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Morphological Image Processing Approach on the Detection of Hard Exudates in Fundus Images

Sindhu T S[1], Senthil Kumar T[2]

PG Scholar, Dept. of ECE, Kingston Engineering College, Vellore, Tamil Nadu, India[1]

Assistant Professor, Dept. of ECE, Kingston Engineering College, Vellore, Tamil Nadu, India[2]

ABSTRACT: Identifying retinal pathologies in fundus images is an overwhelming issue. It can be solved using upcoming process. This paper presents, the best way to segment a Fundus Image is unsupervised iterative vessel segmentation algorithm. First, a enhanced vessel image is generated by Morphological reconstruction of the green plane image. An initial estimate of the segmented vessel is extracted by the global thresholding the vessel enhanced image. Then new pixels are identified iteratively by adjustable thresholding of the leftover image achieved by masking out the existing segmented vessel estimate from the vessel enhanced image. The new vessel pixels are then region grown into the existing vessel, thereby resulting in an iterative enrichment of the segmented vessel structure. The number of false edge pixels are identified as new vessel pixels compared with actual vessel pixels by the iteration progress. The high segmentation accuracy can be achieved by means of novel stopping criteria in the iterative process.

KEYWORDS: Fundus image, Morphological Operation and Iterative Segmentation.

I. INTRODUCTION

Retinal blood vasculature segmentation using fundus images has played a important role in assessing the severity of retinal pathologies that can lead to acquired blindness such as prematurity, Vein Occlusions and Diabetic Retinopathy (DR).

The Automated blood vessel segmentation system can be useful in determining variation in the blood vessels and it is based on the vessel width, branching patterns of vessels density as the pathology progresses in patients. The existing Algorithms for blood vessel segmentation can be broadly classified into supervised and unsupervised methods. The comparative analysis of these two methods is given below. The existing supervised algorithm and classifiers is K-nearest neighbour [1], Gaussian Mixture Model (GMM) [2], Support Vector Machine (SVM) [3], Neural Networks[4]. Decision trees [5] and Adaboost [6]. These can be applied in order to classify vessel pixels from the non-vessels. The unsupervised Algorithms are matched filtering [7], Morphological transformations [8], Line detectors [9], Model–based methods [10] and multi-scale vessel [11] [12] segmentation methods. The supervised vessel classification methods are depends on the training data and it all sensitive to false edges. While unsupervised methods are computationally complex. Most of the existing methods like GMM, line detectors and model based methods [2], [8] and [12] will perform only on healthy retinal images but low segmentation accuracy on pathology images. So there is a need for high segmentation accuracy and low computational complexity for normal as well as pathological fundus images.

In this method, we propose an iterative vessel segmentation Algorithm. It segments the major vessels first followed by addition of finer vessel branches by adaptive thresholding in iterative steps. This approach has high segmentation accuracy for vasculature in normal and abnormal retinal images. Also this iterative approach has low computational complexity than most existing supervised and unsupervised approaches. The main contribution of this approach includes a novel iterative blood vessel segmentation Algorithm where vasculature estimates are identified by adding new pixels, interactively using adaptive global thresholding.

The Novel stopping criterion is to terminate the interactive vessel addition process there by reducing the number of false edge pixels in the segmented image. The proposed Algorithm is robust to both image variability and inter observer variability in the ground truth.

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II. METHODS

The main idea behind, this iterative vessel segmentation is that in a vessel enhanced image, the bright and large vessels overshadow the thinner fine vessels branches. In this situation global thresholding would extract major vessels while remaining fine vessels would remain unsegmented.

In order to segmentation this fine vessels Iterative Adaptive global thresholding is proposed. Each color fundus image can be converted into a green plane image in order to perform the morphological to hat reconstruction. From this enhanced vessel image obtained and the brightest pixels are extracted as the major portion of the vasculature/ major vessels from this enhanced image. By using contrast adjustment and adaptive thresholding the residual images is generated from above enhanced image by masking major vessels. This method of iterative vessel addition and novel stopping criterion for estimating the best segmentation vasculature is presented in this section.

III. SYSTEM MODEL

A. Preprocessing Stage:

In preprocessing stage the input fundus image is scaled. That is resized into [256,256]. If the input image is RGB color image means then plane separation can be carried out and green plane can be retrieved. Because green plane has high contrast which are placed between blood vessels and background. After preprocessing the filtering can be done in order to avoid the noises present in the input image. In this method median filter can be used in order to avoid the salt and pepper noise and also any other noises present in the fundus image.

B. Blood Vessel Segmentation:

The existence of blood vessels within the optic disc region may cause the misdetection of pixels In order to detect and segment the retinal blood vessel accurately, the optic disc should be detected and eliminated from the fundus image for further processing.

C. Morphological Operation:

Morphological operation applied on segmented image for smoothening the image. It processes the image based on shapes and performs on image using structuring element. The vessel edge will be detected by applying dilation and erosion process to an image seed on multi structure elements to enhance the vessel edges and smoothening the regions.

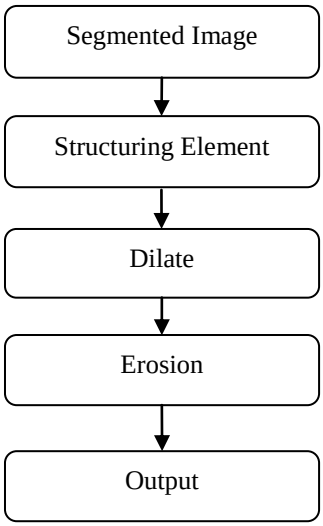

Figure.1: Morphological operation

Dilation: It is the process of adding a pixel at object boundary based on structuring element. The rule to find output pixel is the maximum of input pixels neighbourhood matrix. Erosion: It is to remove the pixel from the object boundary depends on structuring element. The rule to find output pixel is the maximum of input pixels neighbourhood matrix.

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D. Iterative Vessel Segmentation:

In this iterative vessel segmentation can be done by means of Region Growing Algorithm (RGA) for segmentation. The main goal of segmentation is to partition an image into regions based on the similarity criteria like Intensity value, texture, color, size, likeness between a candidate pixel and the pixels grown so far. In this "Thresholding" method is used to achieve this goal by looking for the boundaries between regions based on discontinuities in gray levels or color properties. The flow of RGA is shown in figure 2.

(i)Basic concept of seed points:

The first step in region growing is to select a set of seed points. Seed point selection is based on some user criterion. The initial region begins as the exact location of these seeds. The regions are then grown from these seed points to adjacent points depending on a region membership criterion.

(ii)Disease part segmentation

In the first iteration, vessel centre line pixels are used as seeds for a region growing algorithm, which breed these points by aggregating the pixels in the reconstructed image derived from the morphological operator with the smallest structuring element size. In each of the subsequent three iterations, there constructed images corresponding to the vessels with increasing width are in turn used for extending the output of the previous region growing step. The final iterative segmentation is obtained after a cleaning operation aiming at removing all pixels completely surrounded by vessel points, but not labelled as part of a vessel. Finally the segmented disease part is obtained.

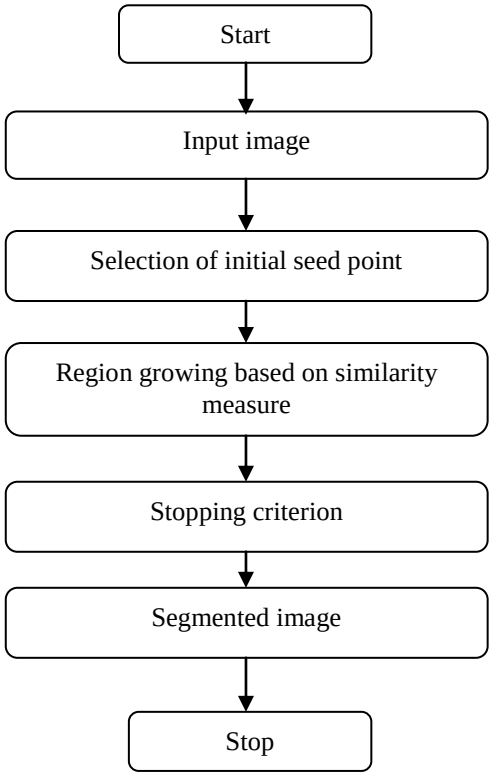

Figure.2: Flow chart for Region Growing Algorithm

The above figure 2 shows flow chart for Region Growing Algorithm. It describes the process of region growing algorithm.

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(iii)Performance Measure

In order to find the segmentation accuracy and sensitivity of the segmented fundus image the four parameters can be used. They are true positive(tp_t),true negative(tn_t),false positive(fp_t),false negative(fn_t).these can be calculated by the below formulas. for binary V_t,iteration t and fundus image with $[n_1, n_2]$ we define $\forall(i,j)$, i ϵ [1, 2…..n_1], j ϵ [1, 2…..n_2]

$$tp_t(i,j) = 1, \ \ if, [V(i,j) = 1, V_t(i,j) = 1] \quad \text{eq. (1)}$$
$$tn_t(i,j) = 1, \ \ if, [V(i,j) = 0, V_t(i,j) = 0] \quad \text{eq. (2)}$$
$$fp_t(i,j) = 1, \ \ if, [V(i,j) = 0, V_t(i,j) = 1] \quad \text{eq. (3)}$$
$$fn_t(i,j) = 1, \ \ if, [V(i,j) = 1, V_t(i,j) = 0] \quad \text{eq. (4)}$$
$$\sum_{i=1}^{n1} \sum_{j=1}^{n2} tp_t(i,j) = TP_t \quad \text{eq. (5)}$$
$$\sum_{i=1}^{n1} \sum_{j=1}^{n2} tn_t(i,j) = TN_t \quad \text{eq. (6)}$$
$$\sum_{i=1}^{n1} \sum_{j=1}^{n2} fp_t(i,j) = FP_t \quad \text{eq. (7)}$$
$$\sum_{i=1}^{n1} \sum_{j=1}^{n2} fn_t(i,j) = FN_t \quad \text{eq. (8)}$$

The sum of all pixels in binary image V_t represents the total number of TP_t, FP_t pixels in V_t

$$\sum_{i=1}^{n1} \sum_{j=1}^{n2} V_t(i,j) = TP_t + FP_t \quad \text{eq. (9)}$$

$$\text{Also } n_1 . n_2 = TP_t + TN_t + FP_t + FN_t \quad \text{eq. (10)}$$

From the above equation the accuracy and sensitivity of the selected fundus image can be obtained from segmentation.

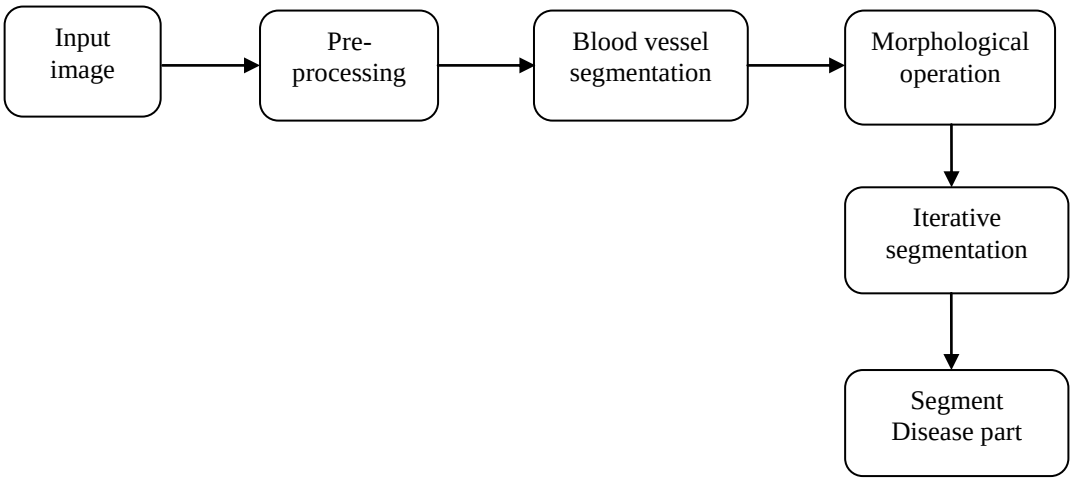

Figure.3: Flow of segmentation process

The above figure 3 shows the flow of the blood vessel segmentation and disease part identification in the fundus image.

IV. SIMULATION RESULT

The blood vessel segmentation and disease part identification are based in the false pixel identification and thresholding. Here for selected input and the simulation results are shown below in figure 4(a), 4(b) and 4(c).In this the normal fundus image is taken and it can be processed for disease localization. The fundus image is taken as input. The

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image is converted as grayscale image if it is a RGB color image**.**Noises are removed from the green plane and pre processed image is obtained for further processing.

Then segmented image is obtained using morphological operation. Diagnosing disease part using RGA by iterative segmentation is done in final processing stage. In this the input is a normal image hence no disease part can be identified which are shown in below figure.

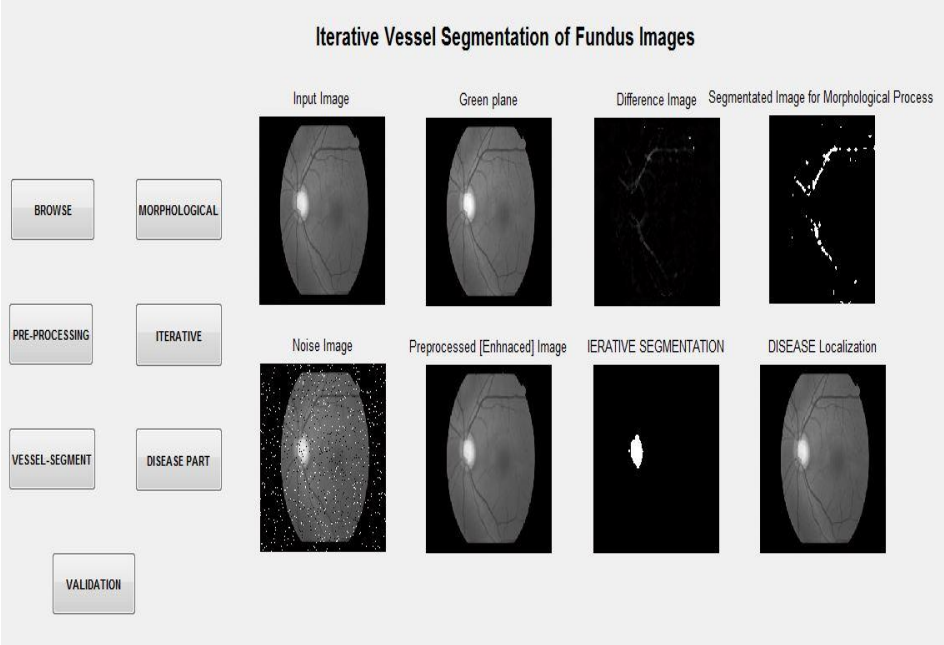

Figure.4a: Segmentation of normal fundus image

The above figure 4(a) shows the segmentation of normal fundus image. Because it does not find any disease part.

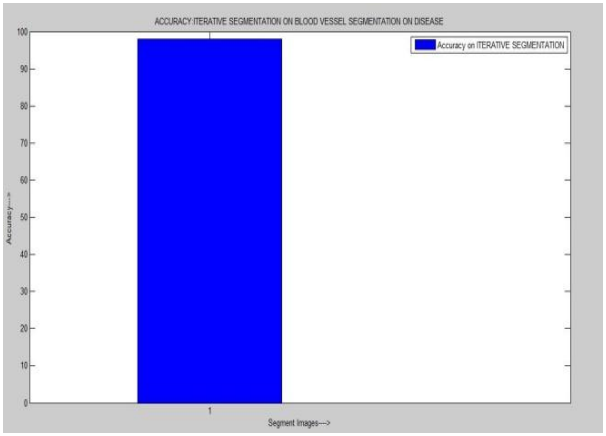

Figure.4b: Accuracy

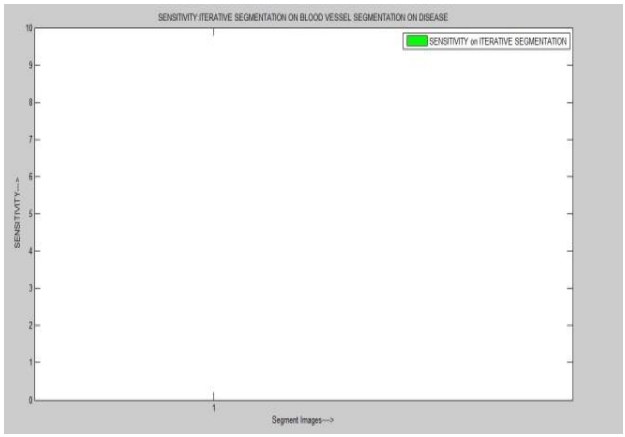

Figure.4c: Sensitivity

The segmentation Accuracy and sensitivity levels for the given input image are shown in figure 4(b) and 4(c). It can be calculated by the equation (1) to (10) given performance measure. Here the sensitivity level of input image is zero. Because it is not affected by the any retinal pathologies.

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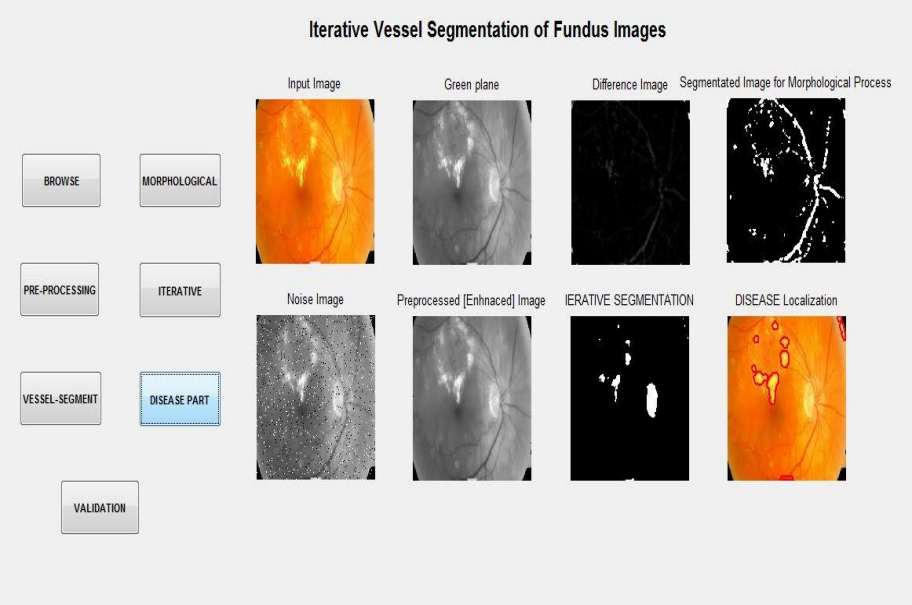

Figure.5 (a): Segmentation of affected fundus image

The above figure 5(a) shows the segmentation of affected fundus image. Hence it finds the disease part region.

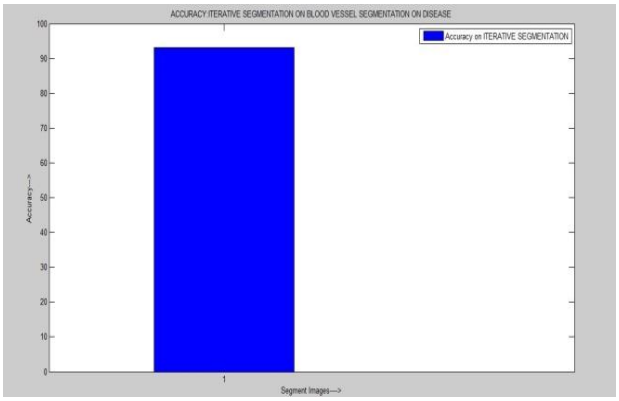

Figure.5b Accuracy

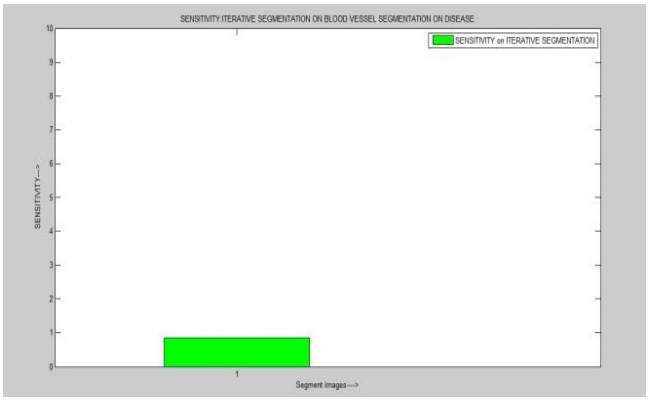

Figure.5c Sensitivity

The segmentation Accuracy and sensitivity levels for the given input image are shown in figure 5(b) and 5(c). It can be calculated by the equation (1) to (10) given performance measure. Here it shows the sensitivity level because the input image is affected by retinal pathology.

V. CONCLUSION AND FUTURE WORK

In this, a new blood vessel segmentation algorithm can be carried out in order to diagnose the disease part in retinal image. By applying Region Growing algorithm we can achieve the better segmentation accuracy with less computational time. In future we can increase the level of segmentation accuracy .

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BIOGRAPHY

Sindhu T S[1] pursuing Master of Engineering (ME) in the Electronics and Communication Department, Kingston Engineering College, Anna University, Chennai, India. She received Bachelor of Engineering (ECE) degree in 2014 from Anna University, Chennai, India.

Senthil Kumar T. ME, (PH.D)[2] is a Assistant Professor in the Department of Electronics and Communication**,** Kingston Engineering College, Vellore, Tamil Nadu, India. He received his BE (ECE) from University of Madras in 2002 and received his M.E from Sathyabama university in 2005.He is currently pursuing his Ph.D in Digital Image Processing.