Postprint of Image Enhancement Method Based on Multi-layer Fusion and Detail Restoration

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Abstract

To address issues such as low contrast and invisible details in some images under non-uniform illumination, overexposure, or underexposure, an image enhancement method based on multi-layer fusion and detail restoration is proposed. First, in the HSV image space, the V channel is equivalently replicated into three layers: a Retinex enhancement layer, a brightness enhancement layer, and a detail prominence layer. In the Retinex enhancement layer, a combination of weighted guided filtering and morphology is employed to eliminate halo artifacts, and the improved Retinex is used to enhance image brightness and details; in the brightness enhancement layer, brightness is further enhanced through adaptive normalization; in the detail prominence layer, the artificial bee colony optimization algorithm is used to optimize an improved local linear enhancement model to highlight image details. Finally, based on the characteristics of Gamma correction and neighborhood pixel relationships, a detail restoration scheme is proposed to avoid partial detail blurring caused by fusion. Experimental data demonstrate that the algorithm can more effectively highlight image details and improve contrast. In objective quantitative comparisons with existing algorithms, its comprehensive performance is superior, particularly in terms of clarity metrics which far exceed those of other algorithms.

Full Text

Preamble

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Image Enhancement Method Based on Multi-layer Fusion and Detail Recovery

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Abstract: This paper proposes an image enhancement method based on multi-layer fusion and detail recovery to address issues such as low contrast and invisible details in images with non-uniform, overexposed, or underexposed illumination. First, in HSV color space, the V channel is equivalently replicated into three layers: a Retinex enhancement layer, a brightness enhancement layer, and a detail enhancement layer. In the Retinex enhancement layer, weighted guided filtering combined with morphological operations eliminates halo artifacts and improves brightness and detail through an enhanced Retinex approach. In the brightness enhancement layer, adaptive normalization further enhances brightness. In the detail enhancement layer, an artificial bee colony algorithm optimizes an improved local linear enhancement model to highlight image details. Finally, based on Gamma correction characteristics and neighborhood pixel relationships, a detail recovery scheme is proposed to avoid partial detail blurring caused by fusion. Experimental results demonstrate that the algorithm more effectively highlights image details and improves contrast. Compared with existing algorithms in terms of objective quantitative metrics, the comprehensive performance is superior, especially in sharpness metrics where it far exceeds other algorithms.

Keywords: image enhancement; multi-layer; detail recovery

0 Introduction

During image capture, non-ideal lighting conditions such as non-uniform illumination, low light, or strong light can cause severe image quality degradation, resulting in low contrast, overall darkness, and poor visual effects that make it difficult to extract sufficient useful information. To overcome these defects, researchers have attempted to improve image quality through dynamic range adjustment, edge enhancement, detail feature highlighting, and contrast improvement [1]. Current mainstream image enhancement methods include histogram-based enhancement, fusion-based enhancement, and Retinex-based enhancement [2].

Classic histogram-based enhancement algorithms include Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE). When processing low-contrast images, these methods often produce over-enhancement and noise amplification because they assume a uniform histogram distribution without considering the overall shape of the image histogram, mechanically stretching its dynamic range [2]. To address these issues, numerous improved histogram-based algorithms have been proposed, such as Weighted Threshold Histogram Equalization [3], Clipped Histogram Equalization [4], and

Non-parametric Modified Histogram Equalization [5]. Reference [4] enhances dark regions and highlights bright area details by detecting the image dynamic range. Reference [5] achieves illumination-independent image enhancement by modifying histogram grayscale spatial variations. However, these methods constrain histogram stretching through limited patterns and fail to enhance extremely dark regions effectively.

Image fusion enhancement is primarily divided into spatial domain fusion and transform domain fusion. Spatial domain methods enhance images through gradient information [6]. Transform domain methods first convert images to another domain before fusing useful information for enhancement. Although fusion methods can effectively improve contrast and sharpness, they still suffer from over-enhancement. Reference [6] achieves enhancement by introducing a convolutional sparse representation framework that separates the original image into detail and base layers. Reference [7] proposes gradient bilateral filtering fusion by constructing a gradient similarity kernel function to replace the bilateral filtering kernel function. Despite these improvements, such methods can only process single images, suffer from high time complexity, and often produce unnatural visual results.

Retinex is a visual model of human perception of brightness and chromaticity [1]. Classic algorithms include single-scale, multi-scale, and multi-scale with color restoration. Single-scale Retinex primarily targets grayscale images, while multi-scale Retinex is a linear combination of different single-scale versions that easily produces pseudo-halo artifacts at edge details. Multi-scale Retinex with color restoration adds color restoration coefficients but can only adjust image contrast and brightness within a limited range, often causing color distortion beyond this range [8].

To address these issues, reference [9] employs fast mean estimation for image brightness in single-scale Retinex and introduces enhancement factors in HSV space, effectively avoiding color distortion and noise amplification. Reference [10] introduces guided filtering for brightness estimation in multi-scale Retinex and optimizes enhanced images through improved image evaluation methods and quantum-behaved particle swarm optimization. To further highlight image details and improve contrast, this paper proposes an image enhancement method based on multi-layer fusion and detail recovery. First, the V channel in HSV space is equivalently replicated into three layers. Unlike reference [2] which adopts a serial layered pattern, our layered approach is not affected by upper-layer enhancement results, with each layer processing the image independently, compensating for shortcomings and highlighting respective advantages. Finally, Laplacian feature fusion combines the strengths of each layer. Weighted guided filtering [11] combined with morphological operations serves as the single-scale estimation method, while incorporating local detail adjustment models and overall brightness adjustment factors that consider image entropy to enhance details and brightness—denoted as the Retinex enhancement layer. To further improve brightness, an inverse trigonometric function-based adaptive normalization highlights image brightness, denoted as the brightness enhancement layer. An artificial bee colony algorithm optimizes an improved local linear model considering PSNR values to highlight image details, denoted as the detail enhancement layer. Finally, to avoid partial detail blurring caused by fusion, a detail recovery scheme is proposed based on Gamma correction characteristics and neighborhood pixel relationships. Performance is verified through comparisons with CLAHE, reference [9], reference [12], and reference [13] algorithms under low-light, strong-light, and non-uniform illumination conditions.

1.1 Algorithm Introduction

The basic framework of our algorithm is shown in Figure 1 [Figure 1: see original paper]. First, the input image is converted to HSV space, where the V channel is equivalently replicated into three layers that are processed independently. The three layers are then fused via Laplacian feature fusion to generate V*. In the Retinex enhancement layer, we avoid the halo problems and shadow phenomena at image detail edges caused by gradient reversal in traditional Retinex enhancement, thereby enhancing image details and brightness. In the brightness enhancement layer, adaptive normalization further improves brightness. In the detail enhancement layer, the artificial bee colony algorithm highlights image details by optimizing a simplified model from reference [16]. Finally, in the detail recovery stage, we restore lost details from fusion based on the variance and mean relationships between pixels and their four directional neighbors, combined with Gamma correction characteristics. The Retinex enhancement layer, brightness enhancement layer, detail enhancement layer, and detail recovery are described in detail in the following sections.

1.2 Retinex Enhancement Layer

Guided filtering possesses smoothing and edge-preserving properties that can transfer the structure of a guide image to the filtering result [14]. Weighted guided filtering adds adaptive weighting coefficients to eliminate pseudo-halo artifacts that may occur at edges in guided filtering [11]. Therefore, our algorithm employs weighted guided filtering for brightness estimation. If the brightness image is directly used as the guide image in weighted guided filtering, excessive redundant information may transfer to the enhanced image, causing pseudo-halo artifacts. Our algorithm uses the smoothed Y channel in YCbCr space as the guide image, as it more accurately reflects the image scene and prevents redundant information transfer [10]. The smoothed Y channel is achieved through three weighted morphological closing operations. Compared with the Gaussian smoothing used in reference [10], morphological closing operations avoid excessive smoothing at edge contours. Equation (1) shows its expression:

$$Y_f = \sum_{i=1}^{3} w_i \cdot (Y \circ P_i)$$

where P_i represents the i-th structural element, $*$ denotes pixel-wise multiplication, $\cdot$ denotes morphological closing operation, Y_f represents the smoothed Y channel image, and w_i represents the weighting value for the i-th morphological operation.

Using Y_f as the guide image, brightness is expressed as:

$$L(x,y) = \frac{1}{|w(x,y)|} \sum_{(u,v)\in w(x,y)} (a(u,v)Y_f(x,y) + b(u,v))$$

where $L(x,y)$ is the brightness estimation output, $Y_f(x,y)$ is the guide image, $w(x,y)$ represents the local neighborhood at (x,y), and $|w(x,y)|$ is the number of pixels in the local neighborhood. Coefficients $a(u,v)$ and $b(u,v)$ are calculated according to equations (3) and (4):

$$a(u,v) = \frac{\sigma^2_{Y_f}(u,v)}{\sigma^2_I(u,v) + \sigma^2_{Y_f}(u,v) + \varepsilon}$$

$$b(u,v) = \mu_{Y_f}(u,v) - a(u,v)\mu_{Y_f}(u,v)$$

where $\mu(u,v)$ represents the mean of the input image in neighborhood $|w(u,v)|$, $\mu_{Y_f}(u,v)$ and $\sigma^2_{Y_f}(u,v)$ represent the mean and variance of the guide image in neighborhood $|w(u,v)|$, ε is the regularization parameter, σ^2_I is the variance of the input image in a 3×3 neighborhood, $\sigma^2_{Y_f}$ is the variance of the guide image in a 3×3 neighborhood, and x is a constant.

After brightness estimation, the image reflectance must be calculated. Building upon single-scale Retinex, we improve it by introducing an overall brightness adjustment factor and a local detail adjustment model to enhance overall brightness and highlight local details, as shown in equations (5) and (6):

$$R(x,y) = \log(I(x,y)) - \log(L(x,y)) \cdot \alpha \cdot \beta$$

$$\beta = 1 - \sin^2\left(\frac{\pi}{2} \cdot \frac{L(x,y)}{I(x,y)}\right)$$

where $R(x,y)$ is the reflectance output, $I(x,y)$ is the original image, $L(x,y)$ is the brightness estimation image, α is the overall brightness adjustment factor, and β is the local detail adjustment factor.

However, in the logarithmic domain, $R(x, y)$ cannot satisfy all pixels within the specified value range. Therefore, after calculating reflectance, it must be stretched to a range suitable for visual requirements. Traditional linear stretching easily loses local details [10]. To better adjust the output information, non-local linear stretching is adopted, as implemented in equations (7) and (8):

$$R_{out}(x, y) = \begin{cases} 0, & R(x, y) < R_{low} \\ 255 \cdot \frac{R(x,y) - R_{low}}{R_{high} - R_{low}}, & R_{low} < R(x, y) < R_{high} \\ 255, & R(x, y) > R_{high} \end{cases}$$

$$R_{low} = \text{mean} - d \cdot \alpha, \quad R_{high} = \text{mean} + d \cdot \alpha$$

where mean is the mean of $R(x, y)$, α is the variance of $R(x, y)$, and d is the truncation factor controlling the stretching range.

For different images, the truncation factor d and overall adjustment factor α require different values. To achieve adaptive effects, d and α need optimization. This paper employs the artificial bee colony algorithm to optimize d and α due to its relatively simple operation, fewer control parameters, and high solution quality [15]. Image information entropy represents the amount of information in an image; larger values indicate richer information, more details, and better image quality [1]. Entropy is used as the fitness function to optimize the enhanced image, defined as:

$$\text{fit}_1 = -\sum_{i=0}^{255} P(i) \log(P(i))$$

where $P(i)$ represents the proportion of pixels with grayscale value i.

1.3 Brightness Enhancement Layer

Experiments reveal that the Retinex enhancement layer provides slightly insufficient brightness enhancement. To further improve image brightness, inspired by Gamma correction and Sigmoid functions, we propose a new normalization function, as shown in equation (10):

$$\text{Norm}(x, y) = \frac{255}{\pi} \cdot \arctan(\lambda \cdot I(x, y))$$

where λ is the adjustment factor controlling brightness levels, and $\text{Norm}(x, y)$ is the normalized $I(x, y)$. Different images require different λ values, so λ should be adaptive, defined as:

$$\lambda = \frac{5}{\text{Imean}} + 1$$

where Imean represents the mean of $I(x, y)$. Darker images have smaller Imean values, resulting in larger λ values, which significantly increases brightness for darker images.

The parameter ranges are: $\alpha \in (1.5, 2.5)$, truncation factor $d \in (2.0, 3.0)$, bee colony size of 20, and iteration count of 30.

Figure 2 shows brightness comparisons. It can be observed that the brightness enhancement layer achieves significantly higher brightness than the Retinex enhancement layer, validating the rationality of the normalization function.

1.4 Detail Enhancement Layer

In the Retinex enhancement layer, image detail enhancement is achieved. However, to highlight enhanced details and fully exploit hidden details using global and local information, we improve a local linear enhancement model [16]. The improved model is shown in equation (12):

$$E_{\text{local}}(x, y) = [I(x, y) - b \cdot m(x, y)] \cdot \frac{D}{m(x, y) + a \cdot \sigma(x, y)}$$

where $E_{\text{local}}(x, y)$ is the enhanced output, $m(x, y)$ is the mean in an $n \times n$ local neighborhood, D is the global mean of input image $I(x, y)$, $M \times N$ is the input image size, and $\sigma(x, y)$ is the standard deviation in an $n \times n$ local neighborhood. The specific implementation is shown in equation (13):

$$\sigma(x, y) = \sqrt{\frac{1}{n^2} \sum_{i=x-\frac{n-1}{2}}^{x+\frac{n-1}{2}} \sum_{j=y-\frac{n-1}{2}}^{y+\frac{n-1}{2}} (I(i, j) - m(x, y))^2}$$

In the model, $m(x, y)$ and $\sigma(x, y)$ determine local detail information, where a avoids division by zero when $\sigma(x, y) = 0$, b controls the degree of pixel deviation from the local mean, and D enhances the image globally. Parameter ranges are $a \in (0, 0.5)$ and $b \in (0, 1)$.

Since different images require different a and b values, and to achieve optimal adaptive enhancement, the artificial bee colony algorithm is used to optimize parameters a and b.

PSNR is widely used in image quality assessment; higher PSNR values indicate less distortion [16]. In optimization, PSNR serves as the fitness function for local model optimization, defined as:

$$\text{fit}_2 = 10\log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(I(x,y)-E(x,y))^2}\right)$$

where L represents the grayscale level (256), and $E(x, y)$ is the enhanced image.

As shown in equation (12), our model uses two parameters for constraint, while reference [16] employs four parameters. Although more constraints are used in [16], the actual effect is not optimal. Figure 3 compares the models. Reference [16] enhances image details but produces insufficiently prominent local details, particularly in grass and sail areas, resulting in overall blurriness. In contrast, our improved model clearly shows grass and sail details, with visible stripes on the woman' s clothing, and processes faster under the same conditions.

1.5 Detail Recovery

To obtain better enhancement results that combine the characteristics of each layer, we fuse the Retinex base layer, brightness enhancement layer, and detail enhancement layer using Laplacian pyramid fusion [17]. Experiments reveal that Laplacian fusion causes partial detail blurring, so we design a detail recovery scheme. Since image detail levels vary across different neighborhoods, regional detail recovery based on local properties can prevent detail loss. We propose a detail recovery scheme utilizing relationships between pixel values and their neighborhood means and variances, combined with Gamma correction characteristics.

Detail Recovery Scheme:

a) First, convert the input image to grayscale and normalize it.

b) Calculate the mean $M(x, y)$ of four neighboring domains and the deviation $\alpha_2(x, y)$ from this mean, as defined in equations (15) and (16):

$$M(x,y) = \frac{1}{4}\sum_{m\in\{x-1,x+1\}}\sum_{n\in\{y-1,y+1\}} I(m,n)$$

$$\alpha_2(x,y) = \frac{1}{5}\sum_{m\in\{x-1,x+1\}}\sum_{n\in\{y-1,y+1\}} (I(m,n)-M(x,y))^2$$

c) Calculate the Gamma correction value I_{ga}, defined in equation (17):

$$I_{ga}(x,y) = \frac{M(x,y)+\alpha_2(x,y)}{I(x,y)+\alpha_2(x,y)}$$

d) Calculate the final enhanced result I_{fina}, as shown in equation (18):

$$I_{fina}(x,y) = I_{ga}(x,y) \cdot I_h(x,y)$$

where $I_{gray}(x,y)$ is the grayscale image, and $I_h(x,y)$ is the image after Laplacian fusion converted back to R, G, B channels.

Figure 4 compares results before and after recovery. Figure 4(a) shows the entire image appears blurred due to insufficient detail prominence, particularly in grass and coastal areas. Figure 4(b) after recovery shows clear grass details and sharp sails, eliminating partial detail blurring caused by Laplacian fusion and proving the scheme' s rationality.

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2 Experimental Analysis and Discussion

To verify our algorithm' s performance, the testing environment is VS 2013 + OpenCV 2.4.9, with all experimental results implemented in C++. Test images are from [18]. We selected three representative image types: image18 captured under low-light conditions, image2 captured under strong-light conditions, and image15 captured under non-uniform illumination conditions. Below we present our algorithm's enhancement results and compare them with CLAHE, reference [9], reference [12], and reference [13].

Figure 5 [Figure 5: see original paper] shows experimental result comparisons for image18 under low-light conditions. CLAHE improves brightness but suffers from color overflow, particularly with blackened lake surfaces, inability to highlight grass details, and overly bright sails, resulting in an overall dark visual effect. Reference [9] produces relatively clear textures but weak contrast, with whitened seawater and coastlines, severe noise, and insufficient overall brightness. Reference [12] enhances contrast globally but produces unnatural results with a hazy appearance and blurred grass details due to neglecting local information. Reference [13] exhibits excessive brightness enhancement, particularly in sails and seawater, with significant detail loss in local areas due to global normalization, causing blurred grass. Our proposed algorithm appropriately improves contrast and brightness, producing more natural enhancement results with more prominent details, clearly visible grass details, and no noise amplification.

Figure 6 [Figure 6: see original paper] shows experimental result comparisons for image2 under strong-light conditions. Under strong illumination, CLAHE produces over-enhancement with excessively bright tires and whitened boy' s face. Reference [9] shows weak contrast enhancement and severe blurring due to poor detail highlighting, accompanied by noise amplification. References [12] and [13] both exhibit over-enhancement, with whitened tires and overly bright boy' s chest. Reference [13] is particularly severe around the tire, and the bear on the shirt becomes unrecognizable due to brightness effects. Our algorithm achieves better overall results with higher clarity and more natural appearance, appropriately enhanced tires without over-brightness, clear textures, recognizable bear on the shirt, and no halo artifacts on the boy' s face.

Figure 7 [Figure 7: see original paper] shows experimental result comparisons for image15 under non-uniform illumination conditions. Under non-uniform lighting, CLAHE produces poor enhancement effects, failing to highlight details such as the darkened lower part of the girl' s dress and blurred hair top and wooden fence. Reference [9] improves contrast but suffers from severe tone degradation, making the wooden fence tone almost unrecognizable with noise amplification. Reference [12] shows excessive brightness, particularly yellowing of the girl' s dress due to brightness, with blurred wooden fence and window details. Reference [13] handles wooden fence details well but blurs window details due to over-enhancement. Our algorithm appropriately improves brightness while highlighting details, particularly clear wooden fence and window details, without over-brightening the dress.

The above analysis demonstrates that under low-light, strong-light, and non-uniform illumination conditions, our algorithm outperforms the other four algorithms by appropriately improving brightness and highlighting image details.

Next, we analyze experimental effects using objective metrics: PSNR, Tenengrad criterion, and detail contrast [16]. Higher PSNR values objectively indicate less distortion and chaos. Tenengrad is a sharpness evaluation metric; larger values generally indicate better image quality [19]. Detail contrast is calculated using image entropy, edge strength, and edge count. Larger values indicate richer details and better quality, computed through equation (19):

$$\text{Contrast} = \frac{H(I_e) \times \text{edgels}(I_e)}{\log(\log(MN))} \times \frac{E(I_e)}{MN}$$

where I_e is the enhanced image, $\text{edgels}(I_e)$ is the number of visible edges, $H(I_e)$ is the entropy of the enhanced image, $M \times N$ is the image size, and $E(I_e)$ is the sum of visible edge pixel values. We use Sobel operator for edge detection.

Table 1 shows metric test results. Under low-light, strong-light, and non-uniform illumination conditions, our proposed algorithm achieves higher scores across all three metrics than the other four algorithms, demonstrating superior comprehensive performance, particularly in Tenengrad metric where it far exceeds the others. This objectively proves that our algorithm effectively improves brightness, contrast, and highlights image details.

3 Conclusion

To address low contrast and indistinct details in images under low-light, strong-light, and non-uniform illumination conditions, this paper proposes an improved multi-layer fusion and detail recovery image enhancement method. This effectively solves problems such as color overflow, detail loss, halo artifacts, and poor visual effects during enhancement, improving contrast and highlighting details. First, the image is equivalently replicated into three layers. In the Retinex enhancement layer, considering halo problems in traditional Retinex enhancement, we combine guided filtering and morphological operations as the single-scale brightness estimation method, introducing brightness factors and local detail adjustment models to enhance brightness and details. In the brightness enhancement layer, we propose a new image normalization method to further highlight brightness. In the detail enhancement layer, we simplify a local contrast enhancement model and combine it with the artificial bee colony algorithm to further highlight image details. Finally, to avoid detail loss after fusion, we propose a detail recovery scheme. Experimental results demonstrate that our algorithm effectively improves contrast and highlights image details, laying a foundation for subsequent image processing.

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Note: Figure translations are in progress. See original paper for figures.