Supervised Retinal Vessel Segmentation Based on Neural Network Using Broader Aging Dataset

Mohd Zulfaezal Che Azemin[1], Fadilah Abd Hamid[1],
Mohd Izzuddin Mohd Tamrin[2], and Anang Hudaya Muhamad Amin[3]

[1]KAHS, International Islamic University Malaysia, Malaysia
[2]KICT, International Islamic University Malaysia, Malaysia
[3]FIST, Multimedia University, Malaysia

Abstract. Retina image quality is affected by numerous factors including aging, refractive condition, and media opacity. Distracters that exist in certain age groups may not be present in another. This is evident when the retinal nerve fiber is more visible in younger age group, tricking the vessel segmentation algorithm to label it as vessel thus affecting the specificity performance of the supervised retinal vessel segmentation. This research work aims to investigate the impact of aging to the performance of the supervised vessel segmentation. The results suggest different age groups affect different aspect of the segmentation performance. Sensitivity is estimated to reduce by 4.633% for every 10- year increase of age ($p<0.001$), and specificity is estimated to reduce by 0.543% for every 10-year decrease of age ($p<0.001$).

1 Introduction

Manual segmentation of retinal vessels enables the development of supervised machine learning techniques to classify pixels as vessels and non-vessels. The currently available datasets only provide limited images labeled by human experts. The need for splitting the training and testing datasets making the generalization less effective when supervised methods are used in small sample size. Retina image quality is affected by numerous factors including age, refractive condition, and media opacity. Distracters that exist in certain age groups may not be present in another. This is evident when the retinal nerve fiber layer is more visible in younger age group, tricking the vessel segmentation algorithm to label it as vessel thus affecting the specificity performance of the supervised retinal vessel segmentation. In older age group, the issue of poorer image quality due to lens opacity has also been highlighted previously [1]. This research work hypothesizes that well-performed supervised retinal vessel segmentation may be affected by biological changes in the retina when applied on images from broader age spectrum.

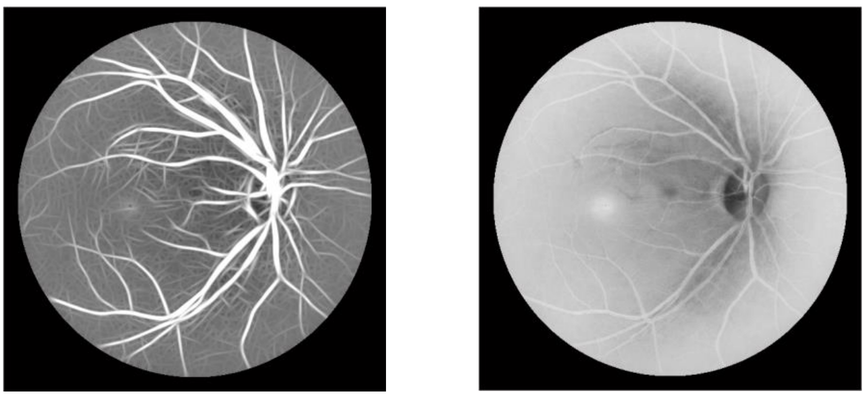
2 Method

Section 2.1 explains general method of vessel segmentation employed in this research work, and Section 2.2 elaborates the implementation of the vessel segmentation on publicly available retina dataset and aging dataset.

2.1 Supervised Vessel Segmentation

Vessel segmentation is a process of converting original color retina image to binary image with vessels labeled as white and background as black pixels. Supervised vessel segmentation consists of two steps, first: (1) Extracting features from the color image. (2) The features in the first step are fed into a classifier to learn to recognize pixels as vessel or non-vessel.

The first step in feature extraction is to identify possible image enhancement that can enhance the contrast between the retinal vasculature and the background as demonstrated in Fig. 1. Table 1 summarizes all the features used in this paper.



(a) (b)

Fig. 1. Possible image enhancements techniques to improve the contrast between blood vessel and background. (a) Matched-filter Gabor wavelet. (b) $L*$ channel from $L*a*b*$ color space.

Table 1. Summary of the features used for the supervised vessel segmentation

Type	Number of features
RGB color space	3
CIE *L*a*b** color space	3
CIE *XYZ* color space	3
CIE *uvY* color space	3
Matched-filter Gabor wavelet with different scales [2]	4
Multiscale vessel enhancement filter based on Frangi's [3]	5
Total	21

Artificial Neural Network (ANN) was used to learn to recognize vessel from background. Fig. 2 illustrates the architecture of the ANN constructed which comprises of 10 hidden neurons, scaled conjugate gradient method was used to update the weight and bias values [4].

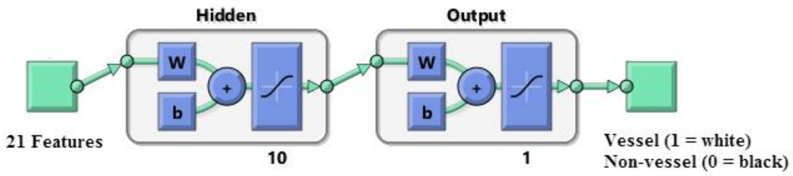


Fig. 2. Artificial Neural Network Architecture for Supervised Vessel Segmentation

The ANN model was optimized in the training phase and the performance of the model was tested on the unseen data by comparing pixels resulted from the classifier and pixels labeled by an expert. The output of the classifier is a continuous value from 0 (non-vessel) to 1 (vessel). A fixed threshold of 0.5 is used for hard classification.

2.2 Vessel Segmentation Implementation

We tested the classifier formed in Section 2.1 on two retina database:

- DRIVE is a public dataset commonly used in vessel segmentation research [5], the dataset contains 40 images, 20 images are used for training stage and another 20 images are used for testing stage.
- The second database comprises of 195 images of healthy individuals with reasonable quality from IIUM Optometry Aging dataset [6], 98 images for training and 97 images for testing. Both datasets include images labeled by an expert as ground truths.

3 Results

To validate the performance of our segmentation method we first tested the ANN model using the DRIVE dataset. Table 2 summarizes the performance of the technique in comparison to other state-of-the art methods.

Table 2. Comparative performance analysis summary of the current vessel segmentation technique.

Method	Area under ROC Curve	Accuracy	Kappa
Human expert	n/a	0.9473	0.7589
Current method	**0.9616**	**0.9456**	**0.7282**
Wang [7]	0.9543	0.9461	n/a
Soares [2]	0.9614	0.9466	n/a
Staal [8]	0.9520	0.9442	0.7345
Niemeijer [5]	0.9294	0.9416	0.7145
Zana [9]	0.8984	0.9377	0.6971
Al-Diri [10]	n/a	0.9258	0.6716
Jiang [11]	0.9114	0.9212	0.6399
Chaudhuri [12]	0.7878	0.8773	0.3357
All background	n/a	0.8727	0

The results indicate that the current approach for the vessel segmentation is comparable if not outperforming the other techniques when tested on the publicly available dataset.

The aging dataset was used to assess the impact of age to the performance of the well-performed classifier tested on the public database. Fig. 3 demonstrates the segmentation result from this dataset.

(a) (b)

Fig. 3. Vessel segmentation on the aging dataset. (a) Color retina image. (b) Corresponding vessel segmentation vessel segmentation result processed using our technique.

Linear trend analysis was performed to estimate the effect age on the performance of the retinal vessel segmentation. Fig. 4 shows a linear decreasing trend (R^2=0.2561, p<0.001) of sensitivity (measure of the ability of the classifier to detect correct vessel pixels) as aging advances. It is estimated that the sensitivity is reduced by 4.633% for every 10-year increase of age. Specificity (measure of the ability of the classifier to correctly classify non-vessel pixels) as shown in Fig. 5 is reduced in retina image of younger subjects (R^2=0.4102, p<0.001). Specificity is estimated to reduce by 0.543% for every 10-year decrease of age.

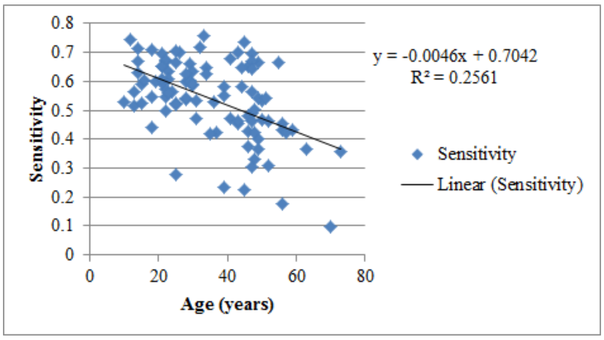


Fig. 4. Impact of age on the vessel segmentation sensitivity performance.

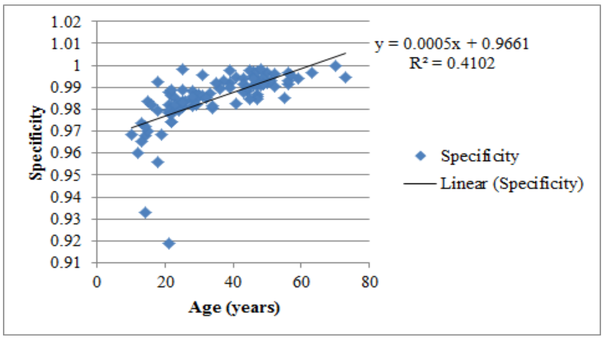
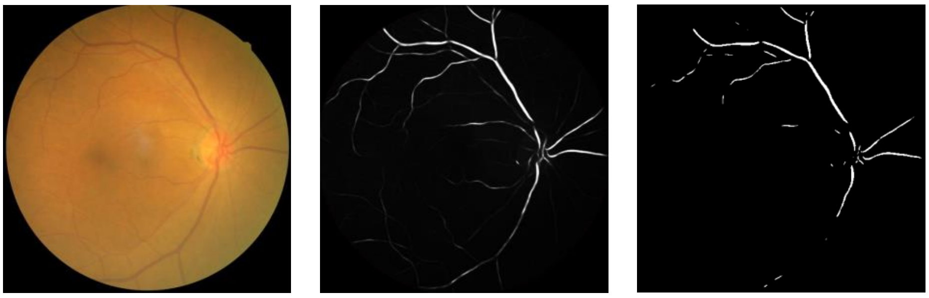


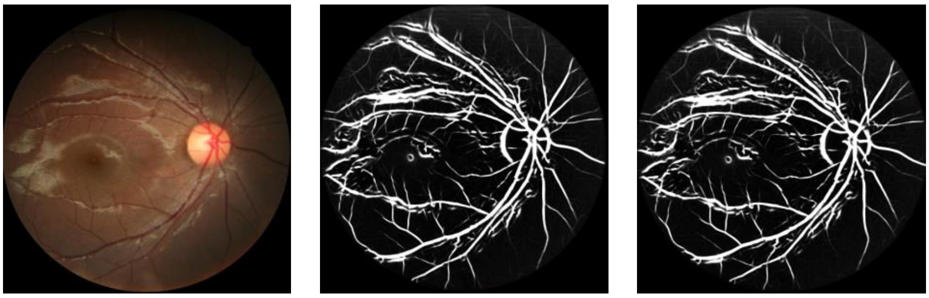
Fig. 5. Impact of age on the vessel segmentation specificity performance.

Fig. 6 and Fig. 7 illustrate the reduced sensitivity and specificity in old and young age groups respectively. The reduced sensitivity in images of old subjects maybe due to the poor contrast of the vessels and background and the use of a fixed threshold. Images in young subjects suffer from retinal nerve fiber artifacts which share similar characteristics with the vessels as indicated from the reduced specificity.



(a) (b) (c)

Fig. 6. Vessel segmentation on retina image of an old subject. (a) Original retina image. (b) Soft classification (greyscale). (c) Hard classification (binary image).



(a) (b) (c)

Fig. 7. Vessel segmentation on retina image of a young subject. (a) Original retina image. (b) Soft classification (greyscale). (c) Hard classification (binary image).

4 Conclusion

This research work suggests that different age groups affect different aspect of the segmentation performance. Retina images of older subjects maybe improved with the use of adaptive thresholding prior to hard classification and better features are needed to better discriminate vessels and other artifacts which commonly exist in younger subjects.

Care must be taken when using automated vessel segmentation, while the performance of an algorithm on the publicly available dataset shows comparable performance with human experts, it may not perform very well in the unseen data. The use of semi-automated approach as outlined in [13] is advisable to ensure the quality of the retinal vasculature analysis.

Acknowledgment

This research was supported by Ministry of Education, Malaysia under Research Acculturation Grant Scheme RAGS13-029-0092.

References

1. Li, H., Mitchell, P., Liew, G., Rochtchina, E., Kifley, A., Wong, T.Y., Hsu, W., Lee, M.L., Zhang, Y.P., Wang, J.J.: Lens opacity and refractive influences on the measurement of retinal vascular fractal dimension. Acta Ophthalmol. 88, e234-e240 (2010)
2. Soares, J.V., Leandro, J.J., Cesar, R.M., Jelinek, H.F., Cree, M.J.: Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification. IEEE Trans. Med. Imaging 25, 1214-1222 (2006)

3. Frangi, A.F., Niessen, W.J., Vincken, K.L., Viergever, M.A.: Multiscale vessel enhancement filtering. Medical Image Computing and Computer-Assisted Interventation—MICCAI'98, pp. 130-137. Springer (1998)
4. Møller, M.F.: A scaled conjugate gradient algorithm for fast supervised learning. Neural networks 6, 525-533 (1993)
5. Niemeijer, M., Staal, J., Ginneken, B., Loog, M., Abramoff, M.: DRIVE: digital retinal images for vessel extraction. (2004)
6. Che Azemin, M., Ab Hamid, F., Aminuddin, A., Wang, J., Kawasaki, R., Kumar, D.: Age-related rarefaction in retinal vasculature is not linear. Experimental Eye Research 116, 355-358 (2013)
7. Wang, Y., Ji, G., Lin, P., Trucco, E.: Retinal vessel segmentation using multiwavelet kernels and multiscale hierarchical decomposition. Pattern Recognition (2013)
8. Staal, J., Abràmoff, M.D., Niemeijer, M., Viergever, M.A., van Ginneken, B.: Ridge-based vessel segmentation in color images of the retina. Medical Imaging, IEEE Transactions on 23, 501-509 (2004)
9. Zana, F., Klein, J.-C.: Segmentation of vessel-like patterns using mathematical morphology and curvature evaluation. Image Processing, IEEE Transactions on 10, 1010-1019 (2001)
10. Al-Diri, B., Hunter, A., Steel, D.: An active contour model for segmenting and measuring retinal vessels. Medical Imaging, IEEE Transactions on 28, 1488-1497 (2009)
11. Jiang, X., Mojon, D.: Adaptive local thresholding by verification-based multithreshold probing with application to vessel detection in retinal images. Pattern Analysis and Machine Intelligence, IEEE Transactions on 25, 131-137 (2003)
12. Chaudhuri, S., Chatterjee, S., Katz, N., Nelson, M., Goldbaum, M.: Detection of blood vessels in retinal images using two-dimensional matched filters. IEEE Transactions on Medical Imaging 8, 263-269 (1989)
13. Liew, G., Wang, J.J., Cheung, N., Zhang, Y.P., Hsu, W., Lee, M.L., Mitchell, P., Tikellis, G., Taylor, B., Wong, T.Y.: The Retinal Vasculature as a Fractal: Methodology, Reliability, and Relationship to Blood Pressure. Ophthalmology 115, 1951-1956.e1951 (2008)