A Novel Multi-Orientation Kernel for Retina Vessel Detection

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Abstract: Retina is a thinnest tissue comprises of millions of blood vessels. It plays a vital role in the human eye that carries the visual signals to the brain for the interpretation. Any damage to the blood vessels in the retina causes serious issues related to the vision and it leads to the chronicle eye diseases like glaucoma, macular degeneration, diabetic retinopathy etc. Diabetic Retinopathy (DR) is a threatening disease among the diabetic patients in the recent years. Damage to the blood vessels causes DR. As the number of diabetic patients are comparatively high these days, it has become mandatory for the development of accurate system for segmenting the blood vessels in the retina which will reduce the work load of ophthalmologists to a greater extent. In this work we propose a novel technique named Multi-Orientation Kernel (MOK) for blood vessel detection. We also propose a framework for segmentation of retina blood vessels which follows the sequence of steps such as preprocessing, blood vessel extraction using proposed kernel (MOK) and refinement usingActive Contour method. This proposed method is tested on DRIVE and CHASE_DB1 dataset. The proposed algorithm produced 95% of accuracy on DRIVE datasetand 96% of accuracy on CHASE_DB1 dataset respectively. The performance of proposed approach is compared with few existing techniques.

Keywords: *Kernel, retina, Blood vessels, Segmentation, Active Contour, Detection*.

1.Introduction

Human eye is made up of millions of arteries and veins. Blood vessels in retina consists of multiple branches that carries blood to all parts of the eye. These vessels in the retina look like a thin hair like structure. Segmentation of blood vessels plays a significant role which helps ophthalmologists for identifying different types of eye diseases like cataracts, macular edema, glaucoma, diabetic retinopathy etc. Each retinal disease has different symptoms and disorder ranging from mild defects to severe defects causing blindness. Because of the increase of diabetic patients day by day, diabetic retinopathy has become a vision threatening disease among the patients with diabetic retinopathy and therefore the demand for the automated system has also increased which reduces the workload of the physicians. When there is a mild defect, it is necessary for the eyes to be checked and take treatment. In mild defect, the conditions may benign, but in severe cases it may lead to serious issues. Early detection and treatment is important for diabetic retinopathy. In the earlier stage, laser treatment can be given to patients to avoid the damage to the blood vessels, because the advanced stage of this disease causes total blindness. Manual screening is always a difficult and challenging tasks for the ophthalmologists in diagnosing eye diseases. The type of an image acquired as well as the quality of an image, also decide the accuracy of blood vessel segmentation. Features like length of the vessel, reddish spots on the vessels and branches of blood vessels are extremely difficult to segment manually. Before applying the segmentation techniques most of the images require preprocessing step which enhances the quality of the image thereby improving the accuracy of segmentation.

1.1 Motivations

A study suggests [1], 285 million people have visual defect globally. In the year of 2020, there were about 12,000 ophthalmologists for 135 billion people, in India. It is observed that there exists one ophthalmologist for 90,000 people. There is a higher demand for ophthalmologists throughout globally. It is expected to be 25,000 but still our Nation has only 12,000 specialists to treat eye deformities. Manual screening is always a time consuming process. Computer Aided Diagnosis (CAD) system reduces the amount of workload of ophthalmologist in diagnosing the retinal disease. Motivated by this fact, we propose a novel Multi-Orientation Kernel for retina vessel detection and a framework for vessel segmentation which can also be used for CAD system development.

1.2Issues and Challenges in Retinal Image Analysis

- The major issue in retinal image analysis is the quality of the image captured. Some cameras are subject to significant amount of noise which are used for acquiring the retina images. The quality of the camera is taken into account. The captured image must be of high quality for image analysis. Noise may be produced if the camera is not a quality one.
- Another important issue in retinal image is about the movement of eye ball of a patient while capturing the image. During funduscopic examination some patients are not able to co-operate due to anxiety. Because of the abnormal movement of eye ball and non-cooperation of the patients, ophthalmologist might acquire a blurred image of retina.

- Moreover, the blood vessels in the human eye are very tiny in nature. Because of the thin and tiny structure of the vessels, it is always a challenging task in segmenting the tiny vessels correctly.
- Because of the high illumination in the image, some portions of the image might appear to be more bright compared to other portions. In such cases, it will be quite difficult to extract the blood vessels.
- Along with the above issues mentioned, blood vessels in retina possess a non-uniformity in its width. The origin of the blood vessels are thick in nature whereas the end points in the branches of the retina are very thin in nature. Hence the extraction of thin vessels is quite difficult process compared with the extraction of thick vessels.

1.3 Contributions

The following are the contributions made in accordance with the proposed work

(i)A Multi-Orientation Kernel (MOK) is proposed for detection of blood vessels from the retina image.

(ii) A framework is proposed for retinal blood vessel segmentation which includes sequence of steps such as preprocessing, blood vessel detection using proposed technique MOK and refinement using Active Contour method.

(iii) Performance of the proposed technique is tested on DRIVE and CHASE_DB1 dataset for retina blood vessel segmentation. Comparative analysis is carried out with the existing techniques for blood vessel segmentation is done.

2.Literature Review

Zhao et al. [2] presented an Active Contour segmentation method using the region details of retina which includes the boundary features of the retina, length of the blood vessels etc. Zhao et al. [3] proposed a technique of saliency detection method to detect the blood vessels from the Region of Interest (ROI).Karn et al. [4] presented a method which used Gradient Vector Flow (GVF) to segment the blood vessels. Bottom hat transformation is used so the edge details of the retina is preserved. Along with GVF method, snake model and balloon model of Active Contour technique is used to produce better results. Al-Diri et al. [5] presented a method which uses 4 contour to acquire the width of the blood vessels. Morphological filter technique is used to locate the vessel centerlines.Badsha et al. [6] used different preprocessing techniques for noise removal and enhancing the quality of the image. Standard Kirsch template used for vessel detection. Bajčeta et al. [7] used Ant Colony Optimization (ACO) technique for segmenting the blood vessels. In this method, the features are extracted from the image. The movement of ants' is considered here for extracting the vessels. Lermé et al. [8] proposed a model which treated blood vessels as curves. Using these curves the centerline of the blood vessels are detected. Then a deformable model along with parallelism constraint is applied to extract the vessels. Liskowski et al. [9] proposed a supervised deep learning technique for extracting the blood vessels. Different preprocessing techniques like contrast enhancement, gamma correction method are applied to the retinal image. Structure prediction of blood vessels are done using deep learning so that blood vessels are extracted. Mendonca et al. [10] proposed a method in which the extraction of blood vessels starts from the centerline pixels. Then the connected components are identified from the center pixel of the blood vessel. Ozkava et al. [11] presented a method to extract the blood vessels using morphological operators. Adaptive thresholding along with Gaussian window is applied to the blood vessels to estimate the length of the vessels. Weiner filter is applied to retinal image followed by the morphological operator to segment the vessels from the retina. Zhao et al. [12] proposed a region growing method to segment the vessels from retina. In this method, the author used 2D Gabor wavelet for image enhancement. On the enhanced image, active contour based region growing method is applied to extract the blood vessels. Chen et al. [13] used a hybrid method of Active Contour model for extracting the vessels. Local intensity property technique is used for the segmentation. Shrichandran et al. [14] proposed a method named Quantum Evolutionary Algorithm (QEA). In this method, Gabor filter and Frost filter are used for preprocessing. Snake model of Active Contour method is used for the efficient segmentation of blood vessels from the retina. Bhadauria et al. [15] used Kirsch's template for segmenting the blood vessels from the retina. It employs 8 filters in all directions using compass rotation technique. Pan et al. [16] used a technique named as KDABC algorithm which used K-means algorithm for finding the initial honey cluster. Starting from the initial honey cluster and depending on the number of iterations the blood vessels are segmented. Yang et al. [17] proposed a hybrid technique which uses morphological operations for smoothening process. Fuzzy clustering algorithm is used for segmentation.Yavuz et al. [18] proposed a technique which uses Gabor and Gaussian filters for enhancing the retinal image. On the enhanced image, K-means algorithm and Fuzzy C-Means algorithm is applied to obtain binary vessel map and vessels. Dash et al. [19] proposed a technique which used CLAHE for image enhancement. Blood vessels in the retina is extracted using ISODATA technique. Dash et al. [20] proposed a technique which used CLAHE and anistrophic diffusion filter for enhancement. For segmentation, the author used Kirsch template and morphological cleaning operation. Soomro et al.[21] used filtering methods to balance the background noise and uneven illumination. The blood vessels are extracted using double thresholding technique and region growing method. Gou et al.[22] proposed a technique which used a dynamic scale allocation scheme along with filters for enhancement.

The scales are selected by applying a Gaussian filter on sub images there by the blood vessels are extracted. Halder et al.[23] used morphological operations for extraction of blood vessels. Using morphological filters, the connected component of the vessels which have lesser pixel width than the actual pixelwidth are removed. Sutanty et al. [24] used a combination of median filter and Gaussian filter is used to locate the bifurcation point of blood vessels. The common pixel intensities are taken as parameters for extraction of blood vessels in retina.Dash et al.[25] used CLAHE for contrast enhancement. For segmentation of blood vessels, morphological filtering operations are used followed by a hysteresis thresholding. Latib et al.[26] extracted green channel for enhancement. Vessels are extracted using bit plane slicing technique followed by Ostuthersholding.Chouchene et al. [27] proposed a technique which uses mathematical morphology operations along with entropy information for extraction of blood vessels. Hysteresis thresholding technique is applied on the extracted entropy informationpreserving the smoothness and spatial coherence of the pixels. Ramos-Soto et al. [28] used filtering for image smoothing. For segmentation, the author used top hat filtering, median filter, matched filter. Cuevas et al.[29] used lateral inhibition for enhancement. Differential Evolution technique with a threshold value is used to find whether the pixel is a vessel or a non-vessel. Cross entropy minimization is used to extract the vessels.

3. Methodology

In general, segmentation is carried out using either by similarity property or discontinuity property of the image. Edge detectors are developed using the discontinuity characteristics. In this work, we propose a technique which follows the concept of edge detection for extracting the blood vessels.In the following Section 3.1, the different edge detectors that are commonly used for edge detection is discussed. Then, the proposed Multi-Orientation Kernel is presented.

3.1Background

Detection of blood vessels is always a tedious and time consuming process. In general, there exists few image processing techniques and different edge detectors for extraction of retina blood vessels. In this work, we focus on edge detection techniques.The techniques that are used for blood vessel extraction and its drawbacks are discussed in the following sections

a.Thresholding technique:

A simple method for blood vessel extraction can be done using thresholding technique. Since there is a intensity difference between the ROI and non-ROI of retina imagea single threshold value is used for segmenting the blood vessels. Anyhow, tiny blood vessels may be missed out when we use a single thresholding technique.

b. Sobel edge detector:

Sobeledge detector uses two convolution masks S1 and S2 for edge detection. Magnitudes in Sobeledge detector is of non-uniform in nature. This detector fails to detect the tiny edges comparatively. Though the computational time is less in Sobel operator, it does not produce accurate results for images with noise. For complex images, this operator produces blurred results with overlapped edges. Fig.1 represents the convolution mask of Sobel Operator.

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

(a)

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

(b)

Fig. 1 (a) Convolution mask for Horizontal line detection (b) Convolution mask for Vertical line detection

Sobeledge detector uses two 3x3 kernel for detecting the edges out of which, one kernel detects vertical line and other detects horizontal line. Retina of human eye contains branches of blood vessels which will not be always vertical or horizontal. Hence Sobel operator can miss the edges which are neither horizontal nor vertical.

c. Canny edge detector:

Canny edge detector also uses two convolution masks. One mask is used for detecting the horizontal edges and other masks is used for detecting vertical edges. It does not gives a good approximation of rotational symmetry. In this edge detector different orientations are not considered. Double thresholding technique is used so that time complexity and computational complexity is comparatively high in Canny operator. Weak edges and edges which are not connected to strong edges are suppressed and becomes difficult to identify.

d. Kirsch's Kernel

Kirsch's kernel was proposed by Kirsch [32]which can be used for edge detection using predetermined directions. This kernel considers 8 different orientations. This kernel works well for the images for which foreground and background regions are distinct. Noisy images does not produce better results while using this 3x3 kernel. Fig. 2 represents the different orientations for detecting the edges using 3x3 kernel.

5	5	-3
5	0	-3
-3	-3	-3

a)

5	5	5
-3	0	-3
-3	-3	-3

b)

-3	5	5
-3	0	5
-3	-3	-3

c)

-3	-3	5
-3	0	5
-3	-3	5

d)

-3	-3	-3
-3	0	5
-3	5	5

e)

-3	-3	-3
-3	0	-3
5	5	5

f)

-3	-3	-3
5	0	-3
5	5	-3

g)

5	-3	-3
5	0	-3
5	-3	-3

h)

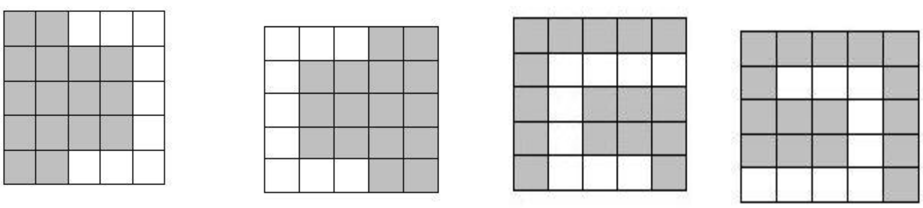
Fig. 2 (a) - (h) Different orientations for detecting the edges using 3x3 kernel.

3.2 Proposed Technique:

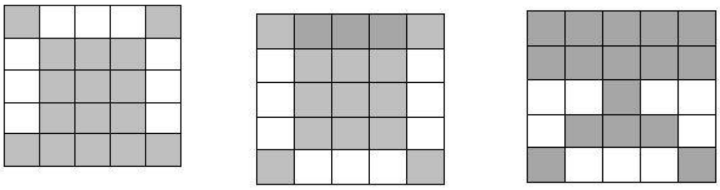
In general, the retina of a human eye contains more number of blood vessels which follows the branch like structure and looks very thin in nature. From the analysis of existing methods it is found that edge detectors such as Sobel and Canny focuses on two directions such as vertical and horizontal. But the retina blood vessels contains curvature shaped blood vessels in nature. Due to the existence of different intensity edges, global thresholding method is not suitable one for blood vessel detection. It is understood that still there is a need for an efficient method to detect the blood vessels without missing any tiny vessels of retina image. By understanding the need, an edge detection based technique for retina image is proposed in this work. Edge detection based technique works well for the medical images like lungs, retina, heart etc. which have curved or closed type of ROI.In this work, the following steps are followed for detecting the blood vessels of retina images.

(i) Generate the Multi-Orientation kernel.
(ii) Convolve the kernel with an image.
(iii) Detect the vessels using maximum responses.

We consider different orientations in designing the proposed kernel for retinal vessel detection. This proposed technique reduces the false detection of the blood vessels to a greater extent. This work helps in preserving the continuity of the blood vessels in the image. The results can be obtained faster if we have lesser kernels, but for an accurate vessel detection at least 7 such kernels are required. The number of kernels can be increased but the computation time also increases. Hence the proposed method namely 'Multi-Orientation Kernel'uses a 5x5 size window for detecting the blood vessels in the retina by considering all possible directions so that most of the vessels will be detected.The directions used for vessel detection are predetermined for detecting the blood vessels. The 7 kernels are obtained by taking one kernel and it is made to rotate in 7 major orientations like right, left, left middle, right middle, top, bottom and bottom middle in 45^0in clockwise and anti-clockwise direction and the responses are measured. A 5x5 kernel which considers 7 orientations which are circumflex in nature is illustrated in Fig.3



a) b) c) d)



e) f) g)

Fig. 3 A 5x5 kernel for seven orientations a)Right circumflex b) Left circumflex c) Left middle circumflex d) Right middle circumflex e) Top circumflex f) Bottom circumflex g) Bottom middle circumflex

The centre pixel intensity of the kernel is taken as 0. In each kernel, depending upon the orientation, the co-efficient in the kernel can be either positive or negative. In Fig. 3 the darker cells of the kernel contains the weighted co-efficient of -3 and the brighter cells contains 5 as the weighted co-efficient. In short, the darker cells contains negative values and the brighter cells contains positive values. It is clearly differentiated for each orientations such as right, left, left middle, right middle, top, bottom and bottom middle. The co-efficient of the kernel is balanced when the window size is 5x5. The co-efficient which contains negative value helps to suppressthe unwanted portion and the positive values helps to retain blood vessels. The final edge is estimated by identifying the maximum response of all the seven orientations. By convolving with multi-orientation kernel, the edges are identified.The response of the kernel are calculated as follows:

$$U(1)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(1)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(1)$$

$$U(2)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(2)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(2)$$

$$U(3)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(3)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(3)$$

$$U(4)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(4)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(4)$$

$$U(5)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(5)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(5)$$

$$U(6)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(6)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(6)$$

$$U(7)_{a,b} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} w(7)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(7)$$

The general form of Multi-Orientation Kernel may be written as follows

$$U(k)_{a,b} = \sum_{i=-r}^{r} \sum_{j=-r}^{r} w(k)_{i,j} * f_{a+i,b+j} \qquad \dots\dots..(8)$$

where w represents the Multi-Orientation Kernel for k^{th}orientation and f represents the co ordinates of the pixel and r represents the radius which can take the value of 3,5,7 and so on. Based on the radius (r) the size of the kernel will vary. When r=1 the size of the kernel will be 3x3 and when r=2 the size of the kernel will be 5x5 and so on.

The threshold which plays an important role in detecting the blood vessels. A threshold value is used in this kernel for estimating the edges. The threshold value helps to select the best value (maximum value) among the 7 responses obtained for 7 different orientations. The threshold value is set as 5 in this kernel. Upon trying with the threshold 3, there are so many discontinuity of blood vessels. Most of the blood vessels are missed out. The accuracy obtained using this technique is comparatively low. When the threshold is set as 7, it produced results with more noise. Portions which are not identified as blood vessels are also extracted. The threshold 3 and 7 does not produce promising results and hence the threshold has been made to be 5 throughout the process.

Among all the responses for 7 orientations, the maximum value is considered as the best response for detecting the blood vessels using Equation (9)

$$Z_{a,b} = \max\left(U_{(k)}\right), \quad \text{....}(9)$$

where k ranges from 1 to 7.

3.3 Framework for retina blood vessel segmentation using MOK:

In this work, we propose a framework for blood vessel segmentation using Multi-Orientation Kernel.The following Fig. 4 represents the process flow diagram of the proposed framework.

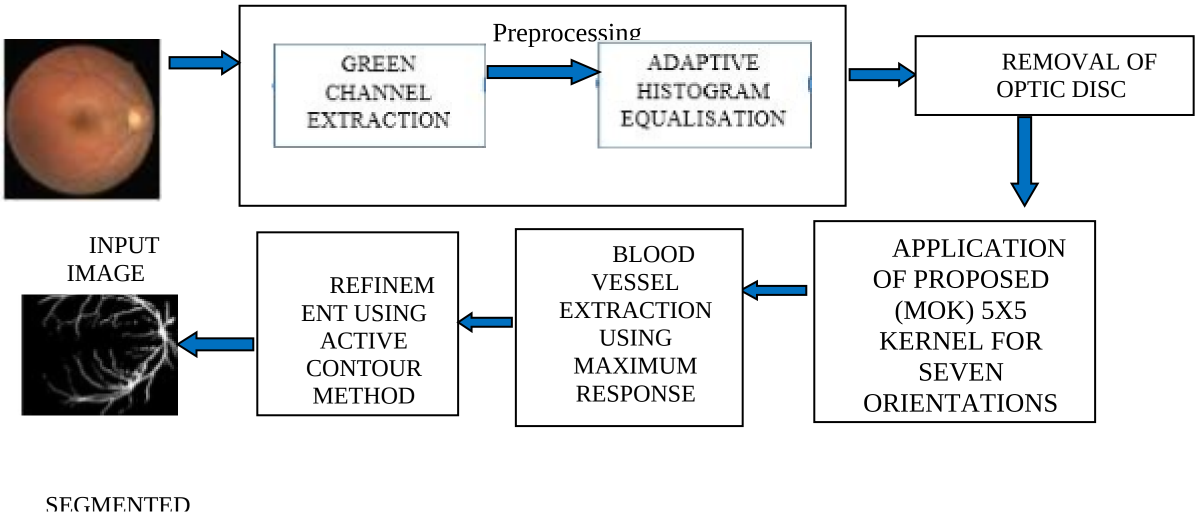


Fig.4 Overview of the framework

The proposed framework includes the extraction of green channel from the retinal image, application of adaptive histogram equalization for contrast enhancement, removal of optic disc, followed by extraction of blood vessels using the proposed technique "Multi-Orientation Kernel" and for further refinementActive Contour method is applied to get the segmented blood vessels. The steps involved in this framework are clearly explained in the following sections.

3.3.1Preprocessing techniques

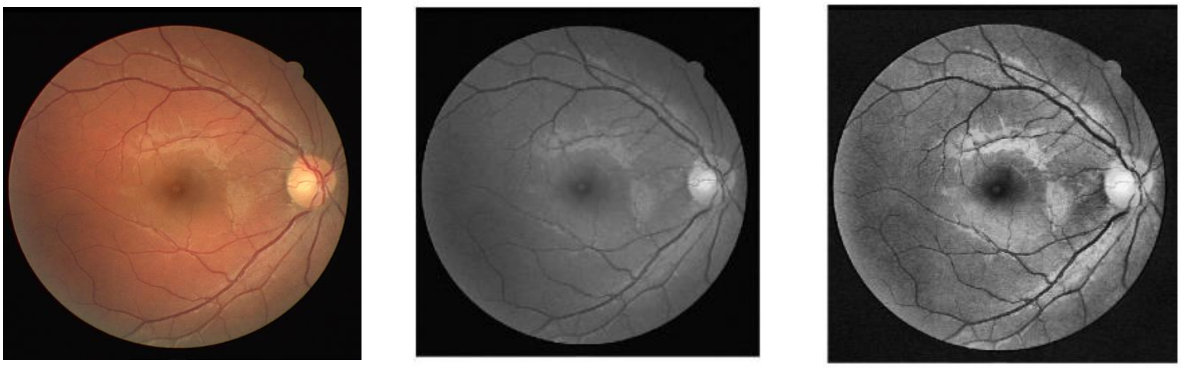
Enhancement in any type of image brings out the very finer information about the image which helps in obtaining the important characteristics of the target image.Preprocessing contains two processes namely green channel extraction and enhancement of the image using CLAHE method.

a) Green channel extraction

The retina images captured using fundus camera are RGB format in nature. They are also of non-uniform illumination and low in contrast. Red and blue channels of retinal image consists of more noise.Green channel is found as the suitable channel for retina image analysis. Due to high contrast, fine details like micro aneurysms and tiny blood vessels are clearly seen in green channel. For extracting the blood vessels, the green channel of the image is extracted.During green channel extraction, the images are converted to a gray scale image. From Figure 5,it is clear that blood vessels are prominently seen in green channel of the retinal image.

b)CLAHE

Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied on the extracted green channel of the image to improve the contrast so that the blood vessels in the retina are clearly visible. Fig.5 represents the green channel extraction and contrast enhanced retina image which is taken from DRIVE dataset ('37_training.TIF').



a) b) c)

Fig. 5 Preprocessing a) Original Image b) Green channel extraction c) Contrast enhanced image of retina using CLAHE

3.3.2Removal of Optic disc

For further processing, it is necessary to approximate the optic disc from the retina and to remove it from the image for which the morphological operation is used. Morphological operation is performed on the input image with suitable shapes. In this method,disk shapeand radius are taken as parameters to approximate the optic disc inside the retina, followed by the bottom hat operation. Bottom-hat processis also one of the operation which helps to connect the discontinued regions by means of closing operation. The closing operation is defined as $(A \ominus$. The output from this operation is subtracted from the original image as given in Equation(11)

$A.B = A - (A \ominus$ ..... *(11)*

where A is the input image and B is the structuring element.

3.4 Blood vessel extraction using MOK:

The blood vessels are extracted using the proposed Multi Orientation kernel. The following are the steps involved in the extraction of retinal blood vessels.

Input: Pre- Processed retina image

Output: Extracted blood vessels.

Step 1: Take 5x5 sub images from the input image

Apply Multi-Orientation Kernels on the sub image using.

$$U(k)_{a,b} = \sum_{i=-r}^{r} \sum_{j=-r}^{r} w(k)_{i,j} * \ f_{a+i}$$

Step 2: Find the maximum response among the responses for seven orientations. Replace the center pixel value by maximum value

$$Z_{a,b} = \max(U$$

Step 3: Repeat the steps 1 and 2 for the complete image using

Sliding window concept.

3.5Refinement using Active Contour Method

In this work, the image after applying multi-orientation kernel will be given as an input for Active Contour method. For further refinement Active Contour method uses energy sources and constraints to group the pixels. This method considers two energies namely internal energy and external energy as given in Equation (12) and (13) respectively. It helps to group the pixels based on the similarity.Active Contour methodworks based on the principle of energy minimization.The grouping of pixels will be stopped at one point where the pixel intensity convergence. At that particular point, the energy will be minimized. The energy includes internal force of energy and external force of energy.

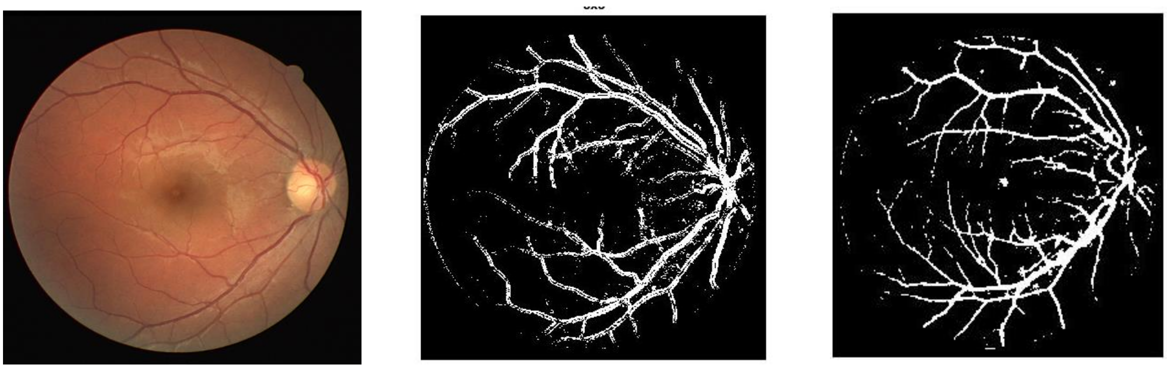
$$min_{\varepsilon} = \int_{\varepsilon} E_{external} \ ((r(s))ds \qquad ...(12)$$

$$min_i = \int_s E_{internal} ((r(s))ds \quad .. (13)$$

$$min \to J_{s=}(min_e + mi \quad ... (14)$$

The convergence point will be calculated using the external energy and internal energy as given in Equation (14).

In this work, E_{exter} and E_{inter} are the energies that are calculated from the blood vessels in the retinal image which is obtained using the Multi-Orientation kernel.The convergence starts from two points of discontinuity regions (starting and ending) and converges at one point. This process is repeated until all possible edges in the retinal vessels are detected or all discontinued edges are connected. Fig 6 represents the output of 5x5 kernel and output obtained after applying Active Contour for refinement.



a) b) c)

Fig6 Refinement a) Original Image b) Output of 5x5 kernel c) Output after refinement using Active Contour method

4. Experimental Results and Performance Analysis

In this section we explained about the dataset used in this work and the performance metrics that are used for the evaluation of proposed technique and experimental results.

4.1 Dataset

Dataset is a collection or a repository of raw data or a processed data. Various retina datasets are available for research purposes. The dataset used in this work is DRIVE[30] and CHASE_DB1 [31] for blood vessel segmentation. DRIVE dataset is the most commonly and widely used dataset for retinal image analysis. This dataset contains 40 images under training and testing samples along with ground truth images. CHASE_DB1 dataset contains 28 images of 14 patients which includes both left and right eye of a patient. In this work, we used both datasets DRIVE and CHASE_DB1to analyse the performance of the proposed work.

4.2 Performance metrics

Performance metrics ensures the accurate segmentation of blood vessels in the Region Of Interest (ROI).The proposed technique and framework are used for segmenting the blood vessels of retina images. The metrics such as accuracy, sensitivity, specificity, precision and f_measure are considered for evaluation of proposed techniques. The parameters like True Negative (TN), True Positive (TP), False Positive (FP) and False Negative (FN) of segmented output are taken into account. The formula for performance metrics are given as follows:

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN} \quad ... (15)$$

$$Sensitivity(SE) = \frac{TP}{TP + FN} \quad ... (16)$$

$$Specificity = \frac{TN}{TP + FN} \quad ... (17)$$

$$Precision(PR) = \frac{TP}{TP + FP} \quad ... (18)$$

$$F1\ Measure = \frac{2.PR.SE}{PR + SE} \quad .. (19)$$

4.3 Experimental Results:

The proposed technique and the framework are tested on DRIVE and CHASE_DB1 dataset for retina blood vessel segmentation. In this first experiment, we tested the 3x3 kernel on CHASE_DB1 dataset. Then the same experiment is conducted with 5x5 size kernel.

4.3.1 Performance analysis of 3x3 kernel on CHASE_DB1 dataset

The 3x3 kernel looks similar to that of Kirsch template [32]. Initially the 3x3 kernel is tested for CHASE_DB1 dataset and further testing is done on the same dataset using 5x5 size kernel. The 3x3 kernel is applied on CHASE_DB1 dataset which contains 28 images of 14 patients. The resultsare obtained using 3x3 kernel for the images in CHASE_DB1 is tabulated in Table 1. The metrics accuracy, sensitivity, specificity are estimated using the ground truth images acquired by the first observer and second observer respectively.

Table 1 Performance analysis of 3x3 kernel on CHASE_DB1 dataset.

INPUT IMAGE	First Observer			Second Observer		
	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
Image_01L	84.42	58.72	86.35	84.27	58.11	86.11
Image_01R	84.63	55.02	87.06	84.62	55.93	86.56
Image_02L	82.30	57.95	84.45	82.20	59.66	83.67
Image_02R	82.76	56.24	85.01	82.94	59.16	84.53
Image_03L	82.08	61.82	83.81	82.07	65.30	83.14
Image_03R	82.97	55.63	85.20	83.41	60.86	84.84
Image_04L	84.02	53.87	86.58	83.97	54.13	86.14
Image_04R	83.18	50.38	85.92	83.48	53.15	85.29
Image_05L	80.62	58.99	82.48	80.76	62.81	81.93
Image_05R	82.27	62.10	84.15	82.02	63.25	83.39
Image_06L	83.80	53.60	86.27	84.16	57.60	85.84
Image_06R	82.90	56.37	85.05	82.93	57.30	84.78
Image_07L	83.03	60.73	84.91	82.97	61.31	84.63
Image_07R	83.44	60.49	85.33	83.29	59.67	85.19
Image_08L	87.45	54.71	89.71	87.02	51.12	90.14
Image_08R	86.99	54.22	89.21	86.88	53.21	89.32
Image_09L	89.92	56.01	91.73	89.93	55.35	92.07
Image_09R	90.53	63.03	92.01	90.69	63.55	92.27
Image_10L	85.87	55.98	87.87	85.64	53.16	88.52
Image_10R	83.97	55.09	85.88	83.79	53.22	86.07
Image_11L	86.84	58.98	88.41	86.92	58.83	88.67
Image_11R	89.43	55.83	91.32	89.29	53.99	91.6
Image_12L	84.69	51.37	87.28	84.62	50.79	87.52
Image_12R	81.68	63.43	83.13	81.7	62.16	83.45
Image_13L	87.6	53.25	89.85	87.64	53.44	89.95
Image_13R	89.28	49.55	91.96	89.06	47.91	92.01
Image_14L	81.74	65.84	82.92	81.66	64.81	82.95
Image_14R	85.66	52.73	87.71	85.47	51.00	87.88
MINIMUM	80.62	49.55	82.48	80.76	47.91	81.93
MAXIMUM	90.53	65.84	92.01	90.69	65.30	92.27
AVERAGE	84.78	56.85	86.84	84.76	57.17	86.73

On applying 3x3 kernel, an accuracy of more than 80% is obtained in first_observer and second_ observer respectively.

4.3.2 Performance analysis of 5x5 kernel on CHASE_DB1 dataset

The proposed 5x5 kernel is applied on CHASE_DB1 dataset which contains 28 images of 14 patients. The results are obtained using 5x5 kernel for the images in CHASE_DB1 is tabulated in Table 2. The metrics accuracy, sensitivity, specificity are estimated using the ground truth images acquired by the first observer and second observer respectively.

Table 2 Performance analysis of proposed Multi-Orientation 5x5 kernel on CHASE_DB1 dataset

INPUT IMAGE	First Observer			Second Observer		
	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
Image_01L	93.47	79.08	94.48	93.01	76.36	94.15
Image_01R	93.89	71.91	95.63	93.44	71.36	94.96
Image_02L	91.40	82.30	92.16	90.49	83.47	90.94
Image_02R	91.79	77.32	92.94	91.15	77.00	92.10
Image_03L	93.46	87.20	93.95	92.21	85.75	92.61
Image_03R	94.73	76.38	96.17	93.75	74.09	94.99
Image_04L	94.42	78.03	95.77	93.55	74.93	94.91
Image_04R	94.18	78.01	95.46	93.43	80.05	94.23
Image_05L	93.47	82.70	94.37	92.53	83.20	93.14
Image_05R	94.34	84.94	95.17	93.20	83.51	93.90
Image_06L	93.68	71.39	95.42	93.51	73.94	94.79
Image_06R	93.09	78.71	94.17	92.14	72.45	93.58
Image_07L	93.46	77.45	94.74	93.01	74.91	94.43
Image_07R	93.24	77.56	94.46	92.46	71.24	94.19
Image_08L	91.85	80.06	92.64	91.79	72.83	93.46
Image_08R	92.89	85.25	93.40	92.79	81.02	93.65
Image_09L	90.71	82.55	91.13	91.04	80.19	91.71
Image_09R	90.73	80.71	91.24	90.93	78.26	91.67
Image_10L	89.37	81.92	89.83	89.25	71.77	90.83
Image_10R	90.41	85.67	90.70	90.20	77.62	91.14
Image_11L	87.44	90.25	87.29	87.58	85.63	87.70
Image_11R	91.80	81.46	92.36	92.25	80.39	93.01
Image_12L	93.41	73.97	94.87	93.25	70.13	95.24
Image_12R	92.26	87.61	92.61	91.88	79.74	92.98
Image_13L	93.43	69.46	94.98	93.24	67.07	95.02
Image_13R	94.00	67.14	95.75	93.20	59.68	95.63
Image_14L	93.93	81.11	94.87	93.74	78.69	94.89
Image_14R	94.36	73.88	95.63	93.86	67.28	95.75
MINIMUM	87.44	67.14	87.29	87.58	59.68	87.70
MAXIMUM	94.73	90.25	96.17	93.86	85.75	95.75
AVERAGE	96.45	79.43	93.65	92.25	76.16	93.41

In this experiment, 5x5 kernel is applied for all the 28 images of CHASE_DB1 dataset. On applying 5x5 kernel, an accuracy of more than 90% is obtained in first_observer and second_ observer respectively. The accuracy obtained using 5x5 kernel is comparatively higher than 3x3 kernel.

4.3.3 Comparison of proposed technique (MOK) with existing methods:

The proposed method is compared with the existing segmentation methods proposed by different researchers. Table 3 specifies the comparative analysis of results obtained from other methodologies over the proposed method. The results of the proposed method obtained from CHASE_DB1 dataset is compared with the existing techniques in terms of accuracy, sensitivity, specificity, precision, F1_measure.

Table 3 Comparative analysis of proposed method with existing techniques on datasetCHASE_DB1

CHASE_DB1	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)	PRECISION (%)	F1_MEASURE (%)
Orlando et al. [33]	-	72	97	74	73
Biswal et al. [34]	-	76	97	76	75
Roychowdhury et al. [35]	94	75	96	-	-
Zhang et al. [36]	96	77	98	-	-
Fan et al. [37]	95	65	97	-	-
Proposed Method	**96**	**79**	**93**	**75**	**76**

The results of the proposed method obtained using DRIVE dataset is compared with the existing techniques in terms of accuracy, sensitivity, specificity, precision, F1_measure. It is observed from the results that the proposed method outperforms other methods in terms of sensitivity. The performance of the proposed technique is superior tothe technique used in [35] and [37] in terms of accuracy and equivalent to the technique used in [36] which produced the accuracy of 96 as proposed method. As far as specificity metric is considered the proposed method is inferior.

Table 3 Comparative analysis of proposed method with existing techniques on dataset DRIVE

DRIVE	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)	PRECISION (%)	F1_MEASURE (%)
Zhao et al. [1]	95	74	98	-	-
Biswal et al. [34]	95	71	97	84	78
Fraz et al. [38]	94	71	97	82	76
Fraz et al. [39]	94	73	97	81	76
Odstrcilik et al. [40]	93	70	96	-	-
Proposed Method	**95**	**75**	**98**	**73**	**74**

Orlando et al. [32] used conditional random field model for segmentation of blood vessels. The performance is measured in terms of sensitivity and specificity only. Accuracy is not considered for evaluation. This method works well for long elongated structure of blood vessels, whereas thin vessels are not extracted here. Biswal et al. [33] used multi scale line detectors for extracting the blood vessels. This method works well for high resolution retinal images rather than blurry images. Roychowdhury et al. [34] used an iterative method of vessel segmentation technique. The drawback of this technique is that, as the iterative process starts some of the false edge pixels are also identified as true edges and so the accuracy is less when compared to other existing techniques.Odstrcilik et al. [39] used matched filtering technique for segmentation of blood vessels. This technique does not produce promising results in segmentation. On observing the results of 3x3 kernel, it does not produce promising results for CHASE_DB1 dataset. 3x3 kernel concentrates on the thicker blood vessels. On the other hand 5x5 kernel used 7 orientations for processing all the corners of the retina so that most of the thin and thick blood vessels are extracted. Curved shaped edges in the retina are also covered. Thinner blood vessels present in the retina are also extracted. This kernel rotates in all possible directions in clockwise and anti-clock wise direction thereby detecting the blood vessels correctly. It produced better accuracy results on CHASE_DB1 data set. The results obtained from the proposed technique MOK is refined using Active Contour method. The difficulty in finding the thinner vessels by the human observers are resolved using this technique. All the boundaries and major portions of the retina are covered using 5x5 kernel compared with 3x3 kernel. This 5x5 kernel produced higher accuracy in CHASE_DB1 dataset and higher specificity in DRIVE dataset.

5.Conclusion

The proposed technique uses A Multi-Orientation Kernel (MOK) for extraction of blood vessels from the retina. A framework is proposed for retinal blood vessel segmentation which includes sequence of steps such as preprocessing, blood vessel extraction using proposed technique MOK and refinement using Active Contour method. The proposed technique has been tested on two publicly available datasets such as DRIVE and CHASE_DB1. A 3x3 kernel is tested on CHASE_DB1 dataset which produced 85% of accuracy, 57% of sensitivity and 87% of specificity. For improving the performance, 5x5 kernel is tested on CHASE_DB1 dataset. The proposed MOK produced 96 % of accuracy, 79% of sensitivity and 93% of specificity on CHASE_DB1 dataset. On DRIVE dataset, the proposed technique MOK produced 95% of accuracy, 75% of sensitivity and 98% of specificity respectively. The proposed technique is compared with few existing techniques. Our proposed method produced promising results. The proposed algorithm here can be used for any type of medical images which contains oval or spherical shape ROI.

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