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A novel equalization scheme for the selective enhancement of optical disc and cup regions and background suppression in fundus imagery

Fousia M. Shamsudeen*[1], G. Raju[2]
[1]School of Computer Science, MG University, Kottayam, Kerala, India
[1]Department of Computer Application, TKM College of Engineering, Kollam, Kerala, India
[2]Department of Computer Science and Engineering,
Faculty of Engineering Christ (Deemed to be University), Kanminike, India
*Corresponding author, e-mail: fousiaresearch@gmail.com[1], kurupraju@gmail.com[2]

Abstract

The ratio of the diameters of Optic Cup (OC) and Optic Disc (OD), termed as 'Cup to Disc Ratio' (CDR), derived from the fundus imagery is a popular biomarker used for the diagnosis of glaucoma. Demarcation of OC and OD either manually or through automated image processing algorithms is error prone because of poor grey level contrast and their vague boundaries. A dedicated equalization which simultaneously compresses the dynamic range of the background and stretches the range of ODis proposed in this paper. Unlike the conventional GHE, in the proposed equalization, the original histogram is inverted and weighted nonlinearly before computing the Cumulative Probability Density (CPD). The equalization scheme is compared with Adaptive Histogram Equalization (AHE), Global Histogram Equalization (GHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) in terms of the difference between the mean grey levels of OD and the background, using a quantitative metric known as Contrast Improvement Index (CII). The CII exhibited by CLAHE, GHE and the proposed scheme are 1.1977 ± 0.0326, 1.0862 ± 0.0304 and 1.3312 ± 0.0486, respectively.The proposed method is observed to be superior to CLAHE, GHE and AHE and it can be employed in Computerized Clinical Decision Support Systems (CCDSS) to improve the accuracy of localizing the OD and the computation of CDR.

Keywords: *contrast enhancement, cup to disc ratio, fundus image, glaucoma, histogram equalization*

1. Introduction

Glaucoma is a disease which refers to the damage of optic nerve caused by increased Intra-Ocular Pressure (IOP).It is one of the most common reasons for blindness. About 79 million in the world are likely to be afflicted with glaucoma by the year 2020 [1]. ElevatedIOP is one of the specific symptoms of glaucoma [2]. However, the instrumentation necessary for measuring IOP and the measurement procedure itself are complex [3]. In glaucoma, minute nerve fibres along the rim of the optic nerve get degenerated and the Optic Cup (OC) seems to be enlarged because of the thinning of the neuro-retinal rim [4]. Cup to Disc Ratio (CDR) is a quantitative index used to express the enlargement of OC. Normal CDR is about 1/3. Increased CDR is usually referred as cupping and it is accepted as specific as elevated IOP or even more reliable than it, for screening glaucoma [4].

Recent studies [2-9] also have shown that automated or computerized assessment of the Optic Nerve Head (ONH), via fundus images is promising for screening glaucoma because of low cost and simplicity. These methods [2-9] for the automated screening of glaucoma are based on the unique feature known as 'Cup to Disc Ratio', as mentioned already. It is the ratio of diameters of OC and Optical Disc (OD). Minute fibres originating from the retina, which constitute the optic nerve, bend approximately 90^o at the interface of retinal surface and ONH. OC is the small crater-like depression seen at the optic nerve head. Whereas, OD is the location, where axons of ganglion cells, coming from the photo receptors exit the retina, to form the optic nerve [5]. On fundus image, the OD is seen as two distinct zones, a central enhanced zone, OC and a peripheral region called the neuro-retinal rim [6]. Not only in glaucoma but in the diagnosis of diseases like multiple sclerosis, brain tumors and optic nerve

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trauma etc. also, imaging studies of optic nerve is informative. The nerve head may look blurred and pale in such cases [7].

The Problem accurate localization of OD and delineation of OC is the principal and most crucial step in the automated diagnosis of glaucomafrom fundus images [8]. Unfortunately, because of the poor contrast of fundus imagery, it is not trivial to localize OD and discern regions of OC and OD [9]. Few methods [10-16] to enhance the fundus imagery are available in literature. Out of which, in the method suggested by Dai et al. [10], an image which contains the basic information of the background had been extracted from the original image through a normalized convolution algorithm which includes a domain transform. Then, the image with the basic information of the background was fused with the original image to yield the enhanced image. Finally, the fused image was denoized by a two-stage filter comprising fourth order PDEs and a relaxed median filter. Quite different from the method suggested by Dai et al. [10], Wang et al. [11] used inverse anisotropic diffusion to particularly strengthen the edges. Another technique in the same direction, proposed by Youssifet al. [12] involves two stages, illumination equalization and a specially designed 'Adaptive Histogram Equalization' (AHE). To improve the extraction of vascular network from the fundus imagery, Badsha et al. [13] used Kirsch's template for enhancing the edge strength and the conventional Global Histogram Equalization (GHE) for increasing the grey level contrast. Other popular methods available in literature for enhancing fundus imagery are Contrast Limited Adaptive Histogram Equalization (CLAHE) [14, 15] and CLAHE with Rayleigh histogram specification [16].

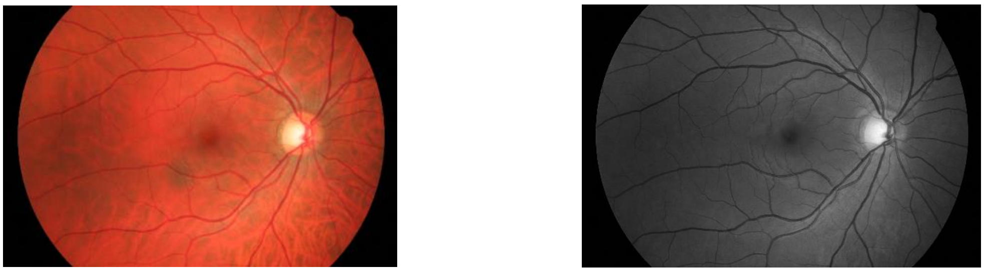
Perhaps, the method suggested by Dai et al. [10] may improve overall contrast of the image. But the method is not specific enough to enhance the OD region selectively. The methods [11-13] are exclusively meant for edge enhancement. Reverse diffusion [11] used for edge enhancement is highly unstable and induce artefacts. Illumination equalization involved in the method suggested by Youssif et al. [12] compresses the dynamic range of the image, which is not appreciable as far as an enhancement scheme is concerned. This method is computationally intense because of its local processing. The methods available in [11-13] are meant for the extraction of vascular network from the fundus imagery. The vasculature is inherently well defined on fundus imagery and exhibit good gradient strength. Even conventional edge detection kernels can accurately extract the vascular network. The localization of OD is more challenging than this because of the poor grey level contrast between the OD and the background. Moreover, edge based segmentation schemes are less reliable for localizing OD, as OD does not have clearly defined boundaries.

Predominantly frequent grey levels may get over enhanced in GHE [13]. In some cases the mean brightness the equalized image would be intolerably different from that of the original image. The enhanced image may appear 'washed out' or 'saturated'. GHE alters the natural histogram statistics of the image and amplify noise. The performance of CLAHE [14-16] and the quality of the enhanced image highly depends on the selection of the tile size, cliplimit, number of histogram bins, intensity range of the enhanced image, specified 'distribution' of the image tiles and the parameters of the specified distribution itself. The process of tuning multiple operational parameters together is complex. The procedure of enhancing the image tile by tile or locally is computationally intense. Even though the grey levels at the boundary of the tiles in the enhanced image are estimated via bilinear interpolation, the possibility of artificially induced inter-tile edges are unavoidable. None of the methods available in literature [10-16] can selectively enhance the contrast between the OD and the background.

The proposed solution, the contribution in this paper is a customized version of the conventional histogram equalization which selectively magnifies the contrast between OD and the background in fundus imagery. This will help to increase the accuracy of localizing the OD and computation of CDR. A contrast enhancement scheme fully customized for improving the grey level contrast between OD and background in the fundus image is a novel concept among its kind. An important highlight is that the transform involved in the customized histogram equalization is able to stretch the contrast at higher grey levels and compress the contrast at low grey levels. The analytical formulation of the proposed equalization scheme is furnished in section 2. In section 3, the scheme is compared with contrast enhancement schemes available in literature, AHE [12], GHE [13] and CLAHE [14-16] in terms of the contrast between OD and the background.

2. Methodology

It has been empirically observed that the green channel accounts for majority of the information content in the fundus image in RGB colour space, than red and blue channels. Hence, in the proposed scheme only green channel is enhanced, maintaining R and B channels intact. The practice of using the green channel for processing is a widely accepted one [17-20]. The original image and its green channel are shown in Figure 1 (a) and Figure 1 (b). It can be appreciated from Figure 1 that the green channel is able to fully account for the information content in the original image, in grey scale space. In the green channel image, the OD and OC seem to be relatively bright and enhanced compared to the background. However, the grey level contrast is not sufficient to allow their easy segmentation. From the normalized histogram available in the Figure 2 (a), it can be observed that the histogram amplitude at the greylevels which constitute the OC and OD are less than the frequency of grey levels which constitute the background. If GHE is employed for enhancing the fundus image, it will enhance the background region with larger histogram peaks uncontrollably. Instead, the bright intensities in the image whose histogram height is comparatively less has to be enhanced selectively. Simultaneously, the background corresponding to larger histogram peaks and darker greylevels has to be suppressed. This means, the contrast at the OD has to be enhanced selectively while penalizing the contrast at the background. Unlike the conventional GHE, in the proposed method, the original histogram is inverted and weighted nonlinearly before computing the Cumulative Probability Density (CPD).



(a) (b)

Figure 1. (a) Fundus image in RGB colour space (b) Green Channel

The contrast enhanced grey level corresponding to the original grey level, ‘k’ is computed as,

$$T(k) = C(k)(L-1) \; Given \; C(k) = \sum_{i=0}^{k} W(k) \quad (1)$$

the transformed grey level, ‘T(k)’ is the product of the CPD of the k^{th} grey level, ‘Ç(k)’ and the maximum possible value of the grey level (L-1), as evident in (1). The inverted form of the original histogram P(k) is computed as,

$$Q(k) = \frac{P_{max}-P(k)}{\sum_{k=0}^{L-1} P_{max}-P(k)} \; So \; that \; \sum_{k=0}^{L-1} Q(k) = 1 \; Given \quad P(k) = \frac{n(k)}{MN} \quad (2)$$

where MN is the dimension of the image, ‘P_{max}’ is the largest peak of the histogram, ‘P(k)’ and ‘n(k)’ is the number of occurrence of the k^{th} grey level. After inversion, the less frequent grey levels get more significance, during the equalization. To impose greater significance to higher grey levels, the inverted histogram ‘Q(k)’ is weighted non-linearly before computing the CDF as,

$$W(k) = \frac{k^{\alpha} Q(k)}{\sum_{k=0}^{L-1} k^{\alpha} Q(k)} \; such \; that \; \sum_{k=0}^{L-1} W(k) = 1 \quad (3)$$

where ‘α’ is an arbitrary constant which controls the extent to which the background grey levels are penalized.

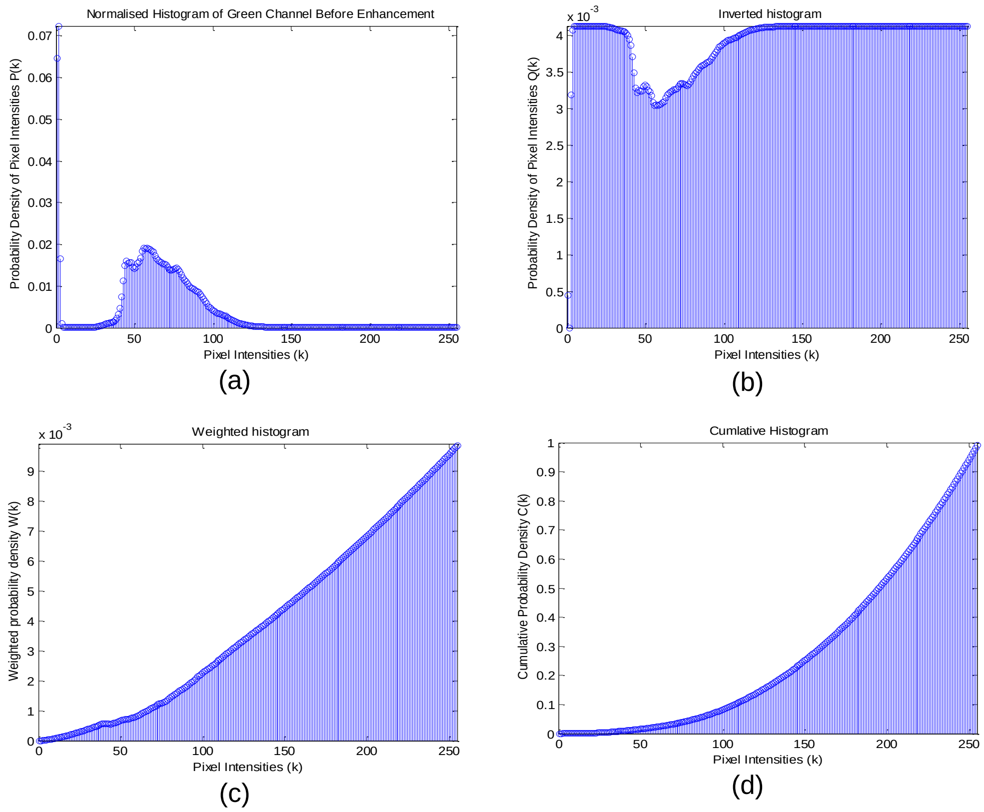


Figure 2. (a) Normalized histogram of green channelP(k)
(b) Inverted histogram Q(k) (c) Weighted histogram W(k) (d) CPD C(k)

Contrast Improvement Index (CII) is used in this paper to compare the performance of the proposed enhancement scheme with GHE, AHE and CLAHE. It quantitatively expresses how much the contrast between the OD and background has increased in the enhanced image,with reference to the contrast between the OD and background in the original image.

$$CII = \frac{C_O}{C_E}, C = \frac{\mu_B - \mu_{OD}}{\mu_B + \mu_{OD}} \quad (4)$$

where 'μ_B' and 'μ_{OD}' are the mean intensities of the background and optic disc, respectively. 'C_O' and 'C_E' are the contrast between the OD and background in the original and enhanced images. For a good enhancement scheme CII would be well above 1. CII equal to one indicates no enhancement. The fundus images used in this paper is collected from High-Resolution Fundus (HRF) Image Database, maintained byPattern Recognition Lab, Department of Informatik, Friedrich-Alexander-Universität, Germany [21-25]. The images belong to glaucoma patients acquired with a Canon CR-1 fundus camera with a field of view of 45°. The computations are performed in Matlab®.

3. Result and Discussions

The arbitrary parameter, 'α' is the factor which determines the extent to which the contrast of OD is enhanced and the grey levels in the background region are suppressed, as mentioned. The transformation function for different values of α is shown in Figure 3. As α tends to zero, the transformation function becomes linear and the transformed image approximates to the original one. The more the value of α, the more will be the background suppression and the contrast between OD and the background.This can be visually observed on the transformed images available in Figure 4 (a) to Figure 4 (f). From the quality of the enhanced images and the shape of the transformation function for different values of α, it can be inferred empirically that the value of α approximately around 1.5 is advisable.

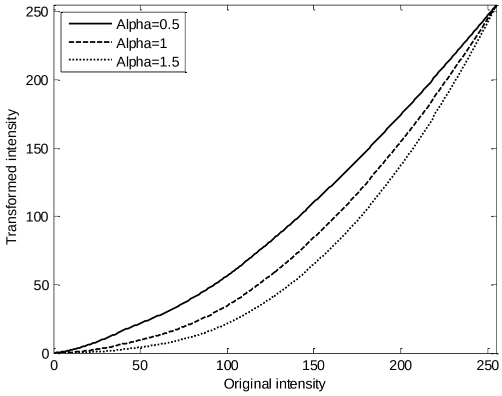


Figure 3. The transformation function for different values of α

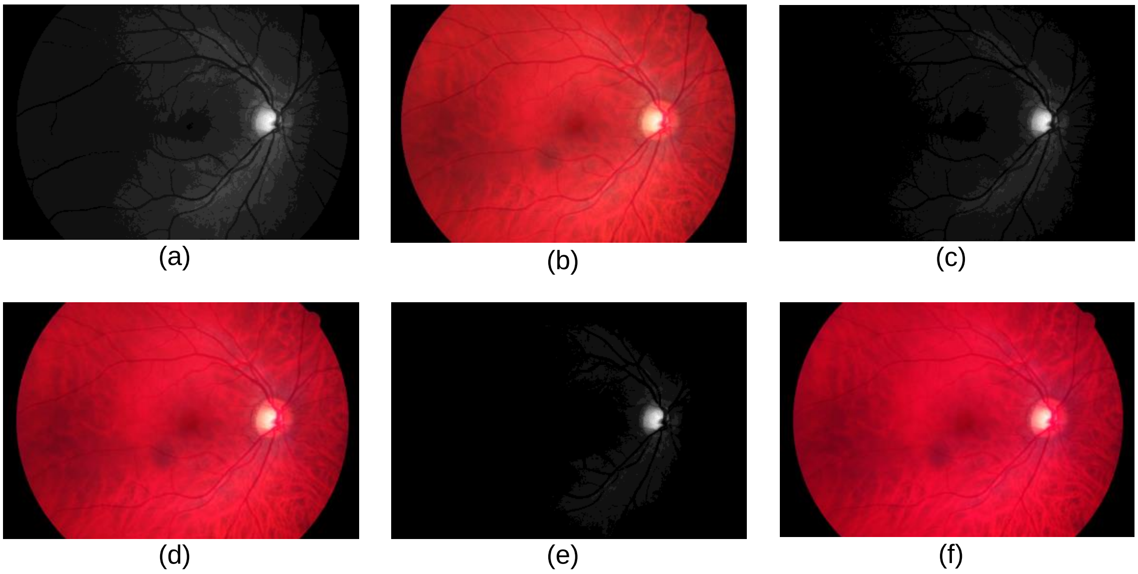


Figure 4. Enhanced green channel and RGB image for different values of α
(a) enhanced green channel for α=0.5 (b) enhanced RGB image for α=0.5
(c) enhanced green channel for α=1 (d) enhanced RGB image for α=1
(e) enhanced green channel for α=1.5 (f) enhanced RGB image for α=1.5

Figure 5 (a) and 5 (b) reveals that AHE suggested by Youssif et al. [12] is quite useful for extracting the vascular network from the fundus images. It is a kind of edge enhancement scheme like the reverse diffusion [11], rather than a scheme for enhancing the grey level contrast. It is not a suitable scheme for enhancing the OD. The CLAHE (Figure 5 (c) and Figure 5 (d) enhances both the background and the OD region simultaneously. So the grey level difference between the OD and the background remains the same as in the original image. The interface between the OD and background and the interface between the OD and OC are not well defined. Hence the delineation of OC out of OD is tedious in Figure 5 (c) and Figure 5 (d). GHE (Figure 5 (e) and Figure 5 (f)) over enhances the image fully. The region of OD becomes saturated and cannot be distinguished from the background. The proposed equalization scheme (Figure 5 (g) and Figure 5 (h)) performs the background suppression and enhancement of OD simultaneously. Consequently, the grey level difference between the background and OD is relatively more compared to the difference possible with GHE [13] and CLAHE [14-16]. The numerical values of CII offered by GHE, CLAHE and the proposed scheme are furnished in Table 1. The proposed scheme exhibits better CII than GHE and CLAHE.

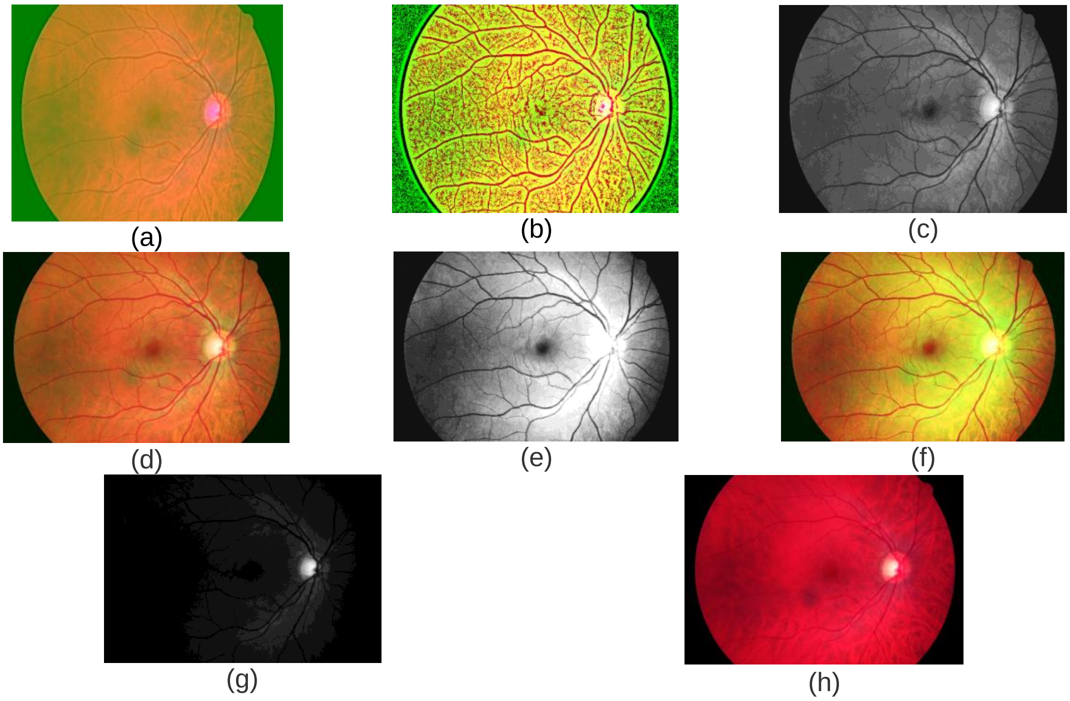


Figure 5. (a) Illumination equalized image [12] (b) Illumination equalized image after AHE [12] (c) Green channel equalized with CLAHE (d) Enhanced RGB image for CLAHE (e) Green channel equalized with GHE (f) Enhanced RGB image for GHE (g) Green channel equalized with the proposed scheme (h) Enhanced RGB image for the proposed scheme

Table 1. Numerical Values of CII for CLAHE, GHE and the Proposed Method

Si no of image	CLAHE	GHE	Proposed
1	1.23	1.11	1.38
2	1.15	1.04	1.314
3	1.25	1.13	1.41
4	1.23	1.12	1.392
5	1.203	1.1	1.309
6	1.18	1.07	1.289
7	1.21	1.1	1.301
8	1.17	1.06	1.287
9	1.19	1.08	1.354
10	1.164	1.052	1.276

4. Conclusion

A customized equalization scheme which selectively magnifies the contrast between OD and the background in fundus imagery was proposed in this paper. In this scheme, the background and OD regions are stretched apart in the grey scale space. The transformation involved in this scheme compresses the dynamic range of the background and stretches the range of OD, simultaneously. The proposed method of enhancement will help to increase the accuracy of localizing the OD and computation of CDR. It will resolve the subjectivity inherent in the demarcation of OD and OC.

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