IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 2, Issue 2, Apr-May, 2014
ISSN: 2320 – 8791 (Impact Factor: 1.479)
www.ijreat.org

Sorting of Various Stages of Diabetic Retinopathy Using Back Propagation Algorithm

C.Senthil Kumar[1], R.Aandal[2], R.Rajathi[3], C.Vinothkumar[4]

[1, 2, 3, 4]**Assistant Professor, Department of Electronics and Communication Engineering, Mahakavi Bharathiyar College of Engineering and Technology, Vasudevanallur, Tamil Nadu, India**

Abstract

Diabetes affects slowly the circulatory system including that of the retina. So the vision of a patient may start to deteriorate and lead to diabetic retinopathy. This work proposes an algorithm for the detection of retinal landmarks (optic nerve head, macula and vasculature) based on optic cup location and anatomical structural details from diabetic retinopathy (DR) images of both left and right eye. This algorithm uses color fundus images obtained from mydriatic camera. The algorithm proceeds through four main steps. (i) Color image pre-processing- To enhance and remove noise from the image. (ii) Detection of optic nerve head -Optic nerve head is located by increasing the area of interest around the optic cup. Since we detect optic cup first, which is embedded in optic nerve head. (iii)Detection of macula-It is located at a distance of approximately twice the diameter of the optic nerve head just below the horizontal axis of the optic nerve head. (iv) Detection of vasculature-It uses logical AND operation on two images, one being a threshold image and another being an edge detected image. Detected optic disc area is validated. The quantitative performance is evaluated by calculating sensitivity, specificity and predictive value. Overall sensitivity (Se), specificity (Sp) and predictive value (PV) obtained in detecting optic nerve head from normal images and from abnormal images.

Keywords *— Diabetic Retinopathy, Retinal landmarks, Macula, Vasculature, Mydriatic Camera.*

1. INTRODUCTION

The Diabetic Retinopathy (DR) is a complication of diabetes that is caused by changes in the blood vessels of retina. The symptoms can distort or blur the patient's vision and are the main causes of blindness. The identification of fundal landmark features such as optic nerve head, macula and the retinal vessels as reference co-ordinates, is a prerequisite before systems can achieve more complex tasks of identifying pathological entities from DR images. Position of optic nerve head with respect to macula is used to differentiate left eye and right eye. When optic nerve head is swollen and lesions particularly exudates, are very near to optic nerve head and if the size and brightness of exudates are same as that of optic nerve head in that case there is possibility of false detection of optic disc. The location of optic nerve head is important in retinal image analysis, to locate anatomical components in retinal images, for vessel tracking, as a reference length for measuring distances in the retinal images and for registering changes within the optic disc region due to disease.

In earlier research work optic nerve head is detected base on brightness, shape and size. These methods work well when the area of the exudates is not large and optic nerve head is round in shape, normal in size. Hence, a method based on lone features such as shape, brightness and size shows a large variance and makes this detection erratic, particularly in the presence of retinal disease.

In proposed method contrast-limited adaptive histogram equalization (CLAHE) is used to enhance contrast of small regions in the image. By selecting suitable threshold, histogram equalized image is thresholded so that only dark regions (including blood vessels) are visible. This threshold value is selected by trial and error method. Dilation operation is performed to achieve continuity in detected blood vessels. Edge detection is performed on the green component image using canny filter with suitable threshold. Dilation operation is performed to add pixels around the existing ones. Logical AND operation is performed on thresholded and canny edge detected images.

2. RELATED WORK

The work proposed by [6], is about an image processing algorithm for the localization of the optic disk (OD) in low-resolution (about 20 /pixel) color fundus images. Although the focus of the paper is on optic disc detection, other applications

IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 2, Issue 2, Apr-May, 2014
ISSN: 2320 – 8791 (Impact Factor: 1.479)
www.ijreat.org

that require the localization of a rigid shape may be solved by the proposed combination of techniques. Another work proposed by [7], presents an algorithm for the localization and segmentation of the optic nerve head boundary in low-resolution images (about 20 /pixel).It uses a global elliptical model and a local deformable model with variable edge-strength contingent stiffness. The algorithm is evaluated against a randomly selected database of 100 images from a diabetic screening program. In [4], the advancement of an automatic fundus image processing and analytic system to facilitate diagnosis of the eye specialist is proposed. The algorithms to detect the optic nerve head, blood vessels and exudates are trace out. And in [8], the Optic nerve head is localized by the Principle Component Analysis (PCA) and its shape is detected by a modified Active Shape Model (ASM). Exudates are extracted by the combined region growing and edge detection. A fundus coordinate system is further set up based on the fovea localization to provide a better description of the features in eye images. The success rates which is achieved are 99%, 94%, and 100% for disk localization, disk boundary detection, and fovea localization respectively.

3. EXISTING SYSTEM

The paper **[6],** design and test an image processing algorithm for the localization of the optic disk (OD) in low-resolution (about 20 /pixel) color fundus images. The design relies on the combination of two procedures: 1) a Hausdorff -based template matching technique on edge map, guided by 2) a pyramidal decomposition for large scale object tracking. An average error of 7% on OD center positioning is reached with no false detection.

Also the paper [4] presents an algorithm for the localization and segmentation of the optic nerve head boundary in low-resolution images (about 20 /pixel). Optic disk localization is achieved using specialized template matching and segmentation by a deformable contour model. The latter uses a global elliptical model and a local deformable model with variable edge-strength dependent stiffness.

4. PROPOSED SYSTEM

4.1 IMAGE PREPROCESSING

Contrast of the color image is enhanced and then median filter which is a nonlinear filter is used to reduce ‘salt and pepper’ noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. We choose only green component of the color image since in this channel all the features of the image are clear as compared to red and blue channel. Red channel is discarded because it tends to be saturated and has less contrast than green one while blue channel contains only noise. Then contrast-limited adaptive histogram equalization (CLAHE) is used to enhance contrast of small regions in the image. CLAHE operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image. By selecting suitable threshold, histogram equalized image is thresholded so that only dark regions (including blood vessels) are visible. This threshold value is selected by trial and error method. Dilation operation is performed to achieve continuity in detected blood vessels. Edge detection is performed on the green component image using canny filter with suitable threshold. Dilation operation is performed to add pixels around the existing ones. Logical AND operation is performed on thresholded and canny edge detected images. Fig.1 shows procedure for detection of vasculature.

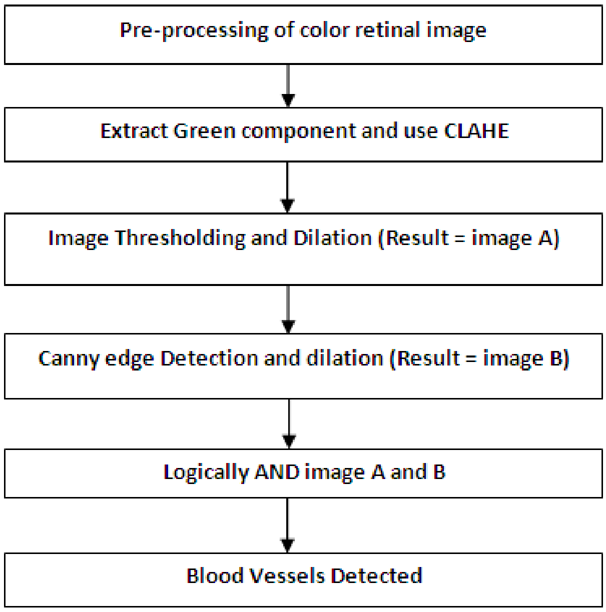


Figure.1 Flow Chart for detection of Vasculature.

5. DETECTION OF OPTIC NERVE HEAD AND MACULA

For detecting optic nerve head we use green component of the image which is enhanced using CLAHE. A mask of size 50x50 is defined (50x50 is approximate area of optic cup).The mean values of the sub images under the mask are calculated and the coordinates of the sub image with maximum mean is stored. These coordinates give the position of optic cup, the brightest region in the optic nerve head. Using this knowledge the optic nerve head region is located by increasing the coordinates around optic cup for both left and right eye to obtain optic nerve head region. The end coordinates of this optic nerve head region (a rectangular region) are used to locate the macula. Macula is segmented using the anatomical details, that the macula is situated at a distance of around twice the diameter of the optic nerve head and just below the horizontal axis of optic nerve head. Now the coordinates are shifted accordingly to get the macular region. Fig.3 shows procedures for detection of optic nerve head and macula.

6. METHODOLOGY

Nowadays there are many different methods how to segment the retinal vasculature from the eye images. For example, blood vessel segmentation using wavelet transform & region growing or adaptive filtering have been used. However, due to the unique properties of each technique, a single generally accepted vessel detection algorithm does not exist. Moreover usually the better segmentation method is used the more time the computation takes. The main goal of presented method is a fast blood-vessels segmentation based on two-dimensional discrete wavelet transform (2D DWT). In this paper I will introduce a method which is composed from four main parts.

i. Preprocessing
ii. Decomposition by 2D DWT
iii. Thresholding procedure
iv. Reconstruction with summation

6.1 PREPROCESSING

In Preprocessing (image enhancement) - The retinal images has been taken in a RGB mode by fundus camera Canon CF-60UDi with a digital camera Canon D20. However, the best vasculature information is in the green channel. So the first step is to separate this channel to a new image. Before applying the vessel segmentation algorithm it is necessary to denois the image. This is realized by a filter based on anisotropic diffusion. The filter iteratively uses diffusion equation in combination with information about the edges. As a consequence, the homogenic (but noisy) areas are blurred and the edges are preserved.

Index t denotes the time (iterations).Original RGB retinal image on the left, G channel which is separated from the original RGB image in the middle, G channel image filtered by an anisotropic diffusion filter on the right. Histogram equalization technique increases the dynamic range of the histogram of an image. It assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities.

Hemorrhages and micro aneurysms contribute to defects in a retina with diabetic retinopathy. All stages of diabetic retinopathy show such defects. Therefore, it is important to distinguish them from the noisy background of the retina image. The algorithm developed uses a morphological operation to smooth the background and, as a result, veins, hemorrhages and micro aneurysms can be seen clearly.

6.2 DECOMPOSITION BY 2D DWT

In blood vessel extraction the 2D discrete wavelet transform is used based on a bank of filters, which corresponds to specific type of a wavelet. This algorithm used the Reversed Bi orthogonal wavelet (RBIO) as denoted in Matlab. The shape of this wavelet almost correspondents to the shape of blood vessels in the retinal image.

The wavelet transform decompose the image to levels, where each level represents specific frequency band of the wavelet. Its choose 3 levels 2D DWT, which is sufficient for detecting the retinal vasculature. Each level is then decomposed in three directions: vertical, horizontal and diagonal and Bi orthogonal wavelet: rbio on the left, shape of a blood vessel on the right One decomposition level of 2D DWT.

6.3 THRESHOLDING

The next step is to threshold within each direction in each level. The main task of thresholding is to highlight high values of wavelet coefficients which almost correspond to the blood-vessels and suppress small values which correspond to noise or unimportant structures in the image. The key parameter in this process is the choice of the threshold value. A good way how to get this value is to use the histogram of the image. 88 % of the pixels in the wavelet coefficient image are noise or unimportant structures and only 12 %belongs to the blood-vessels (determined as a result of the experiments). The threshold value has been set to brightness value 30, because 88% of pixels are below this value.

To binarize the image, a threshold should be carefully chosen. Too small a threshold will produce an image that has edges linked together. However, a big threshold will produce edge segments that form curves. It obtained good results by setting the threshold at 25% of the gray intensities contained into the image.

6.4 RECONSTRUCTION WITH SUMMATION

Now it is necessary to reconstruct the final binary image. The first step is to logically add all threshold directions in each level (Fig 5.6). So three images (for three levels) which reflect the segmented blood vessels. Due to the 2D DWT, before adding those images in a final image, it is needed to interpolate them to the same size by bilinear interpolation. However the final image has to be binary. Further more each

IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 2, Issue 2, Apr-May, 2014
ISSN: 2320 – 8791 (Impact Factor: 1.479)
www.ijreat.org

image includes some noise, which is needed to remove.The possibly way how to do it is to add the three images and take away the two lower layers. This will create the final binary image, which shows the segmented vasculature from the eye background.

7. BACK PROPAGATION (BPA) ALGORITHM FOR CLASSIFICATION

Back propagation (BPA) algorithm is a supervised learning technique used for training artificial neural networks (ANN). It is most useful for feed-forward networks (networks that have no feedback). It requires that the transfer function (Sigmoid) used by the artificial neurons (or ''nodes'') be differentiable. This algorithm is also known as ''The generalized delta rule''. The neurons in layers, other than the input and output layers of a neural network are called hidden units or hidden nodes, as their outputs do not directly interact with the environment. With the BPA, the weights associated with the hidden layers can be adjusted and thus enable the pre-selected neural network to learn.

The above-stated problem tried with different number of hidden layers; ranging from 1 to 4 layers. Based on the results obtained, a neural network with one hidden layer and eight neurons gave the best classification result. In the present case, a learning constant g = 0.9 (which controls the step size), is chosen by trial and error.

The figure below shows the configuration of the neural network classifier used for this work. The output layer has 4 neurons, giving rise to an output domain of 16 possible classes. Then the network is trained to identify only four classes (normal, moderate DR, severe DR and proliferative DR) given by decoded binary outputs from the artificial neural networks. Values of the area and perimeter of the red, green and blue layers of the image are computed and fed as input to the classifier. Figure 6.0. Features Six features namely, red layer of perimeter (RLP), green layer of perimeter (GLP), blue layer of perimeter (BLP), red layer of area (RLA), green layer of area (GLA) and blue layer of area (BLA) are extracted from the images after preprocessing by the morphological operations.

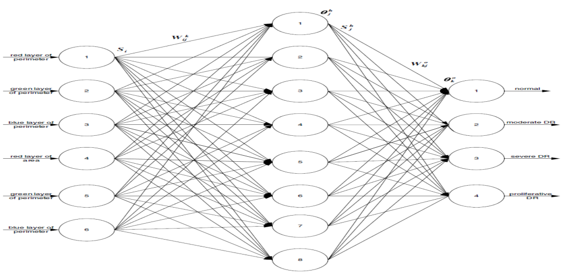
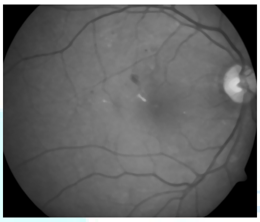
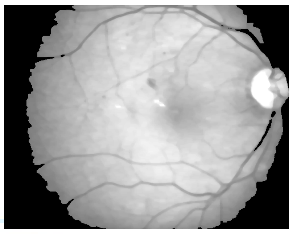


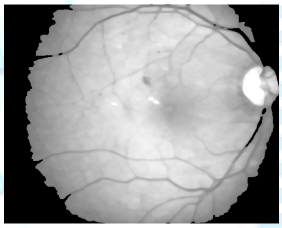
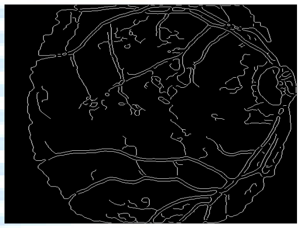
Figure 2: Back propagation Algorithm

8. RESULTS

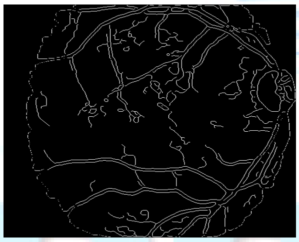
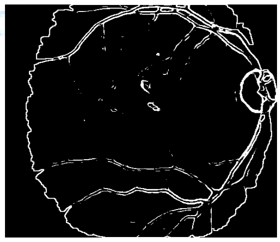

INPUT IMAGE **INTENSITY GRAYIMAGE**

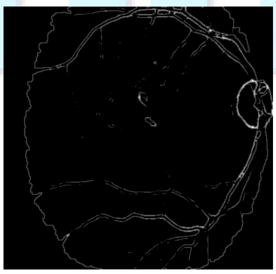
MEDIAN FILTERED IMAGE **ENHANCED IMAGE**

DILATION AFTER THERSHOLDING **CANNY EDGE DETECTED**

LOGICAL AND IMAGE DETECTION A & B **BLOOD VESSEL**




ERODED BLOOD VESSEL **OPTIC NERVE HEAD**

9. CONCLUSION

In this algorithm investigated and proposed a method based on anatomical structural details and retinal image information. This system intends to help the ophthalmologists not only in DR screening process but any other eye related abnormality which is based on retinal photography. It is not a final result application but it can be a preliminary diagnosis tool or a decision support system for ophthalmologists. Human ophthalmologists are still needed for the cases where detection results are not very obvious. This type of presentation will enable clinicians to identify retinal landmarks more quickly and will also help to take decision while treating the abnormality, particularly maculopathy.

REFERENCES

1. A.Can,H.Shen, (March 1999),'Rapid automated tracing and feature extraction from live high resolution retinal images using direct exploratory algorithms', IEEE Transactions on Info.Tech.for Biomedicine,Vol.3, No. 2 , pp.125-138.

2. Giri Babu, T. Satya Savithri, (Dec 2007) , 'Segmentation of Vessels in fundus Images using Spatially Weighted fuzzy c-Means Clustering Algorithm', IJCSNS International Journal of Computer Science and Network Security, Vol.7, No.12, Volume 2.

3. Huan Wang, Wynne Hsu, (June 2000). 'An effective approach to detect lesions in color retinal images', IEEE Conference on Computer Vision and Pattern Recognition, Vol.2, pp. 181-186.

4. Huiqi Li and Opas Chutatape, (July 2000), 'Fundus image features extraction', in Proceedings of the Annual IEEE International Conference of EMBS, Vol.4, pp. 3071-3073.

5. D.Kavitha, S.Shenbagadevi, (Jan 2005), 'Automatic detection of optic disc and exudates in retinal images', in Proceedings of the ICISIP, pp.501-506.

6. M.Lalonde, M.Beaulieu and L.Gagnon, (November 2001), 'Fast and robust optic disc detection using pyramidal decomposition and Hausdroffbased template matching', IEEE Transactions on Medical Imaging, Vol.23, Issue 11, pp.1193-1200.

7. J.Lowell , A.Hunter,D.Steel, A.Basu,R.Ryder and E. Fletcher (February 2004), 'Optic Nerve Head Segmentation', IEEE Transactions on Medical Imaging, Vol.23, No.2, pp.256-264.
8. H.Li and O.Chutatape, (October 2003), 'A model based approach for automated feature extraction in fundus images', in Proceedings of the 9th International Conference on Computer Vision, pp. 3941-399.

9. Mira park, Jesse S,(July 2006) ,'Locating the optic disc in retinal images',in Proceedings of the International Conference on Computer Graphics, Imaging and Visualization, pp.141-145.

10. Shuying Huang and Erhu Zhang, (June 2006),'A method for segmentation of retinal image vessels', in Proceedings of the 6th World congress on Intelligent Control and Automation, Vol.2,pp.9673-9676.

11.Zhang, Opas Chutatatape,(October 2004),'Detection and classification of bright lesions in color fundus images', International Conference on Image processing, Vol. 1, pp. 139-142.