Blood Vessels And Lesions Detection In Color Retinal Images

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Abstract
Diabetic-retinopathy is the leading cause of blindness in the working age population. So far the most effective treatment for these eye diseases is early detection through regular screenings. To decrease the cost of such screenings, we employ methods image processing techniques to automatically detect the presence of abnormalities in the retinal images obtained during the screenings. In this paper, we used two methods. First approach is that detection of lesions using minimum distance discriminat (MDD) algorithm with brightness adjustment procedure. Second method is detection of blood vessels using Krisch's method. Experimental results indicate that we are able to achieve 100% accuracy in terms of identifying all the retinal images with exudates while maintaining a 75% accuracy in correctly classifying the truly normal retinal images as normal and also detects the affected blood vessels in the retinal image . This translates to a huge amount of savings in terms of the number of retinal images that need to be manually reviewed by the ophthalmologists.

1. Introduction

Diabetic-related eye diseases are the most common cause of blindness in the world. Diabetic retinopathy remains to be the leading cause of legal blindness in the working age population. More than 90% of visual loss resulting from diabetic retinopathy can be prevented with prompt treatment if the retinopathy is detected early[1] .During the screenings, color retinal images are obtained using fundus camera. In other words, ophthalmologists have to spend a more time and energy to review these photographs[2]. It would be more cost Effective if the initial task of analyzing the retinal photographs can be automated so that only the abnormal retinal images need to be reviewed by the ophthalmologists. Figure1 shows an example of a healthy color fundus image.

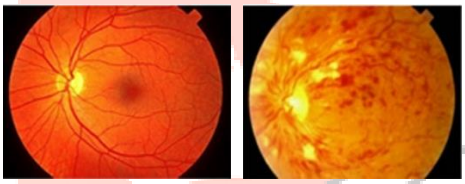

Figure 1. Healthy and unhealthy color retinal images.

In the unhealthy abnormal fundus images usually exhibit some abnormalities, one of which is the presence of exudates/lesions. Exudates/lesions are typically manifested as random whitish/yellowish patches of varying sizes, shapes and locations.

2. Working Module

Figure 2 shows working procedure for detection of lesions in the diabetic retinopathy block by block. Initially it is given the diabetic patient retina image then it is processed using RGB conversion modules. Then we are extracting features from the retina image. After extracting using some of the parameters we are calculating the lesions in than image after it is classifying we are finding out how much amount of lesions present in that image.

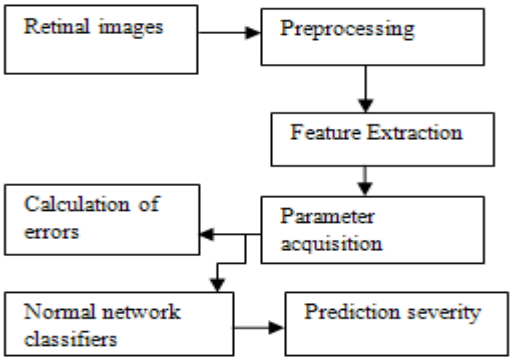

Figure 2: Flow diagram of the diabetic retinopathy for the detection of lesions.

3. Exudates Detection Methods

3.1 MDD algorithm Method with brightness adjustment

Objects in an image usually can be described in terms of some features *f1*, *f2*… *fk* such as color, size, shape, texture and other more complex characteristics. These features, *f1*, *f2*… *fk*, form a k-dimensional feature space, **F**. Ideally, we would like to find a space **F** such that different objects map to different, non-intersecting clusters in this feature space. Let **C***i* (*fi1*, *fi2*… *fik*) denote the center of class *i* (cluster *i*) in the k-dimensional feature space **F**, where *i=1,2, …, N*. Let **X**(*x1*, *x2*…*xk*) be the unknown object's feature measurement values in **F**. Let D*i*(**X**), *i=1,2,…N*, be the discriminat function that is used to determine whether **X** should be classified as belonging to class *i*. Given a specified pixel *x* with feature vector **X**, we classify pixel *x* as belonging to class *i* if D*i*(**X**) is the maximum along all D*j* (**X**), where *j=1,2,…N* and *j*&*i*. Two issues need to be resolved before we can apply the above statistical classification to the detection of lesions[1]. The color fundus retinal image consists of three planes—red, green and blue, each plane with 256 levels of intensity denoted as (R, G, B). Color be also represented by θ,φ and L in the spherical coordinates . The relation between the two color spaces is expressed as

$$L = (R^2 + G^2 + B^2)^{1/2}$$

$\theta = \text{Arc tan}(G/R)$, $\varphi = \text{Arc cos}(B/L)$

L denotes the exposure or brightness of an image, whereas θ, φ emphasize the differences or changes of colors. When L is held constant, θ and φ describe the chromaticity in an iso illuminant surface. Using only two color features θ and. φ Since our focus is to differentiate between yellowish lesions and other darker objects in the color retinal images, we need to include both the brightness/exposure of the image as well as the changes of color information. Hence, we have selected L, θ, φ as our feature space, **F**(fL,f_θ, f_φ). Next, we need to derive an appropriate discriminant function.

Our discriminant D(**X**) is derived from Bayes rule. Let P(**C***i*/**X**) be the posterior probability. It denotes the probability of measurement vector **X** belonging to event *i*(class *i*). If P(**C***i*/**X**) is greater than P(**C***j*/**X**), where *j=1,2,…N*, and then we should conclude that **X** belongs to event *i*(class *i*). According to Bayes' theory, P(**C***i*/**X**) can be expressed as:

$$\mathbf{P(C}i\mathbf{/X) = P(C}i\mathbf{)P(X/C}i\mathbf{)/P(X)} \quad (1)$$

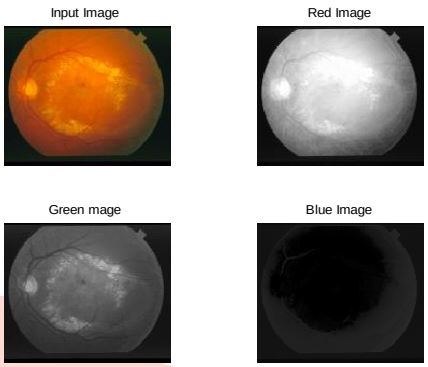

Figure 3: RGB Extraction for the detection of lesions.

Here, P(**C***i*) is the priori probability of class *i* in the image to be classified. P(**X**/**C***i*) is the conditional probability of **X** given class **C**.. In other words, the discriminant factor can be defined as a posterior probability:

$$\mathbf{D}i\mathbf{(X) = P(C}i\mathbf{/X)=P(C}i\mathbf{)P(X/C}i\mathbf{)/P(X)} \quad (2)$$

Since P(**X**) is independent of any class, it will not affect the discriminating power of D*i*(**X**), so it can be safely ignored/discarded. Then, it is reasonable to approximate P(**X**/**C***i*) to a normal distribution. Finally we further assume that the covariance matrix *i=1,2,…,N* in is almost identity for all classes and that P(**C***i*) is almost equally likely for *i=1, 2, …,N*. Applying logarithmic operator to formula (2), we obtain the f which is also called the "minimum distance discriminant (MDD)." The feature centers of lesions and background, **C***lesion*(fL,f_θ, f_φ) and **C***bkgrnd* (fL, f_θ, f_φ) can be obtained and trained by selecting small windows inside exudates patches and background regions respectively in a set of typical sample images. The means of exudates and background are then computed and stored as feature centers for the two classes respectively. For each pixel **X**(xL, x_θ, x_φ) from the retinal image, the discriminant D*lesion*(**X**)

and D*bkgrnd*(**X**) are calculated. If D*lesion*(**X**) is less than D*bkgrnd*(**X**), then pixel **X** is classified as lesion otherwise it is being classified as background. In this way, exudates or other yellowish lesions can be quickly detected. Our simple and fast MDD algorithm is able to achieve good accuracy in the detection of exudates in color fundus images.

$$\mathbf{D = D_{i+1}(X) - D_i(X)} \quad (3)$$

Where $D_{i+1}(\mathbf{X})$ =adjacent pixel value. $D_i(\mathbf{X})$ = original pixel value.

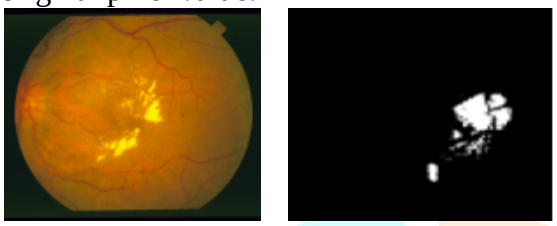

Figure 4: (Left) original color retinal image containing yellowish lesion. (Right) classified image by MDD (white points: lesions, black points: background).

3.1.1Brightness adjustment for Non-uniformity of Illumination

Though the minimum distance discriminant function approach seems to work well for images under the same illumination conditions, in practice, we find a large variance among the images obtained. This variation is due to a number of factors, such as the intrinsic attribute of lesions, decreasing color saturation at the lesion boundary or lighting variation over an image, etc.. Under such circumstances, these lesions would be wrongly classified as "background" instead of "lesion" by MDD classifier[1].This is achieved using a brightness transform function as shown below: $Y = M*X^{\alpha}$

Where *X* is the pixel value of the original input image, *Y* is the pixel value after brightness adjustment, and $0 \le \alpha \le 1$ *Where* $M = inmax^{1-\alpha,}$ and *inmax* is the value of upper limit intensity (brightness) of input image desired in transform function

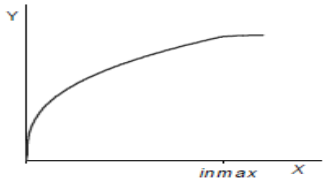

Figure 5: Expected function for brightness adjustment

Applying this brightness adjustment procedure[1] to the color retinal images, we are able to detect even those dim lesions that are distributed in the darker regions using our Bayes MDD classifier (see Figure 5).

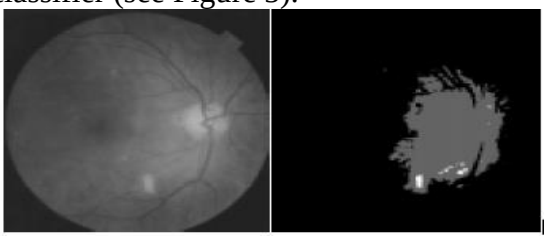

Figure 6. (Left column) original image. (Right column) processed images by Brightness adjustment, MDD classification and dim lesions preliminarily identified. White points: final confirmed lesions and black points: background

3.2 Kirsch's Method

Kirsch's method is used in the detection of blood vessels .it computes the gradient by convolution the image with eight template impulse responses arrays(H1-H8) as shown in the figure below. The scale factor is 1/15. In the edge based methods are used to locate sharp changes in the intensity function Edges are pixels where brightness changes abruptly[5]. Numerous kernels have been proposed for finding edges, they are Roberts, Sobels, and Prewitt. In all these masks, The gradient is estimated in eight (for a 3 x 3 convolution mask) possible directions, and the convolution result of greatest magnitude indicates the gradient direction. A threshold image is considered the rule as follows.

$$G(x,y) = \begin{cases} 1 & \text{if } f(x,y) \ge T \\ 0 & \text{if } f(x,y) < T \end{cases}$$

Hence the impulse response arrays used in the kirsch's method are as follows. They are used for the detection of affected blood vessels in the unhealthy retina image and healthy retina image in order to know the severity in the images.

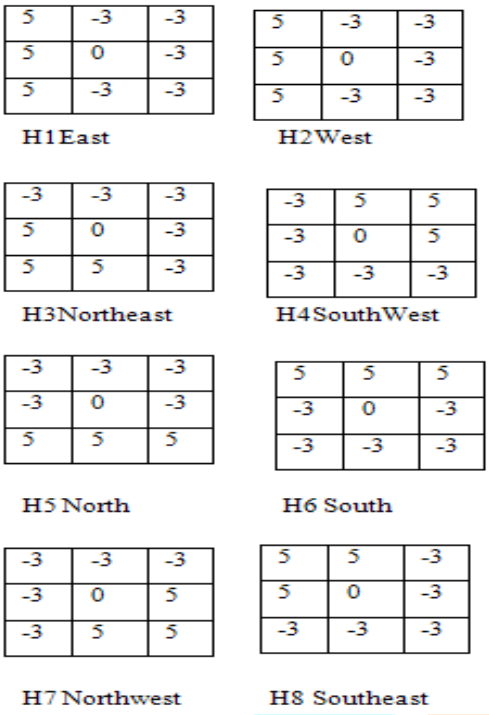

Figure 7: Impulse response arrays of Kirsch's method

The gradient of different directions is obtained by convolving the image with eight impulse response arrays. the final gradient is set to the largest gradient among different directions. Thus the edge is enhanced by Kirsch's method[4]. a threshold is set after edge enhancement to determine if pixel belongs to the edge or not.

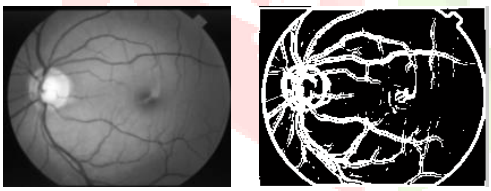

Figure 8: Results of the Blood vessels detection. Left (original image),Right (vessels detected image)using Kirsch's method.

4. Results and discussions

We perform two sets of experiments to test the effectiveness of our proposed approach. In all the experiments, we set the parameters as follows: In the brightness adjustment procedure: we have *inmax*=195, 135, 95 and α=0.2, 0.2, 0.25 for R, G, B planes respectively., In our first experiment, the objective is to ensure that our approach will not wrongly classify an abnormal image as normal. All known cases of abnormal images are used in this experiment. These images are of varying qualities.

Table1. Experiment Results of both the methods

	Detected as Abnormal	Detected as Normal	Accuracy
MDD algorithm	36	27	75%
Kirsch's method	40	0	100%

5. Conclusions

On the basis of color information, the presence of lesions can be preliminarily detected by using MDD classifier based on statistical pattern recognition techniques. To deal with the problem of non-uniform illumination in the retinal images, an effective preprocessing step, the brightness adjustment procedure, is proposed to ensure dim lesion patches that are scattered in darker background would not be missed and would not be regarded as background. Finally, a local window feature D is used to verify the classification result. With this, we are able to achieve 100% accuracy in terms of identifying all the retinal images with lesions while maintaining a 75% accuracy in correctly classifying the truly normal retinal images as normal. This translates to a huge amount of savings in terms of the number of retinal images that need to be manually reviewed by the medical professionals each year.

References

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