



INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

PREPROCESSING EYE FUNDUS IMAGE AND FEATURE EXTRACTION METHOD USING GRAY LEVEL AND MOMENT INVARIANT BASED FEATURES FOR VESSEL STRUCTURE SEGMENTATION

SONAL S. HONALE¹, VINAY S. KAPSE²,

1. Department of Computer Science and Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technology. Nagpur, India.
2. Department of Computer Science and Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technology. Nagpur, India.

Abstract

Accepted Date:

27/02/2013

Publish Date:

01/04/2013

Keywords

Medical imaging,
Vessel segmentation,
Moment invariants,
Diabetic Retinopathy.

Corresponding Author

Ms. Sonal S. Honale

Eye diseases like Diabetic Retinopathy are required to be detected in the early stages. The patients require frequent eye examinations. An automated blood vessel segmentation method can be integrated into a pre-screening system for early eye disease detection. Blood vessel segmentation is a challenge as the eye fundus images are 2D digital images with inadequate contrast, lighting variations, and noise, affecting background texture and the blood vessels structure. It is required to reduce these imperfections. This paper gives a method for improving image quality prior to image pixel feature extraction. The pre-processing method employs extracting the green channel from original RGB retinal image, removing central light reflex from vessel, fundus image background homogenization, and finally blood vessel enhancement. Further in this paper we give the feature extraction from the pre-processed image using the gray level features based on differences in pixel intensities and moment invariant features based on shape descriptors invariant to translation, rotation and scale change.

INTRODUCTION

Diabetic retinopathy (DR) is one of the leading causes of blindness among people suffering from diabetes. It is observed that about 2% of the patients affected by this disorder are blind and 10% undergo vision degradation after 15 years of diabetes. [1] DR is not a curable disease, but laser treatment can prevent major vision loss if detected in the early stages. So, diabetic patients need frequent eye-fundus examination. An automated blood vessel segmentation method can be a useful tool for being integrated into a complete pre-screening system for early DR detection. [2]

This kind of systems should require no user interaction, and be robust enough to analyze different kinds of images. It is a huge challenge, since large variability is observed in the image acquisition process and a natural variation is reported in the appearance of the retina. The eye fundus photographs present inadequate contrast, lighting variations, noise influence and anatomic variability affecting both the retinal background texture and the blood vessels structure. As blood vessels segmentation becomes essential for several

medical diagnostic systems, numerous research efforts have been done in this field.

This research work comprises methodology for blood vessel segmentation based on a supervised approach. The supervised method is based on pixel classification using a pixel feature vector extracted from preprocessed retinal images and given as input to a classifier. Classification results classify each pixel into two classes: vessel and nonvessel. This paper focuses on first improving the input image quality i.e. preprocessing. Then the feature extraction for pixel representation is proposed using gray level based and moment invariant based features. The classification is to be considered as future studies which can be performed by using a suitable classifier. The rest of the paper is structured as; In Section 2 is Related Work. In Section 3 we give Materials And Proposed Method. In Section 4 we give Results And Discussion and finally in Section 5 we give Conclusion to the paper.

RELATED WORK

The retinal vessel segmentation methods can be broadly divided into two group's

rule-based methods and supervised methods.

The tracking based methods start from an initial set of points, the vessels are traced by deciding most appropriate candidate pixel close to the pixels under evaluation. A fuzzy approach is studied in [3], while [4] uses a recursive dual edge tracking and connectivity recovering technique. The mathematical morphology methods use the knowledge of vessel shape features, applying morphological operators, vessel structure is filtered from the background for final segmentation. The top-hat-transform [5], [6] causes vessel pixels to darken; border pixels take the value of the closing. The matched filter [8], [9] uses a 2-D linear structuring element with a Gaussian cross section for vessel identification. The model-based locally adaptive thresholding [10], the deformable or snake models [11], multiscale feature extraction method [12], are some of the other methods.

The supervised methods are based on pixel classification into two classes, vessel and non-vessel. The classifiers are trained by learning from manually-labelled images. The

classifiers are the Bayesian classifier [13], kNN method [14], support vector machines [15] and neural networks [16].

The review shows that work done in retinal vessel segmentation by supervised approach methods have improved performance as regards accuracy over rule based methods. This paper gives a method for preprocessing and feature extraction from retinal images for retina vessel segmentation by a supervised method.

MATERIALS AND PROPOSED METHOD

Preprocessing

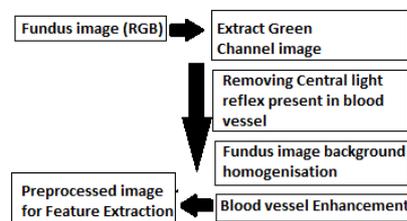


Figure 1: Systematic Overview of proposed approach

Green channel extraction from the original RGB eye fundus image

The eye fundus images acquired in dataset are color digital images. It is observed that blood containing elements in the retina like

the blood vessels are best represented and have higher contrast in the green channel.[17] The input images I_g used for our method are monochrome and are obtained by extracting the green channel image from original RGB retinal images.

Removing central light reflex present in blood vessel

The typical vessel cross-sectional gray-level profile can be approximated by a Gaussian shaped curve. To make intensities uniform over the vessels, remove the brighter strip running along the central length part of the blood vessel called the central light reflex, the green plane image I_g is filtered by applying a morphological opening using a 3 pixel diameter disc, using eight-connectivity, as SE. Disc diameter was fixed to the possible minimum value to reduce the risk of merging close vessels. Image I_v is obtained.

Fundus image background homogenisation

Fundus images often face the problem of background intensity variation. Besides these there are variations between images

due to different illumination conditions in the acquisition process.

To remove background illumination variation, a shade-corrected image is accomplished from a background estimate. A sequence of mean filters is applied. A 3×3 mean filter is applied to smooth the salt-and-pepper noise. Further noise smoothing by convolving with a Gaussian filter of dimensions 9×9 , mean=0 and variance= 1.8^2 . Then a background image I_b is produced by applying a 69×69 mean filter. When this filter is applied to the pixels in the FOV near the border, the results are blurred. To overcome this problem, a 3×3 mean filter is applied out-of-the FOV. The subtractive approach is used for shade correction, the intensities of pixels of I_b are subtracted from intensities of corresponding pixels of I_v to form a difference image I_d .

A homogenized image I_h is produced as follows: the histogram of image I_d is displaced toward the middle of the gray-scale by following gray-level transformation function:

$$I_h(x,y) = \begin{cases} 0 & \text{if } g < 0, \end{cases}$$

255 if $g > 255$,

g otherwise

Where $g = I_d(x,y) + 128 - g_{input_max}$ (1)

$I_d(x,y)$ and $I_h(x,y)$ are the gray-level variables of input I_d and output I_h images respectively. The variable denoted by g_{input_max} defines the gray-level presenting the highest number of pixels in I_d . By this operation, pixels with gray-level g_{input_max} , which are observed to correspond to the background of the retina, will standardize their intensity around to 128. The output is the background homogenised image I_h .

Blood vessel enhancement

The enhancement step consists on generating a new vessel-enhanced image, which is more suitable for feature extraction. Steps:

1. Finding the complementary image of the homogenized image I_h , $I_{hc}(x,y) = 255 - I_h(x,y)$
2. Applying the morphological Top-Hat transformation given by: $I_{ve} = I_c - \gamma(I_c)$ where, γ - morphological opening using a disc of

radius 8 pixels. Thus, it is observed that bright artifacts in the retina fundus image are removed corresponding to optic disc etc and the darker articles become enhanced corresponding to blood vessels, fovea etc remaining, after the opening operation. The output Image I_{ve} is used for feature extraction.

Feature Extraction

The feature extraction is used to obtain a pixel representation in terms of some measure which can be used in the classification stage to decide whether a pixel belong to a blood vessel or not. In this paper two types of features are extracted from the pre-processed image, the gray level based features and the moment invariant based features.

Gray-level-based Features

Retinal blood vessels are always darker than their surroundings. The features which take into consideration the gray-level variation in the surroundings of pixel under focus can be used to describe the candidate pixel.

The gray level features are derived from pre-processed image considering a 3 x 3 pixel

region centred on the described pixel (x,y). The five gray level descriptors at (x,y) are given as,

$$f1(x,y) = I_{ve}(x,y) - \min_{(s,t) \in S_{x,y}^3} \{I_{ve}(s,t)\} \quad (2)$$

$$f2(x,y) = \max_{(s,t) \in S_{x,y}^3} \{I_{ve}(s,t)\} - I_{ve}(x,y) \quad (3)$$

$$f3(x,y) = I_{ve}(x,y) - \text{mean}_{(s,t) \in S_{x,y}^3} \{I_{ve}(s,t)\} \quad (4)$$

$$f4(x,y) = \text{std}_{(s,t) \in S_{x,y}^3} \{I_{ve}(s,t)\} \quad (5)$$

$$f5(x,y) = I_{ve}(x,y) \quad (6)$$

S_{xy}^3 stands for the set of coordinates in a 3 x 3 sized square window centred on point (x,y).

Moment invariant based features

Retinal blood vessel structure is known to be piecewise linear and have quasi-linear shapes, which is not equally wide and may be oriented at any angle. Hu [18] gives a set of moment invariants under size, translation, and rotation, which can be

derived from combinations of regular moments.

If moments are computed directly over the subimage, it characterises a vessel independently of its width, orientation and location in the subimage but it does not distinguish the center pixel in terms of vessel or nonvessel. So the subimage is first convoluted with a 17 X 17 Gaussian filter whose mean is 0 and variance is 1.7. The size includes an approximately equal number of vessel and nonvessel pixels.

To calculate moment invariants, for pixel (x,y) of the preprocessed image, a 17 x 17 region given as $S_{x,y}^{17}$ is considered. For this subimage, denoted by I (i,j), the two Hu moment invariants [18] given by,

$$a1 = (\eta_{20} + \eta_{02}) \quad (7)$$

$$a2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (8)$$

Where, η_{20} , η_{02} , η_{11} are regular moments are calculated. The two moment invariant descriptors at (x,y) are given as,

$$f6(x,y) = |\log(a1)| \quad (9)$$

$$f7(x,y) = |\log(a2)| \quad (10)$$

By using the logarithm complex numbers generated by calculating the logarithm of negative moment invariants can be avoided.

RESULTS AND DISCUSSION

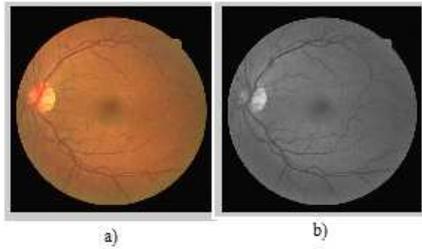


Figure 2: a) Original image, b) Green channel image

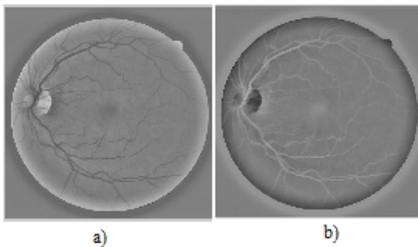


Figure 3: a) Background Homogenised image, b) Vessel enhanced image

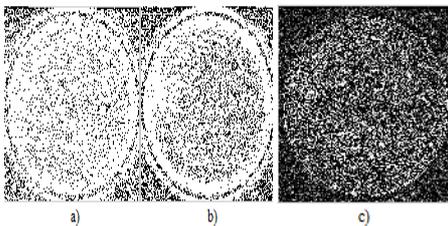


Figure 4: The features f1, f2, f3, f4, f5, f6, f7 respectively

CONCLUSION

This paper proposes a method for improving image quality prior to retinal image pixel feature extraction. The preprocessing method employees extracting the green channel from original RGB retinal image as green channel images provide better contrast. The technique for removing central light reflex from vessel is proposed. The fundus image background homogenization is carried out to remove illumination variation and background intensity variation, and finally blood vessel enhancement is done for vessel enhancement. The feature extraction for pixel representation is proposed using gray

level based and moment invariant based features. Using a suitable classifier the blood vessel structure can be segmented from the retinal images.

REFERENCES

1. R. Klein, S. M. Meuer, "Retinal microaneurysm counts and 10-year progression of diabetic retinopathy," *Arch. Ophthalmol.*, vol. 113, pp.1386–1391, 1995.
2. "Economic costs of diabetes in the U.S. in 2007," in *Diabetes Care: American Diabetes Association*, vol. 31, pp.596–615,2008.
3. Y. A. Tolias, S. M. Panas, "A fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering," *IEEE Trans. Med. Imag.*, vol. 17, pp.263–273, Apr. 1998.
4. L. Gagnon, M. Lalonde, "Procedure to detect anatomical structures in optical fundus images," *Proc. SPIE Med. Imaging.: Image Process.*, vol. 4322, pp.1218–1225, 2001.
5. T. Walter, J. C. Klein, "Segmentation of color fundus images of the human retina: Detection of the optic disc and the vascular tree using morphological techniques," in *Medical Data Analysis, Lecture Notes*, Springer-Verlag, pp. 282–287, 2001.
6. F. Zana and J. C. Klein, "Segmentation of vessel-like patterns using mathematical morphology and curvature evaluation," *IEEE Trans. on Image Processing.*, vol. 10, pp. 1010–1019, Jul. 2001.
7. A. M. Mendonça, A. Campilho, "Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction," *IEEE Trans. Med. Imag.*, vol. 25, pp.1200–1213, Sep. 2006.
8. S. Chaudhuri, S. Chatterjee, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Transactions on Medical Imaging*, vol. 8, pp. 263–269, Sep. 1989.
9. M. Al-Rawi, M. Qutaishat, "An improved matched filter for blood vessel detection of digital retinal images," *Computers in Bio and Medicine.*, vol. 37, pp. 262–267, 2007.
10. X. Jiang, D. Mojon, "Adaptive local thresholding by verification based multithreshold probing with application to

vessel detection in retinal images,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, pp. 131–137, Jan. 2003.

11. L. Espona, M. J. Carreira, “A snake for retinal vessel segmentation,” Pattern Recognition and Image Analysis, vol. 4478, pp. 178–185, 2007.

12. M. E. Martinez-Perez, A. D. Hughes, “Segmentation of blood vessels from red-free and fluorescein retinal images,” Med. Imag. Anal., vol. 11, pp. 47–61, 2007.

13. V. B. Soares, J. J. G. Leandro, “Retinal vessel segmentation using the 2D Gabor wavelet and supervised classification,” IEEE Transactions on Medical Imaging, vol. 25, pp.1214–1222, Sep. 2006.

14. J. Staal, M. D. Abràmoff, “Ridge based vessel segmentation in color images of the retina,” IEEE Transactions on Medical

Imaging., vol. 23, no. 4, pp. 501–509, Apr. 2009.

15. E. Ricci, R. Perfetti, “Retinal blood vessel segmentation using line operators and support vector classification,” IEEE Trans. Med. Imag., vol. 26, pp. 1357–1365, Oct. 2007.

16. Diego Marín, Arturo Aquino, “A New Supervised Method for Blood Vessel Segmentation in Retinal Images by Using Gray Level and Moment Invariants-Based Features,” IEEE Transactions on Medical Imaging, vol. 30, JAN 2011.

17. T. Walter, P. Massin, “Automatic detection of microaneurysms in color fundus images,” Med. Image Anal., vol. 11, pp. 555–566, 2007.

18. M. K. Hu, “Visual pattern recognition by moment invariants,” IRE Trans. Inform. Theory, vol. IT-8, pp. 179–187, 1962.