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Analysis of Enhancement Techniques for Retinal Images

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Abstract – In this paper, analysis of retinal image enhancement techniques is presented to facilitate the detection of certain pathologies and for automatic extraction of anatomical ocular structures. Adaptive gamma correction, modified histogram equalization, adaptive intensity transformation, dynamic stochastic resonance and principal components analysis enhancement techniques are applied on the retinal images and the performance is compared. The simulation results indicate PCA enhancement technique is better for further analysis of any retinal disorder diagnosis.

Index Terms – Enhancement, Gamma Correction, Histogram Equalizatin, Principal Component Analysis, Eigen value, Cumulative distribution function, Fundus image

1 Introduction

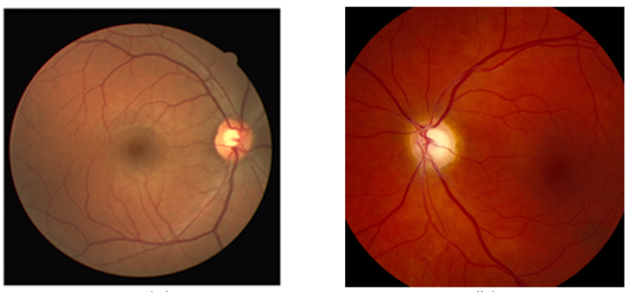
Digital fundus imaging in ophthalmology plays an important role in diagnosis of visual impairments and blindness including diabetic retinopathy, hyper tension, glaucoma and macular degeneration. Retinal images can be used for other applications such as ocular fundus operations and human recognition. Due to the acquisition process, these images have low contrast and dynamic range, which can seriously affect the results of retinal disorder diagnostic procedure. Contrast enhancement plays an important role in the improvement of visual quality for processing the retinal images. Usually, the retinal images are enhanced by various preprocessing techniques to discriminate the ocular structures like optic disc, blood vessel, macula and other diseased patches and to improve the contrast.

Number of image enhancement techniques that inspires the redistribution of bright intensity value in high dynamic range is found in the literature. Eunsung Lee et al. [2] have proposed a novel contrast enhancement technique to improve the overall quality and visibility of local details in remote sensing images that is based on adaptive intensity transformation with modified gamma correction function. Shih-chia Huang et al. [3] presented an adaptive gamma correction with the weighting distribution function to enhance a colour image without artifacts. Hyunsup Yoon et al. [4] proposed an enhancement technique which divides the input image histogram into a number of sub histograms, on which histogram equalisation is performed. R. Chouhan et al. [5] have proposed new algorithm for image enhancement based on the dynamic stochastic resonance. P. Feng et al. [8] have implemented countourlet transform on the histogram stretched retinal image for enhancement. They have modified the coefficients of the countourlet in corresponding subband using linear functions. Mohammad Saleh Miri et al. [11] presented an algorithm for retinal image contrast enhancement based on curvelet transform.

This paper examines the various enhancement techniques on retinal images to improve the detection of various pathologies. The paper is organised as, Section II discusses the various enhancement techniques and Section III compares the experimental results obtained from the enhancement techniques.

2 Retinal Image Enhancement

The enhancement as pre-processing technique plays a vital role in retinal image analysis to discriminate in detail the optic disc, blood vessel, macula and hard exudates (white diseased patches). In general, most of the researchers use CLAHE (Contrast Limited Adaptive Histogram Equalization) method [13] and wavelet-based CLAHE method for enhancing the retinal image. In this section, five different retinal image enhancement techniques have been analysed. The input test images are the retinal fundus images shown in Fig.1.



(a) (b)

Fig. 1 Retinal Fundus Image (a) Normal (b)Abnormal

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A. Adaptive Intensity Transformation for Contrast Enhancement (AITCE)

This method is based on the contrast enhancement technique for remote sensing images [2] using the dominant brightness level and the adaptive intensity transformation. This method effectively enhances the overall contrast and visibility of the local details in remote sensing images which also meet the requirements for the retinal image analysis to segment the Optic Disc. The method is implemented by applying the DWT to the retinal image which separates the image into LL, LH, HL, HH sub regions. According to equation (1) the dominant brightness level is obtained from the LL sub band since it has more luminance information. Based on the computed Log average luminance, the LL sub region is separated into three layers of High, mid and low intensity range. The knee point is computed in each intensity region to obtain the knee transfer function [2]. The knee point is computed in each layer of LL sub region for low, high and mid intensity layer using the equation (2), (3), (4) respectively.

$$\mathrm{L_{avg}} = \exp\left\{\frac{1}{N}(\mathrm{sum}[\log(\mathrm{delta} + \mathrm{L_w}(x,y))])\right\} \tag{1}$$

where L_{avg} is the log average luminance, N is number of pixels in the image, delta is the space luminance of the pixel p(x,y)

$$\mathrm{K_{pl}} = \mathrm{r_l} + \mathrm{T_l}(\mathrm{r_l} + \mu_\mathrm{l}) \tag{2}$$

$$\mathrm{K_{ph}} = \mathrm{r_h} + \mathrm{T_h}(\mathrm{r_h} + \mu_\mathrm{h}) \tag{3}$$

$$\mathrm{K_{pml}} = \mathrm{r_l} - \mathrm{T_m}(\mathrm{r_{ml}} + \mu_\mathrm{m}) + (\mathrm{K_{pl}} - \mathrm{K_{ph}}) \tag{4a}$$

$$\mathrm{K_{pmh}} = \mathrm{r_h} - \mathrm{T_m}(\mathrm{r_{mh}} + \mu_\mathrm{m}) + (\mathrm{K_{pl}} - \mathrm{K_{ph}}) \tag{4b}$$

where rl ,rh , rml , rmh are the low , high , mid low and mid high range of each layer respectively and Tl, Th, Tm are the tuning parameters of the low, high and mid layer respectively. µl, µh, µm corresponds to mean of brightness level in each layer.

Adaptive intensity transformation based on knee transfer and gamma adjustment function obtained from the dominant brightness level, computed from each layer of the LL sub region is applied to same layer to enhance the contrast. The modified gamma correction function incorporating the knee transfer function is given in (5). The adaptive intensity transformed and gamma corrected layer of LL sub region are then fused to which the inverse DWT is applied together with unprocessed LH, HL, HH sub regions, to obtain the enhanced retinal image as shown in Fig.2 .The fused image FI is computed as in (6). Most significant two bits from each layer is extracted from each intensity layer (low, mid, high) for generating the weighting map and the sum of two bit value is computed in each layer. Weighting maps are employed with Gaussian boundary smoothing filter to avoid unnatural borders in image fusion.W1 and W2 corresponds to first and second largest weighting map. cl, cm, ch represents the contrast enhanced brightness in low, mid, high intensity layer respectively.

$$GC_i(I) = \left\{\left(\frac{I}{S_i}\right)^{1/\gamma} - \left(1 - \frac{I}{S_i}\right)^{1/\gamma} + 1\right\} \quad \text{for } i\epsilon(\mathrm{l,m,h}) \tag{5}$$

where S represents the size of each section.

$$FI = W_1 * c_1 + (1 - W_1) * \{W_2 * c_m + (1 - W_2) * c_h\} \tag{6}$$

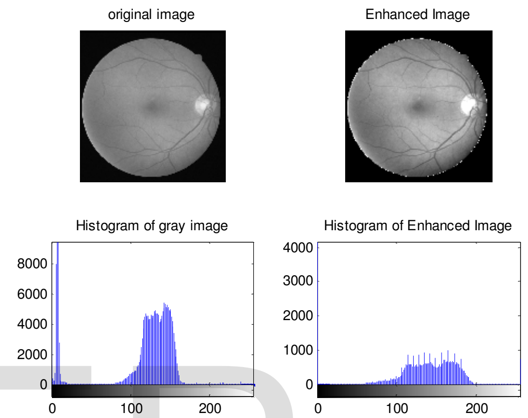

Fig. 2: Adaptive Intensity Transformation based Contrast Enhancement for Normal Image

B. Adaptive Gamma Correction with weighting distribution for Contrast Enhancement (AGCWD)

This method is based on histogram analysis to obtain the probability and statistical parameters [3] which is incorporated in the adaptive gamma correction with weighting distribution function. First the hybrid Histogram modification is computed by combining Transform based gamma correction (TGC) and Traditional histogram equalisation (THE). The transform based gamma correction is formulated in (7) where Imax is the maximum intensity of the input image and I is the intensity of each pixel (γ=1). The probability density function is given by (8) where nI is the number of pixels with I intensity and MN is the size of the image. The cumulative distribution function (cdf) is computed by (9) and traditional histogram equalisation is obtained by (10)

$$\mathrm{T(I)} = \mathrm{I_{max}}\left(\frac{\mathrm{I}}{\mathrm{I_{max}}}\right)^{\gamma} \tag{7}$$

$$\mathrm{pdf(I)} = \frac{\mathrm{n_I}}{\mathrm{MN}} \tag{8}$$

$$\mathrm{cdf(I)} = \mathrm{sum}\big(\mathrm{pdf(k)}\big), \quad \text{for } \mathrm{k} = 0 \text{ to } \mathrm{I} \tag{9}$$

$$\mathrm{T(I)} = \mathrm{cdf(I)I_{max}} \tag{10}$$

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The combined method of TGC and THE leads to over-enhancement and under-enhancement challenges due to the unnatural changes in CDF. As a result of these challenges a compensated CDF is employed as an adaptive parameter which leads to progressive increment in the low intensity and avoid significant decrement in the high intensity. The Adaptive Gamma correction (AGC) is formulated using (11). To reduce adverse effect that is to reduce the over-enhancement of the Gamma correction or to smoothen the fluctuant phenomenon, the weighting distribution function is applied to modify the statistical histogram .The weighting distribution function is formulated as in (12) and the modified cdf(I) is computed by (13).

$$T(I) = I_{max}\left(\frac{I}{I_{max}}\right)^{\gamma} = I_{max}\left(\frac{I}{I_{max}}\right)^{(1-cdf(I))} \tag{11}$$

$$pdf_w(I) = pdf_{max}\left(\frac{pdf(I)-pdf_{min}}{pdf_{max}-pdf_{min}}\right)^{a} \tag{12}$$

where ‘a’ is the adjustable parameter, pdfmax, pdfmin, are the maximum and minimum values of the histogram.

$$cdf_w(I) = sum\left(\frac{pdf_w(I)}{sum(pdf_w)}\right) \tag{13}$$

where I varies from 0 to Imax and the sum(pdfW) is computed as

$$sum(pdf_w) = sum[pdf_w(I)] \quad \text{for } I = 0 \text{ to } I_{max} \tag{14}$$

Thus the gamma parameter is modified as γ = 1 – cdfw(I). The adaptive Gamma correction with the weighting distribution function is computed by (15).

$$T(I) = I_{max}\left(\frac{I}{I_{max}}\right)^{(1-cdf_w(I))} \tag{15}$$

The input image is converted to the HSV model where the Value V component of the model represents the luminance intensity. The colour image is enhanced by enhancing the V and preserving H and S .The AGC with WDF is applied to the V component of the image. This method enhances the colour image without generating the artifacts Fig 3.

C. Dynamic Stochastic Resonance based Enhancement (DSRE)

For enhancing the dark and low contrast images, a spatial domain enhancement technique based on stochastic resonance is employed [5]. Due to insufficient illumination the dark and low contrast images may be formed. As a first step of this method the RGB image is converted to HSV colour space model to minimize the computation complexity and to preserve the colour of the image. DSR is applied to the V(x,y) in the HSV space to obtain the stochastically enhanced set of values given by (16)

$$v(x,y)_{enhanced} = DSR[v(x,y)] \tag{16}$$

$$x(n+1) = x(n) + \Delta t[ax(n) - bx^3(n) + input] \tag{17}$$

The DSR parameters used are a=2σ02, b=0.00001*(4a3)/27 and Δt = 0.01, where x(n+1) denotes the set of tuned coefficients after n+1 iteration and σ0 is the standard deviation of the intensity values. A fraction factor very much less than unity must be multiplied to ensure that b is less than its maximum value and eligible for the application of DSR. The stochastic differential equation is solved using Euler – Maruyama’s method of the iterative discretisation given by (17). After each iteration, new HSV image is computed with the initial Hue and Saturation values, Fig 4.

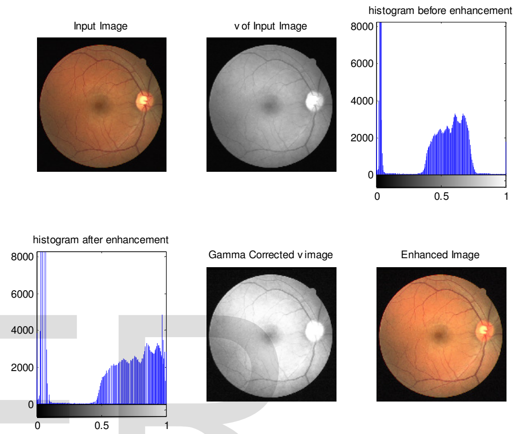

Fig. 3: AGCWD for Contrast Enhancement of Normal Image

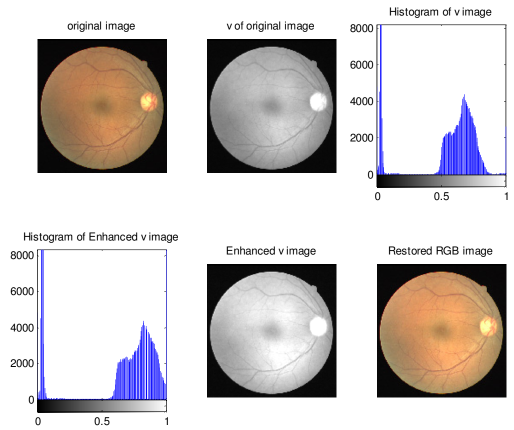

Fig. 4: Dynamic Stochastic Resonance based Enhancement for Normal Image

D. Sub-histogram Equalization Technique for Enhancement (SHETE)

Contrast enhancement is acquired by stretching interval between dark and bright area. The contrast enhanced image will provide clear image to assist feature extraction. The original

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histogram is divided into sub histogram and then each sub-histogram is equalised based on the mean and variance. The histogram density is analysed by equation (18) to divide into low and high distribution area. The equalised sub histogram is merged to obtain the final enhanced image [4]. First, the histogram density function is calculated and then the density function is sorted in the descending order. Then histogram is segmented to sub histogram and region boundary is determined using the Gaussian approximation given in equation (19). Each sub histogram is equalised and then it is merged, Fig. 5.

$$D_n = \sum_{i=n-w/2}^{n+w/2} f(x_i) \tag{18}$$

where n in the above equation (16) represents the brightness value and f(xi) represents the frequency of the xi th brightness.

$$g_n(x) = \frac{1}{\sigma n\sqrt{2\Pi}} \exp(-\frac{x-\mu_n}{2\sigma_n}) \tag{19}$$

gn(x) is the Gaussian approximation function with the centre value, µn of the selected region.

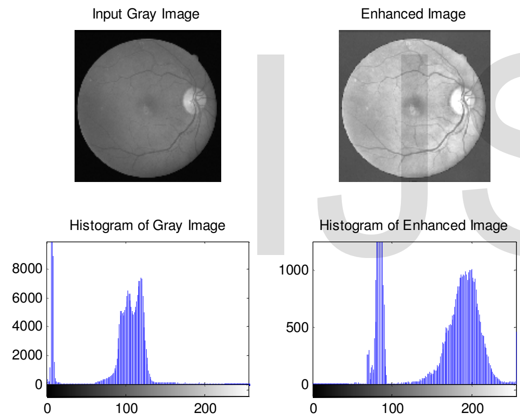


Fig. 5: Sub-histogram Equalization Technique for Enhancement for Normal Image

E. PCA and Contrast Enhancement

In Principal Component Analysis (PCA) method [6], principal components are obtained by calculating Eigen values of the co-variance matrix (20) for the input color retinal image.

$$\begin{bmatrix} C_{rr} & C_{rg} & C_{rb} \\ C_{gr} & C_{gg} & C_{bb} \\ C_{br} & C_{bg} & C_{bb} \end{bmatrix} \tag{20}$$

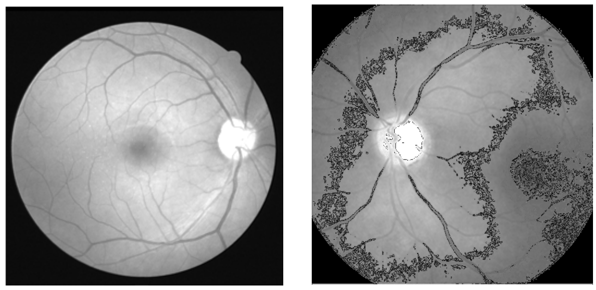
The covariance is computed by

$$C_{rr} = \frac{1}{N} * \sum_{i=1}^{N}(f_i - \text{mean}(f))((f_i - \text{mean}(f)) \tag{21}$$

where, ‘f ’ is the input image, Crr corresponds the covariance between red components of the image, Crg corresponds the covariance between red and green component of the image and so on. The first principal corresponds to the Eigen vector of the highest eigen value, contains most of the structural contrast and information. Then, the input image is projected in the direction of the principal component by

$$PC_k = e_{kR}f_R + e_{kG}f_G + e_{kB}f_B \tag{22}$$

where, f_R, f_G, and f_B are the red, green and blue components of input image; e_{kR}, e_{kG} and e_{kB} are the first, second and third element of the eigen vector of maximum eigen value.



(a) (b)

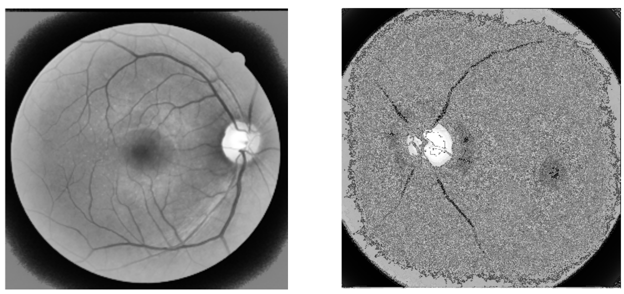
Fig. 6: First Principal Component
(a) Normal (b) Abnormal

Fig.6. shows the first principal components of normal and abnormal retinal image. Secondly, Contrast enhancement is performed on first principal component to improve the visual perception. The transformation for contrast stretching is given by,

Enhanced Image

$$= \left(\frac{\mu_{max} - \mu_{min}}{2(\mu_f - t_{min})}\right) * (t - t_{min}), \quad \text{if } t \le \mu_f$$
$$= \left(\frac{\mu_{max} - \mu_{min}}{2(\mu_f - t_{max})}\right) * (t - t_{max}), \quad \text{if } t > \mu_f \tag{23}$$

where,
- µmax = 255, µmin = 0
- µf is the mean value of the image within the window
- tmaxis maximum gray level of the image
- tmin is minimum gray level of the image
- r is the contrast increasing factor



(a) (b)

Fig. 7: Enhanced Image of first Principal Component
(a) Normal (b)Abnormal

The non-uniform illumination of the grey image is also cor-

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rected and its contrast is increased through this local transformation. Fig.8. shows the first principal component image enhanced by using the above formula.

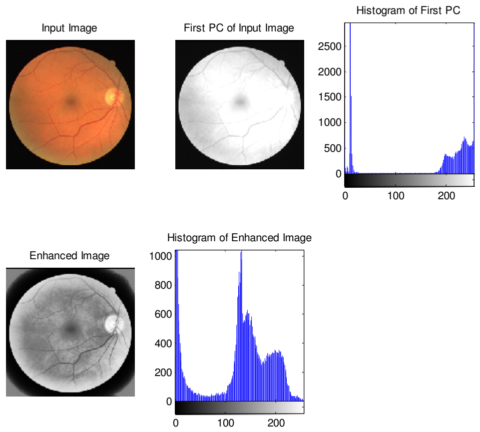

Fig. 8: PCA and Contrast Enhancement for Normal Image

3. Experimental Results

The various enhancement techniques which are discussed in Section II are implemented in retinal images and the results are shown in Fig. 2 to 8. Retinal images with normal and diseased conditions, obtained from STARE and MESSIDOR database are used for the analysis. The retinal image is enhanced by AITCE, AGCWD, DSR, SHETE and PCA techniques. The performance of the different enhancement techniques are analysed using three metrics namely EME, RCEF and AMBE. In this AMBE should be as high as possible and EME & RCEF should be greater than one thus represents better enhancement. The metrics are defined as follows

Enhancement Measurement Error (EME):

$$\mathrm{EME} = \frac{1}{k_1 k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\frac{I_{max}(k,l)}{I_{min}(k,l)+c}\ln\left(\frac{I_{max}(k,l)}{I_{min}(k,l)+c}\right) \tag{24}$$

where
k1, k2 – total number of sub-blocks in the enhanced image
Imax(k,l) – maximum value in the sub-block
Imin(k,l) – minimum value in the sub-block
c – small constant to avoid dividing by zero

Relative Contrast Enhancement Factor (RCEF):

$$F = \frac{Q_B}{Q_A} = \frac{\sigma_B^2/\mu_B}{\sigma_A^2/\mu_A} \tag{25}$$

where
QB – Quality index of post-enhancement
QA – Quality index of pre-enhancement

Absolute Mean Brightness Error (AMBE):

AMBE = Mean (Enhanced Image) – Mean (Input Image) (26)

Table 1
Performance Analysis For Enhancement Techniques

Image	Method	EME	RCEF	AMBE
Image 1	PCA	1.09	0.97	36.91
	AITCE	0.25	0.52	9.79
	AGCWD	4.20	1.33	9.15
	DSR	2.18	1.19	10.08
	SHETE	0.22	0.72	20.12
Image 2	PCA	0.96	1.02	41.91
	AITCE	0.19	0.41	21.12
	AGCWD	3.30	1.21	09.12
	DSR	1.93	1.22	11.10
	SHETE	0.17	0.61	23.19

The Table-1 shows the comparative performance results for clinically proven normal (Image1) and abnormal (Image2) images, using AITCE, AGCWD, DSRE, SHETE and PCA. The EME and RCEF is higher for AGCWD and DSR, but PCA yields better EME, RCEF and AMBE value compared to other enhancement techniques.

4 Conclusion

In this paper, we have analysed five different enhancement methods such as PCA, AITCE, AGCWD, DSR and SHETE for normal and abnormal retinal images. EME, RCEF and AMBE metrics are used to evaluate the techniques. From the simulated results, PCA method is found to be more efficient for enhancing the ocular structures, which can be further used for diagnosis of retinal disorders.

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