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Image De-Hazing Using Globally Guided Image Filtering

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Abstract: De-hazing is the process of eliminating haze from photographs, with various filters designed for this purpose. The latest technology in de-hazing involves globally directed picture filtering, aiming to remove haze while preserving the picture's authenticity. It is crucial for the image structure to align with the colour scheme, and a bilateral filter de-noising approach, in combination with the existing GGIF method, can be employed for this purpose. The program's effectiveness will be assessed using a performance parameter named perceptual fog density.

Addressing reduced visibility in the field of computer vision and image manipulation scenarios caused by atmospheric haze or fog is a significant task. The approach titled "Image de-hazing using globally guided image filtering" introduces an innovative method. This technique utilizes a globally guided image filtering mechanism, considering information from the entire image during the de-hazing process. Unlike local filtering methods, this global approach takes into account the overall context of the image, ensuring more precise haze removal and preservation of essential image details.

The method's key strength lies in its capability to effectively handle intricate atmospheric conditions leading to haze. By leveraging global guidance, the filtering process can adapt to varying haze levels across different parts of the image, resulting in a uniform and visually appealing de-hazing outcome.

Keywords: Image de-hazing, Guided Filter, GGIF, De-noising, Bilateral Filter, Atmospheric Haze, Image Processing, Visibility Enhancement, Global Guidance.

1. Introduction:

1.1 Overview:

Image de-hazing is a crucial undertaking within the realms visual intelligence and image analysis, dedicated to alleviating the impact of atmospheric haze on visual data. The presence of atmospheric haze, stemming from suspended particles like dust, smoke, or water droplets, leads to the deterioration of image quality through light scattering and absorption. This degradation presents a formidable challenge in fields such as outdoor photography, surveillance, and various computer vision applications, where unimpeded visibility is indispensable for precise interpretation and analysis.

Our project "Image de-hazing using globally guided image filtering" is geared towards confronting the above challenge. In contrast to localized filtering methods, this approach embraces a globally guided strategy, incorporating information from the entire image. The primary objective is to deliver a comprehensive and context-aware solution to image de-hazing, capable of adapting to diverse haze levels across different segments of the image. This adaptability proves pivotal in scenarios marked by spatially variable atmospheric conditions, as encountered in landscapes characterized by a multitude of visual elements.

1.2 Background History:

Atmospheric haze persistently poses challenges in terrestrial photography, affecting the penetration of light through dense environments. This issue results in a diminished intricacy of captured subjects due to the gradual attenuation of light by haze particles. The detrimental consequences of haze become particularly pronounced in situations where capturing inaccessible subjects or preserving aesthetic clarity is imperative. This project aims to address historical challenges associated with image de-hazing, focusing on enhancing existing strategies to retain intricate picture structures while mitigating the effects of haze.

The chosen approach incorporates advanced image filtering techniques, cantering on globally guided filtering. This method adeptly tackles challenges arising from atmospheric haze while safeguarding vital image details and structures.

1.3 Supported Technologies and Algorithm:

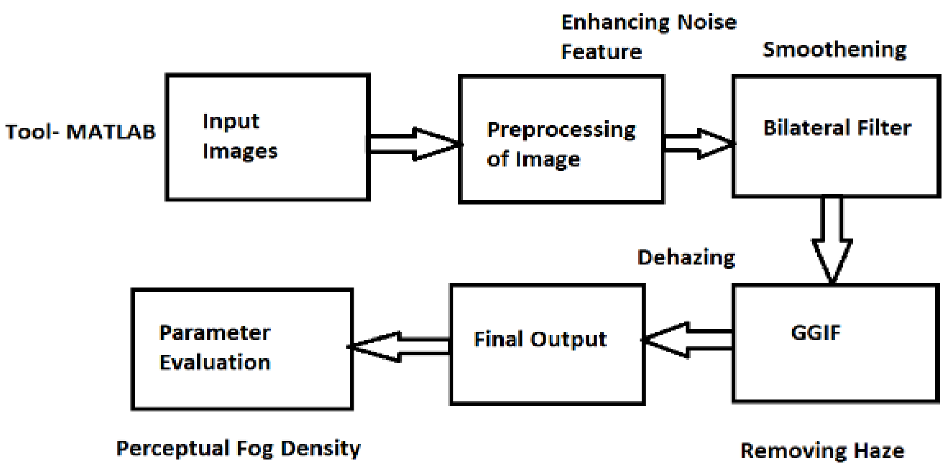
The essence of the project lies in employing advanced image filtering techniques, specifically utilizing the globally guided image filtering method. This algorithm is notable for its effectiveness in handling intricate atmospheric conditions. Through strategic application of filters and consideration of the overall image context, the method aims to generate visually appealing and information-rich images, applicable in scenarios ranging from scenic landscapes with varying levels of haze to enhancing visibility in surveillance footage.

The supported technologies encompass the implementation of the globally guided image filtering algorithm, supplemented by additional methods such as bilateral filter de-noising. These technologies collaborate synergistically to fulfil the project's primary objective: enhancing strategies for preserving fine picture structures and eliminating haze. The focus is on improving image quality and interpretation, rendering the project pertinent and valuable in diverse applications across consumer photography and various computer vision domains.

2. Proposed Work Plan:

2.1 General Architecture:

The specific modules used in the "Image de-hazing using globally guided image filtering" technique may vary based on the implementation details.



1. Image Preprocessing:

- Haze Estimation: This module assesses the degree of haze present in the image. It may involve estimating the sky light and the haze distribution, which represents the fraction of light that reaches the camera through the haze.

2. Image Enhancement:

- Contrast and Colour Adjustment: Post de-hazing, adjustments may be made to enhance contrast and colour in the image. This could involve techniques to improve the overall visual appeal of the de-hazed result.

3. Global Guidance:

- Guided Filtering: This is a crucial component where guided filtering is applied to the entire image. Guided filtering uses a guidance image (often derived from the input image) to filter another image. In the context of de-hazing, it helps in adapting the filter to the local structures and details in the image, contributing to the global guidance approach.

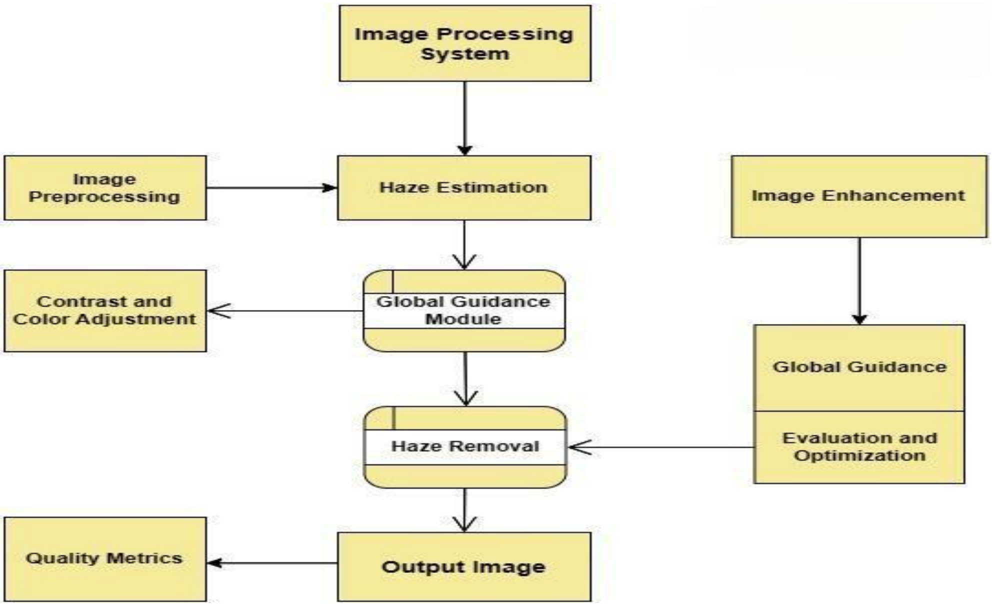
4. Haze Removal:

- Transmission Refinement: The transmission map obtained during haze estimation is refined to improve accuracy. This refinement may involve incorporating additional information to better represent the spatial variations of haze across the images.

5. Evaluation and Optimization:

- Quality Metrics: Modules to evaluate the quality of the de-hazed image. This could include metrics that assess visual clarity, preservation of details, and overall improvement in image quality.

- Parameter Optimization: Depending on the specific algorithm, there might be modules dedicated to optimizing parameters for the de-hazing process to achieve the best results.



2.2 Module Description:

1. **Module 1:** This module is designed to perform image de-hazing using Weighted Guided Image Filtering (WGIF), Guided Image Filtering (GIF), and Globally Guided Image Filtering (GGIF). The module reads a hazed image, resizes it, and applies the filters to enhance the image. The results of each filtering method are displayed in separate subplots. Finally, the FADE (Fog Aware Density Estimation) method is applied to the enhanced images to evaluate the dehazing performance.

2. **Module 2:** This module performs image de-hazing using Globally Guided Image Filtering (GGIF). The module reads a hazed image, resizes it, and applies GGIF with different radius values (70, 50, 120, 190, These values may be changed according to the requirement). The enhanced images are displayed in separate subplots, each corresponding to a different radius value. This allows for a comparison of the de-hazing effect with different radius values in GGIF. The title of each subplot indicates the radius value used for that image enhancement.

3. **Module 3:** This module performs image de-hazing using a Globally Guided Image Filter (GGIF). The module reads a hazed image, resizes it, and calculates the dark channel of the image. It then applies a Weighted Least Squares filter to the dark channel to obtain the transfer function of the filter. The GGIF is applied to the dark channel and the transfer function, and the result is displayed. This process helps in enhancing the visibility of the image by reducing the effect of haze.

4. **Module 4:** This module performs image de-hazing using Guided Image Filtering (GIF), Weighted Guided Image Filtering (WGIF), and Globally Guided Image Filtering (GGIF). It then combines the results of these filters to create a hybrid image. The hybrid image is further processed using a bilateral filter for edge-smoothing, resulting in a Hybrid Edge Smoothing Filter (HESF) image. The module also calculates the Perceptual Fog Density (FADE) for each of the GGIF, hybrid, and HESF images to evaluate the de-hazing performance.

2.3 Main Components Algorithm:

1. GGIF Algorithm:

1. Input:

i) I: Input image

ii) p: Guided image

iii) r: Radius of the local patch

iv) eps: Regularization parameter

2. Output:

1. q: Output filtered image

3. Algorithm: GGIF

1. Initialization:

- Obtain width and height of input image I as wid and hei.
- Calculate the normalization factor N using boxfilter(ones(hei, wid), r).

2. Mean and Covariance Computation:

- Compute the mean of I (mean_I) using boxfilter(I, r) ./ N.
- Compute the mean of p (mean_p) using boxfilter(p, r) ./ N.
- Compute the mean of element-wise multiplication of I and p (mean_Ip) using boxfilter(I.*p, r) ./ N.
- Compute the covariance of I and p (cov_Ip) using mean_Ip - mean_I .* mean_p.
- Compute the mean of I^2 (mean_II) using boxfilter(I.*I, r) ./ N.
- Compute the variance of I (var_I) using mean_II - mean_I .* mean_I.

3. Secondary Mean and Variance Computation:

- Set a smaller radius r2 = 1.
- Compute a new normalization factor N2 using boxfilter(ones(hei, wid), r2).
- Compute the mean of I with the smaller radius (mean_I2) using boxfilter(I, r2) ./ N2.
- Compute the mean of I^2 with the smaller radius (mean_II2) using boxfilter(I.*I, r2) ./ N2.
- Calculate variance of I with the smaller radius (var_I2) using mean_II2 - mean_I2 .* mean_I2.

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4. Variance Enhancement:

- Calculate square root of product of variances (var) using (var_I2.*var_I).^0.5.
- Set a small value eps0 = (0.001)^2.
- Enhance the variance by adding eps0 and normalize using (var+eps0)*sum(sum(1./(var+eps0)))/(hei*wid).

5. Weight Calculation:

- Find the minimum (minV) and mean (meanV) of the enhanced variance.
- Set alpha to the mean variance.
- Calculate a scaling factor kk as -4/(minV-alpha).
- Compute the weight w using 1-1./(1+exp(kk*(var-alpha))).

6. Filter Coefficients:

- Compute the filter coefficient a using (cov_Ip + eps*w./varfinal) ./ (var_I + eps./varfinal).
- Compute the filter offset b using mean_p - a .* mean_I.

7. Mean Filtering:

- Compute the mean of a (mean_a) using boxfilter(a, r) ./ N.
- Compute the mean of b (mean_b) using boxfilter(b, r) ./ N.

8. Output Calculation:

- Compute the filtered output q using q = mean_a .X I + mean_b.

9. Output:

- Give the filtered image q.

2. **<u>Bilateral filter Algorithm:</u>**

1. Input:

i) A: Input image (grayscale or colour)

ii) w: Window size

iii) sigma_d: Spatial domain standard deviation

iv) sigma_r: Range domain standard deviation

2. Output:

i) B: Filtered image

3. Algorithm: Bilateral Filter for Grayscale Images:

1. Verify Input:

a. Check if the input image A is valid

2. Verify Parameters:

a. Check and set the window size w to 5 if not provided.

b. Check and set the standard deviations sigma to [3, 0.1] if not provided.

3. Apply Colour/Grayscale Filter:

a. If the input image is grayscale, apply bfltGray.

b. If the input image is colour, convert it to the CIELab colour space and apply bfltColour.

4. Pre-compute Gaussian Distance Weights:

a. Create a meshgrid of size (-w:w, -w:w).

b. Compute the Gaussian weights (G) based on the spatial domain standard deviation (sigma_d).

5. Apply Filter:

a. Create a waitbar for visualization.

b. Loop over each pixel in the image.

i. Extract the local region around the pixel.
ii. Compute Gaussian intensity weights (H) based on the range domain standard deviation (sigma_r).
iii. Calculate the filter response (F) as the product of H and G.
iv. Update the filtered pixel value (B(i,j)) based on the weighted sum of the local region.

c. Close the waitbar.

Bilateral Filter for Colour Images

6. Convert to CIELab Colour Space:

a. If applycform is available, convert the input RGB image to CIELab colour space; otherwise, use colour space.

7. Pre-compute Gaussian Domain Weights:

a. Create a meshgrid of size (-w:w, -w:w).

b. Compute the Gaussian weights (G) based on the spatial domain standard deviation (sigma_d).

8. Rescale Range Variance:

a. Rescale the range variance (sigma_r) using the maximum luminance (100).

9. Apply Filter:

a. Create a waitbar for visualization.

b. Loop over each pixel in the image.

i. Extract the local region around the pixel.
ii. Compute Gaussian range weights (H) based on the range domain standard deviation (sigma_r).
iii. Calculate the filter response (F) as the product of H and G.
iv. Normalize F.
v. Update the filtered pixel values (B(i,j,1:3)) based on the weighted sum of the local region.

c. Close the waitbar.

10. Convert to sRGB Colour Space:

a. If applycform is available, convert the filtered image back to sRGB colour space; otherwise, use colourspace.

11. Output:

a. Return the filtered image (B).

3. Experimental Result Analysis:

1. Image 1:

2. Image 2:

4. Conclusion:

In conclusion, our project addresses atmospheric haze in images, focusing on computer vision and image processing. This method, incorporating advanced techniques like GIF, WGIF, and GGIF, proves effective in handling complex atmospheric conditions. The global guidance feature enables adaptive filtering, resulting in visually appealing outcomes crucial for diverse applications.

Our project utilizes sophisticated algorithms, including GGIF and Bilateral Filter, for haze estimation, image enhancement, and removal. Experimental results affirm the effectiveness of our approach. Modules such as Contrast and Colour Adjustment and Quality Metrics contribute to the project's success.

The proposed work plan outlines a structured framework for implementing the technique, with each module playing a crucial role in achieving the project's objectives. The proposed work holds significant potential for future development, particularly in the continually advancing field of Image Dehazing/Enhancement.

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