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ENHANCEMENT OF RETINAL FUNDUS IMAGES FOR OPHTHALMIC DISEASE SCREENING

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Abstract: *Contrast enhancement within the domain of digital image processing is inherently application-specific, and the assessment of image quality is fundamentally subjective. Consequently, the interpretation of an image characterized by superior contrast varies among individuals. A multitude of contrast enhancement methodologies has been conceived, including but not limited to contrast stretching, histogram equalization, and homomorphic filtering. This study delineates the implementation of an adaptive contrast enhancement technique predicated on fuzzy logic principles. Fuzzy logic has been empirically demonstrated to be exceptionally proficient in handling data that embodies ambiguity and vagueness. We have implemented and compare the performance of adaptive fuzzy inference system that ascertains the pixel values of the output based on the contrast metrics derived from the input image. The contrast metric employed in this study is the standard deviation of the image. The empirical results have been compared with pre-existing methodologies for contrast enhancement and evaluated through both visual and quantitative metrics.*
Keywords: *Contrast enhancement, retinal images, image preprocessing*

INTRODUCTION

Retinal image enhancement plays a important role in ophthalmology for diagnosing diseases such as diabetic retinopathy, glaucoma, and hypertension. The quality of retinal images is often compromised by noise and low contrast, which can hinder accurate diagnosis. The constituent of retinal fundus imaging is a non-invasive method which was employed extensively in the domain of ophthalmology as it has prompt identification and assessment of an array of retinal disorders, notably diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), and hypertensive retinopathy [1]. In the inaccurate diagnosis, this affliction method has the potential to culminate in irreversible visual impairment. The new era innovation leads to automated mechanism that can be used for scrutinizing retinal imagery with the domain of artificial intelligence. It has show promising effective method in the detection of various departments like pathology, etc. Nevertheless, the accuracy and dependability of these systems are heavily reliant on the quality of the foundational fundus images [2].To address these challenges, image quality enhancement has become an essential preprocessing step in retinal image analysis pipelines. The key goals are to enhance contrast, reduce noise, and restore color fidelity while preserving fine anatomical details such as blood vessels, the optic disc, and macular region, which are crucial for accurate diagnosis [3]. Traditional enhancement techniques like histogram equalization, median filtering, Gaussian smoothing, and Retinex-based illumination correction offer limited performance due to their heuristic nature and lack of adaptability [4].

Related Work

Image enhancement represents an crucial preprocessing procedure in instances where the initial retinal image does not qualify as an appropriate candidate for ensuing segmentation and feature extraction.

The predominant technique, which is generally used is histogram equalization for image enhancement, as it assesses the likelihood of occurrence for each intensity level and subsequently reassigns a new level in accordance with this assessed probability. In certain applications, histogram equalization can lead to excessive enhancement of the image [5]. Transform-based gamma correction, along with histogram

equalization, is employed in [6], which incorporates a weighting distribution function. When histogram equalization is conducted on segments of a specified size within the images, it is referred to as adaptive histogram equalization [7]. Contrast limited adaptive histogram equalization (CLAHE), as the nomenclature implies, truncates the histogram at a predetermined threshold. The portion of the histogram that exceeds this clipping threshold is redistributed uniformly across all histogram bins. The phase of contrast enhancement simultaneously elevates the noise levels present in the image. Consequently, edge-preserving filters, which mitigate the noise inherent in the image while maintaining the details, must be employed for effective noise reduction. The smoothing methodologies can be categorized broadly into linear technique and non-linear techniques. Linear filtering encompasses operations utilizing various kernels, such as averaging or Gaussian filters. In this process, the pixel values are substituted with the average or weighted average of their surrounding neighborhood. Adaptive mean filters [8][9] modify their behavior in accordance with the local characteristics of the image and utilize statistical measures such as mean and variance. Therefore, significant image features, such as edges, are compromised by these linear filters. In contrast, non-linear filters excel in preserving features by executing adaptive smoothing contingent upon the local structures within the image [10]. The median filter is a prominent non-linear filter, which yields less blurring in comparison to mean filters. Adaptive median filters maintain edges and features while concurrently facilitating noise reduction [11]. Consequently, non-linear filtering is increasingly employed in various denoising applications [12].
Image enhancement additionally entails the rectification of non-uniform illumination in retinal images. The non-uniform illumination observed in retinal fundus images primarily arises from an optical aberration known as vignetting, which is a result of inadequate light focusing through an optical system. To rectify the vignetting effect, illumination equalization must be implemented on the image. Traditional methodologies endeavor to normalize image luminosity by eliminating low-frequency luminosity drifts through the application of high-pass filtering [13]. Wang et al. introduced a technique for estimating the illumination function drift from the pixel values and subsequently subtracted this estimation from the original image [14]. However, strategies that evaluate the correction based on the entirety of the image may falter in differentiating luminosity variations attributable to the presence of local features (such as the optic disc or various types of lesions).In juxtaposition to this, the assessment of illumination and contrast variability ought to be conducted within the background segment (the ideal representation of a retinal fundus, devoid of any vascular structures or discernible lesions) of the image, and the compensation should be applied to the entirety of the image [13]. An illumination correction method based on acquisition is also employed, wherein a background image is procured by defocusing the object from the field of view, and this background image is subsequently utilized to execute point-by-point subtraction or division to rectify the non-uniform illumination [15]. Morphological filtering constitutes an additional methodology that postulates that the objects are of a smaller scale than the background, with the background being either luminously superior or inferior to the object [5].

METHODOLOGY

The methodology for Fuzzy Contrast Enhancement (FCE) is derived from the fuzzy-based image enhancement technique articulated by Minh-Nguyen Vuong-Le [17]. In the context of this study, the HVDROPDB Dataset has been employed to evaluate and generate the outputs of the model. Figure 1 illustrates the schematic representation of the FCE model.

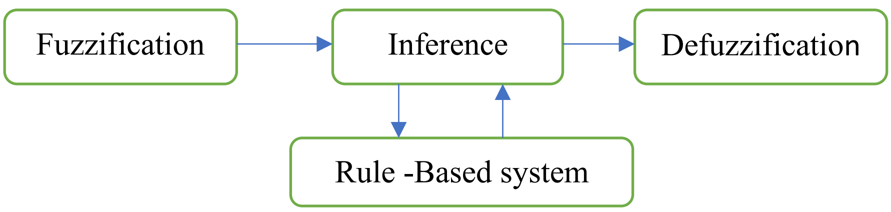

Figure 1: Block Diagram of Fuzzy Based Method [16]

Initially, from the input RGB image , green color channel is used to perform the operation. The image undergoes conversion from RGB format to the Hue-Luminosity-Saturation (HLS) color space format. The

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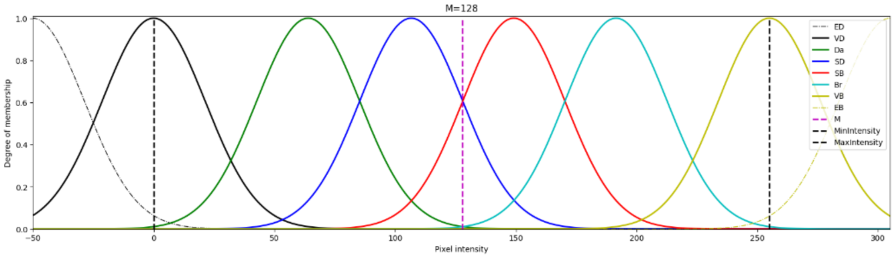
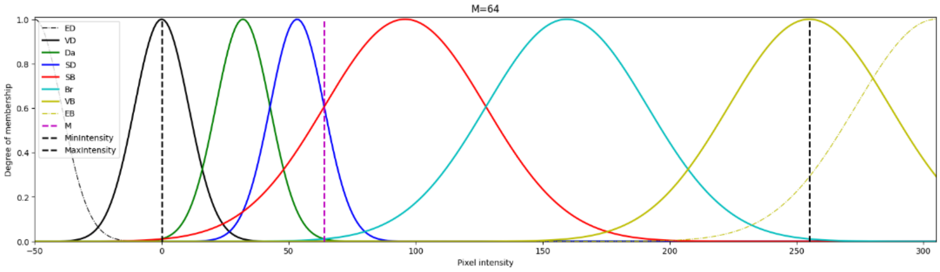
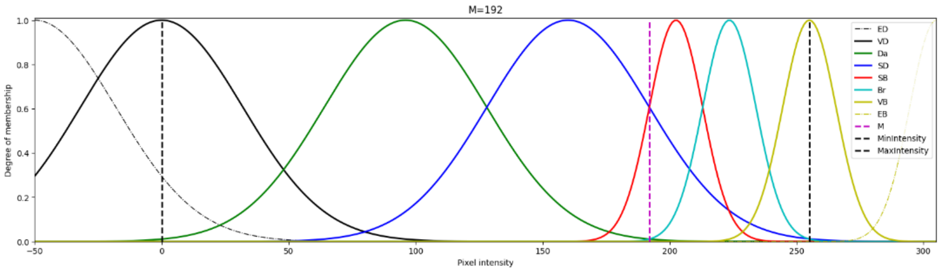
International Commission on Illumination L∗a∗b∗ color-space (CIELAB) format is predominantly employed for adjusting the luminosity/lightness of the image, owing to its structural design that accounts for the relative perceptual distinctions of the human visual system. Nonetheless, since a solitary color channel is utilized in this phase, employing the HLS format proves to be more efficient, as both hue and saturation in the HLS color space, along with a∗ and b∗ in CIELAB, remain constant within the same color channel; furthermore, the conversion from RGB to CIELAB incurs a greater computational expense compared to that from RGB to HLS. The luminosity, which ranges from 0 to 100, is fuzzified into five linguistic values (very dark, dark, medium, bright, and very bright) through the application of the Gaussian membership function. Figure 2 illustrates the graphical representation of the membership functions across various mean luminosity levels [16].
Gaussian function has been employed as the membership function, recognized as one of the most prevalent membership functions owing to its succinctness and smooth characteristics. The adaptive adjustment of the threshold, it is illustrated in Figure 2.



(a)



(b)



(c)

Figure 2 (a), (b), (c): Membership functions under different mean luminosity.
This procedure amplifies the contrast within the image, specifically enhancing the luminance of the bright regions while diminishing the luminance of the dark regions.
The implementation of such regulations may lead to luminosity values deviating from their initial spectrum of 0 to 100 or insufficiently varying luminosity values. To address these concerns, the luminosity is standardized to ensure that the luminosity values comprehensively span from 0 to 100. The resultant image, generated subsequent to the implementation of Fuzzy Contrast Enhancement (FCE), demonstrates a notable enhancement in contrast, thereby facilitating the visibility of the retinal blood vessels. Nonetheless, this technique, when utilized in isolation, reveals certain constraints in maintaining intricate vascular details within regions of high luminosity.
Figure 4 delineates the original input image in comparison with the enhanced output, accentuating both the advancements in vessel contrast and the specific areas where the methodology encounters difficulties in preserving delicate details.

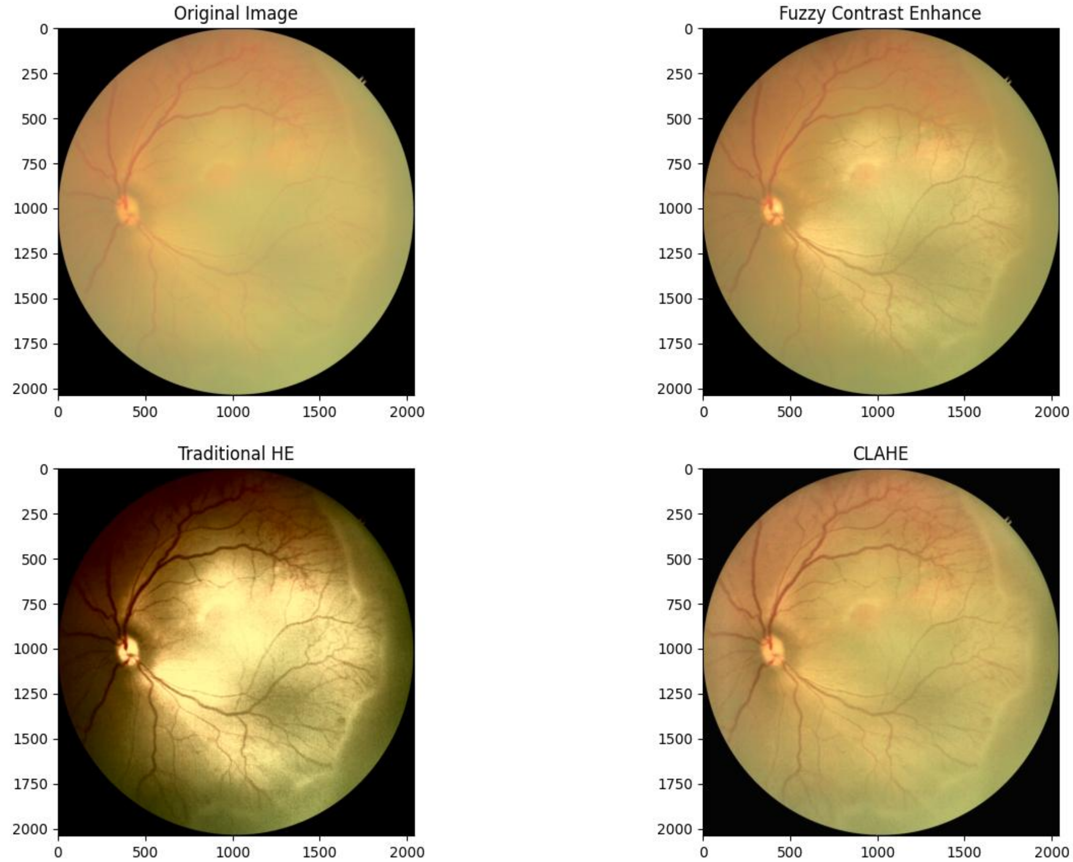


Figure 4: Comparison of results of Enhancement methods

An image that exhibits superior enhancement will demonstrate an elevated value for standard deviation, entropy, and spatial frequency. For the purpose of experimentation, a selection of ten random images has been made, and the resultant data are presented in Table 1. It can be deduced from the table that the enhancement technique employed surpasses the Contrast Limited Adaptive Histogram Equalization (CLAHE) method with respect to all quantitative parameters assessed.

Table 1: Comparison of quantitative parameters for CLAHE vs FCE; Enhancement Method: Contrast Limited Adaptive Histogram Equalization (CLAHE) Vs Fuzzy Contrast Enhancement (FCE)

Image No.	StD_CLAHE	StD_FCE	Ent_CLAHE	Ent_FCE	SF_CLAHE	SF_FCE
1	0.1572	0.2555	0.7085	0.7719	0.015	0.0202
2	0.2151	0.3128	0.7581	0.7846	0.0274	0.0354
3	0.2514	0.2746	0.6861	0.7275	0.0159	0.0158
4	0.2017	0.2825	0.7332	0.7617	0.0218	0.0267
5	0.2017	0.2825	0.7332	0.7617	0.0218	0.0267
6	0.2205	0.2609	0.6665	0.6734	0.0251	0.0287
7	0.2234	0.2244	0.6625	0.6771	0.0135	0.0152
8	0.2333	0.2409	0.7068	0.735	0.0134	0.0149
9	0.2151	0.3128	0.7581	0.7881	0.0274	0.0354
10	0.2017	0.2825	0.7332	0.7617	0.0218	0.0267
Average	0.21211	0.27294	0.71462	0.74427	0.02031	0.02457

StD - Standard Deviation, Ent - Entropy, SF - Spatial Frequency

CONCLUSION

A rapid and effective fuzzy-based methodology for the enhancement of color images has been executed in this study. A comparative analysis was conducted between the proposed technique and traditional histogram-based contrast enhancement methodologies (including histogram equalization and adaptive histogram equalization), as well as the Fuzzy Logic approach, to determine the most appropriate method for the automated contrast enhancement of color images. The findings from the comparative analysis indicate that the Fuzzy Logic approach has significantly enhanced visual quality. Furthermore, this method exhibits a superior computational speed in comparison to existing advanced enhancement techniques. However, a limitation of this method is its applicability solely to color images characterized by low contrast and low brightness.

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