

AN EFFICIENT AUTOMATED SYSTEM FOR GLAUCOMA DETECTION USING FUNDUS IMAGE

¹K.NARASIMHAN, ²Dr.K.VIJAYAREKHA

¹Asstt Prof., Department of ECE, SASTRA

²Assoc. Dean., Department of EEE, SASTRA

E-mail: knr@ece.sastra.edu, kvrekha11@gmail.com

ABSTRACT

This paper proposes a new method for the detection of glaucoma using fundus image which mainly affects the optic disc by increasing the cup size is proposed. The ratio of the optic cup to disc (CDR) in retinal fundus images is one of the primary physiological parameter for the diagnosis of glaucoma. The K-means clustering technique is recursively applied to extract the optic disc and optic cup region and an elliptical fitting technique is applied to find the CDR values. The blood vessels in the optic disc region are detected by using local entropy thresholding approach. The ratio of area of blood vessels in the inferior-superior side to area of blood vessels in the nasal-temporal side (ISNT) is combined with the CDR for the classification of fundus image as normal or glaucoma by using K-Nearest neighbor, Support Vector Machine and Bayes classifier. A batch of 36 retinal images obtained from the **Aravind Eye Hospital, Madurai, Tamilnadu, India** is used to assess the performance of the proposed system and a classification rate of 95% is achieved.

Keywords: *Glaucoma, K-Means Clustering, Thresholding, Fundus Image, CDR, ISNT, K-Nearest Neighbor, Support Vector Machine, Bayesian Classifier*

1. 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 multidimensional 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 is 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.

2. PROPOSED METHOD

The proposed system mainly consists of three different stages. They are Region of Interest (ROI) Extraction, Feature extraction stage and classification stage. All the stages are explained in detail in the following sub sections.

2.1 ROI EXTRACTION

The ROI Extraction stage is shown in Figure 1. The retinal images have been taken in an RGB mode by fundus camera. The size of the fundus image is 1504 x 1000 pixels. G plane is considered for the extraction of optic disc and optic cup, because G plane provides better contrast than the other two planes R and B planes. Hence it is necessary to separate the G plane for further analysis.

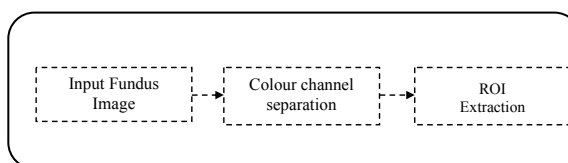


Figure 1 ROI Extraction stage

The optic disc is the entrance of the vessels and the optic nerve into the retina. In fundus images, the optic disc belongs to the brightest point of the image [17]. Hence the maximum brightest point within the optic disc in the G plane is determined for extracting the optic disc. The approximate region around the identified brightest point is to be selected for initial optic disc region as ROI. After analyzing the entire collection of fundus image, a square of size 360 X 360 pixels with the brightest pixel as the centre point is decided to consider as ROI. The initial ROI covers mainly the entire optic disc along with a small portion of other regions of the image. Figure 2 shows the images in the ROI Extraction stage.

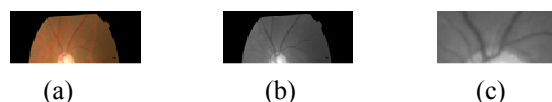


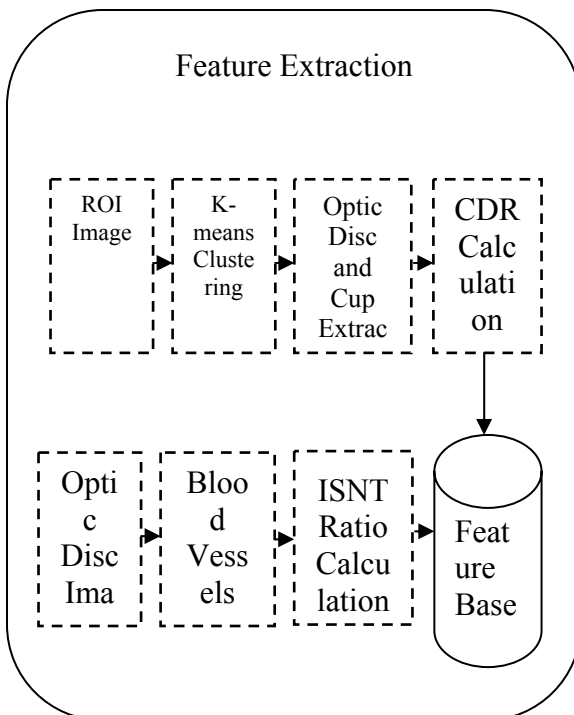
Figure 2 (a) Fundus Image (b) Green Channel (c) ROI Image

2.2 FEATURE EXTRACTION

K-means clustering plays a vital role in the feature extraction stage to compute one of the features CDR. It is an unsupervised learning algorithm that solves the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. At this point k new centroids are calculated as the mean of the clusters resulting from the previous step. As a result of repetitive application of these two steps, the k centroids change their location step by step until no more changes take place. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an objective function (squared error function). The objective function is

$$J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2$$

Where $\|x_i^{(j)} - c_j\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j , is an indicator of the distance of the n data points from their respective cluster centers. Figure 3 shows the feature extraction stage.



2.2.1 LOCALIZING THE OPTIC DISC AND CUP

The K-means algorithm is an iterative technique that is used to partition the ROI image into K clusters. The ROI covers mainly the entire optic disc, optic cup and a small portion of other regions of the image. Hence the K value is chosen as 3. From the three clusters as shown in Figure 4 (a), the optic disc cluster has to be identified as follows. The cluster which contains the border region belongs to the other region of the ROI image that does not contain the optic disc and optic cup. Hence, the cluster is removed for the extraction of optic disc and the remaining two clusters form the optic disc region which is shown in Figure 4 (b). Since it is clearly known that the optic cup is inside the optic disc, the cluster in the center of the image forms the optic cup which is shown in Figure 4 (c). Finally, the morphological operation is performed to fill the holes and small region inside optic disc clusters and optic cup cluster.

After extracting optic disc, connected components technique is applied to form the rectangle that contains the whole disc region and cup region as shown in Figure 5(a) and 5(b) respectively. From the centre of the rectangle an ellipse is drawn that is inscribed in the rectangle. The area of the ellipse as well as the area of the optic disc is calculated by using the formula (2)

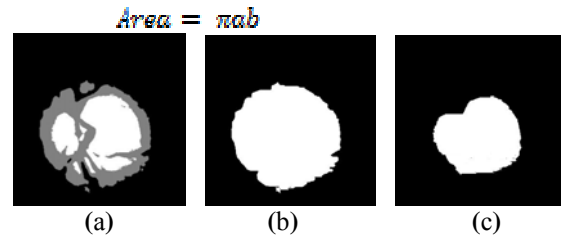


Figure 4 (a) K means clustering Image (b) Optic disc (c) Optic cup

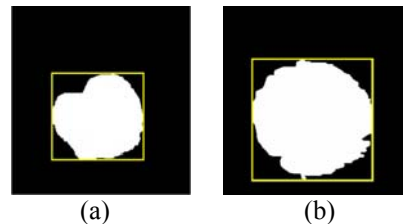


Figure 5 (a) Rectangle for Optic disc region (b) Optic cup region

where a and b are major axis length (half of the rectangle width) and minor axis length (half of the

rectangle height) respectively. The area of optic cup is also computed in the same manner. The CDR which is the ratio between the area of the optic cup and the area of the optic disc is computed and used as one of the features for the detection of glaucoma. Figure 6 shows the exact optic disc and optic cup in the ROI image

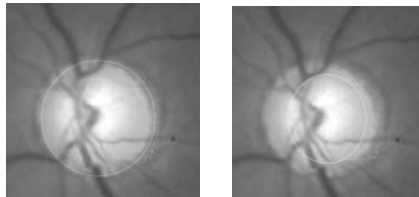


Figure 6 (a) Optic disc (b) Optic cup

2.2.2 ISNT RATIO

The ISNT ratio is calculated by measuring the area of the blood vessels in ISNT quadrants. First, the blood vessels in the segmented optic disc region are detected by using the local entropy thresholding technique described in [16]. Figure 7 shows the detection of blood vessels for the given ROI.

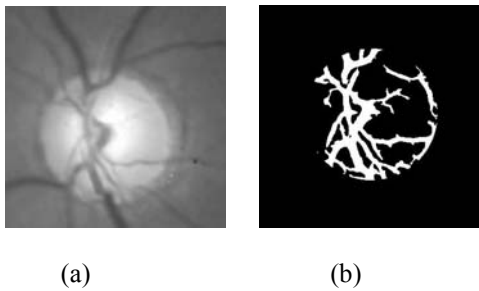


Figure 7 (a) ROI Image (b) detection of blood vessels

A mask image (360×360) is used to measure the area of the blood vessels in the ISNT quadrant. The mask is rotated by 90° each time and is used to obtain the area covered by blood vessels in each quadrant. The mask fits the image perfectly as both the cropped image and the mask have the same dimensions of 360×360. Figure 8 shows the mask and the blood vessels inside the mask.

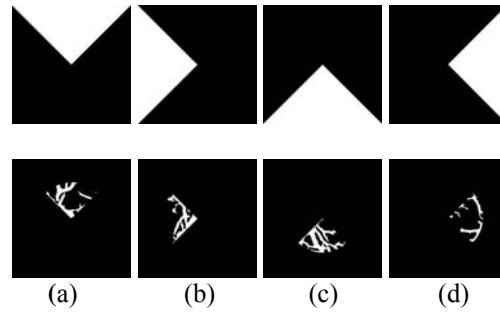


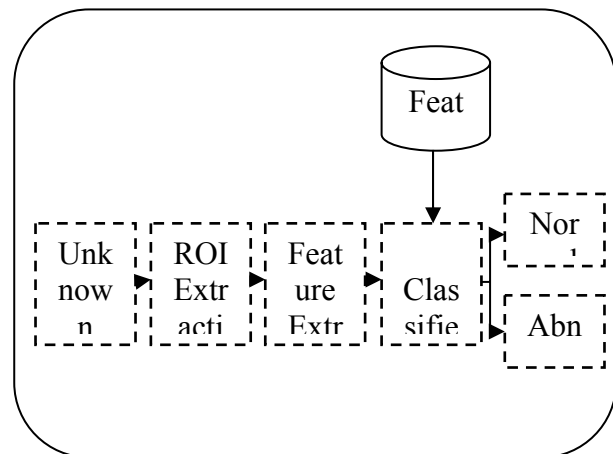
Figure 8 Masks used in the proposed method and the blood vessels inside the mask.
(a) Superior side (b) Temporal side (c) Inferior side (d) Nasal side

2.2.3 FEATURE BASE CREATION

The numbers of training and testing sets are shown in Table 1. From the table, totally 16 fundus images are used to train the classifier. The proposed features CDR and ISNT Ratio are calculated for all the training images and stored in an array. This array is called the Feature base and the size of the feature base is 15x2.

2.3 CLASSIFICATION STAGE

In this classification stage, the ROI of an unknown fundus image is extracted and the features CDR and ISNT ratio are calculated. These two features are processed with the features in the database to classify whether the given fundus image as normal or glaucoma –affected by using the classifiers. The performance of the proposed system is measured as the percentage of test set images classified into the correct feature class. The classification stage is shown in Figure 9.



3. EXPERIMENTAL RESULTS:

The proposed algorithm is tested on 15 normal fundus images and 21 fundus images obtained from glaucoma patients. Three different classifiers, KNN, SVM and Bayes classifier are used to analyze the performance of the proposed system. The distance measure used in KNN classifier is Euclidean distance and the rule used to classify the unknown is nearest point tie-break. In Bayes classifier, normal Gaussian distribution is used to fit or model the feature base and it estimates the prior probabilities from the relative frequencies of the classes in training. In SVM classifier, linear kernel is used to map the training data into the kernel space. The classification rate for three different classifiers is tabulated in Table 2. Figure 10 shows the graphical representation of the performance of three classifiers.

From the Table 2, it can be observed that the proposed method has a higher classification rate while using SVM classifier due to the fact that a data point is viewed as a p -dimensional vector (a list of p numbers), such points are separated with a $(p - 1)$ dimensional hyperplane i.e., linear classifier. There are many hyperplanes that might classify the data. The best hyperplane is chosen that represents the largest separation, or margin, between the two classes which results in higher classification rate. In KNN classifier, only the distance measure between the training set and testing set is used for the classification which results in misclassification if the feature scales are inconsistent. The imbalance between the number of training samples per class in Bayes classifier, results in poor choices of weights for linear decision boundary that leads in misclassification.

Table 1 Number of training set and testing set

Category	No. of Training Set	No. of testing Set
Normal	7	15
Abnormal	9	21

Table 2 Classification rates of Normal and Abnormal image

Classifier	Normal (%)	Abnormal (%)
KNN	93.3	80.9
BAYES	86.6	95.23
SVM	100	95.23

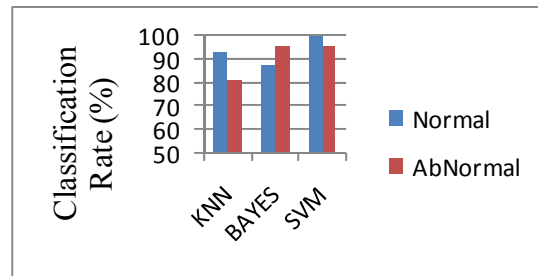


Figure 10 Graphical representation of performance of the classifiers KNN, Bayes and SVM

4. CONCLUSION

In this paper, a new method for the detection of glaucoma based on two features CDR and ISNT ratio is presented. K-means clustering is recursively applied to ROI to localize the optic disc and optic cup region and an elliptical fitting technique is applied to find the CDR values. Local entropy thresholding is used to extract the blood vessels inside the optic disc and four different masks are used to calculate the ISNT ratio. The features, such as CDR and ISNT ratio are computed automatically and the performance of the proposed algorithm is tested on three different classifiers. Experimental results show that the maximum classification rate 95% for glaucoma is achieved while using the SVM classifier.

REFERENCES

[1] R. Chrastek a, M. Wolf a, K. Donath, "Automated segmentation of the optic nerve head for diagnosis of glaucoma", Journal of Medical Image Analysis in Elsevier, Functional Imaging and Modeling of the Heart, August 2005, pp 297-314.
 [2] Ravishankar, S. Jain, A. Mittal, "Automated feature extraction for early detection of diabetic retinopathy in fundus images", IEEE



- conference on Computer Vision and Pattern Recognition, 2009, pp 210-217.
- [3] Ahmed Wasif Reza & C. Eswaran & Subhas Hati, "Automatic Tracing of Optic Disc and Exudates from Color Fundus Images Using Fixed and Variable Thresholds", *Journal of Medical Systems*, Feb 2009, pp 73 -80.
- [4] Mei-Ling Huang, Hsin-Yi Chen, Jian-Jun Huang, "Glaucoma detection using adaptive neuro-fuzzy inference system", *Journal of Expert Systems with Applications*, 2007, pp 458-468.
- [5] S.Kavitha, S.Karthikeyan, Dr.K.Duraiswamy, "Early Detection of Glaucoma in Retinal Images Using Cup to Disc Ratio", *IEEE Second International conference on Computing, Communication and Networking Technologies*, 2010, pp 1-5.
- [6] J. Liu, D. W. K. Wong, J.H. Lim, X. Jia, "Optic Cup and Disk Extraction from Retinal Fundus Images for Determination of Cup-to-Disc Ratio", *IEEE third conference on Industrial Electronics and Applications*, June 2008, pp 1828 -1832.
- [7] Gopal Datt Joshi, Jayanthi Sivaswamy, "Optic Disk and Cup Segmentation From Monocular Color Retinal Images for Glaucoma Assessment", *IEEE Transactions On Medical Imaging*, June 2011, pp 1192-1205
- [8] Arturo Aquino, Manuel Emilio Gegundez-Arias, and Diego Marin, "Detecting the Optic Disc Boundary in Digital Fundus Images Using Morphological, Edge Detection, and Feature Extraction Techniques", *IEEE Transactions on Medical Imaging*, Nov 2010, pp 1860-1869.
- [9] U. Rajendra Acharya, Sumeet Dua, Xian Du, "Automated Diagnosis of Glaucoma Using Texture and Higher Order Spectra Features", *IEEE Transactions On Information Technology In Biomedicine*, May 2011, pp 449-455.
- [10] Haogang Zhu, David P Crabb, David F Garway-Heath, "A Bayesian Radial Basis Function Model to Link Retinal Structure and Visual Function in Glaucoma", *IEEE third conference on Bioinformatics and Biomedical Engineering*, June 2009, pp 1-4.
- [11] H. J. Kong, S. K. Kim, J.M. Seo, "Three Dimensional Reconstruction of Conventional Stereo Optic Disc Image", *IEEE Proceedings of the 26th Annual International Conference*, Sep 2004, pp 1229-1232.
- [12] Jun Cheng, Jiang Liu, Beng Hai Lee, "Closed Angle Glaucoma Detection in RetCam Images", *IEEE Proceedings of the 32nd Annual International Conference*, Sep 2004, pp 4096-4099.
- [13] Zhuo Zhang, Jiang Liu, Wing Kee Wong, "Neuro-Retinal Optic Cup Detection in Glaucoma Diagnosis", *IEEE Proceedings of the 2nd International Conference on Biomedical Engineering and Informatics*, Oct 2009, pp 1-4.
- [14] Koen A. Vermeer, Frans M. Vos, Barrick Lo, "Modeling of Scanning Laser Polarimetry Images of the Human Retina for Progression Detection of Glaucoma", *IEEE Transactions On Medical Imaging*, May 2006, pp 517-528.
- [15] Vahabi Z, Vafadoost M, Gharibzadeh Sh, "The new approach to Automatic detection of Optic Disc from non-dilated retinal images", *IEEE Proceedings of the 17th Iranian Conference of Biomedical Engineering*, Nov 2010, pp 1-6.
- [16] Thitiporn Chanwimaluang and Guoliang Fan, "An efficient blood vessel detection algorithm for retinal images using local entropy thresholding", *IEEE Proceedings of the International Symposium on Circuits and Systems*, May 2003, pp 21-24.
- [17] T. Walter and J. C. Klein, "Automatic analysis of color fundus photographs and its application to the diagnosis of diabetic retinopathy," in *Handbook of Biomedical Image Analysis*, vol. 2, pp. 315-368, 2005.

AUTHOR PROFILES:



K.Narasimhan received M.Sc degree with Electronics Specialization from Bharathidasan University, and M.Tech. in Non destructive Testing from Regional Engineering College, Trichy., He is currently working

towards his Ph.D. Degree in SASTRA University. His research interests include Digital Image Processing, Medical Image analysis, Pattern Recognition, Digital Signal processing



Dr.K.Vijayarekha received the B.E. degree in electrical engineering from Madurai Kamaraj University and M.E in power system, from Bharathidasan University. She received the Ph.D. degree from the SASTRA University. Currently, she is

working as an Associate Dean in the Department of EEE. His research interests include , Machine vision, image processing and neural network and Control Systems.