Automatic Microaneurysms Detection on Retinal Images Using Deep Convolution Neural Network

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***Abstract*— Visual loss can be prevented by early detection and treatment of disease. Diabetic retinopathy is the leading cause of vision loss, and microaneurysms (MAs) are an early symptom of this disease. The fundus examination is effective at early detection of diabetic retinopathy. However, detecting MAs on retinal images is difficult for physicians because MAs typically appear as small dark dots. Therefore, many studies on automated MA detection have been conducted. This study itself proposes an MA detector that combines three existing types of detectors: the double-ring filter, shape index based on the Hessian matrix, and Gabor filter. However, because deep convolutional neural networks (DCNN) have shown superior performance in image recognition studies, this study conducts automated MA detection using DCNN. The proposed method is structured with a two-step DCNN and three-layer perceptron with 48 features for false positives (FPs) reduction. In the two-step DCNN, the first DCNN is for initial MA detection and the second DCNN is for FPs reduction. By applying the proposed method to the DIARETDB1 database, the proposed method shows superior performance.**

Keywords—microaneurysm detection, diabetic retinopathy, deep convolution neural network, mass screening

I. Introduction

Diabetic retinopathy (DR) is a complication of diabetes and the leading cause of vision loss [1]. To prevent vision loss, early detection and treatment of DR is critical. Because a microaneurysm (MA) is an early symptom of DR, MA detection can enable early detection of DR. Non-contrast retinal images are used in screening and periodical check-ups MAs appear as small dark dots in a retinal image, as shown in Fig. 1. Thus, detecting MAs in non-contrast retinal images is challenging.

Several research groups have been developing automated MA detection methods using retinal images [2–7]. Adal et al. proposed an MA detection method using two eigenvalues based on the Hessian matrix [2], and Antal et al. proposed a method based on an ensemble of MA detectors [3]. Seoud et al. proposed a method based on dynamic shape features [4], whereas Dai et al. proposed method based on density gradient vector analysis [5]. Finally, Niemeijer et al. provided a comparison of several methods using the Retinopathy Online Challenge (ROC) database [6]. We also propose a method that combines three MA detectors: double-ring filter, Gabor filter, and shape index based on Hessian matrix [7]. These previous methods had to set many parameters. However, because the deep convolutional neural network (DCNN) is a breakthrough technique in object classification and pattern recognition, this study presents an MA detection method based on DCNN.

II. Methods

The proposed method was structured by MAs detection using DCNN, reduction of false positives (FPs) using DCNN, and FPs reduction using 48 kinds of features.

A. Database

We used the standard Diabetic Retinopathy Database Calibration Level 1 (DIARETDB1) database [8] in this study. In the 28 training images, the ground truth for 83 MAs as determined by four experts was provided. The 61 test images included 100 MAs determined by four experts.

B. Pre-processing

The contrast between an MA and the retinal area is highest in the green channel of a color image. Therefore, we obtained the green channel component image for blood vessel extraction and MA detection. Differences exist in the contrast of MAs in retinal images. To reduce the adverse effects of these differences on image processing, we applied a double-ring filter, Gabor filter, and shape index based on the Hessian matrix [7].

C. MA Detection

MAs were detected using DCNN. GoogLeNet [9] was applied as the DCNN. It scans the entire image and performs MA prediction for every pixel based on the image patch, the size of which in our study was 21 x 21 pixels. To train this DCNN, we used 246 MAs. These included 83 and 163 MAs

(a) (b)

Fig. 1. Example of a retinal image. The white box in (a) shows an MA example, and an enlarged version is given as (b).

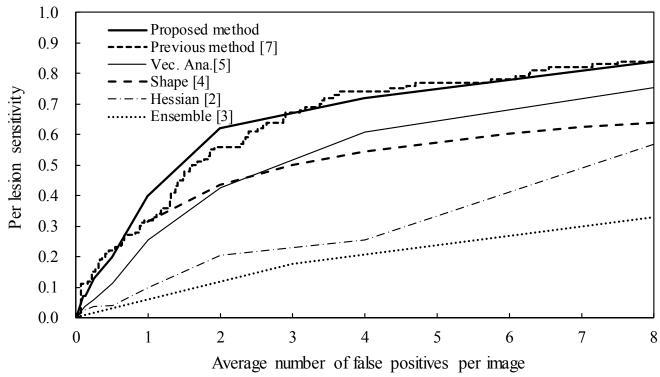

Fig. 2. FROC curves for the 61 test images from the DIARETDB1 database.

from the training images of the DIARETDB1 and ROC databases [6], respectively. We augmented from 246 to 2460 MA patches by using horizontal inversion, vertical inversion, parallel moving, smoothing, and luminance adjusting. Therefore, we used a total of 2460 normal patches, which included no MAs, to train this DCNN.

D. Reducing the number of FPs

The DCNN of MA detection classified 883 normal patches as FPs. Thus, those patches were classified as MAs and FPs by using another DCNN. The FPs were augmented to 7064 patches by using horizontal inversion, vertical inversion, smoothing, and luminance adjusting. GoogLeNet was also used for this DCNN. This DCNN was trained using these FP and the 2460 MA patches.

Moreover, the candidate MA regions included so many FPs that the candidates were classified into MAs and FPs using a support vector machine with 48 features [7]. These features were area, circularity, aspect ratio, mean of pixel values, similarity of blood vessels, candidate location, and texture features. These texture features included 13 features from a co-occurrence matrix, two from differential statistics, and five each from vertical and horizontal run-length matrices.

III. Results and Conclusion

Using test images from the DIARETDB1 database, we tested the proposed method. Fig. 2 shows free-response receiver operating characteristic (FROC) curves. Overall performance of the proposed method was superior to four other methods, as shown in Fig. 2. When the number of FPs was fewer than three, the proposed method was the best. However, when the number of FPs was more than three, our previous method was slightly better. In this study, the previous FPs reduction method [7] was applied to the proposed method with no change. Therefore, we would have to improve that method.

The performance results of the proposed method showed that the sensitivity was 84% of 8.0 FPs per image. This result was the same as that of the previous method [7]. One of the problems of the previous method was the existence of too many rules. Several parameters such as the threshold values of double-ring filter, Gabor filter, and shape index, as well as parameters for combining MA detectors, were all experimentally determined from test results. In the proposed study, these parameters could be automatically learned. The method could be further improved by optimizing the network architecture and adding a post-processing method.

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