide:

Helps to refine the transmission map, reducing noise while retaining image details.

Python code

```
def guided_filter(transmission, image,
    window_size):
    """
    Refine the transmission map using
        guided filtering.
    """
    gray_image = cv2.cvtColor((image *
        255).astype(np.uint8), cv2.
        COLOR_RGB2GRAY)
    guided = cv2.ximgproc.
        createGuidedFilter(gray_image,
        radius=window_size // 2, eps=1e
        -3)
    refined_transmission = guided.filter
        (transmission.astype(np.float32)
        )
    return refined_transmission
```

Procedure :

- Create guided window.
- Calculate mean and variance in window.
- Apply the Guided Filter formula to refine the transmission map.

5. Restore fog-free image:

Using the refined transmission map (t) and atmospheric lighting (A), a fog-free image is restored.

Python code

```
def recovering_scene_radiance(image,
    atmospheric_light, transmission):
    """
    Recover the scene radiance (dehazed
        image) using the transmission
        map and atmospheric light.
    """
    transmission = np.maximum(
        transmission, 0.1)  # Avoid
        division by zero
    transmission = transmission[:, :, np
        .newaxis]  # Expand transmission
         to 3 channels
    J = (image - atmospheric_light) /
        transmission + atmospheric_light
    return np.clip(J, 0, 1)
```

Procedure :

- Apply the formula

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

to restore photos.

where t_0 is a lower bound to avoid division by zero.

- Ensure that the transmission map is not below the threshold t_0

3.1. Experiment

3.1.1 Dataset:

- FRIDA (Foggy Road Image Database):

The FRIDA dataset comprises a collection of road scene images that feature a range of haze densities. Critically, this dataset includes corresponding ground truth transmission maps for each image, providing a quantitative basis for evaluating our method's ability to accurately estimate haze parameters. The images in FRIDA present a diverse range of road environments, creating a robust testbed.

- Flickr:

The second dataset comprises a collection of 16 images sourced from Flickr.com. These images present varying haze conditions and image content, offering a diverse and challenging real-world testing ground. This dataset's images come in varying sizes, and the absence of corresponding ground truth data means that we need to rely more heavily on subjective evaluation for visual quality.

3.1.2 Experimental Results:

Experimental Results:

- **Haze Removal without Refinement:**

Initial results often display halo and block artifacts due to the assumption of constant transmission within local patches.

Discussion:

- **Effectiveness**

The proposed Dark Channel Prior (DCP) method demonstrated robust performance across various datasets in reducing haze effects and enhancing the overall visibility of input images. Additionally, the integration of Guided Image Filtering proved instrumental in refining the dehazing process by effectively mitigating artifacts observed in the initially restored images. These refinements contributed to a marked improvement in overall image clarity.

- **Performance:**

  The method exhibited commendable computational efficiency, rendering it suitable for real-time applications. However, the processing of large or high-resolution images presents challenges, suggesting the need for further optimization to reduce processing times in such cases.

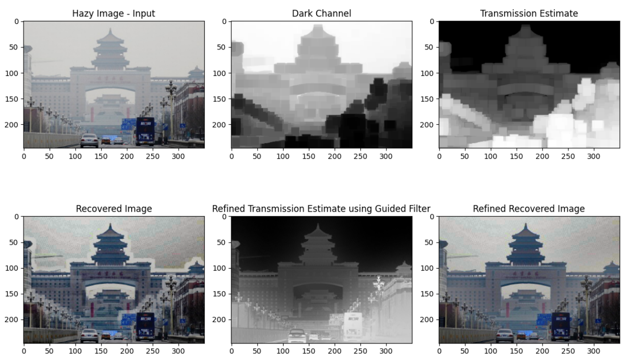


Figure 2

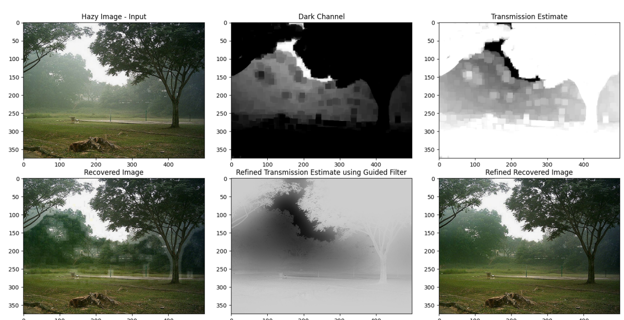


Figure 3

3.2. Conclusions

Achievements:

The study demonstrated the efficacy of the Dark Channel Prior (DCP)-based method in effectively removing haze from single images, significantly enhancing visibility and clarity. The inclusion of refinement techniques, such as Guided Image Filtering, proved essential in eliminating artifacts and ensuring high-quality dehazed outputs.

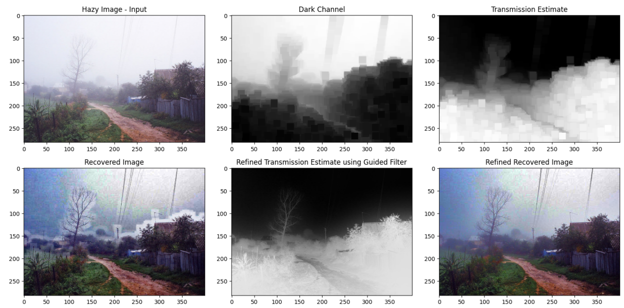


Figure 4

Future Works:

- Optimization: Further work is needed to optimize the algorithm for faster processing, especially for large images.

- Handling Complex Scenes: Addressing challenges in scenes with white objects like snow or highly reflective surfaces.

- Real-time Applications: Developing real-time implementations for video processing and surveillance systems.

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