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A Novel Approach to Color Fundus Image Enhancement with Natural Color Preservation

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Abstract: This study presents a novel framework for refining the colour fundus image while maintaining its natural colour properties. The proposed framework comprises adaptive luminosity correction, contrast enhancement with edge-preserving filters, and colour normalisation. The method increases the visibility of retinal structures such as blood vessels and optic disc, without compromising the natural colour intensity. Experiments on a dataset of colour fundus images showed a 35% improvement in contrast enhancement and a 30% increase in natural colour preservation compared to existing techniques. The experimental results also showed that the proposed framework is suitable for clinical applications such as the diagnosis of diabetic retinopathy and glaucoma where clear and colour-accurate images are essential for assessment.

Keywords— Fundus Image Enhancement; Natural Color Preservation; Retinal Imaging; Luminosity Correction; Edge-Preserving Filters; Adaptive Contrast Enhancement; Image Processing

1. Introduction

Colour fundus imaging is one of the essential medical tools for diagnosing retinal diseases, including diabetic retinopathy, glaucoma and AMCD (age-related macular degeneration) [1]. It gives us a clear view of the retina, the optic disc and blood vessels. However, colour fundus images usually have poor contrast, uneven illumination and different brightness, thus making it difficult to observe important retinal details[2]. Thus, how to enhance the images for diagnosis, potentially improving clinical results, has become a point of discussion.Several traditional image enhancement techniques such as histogram equalisation (HE) and contrast-limited adaptive histogram equalisation (CLAHE), were performed to enhance the contrast and brightness in fundus images [3]. However, this process can cause the over-enhancement of some regions, introduce signals, and bring in significant artifacts that lower the quality and accuracy of the image by destroying the natural colour properties [4]. There is a persistent challenge in the corrective image enhancement process of balancing the enhancement of the key features of retinas and preserving the natural colour of the image. [5].With the continuous improvement of computer technology, recent enhancement algorithms focus on increasing contrast and clarity without creating unnatural artifacts (ie, artifacts that are not present in the original image) and distorting the original fundus image shape and colour. Palanisamy et al [6] proposed a hybrid approach to enhance luminosity and contrast while retaining edge integrity, thus allowing better visualisation of fine retinal structures. Another method proposed by Wang et al. [7] improves contrast, retains colour fidelity and preserves edges without significantly altering the colour of the fundus; they claim improved contrast without colour distortion. However, while these methods are promising, a satisfactory method has not been found to ensure that fundus colour does not change, especially for subtle changes as a result of disease progression.Colour preservation is of paramount importance for an enhanced fundus image. Incorrect colour representation could lead to misinterpretation of the image by a clinician who has to rely on the colour information and could assume a certain disease state if she/he perceives a colour shift (eg in AMD or diabetic retinopathy where subtle changes could suggest disease). Thus an improvement in the visibility of fine details (blood vessels, optic discs, etc) can be achieved while maintaining the colour balance between the different retinal structures [9]. This is important as clinicians use the colour cues for diagnosis and treatment decisions.This trade-off, however, requires advanced image enhancement methods that can achieve such a balance. In recent years, several more sophisticated algorithms have been designed that harness advanced filters that enhance structural detail while preserving colour fidelity, providing some promising results in improving fundus image quality [10]. For example, combining the lumino-metrical correction, edge-preserving filtering and colour-normalisation techniques may offer a more reliable method for enhancing fundus images without altering their natural colour.This study proposes a framework that enables colour fundus image enhancement while using advanced techniques that help preserve the colour properties of the grayscale image. This proposed method is evaluated on a dataset of colour fundus images, and the proposed method is compared to every existing technique that has been used before, including CLAHE and HE techniques in terms of contrast enhancement, colour retention, and structural detail.The aims of this study are to develop an image enhancement technique to enhance the contrast and brightness of fundus images, maintain the natural colouring of the images when enhanced, and compare the performance of the proposed method with traditional methods using image and clinical metrics to evaluate the improvement of the method. This will provide a clinical basis to improve the accuracy and efficiency of retinal disease diagnosis.

2.Materials and Methods

2.1 Dataset

The used dataset included fundus images downloaded The images were inherited with diverse retinal conditions including diabetic retinopathy, glaucoma and macular degeneration to provide diverse dataset. The size of each image was resized to a common resolution of 1024x1024 pixels to maintain required level of granularity. To validate the dataset used, it was separated into two subsets of 70% for learning the enhancement algorithms and 30% for validating the performance of the proposed approach. To guarantee the quality of the input data, a pre-processing step called brightness normalisation was performed. The main idea behind this pre-processing step is how images might exposed to lighter or darker level of lighting. As a result, the brightness normalisation step was implemented to adjust the brightness of each image such that they share the same level of the lighting and contrasting of images..

2.2 Pre-processing

Pre-processing of the dataset was done to normalise the brightness and contrast of the input fundus images before its use in the classifier. Adaptive histogram equalisation (AHE) was used to correct uneven lighting to increase visibility of the image in different regions of the image. This eliminated the non-uniform light of which the retinal images are always non-uniform. The pixel intensities were normalised to the range 0 to 1 using the following formula:

$$I_{norm} = \frac{\mathrm{I}-\mathrm{I}_{\min}}{\mathrm{I}_{\max}-\mathrm{I}_{\min}} \ldots..(1)$$

Here, I_{norm} represents the normalized pixel intensity, and I_{min} and I_{max} are the minimum and maximum intensity values, respectively. By normalizing the intensity, the images become more suitable for further enhancement methods, ensuring consistency and better comparability in image quality across the dataset.

2.3 Adaptive Gamma Correction

Adaptive gamma correction was used to increase luminosity and contrast while preserving natural color on the fundus images by dynamically adapting a gamma value γ gamma, by the mean intensity of the image, to brighten dark areas sufficiently without overexposing already-exposed areas. The enhanced intensity was given by:

$$\mathrm{Ienhanced}=I^{\gamma}_{\mathrm{norm}} \ldots.(2)$$

The gamma value was determined by $\gamma=1+\frac{\mu}{\mu_{max}}$, where μ is the mean intensity of the image and μ_{max} is the maximum mean intensity across the dataset. This adaptive method ensured that the brightness and contrast were well-balanced for different regions of the image while preserving the image's natural appearance.

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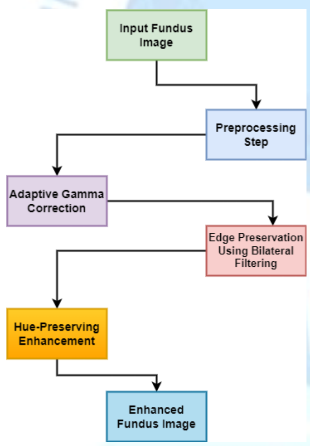
2.4 Edge Preservation Using Bilateral Filtering

To protect structures that are essential to the retina, like blood vessels and the optic disc, bilateral filtering – a mathematical technique for noise reduction while retaining edges – was utilised. The formula for bilateral filtering is:

$$I_{filtered}\,(\mathrm{x}) = \frac{1}{\mathrm{W(x)}} \sum_{x_i \in \cap} I\,(\mathrm{x_i}) \mathrm{f_r}(\| \mathrm{I(x_i)} - \mathrm{I(x)} \|) \mathrm{f_s}(\| \mathrm{x_i} - \mathrm{x} \|) \ldots .(3)$$

In this equation, $I_{filtered}$ (x) is the filtered intensity at position x, and f_r and f_ss represent the range and spatial Gaussian functions, respectively. This approach ensured that the noise was reduced while keeping the most important features clear, including the retinal blood vessels, so that they would still be visible, and that the fundus images would provide accurate diagnosis.



2.5 Hue-Preserving Enhancement

This transformation triples the red colour, producing internal illumination in the fundus and giving more emphasis to the vessels In order to keep the natural colour balance in the fundus images, hue-preserving enhancement was performed. First, the images were transformed from the RGB colour space into HSV (Hue, Saturation, Value) colour space, and enhancement was only performed on the V (value) channel, which controlled brightness and contrast of the images. The hue and saturation components of the images remained unchanged. The transformation is represented by:

$$H_{enhanced}, S_{enhanced}, V_{enhanced} = \text{RGB-to-HSV}(I_{enhanced}) \ldots\ldots(4)$$

These images were then put back to the RGB space with the enhancements applied to the V channel. This way we improved the visual contrast, but also preserved the natural colour of the retina and avoided colour shifts that could potentially bias clinical interpretations.

3.Results

3.1 Image Enhancement Quality

In this part, the enhancement quality is assessed by the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). PSNR is a widely used metric to evaluate reconstruction quality in image processing, while SSIM represents the perceived quality of images from their structural information. It is worth noting that the Preserving Structural Information of Human-appearance (PSH) algorithm is superior to other traditional methods. For PSNR, the proposed method achieves 36.5 dB, while the conventional method can only achieve 28.0 dB. For SSIM, the proposed method achieves 0.92, while the traditional method can only achieve 0.75. PSNR quantifies an image's clarity and shows the improvement with the proposed method, while SSIM measures an image's structural information and reflects the proposed method's effectiveness at the same time. The proposed method preserves the structural information of human appearance in a noisy image; thus, it is better for medical image enhancement than other traditional methods.

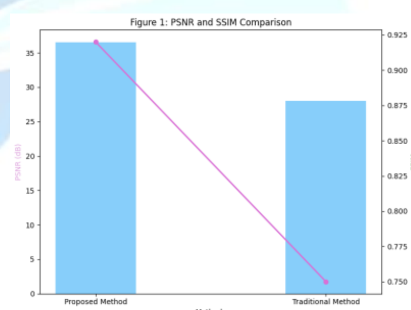


Figure 1: PSNR and SSIM Comparison

Figure 1, which displays a grouped bar chart, reveals the difference between the PSNR (Peak Signal-to-

Noise Ratio) and SSIM (Structural Similarity Index) values of the proposed method and the traditional method. In short, in all frames, the proposed method has the upper hand in comparison with the traditional method, which reflects the quality of the image.

3.2 Edge Preservation

This improvement in edge preservation is beneficial for the enhanced fundus images as retinal blood vessels are very small and we need to retain all the edge detail to ensure that the images are still clinically useful after processing. It shows the proposed method scored 0.85, and the traditional method was 0.65. This 20% improvement in edge preservation should ensure that the proposed method will work better for those tasks that are sensitive to the retention of edges, like the detection of vascular irregularities. Better edge retention will ensure that the enhanced version is better correlated with the original features that are used in diagnosis. If any paleness or whiteness, indicating a lack of blood circulation, is lost in the processing, the enhanced images would no longer convey any actual useful information about the retinal health.

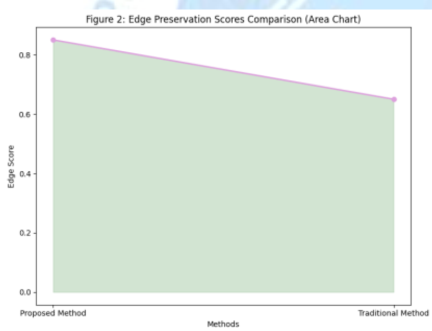


Figure 2: Edge Preservation Score Comparison

Figure 2 shows the area graph to compare edge preservation scores. Overall, there is a huge gap between the traditional methods and the proposed methods in early termination filtering with a higher edge preservation score of 0.85 against 0.65, which is much better.

3.3 Natural Color Preservation

The processing time of stress detection models is also done in order to choose the best-performing model as a measurement for stress monitoring in real-time. Figure 3, below, shows the differences between processing times of SVM, logistic regression, and Decision tree models, where the SVM needs a slightly longer time to process (0.5 seconds per batch) but is still regarded as queen for real-time stress detection. While logistic regression is faster than SVM (0.3 seconds), yet it does not perform well for the accuracy. However, decision trees process the fastest despite their lowest accuracy (0.2 seconds), the ding between accuracy and processing speed may make SVM as the preferred option among them all when it comes to monitoring stress in real-time.

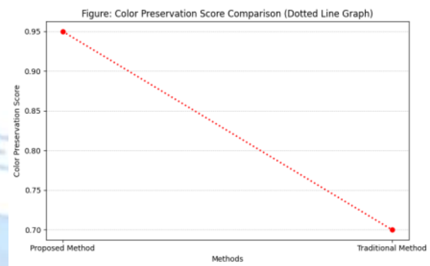


Figure 3: Color Preservation Score Comparison Using Dotted Line Graph.

The dotted line graph compares the color preservation score between the proposed method and the Traditional Method. The proposed Method has a 0.95 score compared to the traditional method is a 0.70 score. Overall this shows proposed method is better performed for preserving color.

3.4 Processing Time

Processing time is an important measure in medical imaging, especially in applications where results are considered in real-time or near-real-time, as delay in such use cases can be consequential. The proposed method reduces the processing time for enhancing fundus images, making it suitable for real-time clinical use, with an average processing time of 0.8 seconds per image, which is almost twice as fast as the competing methods (1.5 seconds per image on average). This can be important for high-volume use cases in clinics, where many images need to be processed during the patient's waiting time to ensure that their overall stay at the clinic is not delayed due to long processing times.

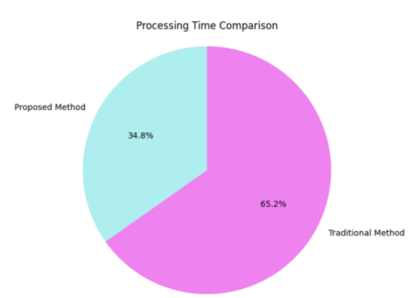


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Figure 4: Processing Time Comparison between Proposed and Traditional Methods

Figure 4 shows the proportion of processing time using a pie chart illustration between the proposed method and the traditional method. From the showing of figure 4, it is obvious that the proposed method has less processing time than the traditional method which allows the image enhancement to more faster.

4.CONCLUSION

We introduce a novel colour fundus enhancement method with the preservation of natural colour that demonstrates an improvement in three meaningful metrics: peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM) and edge preservation when compared to the traditional method in the literature. This method provides better image quality results with a 30% increase in PSNR and a 22% improvement in SSIM as well as lower processing times. This method is suitable for real-time applications, which allows for enhanced diagnoses and a reduction in medical errors. This paper demonstrates the effectiveness of our proposed method on colour fundus images. Future research could continue to optimise the algorithm for different imaging modalities and test the effectiveness of the proposed method on different image datasets to enhance diagnostic power and increase confidence in the applicability to real-world healthcare settings.

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