

Unsupervised Low-Light Image Enhancement Algorithm Based on Prior Information

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Abstract. Images captured in dimly illuminated surroundings often suffer from low contrast and severe loss of details, which directly affect the accuracy of subsequent image classification, recognition, and detection tasks. This paper addresses the challenges of low-light image enhancement, which relies on real data training and the insufficient availability of effective information in low-light images. An unsupervised low-light image enhancement algorithm, based on prior information, is proposed by us. By performing histogram equalization on the preprocessed images before network training, hidden information in the images is obtained. The optimization of initialization information is achieved by extracting the reflectance and illumination maps of the low-light images, which preserves the relative structural integrity of the images and improves the brightness restoration effect. The experimental outcomes validate the efficacy of the proposed algorithm in restoring brightness and reproducing natural colors in images. In comparison to other algorithms, it demonstrates superior performance on the LOL dataset in terms of peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and natural image quality evaluation metrics (NIQE). Specifically, it achieves improvements of 1.433 dB, 0.040, and 1.285, respectively.

Keyword: Image Enhancement · Prior Information · Low Illumination

1 Introduction

Low-light scenes often result in low image contrast, desaturated colors, limited dynamic range, and loss of important visual information in natural environments. These issues subsequently degrade the performance of image recognition, classification, and detection, necessitating the development of low-light image enhancement techniques to meet the demands of visual interpretation. Currently, deep learning methods are primarily employed for low-light image enhancement, primarily leveraging the GAN (Generative Adversarial Network) mechanism [1, 2] and adaptive fitting of implicit priors in optimization modules [3]. These approaches extract the necessary information from large-scale unpaired image data and learn from reference-free loss functions. However, they suffer from limitations such as dependence on paired images and high requirements for effective information initialization in unsupervised learning. In this study, building upon the brightness enhancement network [4], An unsupervised low-light image enhancement

algorithm, based on prior information, is proposed by us. We design a novel brightness enhancement model that fully utilizes the input image data and extracted feature maps through a designed prior network. This approach enables us to obtain richer information regarding image dynamic range, reflectance, and texture, thereby enhancing the effectiveness of image enhancement and brightness detail restoration.

2 Unsupervised Low-Light Image Enhancement Algorithm Based on Prior Information

The algorithm model for unsupervised low-light image enhancement based on prior information is illustrated in Fig. 1.

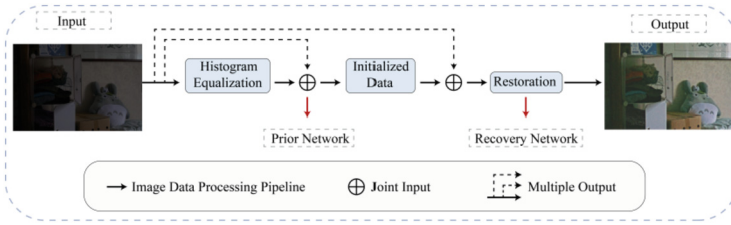


Fig. 1. Algorithm model of unsupervised low-light image enhancement based on prior information.

2.1 Prior Network Module

The prior network module, proposed in this paper, is depicted in Fig. 2.

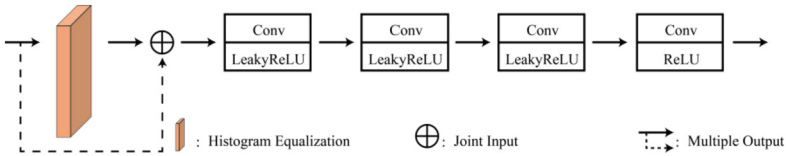


Fig. 2. Prior network architecture

To address the issue of insufficient effective information in low-light images, this study employs an improved histogram equalization method enhanced by VGG feature maps [5, 6] for feature extraction. Additionally, a fully convolutional network is utilized to enrich the learning of initialization information [7]. This network has the capability to adaptively learn the illumination and reflectance.

This paper addresses the issue of lacking real image samples to obtain the two feature components close to the original low-light image. To tackle this, the paper proposes an

approach using illumination initialization based on normal illumination images. The loss function is defined as follows:

$$\mathcal{L}_{init} = \hat{\lambda} \left(\hat{w} - \max_{c \in \{R, G, B\}} \hat{\rho}_F^{(c)2} + e^{-\eta \nabla \hat{x}} \cdot \nabla \hat{w} \right) + F(\rho) - F(X)_2^2 \quad (1)$$

where $\|\cdot\|_F$ and $\|\cdot\|_1$ represent the F -norm and l_1 -norm, respectively. $\hat{\lambda}$ and η are hyperparameters. $c \in \{R, G, B\}$ represents the RGB channels, $\nabla(\cdot)$ denotes gradient computation, and $F(\cdot)$ indicates the feature maps extracted from the pre-trained VGG-19 model on ImageNet. The loss function computes the difference between the feature maps of the output reflectance image and the input image.

2.2 Brightness Detail Restoration Module

The brightness detail restoration module decomposes the low-light image into a reflectance map and an illumination map and enhances the image's brightness based on the Retinex [8]. Its natural modeling is represented by Eq. (2):

$$X = \rho \odot W \quad (2)$$

where X represents the input low-light image, ρ represents the reflectance map, W represents the illumination map, and \odot denotes element-wise multiplication.

To restore brightness details, an improved brightness enhancement network is employed to recover the illumination of low-light images. Based on the Retinex theory, the network decomposes the image into two components: illumination and reflectance.

This paper employs the LeakyReLU activation function, which can reduce the phenomenon of neuron death, to improve the brightness enhancement network.

$$f(x) = \max(0.01x, x) \quad (3)$$

where x represents the output from the upper layers of the network. The LeakyReLU activation function is utilized in the network, where a small initialization value is assigned to the LeakyReLU neurons. Consequently, it enables the adequate restoration of the illumination in low-light images, thereby achieving the goal of brightness detail recovery (Fig. 3).

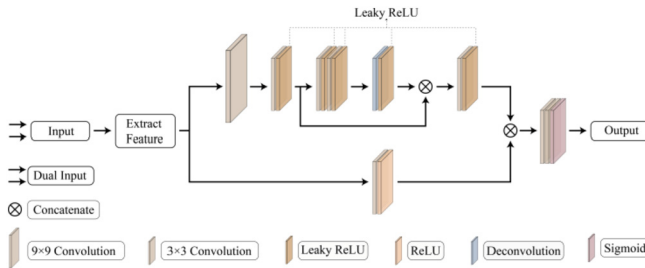


Fig. 3. Network layer structure

It is necessary to reconstruct the loss function to fuse the output reflectance map and illumination map after decomposing the image into the reflectance map and the illumination map, ensuring the quality of the generated image. The loss function is defined as follows:

$$\mathcal{L}_{recon} = \min_{\hat{\rho}, \hat{w}} \hat{X} - \hat{\rho} \cdot \hat{w}_1 \quad (4)$$

In the equation, \hat{X} represents the normal light image, $\hat{\rho}$ represents the reflectance map of \hat{X} , and \hat{W} represents the illumination map. The loss function is used to guide the network optimization and ensure that the generated image has a minimal difference in illumination compared to the normal light image.

3 Experimental Results and Analysis

This study utilized the LOL-datasets with 500 paired images as the training dataset. Our algorithm only uses the low light part for training.

3.1 Objective Evaluation Index of Model Performance

The performance evaluation of the algorithm in this study was based on objective assessment metrics, including PSNR, SSIM, and NIQE. These metrics were calculated using the following formulas (Eqs. 5, 6, and 7) respectively.

$$PSNR = 10 \cdot \log_{10} \left(\frac{(2^N - 1)^2}{MSE} \right) \quad (5)$$

In the mentioned formulas, N represents the number of bits used to store each pixel, and MSE refers to the mean squared error of the image.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (6)$$

In the given formulas, x and y represent the two images being compared, μ_x and μ_y are the mean values of x and y , σ_x and σ_y are the standard deviations of x and y , and σ_{xy} represents the covariance between x and y . C_1 and C_2 are positive constants.

$$NIQE_{e_1, e_2, o_1, o_2} = \sqrt{((e_1 - e_2)^T \left(\frac{o_1 + o_2}{2} \right)^{-1} (e_1 - e_2))} \quad (7)$$

Within the provided formula, the mean vectors and covariance matrices of the natural MVG (Multivariate Gaussian) model and the distorted image MVG model are denoted by e_1 , e_2 , o_1 , and o_2 , respectively.

3.2 Analysis of Model Experiment Results

The experimental evaluation of the compared models, Lime (Low-light Image Enhancement) [9], NPE (Naturalness Preserved Enhancement), RUAS (Retinex Unrolling Architecture Search), EnlightenGAN (EGAN), and ZeroDCE (Zero-Reference Deep Curve Estimation), was conducted from both objective and subjective perspectives. The evaluation results are as follows:

Objective Evaluation. Table 1 presents the experimental results comparing the proposed algorithm with Lime, NPE, RUAS, EnlightenGAN, and ZeroDCE. It can be observed that the proposed algorithm outperforms the other methods. Compared to the second-best RUAS algorithm, the proposed algorithm achieves improvements of 1.433 dB in PSNR, 0.040 in SSIM, and 1.285 in NIQE.

Table 1. Performance comparison on datasets

Measure	LIME	NPE	RUAS	EGAN	ZeroDCE	Our
PSNR↑	16.74	16.97	18.23	17.48	14.86	19.66
SSIM↑	0.444	0.482	0.717	0.654	0.562	0.757
NIQE↓	9.779	9.788	6.340	5.238	8.811	5.055

Subjective Evaluation. Figure 4 depicts the experimental results of the proposed algorithm compared to Lime, NPE, RUAS, EnlightenGAN, and ZeroDCE. After enhancing the images using the proposed model, there is a noticeable improvement in image quality. The brightness is appropriately adjusted, there are fewer artifacts, and the details are preserved more accurately. Particularly, in terms of fine details, such as the smoothness of cabinet surfaces and the increased reflection details on metal bowls, the proposed algorithm exhibits a more natural and visually appealing effect.

3.3 Analysis of the Efficiency of the Method

To examine the effectiveness of the algorithm on out-of-dataset samples, this study employed five images from the EGAN dataset and enhanced them using the proposed algorithm. The NIQE values before and after enhancement are presented in Table 2. The comparative results indicate that the algorithm exhibits a certain level of perceptual understanding and effectiveness when applied to images from outside the dataset.

Figure 5 presents a visual comparison of the images before and after enhancement. Based on subjective evaluations, it is evident that the proposed algorithm demonstrates good effectiveness in enhancing out-of-dataset images. It

restores the brightness of the images while preserving their structural integrity.



Fig. 4. Comparison of sample enhancement results for LOL dataset

Table 2. NIQE comparison before and after enhancement

Type	Image_1	Image_2	Image_3	Image_4	Image_5
Source	9.4396	5.7256	6.9990	8.0333	9.8014
Enhanced	6.2482	4.8568	4.3670	6.8001	6.8812



Fig. 5. Image enhancement before and after contrast

4 Conclusion

We have introduced a low-light image enhancement algorithm based on prior information. By introducing a prior network module, it fully extracts and utilizes the hidden information in low-light images, addressing the limitations of relying on real data training and insufficient effective information in low-light images for enhancement. By leveraging prior information, the proposed algorithm effectively achieves illumination enhancement and preserves intricate details, thereby mitigating the reliance on empirical

data for training purposes. It provides valuable insights for research on low-light image enhancement and improves the feasibility of practical applications in low-light image enhancement engineering.

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