Performance Analysis of Retinex Based Algorithms for Enhancement of Low Light Images

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Abstract. The images captured under low and poor light conditions may suffer low contrast and blurring problems which will affect its interpretation and recognition. Hence it is important to enhance and restore such low contrast images. The enhancement of the captured images in the low light environment through various image enhancement algorithms is discussed in this work. The set of algorithms tested includes single scale retinex, multiscale retinex color preservation, multiscale retinex color restoration, contrast limited enhanced adaptive histogram equalization, dark channel prior, and gamma correction algorithms. This paper discusses the various variants of retinex models, which are considered powerful methods for image enhancement and restoration. The proposed work involves the study of various image enhancement algorithms and their comparison on the basis of a reference original low light image and human eye perception models. The performance of various retinex derivative algorithms is experimented with using the LIME dataset, and the histogram equalization is analyzed for metrics such as peak signal to noise ratio, structural similarity index, and discrete entropy.

Keywords: retinex, LIME dataset, image enhancement, and restoration

1. Introduction
The retinex theory and its derivatives involve the human color perception methods to enhance the local contrast of the image. In this paper, we have reviewed and analyzed traditional retinex methods along with contrast limited enhanced adaptive histogram equalization, dark channel prior, and gamma-corrected methods. In view of human perception, direct enhancement of image contrast for image quality improvement is achieved mostly from the HE and the retinex method.

The homomorphic filtering approach [1] uses the single-scale Retinex (SSR) algorithm, and it was not successful in solving issues with dynamic range, tonal contrast, and halo in the resultant image. SSR algorithms [2] of the center and surround approaches [3] were introduced to typically perform a random choice on pixels leading to the increased complexity in computation. To overcome these difficulties in SSR, Multi-Scale Retinex theory (MSR) based solutions were proposed, but unfortunately, MSR algorithm leads to a high amount of color distortion. Multiple solutions [4][5] were proposed to address the color distortion of MSR, which paved the way for Multi-Scale Retinex with Color Restoration(MSRCR)schemes.

MSR-based haze-free algorithm and guided filter approach [6] enhances the image under optimization and improves the brightness to highlight the details. Particle Swarm Optimization(PSO) based solutions[7] adjusts the parameters for Multiscale Retinex[8] with Chromaticity Preservation and provide true color features under low light conditions, and also avoids color distortion[9]. Low-
light luminance images [10] can still be enhanced by preserving image contrast using HIS color space's inherent advantage. A simple DCP [11] is deployed to remove haze by estimating the haze density and transforms it into the haze-reduced image. Analysis performed [12] to confirm the validity of MSRCP, MSRCR delivers [13] excellent results based on histogram equalization. It focuses on finding the comparatively better image enhancement algorithm by testing various image enhancement algorithms on low-light images [14].

This paper is organized as follows. Section 2 describes the retinex variants, and performance analysis is explained in section 3, with conclusions drawn in section 4.

2. Retinex Theory

Enhancement of images based on the retinex concept is the comprehension of the human visual system (HVS). Actually Weber-Fechner's Law builds up a connection between the input image's actual brightness and brightness as perceived by the human eye. The retinex algorithm shown in Figure 1 divides the source image \( I(x,y) \) into illumination \( S(x,y) \) and reflection \( R(x,y) \) components. It is inferred that when we subtract or remove the illumination part and keep the reflection part of the image, the original image comes about dramatically enhanced.

\[
S(x,y) = I(x,y) \ast F(x,y) \tag{1}
\]

Where \( F(x,y) \) is the surround function, subsequently various retinex algorithms are discussed one by one in this section.

2.1. Single-scale Retinex

The single-scale retinex belongs to the class of center or surround functions wherein the difference of the input value gaussian low pass filtering is given by

\[
R_i(x,y) = \log I_i(x,y) - \log[I_i(x,y) \ast F(x,y)] \tag{2}
\]

Where \( I \) refers the applied source image on the with the color channel, \( R_i \) is the retinex image while \( F \) is defined as the surround function, for each color channel of the image, the above equation is applied to obtain the \( R_i \) component with illumination \( S \) and scene reflectance

\[
I_i(x,y) = S_i(x,y) \cdot r_i(x,y) \tag{3}
\]

\[
R_i = \log \frac{S_i \cdot r_i}{S \cdot r_i} \tag{4}
\]

Signify the weighted average value, and it is presumed that \( S \) varies smoothly and is almost constant.

\[
R_i = \log \frac{r_i}{r_i} \tag{5}
\]

The singular surround function whose integral is infinite in the continuous domain and the gaussian function is given in (6) and (7).
\[ F(x, y) = \frac{C}{x^2 + y^2} \]  

\[ F_n(x, y) = C_n \exp \left[ -\frac{(x^2 + y^2)}{2 \sigma_n^2} \right] \]

Where filter standard deviation \( \sigma_n \) controls the number of spatial details and \( C \) is a normalization factor such that \( \int dxdy = 1 \), by trial and error, it is found that \( \sigma = 80 \) is a fine choice. The logarithmic processing after the surround convolution is given in equations (8) and (9).

\[ R_1(x, y) = \log I(x, y) - \log [I(x, y) * F(x, y)] \]  

\[ R_2(x, y) = \log I(x, y) - [ \log x I(x, y) * F(x, y)] \]

\( R_1(x,y) \) depicts the ratio of the image to its weighted average, whereas \( R_2(x,y) \) is the ratio between the image and weighted product where the choice is to deploy arithmetic or a geometrical mean. SSR algorithm caused halo effect near the edges of the resulting image due to the continuity of the image’s illumination component.

2.2. Multiscale Retinex

The multiscale retinex algorithm illustrated in Figure 2 uses more than one Gaussian kernel with varied standard deviation values (\( \sigma \)). Using the multi-scaled Gaussian function, the dynamic range is squashed and the illumination component of the image belonging to a scene is gauged successfully.

\[ R_{MSR_i} = \sum_{n=1}^{N} w_n R_{n_i} = \sum_{n=1}^{N} w_n \left[ \log I_i - \log (I_i * F_n) \right] \]

Where and when denotes the scales and weight of each scale. \( F_n \) is the gaussian surrounding function.

\[ I(x, y) = (I_r + I_g + I_b) / 3.0 \]

Are used to compose each R, G, and B channel in SSR image. But due to the Gaussian filtering, the restoration of image contrast is a failure. So, the quality of the output image is highly dependent on the size of the Gaussian filter used. Hence it is not successful in completely eradicating the snag of SSR.

2.3. Multiscale Retinex Color Restoration

Though MSR seemed to work much better than SSR, it faced color distortion, which is overcome by MSRCR algorithm. First is the grey world presumption, which expresses that a picture with an
adequate measure of color distinction, the mean value of the RGB part of the picture must estimate out to a routine grey value. In pictures that disregard this assumption, i.e., pictures where a specific color may overwhelm, the MSR strategy produces greyish pictures by diminishing the color saturation. To resolve this drawback, a color restoration stage is added to the MSR algorithm by multiplying the output of the MSR with a color restoration function as in Figure 3.

Figure 3: Signal flow diagram representing MSRCR algorithm

The primary step is to enumerate the chromaticity coordinates for the \( i \)th color band,

\[
I_i' = \frac{I_i(x, y)}{\sum_{j=1}^{S} I_j(x, y)}
\] (12)

Where \( S \) denotes spectral channels (\( S = 3 \) for RGB), the reconstructed color MSR\[11\] is given by the \( i \)th band of the Color Restoration Function (CRF).

\[
R_{MSRCRI}(x, y) = C_i(x, y) \cdot R_{MSRI}(x, y)
\]

\[
C_i = f(I_i)
\]

\[
C_i = \beta \cdot \log (\alpha \cdot I_i)
\] (15)

Where \( \beta \) signifies gain and \( \alpha \) controls non-linearity. The maximum and minimum of the RGB is given by

\[
R_{MSRCRI}(x, y) = 255 \cdot \frac{R_{MSRCRI}(x, y) - \min_1 (\min_{(x,y)} R_{MSRCRI}(x,y))}{\max_1 (\max_{(x,y)} R_{MSRCRI}(x,y)) - \min_1 (\min_{(x,y)} R_{MSRCRI}(x,y))}
\] (16)

It is inferred that there is a linear transformation and expected to accomplish a fine contrast for which canonical gain/offset is introduced. The retinex of MSRCR is computed by

\[
R_{MSRCRI}(x, y) = G[R_{MSRCRI}(x, y) - b]
\] (17)

Where \( G \) and \( b \) denote the gain and offset parameters. MSRCR procedure has the drawback of manifestation of halo artifacts in high contrast margins, low contrast areas graying out, and poor color presentation, which is addressed using adaptive filters.

2.4. Multiscale Retinex Color Preservation
MSRP algorithm uses each of the image channels intensity information and the MSR algorithm to enhance the image. For images having accurate color distribution and exposure of white light, the outcome on implementing MSRCP conserves the color balance and is given by
\[ I(x,y) = \frac{\sum_{j=1}^{S} I_j(x,y)}{S} \]  

where \( S \) represents the number of channels. A linear transformation is implemented so that the resultant output intensity is stretched to [0,255] and represented as

\[ R_{\text{MSR}}(x,y) = \sum \log(I(x,y)) - \log(I(x,y)) \ast F_{\sigma_i} \]  

\[ R_{\text{MSRCP}}^i = \min \left( \frac{255}{\max(I_{r_i},I_{b_i},I_{g_i})}, \text{int}(i) \right) \]  

where \( I \) is the input image, \( \sigma_i \) is scaled, \( F \) stands for gaussian surround function, \( \text{int}_I \) is the simplest color balance \( (R_{\text{MSR}},s_1,s_2) \), and \( s \) denotes percentage of clipping pixel on each side. Theretinexof MSRPCP is computed as

\[ R_{\text{MSRPCP}} = G \cdot [R_{\text{MSRCP}}^i] + b \]  

where \( G \) and \( b \) denote the gain and offset parameters.

2.5. Dark Channel Prior

The model[10] used to represent the haze image is described as follows

\[ I(x) = J(x) \ast t(x) + A \ast (1 - t(x)) \]  

where \( I \) is the input haze image also observed intensity, \( A \) is the atmospheric light value, \( J \) is the haze-free image or radiance, and \( t \) is the transmission map describing the amount of the light that is not getting scattered and reaches the camera.

2.6. Gamma Correction

Gamma correction [13] is an application of power-law transform or 'rise to power' technique in which the values of input pixels are raised to a set power, refer to equation

\[ \hat{G}(i,j) = C \ast G(i,j)^\gamma \]  

\( C \) refers to a constant factor that can be greater or lower than one, taken equals 1. \( \gamma \) has been set in this experiment to four different values (0.2, 0.4, 0.5, and 0.6).

2.7. Histogram Equalization

The CLAHE is used to optimize the input image by maximizing entropy and limiting its contrast. CLAHE [12-13] is based on dividing the input image into several dissimilar unique regions with the same dimension and then set desired crop limit for each region. In each block or region, there are three different sub-regions: corner regions, border regions, and inner regions covering the whole block area.

\[ g = [g_{\text{max}} - g_{\text{min}}] \ast P(f) + g_{\text{min}} \]  

where \( g \) is the computed picture element magnitude, \( g_{\text{max}} \) is the maximum picture element value, \( g_{\text{min}} \) is the minimum picture element magnitude, \( P(f) \) is the cumulative distributive function.

3. Performance Analysis

Experiments have been performed in Matlab R2019b on a personal computer with a 2.60 GHz Intel Pentium dual-core processor and 4G RAM. We used a Low Illumination Image Dataset (LIME) and Low Light Intensity (LOL) dataset comprising of 485 Ground Truth (GT) images. In this paper, seven of the state-of-the-art images are compared based on MSR, MSRCR, MSRPCP, DCP and CLAHE. The major parameters such as patch sizes \((n=3)\) and the Gaussian functions are set to scale at \( \sigma = 15, 80, \) and 250, respectively.
Fig. 4: The output images for various algorithms of the given LIME dataset - lighthouse

Fig. 5: Histogram plot of input image lighthouse for various algorithms

The results are compared on the intensity channel by applying it to each color band of RGB images. From the above Figure 4, it is obvious the MSRCP algorithm outperforms all the other algorithms visual perception regarding the color contrast. A histogram of an image is a chart that shows the distribution of intensities in an indexed or grayscale image. If the input is an RGB image, the source image file is read into an image matrix and converted to grayscale for RGB channels and then iterates the image matrix to count the frequency of every possible intensity. Figure 5 depicts the histogram for different algorithms. In the input image, which is dark due to low light, the grayscale distribution of RGB channels is narrow and compressed. Numerically the range of grayscale is less than 100 with intensity values over 4x10^4 to 8x10^4. For MSRP, the range of grayscale is less in dark scale and evenly distributed up to 200 with intensity values maximum up to 10x10^4. Also, DCP and CLAHE have poor intensity distribution. It is obvious that the MSRCP algorithm enhances the low
light image at a good rate with color preservation than other retinex based algorithm. Also, DCP and CLAHE have poor intensity distribution.

![Image](light Image at a good rate with color preservation than other retinex based algorithm. Also, DCP and CLAHE have poor intensity distribution.]

**Figure 6:** The output images for various algorithms on LIME dataset beach image.

From the Figure 6, it is understood that DCP, CLAHE, and Gamma corrected algorithms have poor brightness while the retinex based algorithms result in better contrast. Figure 7 shows the histograms of the algorithms that justify the above statement that the intensity is evenly distributed for retinex algorithms. The range of grayscale is from 0-30 is very narrow, and the pixels are located only in dark regions with intensity values up to 3x10^4. The MSRCR algorithm has a range of grayscale evenly distributed up to 250 with intensity values over 15x10^3. And it is obvious; the MSRCP algorithm has better colour balance and preserves color better than the other algorithms.

![Image](Histogram plot of LIME dataset seashore image)

**Figure 7:** Histogram plot of LIME dataset seashore image
The underwater image in Figure 8 presents a greenish light on the entire image, and it is inferred that CLAHE enhances the green concept while the retinex based algorithms removes the green veil. Again among the retinex algorithms, MSRCR restores the color balance of green shade without overwhelming brightness. Histogram in Figure 9 shows that for the input image numerically, the range of grayscale is from 40-250 with intensity values up to $1 \times 10^3$. The histogram shows that CLAHE enhances the green concept. But the MSRP with grayscale vary from 0-250 with pixel intensity values evenly distributed and performs color balance effect that stimulates color perception. Over all, the results of MSRCR and MSRCP, we found MSRCR restores the color balance and MSRCP obviously preserves better the image chromaticity.

Figure 8: Histogram plot of LIME under water input image for various algorithms

Figure 9: Histogram of LIME under water input image for various algorithms
3.1. Quantitative Analysis
A few number of LOL indoor images dataset is analyzed in Figure 10 in terms of peak signal to noise ratio (PSNR), structural similarity index (SSIM) and discrete entropy [15].

![Figure 10: Output images of six input images from the LOL indoor dataset](image)

| Metric | Image   | CLAHE | DCP | GC   | SSR  | MSR  | MSRP | MSRCR |
|--------|---------|-------|-----|------|------|------|------|-------|
| PSNR   | LOL_01  | 12.5526 | 15.0347 | 12.7439 | 15.4015 | 16.2632 | 14.9997 | 16.4282 |
|        | LOL_22  | 7.3199  | 15.6472 | 10.9556 | 18.8133 | 18.0751 | 19.8136 | 16.79  |
|        | LOL_55  | 5.2528  | 11.8773 | 7.3528  | 18.6549 | 18.9487 | 20.5288 | 17.4732 |
|        | LOL_79  | 6.2643  | 18.3795 | 9.7449  | 18.262  | 18.7233 | 18.3779 | 18.0972 |
|        | LOL_146 | 7.6871  | 17.7987 | 12.0461 | 14.6989 | 14.8889 | 15.8945 | 16.3522 |
|        | LOL_179 | 13.9565 | 15.5759 | 18.5476 | 10.3128 | 10.3926 | 10.1512 | 12.6718 |

| Metric | Image   | CLAHE | DCP | GC   | SSR  | MSR  | MSRP | MSRCR |
|--------|---------|-------|-----|------|------|------|------|-------|
| SSIM   | LOL_01  | 0.5615 | 0.6097 | 0.6636 | 0.5161 | 0.6421 | 0.5864 | 0.6435 |
|        | LOL_22  | 0.3284 | 0.6109 | 0.6147 | 0.6752 | 0.5908 | 0.4334 | 0.7268 |
|        | LOL_55  | 0.1763 | 0.4272 | 0.3904 | 0.5781 | 0.5773 | 0.4859 | 0.6192 |
|        | LOL_79  | 0.3232 | 0.6411 | 0.601  | 0.7241 | 0.7892 | 0.5641 | 0.7204 |
|        | LOL_146 | 0.2618 | 0.625  | 0.4874 | 0.5634 | 0.5646 | 0.6298 | 0.5514 |
|        | LOL_179 | 0.3432 | 0.8036 | 0.7016 | 0.5161 | 0.5117 | 0.5857 | 0.5953 |

| Metric | Image   | CLAHE | DCP | GC   | SSR  | MSR  | MSRP | MSRCR |
|--------|---------|-------|-----|------|------|------|------|-------|
| DE     | LOL_01  | 0.3234 | 0.4726 | 0.3164 | 0.5321 | 0.5482 | 0.5465 | 0.6546 |
|        | LOL_22  | 0.1614 | 0.4167 | 0.2066 | 0.3372 | 0.3375 | 0.4546 | 0.3616 |
|        | LOL_55  | 0.0913 | 0.3587 | 0.1388 | 0.4368 | 0.4706 | 0.3399 | 0.4434 |
|        | LOL_79  | 0.3365 | 0.7099 | 0.3198 | 0.3449 | 0.3445 | 0.4167 | 0.356  |
|        | LOL_146 | 0.32   | 0.6763 | 0.3543 | 0.4674 | 0.4862 | 0.6515 | 0.5412 |
|        | LOL_179 | 0.3072 | 0.6473 | 0.3767 | 0.4467 | 0.3986 | 0.6762 | 0.5033 |

**Table 1**: Performance metrics of retinex variant algorithms
The performance metrics PSNR, SSIM and discrete entropy (DE) are measured for the low-light image (LOL) dataset and is tabulated.

From Table 1, it is inferred that the PSNR quality index values of the MSR are much higher than other non-retinex algorithms, which implies that MSR methods are tremendously enhances the visibility. The average PSNR value of MSRCP is 46.7% over CLAHE, 4% better than SSR and 28.3% better over GC. Similarly, the average PSNR value of MSRCR is 45.8% over CLAHE, 3% better than SSR and 27.1% better over GC. We observe that LOL-55 image with MSRCR is 44% than GC and 26% better than CLAHE. Similarly, MSR is 40% better than CLAHE and 18% better than CLAHE. For the image of LOL-146, MSRCP is 36% better than CLAHE and 14% better than GC. Similarly, MSRCR is 29% better than CLAHE and 7% than GC. From the evaluation table we observe for image LOL-1 MSRCR is 51.72% better than GC, CLAHE. Similarly, MSRCP is 42.15 better than CLAHE and CLAHE. For the image LOL-22 MSRCR is 55% better than CLAHE and 45% better than GC. Similarly, MSRCP is 64% better than CLAHE and 56% better than GC.

4. Conclusion
The enhancement of the captured images in the low light environment through various image enhancement algorithms is discussed in this work. The set of algorithms tested includes SSR, MSRCR, MSRCP, CLAHE, DCP and gamma correction algorithms. The average PSNR value of MSRCR is 45.8% over CLAHE and 3% better than SSR and 27.1% high in performance over GC. The DE of MSRCR is 55% improved than CLAHE and 45% than GC. The SSIM value of MSRCP is 36% better than CLAHE and 14% than GC. With the inference obtained in this work, it is recommended to use MSRCR for scenes with colored illumination. This paper summarizes the performance analysis of various retinex derivatives and provides validation to use MSRCP in the aspect of color and white light distribution and MSRCP provides better preservation of color distribution.

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