Optic Disc Segmentation in retinal fundus images using level set approach technique

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Abstract— The main objective of this paper is to analyze the performance of the proposed level set segmentation method which is used to segment the optic disc (OD) from fundus images. Glaucoma is a chronic eye disease that causes blindness. It is one of the most common causes of blindness in the world. It results in the loss of vision which cannot be regained. Although glaucoma is not curable, detection of the disease at an appropriate time can stop its further progression. The OD constitutes the important features in a retinal image that can be used to diagnose certain retinal diseases. In this paper, the level set method is implemented to segment the OD region in optical fundus images and its performance is compared with the morphological segmentation to find out the best method to segment OD. To analyze the performance of a segmentation method several performance metrics are used. This paper uses Precision Rate, Recall Rate, F-Measure, Sensitivity, and Specificity to analyze the performance. From the experimental results, it is shown that the level set approach method performs better than the other method.

Keywords— Retinal fundus images, level set segmentation, optical disc, Glaucoma, morphological segmentation.

I. INTRODUCTION

Glaucoma is a disease of the eye causing optic nerve damage. The severity of the disease can be understood by the fact that it is the second leading cause of blindness in the world (Narasimhan and Vijayarekha 2011; Bulletin of the World Health Organization 2004). There is a gradual loss of vision as the disease progresses which occur over a long interval of time. Glaucoma is called the ''silent thief of sight'', as the patient is quite unaware of the disease until it has reached an advanced stage (National Eye Institute 2014). This disease is incurable, however, by proper treatment in time its development can be prolonged. Therefore, early detection of glaucoma plays an indispensable part in the diagnosis of the disease. Diagnosis of glaucoma is mainly based on the Intra Ocular Pressure (IOP), medical history of patient's family [4], and change in optic disc structure [5]. Glaucoma suspect will have IOP more than 21 mmHg [6]. Other methods of monitoring glaucoma involve Optical Nerve Hypoplasia Stereo Photographs (ONHSPs), advanced imaging technology such as Optical Coherence Tomography (OCT), Scanning Laser Polarimetry (SLP), and Confocal Scanning Laser Ophthalmoscopy (CSLO) to generate reference images to study the eye and its internal structure [5]. These methods are expensive and require skilled supervision. It is suggested that combining various imaging methods will significantly improve the accuracy of glaucoma identification. The glaucoma disease is characterized by a change in the structure of nerve fibers and optic disc parameters such as diameter, volume, and area [5], [7]. Structural changes occur due to obstruction to the discharge of aqueous humor, which in turn increases IOP. This injures the optic nerve fiber and prevents the transmission of information from the eye to the brain [8].

Ophthalmologists examine distinct regions to identify disease during eye inspection. Different methods have been employed to determine representative features such as irregularity of blood vessels [9]. The fundus images are used for the diagnosis of glaucoma [10], [11] and diabetic retinopathy [12]. Damage to optic nerve fiber is detected using the morphological features of fundus images [13]. Morphological features such as cup to disc ratio, the ratio of the area of blood vessels in the inferior-superior side to the nasal-temporal side, and the ratio of the distance between the optic disc center and optic nerve head to the diameter of the optic disc are used to detect glaucoma [10]. In morphological methods, choosing structural elements is difficult which may not yield high classification accuracy [1], [10].

Image segmentation based techniques have been used for glaucoma detection [10], [14]. This segmentation has shortcomings like localization, thresholding or demarcation which may lead to unacceptable results and unavoidable errors in glaucoma diagnosis [1]. In order to overcome these difficulties, automated diagnosis methods are preferred for glaucoma diagnosis. Selection of robust features is necessary to develop a robust system. Recent studies have shown that texture features [1], [15], [16] are very effective for glaucoma image detection. Higher Order Spectra (HOS) coupled with texture features are used to improve the classification accuracy [15]. In [16], Discrete Wavelet Transform (DWT) energies are used as features for glaucoma detection. The HOS bispectrum

features and wavelet energy features are used for glaucoma diagnosis in [1]. Unlike DWT, the Empirical Wavelet Transform (EWT) is a signal dependent decomposition technique. The DWT has a set of fixed basis functions that are signal independent. The working principle of EWT depends upon frequency spectrum of the signal.
Section 2 of this paper gives an overview of the methodology to be followed in segmenting OD, section 3 elaborates the review of literature closed to this study, section 4 highlights the performance of the proposed method and section 5 concludes the paper.

II. METHODOLOGY

To detect diseases affecting an eye, the affected retinal fundus image is given as input. From the input image the optic disc region must be segmented. Here we discuss the two methodologies followed to segment the region of interest from the given input image.

I. MATHMETICAL MORPHOLOGY ALGORITHM

In the first methodology, morphological operations are used to segment the optic disc. Fig 1 shows the steps followed in this approach.

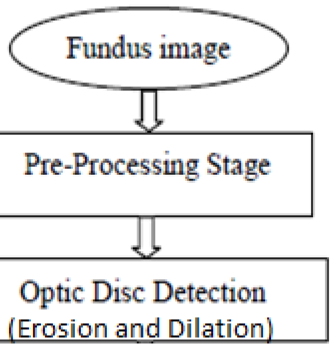

Fig. 1. OD segmentation using morphological operations

A . Fundus image

All digital retinal images are taken from patients using the non-mydriatic retinal fundus camera. The images are stored in JPEG image format file (.jpg) and taken from "Eye and ENT General Hospital (Mandalay)". In this research, the retinal images are taken from the "Eye and ENT General Hospital (Mandalay)" and also from the websites.
The original (RGB) image is transformed into appropriate color space for further processes. And then, a filtering technique is used to reduce the effect of noise. After using the filtering technique, the noise such as salt and pepper noise is removed from the image. Then contrast-limited adaptive histogram equalization (CLAHE) is used for image enhancement. Unlike histogram, it operates on small data regions rather than the entire image. This function uses a contrast-enhancement method that works significantly better than regular histogram equalization for most images.

B. Pre-Processing Stage

1. Converting Colours from RGB to HSI

In a digital image, the input image can be in RGB (Red, Green, and Blue) color model or other color model. The RGB image can be described as M x N x 3 arrays of color pixels. In this paper, the RGB input image is transformed into HSI (Hue, Saturation, and Intensity) color space for further processing. The HSI component of each RGB pixel is obtained using the following equations:

$$H = \begin{cases} \theta & \text{If } B \le G \\ 360-\theta & \text{If } B > G \end{cases}$$

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\}$$

$$S = 1 - \frac{3}{(r+g+b)}\left[\min(R,G,B)\right]$$

$$I = \frac{1}{3}(R+G+B)$$

2. Removing noise using filters

Noise can cause the trouble in the detection of disease. The noise contains in the image is reduced by using the filtering technique such as median filter, averaging filter and Wiener filter.

- **Median Filter** The median filter is a non-linear filter type and which is used to reduce the effect of noise without blurring the sharp edge. The operation of the median filter is – first arrange the pixel values in either the ascending or descending order and then compute the median value of the neighborhood pixels.
- **Averaging Filter** Averaging filter is useful for removing grain noise from a photograph. Each pixel gets set to the average of the pixels in its neighborhood.
- **Wiener Filter** The Wiener filter is used for minimizing the mean square error between input and output image. But the wiener filter requires knowing the power spectral density of the original image which is unavailable in practice. From the resulting output images, it is obvious that the median filter is the best suited to reduce the effect of the noise. And also, it can reduce the noise without blurring the edge. Therefore, the median filter is chosen for the filtering purpose.

3. *Image Enhancement*

The resulting image of the median filter is enhanced by using the histogram equalization technique. The histogram equalization technique is used to overcome the uneven-illumination case. There are two methods to enhance the image:

- **Histogram Equalization** It enhances the contrast of the images by transforming the values in an intensity image. The procedure of the histogram equalization is- (i) Find the running sum of the pixel values (ii) Normalize the values by dividing the total number of pixels (iii) Multiply by the maximum gray-level value and round the value
- **Adaptive Histogram Equalization** Unlike histogram, it operates on small data regions (tiles) rather than the entire image. And also contrast enhancement can be limited in order to avoid amplifying the noise which might be present in the image. So, adaptive histogram equalization technique works significantly better than regular histogram equalization for most images. According to the results, the adaptive histogram equalization technique is used for image enhancement purpose

C. Optic Disc Detection

The morphological methods that are used to detect optic disc and blood vessels are: i) dilation which is used for add pixels to the boundaries of object in an image. ii) Erosion removes pixels on object boundaries. The compound morphological operations are iii) Opening is an erosion followed by a dilation, using the same structuring element for both operation. iv) Closing is an operation of dilation following erosion and rest as the same. The optic disc is the largest brightest region of the image. The optic disc detection of useful because of it can reduce the false positive image detection of the exudates.

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II. LEVEL SET SEGMENTATION ALGORITHM

In the second methodology, Level set segmentation algorithm is used to segment the optic disc. Fig 2 shows the steps followed in this approach. The OD is segmented using the level set method. The proposed method is simple and computationally efficient. The segmented region can be used in the computer assisted diagnosis of glaucoma.

The overall block diagram of the proposed method is shown in Fig. 2. In the first module, the disease affected part of the input thermal image is given as an input. In the second module, the input thermal image is enhanced using preprocessing techniques. In the last module, the level set segmentation approach is used for finding the affected disease in the input thermal image.

A. Optic Disc Detection

Optic Disc detection is used for determining the location of the disk center. This project used the directional matched filter for this purpose. Before applying the directional matched filter split the green channel image from the input. After that this matched filter is convolved with the green channel image in order to detect the main vessels on the OD. In the direction of the vessel is assumed to be aligned along the y-axis to approximate the direction of the main vessels that cross the OD region. The kernel size depends on the maximum central vessel width inside the OD. To increase the OD detection success rate, a rectangular region is used with each OD candidate for vertical matched filtering of the original image border by half of the filter window size. Each pixel's intensity for the out-of-field-of-vision (FOV) dark region is replaced by averaging gray levels of pixels in the FOV. The purpose of the expansion is to remove the artifacts at the image border in the processed image due to the large size of the filter and the black background.

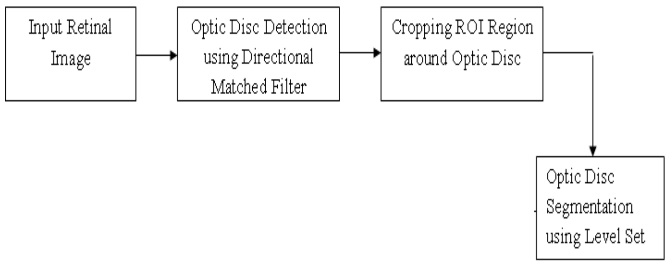

Fig. 2. OD segmentation using Level Set

B. Cropping ROI

In this step, obtain the region of interest (ROI), which consists of the OD region. The OD region is found by using Directional Matched Filter. Based on the OD location the ROI region is detected and cropped. ROI region extracting process is used to save the execution time.

C. Optic Disc Segmentation

In this step, the optic disc is segmented by using the watershed segmentation. There are several issues that need to be addressed prior to OD segmentation like detecting red channel saturation and removing artifacts/distracters. In the red channel, the OD often appears with the most contrast against the background, while vessels appear less prominently. Thus, the OD segmentation algorithm is performed in the red channel. Unfortunately, in some images, the red channel is saturated around the OD. To avoid this issue, first detect the saturation level in the red channel based on the statistics of the red channel ROI. Interference of blood vessels is one of the main difficulties in accurate OD boundary segmentation.

III. LITERATURE REVIEW

In [3], R. Bock, J. Meier, L. G. Ny´ul, J. Hornegger, and G. Michelson et al propose a novel automated glaucoma detection system that operates on inexpensive to acquire and widely used digital color fundus images. After a glaucoma specific preprocessing, different generic feature types are compressed by an appearance-based dimension reduction technique. Subsequently, a probabilistic two-stage classification scheme combines these features types to extract the novel Glaucoma Risk Index (GRI) that shows a reasonable glaucoma detection performance.

In [7], L. G. Ny´ul et al. presented a novel automated glaucoma classification system using digital fundus images. In contrast to the commonly used segmentation-based measurements, it is purely data-driven and uses image-based features that are new in the domain of glaucoma recognition. The proposed two stage SVM classification and the feature extraction methods that provide complementary information with different spatial and frequency resolution, and evaluated which feature type is applicable for glaucoma classification. The classification using each feature extraction method separately showed varying correctness.

In [10] J. Nayak, U. R. Acharya, P. S. Bhat, N. Shetty, and T. C. Lim, et al., presents a novel method for glaucoma detection using digital fundus images. Digital image processing techniques, such as preprocessing, morphological operations and thresholding, are widely used for the automatic detection of the optic disc, blood vessels, and computation of the features. The researchers have extracted features such as cup to disc (c/d) ratio, the ratio of the distance between optic disc center and optic nerve head to the diameter of the optic disc, and the ratio of blood vessels area in the inferior-superior side to the area of a blood vessel in the nasal-temporal side. These features are validated by classifying the normal and glaucoma images using neural network classifier. The results presented in this paper indicate that the features are clinically significant in the detection of glaucoma. The system is able to classify glaucoma automatically with a sensitivity and specificity of 100% and 80% respectively.

In [12] J. Nayak, P. S. Bhat, U. R. Acharya, C. Lim, and M. Kagathi, et al. proposed a computer-based approach for the detection of diabetic retinopathy stage using fundus images. Image preprocessing, morphological processing techniques and texture analysis methods are applied to the fundus images to detect the features such as area of hard exudates, area of the blood vessels and the contrast. The morphological operation such as dilation and erosion are applied to retinal blood vessels to preprocess the image. These features are then used as an input to the artificial neural network (ANN) for an automatic classification. The detection results are validated by comparing it with expert ophthalmologists. He is classify demonstrated a classification accuracy of 93%, sensitivity of 90% and specificity of 100%.

In [17], the paper authored by D. Siva sundhara raja, Dr.S. Vashuki, D.Rajeshkumar et al. classification based approach for blood vessels segmentation of retinal image by using morphological operation. SVM classification is applied in retinal blood vessels. The morphological operation such as dilation and erosion are applied to retinal blood vessels to preprocess the image.

In [18], Xiayu et al. used graph-based approach for blood vessel boundary delineation. The widths of the retinal blood vessels are measured and its edges are segmented. The graph is constructed based on the vessels weight.The REVIEW database was used in this work. This paper has some deficiencies, such as the crossing points and branching points are currently not treated individually, and consequently, the blood vessel detection points are not clearly indicated.

In [19], Benson et al. proposed line-shape concavity measuring model to remove dark lesions which have an intensity structure different from the line-shaped vessels in a retina. This method achieved 95.67% of an average accuracy for the blood vessel detection with respect to ground truth images in DRIVE database, while provided 95.56 % of an average accuracy for the blood vessel detection with respect to ground truth images in STARE database.

In [20], Miguel et al. presented multi-scale feature extraction and region growing algorithm for retinal blood vessels segmentation. This implementation allowed a faster processing of these images and was based on a data partitioning.

In [21], both magnitude and phase components of the histogram features are computed. First, the Region of Interest (ROI) was selected, then Gabor Filtering was applied and then Local Binary Pattern (LPB) was performed to extract the features. Daugman's algorithm was used to accomplish feature set extraction. The image is then transformed into an array using image operators which forms the histogram features for image analysis. Euclidean distances are analyzed. The system produced a sensitivity of 95.45%. It uses a predefined value for all the images.

In [22], an algorithm for automated detection of glaucoma and classification by pixel grouping using super pixel classification was proposed. This method extracted features like RNFL thickness and reflectivity from the OCT (Optical Coherence Tomography) images and then they were combined to obtain a feature map. Then, the feature map was segmented into hundred parts using the pixel segmentation. Feature vector was calculated using histogram distribution, mean and standard deviation of each superpixel.

In [23], illumination correction, Optic Head Normalization and vessel removal for the pre-processing of the fundus images were used. The illumination method correction method removes the retinal background from the original image to get an evenly illuminated fundus image. The estimation is done by average intensity filtering. The vessel structures in the eye ground were removed by using segmentation and also the convergence of vessel-tree was applied for ONH normalization.

IV. EXPERIMENTAL RESULTS

A. *Experimental Images*

Experiments were conducted on a group of color images to verify the effectiveness of the proposed scheme. For the experimental purpose several standards, 512 × 512 cover images are taken. Some of these images are shown in Fig. 4

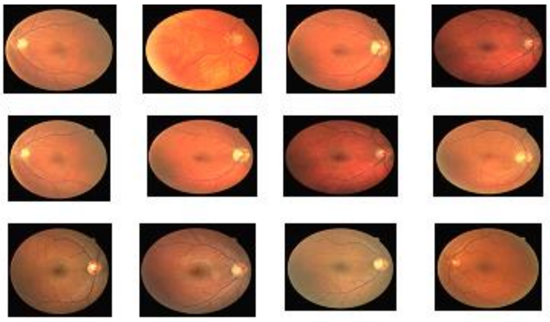

Fig. 3. Experimental Images

B. Performance Analysis

To evaluate the performance of the proposed method several performance metrics are available. This paper uses the Precision Rate, Recall Rate, Sensitivity, Specificity and F-Measure to analyses the performance.

1. Precision Rate

The precision is the fraction of retrieved instances that are relevant to the find.

$$Precision = \frac{TP}{TP + FP}$$

where TP = True Positive (Equivalent with Hits)
FP = False Positive (Equivalent with False Alarm)

2. Recall Rate

The recall rate is the fraction of relevant instances that are retrieved according to the query.

$$Recall = \frac{TP}{TP + FN}$$

Where TP = True Positive (Equivalent with Hits)
FP = False Negative (Equivalent with Miss)

3. F-Measure

F-measure is the ratio of the product of precision and recall to the sum of precision and recall. The f-measure can be calculated as,

$$F_m = (1 + \alpha) * \frac{Precision * Recall}{\alpha * (Precision * Recall)}$$

4. Sensitivity

Sensitivity also called the true positive rate or the recall rate in some field's measures the proportion of actual positives.

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

where, TP – True Positive (equivalent to hit)
FN – False Negative (equivalent with the miss)

5. Specificity

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

$$\text{Specificity} = \frac{\text{TN}}{(\text{FP} + \text{TN})}$$

where, TN – True Negative (equivalent with correct rejection)
FP – False Positive (equivalent to false alarm)

To analyze the performance of the proposed system, it is compared with various techniques by using the performance metrics which are mentioned above. This is shown in the below tables and graphs.

Table 1: OD Segmentation Precision Rate

Methods	***Precision Rate(%)***
Morphology	0.73
Level Set	0.79

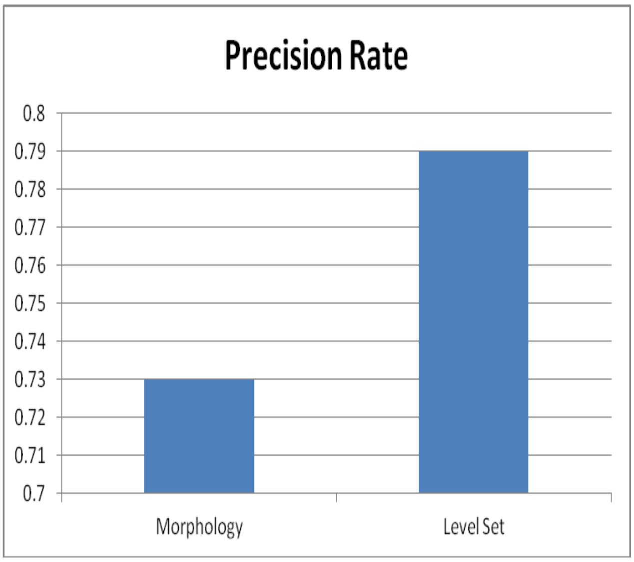

Fig . 4. OD segmentation Precision Rate

Table 2: OD Segmentation Recall Rate

Methods	***Recall Rate(%)***
Morphology	0.78
Level Set	0.81

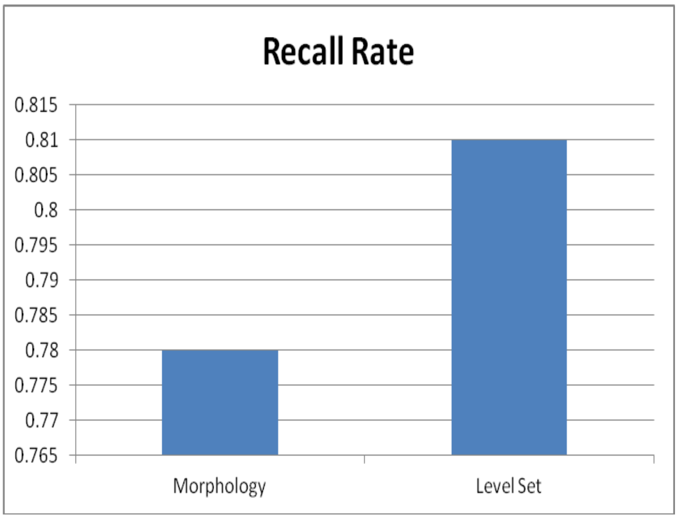

Fig. 5. OD segmentation Recall Rate

Table 3: OD Segmentation Precision Rate

Methods	***F-Measure(%)***
Morphology	0.74
Level Set	0.77

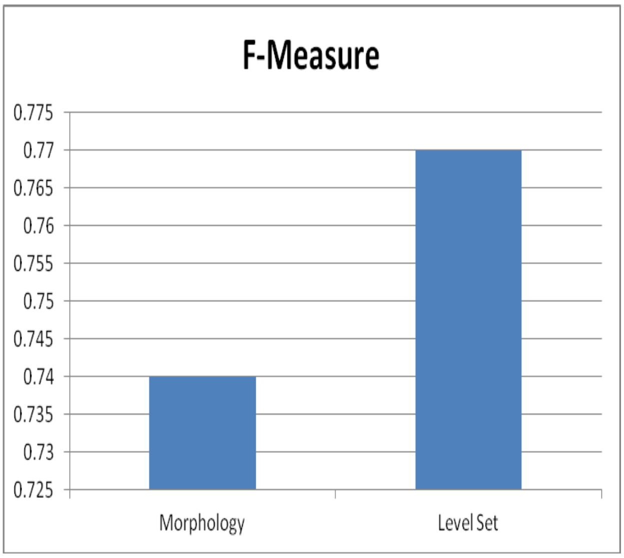

Fig. 6. OD segmentation F-Measure

Table 4: OD Segmentation Sensitivity

Methods	***Sensitivity(%)***
Morphology	0.75
Level Set	0.79

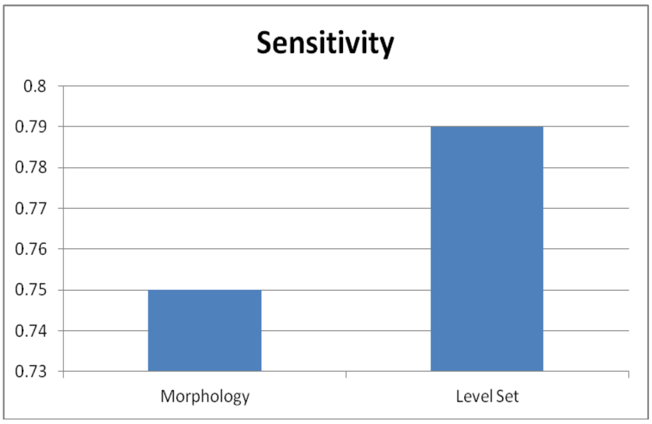

Fig. 7. OD segmentation Sensitivity

OD Segmentation Specificity

Methods	***Specificity***
Morphology	0.76
Level Set	0.80

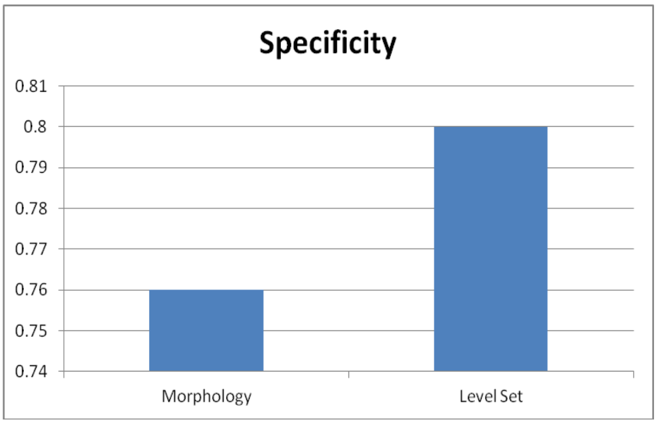

Fig. 8. OD segmentation Specificity

V. CONCLUSION

This paper implements the level set segmentation technique to extract OD regions from retinal fundus images. The experimental results are compared with the performance of morphological segmentation method which is also widely used to segment the optic disc from the digital fundus images. Glaucoma is a chronic eye disease that causes blindness. It is one of the most common causes of blindness in the world. It results in the loss of vision which cannot be regained. Although glaucoma is not curable, detection of the disease in proper time can stop its further progression. The optic disk (OD constitute the important features in a retinal image that can be used to diagnose certain retinal diseases. In this paper, two methods are implemented and their performance is compared to find the best method to segment the brain tumor with high quality. The first method segments the optic disc using mathematical morphological approach. The second method uses level set approach for segmenting the optic disc. To analyze the performance of this method several performance metrics are used. This paper uses Precision Rate, Recall Rate, F-Measure, Sensitivity, and Specificity to analyses the performance. From the experimental results, it is shown that the level set method performs better than the morphological method.

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