Optic Disk Segmentation through Edge Density Filter in Retinal Images

Y. Madhu Sudhana Reddy, R. S. Ernest Ravindran

Abstract: Accurate and Efficient Detection of Optic Disk (OD) is an important task for the diagnosis of various eye related diseases such as Diabetic Retinopathy, Glaucoma, and papilledema in automatic retinal image analysis. This paper presents a novel and robust OD detection framework which starts with the detection of OD pixel, a center of OD region. Next, based on the ODP, a sub-image extraction is accomplished and it is processed for blood vessel removal through morphological technique. Finally, a new filter, called as Edge Density Filter (EDF) is accomplished to find out the extract the OD region in the Blood vessel removed, Edge detected and binarized sub-image. Two publicly available datasets, MESSIDOR and DRIVE were used to evaluate the performance of proposed method and the performance is measured through performance metrics such as Overlap Score, Sensitivity and Accuracy.

Keywords : Retinal Image, Optic Disk, Optic Disk Pixel, Edge Density Filter, MESSIDOR, DRIVE, Sensitivity, Accuracy.

I. INTRODUCTION

In recent years, the automatic retinal image analysis has gained much research interest due to the effective utilization of retinal image by biomarkers in the early identification of several disorders such as Heart diseases, Hypertension, and Diabetic Retinopathy (DR) etc. Among these disorders, the DR is open of the leading causes of blindness due to which approximately 415 million people are suffering across worldwide [1]. DR is an eye abnormality, occurs due to the long-term diabetes, which can effect on the vision of human or even causes a permanent vision loss [2]. But at the initial stages of DR, the patient can't realize the vision impairment which may result a permanent vision loss in advance stages. Hence there is a necessity of regular examinations for a patient which can help him/her to delay the progression of vision loss or blindness. Further the DR can be recognized at its early stages through expert ophthalmologists by analyzing the retinal image of patient more carefully. This can lead to the proper administration of curing treatments and effective therapies to avoid vision loss and its further consequences.

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However, the limited number of expertized ophthalmologists cannot keep pace with the drastically increasing number of DR patients. Hence there is an immediate and urgent requirement to design an automatic DR detection system based on the digital retinal fundus image [3].
The automatic DR detection system mainly works based on the analysis of retinal images features such as Optic Disk (OD), Retinal Vessels, Educates, etc. Generally, an automatic DR screening system focuses over the Retinal Vessels and Optic Disc only because, the major portion of retina image is occupied by these two features only.

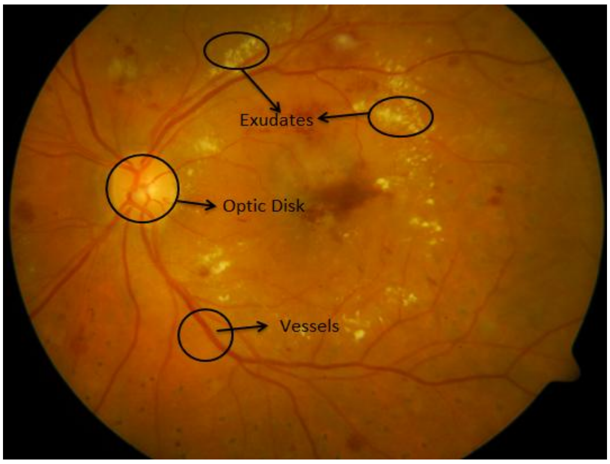

Figure.1 features of retinal image

For an efficient and early detection of DR, an accurate segmentation of OD is the preliminary step. Here the DR is characterized by the change in shape, color and depth of OD [4]. The presence of various abnormalities in the OD is a major sign for the analysis of DR. Particular, the DR mostly effects over the optic nerve which starts from center of OD. Moreover, the progression in the optic nerve fiber damage results in the structural changes in OD like an increased cup to dick ratio (CDR). The CDR is measured based on the area and diameter of OD. To achieve an effective CDR, OD needs to be segmented more accurately [5] from the retinal image, which is most important step in the development of automatic DR diagnosis system for large population based countries.
This paper proposes a new OD segmentation technique based on the statistical properties of OD. Initially, this approach focused over the localization of the center pixel of OD which can also be called as Optic Disk Pixel (ODP). Once the ODP is extracted from retina image, a sub-image is cropped and processed for blood vessel removal. Further, a new OD segmentation mechanism is accomplished through the Otsu Thresholding (OT) and Edge Density Filter (EDF).

Simulations are conducted over various benchmark datasets to alleviate the performance effectiveness.

Rest of the paper is organized s follows; Section II illustrates the details of Literature survey. Section III illustrates the details of Proposed Methodology. Section IV illustrates the details of simulation experiments and performance evaluation and finally the conclusions are provided in section V.

II. LITERATURE SURVEY

In many real time applications, there exist some challenging issues for segmentation of OD due to its complex appearance caused by some abnormalities such as peripapillary atrophy (PPA), poor image quality, Blood vessels covered, and myelinated nerve fibers. Hence many researchers have been focused over developing efficient methodologies to achieve an improved precision of OD boundary extraction. Based on the methodology accomplished at extraction, they are classified as Classifier based methods [6-10], Template matching based methods [11-15], Morphology based methods [16-18] and Active Contour Model based methods.

Under the first class, i.e., Classifier based methods; a number of methods are developed. All these method are based on the pixel-level features or super-pixel level features extracted from retinal images. Considering this fact, Cheng et. al., [6] proposed an OD segmentation mechanism based on super-pixel classification. In this method, the histograms and center surround characteristics are used for classifying the OD and Non-OD. Next, Kishore Dutta et. al., [7] proposed a new method for OD segmentation based on a double threshold, one is to remove the blood vessel and another is to segmenting the super intensity pixels existing in the OD and Optic Cup. By extending the Super-pixel classification concept, Tan et. al., [8] proposed a new method to integrate the multiple super-pixel resolutions and proposed a unified feature for better Optic Cup boundary extraction. Next, Zhou et. al., [9] proposed a novel unsupervised pixel classification method based on the based on Sparse Posterior Cerebral Artery (PCA). Further, Zhou et. al., [10] developed a novel approach called as Super-pixel multi-feature classification for automatic detection of Exudates which have similar characteristics with OD at the brightness level. Totally, 20 features, including 19 multi-channel intensity features and a novel contextual feature, are proposed for characterizing each candidate. Further a supervised multi-variable classification algorithm is accomplished for classification purpose. Though these approaches have more effective due to the classifier training, they are variant to the size of retinal image sample. Clearly, the OD results obtained after segmentation have larger bias if the size of training dataset is less. Along this, it is also a time-consuming process when dealing with larger volume data at training phase.

The next category class is template matching based approaches. These approaches consider the shape of OD in prior, i.e., the elliptical or circular shape to match the edges extracted from the fundus retinal image. Morales et. al., [11] proposed to extract the OD contour mainly through Principal Component Analysis (PCA) and mathematical Morphology. This approach makes use of Different operators such as Generalized Distance Function (GDF), Geodesic transformation, Stochastic Watershed and also a variant of watershed algorithm. Next, S R Chowdhury et. al., [12] proposed a novel OD classification based on the detection of OD boundary and Vessel Origin. This approach considered totally six-region based features and the Gaussian Mixture Model (GMM) for classifying the OD regions from Non-OD regions. Further to obtain the circular shape of OD, a best-fit ellipse method is accomplished. Next, Zhang et. al., [13] proposed an OD detection method through the extraction of OD center and used Gaussian Filtering and vessels' directional matched filter (VDMF) [14]. This approach tried to extract the OD center through the evaluation of neighborhood pixels difference followed by vascular structure; however the complete vascular structure extraction is a complex and time consuming task. Yu et. al., [15] proposed to extract the OD center based on template matching. Based on the obtained OD center and with the help of a constant radius, a fast, hybrid level-set [20] method is accomplished for OD boundary segmentation. However, the abnormal gray-levels at the boundary results in a non-continuous OD boundary. However these methods are not successful in et detection of ODs with varying shapes.

Further some morphology based techniques are accomplished to extract the exact boundary, e.g., Welfer et. al., [16] proposed a two-stage morphological for OD detection in color retinal fundus image. This approach aimed to detect the location of OD and Optic Rim. Further S. pal and S. Chatterjee [17] proposed a morphological approach to detect the OD based on the individual color channels of RGB space retinal image. Canny edge detection technique, assisted with further morphological operations has been used to segment the optic disk. Further, Wisaeng, Worawat [18] proposed to combine the Mathematical morphology with marker-controlled watershed segmentation [19] algorithm to detect the OD.

In the class of Active Contour Model based methods, Zhou et. al., proposed a novel optic disc detection approach based on saliency object detection and modified local intensity clustering model. In this approach, a series of OD candidates can be firstly extracted using morphological opening by reconstruction. 1en, a set of features are used to distinguish the true OD from the non-OD candidates. By extending this approach, Yuan Gao et. al., proposed an effective and adaptive initial level set contour extraction approach using saliency detection and threshold technique for OD Segmentation.

Some more methods are proposed based on different strategies. Kamble et. al., proposed a novel approach for fast and accurate localization of OD based on the 1-D scanned intensity profile analysis. This method is accomplished with the help of both time and frequency domain of image. Finally the OD is localized as peak-valley detection in time domain and discontinuity detection is frequency domain. Furthe Sarathi et. al., proposed an OD localization method based on the staining of Vessels around the OD. After detection of OD center, an adaptive threshold based region-growing technique is applied to extract the complete OD region.

Even though so many approaches are proposed for OD segmentation, a common problem observed is a non-continuous OD boundary extraction. Due to the high gray-level intensity variations at the boundary of OD, extracting a continuous OD is a complex task.

III. SEGMENTATION METHOD

The main objective of this method is to obtain the Optic Disk Region from the retinal image more effectively that contains the complete circular boundary approximation. This method proposes a new methodology to extract the complete OD region based on the seed of OD, i.e., starting point or center of OD which can also be called as OD pixel (ODP). The proposed methodology for ODP extraction works on the all color channels of retinal image such as Red, Green and Blue. Once the ODP is extracted, a constant sized region is cropped from all the four sides of ODP, can be called as Retinal Sub-Image. This is accomplished to reduce the additional computational burden over the system. Further the extracted Retinal sub-Image is processed for Final OD region segmentation after removing the vessel pixels from it. Here the vessel pixels are removed based on the statistical properties of image pixels and the final OD regions candidates are segmented through the Edge Density Filter (EDF).

A. ODP Location

In this method, the methodology obtains the ODP which is a main seed of the Optic Disk. This method comprised of three different techniques. The three methods are applied over the green channel of RGB spaced retinal image due to the provision of best contrast. All these three techniques try to locate the ODP through different scenarios. For every technique, three candidate locations are obtained. Next, one centroid is evaluated based on the size of image; the centroid is obtained by averaging the obtained candidate pixels through three different method. Here the centroid is approximated at the one-fifth of the image size, maximum OD diameter estimation. Finally based on these three candidate locations, one location is finalized based on; 1. If the three candidate locations are nearer to the centroid, then the centroid itself becomes the ODP. 2. If only two candidate locations are nearer to the centroid, then the obtained ODP is an average of those two candidate locations. Here all the techniques are applied over green channel only, because the green channel only gives best contrast. The methodology of the ODP locating method is described in the following subsections;

1. Median Filtered Method

In this method, the median filter of size 21×21 is initially applied over the green channel of retinal image. After this accomplishment, for every window the maximum difference pixel is found by subtracting the minimum gray-level pixel from the maximum gray-level pixel. OD is generally appears brighter than other regions and also the maximum gray-level variations are occurred within the OD. Further, the originating point for vascular structure is also resides in the OD, is also one of the main causes for these variations. Let I be the gray-level image, apply the media filter over it and Let the filtered image is I_M. Here the median filter almost removes the non-significant pixels from the gray-level image. Then the maximum difference method is applied over the median filtered image to obtain the OD pixel location as;

$$d(i,j) = [(I_M)_W^{max}(i,j) - (I_M)_W^{min}(i,j)] \quad (1)$$

$$P_M = \arg_{(i,j)}[\max(d(i,j))] \quad (2)$$

Where

$$(I_M)_W^{max}(i,j) = \max_{(i,j)}(I_M(i = 1\ to\ 21, j = 1to\ 21)) \quad (3)$$

$$(I_M)_W^{min}(i,j) = \min_{(i,j)}(I_M(i = 1\ to\ 21, j = 1to\ 21)) \quad (4)$$

Are the maximum and minimum values of the pixels within the median filtered image I_M and within the window, W of size 21×21 where the pixel (i,j) is at center. The pixel location obtained for a green channel retinal image through the median filtered method is shown in figure.2.

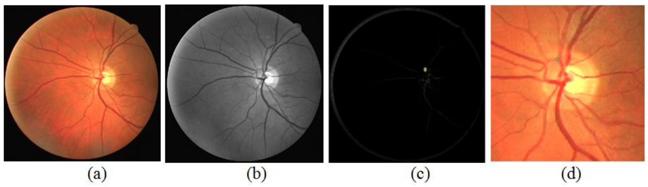

Figure.2 ODP Locating through Median filtering method (a) Original image, (b) Green channel, (c) Media Filtered Image with ODP candidate (Green dot), (d) ODP candidate located in original image

1. VARIANCE METHOD

Instead of simple difference evaluation, this method finds the statistical variance of every pixel in the green channel of retinal image. Unlike to the median filtering method, in this method the OD pixel is located based on the maximum pixel variance. Here the window size is considered as 51×51 (this is obtained after testing different sizes over different retinal image samples). In this process, for a pixel (i,j) located at the center of window, the variance is evaluated as follows;

$$V(i,j) = \frac{\sum_{i=1}^{51}\sum_{j=1}^{51}(I_W(i,j)-\bar{M}(I_W))^2}{L(I_W)-1} \quad (5)$$

$$P_V = \arg_{(i,j)}[\max(V(i,j))] \quad (6)$$

Where

$$\bar{M}(I_W) = \sum_{i=-51}^{51}\sum_{j=-51}^{51} I_W(i,j) \quad (7)$$

Where I_W is window of size 51×51 within the gray-scale image I, $\bar{M}(I_W)$ is the mean of a window image (I_W) of a pixel located at the center. The OD pixel returned by this method is the pixel with maximum variance pixel showing at least 10 brighter pixels around its neighborhood. The pixel location obtained for a green channel retinal image through the variance method is shown in figure.3.

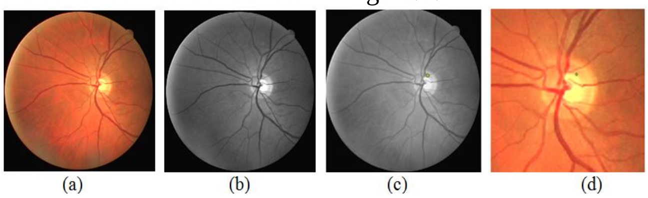

Figure.3 ODP Locating through Variance Method, (a) Original image, (b) Green channel, (c) Variance Image with ODP candidate (Green dot), (d) ODP candidate located in original image

3. Gaussian Filtered method

This method is applied over the green channel of retinal image to locate exact OD pixel. Generally the OD region appears as a brighter region compared to the other regions in the retinal image and the OD pixel have higher gray-level value compared to the other pixels in the OD region. Sometimes, even though the OD is a brighter region, the pixel with higher brightness may or may not exist in the OD region. It can be exists in the exudates also which also have almost similar brightness characteristics with OD.

To overcome this confusion, in this method the gray-scale image transformed into frequency domain from image domain and then filtered by Gaussian Low Pass Filter (GLPF). Hence the OD pixel of this method is a pixel with maximum gray-level from the low pass filtered image transformed from frequency domain to spatial domain after finding the pixel with maximum gray-level. The pixel in the frequency domain is obtained as

$$H(i,j) = \exp\left(\frac{-d^2(i,j)}{2d_0^2}\right) \quad (8)$$

And

$$P_G = \arg_{(i,j)}[\max(H(i,j))] \quad (9)$$

Where $d^2(i,j)$ is the Euclidean Distance between the points at (i,j) and the origin of frequency plane and d_0 is a cut-off frequency. The pixel location obtained for a green channel retinal image through the Gaussian Filter Method is shown in figure.4. After obtaining the OD pixel candidates through the three different techniques, the final OD pixel selection is accomplished based on rules formulated at the starting of this section.

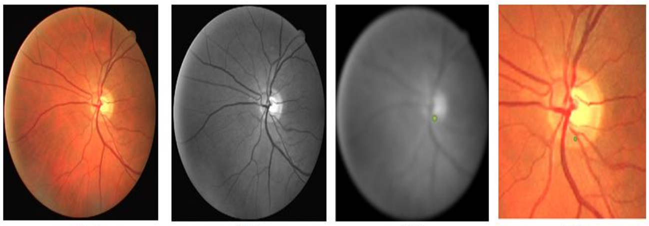
(a) (b) (c) (d)

Figure.4 ODP Locating through Gaussian Filter Method, (a) Original image, (b) Green channel, (c) Gaussian Filtered Image with ODP candidate (Green Dot), (d) ODP candidate located in original image

B. OD Segmentation

In this section, the OD region is segmented based on the OD pixel obtained in the previous section. This accomplishment is done over the RDG color space sub-image originated from the original RGB color spaced retinal image. The sub-image is extracted by considering the ODP as a center and accumulating a region of size 400×400 in all sides, i.e., along both row side and column side. Initially for a given retinal sub-image, the green channel is extracted and blood vessels are removed from it. Next the Non-vessel Sub-image is subjected to edge detection and binarization through Otsu Thresholding. Finally the obtained binarized image is subjected to Edge Density Filter for OD candidates detection.

1. Blood Vessel Removal

Since the blood vessels are more dominant distractors in the retinal image, they need to remove to obtain a proper and effective OD region. Further OD is originating point for retinal vasculature, the retinal vascular structure can be observed even in the region very nearer to the ODP. Here a new method is proposed to remove the blood vessels from retinal sub-image based on their characteristics. Generally the retinal vessels are formulated as a linear shapes having length *L* and width *W* (*W*<<*L*). Furthermore, these linear shaped retinal vessels are also of having constant gray-level value. And this constant gray-level value is somewhat less than the gray-level value of non-vessel pixels which are around the vessel pixels. Based on these characteristics, this method accomplished a rotating linear structuring element for every pixel. The structuring element, S is having the length l_1 and width 1 is rotated with a rotation gap of 20^0 for every rotation. For every pixel, a maximum gray-level variance is evaluated after rotating it through the linear structuring element. The retinal vessels can be eliminated from the image I by detecting, for every pixel, the maximum gray-level variance and considering the rotation at which that was obtained. Mathematically it is formulated as,

$$I_{NV}(i,j) = \max_{(i,j)}\left(I_{S_r}(i,j)\right) \quad (10)$$

Where S_r is a structuring element at rotation r and I_{NV} is a non-vessel sub image. Here the term $\max_{(i,j)}(.)$ gives a maximum gray-level value at rotation *r* in the neighborhood of (i,j) defined by the structuring element. Further the process not considers the gray-level directly, instead it considers the gray-level variance for every pixel and it is formulated as,

$$V(i,j) = Var(I_{S_r}(i,j), k = 1,2,\ldots,9) \quad (11)$$

Based on this expression, the final rotation at which the maximum gray-level variance occurs is found, as

$$r = \arg_{(k)}(\max(V_k(i,j))) \quad (12)$$

Where $V_k(i,j)$ is the variance of pixel (i,j) at rotation k and it varies from 1 to 9 (180/20=9). It means for every pixel, the structuring element rotates for 9 times and one final value is selected based on the maximum gray-level variance. An example of obtained non-vessel sub-image through this method is shown in the figure.5.

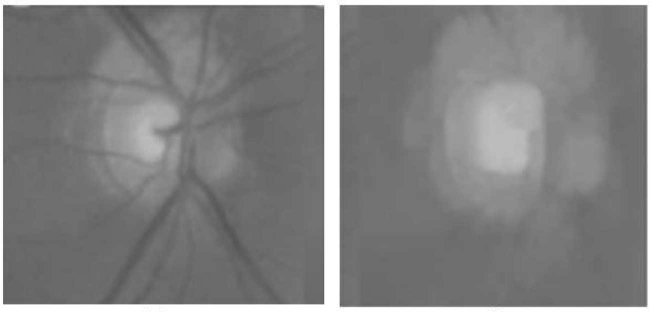
(a) (b)

Figure.5 Gray-level image (a) with vessles (b) without vessles

2. Final OD Segmentation

Once the blood vessels are removed from the retinal sub-images, the resultant image is only consisting of OD region and some background region. Now this section tries to obtain all the OD region candidate pixels with more effectively.

a. Edge Detection and Binarization

For this purpose, initially the non-vessel gray-scale image I_{NV} is subjected to edge detection through canny edge operator. Here the OD boundary acts like a frontier between the OD and background. The OD boundary can be characterized by sudden variations in the gray-levels when moving from inside OD to outside OD. These sudden variations can be regarded as gradients or edges and here the canny edge operator extracts the OD boundary more effectively. This operator estimates the image edge and orientation by convolving two 3×3 kernels with appropriate derivatives for vertical and horizontal changes. Finally the gradient magnitude is obtained by measuring the modulo of partial derivatives for every pixel.
Further to extract the final OD candidates, this method accomplished Otsu thresholding followed by Edge Density Filter. Otsu thresholding is an automatic threshold deciding technique based on the composition of foreground and background. Then the threshold T_{Otsu} is derived by the maximization of class variance between two classes such as foreground and background. Based on the obtained Otsu threshold, the edge image is binarized as

$$I_B(i,j) = \begin{cases} 0, & if\, I_E(i,j) \le T_{Otsu} \\ 1, & if\, I_E(i,j) > T_{Otsu} \end{cases} \tag{13}$$

Where I_E is the edge image obtained at the canny edge operator and I_B is a binarized image. Next the binarized image is processed through Edge Density Filter for complete and continuous OD candidates extraction.

b. Edge Density Filter

This filter is applied over the binary edge image I_B to extract the OD candidate pixels. Based on the connectivity of pixels in every OD region, this filter has achieved efficient results in the segmentation of OD. The main reason behind the consideration of EDF is the exposure of high edge density of OD candidate pixels. The main working methodology of the EDF is by observing the above mentioned clues. The EDF connects the regions with high edge density and removes the other regions from the binary edge image I_B. A simple illustration about the EDF is depicted in the figure.6, below.

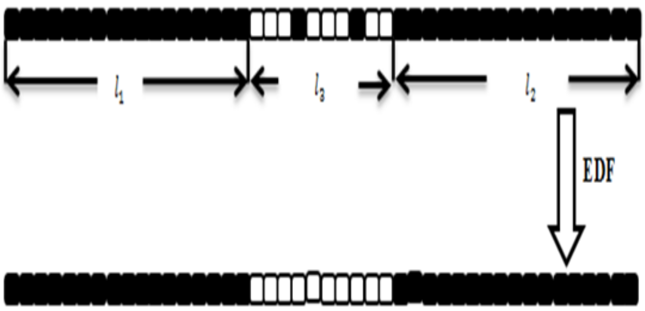

Figure.6. EDF Accomplishment

According to figure.4, the black dot spots represent the non-edge pixels and white dot spots represent the edge pixels. For instance, let l_1 and l_2 are the two continuous black line segments of lengths l_{b1} and l_{b2} respectively. Our main aim is to quantify the target line segment l_3 based on the number of white spots and number of black spots. Let w_l be the number of white spots in the target line segment and b_l be the number of black spots in the target line segment, the decision based on the line density l_d is measured as

$$l_d = {}^{w_l}/_{w_l + b_l} \tag{14}$$

Further, for the obtained binary edge image, there is a chance to observe a non-OD on the both sides, which can be a long black line segments l_1 and l_2. Once the OD region is initialized in the image, we can observe a non-lengthy black line segments. Here the length map is obtained by accumulating the continuous white and black pixels. Here the black pixel is counter as 1 and white pixel is counted as -1. If continuous black pixels are observed, they are grouped together. Similarly if continuous white pixels are observed, a cumulative length is measured by grouping them but in negative. For example, if we observe 12 continuous black pixels are observed then the cumulative length map is 12 whereas for continuous white pixels, it is -12. This process obtains only the character regions in the horizontal direction only. To obtain the characters in the next line, the vertical scanning is applied based on the obtained line length maps for each character in the binary image, we apply proposed EDF to extract the OD region. It is based on the parameters such as binary edge image I_B; minimum length threshold for black line T_{min}, for l_1 and l_2; the gap length threshold T_{gap}, for line segment l_3; and the line density threshold T_{dl}, for l_3. For a given binary image I_B, for each line segment, if we found two line segments l_1 and l_2 of lengths l_{b1} and l_{b2} respectively, if $l_{b1} > T_{min}$ and $l_{b2} > T_{min}$, then calculate l_d using Eq.(14) for l_3 and compare it with the line density threshold T_{dl}. If it is greater than the T_{dl}, set all the pixels of l_3 to white in I_B, otherwise set them to black.
From this strategy, we will get the complete OD pixels for a given retinal image. Based on these pixel locations, a circular mask is applied over the RGB space color retinal image to get the OD region.

IV. SIMULATION EXPERIMENTS

The section deals with the simulation experiments conducted over the proposed approach. Two benchmark datasets namely MESSIDOR and DRIVE are considered here for simulation experiments. Overlapping score is measured as a performance metric.

A. Dataset Details

To perform the simulation, this work used the publicly available MESSIDOR dataset. This dataset consist of 1200 eye fundus images, among them 800 are acquired with pupil dilation and remaining 400 are acquired without dilation.

The images in the dataset are captured with 'Topcon TRC NW6 non-mydriatic retinograph' with a 45^0 FOV. All the images are in the .TIFF format and consist of eight bit color planes. All the images are not of same size and on summary they are consists of three sizes such as 2240×1488, 1440×960 and 2304×1536.

Further this work also executed over one more dataset, DRIVE. DRIVE is a publicly available dataset which consists of 40 fundus images and all images are in the .TIFF format. The size of every image in the DRIVE dataset is 565×864. The fundus images in DRIVE dataset are captured through Canon CR5 non-mydriatic 3 CCD camera at a 450 field of view (FOV).

B. Results

The obtained segmentation results after the accomplishment of proposed approach over the retinal image from both datasets are illustrated below.

Table.1 Segmented results for retinal Images of MESSIDOR Dataset

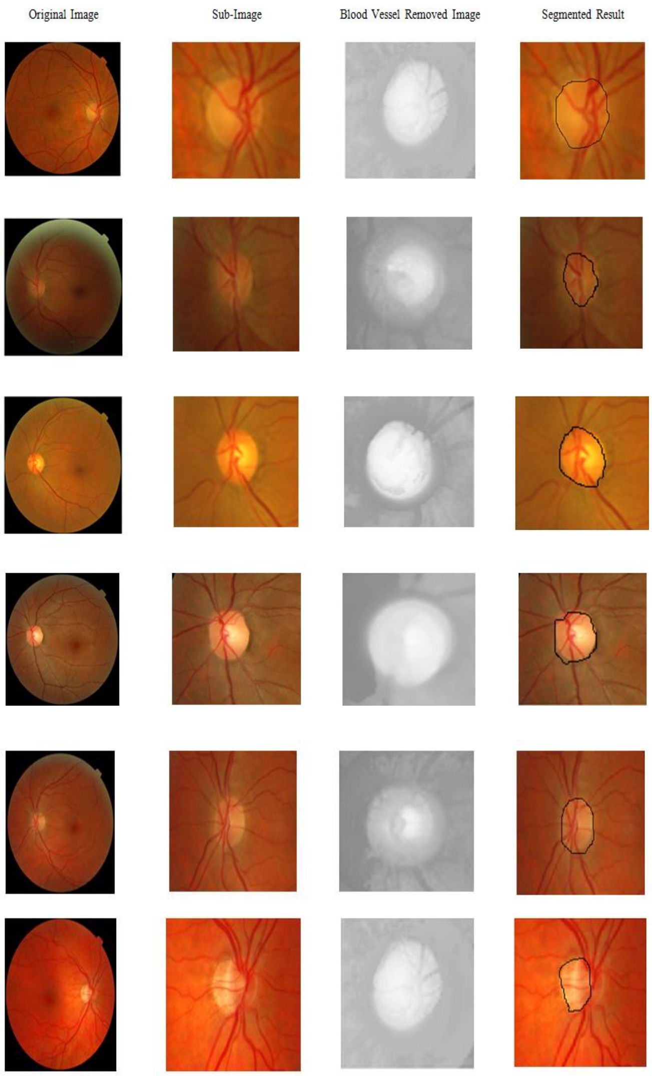

Table.2 Segmented results for retinal Images of DRIVE Dataset

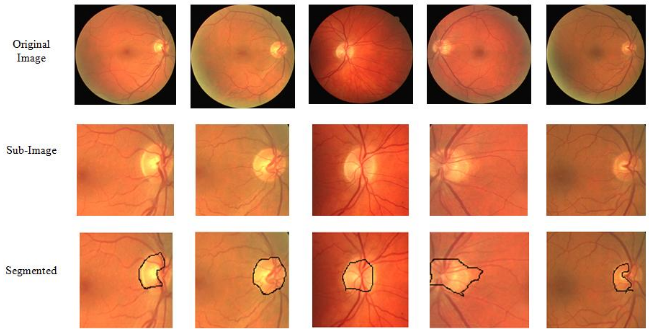

Table.1 shows the obtained segmented results of OD over the accomplishment of proposed approach on the MESSIDOR image dataset. Further table.2 shows the results if DRIVE dataset. In both simulation studies it has been shown in the above figures, the obtained segmented region of OD is more accurate through the proposed methodology. Furthermore, the highlighted region with black circular mark is very continuous in nature and this is possible only when every pixel is scanned clearly. The proposed approach discovered the pixel whether it belongs to OD or not just by analyzing its edge value. Though there are number of approaches developed in earlier for OD segmentation. No approach is there which has detected the complete OD region and this method achieved a continuous OD boundary.

C. Performance Analysis

To evaluate the performance of the proposed methodology, some performance metrics are considered through which the performance efficiency is alleviated. Here four performance metrics namely, Overlap Score, Sensitivity, Specificity, and Accuracy are measured. The mathematical formulae for these metrics are formulated as follows;

$$S = \frac{Area(T \cap D)}{Area(T \cup D)} \tag{15}$$

Where S is the overlap Score, T is the true OD region, which is manually marked by the ophthalmologist and D is the detected OD region obtained using the proposed method.

Sensitivity is defined as total number of Pixels correctly classified as OD for over the total original OD pixels. Here the original total OD pixels are marked by the expert ophthalmologist. Mathematically sensitivity is represented as;

$$Sensitivity = \frac{TP}{TP+FN} \tag{16}$$

Where TP is the true positive pixels and FN is the false negative pixels.

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{17}$$

Specificity measures the proportion of negatives that are correctly identified as such.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{18}$$

The proposed approach was tested over different image samples from both datasets and for illustration, table.3 shows the details Overlap Score,

Sensitivity, Specificity and Accuracy for Forty samples (20 samples are considered from MESSIDOR dataset and 20 are from DRIVE dataset).

Table.3 Performance Analysis over some images samples

Image Sample	MESSIDOR			DRIVE		
	Sensitivity	Specificity	Overlap Score (S)	Sensitivity	Specificity	Overlap Score (S)
S1	0.8833	0.9157	0.8534	0.8767	0.8267	0.8049
S2	0.8366	0.9192	0.8067	0.8363	0.7790	0.7582
S3	0.8372	0.9068	0.8073	0.8306	0.7796	0.7588
S4	0.8582	0.9285	0.8283	0.8516	0.8006	0.7798
S5	0.8856	0.9115	0.8557	0.8790	0.8282	0.8072
S6	0.8439	0.9245	0.8140	0.8373	0.7863	0.7655
S7	0.8369	0.9074	0.8070	0.8303	0.7793	0.7585
S8	0.9133	0.9045	0.8834	0.9067	0.8557	0.8349
S9	0.9182	0.9120	0.8883	0.9116	0.8606	0.8398
S10	0.8957	0.8999	0.8658	0.8891	0.8381	0.8173
S11	0.8463	0.9092	0.8164	0.8397	0.7887	0.7679
S12	0.8757	0.9104	0.8458	0.8691	0.8181	0.7973
S13	0.8527	0.9057	0.8228	0.8461	0.7951	0.7743
S14	0.9266	0.8917	0.8967	0.9203	0.8690	0.8482
S15	0.9333	0.9096	0.9034	0.9241	0.8757	0.8549
S16	0.8859	0.9123	0.8560	0.8793	0.8383	0.8075
S17	0.8563	0.9274	0.8264	0.8497	0.7987	0.7779
S18	0.8958	0.9069	0.8659	0.8892	0.8382	0.8174
S19	0.9584	0.9228	0.8485	0.9247	0.8208	0.80014
S20	0.9291	0.9129	0.8392	0.9123	0.8115	0.7945

D. Comparison

Under this comparative analysis, the proposed approach is compared with the conventional approaches with respect to the performance metrics such as Accuracy, Sensitivity, Specificity and Overlap Score. Here the final value of any of these metric is obtained by averaging the all values obtained at individual image level. The conventional approaches considered here for comparative analysis are Acquino et. al., Yu et.al., [15], Morales et.al., [11] and S. R. chowdhury [12]. Comparative analysis between the proposed and conventional approaches is shown through the following figures.

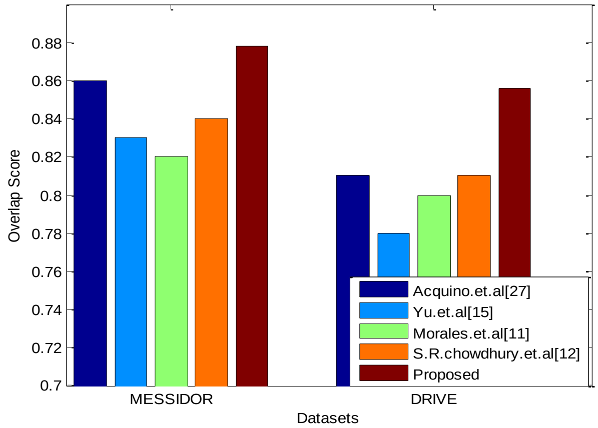

Figure.7 Comparison through Overlap Score

Figure.7 shows the comparative analysis between the proposed and conventional approaches through the performance metric, Overlap Score. The overlap score is obtained by calculating the common area between the obtained OD region and manually segmented OD region. A higher value of Overlap Score indicates the better performance. In the above figure, the overlap score of proposed approach is high compared to all the conventional approaches. This is achieved due to the accomplishment of pixel by pixel scanning through edge density filter on the binarized sub-image. Since the proposed approach aimed to locate the OD with a continuous boundary extraction, the EDF has shown its effect in achieving it by which overlap score is higher. Since the OD boundary is composed of abnormal variations due to the composition of both background and OD, a careful study only reveals the real nature of pixel. The proposed method has achieved a greater performance at this aspect. It is also shown in the visual results that the circular region covered the OD is not a perfect circle. It is a non-uniform circle and this is obtained due to the abnormal gray-level variations at the boundary. The approximate overlap score of proposed approach is observed as 0.879 whereas the overlap score of all conventional approaches is less and they are 0.86, 0.83, 0.82 and 0.84 for Acquino et. al., Yu et.al., [15], Morales et.al., [11] and S. R. chowdhury [12] respectively.

Sensitivity is measured as the total number of pixels correctly classified to the total number of pixels present in the OD region. According to the sensitivity formula, the TP is obtained by the accumulation of total number of pixels classified as OD pixels out of total original OD pixels and FN is obtained as the total number of pixel those are classified as Non-OD pixels for a given OD pixel. Higher value of this metric denotes the better performance and from figure.8, it has been proved that the proposed approach has higher sensitivity.

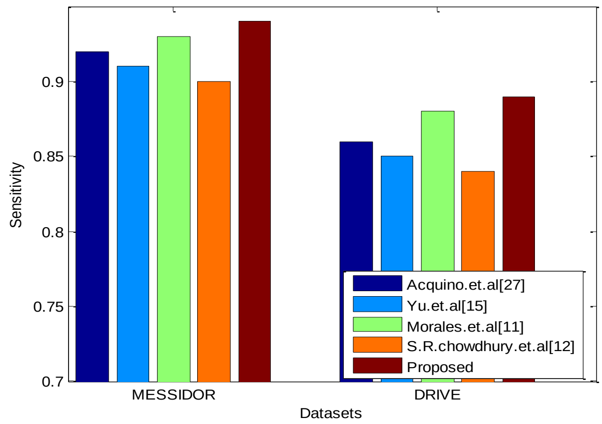

Figure.8 Comparison through Sensitivity

In this paper, the proposed approach accomplished a new way of edge detection at which the boundary regions will get highlighted. Further due to the proposed EDF, every pixel is clearly revealed its nature about the representation of OD or background. These two aspects made the proposed approach more effective in the classification of Pixel into their appropriate classes which results a higher sensitivity. On an average the sensitivity of proposed approach is observed as 0.92 whereas for the conventional approaches, it is of 0.90, 0.89, 0.91, and 0.88 for Acquino et. al., [27], Yu et.al., [15], Morales et.al., [11] and S. R. chowdhury [12] respectively.

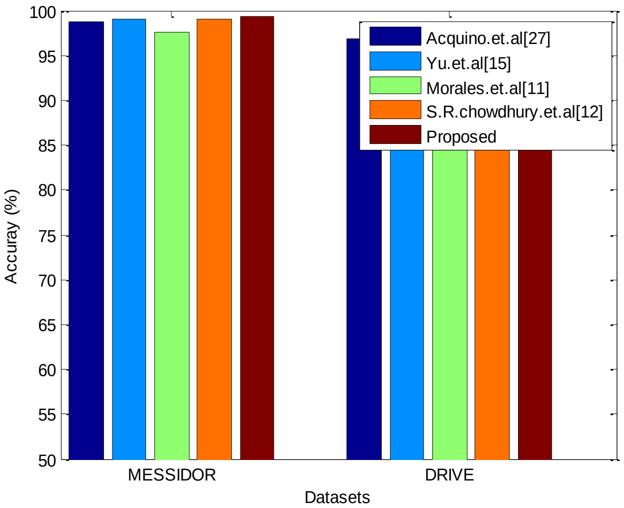

Figure.9 Comparison through Accuracy

Accuracy reveals the performance details in the view of correct classification for both required and non-required classes. Here the required class is OD pixel and non-required class if non-OD pixel. According to the Accuracy formula, the TP is evaluated by accumulating the total number of pixels classified as OD when they are also belongs to OD. Further the TN is measured by accumulating the total number of pixels classified as non-OD when they are also belongs to non-OD. A higher value of accuracy indicates the better performance and from that figure.9, it has been proved that the proposed approach attained a greater accuracy. This achievement is due to the proposed edge detection and binarization method. To classify a pixel more accurately, a proper representation is required and this is done by the threshold after binarization. On an average the accuracy of proposed approach is observed as 99.35%, whereas the conventional approaches have 98.83%, 99.08%, 97.523%, and 99.12% for Acquino et. al., Yu et. al., [15], Morales et. al., [11] and S. R. Chowdhury [12] respectively.

V. CONCLUSION

In this paper, a new OD segmentation technique is proposed based on the statistical properties of retinal fundus image. This method is accomplished totally in three phases namely, ODP location, Blood vessel Removal and OD region extraction. The proposed ODP locating method is accomplished as pre-processing phase to find out the exact starting point of vessel structure which is also the center point of OD. Further the blood vessels are removed through some morphological techniques and finally the OD regions are extracted by the Edge detection and EDF. Simulation experiments are conducted over the proposed method through two standard benchmark datasets, MESSIDOR and DRIVE. Further the performance is measured through the performance metrics and also compared with the conventional approaches. Finally, the Accuracy obtained through the proposed method for the MESSIDOR dataset is observed as approximately 99.35% and for DRIVE dataset it of 89.96%. These two approximate values are higher than the approximate accuracies of conventional approaches which had shown the performance effectiveness of proposed approach.

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