Automated Retinal Hemorrhage Detection Using Morphological Top Hat and Rule-based Classification

Nutnaree Kleawsirikul, Smith Gulati, and Bunyarit Uyyanonvara

Abstract—Diabetic Retinopathy is an eye disease that causes damage to the retina. It can develop in patients with diabetes, and if not treated carefully within the early stage, the condition can deteriorate and eventually lead to blindness. In the past years, there are many automated methods for detection of diabetic retinopathy in fundus images. This work focuses on the computerized detection of hemorrhage which is an early symptom of diabetic retinopathy. The study involves analysis of 7571 blobs from 20 fundus images taken from DIARETDB1 [21] along with the attempt to device an effective algorithm to detect hemorrhage. First, the green channel is extracted from the fundus image, inverted and applied CLAHE for preprocessing. Then morphological top hat is applied to extract the hemorrhage candidates. Finally rule based classification is used to classify hemorrhages based on their features, for instance, compactness, area and eccentricity. The proposed method achieved the sensitivity of 80.37%, specificity of 99.53% and accuracy of 99.12%.

Keywords—Diabetes, Diabetic Retinopathy, Fundus Image, Hemorrhage, Image Processing, Red Lesion.

I. INTRODUCTION

In recent years, about 80% of patients suffering from diabetes for over ten years have also suffered from diabetic retinopathy (DR) [2]. In fact, it is 4.8% of all the cases of blindness worldwide [1]. DR is a group of eye diseases which causes damage to the retina, the tissue at the rear end in the eyes that is sensitive to light. The severity depends on the years that the specific patient has experienced the disease, and in worst case, can eventually lead to blindness [3].

In general, the severity of DR can be diagnosed into two main stages, namely Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [4], [6]. NPDR is the early stage in which the retinal vessels in which blood or lipids may leak into the retina. The leakage of blood in the form of small red lesions is called hemorrhages while the leakage of lipids in the form of yellow dots is called exudates (Fig. 1). Patients identified with either hemorrhage or exudates in the fundus image are diagnosed to be in the stage of NPDR. PDR is the advance stage of DR, in which the retinal vessel may become blocked causing the retina to grow new vessels which is weak and prone to leakage. These new vessels may swell and becomes fluffy white patches called cotton wool spots. Moreover, blood from the vessels may leak into the vitreous, the gel in the center of the eyes. This is called vitreous hemorrhage. It can prevent the light to go through to the retina, and thus lead to bad vision. To most researchers, the lesions in the DR are classified into red lesions, consisting of hemorrhages and microaneurysm, and bright lesions, consisting of exudates and cotton wool spots.

In this article, the focus will be on the detection of hemorrhages which are very important as they represent the early sign of DR. It is beneficial to detect the disease in the earliest stage possible since it will decrease the chance of the disease getting worse and eventually leading to blindness. Normally, ophthalmologists can diagnose DR by observing retinal images taken by fundus cameras. Recently many automated detection techniques are constantly devised and implemented to help ophthalmologists detect hemorrhage by applying image processing and pattern recognition techniques.

Acharya et al. [8] used morphological image processing to detect various lesions. First, an image with blood vessels was extracted by using ‘ball’ shaped structuring elements, in addition to morphological operations. Then, other image with the vessels as well as hemorrhages was extracted using the same technique but slightly increased the ball size. The final detection was obtained by subtracting the image with vessels alone from the image with vessels as well as hemorrhage.
Other works which have included morphological operators in to account are [5], [14], [15] and [16].

Sinthanayothin et al. [24] also used the concept of region growing in their research but in a very different way. First, the main features of the retinal image such as optic disc, fovea, blood vessels etc. were defined. Then Moat Operator was used to define the features of hemorrhage followed by the application of adaptive intensity thresholding. The candidates then undergo the process of recursive region growing segmentation. Bae et al. [5] have also incorporated the region growing technique into their work.

Hatanaka et al. [10] proposed a new improvement over the HSV space to correct non-uniform brightness of the fundus image. The p-tile thresholding method is used to extract the optic disc. Density analysis was used to extract blood vessels and hemorrhage candidates. Then the hemorrhages candidates are classified using rule-based method and three Mahalonobis distance classifiers. Other works that include classification techniques such as artificial neural network, support vector machines etc. are [7], [9], [10], [11], [12], [13] and [17].

These approaches rather prove to be more convenient and efficient in terms of time than the manual detection by the ophthalmologists.

II. METHOD

The proposed method in fig. 2 is a result of the application of morphological operation together with rule-based classification. First, the fundus image is preprocessed and then the resulting image undergoes hemorrhage candidate extraction employing morphological top hat operation, and finally, rule-based classification is applied to classify the hemorrhage based on predefined features.

A. Preprocessing

The fundus images taken by the fundus cameras often have the problems of noises and non uniform illumination which usually make it complicated to extract the required features with similar intensity from the background [7]. Therefore most of the times many image processing techniques are applied on the image to enhance its brightness and/or contrast so that feature extraction can be easily and effectively be implemented.

Typically, fundus images are in RGB color space which consists of three color channels namely, red, green, and blue. Among these three, the green channel clearly exhibits the red color features of both hemorrhages and retinal blood vessels well when compared to other channels [5]. Therefore, in the proposed method, green channel is extracted from the original fundus image at the start (Fig.4b). The extracted green channel image now displays the hemorrhages and vessels in dark color of the gray scale. The image is then inverted in order to emphasize the areas of interest, the hemorrhages, in white [8] (Fig. 4c). After that, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the image to increase its contrast [5]. CLAHE will divide the image into smaller regions called tiles. On each of these tiles, equalization is applied to locally even out the distribution of gray-scale intensity, making use of the full range of the gray level value. This will expose the image with more uniformly distributed contrast and further emphasize some hidden features which were unclear before CLAHE was applied.

B. Extraction of Hemorrhage Candidates

Morphological top hat transform is an operation which is used to extract small objects from an image. Generally, it can be divided into two techniques; white top hat and black top hat [19]. White top hat is the difference between the image and the opening of the image while black top hat can be described as the difference between the image and the closing of the image. The two operations can be defined by the following equations:

White top hat: \[ T_w = I - (I \circ SE) \] (1)

Black top hat: \[ T_b = (I \bullet SE) - I \] (2)

Where, I is the image,
○ is the structuring element,
○ is the opening operator,
and ● is the closing operator.

The white top hat operation aims to obtain the resulting image which contains bright and thin features with the size smaller than the structuring elements. Morphological opening itself is the operation in which the erosion and dilation is applied to the image accordingly. The opening operation can be described by the following:
\[
I \circ SE = (I \ominus SE) \oplus SE
\]  

(3)

Where, \(I\) is the image,

\(SE\) is the structuring element,

\(\ominus\) is erosion operator,

and \(\oplus\) is dilation operator.

In this paper, white morphological top hat is applied to the preprocessed image (Fig. 4d). Firstly, opening is used on the image to obtain the filtered background using ball shape structuring element. Then the filtered background is subtracted from the image. After that the image is binarized. This outputs the binary image with skeletons of the retinal vessels and hemorrhage candidates in white and the background in black (Fig. 4e). These white objects are called binary large objects or blobs. To further enhance the image, median filter is applied to remove the noises.

C. Hemorrhage Classification

The blobs obtained from the previous stage are analyzed to identify and extract features of each blob. Then the classification is done using rule based classification technique which works similar to if-then statement.

From a training set, a set of rules is generated, each containing a condition, which includes the conjunction of several feature tests, and a conclusion. From 4309 blobs generated from 12 fundus images in the training set, rules are devised for the purpose of classifying the hemorrhages according to the shape of the blobs. The features that were used to classify are for instance, area, color, eccentricity and compactness of the blobs. The area is calculated from the number of pixels of each blob. In addition, the color of the blobs must be close to red which is the color of hemorrhage.

Apart from this, eccentricity, compactness and minor axis length define the actual shapes of the hemorrhages. There are two shapes that can be classified to be hemorrhages in this method (Fig. 3). The first is a round shape hemorrhage which uses color, area, eccentricity and compactness as the features to identify the hemorrhage. The compactness value should be very close to 1 and eccentricity should be close to 0, defining the hemorrhage as having a circular shape. The second is a slim shape hemorrhage which uses the features area, eccentricity, color, compactness and minor axis length to identify the hemorrhages. This compactness should be very low while the eccentricity is close to but less than 1. The minor axis length identifies the width of the slim hemorrhages

![Fig. 3 Classification of blobs](image-url)

Fig. 4 a) Original Image (b) Green channel (c) After preprocessing (d) After top hat (e) Hemorrhage candidates (f) Result from classification
apart from the blood vessels which have thinner width. For each blob, if all the features are true according to the rules (if-then statements), the blob will be considered as a hemorrhage. If one or more features do not satisfy the rules, then it will not be recognized as hemorrhages. After the classification, the image is left with the blobs which are likely to be hemorrhages. This image is treated as the detection result (Fig. 4f).

**D. Evaluation**

In order to access the proposed method as well as comparing it with the existing methods, an evaluation technique is required. There are many evaluation techniques and measures available which are being used by the researchers [20]. This paper uses sensitivity, specificity and accuracy as the performance measure. Sensitivity is the measure of the proportion of positives which were correctly detected, while specificity is the measure of the proportion of negatives which were correctly detected. Accuracy is the proportion of pixels which are identified correctly (both positive and negative) out of all pixels in the image. The evaluation was conducted by using pixel based technique, in which each pixel of the detection result is compared to the ground truth image. From the comparison, the number of pixels that are true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) can be obtained. Sensitivity, specificity and accuracy can be calculated by the following equations:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (4)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \quad (5)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)
\]

**III. RESULT AND DISCUSSION**

Totally, 7571 blobs from 20 fundus images were used in this study, out of which 12 were training images (4309 blobs) and 8 were test images (3262 blobs). All the images were 1500 x 1152 pixels. The brightness differs from image to image and there is considerable variation in the shape of hemorrhage among the images.

Table I shows evaluation result of the proposed method on training set, test set and all images:

<table>
<thead>
<tr>
<th>TABLE I: PERFORMANCE OF THE PROPOSED METHOD</th>
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<tr>
<td><strong>Sensitivity</strong></td>
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<tr>
<td>Training Set (12 images)</td>
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<tr>
<td>Test Set (8 images)</td>
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<tr>
<td>All (20 images)</td>
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From table I, it can be said that the probability of positive hemorrhage test given that the patient really suffers from hemorrhage is 80.37% while the probability of negative test given that the patient does not suffer from hemorrhage is 99.53%.

When compared to the existing methods for automated hemorrhage detection, the proposed method is more reliable than the other in terms of adaptability. If more images are added to the training set, the proposed method will have even better performance. Table II shows the comparisons between the proposed method and the existing methods.

<table>
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<tr>
<th>TABLE II: PERFORMANCE OF PROPOSED METHOD AS COMPARED TO EXISTING METHODS</th>
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<tr>
<td>Authors</td>
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<tr>
<td>Proposed Method</td>
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<tr>
<td>Bae et al. [5]</td>
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<td>Esmaeili et al. [7]</td>
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<td>Acharya et al. [8]</td>
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<td>Marwan and Eswaran [9]</td>
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<td>Hatanaka et al. [10]</td>
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<td>Köse et al. [11]</td>
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<td>Zhang et al. [12]</td>
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<td>Zhang and Chutatape [13]</td>
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<td>Kande et al. [14]</td>
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<td>Fleming et al. [15]</td>
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<td>Shivaram et al. [16]</td>
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<td>Garcia et al. [17]</td>
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<td>Sinthanayothin et al. [18]</td>
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**IV. CONCLUSION**

Diabetic retinopathy, one of the main causes for blindness, can be detected by the presents of microaneurysms and hemorrhages. The detection of hemorrhages is one of the most complex areas of researches in image processing because hemorrhages have similar intensity to the retinal vessels, making it difficult to distinguish them from each other. The other reason is that hemorrhages also vary in size and shape. Image preprocessing is an unavoidable component of the detection process. Therefore the need for effective detection methods is inevitable. There are several detection algorithms that have already been developed and proposed which perform satisfactorily (Table II). This paper proposed a robust, adaptive and efficient method for hemorrhage detection. The method is a hybrid approach of morphological operation and rule based classification. It achieved the average sensitivity of 80.37%, specificity of 99.53% and accuracy of 99.12%. This method has prospects of improvement either by increasing number of features used in classification or increasing the number of images used in training and test sets.
REFERENCES


