Method for Correcting Low-illumination Images Based on Adaptive Two-dimensional Gamma Function

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Abstract: A two-dimensional gamma function-based color image correction method based on the illumination-reflection model and multi-scale theory is proposed. Firstly, the original image is histogram equalized, then converted to HSV color space, and the light components of the scene are extracted by multi-scale Gaussian function, and then the parameters of the 2D gamma function are adjusted by the distribution characteristics of the light components to construct a 2D gamma function to enhance the image. Finally, the images are fused. The comparison with the classical algorithm shows that the algorithm in this paper can better reduce the effect of uneven illumination on the image and improve the brightness and contrast of the image.

Keywords: Multiscale; Uneven illumination; Low illumination image; Two-dimensional gamma function

1. Introduction

Digital image processing has an important role in areas such as video surveillance, remote sensing monitoring and surveillance[1]. However, in the process of video and image acquisition, the scene is often unevenly lit, which seriously affects the visual effect and application value of the image. Therefore, how to obtain clear images under low illumination conditions has become a hot research topic[2][3][4].

Low-illumination image enhancement as a classical problem has generated a lot of discussion and research. The current methods for correction of non-referenced illumination inhomogeneities include algorithms based on Retinex theory, histogram equalization (HE) methods, unsharp masking methods, morphological filtering methods, and methods based on spatial illumination maps[5][6]. This paper presents an adaptive low-illumination image enhancement method based on multi-scale fusion.

2. Related work

Traditional algorithms for low illumination image processing include gray transform, histogram and wavelet transform[7]. Kim et al. [8] designated standard adaptive histogramequalization (AHE). Wang et al. proposed equal-size dual subimage histogram equalization (DSIHE) [9]. Jobson et al. proposed a single scale retina (SSR) algorithm [10] based on the retinal illumination-reflection model established by Land et al. In recent years, image enhancement methods based on machine learning continue to emerge.

According to the imaging principle, the image formed in the visible range is produced when light from the surface of an object in the scene reaches the imaging unit. Generally, a digital image can be regarded as a two-dimensional function F(x, y), and the value of the function is the brightness value of the image at the coordinates (x, y) point. F(x, y) consists of the product of the incident light component I(x, y) into the scene and the reflected component R(x, y) from the surface of the object. The basic theoretical model is expressed as follows.

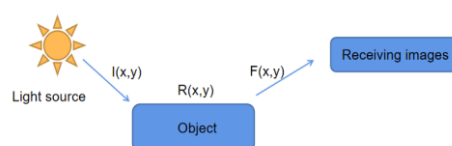$$F (x, y) = I (x, y) R (x, y). \tag{1}$$

Figure 1: Illumination-refection model.

This model is called the illumination-reflection imaging model, and its spatial relationship is shown in Figure 1.

3. Our method

In this paper, we first perform histogram equalization on the image and extract the light component by multi-scale Gaussian function, and then use the distribution characteristics of the light component in the image to adaptively adjust the parameters of the two-dimensional gamma function to correct the light component by the gamma function to obtain two images. Finally, image fusion is performed and the image is converted from HSV space back to RGB space. The whole process is shown in Figure 2.
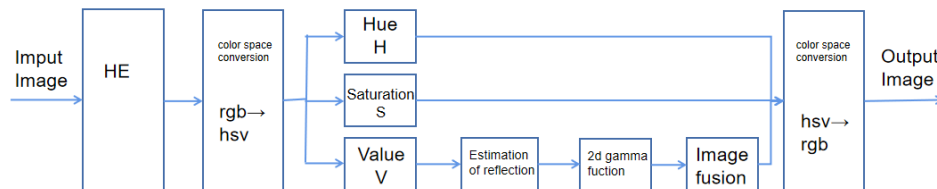

Figure 2: Framework of the proposed algorithm. (left)

3.1. Histogram Equilibrium

Histogram equalization is based on the fact that the image is most informative when the pixels in the image are uniformly distributed and and the contrast of the image is also maximum. According to this principle, histogram equalization means that the gray levels in the image with higher density are stretched, and the gray levels in the image with lower density are stretched. The image pixels are evenly distributed so that the contrast of the image will increase and the image will be enhanced.

As shown in Figure 3, the original image is relatively dark, and most of the image pixels are distributed in the left part of the grayscale histogram, and the grayscale range they occupy is relatively narrow. After the histogram equalization process, the brightness of the image increases significantly, and the histogram shows that the grayscale range increases and tends to be evenly distri.
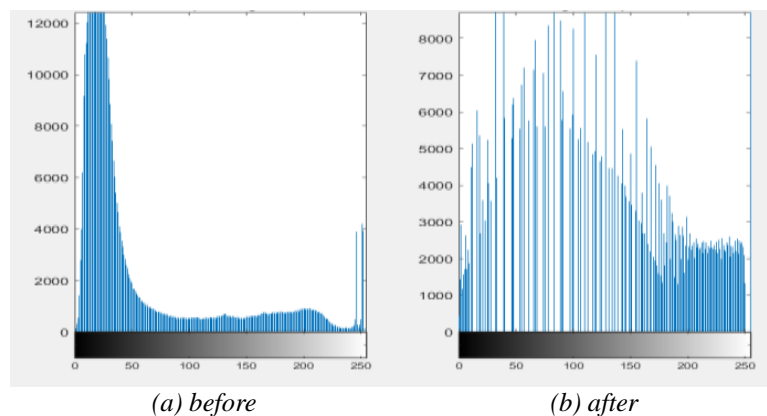

(a) before   *(b) after*

Figure 3: Histograms of images before and after histogram equalization correction(right)

3.2. Space conversion

From the perceptual characteristics of the human eye, it is clear that the human eye is more sensitive to luminance than to color, so the correction of the luminance component is the key to the illumination unevenness correction algorithm. For color images, since the HSV color space is more consistent with the visual properties of human eyes, and the hue (H), saturation (S) and luminance (V) in HSV color space are independent of each other, the operation of luminance V will not affect the color information of the image, so this paper chooses to implement the correction process of color images in HSV color space. After the conversion from RGB space to HSV space, the subimages $I_h(x, y)$, $I_s(x, y)$, and $I_v(x, y)$ corresponding to each component value (H, S, V) are obtained, as shown in Fig. 4.
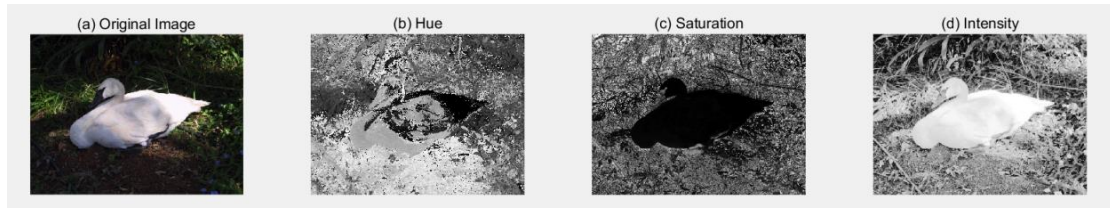
Figure 4: Example of the conversion from RGB space to HSV space.

3.3. Estimation of the reflection component

In order to correct the image, it is necessary to extract the light component of the scene accurately. This paper calculates the illumination component from the original image by building a mathematical model based on the Retinex theory.

According to the Retinex theory, the following assumptions are made: the illumination component of the real scene image exists mainly in the low-frequency part of the image and the overall change is smooth; while the reflection component exists mainly in the high-frequency part of the image and its change is more violent. Since the multi-scale Gaussian function can effectively compress the dynamic range and accurately estimate the illumination component of the scene, the multi-scale Gaussian function is used to extract the illumination component of the image. The Gaussian function is used in the following form:

$$G(x, y) = \lambda \exp(-\frac{x^2 + y^2}{c^2}) \tag{2}$$

Using the Gaussian function and the original image,

$$I(x, y) = F(x, y)G(x, y) \tag{3}$$

Where F (x, y) is the input image; I (x, y) is the estimated illumination component.

The larger the value of c, the larger the range of the convolution kernel of the Gaussian function, the stronger the ability of hue preservation, and the better the global characteristics of the extracted illumination values; conversely, the better the dynamic range compression, and the more obvious the local characteristics of the extracted illumination values. This paper adopts the method of multi-scale Gaussian function, using Gaussian functions of different scales to extract the illumination components of the scene separately and then weight them, and finally obtain the estimated values of illumination components. The expression is as follows:

$$I(x, y) = \sum_{i=1}^{N} \omega_i [F(x, y)G_i(x, y)] \tag{4}$$

Where I(x, y) is the light component extracted and weighted by Gaussian functions of different scales at the point (x, y); ω_i is the weight factor of the light component extracted by the Gaussian function of the i-th scale; i is the number of scales used.

Considering the accuracy of the light component extraction and the balance of the operation, this paper takes i = 3, and the weight coefficient of the light component extracted by each scale is set to 1/3.
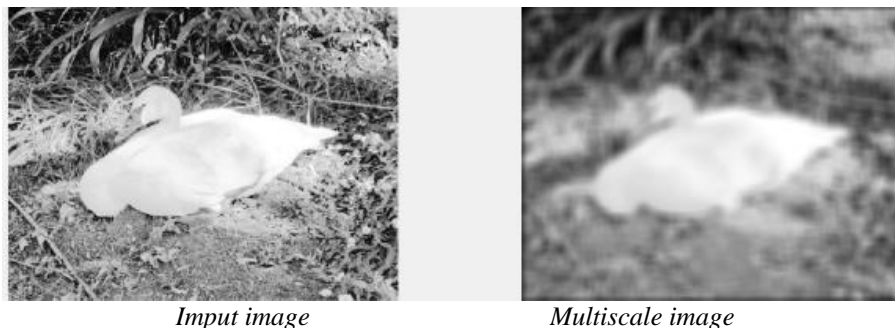

Imput image *Multiscale image*

Figure 5: Light components extracted by multi-scale Gaussian function (left)

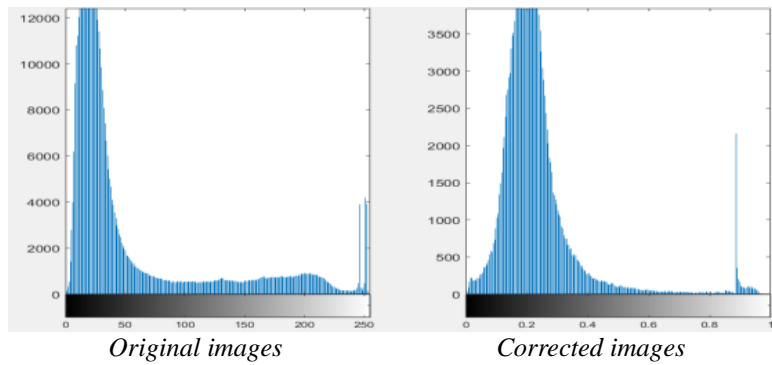Original images   Corrected images

Figure 6: Histograms of images before and after corrected by the 2D Gamma function proposed (right)

3.4. Two-dimensional gamma function correction

In order to achieve the adjustment of image illumination unevenness, this paper uses the adaptive luminance correction method of 2D gamma function to adjust the parameters of the 2D gamma function adaptively by using the distribution characteristics of the illumination components of the image.

For the input image F(x, y), assuming that the extracted light component is I(x, y), a new two-dimensional gamma function is constructed with the following expression:

$$O(x,y) = 255(\frac{F(x,y)}{255})^\gamma, \gamma = (\frac{1}{2})^{\frac{m-I(x,y)}{m}} \tag{5}$$

Where: O(x, y) is the luminance value of the corrected output image; γ is the exponential value for luminance enhancement; m is the luminance mean value of the light component. m is the mean value of the luminance of the illuminance component.

As can be seen from the formula, when the light value at a point (x, y) is less than the average value of the entire light component, the two-dimensional gamma function will cause the brightness value of the original image at that point to increase exponentially. Conversely, the brightness of the original image is attenuated. Figure 6 shows the contrast of the histogram of the image before and after correction using the two-dimensional gamma function constructed in this paper.

3.5. Image fusion

Fusion of key information from multiple sub images is an effective way to obtain salient features of images using image fusion techniques. In low-noise image fusion, multi-resolution pyramidal decomposition methods such as wavelet transform and Laplace transform can achieve good results, but they are computationally intensive and susceptible to noise interference. Since the fused images are more similar, this paper uses principal component analysis (PCA) to determine the image fusion algorithm with weighting coefficients

For two source images, S1 and S2, each image is considered as an n-dimensional vector, denoted alternatively as X_p, p=1,2.

The steps of the image fusion process are as follows

(1) Construct the matrix X using the source image

$$X = \begin{bmatrix} x_{11} & x_{21} \\ x_{12} & x_{22} \\ \vdots & \vdots \\ x_{1n} & x_{2n} \end{bmatrix} = [x_1, x_2] \tag{6}$$

(2) Calculate the covariance matrix C of the data matrix X.

$$c = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix} \tag{7}$$

σ_{ij}^2 is the covariance of the image, which satisfies:

$$\sigma_{i,j}^2 = \frac{1}{n}\sum_{l=1}^{n}(x_{i,l} - x_i)(x_{j,l} - x_j) \tag{8}$$

(3) Create the eigenvalue formula $|\lambda I - C| = 0$ and calculate the eigenvalue (λ_1, λ_2) and feature vector (ξ_1, ξ_2) of the covariance matrix C, where ξ i is a vector $\begin{bmatrix} \xi_{i1} \\ \xi_{i2} \end{bmatrix}$ whose size is 2×1.

(4) Select a large eigenvalue.

$$p = \arg\max(\lambda_p) \ \ p = 1 \text{ or } 2 \tag{9}$$

(5) Calculate the weight coefficient using the feature vector corresponding to the largest eigenvalue.

$$\omega_1 = \frac{\xi_{i1}}{\xi_{i1}+\xi_{i2}} \ and \omega_2 = \frac{\xi_{i2}}{\xi_{i1}+\xi_{i2}} \tag{10}$$

(6) Calculate the fused image F.

$$F = \omega_1 S_1 + \omega_2 S_2 \tag{11}$$

In the principal component analysis method, image fusion is performed based on the correlation between the selected component images. The data of shared features are compressed, while the data of unique features are enhanced.

4. Experiment and analysis

To test the effectiveness of the algorithm, a laptop-based (Intel(R) Core (TM) i5-8265U CPU @ 1.60 GHz 1.80 GHz and Windows 10 Professional OS) testbed was built. The test software was MATLAB 2018a. Some of the experimental results are shown in Figure 7. The five sets of experimental images are named as "road", "swan", "room", "house" and "station". From the experimental results, we can get a clear image with natural color after image enhancement, no matter the source image is a distant scene or a close scene, which proves the effectiveness and adaptability of the method.

(a)road　　*(b)swan*　　*(c)room*　　*(d)house*　　*(e)station*

Figure 7: Part of the experimental results.

4.1. Subjective visual evaluation

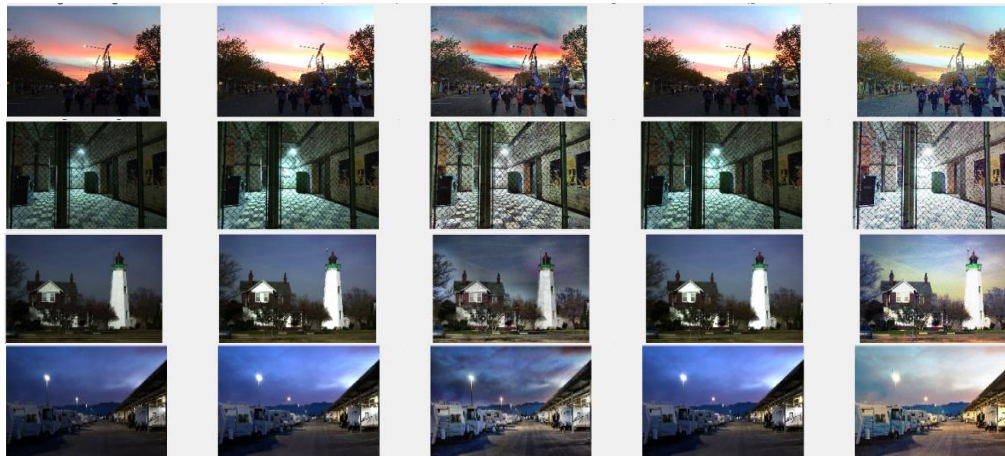**Comparison with several conventional image enhancement algorithms**

Figure 8: Comparison of the proposed algorithm with several conventional algorithms.

In Figure 8, we compare the results of this algorithm with those of several conventional algorithms. Four groups of photos, namely "road", "room", "house" and "station", are selected to obtain the processing results. Each pattern, from left to right, shows the original image and the images obtained by linear transformation (a=1.5, b=0.2), adaptive histogram equalization, gamma transformation (gamma=0.5) and the algorithm of this paper. The processed images by linear transform and gamma transform have less variation, while the images processed by AHE method are more colorful, in contrast, the method proposed in this paper significantly improves the color and details and outperforms other algorithms in terms of visual effects.

4.2. Objective quantitative analysis

To further compare the processing effects of different algorithms, objective metrics such as average gradient and entropy are used to measure in this paper. From the data in the table, it can be seen that the quality of the images has generally improved after the algorithms in this paper, mainly in the form of a greater increase in the gradient value, which indicates that the sharpness of the processed images has improved; an increase in the entropy value, which indicates that the amount of information contained in the corrected images has further increased, and thus more information can be extracted from them.

Table 1: The information entropy of the images in Fig. 8.

	Original	Linear	AHE	Gamma	Our
Image "road"	7.1365	7.2139	7.608	7.2139	7.8736
Image "room"	6.7691	7.2479	7.755	7.2479	7.8393
Image "house"	6.6126	6.9153	7.3614	6.9153	7.8712
Image "station"	7.2075	7.0428	7.5496	7.0428	7.8961
Average value	6.9314	7.1050	7.5685	7.1050	7.8701

Table 2: The average gradients of the images in Fig. 8.

	Original	Linear	AHE	Gamma	Our
Image "road"	6.70	9.24	12.08	9.24	11.74
Image "room"	12.4	18.06	29.63	18.06	29.38
Image "house"	2.32	3.32	5.74	3.32	6.44
Image "station"	4.12	5.96	9.20	5.96	9.26
Average value	6.385	9.145	14.16	9.145	14.025

5. Conclusion

In order to reduce the impact of uneven illumination on image quality and the deficiency that ordinary algorithms are difficult to generalize, this paper proposes a gamma transform-based color image correction method based on light reflection model and multiscale theory to perform adaptive correction processing for images with uneven illumination, and achieves a relatively good correction effect. The algorithm can effectively recover the color as well as details in dark areas. The main drawback of this algorithm is that the real-time performance is poor and it is difficult to be used to enhance the quality of video images.

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