

Automatic Detection of Retinal Lesions for Screening of Diabetic Retinopathy

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ABSTRACT

Diabetic Retinopathy is one of the disease which is identified by determination of different types of lesions occurred in the retina. The different types of lesions such as Microaneurysms(MAs), Hemorrhages(HEM), and Exudates(EXs). Detection of these lesions plays significant role for early diagnosis of DR. It contains four methods that includes vessel extraction and optic disc removal, preprocessing, candidate lesion detection, and post processing. Diabetic retinopathy is one of the medical condition where the retina is damaged because fluid leaks from blood vessels into the retina. Automatic identification of diabetic retinopathy lesions such as exudates, in fundus images can contribute to early diagnosis. Regular screening for diabetic retinopathy and diabetic maculopathy disease is necessary in order to identify the group at risk of visual impairment.

Keywords: Diabetic Retinopathy, Exudates, Hemorrhages, Maculopathy, Matched filter, Microaneurysm, Mutual Information.

1.INTRODUCTION

Diabetic retinopathy is one of the complications of diabetes that develop in most of the patients with longstanding illness, and the leading cause of blindness in the developed countries. Effective treatments for DR are available, though it requires early diagnosis and the continuous monitoring of diabetic patients. Diagnosis of DR is performed by the evaluation of retinal (fundus) images. Manual grading of these images to determine the severity of DR is rather slow and resource demanding. The presence of microaneurysms (MAs) on the retina is the first and most characteristics symptoms of this disease. MAs on the retina appear as small, round shaped red dots. Diabetic retinopathy results in visual disturbances and can lead to permanent blindness. Therefore, an effective diabetic retinopathy screening is essential for early treatment, along with an effective risk factor management to prevent diabetic complications and reduce morbidity and mortality impact. It contains two types. The first types is mydriatic, where the pupil dilation is required. The second type is non – mydriatic, which is easy to use, patient - - friendly and pupil dilation is done only if necessary.

II. BLOOD VESSEL EXTRACTION AND OPTIC DISC REMOVAL

Blood vessels in retinal images emanate from the optic disc (OD). Proper removal of blood vessels and OD is necessary in lesion detection since blood vessels and OD are the significant sources of false positive for dark and bright lesion detection, respectively. Since blood vessels appear as dark elongated structures in retinal images, inaccurate removal of blood vessels would hamper dark lesion detection while the former (blood vessels) is less-likely to be hampered by improper OD removal. On otherhand, being high contrast object, inaccurate removal of OD may suppress some of the bright lesions also. Thus the blood vessel extraction and OD detection are to be done properly so that the overall lesion detection performance is not affected. Again the assumption of OD localization and its removal is done using the method proposed due to high accuracy following a series of morphological processing. Once detected vessels and OD region are suppressed to facilitate lesion detection. Fig 1 shows the resulting image after the proposed method.

III. PRE-PROCESSING

The appearance of different DR lesions differs, for example being dark spots MAs and HEMs are mostly inseparable from the background whereas Exs are yellowish objects of high contrast. Some of sort of edge enhancement operation is therefore necessary to distinguish dark lesions from the background. On other hand, preprocessing for EX detection is more of contrast enhancement rather than edge processing. Hence different preprocessing operation are done as follows:

3.1 Curvelet Based Edge Enhancement For Dark Lesions

Curvelet transform is found efficient to identify horizontal, vertical and diagonal edge, directional information, contours, curvatures, missing and imprecise boundary information and helps to detect the edges of the dark lesions from the background. The image is decomposed first into a number of sub bands using curvelet transform. The approximate sub band is suppressed while the remaining (detailed) sub bands are multiplied by some amplification factor.

3.2 Optimal Band Pass Filter for Bright Lesion Enhancement

To preserve the bright regions morphological closing is performed on the image under consideration. This smooths out the background components and suppresses the thin vascular nets (that are missed out during blood vessel detection) keeping the bright lesions almost intact. This closing operation reduces the image contrast too. To increase the contrast of the Exs, the image is passed through a WBBF structure.

IV. CANDIDATE LESION DETECTION

The steps for candidate lesion detection are follows:

4.1 Matched Filtering and Laplacian Of Gaussian Filtering

Matched filter with a 2D Gaussian kernel produces high response for both the dark and the bright lesions that can be modeled as gaussian and step edges, respectively. On other hand at a sharp intensity transition of the bright

lesions, the response of LOG shows zero crossing about its center. Thus LOG filter along with MF, is used to detect the transient- like bright lesions and the dark lesions with Gaussian – like intensity profile.

4.2 Mutual Information Maximization Using DE

Mutual information MI, denoted by $I(X;Y)$ for discrete independent random variables (X,Y) with probability distribution $p(x)$ and $p(y)$, respectively is defined in the equation (4.2.1)

$$I(X;Y) = H(X) + H(Y) - H(X,Y) \dots\dots\dots(4.2.1)$$

V.POST PROCESSING

Different spurious components, background pixels may also be erroneously detected as candidate lesions. Now proper post processing is necessary for each lesion type. For MA detection, if the number of neighboring pixel is less than a certain threshold, the pixel is considered to be an isolated point and that is removed. Fig 2 shows the MA detection. For HEM detection, the candidate region whose area is less than a certain threshold is first eliminated. Fig 3 shows the HEM detection. For Exs, candidate regions with area above a certain threshold are first closed using disk shaped structuring element(SE). Fig 4 shows the Exs detection image.

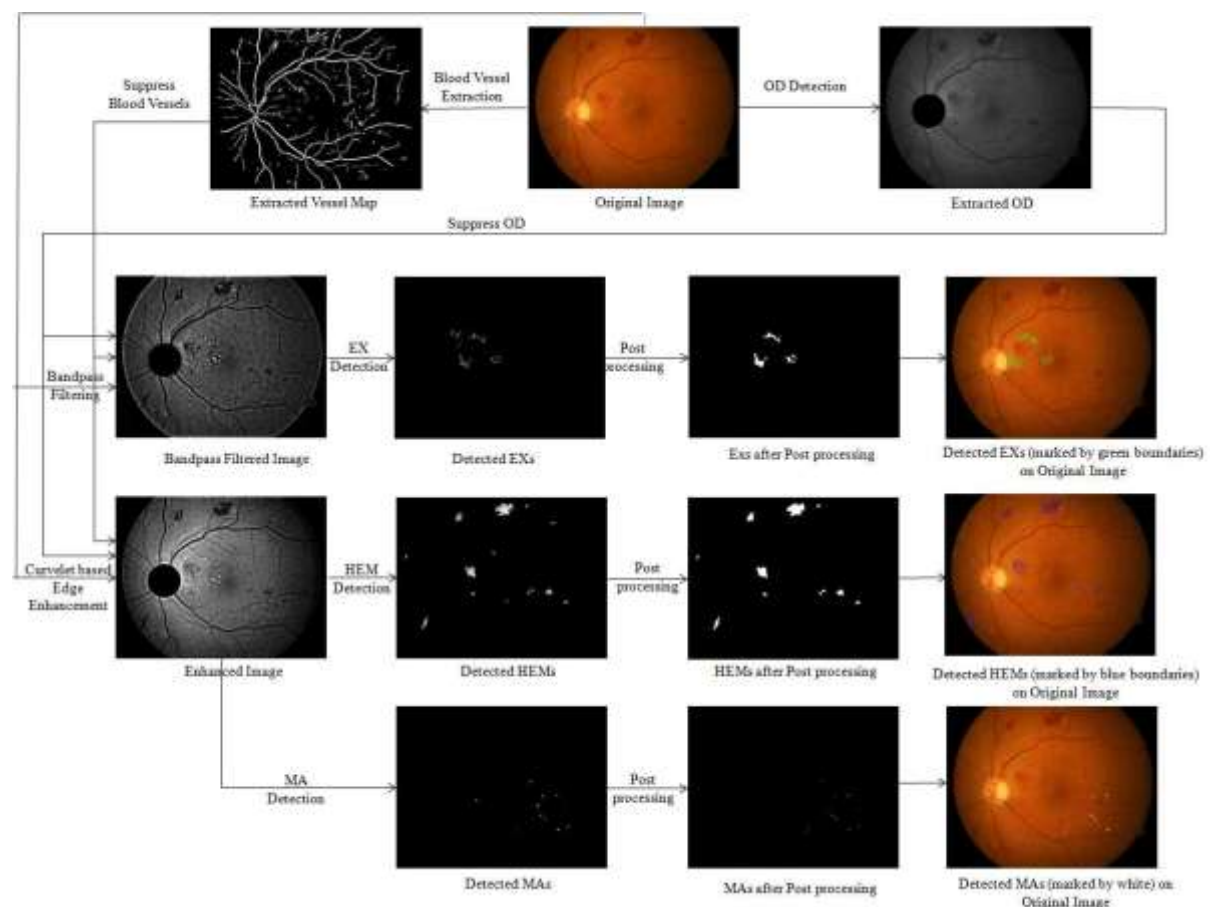


Fig. 1: Resulting images after different stages of the Proposed Method

VI. EXPERIMENTAL RESULTS

6.1 Material

To evaluate the efficiency of the proposed method for lesion detection, performance of the algorithm is evaluated on four publicly available benchmark databases, namely DRIVE, STARE, DIARETDBI and MESSIDOR. Performance of the proposed method for MA detection is further evaluated on the new online database called Retinopathy Online Challenge (ROCh).

6.2 Image Level and Lesion Level Database Description

Performance of the proposed framework is evaluated both at image level and lesion level based on the comments and suggestions of the domain experts i.e., ophthalmologists. At image level, an image is categorized as 'normal' if it contains no lesion while treated as 'abnormal' when it contains at least one lesion.

6.3 Results of Lesion Detection

Performance evaluation is done by randomly selecting 50% images from each of the DRIVE, STARE, DIARETDBI and ROCh databases. For MESSIDOR database that contains 1200 images, randomly select 300 images. Altogether we have tested the performance of the proposed method on 434 retinal images (among which 123 are normal and 311 with signs of DR) from different databases. The number of lesions contained in the images selected for evaluation from DRIVE, STARE, DIARETDBI, MESSIDOR and ROCh database are 58, 790, 902, 1790 and 883, respectively.

6.4 Statistical Performance Analysis

Statistical performance is analyzed using Receiver Operating Characteristics (ROC) curve which is the plot between True Positive Rate (TPR=Sensitivity) versus False Positive Rate (FPR=1-Specificity). Based on lesion level evaluation, ROC curve for the red and the bright lesion detection are depicted. As a typical example, the set of TPR and FPR values are found to be 0.895 and 0.0736, respectively. The ROC curves for bright lesion and dark lesions are included to highlight the relative performance gain of the proposed method.

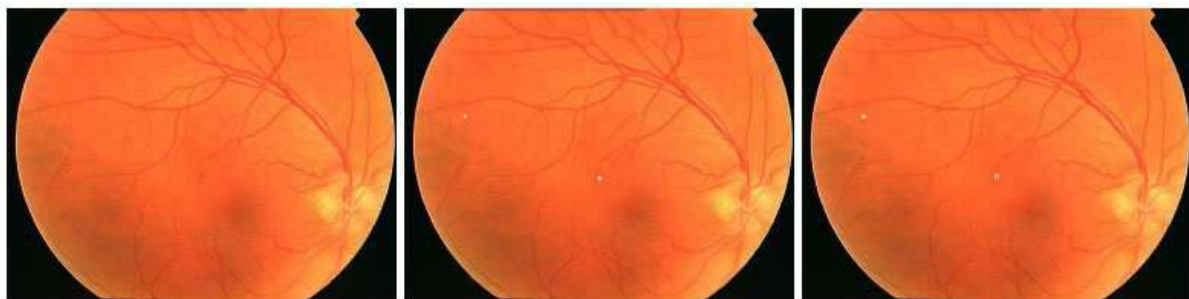


Fig. 2: Result of MA detection (marked by white dots) on 'image13 training.jpg' of ROCh database: (a) Original Image. Detected MA by (b) proposed method and (c) Akram et al.

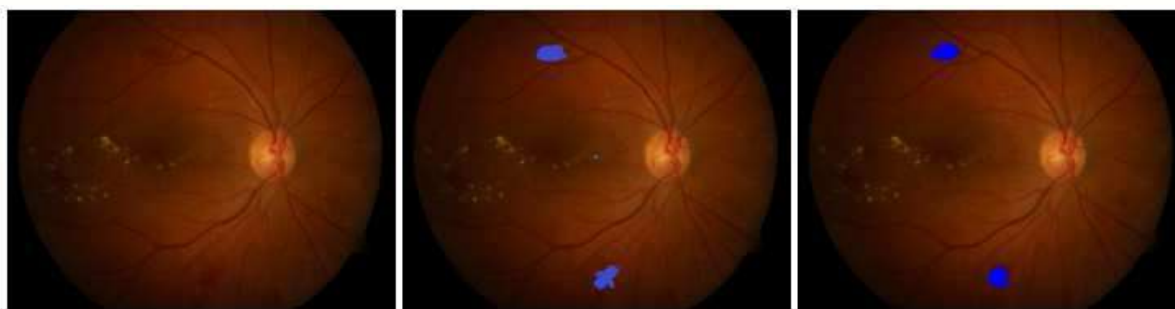


Fig. 3: Result of HEM detection (marked by blue region) on 'image007.png' of DIRETDB1 database: (a) Original Image, Detected HEM by (b) proposed method and (c) Akram et al.

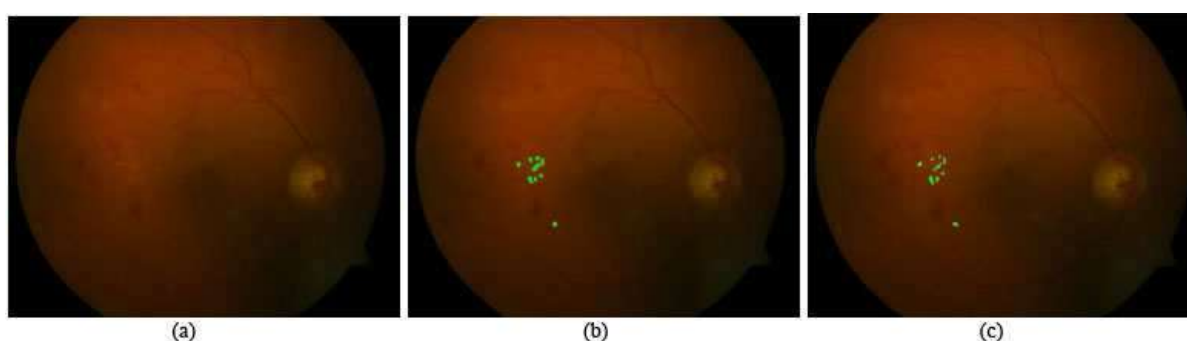


Fig. 4: Result of EX detection (marked by green region) on 'image023.png' of DIRETDB1 database: (a) Original Image, Detected EX by (b) proposed method and (c) Akram et al.

VII.CONCLUSION

A set of features is extracted from each splat to describe its characteristics. These splats are taken as samples for supervised classification in a selected feature space. A simple yet effective integrated scheme for lesion detection is suggested that includes different pre-processing techniques, coupled with MF and LoG filter followed by post-processing operations. These techniques when combined in a sequential and an intelligent manner, offer a very much effective and efficient scheme to detect the different lesions irrespective of their texture, shape, size etc. Curvelet transform is a very good candidate for dark lesion enhancement. The optimally designed BPF is well-suited for bright lesion enhancement. The gain and the cut-off frequencies of the BPF are obtained automatically through MSSIM maximization. Although improved performance over the existing methods are found, the proposed method is slightly weaker for red lesion detection. It might be due to the fact that red lesions appear as dark patches and are often indistinguishable from the background in presence of poor illumination.

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REFERENCES

- [1]. C. Pereira, L. Goncalves, and M. Ferreira, *Exudate segmentation in fundus images using an ant colony optimization approach*, *Information Sciences*, vol. 296, pp. 14–24, 2015.
- [2]. B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, *Detection of microaneurysms using multi-scale correlation coefficients*, *Pattern Recognition*, vol. 43, no. 6, pp. 2237 – 2248, 2010.
- [3]. B. Harangi and A. Hajdu, *Automatic exudate detection by fusing multiple active contours and regionwise classification*, *Computers in Biology and Medicine*, vol. 54, pp. 156 – 171, 2014.
- [4]. I. Lazar and A. Hajdu, *Retinal microaneurysm detection through local rotating cross-section profile analysis*, *IEEE Transactions on Medical Imaging*, vol. 32, no. 2, pp. 400–407, 2013.
- [5]. D. L. Donoho and M. R. Duncan, *Digital Curvelet Transform: Strategy, Implementation and Experiments*, *Department of Statistics Stanford University*, November 1999.
- [6]. I. Figueiredo, S. Kumar, C. Oliveira, J. Ramos, and B. Engquist, *Automated lesion detectors in retinal fundus images*, *Computers in Biology and Medicine*, vol. 66, pp. 47 – 65, 2015.
- [7]. L. Tang, M. Niemeijer, J. M. Reinhardt, M. K. Garvin, and M. D. Abramoff, *Splat feature classification with application to retinal hemorrhage detection in fundus images*, *IEEE Transactions on Medical Imaging*, vol. 32, pp. 364–375, Feb 2013.
- [8]. M. U. Akram, S. Khalid, A. Tariq, S. A. Khan, and F. Azam, *Detection and classification of retinal lesions for grading of diabetic retinopathy*, *Computers in Biology and Medicine*, vol. 45, pp. 161 – 171, 2014.
- [9]. M. Niemeijer, B. Ginneken, S.R.Russell, S.A.Maria, and S. And M.D. Abramoff, *Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis*, *Investigative Ophthalmology & Visual Science*, vol. 48, no. 5, pp. 2260–7, 2007.
- [10]. C. I. Sanchez, M. Garcia, A. Mayo, M. I. Lopez, and R. Hornero, *Retinal image analysis based on mixture models to detect hard exudates*, *Medical Image Analysis*, vol. 13, no. 4, pp. 650 – 658, 2009.