A Semi-supervised Approach to Segment Retinal Blood Vessels in Color Fundus Photographs

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Abstract. Segmentation of retinal blood vessels is an important diagnostic procedure in ophthalmology. In this paper we propose an automated blood vessels segmentation method that combines both supervised and un-supervised approaches. A novel descriptor named Local Haar Pattern (LHP) is proposed to describe retinal pixel of interest. The performance of the proposed method has been evaluated on three publicly available DRIVE, STARE and CHASE_DB1 datasets. The proposed method achieves an overall segmentation accuracy of 96%, 96% and 95% respectively on DRIVE, STARE, and CHASE DB1 datasets, which are better than the state-of-the-art methods.

Keywords: Color fundus photographs · Vessel segmentation · Haar feature · Multiscale line detector · Random forest

1 Introduction

Segmentation of retinal blood vessel is an important step in several retinal image analysis tasks including automated pathology detection and registration of retinal images [1]. Manual segmentation of retinal blood vessels is a long and tedious task. That is why, over the last two decades a large number of methods have been proposed to automatically segment retinal blood vessels. However, still there are challenges to address.

Ricci et al. [2] proposed a simple yet efficient segmentation method based on basic line operators and support vector machine. Despite addressing many of the important challenges in vessel segmentation [3], the method fails in the presence of central vessel reflex, at bifurcation and crossover regions. To overcome these problems, Nguyen et al. [3] proposed a method based on multi-scale line detector. While the method is one of the best in its category, the method fails to segment blood vessels accurately in the presence of pathology. On that perspective, in this work we aim to augment the method proposed by Nguyen et al. [3], so that blood vessels can be segmented accurately even with the presence of pathology.

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2 Proposed Method

A preliminary segmentation of the blood vessels is performed relying on multi-scale line detector approach [3]. Each of the pixels that are determined as vessels (that also contain misclassified pathology pixels) are then defined using Local Haar Pattern (LHP) descriptor (proposed here; described below). A random forest (RF) classifier [4] then determines a pixel as true vessel or not depending on its LHP description. While training the RF classifier, manual labeling (done by expert grader) of the actual vessel and pathology pixels were made available. A diagram of the proposed system is shown in Fig. 1.

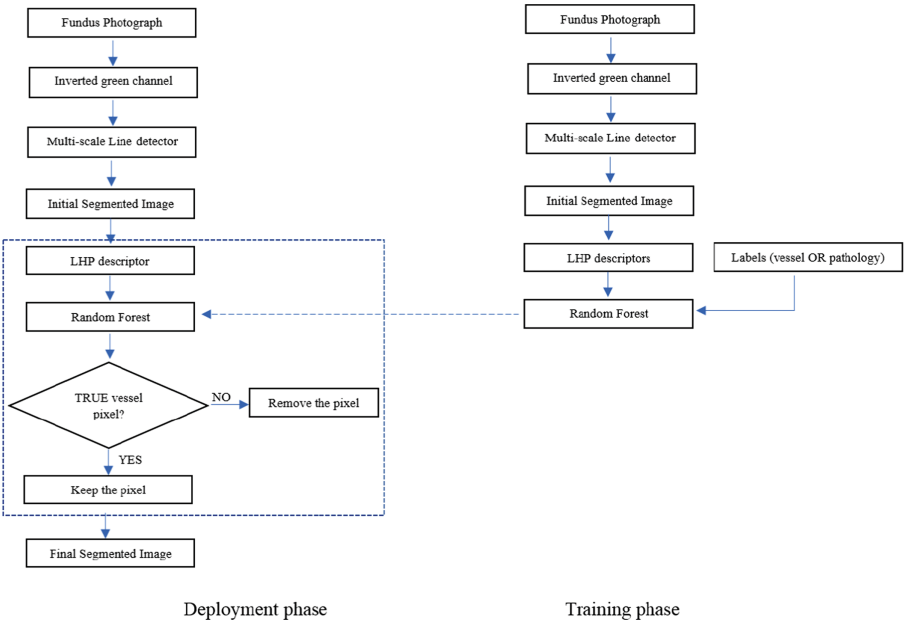

Fig. 1. Diagram of the proposed system. Operations shown within the dotted box are performed pixel-wise.

2.1 Local Haar Pattern (LHP) to Describe Retinal Pixel of Interest

A novel descriptor named Local Haar Pattern (LHP) is proposed here. LHP is inspired by the earlier works of Saha et al. in [5]. Rather than comparing the intensity of two groups of pixels to generate one bit of the descriptor as in [5], in this work, we compute and store the actual intensity difference, which is to some extent similar to Speeded Up Robust Feature (SURF) [6]. In order to perform pixels grouping, we define a set of 16-pixel patterns depicted in Fig. 2, which are reminiscent of Haar basis function [7].

In order to compute the LHP descriptor a patch p of size 32×32 is consider around the pixel of interest, and vector of size 128 bytes is calculated that represents the patch.

Each byte of the vector is computed based on the intensity comparisons of two-pixel groups as defined below:

$$\mathrm{T}(\mathrm{p}, \mathrm{X}, \mathrm{Y}) = \overline{\mathrm{I_X}} - \overline{I_Y}\,. \tag{1}$$

Here, $\overline{I_X}$ and $\overline{I_Y}$ represent the mean intensities of two different pixel groups X and Y belonging to the patch p. 128 bytes vector is generated in three steps. At the first step, all the 16 patterns are considered to perform intensity comparisons (Eq. 1) on the whole patch, that results 16 bytes vector. In the second step, the patch is divided into 4 sub-patches of size 16×16. All the 16 patterns are considered and intensity comparisons are performed on each of these sub-patches, which results 64 (=4×16) bytes vector. In third stage, each of the sub-patches is further divided into 4 sub-patches of size 8×8 and the first three of 16 patterns are considered to perform intensity comparisons, which results 48 (=16×3)-bytes vector.

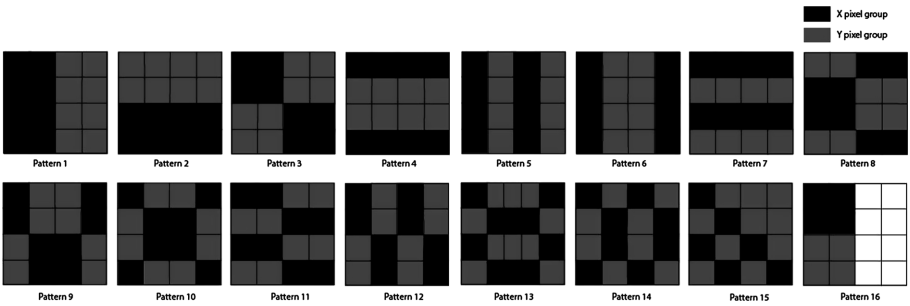

Fig. 2. All of the 16-pixel patterns used to compute LHP descriptor.

All these vectors are concatenated at the end and a feature vector of size 128-bytes is formed. Finally, the feature vector is normalized and LHP descriptor is formed.

3 Experiments and Results

Experiments are conducted on three publicly available datasets: DRIVE [8], STARE [9], and CHASE_DB1 [10]. 90% of these images are used for training and the rest 10% are used for testing (10-fold cross validation approach). Some sample outputs produced by the proposed method and Nguyen et al.'s method is shown in Fig. 3.

Sensitivity, specificity, accuracy and area under the curve (AUC) as computed in [11] are used to quantitatively the measure the performance of the proposed and the state-of-the-art methods. Table 1 compares the performance of the proposed method with the state-of-the-art methods on DRIVE, STARE, and CHASE_DB1 datasets.

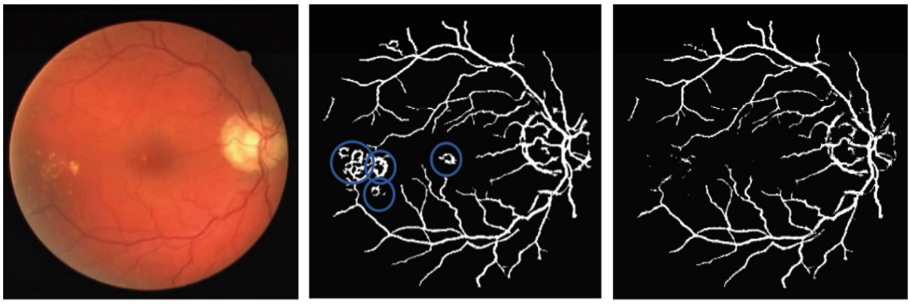

Fig. 3. Sample outputs. (a) Original image, (b) segmentation by Nguyen et al.'s method, (c) segmentation by proposed method. Misclassified pathology pixels are circled in blue. (Color figure online)

Table 1. Comparison of performance on DRIVE, STARE, and CHASE_DB1 datasets.

Methods	Datasets											
	DRIVE				STARE				CHASE_DB1			
	Acc	AUC	SE	SP	Acc	AUC	SE	SP	Acc	AUC	SE	SP
Supervised												
Staal et al. [12]	.944	–	–	–	.952	–	–	–	–	–	–	–
Soares et al. [13]	.946	–	–	–	.948	–	–	–	–	–	–	–
Marin et al. [14]	.945	.843	.706	.980	.952	.838	.694	.982	–	–	–	–
Unsupervised												
Mendoca et al. [15]	.945	.855	.734	.976	.944	.836	.699	.973	–	–	–	–
Budai et al. [16]	.957	.816	.644	.987	.938	.781	.580	.982	–	–	–	–
Nguyen et al. [3]	.941	–	–	–	.932	–	–	–	.934	.870	.791	.950
Proposed	**.961**	**.847**	**.711**	**.983**	**.960**	**.878**	**.790**	**.973**	**.951**	**.854**	**.742**	**.967**

(Acc = Accuracy, SE = sensitivity, SP = specificity)

4 Conclusion

In this paper, a semi-supervised method for retinal blood vessels segmentation is proposed. The method augments the multi-scale line detector approach [3] of Nguyen et al. by incorporating a supervised step with it. A novel descriptor named LHP is proposed to describe retinal pixels of interest. The descriptor encodes rich texture information around the pixel of interest. LHP descriptor together with random forest classifier is applied to separate vessel pixels from pathology pixels. Experimental results have shown that the proposed method produces higher accuracy (0.961 for DRIVE, 0.960 for STARE, and 0.951 for CHASE DB1), than the state-of-the-art methods,

with comparable or higher sensitivity, specificity, and AUC. Future work will be focused on identifying more optimized pixel patterns to compute the descriptor and designing of more effective segmentation model. Ensemble learning may be a way for boosting the performance of the classifiers.

References

1. Saha, S.K., Xiao, D., Bhuiyan, A., Wong, T.Y., Kanagasingam, Y.: Color fundus image registration techniques and applications for automated analysis of diabetic retinopathy progression: a review. Biomed. Signal Process. Control **47**, 288–302 (2019)
2. Ricci, E., Perfetti, R.: Retinal blood vessel segmentation using line operators and support vector classification. IEEE Trans. Med. Imaging **26**(10), 1357–1365 (2007)
3. Nguyen, U.T., Bhuiyan, A., Park, L.A., Ramamohanarao, K.: An effective retinal blood vessel segmentation method using multi-scale line detection. Pattern Recogn. **46**(3), 703–715 (2013)
4. Breiman, L.: Random forests. Mach. Learn. **45**(1), 5–32 (2001)
5. Saha, S., Dmoulin, V.: ALOHA: an efficient binary descriptor based on Haar features. In: 19th IEEE International Conference 2012, ICIP, Lake Buena Vista, Orlando, FL, USA, pp. 2345–2348. IEEE (2012)
6. Bay, H., Ess, A., Tuytelaars, T., Van Gool, L.: Speeded-up robust features (SURF). Comput. Vis. Image Underst. **110**(3), 346–359 (2008)
7. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. In: Computer Vision and Pattern Recognition, CVPR 2001, Proceedings of the 2001 IEEE Computer Society Conference, vol. 1, pp. I-511–I-518. IEEE (2001)
8. DRIVE Homepage. https://www.isi.uu.nl/Research/Databases/DRIVE/. Accessed 08 July 2018
9. STARE Homepage. http://cecas.clemson.edu/∼ahoover/stare/. Accessed 29 Nov 2018
10. CHASE DB1 Homepage. https://blogs.kingston.ac.uk/retinal/chasedb1/. Accessed 15 Nov 2018
11. Fan, Z., Lu, J., Wei, C., Huang, H., Cai, X., Chen, X.: A hierarchical image matting model for blood vessel segmentation in fundus images. IEEE Trans. Image Process. (2018)
12. Staal, J., Abrmoff, M.D., Niemeijer, M., Viergever, M.A., Van Ginneken, B.: Ridge-based vessel segmentation in color images of the retina. IEEE Trans. Med. Imaging **23**(4), 501–509 (2004)
13. Soares, J.V.B., Leandro, J.J.G., 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**(9), 1214–1222 (2006)
14. Marin, D., Aquino, A., Gegndez-Arias, M.E., Bravo, J.M.: A new supervised method for blood vessel segmentation in retinal images by using gray-level and moment invariants-based features. IEEE Trans. Med. Imaging **30**(1), 146 (2011)
15. Mendonca, A.M., Campilho, A.: Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction. IEEE Trans. Med. Imaging **25**(9), 1200–1213 (2006)
16. Budai, A., Bock, R., Maier, A., Hornegger, J., Michelson, G.: Robust vessel segmentation in fundus images. Int. J. Biomed. Imaging **2013** (2013)