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A Review on Hemorrhage Detection Methods for Diabetic Retinopathy Using Fundus Images

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Abstract**—**Diabetes is a disease that occurs when body does not produce adequate insulin in order to function properly. Diabetic retinopathy is a common symptom of diabetes which is one of the world's leading causes of blindness. This condition can be prevented if diagnosed and treated in early stage. The advancement in technology leads to the increasing trend of interest in the field of medical image processing. There are many techniques and algorithms that serve the purpose of hemorrhage detection using retinal images. The work extensively reviews, classifies and compares the algorithms and techniques previously proposed in order to support and provide current and future researchers with an elaborated summary of such algorithms.

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

I. Introduction

ONE of the world leading causes of blindness, Diabetic Retinopathy (DR), is accountable for 4.8% of 37 million cases of blindness worldwide [1]. In fact, it is the most common eye disease that manifested 80% in patients who have suffered diabetes for 10 years or more [2]. However, out of 80%, only 90% with careful and proper treatment could the disease be reduced. The severity is directly proportional to the duration of the patient suffered from the disease [3].

Retina mainly consists of a network of blood vessels and an optic disc (Fig. 1). Ophthalmologists often categorize DR into two stages namely, Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [4], [6]. The initial stage of DR is NPDR. In this stage, the blood vessels in the retinal become thin and leak fluids, leading to microaneurysm and hemorrhage in case of blood leakage, and exudates in case of fat or protein leakage. Microaneurysm and hemorrhage are red in color while exudates are yellow (Fig. 1). Moreover, blood vessels can swell and become fluffy white patches called cotton wool spots [4] (Fig.1). The later stage of DR is PDR. In this stage, due to circulation problem, the blood vessels in the retina receive inadequate oxygen causing the blood vessels to grow in order to maintain adequate oxygen level. These newly grown vessels are weak and prone to leakage which decreases the vision.

Ophthalmologists diagnose DR by either mere eye observation or using computerized systems with complex detection algorithms. Due to the reason that the latter provides faster detection, the automated detection of DR became area of interest among the researchers. Some of the works of these researchers grouped microaneurysm and hemorrhage into dark or red lesions, and exudates and cotton wool spots into bright lesions. This paper emphasizes on hemorrhages detection algorithms which are more complicated as compared to other types of lesions. These algorithms will be reviewed thoroughly in this paper.

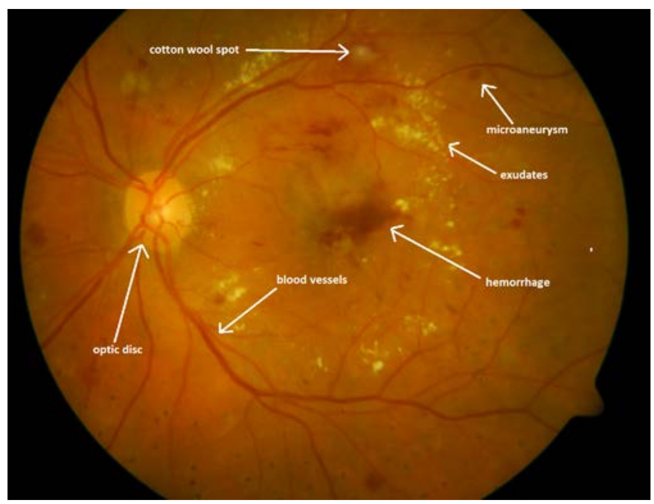

Fig. 1 Retinal image containing different types of lesion

II. Review of Methods

The methodologies used in the existing algorithms and techniques follow somewhat similar flow of process. Many researchers have proposed their own flow of hemorrhage detection process in order to distinguish their work from others'. These nontraditional flows were however, derived from this base flow. Fig. 2 summarizes the general process of automated hemorrhage detection.

According to Fig. 2, in order to obtain the final results, i.e. the area under hemorrhage on the retinal image, the original image has to go through many phases. The methods used in each phases by the researchers are reviewed below.

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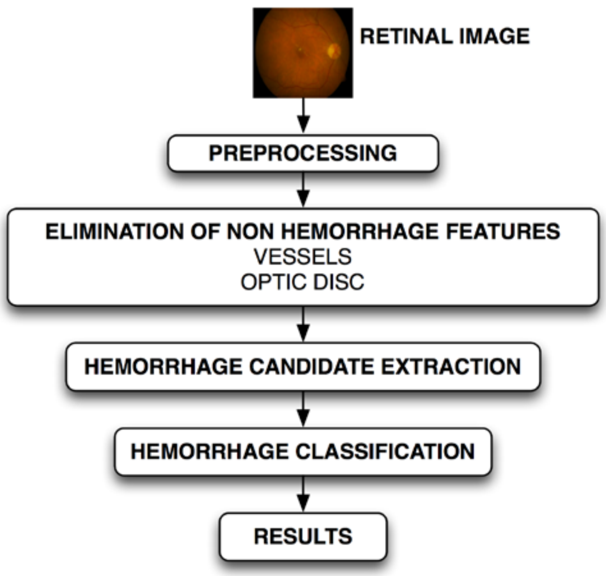


Fig. 2 The general process of automated hemorrhage detection

A. Preprocessing

The images taken by the fundus cameras usually have noise and non-uniform illumination with the brightness centering on the optic disc and decreasing outwards to other regions. This often makes it complicated to extract hemorrhages from the images as they have similar color to the vessels and background. Therefore, preprocessing is needed for the ease of feature extraction. The common characteristics of the preprocessing techniques are to adjust the brightness in order to make it uniform and intensify the contrast between the areas of interest and the background [5], [7]. The techniques are often performed on the green channel of RGB color images, which exhibits the area of interest better in terms of contrast than the other channels [5]. Though in this phase, the number of techniques used by most of the researchers is limited to a small number, there are some of them who applied unique techniques.

Bae et al. [5] used two steps to preprocess a fundus image. Hue Saturation Value (HSV) brightness correction was applied to the green channel of the image to make the brightness in the image uniform. Then Contrast-limited Adaptive Histogram Equalization (CLAHE) is used along with other enhancement algorithms to enhance the contrast between the components in the image and the background.

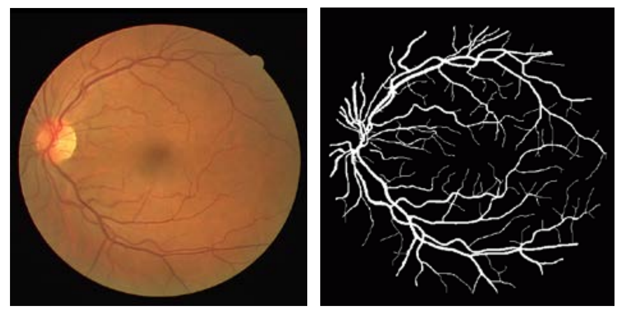
Esmaeili et al. [7] proposed a new illumination equalization method to correct the non-uniform illumination of the image and prevent the creation of the shadow around the light lesions. To implement this, each pixel f(i, j) in the green channel is adjusted by g(i, j):

$$g(i,j) = 5f(i,j) - 5\overline{f}_W + \frac{60Max(f_W)}{\overline{f}_W + 1} + 0.4Max(f_W) \quad (1)$$

Where f_W represents the intensity value of the image within a 10x10 window.

B. Elimination of Non-hemorrhage Features

Due to the reason that the color of hemorrhage is almost the same as the blood vessels and the false detected area are mostly blood vessels, many researchers tried to find techniques recognizing the blood vessels in order to improve the accuracy of their techniques (Fig. 3). Although optic discs are not as much problematic as blood vessels in terms of red lesion detection, they are identified for the sake of uniform illumination. Some of the works had completely eliminated these features from the original images to pave the way for later phases.



(a) (b)

Fig. 3 (a) The original image (b) Blood vessels detected

Most of the methods for detection of blood vessels utilize thresholding based techniques. Matei et al. [8] employed thresholding along with morphologically defined features to detect blood vessels. The threshold value chosen is optimal for image segmentation. The image details are removed through erosion operation. The objects of interests are also eroded with this technique. To solve this problem they used the technique called dilation, which is essentially the reverse operation of erosion, to obtain back the objects of interest.

Acharya et al. [9] used morphological processing techniques to detect blood vessels. The technique starts with inverting the image intensity level. Then the adaptive equalization was performed on the image using histogram. Then in order to detect the blood vessels morphological 'opening' operation was used. This technique clearly increases the intensity of blood vessels compared to the background. The resulted image was then binarized using thresholding method. Then the border was created in order to eliminate the blood vessels from the image.

Optic discs detection is another important component of the algorithms for computer based DR diagnosis. Marwan and Eswaran [10] detected and removed the optic disc by using median filter. The technique starts with focusing in the center of the image where the optic disc is most likely to be detected. Then median filter is applied to the image in order to fill up the thin blood vessels inside the optic disc. Then the contrast of the optic disc and the background was enhanced so that the thresholding can be performed easily in order to eliminate the optic disc from the image.

After preprocessing and elimination of non-hemorrhage features, the image is now ready to undergo the most important phase i.e. the detection algorithm.

C. Hemorrhage Candidate Extraction and Classification

Although defined separately in Fig. 2, hemorrhage candidate extraction and classification are overlapping by nature. Most of the works have separated these phases into two independent working blocks in the algorithm but some have not state the exact distinction. These phases are in fact, the most important components of automated hemorrhage detection algorithms as they contribute to the actual detection. Few researchers gave the preprocessing phase the more importance and opted to use an existing method in these phases. Following are the review of the works proposed by researchers for hemorrhage candidate extraction and classification:

Hatanaka et al. [11] 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.

Köse et al. [12] presented a new application to the techniques in [13]. Unlike other methods, which focus on the unhealthy regions, this method used inverse segmentation method to separate the healthy region from the unhealthy region. Based on the fact that the texture of healthy region does not vary as much as the texture of the unhealthy region, it is more accurate to extract the healthy region. Then dark lesions are left after segmentation using the intensity value that is lower than the background intensity value, and extraction of vessels.

Zhang et al. [14] proposed a background estimation algorithm to detect hemorrhage. They saw the area of interest e.g. hemorrhages and vessels as foreground that will be visibly contrast with background. To extract non-hemorrhage features, they introduced non-vessel inhibition operator using Gabor filter to detect vessel feature and applied a multi-thresholds scheme based on standard hysteresis thresholding methods [15] to help separate connective elongated vessels from scattered residual edge. The background estimation used Mahalanobis distance along with a threshold technique to separate foreground from background.

The bottom-up methods that focus only on color information may be insufficient to detect hemorrhages. Zhang and Chutatape [16] proposed a top-down method for hemorrhage extraction, in which after preprocessing, the hemorrhages were located in the region of interest by using Support Vector Machine (SVM) to calculate the evidence value of every pixel. Combined Two-Dimensional Principal Component Analysis (Combined 2DPCA) was used to extract features which then will be input vector for the SVM classifier. After the location of hemorrhage features was found, the post-processing process can then segment the boundary if the hemorrhages in the region of interest. The combination of Combined 2DPCA and SVM was expected to achieve higher accuracy of classification.

Tang et al. [19] purposed a large hemorrhage detection method based on splat feature classification. The fundus image was segmented in to several splats of the same color based on the assumption that the pixels of the same structure have similar color and are located spatially. Each splat can be extracted as a distinct feature e.g., hemorrhages and blood vessels. A classifier was trained to recognize the splats with vessels and then used to extract the vessels from the image, leaving what considered hemorrhage candidates behind.

Kande et al. [17] proposed a method to detect red lesions. They first applied relative entropy based thresholding to segment the red lesions regions after preprocessing. The morphological top-hat is then applied to extract the vessels. After that, SVM was used to classify the red lesions from the background.

Acharya et al. [9] 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.

Narasimhan et al. [18] proposed a detection method based on filtering operations. Morphological top-hat transformation was applied to the normalized green channel of the image. Then a geodesic reconstruction was used to recover the linear features. A thresholding technique was applied to enhance the image and region growing method was employed to extract features for the detection of microaneurysm and hemorrhage.

Singh and Tripathi [20], Shivaram et al. [22] and Fleming et al. [21] have also used morphological operators in their hemorrhage detection algorithms. Erosion, dilation, opening, closing and top-hat are some examples of operators utilized in these works.

Esmaeili et al. [7] proposed an algorithm based on multi-scale approach called Digital Curvelet Transform (DCUT). DCUT is a multi-scale direction transform algorithm which allows a sparse representation of objects in an image. Curvelet coefficients were defined in such a way that red lesions, especially hemorrhage can be easily distinguished from other parts of the image.

García et al. [23] used neural network based classifiers to automatically segment the hemorrhage candidates. Color and shape features were extracted from the image with the help of logistic regression. Then the image was segmented by using four neural network based classifiers namely, Multilayer Perceptron (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM) and Majority Voting (MV) schema.

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] applied the methods of template matching in addition to region growing segmentation. The technique uses circular shaped template and a program performing template matching. The template matching technique which performs the extraction of hemorrhage candidates is called Normalized Cross-correlation (NCC). The candidates extracted lack information of the exact shape. This problem has been solved by applying region growing segmentation.

D.Results

In this phase, the performance of the algorithms reviewed in above will be compared. Researchers came up with many measures to evaluate the performance of their algorithms. The performance measures chosen for comparison in this paper are sensitivity and specificity as these two were the most commonly used. 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. Table I shows the sensitivity and specificity of the algorithms reviewed in this paper.

TABLE I
PERFORMANCE OF THE ALGORITHMS

Authors	**Performance Measures**	
	Sensitivity	***Specificity***
Bae et al. [5]	85%	Not Reported
Esmaeili et al. [7]	94%	87%
Acharya et al. [9]	82%	86%
Marwan and Eswaran [10]	87.53%	95.08%
Hatanaka et al. [11]	80%	80%
Köse et al. [12]	93.2%	98.3%
Zhang et al. [14]	91.3%	81.6%
Zhang and Chutatape [16]	Max. 93.2%	Not Reported
Kande et al. [17]	96.22%	99.53%
Fleming et al. [21]	Max. 98.6%	Max. 95.5%
Shivaram et al. [22]	89.49%	99.89%
García et al. [23]	100%	56%
Sinthanayothin et al. [24]	77.5%	88.7%

III. CONCLUSION

The early signs of DR can be notified by the presences of microaneurysms and hemorrhages in fundus images. Hemorrhage detection algorithms present one of the most complex problems in the area of medical image processing as distinguishing hemorrhages from background is difficult due to the low contrast and variance in size of the hemorrhages. Preprocessing and elimination of non-hemorrhage features are unavoidable component of the detection process. Therefore the need for effective detection algorithms is inevitable. There are several detection algorithms that have already been developed and proposed which perform satisfactorily (Table I). This paper can act as a resource for the future researchers interested in automated hemorrhage detection and help them to get an overview of this field in order to develop more efficient algorithms.

REFERENCES

[1] VISION 2020: The Right to Sight - Diabetic Retinopathy [Online]. Available: http://www.vision2020.org/main.cfm?type=WIBDIEBETIC.

[2] Kertes PJ, Johnson CA, “Evidence based eye care”, 1st ed., Lippincott Williams & Wilkins, 2007.

[3] Tapp RJ, Shaw JE, Harper CA, de Courten MP, Balkau B, McCarty DJ et al., “The prevalence of and factors associated with diabetic retinopathy in the Australian population.,” *Diabetes Care*, vol. 26, pp. 1731-1737, June 2003.

[4] National Eye Institute, National Institutes of Health, “Diabetic Retinopathy: What you should know,” Booklet, NIH Publication, No: 06-2171, 2003.

[5] Bae JP, Kim KG, Kang HC, Jeong CB, Park KH, Hwang JM, “A Study on Hemorrhage Detection Using Hybrid Method in Fundus Image,” *J. Digital Image*, vol. 24(3), pp. 394-404, June 2011 .

[6] Nayak J, Bhat PS, Acharya R, Lim CM, Kagathi M, “Automated Identification of Diabetic Retinipathy Stages Using Digital Fundus Images”, *J. Med. Syst.*, vol. 32, pp. 107-115, April 2008.

[7] Esmaeili M, Rabbani H, Dehnavi AM, Dehghani A, “A new curvelet transform based method for extraction of red lesions in digital color retinal images,” *in Proc. IEEE 17th Int. Conf. Image Processing*, Hong Kong, pp. 4093-4096, September 2010.

[8] Matei D, Matei R, “Detection of diabetic symptoms in retinal images using analog algorithms,” in *Proc. 7th WSEAS Int. Conf. Signal Processing, Robotics and Automation*, pp. 198-203, 2008.

[9] Acharya UR, Lim CM, Ng EYK et al., “Computer-based detection of diabetes retinopathy stages using digital fundus images,” *in Proc. Inst. Mech. Eng.*, pp. 545-553, July 2009

[10] Marwan DS, Eswaran C, “An automated decision-support system for non-proliferative diabetic retinopathy disease based on MAs and Has detection,” *Comput. Methods Programs Biomed.*, electronically published, April 2012.

[11] Hatanaka Y, Nakagawa T, Hayashi Y, Hara T, Fujita H, “Improvement of automated detection method of hemorrhages in fundus images,” *In: 30th Annu. Int. IEEE EMBS Conf.*, pp. 5429-5432, August 2008.

[12] Köse C, Şevik U, Ikibaş C, Erdöl H, "Simple methods for segmentation and measurement of diabetic retinopathy lesions in retinal fundus images," *Computer Methods Programs Biomed.*, vol. 107(2), pp. 274-293, August 2012.

[13] Köse C, Sevik U, Gençalioğlu O, “Automatic segmentation of age-related macular degeneration in retinal fundus images,” *Comput. Bio. and Med.*, vol. 38(5), pp. 611–619, May 2008.

[14] Zhang D, Li X, Shang X, Yi Y, Wang Y, “Robust hemorrhage detection in diabetic retinopathy image,” *1st ACPR2011*, pp. 209-213, November 2011.

[15] Grigorescu C, Petkov N, Westenberg MA, “Contour and boundary detection improved by surround suppression of texture edges,” *J. Image Vision Computing*, vol.22(8), pp. 609–622, 2004.

[16] Zhang X, Chutatape O, “A SVM approach for detection of hemorrhages in background diabetic retinopathy,” *In: Proc. Int. Joint Conf. Neural Networks*, pp. 1435-1440, July-August 2005.

[17] Kande GB, Savithri TS, Subbaiah PV, Tagore MRN, “Detection of red lesions in digital fundus images,” *In: 2009 IEEE Int. Symp. Biomed. Imaging: From Nano to Macro*, pp. 558-561, June-July 2009.

[18] Narasimhan K, Neha VC, Vijayarekha K, “An efficient automated system for detection of diabetic retinopathy from fundus images using support vector machine and bayesian classifiers,” *In: 2012 Int. Conf. Computing, Electron. Elect. Technologies*, pp. 964-969, March 2012.

[19] Tang L, Niemeijer M, Abràmoff MD, “Splat feature classification: Detection of the presence of large retinal hemorrhages,” *In: 8th IEEE Int. Symp. Biomed. Imaging: From Nano to Macro*, pp. 681-684, March-April 2011.

[20] Singh N, Tripathi RC, “Automated early detection of diabetic retinopathy using image analysis techniques,” *Int. J. of Comput. Applicat.*, vol. 8(2), pp. 18-23, October 2010.

[21] Fleming AD, Goatman KA, Williams GJ, Phillip S, Sharp PF, Olson JA, “Automated detection of blot haemorrhages as a sign of referable

diabetic retinopathy," *In: Proc: Med. Image Understanding and Anal.*, 2008.

[22] Shivaram JM, Patil R, Aravind HS, "Automated etection and quantification of hemorrhages in diabetic retinopathy images using image arithmetic and mathematical morphology methods," *Int. J. Recent Trends Eng.*, vol. 2(6), pp. 174-176, November 2009.

[23] García M, López MI, Álvarez D, Hornero R, "Assessment of four neural network based classifiers to automatically detect red lesions in retinal images," *Med. Eng. Phys.*, vol. 32(10), pp. 1085-1093, December 2010.

[24] Sinthanayothin C, Boyce JF, Williamson TH, Cook HL, Mensah E, Lal S et al., "Automated detection of diabetic retinopathy on digital fundus images," *Diabet. Med.*, vol. 19(2), pp. 105-112, February 2002.