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Qualitative Comparison of OTSU Thresholding with Morphology Based Thresholding for Vessels Segmentation of Retinal Fundus Images of Human Eye

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Abstract:*Threshold Segmentation is an important image segmentation method and one of the most important preconditioning steps of image detection and recognition, and it has very extensive application on the research scopes of image processing and computer vision. Thresholding is one of the simplest approach to separate out the object from the background image. Object background classification is the basic problem of an object tracking in image processing and computer vision area. The solutions using threshold segmentation techniques become more complex when the image is blurred or low contrast.Assessment of retinal vessel is asignificant factor for the many medical syndromes. The retinal vessel analysis is done by first extracting the retinal images from the background image. The variations in the retinal vessels due to the pathologies can be easily recognized by segmenting out the retinal vessels. In this paper two methods have been implemented to segment out the retinal vessels and a qualitative comparison has been done between this two methods.*

Keywords:*Image Segmentation, OTSU Global Thresholding, Image Morphology, Histogram Analysis, Vessels Structure.*

I. Introduction

Human retina is the only position where blood arteries and veinsare being directly visualized in a non-invasive way. Growing technology leads to the progress of digital image processing systems over the past few decades has developed fundal image processing. While digital image processing doesn’t have the tenacity of conventional photography, modern digital image processing systems offer very high-resolution images that are adequate for most clinical situations [2]. In addition, digital image processing has the benefit of easily storage on media that do not deteriorate in the quality with time varying, can be easily transmitted over the short distances within a clinic or over the large distances via electronic transfer systems, can be treated to improve image quality, and subjected to image analysis to achieve objective measureable analysis of fundal images and the potential for the automatic diagnosis. In the research activities, large databases of fundal images are being automatically classified and managed more readily than the labor-intensive observer-driven techniques. Automatic diagnosis may also aid decision-making for ophthalmologist. A retinal fundus image with vessels structure is shown in figure 1.

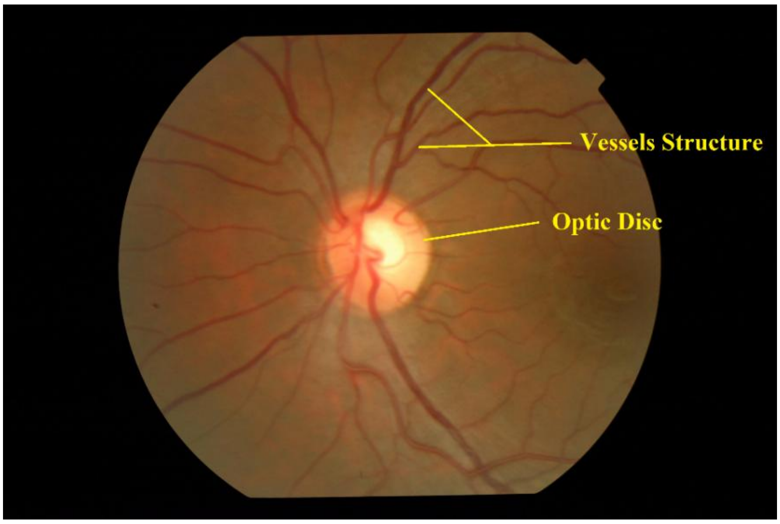

Figure 1: Input Color Image taken by Fundus Camera

The techniques used to automatically identifyinnovative features of the fundus images, such as the optic disc, optic cup, blood vessels, and vessels bifurcation and termination points has been discussed here.The use of image analysis in the automatic diagnosis of pathology, its role in defining and performing measurements of vascular structure, its 'optimization' principles and how it is used to describe the relationship between systemic cardiovascular disease and retinal vascular changes has been reviewed.

II. Experimental Methodology

2.1 Algorithm for segmentation of blood vessels using OTSU Thresholding:

The main algorithm to segment out the blood vessels using OTSU thresholding from an optical fundus image of human eye consists of the following steps.

1. Read the gray scale optical fundus image of human eye.
2. Identify the image histogram.
3. Select a threshold value, here mentioned as t

3.1 Calculate the foreground variance, σ_f^2

3.2 Calculate the background variance, σ_b^2

4. Calculate the within-class variance, σ_w^2
5. For all threshold values repeat the step 3 and step 4 for all possible threshold values.
6. The final global threshold denoted by T is the threshold in MIN (within-class variance).
7. Finally, the segmented binarized image = gray scale image > T

2.1.1 Formulation:

Consider the pixels of a given gray scale image be represented in L gray levels [1, 2, 3…. L].The number of pixels at level I is denoted by n_i and the total number of pixels

$N = n1 + n2 + n3 + ... + nL$

Now if we divide the pixels into two classes as background, C_b and foreground, C_f by a given threshold at a level t. Therefore C_b represents the pixel level $[1,2,3,......,t]$ and C_f represents the pixel level $[t+1, t+2, t+3,....., L]$.

The mathematical expressions to find out the background and foreground variance for a single threshold value t are mentioned below.

Consider the background pixels, C_b

Weight, $W_b = \sum_{i=1}^{t} \frac{n_i}{N}$

Mean, $\mu_b = \frac{\sum_{i=1}^{t} i * n_i}{\sum_{i=1}^{t} n_i}$

Variance, $\sigma_b^2 = \frac{\sum_{i=1}^{t} (i - \mu_b)^2 * n_i}{\sum_{i=1}^{t} n_i}$

Consider the foreground pixels, C_f

Weight, $W_f = \sum_{i=t+1}^{L} \frac{n_i}{N}$

Mean, $\mu_f = \dfrac{\sum_{i=t+1}^{L} i * n_i}{\sum_{i=t+1}^{L} n_i}$

Variance, $\sigma_f^2 = \dfrac{\sum_{i=t+1}^{L} (i-\mu_f)^2 * n_i}{\sum_{i=t+1}^{L} n_i}$

Then the within class variance, σ_w^2 is simply the summation of the two variances multiplied by their associated weights.

Within-class variance, $\sigma_w^2 = W_b\sigma_b^2 + W_f\sigma_f^2$

This final value denotes the summation of all weighted variances for the threshold value represented by t. This similar expression needs to perform iteratively for all the possible threshold values 1 to L where the value of L is 256. Finally a threshold T is needed to select, that has the lowest sum of weighted variances to be the final globally selected threshold. All pixels with a level less than T are background and all those with a level greater than or equal toT are foreground.

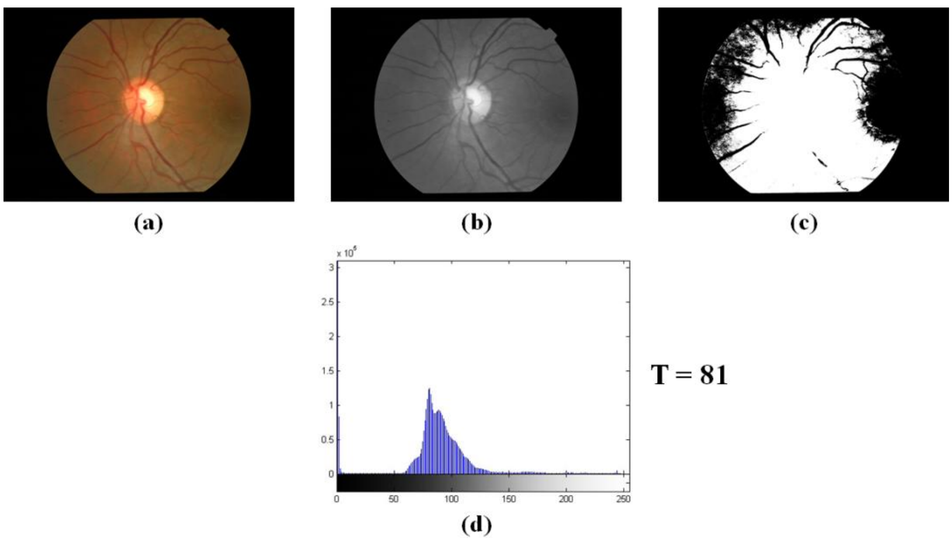

Figure 2: Application of OTSU thresholding to fundus image, (a) original RGB image, (b) gray scale image, (c) vessels segmented image, (d) histogram with global threshold value, T = 81

2.2Algorithm for segmentation of blood vessels using proposed method:

The first step of digital fundus image processing is the formation of a set of digital fundus images. In this project the used fundus images are collected from the Ophthalmology section of the Medical College and Hospital, Kolkata, West Bengal, India. The algorithm for the proposed method has been explained in figure 3.

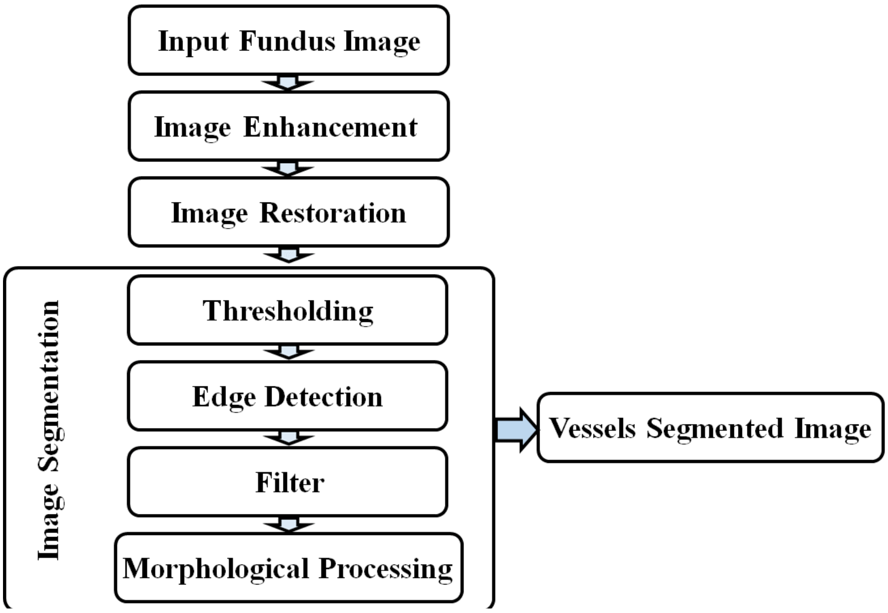

Figure 3: Algorithm for proposed method

1.2.1 Image Enhancement:

One of the difficulties in capturing the image of the ocular fundus is image quality which is affected by various factors, such as medial opacities, defocusing or presence of artefact (Kristinsson et al., 1997; Liesenfeld et al., 2000). Adjustment of image intensities to enhance the image contrast, histogram equalization technique has been used.

If f be an input image represented by a m_r by m_c matrix of integer pixel intensities ranging from 0 to $L-1$ where L has a possible intensity value, often 256. Let p be the normalized histogram of f .

$$p_n = \frac{\text{number of pixels with intensity } n}{\text{total number of pixels}} \quad \text{,where } n = 0,1,2,\ldots\ldots. L-1$$

The image after histogram equalization, g is given by

$$g_{i,j} = floor\left((L-1)\sum_{n=0}^{f_{i,j}} p_n \right), \tag{1}$$

where floor() is used to round down to the nearest integer. This is equivalent to transforming the pixel intensities, k, of input image f by the function

$$T(k) = floor\left((L-1)\sum_{n=0}^{k} p_n \right).$$

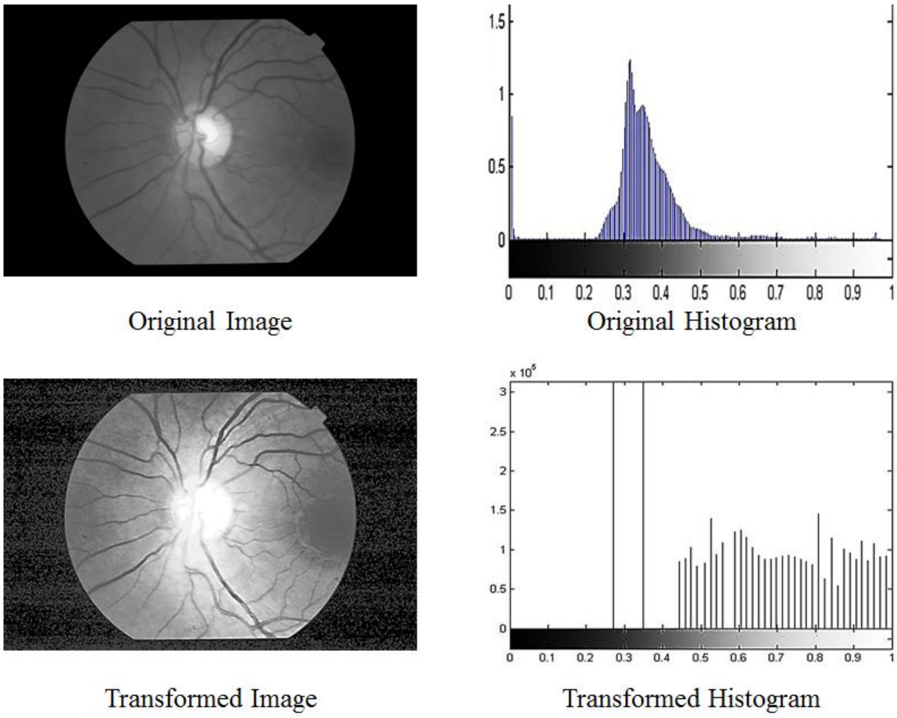

Figure 4: Histogram equalization applied to low contrast input image

1.2.2 Image Restoration:

Image restoration aims to reverse the damage by known causes. Algorithms such as deblurring or removal of interference patterns fit to this category. Noise arises due to the errors in pixel values caused by some external disturbance. There are various forms of noise, such that salt-and-pepper noise, Gaussian noise or periodic noise.

Salt-and-pepper noise causes due to the appearance of randomly scattered black or white pixels all over the image but it may possible to reduce that noise by using some filters in which the mask evens out the abnormalities or ignores extremely high or low values. Gaussian noise is occurred by random fluctuations in the signal. It can be reduced by using several versions of the same image and averaging the values for each pixel. Periodic noise occurs if the imaging equipment is subjected to electronic repeating disturbances. Periodic noise can be reduced by transforming the image to a different structure known as a Fourier transform, then applying the noise filters before transforming back to the original image. Deblur functions rely on modelling of the blurring process then using filters to remove the known effects of blur.

1.2.3 Image Segmentation:

Image segmentation process involves partitioning an image into multiple segments which have different interests such as the defining areas of an image which are suitable to be subsequently analyzed for finding circles, lines or other shapes of interest in the main image. It is an important signal processing tool that is widely applied in different applications containing object recognition, object-based coding, object tracking, image retrieval, clinical organ or tissue identification. Segmentation algorithms for monochrome images are generally based on discontinuity in image intensities such as edges in an image, or on resemblances judged by predefined criteria (see below).

1.2.3.1 Thresholding:

Thresholding is the most widely used technology for image segmentation. It is useful in recognizing foreground from the background. Thresholding allows the separation of an image into separate components by converting main color image into binary image. The binary image should contain all of the essential information about the shape and position of the main image (foreground). The advantage of obtaining a binary image is that it reduces the complexity of the data and simplifies the process of recognition and classification. This binary image generally used to separate the image of interest into white or black pixels on the basis of whether their intensity value is greater or less than a certain threshold level. The process, thresholding may also particularly be useful to remove unnecessary detail or variations and highlight detail that is of main interest. An adequate threshold value may be chosen automatically or on the basis of bright points in the image histogram that would allow for efficient segmenting of the main image. More complex intensity criteria may be used to determine whether pixel values become white or black. For some images adaptive or local thresholding is useful for image segmentation where different threshold values are applied to different portions of the image, e.g., the image has different levels of background illumination.

1.2.3.2 Edge Detection:

Edges of an image contain most essential information regarding the shapes of object in the scene. They can be used to measure the size of objects or to recognize and isolate objects. An edge in a digital image consists of an observable difference in pixel values within a certain area. The major property of the edge detection technique is its ability to determine the precise edge line with good alignment as well as more literature about edge detection has been available in the past three decades.

There are so many edge detection techniques in the present literature for image segmentation. The most frequently used discontinuity based edge detection techniques are Robert's edge detection, Sobel Edge Detection, Canny Edge Detection etc.

The Sobel edge detector uses a pair of convolution masks, where one estimates the gradient in the x-direction (columns) and the other estimates the gradient in the y-direction (rows). If A is the binarized image, G_x and G_y are the two images which at each point contain respectively the horizontal and vertical derivative approximations, the computations are as follows:

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A \text{ and } G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * A$$

Where $*$ represents the 2D convolution operator. The resulting gradient expression for sobel filter is given as,

$$G\sqrt{G_x^2 + G_y^2}$$

Using those information, the gradient's direction can be calculated as,

$$\theta = are\tan\left(G_y / G_x\right)$$

1.2.3.3 Filters:

Neighborhood processing coversthe power of processing algorithms by combiningvalues of neighboring pixels in calculations. A user defined matrix,or mask has been defined with enough elements to cover not only a single pixel but also some of its neighboringpixels. Each pixel enclosed by the elements of the mask is subject to a consistent function. The combination of mask andfunctionarenamed a filter. Thus, the result of applying a mask to a specific location is that the final resultant value is a function not only of the central pixel's values but also of its neighboring pixel values.

1.2.3.4 Morphological Processing:

In Image Processing mathematical morphological operation is more suitable and acceptable for detecting the shapes in images. There are four processes in morphological operation; whereas two main processes- dilation and erosion are extensively used in Image Processing for various operations. These processes involve a special technique of combining two sets of pixels. In these two sets, one set consists of the main image which is to be processed and the next is a relatively smaller set of pixels, known as a structuring element (SE) or kernel.

In dilation operation, every point in the image is superimposed by the SE, with its surrounding pixels. This is a thickening operation where the operation is controlled by the shape of the SE. The effect of this dilation operation is to increase the size of the original image. One of the most important applications of dilation operation is filling gaps in the image. An example of dilation on binary image in shown in figure 5.

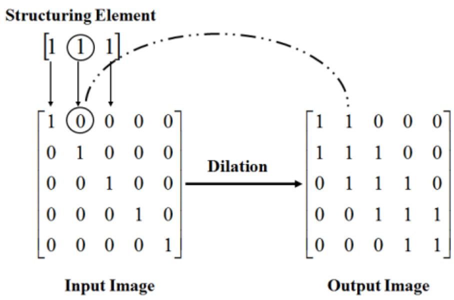

Figure 5: Dilation on a binary image

Erosion is another morphological operation in which main image is thinned through subtraction via a structuring element or kernel. It is also called shrinking operation. Here the kernel is superimposed onto the original image and only at locations where it fits entirely within its boundaries, a resultant central pixel value of the image is accepted and the image details smaller than the kernel are removed from the original image. An example of erosion on binary image is shown in figure 6.

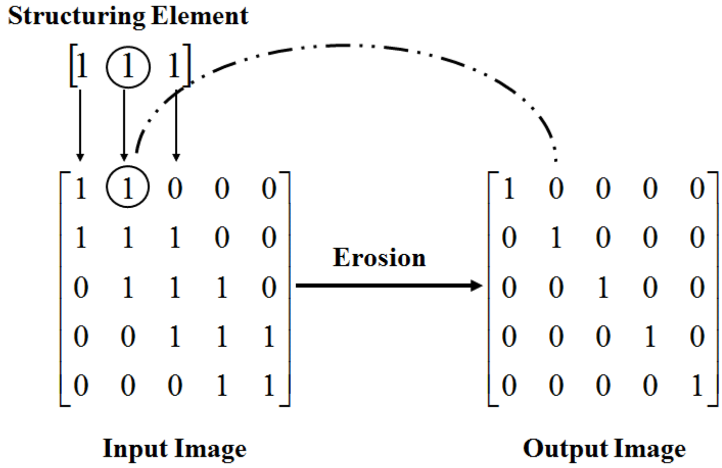

Figure 6: Erosion on a binary image

There are other two morphological operations- opening and closing, which are based upon the above two processes. Opening consists of erosion followed by dilation, and tends to smoothing an image, breaking narrow joints and removing thin protrusions. Closing consists of dilation followed by erosion, which also smoothest images, but by fusing narrow breaks and gulfs and eliminating small holes. Algorithms combining the above all morphological processes are used to create mechanisms of edge detection, noise reduction and background removal as well as for finding specific shapes in images.

III. Results

More than 50 images were tested and trained under the combination of multi structure morphological process and Segmentation technique which was used effectively for retinal vessel detection. Morphological operations are applied on segmented image for smoothening the vessels edges. It processes the image based on shapes and it performs on image using 'line' structuring element. Dilation and erosion process will be used to enhance (smoothening) the vessels region by removing the unwanted pixels from outside region of vessels part. The result of segmented vessels is shown in figure 7. Segmented vessels using morphological based method is more prominent than the OTSU method.

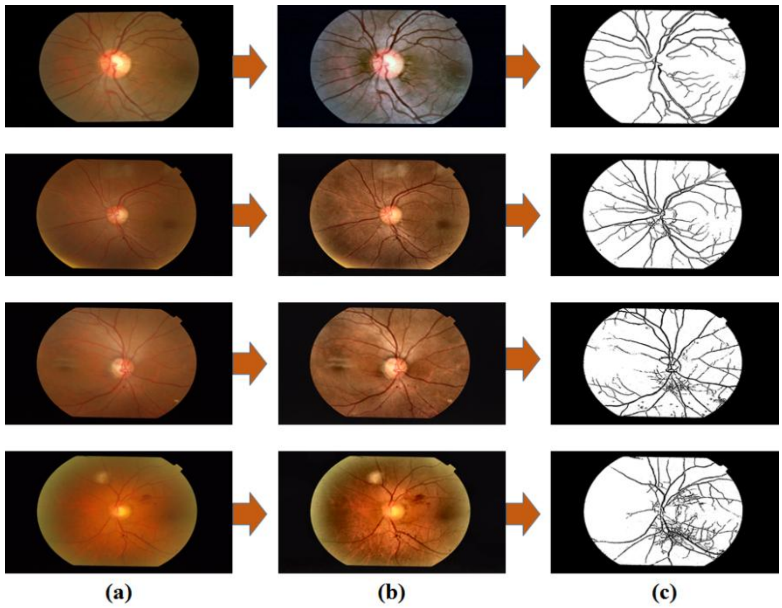

Fig. 7: The figure represents (a) the input images, (b) enhancement of input images, (c) segmented vessels.

IV. Conclusion

The method proposed in this paper has proved to be a valuable tool for the segmentation of the vascular network in retinal images. An interesting conclusion of this work is that for well contrasted images, as it happens with those in DRIVE database, the use of the luminance image can be a good alternative to the green channel because the performance of the centerline detection algorithm is, in general, less sensitive to the background noise, which is more intense in the green channel. Better contrast enhancement, accurate retina vessel and execute detection. It is useful in Diabetic diagnosis. The Process time is faster than other clustering with more number of data points. The deficiency of missing some thin vessels is because of our utilizing a simple thresholding method. While avoiding false-edge pixel detection, the quantitative performance results of both segmentation and enhancement steps show that there is a need for a proper thresholding algorithm to find the small vessels. Also, in retinal images containing severe lesions, the algorithm needs to benefit from a higher level thresholding method or a more proper scheme. Hence, our future work is to replace the simple threshold method with a more proper approach in order to increase the accuracy of this method and deal with the problem of the presence of severe lesions in retinal fundus images.

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