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Segmented Retinal Blood Vessels of Healthy and Diabetic Retinopathy Individual

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Abstract: Diabetic retinopathy is a micro vascular complication of diabetes which alters the retinal vascular patterns. The increase in this alteration may result in the complete damage of retinal blood vessels and eventually lead to total sight loss or blindness. However, early diagnosis and detection of these changes in the blood vessel patterns could help diagnose Diabetic Retinopathy (DR), determine its stage and define the required treatment to be proffered. This data study presents image files of 50 high resolution blood vessels images that were segmented from Diabetic Retinopathy Image Database (DRIDB). Prior to blood vessel extraction, the green component of the raw images was extracted and converted to a grayscale image. Afterwards, the images were preprocessed using median filter, mahalanobis distance and contrast limited adaptive histogram equalization. The segmented blood vessels can be used to study blood vessel patterns with a view to detect any alteration that could signify the presence of DR. Furthermore, the automatically segmented blood vessels can be compared with other manually segmented blood vessels in order to validate the technique adopted. Prospective researchers can also make use of the blood vessels in developing retina recognition systems.

Key words: Blood vessels dataset, diabetic retinopathy, DRIDB, retinal, segmentation, retinal vascular patterns

INTRODUCTION

The population of diabetic patient is expected to increase from 171 million people in year 2000-366 million in year 2030 (Welikala *et al*., 2014), therefore, Diabetic Retinopathy (DR) victims are also expected to be on the increase. DR arises as a result of microvascular complication of diabetes whose signs may not be visible at the early stage (Amin *et al*., 2016). Research has shown that DR remains a major cause of most visual impairment and blindness, yet its victims are increasing day by day (Mahendran and Dhanasekaran, 2015; Barkana *et al*., 2017). However as a microvascular disorder, the symptoms of DR could be diagnosed by analyzing the changes in retinal vascular structure (Valverde *et al*., 2016; Guedri *et al*., 2017). Generally, DR could be categorized into two stages: Non-Proliferative DR (NPDR) and Proliferative DR (PDR) stage (Akram *et al*., 2014). These stages of DR have symptoms that are traceable to the retinal blood vessels, hence, the analysis of retinal blood vessels could help in DR detection as well as grading.

One of the early symptoms of NPDR stage is the presence of swollen blood vessels which may later spill blood or protein particles on the surface of the retina (Banerjee and Kayal, 2016). Additional symptoms of NPDR include the appearance of symptoms such as microaneurysms, soft and hard exudates and hemorrhages (Amin *et al*., 2016). Moreover, PDR stage may also result in a change of blood vessel diameter and growth of abnormal vessels (Welikala *et al*., 2014; Franklin and Rajan, 2014a, b). While NPDR may result in the impairment or partial loss of sight, PDR result in irreversible and total blindness. Therefore, early detection of the symptoms of DR through retinal blood vessels analysis could help prevent the severe effects of DR. Manual segmented of retinal blood vessels and subsequent diagnosis of the symptoms of DR is known to be tedious and time consuming (Bhargavi *et al*., 2016; Fraz *et al*., 2012) therefore, it is not generally efficient. On the contrary, the automated method of retina blood vessel segmentation and subsequent DR diagnosis has proved to be fast and efficient (Mahendran and Dhanasekaran, 2015; Wang *et al*., 2015).

This study presents 50 high resolution retinal blood vessels images extracted from publicly available retinal images sourced from DRIDB. The 36 of these blood vessels were extracted from individuals whose retina has

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symptoms of DR while 14 are from retina of individuals without DR symptoms. The blood vessels were extracted using Dempster-Shafer (D-S) edge based detector (Banerjee and Kayal, 2016) segmentation technique. It is expected that the blood vessel dataset could be used to study the changes in retina blood vessel patterns which could be useful to diagnose and detect pathological symptoms of DR. Furthermore, the automatically segmented blood vessels can be used to validate manually segmented ones as well as other blood vessels segmentation techniques. Prospective researchers could also employ the dataset to develop retina recognition systems by deploying a robust feature extraction technique to extract features from the blood vessels.

Literature review: Several automated techniques have been employed in the literature for retinal blood vessel segmentation. A multi-scale line detection technique was employed by Nguyen *et al.* (2013) for retinal blood vessel segmentation. The technique leveraged on the fact that a change in the length of a basis line detector results in a change of line detectors at varying scales. These line changes at varying scales were then linearly combined for retinal blood vessel segmentation. High accuracies were achieved when compared with STARE, DRIVE and REVIEW publicly available retinal datasets. Directional mathematical morphology and fuzzy classification was employed for vessel segmentation by Sigurosson *et al.* (2014). The technique proposed entails the extraction of two vessel features vectors that uses blood vessels contrast and their linear connectivity to determine pixels that belongs to blood vessels.

The features were extracted using advanced morphological directional filter after which a vessel map was constructed to extract the blood vessels. Similarly, morphological operations was employed for blood vessels segmentation by Kurilova *et al.* (2015). Grey level thresholding was used to preprocess the retinal images after which disc shaped structural element was applied to eliminate vessel like parts in the retinal image. Binary mask was then used to mark blood vessels pixels in the retinal image.

Artificial neural network technique with Gabor and moment invariants based features were employed for vessel segmentation by Franklin and Rajan, (2014a, b). The pixels in the retinal images were first segmented into vessel and non-vessel pixels using Gabor and moment invariants-based features, afterwards, multilayer perceptron neural network was used to map out the blood vessels. Wang *et al.* (2015) introduced a retinal blood vessels segmentation technique using Convolutional Neural Network (CNN) and Random Forest (RF). CNN was used to as a hierarchical feature extractor while ensemble random forest was used as a trainable classifier. An improved way to blood vessel segmentation using Morphological Component Analysis (MCA) was introduced by Imani *et al.* (2015). Prior to blood vessel segmentation, MCA was used to separate the lesions in the diseased retinal image before a vessel map was created from a clean retinal image for effective blood vessel segmentation, both supervised and unsupervised learning using principal component analysis and mathematical morphological techniques, respectively were employed by Ramani and Balasubramanian (2016).

An average accuracy of 94.70 and 95.52% was achieved when the technique was evaluated on diseased and normal retina images, respectively. Blood vessel extraction using three enhancement filtering and unsupervised classification was proposed by Yavuz and Kose (2017). Top-hat transform was applied to the output of Gabor filter, Gaussian filter and Frangi filter to increase the contrast between the retina blood vessels and its background. Afterwards, k-means and fuzzy C-means clustering algorithm was applied to the binary results to obtain the blood vessels. Srividhyaa and Sumalatha (2017) implemented a graph based retinal blood vessel segmentation technique.

MATERIALS AND METHODS

The detailed steps employed for the vessel segmentation is discussed in this study.

Data collection: All raw retinal images available in DRiDB were used in this research. DRiDB contains 50 coloured retinal images that were captured with ZEISS VISUCAM 200 fundus camera at 45° field of view (Prentasic *et al.*, 2013). The images are of 720×576 resolution and 8-bits per color plane. The 36 of the images have signs of DR while 14 does not show any signs of DR.

Image preprocessing: For an effective vessel segmentation and also to remove noise from the images, all the images were preprocessed. The green channel of retinal images is generally believed to be the most suitable channel for medical analysis as it has the best vessel and background contrast (Zhu *et al.*, 2017).

Therefore, prior to preprocessing task, the green channel of the raw images in RGB space were removed. Furthermore, the extracted green channel was converted to grayscale, so as to eliminate hue and saturation component while retaining the luminance component of the image. The process of acquiring retina image is intrusive due to its location at the posterior region of the eye, therefore the quality of the captured retina image m ay not be suitable for medical analysis. As a result of this the retina images used were preprocessed using median filter, mahalanobis distance and Contrast Limited Adaptive Histogram Equalization (CLAHE). Median filter was used to remove noise from the image while mahalanobis distance was used to separate the back ground image from the foreground image before CLAHE was used to enhance the contrast of the foreground image.

Blood vessel segmentation: After preprocessing, blood vessels were automatically segmented from the preprocessed retinal images using Dempster-Shafer (D-S) edge based detector (Li and Wee, 2014). D-S uses probability-based fusion to merge the outputs of Laplacian of Gaussian (LoG) and canny edge detection filters in determining the continuous paths of a vessel after the starting point has been determined. LoG filter was used to determine edge pixels among the pixels of the input retinal images. This was computed using Eq. 1-3:

$$h(x, y) = \exp\left(-\frac{x^2+y^2}{2\sigma_N^2}\right) \quad (1)$$

$$\nabla^2 h(x, y) = \left(\frac{x^2+y^2-\sigma^2}{\sigma_N^4}\right)\exp\left(-\frac{x^2+y^2}{2\sigma_N^2}\right) \quad (2)$$

$$g(x, y) = \nabla^2 h(x, y) * F_{enc} \quad (3)$$

Where:

F_{enc} = Remains the input enhanced foreground image of the input retina
$g(x, y)$ = The output image
σ_N = Remains the standard deviation
$h(x, y)$ = The 2D gaussian function
$\nabla^2 h(x, y)$ = The LoG filter

Furthermore, in the edge detection task after determining the edge pixels in the input image, Canny filter was used to determine the horizontal, vertical and diagonal edges. The resulting edge gradient and direction was determined using Eq. 4:

$$G = \sqrt{\left(\partial_x I(x. y)\right)^2 + \left(\partial_y I(x. y)\right)^2} \quad (4)$$

Subsequently, the horizontal direction G_y and the vertical direction G_x were computed from gradient G using Eq. 5 and 6, respectively:

$$G_x = \partial_x F_{enc}(x, y) \quad (5)$$

$$G_y = \partial_y F_{enc}(x, y) \quad (6)$$

To achieve a more accurate and stable vessel edge detection, D-S based edge detector fuses the outputs g(x, y) of the LoG filter and the output G of the canny edge. This is referred to as a joint $m_1 \oplus m_2$ where m_1 and m_2 are the outputs of LoG and Canny edge filter, respectively. The joint $m_1 \oplus_2$ was obtained using Eq. 7 while the conflicting events caused by LoG and canny filter were removed using Eq. 8. Finally, the basic probability mass "K" associated with the conflicts w as calculated using Eq. 9:

$$m_1 \oplus m_2(A) = \frac{\sum_{B\cap C = A} m_1(B) m_2(C)}{1\text{-}K} \quad (7)$$

$$(m_1 \oplus m_2)_{(\ell)} = 0 \quad (8)$$

$$K = \sum_{B\cap C = \ell} m_1(B) m_2(C) \quad (9)$$

A-C are event set produced by the D-S fusion, LoG filter and canny edge filter, respectively. The implementation was carried out in MATLAB R2015a programming environment.

RESULTS AND DISCUSSION

The resultant blood vessel images are PNG grayscale images in 686×549-pixel resolution. Samples of images obtained after the preprocessing task are shown in Fig. 1. Selected samples of raw retinal images and the respective segmented blood vessels are shown in Fig. 2.

Data availability: The blood vessels dataset reported in this study is available at for academic and research purposes.

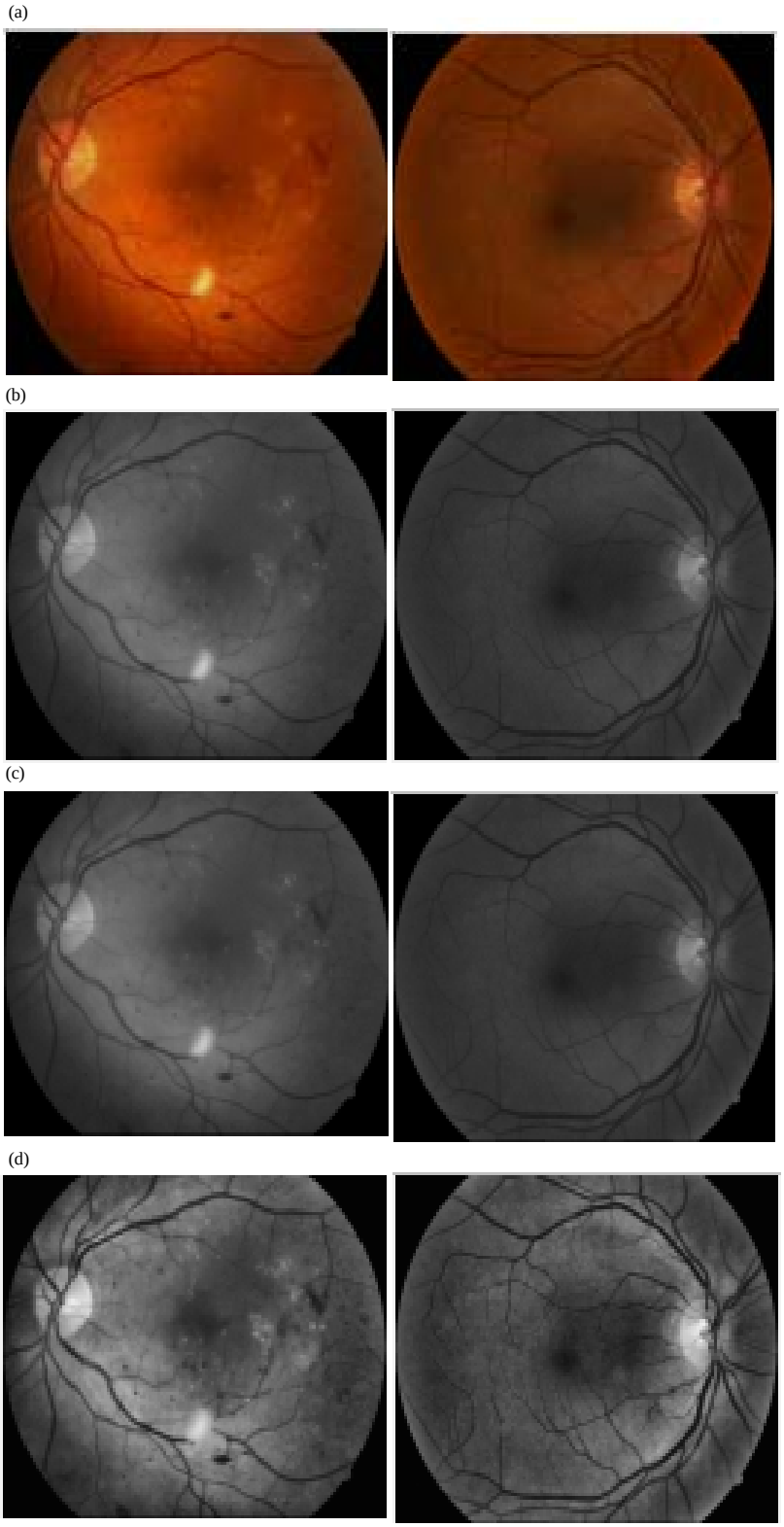

Fig. 1: Preprocessing stages; a) Original fundus images; b) Grayscale images; c) Median filtered images and d) Images after mahalanobis and CLAHE preprocessing

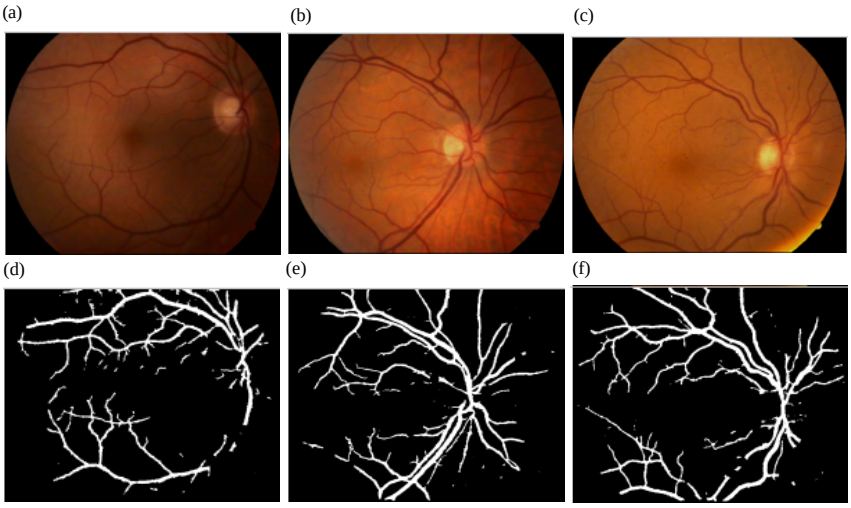

Fig. 2: a-f) Raw fundus images and their respective segmented blood vessels

CONCLUSION

This study has reported the importance of retinal blood vessels to retina diseases diagnosis. It has further presented high resolution retinal images extracted from publicly available DRiDB. It is expected that the dataset could be used to validate other manual or automatically segmented retinal images. furthermore it could assist ophthalmologists in retina diseases diagnosis. Also, researchers interested in developing recognition systems could employ the blood vessels dataset to train their recognition system.

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REFERENCES

Akram, M.U., A. Tariq, S.A. Khan and M.Y. Javed, 2014. Automated detection of exudates and macula for grading of diabetic macular edema. Comput. Methods Programs Biomed., 114: 141-152.

Amin, J., M. Sharif and M. Yasmin, 2016. A review on recent developments for detection of diabetic retinopathy. Sci., 2016: 1-20.

Banerjee, S. and D. Kayal, 2016. Detection of hard exudates using mean shift and normalized cut method. Biocybernetics Biomed. Eng., 36: 679-685.

Barkana, B.D., I. Saricicek and B. Yildirim, 2017. Performance analysis of descriptive statistical features in retinal vessel segmentation via fuzzy logic, ANN, SVM and classifier fusion. Knowl. Based Syst., 118: 165-176.

Bhargavi, R.V., R.K. Senapati, G. Swain and P.M.K. Prasad, 2016. Computerized diabetic patients fundus image screening for lesion regions detection and grading. Biomed. Res. India, 27: S443-S449.

Franklin, S.W. and S.E. Rajan, 2014b. Computerized screening of diabetic retinopathy employing blood vessel segmentation in retinal images. Biocybernetics Biomed. Eng., 34: 117-124.

Franklin, S.W. and S.E. Rajan, 2014a. Retinal vessel segmentation employing ANN technique by Gabor and moment invariants-based features. Appl. Soft Comput., 22: 94-100.

Fraz, M.M., P. Remagnino, A. Hoppe, B. Uyyanonvara and A.R. Rudnicka *et al*., 2012. Blood vessel segmentation methodologies in retinal images-a survey. Comput. Methods Programs Biomed., 108: 407-433.

Guedri, H., M.B. Abdallah, F. Echouchene and H. Belmabrouk, 2017. Novel computerized method for measurement of retinal vessel diameters. Biomedicines, 5: 1-17.

Imani, E., M. Javidi and H.R. Pourreza, 2015. Improvement of retinal blood vessel detection using morphological component analysis. Comput. Methods Programs biomed., 118: 263-279.

Kurilova, V., J. Pavlovicova, M. Oravec, R. Rakar and I. Marcek, 2015. Retinal blood vessels extraction using morphological operations. Proceedings of the 2015 International Conference on Systems, Signals and Image Processing (IWSSIP), September 10-12, 2015, IEEE, London, UK., ISBN:978-1-4673-8353-0, pp: 265-268.

Li, X. and W.G. Wee, 2014. Retinal vessel detection and measurement for computer-aided medical diagnosis. J. Digital Imag., 27: 120-132.

Mahendran, G. and R. Dhanasekaran, 2015. Investigation of the severity level of diabetic retinopathy using supervised classifier algorithms. Comput. Electr. Eng., 45: 312-323.

Nguyen, U.T.V., A. Bhuiyan, L.A. Park and K. Ramamohanarao, 2013. An effective retinal blood vessel segmentation method using multi-scale line detection. Pattern Recognit., 46: 703-715.

Prentasic, P., S. Loncaric, Z. Vatavuk, G. Bencic and M. Subasic *et al*., 2013. Diabetic retinopathy image database (DRiDB): A new database for diabetic retinopathy screening programs research. Proceedings of the 2013 8th International Symposium on Image and Signal Processing and Analysis (ISPA), September 4-6, 2013, IEEE, Trieste, Italy, pp: 711-716.

Ramani, R.G. and L. Balasubramanian, 2016. Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis. Biocybernet. Biomed. Eng., 36: 102-118.

Sigurosson, E.M., S. Valero, J.A. Benediktsson, J. Chanussot and H. Talbot *et al*., 2014. Automatic retinal vessel extraction based on directional mathematical morphology and fuzzy classification. Pattern Recognit. Lett., 47: 164-171.

Srividhyaa, R. and V. Sumalatha, 2017. A graph based segmentation for extraction of blood vessels in retinal images. Intl. J. Pure Appl. Math., 116: 675-684.

Valverde, C., M. Garcia, R. Hornero and M.I. Lopez-Galvez, 2016. Automated detection of diabetic retinopathy in retinal images. Indian J. Ophthalmol., 64: 26-32.

Wang, S., Y. Yin, G. Cao, B. Wei and Y. Zheng *et al*., 2015. Hierarchical retinal blood vessel segmentation based on feature and ensemble learning. Neurocomputing, 149: 708-717.

Welikala, R.A., J. Dehmeshki, A. Hoppe, V. Tah and S. Mann *et al*., 2014. Automated detection of proliferative diabetic retinopathy using a modified line operator and dual classification. Comput. Methods Programs Biomed., 114: 247-261.

Yavuz, Z. and C. Kose, 2017. Blood vessel extraction in color retinal fundus images with enhancement filtering and unsupervised classification. J. Healthcare Eng., 2017: 1-12.

Zhu, C., B. Zou, R. Zhao, J.Cui, X. Duan, Z. Chen and Y. Liang, 2017. Retinal vessel segmetation in colour fundus images using extreme learning machine. Comput. Med. Imag. Graphics, 55: 68-77.