

COMBINED DISCRETE WAVELET TRANSFORM AND NOISE-PRIOR RETINEX MODEL FOR NOISY LOW-LIGHT IMAGE ENHANCEMENT

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ABSTRACT

Retinex-based low-light image enhancement methods have drawn significant interest due to their excellent performance and extensibility. However, most of them exhibit poor robustness when images are corrupted by noise. The main reason is that traditional Retinex models cannot effectively characterize the coupling between noise, reflectance, and illumination in noisy low-light images. To address this limitation, this paper modifies the existing noise-aware Retinex model to better characterize the noise component during noisy image decomposition. To further model the noise distribution, the discrete wavelet transform (DWT) is employed to construct a noise prior in the wavelet domain, which effectively captures noise information in different frequency subbands. Furthermore, contour, texture, and noise gradient correlations are incorporated as prior terms for the illumination, reflectance, and noise components, respectively, leading to a unified optimization model. In addition, an improved illumination stretching function is designed to enhance image contrast while suppressing halo artifacts and noise. Experimental results demonstrate that the proposed algorithm achieves competitive performance compared with representative Retinex-based methods and state-of-the-art deep learning-based low-light enhancement methods in terms of noise robustness and quantitative performance.

Keywords: discrete wavelet transform, image enhancement, noise suppression, Retinex theory.

INTRODUCTION

Low-light image enhancement is a critical technology in computer vision, aiming to adjust the color distribution and balance the brightness distribution of images, thereby enhancing overall contrast. By improving image quality, this process facilitates subsequent tasks such as image understanding and advanced image processing.

Recently, the popular low-light image enhancement methods can be broadly categorized into learning-based methods (Li *et al.*, 2021; Liu *et al.*, 2019; Zhao *et al.*, 2021; Wang *et al.*, 2023) and Retinex-based methods (Liu *et al.*, 2021; Guo *et al.*, 2016; Li *et al.*, 2018; Xu *et al.*, 2020). Learning-based methods achieve low-light image enhancement by capturing the complex features of the images through a designed multi-layer network structure. However, these methods typically require extensive training data and preprocessing efforts. Retinex-based methods have attracted much attention due to their high efficiency and interpretability. Notably, Retinex-based algorithms account for over 25% of all existing low-light image enhancement methods (Qi *et al.*, 2021).

Retinex theory was first proposed by Land and McCann (1971), which decomposes a scene into illuminance and reflectance components, and then processes the illumination component to improve the visual effect. Its main applications are scene image enhancement, and color correction (Zhang *et*

al., 2022; Lin *et al.*, 2023). Nowadays, Retinex-based low-light image enhancement methods can be broadly divided into two classes: classical methods and variational methods. Next, we provide an overview for the variational Retinex-based low-light image enhancement methods.

Variational methods (Palma-Amestoy *et al.*, 2008; Kimmel *et al.*, 2003; Ng and Wang, 2011) formulate image decomposition as a variational optimization problem. Kimmel *et al.* (2003) introduced the variational framework (VF), which represents the first Retinex-based variational algorithm. To decompose the image, VF constructs an objective function that incorporates a smoothness prior term for the illumination component. While this framework demonstrates parameter robustness and computational efficiency, it lacks a prior term for the reflectance component. Building on this, Ng and Wang (2011) incorporated the reflectance component into the objective function and proposed a Retinex-based total variation model (TVM), which employs Bregman iteration to solve the optimization problem. While TVM achieves improved enhancement performance, it suffers from some loss of detail preservation due to the side effects of logarithmic transformation. Wang *et al.* (2014) introduced a variational Bayesian method (VBM), which leverages Gibbs distributions as prior information for both reflectance and illumination components and constructs a hierarchical Bayesian model. VBM provides superior visual quality and requires fewer parameters. Fu *et al.*

(2015) presented a simultaneous reflectance and illumination estimation (SRIE) algorithm, which formulates a maximum a posteriori (MAP)-based probabilistic model to decompose the scene in the linear domain. SRIE demonstrates excellent enhancement performance. To further enhance performance, Fu *et al.* (2016) introduced weighted parameters to refine the regularization terms and proposed a weighted variational model (WVM). While WVM achieves satisfactory enhancement effects and computational efficiency, it may disrupt brightness information in the scene due to the unconstrained smoothing of the illumination prior term. Guo *et al.* (2016) presented a low-light image enhancement via illumination map estimation (LIME). This algorithm constructs the initial illumination component by selecting the maximum pixel values across the R, G, and B channels in images and then refines the illumination component using prior information. Additionally, LIME relies solely on the illumination component for image enhancement, which reduces the number of parameters and improves computational efficiency. Cai *et al.* (2017) proposed a joint intrinsic-extrinsic prior (JieP) model, which incorporates local variation deviation as a structure-preserving measure to characterize the properties of three-dimensional objects in the scene. This model demonstrates excellent structure-preserving capabilities. To enhance the noise robustness of the algorithm, Li *et al.* (2018) introduced a robust Retinex model (RRM), which extracts noise by incorporating a noise component into the Retinex-based objective function to isolate noise points. While RRM exhibits certain noise robustness, it remains sensitive to high-intensity noise due to its failure to account for noise in both the illumination and reflectance components. Xu *et al.* (2020) employed an exponentialized mean local variance (EMLV) filter to extract structure and texture maps from low-light images and proposed the structure and texture aware Retinex (STAR) algorithm. STAR achieves superior visual quality and detail preservation. However, it requires tuning numerous parameters and involves two iterative steps to complete the enhancement. To remove noise in low-light images, Ren *et al.* (2020) presented a low-rank regularized Retinex model (LR3M). LR3M incorporates a low-rank prior into the Retinex model to suppress noise in the reflectance component and employs piece-wise smoothed illumination to eliminate noise in both reflectance and illumination components, respectively. Meanwhile, Hao *et al.* (2020) proposed a low-light image enhancement method based on semi-decoupled decomposition (SDD). This algorithm designs a Gaussian Total Variation (GTV) filter to estimate the illumination component and constructs a joint Retinex-based

framework to estimate the reflectance component. SDD effectively suppresses imaging noise in the reflectance component and provides satisfactory results. However, SDD remains sensitive to noise when the image is corrupted by strong noise. Cai and Chen (2023) introduced a brain-like Retinex (BRAIN) algorithm. This method extracts image edges, separates them into contour and texture gradient, and incorporates these image details as prior information to construct a variational Retinex model. BRAIN demonstrates superior scalability and enhancement performance. Li and He (2024) proposed a fractional structure and texture-aware Retinex (FSTAR) algorithm. FSTAR introduces the Maximum Fractional Difference (MFD) as a structure-aware measure and constructs fractional structure-texture maps as weighting matrices in the regularization terms for illumination and reflectance. FSTAR achieves robust enhancement effects and maintains an appropriate illumination range in low-light images.

Although the aforementioned methods have been widely adopted due to their impressive enhancement performance, most of them remain sensitive to noise. As illustrated in Fig. 1, RRM fails to completely isolate noise during decomposition, resulting in residual noise in the estimated reflectance and illumination components. This issue primarily arises because the employed prior information is sensitive to regions with drastic color variations, where noise is often misinterpreted as part of the reflectance component. Moreover, when the image is corrupted by high-intensity noise, simple smoothing or blurring operations are insufficient to remove most of the noise, leading to residual noise in the illumination component. Due to these decomposition inaccuracies, existing noise-related Retinex models struggle to reliably decompose noisy low-light images. These limitations highlight the necessity of a more robust Retinex formulation capable of explicitly modeling and separating noise in both reflectance and illumination components.

In this paper, we first analyze the limitations of existing Retinex-based methods in handling noisy low-light images. Then, we propose an improved noise-aware Retinex model, which explicitly decouples the noise component from the reflectance component, thereby enabling more reliable decomposition for noisy low-light images. Based on this model, contour and texture gradient priors are incorporated to preserve structural details while suppressing noise. Furthermore, an edge-suppressed wavelet-domain noise prior and a gradient-consistency constraint are introduced to improve noise robustness and prevent structural edges from leaking into the

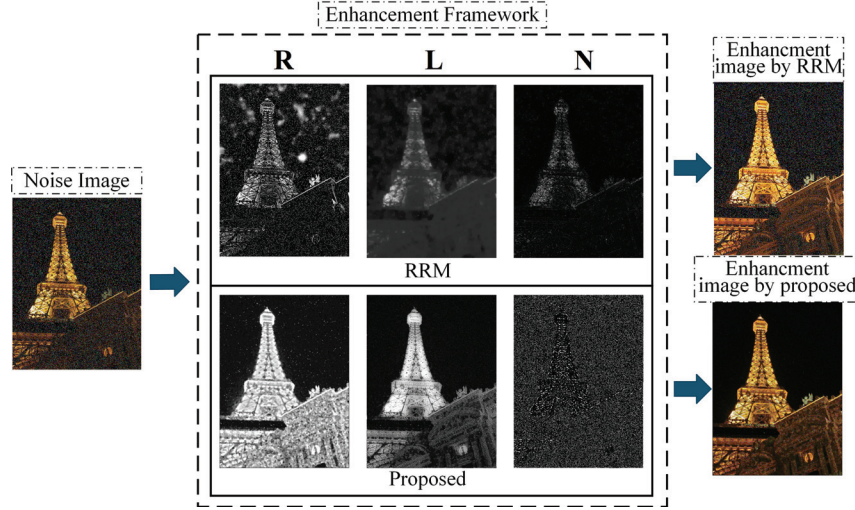


Fig. 1. Visual components of robust local information Retinex model and robust Retinex model

noise estimation. Overall, a robust Retinex-based enhancement framework is developed to jointly perform low-light enhancement and noise removal.

The contributions of this work are summarized as follows:

1. An improved noise-aware Retinex model is formulated for noisy low-light image decomposition, in which the noise component is explicitly introduced and linearly decoupled from the reflectance component to achieve more robust estimation of the illumination, reflectance, and noise components.
2. By utilizing contour, texture gradient, and an edge-suppressed high-frequency prior derived from the reflectance component as priors for the illumination, reflectance, and noise components, respectively, a unified Retinex-based enhancement framework is developed for the joint estimation of illumination, reflectance, and noise components.
3. An improved illumination stretching function is designed to enhance the illumination component while suppressing noise amplification, thereby effectively reducing halo artifacts and residual noise in the enhanced images.
4. Experimental results on various low-light image datasets demonstrate that the proposed algorithm achieves competitive performance compared with representative Retinex-based and deep learning-based methods under both noisy and noise-free conditions.

The rest of this paper is organized as follows. Section 2 introduces the theoretical background and related Retinex-based methods. Section 3 presents the proposed noise-aware Retinex model and its optimization framework. Section 4 reports and analyzes

the experimental results. Section 5 discusses the methodological characteristics and limitations of the proposed algorithm. Finally, Section 6 concludes the paper.

RELATED WORK

This section presents the theoretical background of Retinex-based image enhancement algorithms and the discrete wavelet transform. In the following derivation, I denotes the input color image, and S denotes a single-channel image to be enhanced. For most Retinex models, S can be regarded as the value channel of I in the HSV color space.

RETINEX MODEL

The classic Retinex model generally processes the value channel S to decompose the image. The Retinex model assumes that the value channel S can be decomposed into the illumination component L and the reflectance component R , which is given as follows:

$$S = L \circ R \quad (1)$$

where the $\circ$ represents the element-wise multiplication. Based on the Retinex model, the related optimization model is given by:

$$\arg \min_{R, L} \|S - R \circ L\|_F^2 + \alpha \mathcal{R}_1(R) + \beta \mathcal{R}_2(L) \quad (2)$$

where α and β denote the weight of prior terms for R and L , respectively. $\|\cdot\|_F$ is the Frobenius norm. The prior term $\mathcal{R}_1(R)$ ensures that the reflectance component is close to the gradient image ∇S , and

the prior term $\mathcal{R}_2(\mathbf{L})$ ensures that the illumination component is smooth.

The classical Retinex model decomposes an image into illumination and reflectance components, and then adjusts the illumination component to improve visual quality. However, the prior term of $\mathbf{R}$ considers the gradient information, resulting in sensitivity to noise.

ROBUST RETINEX MODEL

To improve the robustness and enhancement performance of the algorithm, Li *et al.* (2018) proposed the RRM, which introduces the noise component in the classic Retinex model. The RRM is given as follows:

$$\mathbf{S} = \mathbf{L} \circ \mathbf{R} + \mathbf{N} \quad (3)$$

where $\mathbf{N}$ denotes the noise component. Based on this, the related optimization model is given by:

$$\begin{aligned} \arg \min_{\mathbf{R}, \mathbf{L}, \mathbf{N}} & \|\mathbf{S} - \mathbf{R} \circ \mathbf{L} - \mathbf{N}\|_F^2 + \alpha \|\nabla \mathbf{L}\|_1 + \beta \|\nabla \mathbf{R} - \mathbf{W}\|_F^2 \\ & + \delta \|\mathbf{N}\|_F^2 \end{aligned} \quad (4)$$

where δ is the weight of the prior term for the noise component, $\mathbf{W}$ is the amplified image gradient. Through the alternating direction method of multipliers (ADMM) (Boyd *et al.*, 2011), the iterative formulas of reflectance, illumination and noise components are shown as follows:

$$\mathbf{r} = \frac{(\bar{\mathbf{l}})^T (\mathbf{s} - \mathbf{n}) + \beta \mathbf{D}^T \mathbf{w}}{(\bar{\mathbf{l}})^T \bar{\mathbf{l}} + \beta \mathbf{D}^T \mathbf{D}} \quad (5)$$

$$\mathbf{l} = \frac{2(\bar{\mathbf{r}})^T (\mathbf{s} - \mathbf{n}) + \mu \mathbf{D}^T (\mathbf{t} - \frac{\mathbf{z}}{\mu})}{2(\bar{\mathbf{r}})^T (\bar{\mathbf{r}}) + \mu \mathbf{D}^T \mathbf{D}} \quad (6)$$

$$\mathbf{N} = (\mathbf{S} - \mathbf{R} \circ \mathbf{L}) / (1 + \delta) \quad (7)$$

where $\mathbf{r}$ is the vectorized form of $\mathbf{R}$, and $\bar{\mathbf{r}}$ is the diagonal matrix about $\mathbf{r}$. The same notation is also applied to other matrices, such as $\mathbf{l}$, $\mathbf{n}$, etc. The $\mathbf{z}$ and μ are the Lagrange multiplier and positive scalar in ADMM. The RRM first incorporates noise into the Retinex model, which improves robustness to some extent. However, its noise prior assumes that the noise is sufficiently small and independent of the reflectance and illumination components, thereby limiting its robustness in high-noise environments.

BRAIN-LIKE RETINEX MODEL

To improve the structure preservation of Retinex-based enhancement model, Cai and Chen (2023) proposed the BRAIN. The BRAIN introduces contour

and texture gradient components to describe the detail information. The optimization model of BRAIN is given by:

$$\begin{aligned} \arg \min_{\mathbf{R}, \mathbf{L}} & \|\mathbf{S} - \mathbf{R} \circ \mathbf{L}\|_F^2 + \alpha \|\mathbf{R} \circ \nabla \mathbf{L} - \mathbf{C}\|_F^2 + \\ & \beta \|\nabla \mathbf{R} \circ \mathbf{L} - \mathbf{G}\|_F^2 \end{aligned} \quad (8)$$

where α and β are the weights of prior terms, the $\mathbf{C}$ and $\mathbf{G}$ denote contour component and texture gradient component, respectively. The $\nabla \mathbf{L}$ represents illumination gradient component, which is obtained as follows:

$$\nabla \mathbf{L} = \mathbf{K}_C \circ \mathbf{C} \quad (9)$$

where $\mathbf{K}_C$ denotes the weighting matrix. Similarly, the gradient of reflectance component $\nabla \mathbf{R}$ is calculated as:

$$\nabla \mathbf{R} = \mathbf{K}_G \circ \mathbf{G} \quad (10)$$

where $\mathbf{K}_G$ denotes the weighting matrix. The $\mathbf{K}_G$ is calculated by:

$$\mathbf{K}_G = \text{Fun}(\mathbf{Q}_G, \max(\mathbf{Q}_G)) \quad (11)$$

where $\mathbf{Q}_G$ is given by $\text{Gaussian}_1(\mathbf{R}) - \kappa \cdot \text{Gaussian}_2(\mathbf{R})$, the $\text{Gaussian}_1(\cdot)$ and $\text{Gaussian}_2(\cdot)$ denote Gaussian filter with different filtering windows, κ is user-defined parameter. The $\text{Fun}(\mathbf{A}, \mathbf{B})$ processes each element in $\mathbf{A}$ and returns 1 if element is bigger, 0 otherwise. The $\mathbf{K}_C$ can be obtained by similar processing.

Through the ADMM, the iterative formulas of reflectance and illumination components are given as follows:

$$\mathbf{r} = \frac{(\bar{\mathbf{l}}')^T \mathbf{s} + \alpha (\bar{\mathbf{l}}')^T \mathbf{c}}{(\bar{\mathbf{l}}')^T \bar{\mathbf{l}} + \alpha (\bar{\mathbf{l}}')^T \bar{\mathbf{l}}'} \quad (12)$$

$$\mathbf{l} = \frac{(\bar{\mathbf{r}})^T \mathbf{s} + \beta (\bar{\mathbf{r}}')^T \mathbf{g}}{(\bar{\mathbf{r}})^T \bar{\mathbf{r}} + \beta (\bar{\mathbf{r}}')^T \bar{\mathbf{r}}'} \quad (13)$$

where $\mathbf{l}'$ and $\mathbf{r}'$ denote the vectorized form of $\nabla \mathbf{L}$ and $\nabla \mathbf{R}$, respectively.

The BRAIN utilizes contour and texture gradient components to improve enhancement performance. However, due to the lack of explicit noise modeling in the Retinex model, BRAIN still amplifies noise when the image is contaminated by noise.

DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is a signal-processing technique that decomposes an image into low-frequency and high-frequency subbands through filtering and downsampling operations. The DWT is

widely used in image analysis, data compression, and noise filtering. For the input image I , the DWT with Haar wavelet utilizes high-pass $h_{high} = (1/\sqrt{2}, -1/\sqrt{2})$ and low-pass $h_{low} = (1/\sqrt{2}, 1/\sqrt{2})$ to perform convolution operations on it, which generates four frequency subbands:

$$I_{LL}, I_{HL}, I_{LH}, I_{HH} = DWT(I) \quad (14)$$

where $DWT(\cdot)$ denotes the Haar wavelet transform, the I_{LL} includes the low-frequency information of I and I_{HL}, I_{LH}, I_{HH} include the high-frequency information. The DWT utilizes four filters to decompose the original image and generates the low and high frequency components. In addition, the low and high frequency components could be integrated into the original image. For noisy low-light images, the low-frequency information includes the background and global information. The high-frequency information includes the noisy and edge information. Therefore, we combine the DWT and then construct a novel optimization model for noise removal.

PROPOSED ALGORITHM

This section is organized into five subsections, including the noise-aware Retinex decomposition model, the noise prior, the proposed optimization framework, the improved illumination stretching function, and the detailed optimization procedure. The overall framework of the proposed algorithm is shown in Fig. 2.

RETINEX LOCAL INFORMATION MODEL

Existing noise-related Retinex models (Li *et al.*, 2018; Yu *et al.*, 2017; Elad, 2005) construct robust optimization frameworks that suppress noise and improve enhancement performance to a certain extent. However, most of these methods either handle noise in the reflectance component only in the logarithmic domain or fail to explicitly account for noise in the reflectance component.

To more appropriately decompose noisy low-light images, we construct a noise-related Retinex model, which is given by

$$S = (R + N) \circ L \quad (15)$$

The prior information of the reflectance component assumes that it should be close to the image gradient, which is highly sensitive to noise. In contrast, the prior term for the illumination component enforces spatial smoothness and thus exhibits robustness to noise

to a certain extent. Motivated by these observations, the proposed model explicitly separates the noise component from the reflectance component, providing a more appropriate prior formulation for characterizing the properties of noisy images.

In BRAIN-like Retinex model, the gradient image ∇S is expressed as follows:

$$\nabla S = C + G \quad (16)$$

Eq. (16) is mainly suitable for noise-free conditions. However, when an image is corrupted by noise, noise-induced gradients may be incorrectly absorbed into the contour component C and the texture gradient component G , leading to biased priors. To solve this problem, instead of directly assuming an explicit noise gradient, we introduce a gradient residual term to capture noise-related components:

$$E \triangleq \nabla S - C - G \quad (17)$$

where E represents the gradient residual. Taking the spatial gradient of both sides of Eq. (15), we obtain:

$$\nabla S = \nabla R \circ L + \nabla N \circ L + R \circ \nabla L + N \circ \nabla L \quad (18)$$

From Eq. (18), the noise-related contribution to the gradient is given by:

$$E \approx \nabla N \circ L + N \circ \nabla L \quad (19)$$

Therefore, by combining Eq. (18) and Eq. (19), we construct a new objective function to enforce consistency between the gradient decomposition and the proposed noise-related Retinex model, given by:

$$\begin{aligned} \arg \min_{R, L, N} & ||R \circ \nabla L - C||_F^2 + ||\nabla R \circ L - G||_F^2 \\ & + ||\nabla N \circ L + N \circ \nabla L - E||_F^2 \end{aligned} \quad (20)$$

where the first and second terms constrain the contour and texture gradient information to be consistent with the Hadamard product of illumination, reflectance, and their corresponding gradient components. The third term models the noise-related gradient residual, preventing noise-induced gradients from being incorrectly absorbed into contour C and texture gradient G .

NOISE PRIOR

In the above section, we observe that noise can be significantly amplified in the estimated reflectance component. To reduce the leakage of noise into the reflectance component, we construct a DWT-based

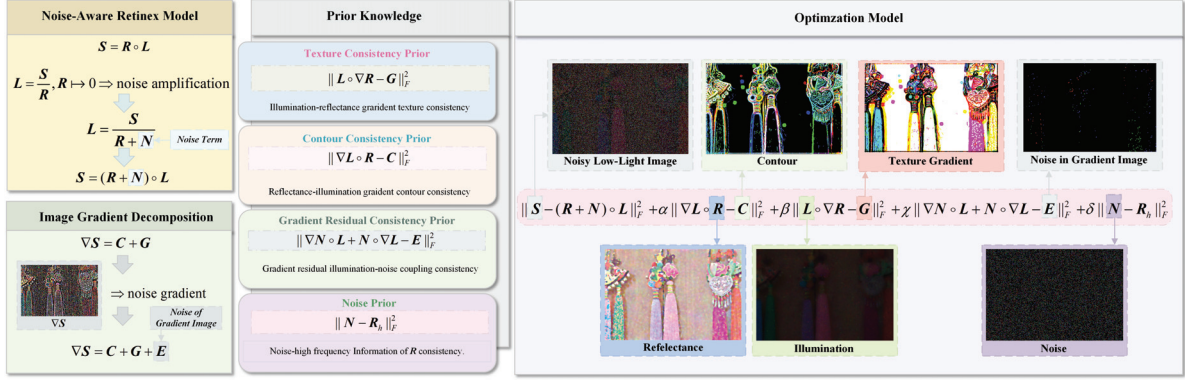


Fig. 2. Framework of proposed algorithm

noise prior from the high-frequency information of the reflectance component $\mathbf{R}$. Specifically, a one-level two-dimensional Haar DWT is performed on the reflectance component $\mathbf{R}$ as follows:

$$\mathbf{R}_{LL}, \mathbf{R}_{HL}, \mathbf{R}_{LH}, \mathbf{R}_{HH} = DWT(\mathbf{R}) \quad (21)$$

Common noise in low-light images usually appears as high-frequency disturbances. In particular, impulse noise, such as salt-and-pepper noise, is often randomly and sparsely distributed as abnormal pixels, while Gaussian noise and speckle noise also introduce local high-frequency fluctuations. Based on this property, the high-frequency information extracted from the reflectance component is used to construct a noise prior, which guides the estimation of the noise component, as follows:

$$\mathbf{R}_h = iDWT(\mathbf{0}, \mathbf{R}_{HL}, \mathbf{R}_{LH}, \mathbf{R}_{HH}) \quad (22)$$

where $iDWT$ denotes the inverse DWT and $\mathbf{0}$ is a zero matrix with the same size as the low-frequency subband $\mathbf{R}_{LL}$. Note that $\mathbf{R}_h$ contains not only noise but also edge-related high frequency details. To suppress structural edges, we build an edge-strength map using the gradient magnitude of a guidance image $\mathbf{S}_g$:

$$\mathbf{M} = \frac{\sqrt{(d_x \mathbf{S}_g)^2 + (d_y \mathbf{S}_g)^2}}{\max(\sqrt{(d_x \mathbf{S}_g)^2 + (d_y \mathbf{S}_g)^2})} \quad (23)$$

where the $\mathbf{S}_g$ is obtained by guided filtering, the d_x and d_y denote horizontal and vertical difference operators. Next, we utilize the gradient magnitude $\mathbf{M}$ to construct the suppression weights:

$$\mathbf{W} = \exp\left(-\left(\frac{\mathbf{M}}{\sigma_e}\right)^2\right) \quad (24)$$

where σ_e controls the degree of edge suppression, and is usually set to 0.5. Finally, we combine the $\mathbf{W}$ and

$\mathbf{R}_h$, and then provide the noise prior, which is given as follows:

$$\bar{\mathbf{R}}_h = \mathbf{W} \circ \mathbf{R}_h \quad (25)$$

Through this operation, a noise prior is extracted from the reflectance component, which guides the estimation of the noise component and indirectly reduces noise leakage into the reflectance component.

OPTIMIZATION MODEL

Based on the proposed Retinex model, we introduce the contour and texture gradient components to improve detail preservation, and then construct a new optimization model. The optimization model is given as follows:

$$\begin{aligned} \arg \min_{\mathbf{N}, \mathbf{L}, \mathbf{R}} & \|\mathbf{S} - (\mathbf{R} + \mathbf{N}) \circ \mathbf{L}\|_F^2 + \alpha \|\nabla \mathbf{L} \circ \mathbf{R} - \mathbf{C}\|_F^2 \\ & + \beta \|\mathbf{L} \circ \nabla \mathbf{R} - \mathbf{G}\|_F^2 + \chi \|\nabla \mathbf{N} \circ \mathbf{L} + \mathbf{N} \circ \nabla \mathbf{L} - \mathbf{E}\|_F^2 \\ & + \delta \|\mathbf{N} - \bar{\mathbf{R}}_h\|_F^2 \end{aligned} \quad (26)$$

where the $\nabla \mathbf{L}$, $\nabla \mathbf{R}$ and $\nabla \mathbf{N}$ can be calculated by $\nabla \mathbf{L} = \mathbf{K}_C \circ \mathbf{C}$, $\nabla \mathbf{R} = \mathbf{K}_G \circ \mathbf{G}$ and $\nabla \mathbf{N} = \mathcal{F}(\mathbf{N})$, respectively. The $\mathcal{F}(\cdot)$ denotes the Difference of Gaussian gradient operation. The $\mathbf{E}$ can be computed by $\mathbf{E} = \nabla \mathbf{S} - \mathbf{C} - \mathbf{G}$, the α , β , χ and δ are weight parameters. For the noise prior term, the $\mathbf{N}$ is constrained to approach the high-frequency information of $\mathbf{R}$ and capture the noise information.

The proposed optimization model consists of five terms with different optimization objectives. The first term is the reconstruction term, which ensures that the noisy low-light image can be reconstructed from the estimated illumination, reflectance, and noise components. The second term introduces the contour prior to regularize the illumination component, so that the estimated illumination can preserve major structural information while avoiding excessive fluctuation. The third term imposes the textural gradient prior on the

reflectance component to maintain local texture and detail information. The fourth term constrains the noise-related gradient residual, which prevents noise-induced gradients from being incorrectly absorbed into the contour and texture components. The last term incorporates the DWT-based noise prior, which guides the estimated noise component to approach the high-frequency information and reduces the leakage of noise into the reflectance component. Therefore, the proposed model provides a unified optimization framework for the joint estimation of illumination, reflectance, and noise.

Since the objective function consists only of quadratic terms after fixing the gradient-related priors, the optimization problem can be solved by the least-squares method and decomposed into three subproblems with respect to $\mathbf{L}$, $\mathbf{R}$, and $\mathbf{N}$, respectively. In addition, during the alternating optimization, the gradient-related auxiliary terms are treated as fixed within their corresponding subproblems. After updating the reflectance component, the DWT-based high-frequency prior is recomputed from the latest reflectance estimate and then used to update the noise component.

Subproblem 1: solving $\mathbf{R}$, we reconstruct optimization model with respect to $\mathbf{R}$, which is as follows:

$$\arg \min_{\mathbf{R}} \|\mathbf{S} - (\mathbf{R} + \mathbf{N}) \circ \mathbf{L}\|_F^2 + \alpha \|\nabla \mathbf{L} \circ \mathbf{R} - \mathbf{C}\|_F^2 \quad (27)$$

For Eq. (27), we process each pixel individually and transform the subproblem into scalar form:

$$\arg \min_{\mathbf{R}_i} (S_i - (\mathbf{R}_i + \mathbf{N}_i) \mathbf{L}_i)^2 + \alpha (\nabla \mathbf{L}_i \mathbf{R}_i - \mathbf{C}_i)^2 \quad (28)$$

where S_i denotes the value of i -th pixel in $\mathbf{S}$. The same notation is also applied to $\mathbf{L}$, $\mathbf{R}$, $\mathbf{N}$, $\mathbf{C}$ and $\mathbf{G}$. We take the partial derivatives with respect to reflectance component $\mathbf{R}_i$ and obtain the iterative formula of $\mathbf{R}_i$ as follows:

$$\mathbf{R}_i = \frac{\mathbf{L}_i \mathbf{S}_i + \alpha \nabla \mathbf{L}_i \mathbf{C}_i - \mathbf{L}_i \mathbf{L}_i \mathbf{N}_i}{\mathbf{L}_i \mathbf{L}_i + \alpha \nabla \mathbf{L}_i \nabla \mathbf{L}_i} \quad (29)$$

For Eq. (29), we transform it to matrix form, which is given as follows:

$$\mathbf{R} = \frac{\mathbf{L} \circ \mathbf{S} + \alpha \nabla \mathbf{L} \circ \mathbf{C} - \mathbf{L} \circ \mathbf{L} \circ \mathbf{N}}{\mathbf{L} \circ \mathbf{L} + \alpha \nabla \mathbf{L} \circ \nabla \mathbf{L}} \quad (30)$$

Subproblem 2: solving $\mathbf{L}$, we reconstruct quadratic minimization problem with respect to illumination component $\mathbf{L}$, which is as follows:

$$\arg \min_{\mathbf{L}} \|\mathbf{S} - (\mathbf{R} + \mathbf{N}) \circ \mathbf{L}\|_F^2 + \beta \|\mathbf{L} \circ \nabla \mathbf{R} - \mathbf{G}\|_F^2 + \chi \|\nabla \mathbf{N} \circ \mathbf{L} + \mathbf{N} \circ \nabla \mathbf{L} - \mathbf{E}\|_F^2 \quad (31)$$

For Eq. (31), we process each pixel individually and transform the subproblem into scalar form:

$$\arg \min_{\mathbf{L}_i} (S_i - (\mathbf{R}_i + \mathbf{N}_i) \mathbf{L}_i)^2 + \beta (\mathbf{L}_i \nabla \mathbf{R}_i - \mathbf{G}_i)^2 + \chi (\nabla \mathbf{N}_i \mathbf{L}_i + \mathbf{N}_i \nabla \mathbf{L}_i - \mathbf{E}_i)^2 \quad (32)$$

We take the partial derivatives with respect to illumination component $\mathbf{L}_i$, the iterative formula of $\mathbf{L}_i$ is obtained as follows:

$$\mathbf{L}_i = \frac{(\mathbf{R}_i + \mathbf{N}_i) \mathbf{S}_i + \beta \nabla \mathbf{R}_i \mathbf{G}_i + \chi \nabla \mathbf{N}_i \mathbf{E}_i - \chi \nabla \mathbf{N}_i \mathbf{N}_i \nabla \mathbf{L}_i}{(\mathbf{R}_i + \mathbf{N}_i)^2 + \chi \nabla \mathbf{N}_i^2 + \beta \nabla \mathbf{R}_i^2} \quad (33)$$

For Eq. (33), we transform it to matrix form, which is given as follows:

$$\mathbf{L} = \frac{(\mathbf{R} + \mathbf{N}) \circ \mathbf{S} + \beta \nabla \mathbf{R} \circ \mathbf{G} + \chi \nabla \mathbf{N} \circ (\mathbf{E} - \mathbf{N} \circ \nabla \mathbf{L})}{(\mathbf{R} + \mathbf{N}) \circ (\mathbf{R} + \mathbf{N}) + \chi \nabla \mathbf{N} \circ \nabla \mathbf{N} + \beta \nabla \mathbf{R} \circ \nabla \mathbf{R}} \quad (34)$$

Subproblem 3: solving $\mathbf{N}$, $\mathbf{N}$ is updated by solving the following problem:

$$\arg \min_{\mathbf{N}} \|\mathbf{S} - (\mathbf{R} + \mathbf{N}) \circ \mathbf{L}\|_F^2 + \chi \|\nabla \mathbf{N} \circ \mathbf{L} + \mathbf{N} \circ \nabla \mathbf{L} - \mathbf{E}\|_F^2 + \delta \|\mathbf{N} - \bar{\mathbf{R}}_h\|_F^2 \quad (35)$$

For Eq. (35), we process each pixel and transform it to scalar form as follows:

$$\arg \min_{\mathbf{N}_i} (S_i - (\mathbf{R}_i + \mathbf{N}_i) \mathbf{L}_i)^2 + \chi (\nabla \mathbf{N}_i \mathbf{L}_i + \mathbf{N}_i \nabla \mathbf{L}_i - \mathbf{E}_i)^2 + \delta (\mathbf{N}_i - \bar{\mathbf{R}}_{h,i})^2 \quad (36)$$

We take the partial derivatives with respect to noise component $\mathbf{N}_i$, the iterative formula of $\mathbf{N}_i$ is obtained as follows:

$$\mathbf{N}_i = \frac{\mathbf{L}_i \mathbf{S}_i - \mathbf{L}_i^2 \mathbf{R}_i + \chi \nabla \mathbf{L}_i (\mathbf{E}_i - \nabla \mathbf{N}_i \mathbf{L}_i) + \delta \bar{\mathbf{R}}_{h,i}}{\mathbf{L}_i^2 + \chi \nabla \mathbf{L}_i^2 + \delta} \quad (37)$$

For Eq. (37), we transform it to matrix form, which is given as follows:

$$\mathbf{N} = \frac{\mathbf{L} \circ \mathbf{S} - \mathbf{L} \circ \mathbf{L} \circ \mathbf{R} + \chi \nabla \mathbf{L} \circ (\mathbf{E} - \nabla \mathbf{N} \circ \mathbf{L}) + \delta \bar{\mathbf{R}}_h}{\mathbf{L} \circ \mathbf{L} + \chi \nabla \mathbf{L} \circ \nabla \mathbf{L} + \delta} \quad (38)$$

Through the above processing, the optimization problem is solved and the illumination, reflectance and noise components are obtained. The pseudocode of the proposed algorithm is given in Algorithm 1.

Algorithm 1 Combined Discrete Wavelet Transform and Noise-Prior Retinex-Based Enhancement

Input: the low-light image S , error threshold ε , maximum iteration T , weight parameters α , β , χ , σ_e , and δ , and illumination stretching exponent γ .

Output: the illumination component L , reflectance component R , and enhanced image $\hat{S}$.

Initialization:

for $i = 1$ to 3 **do**

 Compute the texture gradient component G of $S(:, :, i)$;

 Compute the contour component C of $S(:, :, i)$;

 Compute the gradient image ∇S of $S(:, :, i)$;

 Compute E by $E = \nabla S - C - G$;

 Initialize the noise component $N^{(0)} = [0]_{m \times n}$;

 Initialize the illumination component $L^{(0)}$ by using a Gaussian filter to blur $S(:, :, i)$;

 Initialize the reflectance component $R^{(0)}$;

 Set $t = 0$;

repeat:

$t = t + 1$;

 Update $\nabla L^{(t)}$ by Eq. (9);

 Update $\nabla R^{(t)}$ by Eq. (10);

 Update $\nabla N^{(t)}$ by $\nabla N^{(t)} = \mathcal{F}(N^{(t-1)})$;

 Update $R^{(t)}$ by Eq. (30);

 Update $L^{(t)}$ by Eq. (34);

 Update $\bar{R}_h$ by Eq. (25);

 Update $N^{(t)}$ by Eq. (38);

until $[||R^{(t)} - R^{(t-1)}||^2 \leq \varepsilon \text{ and } ||L^{(t)} - L^{(t-1)}||^2 \leq \varepsilon]$ or $t > T$.

end for

Obtain the enhanced image $\hat{S}$ by Eq. (39);

Return R , L , and $\hat{S}$.

STRETCHING FUNCTION

When the image is corrupted by high-level noise, the noise of illumination component cannot be eliminated by blurring the low-light image. At this time, if the illumination component is stretched directly, it will result in a lot of halos in the enhanced image. Thus, we construct a new stretching function as follows:

$$\hat{S} = R \circ \max(L - \sigma N, 0)^{\frac{1}{\gamma}} \quad (39)$$

where $\sigma = \frac{\max(L) - \min(L)}{\max(R) - \min(R)}$ is used to rescale the estimated noise component from the reflectance range to the illumination range. The parameter γ denotes the illumination stretching exponent and is set to 2.2. $\hat{S}$ denotes the enhanced image. The proposed stretching function suppresses the influence of the estimated noise component during illumination enhancement, thereby improving enhancement performance and reducing halo artifacts and residual noise.

PARTIAL DERIVATIVE DETAILS

In this section, we present the detailed derivations of the three subproblems in Section 3.3. For computational efficiency, a fixed-gradient strategy is adopted. At the t -th iteration, $\nabla N^{(t)}$ is computed from $N^{(t-1)}$ and treated as fixed. The reflectance and illumination components are then updated. Subsequently, the DWT-based high-frequency prior $\bar{R}_h^{(t)}$ is obtained from the latest reflectance estimate $R^{(t)}$ and used to update $N^{(t)}$. All auxiliary quantities are treated as constants within their corresponding subproblems. For **Subproblem 1**, we take the partial derivative of Eq. (28) with respect to R_i

$$\begin{aligned} -2L_i(S_i - L_i R_i - L_i N_i) + 2\alpha \nabla L_i(\nabla L_i R_i - C_i) &= 0 \\ \alpha \nabla L_i(\nabla L_i R_i - C_i) &= L_i S_i - L_i L_i R_i - L_i L_i N_i \\ L_i L_i R_i + \alpha \nabla L_i \nabla L_i R_i &= L_i S_i + \alpha \nabla L_i C_i - L_i L_i N_i \\ R_i &= \frac{L_i S_i + \alpha \nabla L_i C_i - L_i L_i N_i}{L_i L_i + \alpha \nabla L_i \nabla L_i} \end{aligned} \quad (40)$$

For **Subproblem 2**, we take the partial derivative of Eq. (32) with respect to L_i

$$\begin{aligned} -2(R_i + N_i)(S_i - (R_i + N_i)L_i) + 2\beta \nabla R_i(L_i \nabla R_i - G_i) \\ + 2\chi \nabla N_i(\nabla N_i L_i + N_i \nabla L_i - E_i) &= 0 \end{aligned}$$

$$\begin{aligned} -(R_i + N_i)S_i + (R_i + N_i)^2 L_i + \beta L_i \nabla R_i^2 \\ - \beta \nabla R_i G_i + \chi \nabla N_i^2 L_i + \chi \nabla N_i N_i \nabla L_i - \chi \nabla N_i E_i &= 0 \end{aligned}$$

$$\begin{aligned} (R_i + N_i)^2 L_i + \chi \nabla N_i^2 L_i + \beta L_i \nabla R_i^2 \\ = (R_i + N_i)S_i + \beta \nabla R_i G_i + \chi \nabla N_i E_i - \chi \nabla N_i N_i \nabla L_i \end{aligned}$$

$$\begin{aligned} L_i((R_i + N_i)^2 + \chi \nabla N_i^2 + \beta \nabla R_i^2) \\ = (R_i + N_i)S_i + \beta \nabla R_i G_i + \chi \nabla N_i E_i - \chi \nabla N_i N_i \nabla L_i \end{aligned}$$

$$L_i = \frac{(R_i + N_i)S_i + \beta \nabla R_i G_i + \chi \nabla N_i E_i - \chi \nabla N_i N_i \nabla L_i}{(R_i + N_i)^2 + \chi \nabla N_i^2 + \beta \nabla R_i^2} \quad (41)$$

For **Subproblem 3**, we take the partial derivative of Eq. (36) with respect to N_i

Table 1. Detailed information on the adopted datasets

Dataset	No. of images	No. of images used for evaluation	Paired reference images
LIME	10	3	✗
NPE	75	3	✗
LOLv1	485 / 15	500	✓
LSRW	5600 / 50	50	✓

*Bold numbers indicate the subsets used for evaluation

$$\begin{aligned}
& -2L_i(S_i - (R_i + N_i)L_i) + \\
& 2\chi\nabla L_i(\nabla N_i L_i + N_i\nabla L_i - E_i) + 2\delta(N_i - \bar{R}_{h,i}) = 0 \\
& -L_i S_i + L_i^2(R_i + N_i) + \chi\nabla L_i\nabla N_i L_i + \chi\nabla L_i^2 N_i \\
& -\chi\nabla L_i E_i + \delta N_i - \delta\bar{R}_{h,i} = 0
\end{aligned}$$

$$\begin{aligned}
& L_i^2 N_i + \chi\nabla L_i^2 N_i + \delta N_i \\
& = L_i S_i - L_i^2 R_i - \chi\nabla L_i\nabla N_i L_i + \chi\nabla L_i E_i + \delta\bar{R}_{h,i} \\
& N_i = \frac{L_i S_i - L_i^2 R_i + \chi\nabla L_i(E_i - \nabla N_i L_i) + \delta\bar{R}_{h,i}}{L_i^2 + \chi\nabla L_i^2 + \delta}
\end{aligned} \tag{42}$$

EXPERIMENTAL RESULTS AND ANALYSIS

To verify the performance of the proposed algorithm, we compare it with representative Retinex-based methods, including LIME (Guo *et al.*, 2016), STAR (Xu *et al.*, 2020), RBMP (Al-Hashim and Al-Ameen, 2020), WVM (Fu *et al.*, 2016), BIMEF (Ying *et al.*, 2017), RRM (Li *et al.*, 2018), LR3M (Ren *et al.*, 2020), SDD (Hao *et al.*, 2020), BRAIN (Cai and Chen, 2023), FSTAR (Li and He, 2024). In addition, to further evaluate the proposed algorithm, state-of-the-art (SOTA) deep learning-based methods (Wei *et al.*, 2025; Yan *et al.*, 2025; Zhu *et al.*, 2025) are compared with the proposed algorithm. The experimental platform is an HP laptop equipped with an Intel Core i5-7300HQ processor, 8 GB RAM, and MATLAB 2017b software environment. For the deep learning-based methods, the software platform is Python 3.7 and the default parameter settings are used. The input images come from LIME (Guo *et al.*, 2016), NPE (Wang *et al.*, 2013), LOLv1 (Wei *et al.*, 2018) and LSRW (Jiang *et al.*, 2023) datasets and the detailed information on these datasets is provided in Table 1.

As shown in Table 1, the notation / separates the training set and testing set. The LIME and NPE datasets do not provide corresponding normal-light reference

Table 2. Average performance metrics of algorithms on entire LOLv1 dataset

Algorithm	PSNR↑	SSIM↑	LOE↓	NIQE↓
LIME	15.7486	0.5093	1476.3735	6.2303
STAR	11.4049	0.5024	440.5768	4.7525
RBMP	15.0218	0.5939	28.5439	3.4117
WVM	15.9430	0.5672	302.4418	5.8590
BIMEF	15.3512	0.5931	412.1232	4.2135
RRM	13.1395	<u>0.6093</u>	452.4943	<u>4.1867</u>
BRAIN	10.7999	0.4678	437.2339	5.0092
FSTAR	11.6748	0.5103	360.1440	5.9950
LR3M	9.5075	0.3700	495.8730	5.4234
SDD	12.7926	0.5669	466.4938	6.3252
Proposed	15.5692	0.6143	437.3472	4.9803

images. In contrast, the LOLv1 and LSRW datasets provide corresponding normal-light reference images. Furthermore, the parameters of the proposed algorithm are set to $\alpha = 10^{-4}$, $\beta = 10^{-4}$, $\chi = 10^{-4}$, $\delta = 0.01$, $\sigma_e = 0.5$ and $\gamma = 2.2$. The window size of the guided filter is 3×3 . To quantitatively evaluate these algorithms, we use PSNR (Huynh-Thu and Ghanbari, 2008), SSIM (Wang *et al.*, 2004), NIQE (Mittal *et al.*, 2013), LOE (Wang *et al.*, 2013), and BRISQUE as performance metrics. Since the LOLv1 and LSRW datasets provide corresponding normal-light images, PSNR, SSIM, NIQE, and LOE are used for quantitative evaluation on these paired datasets. In contrast, the LIME and NPE datasets do not provide paired ground-truth images. Therefore, NIQE and BRISQUE are adopted as no-reference metrics to evaluate the enhancement performance on these unpaired datasets. In addition, due to the uniform distribution of noise on the three image channels, we execute the proposed algorithm in three channels separately, and then merge the three temporary results to obtain the final enhancement result. The main reason is that noise distributed across the RGB channels may still remain in the hue and saturation components after conversion to the HSV color space. Therefore, processing only the value channel may weaken the noise-suppression capability of the proposed algorithm.

ALGORITHM EFFECTIVENESS ANALYSIS

In this section, to verify the effectiveness of these algorithms, we select six images for testing. The input images #1, #3, and #10 are from the LIME dataset, whereas #BelgiumHouse, #Cadik, and #Candle are from the NPE dataset. The enhancement results of these algorithms are given in Fig. 4, and corresponding performance metrics are shown in Fig. 3.

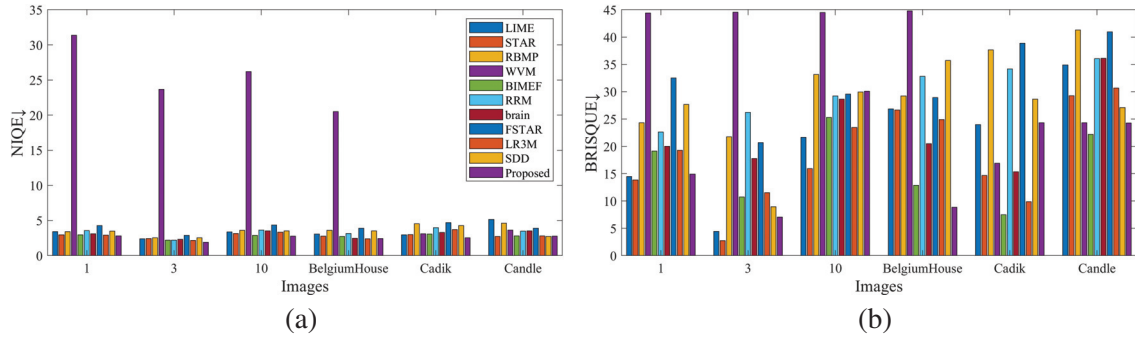


Fig. 3. The performance metrics of these algorithms on low-light images. (a) NIQE; (b) BRISQUE.



Fig. 4. Enhancement results of these algorithms on low-light images. (a) #1; (b) #3; (c) #10; (d) #BelgiumHouse; (e) #Cadik; (f) #Candle. *From top to bottom, each row denotes low-light images, LIME, STAR, RBMP, WVM, BIMEF, RRM, BRAIN, FSTAR, LR3M, SDD and the proposed algorithm, respectively.

Table 3. Average performance metrics of these algorithms on testing set of LSRW dataset

Algorithm	PSNR↑	SSIM↑	LOE↓	NIQE↓
LIME	15.9415	0.5516	976.3596	4.2581
STAR	14.2789	0.5432	403.9366	4.0560
RBMP	16.1907	0.6314	<u>372.7877</u>	4.4886
WVM	<u>16.7285</u>	0.6150	381.8889	<u>4.1873</u>
BIMEF	13.6603	0.5124	376.3331	4.4853
RRM	13.2332	0.5330	658.1548	5.3110
BRAIN	15.7126	<u>0.6271</u>	487.2684	4.7146
FSTAR	12.9501	0.4987	427.2185	4.3130
LR3M	14.4693	0.5824	382.0768	4.3455
SDD	13.1362	0.4792	523.5458	5.4546
Proposed	16.8011	0.6159	348.7507	4.3842

As shown in Fig. 4, all algorithms complete the enhancement task, but they differ in detail preservation and illumination range. The STAR and FSTAR produce the worst enhancement results, with low brightness and poor visual quality. The LIME achieves better enhancement results, but its results contain numerous noise points and exhibit an abnormal brightness range. The LR3M produces low-brightness results in scenes without high-brightness illuminants. However, compared with the aforementioned algorithms, the LR3M demonstrates a better enhancement effect. The BRAIN, RBMP, and BIMEF provide a more appropriate illumination range, but their results still contain visible noise. The RRM and SDD achieve better enhancement effects by removing noise from low-light images, but their results exhibit halo artifacts in the presence of high-brightness illuminants. In contrast, the proposed algorithm provides favorable enhancement results, with more natural colors and appropriate brightness. As shown in Fig. 3, the proposed algorithm provides the lowest NIQE for all testing images, and produces the lowest BRISQUE for image #BelgiumHouse.

ALGORITHM GENERALIZATION ANALYSIS

To further assess the performance of these algorithms, we conduct experiments on the entire LOLv1 dataset and the testing set of the LSRW dataset. The partial enhancement results are shown in Fig. 5, and the corresponding performance metrics are given in Tables 2 and 3.

As shown in Fig. 5 and Table 2, the LR3M provides the worst enhancement effect. The STAR, BRAIN, and FSTAR perform better than the LR3M, but their enhancement effects remain limited. In comparison, the LIME, BIMEF, and WVM achieve enhancement

Table 4. Average performance metrics of algorithms on the testing set of the LOLv1 dataset with SPN(0.1)

Algorithm	PSNR↑	SSIM↑	LOE↓	NIQE↓
LIME	9.0732	0.0848	2093.8315	19.2976
STAR	8.4666	0.0591	2090.0554	20.0576
RBMP	<u>11.8780</u>	<u>0.1595</u>	<u>2007.2992</u>	14.1534
WVM	8.6013	0.0654	2007.7535	18.7460
BIMEF	10.2197	0.1058	2094.4946	16.6715
RRM	8.8401	0.0734	2093.8315	20.2242
BRAIN	9.2103	0.0894	2225.2835	<u>14.5898</u>
FSTAR	9.4393	0.0954	2023.5435	16.4889
LR3M	10.1373	0.1174	2057.2872	17.6671
SDD	8.7485	0.0674	2093.8315	19.6456
Proposed	17.1513	0.4471	587.7165	16.6125

results with more appropriate brightness. However, their results still contain many noise points. The RBMP provides better enhancement performance, but some noise remains in its enhanced results. The RRM and SDD produce results with promising brightness and less noise because they introduce the noise component into the Retinex model. Although the proposed algorithm does not produce the brightest enhancement, the improved illumination stretching function can suppress abnormal brightness amplification and reduce noise interference. Therefore, it generates results with less noise and achieves higher SSIM than the other compared algorithms on the LOLv1 dataset. As further shown in Table 3, the proposed algorithm also outperforms the other compared algorithms in terms of PSNR and LOE on testing set of the LSRW dataset.

ALGORITHM ROBUSTNESS ANALYSIS

This section evaluates the noise robustness of the compared algorithms and the proposed algorithm on the testing set of the LOLv1 dataset. Different types and intensity levels of noise are added to the input images, including salt-and-pepper noise, Gaussian noise, and speckle noise. SPN(0.1), GN(0.1), and SN(0.1) represent images contaminated by salt-and-pepper noise with an intensity of 0.1, Gaussian noise with a mean of 0 and a normalized variance of 0.1, and speckle noise with a normalized variance of 0.1, respectively. For the noisy images, the average performance over all images is used to evaluate the robustness of different algorithms. The partial results are shown in Fig. 6 and corresponding performance metrics are given in Tables 4, 5 and 6.

As shown in Fig. 6, when the images are contaminated by SPN(0.1), all compared algorithms produce enhanced results with many noise points,

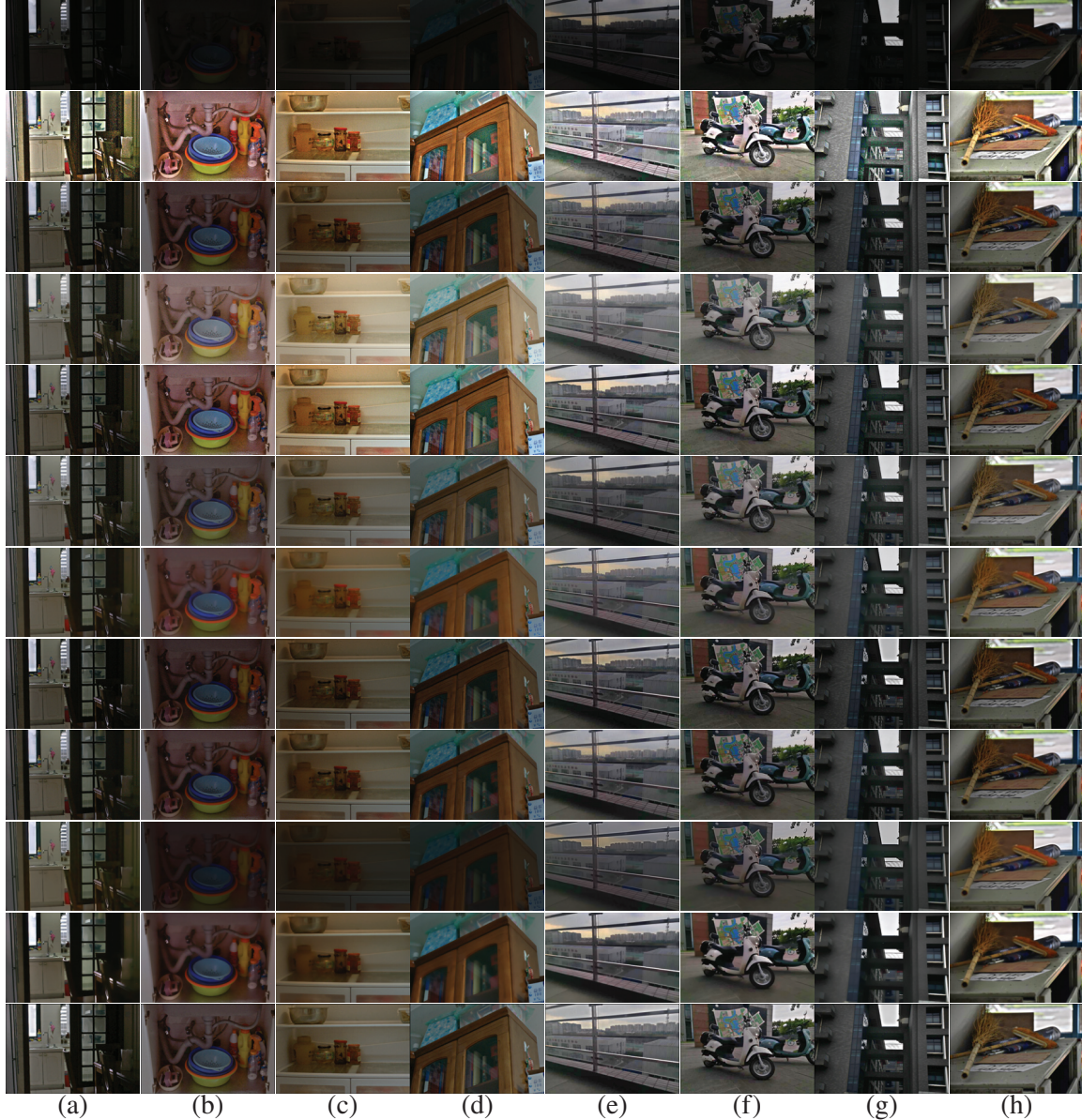


Fig. 5. Enhancement results of these algorithms on LOLv1 and LSRW datasets. (a) #102. (b) #105; (c) #119; (d) #169; (e) #2051; (f) #2064; (g) #3013; (h) #3020. *From top to bottom, each row denotes the low-light images, LIME, STAR, RBMP, WVM, BIMEF, RRM, BRAIN, FSTAR, LR3M, SDD and the proposed algorithm, respectively.

which are unsuitable for subsequent image processing. In contrast, the proposed algorithm achieves favorable enhancement performance by effectively enhancing the images while suppressing salt-and-pepper noise. When the images are contaminated by GN(0.1), all algorithms show limited enhancement effects, and their results contain a large amount of noise. This is mainly because Gaussian noise is distributed across the entire image and has high-frequency characteristics similar to real contour and details. Therefore, existing enhancement algorithms may mistakenly preserve or even amplify noise during illumination correction and detail enhancement. When the images are contaminated by SN(0.1), all algorithms obtain better enhancement

results, indicating that these algorithms have a certain degree of robustness to speckle noise. Among them, LIME provides a brighter enhancement effect, but its results still contain many noise points. RRM suppresses part of the noise because it introduces a noise component, but its performance is still limited under strong noise. The proposed algorithm provides favorable enhancement results and demonstrates promising robustness to speckle noise. As shown in Tables 4, 5, and 6, the proposed algorithm achieves the highest PSNR and SSIM and the lowest LOE on the testing set of the LOLv1 dataset with SPN(0.1). The proposed algorithm outperforms the other compared algorithms in terms of all performance metrics for

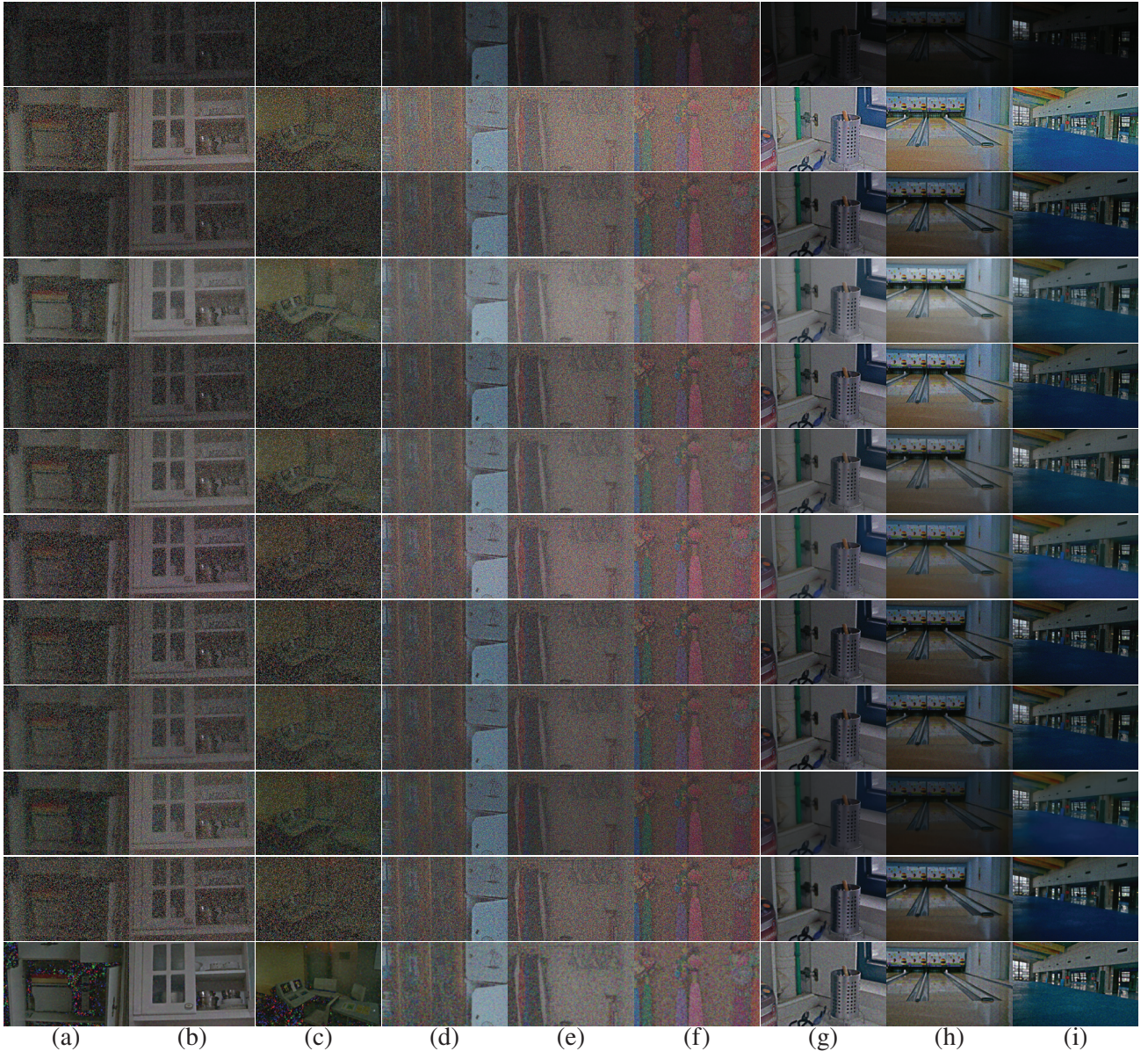


Fig. 6. Enhancement results of these algorithms on noisy LOLv1 dataset. (a) #55 with SPN(0.1); (b) #79 with SPN(0.1); (c) #665 with SPN(0.1); (d) #1 with GN(0.1); (e) #146 with GN(0.1); (f) #179 with GN(0.1); (g) #111 with SN(0.1); (h) #669 with SN(0.1); (i) #780 with SN(0.1). *From top to bottom, each row denotes noisy low-light images, LIME, STAR, RBMP, WVM, BIMEF, RRM, BRAIN, FSTAR, LR3M, SDD and the proposed algorithm, respectively.

testing set of LOLv1 dataset with GN(0.1) and is superior to the other compared algorithms in terms of PSNR, SSIM, NIQE for the LOLv1 dataset with SN(0.1).

COMPARISON WITH SOTA DEEP LEARNING-BASED ALGORITHMS

In this section, we compare the proposed algorithm with state-of-the-art (SOTA) deep learning-based algorithms, including MWFFnet (Wei *et al.*, 2025), HVI-CIDNet (Yan *et al.*, 2025), and Ghillie (Zhu *et al.*, 2025). These methods were proposed in 2025.

Since full-reference metrics require paired ground-truth images, we evaluate these algorithms on the testing set of the LSRW-Huawei dataset.

For the LSRW-Huawei dataset, salt and pepper noise, Gaussian noise, and speckle noise are added to the images, respectively. We present partial visual results and average performance metrics of these algorithms under three noise conditions, including SPN(0.1), GN(0.1), and SN(0.1). The visual results are shown in Fig. 7, and the average quantitative results are reported in Table 7.

As shown in Fig. 7, when the image is

Table 5. Average performance metrics of algorithms on the testing set of the LOLv1 dataset with GN(0.1)

Algorithm	PSNR↑	SSIM↑	LOE↓	NIQE↓
LIME	8.5082	0.0359	2093.8315	21.8744
STAR	9.4176	0.0452	2091.1848	17.6954
RBMP	<u>10.9832</u>	0.0560	<u>1623.9358</u>	15.4277
WVM	9.5927	0.0500	1626.3622	18.1939
BIMEF	10.4029	0.0526	1830.7645	16.1060
RRM	8.7664	0.0351	2093.8315	20.0551
BRAIN	9.8874	0.0548	1885.6172	15.0369
FSTAR	9.6884	0.0501	1627.1986	18.8168
LR3M	10.4129	<u>0.0682</u>	1855.2985	<u>13.5358</u>
SDD	9.5149	<u>0.0469</u>	2093.7830	16.5912
Proposed	11.3204	0.1692	1466.3702	12.7566

Table 6. Average performance metrics of algorithms on the testing set of the LOLv1 dataset with SN(0.1)

Algorithm	PSNR↑	SSIM↑	LOE↓	NIQE↓
LIME	<u>14.9395</u>	0.4060	1650.8558	9.2627
STAR	<u>11.2770</u>	0.3797	484.0296	5.8721
RBMP	14.2938	<u>0.5470</u>	447.0037	7.4666
WVM	13.6447	<u>0.4502</u>	413.1789	9.0020
BIMEF	13.6599	0.4926	430.1063	7.2313
RRM	13.2911	0.4916	436.5444	5.9662
BRAIN	10.8513	0.3628	499.2811	6.2983
FSTAR	11.3553	0.3928	<u>426.4237</u>	7.0593
LR3M	10.0574	0.3796	460.2705	<u>4.5103</u>
SDD	12.8832	0.5216	474.5604	4.8626
Proposed	15.9891	0.5749	468.0755	3.1587

corrupted by SPN(0.1), MWFFnet produces weak enhancement results and fails to clearly distinguish the objects. HVI-CIDNet and Ghillie also obtain unsatisfactory enhancement results, which contain a large amount of salt-and-pepper noise. Although the proposed algorithm still exhibits some artifacts, it effectively suppresses noise and achieves a promising enhancement effect. When the image is corrupted by GN(0.1), all algorithms are affected by Gaussian noise, and their enhancement results contain substantial noise. Benefiting from filtering operations and local information, the proposed algorithm can suppress noise to a certain extent. When the image is corrupted by SN(0.1), MWFFnet, HVI-CIDNet, and Ghillie produce results with inappropriate color distributions and substantial noise, as observed in the third test image. In contrast, the proposed algorithm achieves better enhancement performance with an appropriate brightness range. As shown in Table 7, the proposed algorithm achieves the highest PSNR and SSIM and the lowest LOE and NIQE when the image is corrupted

by SPN(0.1). When the image is corrupted by GN(0.1), the proposed algorithm obtains the highest PSNR and SSIM and the lowest NIQE. When the image is corrupted by SN(0.1), the proposed algorithm achieves the second-highest PSNR.

ABLATION STUDY

In this section, we analyze the contributions of the proposed Retinex model and stretching function to the enhancement performance on the testing set of the LOLv1 dataset. The RRM and the proposed algorithm are employed to decompose low-light images because both methods can estimate the noise component. Then, the traditional and proposed stretching functions are applied to improve the brightness of the decomposed results. RRM+T and RRM+P denote RRM using the traditional and proposed stretching functions, respectively. The same abbreviation rule is applied to the proposed algorithm.

The enhancement results of these methods are presented in Fig. 8, and the corresponding performance metrics are shown in Table 8. It should be noted that the quantitative results in this ablation study are evaluated on the testing subset of LOLv1, and therefore they are not directly comparable with the results reported on the entire LOLv1 dataset in Table 2. In Fig. 8, from top to bottom, the rows correspond to images #748 and #778, images #1 and #22 contaminated by SPN(0.1), images #111 and #179 contaminated by GN(0.1), and images #665 and #669 contaminated by SN(0.1), respectively.

As shown in Fig. 8, when the image is corrupted by SPN(0.1), the proposed stretching function shows promising noise-suppression ability. Both the proposed algorithm and RRM achieve better visual effects and remove part of the noise. When the image is corrupted by GN(0.1) or SN(0.1), RRM and the proposed algorithm with the traditional and proposed stretching functions all provide visual improvement to different degrees. As shown in Table 8, the proposed Retinex model generally improves PSNR and SSIM compared with RRM under different noise conditions. In addition, the proposed stretching function generally improves several performance metrics compared with the traditional stretching function. Notably, the proposed stretching function achieves a satisfactory effect when the image is corrupted by SPN(0.1).

In addition, to further analyze the effect of DWT-based noise prior, we tune δ from 0 to 0.1 and test the visual effect and performance metrics of the proposed algorithm. The visual results are given in Fig. 9 and corresponding performance metrics are shown in Table 9. In Fig. 9, from top to bottom, the six rows show the enhanced image, noise component, and reflectance

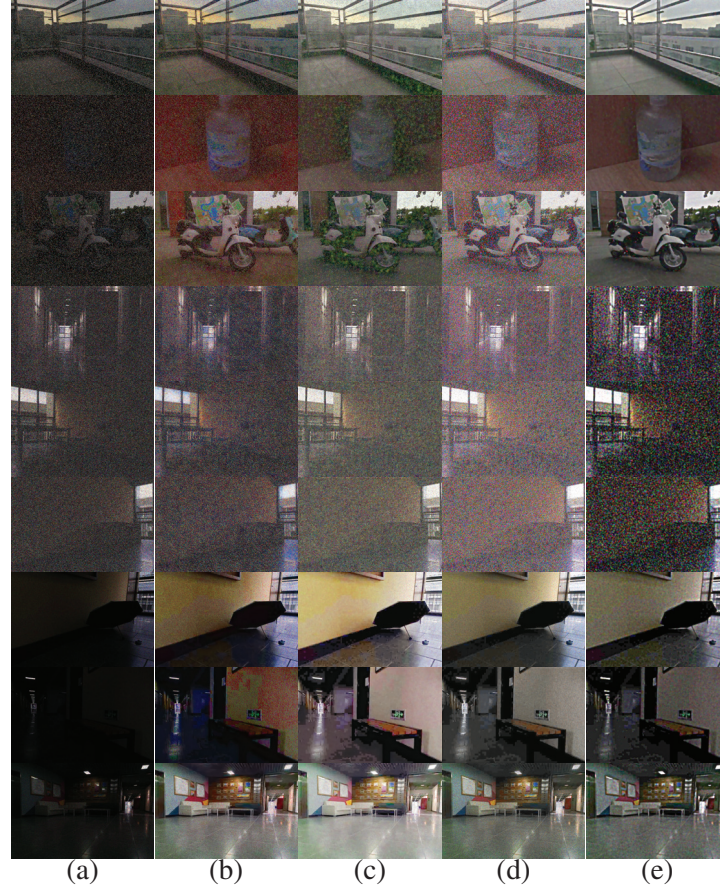


Fig. 7. Enhancement results of different deep learning-based algorithms on noisy LSRW-Huawei Dataset. (a) noisy images; (b) HVI-CIDNet; (c) MWFFnet; (d) Ghillie; (e) Proposed. *From top to bottom, the rows correspond to #2062–#2064 corrupted by SPN(0.1), #2047–#2049 corrupted by GN(0.1), and #2037–#2039 corrupted by SN(0.1), respectively.

Table 7. Average performance metrics of different deep learning-based algorithms on noisy testing set of LSRW-Huawei dataset

Noise Type	Metrics	MWFFnet	HVI-CIDNet	Ghillie	Proposed
SPN(0.1)	PSNR $\uparrow$	12.0533	11.6583	<u>13.1796</u>	15.4074
	SSIM $\uparrow$	0.0963	<u>0.1642</u>	0.1385	0.5223
	LOE $\downarrow$	1848.2946	<u>1619.1920</u>	1840.8287	1261.3644
	NIQE $\downarrow$	23.2506	<u>18.2629</u>	<u>15.5242</u>	5.7355
GN(0.1)	PSNR $\uparrow$	<u>11.7334</u>	10.3567	11.3390	12.7513
	SSIM $\uparrow$	0.0509	0.0309	<u>0.0642</u>	0.1053
	LOE $\downarrow$	1828.7032	1402.4843	1649.6034	<u>1461.4496</u>
	NIQE $\downarrow$	25.5094	<u>15.2521</u>	45.8774	9.2342
SN(0.1)	PSNR $\uparrow$	17.7621	18.1056	19.3313	<u>18.6632</u>
	SSIM $\uparrow$	0.6076	0.5493	<u>0.6034</u>	0.5500
	LOE $\downarrow$	<u>375.8805</u>	367.6593	391.9190	464.5300
	NIQE $\downarrow$	<u>4.2437</u>	3.8321	4.7897	5.1411

component of image #179, followed by the enhanced image, noise component, and reflectance component of image #547.

As shown in Fig. 9, when $\delta = 0$, the DWT-based noise prior does not contribute to the noise iteration, and the estimated noise component contains considerable edge information. When $\delta = 0.0001$,



Fig. 8. Visual results of Algorithms with Different Stretching Functions on the Noisy LOLv1. (a) Noisy images; (b) RRM+T; (c) RRM+P; (d) Proposed+T; (e) Proposed+P.

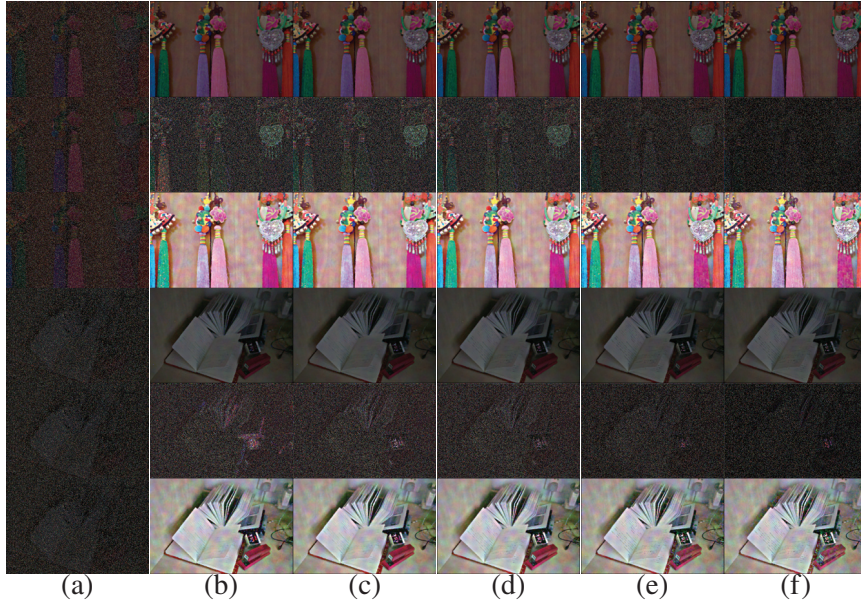


Fig. 9. Ablation study results under different values of δ on the noisy testing set of LOLv1 corrupted by SPN(0.1). (a) Noisy low-light images; (b) $\delta = 0$; (c) $\delta = 0.0001$; (d) $\delta = 0.001$; (e) $\delta = 0.01$; (f) $\delta = 0.1$.

the noise estimation is improved compared with that obtained at $\delta = 0$, but obvious edge information still remains. As δ increases, less structural edge information is captured by the noise component, indicating that the proposed DWT-based noise prior can

effectively suppress edge leakage and improve noise-removal ability. As reported in Table 9, the proposed algorithm achieves the highest PSNR and SSIM when $\delta = 0.001$, while the lowest LOE and NIQE are obtained when $\delta = 0.01$. Therefore, considering both

Table 8. Average performance metrics of algorithms with different stretching functions on the noisy testing set of the LOLv1 dataset

Noise Type	Metrics	RRM+T	RRM+P	Proposed+T	Proposed+P
No Noise	PSNR↑	13.1395	13.7747	<u>19.0363</u>	19.5692
	SSIM↑	0.6093	0.5971	<u>0.5737</u>	0.6531
	LOE↓	452.4943	<u>412.9817</u>	372.1384	437.3472
	NIQE↓	<u>4.1867</u>	3.9253	4.6223	6.5688
SPN(0.1)	PSNR↑	8.8401	15.3657	<u>17.0455</u>	17.1513
	SSIM↑	0.0734	0.0892	<u>0.4415</u>	0.4471
	LOE↓	2093.8315	1625.3670	<u>589.1854</u>	587.7165
	NIQE↓	<u>20.2242</u>	23.2988	21.9864	16.6125
GN(0.1)	PSNR↑	8.7664	<u>9.4211</u>	9.0122	11.3204
	SSIM↑	0.0351	0.0443	<u>0.1188</u>	0.1692
	LOE↓	2093.8315	1803.0647	1449.4529	<u>1466.3702</u>
	NIQE↓	20.0551	57.8844	9.9827	<u>12.7566</u>
SN(0.1)	PSNR↑	13.2911	13.7456	<u>15.1760</u>	15.9891
	SSIM↑	0.4916	<u>0.5153</u>	0.5109	0.5749
	LOE↓	<u>436.5444</u>	402.2339	465.0863	468.0755
	NIQE↓	5.9662	7.2053	<u>3.5132</u>	3.1587

Table 9. Average performance metrics under different δ on noisy testing set of LOLv1 dataset with SPN(0.1)

δ	PSNR↑	SSIM↑	LOE↓	NIQE↓
0	17.1128	0.4340	473.3914	5.0362
0.0001	17.1709	<u>0.4414</u>	435.4591	4.9496
0.001	17.2396	0.4455	414.8872	4.8239
0.01	<u>17.2100</u>	0.4344	405.5436	4.6233
0.1	17.1246	0.4253	<u>412.2710</u>	<u>4.6700</u>

quantitative performance and visual detail preservation, we set $\delta = 0.01$ in all experiments.

DISCUSSION

In this section, we compare the proposed algorithm with recent related Retinex-based methods in terms of methodological characteristics, including two noise-aware Retinex models, namely the anisotropic p th-order total variation-based Retinex model (ApTVRM) (Hsieh and Yang, 2026) and the detail-preserving noise-aware Retinex model (DPNRM) (Veluchamy and Subramani, 2025), as well as the DWT-Retinex-based improved multi-scale Retinex method (IMSRM) (Guo *et al.*, 2025). The comparison results are shown in Table 10.

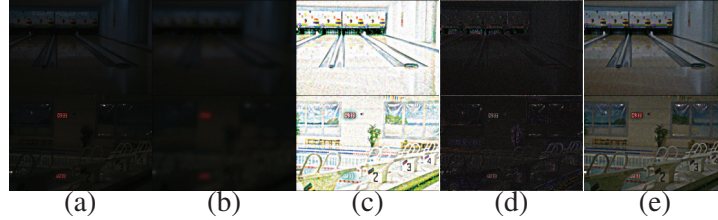
As shown in Table 10, ApTVRM adopts an

additive-noise Retinex formulation, which is similar to the RRM in explicitly considering the noise term in the Retinex model. It is clear that the noise suppression of ApTVRM mainly relies on adaptive reflectance regularization to reduce noise amplification during reflectance estimation. DPNRM adopts the traditional Retinex model to estimate the illumination and reflectance components, and its noise removal is mainly achieved by applying a bilateral filter to the enhanced value channel. IMSRM combines wavelet transform with the Retinex framework. It decomposes the intensity channel into low-frequency and high-frequency subbands, enhances the low-frequency subband using an improved MSRCR strategy, and processes the high-frequency subbands to preserve image details. However, high-frequency noise is not explicitly modeled in the Retinex decomposition process. In contrast, the proposed algorithm assumes that the noise component is coupled with the reflectance-related term and explicitly separates it from the reflectance component. Moreover, noise-aware priors are constructed in the unified optimization model to jointly constrain illumination, reflectance, and noise components.

In addition, we discuss the limitations of the proposed algorithm. The joint Retinex model $S = L \circ (R + N)$ models the noise component on the reflectance side and couples it with illumination, which is different from the additive residual used in RRM. However, in practical low-light imaging scenarios,

Table 10. Comparison of recent Retinex-based methods for noisy low-light image enhancement

Algorithms	ApTVRM	DPNRM	IMSRM	Proposed
Category	Noise-aware Retinex model	Noise-aware Retinex model	Wavelet-Retinex-based model	Noise-aware Retinex model
Retinex model	$S = L \circ R + N$	$S = L \circ R$	$S_{LL} = L_{LL} \circ R_{LL}$	$S = L \circ (R + N)$
Noise Removal	Adaptive Ap reflectance regularization	Bilateral filtering-based noise suppression	High-frequency noise is not explicitly modeled in Retinex decomposition	Explicit noise modeling and noise-prior constraint in the unified optimization model

Fig. 10. Visual results of the proposed algorithm on the images corrupted by Poisson noise. (a) Noisy low-light images; (b) L ; (c) R ; (d) N ; (e) enhanced results.

noise is not always purely additive and may exhibit signal-dependent characteristics. For example, photon shot noise is commonly modeled as Poisson noise, whose variance is related to the image intensity. To further analyze the behavior of the proposed method under signal-dependent noise, we conduct an additional experiment on low-light images corrupted by Poisson noise. The corresponding visual results are shown in Fig. 10.

As can be seen in Fig. 10, the estimated noise component captures many noise points when the image is corrupted by Poisson noise. However, it also contains considerable edge information, indicating that some structural details are still incorrectly absorbed into the noise component. It is clear that the proposed reflectance-side noise formulation can only approximate Poisson noise to a limited extent, since Poisson noise is signal-dependent and coupled with image intensity. Therefore, although the proposed method can still enhance the brightness and suppress part of the noise, more accurate signal-dependent noise modelling should be considered in future work.

CONCLUSION

In this paper, we improve the noise-aware Retinex model to better characterize the noise component during the decomposition process. In particular, the proposed model explicitly separates the noise component from the reflectance component, rather than simply treating noise as an additive term in the Retinex model. Then, contour, texture gradient, and reflectance-derived high-frequency priors are incorporated into a unified optimization model to

constrain the illumination, reflectance, and noise components. By solving this optimization model, the iterative formulas for illumination, reflectance, and noise are derived. Finally, an improved illumination stretching function is designed to enhance image contrast while suppressing noise amplification and halo artifacts. Experimental results demonstrate that the proposed algorithm achieves competitive performance compared with representative Retinex-based and deep learning-based low-light enhancement algorithms in terms of both visual quality and quantitative performance. In future work, we will explore adaptive weight estimation strategies to automatically determine the optimal parameter values and further improve the generalization of the proposed algorithm.

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