Glaucoma Detection And Classification Using Adaptive Thresholding

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ABSTRACT

Glaucoma is an optic neuropathy which is one of the main causes of permanent blindness worldwide. This paper presents an automatic image processing based method for detection of glaucoma from the digital fundus images. In this proposed work, the discriminatory parameters of glaucoma infection, such as cup to disc ratio (CDR) and blood vessels in different regions of the optic disc has been used as features and fed as inputs to learning algorithms for glaucoma diagnosis. These features which have discriminatory changes with the occurrence of glaucoma are strategically used for training the classifiers to improve the accuracy of identification. The segmentation of optic disc and cup based on adaptive threshold of the pixel intensities lying in the optic nerve head region. Unlike existing methods the proposed algorithm is based on an adaptive threshold that uses local features from the fundus image for segmentation of optic cup and optic disc making it invariant to the quality of the image and noise content which may find wider acceptability. The experimental results indicate that such features are more significant in comparison to the statistical or textural features as considered in existing works. The proposed work achieves an accuracy of 95.10% A comparison of the proposed work with the existing methods indicates that the proposed approach has improved accuracy of classification glaucoma from a digital fundus which may be considered clinically significant.

Keywords: Glaucoma, Optic disc, Optic cup, Cup to disc ratio, Adaptive threshold, Fundus image.

I. INTRODUCTION

Glaucoma is the second most common cause of blindness worldwide. Low awareness and high costs connected to glaucoma are reasons to improve methods of screening and therapy. A method for optic nerve head segmentation and its validation, based on morphological operations, Hough transform, and an anchored active contour model is proposed in [1]. A robust and computationally efficient approach for the localization of the different features and lesions in a fundus retinal image is presented in [2]. A constraint in optic disc detection is that the major blood vessels are detected first and the intersection of these to find the approximate location of the optic disc.

A novel approach to automatically segment the OD and exudates is proposed in [3]. It makes use of the green component of the image and preprocessing steps such as average filtering, contrast adjustment, and thresholding. The other processing techniques used are morphological opening, extended maxima operator, minima imposition, and watershed transformation. An automated classifier based on adaptive neuro-fuzzy inference system (ANFIS) to differentiate between normal and glaucomatous eyes from the quantitative assessment of summary data reports of the Stratus optical coherence tomography is presented in [4].There are two methods to extract the disc automatically, as proposed in [5]. The component analysis method and Region of Interest (ROI) based segmentation are used for the detection of disc. For the cup, component analysis method is used. Later the active contour is used to plot the boundary accurately. To automatically extract the disc, a variation level set method is proposed in [6]. For the cup, two methods making use of color intensity and threshold level set are evaluated. An automatic OD parameterization technique based on segmented OD and cup regions obtained from monocular retinal images is proposed in [7]. A novel OD segmentation method is proposed 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. A new template-based methodology for segmenting the OD from digital retinal images s presented in [8]. Morphological and edge detection techniques followed by the Circular Hough Transform are used to obtain a circular OD boundary approximation which requires a pixel located within the OD as initial information.

A novel method for glaucoma detection using a combination of texture and higher order spectra (HOS) features from digital fundus images is proposed in [9]. Support vector machine, sequential minimal optimization, naive Bayesian, and random-forest classifiers are used to perform supervised classification. A mathematical
framework to link retinal nerve fiber layer (RNFL) structure and visual function using the data typically acquired in the clinical management of glaucoma is proposed in [10]. The model performed and generalized well over different populations from three clinical

centers. The derived structure-function relationship accorded well with RNFL anatomy, and could be applied to reduce the variability that confounds the measurement of glaucoma damage.

Stereo disc photograph is analyzed and reconstructed as 3 dimensional contour images to evaluate the status of the optic nerve head for the early detection of glaucoma and the evaluation of the efficacy of treatment is presented in [11]. To detect the edge of the optic nerve head and retinal vessels and to reduce noises, stepwise preprocessing is introduced. RetCam is a new imaging modality that captures the image of iridocorneal angle for the classification is presented in [12]. Glaucoma is the one of the two major causes of blindness, which can be diagnosed through measurement of neuro-retinal CDR is described in [13]. Automatic calculation of optic cup boundary is challenging due to the interweavement of blood vessels with the surrounding tissues around the cup. A multimodality fusion approach for neuro retinal cup detection improves the accuracy of the boundary estimation. Modeling of Scanning Laser polarimetry method is presented in [14] to model the change in images acquired by scanning laser polarimetry for the detection of glaucomatous progression. The Optic Disc is the exit point of retinal nerve fibers from the eye and the entrance and exit point for retinal blood vessels. A new filtering approach in the wavelet domain for image preprocessing is described in [15]. Sobel edge detection, Texture Analysis, Intensity and Template matching techniques are used to detect Optic Disc.

1. LITERATURE SURVEY

In [1], 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 [2], 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 [3], 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 [4]-[10], different methods for blood vessel detection and segmentation is presented.

Staal [14] et al. proposed a pixel feature based method that additionally analyzed the vessels as elongated structures. The edge-based methods can be further classified into window-based and tracking-based methods. Window-based method estimates a match at each pixel against the pixel‘s surrounding window. In order to trace the vessels, the tracking approach makes use of local image properties from an initial point.

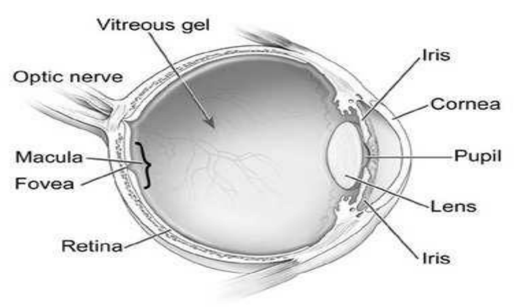

Fig 1: Eye diagram showing the retina, the light-sensitive tissue at the back of the eye

2. METHODOLOGY

A. Region of interest (ROI)

Extract the optic disc, a region of interest around the optic disc must first be delineated, as the optic disc generally occupies less than 5% of the pixels in a typical fundus image. While the optic disc extraction can be performed on the entire image, localizing the ROI would help to reduce the computational cost as well as improve segmentation accuracy. In the images, regions are labeled by using the neighbourhood connecting pixels [2]. The fundus image is subdivided into number of regions, and an approximate ROI Centre is selected based on the region containing the highest number of pre-selected pixels shown in fig. 2.

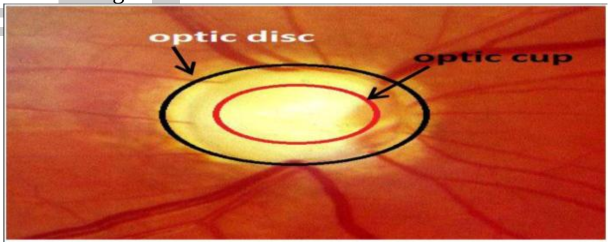

Fig2: Glaucoma image.

B. Optic disc segmentation

The optic disc has to be segmented from the fundus images. The segmentation of object pixel is given thresholding value of „1 while a background pixel is given thresholding value of „0. The threshold value is using the extraction of optic disc boundary. In this paper, the optical disc boundary is localized using color planes as choose by the color analysis. The segmented optic disc uses edge detection.

The optic disc is segmented and edge detection, but still the actual shape of optic disc boundary is not obtained as desired. Therefore, the ellipse fitting algorithm is used.

C. Optic Cup Segmentation

The localization of the optic disc boundary, then cup segmentation provides to localize the optic cup boundary. The extraction of the cup from the optic disc boundary, image processing technique is used to segmentation of the optic cup.

D. Optic Disc Smoothing

After the cup boundary localization, the ellipse fitting algorithms is used for accurate curvature. The CDR is consequentially obtained based on the height of detected cup and disc. F. Ellipse fitting Ellipse fitting algorithm can be used to smooth the optic cup and disc boundary. Ellipse fitting is usually based on the least square fitting algorithm which assumes that the best-fit curve of a given type is the curve that has the minimal sum of the deviations squared from, given data points shown in the Fig. 8 [2]. Direct Least Square Fitting Algorithm is chosen to fit the optic disc over other popular ellipse fitting algorithms like Bookstein Algorithm and Taubin Algorithm. This algorithm complicated for fit optic disc. It is ellipse specific, thus the effect of noise (ocular blood vessel, hemorrhage, drusen, etc.) around the disc area can be minimized while forming the ellipse. It can also be easily solved naturally by a generalized Eigen system.

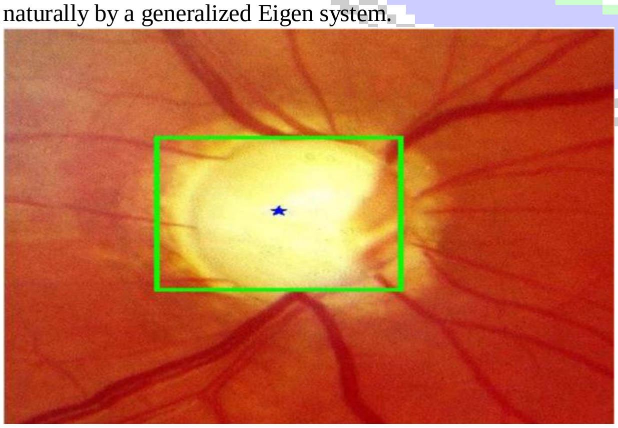

Fig3: Region of interest

In Fitting algorithm, a quadratic constraint is set on the parameters to avoid trivial and unwanted solutions. The goal is to search for a vector parameter which contains the six coefficients of the standard form of a conic [2].

An ellipse is a general conic equation which can be described second order polynomial.

F(x,y) = ax2+bxy+cy2+dx+ey+f=0 (1)

With an ellipse-specific constraint

b2 – 4ac<0 (2)

Where a, b, c, d, e, f are coefficients of the ellipse and (x, y) are co- ordinates of points lying on it.

By introducing vectors

A=[a, b, c, d, e, f]

T x= [x2, xy, y2, x, y, 1] (3)

It can be rewritten to the vector form

F a(x) = x.a = 0 (4)

The fitting of a general conic to a set of points (xi,yi),i–1…N may be approached by minimizing the sum of squared algebraic distances of the points to the conic coefficient a:

$$\min \sum_{i=1}^{N} F\left(x_i, y_i\right)^2 = \min \sum_{i=1}^{N} F_a\left(\left(x_i\right)^2\right) \qquad (5)$$

The problem (5) can be solved by the standard least squares approach, but the result of such fitting is a general conic and it need not to be an ellipse. To ensure an ellipse–specificity of the solution, the appropriate constraint (2) have to be considered Under a proper scaling, the inequality constraint in (2) can be changed into an equality constraint.

3. PROPOSED SYSTEM

Algorithm

Step 1. The Color Retinal Fundus Image in Gray scale is converted from green channel.

Step 2. Adaptive histogram equalization [6] is carried out on the gray image.

Step 3. The background is subtracted from the foreground of the image using median filter.

Step 4. FCM is applied on the image followed by binarization and filtering.

Step 5: The ground truth image is compared with the corresponding disease.

Step 6. The Sensitivity, Specificity, PPV, PLR and Accuracy are calculated.

The proposed system consists of three stages-first is preprocessing of retinal image to separate the green channel and second stage is retinal image enhancement and third stage is blood vessel segmentation using morphological operations and SVM Classifier. The proposed system for blood vessel segmentation is illustrated in Fig. 4.

A. Preprocessing

Initially the retinal image is enhanced using adaptive histogram equalization technique in order to enhance the blood vessels. Then, the retinal fundus image is divided in to three primary components such as Red Channel (R), Green Channel (G) and Blue Channel (B). The green channel is high sensitive to the blood vessels. Hence this channel is considered for the detection and segmentation of retinal blood vessels from the retinal image.

B. Morphological Operations

The morphological operations are applied on the preprocessed green channel. Morphological operation processes the preprocessed image with structuring element. The retinal blood vessels are detected by applying dilation and erosion process to a preprocessed image. The morphological opening and closing operation are applied to an image based on multi structure elements to enhance the vessel edges. Morphological opening and closing operation is performed by using dilation and erosion. The morphologically processed opened image and morphologically processed closed images are absolutely subtracted to detect the blood vessels from retina fundus image. The combination of dilation and erosion operations is performed on image with different structuring element of radius 3. Then, an absolute difference mapping image is formed by absolute subtraction of retinal image from the morphologically processed sub-band image.

C. Feature Extraction and Classifier

The Local Binary Pattern (ELBP) features and GLCM features are extracted from the morphologically processed image. It can be computed as in Eq. 6,

$$LBP = \sum_{p=1}^{8} 2^p * K(I_N - I_C) \qquad (6)$$

where, I_N denotes the neighboring pixel in a square window (3×3), I_C is the center pixel in the 3×3 mask, 'p' represents the number of surrounding pixels, 'K' denotes c function and $K(I_N - I_C)$ is marked as the threshold value and it is estimated as,

$$K(I_N - I_C) = \begin{cases} 1, & if \quad (I_N - I_C) \geq 0 \\ 0, & if \quad (I_N - I_C) < 0 \end{cases} \qquad (7)$$

D. GLCM Features

The Co-occurrence features can be extracted from each Co-occurrence Matrix. Energy, contrast, correlation and homogeneity are used as GLCM features.

GLCM Features	Feature Representations
'Contrast'	∑|i-j|^2.p(I,j)
'Energy'	∑p(I,j)^2
'Homogeneity'	∑p(I,j)/[1+|i-j|]
'Correlation'	∑(i-µi)(j-µj).p(I,j)/[σi.σj]

Table 1 Feature Representations

The extracted features are trained and the given retinal images are classified in accordance with the trained values SVM Classifier. The SVM classifies each pixel in the retinal image as blood vessel or nonblood vessel pixels.

4. RESULTS AND DISCUSSIONS

The proposed blood vessel detection and segmentation methodology is applied on images available in DRIVE and STARE databases and the segmentation results were compared with their respective ground truth images.

To measure the performance of the proposed method for the detection of blood vessels on the fundus image, the proposed vessel segmentation method is compared to its corresponding ground truth images. The performance of proposed vessel detected image is experimentally validated with ground truth images.

The performance of proposed blood vessel segmentation methodology is analyzed with the following parameters:

- Sensitivity (Se=TP/(TP+FN))
- Accuracy (Acc=(TP+TN)/(TP+FN+TN+FP))

where, TP denotes true positive, FP denotes false positive, FN denotes false negative and TN denotes true negative. True Positive refers to the correctly detected blood vessels, True Negative refers to the wrongly detected blood vessels, False Positive refers to the correctly and wrongly detected non blood vessel pixels.

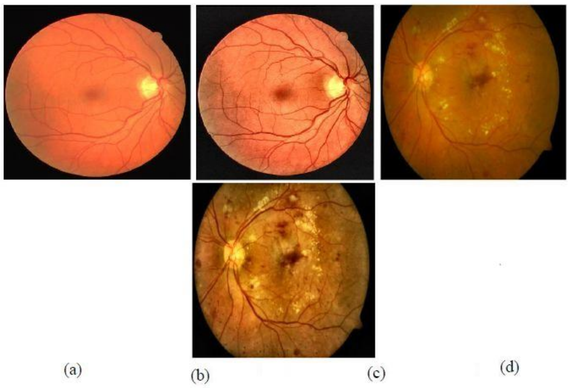

Fig. 5. Retinal image enhancement (a) Normal retinal image (b) Abnormal retinal image (c)-(d) Enhanced retinal image.

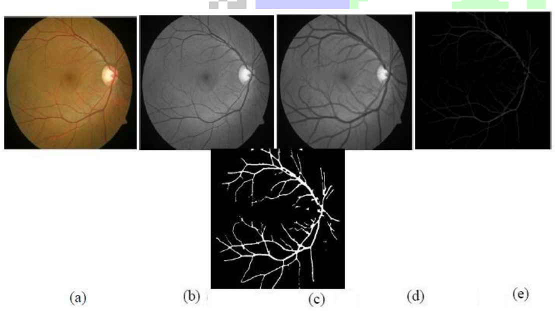

Fig.6. Blood vessel segmentation of normal retinal image (a) Normal retinal image (b) Green channel image (c) Morphologically processed image (d) Absolute difference image (e) Blood vessel segmented image.

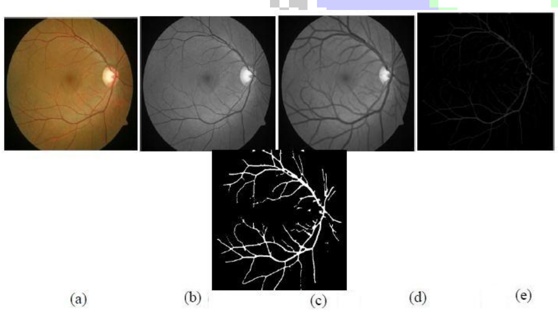

Fig. 7. Blood vessel segmentation of abnormal retinal image (a) Abnormal retinal image (b) Green channel image (c) Morphologically processed image (d) Absolute difference image (e) Blood vessel segmented image.

Methodology	Se	Sp	Acc
Proposed	0.7800	0.9799	0.9510
Soares et al. [15]	0.7283	0.9788	0.9466
Mendonc et al. [16]	0.7344	0.9764	0.9452

Table 2 Performance Analysis of Vessel Segmentation

The experimental result shows that, Morphological and SVM based blood vessel segmentation achieves a performance appraisal of 78% sensitivity, 97.99%specificity, and 95.1% accuracy, which is clearly shown in Table II.

5. CONCLUSION

The blood vessel detection and segmentation is an important for diabetic retinopathy diagnosis at earlier stage. The morphological and SVM classifier is proposed in this paper to detect and segment the blood vessels from the retinal image .The local binary pattern and GLCM features are extracted from the morphologically processed image and used as blood vessels features. The proposed method detected blood vessels with an average sensitivity of 78%, average specificity of 97.99% and an average accuracy of 99.6% in the retinal fundus images.

6. SCOPE FOR FURTHER STUDIES

SVM have shown promising results in object detection and recognition, content-based image retrieval, text recognition, biometrics, speech recognition and also used for regression. SVM became famous when using images as input, it gave accuracy comparable to neural-networks with hand-designed features in a handwriting recognition tasks.

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