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RESEARCH ARTICLE

Detection of Diabetic Retinopathy in Fundus Image

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Abstract- Retinal image plays a major role in ocular fundus operations and detection of diabetes in early stages. In this paper a new algorithm to detect the blood vessels effectively has been proposed. The initial enhancement of the image is carried out using pre-processing stage, followed by curvelet Transforms that are applied to the equalized image. This enhanced image is used for the extraction of the blood vessels. The estimation of exudates are obtained from blood vessels and optic disc extracted image. The results shows the enhanced retinal images of blood vessels have a better PSNR and area shows the exudates severity.

Index Terms: Diabetic retinopathy, Blood vessels segmentation, curve-let transform, Morphological operators and retinal image.

I. INTRODUCTION

Retinal images play a major role in the ocular fundus operations and detection of diabetes in early stages (by comparing the states of retinal blood vessels and optic disc). The present work developed a system to identify patients with proliferate diabetic retinopathy (PDR) from the retina. The different diabetic retinopathy diseases that are of interest include red spots, microaneurysm, neovascularisation and exudates are fall between BDR and PDR stages of the disease. To detect the PDR, blood vessels of the fundus image are removed by curvelet transform and morphological erosion and dilation process. Then optics disc in the image are removed by using circular fitting method and blood vessels are separated by using canny edge detection. Finally remaining portion of image are referred to as exudates region.

II. METHODOLOGY

The images are pre- processed to correct the uneven illumination problem, nonsufficient contrast between exudates and image background pixels and presence of noise in the input fundus image. The block diagram of the sub sections that constitute the Pre- Processing stage (PPS) as shown in Figure.1. Median filtering operation replaces a pixel by the median of all pixels in the neighbourhood of small sliding window. It gives better results than the neighbourhood averaging (noise is impulsive). Median filter is robust and has the capability to filter only outliers. It is an excellent choice for the removal of salt and pepper noise and horizontal scanning artefacts. Adaptive histogram equalization (AHE) is suitable for improving the local contrast of an image and bringing out more detail. However, it has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification.

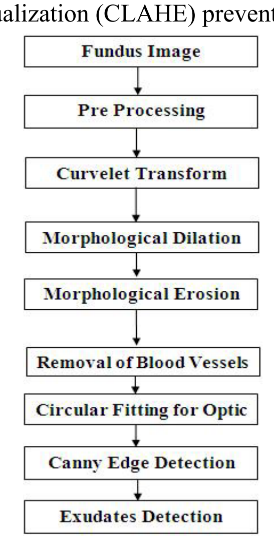


Figure.1 Overview f Retinopathy detection system

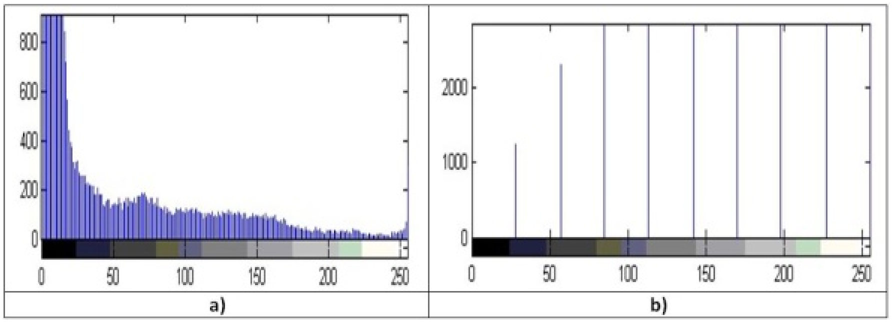


Figure 2 a) Original Image b) Image after Histogram Equalization

CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The clip limit depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4 times the histogram mean value. It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins. The redistribution will push some bins over the clip limit again (region shaded green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution procedure can be repeated recursively until the excess is negligible. Adaptive histogram equalization in its straightforward form presented above, both with and without contrast limiting, requires the computation of a different neighbourhood histogram and transformation function for each pixel in the image. This makes the method very expensive computationally. Interpolation allows a significant improvement in efficiency without compromising the quality. The image is partitioned into equally sized rectangular tiles as shown figure 2b. A histogram, CDF and transformation function is then computed for each of the tiles. All other pixels are transformed with up to four transformation functions of the tiles with center pixels closest to them, and are assigned interpolated values. Pixels in the bulk of the image (shaded blue) are bilinearly interpolated, pixels close to the boundary (shaded green) are linearly interpolated, and pixels near corners (shaded red) are transformed with the transformation function of the corner tile. The interpolation coefficients reflect the location of pixels between the closest tile center pixels, so that the result is continuous as the pixel approaches a tile center.

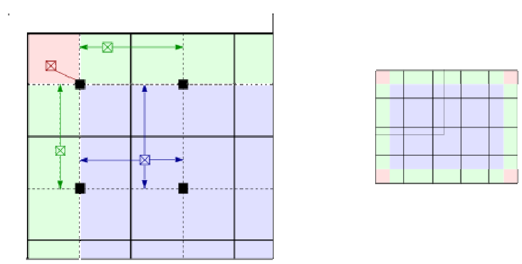
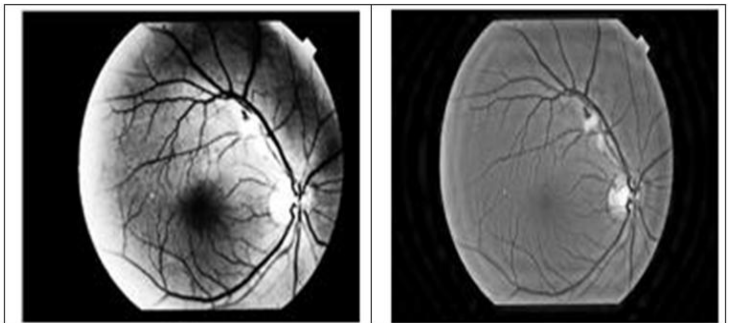


Figure.3 Adaptive Histogram Equalization

This procedure reduces the number of transformation functions to be computed dramatically and only imposes the small additional cost of linear interpolation. The edge plays an important role in image identifying. The approach of image enhancement is describe as follows: First, apply the curvelet transform to the image. Then, according to noise ratio of each sub band, enforce sectional nonlinear enhancement to the coefficients. At last, apply the inverse curvelet transform to the coefficients and come out the image with image enhancement on edge. The band pass is set so that the curvelet length and width at fine scales are related by a scaling law and so the anisotropy increases with decreasing scale like a power law. Curvelet coefficients can be modified to enhance the edges in an image, which is then improves the image contrast. To this end we improve the nonlinear function to modify the representation coefficients in such a way that the details of the smaller amplitude are enhanced at the expense of the larger ones and perform this uniformly over all scales. Therefore, there is a need for a nonlinear function, such as y, to multiply against the transform coefficients.

$$y(x) = \begin{cases} k_1 \; —^{p} & \text{if } |x| < ac \\ k_2 \; —^{p} & \text{if } ac \leq |x| < m \\ k_3 & \text{if } |x| \geq m \end{cases} \qquad (2)$$

where x is the curvelet coefficient, $0 < p < 1$ determines the degree of nonlinearity.k1, k2 and k3 are assigned weights to each function part to allow us to control the modification of coefficients. Due to the assigned weights, it is possible to indicate how much the coefficients became magnified or reduced or even be unchanged. The adjustment parameter makes it possible to determine and regulate the coefficients modification interval. Parameters c and m are involved in determining the coefficients modification interval as well as the amplitude of corresponding multiplying y. These parameters are defined according to two statistical features of coefficients. The first one is the noise standard deviation, with the aim of preventing the noise amplification, and the second one is the maximum value of coefficients in each band. We choose c = σji, where σj iis the noise standard deviation of coefficients being in the same direction and same scale. m can be derived from maximum curvelet coefficients of the relative and MC (m = kMC). k is an additional and independent parameter from the curvelet coefficient values, and therefore, much easier for a user to set. The assigned weights and adjustment parameter are experimentally tuned based on intrinsic characteristics of the input image. Curvelet transform is well adopted to represent the image containing edges and is good for edge enhancement.



a) Histogram Equalization	b) Curvelet Transform

Figure.4 Images of a) Histogram equalization b) Curvelet transform

III. MORPHOLOGICAL APPROACH

The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the *structuring element* used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. Dilation finds local maxima in binary or intensity images. A structuring element is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. Two-dimensional, or *flat*, structuring elements are typically much smaller than the image being processed. The center pixel of the structuring element, called the *origin*, identifies the pixel of interest, the pixel being processed. The pixels in the structuring element containing 1's define the *neighbourhood* of the structuring element. These pixels are also considered in dilation or erosion processing. Three- dimensional, or *non flat*, structuring elements use 0's and 1's to define the extent of the structuring element in the *x*- and *y*-planes and add height values to define the third dimension. In order to calculate the Hough Transform, the edge of the OD's circular shape is needed. Canny Edge detection operator is applied to the image as a first step in this process. This removes most of the noise due to its fine texture leaving only the required edges of the OD. It can be used for representing objects as

$$(x-a)^2+(y-b)^2=r^2 \tag{3}$$

Where (a,b) is the coordinate of center of the circle that passes through (x,y) and r is its radius. From this equation, it can be seen that three parameters are used to formalize a circle which means that Hough space will be 3D space for this case. For the rough calculation of OD, the accumulator parameter array is filled where each array is composed of cells for (x,y) coordinates of the center of circle. The edge image is scanned and all the points in this space are mapped to Hough space. A value in particular point in Hough space is accumulated if there is a corresponding point in the retinal image space. The process is repeated until all the points in the retinal image space are processed. The resulting image is scaled between 0 and 1. Then it was threshold to leave only those points with high probability of being the centres which are then labeled with different numbers. Afterwards the different regions were matched by different circles and the output image is computed by drawing circle with these points and adding this to the input image. Then numbers of pixels which are in the vicinity of detected circle's edge are counted. A mask of a ring shaped is put on the binary edge image on the same location of each of the detected circle. Number of edge pixels under this mask will be counted and compared for all the detected circles. The best circle shows the location of the detected optic disc.

IV. CANNY EDGE DETECTOR

The Canny Edge Detector works in a multi-stage process. First of all the image is smoothed by Gaussian convolution. Then a simple 2-D first derivative operator is applied to the smoothed image to highlight regions of the image with high first spatial derivatives. Edges give rise to ridges in the gradient magnitude image. The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top so as to give a thin line in the output, a process known as non-maximal suppression. The tracking process exhibits hysteresis controlled by two thresholds: T1 and T2, with T1 > T2. Tracking can only begin at a point on a ridge higher than T1. Tracking then continues in both directions out from that point until the height of the ridge falls below T2. This hysteresis helps to ensure that noisy edges are not broken up into multiple edge fragments. The Sobel operator performs a 2-D spatial gradient measurement on an image. Then, the approximate absolute gradient magnitude at each point can be found. The Sobel operator uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). They are shown below:

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Figure.5 Convolution Masks

The magnitude, or edge strength, of the gradient is then approximated using the formula: $|G| = |Gx| + |Gy|$

Edge tracking is implemented by BLOB-analysis (Binary Large Object). The edge pixels are divided into connected BLOB's using 8-connected neighbourhood. BLOB's containing at least one strong edge pixel is then preserved, while other BLOB's are suppressed. After eliminating the blood vessels and optic disc remaining image are refer as a exudates located image and exudates obtained area is calculated. By using this exudates area we can show the difference between severities of disease.

V. RESULT AND ANALYSIS

The retinal image edge enhancement and contrast was improved using curvelet transform and prepared better for segmentation, blood vessels are removed by using morphological dilation and erosion process and optic disc are masked by using circular fitting method. Then finally remaining image are refer as a exudates located image. By using this approach we can detect the exudates accurately for differentiating diseased persons from the normal persons. The Table.1 shows the Enhancement Analysis and Area Obtained. The Figure.6 show the input Image and its Adaptive histogram equlaization that is followed by Enhanced Image. Also the Figure 7 shows the image of an Morpological erode, Blood vessels and Exudates located color.

Table.1 Enhancement Analysis and Area Obtained

Images	**Histogram equalization**		**Curvelet transform**		**Area**
	PSNR	**MSE**	**PSNR**	**MSE**	
1	**24.6426**	**14.9426**	**41.0952**	**2.2479**	**2052**
2	**27.2354**	**11.0558**	**65.8705**	**0.12972**	**223**
3	**24.64**	**14.9465**	**38.4727**	**3.0402**	**532**
4	**26.6301**	**11.886**	**35.2062**	**4.4282**	**752**

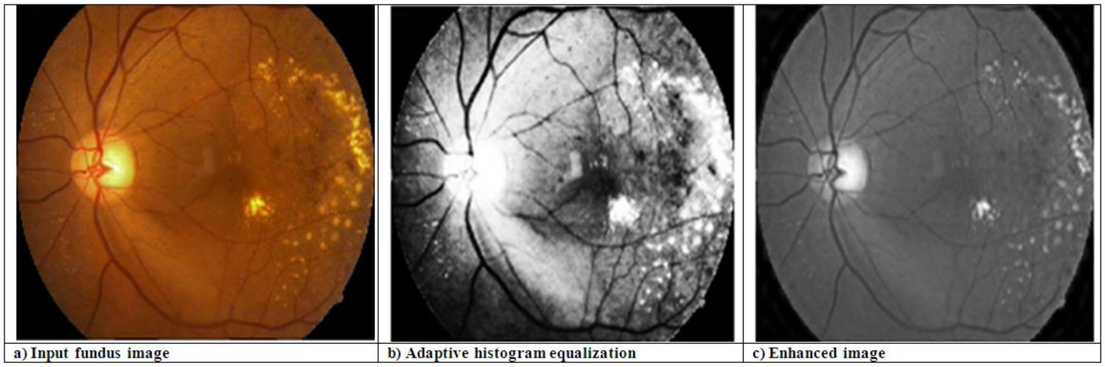


Figure.6 Image of a) Input b) Adaptive histogram equlaization c) Enhanced Image

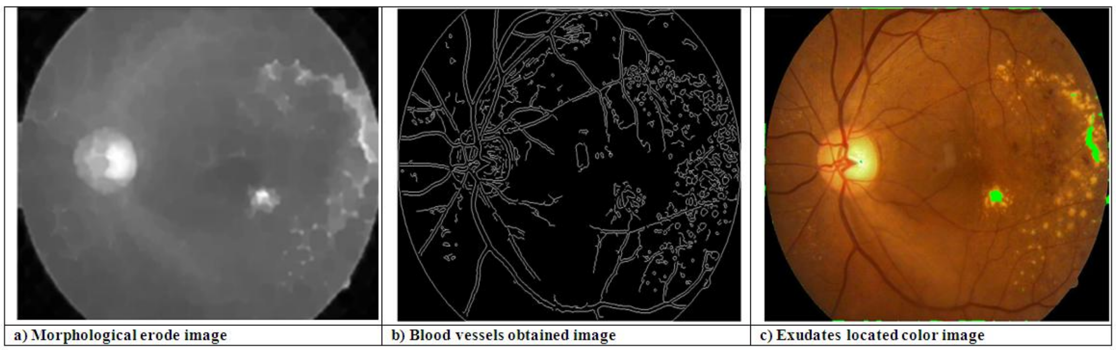


Figure 7 Image of a) Morpological erode b) Blood vessels c) Exudates located color

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