MSRCR with SVD and Guided Filter Research for Image Enhancement and Denoising

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Abstract. Multi-scale Retinex with the Color Restoration(MSRCR) algorithm with perfect dynamic range compression and color constancy, can recur the content of the image which may be blur or foggy. However, multi-scale Retinex algorithms may amplify the noises in the images while processing them. It not only decreases the quality of images but also interferes with target recognition and image retrieval. The method based on the MSRCR algorithm combines with a dual noise reduction algorithm of singular value decomposition and guided filter to implement the process of noise reduction firstly, and then enhancement, and denoising again. Experiments demonstrate that our method not only does not degrade the image quality like other denoising algorithms but also effectively reduces noise and maintains the result of the multi-scale Retinex algorithm. By subjective perception and objective evaluation, our method gains a better effect than the primary multi-scale Retinex algorithm.

Keywords: Multi-scale Retinex with color restoration(MSRCR), Singular Value Decomposition (SVD), Guided Filter

1. INTRODUCTION

We usually feel uncomfortable observing a severely blurred image. The reason is that the blur affects our vision and we cannot directly capture the information that it represents. And an image with distorted details or with noise may be a result of several factors, such as acquisition, compression, processing, and dumping, all of which may cause loss of detail or add noise to the image[1]. And image enhancement can eliminate or reduce the noisy part or enhance the information we want, which will benefit its utility.

Image enhancement is one of the common image processing techniques and is widely used in the fields of image recognition, image retrieval, and matching, etc.

The common methods of image enhancements are grayscale transform, histogram equalization, image sharpening, gamma transform, logarithmic transform. Histogram Equalization(HE)[2] can adjust the overall image gray value in a uniformly dense rectangular region by obtaining the gray value of the input image. However, some experiments[10] show that histogram equalization only makes the output image brightness in the middle of the input image brightness, and HE performs badly for image brightness retention, and even produces halo artifacts. To solve the image brightness preservation problem, Kim et al. proposed the mean preserving Bi-Histogram Equalization(BBHE)[3] to bifurcate the image according to the overall gray value and equalize them separately. Compared to HE, BBHE maintains the brightness more effectively. Since HE equalizes only the global, it results in insufficient enhancement for some local details. Furthermore, the Adaptive Histogram Equalization[4] takes the approach of dividing the image into multiple sub-images and performs histogram equalization on these sub-images separately, which improves the local contrast. However, with the local contrast increasing, image distortion and unnatural colors appear.

In 1971, Land[1] proposed the human retinal cortex theory(Retinex) based on the human visual system, arguing that reflectance does not change with the scene illumination. Human vision observed a strong correlation between the color of an object and its reflectance, after which many hypotheses based on the theory of the human retinal cortex emerged to enhance reflectance by various methods to achieve the enhancement effect. Jobson el at. performed Retinex wrap-around estimation by comparing multiple functions and found that the Gaussian function was optimal[5], and then proposed the optimized of the Single Scale Retinex(SSR) method. However, it was found that SSR did not achieve a trade-off between preserving the color and complete dynamic range compression. So Jobson considered that the Multi-scales Retinex(MSR) are supposed to perform more in line with human vision. MSR is processed using the usual three scales of a small, medium, and large[5]. And finally, the mean value of the three scales is taken. Although MSR weighs color retention and dynamic range compression and performs more consistently than SSR, it still suffers from color imbalance and loss of detail. Jobson and Raham also proposed Multi-scale Retinex with the Color Restoration algorithm(MSRCR)[6], which inherits from MSR strengths and adds a color recovery factor to make the image closer to the human visual system. In addition, MSRCR also has an exposure adjustment function and has a good effect on image defogging. There are many other improved methods based on SSR/MSR. Multi-scale Retinex with Chromaticity Preservation (MSRCP)[7] enhances the color image separately for the three color channels, namely Red, Green, and Blue, and takes the calculation in the fourier domain instead of the original image with the Gaussian function convolution, which not only improves the operation speed but also avoids the edge loss. Lin and Shi[8] adopted the use of the Sigmod function instead of the log function because the characteristics of the Sigmod function not only diminish the deviation of extreme values but also eliminates the process of gain/offset. In [9, 10] they transferred the image with RGB color space to HSV(Hue, Saturation, Value) color space and enhanced only the Value channel with Retinex algorithm while using adaptive stretching for the Saturation channel, which effectively reduces the chromatic aberration and also adapts to a wider range of illumination conditions. The Illuminance-Reflectance Model considering Noise for Enhancement (IRMNE)[11] converts the RGB image to grayscale firstly and then adopts guided filtering for reflectance enhancement and dynamic range adjustment for the illumination component. In the end, color recovery is performed and converted to an RGB image.

Although MSRCR has a good enhancement effect on low light images or fogged images, some noise inevitably exists in low light images [8,9,13]. Besides, the noise is also amplified and even new noise may be generated in the enhanced images. The usual denoising methods are median filtering, Gaussian filtering, and Max/Min filtering. Median filtering is a simple and effective method that uses a nonlinear N × N filter to eliminate noise. At the same time, median filtering causes loss of image edge information and image details and has a long operation time. It is a way created by Li et al. to add a new regular term to the joint illumination and reflectance optimization function to mitigate the effect of noise[12]. However, it also involves the adjustment of numerous parameters and the time complexity has to be reduced. With the rapid development of neural networks, people started to study enhancement methods for low-light images in combination with deep neural networks. Wei et al. proposed the Retinex-net to enhance the reflectance by augmenting the network and introducing a multiscale cascade to eliminate the noise[13].

On account of the fact that images themselves carry noise and may still generate new noise after enhancement, we combine Singular Value Decomposition(SVD) and Guided Filtering based on MSRCR to achieve noise reduction while enhancing low-lightness images or erasing shadows. We compare our proposed method with Homomorphic Filtering, MSRCR, and MSRCP by subjective visual perception and objective metric evaluation.

In section 2 we will present the Retinex method and our improved MSRCR-based image enhancement method; in section 3 we are going to conduct experiments and show the results; in section 4 we attend to make a conclusion and discussion.

2. METHODOLOGY

2.1. Retinex algorithm

Land et al. define that the image S(x, y), as seen by the human eye vision, is jointly represented by the illumination L(x, y) and the reflectance R(x, y)[1]. The equation is as follows:

$$S(x, y) = L(x, y)\cdot R(x, y) \tag{1}$$

Land states that the color information seen by the human eye depends only on R(x, y), and therefore L(x, y) should be reduced. So Jobson and Rahman research three algorithms.

Firstly, SSR is expressed as follows:

$$R(x , y)=\frac{S(x , y)}{L(x , y)} \tag{2}$$

$$R(x , y) = \log S (x , y)- \log L (x , y) \tag{3}$$

$$R(x , y)=\log S(x , y)-\log[F(x , y)\cdot S(x , y)] \tag{4}$$

The illumination L(x, y) can be represented by a Gaussian function and the convolution of the original image instead. The "·" is the product of the original image and F(x, y). F(x, y) is the function:

$$F(x , y)=Ae^{\frac{-(x^2+y^2)}{c^2}} \tag{5}$$

“c”, which denotes the scale of the Gaussian surround function, is an essential influence factor. “A” represents the normalization parameter and is determined by the following function.

$$\iint F(x , y)dxdy = 1 \tag{6}$$

What’s more, x and y are the position coordinates of the corresponding pixel.

Secondly, MSR picks several different scale factors “c” for SSR and then calculates their average. three scales c1=15, c2=80, c3=250 are selected[5].

Different scale factors have different effects: small scale factors have good detail representation and weak tonal or color reproduction likewise[5].
The MSR is expressed as follows:

$$R_{MSR}(x , y)=\sum_{k=1}^{3} w_k R(x, y) \tag{7}$$

w_k is the weights accounted for different scale factors. The authors in [5,6] proved that $w_k = 1/3$, k = 1,2,3 is sufficient for using experimentally.
Thirdly, in order to display the intact color information of the image, the color restoration factor is added to improve the color reproduction at the cost of appropriately reducing the color consistency. Therefore, MSR and the color reproduction reo MSRCR.
The MSRCR is expressed as follows:

$$R_{MSRCR}(x, y)=G\{C(x, y)R_{MSR}(x, y)+b\} \tag{8}$$

G and b are constant parameters, this paper takes G = 30, b = 6.

$$C(x, y)=\beta\{\log[\alpha S(x, y)]-\log[\Sigma S(x, y)]\} \tag{9}$$

b and a take 46 and 125 respectively. For an RGB image, we should calculate by per channel.

2.2. Ours

The Retinex algorithm is a rather salutary enhancement method and is widely used. However, we proposed the following two problems with the Retinex algorithms in our experiments:

- As processing noisy low-light images, the Retinex algorithms will amplify the noise.
- New noise comes into being by the Retinex algorithms.

Therefore, we modify the (1) and (8), namely:

$$S = L\cdot R+N_0 \tag{10}$$

$$R_{MSRCR}=R+N_1 \tag{11}$$

N_0 is naturally carried with images, and N_1 is generated by MSRCR.
Referring to (10) and (11), we must remove the noise N_0 and N_1 to get a satisfactory result. In this paper, we apply SVD and Guided Filtering to denoise.

2.2.1 SVD

The core of SVD for digital image matrices is decomposition and reorganization. The decomposition disassembles singular values and singular vectors based on linear matrices.

$$S=U\Sigma V^T=\sum_{i=1}^{n} \sigma_i\, u_i v_i^T \tag{12}$$

$U=(u_1,\ldots,u_n)\in S^{M\times N}$, $V=(v_1,\ldots,v_n)\in S^{N\times N}U$
U and V represent the left and right singular vectors of S, respectively. σ_i is the singular value of S ($\sigma_1>\sigma_2>\sigma_3...>\sigma_n$), and $\sum_{i=1}^{n}\sigma_i$ is the diagonal matrix of σ vector.

The reorganization part is to eliminate the noise in the low-frequencies through selecting a new and optimal singular value vector.

$$\overline{\sigma_r} = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_r \end{pmatrix} \tag{13}$$

The scale size "r" is closely related to the noise reduction and loss of the image. Through a large number of experiments, it is found that the image is more blurred when "r" takes a smaller value, and the acquired image is gradually clearer as the value of "r" increases. For example, in an image of size 256 × 256, when e = 160, the structure of the image is comparable to the original image but a bit misty. As e = 240, on the one hand, the image sharpness and quality make great progress. On the other hand, the number of noise is reduced.

2.2.2 Guided Filtering

To deal with N_1 in (7) and reduce the interference of the denoising process on the quality of the image after MSRCR enhancement, We adopt the guided filtering method[14].

$$\overline{R_i}=\overline{a_i}R_i+\overline{b_i},\forall i\in\omega_k \tag{14}$$

R is the result of MSRCR, "ω_k" represents the filter's window and i is the center pixel of the window.

$$\overline{a_i}=\frac{1}{|\omega|}\sum_{k\mid i\in\omega_k} a_k \tag{15}$$

$$\overline{b_i}=\frac{1}{|\omega|}\sum_{k\mid i\in\omega_k} \overline{R_k}- a_k\mu_k \tag{16}$$

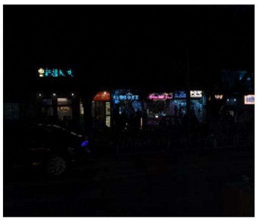
$\overline{a_i}$ and $\overline{b_i}$ denote that all "ω_k" windows centered on "i" pixel of the average coefficient.

$$a_k=\frac{\frac{1}{|\omega|}\sum_{i\in\omega_k} R_i^2-\mu_k\overline{R_k}}{\sigma_k^2+\epsilon} \tag{17}$$

$|\omega|$ indicates the number of pixels in the "ω_k". μ_k and σ_k^2 are the mean and variance of "ω_k", respectively. What's more, window's size and "ϵ" are variable parameters.

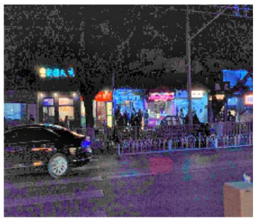
2.2.3 Our Algorithm

Input: S
Output: R
Step 1: Decompose S and denoise for S by SVD before enhancement.
Step 2: Process the return value from Step 1 with MSRCR.
Step 3: Perform frequency domain stretching for the return value from Step 2, balancing low and high-frequency bands based on probability distribution.
Step 4: The return from Step 3 will be resolve by R,



Original

(a)MSRCR

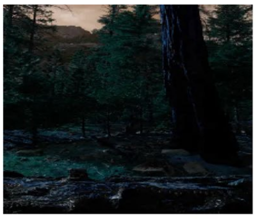


(b)MSRCP

(c)Homomorphic Filter

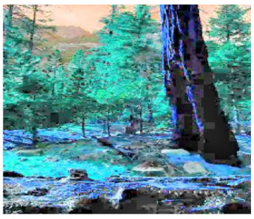
(d)Ours

Fig.1 Original image of the street taken in the dark



Original

(a)MSRCR



(b)MSRCP

(c)Homomorphic Filter

(d)Ours

Fig.2 Dim woods

Original

(a)MSRCR

(b)MSRCP

(c)Homomorphic Filter

(d)Ours

Fig.3 Woman face expressions from Japanese jaffe database

G and B color bands and enhance with Guided Filtering, respectively. Then it is recombined to obtain the final output “R”.

Table.1 PSNR, SSIM, Entropy, and NIQE on Fig.1

	HF	MSRCR	MSRCP	Ours
PSNR	**33.629**	28.648	27.658	<u>28.691</u>
SSIM	**0.763**	0.568	0.537	<u>0.572</u>
Entropy	4.59	6.49	**7.07**	<u>6.72</u>
NIQE	<u>25.16</u>	29.32	29.04	**19.46**

Table.2 PSNR, SSIM, Entropy, and NIQE on Fig.2

	HF	MSRCR	MSRCP	Ours
PSNR	28.320	<u>28.543</u>	27.961	**28.638**
SSIM	**0.741**	<u>0.634</u>	0.584	0.627
Entropy	7.19	7.38	**7.63**	<u>7.48</u>
NIQE	**21.983**	23.936	<u>22.234</u>	22.569

Table.3 PSNR, SSIM, Entropy, and NIQE on Fig.3

	HF	MSRCR	MSRCP	Ours
PSNR	28.275	<u>28.787</u>	27.881	**28.833**
SSIM	0.803	**0.831**	0.794	**0.831**
Entropy	5.19	<u>6.85</u>	**6.87**	6.81
NIQE	**20.378**	26.946	40.498	<u>20.393</u>

3. EXPERIMENTS

We compare our algorithm with Homomorphic Filtering (HF) which is similar to Retinex theory but has a different way, MSRCP, and MSRCR by subjective judgment and objective evaluation of signal peak ratio (PSNR), structural similarity SSIM, information entropy (Entropy) and natural image quality evaluation (NIQE). The higher PSNR value, the better the image quality. The higher SSIM value, the higher the image similarity. The larger Entropy, the more informative images. The smaller NIQE values, the closer to human vision. We firstly perform a comparison of color photos in a low-light environment and then compare gray images. In tables, The bolded data is the best of the four algorithms in comparison, followed by the underlined.

Fig.3. illustrates a driveway in the dark and the photo is so dim that you can barely tell what is in the image, only the various colors of lights are visible. After processing by the four algorithms, the original dim and indistinct images are enhanced to different degrees. With MSRCR processing, the image is clear and has terrific contrast, color recovery, and detail retention, while the MSRCP image is clearer and can distinguish cars and shops along the road, but the colors are somewhat out of tune and there are a great deal of unsmooth areas due to the influence of various neon lights. After homomorphic filtering, the treatment is the worst among the four methods and the main colors are shifted. Our method is almost indistinguishable from MSRCR except that it is smoother from a subjective point of view. But from Table.1. we see that in terms of SSIM, Entropy, and NIQE objective evaluation, Ours improves 0.7%, 3.5%, and 33.6% respectively relative to MSRCR, which means our method can improve the image quality. Homomorphic Filtering’s PSNR and SSIM are greater than Ours but subjective vision is not natural and satisfactory, implying that homomorphic filtering is excellent in maintaining the structure and details of the image, but does not serve the purpose of color rendition. And by MSRCP, the image is more colorful but the noise is amplified by the naked eye alone. Ours not only achieves subjectively better visual results but is competitive in objective metrics.

From Fig.4, on a subjective point of view, the MSRCP and Homomorphic Filtering methods are clearly out of tune, with the former having a very bright green hue and the latter a yellowish background color, neither of which satisfies human visual perception. In contrast, the MSRCR and Our processing are more consistent with human vision. Objectively evaluated, it is seen from Table.2 that Ours has improved PSNR, Entropy, and NIQE compared to MSRCR by denoising the images.

Fig.5 has shadows on the image due to the environment in which it was taken. Subjectively, MSRCP has the best effect on Fig.5. This is followed by Ours and MSRCR, while the homomorphic filtering process makes the image too bright and does not remove the shadows well. From Table.3, Ours objectively has higher image quality compared to MSRCR, with 0.16% and 24.3% higher PSNR and NIQE, respectively, despite a small reduction in the amount of information.

4. CONCLUSION & DISCUSSION

For images that are inherently noisy and where new noise is accumulated during the enhancement process, we propose a method based on SVD and Guided Filtering to improve the MSRCR algorithm.

Through experiments and analysis, our proposed method has better noise reduction relative to the original MSRCR by evaluating PSNR, SSIM, information entropy, and NIQE from subjective observation and objective metrics. And it also maintains a good natural visual with MSRCR contrasted to Homomorphic Filtering and MSRCP. However, our method still needs improvement in detail processing and color retention, and in the future, we will explore improving the Gaussian function of MSRCR or replacing it with a more optimized function.

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