Spatial Correlation Based Contrast Enhancement for Retinal Images

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Abstract-A Novel Contrast Enhancement Approach is proposed in this paper to enhance the quality of low contrast retinal images such that the automatic diagnosis of Diabetic Retinopathy results in more accurate results. Unlike the conventional approaches, this approach considers the spatial correlations between image pixels along with image pixel intensities. Due to the consideration of spatial correlations, the pixel intensities in the output image are not only linear combinations of input pixels but also relate to the neighboring pixel intensities. Extensive simulations are carried out over the proposed approach through the standard fundus image datasets such as DRIVE and DIARETDB1. Further the proposed approach is compared with conventional approaches and the performance enhancement is measured through the performance metrics like contrast improvement index and linear index of fuzziness and observed that the proposed approach outperforms the conventional approaches.

Keywords- Diabetic Retinopathy, Contrast Enhancement, Histogram, CLAHE, DRIVE, CII, LIF.

I. INTRODUCTION

Retinal Fundus (RF) Images are more informative and much helpful in the analysis of eye related diseases like cardiovascular diseases, stroke, hypertension, arteriosclerosis, and diabetes [1]. Among these diseases, Diabetes related eye disease; Diabetic Retinopathy (DR) is the most chronic disease which affects nearly one out of every ten persons with diabetes, according to point prevalence estimates [2]. However, the RF images are generally having low contrast, variations in the illumination, and blurred in nature due to the typical image capturing environments. Due to the typical configurations in the image capture, the Retinal images acquired through the fundus camera are of low contrast. Some of the important factors those effect on the image capturing are some cataract related diseases, abrupt movements in the eye of patient, dilation degree, and retinal curved surface [3]. The low contrast due to the uneven illuminations is often occurred due to three factors. Moreover, the retinal images with blur are usually found due to the cataract, which stops the light form reaching the retina. All these actors makes the automatic DR diagnosis system less robust and results in less diagnosis accuracy. Hence there is a necessity to design an efficient image contrast enhancement approach to increase the quality of image such that the required regions of retinal image such as retinal vessels, optic disk, exudates will be highlighted.

The purpose of RF image enhancement is to increase the contrast and highlight the retinal vessels [2]. Based on the features of image considered for contrast enhancement the earlier approaches are classified as spatial domain contrast enhancement approaches and transform domain contrast enhancement approaches. In the first case, the pixel intensities in the contrast enhanced output image is linearly related to the pixel intensities of input image, i.e., the processing mechanism considers the pixel intensities directly. Whereas, the transform domain approaches, the output image is obtained through the modification over the transformed coefficients of input image. Simplicity is the main advantage of spatial domain approaches and sometimes results in the output image with over brightness. Appropriate contrast enhancement is the advantage with transform domain approaches but results in the additional computational overhead over the system. Some of the approaches are also proposed in earlier by combining the spatial domain and transform domain approaches and called as hybrid approaches. The hybrid approaches gives a contrast enhanced image with less computational complexity.

In this paper a novel hybrid contrast enhancement approach is proposed based on the spatial correlations between the image pixels. Unlike the conventional approaches which considered only the image pixels for contrast enhancement, this approach also considered the spatial correlations between the image pixels to obtain an efficient contrast enhanced image. The proposed approach is carried out as global contrast enhancement followed by local contrast enhancement. Initially the green channel of retinal image is processed for global contrast enhancement and further the obtained image is subjected to local contrast enhancement. Rest of the paper is organized as follows: section II describes the details of literature survey. Section III describes the details of proposed approach. Section IV illustrates the details of simulation results and finally the conclusions are provided in section V.

II. LITERATURE SURVEY

A lot of research has been carried out considering the contrast enhancement as a main objective in automatic detection of DR. Global Histogram equalization (GHE) [4], [5] and histogram matching [6] are the main techniques which are applied in earlier for contrast enhancement in retinal images. The main disadvantage with GHE is its over enhancement at the large peaks of pixel intensity which results in an noisy and harshly appearance of image. 'Contrast Limited Adaptive Histogram Equalization (CLAHE)' [7] overcomes the problem of over enhancement with GHE. But CLAHE introduces artifacts at the image

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boundaries at where there are sharp change sin the pixel intensities. Focusing towards the retinal images, they need a specific design to enhance their contrast. Focusing over the contrast of retinal images, Setiawan et al. [8] developed a new enhancement approach based on CLAHE over only the Green channel of retinal image. Further, a new method based on wavelet homomorphic filer is proposed by Ashiba et al. [9] to improve the contrast of retinal image followed an increased dynamic grey range. This approach obtained the advantages of both wavelet transform and homomorphic filter. Initially, the low contrast retinal image is decomposed into sub bands through additive wavelet transform and then the proposed homomorphic filter is applied over every band independently. Duet to the accomplishment of contrast enhancement on illumination and reflection parts of images, this approach gained good results but constitutes an additional complexity. Further, it is very difficult to find an appropriate structuring element (SE) for morphological filter (MF).

Extending the [9] with differential evolution (DE), a new method is developed by Oh and Hwang [10]. In this method, initially the image is decomposed into sub bands through MF and the DE algorithm is accomplished to find the most appropriate SE for every sub band. But the limitation of this method is input target image region, which limits the applicability to various applications. Next, an approach assisted with blind deocnvolution (BD) and maximum likelihood estimation (MLE) is proposed by U. Qidwai [11]. Further, to extract the required regions from the retinal image, some post processing mechanism is proposed by which the only specific regions are extracted and makes easy to doctors to analyze. The post-processing includes conversion of image from color space, thresholding, edge detection and region growing. Further, a Gabor filter assisted fundus image enhancement technique is developed by Fraz et al [12] to enhance the retinal image at vessels portions in multiple directions. But, this method considered some sensitive parameters which makes the approach not robust for all types of images. A top-hat transform assisted image enhancement method is accomplished by Bai et al. [13] though this method got effective results in the enhancement; the contrast of that image is not much enhanced.

III. PROPOSED APPROACH

In this section, the complete details of proposed approach are outlined briefly. The proposed considers the spatial correlations between the gray-levels for contrast enhancement whereas the conventional approach didn't considered these spatial dependencies by which the gray-levels in the contrast enhanced image don't have any relationship with neighboring pixels which makes the entire process more complex and not clear. The proposed approach tends to achieve the contrast of an image both globally and locally. Hence the proposed approach is accomplishes the global contrast enhancement and further the local contrast enhancement. The complete details or proposed approach is outlined as follows;

Let's the input image 'I' of size $H*W$ and having a range of gray-levels $[I_d, I_u]$ and the output image 'O' of range $[O_d, O_u]$, having more visual quality than the input image 'I'. Mathematically these input and output images are represented as,

$$\begin{aligned} I &= \{I(m,n) | 0 \le m \le M-1, 0 \le n \le N-1\} \\ O &= \{O(m,n) | 0 \le m \le M-1, 0 \le n \le N-1\} \end{aligned} \quad (1)$$

Here the range of input and output images such as $I(m,n) \in [I_d, I_u]$ and $O(m,n) \in [O_d, O_u]$ varies from 0 to 255 for an 8-bit image. This range is ideal, i.e., 0-255 only if the enhancement process utilizes the entire dynamic gray-level range. In such case, the lower limit $O_d = 0$ and the upper limit $O_u = 255$.

A. Spatial Entropy based Contrast Enhancement (SECE) [14]

Let the input image I has K distinct gray levels and are sorted in an ascending order like $\{I_1, I_2, \dots, I_K\}$. An input image I is divided into H*W spatial grids. The 2D spatial histogram of a gray-level I_k on the spatial grid of I is computed as,

$$h_k = \{h_k(h,w) | 1 \le h \le H, 1 \le w \le W\} \; (2)$$

Where $h_k(h,w)$ defines the number of occurrences of gray-level I_k in the spatial grid located in the image region of $\left[((h-1)*\frac{M}{H}, h*\frac{M}{H}) \times ((w-1)*\frac{N}{W}, w*\frac{N}{W})\right]$. The total number of grids on the 2D histogram is HW which was estimated dynamically using the aspect ratio, $r = \frac{M}{N} = \frac{H}{W}$.

$$W = \left\lfloor \left(\frac{K}{r}\right)^{1/2} \right\rfloor \text{ and } H = \left\lfloor (Kr)^{1/2} \right\rfloor \; (3)$$

Where the operator $\lfloor . \rfloor$ makes the argument round off to its nearest neighbor value.

In the every grid, the distribution of a gray-level I_k can be measured trough the spatial entropy and the spatial entropy S_k for a gray-level I_k is obtained according to

$$S_k = -\sum_{h=1}^{H} \sum_{w=1}^{W} h_k(h,w) \; \log_2 h_k(h,w) \; (4)$$

Further, the obtained spatial distribution has to evaluate with respect to the distributions of the other gray-levels to know the importance and it is measured through a discrete function f_k as,

$$f_k = S_k / \sum_{l=1, l \ne k}^{K} S_l \; (5)$$

Further the obtained discrete function f_k is normalized as,

$$\hat{f}_k = f_k / \sum_{l=1,}^{K} f_l \; (6)$$

And based on the obtained normalized discrete function $\hat{f}_k$, a cumulative distribution function F_k, of a gray-level I_k is defined as,

$$F_k = \sum_{l=1,}^{k} f_l \; (7)$$

Finally the gray-level of an output image O is obtained through the following mapping function

$$O_k = \lfloor F_k(O_u - O_d) + O_d \rfloor \; (8)$$

The final output O denotes the contrast enhanced image. Further the performance f this mechanism is measured through the performance metrics like expected measure of enhancement by gradient (EMEG) and gradient magnitude similarity deviation.

B. Spatial Correlation based Contrast Enhancement (SCCE)

Though the conventional approach achieved an increased contrast in the output image, this method didn't studied the spatial relationships between the gray levels, hence, almost the output gray-levels are simply obtained through the linear mapping of input gray-levels, i.e., a particular gray-level in the output image is just linearly related to the input gray-level and don't have any spatial relationship with the other gray-levels. In order to address this issue, this work proposes a new contrast enhancement mechanism by considering the spatial relations between the gray-levels. To obtain a normalized 2D spatial histogram, the 2D histogram entries are further normalized as

$$h_k(h,w) = h_k(h,w)/HW \quad (9)$$

Such that

$$\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{w=1}^{W} h_k(h,w) = 1 \quad (10)$$

Here the spatial entropy is measured by evaluating the joint 2D spatial histograms for a given two gray-levels I_k and I_l on the spatial grid located on the image region of $\left[(h*\frac{M}{H},(h+1)*\frac{M}{H})\times(w*\frac{N}{W},(w+1)*\frac{N}{W})\right]$, as

$$h_{k,l}(h,w) = \min\left(h_k(h,w), h_l(h,w)\right) \quad (11)$$

The above expression gives a new evaluation procedure to measure the spatial relationships between two gray-levels I_k and I_l. Further to obtain the spatial dependencies of gray-levels and their spatial spread over the image domain, a new metric called Spatial Correlation (SC) is derived here and formulated as,

$$SC_{k,l} = \sum_{h=0}^{H-1}\sum_{w=0}^{W-1} h_{k,l}(h,w)\left(\frac{h_{k,l}(h,w)}{h_k(h,w)h_l(h,w)}\right) \quad (12)$$

Where $SC_{k,l}$ is the spatial correlation between two gray-levels I_k and I_l. The above expression gives a spatial relationship between the gray-levels I_k and I_l. The SC is high when the gray-levels I_k and I_l happen jointly on the regions which are spatially close and distributes over image spatial domain. Hence, this method succeeds in the provision of higher gaos between upper and lower limits O_k and O_l such that the obtained contrast will be optimal.

After measuring the spatial correlations for every gray-level with respect to all other gray-levels, one rank is assigned to that relation based on the closeness and finally the output gray-level O_k is obtained through the following mapping function,

$$O_k = \lfloor O_{k-1} + \Delta_{k-1,k}(O_u - O_d) \rfloor \quad (13)$$

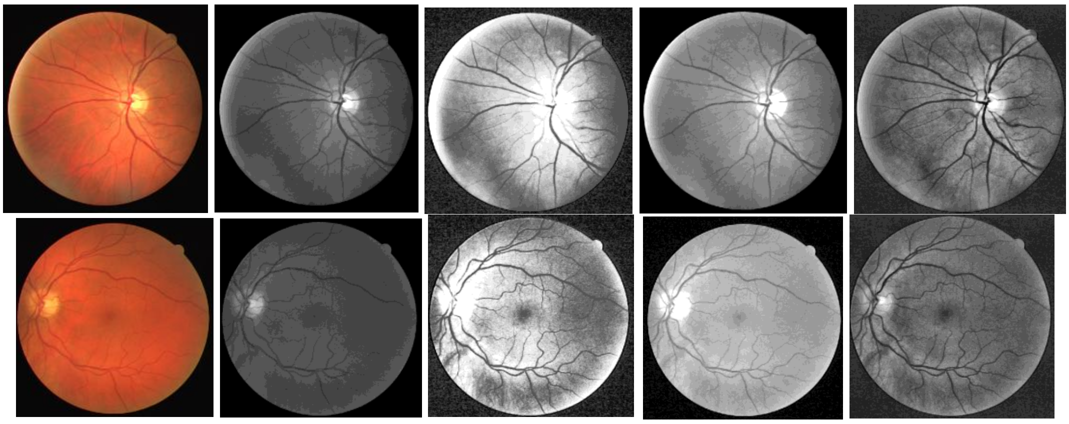
Where

$$\Delta_{k-1,k} = \frac{r(k-1)+r(k)}{2} \quad (14)$$

The term $\Delta_{k-1,k}(O_u - O_d)$ in Eq. (13) represents the gap between two successive gray-levels O_{k-1} and O_k. This gap is evaluated based on the joint impact of the two successive gray-levels which is determined as average of their ranks. The mapping function always assurances that the maximum and minimum gray-level values in the output image are in the range of defined maximum and minimum of obtained dynamic range. Thus the proposed approach proficiently exploits the defined dynamic range and produces an effective contrast enhanced image.

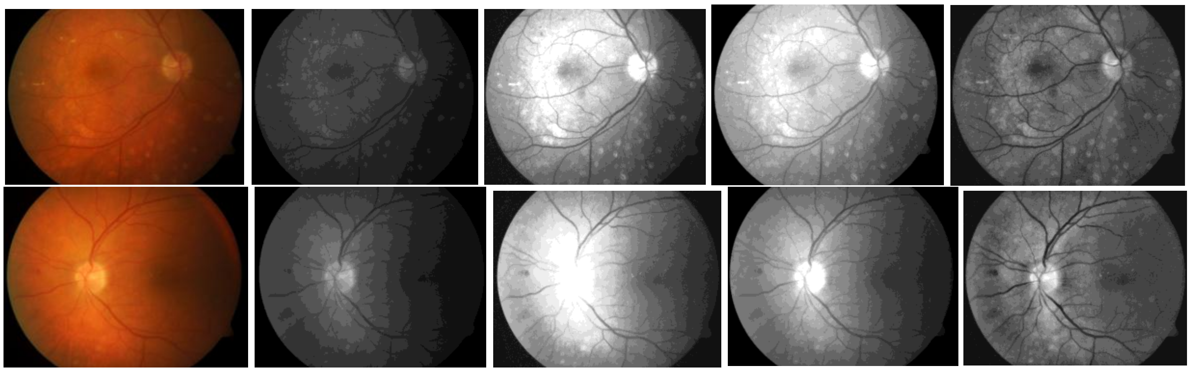
IV. SIMULATION RESULTS

This section illustrates the details of performance evaluation carried out over different retinal image through the proposed approach. Number of images are taken form the most popular retinal image datasets such as DRIVE and DIARETDB1 to test the proposed mechanism. Simultaneously some of the conventional approaches are also applied over the same images to alleviate the enhancement of proposed approach. The image enhancement results of the proposed method are color images. Yet, the green channel image is generally used to evaluate image enhancement results. So only the green channel of the enhanced image is used in image evaluation step. The comparative analysis is carried out with Histogram Equalization and Contrast Limited Adaptive Histogram Equalization. The obtained results are shown below.



(a) (b) (c) (d) (e)

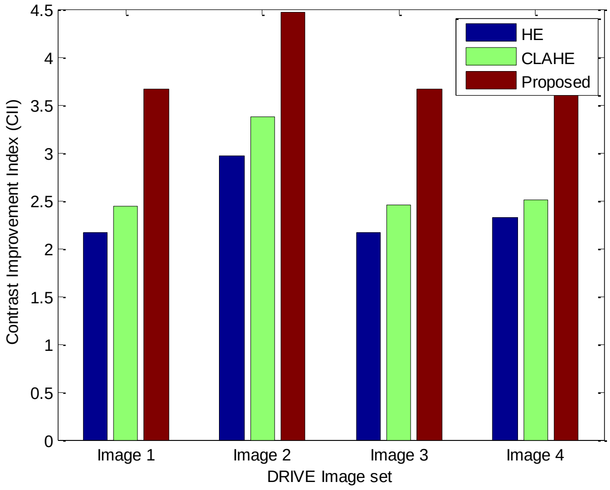
Figure.1 Obtained simulation results of DRIVE dataset (a) Original color retinal image, (b) Green channel, (c) Histogram equalization, (d) CLAHE, (e) Proposed



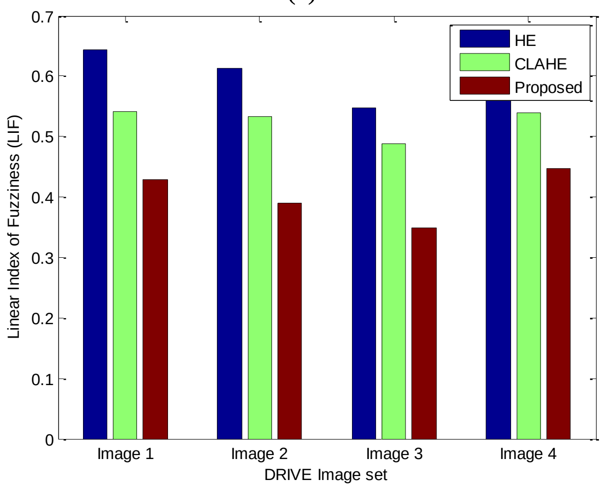
(a) (b) (c) (d) (e)

Figure.2 Obtained simulation results of DIARETDB1 dataset (a) Original color retinal image, (b) Green channel, (c) Histogram equalization, (d) CLAHE, (e) Proposed

Further theperformance of proposed approach is measured with respect to two performance metrics, contrast improvement index (CII) [15] and linear index of fuzziness (LIF) [16]. A larger value of CII shows that the retinal vessels are enhanced better. A smaller value of LIF shows that the whole enhanced image is clearer and has less noise. Thus, a large value of CII and a small value of LIF indicate a good image enhancement method. The obtained CII and LIF values for the above test images are represented in the following figures.

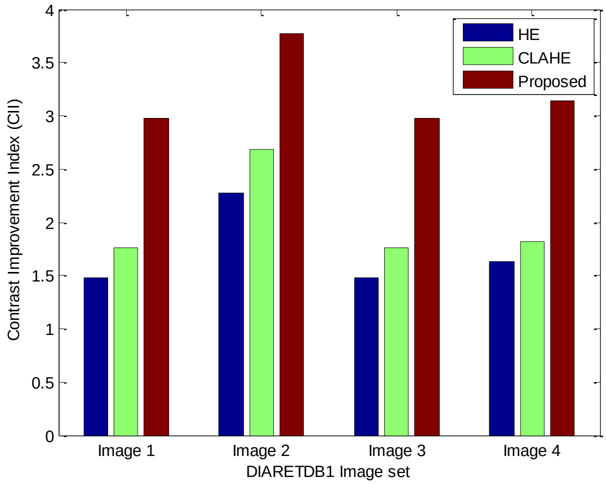


(a)

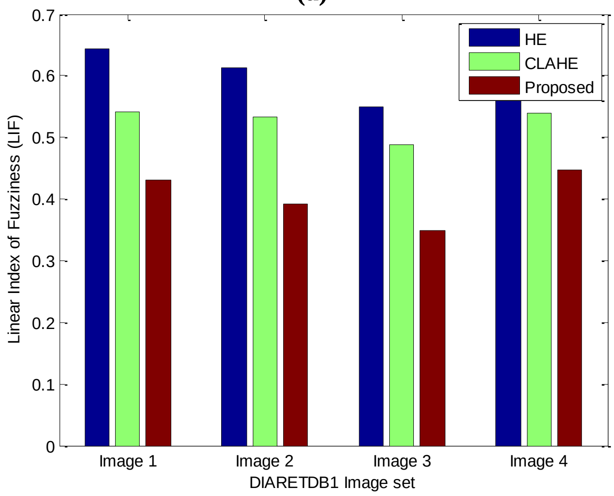


(b)

Figure.3 comparative results through DRIVE dataset (a) CII, (b) LIF



(a)



(b)

Figure.4 comparative results through DIARETDB1 dataset (a) CII, (b) LIF

V. V. CONCLUSIONS

In this paper, a novel contrast enhancement approach is proposed to make the retinal fundus images to qualitative such that Diagnosis of Diabetic Retinopathy achieves more accurate results. The complete mechanism is accomplished in two phase, the first phase involves the global contrast enhancement and the second phase processes the local contrast enhancement. Performance evaluation is carried out through two datasets namely DRIVE and DIARETDB1 and the performance enhancement is observed by measuring the parameters namely CII and LIF. The obtained results outperform the conventional approach both qualitatively and quantitatively.

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