Methods for Quality Enhancement of Digital Fundus Imagery in the Context of Diabetic Retinopathy: A Comprehensive Study

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Abstract **-** Diabetic Retinopathy-the retinal complication due to diabetes, can cause complete vision loss if left untreated. One of the prime steps to prevent vision loss in diabetic patients due to DR, is to arrest it in the early stages which would require at-least a bi-annual examination ofthe retinal surfaces for the detection of pathological evidences. The images acquired through non-invasive techniques (mydriatic and non-mydriatic) often have low grey level contrast and illumination, making quality enhancement an almost inevitable step before considering the image for any clinical grading or detection processes. A number of methods have been proposed in the literature, focusing on different aspects and factors of image quality. Through this paper, a conscious effort has been made to enlist the widely adopted quality enhancement methods for fundus images and the key factors which should be taken into account while improving the image quality especially with respect to diabetic retinopathy.

Keywords **-** Diabetic Retinopathy, quality enhancement; contrast, illumination, focus, color

I. INTRODUCTION

Elevated blood glucose level-a common medical condition known as Diabetic Mellitus, is a major cause of health concern especially in a country like India. Majority of our working population suffers from heart, eyes and kidney related complications associated with diabetes from a very early age.

One of the most neglected areas among the diabetic community are the eye-related ailments. Patients do not undergo any regular eye examinations until they experience severe difficulties in their vision. According to retinal specialists, a diabetic patient must undergo retinal examinations at least [17] twice a year to prevent and detect any vision threatening conditions. Diabetic Retinopathy is the retinal complication occurring due to damage caused in the retinal blood vessels as a result of diabetes. The damage to the retinal vessel walls could be due to swelling in them, rupture of weak vessels or formation new vessels [15] [16].The earliest sign of DR appears [1] [16] as small red dots on the retina called (MN) Microaneurysms (mild non-proliferative DR) and dot haemorrhages (HE).The next stage of DR is detected by the presence of blot haemorrhages which are mainly due to rupture of blood vessels in deeper retinal layers. Lesions of various sizes and shapes may also appear due to plasma leakage of capillaries [13]. Advanced stages of retinopathy shows the formation of cotton wool spots and new vessels. If these developments occur near the fovea, it could be seriously vision threatening.

II. NEED FOR QUALITY ENHANCEMENT

Fundus imagery is used in order to detect pathological evidences on/near the retinal surface. One of the best methods to obtain good contrast fundus images is through fluorescein angiography (FA). But being an invasive method [25], it may induce side effects like seizure attack, myocardial infarction [8] in some patients. Hence digital fundus imagery is the favoured clinical approach for obtaining images of the fundus surface. Often these images, suffer from poor contrast and illumination conditions, making the detection of pathology, an extremely difficult task for the clinician. The images have uneven illumination and low contrast which generally obscures the vasculature and smaller intricate details. Hence it is pivotal to enhance the quality of the acquired fundus images to ensure accurate grading and detection of DR.

III. LITERATURE FINDINGS

There has been a colossal amount of work carried out in this area. Each work emphasises on one or more quality factors and attempts to enhance the same. Broadly we can dividethe literature can be classified into two distinct classes as suggested by Joao [22] and Imani [12]. The first class and the widelyimplemented one, avoids eye structure segmentation and focuses on the generic quality criteria. The second class relies on the structure of the eye and requires segmentation ofimportant landmark points and structures present in the fundus image.

A. Generic Quality Criteria Based Approaches

The literature characterizes color, focus, contrast and illumination as the four primary indicators of image quality.

i). Addressing non-uniform illumination - Illumination has been defined as the amount of source light incident on a unit surface area [18]. In a retinal image [18], non-uniform illumination can be identified as spatial variations(shading artefacts and vignetting) which are usually not visible to human eye but are capable of altering the local statistical properties like mean, median, and variance etc. of an image and hence, can interfere with subsequent grading and classification methods.

The illumination correction methods works either on locally adaptive contrast enhancement techniques or by creating a mathematical model of non-uniformity (which can be later subtracted from the observed image) or by the formation of an image model which separates the background and foreground parts and applies some transformation like shade correction on the foreground part.

A recent study made by Kang Zhou et. al [19] addresses uneven illumination through a multitasking deep learning system using weighted softmax with center loss approach, capable of working on extremely unbalanced good and poor quality fundus image dataset.

Sajibet. al[20] identifies HSV as the best color space for illumination correction w.r.t retinal imaging and proposed a technique based on background subtraction followed by color restoration for illumination correction. The proposed method works with the assumption that the mean color of the optic disk and blood vessel should remain the same before and after illumination correction. The author advocates that since in DR, each pathology is associated with color, identification of the optimum color space to work with is vital to the success of any illumination correction technique. The method gave an overall likelihood of 81.70% of an image to be best after the application of the proposed method.

Balintet. al. [21] discusses about an illumination equalization technique in his paper capable of reducing vignetting, which is often seen due to uneven illumination. Every pixel's intensity is modified by combining its original intensity with the desired average intensity and the local average intensity. This method highlights the microaneurysms appearing on the retinal border and hence can be used as a pre-processing step in algorithms used for early detection of DR.

Joao et. al. [22][11] exemplifies an illumination assessment algorithm which relies on colour indexing using an illumination colormap defined by replacing dark blue with black. As the most and least significant colours of retinal image spreads along a wide range, the author advocates that one can pick up relevant information from the image by defining four illumination measures based on local statistical measures like mean and variance.

ii). Improving the image contrast - Contrast is defined as the perceived brightness. Any contrast enhancement [18] technique aims at altering the visual appearance of an object to make it more distinguishable from other objects and the background. Fundus images are observed to have high contrast in the central area which reduces as we move from centre towards the peripheral area. Out of color, focus, contrast and illumination, contrast has been voted by majority as the most relevant quality assessment feature and hence the one, opted by many, to work with.

Worapanet. al. [23] investigated all four quality features and used contrast histogram in Principal Component Analysis space. PCA projects out the relevant discriminant features over minor misleading ones and also reduces data dimensionality. The method was tested on DRIVE dataset and could achieve an accuracy of 88% when leave-one-out cross-validation was used for evaluation.

Fousiaet. al [24] advocates that in order to enable easy identification of clinical indications from fundus images, their contrast must be improved. According to the author(s), performance on CLAHE relies heavily on color model used, channel/component subjected to equalization and the shape of the specified histogram which can offer maximum grey level contrast. The author states that RGB color model outperforms HSV model, when green channelis equalised and exponential histogram is used for fundus imagery.

Husna et al [25] investigated three enhancement techniques on DRIVE dataset- HE, CLAHE and MD (Mahalanobis Distance) on digital fundus images (which are known to show very low contrast between retinal vasculature and background). CLAHE and MD both showed positive results in blood vessel enhancement producing Gaussian-shaped curve but since in CLAHE, the background pixels also contribute to overall performance, any noise that is present is enhanced as well. On the other hand, MD works only on foreground pixels and hence produces a better result without tampering BVs nearby.

Contrast enhancement methods reported as preprocessing tools (before extraction of candidate lesions) - Ramasubramanianet. al. [27] uses CLAHE on the I-band of fundus images of MESSIDOR and UTHSC SA dataset for contrast enhancement. This step was used for preprocessing images for exudate segmentation using soft clustering algorithm.

Sarniet. al. [28] uses two fuzzy image pre-processing techniques i.e. fuzzy filtering and fuzzy histogram equalization to improve image quality. Fuzzy Switching Median is used to remove variety of noise types and brightness preserving fuzzy histogram equalisation (BPDFHE) is used for contrast enhancement. The system is tested on a novel dataset created by the author. The author also reports the inability of the method to produce the quality desired for microaneurysm detection but works for DR and maculopathy detection.

As is evident in the literature, histogram equalization, AHE, CLAHE are the commonly applied approaches for contrast enhancement. These techniques are known to amplify noise as well.

CLAHE has been favoured by many for contrast improvement but being a neighbourhood based approach and being dependent on the color model, its performance is limited and it may also result in introduction of false artefacts.

iii). Improving the image color: color normalization - The green channel in a RGB image is reported as having the maximum contrast in fundus images as it is less susceptible to non-uniform illumination.

Histogram equalization for each color channel and histogram specification has been widely used in literature for improving image color. HE [10] [18] might overemphasize blue channel information and is ineffective in removing inter-image variations, hence cannot be used

for longitudinal analysis. Histogram specification, on the other hand, might mask specific lesion characteristic if it is not present in the model image.

Winder et al [18] reports that inIHS representation, separation of hue (color) and saturation, helps to normalize intensity channel without changing the perceived relative color values of the pixels.

Pratt et. al [30] applied color normalisation on fundus images with varied levels of lighting. Normalization removes highlighted areas, shadows and makes it easier to identify objects.

Joao et al [22] uses a color assessment algorithm in which the image is color indexed [6] using histogram back projection using 3 different colormaps-bright colormap, dark colormap and normal colormap. Each of the map is used to find three different color measures which are used to index images.

It is clear from the above discussion that, color enhancement and normalization depends heavily on the color model chosen for quality enhancement. Perceptually, the results after enhancement should not produce unnatural colours and should also not obscure any pathological evidences.

B. Eye Structure Based Approaches

There also has been work reported to determine the image quality based on the number of discernible structures from the image. As quoted in [18], this approach targets one of the primary limitation of the former generic quality factor approach. Generic quality factors estimate correction from the whole image and hence are incapable of distinguishing variations in luminance resulting from changes in illumination. Eye structure based approach, targets pixels of a specific retinal feature for overall correction transformation.

Mohd. Saleh Miri et. al. [26] presented second generation curvelet transform [9] [2] as a technique on DRIVE dataset to enhance image contrast without the amplification of noise. The author claims that by modifying the curvelet coefficients, we can better represent the edges than any other multi-resolution techniques like wavelets and contourlets. The method is more adaptive to input images as it is capable of changing its parameters according to the input image and is capable of providing uniform background to the entire image and hence can be helpful to improve performance of blood vessel detection.

Usher et. al [5] have tried to assess the quality of the digital fundus image based on clarity and detected vessel area. The method could achieve a sensitivity of 84.3% on a dataset of 1746 images.

Wang et. al [31] could estimate gradual changes in illumination across vessel pixels which was not found to be much effective due to the difficulty associated with localization of specific vessels .

Although the structure based approach performs better when gradability performance is taken into account, many authors vote in favour of generic quality factor based owing to their simple approach and reduced computational complexity.

C. Combination Approaches

Paulus et. al [4] combined both the above mentioned approaches and used image clustering as specified in [3] and Heralick and sharpness based measures to classify good and poor quality images. The method could achieve a sensitivity of 80% on a dataset of 301 images.

Honggand et al [29] integrated global histogram features, textural features (to detect lightness homogeneity, brightness and contrast) and local perceptual sharpness metric and vessel density to measure sharpness of local structures like optic disc and vasculature network , as a combined tool for quality evaluation[7]. The system used a partial least square classifier to distinguish between low and normal quality images on a representative set of 412 subjects (1884 non-mydriatic retinal images) achieving an ROC curve of 96%.

Joao et. al[22] proposed an overall retinal quality classifier based on histogram back projection which takes into account all four quality factors namely color, focus, illumination and contrast, capable of indicating the quality factor impairing the most a given retinal image. The method was tested in a dataset of 2032 images collated from DRIVE, MESSIDOR, ROC and STARE and reported a specificity of 99.49% and sensitivity of 97.41%

IV. DISCUSSION

In retinal image analysis, one of the most important aspect that has to be dealt with, before the application of any gradability or classification algorithm, is the image quality.

Unless the image has satisfied the minimum quality criteria in both the subjective and objective aspects, the image cannot be further utilized. Of the various quality factors studied as a part of this paper, it is evident that working on only factor at a time might not yield desirable and satisfactory results. One has to provide attention to correct both, the illumination and the contrast of the fundus image in addition ensuring that the correction technique should not result in any false artefacts and unnatural colours in the resultant image.

As is clearly portrayed in the literature, early detection of DR is almost impossible with a low contrast image. The key indicator which is looked for early detection of DR in a fundus image is the presence of microaneurysm (MA) or dot haemorrhages. To facilitate this, the image is subjected to contrast enhancement. After contrast correction, it is often observed that dark regions including noise are also enhanced in the resulting image which may hide pathological evidences in those areas.

A fundus image with non-uniform illumination frequently exhibits vignetting, a phenomenon in which the central area appears brighter than the periphery. This may obscure important clinical information available in the peripheral areas like neovascularization (in retinal periphery) whichhas been categorized asthe most important indicator associated with proliferative diabetic retinopathy by practicing ophthalmologists.Neovascularization is a very commonly observed in aged patients. Hence contrast and illumination

taken independently might not suffice as quality factors. One has to work both, towards a contrast corrected and a uniformly illuminated image to make the image ready for detection of DR.

Also, majority of the contrast enhancement techniques results in formation of false artefacts which can mislead the clinician (may result in a false positive or false negative), so a conscious effort should be employed in the device and development of methods which can minimise the formation of such artefacts. There has been evidence in the literature advocating the usage of Mahalanobis distance instead of CLAHE on RGB color model for better performance and reduction of false artefacts. More such methods should be looked upon and worked with.

Another way to think about this issue could be to have an ensemble-based system for quality enhancement, which could combine multiple contrast improvement and illumination correction techniques. The complexity of the system is something which must be taken care of, but such a system will have a capability of combining the strengths and minimizing the shortcoming of these individual approaches.

To summarize, there is an imminent need for a method which can enhance the quality of the captured fundus images in terms enhancing significant image areas and reducing false artefacts so that the proportion of ungradable images generated during the clinical process can be reduced and hence could facilitate the clinicians and ophthalmologists during the grading and classification process of DR.

V. REFERENCES

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