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Illumination enhancement using adaptive regularization and an improved joint model

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Abstract. The Retinex method, inspired by human visual perception, has been widely used for image illumination enhancement due to its ability to effectively separate illumination and reflectance components. However, the problem of enhancing illumination while preserving details for images from different scenes remains a difficult task. This paper enhances the method proposed by Cai et al, referred to as 'JIEP', by using adaptive weighted regularization parameters based on brightness, achieving stable results with PSNR at 18, SSIM at 0.6, LOE (light order error) at 171, and ARIS at 2.02. The results indicate that the proposed method, a joint intrinsic-extrinsic prior model based on adaptive brightness weights (JIEP_ABW), preserves structural and detailed information while achieving high illumination authenticity.

Keywords. Image Enhancement, Computer Vision, Retinex

1. Introduction

The enhancement of illumination is a fundamental operation in the field of image processing, intending to improve the visual quality of images captured in conditions of poor lighting. Such conditions can result in a reduction in image contrast, loss of detail, color distortion, and a deterioration in visual quality, which can harm the performance of a range of computer vision applications. The Retinex theory, proposed by Edwin H. Land, describes the process of imaging a scene on a particular occasion in a manner that is analogous to the way in which the human visual system perceives light. The Retinex theory decomposes an image into two parts: illumination and reflectance. By enhancing these components separately, Retinex-based methods improve image visibility while retaining natural color reproduction.

1.1. Related work

Many techniques have been developed to improve the quality of images captured in low-light conditions. Traditional methods include histogram equalization and gamma correction, which are designed to improve image contrast and brightness. However, they tend to underperform in maintaining color fidelity and dealing with complex lighting variations. Over time, numerous enhanced Retinex algorithms have been proposed to address their shortcomings, including color distortion and poor saturation. For instance, to preserve structural information, Gao et al. performed a logarithmic transformation and Gaussian filtering on the luminance obtained after decomposition and adjusted the multiscale reflectance component (Gao, Su, and Xu 2022). Similarly, (Li et al. 2018). applied augmented Lagrange multipliers, gamma correction, and bootstrap matrices (Cai et al. 2017) proposed the joint interior-exterior a priori model while (Guo, Li, and Ling 2017) performed a structural prior, and (Xueyang et al. 2016) used a multiscale approach for a weighted combination of processed images. Additionally, a multiscale approach was employed by Ying et al, who introduced a camera response model for the synthesis of exposure images through a weighting matrix, thereby reducing image distortion (Ying, Li, and Gao 2017). Nevertheless, preserving structural information while simultaneously retaining sufficient texture details remains a significant challenge.

Furthermore, in addition to low-illumination images of common scenes, Retinex theory applies to images captured under extreme weather conditions. Furthermore, the method can be employed to decompose images into illuminance and reflectance (Chen et al. 2022; Lei et al. 2023), and can also be used to derive models for imaging airborne particles in extreme weather conditions. Examples of such models include the improved nighttime haze imaging model (Lin et al. 2022; Wang et al. 2022), and the sand reconstruction model (Si et al. 2022). The methods for processing images under extreme weather conditions can also inspire handling of low-light images. For instance, Cai et al. (2017) drew inspiration from the Dark Channel Prior (DCP) method used for dehazing images and employed a similar Bright Channel Prior to extract external brightness information as part of a joint model.

In recent years, there has been a shift towards the integration of traditional methods with deep learning. For instance, Feng et al. have employed the Retinex theory, which divides an image into two parts for processing, namely light and reflectance (Feng et al. 2024). They have applied this theory to the color space, proposing a two-branch processing approach. (Wei et al. 2018) concentrated on the enhancement of luminance following decomposition. (Cai et al. 2023) proposed the RetinexFormer algorithm, which considered corruption based on the original Retinex model. Although these methods yielded satisfactory outcomes, they were both time-consuming and challenging to implement. In certain instances, the enhanced traditional methods were found to be more concise and efficient.

Most referenced studies incorporate regularization parameters to balance parameter ranges and control smoothness. The effectiveness of these parameters can significantly influence the quality and performance of the model. However, tuning many regularization parameters can be time-consuming and labor-intensive, with the results of manual tuning being highly dependent on the specific dataset used. In image enhancement methods, regularization parameters may vary across different scenarios, leading to the development of distinct models. Consequently, the choice of regularization parameters is critical in determining the model's generalization ability and robustness.

Therefore, to preserve structural information while retaining sufficient texture details and enhancing the accuracy and robustness of image processing, this work improves upon the method proposed by Cai et al. by adding an adaptive weighted parameter based on brightness. The proposed improved method, named 'JIEP_ABW', is comprehensively evaluated, demonstrating the rationale and necessity of the enhanced method.

1.2. Research gap

Despite the advancements in Retinex-based image enhancement methods, there are still significant challenges in enhancing illumination while preserving structural details and texture information. Existing methods often suffer from issues like halo artifacts, poor performance in high dynamic range scenes, and color distortion.

2. Retinex method

2.1. The Retinex theory

The Retinex theory, by simulating the principles of retinal imaging, describes the process of forming a two-dimensional image. Its main idea is that the brightness of the external environment (i.e., illumination) and the intrinsic color of an object (i.e., reflectance) combine to form an image, as shown in Eq (1).

$$\mathrm{I}(\mathrm{x},\mathrm{y}) = \mathrm{R}(\mathrm{x},\mathrm{y})\mathrm{L}(\mathrm{x},\mathrm{y}) \tag{1}$$

It is generally used in image enhancement techniques to calculate the reflectance of an object based on the illumination obtained through filtering.

2.2. Intrinsic-extrinsic prior model

Bolun Cai et al., based on the ideas of Retinex theory, proposed a joint intrinsic and extrinsic prior model, which was named ‘JIEP’, by considering that the shape and texture of objects are intrinsic properties while illumination in a scene is an extrinsic property (Cai et al. 2017). This model uses Local Variation Deviation (LVD) as a shape before enhancing the distinction between texture and structure. It employs a texture before ensuring the piece wise continuity of reflectance and uses the bright channel before capturing illumination information. By inverting the image and using the atmospheric scattering model to estimate illumination, a joint objective function is finally established for optimization. The JIEP model is the focus for improvement in this paper

2.2.1. Intrinsic prior model

The shape prior is primarily utilized to maintain or restore the geometric structure and shape features within an image. The energy function, as shown in Eq. (2), can be understood as the combination of relative local deviation values in both the horizontal (x) and vertical (y) directions. These local deviation values are essentially the deviation values of the local image gradient features. They exhibit a weak correlation with texture but a strong correlation with shape, allowing for the effective elimination of texture effects while representing shape information. During image processing, the shape prior helps prevent the loss or distortion of important structures. Typically, the shape prior is based on the low-frequency components of the image, focusing on the overall contours and large-scale structures.

$$E_s(I) = \left|\left|\frac{\nabla_x I}{|\Omega|\sum_\Omega \nabla_x I+\epsilon}\right|\right|_1 + \left|\left|\frac{\nabla_y I}{|\Omega|\sum_\Omega \nabla_y I+\epsilon}\right|\right|_1 \tag{2}$$

In Eq. (2), ∇x/y represents the gradient operator, Ω denotes a local patch with a size of r × r, where r is set to 3 in this investigation, and ϵ is a small constant to prevent division by zero. Compared to the shape prior, the texture prior focuses on the details and texture information within the image, usually based on the high-frequency components of the image. Its energy function, as shown in Eq. (3), is expressed as the gradient of the reflectance R. The texture prior helps in recovering or maintaining the detailed features of the image, preventing the blurring and loss of details. The texture prior usually performs excellently when handling local features.

$$E_t(R) = \left|\left|\nabla_x R\right|\right|_1 + \left|\left|\nabla_y R\right|\right|_1 \tag{3}$$

2.2.2. Extrinsic prior model

The brightness information can be referenced from the dark channel prior in dehazing images. By removing the maximum value among the local three color channels (r, g, b) as the bright channel (B, $B = \max_{\Omega}(\max_{c \in \{r,g,b\}} S^c)$), the bright channel prior can be expressed in the form shown in Eq. (4).

$$E_l(I) = \left\| I - B \right\|_2^2 \tag{4}$$

2.2.3. Joint optimization

To simultaneously consider shape, texture, and brightness information, a joint prior model needs to be established (Eq. 5). In this model, α、β、λ are the regularization parameters for the shape prior, texture prior, and bright channel prior, respectively.

$$\mathrm{E(I, R)} = \left\| I \cdot R - S \right\|_2^2 + \alpha E_s(I) + \beta E_t(R) + \lambda E_l(I) \tag{5}$$

2.3. Evaluation Metrics for Image Quality

2.3.1. Light order error (LOE)

Light Order Error (LOE) is a metric used to measure the accuracy of an image enhancement algorithm in restoring the illumination order of an image. It was proposed by (Wang et al. 2013) as a measure to objectively assess the naturalness preservation. It evaluates the difference between the illumination order of different regions in the enhanced image and the actual scene. Typically, a smaller illumination order error indicates that the enhanced image's illumination order is more consistent with the real scene, displaying a more natural and realistic illumination effect.

The quantitative LOE measure based on the lightness order error between the original image I and its enhanced version I_e. The lightness L(x, y) of an image is given as the maximum of its three color channels:

$$L(x, y) = \max_{c \epsilon \{r,g,b\}} I^c(x, y) \tag{6}$$

For each pixel (x, y), the relative order difference of the lightness between the original image I and its enhanced version Ie is defined as follows:

$$RD(x, y) = \sum_{i=1}^{m} \sum_{j=1}^{n} \Big(U(L(x, y), L(i, j)) \oplus U\big(L_e(x, y), L_e(i, j)\big) \Big) \tag{7}$$

$$U(x, y) = \begin{cases} 1, & for\ x \geq y \\ 0, & else \end{cases} \tag{8}$$

where m and n are the height and the width, U(x,y) is the unit step function, ⊕ is the exclusive-or operator

$$LOE = \frac{1}{m*n} \sum_{i=1}^{m} \sum_{j=1}^{n} RD(i, j) \tag{9}$$

2.3.2. Autoregressive-based image sharpness metric (ARISM)

ARISM (Autoregressive-based Image Sharpness Metric) is an image sharpness evaluation metric based on an autoregressive model, used to quantify the clarity and sharpness of an image. A smaller ARISM value indicates that the edges and details of the image are clearer and sharper, representing that the processed image retains better edge and detail information.

3. Methodology

Although the shape prior and texture prior consider the overall structure and details of the image to some extent, in the Retinex model, the illumination and reflectance are often unevenly distributed. Fixed parameters may not be effective across all image regions simultaneously. Moreover, the distribution of illumination and reflectance can vary significantly across different scenes, and fixed parameters might only be suitable for specific scenarios. In this context, adaptive parameter adjustment becomes particularly important. It not only handles the balance of parameters across different regions and scenes but also reduces the need for extensive manual tuning.

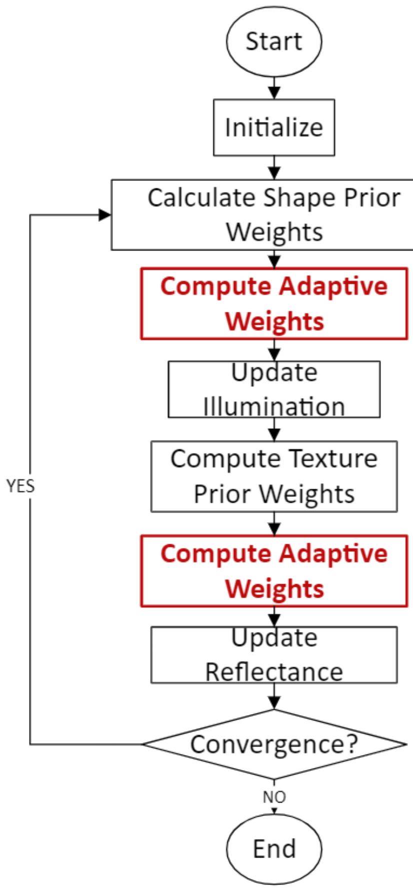


Figure 1 Flow chart of the proposed method, the red boxes indicate the improvement to the original method

Therefore, this paper employs an adaptive parameter adjustment to optimize the original model's parameters, for enhancing processing efficiency and improving accuracy. Compared to the original model, Fig. 1 shows that the proposed model includes an adaptive weighting component, shown in red. Before updating the illumination and reflectance, the adaptive weights are considered, meaning that when solving the linear equations for both illumination and reflectance, the values of the five-point positive definite Laplacian matrix are adjusted using adaptively tuned parameters.

3.1. Adaptive regularization parameters

Given that the original model is designed to preserve more image texture and detail and is based on Retinex theory with priors for brightness, shape, and texture, this investigation primarily focusses on the 2 simple adaptive regularization parameters methods, adaptively adjusting based on the gradient and brightness parameters.

The adaptive regularization formula based on luminance difference is illustrated in Eq. (6), where I is the illumination of the image. This formula employs a decay function to adjust the luminance based on the difference between the local luminance and the local luminance mean. The method is computationally straightforward and is frequently utilized for images exhibiting uneven lighting or pronounced light variations. Its objective is to dynamically adjust the weights to enhance image processing.

$$adaptive\ weights = \exp(-|I - mean(I)|) \tag{6}$$

The adaptive regularization formula based on gradient difference is presented in Eq (7). The fundamental concept is to modify the regions exhibiting significant gradient values in both the horizontal (I_x) and vertical directions (I_y), specifically edges and details, through the utilization of a decay function. This approach aims to prevent the blurring of edges while preserving details. The method is computationally complex and typically highly sensitive to high-frequency information (e.g., texture and details). It is capable of effectively distinguishing between smooth regions and detail-rich regions and adjusting the regularization strength in a targeted manner to reduce noise while preserving details.

$$adaptive\ weights = exp\left(-\gamma \cdot \sqrt{(I_x)^2 + \left(I_y\right)^2}\right) \tag{7}$$

4. Evaluation

In this section two commonly used adaptive regularization parameters methods are explained: the brightness-based adaptive weighting method, named ‘JIEP_ABW’, and the gradient-based adaptive weighting method, named ‘JIEP_AGW’. A comprehensive analysis of these two methods through various experiments is conducted, comparing their visual effects and evaluation metrics to determine which performs better as our proposed method. Subsequently, this method will be compared with the seven methods to further demonstrate the practicality and superiority of our proposed approach.

For objective evaluation comprehensively, in addition to using basic metrics such as PSNR and SSIM, this investigation also employs LOE to describe the authenticity of the illumination effect in the processed images and ARISM to describe the retention of edge details in the processed images.

4.1. Comparisons between the 2 adaptive methods

By Retinex theory, the image can be partitioned into two constituent parts: luminance and reflectance. Figure 2 illustrates the outcomes of a comparative analysis between the two adaptive methodologies (JIEP_ABW and JIEP_AGW) and the original methodology (JIEP) in terms of luminance and reflectance.

As illustrated in Fig. 2 (b) and (c), there is minimal discernible difference in luminance and reflectance when compared to Fig. 2 (a). Upon closer examination, it becomes evident that Fig. 2 (c) exhibits a more discernible structure of the circular roof area at the top of the image on the luminance map, whereas the reflectance map shows no notable alterations, in contrast to the observations made in Fig. 2 (b). This suggests that the impact of the gradient difference-based adaptive regularization adjustment on the structure and texture is not readily discernible, potentially due to the original model already exhibiting a high degree of accuracy in these domains. In contrast, the application of adaptive regularization adjustment based on luminance difference can assist the model in capturing a greater quantity of luminance information, thereby enhancing the accuracy of the model's processing.

In this work, 71 images from the LIME (Guo, Li, and Ling 2017), MF (Xueyang et al. 2016), and DICE datasets were processed using four different methods: the original method (JIEP), the method with adaptive weight adjustment of regularization parameters based on gradient difference (JIEP_AGW), and the method with adaptive weight adjustment of regularization parameters based on illumination difference (JIEP_ABW), the evaluation of the average metric as shown in Table 1.

The results presented in Table 1 indicate that the gradient difference-based adaptive regularization (JIEP_AGW) is not as effective as the original method (JIEP) in retaining details, although it may offer superior color realism, which is evidenced by the lower LOE but higher ARISM values. In contrast, the brightness-based adaptive regularization (JIEP_ABW) is optimized stably in all metrics, thereby retaining more structural texture information to a certain extent. Furthermore, it is more likely to result in more realistic colors, which is in line with the visual effect in Fig. 2.

Table 1 Evaluation Results of 2 Methods

	JIEP	**JIEP_AGW**	**JIEP_ABW**
Average PSNR	18.02685348	0.22%	0.35%
Average SSIM	0.577356517	0.92%	2.30%
Average LOE	171.850773	-2.01%	-0.73%
Average ARISM	2.048052129	4.86%	-1.23%

The performance of JIEP_AGW is not as strong as that of JIEP_ABW, likely because the original method focuses more on preserving image structure and texture. Both the shape prior for structure preservation and the texture prior for details preservation proposed by Cai, are closely related to gradients. The original method already fine-tunes gradient-related parameters to ensure the integrity of texture and structural information in the image. Consequently, using gradient-based adaptive parameters may result in a higher ARISM value, indicating a loss of structural and textural details. In contrast, the original method's bright channel prior primarily extracts brightness information, which is slightly less refined. This presents an opportunity for us to employ adaptive regularization parameters to better adjust brightness-related information.

In short, the adaptive brightness weights method is much more suitable for JIEP to enhance the details preserving and color realism both subjective and objective. Through this modification, the ability of the algorithm has been increased effectively to handle the diversity of image features, enhanced the robustness of the model, and significantly improved the visual quality and stability of the results. So JIEP_ABW is chosen as the proposed method and compare it with other Retinex methods later.

(a) JIEP

(b) JIEP_AGW

(c) JIEP_ABW

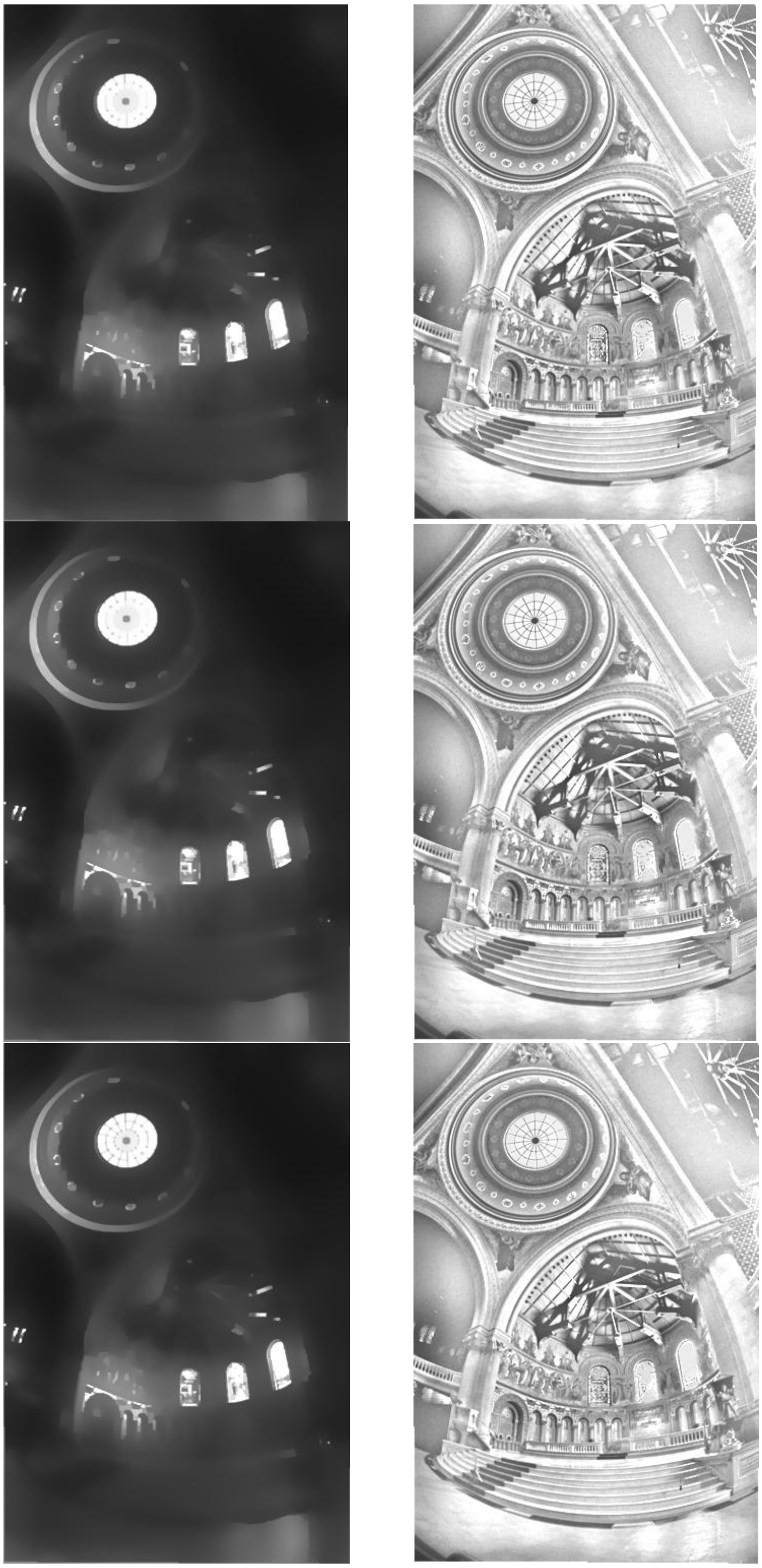
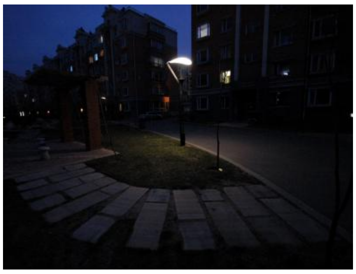


Figure 2 Comparisons of the illumination (the first column) and reflectance (the second column)

4.2. Comparison with other 7 Retinex methods using a single image

Figure 3 below displays the results of the seven methods (Robust Retinex (Li et al. 2018), BIMEF (Ying, Li, and Gao 2017), LIME, MF, NPE (Wang et al. 2013), PM_SIRE (Fu et al. 2015) and JIEP (Cai et al. 2017)), along with our JIEP_ABW, applied to the same image. It also provides the respective PSNR, SSIM, LOE, and ARISM metrics for each method.



(a) Original image
PSNR: none
SSIM: 1
LOE: 0
ARISM: 1.435668835

(b) Robust Retinext
PSNR: 12.86372655
SSIM: 0.273329332
LOE: 202.5212
ARISM: 1.721655871

(c) BIMEF
PSNR: 13.40256446
SSIM: 0.261726111
LOE: 208.4268
ARISM: 1.687481696

(d) LIME
PSNR: 8.77305831
SSIM: 0.116105864
LOE: 493.214
ARISM: 1.799193748

(e) MF
PSNR: 12.14132189
SSIM: 0.204669894
LOE: 217.3768
ARISM: 1.696512411

(f) NPE
PSNR: 11.28724151
SSIM: 0.180828043
LOE: 537.4356
ARISM: 1.7248781

(g) PM_SIRE
PSNR: 16.80570756
SSIM: 0.435291691
LOE: 230.6688
ARISM: 1.602846309

(h) JIEP
PSNR: 16.54882389
SSIM: 0.313307941
LOE: 217.768
ARISM: 1.629989578

(i) JIEP_ABW
PSNR: 16.74279256
SSIM: 0.403347708
LOE: 194.5212
ARISM: 1.624679558

Figure 3 Comparisons of 9 methods with their respective evaluation metrices

From the perspective of image information, the overall color of Fig. 3 (c) tends to be yellowish, with some distortion in the sky areas, giving the images a somewhat hazy and blurry appearance. Fig. 3 (d) - (f) exhibit significant distortion while Fig. 3 (b), and Fig. 3 (g) - (i) appear relatively more realistic. Among these latter, Fig. 3 (b) is relatively brighter but shows some color distortion, especially in the sky area, which lacks the layered texture of a real image. Fig. 3 (g), although initially presenting a clearer and more realistic visual effect, shows large black areas at the edges of the image, particularly in the grass below the white stone bricks at the bottom of the image. This gives the overall image an unrealistic look, with only the central area appearing bright while the surroundings are dark. Fig. 3 (h) and Fig. 3 (i) are almost indistinguishable visually, both offering good visual effects.

The metric information corresponding to this image is consistent with the visual effects as well. Except for Fig. 3 (c), images with significant distortion exhibit lower PSNR and higher ARISM values. Fig. 3 (d) and Fig. 3 (f), which show noticeable color distortion, have higher LOE values compared to the other groups. Fig. 3 (g) - (i) show little difference in metrics and exhibit better visual effects. Although Fig. 3 (g) retains more structural information and appears clearer, they lack the realism of the other two images and have higher LOE values.

4.3. Comprehensive comparison with Robust Retinex and PM_SIRE

To further demonstrate the advantages of our proposed method in enhancing visual effects, two methods from Fig 3 that consistently produced the best visual results—Robust Retinex and PM_SIRE, were selected. These methods were chosen for a more comprehensive comparison with our approach, ensuring that the evaluation is not biased by the performance of only one single image and reduce the risk of any single image disproportionately influencing the results.

By comparing these top-performing methods, this research aim to demonstrate the robustness and effectiveness of our method across different scenarios, thereby providing a more reliable and convincing assessment of its visual enhancement capabilities.

Fig. 4 presents the processing results of 3 kinds of images under different scenes using these three methods.

As shown in the figure, Fig. 4 (a)-(c) represents an outdoor overexposed image, an outdoor underexposed image, and an indoor low-light image, respectively. The Robust Retinex method provides some enhancement across these three scenarios, effectively restoring details in overexposed areas. However, the processed images tend to have dull colors and lack realism. In contrast, the PM_SIRE method produces more realistic color effects, but it fails to restore many details across all three scenarios, leaving several black regions in the processed images. Our proposed method, on the other hand, achieves better visual effects in both detail preservation and color reproduction. Even in the strongly overexposed environment of Fig. 4 (a), it retains the edge structure information of the hot air balloon on the right.

The results of the three methods in Fig. 4 for the 71 images are shown in Table 2, and the average metrics results are referenced to the JIEP method.

The results indicate that, while the Robust Retinex method exhibits superior quality and structural similarity to the JIEP method, its LOE value is relatively high. This may result in image color distortion, which is also evident in the visual effect depicted in Fig. 4. The PM_SIRE method exhibits superior image quality and color realism in comparison to our method, as well as the retention of more structural information. However, when considered alongside the visual effect depicted in Fig. 4, the processed result cannot discern a substantial amount of detail due to the uneven brightness of the image and the insufficient brightness in the exposure area. It should be noted that ARISM is only capable of measuring image clarity and sharpness to a limited extent. Consequently, it is not a wholly representative measure of visual effects. This illustrates that the aforementioned four indicators may be insufficient for fully describing the visual effect of the image to some extent and that our evaluation method is not yet comprehensive.

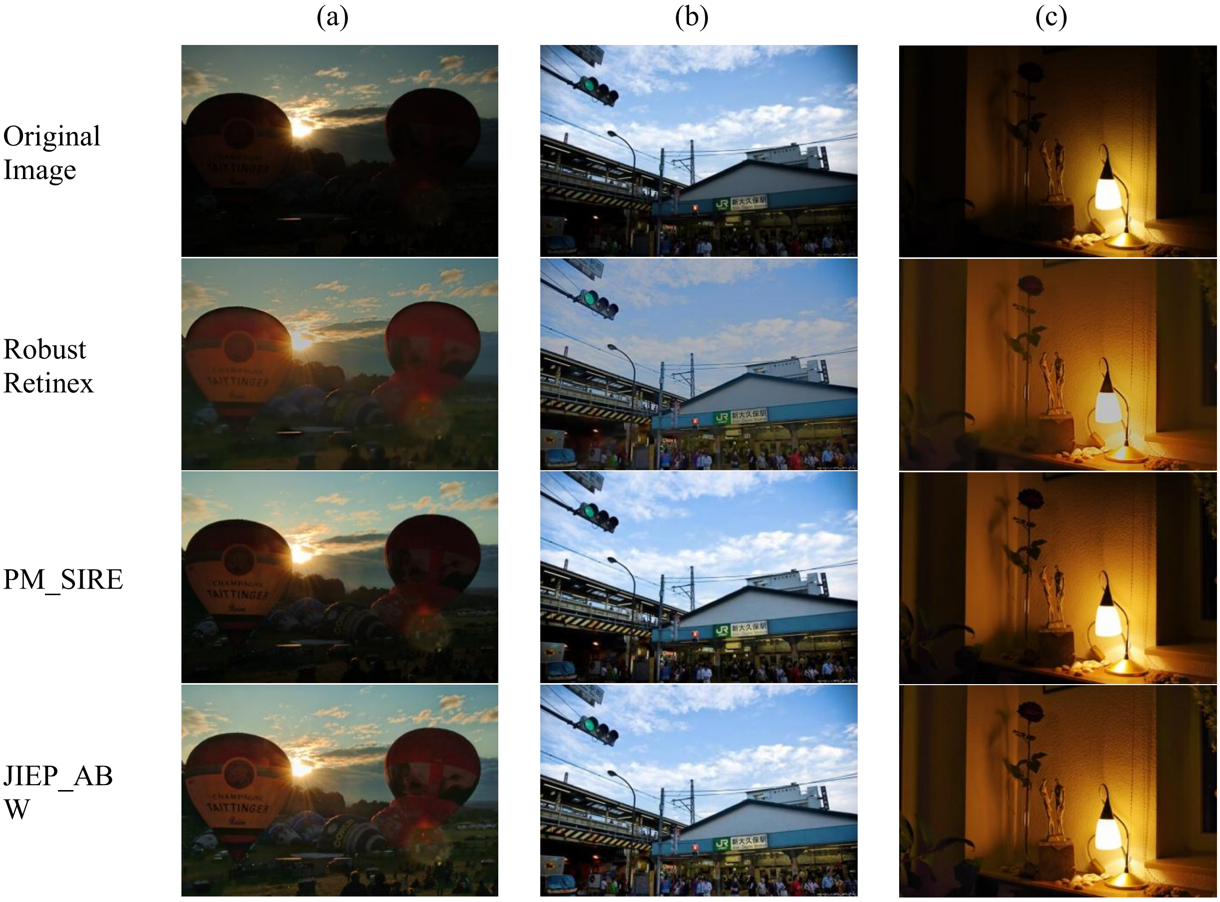


Figure 4 Comparisons of different images using 3 methods with (a) representing an outdoor overexposed image, (b) an outdoor underexposed image, and (c) an indoor low-light image.

Table 2 Evaluation results of 3 methods for 71 images

	JIEP	Robust Retinex	PM_SIRE	JIEP_ABW
Average PSNR	18.02685348	7.33%	5.41%	0.35%
Average SSIM	0.577356517	9.37%	9.37%	2.3%
Average LOE	171.850773	36.84%	-15.78%	-0.73%
Average ARISM	2.048052129	-4.67%	-7.36%	-1.23%

For our JIEP_ABW, steady improvements across all four metrics, although the enhancements were relatively modest when it compared to the other two methods. These results suggest that JIEP_ABW maintains a solid performance, balancing structure and brightness enhancement effectively. Despite the smaller gains, the method's consistent performance indicates that it remains a reliable option, particularly in scenarios where preserving image detail and structure is important.

In conclusion, the method proposed in this paper (JIEP_ABW) can to a certain extent, enhance the precision of the model image processing while also exhibiting a superior visual effect, rendering it well-suited for a diverse range of practical applications.

5. Conclusion

This paper presents a joint Intrinsic-Extrinsic prior based on adaptive brightness weights (JIEP_ABW), that effectively addresses halo artifacts, poor performance in high dynamic range scenes, and color distortion by incorporating adaptive regularization parameters. Experiments on 71 images from the LIME, MF, and DICE datasets demonstrated that the proposed method outperforms existing methods (Robust Retinex (Li et al. 2018), BIMEF, LIME, MF, NPE, PM_SIRE and JIEP (Cai et al. 2017)) in key metrics such as PSNR at 18 with 0.35% percentage improvement, SSIM at 0.6 with 2.3% percentage improvement, LOE at 171 with 0.73% percentage improvement, and ARISM at 2.02 with 1.23% percentage improvement, resulting in better visual quality and detail preservation.
A novel approach was presented to improving existing image brightness enhancement methods by integrating prior models with adaptive regularization parameters. Future work could explore integrating other more complex adaptive regularization parameters, such as multi-scale adaptive regularization, learn-based adaptive regularization, and so on, to further enhance this approach and extend its application to more complex real-world scenarios, providing a robust and effective solution for image illumination enhancement.

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