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An Automatic Detection of Optic Disc in Low Quality Retinal Images by Modified Directional Matched Filter

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Abstract

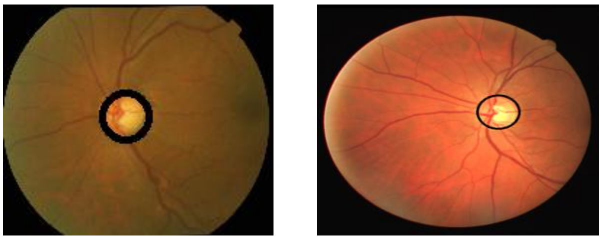
An Automatic Optic Disc detection in retinal images used to screen eye related diseases like diabetic retinopathy. Many techniques are available to detect Optic Disc in high contrast retinal images. Unfortunately, there are no efficient methods to detect Optic Disc in low-quality retinal images. The objective of this research paper is to develop an automated method for detection of Optic Disc in low quality retinal images. This paper proposed a modified directional matched filter parameters of the retinal blood vessels to localize the center of optic disc also made comparative analysis of our method with STARE and DIARETDB0 dataset. The proposed method was implemented in MATLAB and evaluated both normal and abnormal low quality retinal images using the subset of the DRIVE, MESSIDOR, STARE, DIARETDB0 and University of Lincoln and the success percentage was found to be an average of 98.82% for all datasets. This automated method helps ophthalmologists in the screening process of Diabetic Retinopathy to find symptoms and earlier detection of diseases in less computational time.

Index Terms—Diabetic Retinopathy (DR), Retinal Image Processing, Optic Disc, Blood Vessels, Morphological thinning.

I INTRODUCTION

Diabetic Retinopathy (DR) is a complicated eye disease, globally the primary cause of blindness due to diabetes. Based on survey 346 million people are affected by diabetes with more than 80% of people living in low and middle-income countries [1]. Now a day’s DR is common among people who are suffering from diabetes and that leads to blindness in the working population of the western countries for the age group of more than 40-50 years [2].

Optic Disc (OD) localization is an integral part of the screening system for DR. The optic disc is in a vertical oval shape with the horizontal and vertical average dimension of 1.76mm and 1.92mm respectively. It is located at the distance of 3 to 4mm from the nasal side of fovea [3].The dimension of optic disc varies from person to person but its diameter remains the same (80-100 pixels) for standard fundus image [4].The optic disc is a bright yellowish disc that transmits electrical impulses from retina to brain where the blood vessels and optic nerve fibre are present [5]. The Fig(1) shows that manual marking of OD by ophthalmologist. The manual methods graded by clinicians are a time consuming and resource-intensive process.



(a) **(b)**

Fig: 1.Manual marking of Optic Disc (a) left eye (b) right eye.
source :DRIVE dataset.

The Automatic detection process helps ophthalmologists for taking immediate decision of eye diseases. The aim of this paper is to develop an automatic detection of OD center in low quality retinal images with short computation time and high accuracy.

This paper organized as most of the available methods for automatic OD detection are reviewed in Section II. In Section III, a description of the material used is given. Section IV presents the proposed algorithm. The results and discussion are presented in section V and VI respectively. Finally, conclusion and further work are found in Section VI.

II OD DETECTION METHODS: A STATE-OF-ART

Recently several research has been done in locating the OD in retinal images. Rashid *et al.* [6] made a comparison of older OD detection methods and also made a comparative analysis of OD segmentation algorithms. This paper reviewed both older (Table I) and recent OD detection algorithms. Many OD detection algorithms are working for normal and healthy images. Deepli A.Godse *et al.* [7] proposed an ensemble based automated approach to detect OD and its center for both normal and abnormal retinal images.

Jun Cheng *et al.* [8] proposed optic disc and optic cup segmentation using super-pixel classification for glaucoma screening. In optic disc segmentation, histograms, and center surround statistics are used to classify each super-pixel as disc or non-disc. A self-assessment reliability score is computed to evaluate the quality of the automated optic disc segmentation. For optic cup segmentation, in addition to the histograms and center surround statistics, the location information is also included into the feature space to boost the performance.

Jielin Zhang *et al.* [9] proposed an intelligent fusion of methods for the localization of the optic disk in retinal fundus images. Three different approaches are developed to detect the location of the optic disk separately. The first method is the maximum vessel crossing method, which finds the region with the most number of blood vessel crossing points. The second one is the multichannel thresholding method, targeting the area with the highest intensity. The final method searches the vertical and horizontal region-of-interest separately on the basis of blood vessel structure and neighborhood entropy profile. Finally, these three methods are combined using an intelligent fusion method to improve the overall accuracy

Amin Dehghani *et al.* [10] proposed two methods to localize center of OD. The first one is based on corners and bifurcations obtained using Harris corner detector, The second one is based on histogram of each color component as template.

Macular Edema (ME) is the major symptom of DR. Arturo Aquino *et al.* [11] presented two detection methodologies. On one hand, a location methodology obtains a pixel that belongs to the OD using image contrast analysis and structure filtering techniques and, on the other hand, a boundary segmentation methodology estimates a circular approximation of the OD boundary by applying mathematical morphology, edge detection techniques and the Circular Hough Transform.

Early detection of DR helps to minimize the risk of vision loss of diabetic patients. Vasanthi *et al.*[12] proposed a region-based active contour model which utilizes local image information around each point of interest in multi-dimensional feature space to provide robustness against variations found in and around the OD region. This model defines a local energy functional to achieve desired OD segmentation. This energy is minimized to OD boundary using level set method.

H. Yu *et al.* [13] proposed a OD location in which images are identified using template matching and model parameter estimation. The template is designed to adapt to different image resolutions. Then, vessel characteristics (patterns) on the OD are used to determine OD location.

Jaspreet kaur at al [14] developed a method to detect location of OD and its boundary. The OD location is done by optimum threshold and OD boundary is done by level s*et al.*gorithm methods.

Bob Zhang *et al.* [15] proposed a method to locate OD for Asians by applying Multiscale Gaussian filtering. This method complements current algorithms using two steps like OD vessel candidate detection and OD vessel candidate matching. The first step is achieved with multiscale Gaussian filtering, scale production, and double thresholding to initially extract the vessels' directional map of various thicknesses. The map is then thinned before another threshold is applied to remove pixels with low intensities. Thus result forms the OD vessel candidates. In the second step, a Vessels'

Directional Matched Filter (VDMF) of various dimensions is applied to the candidates to be matched, and the pixel with the smallest difference designated the OD center.

Lu and Lim[16] presents a line operator that is designed to locate the OD from retinal images accurately. Line operators have been used to locate linear structures from different types of images.

Gopal Datt Joshi *et al.*[17] presented an automatic OD parameterization technique based on segmented OD and cup regions obtained from monocular retinal images which integrates the local image information around each point of interest in multi-dimensional feature space to provide robustness against variations found in and around the OD region.

Jun Cheng *et al.* [18]proposed another method based on peripapillary atrophy elimination. The elimination is done through edge filtering, constraint elliptical Hough transform and peripapillary atrophy detection. With the elimination, edges that are likely from non-disc structures especially peripapillary atrophy are excluded to make the segmentation more accurate.

Goatman *et al.* [19] has demonstrated an automated system which is able to distinguish normal and abnormal vasculature on the optic disc. It could form part of a system to reduce manual grading workload or a tool to prioritize patient grading queues.

Gopal Datt Joshi *et al.* [20] presented another OD detection using disk parameters. A deformable model guided by regional statistics is used to detect the OD boundary. A cup boundary detection scheme is presented based on the appearance of pallor in Labcolour space and the expected cup symmetry.

Siddalingaswamy *et al.* [21] presented an automatic localization and accurate boundary detection of the optic disc. Iterative thresholding method followed by connected component analysis is employed to locate the approximate center of the optic disc.

Arturo Aquino *et al.* [22] presented a template-based methodology for segmenting the OD from digital retinal images. This methodology uses morphological and edge detection techniques followed by the Circular Hough transform to obtain a circular OD boundary approximation. It requires a pixel located within the OD as initial information. For this purpose, a location methodology based on a voting-type algorithm is also proposed.

Ahmed E. Mahfouz *et al.* [23] presented a technique that is based upon obtaining two projections of certain image features that encode the x- and y-coordinates of the OD. The resulting 1-D projections are then searched to determine the location of the OD. This avoids searching the 2-D image space and thus, enhances the speed of the OD localization process.

Wong D.K. *et al.* [24] proposed a concept based on a supervised learning scheme. The method employs pixel and local neighborhood features extracted from the ROI of a digital retinal fundus photograph. A support vector machine based classification mechanism is used to classify each image point as belonging to the cup and retina.

Balasubramaniyan *et al.* [25] proposed a novel method for BVD based on morphology. We subsequently utilize the method to localize the OD. In our localization of the OD, we use both heuristics in combination. Once the OD is localized, we make use of the method prescribed in [26] that homogenizes the region of the OD and employs the active contour to detect the boundary of the OD.

Based on the above review most of the researchers considered the OD as the brightest region within retinal image. However, this criterion may not be applicable for retinal images those include other bright regions because of diseases like diabetic retinopathy. Some papers considered the OD as the area with highest variation in intensity of adjacent pixels. Both the criteria considered for normal, healthy retinal images. This paper is proposed for both normal and abnormal low quality retinal images with less computation time and high success rate.

TABLE I RESULTS OF VARIOUS OD DETECTION METHODS

Author	**OD Detection method**	**Local**[a]	**STARE**[b]	**DRIVE**[c]
Deepali A Godse *et al.* [7]	An ensemble based approach	100%	-	100%
Jun-chang et el [8]	Super pixel classification	90.5%	-	-
Amin Dehghani *et al.* [10]	Histogram Matching	98.9%	91.36%	100%
Arturo Aquino *et al.* [11]	Edge detection and feature extraction technique	98.83%	-	-
Ashok kumar *et al.*[26]	Bit plane slicing	-	93.3%	-
Jaspreet kaur *et al.* [14]	Optimum threshold followed by level set algorithm	96.6%	-	-
Bob Zhang *et al.*[15]	Multi-scale Gaussian Filtering	99.25%	-	-
Lu and Lim[16]	Line filter approach	-	96.3%	100%
Goatman *et al.*[19]	watershed lines and ridge strength measurement	98.4%	-	-
Rangayan *et al.*[27]	Gabor Filters and Phase Portrait Analysis		88.9%	100%
Gopal Dutt Joshi *et al.*[20]	Active contour	-	96%	-
Siddalingasawamy *et al.* [21]	Highest average variation	99.1%	42%	-
Sekhar *et al.* [28]	Morphological operations	-	82.3%	94.4%
Fleming *et al.* [29]		-	98.4%	-
Balasubramaniyan *et al.* [25]	BVD based on morphology			
Niemeijer *et al.* [2]	kNN regression and a circular template	99.4%	-	-
Juan Xu *et al.* [30]	Deformation contour method	-	94%	-
Tobin *et al.* [31]	Vasculature related OD properties & Bayesian classifier	81%	87.7%	-

Abramoff *et al.*[17]	Vasculature related OD properties & kNN regression	99.9%	-	-
Park [30]	Hough transformation	-	-	90.25%
Frank ter Haar [34]	Resolution pyramid using a simple Haar-based discrete wavelet transform	89%	70.4%	-
Abdel-Ghafar *et al.* [35]	Circular Hough transfrom	No quantitative results reported		
Pallawala *et al.* [36]	Wavelet transform		94%	-
Lowell *et al.* [37]	OD Laplacian of Gaussian template	99%	-	-
Foracchia *et al.* [38]	A geometrical model of the vessel structure using two parabolas	-	98%	-
Li *et al.* [39]	Brightness guided, PCA model based	99%	-	-
Chrastek *et al.* [40]	Highest average intensity	97.3%	-	-
Osarch *et al.* [41]	Averaged OD-images model-based	100%	58%	-
Lalonde *et al.* [42]	Hausdorff-based template matching	100%	71.6%	-
Barrett *et al.* [43]	Hough Transfrom	-	69%	-
Walter *et al.* [44]	Largest brightest connected object	100%	58%	-
Sinthanayothin *et al.*[45]	Highest average variation	99.1%	42%	-
Hoover *et al.* [46]	Fuzzy convergence	-	89%	-
Jelinek *et al.* [47]	Boundary detection,Vessel classification	-	70%	-
Goldbaum *et al.*[48]	Blood vasculature convergence	No quantitative results reported		
Proposed method[d]	Modified directional matched filter	-	98.76%	100%

Local[a] : The success rates shown for local dataset are taken from the corresponding references.
STARE[b]: The success rates shows the STARE dataset are taken from the corresponding references.
DRIVE[c] : The success rates shows the DRIVE dataset are taken from the corresponding references.
Proposed method[d] : our proposed method result is shown in the last row with the highest success percentages in STARE are shaded in light gray.

III MATERIAL

We tested our proposed method by Five publicly available retinal dataset is as shown in Table II. Thus, is a set of 1559 images we identified 380 images as low quality using MATLAB Image Processing Toolbox based on intensity of the every images. Low quality images intensity range is rather narrow. It does not cover the potential range of [0, 255], and is missing the high and low values that would result in good contrast.

TABLE II RETINAL IMAGES DATASET

Dataset	Total no of images	No of low quality Images identified
DRIVE[49]	40	33
MESSIDOR[50]	1200	100
STARE[51]	81	56
DIARETDB0[52]	130	90
University of Lincoln[53]	108	101
Total	1559	380

III PROPOSED METHOD

The proposed method based on Youssif *et al.* [54]. Youssif developed a generalised method for detection of OD, this paper we modified matched filter kernel parameters for low quality images. This method consists of several steps. In particular, we divide this section in to three subsections which deal with retinal image pre-processing, modified directional matched filter and OD detection respectively. The schematic representation of the proposed method is follows Fig.3.1.

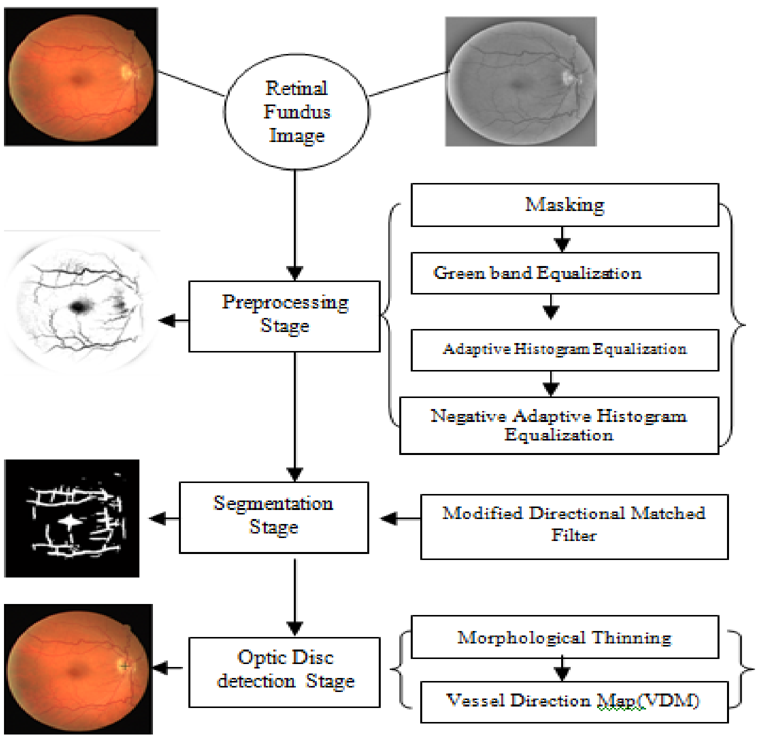


Fig.3.1.Block diagram representation of proposed method

A. Retinal Image Preprocessing
Firstly a binary mask is generated. Then adaptive histogram equalization applied for non-uniformity and a negative adaptive histogram equalization applied for contrast enhancement throught out the image's are equalized.

1. Masking
A mask is a black and white image of the same dimensions as the original image or the region of interest (ROI). Each of the pixels in the mask can have a value of 0 (black) or 1 (white).Label the circular retinal pixels values by ROI in the entire image and the background of the image calculated by thresholding. We used Frank ter Harr [34] method who applied a threshold t=35 to the image's red band. Final ROI mask is in Fig.3.4. (b).

2. Green Band Equalization (GBE)
The retinal images are nonuniform due to uneven illumination. To make uniformity Youssif *et al.* [43] proposed GBE. To eliminate the nonuniform illumination Hoover *et al.* [46] equalized each pixel using the following equation

$$I_g(r,c) = I(r,c) + m - I_w(r,c) \quad (1)$$

Where I(r,c) is indensity of the pixels, m is desired average Intensity(128-8 bit gray scale image). I_w (r,c) mean intensity value of the pixels within a window 'w' of size N x N. We used running window of size 40x40 as applied by Walter *et al.* [44]. The GBE image is in Fig.3.4. (c)

3. Adaptive Histogram Equalization(AHE)
AHE is a computer image processing technique used to normalize and enhance the contrast with in the fundus. It differs from histogram equalization when detecting low contrast levels.AHE is applied to an GBE as proposed in wu *et al.*. [55], where each pixel 'p' is adapted using the following equation:

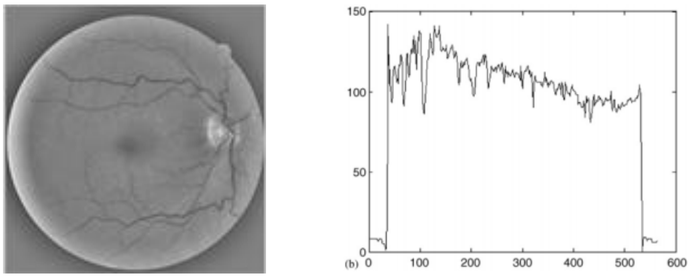
$$I_{AHE}(p) = \left(\sum_{p' R(p)} \frac{s(I(p) - I(p'))}{h^2}\right)^r * M \quad (2)$$

Where M=255, R(p) is the pixel p's neighborhood and h is the square window length which is 81. The AHE image is in Fig.3.4. (d)

4. Negative Adaptive Histogram Equalization(NAHE)
This is achieved by limiting the contrast enhancement of AHE. The contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the labelled OD cumulative distribution function (CDF) and therefore to the value of the histogram at that pixel value[54]. The NAHE image is in Fig.3.4. (d)

B. Blood Vessels Segmentation by Modified Directional Matched Filter
The matched filter is one of the template matching method which is used to detect Blood Vessel in retinal fundus images. The matched filter uses number of samples

taken across a section of retinal Blood Vessels[56]. The gray level profile of these samples is approximated by Gaussian shaped curve in Fig.3.2.



(a) **(b)**

Fig. 3.2. The green band of a digital retina image. (b) Profile of a one pixel width at the 200th row of the retina image shown in (a).

Matched filter is designing based on the following properties of Blood Vessels

- Vessels can be approximated as anti parallel segments.
- Vessels have lower reflectance than other retinal surfaces, so they appear darker relative to the background.
- Vessel size may decrease when moving away from the optic disk, the width of a retina vessel may lie within the range of 2–10 pixels.
- The intensity profile varies by a small amount from vessel to vessel.
- The intensity profile has a Gaussian shape curve that is

$$f(x, y)=A\{1-k \exp(-d^2/2\sigma^2) \qquad (3)$$

where d is the perpendicular distance between the point (x,y) and the straight line passing through the center of the blood vessel in a direction along its length, σ defines the spread of the intensity profile, A is the gray-level intensity of the local background and k is a measure of reflectance of the blood vessel relative to its neighbourhood. Instead of matching a single intensity profile of the vessels cross section, a significant improvement can be achieved by matching number of cross sections of identical profile simultaneously[56]. A prototype matched filter is expressed as

$$k(x, y)=-\exp(-x^2/2\sigma^2) \ \forall |y| \leq L/2, \qquad (4)$$

Where L is the length of the vessel segment that has the same orientation, σ defines the spread of the intensity profile. To be able to detect vessels on all possible orientations, the kernel must be rotated to all possible vessel orientations and the maximum response from the filter bank is registered. Many papers found that rotating by an amount of 15° is adequate to detect vessels with an acceptable amount of accuracy which results in a filter bank with 12 kernels. The authors of [34] made some experiments on the values of Land σ and found that the best parameter values were those that gave the maximum response at L=9 and σ =2. They did not, however, present their experiments of finding L and σ.

A Gaussian curve has infinitely long double sided trails; the trails are truncated at u=±3σ . A neighborhood N is defined such that

$N=\{(u,v), |u|\leq T, |v|\leq L/2\}$, (5)

Where T=3σ. Let P_i be the points that belongs to the neighbourhood n given as

$p_i\,[u,v] = [x,y] \begin{bmatrix} cos\Theta & -sin\Theta \\ sin\Theta & cos\Theta \end{bmatrix}$ (6)

the corresponding weights in the kernel i(i=1,....,12 which is the number of kernel) are given by

$k_i\,(x,y) = -\,exp(-u^2/2\,\sigma^2)\ \forall p_i \in N$ (7)

The filter is normalised to have zero mean as follows

$K'_i(x, y)=k_i(x, y)-m_i,$ *(8)*

Where $m_i = 1/a\ \sum_{pi\in N} ki(x, y)$, and 'a' denotes the number of points in N [57].

1. *Modification Parameters*

To improve the performance of the matched filter we need to find better parameters for L, σ, and T that could be suitable for low quality images. The optimization program is simple in which we use an exhaustive search for the best parameters of L, σ , and T. The search space is not very large since we limit the values of those parameters to L={7,7.1,7.2,...,11}, σ={1.5,1.6,1.7,...,3}, T={2,2.25, 2.5,...,10}. Let the input retina image be f and the output filtered image be $f_{L\sigma T}$ to decide that a filtered image is good or bad, it is threshold according to otsu [64] yielding $g_{L\sigma T}$ and then compared to a corresponding hand labelled retina h image. The hand labelled image is obtained from a retina image by an experienced observer to be used for comparison purposes[58].The final segmented blood vessel is shown in Fig.3.4(f).

2. *Vessels Direction Map(VDM)*

Instead of applying the 12 templates to an averaged green-band image as suggested by Chaudhuri [56], applying them to the adaptively histogram equalized image significantly improves the segmentation algorithm and increases the sensitivity and specificity of the detected vessels [59]. A vessels direction map (VDM) can be obtained from the segmentation algorithm by recording the direction of the template that achieved the maximum response at each pixel. Then, for all the pixels labelled as non-vessel, the corresponding values in the VDM can be assigned to" -1" or not-a number (NAN) in order to exclude them from further processing.

```
OD_template = [135 120 105 105 90 75 75 60 45;
               150 135 120 105 90 75 60 45 30;
               165 150 135 120 90 60 45 30 15;
               0 0 0 0 90 0 0 0 0;
               15 15 30 45 90 135 150 165 165;
               15 30 45 60 90 120 135 150 165;
               30 45 60 75 90 105 120 135 150;
               45 60 75 75 90 105 105 120 135];

OD_template_1 = imresize(OD_template,[241 81],'bilinear');
OD_template_2 = imresize(OD_template,[361 121],'bilinear');
OD_template_3 = imresize(OD_template,[481 161],'bilinear');
OD_template_4 = imresize(OD_template,[601 201],'bilinear');
```

Fig. 3.3. Vessels Direction Map

f. Automatic detection

1. Morphological Thinning of Blood vessels

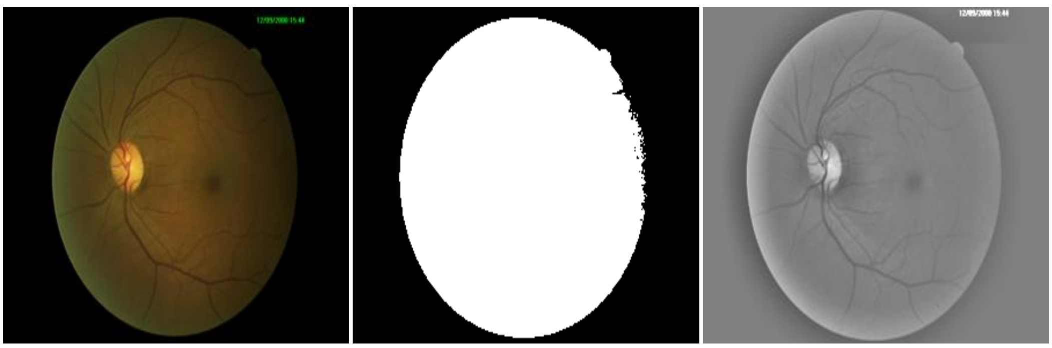
Thinning is the transformation of a digital image into a simplified, but topologically equivalent image. It is a type of topological skeleton, but computed using mathematical morphology operators. The segmented Blood vessel Image Fig(3.4.g) is the binary image with maximum connected stroke so we used morphological thinning to remove pixels so that an object without holes shrinks to a minimally connected stroke, and an object with holes shrinks to a ring halfway between the hold and outer boundary[60]

2. Template Matching with Modified Directional Matched Filter

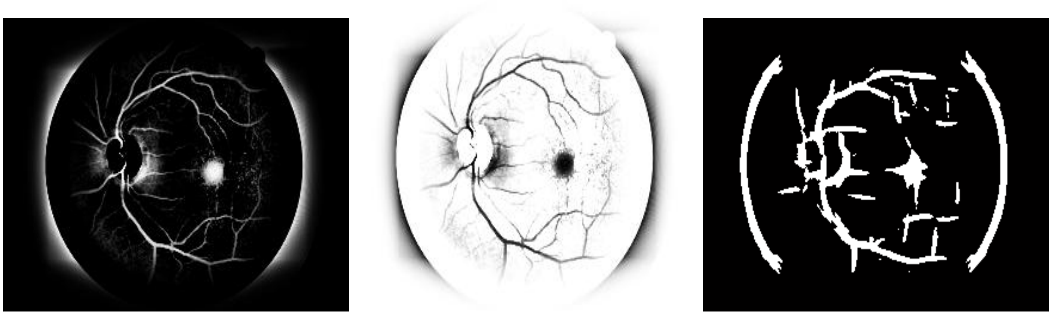
A matched filter describes the expected appearance of a desired signal, for purposes of comparative modelling [61]. Thus, in order to detect the OD, a proposed vessel's direction matched filter is to roughly match the direction of the vessels at the OD vicinity (Fig. 3). The 9x9 template is resized using bilinear interpolation to sizes 241x 81, 361x121, 481x161, and 601x201 to match the structure of the vessels at different scales.

The difference between all four templates (in the single given direction) and a VDM is calculated, and the pixel having the least accumulated difference is selected as the OD center [Fig. 4(h)]. To reduce the computational burden, matched filters are applied only to candidate pixels picked from the fundus image. The binary vessel/nonvessel image is thinned [Fig. 3.4(f)].

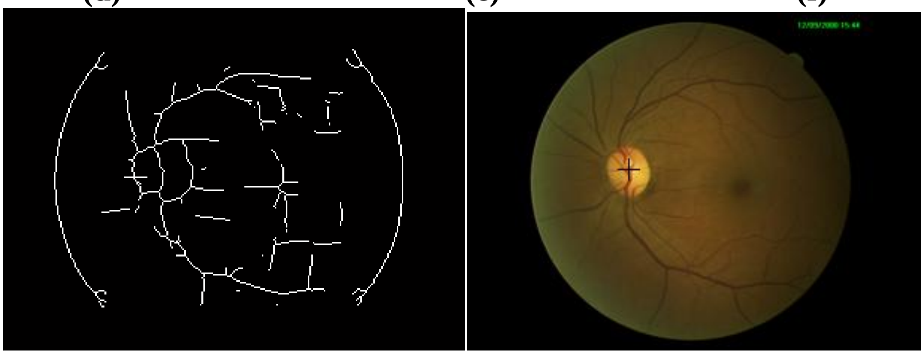
Hence, reducing the amount of pixels labelled as vessels into the vessel's centerline. All remaining vessel-labeled pixels that are not within a 41x41 square centered on each of the highest 4% intensity pixels in the illumination equalized image are labelled as non-vessel pixels [Fig. 4(g)]. This final step aims only to reduce the number of OD candidates, and thus altering the size of the square or the amount of highest intensity pixels simply has no significant effect. The remaining vessel-labeled pixels are potential OD centers, thus selected as candidates for applying the four sizes of the matched filter [54].The detected OD center is shown in Fig.3.4 (h).



(a) **(b)** **(c)**



(d) (e) (f)



(g) (h)

Fig.3.4. Proposed method applied to the fundus image in (h). (a) Input Image (b) Masked Image (c) Green Band Equalized image (d) Adaptive Histogram Equalized image (e) Negative Adaptive Histogram Equalized image (f) Blood Vessel Segmented image (g) Thinned Image (h) OD detected image (Block cross).

IV RESULTS

The proposed method was implemented in MATLAB where runs needed on average 1.5min for each image on a laptop (Pentium(R) Dual-Core2 CPU and T4300@ 2.10GHz, 3.00 GB RAM 64-bit OS).Though using modified directional matched filter the retinal blood vessel segmentation and OD detection involves more success percentage than other state of art methods in stare data set illustrated in Table I.

The proposed method was evaluated both normal and abnormal low quality retinal images using the subset of the DRIVE, STARE, MESSIDOR, DIARETDB0 and UNIVERSITY OF LINCOLN and the success percentage was found to be 98.82% for all datasets.

The OD center was detected correctly in all of the 33 images in DRIVE dataset (Fig. 5.1), 55 out of the 56 in STARE dataset (Fig.5.2), 100 images in MESSIDOR dataset (Fig.5.3), 89 images out of 90 in DIARETDB0dataset (Fig.5.4), and 98 out of 101images in university of Lincoln dataset (Fig.5.5) using our proposed method.

TABLE III NUMBER OF LOW QUALITY RETINAL IMAGES APPLIED FOR TESTING

Dataset	No of low quality Images tested	No of images failed	Accuracy (%)
DRIVE	33	0	100
MESSIDOR	100	0	100
STARE	56	1	98.21
DIARETDB0	90	1	98.88
University of Lincoln	101	3	97.02
Total	380	7	**98.82**

Fig.4.1. Results of the proposed method (Black Cross represent the estimated OD Center) form Drive Data set

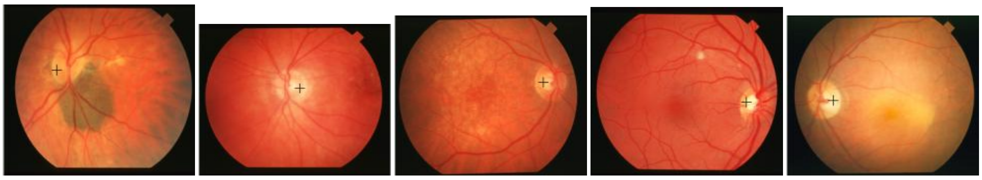
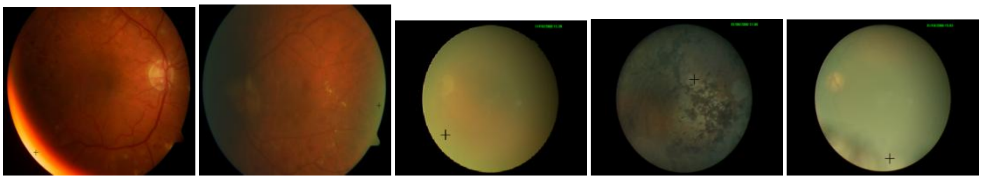


Fig.4.2. Results of the proposed method (Black Cross represent the estimated OD Center) form STARE Data set

Fig.4.3. Results of the proposed method (Black Cross represent the estimated OD Center) form MESSIDOR Data set

Fig.4.4. Results of the proposed method (Black Cross represent the estimated OD Center) form DIARETDB0 Data set

Fig.4.5. Results of the proposed method (Black Cross represent the estimated OD Center) form University of Lincoln Data set



(a) (b) (c) (d) (e)

Fig.4.6.Failure images (a) Stare dataset (b) Diaretdb0 (c-e) University of Lincoln dataset

V DISSCUSSION

The implemented modified directional matched filter is tested with our proposed method for all the 81 images of stare data set and achieved 98.76 success rate which is more than other state-of-art methods in table I. In Table II comparison of the OD detection methods on stare project dataset is tabulated since the number of failure images in stare is very low then other start of art methods.

TABLE IV COMPARISON OF THE OD DETECTION METHODS ON STARE DATASET

Author	No of failed Images	Accuracy(%)
Sinthanayothina *et al.* [45]	47	42
Walter *et al.* [44]	34	58
Hoover *et al.* [46]	9	89
F.ter Haar [34]	5	93.8
Foracchia *et al.* [38]	2	97.5

Abdel *et al.*[25]	1	98.8
Lu and Lim[16]	3	96.3
The proposed method	1	98.76

We also tested our proposed method for all the 130 images of diaretb0 data set and achieved 99.23 success rate which is more than other state-of-art methods in Fig.5.1.

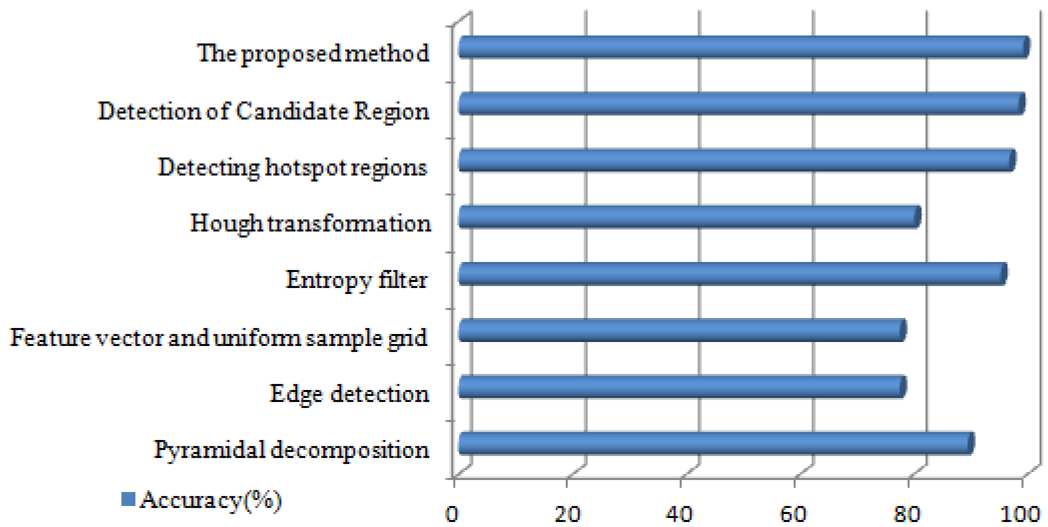


Fig:5.1. Comparison of the OD detection methods on diaretdb0 dataset

The proposed method achieved more comprehensive result for low quality retinal images. The number of failure images are very less by our method (Fig.5.2).

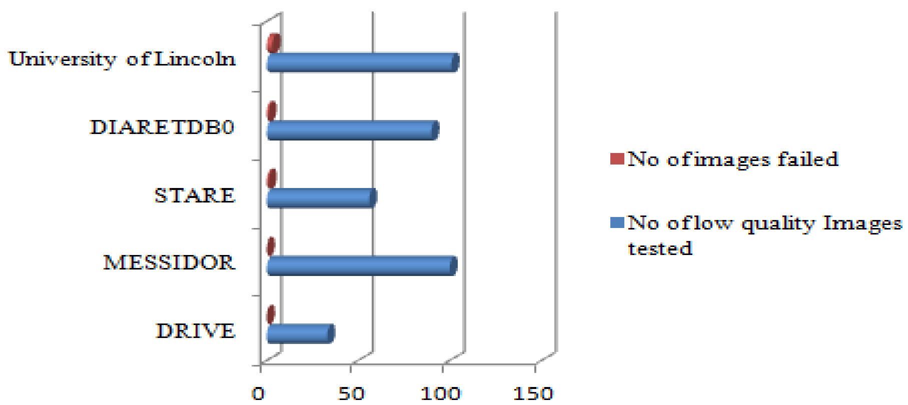


Fig:5.2. Testing of low quality retinal images and failure rate

In Table IV, the average running times of some OD detection methods are indicated. The simple comparison is made based on available data from various authors proposed. Our proposed method achieved less computational time to other start of art methods.

TABLE V COMPARISION OF COMPUTATION

Author	Running Time per image (in sec)	system Configuration
Fleming *et al.* [29]	120	Intel Core 2 Duo 2.4 GHz
Foracchia *et al.* [38]	120	Intel Core 2 Duo 2 GHz and 512 MB RAM
Lalonde *et al.*[42]	110	Configuration not reported
Youssif *et al.* [54]	210	Intel Core 2 Duo 1.7 GHz and 512 MB RAM
Bob-zhang *et al.* [15]	180	Intel centrio pro 2 GB RAM
Proposed method	90	Dual-Core2 2.10GHz, 3.00 GB RAM

VI CONCLUSION AND FUTURE WORK

This paper presented a most efficient technique for OD center detection using modified directional matched filter. The proposed technique achieved better results from various publicly available datasets such as DRIVE, STARE, MESSIDOR, DIARETDB0 and UNIVERSITY OF LINCOLN with short Computational time. This will help the ophthalmologists in diabetic retinopathy and other eye disease screening process to detect symptoms faster and more easily. This is not the final result application but it can be a preliminary diagnosis tool or decision support system for ophthalmologists. Human ophthalmologists are still needed for the cases where detection results are not very obvious.

In future we aim to apply Bi-orthogonal wavelet and Morlet wavelet and Curve let techniques to segment the blood vessels more effectively with high accuracy so as to detect OD and prevent diabetic retinopathy at its earlier stage. To enhance the performance using other large retinal datasets like Origa-light, The Hamilton Eye Institute Macular Edema Dataset (HEI-MED) and University of Huelva Diabetic Retinopathy dataset.

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