Optik 125 (2014) 7143–7148

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Multi-scale retinex improvement for nighttime image enhancement☆

Haoning Lin, Zhenwei Shi*

Image Processing Center, School of Astronautics, Beihang University, Beijing, China

ARTICLE INFO

Article history:
Received 7 December 2013
Accepted 15 July 2014

Keywords:
Retinex
Nighttime image
Image enhancement
Sigmoid function

ABSTRACT

We propose a retinex improvement for nighttime image enhancement. Retinex is often used on images under non-uniform illumination in terms of either color or lightness and has satisfactory results to achieve color constancy and dynamic range compression. Few studies focus retinex on nighttime images, especially those under extreme conditions (i.e., images with over-lighted or extremely under-lighted areas or with noise speckles), on which retinex operation can perform badly. Original multi-scale retinex (MSR) is extremely sensitive to noise speckles that cameras produce in low light areas, and it has unsatisfactory effect on areas with normal or intensive illumination. Moreover, original MSR uses a gain-offset method for prior-to-display treatment and can lead to apparent data loss on nighttime images. This paper replaces the logarithm function in MSR with a customized sigmoid function to minimize data loss, and adapts MSR to nighttime images by merging results from sigmoid-MSR with original images. Experiments show our framework, when applied to nighttime images, can preserve areas with normal or intensive lighting and suppress noise speckles in extreme low light areas.

1. Introduction

Nighttime image enhancement is a particular problem of those dealing with images with variant lighting conditions. Retinex, is one effective theory aiming at simulating Human Visual System (HVS) to achieve color constancy and dynamic range compression. This paper shows that with modifications, retinex can be applicable to nighttime images even under extreme conditions. In 1986, Edwin Land [1] proposed the last version of his retinex theory as a model for human color constancy. Later, several works emerged implementing this retinex theory but with huge computational cost and sometimes low performance in some extreme cases. What caught our attention is the center/surround retinex, which was also brought up by Edwin Land [2] and has the characteristics of easy implementation, fast computation and less parameters. Research from NASA [3,4] further improved this c/s retinex leading to what is called single-scale retinex (SSR) and multi-scale retinex (MSR), which is shown to be able to accomplish color rendition and dynamic range compression at the same time.

Recent research focus on retinex, especially on multi-scale retinex, recedes a bit and only a few works stand out. Work from Jang [5,6] focuses on better color correction for retinex algorithm. Robinson et al. [7] improve MSR by reducing halo artifacts and graying effect. Rahman et al. [8] investigate the relationship between retinex and image compression. Jang [9] improves the MSR with respect to weights of different scales of retinex. And papers [10,11] both propose to accelerate the implementation of MSR.

Through experiments, we see that MSR can have overall acceptable results on nighttime images. It consistently provides color constancy, dynamic range compression and in short, better visual quality. However, one of their post-processing algorithms has to be reconsidered. Due to the logarithm function in c/s retinex and SSR or MSR, the primary results of these retinex processes can have large range of value and are impossible to be displayed as images directly. One approach we now commonly use is proposed in [3] involving a gain-offset method which clips those pixels with too high or too low lightness, in which case, it is shown little information is lost. However, as for nighttime images where extreme high light and low light pixels are of common occurrence, critical information may lose resulting in apparent artifacts.

This is where sigmoid function comes in. Our intuitive idea is to eliminate the uncertainty of the value range of the result from the beginning, where we used to take the logarithm of the ratio between two intensity values. This ratio ranges from 1/256 to 256

☆ The work was supported by the National Natural Science Foundation of China under the Grants 61273245 and 91120301, the 973 Program under the Grant 2010CB327904, and Program for New Century Excellent Talents in University of Ministry of Education of China under the Grant NCET-11-0775. The work was also supported by Beijing Key Laboratory of Digital Media, Beihang University, Beijing 100191, PR China.

* Corresponding author. Tel.: +86 10 823 39 520; fax: +86 10 823 38 798.
E-mail address: shizhenwei@buaa.edu.cn (Z. Shi).

http://dx.doi.org/10.1016/j.ijleo.2014.07.118
0030-4026/

and the logarithm of the ratio makes itself distribute loosely across its range. We set the higher and lower threshold of the gain-offset method empirically. However, considering the extreme conditions in nighttime images, the gain-offset method is not satisfactory. In originally processed nighttime images, too many pixels' lightness exceeds those thresholds. However, to maintain the natural lightness and color of a image, shifting these thresholds is not an option.

So we came up with an idea to replace the logarithm function with the sigmoid function, which has a certain range of output. This certainty is obtained by compressing the 'extreme' pixels rather than clipping them. So unlike the logarithm method, it does not need the gain-offset method which involves clipping and leads to information loss. Combined with other methods discriminating between areas of different illumination, our framework has overall better enhancement effect among nighttime images.

In the following section, we first introduce the well known MSR. Next, Section 3 introduces our proposed method, including the aforesaid sigmoid function and methods to suppress noise and preserve high-light details. Section 4 presents the experiment results to show the improvements.

2. Original MSR

The retinex theory was brought up by Edwin Land [1] to simulate Human Visual System which, when capturing images, is surprisingly good at adapting to variation of lighting condition, compared to how nowadays cameras perform. This paper mainly bases itself on one of retinex's successful formulation from Rahman's work [4]. Its MSR proves to be able to achieve dynamic range compression on daytime images suffering from uneven lighting condition. Nighttime images share the same characteristics but behave more extremely.

The Original MSR [4] can be written as

$$F_i(x, y) = \sum_{n=1}^{N} W_n \cdot \{\log[S_i(x, y)] - \log[S_i(x, y) * M_n(x, y)]\} \tag{1}$$

where F is the result we get from MSR operation, the subscripts $i \in R, G, B$ indicate the 3 color channels, N is the number of scales of retinex computed, and W_n are the weighting factors of each scale. $S_i(x, y)$ is the ith channel 2-dimensional matrix of the input image, mark * is the convolution operator, and the $M_n(x, y)$ are the surround functions given by

$$M_n(x, y) = K_n \exp\left[\frac{-(x^2 + y^2)}{\sigma_n^2}\right] \tag{2}$$

where K_n is to insure $\int\int M_n(x, y)\mathrm{d}x\mathrm{d}y = 1$. Each of the expressions within the summation in Eq. (1) represents an SSR. This expression of SSR can also be written as

$$\log\left[\frac{S_i(x, y)}{S_i(x, y) * M_n(x, y)}\right] \tag{3}$$

which can be intuitively perceived as a comparison between the current pixel and its weighted, surrounding pixels. σ_n are the standard deviations of the gaussian distribution determining the scales of the surrounding neighborhood taken into account. Smaller scales provide more dynamic range compression, and larger ones provide more color constancy.

After the initial retinex process accomplished by Eq. (1), it is shown that among various scenes, there's a characteristic form for the resulting histogram (Fig. 1).

Regardless the various scenes, the data is distributed around zero and has a form of a gaussian distribution. A usual approach to display the result as an image is to clip both the highest and lowest data and use gain-offset method to produce the final image.

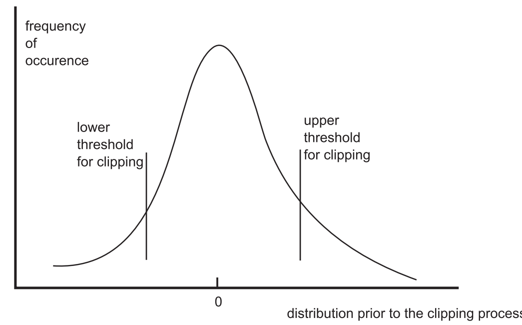

Fig. 1. The clipping method after initial retinex operation illustrated on histogram.

The higher and lower threshold for this clipping step can be determined by

$$T_H = M + \alpha \cdot d \tag{4}$$

$$T_L = M - \alpha \cdot d \tag{5}$$

where M and d is the average lightness and standard deviation of the whole image, respectively. α is a factor determining how much variation of the lightness to keep. Large α keeps more lightness information but has poor visual effect, since the lightness distribution will be closely around the average value and little lightness variation can be perceived. Small α will lead to better lightness distribution but also greater information loss since it has lower T_H and higher T_L. So it's basically a trade-off between more information for highlight/lowlight pixels and more nature visual effect.

3. Proposed method

When directly used on nighttime images, the original MSR may manifest the following defects:

(1) The clipping method prior to display can lead to data loss especially in areas highlighted or non-lighted. This kind of areas are very common in nighttime images unlike those took in normal daytime (See Section 4 for details).
(2) Retinex's nature tends to magnify the lightness difference between pixels to improve clarity, which, in nighttime images where noise is quite common, can significantly increase the noise effect.

What we propose is firstly to replace the logarithm function with a customized sigmoid function, which is intended to act as the logarithm one except that it's nicely bounded and only to compress the lightness close to its bound. Thus no clipping is needed and no apparent data loss is incurred. It is a monotonic increasing function and its form can be easily manipulated, i.e., the upper bound and the lower bound and the derivative at a certain point. Secondly, based on the cause of the magnified noise effect, we implemented a simple method to suppress the noise. Finally we apply a similar method to also preserve areas with good illumination.

3.1. Sigmoid function

A simple form for a sigmoid function is

$$\mathrm{Sig}(x) = \frac{1}{1 + \mathrm{e}^{-x}} \tag{6}$$

and the corresponding shape is shown in Fig. 2.

The function is bounded and is monotonically increasing like logarithm. It needs to be modified so that it has the output range between 0 and 1, appropriate derivative and function value when $x = 1$, and a similar form to the logarithm function.

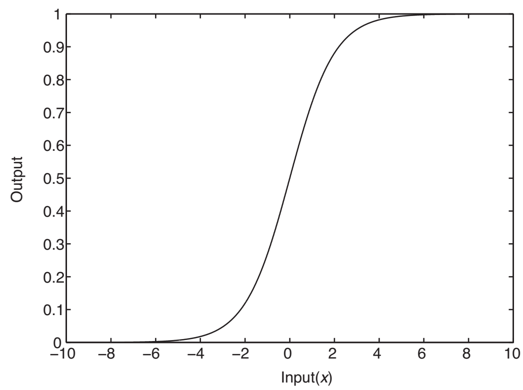

Fig. 2. The shape of a original sigmoid function.

To replace the logarithm function with sigmoid in Eq. (3), we have

$$\mathrm{Sig}\left(\frac{S_i(x,y)}{S_i(x,y)*M_n(x,y)}\right) \tag{7}$$

The input of the Sig( ) function can be regarded as a ratio between 2 images, meaning it is always larger than 0. So we only have to consider the function with a domain on the right side of zero. When the input equals 1, it means the lightness of the current pixel is the same as the weighted average one of the surrounding pixels and the output should be near 0.5, which can be considered as the medium lightness of the picture, conforming to one's common sense.

The sigmoid function we choose is

$$\mathrm{Sig}(x) = \frac{1}{1+\mathrm{e}^{-k\cdot x+b}+c}\cdot\frac{1}{c+1} \tag{8}$$

where k is a factor to determine overall steepness of the sigmoid function – the larger k is, the more sensitive retinex becomes. b and c are parameters to make sure sigmoid goes through point (0, 0) and (1, 0.5), and ends at $(+\infty, 1)$. The corresponding curves with different k are shown in Fig. 3.

This curve is similar to the logarithm one, except it reaches 0 when x comes to 0, 0.5 when 1, and, it gradually approaches 1 when x goes beyond 1 and further.

3.2. Noise suppression

Noise can be distinctive in dark area after the original retinex operation. Firstly it is due to that in nighttime scene where light coming into the camera is limited, high ISO is used and can incur more noise. Secondly, retinex operation's nature is to magnify difference between nearby pixels, and noise can be magnified this way. Thirdly, retinex operation's division part (as can be seen in Eq. (3)) involves dividing one pixel's lightness by it is surrounding pixels' averaged lightness. In dark area, the averaged value is often close to 0 and a noise pixel whose lightness is even slightly larger can be significantly magnified after the division (See Fig. 4). In this section, we propose an approach to limit the noise effect specially in dark area based on the third cause of the retinex noise.

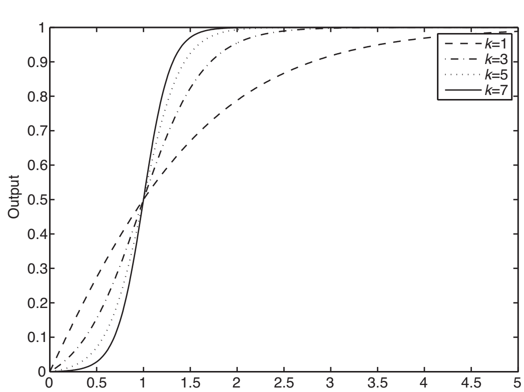

Fig. 3. Sigmoid curves with different ks.

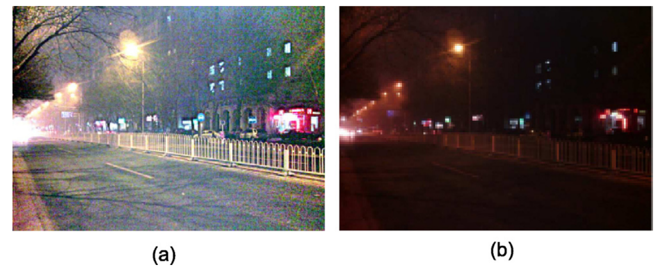

Fig. 4. (a) Origin MSR tends to magnify noise speckles. (b) Original image.

An effective method is to suppress the noise first before applying retinex operation. But denoising can be time consuming and it affects the naturalness of the image. What we see is, when the surrounding lightness is extreme low, the information can be exploited from this area is quite limited since it's full of noise pixel and often damaged by the compression algorithm used in storing pictures/videos.

So, when in a certain area where the lightness is very low, the retinex operation should only produce small effect. We use a weight factor W^1 to achieve this.

$$I_i(x,y) = F_i(x,y)\cdot W_i^1(x,y) + S_i(x,y)\cdot(1-W_i^1(x,y)) \tag{9}$$

where i means a certain color band of the image, I is the final image we get, F is the primary retinex result, and S is the original image. W^1 is the weight factor determining how much of the retinex result we will use to constitute the final image. In very low-light area the retinex result can be basically not utilizable, the W^1 should be near 0. And W^1 should be close to 1 in other areas.

The weight factor we use is

$$W_i^1(x,y) = 1-(1-L_i(x,y))^{20} \tag{10}$$

where

$$L_i(x,y) = S_i(x,y)*M_n(x,y) \tag{11}$$

indicating the surrounding pixel lightness at ith color band. Thus W^1 is determined respectively in each color band. This is because the division takes place separately in each color band.

3.3. High-light preserving

Using the above operation, we have satisfactory results from most nighttime images. Though in nighttime pictures sometimes we encounter areas which have relatively normal illumination. That is to say, some areas are already acceptable to human eyes and therefore the retinex operation may damage the 'good' areas. This is also due to the division step of retinex. In normal lighting area, the overall lightness is high, so the division step will make the 'good' pixel close to medium lightness and lead to lightness reduction. As a matter of fact, the retinex operation tends to move overall pixel lightness and redistribute them around the medium value, 0.5. This 'grayish' effect can have nice outcome on low-light areas and yet not-nice on normal lighting areas.

So, to distinguish poor lighted areas and normal ones, we use

$$H_i(x,y) = \max_{i=1,2,3} L_i(x,y) \tag{12}$$

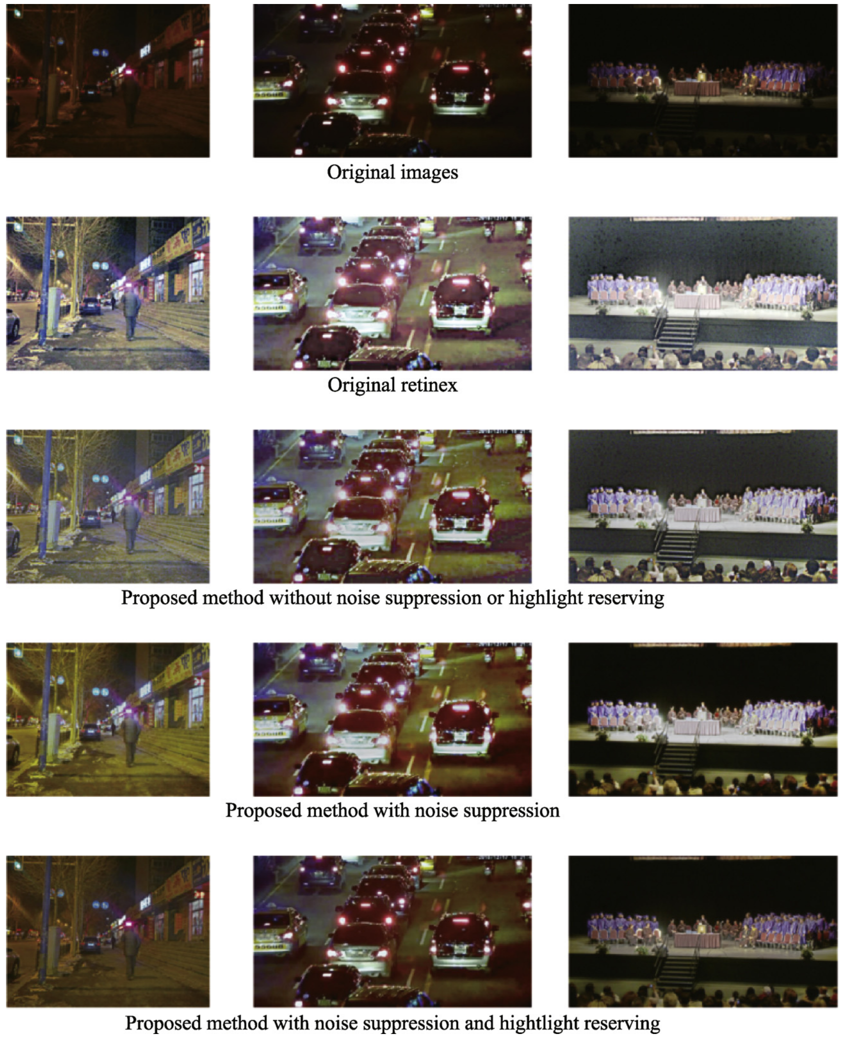

Fig. 5. Origin images and results from different algorithms.

to determine the illumination degree of the current pixel. It is intuitive that in poor lighting areas, all lightness levels of the 3 color bands will be very low. So we only need to use the greatest lightness level over the 3 bands to indicate the lighting level of this area.

To implement the lighting level we create another weight factor

$$W_i^2(x,y) = 1 - H_i(x,y)^{0.5} \tag{13}$$

Finally we get the overall weight through simple multiplication:

$$W_i(x,y) = W_i^1(x,y) \cdot W_i^2(x,y) \tag{14}$$

and the final equation for our proposed MSR:

$$I_i(x,y) = F_i(x,y) \cdot W_i(x,y) + S_i(x,y) \cdot (1 - W_i(x,y)) \tag{15}$$

where

$$F_i(x,y) = \sum_{n=1}^{N} W_n \cdot \{\mathrm{Sig}(S_i(x,y)) - \mathrm{Sig}(S_i(x,y) * M_n(x,y))\} \tag{16}$$

Algorithm 1. Framework for the proposed method

Input: Original nighttime image
Output: The result from our proposed retinex framework
Step 1
Apply different scales of gaussian filter on the original image.
Step 2
Compute the ratio between the lightness of the current pixel and the results from **Step 1**.
Step 3
Take the sigmoid computation of the ratios and calculate the average value.
Step 4
Compute the weight factors based on results from **Step 1**.
Step 5
Apply the weight factors and addition according to 16.

4. Experiments

Fig. 5 shows result from different algorithms, including MSR, our method with and without noise suppression, with and without highlight reserving.

These results show the retinex with logarithm function and the one with sigmoid function have similar overall effect except that sigmoid function needs no pre-display processing or histogram clipping. The noise suppression operation can significantly suppress the noise in dark areas. Notice the dark areas in the 3rd image, original retinex has exaggerated noise pixels. And the highlight reserving can protect good areas from excessive retinex modification. Comparison in the 3rd image is again most noticeable. Due

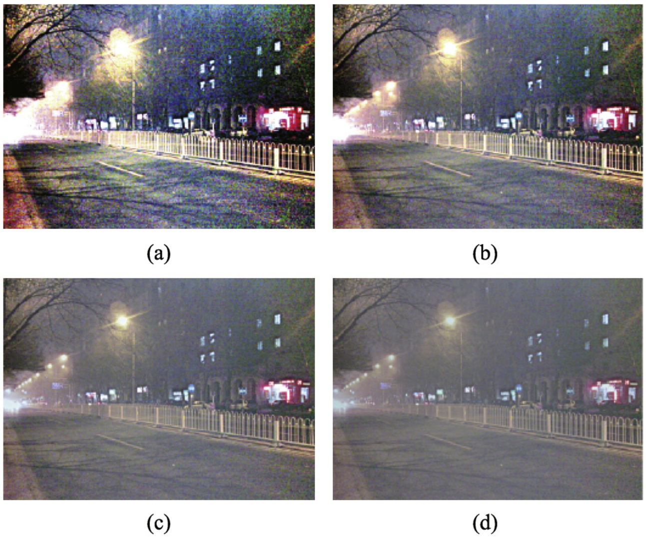

Fig. 6. (a) Result with $\alpha = 1$. (b) Result with $\alpha = 2$. (c) Result with $\alpha = 4$. (d) Result with $\alpha = 6$.

Table 1
Percentage of pixels clipped under different αs.

α	Percentage of pixels clipped (%)
1	41.45
2	7.92
4	0.41
6	0.04

to the dark area around these people on the stage, the middle area is excessively intensified by the original retinex.

In Section 2 we introduced factor α in Eq. (4). Different α will result in different enhance effect and different amount of clipped pixel. Fig. 6 shows results of original algorithm using different αs.

With lower α the picture is more colorful, more natural, yet it also makes noise more intensive and the highlighted areas flooded with white and also entails more pixels to be clipped. When α is lower, the textures are reserved, yet the color is poorly represented and the whole image tends to be grayish.

Table 1 shows the average percentage of pixels, with lightness in at least one channel beyond clipping threshold, of 20 nighttime images after original retinex with different αs.

And in Fig. 7, white pixels indicates those, when $\alpha = 2$, with at least one channel reaching lightness 1 and have to be clipped. Noticeable portion of the pixels are clipped and can lead to unnatural areas.

Whereas the proposed method, though has a parameter similar to α, need not consider clipped data and the results tend to be more natural.

Images usually will be compressed before saved to any media. Most of the compression are lossy ones which omit details deemed

Fig. 7. (a) White pixels are those to be clipped with $\alpha = 2$. (b) The original nighttime image.

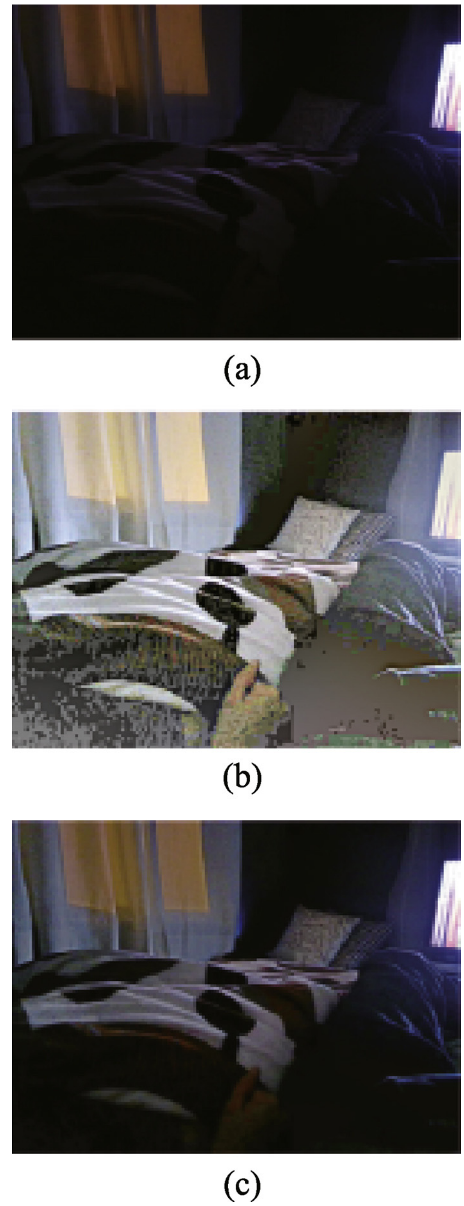

Fig. 8. (a) The original compressed image. (b) The result from original MSR. (c) The result from proposed method.

undetectable by human eyes, including details that have very low lightness. During the experiments we see the original retinex operation can expose these compression artifacts and our noise suppression method is also able to suppress these artifacts. Since the lost details cannot be recovered anyway. We simply use the original parts rather than brutally enhance them. Fig. 8 shows the comparison between these results.

It is clear that areas consisting of squares have little information and produce bad results in original method. Ours tends to skip these areas (Square areas originally have very low lightness and hence endured greater compression) and has better visual quality.

5. Conclusion

Based on some distinct characteristics of nighttime images, we propose an improved retinex framework. This framework replaces the traditionally used logarithm function with a customized sigmoid function which is more suitable for later image displaying step and needs no lightness clipping. This framework is also able to preserve the ‘good’ areas under normal lightings and avoid intensifying noise effect in very dark areas.

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