Review of Image Processing Techniques for Automatic Detection of Eye Diseases

ManjulaSri Rayudu
Department of EIE,
VNR Vignana Jyothi IET
Hyderabad, India.
rmanjulasri@gmail.com

Vaibhav Jain
M.E student (Embedded Systems),
BITS-Pilani-Hyderabad Campus
Hyderabad, India.
Vaibhjain2412@gmail.com

MM.Rao Kunda, SM-IEEE
Department of EEE,
BITS-Pilani-Hyderabad Campus
Hyderabad, India.
kundammrao@gmail.com

Abstract **- The review paper describes the application of image processing techniques for automatic detection of eye diseases. Large percentages of people suffer from eye diseases in rural and semi urban areas in India as well as world over. Image processing techniques greatly help diagnosing various eye diseases. Current diagnosis of retinal disease relies strongly upon optical imaging methods due to the photon sensing nature of the eye over a wide band of wavelengths. The key image processing elements to detect eye diseases include image registration, fusion, segmentation, feature extraction, enhancement, pattern matching, image classification, analysis and statistical measurements. In developing and under developing countries large number of people are suffering from ophthalmic diseases like Glaucoma, Age related Macular Degeneration (AMD), Diabetic Retinopathy, Diabetic hypertension. A large deficit of ophthalmologists exists in these regions. Year after year the number of medical assistants is decreasing, while demand for healthcare is increasing and expected to touch 40% by 2020. Low cost instrumentation with internet and mobile enabled network connectivity with above techniques can help patients in rural and semi urban areas to access well equipped and sophisticated hospitals in cities [1].**

Keywords- Image Enhancement, Registration, Fusion, Segmentation, Feature extraction, ophthalmic diseases.

I. INTRODUCTION

With the tremendous improvement in the Medical imaging techniques, Image Processing simplifies the diagnosis of eye diseases, there by assisting ophthalmologists for easy diagnose of the diseases [2]. In this review paper, the authors dealt with various image processing techniques employed for healthcare to address more number of patients suffering from commonly observed eye diseases. Various image processing algorithms are reviewed for automatic disease detection and analysis.

II. IMAGE PROCESSING TECHNIQUES

The image processing techniques for the detection of different eye diseases include Enhancement, Registration, Fusion, Segmentation, Feature extraction, Pattern matching, Classification, Morphology, Statistical measurements and Analysis [3][4].

Image registration is an important feature in medical imaging for change detection. It has many potential applications in the retinal diagnosis. Image registration is a process of aligning two images in to a common coordinate system. In medical imaging based diagnosis, it is essential to combine data from different images and the images are to be geometrically aligned for better analysis and measurements. The process of mapping points from one image to another image is called image registration. The images to be aligned may be taken at different times or taken with different imaging devices [5]. Image fusion is an approach to combine information acquired from number of imaging devices. The goal of image fusion is to integrate contemporary multi-sensor, multi-temporal or multi-view information into a single image, containing all the information. The multi sensing imaging technology results in large volumes of data. Image fusion effectively reduces the data volume and helps in effective analysis [6]. Segmentation is a process of subdividing an image into its constituent parts such as objects, region containing pixels of similar properties and contiguous regions perceived by humans. Classification is labeling of a pixel or group of pixels based on the grey values and other statistical parameters. Image classification is perhaps the most important technique of digital image analysis, which includes the estimation of statistical parameters based on the gray-level intensities of the image pixels. The image analysis functions are used to understand the content of the image.

III. VARIOUS EYE DISEASES AND REVIEW OF AUTOMATIC DISEASE DETECTION ALGORITHMS

Age related macular degeneration, diabetic retinopathy and glaucoma are the most frequently observed eye diseases in rural and semi urban areas. AMD is degeneration of the macula, which is a part of the retina, responsible for the sharp, central vision needed to read, drive and for face recognition. Glaucoma is characterized by the progressive degeneration of optic nerve fibers and that leads to structural changes of the optic nerve head (ONH), slowly diminishing neuroretinal rim. Diabetic retinopathy (DR) is a complication due to diabetes. DR leads to several abnormalities like microaneurysms, haemorrhages, exudates, cotton wool spots, venous irregularities, new vessels and

978-1-4673-2248-5/12/$31.00 ©2012 IEEE

macular edema. All these lead to vision loss or blindness, if not detected at early stage. Few algorithms to detect these eye diseases are described briefly.

A. AM D detection algorithms

In the recent research, several algorithms are implemented for automatic detection of AMD by detecting the location of macula and its in-homogeneous texture and drusen. Adaptive equalization and wavelets, mathematical morphology on retinal angiography [3], adaptive thresholding, classification of non-homogeneous drusen textures, edge detection and region growing techniques, probabilistic modeling and fuzzy logic, histogram normalization and adaptive segmentation are few to name.

The presence of the drusen in or around the macula of the retina represents a significant development of visual loss from AMD. K. Rapantzikos et al. [13], applied histogram-based adaptive local thresholding (HALT) operators for detecting drusen and mapping of AMD symptoms. In this algorithm a two-stage histogram thresholding approach is used. In the first stage the global otsu threshold is applied which minimizes the intra-class variance, given as a weighted sum of variances of the two classes according to (1) .

$$\sigma_{\omega}^{2}(t)=\omega_{1}(t)\sigma_{1}^{2}(t)+\omega_{2}(t)\sigma_{2}^{2}(t) \quad (1)$$

Where, weights ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2 variances of these classes. In the second stage HALT operator is applied, a local thresholding based on histogram. The image is split into nine non-overlapping windows, within each window, the HALT operator checks the statistics of local histogram and assigns the appropriate threshold. HALT operator uses shape tendency indicators for assessing regions as drusen or actual background. Maryam Mubbashar et al. [14] implemented the detection of macula by localization and detection of centre of optical disk by applying Circular Hough transform, as macula lies in the neighborhood of optical disk. Then 2D Gabor wavelet is applied according to (2), for blood vessels enhancement, to distinguish from drusen.

$$\phi(x,y)=\frac{f^{2}}{\pi\gamma\eta}\exp(-(\frac{f^{2}}{\gamma^{2}}x_{r}^{2}+\frac{f^{2}}{\eta^{2}}y_{r}^{2}))(\exp(j2\pi f x_{r})-K).....(2)$$

Where, x_r=xcosɵ+ysinɵ; y_r=-xsinɵ+ycosɵ, f is the frequency of modulating sinusoidal plane wave, ɵ is orientation of the elliptical Gaussian, and K is offset parameter depending on self defined constants γ and η. Finally macula is detected by finding the distance from the center of the optical disk, thresholding and then finding the darkest area as macula. The algorithm performed well in localizing and detecting macula on DRIVE and STARE database.

Burlina et al.[15] used a Multi resolution locally-adaptive scheme that identified both normal and abnormal regions within the retina. The statistical distribution of normal background retinal tissue, is characterized for a single class classifier and search for areas exhibiting abnormalities in intensity, color, and gradient information. A hybrid parametric constant false alarm rate (CFAR) detector and a non-parametric detector are used for intensity and color space values respectively.The results presented were prelimenary and data set used was small. The size of the data set requires to be increased to define the robustness of the system. Comel kose et al. (2008) [7] applied a simple inverse segmentation method to exploit the homogeneity of healthy areas of the macula rather than unhealthy areas. The inverse segmentation method is simple and inexpensive and generates more accurate results than direct segmentation method; the algorithm can be extended to detect other conditions like DR and lesions. There are also few cases where the algorthm lead to incorrect segmentation.Threshold may vary from image to image. More clinical tests and experiments need to be done to choose more precise threshold value for an intermediate image.

B.Glaucoma detection algorithms:

As Cup to Disc ratio is a widely accepted index for the assessment of Glaucoma, early research was on detection or localization of optic disc (OD). The researchers implemented different algorithms for the localization of OD. The algorithms used were vessel's direction matched filter, curvelet transform, active contour model, fuzzy c-mean clustering, artificial neural networks, kNN regressor, pyramidal decomposition, edge detection, entropy filter and feature vector[16-22]. Recent research reviewed OD detection using averaging filter, template matching technique, canny edge detector, probabilistic classifiers. Other algorithms include techniques to compute open angle and angle open distance at 500µm (AOD 500) from ultrasonic images to measure presence and severity of glaucoma [23] and automatic analysis on Confocal Scanning Laser Tomography (CSLT) images through feature subset selection for classification of optic nerve image [24].

G.C. Sekhar et al. [25] expressed that OD size in OHT patients is smaller compared to POAG patients and normals. The horizontal and the vertical diameters were measured. The OD margin was manually outlined by a series of straight lines joining each other in a polygon. The area of the polygon was calculated as the sum of the areas of the constituent triangles. The mean and standard deviation of each of these parameters for the three groups were compared by analysis of variance (ANOVA). S.Sekhar et al. [26] used Hough transform to detect OD. To find the contours of OD, a region of interest (ROI) is found from the binary image obtained after preprocessing. Morphological operations are used to calculate the magnitude gradient for edge detection.Morphological closing is performed on ROI to fill the vessels according to (3).

$$f \bullet B = (f \oplus B)\Theta B \,. \qquad (3)$$

And to remove any peaks, morphological opening is applied according to (4).

$$f \circ B = (f\Theta B) \oplus B \qquad (4)$$

Where f is the grayscale image, B is binary structuring element; $\oplus$ is dilation and Θ is erosion operators. Use of Hough transform reduced the computational complexity and resulted in improved localiation success rate. The algorithm needs improvement in shade correction technique and automatic thresholding technique. Further work can be done for Identification of OD shape by adjusting the Hough transform to identify both circular and elliptical discs.

Aliaa Abdel et al. [16] proposed a matched filter method in which, luminosity and contrast of the image are normalized using illumination equalization and adaptive histogram equalization methods respectively under preprocessing. The OD detection algorithm is based on matching the expected directional pattern of the retinal blood vessels with a matched filter to roughly match the direction of the vessels at the OD vicinity. The retinal vessels are segmented using a 2-D Gaussian matched filter. Consequently, a vessels direction map of the segmented retinal vessels is obtained using the same segmentation algorithm. The segmented vessels are then thinned, and filtered using local intensity, to represent the OD-center candidates. The difference between the proposed matched filter is resized into four different sizes, and the vessels directionsat the surrounding area of each of the OD-center candidates is measured. The minimum difference provided an estimation of center of the OD. According to Mahdad Esmaeili et al. [17] efficient OD localization and segmentation are important tasks in automated retinal screening. In this digital curvelet transform (DCUT) of the enhanced retinal image is taken and its coefficients are modified based on the sparsity of curvelet coefficients to get probable location of OD. If there are no yellowish objects or their size is negligible, then directly OD location is detected by performing canny edge detector to reconstructed image with modified coefficients. Morphological operations are used to fill these circular regions and erode them to get final locations for candidate regions and remove undesired pixels in edge map. Finally, the boundary of the OD is extracted by using level set deformable model. The algorithm has given better results compared to previously published techniques and resulted in accurate detection of OD with the presence of salient area of yellowish object. This can further be improved by enhancing the vessel segmentation algorithm which in turn improves the performance and efficiency of detecting OD. Rudiger Bock et al. [8] proposed a novel automated glaucoma detection system in which, Glaucoma Risk Index calculation consists of three steps: preprocessing to eliminate the disease independent variations from the input image, Feature Extraction by Principle Component Analysis (PCA) to transform the preprocessed input data to characteristic and compact representation, and a two-stage probabilistic SVM classifier to generate the Glaucoma Risk Index. The algorithm provided a reliable and probabilistic Glaucoma Risk Index from images of the low cost digital fundus cameras. A well-established and expensive method for diagnosis of glaucoma is the examination of the optic nerve head using Scanning Laser Tomography. R. Chrastek et al. [9] presented a method for optic nerve head segmentation and its validation. The method is based on morphological operations, Hough transform, and an anchored active contour model. The problem of manual and subjective measurements of the optic nerve head and assesment of morphometric glaucoma diagnosis is eleminated with this algorithm. The classification between normal eyes and glaucomatous eyes is only 72%- the algorithm is to be improved in this aspect.

Gopal Dat Joshi et al. [27] described Glaucoma detection by calculating cup to disc ratio (CDR). Morphological operations and Hough transform are applied to detect the OD. Cup is segmented using vessel bends and pallor information within the OD region. From the entire set of vessel bends, relavent vessel bends (r-bends) that define the cup boundary are detected. As the r-bends are non-uniformly distributed on the OD region, a local interpolating spline is applied to approximate the cup boundary in regions where r - bends are absent to detect the cup boundary. This algorithm resulted in an effective OD segmentationation. In cup segmentation, boundary detection errors are observed in the regions with no depth information. These errors can be overcome from 3D information of the image.

C. Diabetic Retinopathy detection algorithms

Researchers have been working in the area of image processing for early detection of diabetic retinopathy. The earliest forms of retinopathy are identified by irregularity and oozing of the blood vessels. This leads to formation of hard exudates (HE), cotton wool spots (CWS), microanneurism (MA), hemorrhages and severe DR leading to blindness. During the early years of research, image processing techniques such as thresholding, filtering and morphological operators are used[11][28].Recent research is focused on implementing segmentation ,edge detection, mathematical modeling, feature extraction, classification, pattern recognition and texture analysis techniques for: blood vessel enhancement , detection of HE, CWS, MA and hemorrhages[29-33].

Jorge J.G.Leandro et al. [29] presented two techniques: mathematical morphology and wavelet transforms to detect the blood vessels.In the first alorithm the gray scale image is obtained from the colour fundus image using colour plane extraction. Closing operation is applied to eliminate pixels isolated in the background and to eliminate tiny holes isolated in particles. Then Top-hat transform is applied according to (5) to emphasize smaller vessels in the presence of the back ground, followed by LoG filter for edge detection according to (6).

$$\textit{Top hat}\,(f, B) = f - (f \oplus B) \quad (5)$$

Where $(f \oplus B)$ is dilation as in (3).

LoG in polar coordinates is given as

$$LoG(r) = [(r^2-2\sigma^2)/2\pi\sigma^6]e^{-n} \text{ where } n=(r^2/2\sigma^2) \quad (6)$$

Morphological approach gives finer details of the thin vessels in detail. Wavelet transform aproach has the advantage of specific frequency tuning that allows noise elemination and vessel enhancement in a single step. The authors suggested combination of wavelet transforms and morphological techniques as future work for better performance.

Attila Budai et al. [30] presented an algorithm for vessel segmentation in which Gaussian resolution hierarchy is used to detect vessels of different diameters. The hierarchy consists of three levels (0-2). The original image has the highest resolution (level 0), and each further level has a halved width and height. Then neighborhood analysis is applied on each level of the pyramid. During neighborhood analysis 2x2 Hessian matrix $H(f)$ of the 3 × 3 neighborhood for each pixel of the image are calculated. The down scaled images are up scaled to original resolution. All images are binarized applying a hysteresis threshold. The final vessel segmented image is achieved by fusing grayscale image and up scaled image, using a pixel-wise OR operator.The algorithm achieved a competetive accuracy with reduced computational needs and offered fast and reliable blood vessel segmentation, compared to other segmentation techniques published and human observers.

M.E.Martinez-Perez et al. [31], developed multiscale techniques to provide a way to isolate, analyze and interpret structures of different scales within a single image. One-scale family of images $I(x,y;s)$ is derived by convolving the original image $I(x,y)$ with a Gaussian kernel $G(x,y;s)$ of variance s^2 as in (7).

$$I(x,y;s)=I(x,y) \otimes G(x,y;s) \quad (7)$$

Where, $G(x, y;s)= (1/2\,\pi s^2)e^{-m}$ and $m=(x^2+y^2)/2s^2$

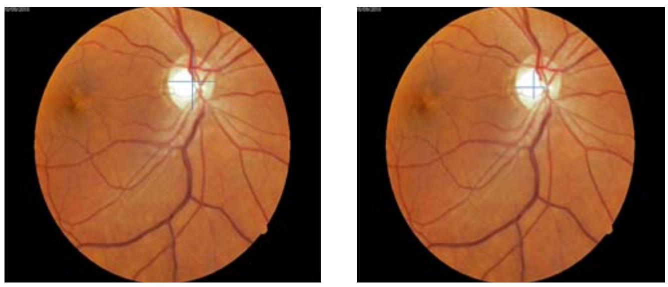
Manual measurement of red-free and flouscein images show a significant difference in the vessel diameter mesurement, flouscein being larger than red-free. But with this automatic algorithm this bias is not observed.

Wong Li Yun et al. [10] worked on deferent stages of diabetic retinopathy, normal retinopathy, moderate non-proliferative diabetic retinopathy, severe non-proliferative diabetic retinopathy and proliferative diabeticretinopathy. Six input features Red, Green and Blue layers of perimeter and areas of blood vessels are extracted from the raw images using the image processing techniques and fed to a neural network based classifier for classification. The algorithm can be further improved by using proper input features and increasing the size of the trained data set in the classifier.

Cemal Kose et al. (2011) [32] applied inverse segmentation method for the automatic screening of diabetic retinopathy. The inverse segmentation provided more accurate and faster result and is inexpensive compared to direct segmentation methods.This algorithm is relatively less successful in locating the OD in retinal images with large degenerations.The approach also shown lower performance in few cases such as image lighting artifacts. More efficient vessel segmentation techniques may be employed for better segmentation of hard exudates and hemorrahges as future work. According to Akara Sopharak et al. [33] optimal morphological operators are used to detect exudates on low contrast, non-dilated pupil images of DR patients. After pre-prosessing for elimination of noise and contrast enhancement to assign exudates and optic disc to the highest intensity values, OD is eliminated from the resulting image to create the marker image. The Exudates are detected using morphological operators and enclosed areas are flood filled. Difference image of the reconstructed image and the marker image, is superimposed on the original image to show the nearness of exudates from macula. There are some incorrect HE detections caused by artifacts. Strong and high contrast choroidal blood vessels are also incorrectly detected as exudates. Other limitation is the algorithm depends on other tasks like detection of OD and vessel removal.

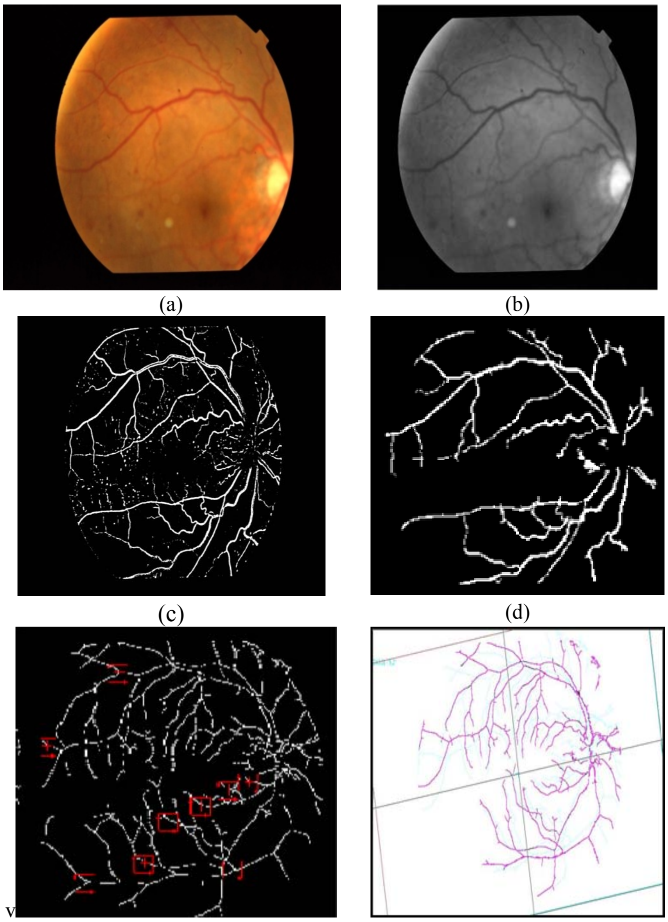
IV. IMPLEMENTATION

As part of the review of these algorithms, the authors have implemented few image processing techniques and algorithms to detect retinal disorders on Lab View software. For the detection of glaucoma, OD and cup are identified and their diameters are measured. Cup to disc ratio is calculated to identify glaucomatous eyes. The corresponding images are shown in Figure 1. For the detection of leisions two flourscein images were taken with a time difference of 10 seconds. The two images were extracted to green plane, thresholded and morphological operators were applied to enhance the vessels. The two enhanced images were fused synchronising the Y-features- to identify discontinuities in the die flow. Figure (2) shows (b) green plane extraction, (c) Thresholding, (d) Morphology, (e) Y-feature extraction and (f) Registration on (a) Original image.



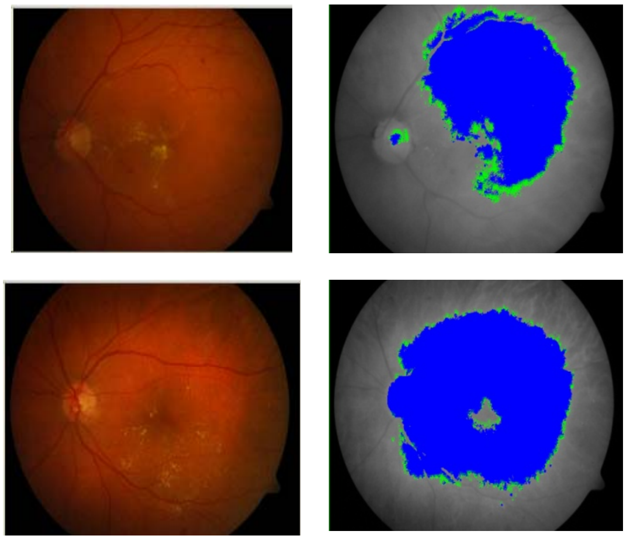
(a) (b)

Figure.1: (a) Cup diameter measurement and (b) disc diameter measurement to detect Glaucoma.



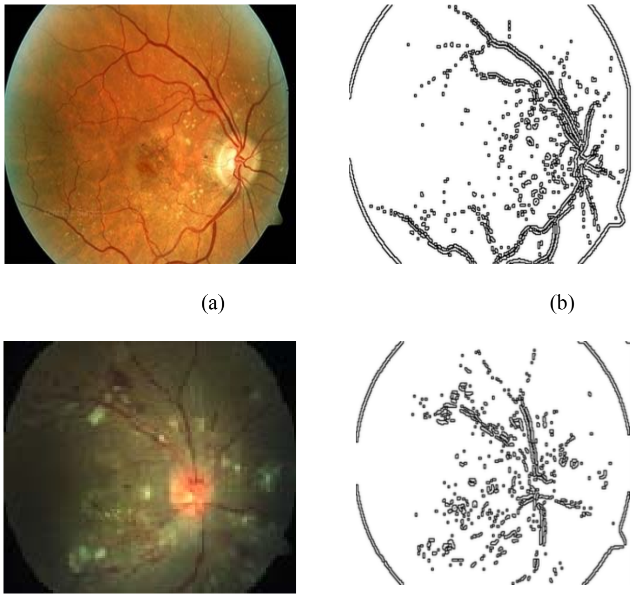
(a) (b) (c) (d) (e) (f)

Figure.2: (a)Original image;(b) green plane extraction to convert into gray scale image ,(c) Thresholding to convert in to binary image,(d) Morphology to remove small objects;(e)Y-feature extraction;(f)Registration with Golden template matching.



(a) (b)

Figure3:(a) original image (b) kNN-Classifier output to detect Hard Exudates in(a)



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

Figure.4: (a)original image of Hypertensive DR;(b) vessel extracted image of (a) ; (c)original image of AMD ;(d) vessel extracted image of (c) ;

To detect hard exudates from an image of diabetic retinopathy, three different classifiers: maximum mean distance, Nearest Neighborhood (NN) and k-NN classifiers were trained and images were tested. The k-NN classifier has given better results. The original and resultant images are shown in Figure 3. Green points show the pixels, where hard exudates are detected. Diameter of retinal blood vessels plays an important role in identifying the retinal disorders. Morphological methods are applied to enhance blood vessels and diameters are measured using measurement tool of LabView.The resulting images are shown in Figure 4.

V.DISCUSSIONS

There are about 70 % people in India stay in rural and semi urban areas and they do not have healthcare facilities. Hence the pressure on urban hospitals is increasing year after year. The main theme of this review is to design a simple inexpensive systems, easily operated by any trained technician and to employ image processing techniques for automatic detection and analysis of eye diseases of large number of patients.The authors have implemented the algorithms to demonstrate that image processing can help meeting the challenges of healthcare for rural and semi urban population. The authors have developed OD analysis software, software for retinal mosaic and medical image fusion, software for feature extracton and fusion of angiographic images for the detection of lesions, k-NNclassifiers for detection of hard exudates and heammorahges; blood vessel enhancement for the detection of vessel based eye diseases.The authors are in regular consultation with ophthalmologic expert doctors during the course of the work.

ACKNOWLEDGEMENTS

The authors thank doctors at LV Prasad Eye Institute, Maxivision Eye Hospital and Padmavathy Netralaya, Hyderabad and Shanker Netralaya, Chennai for providing data base and for their valuable suggestions. Thank Principal, VNRVJIET-Hyderabad for encouraging the research work and providing the facilities. Thank Director, BITS-Pilani-Hyderabad for encouraging research in medical image processing.

REFERENCES

[1] R.Manjulasri and KMM Rao, "Review of image processing and tele ophthalmology research projects world over" in Technology Spectrum Journal, November 2010 pp.42-48.

[2] KMM Rao,"Image Processing For Medical Applications" , Proceedings of the 14th World Conference on Non- Destructive Testing, Delhi, 8-13 December 1996.Vol. 2,pp. 1219 – 1224

[3] R.ManjulaSri,KMM Rao, "Novel Image Processing Techniques to Detect Lesions using Lab View", IEEE Conference Publications on Annual IEEE India Conference INDICON.Publication Year: 2011 , Page(s): 1-4

[4] Viralkumar Bulsara, Surabhi Bothra, Poonam Sharma, K.M.M.Rao, "Low Cost Medical Image Processing System for Rural/Semi Urban Healthcare", IEEE Conference Publications on Recent Advances in Intelligent Computational Systems (RAICS),Publication Year: 2011 , Page(s): 724 - 728

[5] NI Vision Concepts Manual,National instruments,November2005.

[6] Austin , " Digital Image processing using Mathematical Link for LABVIEW", A demo developed for NI week 2002 August 14-16, 2002.

[7] Cemal Köse,U gur ¸ Sevika Okyay and Gençalio˘glub "Automatic segmentation of age-related macular degeneration in retinal fundus images", in Computers in Biology and Medicine ,Vol.38 (2008) ,pp. 611 – 619.

[8] Rudiger Bock , Jorg Meier, Laszlo G. Nyul, Joachim Hornegger and Georg Michelson ,"Glaucoma risk index:Automated glaucoma detection from color fundus images" in Medical Image Analysis, Vol. 14 (2010), pp. 471–481.

[9] R. Chrastek et al. " Automated segmentation of the optic nerve head for diagnosis of glaucoma" in Medical Image Analysis ,Vol.9 (2005),pp. 297–314.

[10] Wong Li Yun et al." Identification of different stages of diabetic retinopathy using retinal optical images" in - Information Sciences,vol. 178 (2008),pp. 106–121.

[11] Bernhard M. Ege et al. "Screening for diabetic retinopathy using computer based image analysis and statistical classification", in Computer Methods and Programs in Biomedicine,Vol. 62 (2000) , pp.165–175,

[12] Thomas Walter et al. "Automatic detection of microaneurysms in color fundus images" in Medical Image Analysis,Vol. 11 (2007), pp. 555–566

[13] K. Rapantzikos, M. Zervakis,K. Balas "Detection and segmentation of drusen deposits on human retina: Potential in the diagnosis of age-relatedmaculardegeneration" in Medical Image Analysis,Vol.7(2003) ,pp. 95–108

[14] Maryam Mubbashar, Anam Usman, M. Usman Akram, " Automated System for Macula Detection in Digital Retinal Images",33rd Annual International Conference of the IEEE EMBS,Boston, Massachusetts USA, August 30 - September 3, 2011

[15] P. Burlina, D.E. Freund, B. Dupas, and N. Bressler,"Automatic Screening of Age-Related Macular Degeneration and Retinal Abnormalities-33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, August 30 - September 3, 2011

[16] Aliaa Abdel-Haleim Abdel-Razik Youssif, Atef Zaki Ghalwas, and AmrAhmed SabryAbdel-Rahman Ghoneim Optic Disc Detection From Normalized Digital Fundus Images by Means of a Vessels' Direction Matched Filter-IEEE Transactions On Medical Imaging, Vol. 27, No. 1, January 2008

[17] Mahdad Esmaeili, Hossein Rabbanin and Alireza Mehri Dehnavi: "Automatic optic disk boundary extraction by the use of curvelet transform and deformable variational level set model" in Pattern Recognition,Vol. 45 (2012) , pp. 2832–2842

[18] Chisako Muramatsu et al.,"Automated segmentation of optic disc region on retinal fundus photographs: Comparison of contour modeling and pixel classification methods" in Computer Methods And Programs In Biomedicine Vol.101 (2011) , pp. 23–32.

[19] Meindert Niemeijer, Michael D. Abràmoff and Bram van Ginneken" Fast detection of the optic disc and fovea in color fundus photographs" in Medical Image analysis, in press.

[20] Rashid Jalal Qureshi et al. "Combining algorithms for automatic detection of optic disc and macula in fundus images; Computer Vision and Image Understanding ,Vol. 116 (2012) ,pp. 138–145

[21] Chih-Yin Ho,Tun-Wen Pai, Hao-Teng Chang and Hsin-Yi Chen, " An automatic fundus image analysis system for clinical diagnosis of glaucoma",-2011 International Conference on Complex, Intelligent, and Software Intensive Systems.

[22] Zhuo Zhang et al. "MRMR Optimized Classification for Automatic Glaucoma Diagnosis"-33rd Annual International Conference of the IEEE EMBS,Boston, Massachusetts USA, August 30 - September 3, 2011.

[23] R.Youmaran, P. Dicorato, R. Munger, T.Hal, A. Adler, "Automatic Detection of Features in Ultrasound Images of the Eye", IMTC 2005 – Instrumentation and Measurement Technology Conference ,Ottawa, Canada, 17-19 May 2005.

[24] Jin Yu, Syed Sibte Raza Abidi, Paul Habib Artes,Andrew McIntyre and Malcolm Heywood, "Automated Optic Nerve Analysis for Diagnostic Support in Glaucoma"-Proceedings of the 18th IEEE Symposium on Computer-Based Medical Systems (CBMS'05)

[25] GC Sekhar, R Nagarajan, TJ Naduvilath, L Dandona, KMM Rao, VDP Rao "Optic disc size in ocular hypertension", in Indian Journal of Ophthalmology, 1999,vol 47,issue 4, pp. 229-231

[26] S.Sekhar,W.Al-Nuaimy and A.K.Nandi,"Automated Localisation Of Retinal Optic Disk Using Hough Transform", 5th IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2008, pp. 1577 - 1580

[27] Gopal Datt Joshi, Jayanthi Sivaswamy, and S. R. Krishnadas,"Optic Disk and Cup Segmentation From Monocular Color Retinal Images for Glaucoma Assessment', IEEE Transactions On Medical Imaging, Vol. 30, No. 6, June 2011,pp.1192-1205.

[28] M. Al-Rawi, M. Qutaishat and M. Arrar, "An improved matched filter for blood vessel detection of digital retinal images", in Computers in Biology and Medicine ,vol. 37 (2007) ,pp. 262–267.

[29] Jorge J.G.Leandro, Roberto M Cesar Jr and Herbert F.Jelinek.," Blood Vessels Segmentation in Retina : Preliminary Assessment of the Mathematical Morphology and of the Wavelet Transform Techniques",-Conference proceedings: Brazilian Symposium on Computer Graphics and Image Processing - SIBGRAPI , pp. 84-90, 2001

[30] Attila Budai, Georg Michelson and Joachim Hornegge, " Multiscale blood vessel segmentation in retinal fundus images", ConfereceProceedings-BVM 2010,Aachen,pp261-265.

[31] M. E. Martinez-Perez, A. D. Hughes, S. A. Thom, A. A. Bharath and K. H. Parker, " Segmentation of Blood Vessels from Red-free and Fluorescein Retinal Images: In *Medical Image Analysis*.vol. 11 (1),pp. 47-61, 2007

[32] Cemal Kose, Ugur Sevik, Cevat Ikibas and Hidayet Erdol," Simple methods for segmentation and measurement of diabetic retinopathy lesions in retinal fundus images", in computer methods and programs in biomedicine(2011) in press.

[33] A.Sopharak,B.Uyyanonvara,S.Barman and T.H.Williamson"Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods" in Computerized Medical Imaging and Graphics ,Vol. 32 (2009) pp. 720–727.