Fundus Image Enhancement using CLAHE

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Abstract. Fundus retinal images are crucial for ophthalmologists to diagnose diseases and monitor changes in the condition. However, due to factors such as lighting conditions, instrument effects, and individual differences, fundus images often have the drawbacks of low contrast and lack of details. To improve the quality and accuracy of images, contrast enhancement technology for fundus images has become a research hotspot. This paper proposes a new CLAHE (Contrast Limited Adaptive Histogram Equalization) method to improve the brightness and contrast of retinal images. The method improves the luminosity of fundus images by using gamma correction in the HSV color space and enhances the contrast of images by limiting contrast histogram equalization in the L*a*b* color space. Finally, the effectiveness of the method is verified through the STARE dataset. The results show that compared with the traditional CLAHE method in the RGB color space and the WAHE method, the method proposed in this paper has better improvement effects on color retinal images, and performs well in adaptability, color fidelity, local detail preservation, and algorithm implementation simplicity, making it suitable for fundus image processing under different lighting conditions. It is also easy to deploy and use in practical applications, providing reference and guidance for researchers and healthcare professionals.

Keywords. Fundus retinal images; Image quality; Contrast enhancement; Histogram equalization; CLAHE

1. Introduction

The prevalence of fundus diseases is indeed showing a continuously increasing trend worldwide. According to the data of the World Health Organization (WHO), about 220 million people worldwide suffer from diabetes, and diabetes retinopathy is one of the common complications of diabetes, which is expected to blind millions of people every year [1]. In addition, it is estimated that approximately 250 million people worldwide suffer from age-related retinal diseases such as macular degeneration, with the majority being elderly people aged 65 and above.

At the same time, poor quality of fundus images is one of the common problems in clinical practice. According to research statistics, about 30% of fundus images have problems such as uneven lighting, insufficient contrast, or unclear details, which poses difficulties for ophthalmologists in their diagnostic work [2]. Some research and medical institutions have reported that the poor quality of some fundus images has led to an increase in misdiagnosis rates among doctors, affecting the treatment effectiveness of patients [3].

Therefore, to improve the quality of fundus images, many research institutions and medical institutions have begun to adopt contrast enhancement techniques. A study shows that after applying contrast enhancement technology to process fundus images, the average contrast of the image is increased by 20-30%, and the clarity of details is also improved. This technology has achieved certain success in practical clinical practice and has been widely recognized and applied by ophthalmologists.

Contrast enhancement refers to adjusting the grayscale level of an image to enhance its details and features, making it easier to observe and analyze. In retinal image processing, there are many commonly used contrast enhancement techniques which can be roughly divided into four types. The first type is spatial domain techniques (such as contrast limited adaptive histogram equalization, weighted adaptive histogram equalization and logarithmic transformation), which enhance contrast by directly adjusting pixel values. The second type is frequency domain techniques (such as Fourier transform and wavelet transform), which enhance contrast by processing the frequency components of the image. The third type is statistical techniques (such as mean and standard deviation adjustment), which optimize contrast using image statistical characteristics. The fourth type is artificial intelligence technology (such as convolutional neural networks and generative adversarial networks), which automatically extracts and enhances image features through training models to achieve intelligent contrast optimization [4]. The fifth type is Retinex, which is commonly used on image enhancement. There are three different implementation methods for the Retinex algorithm: Single Scale Retinex (SSR), Multi-Scale Retinex (MSR), and Multi-Scale Retinex with Color Restoration (MSRCR).

2. Choice of method

CLAHE is an improvement on the traditional histogram equalization method [5]. It divides the image into many small blocks, balances the histograms of each small block, and then uses interpolation techniques to smooth the boundaries between the blocks. This can avoid discontinuous brightness changes between blocks while preserving local details of the image and avoid the problem of excessive enhancement caused by global enhancement [6]. It has strong adaptability and can enhance contrast in different regions, making it suitable for fundus images with uneven lighting. Its algorithm is simple to implement, with high computational efficiency. But CLAHE may cause noise amplification issues, especially when there is a large amount of noise in the image [7].

The principle of WAHE is to introduce weighting factors based on local histogram equalization to achieve finer contrast enhancement. When processing the histogram of each local area, the weighting factor can be adjusted according to the local features and contrast requirements of the image [8]. Finally, the processed images from all local regions are combined to produce the final enhanced image. Through this weighted processing, WAHE can enhance image contrast while maintaining the natural appearance of the image. In addition, WAHE also restricts local contrast to avoid noise amplification and image distortion caused by excessive contrast enhancement, especially is suitable for application scenarios that require fine control of contrast enhancement. However, WAHE needs to select appropriate weighting factors. The computational workload may be large, especially when dealing with large-scale image data [9].

Retinex algorithm enhances the contrast and color of an image by separating its lighting and reflection components [10]. Firstly, the Retinex algorithm performs color restoration operations on the image, removing lighting components to make the color of the image more realistic. Further enhance the reflection components of the image by calculating the difference between pixels and surrounding pixels to improve the contrast of the image. Finally, perform color balance processing on the enhanced image to maintain overall color balance. This processing method makes the Retinex algorithm perform well in improving image clarity and contrast, especially suitable for images with uneven lighting conditions or strong lighting changes. So, Retinex can simulate the visual system of the human eye, preserving the natural colors and details of images [11]. However, the algorithm has high complexity and computational complexity, making it unsuitable for real-time applications [12]. It may be affected by image noise, leading to a decrease in image quality [13].Before enhancing the contrast of fundus images, it is crucial to first improve the luminance and perform luminosity enhancement. Inadequate or uneven luminance

can obscure visual details and lead to missed diagnostic information. Additionally, it is important to ensure that the color of any image element remains unchanged to avoid distorting the image [14][15].
Based on the evaluation of the above technologies, considering the characteristics and application requirements of fundus retinal images, as well as the complexity and practicality of the algorithm, the Contrast Limited Adaptive Histogram Equalization (CLAHE) method is selected as the choice for contrast enhancement of fundus retinal images. CLAHE technology performs excellently in adaptability, local detail preservation, and algorithm implementation simplicity, making it suitable for fundus image processing under different lighting conditions and easy to deploy and use in practical applications. In addition, an improved gamma correction will be used to enhance the luminosity of the fundus images, ensuring that each image has an appropriate gamma value and improving the wide applicability and accuracy of this method.

3. Methodology

All images for the experiment are obtained from the STARE (Structured Analysis of the Retina) dataset [18], which is a publicly available dataset. The STARE dataset contains a total of 400 images, but typically 20 manually annotated fundus images with a resolution of 700 x 605 pixels are used for research. These images include various diseases, such as macular degeneration, hypertensive retinopathy, diabetes retinopathy, etc.
The flow diagram of our proposed method is shown in Figure 1 and the following section describes the main sections of the flowchart.

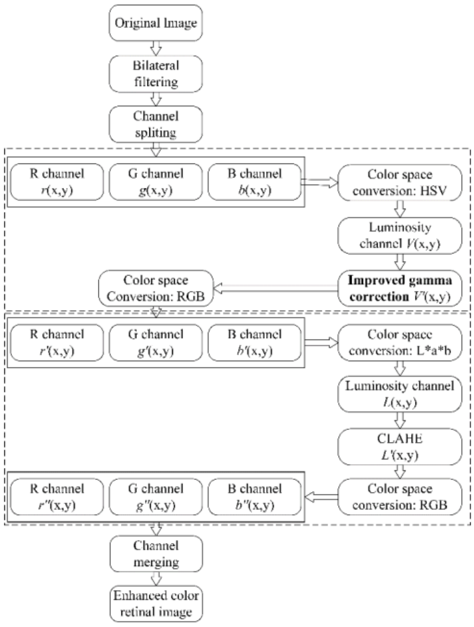


Figure 1. Flowchart of the proposed method, the improved gamma correction method is highlighted in bold

3.1.1. Bilateral filtering

Bilateral filtering is an effective image denoising technique that smooths images by simultaneously considering the similarity between the spatial domain and the pixel value domain. It can remove noise while preserving the edge details of the image. This is crucial for the processing of medical images, as

edge details play a critical role in diagnosis. Bilateral filtering can improve image clarity, allowing doctors to observe retinal lesions and structural changes more accurately.
The bilateral filter achieves effective denoising while preserving edges due to its filter kernels being generated by two distinct functions: the spatial domain kernel and the value domain kernel, as illustrated in Eqs (1) - (2).
The template weight w_(d) is determined by the Euclidean distance between pixel positions [16].

$$w_d(i,j,k,l) = e^{\left[-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2}\right]} \quad (1)$$

Where $q(i,j)$ is the coordinate of other coefficients in the template window; $p(k,l)$ is the center coordinate point of the template window; σ_d is the standard deviation of the Gaussian kernel function in the spatial domain, used to control the weights of pixel positions.
The template weight w_r is determined by the difference in pixel values.

$$w_r(i,j,k,l) = e^{\left[-\frac{||f(i,j)-f(k,l)||}{2\sigma_r^2}\right]} \quad (2)$$

Where $f(i,j)$ represents the pixel value at point $q(i,j)$, and $f(k,l)$ represents the pixel value at point $p(k,l)$. σ_r is the standard deviation of the Gaussian kernel function in the pixel value domain, used to control the weights of pixel values.
Finally, multiplying the above two templates yields the template weights for the bilateral filter.

$$w_d(i,j,k,l) = e^{\left[-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2}-\frac{||f(i,j)-f(k,l)||}{2\sigma_r^2}\right]} \quad (3)$$

Therefore, the data formula for bilateral filters can be expressed as follows [16].

$$g(i,j) = \frac{\sum_{kl} f(k,l)w(i,j,k,l)}{\sum_{kl} w(i,j,k,l)} \quad (4)$$

3.1.2. Channel splitting

Retinal fundus images are usually color images, including three channels: Red, Green, and Blue. Many image processing operations and algorithms, such as histogram equalization, are designed and implemented based on the RGB color space. Converting the original image into the RGB color space facilitates subsequent processing and enhances convenience. A sample of a retinal fundus image along with its Red, Green and Blue Channel images is shown in Figure 2.

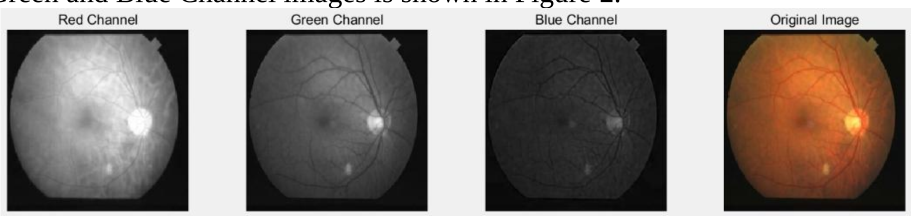


Figure 2. Retinal image with its RGB images

3.1.3. Color space conversion

During the process of luminosity enhancement and contrast enhancement, two color space conversions are required: the exchange between RGB and L*a*b*, and the exchange between RGB and HSV.
The RGB and HSV are two commonly used color models. RGB is used to represent color images, while HSV is mainly used to describe the characteristics of colors. The conversion from RGB to HSV involves the transformation of color geometry and three-dimensional space. RGB color model uses three channels, red, green, and blue, to represent assorted colors. HSV color model uses three components: Hue, Saturation, and Value to describe colors. Hue represents the type or category of color, saturation represents the purity or vividness of the color, and value represents the luminance of the color. The conversion from RGB to HSV requires first dividing the channel values of RGB colors by 255, converting them to decimals within the range of 0-1, and then completing the conversion using Equations (5) - (7).

$$V = \max(R, G, B) \tag{5}$$

$$S = \begin{cases} \frac{V - \min(R,G,B)}{V}, & V > 0 \\ 0, & V = 0 \end{cases} \tag{6}$$

$$H = \begin{cases} \frac{60(G-B)}{SV}, & V = R \\ \frac{60[2+(B-R)]}{SV}, & V = G \\ \frac{60[4+(R-G)]}{SV}, & V = B \\ 0, & V = 0 \\ H + 360, & H < 0 \end{cases} \tag{7}$$

In the L*a*b* color space, the L* channel is mainly used to represent the luminosity information of the image, while the a* and b* channels are used to represent color information. During the conversion process, a series of complex calculations are required, including converting the RGB color space to the CIE 1931 XYZ color space, and then to the L*a*b* color space. This is because the RGB color space is device-dependent, while the CIE 1931 XYZ and L*a*b* color spaces are device-independent, allowing for better representation and processing of color information. The forward transformation process of the L* channel is described in Equations (8)-(10).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} r(x,y) \\ g(x,y) \\ b(x,y) \end{bmatrix} \tag{8}$$

$$L = 116 f\left(\frac{Y}{Y_n}\right) - 16 \tag{9}$$

$$f(t) = \begin{cases} t^{\frac{1}{3}} & t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t + \frac{4}{29} & others \end{cases} \tag{10}$$

where X, Y, and Z are the three components in CIE XYZ color space, and X_n, Y_n and Z_n are the CIE XYZ tristimulus values of the reference white.

3.1.4. *Luminosity enhancement*

The luminosity enhancement process involves converting the RGB to the HSV color space and applying gamma correction to the V channel. Gamma correction is an important nonlinear transformation that exponentially transforms the grayscale values of an input image to correct luminosity deviation. It is commonly used to expand the details of dark tones. In general, when the Gamma correction value is greater than 1, the highlights of the image are compressed while the shadows are expanded; When the value is less than 1, the highlights of the image are expanded while the shadows are compressed. In the simplest case, Gamma correction is defined by the following power-law Eq. (11).

$$s = cr^{\gamma} \tag{11}$$

where c is a constant, and both the input and output values are non-negative real values. In the case of c=1, the range of input and output values is between 0 and 1. The input-output is shown in Figure 3.

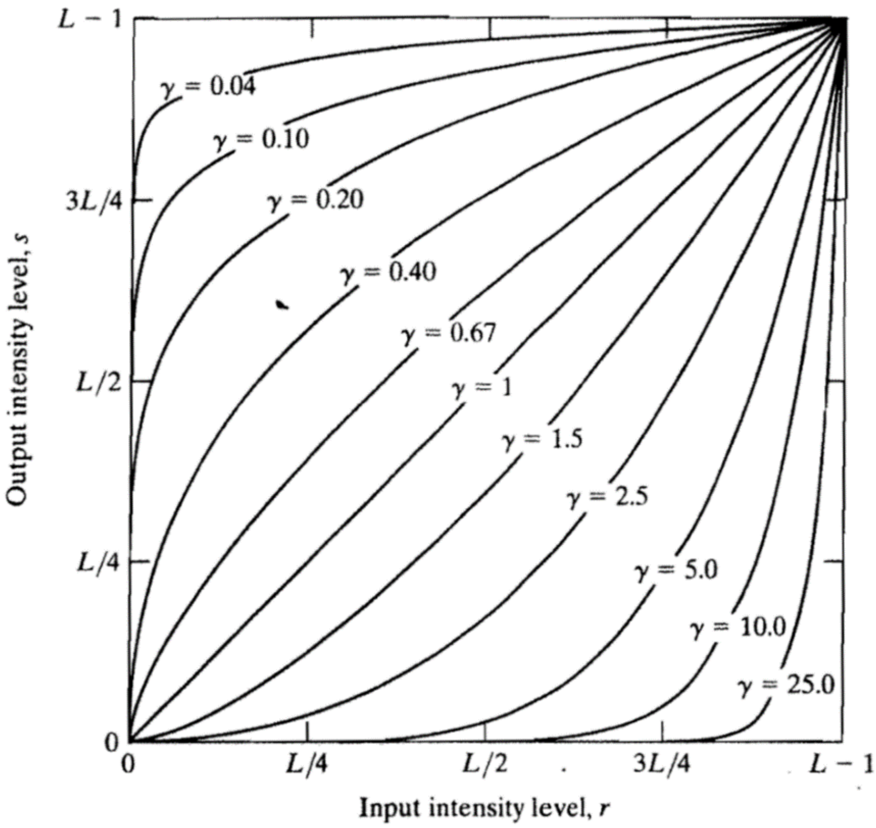


Figure 3. Input and output of gamma correction

A fixed gamma value is not applicable to all retinal images, so the basic gamma correction method needs to be improved. The improved gamma correction adaptively adjusts the gamma value by calculating global luminance and local standard deviation. The flowchart of the steps of the improved gamma correction is shown in Figure 4.

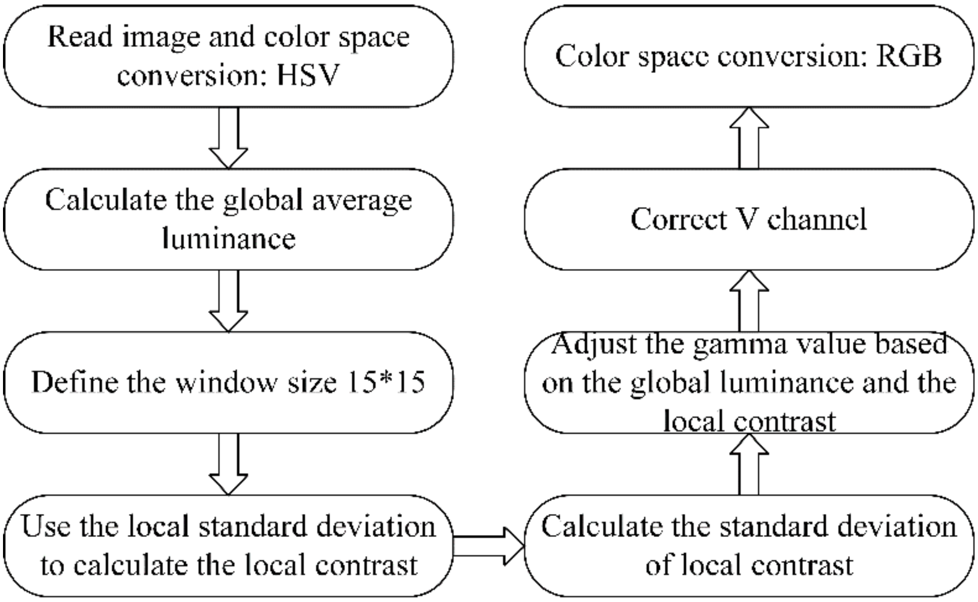


Figure 4. Flowchart of the improved gamma correction

3.1.5. CLAHE

The CLAHE introduces the concept of contrast limitation based on AHE to reduce noise enhancement and artifact issues. The basic idea is to crop the histogram before performing histogram equalization on each small area, limiting its peak value and thus controlling the degree of local contrast enhancement.
The main steps of CLAHE are as follows:

- Image segmentation: Divide the input image into multiple non overlapping subregions (usually referred to as grids or blocks).
- Histogram clipping: For each subregion, calculate its grayscale histogram and set a contrast limit threshold. Any histogram count exceeding this threshold will be clipped and the clipped portion will be evenly distributed to other parts of the histogram. This step can control the degree of contrast enhancement in each subregion to prevent excessive enhancement. The brief schematic diagram is shown in Figure 5.

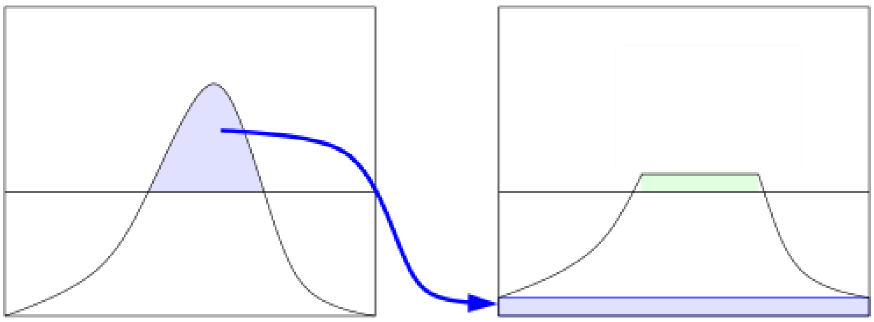


Figure 5. Histogram clipping

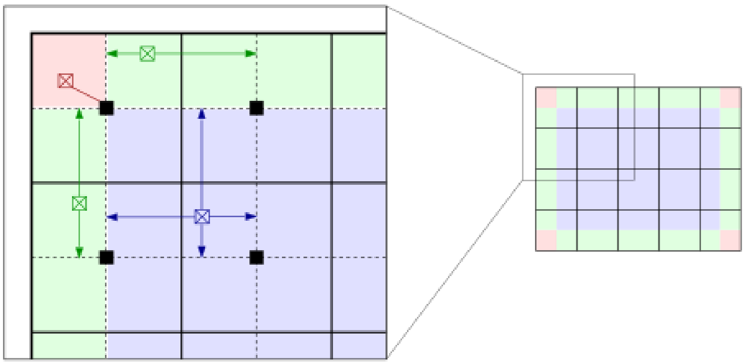


Figure 6. Interpolation

- Histogram equalization: Limits the number of pixels at a specific intensity level in the histogram, redistributes the excess to other levels, and uses the cumulative distribution function to map the original image's pixel values to new ones, thereby enhancing contrast while avoiding noise from over-enhancement.
- Interpolation and merging: To avoid boundary effects caused by region partitioning, CLAHE performs bilinear interpolation on pixel values between adjacent regions to obtain smooth transitions, as shown on the right side of Figure 6. The transformation function is fully aligned with the original definition for the center pixel of the block (depicted as the small black square on the left side of the image below). For other pixels, the transformation functions of the four adjacent blocks are used through interpolation. Pixels within the blue shaded area are interpolated using bilinear interpolation, while those on the edges (green area) are interpolated using linear interpolation. At the corners (red area), the transformation function of the block is directly used.

4. Results and discussion

To verify the effectiveness of the gamma correction method, the CLAHE algorithm is assess in three different color space: the RGB color space, L*a*b* and the V channel in the HSV color space. The results of both groups are then compared and analyzed. The experimental data is sourced from the STARE database. Experiments are conducted on the MATLAB platform.

4.1. Results of luminosity enhancement

For the evaluation of luminosity enhancement, the luminance histogram can be used intuitively to show the effect of enhancement. The images and their luminance histogram are shown in Figures 7 and 8.

Figure 7. Original image and image with gamma correction

In the fundus image on the left side above, the overall luminance is relatively dark and needs to be enhanced, so the gamma value is set to 0.77135 after calculation. From the image on the right side above, the overall luminance has increased, resulting in a better visual effect.

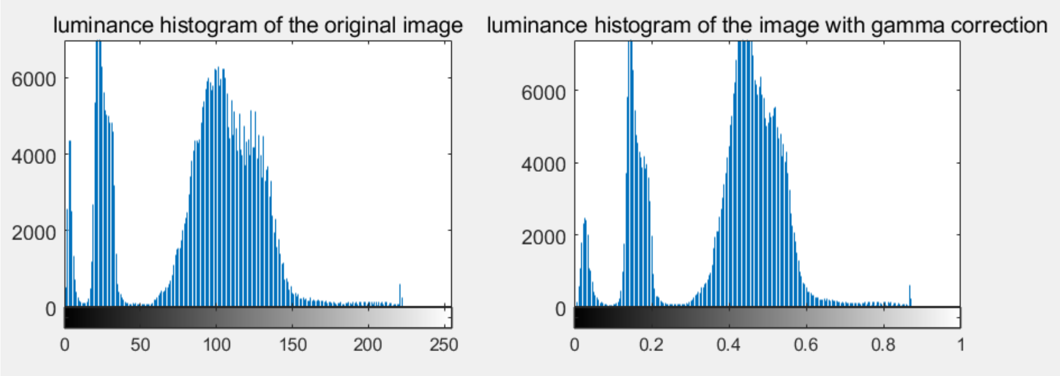
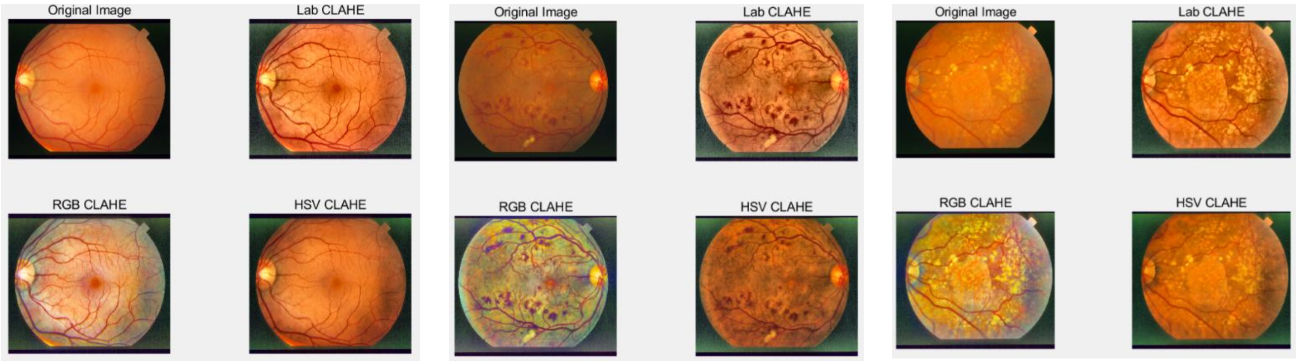


Figure 8. Luminance histogram of the images (horizontal axis is the gray value and the vertical axis is the pixel point)

In the luminance histogram on the right, a segment of the luminance value increases, indicating that after gamma correction, the luminosity of this part of the pixels has been improved. This elevated section corresponds to the medium brightness area in the image. After gamma correction, the luminance values of these pixels are compressed to a more concentrated range, forming a clear peak in the histogram.

4.2. Subjective evaluation results of contrast enhancement

Subjective evaluation of the enhancement algorithm was conducted by selecting normal, bleeding, and exudative fundus images from the database. The results are shown in Figures 9.



(a) **(b)** **(c)**

Figure 9. Different images processing results: (a) Normal image processing results, (b) Bleeding image processing results, (c) Exudate image processing results

From the results, in both normal and pathological color fundus images, CLAHE algorithm in HSV color space has enhanced the brightness of local areas such as blood vessels, optic disc, and macula compared to the original image. However, the overall brightness of the image is still relatively dark, and the contrast of important parts such as blood vessels, optic disc, and macula is not high, with unclear details and low contrast between the fundus and background. CLAHE algorithm in the RGB color space can effectively preserve the information of key areas such as blood vessels, optic disc, and macula, and improve the

overall brightness and contrast of the image. However, the overall image appears white, and the color is severely distorted. CLAHE algorithm in the L*a*b* color space makes the details of blood vessels, macula, optic disc and other parts clearer, with significantly improved contrast, and preserves the color information of the original image without distortion, whitening and other phenomena.
From a subjective perspective, regardless of whether the images are normal or pathological, the gamma correction method proposed in this paper improves the clarity and contrast of the images and can achieve color fidelity in fundus images.

*4.3. Objective evaluation results of contrast enhancement with CLAHE but in different color spaces: RGB, L*a*b* and HSV*

To further validate the effectiveness of the algorithm proposed in this paper, experiments were conducted on 20 images in the STARE database, and objective evaluation metrics were used for quantitative comparison.
Due to the lack of corresponding "perfect" images, using metrics such as mean squared error (MES) and peak signal-to-noise ratio (PSNR) cannot effectively reflect the quality of the enhanced image. Therefore, we adopt multiple dimensional indicators such as quality evaluation indicators, color evaluation indicators, clarity evaluation indicators, and fidelity evaluation indicators to comprehensively measure the performance of the algorithm. Specific indicators include underwater color quality evaluation (UCIQE), average gradient (AG), color image assessment function (CAF), total fidelity rate (TFR), and color of rate (COR).
According to the indicator data, after calculation, the average improvement percentage of the L*a*b * color space relative to the RGB color space on each indicator is shown in Table 1.

Table 1. Average growth percentage (LAB vs RGB)

UCIQE	AG	CAF	TFR	COR
18.76%	14.99%	2.08%	1.88%	13.11%

From objective indicators, it can be concluded that the proposed method implemented in the L*a*b* outperforms when implemented in the traditional CLAHE method in the RGB color space in terms of color deviation, clarity, quality evaluation, and fidelity.

4.4. Benchmarking the newly improved CLAHE with other published works

WAHE method uses five indicators to evaluate the enhancement quality: contrast-enhanced image quality (CEIQ), visual saliency inducted index (VSI), naturalness image quality evaluator (NIQE), the modified measure of enhancement measure (MEME) and edge-based contrast measure (EBCM). To show the progressiveness of CLAHE method, the same indicators are used for evaluation.
According to the calculation results, the average improvement percentage of CLAHE method relative to WAHE method on each indicator is shown in the following Table 2.

Table 2. Average growth percentage (CLAHE vs WAHE)

CEIQ	VSI	NIQE	MEME	EBCM
12.22%	-	7.98%	20.60%	2.21%

From the indicators in the Table 2 above, CLAHE has significant advantages over WAHE in the three indicators of CEIQ, NIQE, and MEME, while EBCM values have also slightly improved. However, CLAHE's performance on VSI is not as good as WAHE, which requires further optimization. CLAHE exhibits higher overall performance in image enhancement quality assessment compared to WAHE.

5. Conclusion

This paper proposes an effective method for enhancing color retinal images based on luminosity and contrast adjustments. Firstly, bilateral filtering is applied to the original image, followed by enhancing the luminance of the colored retinal image through gamma correction. Then, the image contrast is enhanced through CLAHE in the L*a*b* color space. Finally, the proposed method is validated on the STARE dataset. The results indicate that compared with contrast enhancement in other color spaces and methods, the method proposed in this paper has a better improvement effect on color retinal images. Compared with the traditional use of CLAHE in the RGB color space, the method proposed in this paper improved the UCIQE index by 18.76%, the AG index by 14.99%, and the COR index by 13.11%. The improvement in CAF and TFR was relatively small, at 2.08% and 1.88%, respectively. Compared with the WAHE method, the method proposed in this paper improved the CEIQ index by 12.22%, the MEME index by 20.60%, and the NIQE and EBCM indices by 7.98% and 2.21%, respectively. However, it performed poorly in VSI, indicating that the method proposed in this paper needs further improvement in terms of visual saliency in the future. In summary, this method enhances the critical anatomical structures of the retina while preserving the naturalness of the image. This effective color retinal image enhancement approach will significantly aid ophthalmologists in diagnosing diseases through retinal image analysis and improve diagnostic accuracy.

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