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Review on Detection of Diabetic Retinopathy Using Digital Fundus Images

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ABSTRACT

Diabetic retinopathy (DR) is a serious diabetic complication is the earliest lesion in diabetic retinopathy, so early it is one of the most common reasons for blindness in the working-age population of world. This disease which occurs with long-standing untreated diabetes, Diabetic retinopathy (DR) is a eye disease. In this paper, they proposed a new method to detect hard exudates with high accuracy with respect to lesion level. In the present method initially detected the possible candidate exudate lesions by using the back ground subtraction methodology. Following the subsequent steps, in the last stage of algorithm removed the false exudate lesion detections using the de-correlation stretch based method. They tested our algorithm on publicly available Diaret DB database, which contains the ground truth for all images. They achieved high performance results such as sensitivity of 0.87 and F-Score of 0.78 and Positive Predict Value (PPV) of 0.76 for hard exudate lesion level detection, compared to the existing state of art techniques.

Index Terms—Automatic DR screening, Diabetic retinopathy, Fundus image, Hard exudates.

1. INTRODUCTION

The main reason behind blindness is diabetic retinopathy. Diabetic retinopathy (DR) is an infection that inborn mostly in working populace for the most part experiencing diabetes. The result of untreated prolonged diabetes is diabetic retinopathy. The development of DR occurs within 15 to 20 years in greater than 75% of the people, who are diagnosed with diabetes [1-5]. The present statistics for diabetic mellitus are currently more than 170 million people worldwide are effected by DR and the number is estimated to increase by 366 million by 2030 according to world health organization (WHO). As mentioned, number of people affected by diabetes is increasing every year, which results into increase in the number of DR affected people year by year. Prolonged DR can cause the blindness of the affected person. There are two stages of DR 1. Non-Proliferative DR 2. Proliferative DR. blindness can occur in the Proliferative stage of DR. If a patient with DR is diagnosed in the non-proliferative stage then the patient can be treated, so that the disease progression rate can be stopped or reduced[6-10].

Diagnosis of DR is an intensive process, which involves lot of clinical study. Clinical study of a patient involves time, resources and money. The ratio of patients to practitioners is very much high in developing countries like India, so manual screening or diagnosis of DR is taking considerable amount of time. If the automatic screening of DR is available, it reduces a lot of work burden to the clinicians. With introduction of automatic screening of DR, ratio of the number of patients to the clinicians will decrease, which in turn saves a lot of time, money and increases efficient use of available resources. Other advantage with the introduction of automatic screening of the DR is that the patients who cannot access to the medical facilities due to living in remote areas can be treated through the telemedicine[11-15]. In the present state of art there exists lot of automatic screening methods or algorithms. In the present paper we are trying to screen the DR automatically using the digital image processing techniques on fundus images. The three major changes that can occur in the retina due to diabetic retinopathy are Exudates, Hemorrhages and Micro aneurysms. Presence of one or more number of the above lesions in the retina indicates the presence of DR. In the Present algorithm we tried to detect hard exudates in order to screen the fundus images for DR. Exudate detection methods include both supervised and un-supervised techniques, here we used the unsupervised methodology to detect hard exudates[16-`17]. The section involved in this paper is mentioned below. Section II discuss about the materials and methods. Section III discuss about the results. Section IV concludes the paper.

2. MATERIALS AND METHODS

In this method fundus color images are the pictures of the retina, which are captured through the pupil using digital cameras. They are used in automatic screening algorithms to screen DR. Fundus color image mainly contain 3 channels which are Red, Green and Blue. Among the three channels green channel has the highest contrast [2] [3], which enable us to detect the lesions accurately, so the green channel of the fundus image is used for the hard exudate detection. The input image shown in Fig. 3., is used for demonstration of the algorithm. The block diagram of the present algorithm is shown in Fig. 1.

A. Preprocessing

Exudates are bright lesions and they are present as bright zones or patches in the fundus image. We need to enhance the contrast of the image to improve the exudate detection because in the contrast enhanced image the exudates visibility increases. Here, we used the Contrast limited adaptive histogram equalization (CLAHE) technique to enhance the contrast of the image. CLAHE [4] is used as the preprocessing of the fundus images. In the case of CLAHE, transformation function is derived by applying contrast limiting procedure to each neighborhood of the color image. The main advantage of CLAHE is to prevent the over amplification of noise which can be result of application of adaptive histogram equalization. The input image to the algorithm is shown in Fig. 2. The output of the CLAHE on original image is as shown in Fig. 4.(a).

B. Back ground detection and subtraction

Back ground region of the fundus is the portion of the image where no retinal anatomy or lesions present, it consists of only the retinal layer of the fundus so it is an unwanted portion of the fundus image for screening of the DR. The detection of any anatomy or lesion present on the fundus image becomes simple, if we can detect and subtract the back ground region from the fundus image. By removal of back ground information we are left with only the retinal anatomy and lesions on the fore ground image of the fundus. In the literature there are morphological based methods [5] to detect the back ground information of the fundus image. In the present algorithm we used the median filtering operation with large kernel to estimate the background information of the fundus image. The median filtering operation can estimate the back ground information by replacing the median filter kernel's central pixel value with median value of the kernel. The size of the median filter kernel is selected such that it can accommodate the possible large anatomy of the retina. The median filter is applied on the green channel of the contrast enhanced fundus image. The median filter output is the back ground region (which mostly consists of the retina as shown in Fig. 4.(c)) of the fundus image. The background region is subtracted from the fundus image. The resultant image, as shown in Fig. 4.(d), consists of different lesion related information like hard exudates, hemorrhages and eye anatomical structures like blood vessels (BV) and optic disc (OD) etc.

C. Candidate extraction

On the resultant image, we applied a global threshold to detect the hard exudate candidates. The global threshold value is selected by conducting many experiments such that the candidates include all the hard exudates present in the fundus image. The exudates candidate regions consists of exudates, traces of optic disc and small region in between major blood vessels as shown in Fig. 4.(e).

D. Anatomy detection

As mentioned in the above section, the major false candidates for exudates are 1. Optic disc and 2. Region between two near blood vessels. So we need to detect Optic disc and blood vessels to reduce the false alarms. We used the local variance based method [6] to detect the OD on the fundus image. The local variance at the Optic Disc location is high compared to the other fundus image. In this method, we compute the local variance of the fundus image in patch wise for the entire image. The region with the maximum value of the local variance is considered as the OD region. Finally we calculated and applied a threshold range consists of maximum value of the local variance; to detect the region consists of OD. The output image for OD detection is shown in Fig. 4.(i). The portion between the BV regions is detected as the exudates candidates, because of the high intensity pixel values compared to surrounding BV pixel values. Here we detected the Blood vessels using the morphological based method [7].

We applied two closing operations to detect the blood vessels. We used the two different size disc shaped structuring elements for two closing operations respectively. Output of closing operation with smaller size structural element is subtracted from the output of closing operation with bigger size structural element. The subtraction output is threshold. such that all major BV are detected as shown in Fig. 4.(j).

E. False candidate subtraction

Along with the above two anatomies, we used de-correlation stretch of the fundus image to suppress presence any other false candidates [8]. De-correlation stretch of color fundus image enhances the color separation of an image by removing the inter channel correlation that is found in the color image [9]. All hard exudate lesions are enhanced to a high intensity value while other regions have low intensity values in the green channel of the de-correlation stretched image. The De-correlation image as shown in Fig. 4.(f) and its green channel in Fig. 4.(g). The de-correlation stretched fundus image green channel is threshold such that pixel values greater than the threshold are assigned with intensity value 1 and remaining pixels with intensity value 0. The false lesions detected during the candidate extraction step u sing median filter are suppressed initially by using OD and BV anatomies, which were detected earlier. Remaining false candidates are removed by multiplying the threshold de-correlated green channel image with the above resultant image.

F. Region growing

We used the recursive region growing algorithm (RRGA) for detection of bigger exudates, the bigger exudates are not detected completely as the size of bigger exudates are comparable to that of the kernel size of the median filter. In case of the bigger exudates only some portion of the exudates are detected so we used the RRGA [10] to detect the complete exudate. RRGA algorithm, which is based on comparison of local pixel properties (like grey level intensity, color, texture etc.) in the defined local region (without reference to the global values of the image). Regions (or pixels) should be merged to form a bigger region, if they are within the range of the specified threshold value of the considered image property. In the present algorithm we considered pixel intensity for the region growing operation. The final exudate detected image is shown in Fig. 3.

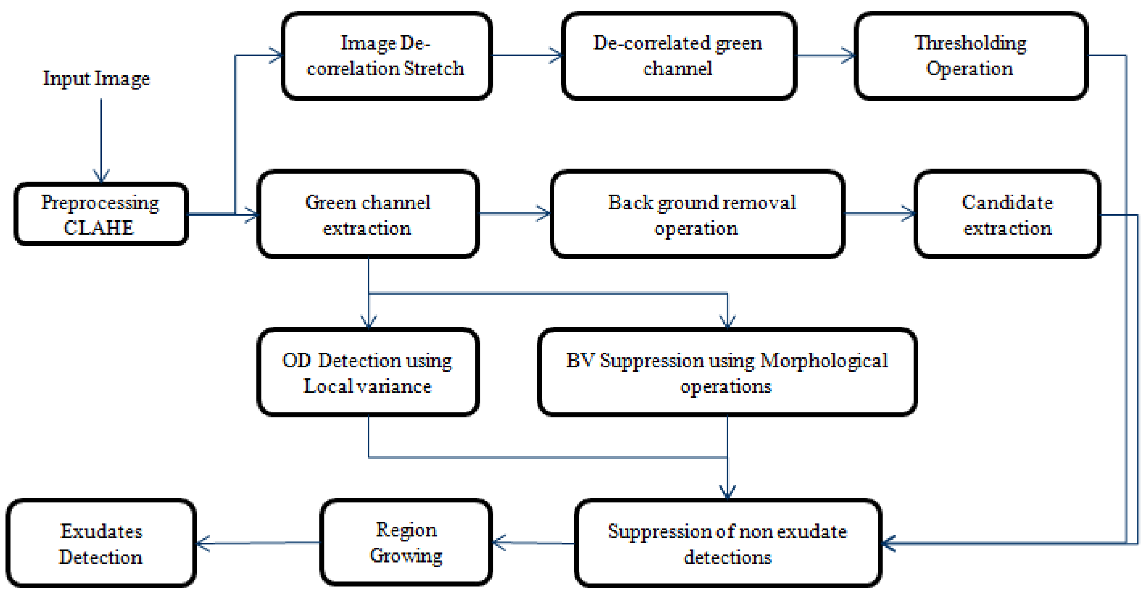

Fig -1. Block diagram of the proposed algorithm

G. Retinal image database

DIARETDB1 [11] Standard Diabetic Retinopathy Database at Calibration level 1. The DIARETDB (Standard Diabetic Retinopathy Database) database was composed in 2008 as a part of the Imageret project. The DIARETDB database was created in two sub-databases as DIARETDB0 and DIARETDB1. In the present work we used DiaretDB1 database. The DiaretDB1 (diabetic retinopathy databse-1) database consists of 89 images of the retina. The images were taken in the Kuopio university hospital. In the DIARETDB1 database 84 images out of 89 contains various symptoms of mild proliferative diabetic retinopathy and the rest 5 are of healthy retina. These images are available in PNG format and are of dimensions 1500 x 1152 with 500 field of view (FOV). For each of the images ground truth for the exudates are available. Ground truth for the above images is done by four experts independently. In the DiareDB1 database there are 38 number of hard exudates with the confidence level 0.75.

3. RESULTS AND DISCUSSION

The evaluation of the algorithm is done on the 38 hard exudate images of the DiaretDB1. We used the ground truth (with greater than or equal to 75% of the confidence) provided by 4 experts on DiareDB1 image database. The performance of the final output is given in the terms of the sensitivity i.e.. True Positive Rate (TPR), TPR is defined as the ratio of total number of exudate pixels in the segmented output to the total number of vessel pixels in the ground truth image. F-score is used as another performance metric. F-score is interpreted as weighted average of the sensitivity. Last performance metric is Positive Predict Value (PPV). A comparative performance of the proposed algorithm along with the state of art performance is shown in Table I. TP=True Positive, FP=False Positive, FN=False Negative.

$$TPR = \frac{TP}{TP + FN} \tag{1}$$

$$PPV = \frac{TP}{TP + FP} \tag{2}$$

$$F - Score = \frac{2 * TPR * PPV}{TPR + PPV} \tag{3}$$

TABLE I
A COMPARATIVE PERFORMANCE OF THE PROPOSED ALGORITHM

Method	TPR	PPV	F-Score
Proposed Method	**0.87**	**0.76**	**0.78**
Walter [12]	0.76	0.59	0.72
Sopharak [13]	0.40	0.91	0.56
Welfer [14]	0.19	0.92	0.31
Jaafar [15]	0.89	0.09	0.17
Sanchez [16]	0.38	0.10	0.15
Sopharak [17]	0.49	0.09	0.16

Fig. 2. Input Image to algorithm

Fig. 3. Output Image of algorithm with exudates marking

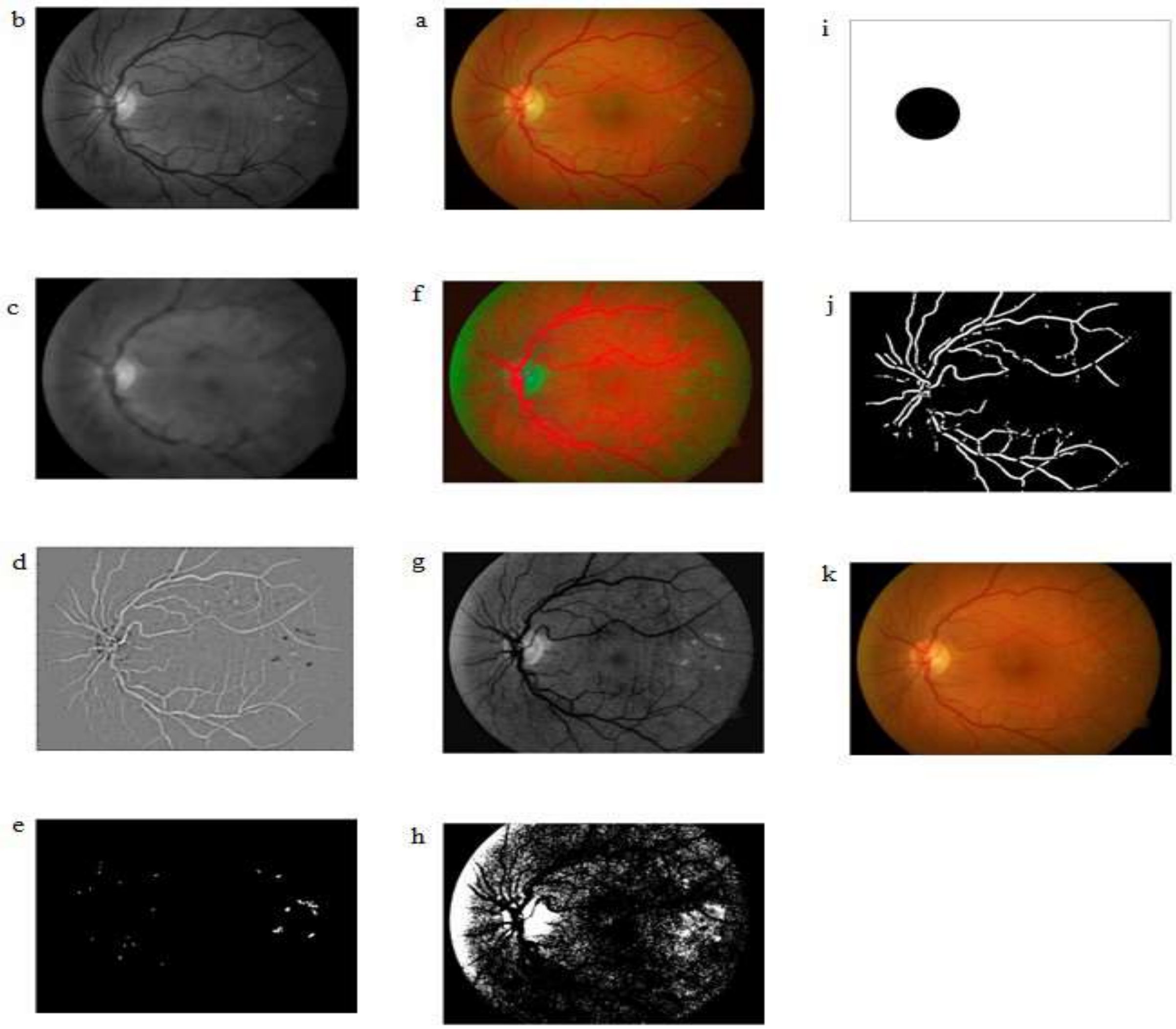

Fig. 4. (a) CLAHE output image; (b) Green channel image; (c) Back ground image; (d) Fore ground image; (e) Candidates image; (f) Decorrelation output image; (g) CLAHE green channel image; (h) Thresholded image; (i) Optic Disc image; (j) Blood vessel image; (k) Hard exudates marked image.

4. CONCLUSIONS

In this present paper, the exudates are detected using the combination of back ground subtraction of fundus image, exudate candidate extraction and other anatomy detection. Compared to the rest of the state of art segmentation techniques the proposed method can identify the hard exudates present in the fundus images with easy and acceptable sensitivity and accuracy. From the experimental results it could be seen that we can use the above methodology to screen the diabetic retinopathy. An improvement in the performance could be achieved by using the machine learning based approach with selection of proper features for the exudates.

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6. REFERENCES

[1]Klein R, Klein BE, Moss SE, Davis MD and DeMets DL, “The Wisconsin epidemiologic study of diabetic retinopathy. II Prevalence and risk of diabetic retinopathy when age at diagnosis is less than 30 years,” Arch Ophthalmology 1984, vol. 102, pp. 527–532.

[2] B. Harangi, I. Lazar and A. Hajdu, “Automatic Exudate Detection Using Active Contour Model and Region wise Classification,” IEEE EMBS 2012, pp.5951–5954.

[3] Balazs Harangi, Balint Antal and Andras Hajdu, “Automatic Exudate Detection with Improved Nave-Bayes Classifier, Computer-Based Medical Systems,” CBMS 2012, pp. 1–4.

[4] K Zuiderveld, “Contrast Limited Adaptive Histogram Equalization,” Graphics Gems IV, Academic Press 1994, pp. 474–485.

[5] M. N. Langroudi and Hamed Sadjedi, “A New Method for Automatic Detection and Diagnosis of Retinopathy Diseases in Colour Fundus Images Based on Morphology,” International Conference on Bioinformatics and Biomedical Technology 2010, pp. 134–138.

[6] K.B. Giribabu, P. Venkata Subbaiah and T. Satya Savithri,“Segmentation of Exudates and Optic Disk in Retinal Images,” Sixth) Indian Conference on Computer Vision, Graphics Image Processing,2008.

[7] S. Ravishankar, Arpit Jain and Anurag Mittal, “ Automated featureextraction for early detection of diabetic retinopathy in fundus images,”IEEE Conference on Computer Vision and Pattern Recognition 2009,pp. 210-217.

[8] Ram K, and Sivaswamy J, “Multi-space clustering for segmentation ofexudates in retinal color photographs.” IEEE Engineering in Medicine and Biology Society (EMBC 09) 2009, pp. 1437-1440.

[9] Ronald E. Alley, “Algorithm Theoretical Basis Document for Decorrelation Stretch,” NASA, JPL 1996.

[10] Sinthanayothin C, Boyce JF, Williamson TH, Cook HL, Mensah E, Lal S and Usher D ,“Automated detection of diabetic retinopathy on digital fundus image,” Journal Diabet Med 2002, pp.5951–5954.

[11] Tomi Kauppi, Valentina Kalesnykiene, Joni-Kristian Kamarainen, Lasse Lensu, Iiris Sorri, Asta Raninen, Raija Voutilainen, Hannu Uusitalo, Heikki K and Juhani P, “DIARETDB1 diabetic retinopathy database and evaluation protocol,”.

[12] T. Walter, J.C. Klein, P. Massin and A. Erginay, “A contribution of image processing to the diagnosis of diabetic retinopathy detection of exudates in color fundus images of the human retina,” IEEE Transactions on Medical Imaging 2002, Vol 21, Issue 10.

[13] A. Sopharak, Bunyarit Uyyanonvara, Sarah Barman and Thomas H.Williamsonc, “Automatic detection of diabetic retinopathy exudates from nondilated retinal images using mathematical morphology methods,” Computerized Medical Imaging and Graphics 2008, pp. 720– 727.

[14] D. Welfer, Jaco bScharcanski and Diane Ruschel Marinho, “A coarsetofine strategy for automatically detecting exudates in color eye fundus images,” Computerized Medical Imaging and Graphic-2010, pp 228– 235.

[15] H. F. Jaafar, Asoke K. Nandi and Waleed Al-Nuaimy, “ Detection of exudates in retinal images using a pure splitting technique,” Engineering in Medicine and Biology Society, EMBC 2010, pp. 6745–6748.

[16] C. I. Snchez, Roberto Hornero, Mara I.Lpez, Mateo Aboy, Jess Poza and Daniel Absolo, “A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis,” Medical Engineering & Physics 2008, pp. 350–357.

[17] A. Sopharak, Bunyarit Uyyanonvara and Sarah Barman, “Automatic exudate detection from nondilated diabetic retinopathy retinal images using fuzzy c-means clustering.” Sensors 2009, vol. 9, no. 3 2009, pp. 2148-2161.