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Recovering Color of Dark Images Using Tone Mapping and MSRCR

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Abstract

Dark images are acquired under low light level condition and they have some weakness about image contrast and distortion of color. However, the most studies about dark image tried not to recover colors of the image, but to improve the image contrast. For this reason, we propose the method combined with the tone mapping and MSRCR in order to recovering the original color. We consider the tone mapping to control brightness of the image and the MSRCR to recover the original color. As experimental images, we employed synthesized images, created from the Barnard's data set. We also consider the Euclidean distance and the angular error between images as the evaluation factors. The performance of the proposed method was evaluated by two experiments. First, we carried out the performance comparison of our method and some well-known color constancy methods. Secondly, we analyzed the performance according to change parameters of MSRCR. The experimental results tell us that the proposed method is more suitable for recovering the color of the dark images than the other methods.

Keywords: *Dark image, Tone mapping, Color constancy, Synthesized image, MSRCR*

1. Introduction

Dark images are acquired under some low light level conditions, such as at night and in a dark basement, hardly affected by light sources. According to the image formation equation, the pixel values in the images acquired by imaging devices depend on the intensity of the light source and illumination. Thus, most pixels of the images have small values and it is caused some problems for using them. For example, the low contrast of the images makes it difficult to perceive the color and the shape of the objects. In addition, the images have another disadvantage of being greatly influenced by random noises or salt and pepper noises than images with high intensity. There are a lot of systems using the images as an input and they require the original color of objects for correct operation. However, the disadvantages of the images are cause of performance degradation of the systems. Accordingly, to recover the color of the images is necessary process in the systems.

So far, various studies are carried out for enhancing the dark images. The histogram operation [1] is one of well-known and simple methods. The methods try to stretch brightness range of the image according to defined probability density function. However, the methods have a problem of losing the information of position since the method is applied to each channel. The gamma correction [2, 3] is another well-known method to enhance the dark images. The method is also applied to the brightness channel of the image for improving the contrast. However, the gamma correction-based method is focus on improving the quality of the images from the point of view of human vision rather than recovering the color of the objects. As another solution for enhancing the images, the color constancy method has been

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studied. The term called the term called color constancy means one of ability in human visual system to recognize original color of object irrespective of the light used to illuminate the objects. In computer vision field, it aims to estimate the color of the light source or the color of the objects under the reference light condition.

This paper proposed the color recovering method based on tone mapping and color constancy method. We use tone mapping process for controlling brightness of the image and try to recover the color by applying the color constancy method to corrected image.

In Chapter 2, we explain a property of the dark images and the proposed tone mapping method. We introduce color constancy method briefly, and deal with suitable color constancy method for low light level condition. Chapter 4 describes overall contents about the experiments, such as experiment image, evaluation factors, performance comparison and analysis of the experimental results. The conclusion and future works of the proposed method are discussed in Chapter 5.

2. Proposed Tone Mapping Method

This chapter deals with proposed tone mapping method for controlling brightness of the dark images. The proposed color recovering method needs some information about the scene, such as the distribution of the reflectance and the property of light source because our method use color constancy. However, most of pixels in the image have small value. It means that we can’t get the correct information, mentioned above, and can’t anticipate competent results despite of adopting color constancy method to the image. For this reason, we proposed the tone mapping method to control the brightness of the images.

The tone mapping methods converts the brightness of the image according to the pre-defined linear or non-linear function, define the relationship of the input and output brightness. The methods are generally used for the contrast enhancement of the images or tone reproduction of the HDR(high dynamic range) image. However, the linear based tone mapping functions can’t be a suitable solution for improving contrast of the low light level images. In order to confirm this, we carried out tone mapping experiment using some functions. Figure 1 shows a dark image and the result images by tone mapping and three different tone mapping functions.

Since the tone mapping is carried out on only brightness channel, we calculate the Y channel of the images as the channel. Figure 1 (b) is resulted by applying the B mapping function of Figure 1 (d) into Figure 1 (a). As the tone mapping result, the function converts dark pixels (less than 125) into bright pixels and the contrast of dark regions is improved. On the contrary, the (b) has the problem that it is difficult to distinguish objects in bright regions with the pixels greater than 125. It is caused that they turn into maximum brightness value. Consequentially, we have a problem that the details of bright regions can’t be retained when we apply the tone mapping function.

Figure 1 (c) is resulted by applying the C mapping function into the (a). Although the function doesn’t include the input range which is mapped into constant value such as the B mapping function, the result image still has a problem that the contrast of the dark regions isn’t improved remarkably. It is caused from small gradient of the function in the range [0, 125]. If the general tone mapping function is applied to low contrast images whose pixels are concentrated in specific RGB range, its contrast will be improved. This is similar to the principle of the histogram stretching technique and the pixels of the result image exist over the entire the range. However, these tone mapping functions can’t make competent results when it is applied to the dark image which has both of bright and dark regions. In this case, we can’t expect enhancing the contrast of dark region and retaining detail of the bright regions because there isn’t any extra range for allocating input pixel values.

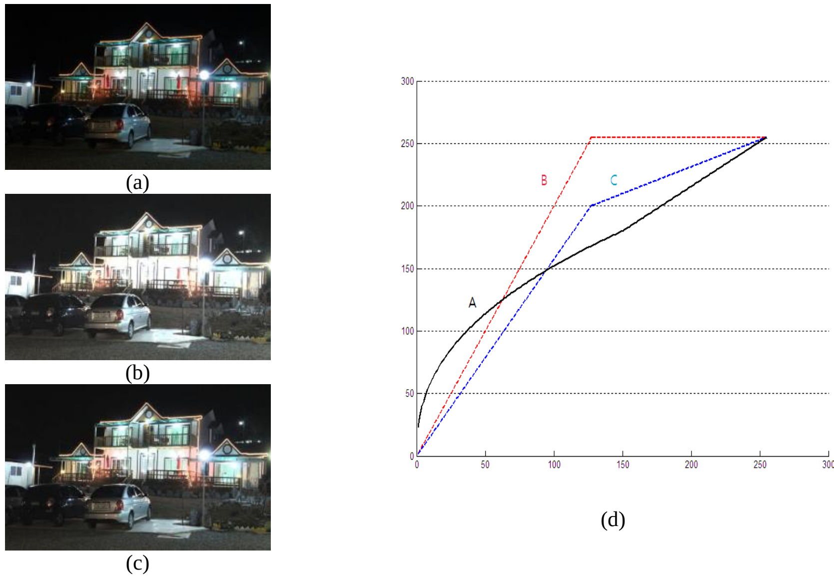

Figure 1. (a) Dark Image (b) Tone Mapping Result using B Function (c) Tone Mapping Result using C Function (d) Three Different Tone Mapping Functions

For this reason, this paper proposed tone mapping function as follows:

$$O(x, y) = \begin{cases} T_2\left(\dfrac{I(x, y)}{T_1}\right) & , \text{if } I(x, y) \le T_1 \\ T_2 + (MAX - T_2)\left(\dfrac{I(x, y) - T_2}{T_1}\right) & , \text{otherwise} \end{cases} \quad (1)$$

where $I(x, y)$ means input brightness and $O(x, y)$ is output one. This tone mapping function is shown in Figure 1 (d). The function consists of two parts according to input brightness level. We consider non-linear function for enhancing the contrast of the dark regions. As a result, the dark pixels in [0, T1] are converted into brighter pixels in [0, T2] and we can get more visibility for the regions. For retaining details of the bright regions, we apply linear mapping function which converts bright regions in [T1, MAX] into the range [T2, MAX].

Figure 3 shows some dark images and the results by applying proposed tone mapping method to the images. The top line includes some dark images acquired from natural scenes and Barnard's data set [4]. The result images are brighter than source images and their contrast of bright regions can be also retained. However, overall contrast of the result image is decreased because the image has more pixels in middle level value. In order to solve this phenomenon, we consider method and deals with it in next chapter.

Figure 2. Some Dark Images and Results Images after Proposed Tone Mapping Method

3. Color Restoration by MSRCR

Generally, estimating the color of the objects of natural images is impossible because it is under constraint condition from the perspective of the equation of image formation. For this problem, color constancy methods use the assumptions about the scene and try to reduce the unknown variable in the estimating process. There is many researches of categorizing color constancy methods [5-7]. The property of illumination is one of the criteria to classify them; all of color constancy methods are classified into uniform and non-uniform model according to the criteria [8]. The uniform model has the advantage of being relatively simple. However, the uniform model based methods don't estimate practical color of the light source and the objects since they suppose that the uniform illumination condition doesn't occur naturally. On the contrary, non-uniform model has the drawback that the calculation cost but the non-uniform model based method can estimate the color of light source and the object practically.

The low light level images have some non-uniform property. For example, the images don't contain a lot of dark regions due to lack of illumination but also some brightness regions affected by light source directly. To reflect this property, this paper restores the color of the low light level images using non-uniform model based color constancy method.

Intrinsic image [9], LASC(local average space color) [10], and retinex [11] are the state of the art color constancy methods based on non-uniform model. The Intrinsic image supposes that the illuminant can be approximated by a black-body radiator and estimate color of the objects from the assumption. However, this method has a problem that the chromaticity of the image is removed when image is projected into RG plane. The methods based on LASC are carried out a convolution with an extended kernel defining a neighborhood around the given pixel. In these methods, the color is computed with a simple method but it is difficult to determine parameters.

For this reason, our color restoration method is based on retinex. The studies about the retinex are classified into the methods based on path, center-surround, and iteration [12]. In this paper, we use the MSRCR [13] which one of well-known method in center-surround based study. The method estimate the color of the objects by applying color restoration function (CRF) into the result of the MSR(multi scale retinex) which consist of the weighted results of the SSR(single scale retinex).

The result of the SSR is the reflectance of the objects at position (x,y) and it is calculated as follows :

$$R_{SSR_i}(x, y) = \log I_i(x, y) - \log[F(x, y) * I_i(x, y) L_i(x, y)] \tag{2}$$

where $I_i(x, y)$ is the input image and $F(x, y)$ means the Gaussian kernel. The operation of the MSR is shown as Eq. 3. The output of MSR $R_{MSR_i}(x, y)$ is sum of $R_{MSR_i}(x, y)$ with different weight and the total weights is generally 1.

$$R_{MSR_i}(x, y) = \sum_{n=1}^{N} w_n R_{SSR_i}(x, y) \tag{3}$$

Then, MSRCR operation with CRF is shown in Eq. 4.

$$R_{MSRCR_i}(x, y) = C_i(x, y) R_{MSR_i}(x, y) \tag{4}$$

The CRF is defined in Eq. 5 and it depends on the parameter of α and β.

$$C_i(x, y) = \beta \log\left[\alpha I_i'(x, y)\right] = \beta\left(\log \alpha \alpha_i(x, y) - \log \sum_{i=1}^{S} I_i(x, y)\right) \tag{5}$$

$I_i'(x, y)$ is input image in sRGB color space as follows :

$$I_i'(x, y) = I_i(x, y) \Big/ \sum_{i=1}^{S} I_i(x, y) . \tag{6}$$

The results of the MSRCR for some low light level images are shown in Figure 3. The images in (b)-(d) column are resulted by applying MSRCR with different α and β into the low light level images in (a) column. All of result images have more brightness in dark regions and retain the details in bright regions than the source image.

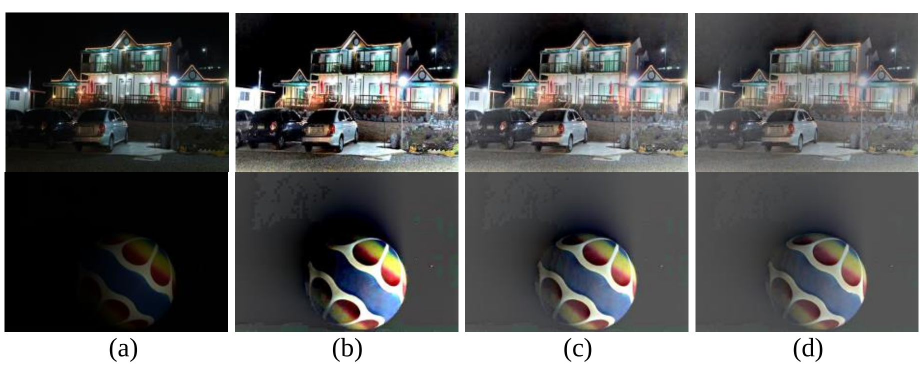

Figure 3. (a) Low Light Level Images, the Results by the MSRCR : (b) α = 0.2, β=0.4, (c) α = 0.4, β=0.6, (d) α = 0.6, β=0.9

4. Experiment

In this chapter, we deal with the overall contents about the experiments.

4.1. Experimental Data

The experimental data are classified into natural data and synthesized data. The natural data consists of outdoor images acquired under low light level condition and the low brightness images in the Barnard's data set. These data is used to evaluate the performance of our method in practical low light level condition. However, it involves a problem of absence of GTD (Ground Truth Data) when we carry out the performance evaluation with the natural images. Since the incident light into camera's sensor depends on light source and illumination condition, the color in the natural images isn't the original color of the objects. The original color is only acquired under reference light condition that the light source has same magnitude across whole wavelength range but the condition doesn't occur naturally. Hence, it is difficult to carry out the quantitative performance evaluation using the GTD.

For this reason, we carried out the experiment using synthesized data. The images in the data are synthesized based on the image formation equation. For this, we consider the camera sensitivity function, the reflectance of the objects, and spectral data of light source in the Barnard's data set. Since we can select the spectrum of the light source and the reflectance of the objects in synthesizing process, the GTD images can be synthesized. In experiments, we used the images synthesized from the low light level spectrum because this paper aims for recovering color of the low light level images. Some of the experimental images are shown in Figure 4.

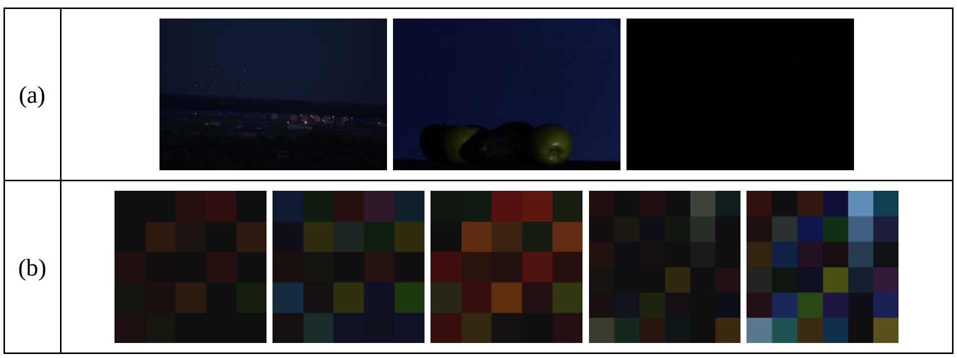

Figure 4. Some of the Experimental Images (a) Natural Images Acquired under Low Light Level Condition (b) the Images Synthesized from Low Light Level Spectrum

4.2. Evaluation Factors

In this paper, we use two factors for performance evaluation and comparison. The first one is average of Euclidean distance in rgb space between the GTD and result images as follows:

$$D_{Euc} = \frac{\sqrt{\sum_{i=1}^{3}\sum_{x,y}\left(I_{GTD\_i}(x,y) - I_{MSRCR\_i}(x,y)\right)}}{xy} \qquad (7)$$

where $I_{GTD\_i}(x,y)$ and $I_{MSRCR\_i}(x,y)$ is i-th channel of the GTD and result images by MSRCR. D_{Euc} is used to calculate the similarity between GTD and result image. If GTD and result image are same, D_{Euc} has a value of 0 and vice versa.

As the second evaluation factor, we consider the angular error between two images [14] as follows:

$$e_{Ang} = \frac{1}{N}\sum_{x,y}\left(\frac{G \cdot R}{\|G\| \times \|R\|}\right) \quad (8)$$

where G and R mean the vectors of the GTD and the result images in rgb space. For performance evaluation, we calculate the average of angular error e_{Ang}. Thus, the similarity of the two images makes smaller e_{Ang} and it means that the method can restore the color of the low light level image effectively.

4.3. Performance Evaluation

For quantitative performance evaluation, we carried out experiment based on synthesized images and out method was compared to another methods to enhance low light level images, such as histogram equalization, gamma correction, and some well-known color constancy methods which can be represented Minkowski norm framework[15]. Figure 5 shows results by applying proposed method and the other methods, mentioned above, into the synthesized images in experimental data.

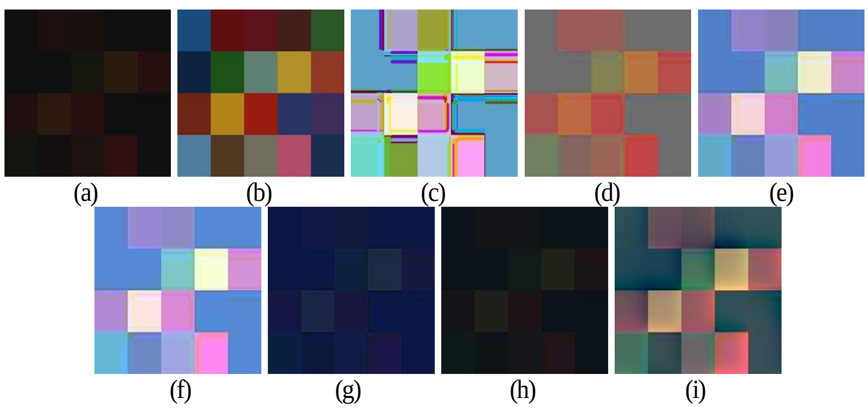

Figure 5. (a) Synthesized Low Light Level Image, (b) the Ground Truth Data, the Result by Applying : (c) the Histogram Equalization (d) the Gamma Correction (e) the White Patch (f) the Grey World (g) the Grey Edge (h) the shades of Grey (i) the Method

Each method makes different result image since their color recovering operation depend on the unique assumption of them. Our method can recover the color close to the GTD compared the other methods.

The experimental images consist of five set and each set contains images synthesized from 10 different illuminant spectrums. The performance evaluation are carried out using the methods, mentioned above, and proposed method. The result of the evaluation is shown in Table 1. In the experiment, we can see that the color constancy methods, represented by Minkowski-norm framework, are makes better results than histogram or gamma correction based methods. Among all of method, the proposed method can be make the best result across whole sets.

Table 1. The Performance Comparison using the Euclidean Distance (D_{Euc})

Scene / Methods	Set 1	Set 2	Set 3	Set 4	Set 5
Histogram Equalization[1]	59.28	51.13	52.60	58.60	44.94
Gamma Correction[2]	34.17	31.17	36.74	30.87	37.70
White Patch [8]	48.80	61.12	51.70	62.92	47.63
Grey World [15]	44.97	61.30	50.48	59.89	47.42
Edge based [16]	43.12	47.60	48.06	44.52	52.08
Shades of Grey [17]	39.75	49.04	45.10	43.88	52.19
Proposed Method	34.11	30.48	30.10	28.59	29.55

The result of performance evaluation using the angular error is shown in Table 2. The proposed method and gamma correction based method showed the better performance in respect of the angular error than the other methods. In two experiments, the proposed method makes best results. It was possible to reduce the difference between scene and the assumption of the MSRCR.

Table 2. The Performance Comparison using the Angular Error (e_{Ang})

Scene / Methods	Set 1	Set 2	Set 3	Set 4	Set 5
Histogram Equalization [1]	0.630	0.564	0.672	0.526	0.613
Gamma Correction [2]	0.161	0.186	0.205	0.222	0.177
White Patch [8]	0.270	0.222	0.306	0.248	0.229
Grey World [15]	0.271	0.236	0.303	0.268	0.235
Edge based [16]	0.486	0.447	0.533	0.448	0.437
Shades of Grey [17]	0.248	0.225	0.296	0.249	0.234
Proposed Method	0.187	0.221	0.264	0.267	0.223

Table 3 shows the performance according to changing parameter of MSRCR. The evaluation was carried out using set 1 of experimental images and the performance was expressed as $D_{Euc}(e_{Ang})$. According to the experimental result, we can get the best performance by Euclidean distance in β is 0.8 irrespective of α. On the contrary, we can see that the bigger α makes the better result calculated by e_{Ang}.

Table 3. The Performance of Proposed Method according to the Parameters of the MSRCR

	β = 0.2	β = 0.4	β = 0.6	β = 0.8
α = 0.3	50.84(0.390)	30.43(0.386)	23.21(0.387)	23.20(0.387)
α = 0.5	75.54(0.247)	46.47(0.240)	29.80(0.240)	22.07(0.240)
α = 0.7	96.65(0.203)	65.92(0.197)	45.45(0.196)	32.53(0.196)
α = 0.9	111.86(0.189)	81.84(0.183)	60.29(0.181)	45.23(0.181)

5. Conclusion

In this paper, we proposed the color restoration method for the low light level images. The method uses the tone mapping function which is consists of two parts for controlling brightness of the image. The aim of the tone mapping is enhancing contrast of dark regions and preserving details of bright regions. Then, we apply MSRCR into the result by tone mapping for recovering color of the images. For objective performance evaluation, we consider the experimental images synthesized from Barnard's dataset and well-known evaluation factors, such as Euclidean distance and angular error. The performance of the method is evaluates by comparing other methods for enhancing dark images. Moreover we analyzed the performance according to changing parameters of the MSRCR. The experimental results showed that our method can be more suitable solution than the other methods.

However, the illumination and intensity of the light source can be always changed in low light level condition. Moreover the MSRCR makes different results according to its parameters. Hence, study about auto-determination of MSRSR parameters according to property of the dark image is necessary as a future work.

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