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Iterative Vessel Segmentation with Stopping Criterion for Fundus Imagery

J. Kanimozhi[1*], P. Vasuki[2], S. Mohamed Mansoor Roomi[3]

[1] ECE Department, K.L.N. College of Information Technology ,Pottapalayam, Tamilnadu, India
[2]ECE Department, K.L.N. College of Information Technology ,Pottapalayam, Tamilnadu, India
[3]ECE Department, ECE Department, Thiagarajar college of Engineering, Madurai, Tamilnadu, India

**Corresponding Author: kanimozhibalamurugan@klncit.edu.in*

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Abstract— Vessel segmentation in fundus images plays vital role in diagnosing and treating patients in Ophthalmology. This proposed vessel segmentation algorithm consists of three stages to improve the lower contrast fundus images includes enhancement followed by thresholding and segmentation. Adaptive histogram equalization method is used to enhance the input image. From the enhanced image the major vessel are extracted by thresholding using gray thresh method. The new vessel pixels are identified iteratively using region growing method in which a new stopping criterion is introduced to improve the accuracy. The proposed method outperforms than the existing method of iterative vessel segmentation which achieves 3% greater in accuracy.

Keywords— Contrast enhancement; Histogram equalization; Segmentation; Stopping criterion; Accuracy; ROC.

I. INTRODUCTION

Digital Image Processing for Ophthalmology is to analyze retina, optic nerve, pigment epithelium and choroid in the ocular fundus. Colour slides have a resolution of 4000 x 3000 pixels. Fluorescein Angiograms have a resolution of 1800 x 1350 pixels. Common standard digital cameras have resolution of 512 x 480, which may be sufficient for obtaining relevant information of blood vessels etc. (Present day technology: 2048 x 2048 element resolution cameras). 8-bit resolution (indicative of contrast) is sufficient for most of the Opthalmology images.

Fundus imaging is the process whereby a 2-D representation of the 3-D retinal semi-transparent tissues projected onto the imaging plane is obtained using reflected light. Thus, any process which results in a 2-D image, where the image intensities represent the amount of a reflected quantity of light, is fundus imaging [1].

Retinal vasculature segmentation using fundus photographs has played a vital role in assessing the severity of retinal pathologies that can lead to acquired blindness such as retinopathy of prematurity , glaucoma, vein occlusions, and diabetic retinopathy (DR). Diabetic retinopathy is one of the major causes of blindness. For a real-time portable DR screening systems vessel segmentation algorithm plays an important role.

Automated blood vessel segmentation algorithms can be very useful in screening patients that are affected by such retinal complications and require follow-up [1]. Also, automated blood vessel segmentation systems can be useful in determining variations in the blood vessels based on the vessel branching patterns, vessel width, tortuosity, and vessel density as the pathology progresses in patients [25]. Such evaluations will help to enhance the resourcefulness of the present-day retinal therapeutics and guide research toward analyzing patients for hypertension [12], variability in retinal vessel diameters due to a history of cold hands and feet [13], and flicker responses [8].

Vessel segmentation is based on supervised and unsupervised method to segment the blood vessel features. Supervised methods such as k-nearest neighbor, Gaussian mixture model (GMM) , support vector machine (SVM), neural networks , decision trees , and AdaBoost are used to classify pixels as vessels or non vessels. Unsupervised method is used for vessel tracking and morphological transformations. The unsupervised method is sub divided into techniques based on the morphological processing, matched filter, line detectors, model based or multi scale analysis and vessel tracking [2][3][10-15][36][37]. The supervised segmentation is used for ground truth data for the classification of vessels based on given features [20] [28].

A comprehensive survey on existing retinal vessel segmentation algorithms and publicly available datasets has been presented in [5]. Also, a comparative analysis of the two categories of vessel segmentation algorithms has been presented in [28]. Most supervised vessel classification methods are dependent on the training data and sensitive to false edges, the existing unsupervised methods are computationally complex, and hence, they are not viable for real-time portable DR screening systems such as [27]. Thus, there is a need for a general method with low computational complexity and high segmentation accuracy for fundus images. In this paper, we propose an iterative vessel segmentation algorithm that segments the major vessels first, followed by addition of finer vessel branches by adaptive thresholding in iterative steps. This iterative approach has high segmentation accuracy for vasculature in retinal images.

II. PROPOSED METHOD

The input image (FUNDUS) is pre-processed. The pre processing steps involves Enhancement. After enhancing the image major vessels are extracted by thresholding. The threshold image is then region grown, followed by iterative vessel segmentation with stopping criterion.

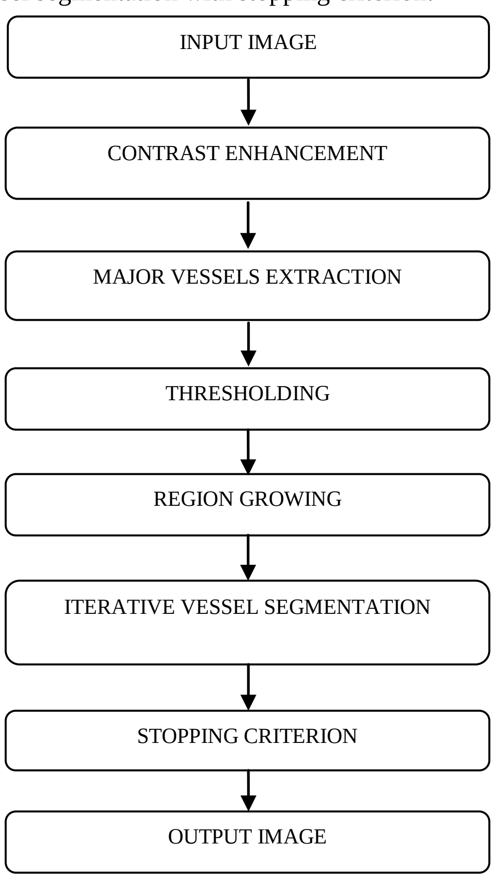


Figure 1: Proposed Flow Diagram

A. Fundus Image Dataset

FUNDUS of the eye is the interior surface of the eye, opposite the lens, and includes the retina, optic disc, macula and fovea &posterior pole. The following datasets have been manually annotated for the blood vessel regions for analyzing the performance of blood vessel segmentation algorithms. The fundus images are taken from 3 data sets, STARE,DRIVE,CHASE_DB1.

STARE[20]: This dataset contains 20 images with 35° FOV of size [605 x 700] pixels that are manually annotated by two independent human observers. Here, ten images represent patients with retinal abnormalities (STARE Abnormal). The other ten images represent normal retina (STARE Normal).

CHASE_DB1 [32]: This dataset contains 28 images with 28 images with 30° FOV of size [960 x 999] pixels corresponding to two images per patient (one image per eye) for 14 children. Each image is annotated by two independent human observers [18].

DRIVE [31]: This dataset contains 40 images with 45° FOV of size [584 x 565] pixels. This dataset is separated by its authors into a training set (DRIVE Train) and (DRIVE test) with 20 images in each set. The DRIVE Train set of images are annotated by one human observer, while the DRIVE Test dataset is annotated by two independent human observers.

B. Fundus Image Enhancement

Image Enhancement is the process of highlighting certain features of interest in an image. There are different techniques used for medical image enhancement. Out of these the adopted technique in the scope of this paper is AHE (Adaptive Histogram Equalization). AHE operates on small regions in the image, called *tiles*, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image.

The enhancement for fundus image is done in 2 methods i.e. Histogram Equalization & Histogram Specification. After comparing different HE and HS methods and calculating PSNR values for them we got highest PSNR value for AHE (Adaptive Histogram Equalization).

Adaptive Histogram Equalization is an excellent contrast enhancement method for both natural images and medical and other initially nonvisual images. In medical imaging its automatic operation and effective presentation of all contrast available in the image data make it competitor to the standard contrast enhancement method, interactive intensity windowing.

[Out] = AHE (a, n, windowsize)
Windowsize = size (a,1) * 0.1
a=input image
n=256

Limitations:
In homogeneous areas, the contrast can be limited to avoid amplifying any noise that might be present in the image. Very highly complex to implement.

C. Thresholding

Thresholding is the simplest method of image processing. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. This method replaces each pixel in an image with a black pixel if the image intensity $I_{i,j}$ is less than some constant or white pixel if the image intensity $I_{i,j}$ is greater than the constant. Graythresh method is used for thresholding the enhanced image in the proposed method. The threshold value used in the proposed method is 0.8.

D. Region Growing

Region Growing methods rely mainly on the assumption that the neighbouring pixels within one region have similar values. The common procedure is to compare one pixel with its neighbours. If a similarity criterion is satisfied, the pixel can be set to belong to the cluster of one or more of its neighbours. One of the region growing method is the seeded region growing method. Another region growing method is the unseeded region growing method.

A modified region growing scheme is used to segment the vessels. Since the region of interest is a vessel, domain knowledge can be exploited to constrain the growth of the region. Medial points detected by the trench detection algorithm serveas seed points. The region is grown only around a selected. neighborhood of the seed point, whose size is determined based on the width of the largest vessel present in the image. The region is grown based on the connectivity of the test pixel with the previously declared vessel pixels and its intensity value. A final dilation step is applied to complete the vessel tree segmentation.

E. Iterative Vessel Segmentation

The newly identified vessels are segmented by using the iteration process, the number of false edge pixels identified as new vessel pixels increases compared to the number of actual vessel pixels. For iteration t > t*5 the number of false edge pixels that are identified and added becomes higher than the number of actual pixels, which in turn reduces the accuracy of the segmented vessel estimate. Thus t=t*5 is the iteration at which the best segmented vasculature with highest accuracy can be estimated.

Algorithm:

Input: f1 → RGB image
f2 → Green Channel Image
Output: out → segmented blood vessel images
Preprocessing
Filtering:
filt → Lee filtered output
Contrast Enhancement
J → AHE enhanced output
Iteration
Iter → 1
Itr → 1:iter
BW → Based on threshold value the multidimensional filtered image is converted into binary image
BW 2 → Removing small objects from binary image and then complemented.
R → Measuring properties of image regions (BW, area)
out, acclabel → region grow (B, BW2, [0 0 0],t)
t → t+1
t → 1 to 9 iteration
t → 5 ← stop

F. Stopping Criterion

The iterative addition of the newly identified vessel regions to the existing vessel estimate is continued till a stopping criterion is met. This stopping criterion can be determined by analyzing the quality of segmented vessel estimates in every iteration. The best vessel estimate occurs at some iteration between t=0 to t=10. Also the iterative vessel segmentation algorithm requires a stopping criterion to stop the iterative vessel addition process at iteration number t where a segmented vasculature with highest accuracy exists.

Stopping Criterion Flow Chart:

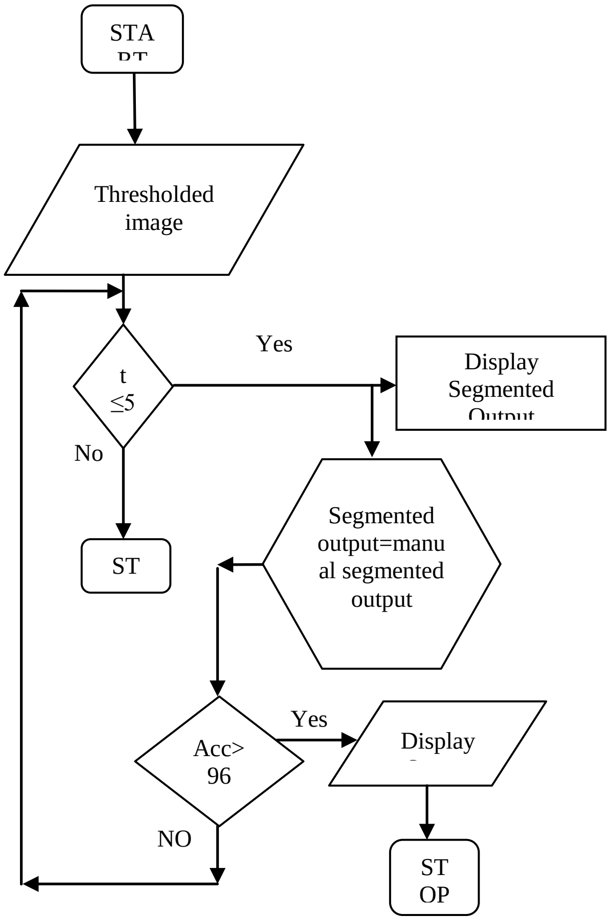
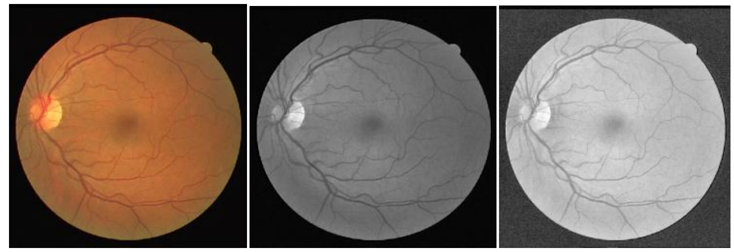


Figure 2 : Flow Chart (Stopping Criteria)

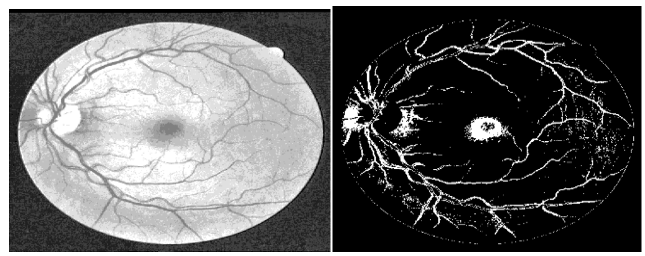
The iteratively segmented image has to be stopped at a point to avoid over segmentation of vessels which are false vessels and for increasing accuracy. This is done by the stopping criterion illustrated in the figure 2 as flow chart.

The number of false edge pixels identified as new vessel pixels is controlled by this stopping criteria. Here, it is controlled based on iteration and accuracy. If the iteration equals or less than 5 or accuracy greater than 96 is set as condition which is identified through trial and error method and based on it the vessel segmentation algorithm is stopped compared with the manual segmented output.

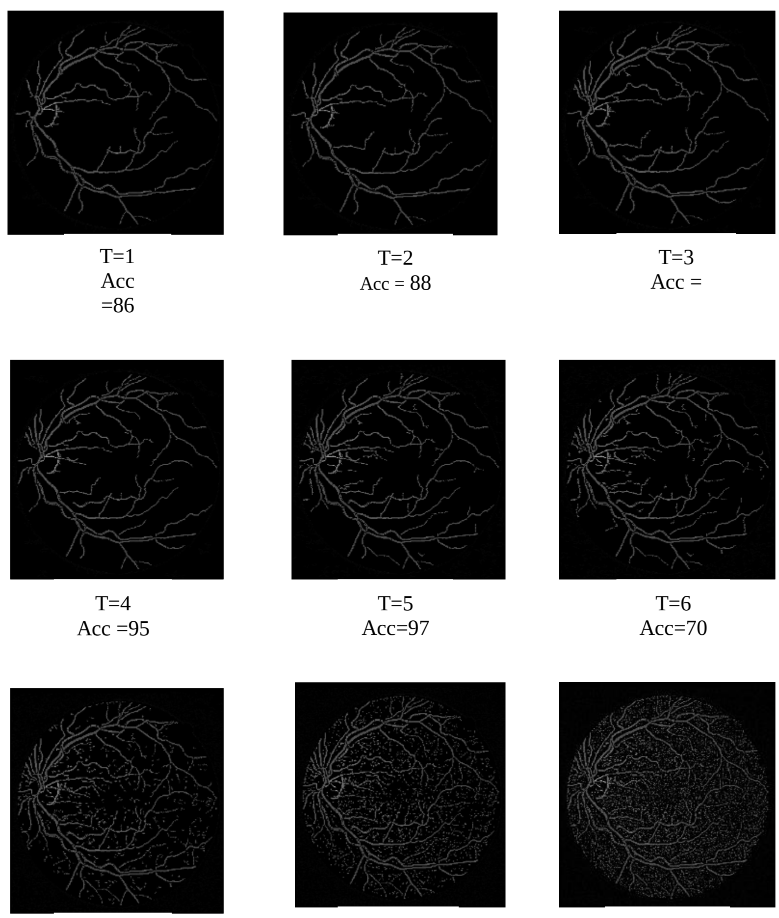
III. RESULTS AND DISCUSSION



(a)Input Image (b) Green Channel Image (C) Enhanced Output



(d)Thresholded Image (e) Major Vessels Segmented

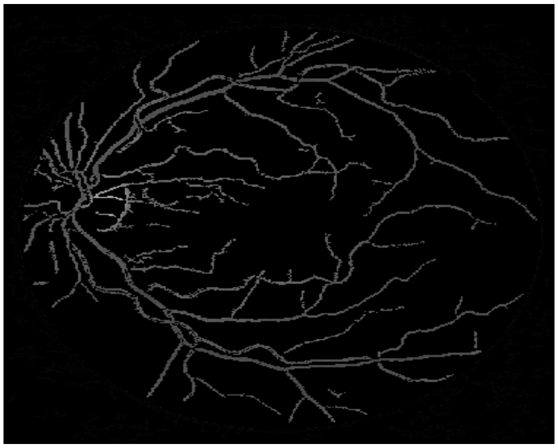


T=1 Acc =86 | T=2 Acc = 88 | T=3 Acc =

T=4 Acc =95 | T=5 Acc=97 | T=6 Acc=70

T=7 Acc =65 | T=8 Acc =54 | T=9 Acc=42

(f) Iterative Segmentation Results



(g) Segmented Blood

The Fig (a) shows the input image (FUNDUS) for the proposed system by using data set of DRIVE test set. The Fig (b) shows the green channel image of the input image. We go for green channel image as the blood vessel appears as dark pixels. To improve the contrast the Adaptive Histogram Equalization is performed shown in fig (c). The Fig (d) shows the threshold image for the major vessel extracted images.This method is based on threshold value to turn a gray-scale image into a binary image. The threshold value is obtained as 0.8. The Fig (e) shows the major vessel extracted from the enhanced image. Major vessels are extracted to obtain the major blood vessels from the fundus image. The Fig (f) shows the iteratively segmented images (t=1 to 9). Vessels are segmented at each iteration. Accuracy 97 is achieved at 5^{th} iteration and after that the vessels are over segmented thereby decreasing the accuracy. The Fig (g) shows the segmented image output for the given thresholded image. Segmented output is achieved at 5^{th} iteration.

A. *Performance Metrics*

Peak Signal to Noise Ratio (PSNR): PSNR is most easily defined via the mean squared error (MSE). Given a noise-free m×n monochrome image I and its noisy approximation K, MSE is defined as:

$$MSE= \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-K(i,j)]^2$$

Where i, j = Pixel
I = Noise free m*n Monochrome image;
K= Noisy approximation
The PSNR (in dB) is defined as:

$$PSNR=10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$= 20.\log_{10}(MAX_I)-10\log_{10}(MSE)$$

Specificity (SP)= TN/(TN + FP)
Sensitivity (SN) =TP/(TP + FN)
Accuracy (Acc)= (TP + TN)/(TN+TP+FP+FN)
Where,
TN=True Negative
FP=False Positive
TP=True Positive
FN=False Negative

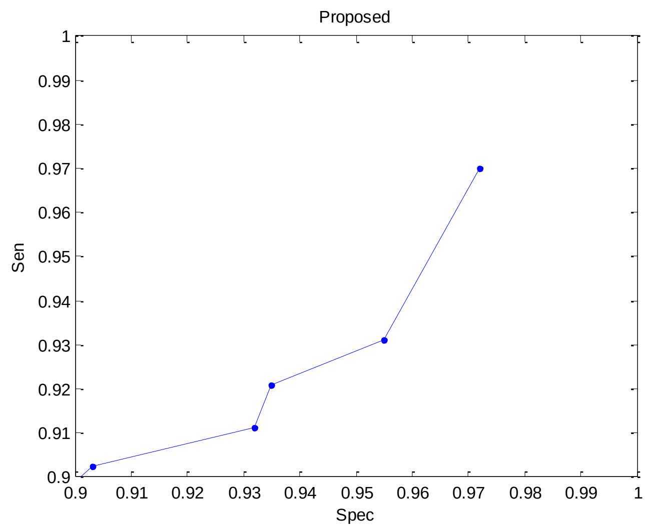


Figure 3 Sensitivity versus Specificity curve

Figure 3 shows the sensitivity versus specificity curve from the segmented image.

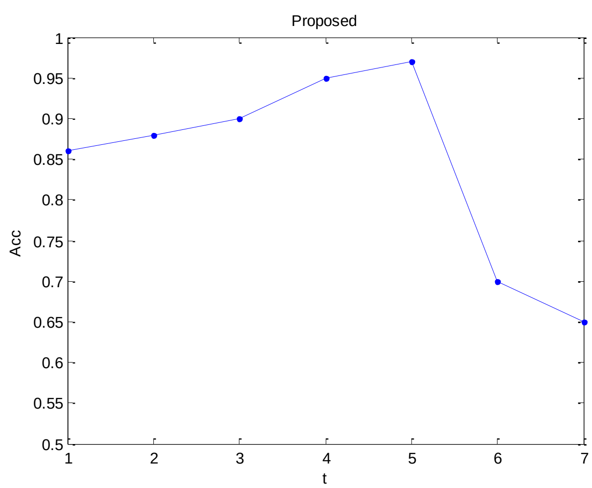


Figure 4 Accuracy versus Iteration curve

Figure 4 shows the Accuracy versus Iterative values curve from the segmented image.

TABLE I: COMPARATIVE PERFORMANCE OF PROPOSED METHOD WITH EXISTING WORKS ON THE DRIVE DATASETS

Test Data:	DRIVE	Test			
METHOD	ACC	SPEC	SEN	AUC	Time
Supervised	**Methods**				
Niemeijer et al. [20]	0.942	0.969	0.689	0.93	-
Staal et al. [31]	0.944	0.977	0.719	0.952	15 min
Soares et al. [30]	0.946	0.978	0.733	0.961	~3 min
Ricci and Perfetti [26]	0.959	0.972	0.775	0.963	-
Marin et al. [17]	0.945	0.98	0.706	0.958	~90 s
Fraz et al. [6]	0.948	0.981	0.74	0.974	~100s
Roychowdhury et al. [27]	0.952	0.983	0.725	0.962	3.11 s
Unsupervised	**Methods**				
Hoover et al. [10]	-	-	-	-	-
Jiang and Mojon [11]	0.891	0.90	0.83	0.932	8-36 s
Mendo&Campil [18]	0.945	0.976	0.734	-	2.5 min
Lam and Yan [16]	-	-	-	-	-
Al-Diri et al. [4]	-	0.955	0.728	-	11 min
Lam et al. [15]	0.947	-	-	0.961	13 min
Budai et al.[2]	0.949	0.968	0.759	-	11 s
Budai et al.[3]	0.957	0.987	0.644	-	~5s
Perez et al. [23]	0.925	0.967	0.644	-	~2 min
Miri et al. [19]	0.943	0.976	0.715	-	~5 s
Nguyen et al. [22]	0.941	-	-	-	2.5 s
Roychowdhury [28]	0.949	0.978	0.739	0.967	2.45s
Proposed	0.974	0.987	0.875	0.975	20-35s

Table 1 shows the comparative performance of proposed method with existing works on the DRIVE dataset. Here existing supervised and unsupervised methods are compared out of this our method shows outstanding performance. Based on accuracy, specificity, sensitivity using our method achieved 97.4, 98.7,87.5 which is improved by 3-8% increased over existing methods . Area Under curve also increased around 5% . However elapsed time is around 20 sec which is minimum compared to existing methods having elapsed time in minutes.

IV. CONCLUSION

An unsupervised segmented iterative blood vessel segmentation algorithm using fundus images and tested using public dataset of DRIVE. Some of the fundus images are low contrast images to enhance the fundus image Adaptive Histogram Equalisation method is used which has PSNR value of 43.1356 which is highest for fundus images compared to existing methods such as HS, HE, BBHE, RMSHE etc.,. This algorithm iteratively extracts the major portion of the blood vessels from the enhanced image. The major vessels extracted are by thresholding and region growing method. The enhanced image is thresholded with value of 0.8 and segmented using region growing method. A novel stopping criterion is introduced to stop the vessel segmentation which helps to achieve high accuracy. An accuracy of 97.4% with average AUC of 0.975 is achieved by iteratively segmenting the image for up to t=5 iterations where maximum accuracy is obtained. The iteration is stopped at t=5 because after that the image is over segmented. This is found using the accuracy value of the image at each iteration.

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Author Profile

Ms. J.Kanimozhi pursed Bachelor of Engineering from K.L.N.College of Information Technology, in 2005 and Master of Engineering from K.L.N.College of Engineering in year 2010. He is currently pursuing Ph.D. and currently working as Assistant Professor in Department of Electronic and Communication, K.L.N.College of Information Technology ,since 2006. He is a member of ISTE & IETE since 2012.

