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HARD EXUDATE DETECTION IN RETINAL IMAGES USING STATISTICAL PARAMETERS

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ABSTRACT

Diabetic retinopathy (DR) is a major cause of blindness. Exudates are one of the primary signs of diabetic retinopathy, which is a main cause of blindness and can be prevented with an early screening process. Early detection of exudates could improve patient's chances to avoid blindness. But detection of exudates in early stages of the disease is extremely difficult only by visual inspection because of small diameter of human eye. A new method for the detection of exudates using intensity thresholding and segmentation is proposed which removes the optic disc automatically from exudates.

KEYWORDS: Diabetic retinopathy, exudates, non-uniform illumination, threshold.

INTRODUCTION

Diabetic retinopathy is a disease commonly found in diabetes mellitus patients. If the disease is detected in its early stages, treatment can slow down the progression of DR. The changes in the retinal blood vessels such as swelling of the vessel, leakage of fluid affects the surface of the retina. The resulting diseases are Micro aneurysms, Hemorrhages, and exudates. However, this is not an easy task, as DR often has no early warning signs. Exudates are blood leakages and are a visible and present an early stage of retinal abnormalities in diabetic retinopathy. If the exudates extend into the macular area, vision loss can occur. It causes severe damage to retina and may lead to complete or partial visual loss. In case of diabetic retinopathy retinal blood vessel gets damaged and protein fat based particles leaked out from the damaged blood vessels and are deposited in the intra-retinal space. They are normally seen as yellowish marks of various shapes and are called as exudates.

Diabetic patients need regular screening because early detection of exudates could help prevent blindness. However, manual examination of the exudates and locating them spatially takes more time. Automatic detection and tracking of retinal exudates, speeds up the progress of the treatment program of patients. Digital image processing can play a vital role in detecting the above diseases with good accuracy in all metrics.

Number of work has been performed for exudates detection based on variety of techniques. Based on experimental work reported in previous work, good quality images are required. Here, the real retinal image of the patient from the hospital and publically available database are also taken. These images may be low quality (non-uniform illumination, low contrast, blur or faint image) do not perform well even when enhancement processes were included. The examination time and effect on the patient could be reduced if the system can succeed on non-dilated pupils. Furthermore, many techniques required intensive computing power for training and classification.

A new preprocessing method was used.[1] which performs normalization, denoising and detect the reflections, artifacts in an image. The candidates are segmented by morphological and finally random forest algorithm was used to detect the exudates. After doing color normalization and contrast enhancement the regions are segmented into exudate.[2] and non-exudate regions. The exudates are the prime marker of DR disease because exudates are directly related to retinal edema and vision loss. Detecting retinal images in a huge amount of images that were generated by screening programmes and need to be repeated at least annually very expensive. The hybrid approach[3] consists of preprocessing, clustering and post processing methods in which morphological, Linde-Buzo-Gray and K means are used.

Classification is an important tool for detecting the retinal exudates, and the Fisher's linear discriminant analysis[4] was used here. A significance of hard exudates is their high intensity, sharpness of edges, so this would help to identify the yellow regions as hard exudates. Hard exudates are yellow lipid deposits which appear as bright yellow lesions.[5] pixels with different colors are segregated into different regions and fuzzy c-means algorithm was used. Contrast adjustment transformation is applied on green channel, only the darker regions have their intensity values enhanced.[6] To obtain binary image thresolding morphological opening, then watershed transformation had been implemented for segmentation. Active contour model is implemented to detect exudates and it was used to obtain accurate borders of[7] lesions.

Then the exudates are extracted using scale invariant feature transform. Improved method automatic exudates detection in retinal images using nonlinear background elimination.[8] The pixel that have intensities higher than the upper bound or lower than the lower bound are defined as unwanted date.

Hard exudates are one of the most occurring lesions caused in DR .They are yellowish or white patches Of vascular damage with leakage, varying in sizes, shapes and locations. The haar wavelet transform is powerful multi-resolution analysis tool.[9] Prolongation of DR may result in permanent blindness. Various methods were used by several people for exudates detection.[10] Every pels in an image is associated with different clusters make certain amount of belongingness instead of related completely to just unique[11] bunch. Pels at the region contours may have less membership compared to the pels at the interior of the regions. Unequal illumination is observed here as portion near to optic disc when compared to the other portions. Abnormality detection in fundus image is very complicated with the differences in luminosity, brightness and contrast inside fundus images .Preprocessing is the essential technique to recover these problems. The retinal fundus images are stored as RGB components. The exudates are discriminated easily in green plane[12] because it has higher contrast and more energy but in our system red also considered because it's brighter intensity. In the detection of exudates, the intensity plays an important role .Each pixel has its own intensity and the maxima could be used to identify the lesion in an image.[13] For non- dilated pupil, morphological operators to be used for exudate detection.[14] And this technique has a very fast computation. A grid circle centered on the macula was added to provide improved diagnosis to the ophthalmologist. An optimal threshold must be set to allow the segmentation of hard exudates from background. A fixed value could not be assigned to that optimum because the histogram varies from image to image.[15] therefore dynamic thresolding was used. In All the images, additional information[16] like quality metric, age of the patient,

patient gender, type of diabetes are supplied. Here the feature vector is based on three types of analysis namely exudate probability map, color analysis and wavelet analysis.

This paper proposes exudates detection techniques based on retinal images of non-dilated pupils that are low quality images.

METHODOLOGY

The digital retinal images of patient's non-dilated pupils were obtained from Data base.These images was stored in a JPEG image format. The image size is 256x190 pixels.

Preprocessing

Initially the retinal image is converted into separate R, G, and B channel. The exudates are yellow in color and are usually brighter than the background, so mostly information is enriched in red, Green channels.

Parameter Normalization

The pixels of the images had been preprocessed and enhanced in all previous methods, instead here; the statistical parameters like average, variance, and standard deviation, of these images are calculated separately and are normalized by their green values of high contrast which have been shown in the functional program.

das = [sig1/av1 , sig2/av2, sig3/av3];

For RGB respectively.

vfac1= das (1)/das (2);

vfac2= das (2)/das (2);

vfac3= das (3)/das (2);

For many images the sigma may be tried between 0 to 2. But our convenience the optimum may be put into 1.5.

The normalization formula is given below

Red channel= Green*vfac1;

Green channel = Green *vfac2;

Blue channel= Green*vfac3;

The normalized vfac value after so many iteration are given below

[0.7168 1.0000 0.7129]

Color Normalization

Hue is the one of the important aspect of RGB color channel. It is defined as the wavelength within the visible light spectrum at which the energy output from source is greatest. Since it has a dominant brightness, the formula for three channels are given below:

hrr= (xr / (xr+xg+xb));

hrg=(xg / (xr+xg+xb));

hrb=(xb / (xr+xg+xb));

Consider an image which has R, G, and B intensity channels. The intensity points of the images have been taken throughout the image and different hues for R channels are calculated as given below. Similarly the hues for G and B channels are also calculated. After performing much iteration, the below span of threshold had been achieved.

Table I: Hue Description for Normalization.

Image No	AvHue	LoHu	Hihu
1	.4124	.460	.750
4	.3371	.31	.590
5	.423	.500	.625
6	.3999	.46	.62
8	.3343	.440	.610
9	.3551	.445	.620
15	.3670	.562	.680
64	.4440	.44	.58
65	.4547	.53	.61
66	.3815	.360	.490
67	.3800	.370	.650
84	.3982	.40	.620

if (hrr>=0.45 && hrr <= 0.685), flagR = 1;

if (hrg>= 0.2 && hrg <= 0.52), flagG = 1;

if (hrb>0.05 && hrb <=0.105), flagB = 1;

If hue of all the three channels are within the above range, then the hue to be assumed to yellow dominant range.The hue value of all the exudates are almost align in the same line.

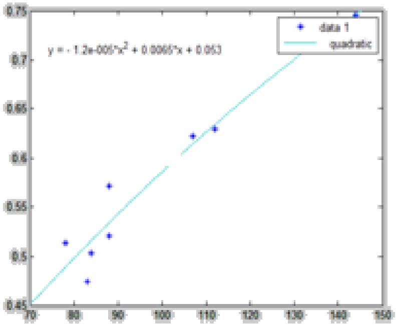

Image-12.

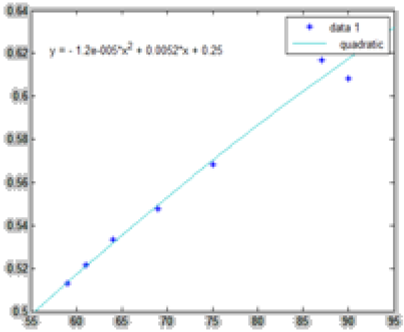

Image-1.

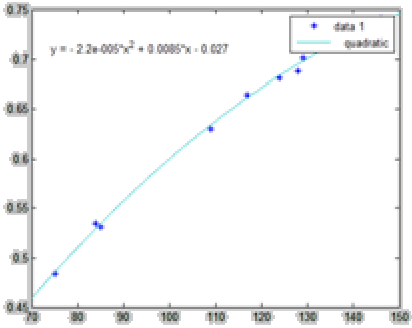

Image-6.

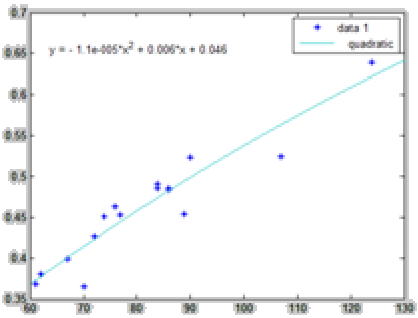

Image-67.

Fig. 1: Line fitting for Green Vs Hue.

To find optimum, a curve is drawn between the green verses hue and approximately straight line fitting curve would be obtained as shown above. It shows that the candidate (exudates) regions are lie along the straight line.

Intensity Threshold

The intensity of each pixel is compared and verified whether it is greater than the average, sigma (standard deviation) and variance, and hue, then the particular intensity is assumed to be a yellow dominant color with varying size. The entire procedure is performed by 9 x 9 mask of the image. During this iteration the defected areas are assumed to be foreground and the normal smooth surfaces are called as background. The thresholds are given in the functional intensity program lines 17, 18, and 19:

```
thres_r= uint8(1.0*av1 +(vsig(1))*av1);
thres_g= uint8(1.0*av2 +(vsig(2))*av2);
thres_b= uint8(1.0*av3 +(vsig(3))*av3);
```

Here, 1.0 is the unit tolerance and all above flags are equal to 1,then that region are called as exudates regions. The resultant images should be in binary form so the identified yellow region are assumed to be white and the remaining non exudate regions assumed to be black. To improve the efficiency median filter post processing is used.

Post Processing

Median filter is used for post processing. It is widely used at removing the noise while preserving edges. It works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. Since, in filtered images, pixels in a close neighborhood originate from overlapping window, they are correlated to some extent and thus the joint distribution of adjacent pixels. Surely it reduces the erroneous identification, and gives better results.

RESULT

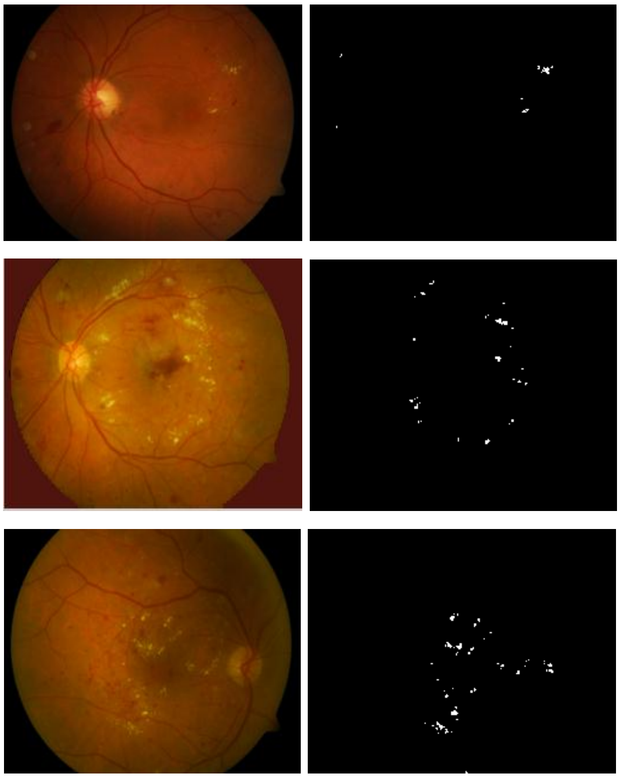

Fig. 2: Retinal input images Vs Detected exudates.

CONCLUSION

In this paper, a new method for exudates detection has been introduced. To enhance the results, preprocessing and post processing operations has been performed. The statistical parameters, hue are normalized and straight line fitting curve would have been drawn. The exudates regions would lie along the curve and properties of exudates have been bringing out.

REFERENCES

1. Xiwei Zhang, Guillaume Thibault, Etienne Deceniere, Beatriz marcotegui, Brunolay, Ronan Danno, Guy Cazuguel, Gwenole Quellec, Mathieu Lamard, Pascale Massin, Agnes Chabouis, Zeynep Victor, Ali Erginary, "Exudate Detection in Color Retinal Images for Mass Screening of Diabetic Retinopathy", Elsevier, march 26, 2014; 1-16.
2. Alireza osareh, Bita Shadgar and Richard markham,"Computational –Intelligent –Based Approach for detection of Exudates in diabetic Retinopathy Images", IEEE transaction on information technoly in biomedicine, July 2009; 13: 4.

3. Dr. H. B. Kekre, Dr, Tanuja k. Sarode, Ms. Tarannum Parkar, “Hybrid approach for Detection of Hard Exudates”, International Journal of Advanced computer science and Applications, 2013; 4(3).
4. Clara I. Sanchez, Roberto Hornero, maria .I.Lopez, Mateo Aboy, Jesus Poza, Daniel Abasolo, “A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis, ELSEVIER, Science Direct, Medical Engineering and Physics, 2008; 30: 350-357.
5. Neera Singh, Ramesh Chandra Tripathi, “Automated Early Detection of diabetic Retinopathy using Image Analysis Techniques, International Journal of Computer Applications, 2010; 8(2): 0975-8887.
6. Kalashree, Sowmya, “A Novel Algorythm for Exudates Detection Using Matlab, International Journal of Advanced Research in Computer Science and Software Engineering, 2015; 5(2).
7. V. RatnaBhargavi and V. Rajesh, “Exudate detection and feature extraction using active contour model and sift in color fundus images”, arpn Journal of Engineering and Applied Sciences, April, 2015; 10: 6.
8. Morium Akter, Atiqur Rahman, A. K. M. Kamrul Islam, “An Improved method of automatic exudates detection in retinal images”, international journal of innovative research in electrical, electronics, instrumentation and control engineering, May 2014; 2(5).
9. Poonam M. Rokade,”Automatic Hard Exudates Detection from Multi-Resolution Retinal Images Using HAAR Duel Tree Wavelet Transform”, International journal of computer science Trends and Technology, 2015; 3(3).
10. Prof. Neha Gaikwad, Prof. Pravinkumar R. Badadapure, “Image Processing Technique for hard Exudates Detection for diagnosis of diabetic Retinopathy”, International Journal on Recent and Innovation Trends in Computing and communication, 2015; 3(4).
11. R. Ravindraiah, Dr. J. L. Mazhar Iqbal, “hard exudates detection in proliferative diabetic retinopathy using gradient controlled fuzzy c means clustering algorithm”, gesj, Computer Science and Telecommunication, 2014; 44: 4.
12. Syna sreng, Noppadol maneerat, don Isarakorn, Bundit Pasaya, Jun-ichi Takada, Ronakorn Panjaphongse M. D. Ruttikorn Varakulsiripunth, “Automatic Exudate Extraction for Early Detection of Diabetic retinopathy,”978-1-4799-0425-9/13-2013 IEEE.

13. Nidhal K. El. Abbadi, Enas Hamood Al-saadi, "Automatic Detection of Exudates in Retinal Images", International Journal of Computer Science Issues, 2013; 10(2): 1.
14. Akara sopharak, Bunyarit Uyyanonvara, Sarah Barman, thomas H. Williamson, "Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods, ELESEVIER, Science diret, Computerized Medical Imaging and Graphics, 2008; 32: 720-727.
15. Clara I.Sanchez, Maria Garcia, Agustin Mayo, Maria I. Lopez, Roberto Hornero, "Retinal Image analysis based on mixture models to detect hard exudates, ELSEVIER, Medical image analysis, 2009; 13: 650-668.
16. Luca giancardo, Fabrice Meriaudeau, Thomas P.Karnowski, Yaqin Li, Seema Garg, Kenneth W. Tobin, Edward Chaum, "Exudate –based diabetic macular edema detection in fundus images using publicaly available datasets", ELSEVIER, Medical Image Analysis, 2012; 16: 216-226.