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Vascular Networks Segmented from Retinal Images of Hypertensive Retinopathy and Glaucoma Patients

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Abstract: Hypertensive Retinopathy (HR) and glaucoma are two of the most common and leading eye problems responsible for human vision loss and blindness. Both cases cause alteration of vascular structures of the retina thereby initiating a gradual vison loss and eventual blindness. It is relieving to know that early detection of the changes in the vascular structure of the retina can help to detect these diseases before the eventual collapse of the eye. This study presents a dataset that contains high resolution biomedical image files of vascular structures extracted from retinal images available in Digital Retinal Images for Optic Nerve Segmentation Database (DRIONS-DB). The database contains 110 retinal images that were captured with HP-Photo Smart-S20 high-resolution scanner. The images are of 600×400 resolution and in JPEG format. Prior to extraction, the raw images were preprocessed using median filter, Mahalanobis distance and Contrast Limited Adaptive Histogram Equalization (CLAHE). The blood vessel segmentation was carried out using Dempster-Shafer (D-S) edge based detector while MATLAB R2015a programming environment was used for the implementation.

INTRODUCTION

Human retina which is located at the posterior region of the eye is known to contain a vast network of vascular structures known as blood vessels. These blood vessels contain features which could be analyzed for the diagnosis of several ophthalmic diseases such as glaucoma, Hypertensive Retinopathy (HR), diabetic retinopathy, stroke, etc. HR and glaucoma are diseases that arise as a result of an increase in blood pressure resulting in the damage of retina blood vessels. This damage is a gradual process which may not be visible on time and could lead to the gradual loss of sight as well as total blindness (Akbar *et al*., 2018a, b). Therefore, an early detection of these changes in the retinal blood vessel through an eye screening and retina blood vessel examination procedure could help to prevent the menace caused by HR and glaucoma. While HR could cause the blood vessels to swell and eventually burst (Triwijoyo and Pradipto, 2017), glaucoma results in the damage to the optic nerve head, high eye pressure, gradual vision loss and complete blindness (Haleem *et al*., 2013). Since, HR and glaucoma are as a result of high blood pressure, ophthalmologists have been measuring Arteriovenous Ratio (AVR) for their detection and grading (Akbar *et al*., 2018a, b; Triwijoyo and Pradipto, 2017; Hubbard *et al*., 1999). AVR is a function of the Central Retinal Venular Equivalent (CRVE) and Central Retinal Artery Equivalent (CRAE). Mild stage of HR has an AVR range of ($0.33 \geq AVR \leq 0.5$), moderate HR has an AVR value of 0.25 while an AVR value <0.20 indicates a malignant stage of HR (Brandenburg and Schrage, 2005; Noronha *et al*., 2012). Though, the mild stage of HR cannot be easily seen or examined manually by ophthalmologists, the manual approach of HR diagnosis is known to be invasive, costly, prone to errors, time consuming and subject to inter-observer variability (Muramatsu *et al*., 2010). Therefore, the manual approach is gradually being replaced with the automated means of diagnosing eye diseases. These automated means often referred to as Computer Aided Designs (CAD) systems rely on high resolution images of blood vessels extracted from the retina. However, the presence of symptoms of eye diseases which results in the alteration of blood vessels of the retina has made the segmentation of retinal blood vessels a hectic task. This has led to the proposal of several segmentation techniques available in literature. High resolution blood vessels datasets extracted from retinal images of HR and glaucoma patients is presented in this study. The 110 images files retina blood vessels were extracted from publicly available Digital Retinal Images for Optic Nerve Segmentation Database (DRIONS-DB). It is believed that the blood vessels datasets could be easily used by other researchers to study the changes in the vascular structures of the retina as a result of HR and glaucoma. This will hasten the screening and grading process of Hypertensive Retinopathy (HR) as well as glaucoma. Also, the dataset could be used as a benchmark for comparing other manually or automatically segmented vascular structures. Researchers interested in coming up with a retinal recognition system could also extract features from the vascular structures for retinal recognition purposes. Similarly, the dataset can be employed in the development of CAD systems or Decision Support Systems (DSS) that could facilitate early diagnosis, detection and grading of HR as well as glaucoma diseases. Finally, the datasets could be used as a yardstick for comparing other blood vessels segmentation techniques.

Literature review: A technique aimed at segmenting and measuring the diameter of blood vessels for AVR computation was proposed by Manikis *et al*. (2011). Iterative thresholding method was used to segment the retinal blood vessels after which a local algorithm was used to estimate blood vessel width. The user is then, expected to supply two points that will be used to measure mean vessel width. Similarly, a technique to compute AVR value from retinal blood vessels was proposed by Niemeijer *et al*. (2011). Pixel classification technique was used to segment blood vessels from the retinal images after which bifurcation points and vessel crossings were removed. Features were further extracted from the remaining vessel centerline pixels and artery vein pairs were generated using an iterative algorithm. The width calculated from the vessels and artery vein pairs were subsequently used to compute the AVR value used for HR diagnosis. Also, a support system for HR detection was proposed by Noronha *et al*. (2012). 2D-matched filter technique was used for blood vessel detection while random transform was used for the blood vessel segmentation. Afterwards, AVR was calculated for HR diagnosis. A decision support system for HR diagnosis using AVR was proposed by Akbar *et al*. (2018a, b). Multi-layered thresholding technique was used to extract retinal blood vessels, afterwards, arteries and veins were separated from the extracted vascular map. Finally, AVR was computed from the separated arteries and veins for the detection and grading of HR in the same vein, a decision support system that uses computed AVR value and 23 features extracted from segmented blood vessels for HR detection and grading was proposed by Akbar *et al*. (2018a, b). Multilayered thresholding approach was also used for the blood vessel segmentation. Comparative analysis carried out between the later and former technique showed that the combination of features extracted from the blood vessels could prevent some of the challenges with inter-subject variability that is common to AVR computation.

It has been established from literature that changes in retinal vasculature could result in the damage of the optic nerves thereby resulting to glaucoma (Chan *et al*., 2018). Also, retinal vessels narrowing has been shown to be a sign of a damaged optic nerve has been damaged (Jonas *et al*., 1989). A population based research carried out by (Wu *et al*., 2013) revealed that retinal vascular parameters such as fractal dimension, branching angle and tortuosity could be used to diagnose glaucoma. This was also supported by a retrospective observational study carried out by Gao *et al*. (2015), Yoo *et al*. (2015). Therefore, the retinal vasculature of the optic disk could be examined for glaucoma diagnosis.

MATERIALS AND METHODS

This study gives an overview of the steps taken to extract blood vessels from the raw retina images.

Data collection: Publicly available retina images obtained from DRIONS-DB were used as raw data in this research. The database contains 110 coloured retina images of individuals diagnosed to have HR and chronic glaucoma. The 8-bit raw retina images were captured using HP-Photo Smart-S20 high-resolution scanner and are of 600×400 resolution. The 23.1% of the raw retinal images belong to patients with chronic glaucoma while the remaining 76.9% are from patients with HR. The raw retina images are in grayscale with 923×596 dimension and PNG format. All the 110 coloured retina images available in DRIONS-DB were used in this research.

Preprocessing task: Every coloured image is made up of intensity, hue and saturation information, however, the most important of these for medical analysis is the intensity (Tian-Swee *et al*., 2014). Therefore, to retain the intensity while removing the hue and saturation component, the images were converted to grayscale. Furthermore, due to the location of the retina, its capturing process is known to be intrusive and it requires maximum level of cooperation from the patient (De Marsico *et al*., 2016). Therefore, a retinal image that will be suitable for analysis must be preprocessed. This was achieved using median filter, mahalanobis distance and CLAHE. Median filter was used to remove noise from the retinal images. Complex background images could also contribute to an increased noise (El Abbadi and Al Saadi, 2014). Therefore, mahalanobis distance was used to separate the background image from the foreground image. The contrast of the foreground image was finally, enhanced using CLAHE.

Blood vessels segmentation: After preprocessing, blood vessels were extracted from each 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 identify edge pixels among the pixels of the input retinal images. This was achieved 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
∇^2h (x, y) = The LoG filter

In addition, after the edge pixels in the input retina image have been determined, Canny filter was used to determine the horizontal, vertical and diagonal edges. The resulting edge gradient and direction were computed using Eq. 4:

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

Consequently, 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 obtain 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 was calculated using Eq. 9:

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

$$(m_{1\oplus} m_2)_{(l)} = 0 \quad (8)$$

$$K = \sum_{B\cap C = 1} m_1(B) m_2(C) \quad (9)$$

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. For easy identification and comparison, the vascular structures extracted from respective retinal images were assigned similar names as in the DRION-DB.

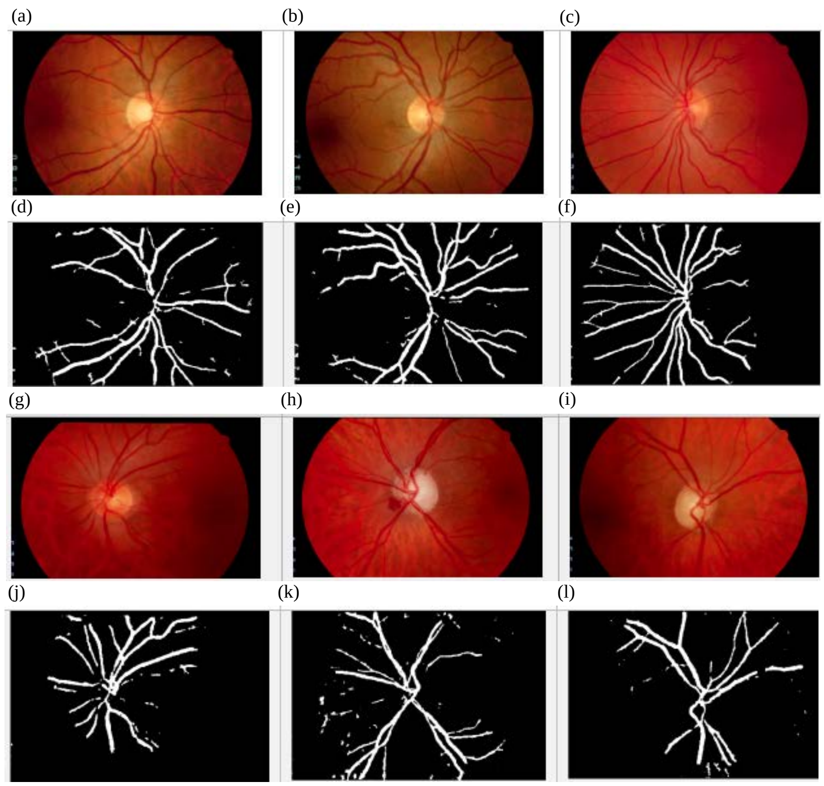

Fig. 1(a-l): Samples of raw retina images available in DRIONS-DB and their respective vascular structures

RESULTS AND DISCUSSION

The 110 blood vessels extracted from DRIONS-DB is publicly available at http://doi.org/10.5281/zenodo.1409114 for academic and research purposes. Samples of the blood vessels are shown in Fig. 1.

CONCLUSION

Early detection of the symptoms of HR and glaucoma could help prevent loss of sight or total blindness and retinal blood vessels remains a key component that could be used for this diagnosis. While several blood vessel segmentation technique has been proposed in literature, there is still room for more new segmentation techniques. The retinal blood vessels reported in this study could be used as a yardstick to compare other segmentation technique. Besides HR and glaucoma diagnosis, features could be extracted from the blood vessels dataset for developing retina recognition systems.

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