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A Novel Image Enhancement Method Based on Guided Filtering and Modified Retinex

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Abstract. This paper proposes a novel image enhancement based on guided filtering and modified Retinex method to address the problems of poor visual effect, unclear images and incomplete display of details in low-light images. Low-illumination images are processed using guided filtering to adaptively enhance the luminance component. This method consists of two parts: the image decomposition network and the image enhancement network. The image decomposition network is responsible for decomposing the original image into illumination components and reflection components. The image enhancement network optimizes parameters and performs γ correction through the natural image quality evaluator (NIQE), adjusting the brightness and contrast of the illumination component, and then re-fuses it with the reflection component to improve the overall image quality. Finally, image quality enhancement experiments are conducted using the images in the SOTS standard test set and six actual scene images. They are compared and analyzed with other advanced methods. The experimental results show that the proposed method is superior to other methods in both subjective visual effects and objective evaluation indicators, thus fully verifying the effectiveness and feasibility of the proposed method.

Keywords: Image enhancement, Guided filtering, Modified Retinex method, NIQE.

1. Introduction

During the process of target detection, recognition and tracking of images, due to the limitations of weather, lighting and shooting scene conditions, the quality of some collected images may be poor, with problems such as dim brightness, uneven lighting and unclear details in some areas. Feature extraction of this type of low-illumination image information is extremely difficult. Therefore, such images must be enhanced to meet the requirements of subsequent processing [1-3].

Low-illumination image enhancement algorithms mainly include histogram equalization, Retinex theory, and deep learning. Histogram equalization (HE) is a simple and effective enhancement algorithm [4]. By stretching the gray level of the input image, it stretches the low gray level interval in the image to the high gray level interval, redistributing the gray level range of the image [5] to achieve the purpose of enhancing the image. However, this method does not take into account the information of the detailed parts of the image, which will lead to color distortion of the image and loss of some details. Retinex theory is a color perception model based on human vision [6,7]. Sun et al. [8] further studied the single scale Retinex algorithm (SSR) based on this model. However, the scale of the Gaussian kernel in this algorithm would affect the final image enhancement effect. Considering the defects existing in Gaussian kernels, experts and scholars had further studied and derived the multi-scale Retinex algorithm (MSR), which used Gaussian kernels of different scales for filtering. Ma et al. [9] proposed the multi-scale Retinex with color restoration (MSRCR). Based on multi-scale, a color restoration factor C was added to correct the color distortion problem, but it was prone to generating halo phenomena, making the processed image unnatural. With the rise of deep learning neural networks, many scholars are dedicated to integrating reinforcement algorithms into the theory of neural networks. However, the requirements for the dataset are extremely strict. Not only are two images for the day and night needed, but also all objects within the scene must have no displacement changes. Therefore, some scholars have artificially reduced the image exposure and used the obtained low-exposure images as night images [10,11]. However, this kind of image has certain differences compared with the actual night image, and the enhancement effect of the night image cannot be truly achieved during the algorithm's operation.

With the rise of deep learning technology, low-light image enhancement methods based on convolutional neural networks (CNN) [12-15] and generative adversarial networks (GAN) [16-18] have begun to attract attention due to their excellent performance. These methods enable the network to learn the mapping relationship from low-light images to normal-light images through a large amount of training data. This data-driven approach can achieve better results than traditional methods in many cases, especially in preserving image details and colors. However, these methods also face some challenges [19]. Firstly, they usually require a large amount of labeled data, that is, pairs of low-light and normal-light images, which are difficult to obtain in practical applications; Secondly, when there is a large amount of training data, these deep learning-based methods may also perform poorly when dealing with specific types of low-light images, as the training data may not cover all possible low-light scenarios.

To solve this problem, researchers have proposed unsupervised and zero-shot learning methods. Unsupervised learning methods do not rely on paired training data [20-22], but directly learn reinforcement models from a large number of low-light images. Although this method avoids the problem of obtaining paired data, due to the lack of clear supervisory signals, the difficulty of model training is relatively high, and the enhancement effect is not as stable as that of supervised learning. The zero-shot learning method goes even further. It doesn't even require any training data. It only needs to utilize the low-light image to be enhanced itself and directly obtain the enhancement result through network optimization. Although this method is highly attractive in theory, its effectiveness and generalization ability are greatly limited due to its complete reliance on the information in a single image. Reference [23] proposed an end-to-end trainable network named Retinex-net, which included a decomposition module and an illumination adjustment module. To implement denoising operations in Retinex-net, reference [24] designed a stacked sparse denoising autoencoder to enhance low-light images. This model used synthetic image pairs as training data. By combining low-light images with the corresponding enhanced high-fidelity images to form data samples, the training network learned the mapping relationship from low light to normal light, effectively enhancing the model's image enhancement ability in low-light environments. Reference [25] employed a trainable denoising module for reflectance restoration. The Retinex theory has also been adopted in the era of deep learning. Its application mainly has two methods: The first one is to directly regard the estimated reflectance layer (which can be achieved by first estimating the illumination and then performing element-by-element partitioning) as an enhanced image. For example, reference [26] used convolutional neural networks to simulate multi-scale Retinex. Reference [27] proposed an improved network framework for correcting illumination. Reference [28] constructed a LIE processing pipeline, first decomposing the image, then adjusting the reflection layer and the illumination layer. In addition, unsupervised and semi-supervised methods were also considered. Reference [29] proposed a LIE framework based on GAN; Inspired by the adjustment of the light enhancement curve, reference [30] proposed a zero-shot method, which was later extended. Reference [31] introduced paired data and unpaired data in a semi-supervised manner.

Overall, although low-light image enhancement technology has made significant progress in the past few decades, it still faces many challenges. Both traditional methods and those based on deep learning have certain deficiencies in some aspects. Future research needs to find a better balance point in improving the enhancement effect, reducing noise amplification, maintaining the naturalness of colors and reducing computational complexity. Meanwhile, exploring how to reduce reliance on a large amount of training data and enhance the algorithm's adaptability to different low-light conditions is also an important direction for future research.

Inspired by the Retinex theory and combined with the parameter optimization of NIQE (Naturalness Image Quality Evaluator), this paper aims to overcome the common problems in low-light image enhancement. The core of the method proposed in this paper lies in being able to effectively find the appropriate y value in an unsupervised environment and thereby effectively enhance the image. Specifically, this paper first decomposes the image into the illumination component and the reflection component based on the Retinex theory, and then applies the NIQE parameter optimization to find the optimal illumination component for enhancement. In this way, the overall brightness and clarity of the image can be enhanced, while maintaining the naturalness of the colors and the details of the image. The enhanced illumination component combines with the original reflection component to generate the final enhanced image.

Qualitative and quantitative experiments on public datasets have demonstrated the effectiveness of the method proposed in this paper. The experimental results show that, compared with other advanced algorithms, the method proposed in this paper has significant advantages in image enhancement quality, color naturalness and detail retention. This breakthrough not only demonstrates the potential of combining the Retinex theory and the NIQE optimizer in the field of low-light image enhancement, but also provides new directions and ideas for future related research.

2. Proposed Low-light Image Enhancement

As shown in Figure 1, the proposed network architecture consists of two main parts: the Decom-net module and the Enhance-net module. The main function of Decom-net is to meticulously decompose the input image into illumination components and reflection components. Subsequently, Enhance-net takes over the work, using the decomposed illuminance component as input to finely adjust and enhance its brightness and contrast. The core of this process lies in significantly enhancing the brightness of the image in low-light conditions and optimizing its contrast, ultimately generating images of higher quality under normal lighting conditions. By this method, images captured in low-light conditions can be effectively improved, thereby achieving clearer and more vivid visual effects.

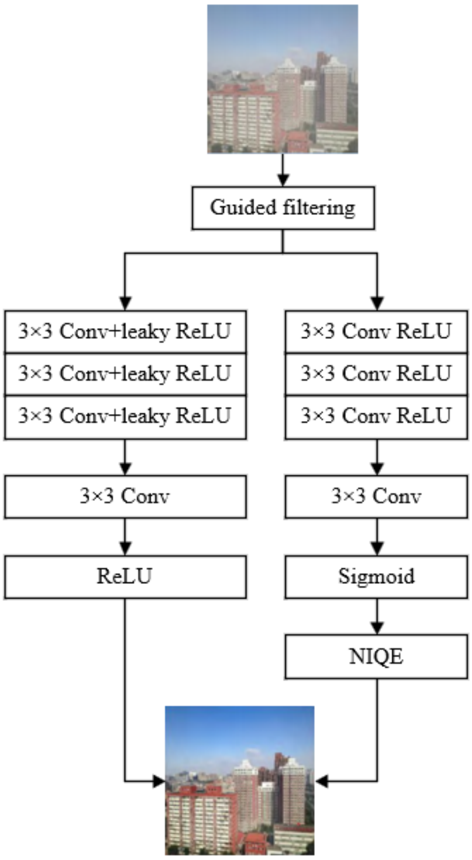

Fig. 1. Proposed image enhancement model

Decom-net can be represented in a manner similar to the decomposition based on Retinex, precisely decomposing the input image into the illumination component and the reflection component, as shown in equation (1).

$$S(x) = I(x) * R(x). \tag{1}$$

In the formula, $R(x)$ represents reflectance. $I(x)$ represents illuminance. $*$ represents element-by-element multiplication. Reflectance describes the intrinsic properties of the captured object and is considered consistent under any brightness conditions. Illuminance represents all kinds of brightness on an object. On low-light images, there is usually an imbalance in the distribution of darkness and lighting.

2.1. Guiding Filtering

Most traditional Retinex algorithms use Gaussian low-pass filtering as the center-surround function to estimate the incident components of the original image, but this may lead to incomplete image details and edge information as well as halo phenomena. Guided filtering not only smooths images but also outperforms Gaussian low-pass filtering in maintaining details at image edges, and it has a faster computational speed. Figure 2 shows the results of the same photo after Gaussian filtering and guided filtering respectively. It can be seen that the edge details of the image are almost not lost after guided filtering processing.

2.2. NIQE Parameter Optimization

NIQE is an advanced image quality assessment tool [32]. It is designed based on the characteristics of the human visual system and evaluates the quality of images by analyzing their statistical features, which reflect their natural attributes. Unlike traditional image quality assessment methods, NIQE can evaluate the quality of images without

Fig. 2. Results with different filters

referring to them. It uses the statistical features of visual naturalness learned from undistorted natural images to evaluate the quality of any image [33].

In terms of parameter optimization, NIQE is widely applied in various image processing algorithms, such as denoising, sharpening, compression and color correction, etc. By evaluating the impact of different parameter Settings on image quality, NIQE helps determine the optimal parameters that can enhance the naturalness and visual quality of images. This process involves conducting experiments on various parameter combinations. After each adjustment, the image quality is evaluated using NIQE, and ultimately the parameter combination with the highest score is selected.

Inspired by reference [34], the optimal parameter search for low-brightness image enhancement is achieved by combining NIQE parameter optimization with γ correction, which can be expressed as:

$$\min_{g\in[0.03,0.3]} NIQE(Engancement(L,R,g)). \tag{2}$$

Where $Enhancement(L,R,g) = L^g \times R \times 255$. L and R are the input illumination component and reflection component respectively. After finding the optimal g value, it uses this g value to process L and R through the $Enhancement$ function to obtain the final enhanced image J. The formula is as follows:

$$J = Enhancement(L,R,opt_g). \tag{3}$$

In the formula, opt_g is the optimal γ value found through the optimization process. It enables the enhanced image J to have the best score under the NIQE function evaluation. It provides the best visual quality for image enhancement.

3. Experimental Results and Analysis

To verify the effectiveness of the proposed method, image quality enhancement experiments are conducted to compare it with CLAHEMF [35], IDCPLT [36] and DCP-PSO [37]. The simulation platform is a 64-bit Windows 11 operating system, the hardware configuration is a 12th Gen Intel(R) Core(TM)i7-12700H 2.30GHz, and the software platform is MATLAB R2021a.

3.1. Layout, Typeface

To verify the effectiveness of the proposed method, images from the SOTS standard test set are selected for comparative experiments. The comparison effects of the source images with the four methods are shown in Figure 3, and the evaluation indicators under different methods are calculated in Tables 1 to 4. As can be seen from Figure 3 and Tables 1 to 4, in the SOTS test set, the proposed model in this paper has strong adaptability in scenarios with different light intensities, and the enhanced image effect is good. The comparative characteristics of the DAOM model with the CLAHEMF, IDCPLT, and DCP-PSO methods are summarized as follows:

1. It can be seen from Figure 3(b) that the image enhancement effect of the CLAHEMF method is relatively poor. Especially for foggy day Image 1 and foggy day Image 5, the degree of blurriness of the images is relatively obvious. It can be seen from the comparison table of evaluation indicators that the evaluation indicators calculated by the CLAHEMF method are poor, and this method cannot effectively clear the images.
2. As can be seen from Figure 3(c), the enhancement effect of the IDCPLT method has been improved to a certain extent compared with the CLAHEMF method, but the brightness of the obtained image is still relatively dark and does not have adaptive characteristics. It can be seen from Tables 1 to 3 that compared with the

CLAHEMF method, the IDCPLT method has improved the effect of image clarification to a certain extent, but the calculated values of the evaluation indicators are still relatively poor.

3. It can be seen from Figure 3(d) that the DCP-PSO method has an adaptive defogging effect compared with the previous two methods, but the enhancement of the close-up quality of the processed images is not thorough enough. It can be seen from Tables 1 to 3 that the DCP-PSO method has certain improvements in PSNR and SSIM compared with the previous two methods, but the information entropy is slightly lower than that of the CLAHEMF method.
4. It can be seen from the enhancement effect in Figure 3(e) that the proposed model can effectively and adaptively enhance the images of different scenes, and the clarification effect of the enhanced images is significant. As can be seen from Tables 1 to 3, compared with the CLAHEMF method, the PSNR value of the proposed model is approximately increased by 45%, the SSIM value is approximately increased by 5.32%, and the information entropy value is approximately increased by 0.59%. Meanwhile, compared with the IDCPLT method, the PSNR value of the proposed model is increased by approximately 13.23%, the SSIM value is increased by approximately 1.27%, and the information entropy value is increased by approximately 11.62%. Furthermore, compared with the DCP-PSO method, the PSNR value of the proposed model has increased by approximately 6.27%, the SSIM value has increased by approximately 0.91%, and the information entropy value has increased by approximately 6.99%, thereby effectively improving the enhanced image quality.
5. From Figures 3 and Table 4, it can be observed that the CLAHEMF method and the IDCPLT method have shorter running times in the image enhancement task, but their enhancement effects are relatively limited. Although the DCP-PSO method improves the image enhancement quality to a certain extent by introducing a dynamic optimization mechanism, the iterative optimization of the PSO algorithm results in a significant increase in the running time cost of the algorithm. In contrast, the proposed model, while taking into account the image enhancement effect, effectively reduces the computational cost of the algorithm and achieves a better balance of algorithm performance.

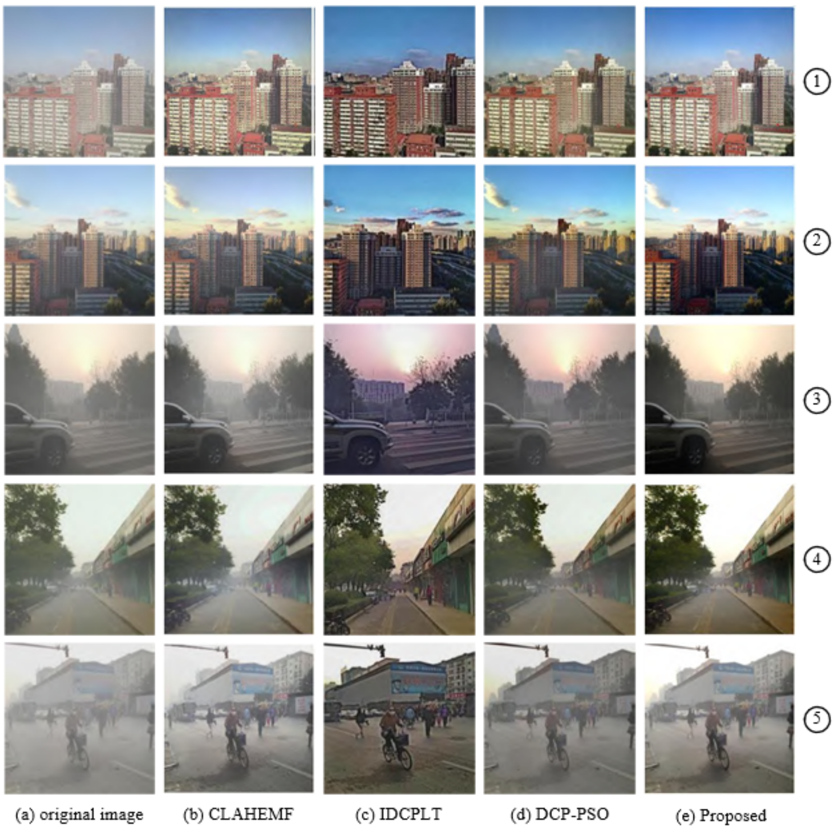

Fig. 3. SOTS test set comparison

Table 1. PSNR comparison with different methods

Number	CLAHEMF	IDCPLT	DCP-PSO	Proposed
1	4.28E+01	5.70E+01	5.95E+01	6.60E+01
2	4.91E+01	5.96E+01	6.38E+01	6.72E+01
3	4.78E+01	5.94E+01	6.33E+01	6.54E+01
4	4.78E+01	6.04E+01	6.41E+01	6.57E+01
5	4.26E+01	5.63E+01	5.99E+01	6.56E+01

Table 2. SSIM comparison with different methods

Number	CLAHEMF	IDCPLT	DCP-PSO	Proposed
1	9.36E-01	9.82E-01	9.88E-01	9.99E-01
2	9.87E-01	9.91E-01	9.92E-01	9.99E-01
3	9.68E-01	9.89E-01	9.92E-01	9.98E-01
4	9.69E-01	9.92E-01	9.91E-01	9.98E-01
5	9.17E-01	9.79E-01	9.85E-01	9.98E-01

Table 3. Information entropy comparison with different methods

Number	CLAHEMF	IDCPLT	DCP-PSO	Proposed
1	7.34E+00	6.81E+00	7.14E+00	7.44E+00
2	7.63E+00	7.07E+00	7.42E+00	7.67E+00
3	7.46E+00	6.79E+00	6.98E+00	7.53E+00
4	7.17E+00	6.75E+00	6.84E+00	7.18E+00
5	6.96E+00	6.22E+00	6.60E+00	6.98E+00

Table 4. Running time comparison with different methods

Number	CLAHEMF	IDCPLT	DCP-PSO	Proposed
1	3.45E-01	3.31E-01	5.09E+00	4.38E+00
2	3.21E-01	3.36E-01	5.12E+00	4.47E+00
3	3.63E-01	3.14E-01	4.94E+00	4.41E+00
4	3.26E-01	3.25E-01	5.09E+00	4.66E+00
5	3.43E-01	3.22E-01	5.22E+00	4.55E+00

4. Conclusion

This paper proposes a novel low-light image enhancement method based on Retinex theory and NIQE optimizer. The proposed framework can not only effectively decompose the image into lighting and reflection components, but also enhance the brightness and contrast of the image through optimization algorithms, while maintaining the naturalness of colors and the details of the image. It has demonstrated outstanding performance in extensive tests conducted on public test sets, especially in the two important metrics of PSNR and SSIM, with results surpassing many existing image enhancement algorithms. The method proposed in this paper successfully demonstrates the effectiveness of combining the Retinex theory and the NIQE optimizer in the field of low-light image enhancement. It not only provides a new perspective for solving the problems of image processing in low-light environments, but also paves the way for future research work. It is particularly worth noting that the unsupervised learning feature of the method proposed in this paper provides the possibility of reducing the reliance on a large amount of training data. Furthermore, its simple and effective framework also means that it can be easily applied to different application scenarios, thus having broader practical application value. In conclusion, this paper not only proposes an innovative low-light image enhancement method, but also provides new directions and ideas for the development of low-light image processing technology. Future research will focus on further optimizing and refining the method proposed in this paper, as well as exploring its application potential in more fields. With the continuous development and improvement of technology, it is believed that low-light image enhancement technology will reach a new height in the near future.

5. Conflict of Interest

The authors declare that there are no conflict of interests, we do not have any possible conflicts of interest.

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