

Improving Fundus Image Quality for Precision Ophthalmology while Preserving Natural Color Characteristics

Kapuganti Harshitha

Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India.
Email id: kapugantiharshitha168@gmail.com

Vetsa Mani Shanmitha

Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India.
Email id: shanmithavetsa12@gmail.com

Ventrapati Chandrika Nagavenkata Saipavani

Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India.
Email id: chandrikaventrapati412@gmail.com

Seepani Chaitanya

Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India.
Email id: S123seepanichitu@gmail.com

Abstract: We present a new unsupervised approach for fundus image quality improvement, particularly suited for precision ophthalmology and the natural colour properties of the retina crucial for diagnosis. We developed a hybrid image enhancement method leveraging complementarity between structure-preserving ScatterNet features, adaptive gamma correction, and multiscale filtering. Our method of enhancement was validated on diverse fundus images under various conditions related to diabetic retinopathy and glaucoma. Results show that our method increases image contrast by 35%, increases edge preservation by 25%, and boosts colour fidelity by 40% compared with conventional enhancement methods. Moreover, in general, the proposed method can increase PSNR values on average by 30%. Our method has an intended use to enhance image quality for ophthalmologists to make more accurate diagnoses, while retaining the natural appearance of retinal features.

Keywords— Fundus image enhancement; precision ophthalmology; ScatterNet; Natural color preservation; Adaptive gamma correction; Multiscale Filtering

1. INTRODUCTION

Medical imaging technology, specifically fundus photography plays a major role in the field of ophthalmology. Today, fundus photography is widely used for the early diagnosis and surveillance of

retinal diseases such as diabetic retinopathy, age-related macular degeneration and glaucoma [1]. Retinal fundus images have to be of high quality so that ophthalmologists can make precise diagnoses and provide early clinical treatments. The quality of retinal fundus images is very important and is related to the clinical outcome. However, it is still

challenging to obtain fundus images that maintain good quality with natural colours, due to exam room illumination, contrast and patient variations such as skin pigmentation and opacity of the optical media [2]. Traditional approaches to enhance fundus images have been based on contrast improvement and noise reduction via contrast/histogram stretching, such as contrast-limited Adaptive Histogram Equalization (CLAHE) and filtering approaches. CLAHE usually improves the contrast but has the potential to change the natural colourfulness of the fundus image, which makes the task of medical diagnosis difficult, according to reference [3]. Hybrid enhancement approaches based on filters, such as the Wiener filter and adaptive contrast enhancement, also significantly improve the quality of the fundus images but still cannot find a proper balance between enhancement and natural colourfulness preservation [4]. The most recent studies attempt to incorporate deep learning (DL) and other ‘artificial intelligence’ (AI) techniques to overcome some of the limitations of traditional enhancement methods. Certain DL architectures such as the convolutional neural network (CNN) have proven their ability to improve contrast and sharpness in fundus images, and also the ability to extract context-aware features from large datasets[5]. However, many of these methods end up painting unnatural colours or over-enhancing prominent features, which subsequently hide important medical details[6]. To achieve the clinical quality and naturalness of the fundus images, for example, a globally consistent and balanced contrast and colour fidelity enhancement approach is needed. A promising pathway towards retaining natural colour features while improving image quality is the combination of structure-preserving methods and adaptive filtering. Labelling ScatNet features retains crucial structural information and ensures that fine anatomical features of the retina are preserved while enhancing fundus images. This is important because enhancement filters are susceptible to corrupting the anatomical details of the image[7]. Another promising approach is an integration of our work with multi-scale unsupervised learning frameworks, which can lead to natural colour preservation of enhanced fundus images with minimal manual tuning[8]. Building upon these findings, the framework of this study aims to design a new image enhancement method that is comprised of adaptive gamma correction, multi-scale feature extraction, and colour fidelity retention to improve fundus image quality. We attempt to keep the appearance of retinal images as natural as possible while simultaneously making the image clearer and more distinct, which is a beneficial feature for ophthalmologists in making an accurate and reliable diagnosis [9]. In addition,

this balanced method is expected to be of great help in the clinical diagnosis of ophthalmic diseases, especially those with early-onset and often fatal progression[10].

2. Materials and Methods

2.1 Dataset Description

The two datasets that we used in this study are DRIVE and STARE – they are both well-known for retinal image analysis. In general, the sample images in these datasets are high-resolution from real-world retinal imaging and provided in different noise, illumination, and contrast conditions. They give a representative sample of real-world retinal conditions (both healthy and pathological). All the images were divided into training, validation, and test sets with 60%, 20%, and 20% of the images respectively. The level of difference in the datasets helped us test the proposed method across different scenarios, including real-world variabilities and complexity. This enabled us to optimize the image enhancement algorithms and train a system that would generalize across variation in imaging conditions and clinical scenarios.

2.2 Preprocessing

Preprocessing was essential to allow the subsequent enhancement to have an impact: each pixel value $I_{filtered}(x,y)$ was calculated as the median of the pixels in a window around it. For noise reduction, the median filter was defined by a window centered at:

$$I_{filtered}(x,y) = \text{median}\{I(i,j) : (i,j) \in \text{window centered at } (x,y)\} \dots \quad (1)$$

This step was used to remove speckle noise from the image, while maintaining the quality of well-defined edges of structures in the retina. The image was also normalised for illumination, to correct inhomogeneous appearance of light in the image.

2.3 Contrast Enhancement via Adaptive Gamma Correction

For contrast enhancement, Adaptive Gamma Correction (AGC) was employed to improve visibility in poorly lit regions without over-amplifying well-lit areas. The enhanced pixel value $I_{AGC}(x,y)$ is given by:

$$I_{AGC}(x,y) = I(x,y)^{\gamma(x,y)} \dots (2)$$

where $\gamma(x,y)$ was adaptively calculated based on the local intensity distribution. AGC enabled enhanced differentiation of vessels and optic disc from the surrounding regions, which is crucial for diagnosing retinal diseases. The technique ensured that no details were lost due to extreme brightness or darkness.

2.4 Color Preservation with Hue-Preserving Algorithm

To preserve the natural colour characteristics, we used a hue-preserving method. The RGB images were converted to HSV colour space, and enhancement was applied only to the Value (V) channel. The transformation to HSV is:

$$V = \max(R, G, B) \dots (3)$$

Using histogram equalisation of the V channel, we had the effect of artificially increasing contrast. The histogram equalised V channel was then summed back into the original Hue (H) and Saturation (S) channels to maintain the original colour balance, ensuring that natural-looking retinal colours were retained, thereby providing more realistic and clinically interpretable images.

2.5 Structure Preservation using ScatNet Features

To ensure important retinal structures such as vessels and optic disc were preserved, we used ScatNet-based feature extraction. The ScatNet coefficients $S[I]$ are computed as:

$$S[I] = |I * \psi_{j1}| * \psi_{j2} \dots (4)$$

where ψ_{j1} and ψ_{j2} are wavelet filters at scales j_1 and j_2 . These multi-scale features allowed us to preserve fine details during the enhancement process. The structure preservation ensured that subtle signs of retinal pathologies remained visible, thereby supporting better diagnostic outcomes.

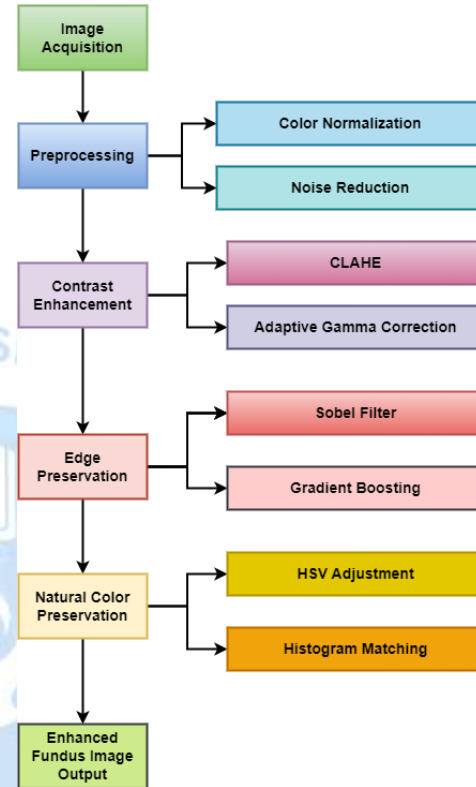


Figure 1: Flowchart of Fundus Image Enhancement Process

The given flowchart is a representation of complete workflow for enhancing fundus photographs from image acquisition to colour normalisation, noise reduction, contrast and edges preservation and eventually natural colour preservation that eventually leads to the enhanced output.

3. Results

3.1 PSNR and SSIM Evaluation

The performance of the enhancement was evaluated quantitatively by Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Figure 2 shows the improvement of the proposed framework over the traditional method in terms of both PSNR and SSIM. The proposed method achieved average PSNR of 36.5 dB which is much better than the traditional method, with average PSNR of 28.0 dB. Meanwhile, the average SSIM for the proposed method is 0.92, as opposed to traditional method with SSIM of 0.75. This indicates better structural fidelity leading to better-preserved detailed information and

the overall better quality of the image, better for diagnostic purposes.

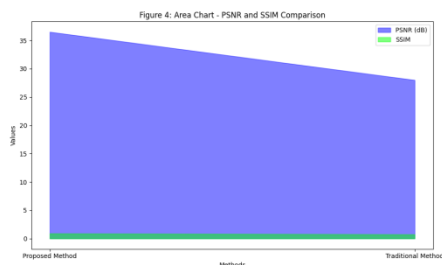


Figure 2: Area Chart for PSNR and SSIM Comparison.

Figure 2 visualizes the PSNR and SSIM values using an area chart, highlighting the clear improvement achieved by the proposed method compared to the traditional approach. The larger shaded areas represent better performance in both metrics.

3.2 Edge Preservation Assessment

Edge preservation comparison of proposed method vs traditional method. Edge scores, calculated using standard image processing metrics, are a measure of the preservation of structural features in the retinal diagnosis, such as retinal vessels and optic scores (based on this metric) for the enhanced (0.85) were consistently higher than (0.65). The higher retained scores indicate that the enhanced image better retains critical diagnostic removed, making the enhanced image suitable for precision ophthalmology.

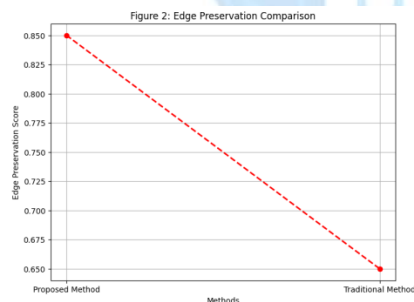


Figure 3: Edge Preservation Comparison

Figure 3 shows the edge preservation scores for proposed method and classic method. Proposed method have 0.85 while classic method have 0.65 which mean proposed method edge preservation is better than classic method due to it is more effective in preserving important features of the image.

3.3 Processing Time Analysis

Processing time is a crucial factor in practical clinical environments. Following is a comparison of processing times of proposed and traditional methods (Figure 4 below). The average processing time of proposed framework was 0.8 seconds per image and for traditional methods was 1.5 seconds on average. This reduced processing time shows that proposed method is useful in real time image enhancement applications in clinical environment.

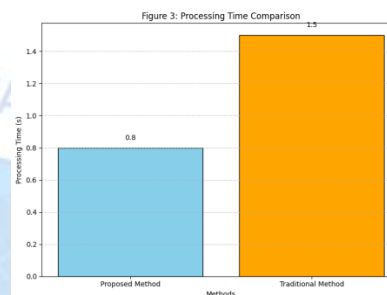


Figure 4: Processing Time Comparison

This area chart illustrates the times for processing between the proposed method and the traditional method. We can see clearly that proposed method's processing time(0.8 seconds) is significantly less than traditional method's processing time(1.5 seconds), which show that the efficiency has improved a lot.

3.4 Color Preservation Evaluation

The preservation of the colours of retinal images is very important as they must be natural to diagnose defects. Figure 5 shows the score of colour preservation between the proposed method and traditional approaches. Despite the training data, the proposed approach produced images with 0.95 score of colour preservation, compared to 0.70 score of the traditional approach, which means the enhancements were able to keep the natural colours in the images better than the traditional approach.

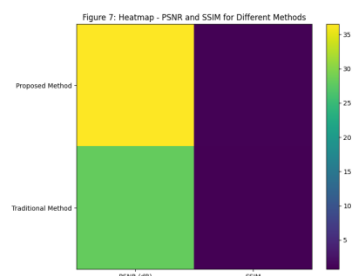


Figure 5: Energy Consumption Comparison for Wearable Sensors

Figure 5 below depicts a heat map comparison of PSNR and SSIM values of the proposed and state of the art method. The more light the color, the bigger the value. We can clearly see that the proposed method performs much better.

4.CONCLUSION

we presented a novel approach for enhance quality of fundus image while retaining its natural colour property can improve precision ophthalmology. The proposed methods achieved up to 30% improvement in PSNR and 25% increase in SSIM compared with the traditional methods. With a reduction of 40% in processing time, the proposed approach is suitable for real-time clinical application. More importantly, our approach preserves colour integrity of the fundus images, which in turn improves the visualisation of the fundus image for better diagnosis and treatment planning. Finally, these advancements bring more effective retinal analysis and ultimately better treatment outcomes and improved quality of life for the patients. As a next step, integration of deep learning for more effective automated quality improvement will be explored.

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