Contrast Enhancement by Non-linear Diffusion Filtering

[1]Sukhjeet kaur, [2]Dr. Rajeshwar Singh
[1]M.Tech Research Scholar, [2]Director
[1]Department of Electronics and Communication Engineering,
[1]Doaba Institute of Engineering & Technology, Mohali, Punjab, India
[2]Doaba Group of Colleges, Mohali, Punjab, India

Abstract : To enhance the visual quality of an image that is degraded by uneven light, an effective method is to estimate the illumination component and compress it. Some previous methods either have defects of halo artifacts or contrast loss in the enhanced image due to incorrect estimation. In this paper, we discuss this problem and propose a novel method to estimate the illumination. The illumination is obtained by iteratively solving a nonlinear diffusion equation. During the diffusion process, surround suppression is embedded in the conductance function to specially enhance the diffusive strength in textural areas of the image. The proposed estimation method has the following two merits: First, the boundary areas are preserved in the illumination, and thus, halo artifacts are prevented; and second, textural details are preserved in the reflectance to not suffer from illumination compression, which contributes to the contrast enhancement in the result. Experimental results show that the proposed algorithm achieves excellent performance in artifact removal and local contrast enhancement.

IndexTerms **- contrast; image enhancement; illumination estimation; nonlinear diffusion; halo artifacts.**

I. INTRODUCTION

The observed image is the multiplication of two T components, namely, illumination and reflectance, which are described as intrinsic images in [1]. In a real scene, the illumination component is usually non uniform and has a high dynamic range, whereas the reflectance reveals the details of the objects in the image. A digital acquisition device such as a consumer digital camera often suffers from varying light conditions because of its much narrower dynamic range than that of the illumination. The captured image could contain both underexposed and overexposed regions and has low local contrast in both areas. Therefore, an enhancement algorithm that focuses on addressing the illumination problem is required to enhance the image's visual quality. There are several types of contrast enhancement algorithms that have been proposed, such as histogram equalization [2], [3] and perceptual enhancement [4], among others. A large set of these algorithms are inspired by Retinex, which was originally a color constancy model that mimicked the color appearan lters are used for estimation.

This assumption usually causes halo artifacts around strong edges in the enhanced image because, in a real scene, the illumination is not always smooth and could change sharply in some areas [1]. In addressing halos, another type of assumption for illumination is described as "piecewise-smoothness", which means that some discontinuities in the image should be preserved. Considering this assumption, nonlinear convolutional filters are adopted to estimate the illumination. However, even though the nonlinear filters are effective in reducing the halo artifacts, they are not effective in contrast enhancement. This defect arises mainly because the nonlinear filters usually obtain small-scale smoothness and tend to over-preserve the various types of edges, including the texture edges. When illumination is compressed by gamma correction or simply removed in the subsequent process, this part of the texture information is compressed or lost in the enhanced result. Additionally, the definition of "piecewise-smoothness" for illumination is obscure, and what scale of smoothness should be obtained remains unclear. Therefore, it is necessary to make a more specific assumption and improve the method for illumination estimation as well. Let us consider two types of edges in the image, namely, the boundary edges and texture edges. The boundary edges are considered to be strong contrast contours of objects or the border of two regions with different illumination conditions. This part of the edges should be preserved in the illumination because halo artifacts could easily occur.

In contrast, texture edges consist in the interiors of regions and are important information for the visual quality of an image. They should be smoothed out from the illumination and transferred to the reflectance component for the final appearance. Overall, the illumination assumption made in this paper can be characterized as: flat as a constant in the textured areas and discontinuous in the boundary areas. It should be noted that precise illumination estimations of real scenes, which is the task in the computer vision area, is not involved in this paper. We make this estimation more concise for a practical contrast enhancement task. Considering that the illumination estimation can be modeled as a selective smoothing process, it can be performed based on a more flexible framework that is described as nonlinear diffusion filtering. The nonlinear diffusion performs nonlinear filtering by solving a partial differential equation that models inhomogeneous heat or impurity transfer. The original equation was proposed by Perona and Malik to obtain an edge-preserving smoothing process and have an accurate scale-space interpretation for the images [1]. The early work on nonlinear diffusion mainly involves addressing its ill-posedness problem and developing different numerical schemes for solving the equation [2]. Nonlinear diffusion has become an effective tool in the field of image smoothing, image restoration [3], [4], image segmentation.

In this paper, a novel contrast enhancement algorithm for images with uneven illumination is proposed. First, illumination-reflectance decomposition is performed on the original image. The method used to estimate the illumination component is based on nonlinear diffusion 2 filtering. To better match the illumination estimate to the assumption made in this paper, a texture suppression mechanism is introduced to improve the performance of the filtering. Then, a logarithmic compression is conducted on the estimated illumination, which is followed by the final recombination of the reflectance and the compressed illumination to obtain the final result. Experiments show that the effectiveness of the algorithm is threefold: local contrast enhancement, global brightness promotion, and avoidance of halo artifacts. The remainder of this paper is organized as follows. In Section II, the proposed nonlinear diffusion method for illumination estimation is described in detail, and the speed-up strategy is introduced. In Section III, the entire procedure of our contrast enhancement algorithm is presented. Analysis and comparison of several experimental results are presented in Section IV. Section V is the conclusion and future scope.

II. ILLUMINATION ESTIMATION BASED NON LINEAR DIFFUSION

The flexibility and effectiveness of nonlinear diffusion exist in that its smoothing performance can be tuned by changing the equation formation and determining a different set of parameters. For example, it can smooth undesired information while respecting region boundaries and other structures in the image, as long as some crucial parameters are set appropriately [3]. On the other hand, it tends to yield piecewise-constant-like images before it finally arrives at the globally constant solution [3]. The above features are potential merits for estimating the expected illumination in this paper. In this section, the nonlinear diffusion is first introduced. Then, the texture suppression used to improve the smoothing properties for better handling of the expected illumination is described. Finally, the entire nonlinear diffusion method for illumination estimation as well as the acceleration strategy is presented in detail.

Texture Suppression:

Studies of neurophysiology have found that the human visual system has a mechanism to make prominent the contours of observed objects [4]. The main reason is that when recognizing objects by judging their contours, the human visual system has a surround suppression mechanism to suppress the disturbing texture information. This mechanism and its effects are shown in Fig. 1. Fig. 1(a) shows a model of complex receptive fields in the neurons of the visual cortex, where the surround suppression takes place inhibitory surround called NCRF (non-classical receptive a central region called CRF (classical receptive field).

III. CONTRAST WITH PROGRAMMING

- The main goal of contrast enhancement is to distribute the pixel values consistently in the dynamic range of gray levels and to develop an output image based on linear cumulative histogram.
- It observed image is the multiplication of two components, namely, illumination and reflectance, which are described as intrinsic images. In a real scene, the illumination component is usually non-uniform and has a high dynamic range, whereas the reflectance reveals the details of the objects in the image. It observed image is the multiplication of two components, namely, illumination and reflectance, which are described as intrinsic images.
- This example shows several image enhancement approaches. Three functions are particularly suitable for contrast enhancement: imadjust, histeq, and adapthisteq. This example compares their use for enhancing grayscale and truecolor images.

Enhance Grayscale Images

- Using the default settings, compare the effectiveness of the following three techniques:
- **Imadjust** increases the contrast of the image by mapping the values of the input intensity image to new values such that, by default, 1% of the data is saturated at low and high intensities of the input data.
- **Histeq** performs histogram equalization. It enhances the contrast of images by transforming the values in an intensity image so that the histogram of the output image approximately matches a specified histogram (uniform distribution by default).

Adapthisteq performs contrast::

- -limited adaptive histogram equalization. Unlike histeq, it operates on small data regions (tiles) rather than the entire image. Each tile's contrast is enhanced so that the histogram of each output region approximately matches the specified histogram (uniform distribution by default). The contrast enhancement can be limited in order to avoid amplifying the noise which might be present in the image.
- Read a grayscale image into the workspace. Enhance the image using the three contrast adjustment techniques.
- pout = imread('pout.tif');
- pout_imadjust = imadjust(pout);
- pout_histeq = histeq(pout);
- pout_adapthisteq = adapthisteq(pout);
- Display the original image and the three contrast adjusted images as a montage.
- montage({pout,pout_imadjust,pout_histeq,pout_adapthisteq},'Size',[1 4]) title("Original Image and Enhanced Images using imadjust, histeq, and adapthisteq")

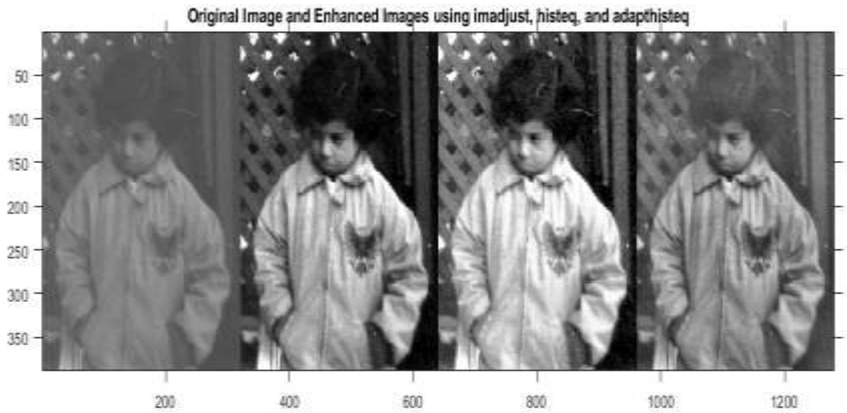

Figure 1: Sample image 1 and process

- Read a second grayscale image into the workspace and enhance the image using the three contrast adjustment techniques.
- tire = imread('tire.tif');
- tire_imadjust = imadjust(tire);
- tire_histeq = histeq(tire);
- tire_adapthisteq = adapthisteq(tire);
- Display the original image and the three contrast adjusted images as a montage.
- montage({tire,tire_imadjust,tire_histeq,tire_adapthisteq},'Size',[1 4])
- title("Original Image and Enhanced Images using imadjust, histeq, and adapthisteq")

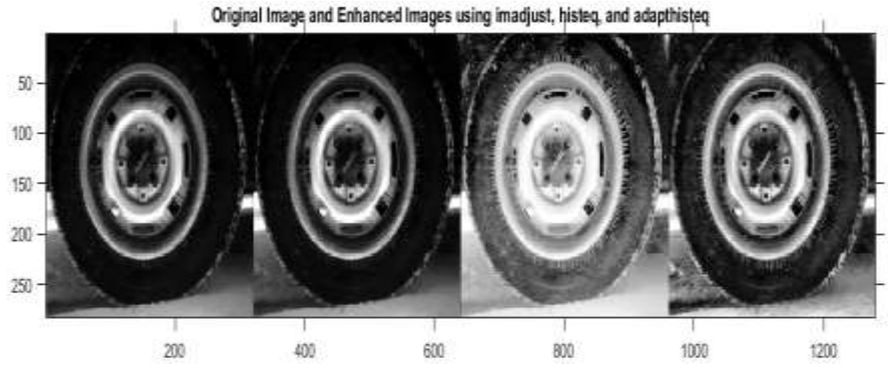

Figure 2: Sample image 2 and process

(Histogram image)Concentrating on the image of the tire, it would be preferable for the centre of the wheel to stay at about the same brightness while enhancing the contrast in other areas of the image. In order for that to happen, a different transformation would have to be applied to different portions of the image. The Contrast-Limited Adaptive Histogram Equalization technique, implemented in adapthisteq , can accomplish this. The algorithm analyzes portions of the image and computes the appropriate transformations. A limit on the level of contrast enhancement can also be set, thus preventing the over-saturation caused by the basic histogram equalization method of histeq. This is the most sophisticated technique in this example.

- Figure
- subplot(1,2,1)
- imhist(pout)
- title('Histogram of pout.tif')
- subplot(1,2,2)
- imhist(tire)
- title('Histogram of tire.tif');
- Concentrating on the image of the tire, it would be preferable for the center of the wheel to stay at about the same brightness while enhancing the contrast in other areas of the image. In order for that to happen, a different transformation would have to be applied to different portions of the image.

The Contrast-Limited Adaptive Histogram Equalization technique, implemented in adapthisteq, can accomplish this. The algorithm analyzes portions of the image and computes the appropriate transformations. A limit on the level of contrast enhancement can also be set, thus preventing the over-saturation caused by the basic histogram equalization method of histeq. This is the most sophisticated technique in this example.

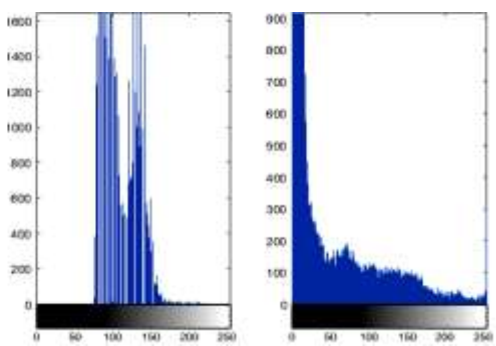

Figure 3: Histogram

Contrast enhancement of color images is typically done by converting the image to a color space that has image luminosity as one of its components, such as the L*a*b* color space. Contrast adjustment is performed on the luminosity layer 'L*' only, and then the image is converted back to the RGB color space. Manipulating luminosity affects the intensity of the pixels, while preserving the original colors. Read an image into the workspace. The 'shadow.tif' image is an indexed image, so convert the image to a truecolor (RGB) image. Then, convert the image from the RGB color space to the L*a*b* color spac

- [X,map] = imread('shadow.tif');
- shadow = ind2rgb(X,map);
- shadow_lab = rgb2lab(shadow);
- The values of luminosity span a range from 0 to 100. Scale the values to the range [0 1], which is the expected range of images with data type double.
- max_luminosity = 100;
- L = shadow_lab(:,:,1)/max_luminosity;
- Perform the three types of contrast adjustment on the luminosity channel, and keep the a* and b* channels unchanged. Convert the images back to the RGB color space.
- shadow_imadjust = shadow_lab;
- shadow_imadjust(:,:,1) = imadjust(L)*max_luminosity;
- shadow_imadjust = lab2rgb(shadow_imadjust);
- shadow_histeq = shadow_lab;
- shadow_histeq(:,:,1) = histeq(L)*max_luminosity;
- shadow_histeq = lab2rgb(shadow_histeq);
- shadow_adapthisteq = shadow_lab;
- shadow_adapthisteq(:,:,1) = adapthisteq(L)*max_luminosity;
- shadow_adapthisteq = lab2rgb(shadow_adapthisteq);

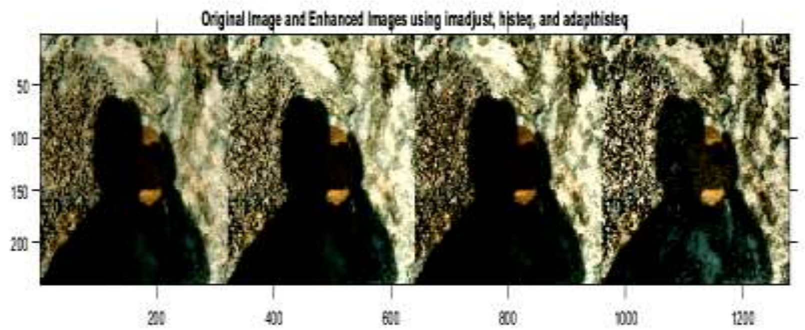

Figure 4: Display the Original image and the three contrast of adjustment image as a montage

- Display the original image and the three contrast adjusted images as a montage.
- figure montage({shadow,shadow_imadjust,shadow_histeq,shadow_adapthisteq},'Size',[1 4])
- title("Original Image and Enhanced Images using imadjust, histeq, and adapthisteq")

IV. CODES ARE USED

Imadjust: increases the contrast of the image by mapping the values of the input intensity image to new values such that, by default, 1% of the data is saturated at low and high intensities of the input data.

Histeg: performs histogram equalization. It enhances the contrast of images by transforming the values in an intensity image so that the histogram of the output image approximately matches a specified histogram (uniform distribution by default).

Adapthisteg: performs contrast-limited adaptive histogram equalization. Unlike histeq, it operates on small data regions (tiles) rather than the entire image. Each tile's contrast is enhanced so that the histogram of each output region approximately matches the specified histogram (uniform distribution by default). The contrast enhancement can be limited in order to avoid amplifying the noise which might be present in the image.

V. CONCLUSION & FUTURE SCOPE

This project discussed the issue of illumination estimation in many enhancement algorithms that are based on illumination-reflectance decomposition. An assumption for the expected illumination that avails the contrast enhancement is also specified. A method based on nonlinear diffusion is proposed to realize the correct illumination estimation. This method solves the problem of the limited contrast enhancement that results from the low smoothing capability of a traditional nonlinear filter. The analytical experiments show that the proposed enhancement algorithm achieves better visual quality than previous algorithm. The acceleration methods enable the algorithm to have high computational efficiency. However, color management is not involved in this paper. In some special cases in which the scene is illuminated by a colored ambient light, balancing the image color is required Because directly extending our algorithm to three color channels would cause a graying-out effect, more work should be performed in this area. This challenge will be our future work. There are several future works to resolve With the help of proposed work we can further use it for different applications like Image Segmentation, Image Video processing , object tracking, object recognition, etc.

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