Assessment of Histogram-Based Medical Image Contrast Enhancement Techniques; An Implementation

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***Abstract*— Medical image contrast enhancement is an important issue playing a prominent role in the digital image processing applications in some areas such as Medical Imaging, Biometric Image Recognition, Satellite, and etc. Basically, image enhancement on the basis of Histogram Equalization fails to provide the better image contrast enhancement and brightness preservation which might cause loss inaccurate diagnostic information of medical images. Hence, in order to improve image quality in computer processing, it can modify the intensity of image pixels by image contrast enhancement. In this research, some important various image contrast enhancement methods such as HE, BBHE, DSIHE, GHE, CLAHE, QWAGC-FIL, are simulated based on retinal image. This practical study attempts to focus upon the comparative analysis of various image contrast enhancement techniques.**

***Keywords*— Medical Imaging, Image Processing, Contrast Enhancement, Histogram Equalization.**

I. Introduction

To diagnose and treat patients, medical imaging has crucial importance. One of the most essential issues in image processing is improving image contrast. Contrast is the degree of difference between maximum and minimum intensities or, in other words, light and dark parts of an image. The purpose of image contrast enhancement is to improve the quality of images and interpretability. In medical imaging applications, namely, X-Ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasonic Scanning (US), Electrons Micrographs and so on, the contrast enhancement play a crucially role. Due to various depths of organs in the body, many inaccuracies in the results to treat diseases might occur. Consequently, the ways of improvement of medical images and noise reduction in image enhancement are essential. Thus, contrast enhancement is important when poor quality images are attained in research such as image investigations and analyses of remote sensing. Histogram Equalization (HE) is a technique for adjusting image intensities to enhance contrast, and widely used due to its accuracy, making the probability distributions flat and thus improving the image contrast by increasing the dynamic range of gray levels. In recent years, a variety range of global Histogram Equalization methods in order to handle the Mean Shift problem has been proposed by researchers [1, 5].

An innovative method, at first, was proposed to preserve the mean brightness and enhance an image contrast, which is known as Brightness Preserving Bi-Histogram Equalization (BBHE). Then a similar method, Dualistic Sub Image Histogram Equalization (DSIHE) was proposed by Wang et al. [6] incorporating segmentation based on the mean value. Compared with (BBHE), (DSIHE) provides better results due to experimental results in regard to entropy and brightness preservation. In 2017, a new method entitled Quad Weighted Histogram Equalization with Adaptive Gama Correction and Homomorphic Filtering (QWAGC-FIL) was developed by Monika Agarwal et al. [4] preserving the maximum entropy with control on enhancement. Other method used with the Otsu [8] to enhance medical images is the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm which explained in the future sections [2].

A. Motivation

Medical imaging in the diagnosis of the diseases assists physicians with deciding effectively how to treat patients. The decisions made to treat changes in body organs are significantly different with those taken on the patients' symptoms. It is quite important in bone diseases and tumors. Therefore, the images with good quality come to physicians' assistance. Enhancing the visual appearance and identifying the desired parts of an image would be improved by the process of medical image contrast enhancement which plays an important role in modern medical diagnoses, and that it is particularly important and helpful in the area of surgery and radiology to detect the abnormal regions. However, noise as well as low contrast might lead to a wrong diagnosis of diseases. Hence, it is vital to improve the poor quality of medical images contrast. Finally, because of the importance of contract enhancing in medical imaging, this paper presents various methods to Histogram Based Medical Image Contrast Enhancement Techniques as following sections.

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This paper is organized as follows. Section II gives a synopsis of Methodology. Section III presents Our Simulation for Comparison between Various Contrast Enhancement Techniques. Section IV is devoted to Conclusion and Future Works.

II. Methodology

A. Histogram Equalization (HE)

Histogram Equalization is a useful method employed in various applications for contrast enhancement owing to its efficacy and simple function. Its function is flattening the Histogram and extending the dynamic range of the gray levels using the image's cumulative density function. Preserving original brightness and improving image contrast to remove the noise are totally essential to consumer electronics devices for which Histogram Equalization is not suitable since the image brightness is changed after that. Adjust intensity values using brightness, contrast, and gamma correction, or by using histogram equalization [9]. Let's assume that *X = X (i, j)* is a gray level digital image and *X (i, j)* is value of the pixel *(i, j)*. Also, suppose that the image has a total of n pixels with intensities quantized into "L" levels of $\{X_0, X_1, X_2, \dots X_{L-1}\}$. It is clear that every *X (i, j)* will be a member of $\{X_0, X_1, X_2, \dots X_{L-1}\}$. Assume that n_k denotes the number of pixels with gray level of X_k within the image X. So, probability density function of X_k will be defined as follows [9]:

$$p(X_k) = \frac{n_k}{n} \quad ; \quad k = 0.1 \dots . L-1 \tag{1}$$

Graphical representation of $p(X_k)$ versus X_k is known as image histogram. Also, the relationship between $p(X_k)$ and X_k is known as Probability Density Function (PDF), thereby the cumulative distribution function is defined as follows:

$$c(X_k) = \sum_{J=0}^{L-1} p(X_j) = \sum_{J=0}^{L-1} \frac{n_k}{n} \tag{2}$$

where k = 0, 1. . . L - 1, and it is obvious that $c\ (X_L - 1) = 1$. Fig. 1 shows the proposed result of HE method on retinal. Fig. 1(a) shows the original retinal image, Fig. 1(b) shows the result of HE method, Fig. 1(c) shows the comparison between (a), (b) histogram images.

B. Global Histogram Equalization (GHE)

This method attempts to change the intensity of the image in a way that it extends the dynamic range of the image Histogram resulting in a more desirable contrast enhancement image. The main idea is that the input Histogram ought to be divided into two sub-parts on the basis of the mean of the input Histogram. Imagine gray levels of pixels of the input image f(x, y) are in the range of [0, L-1]. The cumulative density function (CDF) $C(r_k)$ is defined as Eq. 3:

$$S_k = C(r_k) = \sum_{i=0}^{k} P(r_i) = \sum_{i=0}^{k} \frac{n_i}{n} \tag{3}$$

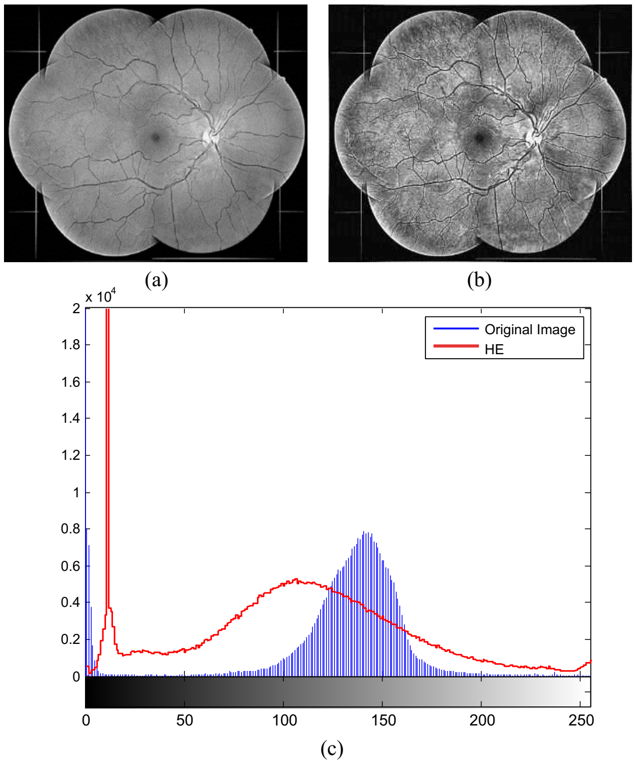

Fig. 1. Histogram Equalization. (a) Original image, (b) HE result, (c) Comparison between (a), (b) Histograms.

where $0 \le s_k \le 1$ and k = 0, 1, 2,…, L-1. Now it can define the transform function *f(x)* using as follows:

$$f(x) = X_0 + (X_{L-1} - X_0)\, c(x) \tag{4}$$

The output image of the GHE process, *Y = Y (i, j)* is as:

$$Y = f(x) = \{f(\,X(i.j)\,)\ \forall\ X(i.j) \in X\} \tag{5}$$

In Eq. 3, n_i is the number of pixels with gray level of r_i, "n" is total number of input image pixels, $P(r_i)$ is the probability density function of r_i. The Cumulative Density Function (CDF) denoted by $C(r_k)$ is formed using the corresponding PDF. Mapping described in Eq. 3 is called Global Histogram Equalization (GHE) or Histogram Linearization. Then, S_k is readily mapped to the range of [0, L-1] after multiplying it by L-1.

Fig. 2 shows the proposed result of GHE method on retinal. Fig. 2(a) shows the original retinal image, Fig. 2(b) shows the result of GHE method, Fig. 2(c) shows the comparison between (a), (b) histogram images.

C. Brightness Bi-Histogram Equalization (BBHE)

To deal with the problem of HE method described in the before section, a brightness preserving Bi-HE (BBHE) was introduced [7]. Fig. 3 indicates the process of applying the BBHE method based on original image decomposed into sub-images by employing the image mean gray-level, then applying HE method to each sub-image.

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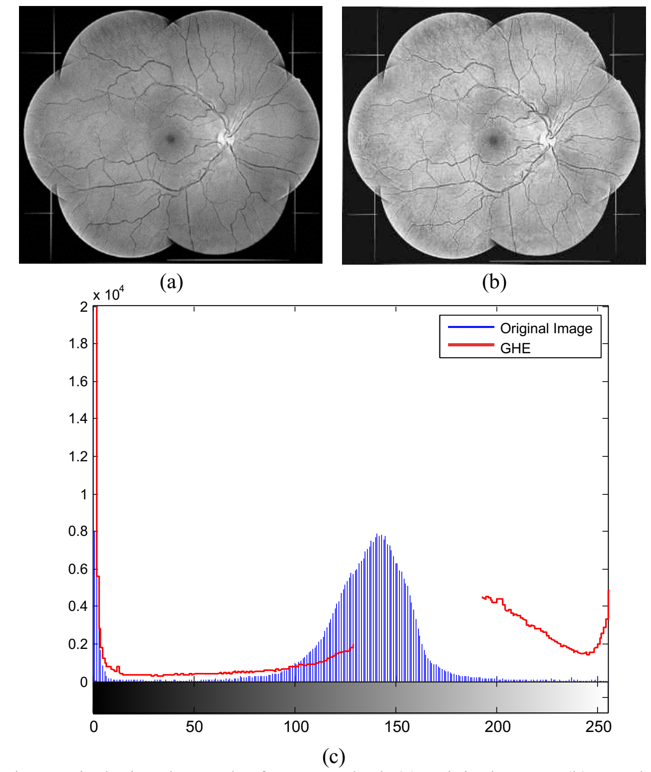

Fig. 2. Displaying the result of GHE method. (a) Original Image, (b) Result of GHE, (c) Comparison between (a), (b) Histograms.

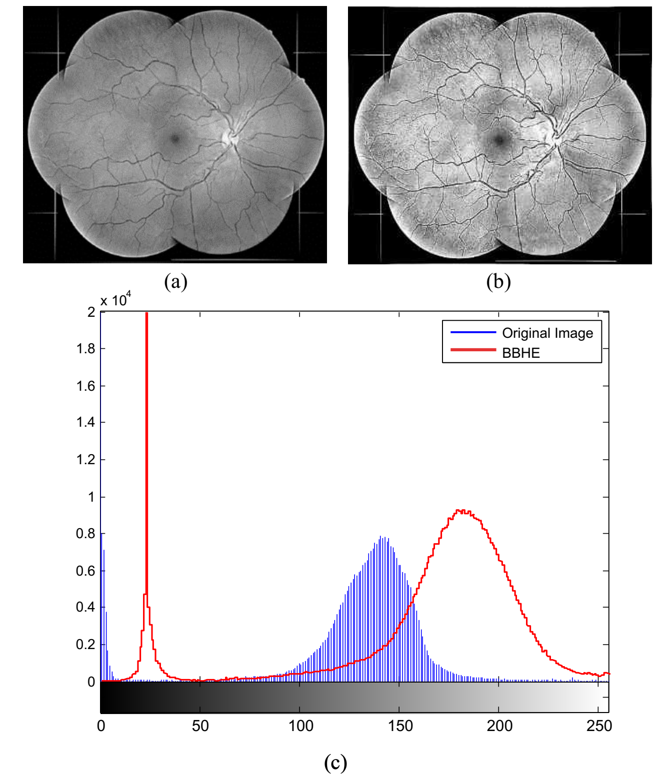

Fig. 4. Displaying the result of BBHE method. (a) Original Image, (b) Result of BBHE, (c) Comparison between (a), (b) Histograms.

The method BBHE is a technique for preserving the brightness and improving the local contrast. This method using the neighborhood matrix and improving the pixel distance can enhance and obtain images in the absence of undesired artifacts that proposed by HE. Fig. 4 shows result of applying the proposed BBHE method on a retinal image. Fig. 4(a) is the original retinal image, output of the BBHE method is shown in Fig. 4(b) and Fig. 4(c) is comparison between histograms of (a) and (b).

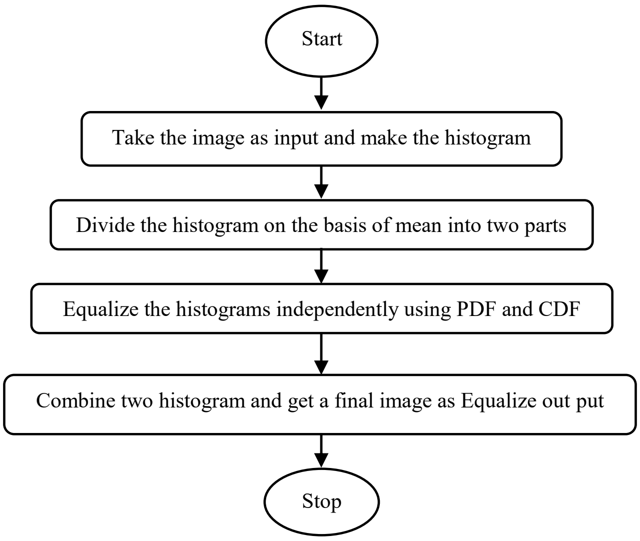

Fig. 3 Block Diagram of BBHE Procedure [7].

D. Dualistic Sub-Image Histogram Equalization (DSIHE)

Input Histogram also is decomposed into two subsections by Dualistic Sub-Image Histogram Equalization (DSIHE) [6].

The methods BBHE and DSIHE, both are analogous but other than that DSIHE performs to separate the Histogram on the basis of the gray level with cumulative probability density equivalent to 0.5 rather than the mean value in BBHE by which the image is decomposed based on its mean gray level. In DSIHE, equal area follows the same idea of BBHE, that is, it decomposes the original image into two sub-images, then separately equalizes the Histograms of the sub-images but not decomposing the image on the basis of its mean gray level. Fig. 5(a) is the original retinal image, Fig. 5(b) shows the result of applying DSIHE method and Fig. 5(c) is comparison between histograms of two images.

The brightness of the output is not changed by this method. The images including large or small object have the same brightness roughly equal to the original image. Thus, small and large object does nothing to affect the output image brightness. In other words, it is preserved prior to and after the contrast enhancement. The result of the DSIHE is acquired after composing the two equalized sub-images into one single image [6].

One important and critical application of digital image processing is in the medical field. Since presence of any noise or low contrast in the medical images may reduce their quality, thus resulting in an incorrect diagnosis by the physician, it is necessary to improve the quality of low contrast medical images [7]. This method especially concentrates upon enhancing images with low contrast along with maximally preserving entropy and controlling on enhancement. Detailed description of each step of the proposed method is given in the following sub-sections. Also, block diagram of the proposed method is shown in Fig. 6.

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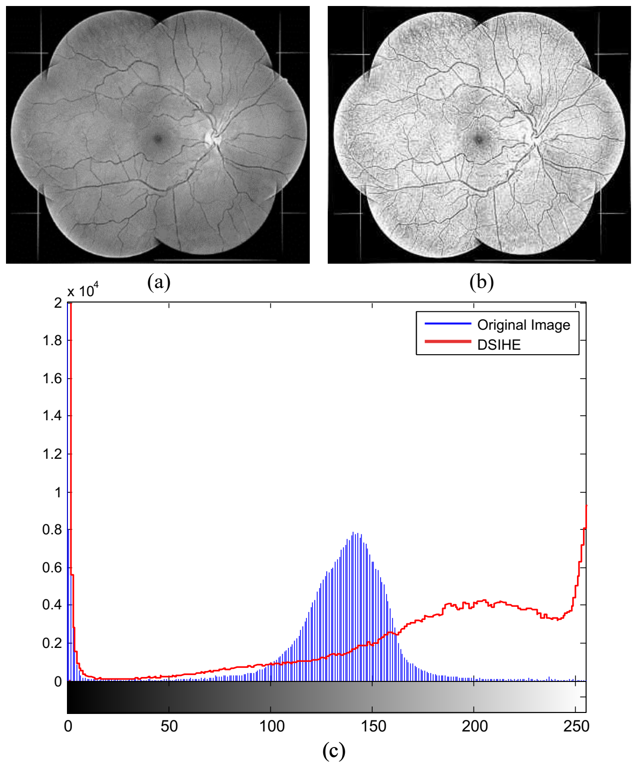

Fig. 5. Displaying the result of DSIHE method. (a) Original Image, (b) Result of DSIHE, (c) Comparison between (a), (b) Histograms.

E. Quad Weighted Histogram Equalization with Adaptive Gama Correction and Homomorphic Filtering (QWAGC-FIL)

One important and critical application of digital image processing is in the medical field. Since presence of any noise or low contrast in the medical images may reduce their quality, thus resulting in an incorrect diagnosis by the physician, it is necessary to improve the quality of low contrast medical images [7]. This method especially concentrates upon enhancing images with low contrast along with maximally preserving entropy and controlling on enhancement. Detailed description of each step of the proposed method is given in the following sub-sections. Also, block diagram of the proposed method is shown in Fig. 6.

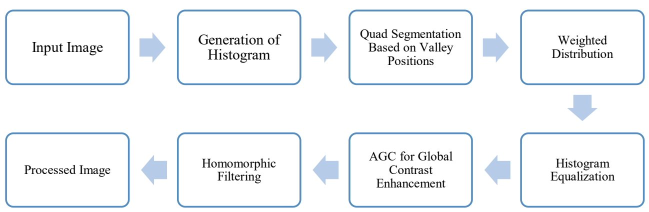

Fig. 6. Block Diagram of QWAGC-FIL Processing [7].

1- Image Acquisition: Performance analysis of the proposed QWAGC0FIL method on low contrast medical test images has been carried out on the retinal images.

2- Histogram creation: An image histogram represents distribution of intensities in the image. The "imhist" function in MATLAM creates a histogram plot by defining "n" equally spaced bins, each representing a range of data values, and then calculating the number of pixels within each range.

3- Input image histogram segmentation on the basis of valley position: The original input image Histogram is segmented into four individual parts on the basis of the valley location. If h(k) < h(k-1) and h(k) < h(k+1) in the input image Histogram h(k) are considered, then the gray level "k" is regarded as a valley. Therefore, in order to discover the precise location of the valley in the Histogram, firstly it has to be found the six successive negative signs followed by the two successive positive sign in the first Histogram derivative. Thus, the change from negative sign to positive sign is regarded as a valley. It is assumed that x_1, x_2, x_3 are the three valley locations of the input image Histogram and that the range of the input image Histogram is [0, 255]. After histogram segmentation of the input image based on location of theses valleys, three segments are in the ranges of [x_1+1, x_2], [x_2+1, x_3], and [x_3+1, 255], respectively.

4- Histogram probabilities weighting process by normalized power Law function: After segmentation, n sub histograms are obtained. Input image histogram is in the range of [0, 255]. The range of i^{th} sub-histogram, $H_i(k)$, is denoted by [l_i, m_i] which l_i and m_i represent the lowest and highest intensity of that, respectively. In order to modify the probabilities, a power law function based weighting distribution has been used. This module gives higher weighs to the gray levels with lower frequency [12]. The production of the four division Histogram based on the location of the valley AGC weight distribution to enhance global contrast Histogram deviation homomorphic processing image filters with uniform intensity distribution Histogram maximum and minimum possible input image based on the Eq. 6 and Eq. 7 is calculated.

$$P_{Max} = \max P_k \qquad 0 \le k \le L-1 \tag{6}$$

$$P_{Min} = \min P_k \qquad 0 \le k \le L-1 \tag{7}$$

Cumulative probability density of i^{th} histogram is obtained as follows:

$$b_i = \sum_{k=l_i}^{m_i} P(k) \qquad 1 \le i \le n \tag{8}$$

where P(k) denotes the probability of k^{th} gray level in the input image. Sum of cumulative probabilities of all sub-histograms is always equal to one.

$$\sum_{i=1}^{n} b_i = 1 \tag{9}$$

P(k) of each sub-histogram can be modified by weighted probability P_w(k) according to the Eq. 10 as follows:

$$P_w(\mathrm{k}) = P_{max}\left(\frac{P_{(k)}-P_{min}}{P_{max}-P_{min}}\right)^{b_i} \quad ; \qquad l_i \le k \le m_i \tag{10}$$

Eq. 10 assigns lower weights to the gray levels with higher frequency and conversely the higher weights to low frequent gray levels. Although sum of all accumulative probabilities is

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always one, this is not true about the weighted probabilities. For this reason, the weighted probabilities $P_w(j)$ are normalized as follows:

$$P_{wn}(j) = \frac{p_w(j)}{\sum_{j=0}^{L-1} p_w(j)} \tag{11}$$

where $P_{w_n}(j)$ is the normalized weighted probability of input image histogram.

5- Histogram Equalization: The next step is to equalize separately each sub-histogram. The Equalization for each sub-Histogram i within the range of $[l_i, m_i]$, occurs on the basis of the Eq. 12:

$$Y_i(k) = l_i + (m_i - l_i) * C_{w_n}(k), \quad 1 \leq i \leq n \tag{12}$$

where the normalized Cumulative Density Function (CDF) function is determined by the following Eq. 13:

$$C_{w_n}(l) = \sum_{l=0}^{l-1} P_{w_n}(l) \tag{13}$$

6- Adaptive Gamma Correction (AGC) for Global Contrast Enhancement: The information preservation and contrast enhancement of medical images are significantly important to medical diagnoses. To serve this purpose, a comparative gamma method is deployed so as to increase the contrast of medical images According to the Eq. 14:

$$T_L = l_{max} \left(\frac{l}{l_{max}}\right)^r \tag{14}$$

7- Homomorphic Filtering for Local Contrast Enhancement: The role of adaptive gamma correction is unequivocally important in order to enhance further the medical images after Histogram Equalization .Nonetheless, the medical images low contrast as well as a complicated structured background [4]. Presence of noise artifacts in some visual areas after contrast enhancement may result in a misdiagnosis. To reduce these noise artifacts, homomorphic filtering has been applied to visual important areas in low contrast medical images. This is applied in frequency domain and improves non-uniform illumination artifacts of low contrast medical images. Light reflected from a point of the object, as per the illumination reflectance model of intensity of each pixel in the image, is defined as background illumination multiplied by reflectance of the object in the background as follows:

$$I(x, y) = L(x, y) * R(x, y) \tag{15}$$

where I is intensity of the point (x, y), L and R denote the object illumination and object reflectance at the point (x, y), respectively. Almost, homomorphic filtering is used for removal of multiplicative noise. A butterwort high pass filter with cut-off frequency of 15 and order of 4, in log domain, is used in this filtering method to eliminate low frequency illumination components and retain high frequency reflectance components. Fig. 7 shows the proposed result of QWAGC-FIL method on retinal.

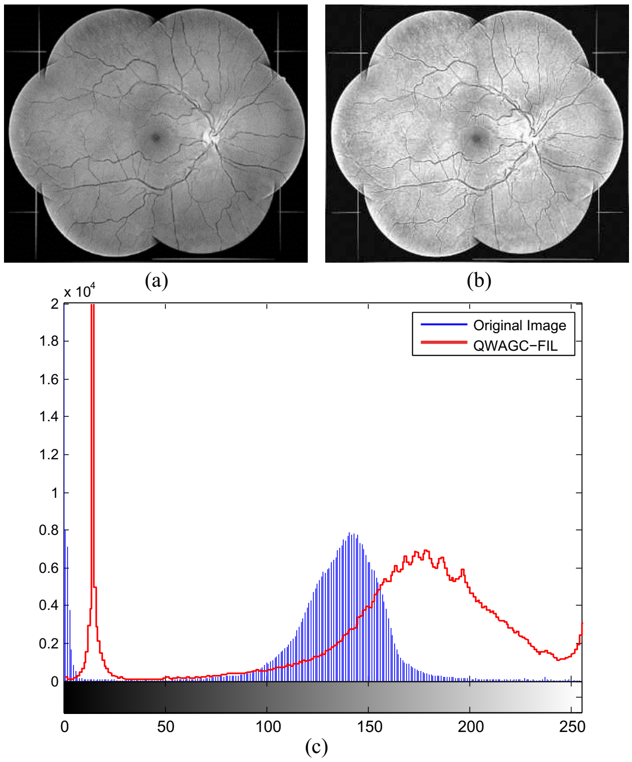

Fig. 7. Displaying the result of QWAGC-FIL method. (a) Original Image, (b) Result of QWAGC-FIL, (c) Comparison between (a), (b) Histograms.

Fig. 7(a) shows the original retinal image, Fig. 7(b) shows the result of QWAGC-FIL method, Fig. 7(c) shows the comparison between (a), (b) histogram images.

F. Contrast Limited Adaptive Histogram Equalization (CLAHE)

It is necessary for a retinal image to improve the quality before the vessel segmentation. It is considered that the retinal images which were extracted in the past section are of low contrast for the purpose of vessel segmentation algorithm. Thus, so as to increase the image contrast, CLAHE method is employed. The CLAHE suggests a clip to assist in resolving drawbacks such as, the peaks arising in the Histogram as well as noise. It controls by clipping the Histogram at a controlled pre-reset value prior to calculating the Cumulative Distribution Function (CDF). Thus, this procedure holds the slope of the CDF and therefore that of the transportation at bay. The clip value known as the clip limit, specifies the normalization of the Histogram, thus depending upon the size of the neighborhood region. The redistribution causes some bins to go over the clip resulting in an efficient clip limit which is larger than limit prescribed and the exact value of which depends upon the image.

The two main parameters recognized for the CLAHE, are Clip Limit (CL) and Block Size (BS) which though heuristically established by users, the significant effect of these parameters is found in controlling the quality of images. CLAHE algorithm is implemented by following steps [8]:

A. Required all the inputs: the number of regions of block size that is assumed 8×8, the number of bins for Histograms (dynamic range), and the normalized clip limit (0.005).

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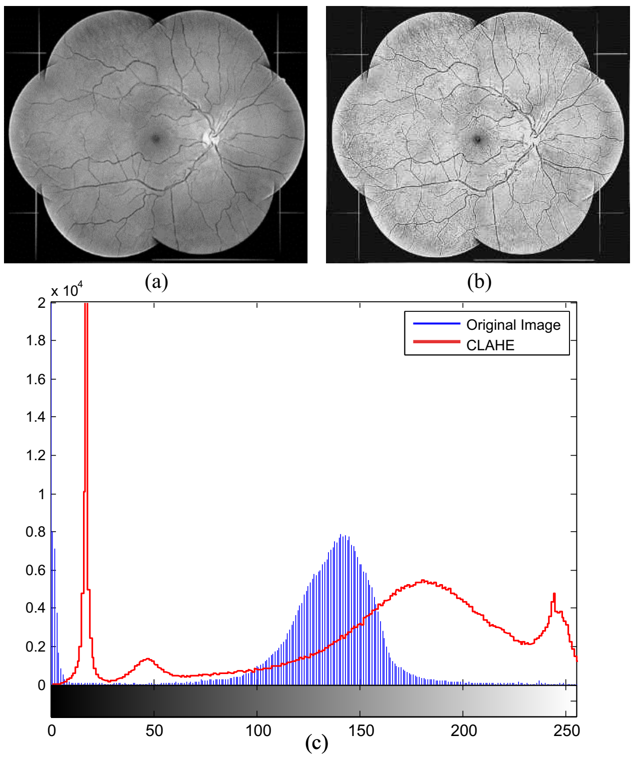

Fig. 8. Result of applying CLAHE method on a retinal image (CL = 0.005, BS = 8 × 8). (a) Original image, (b) the image after applying CLAHE, (c) comparison between histograms of (a) and (b) images.

B. Pre-processing all the inputs obtained in A. Normalized the clip limit value in required, and pad the image prior to dividing into regions.

C. Generating a gray level mapping, and extracting an image region, creating a Histogram for it using the specified number of bins. Processing the image region along with Histogram by employing clip limit.

D. Assembling the final CLAHE image by interpolating of the gray level mappings. Repeating the following process over the whole image:

- Extract cluster consisting of 4 neighboring mapping functions.
- Process image region when partially overlapping each mapping tiles and obtain a pixel.
- Employ 4 mappings towards that pixel.
- Run interpolation among the results to obtain the output pixel.

Fig. 8 shows result of the proposed CLAHE method applied on a retinal image. Fig. 8(a) is the original retinal image, Fig. 8(b) is result of applying CLAHE method and Fig. 8(c) shows the comparison between histograms of (a) and (b) images. In this method, value of the clip limit is 0.005 and the block size is 8 × 8.

III. Comparison between Various Contrast Enhancement Techniques

A. Visual Variations among Various Contrast Enhancement Methods

Fig. 9 shows all histogram-based simulated methods of "b" section from Fig. 1(b) to Fig. 8(b) histogram comparison. This figure represents the distinction among the figures and the degree of contrast variations resulting from different methods. In this section, simulation results of the methods proposed in sections above are shown beside each other to do make an accurate evaluation of the simulations carried out by the authors. Fig. 9 shows that the resulting histogram is close to each other and in the retinal images used in this paper, some methods such as BBHE (Fig. 4(c)) have more brightness and contrast than the rest. However, the final decision about the quality of these methods depends on many conditions, such as the type of imaging, the type of medical images, environmental noise, and etc.

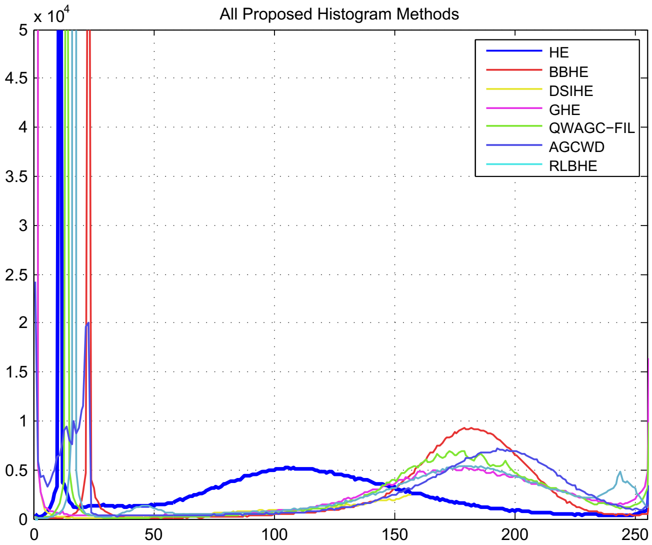

Fig. 9. Displaying and Comparison between all Histogram of b Section from Fig. 1(b) to Fig. 8(b).

B. Hierarchical Time Categorization of conventional Contrast Enhancement Methods

Table 1 presents some conventional contrast enhancement methods and their results. Using this table, researchers are able to compare their own work with the existing works in this field. It can be seen that the methods proposed in sub-sections above has presented different strategies to modify contrast of the medical images in terms of different performance metrics.

IV. Conclusion and Future Works

This research simulated the efficient methods proposed to enhance the controlled medical images contrast which is particularly important to modern medicine. The methods that are implemented by MATLAB® try to improve the contrast and preserve maximum brightness for medical images. Some of these methods try to find the best threshold in histograms of the images which this helps the methods to have an excellent performance in terms of image brightness. Brightness maximization results in superior contrast enhancement and avoids changes in image's normal appearance. In future works, authors try to make a new enhancement method by combining the histogram-based contrast enhancement methods to achieve the best performance in terms of medical image contrast.

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TABLE I. LITERATURE SUMMARY OF VARIOUS CONTRAST ENHANCEMENT TECHNIQUES

Author Name & Year	Method	Performance Measurement Parameters	Remarks
Agarwal (2018) [3]	RLWHE: Segmentation based on the Otsu's method, Weighted HE with RLBHE analysis, AGC followed by homomorphic filtering.	Entropy, PSNR &Visual Quality Assessment	Effective contrast enhancement of medical images with best visual appearance, maximum entropy & brightness preservation
Agarwal (2017) [4]	QWAGC-FIL: Segmentation based on the valley positions, Weighted HE, AGC followed by Homomorphic filtering.	Entropy & Visual Quality assessment	Effective contrast enhancement of visual details of the medical images with maximum entropy preservation.
Bhupendra (2016) [10]	AGC-FIL: GCE using Gama Correction after that homomorphic filtering is used for LCE followed by the normalization.	AMBE & PSNR	Good brightness preservation and better enhancement
Gautam (2015) [11]	Hybrid of range limited Bi-Histogram Equalization method (RLBHE) and Adaptive Gamma Correction(AGC)	AMBE	Make the balance b/w high level visual quality and low computational cost but with large value of AMBE
Baby (2014) [12]	Apply constrained PDF and weighted PDF to the color components of the input image followed by the AGC method.	PSNR, AMBE	Combined the bi-level weighted histogram equalization with AGC for better brightness preservation and contrast enhancement.
Haung (2013) [13]	AGCWD: AGC with WD applied to the V component of the color image	AMBE and Color distortion	less distortion for both color images and video sequences
Gaurav (2013) [14]	SHE: smoothening, segmentation, equalization, dynamic range.	PSNR & AMBE	Highest PSNR and less AMBE
Kim (2008) [15]	RSWHE: Same as RMSHE & RSIHE, difference is including the weighting process.	AMBE, PSNR and Entropy	Preserves good brightness as compare to RMSHE & RSIHE with better contrast enhancement.
Sim (2007) [16]	RSIHE: Same as RMSHE but division based on the median.	MSSI & PSNR	Preserves more brightness, good contrast enhancement and better MSSI and PSNR.
Chen (2003) [17]	MMBEBHE: Division based on the threshold value that gives the minimum AMBE.	AMBE and visual quality assessment	Provides the maximum brightness preservation.
Chen (2003) [18]	RMSHE: Recursive segmentation based on the mean brightness.	Visual quality assessment	Removes the problem of over enhancement and preserves the more brightness.
Wang (1999) [6]	DSIHE: Same as BBHE but division based on the median	Mean, Entropy& Background gray level	Over enhancement but preserves the entropy more than BBHE.
Kim (1997) [7]	BBHE: Division based on the mean brightness	Images& respective Histograms	Over enhancement& over brightness along with annoying artifacts.

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