Low-Light Image Enhancement Based on Retinex Reflectance Compensation

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Abstract

Enhancement of low-light images is a low-level visual task aimed at improving the quality of images captured under low-light conditions. In this study, a low-light image enhancement algorithm is proposed by compensating for the reflection loss of illumination components obtained through object reflection. Specifically, the algorithm first utilizes Gaussian filtering to process the value component (V) of the image, separating the illumination component from the reflection component. Then, through a illumination compensation strategy, the illumination component is processed and combined with the reflectance component to synthesize the enhanced value component (V). Finally, an adaptive global balance strategy is applied to optimize the enhanced value component (V) to ensure that the resulting image appears more natural and conforms to human visual perception habits. Experimental results demonstrate the effectiveness and superiority of our method compared to existing traditional processing algorithms and deep learning methods, showing excellent performance in enhancing dark details of images and maintaining natural colors.

Keywords:Adaptive global balancing, Reflectance estimation, Illumination Component Compensation

1. Introduction

With the rapid development of mobile internet, the importance of images in key areas such as medical analysis, satellite remote sensing, and industrial machine vision is becoming increasingly prominent. However, images captured under low-light conditions often face issues such as low brightness, poor contrast, and high noise, severely affecting their practical application effects. Therefore, low-light image enhancement technology has significant research and application value in the field of computer vision.

Traditional low-light image enhancement methods primarily focus on adjusting global illumination. The Retinex theory [1] is a widely used approach for low-light image enhancement.. According to this theory, the original image $S(x, y)$ can be represented as the product of the illumination component $L(x, y)$ and the reflectance component $R(x, y)$:

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

Early studies such as SSR [2], MSR [3], and MSRCR [4] estimated the illumination component and adjusted the reflectance component to enhance the image. Specifically:

$$R(x, y) = \log(S(x, y)) - \log(G(x, y) * S(x, y)) \tag{2}$$

However, Retinex-based methods can disrupt the balance between light and dark in the original image, often resulting in over-enhancement. To address this, researchers developed methods such as MF [5] and LIME [6], which concentrate on processing the illumination component. MF employs a multi-scale approach to generate a new illumination component, effectively enhancing the image. LIME estimates the illumination of each pixel by identifying the maximum value in the R, G, and B channels and refines the initial illumination map using a structure prior, thus providing a more accurate representation of the illumination component. Nevertheless, these methods can introduce halos in the enhanced images.In conclusion, while traditional methods have made progress in increasing brightness, enhancing details, and preserving the original light-dark relationship, they still struggle to achieve a more comprehensive enhancement.

The development of deep learning has led to many data-driven low-light image enhancement algorithms. For example, RAW [7] proposed a new RAW-guided light enhancement network, which uses paired RAW images for

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DOI: 10.18293/SEKE2024-082

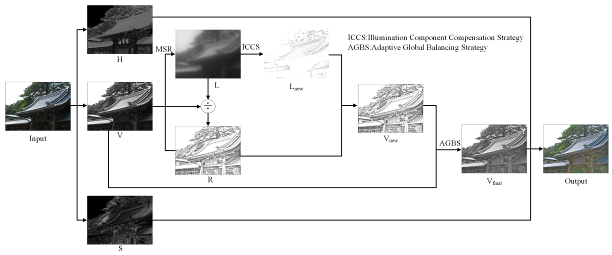

Figure 1: Algorithm Flowchart.

training, directly processes raw image data, and improves image quality without losing details. However, it may encounter problems of detail loss under extremely low-light conditions. Zero-DCE [8] enhances low-light images using a no-reference deep curve estimation method, increasing brightness and contrast under conditions of unpaired images, but may cause color distortion in high-contrast scenes. Ret-Net [9] combines Retinex theory and deep learning to improve illumination and color rendering, but there is room for improvement in noise control. ASV [10] balances illumination and reflection using a self-regularized model, but may result in detail loss under extreme low-light conditions. RUAS [11] uses unsupervised learning to optimize image quality, but lacks robustness in scenes with extremely wide dynamic ranges. SCI [12] processes low-light images with cascaded illumination learning processes and weight-sharing methods, providing a new perspective on handling low-light complexity, but may cause detail blurring in fast-changing scenes. LLDE [13] applies diffusion models to generate enhanced images, which may cause color distortion in high-contrast scenes. LLVIF [14] applies a variational inference framework to accurately separate reflection and illumination, reducing noise, but with high computational complexity, which may affect real-time processing efficiency. Although these methods have made significant progress in enhancing the quality of low-light images, they still face challenges in preserving details, color accuracy, noise control, and processing efficiency. In addition, deep learning methods require a large amount of computational resources and training data, and the complexity of the models may also prolong processing time.

In response to the limitations of existing low-light image enhancement methods, this study proposes a novel enhancement algorithm. The main innovations of this algorithm include:

- Using the Lambert reflectance model to initially estimate the reflectance of the image and further optimize it through refined adjustment functions.
- Separating the illumination component and the reflection component of the image's value component (V) through Gaussian filtering and precisely compensating the illumination component based on the reflectance.
- Introducing an adaptive global balance strategy to adjust the enhanced image to better match the brightness changes of the original image, optimizing the visual experience.

Compared with traditional and deep learning methods, this algorithm has certain advantages in improving the clarity of dark areas, maintaining the original brightness contrast of the image, and optimizing the overall visual effect. The structure of the article is divided into: Section II elaborates on the proposed algorithm in detail; Section III presents experimental results and evaluations; Section IV summarizes the entire article.

2 Proposed Method

In this section, we elaborate on the key technical details of the proposed image enhancement algorithm. Firstly, the algorithm transforms the image from the RGB color space to the HSV space, facilitating separate processing of the V component while maintaining the invariance of hue (H) and saturation (S). The entire process consists of three steps: firstly, employing multi-scale Gaussian filters to process the V component, separating reflection and illumination components; secondly, adjusting the illumination component through an illumination compensation strategy and combining it with the reflection component to generate an updated V component; thirdly, utilizing an adaptive global balancing strategy to merge the updated V component with the original V component through weighting, ultimately combining with the H and S components to form the enhanced image. Algorithm flowchart show in Fig. 1.

2.1 Estimating Illumination Component

Based on the Retinex theory, this study applies multi-scale Retinex (MSR) to process the V component of images. The objective is to separate the illumination and reflection components to enhance local contrast and details of the image while maintaining natural consistency in color and lighting. The calculation of the illumination component is as follows:

$$L(x,y) = \sum_{n=1}^{N} w_n \left(G(x,y) * S(x,y) \right) \tag{3}$$

similarly, the calculation of the reflection component is:

$$R(x,y) = \sum_{n=1}^{N} w_n \left(\frac{S(x,y)}{G(x,y) * S(x,y)} \right) \tag{4}$$

here, N represents the total number of scales, n denotes a specific scale, and w_n represents the weight for each scale.

The study selects three scales (5, 20, 100), each assigned equal weight ($w_1 = w_2 = w_3 = \frac{1}{3}$).

2.2 Derivation of Reflection Loss

In this section, we combine radiometry and photometry principles to explore the calculation of perceived brightness loss of reflected light after illumination hits the object surface. By analyzing factors such as radiant flux, reflectance, and human eye sensitivity to light, we establish a mathematical model that connects the physical properties of light with visual perception.

Radiometry and Photometry Principles From a radiometric perspective, radiant flux (Φ) is used to describe the total energy of the light source, while from a photometric perspective, luminance focuses on brightness perception, introducing illuminance (B_n) to quantify luminous flux. The emphasis is on using the luminous efficiency function $V(\lambda)$ to convert radiant flux into illuminance, establishing a connection between physical measurement and perceptual measurement.

$$B_n = K_m \cdot \Phi \cdot V(\lambda) \tag{5}$$

here, K_m represents the maximum spectral luminous efficiency of vision, with a value of 683 lm/W, reflecting the highest perceived brightness efficiency of light at a specific wavelength, typically peaking at 555 nm in green light.

Derivation of Reflectance-Energy Relationship Reflectance (r) represents the ratio of reflected light energy to incident light energy. The formula is expressed as:

$$E_n = E_0 \cdot r \tag{6}$$

where E_n represents the energy after reflection, E_0 represents the energy before reflection, and r represents the reflectance.

Radiant flux describes how quickly light energy is emitted, transmitted, or received. Therefore, the relationship between radiant flux (Φ) and light energy can be defined by the rate of radiation energy transmission, i.e.,

$$\Phi = \frac{dE}{dt} \tag{7}$$

where E represents radiant energy, and t represents time.

By combining equations (6) and (7), we obtain equation (8):

$$\Phi_n = \Phi_0 \cdot r \tag{8}$$

where Φ_n represents the radiant flux after reflection, and Φ_0 represents the incident radiant flux.

Detailed Derivation of the Mathematical Model According to the formula for converting radiant flux to illuminance, the illuminance B_0 of incident light with radiant flux Φ_0 is:

$$B_0 = K_m \cdot \Phi_0 \cdot V(\lambda) \tag{9}$$

and the illuminance B_n of light reflected from the object surface with radiant flux Φ_n is:

$$B_n = K_m \cdot \Phi_n \cdot V(\lambda) \tag{10}$$

Since K_m and $V(\lambda)$ remain constant in both states, it can be seen from equations (9) and (10) that there is a direct proportional relationship between the illuminance B_n of reflected light and the illuminance B_0 of incident light, as shown in equation (11):

$$B_n = B_0 \cdot r \tag{11}$$

This mathematical model provides us with a framework for quantifying and understanding the perceived brightness of reflected light and how to compensate for the loss of illumination component during the reflection process using principles of physics and photometry.

2.3 Illumination Component Compensation

Based on the derivation of reflection loss in Section 2.2, this section elaborates on the compensation strategy for the illumination component in image enhancement algorithms. After Gaussian filtering, we separate the illumination (L) and reflection (R) components from the V component of the image. The illumination component reflects the combined influence of light reflected from the object surface and scattered light in the atmosphere. The research focuses on analyzing and compensating for the loss of object-reflected illumination, without detailed consideration of the effects of atmospheric scattered light.

Reflectance Estimation In this study, we adopt the Lambertian reflectance model to estimate reflectance. This model assumes that the surface of an object reflects light with the same intensity regardless of the viewing angle and the direction of the light source. Widely used in computer graphics to simulate the reflection properties of non-emissive objects, the model's formula is:

$$I = I_0 \cdot r \cdot \cos(\theta) \tag{12}$$

where I represents the intensity of the reflected light; I_0 denotes the intensity of the incident light; r is the reflectance of the object surface, typically ranging from 0 to 1; θ is the angle between the incident light and the surface normal; $\cos(\theta)$ indicates the cosine value of the angle between the

(a) (b) (c)

Figure 2: (a) Original image, (b) Before using the Adaptive Global Balancing Strategy, (c) After using the Adaptive Global Balancing Strategy.

light ray and the surface normal, representing the influence of incident light intensity on reflected light intensity.

For simplification, we assume $\theta = 0°, I_0 = 255$, i.e., the light is vertically incident on the object surface, and the intensity of the incident light is 255. The minimum value of the RGB channels can better approximate the intensity of the reflected light since it is more likely to represent the weakest part of the illumination among all light sources, thus mitigating the influence of color saturation to some extent. Therefore, we set the value of I as the minimum value of RGB. This method provides an initial estimate of reflectance.

We found that when using the above formula for reflectance to enhance images, there is an issue of disrupting the original brightness relationship of the image. Therefore, we propose an optimization function for reflectance adjustment, formulated as:

$$\tilde{r} = \frac{1}{1 + e^{-\alpha(r_0 - \beta)}} \tag{13}$$

where $\tilde{r}$ is the optimized reflectance, r_0 is the initial estimated reflectance, α controls the curvature of the function, i.e., the rate of growth. Increasing the value of α makes the function steeper around the inflection point, thereby significantly increasing smaller reflectance values. β is the offset, determining the horizontal position of the center point of the optimization function. By adjusting β, the reflectance threshold can be controlled.

Illumination Component Compensation This section introduces an illumination component compensation strategy aimed at appropriately adjusting illumination components. The strategy consists of two steps: firstly, preliminary adjustment of the illumination component L to obtain an illumination component unaffected by atmospheric light; secondly, adjustment based on atmospheric light values and reflectance to ensure the authenticity and naturalness of the illumination component.

According to formula (11), the initial adjustment formula is:

$$L_0 = \frac{L - A * \tilde{r}}{\tilde{r}} \tag{14}$$

where L_0 represents the preliminary adjusted illumination component, L is the initial illumination component obtained through the MSR algorithm, A represents the adjusted local atmospheric light value, and $\tilde{r}$ is the reflectance of different regions in the image. Subtracting $A * \tilde{r}$ from L aims to reduce the influence of atmospheric light on the illumination component, allowing the illumination component to better reflect the brightness of the object itself rather than the lighting conditions of the external environment.

To precisely define the local atmospheric light, we extract the image luminance component from the CIE 1931 XYZ color space as the preliminary estimate of local atmospheric light $\tilde{A}$, and further optimize it through guided filtering to obtain the final local atmospheric light value A:

$$A = GF(\tilde{A}) \tag{15}$$

The calculation formula for the final illumination component is:

$$L_{final} = L_0 + A * \tilde{r} \tag{16}$$

where L_{final} represents the final illumination component, and L_0 represents the preliminary adjusted illumination component. By adding the adjusted atmospheric light value A and reflectance $\tilde{r}$ to L_0, we aim to restore the partial illumination information lost due to atmospheric scattering effects, preserving both the enhancement effect of object surface details and the naturalness and authenticity of the illumination component.

2.4 Adaptive Global Balancing Strategy

Following the illumination component compensation strategy in Section 2.3, we multiply the adjusted illumination and reflection components to obtain the enhanced V component, as shown in the formula below:

$$V_{new} = L_{final} \cdot R \tag{17}$$

The processed results exhibit phenomena of partial overexposure in certain regions, as shown in Fig 2(b). To address the issue of image overexposure, we consider blending the enhanced V component with the initial V component. Considering that fixed weights are difficult to balance between dark enhancement and overexposure suppression, we introduce an adaptive weighting strategy to adjust the blending weights. The weight calculation formula is:

$$\omega = 1 - \left(\frac{V}{255.0}\right)^{\gamma} \tag{18}$$

where γ controls the sensitivity of weight allocation. When V is small, the weight ω approaches 1, allowing the enhanced V_{new} to dominate; whereas when V is large, the weight ω approaches 0, enabling the initial V component to dominate. Through weight allocation, we can balance the issues of dark enhancement and bright overexposure.

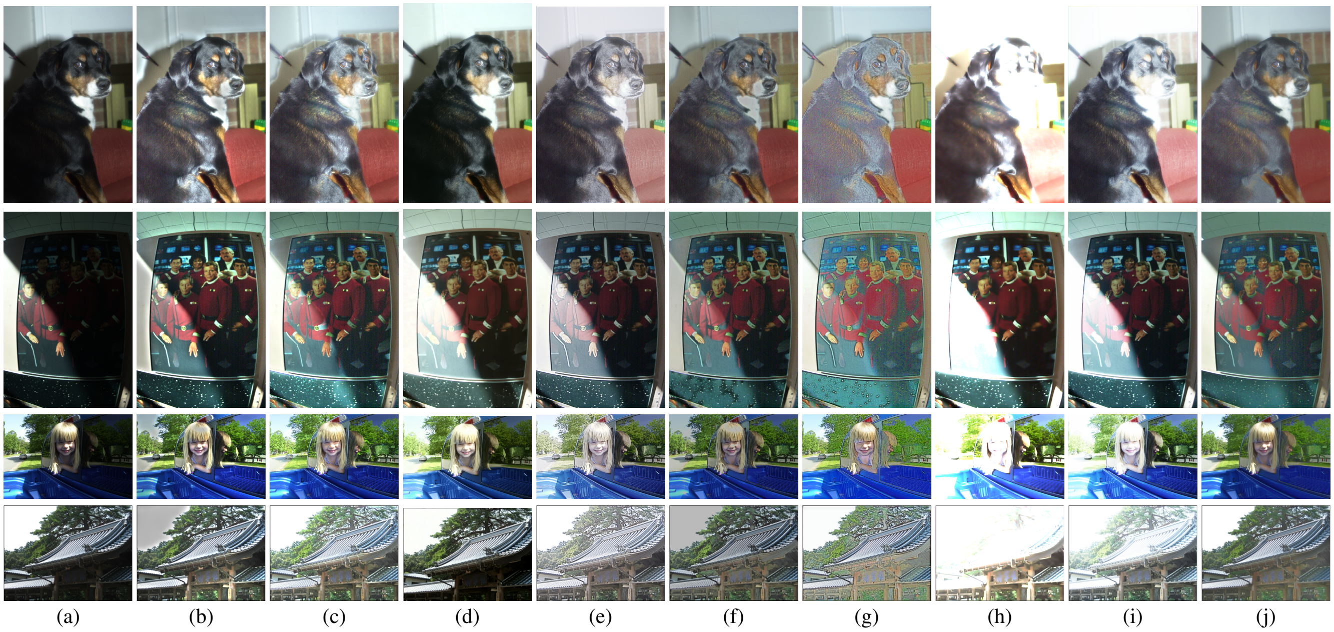

Figure 3: (a)Original image, (b) ASV, (c) LIME, (d) LLDE, (e) LLVIF, (f) MF, (g) Ret-Net, (h) RUAS, (i) SCI, (j) Proposed method. Note:img1 represents the image in the first row, img2 represents the image in the second row, and so on.

Finally, we use the calculated weight ω and its complementary weight $1-\omega$ to blend the enhanced and initial V components:

$$V_{final} = GF(\omega V_{new} + (1-\omega)V) \tag{19}$$

where V_{new} represents the enhanced V component, V represents the initial V component, and GF denotes guided filtering. The results before and after using the adaptive global balance strategy are shown in Fig 2.

3 Experimental Results

This study compares the proposed algorithm with two traditional methods (MF [5], LIME [6]) and six deep learning-based methods (Ret-Net [9], ASV [10], RUAS [11], SCI [12], LLDE [13], LLVIF [14]). All comparison methods are reproduced using publicly available source code and recommended parameters. Key parameter settings include: Gaussian filter scales of 5, 20, 100; reflectance adjustment parameters α as 5, β as 0.5; adaptive balance parameter γ as 0.3. Firstly, we evaluate the effectiveness of each method through visual comparison; secondly, we conduct objective evaluation using the no-reference image quality assessment metric PIQE [15].

3.1 Subjective Evaluation

Due to space limitations, we selected four representative images for display, as shown in the figure below.

For scenes with clear light and dark boundaries in natural light, ASV and LIME tend to produce halos and pseudo-images at the boundaries; LLDE unevenly brightens dark areas, with some areas like faces being prone to overexposure; LLVIF enhances overall but tends to bias towards white, affecting the original color tones; MF can cause brightness and darkness reversal and halos in certain scenes; Ret-Net results in more noise and loss of details; RUAS and SCI, while enhancing brightness significantly, may lead to overexposure in bright areas. In comparison, our algorithm avoids overexposure in bright areas while significantly improving brightness and detail preservation in dark areas. Experimental results are shown in Fig 3, img1 and img2.

In backlit natural light scenes, ASV excels in dark enhancement and color preservation but leads to unnatural brightness contrast in the sky area; LIME tends to cause color deviation in tree leaves and halo phenomena; LLDE and LLVIF, although effective in bright areas, exhibit insufficient performance in dark areas; MF significantly improves dark areas but may cause sky area reversal; Ret-Net, although somewhat effective in handling dark areas, overall demonstrates suboptimal performance with considerable noise. RUAS and SCI can enhance dark areas but result in sky overexposure. In contrast, our research algorithm effectively enhances dark areas while preserving color and brightness relationships, demonstrating better optimization results. Experimental results are shown in Fig 3, img3 and img4.

Overall, although each method has its characteristics and

Table 1: PIQE Score

Img	img1	img2	img3	img4	Avg
ASV	36.21	35.69	34.87	36.68	35.86
LIME	32.75	34.61	33.89	36.38	34.41
LLDE	28.48	65.22	38.71	43.45	43.96
LLVIF	34.38	28.61	30.87	38.67	33.13
MF	31.13	32.80	35.68	34.74	33.59
Ret-net	46.94	44.14	41.24	36.43	42.19
RUAS	31.70	41.82	35.90	60.48	42.48
SCI	31.91	32.65	38.24	39.81	35.65
Pro	31.46	31.45	30.80	30.21	30.98

limitations, the algorithm proposed in this study shows certain advantages in light-dark transitions, color preservation, and detail retention.

3.2 Objective Evaluation

In the experimental evaluation, this study adopts the no-reference image quality assessment metric PIQE (Perceptual Image Quality Evaluator) to accurately measure the image enhancement effect. PIQE, based on human visual perception design, evaluates image quality by analyzing key visual elements of the image such as contrast, texture, detail, and noise. Its advantage lies in simulating human eye response to changes in image quality and synthesizing both local and global statistical characteristics of the image, which are closely related to human visual perception. Therefore, PIQE is an effective tool for evaluating image quality in the absence of original reference images, where a decrease in score indicates an improvement in image quality. Detailed evaluation results are shown in Table 1.

In Table 1, red indicates the best result, and blue indicates the second-best result. The evaluation results show that our method performs excellently in PIQE scores, validating its superiority in image enhancement.

4 Conclusion

This study proposes a low-light image enhancement algorithm based on the Retinex theory. The algorithm is specifically designed for images captured under low-light conditions, effectively improving image brightness, contrast, and detail clarity while preserving natural colors and dynamic range through innovative reflectance estimation, illumination component compensation strategies, and adaptive global balancing strategies. Compared to traditional and deep learning methods, this algorithm demonstrates significant advantages in maintaining image brightness relationships, reducing overexposure, and enhancing visual effects. Experimental results confirm the efficiency and wide applicability of this method.

Acknowledgment

This work was supported by the Natural Science Foundation of Inner Mongolia under Grant 2021BS06004, Inner Mongolia University High Level Talent Research Launch Project under Grant 10000-21311201/068 and the fund of supporting the reform and development of local universities (Disciplinary construction).

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