Retinal Image Enhancement Using Curvelet Based Sigmoid Mapping of Histogram Equalization

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Abstract. Ophthalmologists generally use retinal fundus images to identify certain retinal diseases. However, fundus cameras frequently fail to capture high-quality retinal images due to improper camera settings, eye movement, uneven illumination, and pupil dilation that affect the diagnosis's reliability. To enhance the fundus image's visual clarity, we propose a combination of denoising and enhancement methods. This paper uses a multi-resolution curvelet transform and adaptive sigmoid mapping of histogram equalization for better image denoising and enhancement. Our hybrid technique enhances the quality of fundus image with improvement in Peak Signal to Noise Ratio (PSNR) of 6.85%, Structural Similarity Index (SSIM) of 0.89%, and Correlation coefficient (CoC) of 0.13% compared to existing methods with Gaussian noise of about 0.01.

Keywords: enhancement, denoising, curvelet transform, bi-histogram equalization, retinal image.

1. Introduction
Many image pre-processing techniques are used to produce a clearer and more precise image of the retina, which offers adequate knowledge of the vessel’s structures to analyze retinal disease further. Image denoising and contrast enhancement techniques can improve the fundus image's accuracy taken from the fundus camera. Image denoising is the primary pre-processing method for image processing. We may divide denoising methods into two groups, such as the spatial and frequency domain. In the frequency domain, image transformation followed by filters has been used for denoising. Moreover, image denoising is achieved in the spatial domain through various filtering techniques by direct pixel manipulation.

Wavelet-based transforms virtually eliminate the image's noises and retain the prominent edge information [1]. The wavelet transform method is not appropriate for retinal image contrast improvement since it is insensitive to the edge's smoothness [2]. Compared to the wavelet transform, curvelet transform-based denoising methods efficiently reconstruct the curves and bends in the image while denoising [3]. Miri et al. [4] suggested a second-generation curvelet transform for retinal image enhancement.
Numerous methods have been introduced regarding image enhancement in that histogram Equalization (HE) [5] is the most common process. However, lowering the grey level may lead to information loss in the image.

Setiawan et al.[6] have developed the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique applied on the channel to improve the fundus image quality. Jintasuttisak et al.[7] Suggested Rayleigh CLAHE for retinal image contrast and visual quality enhancement. Fu et al. [8] introduced a wavelet-based histogram equalization approach. After histogram equalization, a wavelet-based enhancement algorithm reduces information loss and increases the image's clarity.

Ashiba et al.[9] proposed an additive wavelet transform with a homomorphic filter for image contrast enhancement. Dai et al.[10] developed a technique to enhance and denoise the retinal image. The normalized convolution algorithm extracts the background information. Later, it is fused with the input image to produce an improved appearance, followed by two-step denoising using fourth-order PDE and median filter. Edgar et al. [11] proposed an image enhancement technique, in which the histogram of the image is divided into two sub-histograms using also mean its CDF's mapped with sigmoid function.

Zhou et al. [12] introduced a technique for retinal image luminance and difference improvement. The image's brightness is improved by constructing a luminance gain matrix in the HSV plane. The image's local contrast is improved by applying CLAHE on the Lab color space's L channel. Gupta et al.[13] introduced an algorithm for enhancing color retinal images wherein contrast improvement is carried out by quantile-based histogram equalization and the Adaptive Gamma correction process for luminance enhancement.

Sahu et al.[14] proposed a retinal image enhancement technique by combining a variety of filters with the CLAHE. In this paper, a hybrid approach proposed for contrast improvement where adaptive sigmoid function mapped with an image's histogram and first-generation curvelet transform is used for noise removal.

The paper's remaining part is structured as the follows-proposed technique is discussed in section 3, followed by Experimental subjective and quantitative outputs are discussed in Section 4. Section 5 concludes the paper.

2. Methodology

Various steps in the algorithm are:
Step1: Apply additive or multiplicative noises to the retinal image with a different variance value.
Step 2: Decompose a noisy image into an RGB channel.
Step 3: Apply the Curvelet besides its inverse transform and the median filter to each color channel.
Step 4: Apply HE with an adaptive sigmoid function to enhance contrast.
Step 5: Combine all three color channels.

![Figure 1: Block diagram representation of the proposed method](image)

The proposed approach workflow is shown in figure 1. Fundus images are influenced by additive and multiplicative noise during the image's acquisition process in the fundus camera. Here we are considering Gaussian noise for additive noise and speckle noise for multiplicative noise. These noises are added to the fundus images at various levels of noise variance. The blurred image is then decomposed into the red, green, and blue channels.
Curvelet transforms along with HE-based adaptive sigmoid function are implemented to each channel. As a result of this algorithm, we can obtain noise-free and improved quality retinal fundus images.

First-generation curvelet-based histogram equalization with adaptive sigmoid function is developed as follows.

Step 1: The first step is sub-band decomposition, in which images are divided into a band of frequencies.

\[ f(m, n) = l_k(m, n) + \sum_{k=1}^{K} w_k(m, n) \]  

\[ I \rightarrow (p_0I, \Delta_1I, \Delta_2I, \ldots) \]  

Where \( l_k \) – coarse information \( w_k \) - Detail information of the original image

Step 2: Every sub-band is windowed into "squares" of a suitable scale to get smooth partitioning. The high-frequency component is partitioned into small blocks to apply the ridgelet transform.

\[ \Delta_sI \rightarrow (w_q\Delta_sI)_{q\epsilon q_s} \]  

Step 3: All the smooth partitioning square blocks are renormalized to unit scale.

\[ g_q = (T_q)^{-1}(w_q\Delta_sI) \]  

Step 4: Each Renormalized square block is applied to Ridgelet Analysis.

Step 5: Hard-thresholding is used to estimate the unknown curvelet coefficient.

Step 6: Reconstructed image is obtained by applying the Inverse curvelet transform.

Step 7: Reconstructed image undergoes Histogram splitting based on a mean intensity histogram in which it is separated into two sub histograms.

Step 8: Calculate the cumulative distribution function (CDF) of two sub histograms.

Step 9: Construct a non-linear sigmoid function for normalizing the input intensity of two sub histograms fit to sigmoid function.

Step 10: Perform mapping by equalization and stretching.

3. Results and Discussion

We conduct our experiments using one of the STARE database [15] images with a size (605*700), captured from Topcon TRV -50 Fundus camera. Figure 2 shows the proposed and existing method's enhanced output image, corrupted by speckle noise with a noise variance of 0.01.
Figure 2: a) Input image b) Speckle noisy image at variance=0.01 c) Median+CLAHE d) Weiner +CLAHE e) Gaussian +CLAHE f) Proposed output.

The proposed algorithm eliminates noises in the fundus image also increases the visual quality compared to the existing method. In the restored image, the vessel features are prominent relative to the original image. It is also useful for subsequent image analysis and diagnosis of the disease. For quantitative analysis, the parameters used to evaluate proposed hybrid algorithms are PSNR, SSIM, and CoC.

PSNR is used for estimating the quality of the reconstructed image. PSNR for color fundus images is calculated by considering all RGB color space.

SSIM calculates image quality deterioration derived from luminance, contrast, and structural term. When the resemblance between the input and the denoised image is excellent, the SSIM will be more.

CoC measures the similarity between the images. When the original and reconstructed images are matching, the association coefficient has the highest value.

Then, we apply our algorithm on fundus image, which is distorted by Gaussian noise and speckle-noise at different levels of noise variance $\sigma=0.001, 0.01, 0.1, 0.2$. The hybrid techniques proposed in the paper are effective in reducing noise and enhancing contrast. Moreover, it preserves the naturalness and enhances detailed information. Table 1-3 shows the presentation comparison of PSNR, SSIM, and CoC for speckle-noise at various noise variance levels.

| Methodology Noise Variance | Median+CLAHE | Weiner+CLAHE | Gaussian filter + CLAHE | Proposed |
|----------------------------|--------------|--------------|------------------------|----------|
| 0.001                      | 37.1454      | 37.2944      | 34.5360                | 38.3451  |
| 0.01                       | 33.4670      | 33.4922      | 34.3730                | 37.0466  |
| 0.1                        | 26.5122      | 26.4729      | 32.6707                | 33.8561  |
| 0.2                        | 23.9530      | 23.9236      | 31.1273                | 31.8665  |
Table 2: Performance comparison of SSIM for speckle-noise at various noise variance

| Methodology | Noise Variance | Median+CLAHE | Weiner+CLAHE | Gaussian filter + CLAHE | Proposed |
|-------------|----------------|--------------|--------------|-------------------------|----------|
|              | 0.001          | 0.9359       | 0.9483       | 0.9028                  | 0.9672   |
|              | 0.01           | 0.7922       | 0.8173       | 0.8999                  | 0.9429   |
|              | 0.1            | 0.5286       | 0.5558       | 0.8752                  | 0.8901   |
|              | 0.2            | 0.4524       | 0.4790       | 0.8555                  | 0.8617   |

Table 3: Performance comparison of CoC for speckle-noise at various noise variance

| Methodology | Noise Variance | Median+CLAHE | Weiner+CLAHE | Gaussian filter + CLAHE | Proposed |
|-------------|----------------|--------------|--------------|-------------------------|----------|
|              | 0.001          | 0.9959       | 0.9967       | 0.9902                  | 0.9968   |
|              | 0.01           | 0.9903       | 0.9913       | 0.9901                  | 0.9947   |
|              | 0.1            | 0.9394       | 0.9389       | 0.9869                  | 0.9880   |
|              | 0.2            | 0.8930       | 0.8905       | 0.9824                  | 0.9815   |

Similarly, tables 4-6 show the performance comparison of PSNR, SSIM, and CoC for Gaussian-noise at various noise variance levels.

Table 4: Performance comparison of PSNR for Gaussian-noise at various noise variance

| Methodology | Noise Variance | Median+CLAHE | Weiner+CLAHE | Gaussian filter + CLAHE | Proposed |
|-------------|----------------|--------------|--------------|-------------------------|----------|
|              | 0.001          | 29.2058      | 28.6120      | 24.3710                 | 31.3466  |
|              | 0.01           | 27.8909      | 27.4243      | 23.8368                 | 29.9416  |
|              | 0.1            | 18.5441      | 18.6857      | 17.8146                 | 19.4617  |
|              | 0.2            | 13.6853      | 13.7558      | 13.5851                 | 14.0855  |
Table 5: Performance comparison of SSIM for Gaussian noise at various noise variance

| Methodology                     | Noise Variance | Median+CLAHE | Weiner+CLAHE | Gaussian filter + CLAHE | Proposed |
|--------------------------------|----------------|--------------|--------------|-------------------------|----------|
| Median+CLAHE                   | 0.01           | 0.7673       | 0.7502       | 0.3744                  | 0.7742   |
| Weiner+CLAHE                   | 0.1            | 0.6915       | 0.6929       | 0.3352                  | 0.6772   |
| Gaussian filter + CLAHE        | 0.2            | 0.6328       | 0.6272       | 0.3117                  | 0.5907   |

Table 6: Performance comparison of CoC for Gaussian noise at various noise variance

| Methodology                     | Noise Variance | Median+CLAHE | Weiner+CLAHE | Gaussian filter + CLAHE | Proposed |
|--------------------------------|----------------|--------------|--------------|-------------------------|----------|
| Median+CLAHE                   | 0.001          | 0.9842       | 0.9851       | 0.9477                  | 0.9860   |
| Weiner+CLAHE                   | 0.01           | 0.9831       | 0.9847       | 0.9474                  | 0.9844   |
| Gaussian filter + CLAHE        | 0.1            | 0.9806       | 0.9820       | 0.9428                  | 0.9832   |
| Proposed                       | 0.2            | 0.9801       | 0.9795       | 0.9428                  | 0.9826   |

From the above table, we can observe that when the image is corrupted by speckle noise in the proposed algorithm, the image enhancement is higher than the Gaussian noise.

Figure 3: PSNR comparison for different methods with Gaussian noise of various noise levels
Figures 3, 4, and 5 represent PSNR, SSIM, and CoC Comparison between different filters for Gaussian noise at various noise levels. From the graph, we can observe that compared to the Median filter with the CLAHE method, the proposed methodology gives 6.85%, 0.89%, and 0.13% improvement in PSNR, SSIM CoC, respectively, for Gaussian-noise of 0.01.
4. Conclusion

This paper has introduced a technique for image denoising and enhancing color retinal images based on adaptive sigmoid function. The hybrid methods effectively eliminate noise and enhance the contrast of the retinal fundus image, and the result shows that the system provides an acceptable value of performance measure. This algorithm is also a better method for pre-processing color fundus images used in computer-supported clinical diagnosis. In the future, luminosity enhancement is also considered along with this combined approach.

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