A Fast Image Enhancement Algorithm Using Bright Channel

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Abstract. After summarizing the poor-illumination image enhancement methods and analyzing the shortcomings of the currently well-performed multi-scale Retinex algorithm, this paper proposed a new image speedy algorithm with detailed illumination component information. It combined illumination imaging model with target reflection features on RGB color channel, raised a new bright channel concept, and obtained computation method of illumination components by analysis. Then, illumination components were gained precisely through image bright channel gray-scale close computation and fast joint bilateral filtering. Consequently, target reflection components on RGB channel could be solved by illumination/reflection imaging model. The proposed algorithm can get excellent edge details through simple and quick computation. After being removed from the illuminative effects, the images gained are natural-colored, highly visible, and with no halo artifacts. This paper also resolved color casting problem. Compared with NASA method based on multi-scale Retinex, the proposed algorithm improved computation speed, received vivid colors and natural enhancement result.

Keywords: image enhancement, Retinex algorithm, bright channel, joint bilateral filtering.

1 Introduction

During the image shooting process, the objects in the scene will get non-uniformed illumination due to light changes, environmental illumination, object blocking, and so on, which degrades the image quality and affects the identification of the local information. And the consequent image detail feature extracting, target identification, tracking, and understanding will not be performed. Therefore, enhancing the images with non-uniformed illumination has been widely concerned. Braun and others [1] used Sigmoidal function for tone mapping, and gained function parameters by combining image mean and variance. This method is very simple and quick, but when

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the image dynamic range is very large, local details will get lost. Partially overlapped sub-block histogram equalization proposed by Kim et al. [2] basically eliminated blocking artifacts in non-overlapped sub-block method, and reduced computation compared with overlapped sub-block method. Although local sub-block gray distribution was concerned by this method, image layering was weakened. Automatic color equalization mode proposed by Rizzi et al.[3] used local self-adaptive filtering when the spatial distribution of color and luminance was taken into account. It enhanced the color contrast of the image. However, for the images that do not meet the gray world assumption, this method will lead to significant color distortion. Fattal [4] transferred images into gradient domain, decreased larger gradients and increased smaller ones when keeping the gradient direction. This method enhanced the details of the dark area in the image but weakened the details of the bright area. Based on light reflection imaging model, spatial homomorphic filtering algorithm [5] took the logarithm of the image and got it through a low-pass filter, then estimated illumination components by using the filtered result. The speed and performance of this algorithm was superior to the traditional frequency homomorphic filter due to the reduction of dynamic region, but it's very hard to choose the weights of the filter model. Land [6] proposed Retinex theory by combining illumination reflection imaging model with perceptual characteristics of human visual system to luminance and color. Jobson and his fellows [7-9] proposed Single Scale, Multi-Scale and Multi-Scale Color Restoration Retinex algorithms. The result of Single Sale Retinex algorithm depended on the magnitude of the scale constant, Multi-Scale Retinex algorithm would cause halo and large computation, Multi-Scale Color Restoration Retinex algorithm[10] restored the colors of the images which violated gray-world assumption, but the color correction results were not significant.

To solve the above problems, this paper deduced a solution to illumination component in optical model after deep analysis on optical image enhancement principle. This paper raised image RGB bright channel principle from a new perspective, thoroughly studied the speedy algorithm of illumination computation, and proposed Max Intensity Channel Image Enhancement (abbr. MICIE) algorithm. The operation steps of the algorithm are as follows: 1) Make preliminary estimation of the illumination component by using RGB bright channel; 2) Make precise estimation of the illumination component by eliminating the influences of low-reflectivity to targets through fast joint bilateral filter; 3) Further compute the estimated scene illumination to get the reflection component of the target through illumination reflection imaging model, and truncate interval between [0, 1]. After the above 3 steps, the colors and illumination of the input image will be quickly restored.

2 Analysis of Multi-scale Retinex Algorithm

2.1 Illumination Reflection Imaging Model

In this model, images are composed of illumination components and reflection components[11], shown as figure 1, and the equation is:

$$I(p) = L(p)R(p) \tag{1}$$

Where $I(p)$ is image collected by the sensor, $L(p)$ is lamination component, i.e. the illumination intensity received by the objects in the scene, $R(p)$ is the target reflection coefficient, which is the inherent characteristic of the object, $p = (x, y)$ is the location of one pixel point in the image.

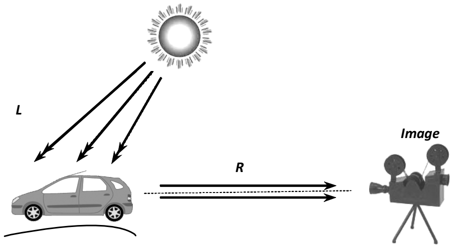


Fig. 1. Illumination imaging model

According to the model presentation in figure 1, it's known that as for image $I(p)$ which is influenced by lumination, if the scene lumination component $L(p)$ is known, reflection coefficient $R(p)$ of the target can be calculated. This means scene image which is not influenced by lumination is gained. However, only $I(p)$ in equation (1) is known, so the solution to the reflection component is an ill-conditioned problem. In general, a certain method is used to estimate lumination component, and then reflection component is solved. And Retinex algorithm is one typical representation among these methods.

2.2 Multi-scale Retinex Algorithm and Its Disadvantage

Retinex theory combined lumination reflection imaging model with perceptual characteristics of human visual system, and regarded that the objects perceived by human visual system depended on illumination and the reflection ability of the objects to illumination. SSR algorithm estimated illumination component through Gaussian filtering to the input image, and transferred data to logarithmic domain to solve reflection component. Equation is shown as follows:

$$R^c(p) = \log I^c(p) - \log[F(p) * I^c(p)] \tag{2}$$

Where $R^c(p)$ is the reflection component value of pixel point p on color channel c, $\log$ is natural logarithm, $*$ is convolution, $F(p)$ is Gaussian surround function, which is shown as:

$$F(p) = K \exp(-\frac{r^2}{c^2}) \tag{3}$$

Where K is normalization factor, c is scale. The smaller c is, the more outstanding image edge detail is, the larger dynamic region is reduced, and the more severely the colors are distorted; the bigger c is, the higher image color fidelity is, but the more indistinct the local detail is. Therefore, SSR algorithm cannot get both clear details and color restoration. While MSR algorithm can get better results in these aspects, it makes weighted average to the big, media, small scaled SSR algorithm results. It is shown as follows:

$$R_{MSR}^{c}(p)=\sum_{n=1}^{N}\omega_n R_n^c(p) \tag{4}$$

Where scale number N is 3, $R_n^c(p)$ is reflection component after SSR algorithm operation, ω_n is the corresponding weight of the n-th scale, and it is 0.33 when scale is 3.

Although MSR algorithm is superior to some other typical algorithm after combining the advantages of different scales, it still has two main disadvantages. Firstly, the premise of the Retinex algorithm is that illumination over the whole scene is changing slowly and evenly. In reality, illumination received by objects will have sudden changes due to illumination source changes, environmental illumination, object blocking, and so on. And these changes usually occur at the edge of the objects. As shown in figure 2(e), there's obvious halo artifacts at the edge between the white building and pine trees. Secondly, MSR algorithm has to process 3 scaled Gaussian filtering for each RGB channel respectively, 9 Gaussian filtering processes for all, which means larges computation, and is unsuitable for real-time application.

3 Image Enhancement Algorithm Based on Bright Channel and Fast Joint Bilateral Filtering

3.1 Bright Channel

In the natural illumination scene, when the reflectivity of the object in the scene approaches 1, i.e. $R(p)\rightarrow 1$, according to illumination reflection imaging model, image intensity gained will approach scene illumination intensity, that is $I(p)\rightarrow L(p)$. Therefore, as for one pixel in three RGB channel, if the intensity value of one channel is bigger, the reflectivity of this channel is also greater, and its gray value is closer to the illumination intensity of this pixel. If the largest value of each pixel in the RGB channel is chosen to form the bright channel chart, we could vividly call it Max Intensity Channel (MIC).

$$I_{MIC}(p)=\max_{c\in\{R,G,B\}}(I^c(p)) \tag{5}$$

Where, $I^c(p)$ is the gray value on a certain channel of the input image $I(p)$, $I_{MIC}(p)$ is the bright channel of the input image $I(p)$.

3.2 Estimation of Illumination Component of Reflection Component

According to equation (5), this paper obtained bright channel of the image by RGB three channels computation, and made illumination component rough estimation $L_{rough}(p)$, as shown in figure 2 (b). It is demonstrated as

$$L_{rough}(p) = I_{MIC}(p) \tag{6}$$

Obviously, the bigger the bright channel intensity value is, the closer to the scene illumination intensity. However, the objects in the scene are not all very bright-colored, and most areas are changing mildly, which means not every pixel point satisfies the conditions of $R(p) \to 1$ and equation (5). Therefore, directly using the estimation result of equation (6) will lead to distortion.

In order to eliminate the influence of low-reflectivity to targets, this paper introduced gray-scale close computation to filter the illumination component. This computation could reduce the sudden changed small dark area while keep the bright area unchanged. After this step, illumination was changing smoothly and mildly in most areas of the image. The result after processing is L_{close}, as shown in figure 2 (c), and demonstrated as

$$L_{close} = L_{rough} \bullet b = \left(L_{rough} \oplus b\right)\Theta b \tag{7}$$

Where b is the gray-scale morphological structuring element, and smoother results can be gained if disk structure is chosen.

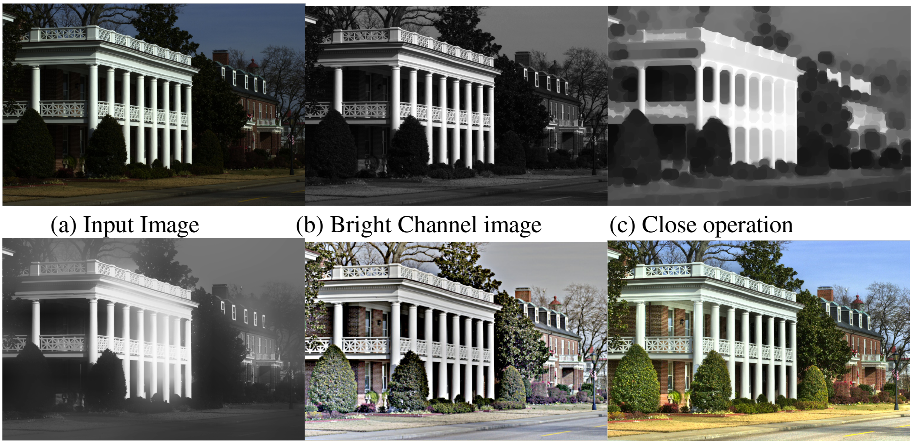
As discussed before, there was a certain degree of illumination mutation at the edges of objects in the scene, and illumination component after gray-scale close computation lost local details and blurred edges. Therefore, in order to get smooth illumination component with edge details, joint bilateral filter was used to refine the bright channel images and results after close computation filtering. Bilateral filter [12] is an edge-preserving filter, its results are related to not only the spatial locations of the surrounding pixels, but also their gray-scale differences. As for gray-scale image I, bilateral filter is defined as

$$bf(I_p) = \frac{1}{W_p}\sum_{q\in\Omega} f(\|p-q\|)\, g(|I_p - I_q|)\, I_q \tag{8}$$

Where f is a Gaussian spatial filter whose center is located at point p, g is a Gaussian range filter of pixel gray-scale value with point p as its center, Ω is the spatial range of f, W_p is the weight sum of $f \cdot g$. Due to the introduction of range filter, if point p is around the edge, weight of g then represents the information of the edge. When weight of g times spatial weight of f, not only edges will be preserved but also both two sides of the edge will be smoothened. Joint bilateral filter applies range filter g of bilateral filter into another image which is full of detailed information. The rough estimation of illumination component I_{rough} owns the detailed information of illumination, therefore, it is used to solve the range Gaussian kernel g. MICIE algorithm processes joint bilateral filtering for both L_{close} and L_{rough}, which can not only preserve the edge information of bright channel L_{rough}, but also further smoothen L_{close}. Namely,

$$L_{refined}(p) = \frac{1}{W_p} \sum_{q \in \Omega} f(\|p-q\|) g(|L_{rough}(p) - L_{rough}(q)|) L_{close}(q) \tag{9}$$

This paper used fast joint bilateral filter [13] to refine illumination component, which greatly improved computation speed. Refined illumination component can be seen in figure 2(d).



(a) Input Image (b) Bright Channel image (c) Close operation

(d) Joint bilateral filtering result (e) Result of MSR (f) Result of MICIE

Fig. 2. Intermediate results of proposed algorithm

After estimation of illumination component, illumination reflection imaging model is transformed to solve the reflection component $R(p)$ of the scene, which is defined as equation (10), and the final enhanced result is shown as figure 2(f).

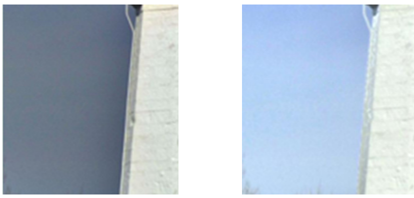
$$R(p) = \frac{I(p)}{L_{refined}(p)} \tag{10}$$

4 Comparison and Analysis of Experimental Results

4.1 Subjective Evaluation

In order to test the proposed algorithm, this paper enhanced some typical non-uniform illumination images on the NASA website [14], and the target images were composed of color-distorted and color-normal images. Figure 3 to figure 5 show the experimental results of the non-uniform illumination images without color distortions. It can be seen from figure 4 that the proposed algorithm better reappears the scene colors than NASA algorithm, and the sky is especially blue and clear. NASA algorithm uses Gaussian filter to give different weights according to target locations, which cannot preserve the illumination mutation at the scene edge; therefore, distortion of illumination estimation will occur at high-contrast edges. Comparisons between figure 3 (d) and (e) show the results of local details. There're obvious halo artifacts at the edge of white tower in figure 3 (d), while bilateral filter can adjust filter weights according to pixel gray-scale difference in the neighborhood, thus, halo is eliminated by this algorithm. Figure 4 demonstrates the input image and the details of the white sole base by these two algorithms. NASA algorithm preserves small part of soil at the sole edge, the white part is over-enhanced, and the colors are too saturated. While the proposed MICIE algorithm well preserves the sole details of the input image, and the colors are more natural and vivid. Detailed comparison can be seen in figure 4 (d) and (e). In figure 5, both two algorithms restore the details of the darker area (car window), but compared with result of NASA algorithm, the restored image by proposed MICIE algorithm are with more vivid colors and better-visible details. For example, the car compartment and house reflected on the window glass in figure 5 (e) are clearer than the ones by NASA algorithm in figure 5 (d), and the sky on the top right corner of the image is better restored.

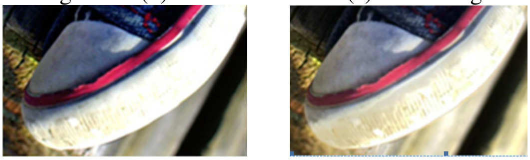
(a) Input image (b) NASA method (c) MICIE algorithm



(d) Detail of NASA (e) Detail of the MICIE

Fig. 3. Comparison of different algorithms

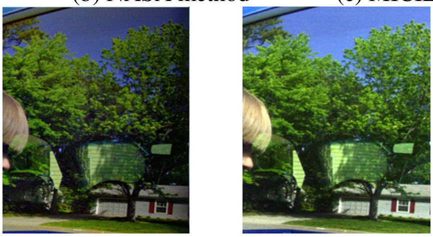
(a) Input image (b) NASA method (c) MICIE algorithm



(d) Detail of NASA (e) Detail of the MICIE

Fig. 4. Comparison of different algorithms

(a) Input image (b) NASA method (c) MICIE algorithm



(d) Detail of NASA (e) Detail of the MICIE

Fig. 5. Comparison of different algorithms

4.2 Objective Evaluation

This paper made objective comparisons to the experimental results by using standard deviation and information entropy (See Table 1). Standard deviation was used to judge the image contrast, and information entropy reflected the size of the information amount included in the image. Since NASA algorithm is based on multi-scale Retinex, Table 2 showed the computing time of the proposed algorithm and multi-scale Retinex algorithm under spatial and frequency domains.

Table 1. Results comparison of different algorithms

Image	Algorithms	Std	Entropy
tower(Fig3(a))	NASA	48.4251	7.6255
2000x1312	MICIE	54.7450	7.7967
shoe(Fig4(a))	NASA	61.9346	7.6407
1312x2000	MICIE	69.1627	7.9105

Table 2. Computing time of different algorithms

Image	Algorithms	Time/s
tower	Spatial MSR	66.72
2000 x 1312	Frequency MSR	20.83
	MICIE	10.66
shoe	Spatial MSR	72.47
1312 x 2000	Frequency MSR	16.61
	MICIE	10.57

It can be seen from table 1 that the image contrast of this algorithm is close to the one of NASA algorithm, and more information of the enhanced image can be gained by MICIE algorithm than by NASA algorithm, so this algorithm can enhance the scene details well. Table 2 shows that MICIE algorithm has greatly improved computing time compared with multi-scale Retinex algorithm.

5 Conclusion

This paper proposed bright channel concept according to reflective characteristic of objects, and calculated illumination component fast and precisely from a new perspective. In this paper, image bright channel was used for rough estimation of the scene illumination, and gray-scale morphological filter and fast joint bilateral filter were used for the refinement of the rough estimation. By this method, the illumination estimated was kept smooth while detailed information of the illumination mutation was also preserved. The final reflection component images gained through illumination reflection imaging model were of vivid colors, outstanding details, and high visibility. This algorithm greatly improved computing time as well as well eliminated halo artifact which was the typical disadvantage of Retinex algorithm. As for color-distorted non-uniform illumination image, this paper also used gain offset correction and information statistics to further correct the colors and obtained good correcting results.

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