AUTOMATIC DETECTION AND DIAGNOSIS OF DIABETIC RETINOPATHY

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ABSTRACT

A computer aided detection and diagnostic system has been developed for diabetic retinopathy (DR). The system detects the fovea, blood vessel network, optic disk, as well as bright and dark lesions associated with DR. The diagnosis is based on the number, type and location of abnormalities relative to the fovea. Detection of normal retinal components was done as part of the overall system development and the work has been reported in literature. Lesion detection is accomplished through the process of eliminating the normal retinal components: blood vessels, fovea and optic disk. Remaining objects in the retinal image include the background and abnormalities if present. The image is partitioned in two regions: fovea and non-fovea, which have different backgrounds. Filtering and statistical adaptive thresholding are applied throughout the remaining data. The diagnostics and final system's layer is a knowledge-based system.

Index Terms— automated diagnostics, diabetic retinopathy, image understanding.

1. INTRODUCTION

Diabetes is a disease that affects blood vessels throughout the body, particularly in the kidneys and eyes. When blood vessels in the eye are affected, the condition is referred to as diabetic retinopathy (DR). DR is the leading cause of new blindness among adults in the United States (US) [1]. According to the American Diabetes Association over 20 million people or 7% of the US population have diabetes. According to the American Obesity Association, obesity is increasing globally. Overweight individuals are at an increased risk of developing diabetes and hypertension.

Diabetic retinopathy is a sight threatening condition that can be treated with much success if detected early. Diabetics should schedule routine eye examinations to prevent complications. In present health care systems, screening is limited by its extensive need for human resources. We have developed an automated system that will aid timely detection of DR through retinal image analysis, segmentation and understanding. The proposed diagnostics system consists of three grading levels: no DR, mild DR and severe DR. The levels are selected based on the number, abnormality type and location referent to the fovea. Blood vessel and fovea detection are presented in [2] and [3] respectively and are an integral part of this system. The vessel network is detected utilizing a multi-window Radon transform. The fovea is detected by utilizing two main components: the blood vessel network, which provides a map of the retina, and by re-mapping the image into probability space. Other features like intensity and shape are also utilized. The abnormality detection algorithm is based on a selection through elimination process. The rationale is to eliminate all normal components from the data set, leaving behind the retinal background and abnormalities, if present. Normal retinal images are composed of the blood vessel network, optical disk, fovea and retinal background. Images from patients suffering from DR will have in addition to the normal components, abnormal components that differ in intensity from the background, either brighter or darker. Dark abnormalities include microaneurysms and hemorrhages. Microaneurysms are the earliest visible changes of DR and they appear as small, round objects. Hemorrhages can be dot, blot or flame shape. Bright abnormalities refer to hard exudates and cotton wool spots. Hard exudates are distinct bright objects that can vary from small specks to large patches. Cotton wool spots are light cloudy type objects with ill define edges. These four types of abnormalities in conjunction with a diagnostic system are the main focus of the work presented here.

2. RELATED WORK

Several methods have been reported in literature for abnormality detection in retinal images. Most of the work focuses on a single type abnormality; either dark or bright that outputs a normal/abnormal type diagnosis, [4], [5], [6]. Work presented in [7] takes a more comprehensive approach by focusing on dark and bright lesions associated with DR. In [7] bright lesions are detected with a three-step method: image enhancement, segmentation by an Improved Fuzzy C-Means algorithm, and classification by means of a Support Vector Machine (SVM). Dark abnormalities are also segmented using SVM followed by a post processing stage [7].

The work presented here is a comprehensive approach to detection and evaluation of DR. The system accounts for normal as well as abnormal components of a retinal image. The number, type and location of the abnormalities within the retinal image are taken into account when performing the final evaluation.

3. ALGORITHM

Retinal images are composed of bright objects, dark objects and retinal background. Bright objects include the optic disk and abnormalities like hard exudates and cotton wool spots. Dark objects include the vessel network, fovea and abnormalities like microaneurysms and hemorrhages. Elimination of the anatomical components from the data set yields background alone or background plus abnormalities. Filtering and statistical analysis for thresholding is applied to the remaining data set to detect objects that do not conform to the background. A modular approach is implemented to minimize background variations where the image is partitioned into fovea and non-fovea regions. The regions are processed in three major stages: 1) image normalization / enhancement and partioning, 2) filtering and thresholding and 3) feature extraction for the non-fovea areas. Figure 1 depicts the system's block diagram.

3.1. Image Normalization and Partition

Inadequate illumination can interfere with the image analysis, detection and diagnostics. In this pre-processing stage we remove illumination changes, normalize and enhance all the images through homomorphic filtering. This type of filter separates the illumination and reflection components of an image. It is assumed that illumination changes are characterized by slow spatial variations. A filter is implemented that attenuates the low frequency components while amplifies the higher components.

The fovea is a depression in the center of macula region and appears as a darker area in a retinal image. The retinal background is neither dark nor bright in intensity, it is in between. The fovea is the area utilized in activities that require discerning sharp details such as reading. Abnormalities present in this region indicate a potential sight threatening condition if left untreated. The patient may not be aware of the presence of the abnormalities if they are small. The algorithm's sensitivity must be high in the fovea region while outside the sensitivity can be lowered to reduce false alarms. The fovea detection algorithm developed in [3] is utilized as the basis for the partitioning.

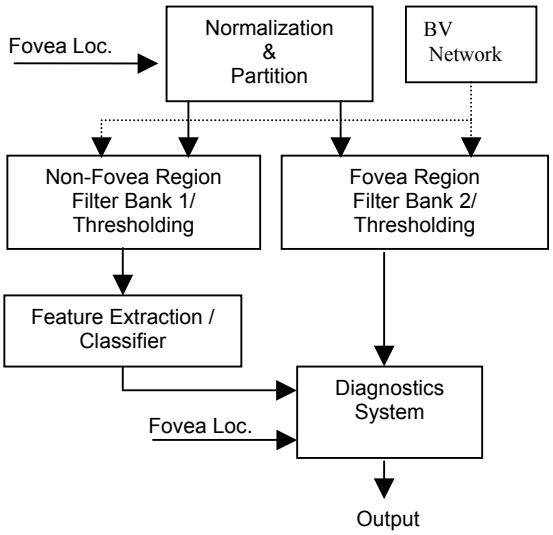


Figure 1. System block diagram.

3.2. Abnormality Detection in the Fovea Region

The data allocated to the fovea region is processed with a filter bank in order to detect objects of varying sizes. The filter bank consists of several filters varying from low-pass to high-pass with band-pass filters in between. The low-pass filter enhances the large abnormalities whereas the higher-pass filter enhances the smaller ones. An adaptive threshold is applied to the output of each filter in order to detect the abnormalities. Figure 2 shows a fovea region with a potential abnormality and its respective histogram before and after filtering.

3.2.1 Adaptive threshold

The adaptive threshold is an extension of that proposed in [8]. The mean, standard deviation, skewness and kurtosis are utilized to adapt the threshold for each filter output. The threshold to detect bright abnormalities is as follows:

$$t = \mu + \alpha\sigma + \left(\frac{1}{s_f} + \frac{1}{k} - s \right)\sigma \qquad \textbf{(1)}$$

where

α , μ, σ => constant, mean and standard deviation

s, k, s_f => skewness before filtering, kurtosis and skewness after filtering.

s_f => $max(1, s_f)$, right side of histogram only

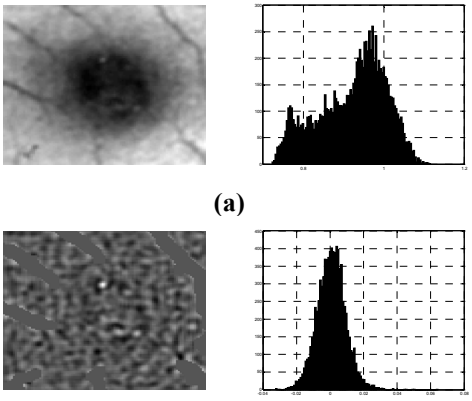


Figure 2. a) Fovea region and its histogram b) High-pass filter output and its histogram

In order for an object to be accepted by the system as a bright abnormality, the following must be true:

$$\left[\left(p_i > t\right) \cap \left(s_f > t_s\right)\right] > 0 \qquad (2)$$

where

p_i => pixel value

t_s => skewness threshold for each filter output

The t_s was empirically determined as part of the training process. The statistics associated with the threshold for bright and dark abnormalities after filtering, include only pixel values above and below the background respectively. Skewness and kurtosis are associated with the third and fourth moments of a distribution. They give an indication of the tail effect as well as the flatness of the resulting distribution providing a measure of success/failure for each filter output. The skewness of the data before filtering provides an indication of whether the fovea area is normal or abnormal. Normal or mostly normal fovea regions produce negative skewness. Positive skewness is an indication of the presence of bright abnormalities. Blood vessels, if present in the region, are removed from the statistical calculations. The threshold to detect dark abnormalities is similar to that of equation 1, but with sign changes.

3.3. Abnormality Detection outside the Fovea Region

Abnormality detection outside the fovea region is accomplished in a similar manner to that of the fovea region, but with additional feature extraction of potential abnormalities. Features include: shape (eccentricity, area, extent), brightness and texture (range, standard deviation, skewness). The region outside the fovea tends to be noisier and thus more prone to false alarms. Illumination changes and retinal background variations can cause false positives for bright abnormality detection. The optic disc, which is a bright object, was detected in [3]. False positives for the dark abnormalities are generally from the smaller vessels, which were not properly detected by the vessel segmentation algorithm in [2]. The calculated features aid in discriminating against false positives, which are fed into a neural network to classify the object as normal or abnormal.

4. DIAGNOSTICS

Once the abnormalities have been detected in both the fovea and non-fovea regions the system makes a diagnosis based on the number, size and location of the abnormalities. This is an expert system approach designed to provide four grading levels:

- Level 1: No DR
- Level 2: Mild DR: Abnormalities are present but distant form critical / fovea region. Patient should consult with an ophthalmologist at some point.
- Level 3: Moderate DR: Abnormalities are present and approaching critical region. Patient should consult with an ophthalmologist.
- Level 4: Severe DR. Abnormalities are present in critical region. Immediate intervention of an ophthalmologist is required.

In all cases it is assumed that patient monitoring will continue. Regular check-ups are essential for diabetic patients in order to prevent blindness or sight deterioration. Figure 3 shows an abnormal image, which was classified as a level four. Figure 4 shows a normal image with its respective system output (no DR). The original image in Figure 4 contains a small speck of dust (just outside the outer radius), which could be incorrectly classified as a microaneurysm. Dust manifests itself as dark, small objects with well defined edges. That is not the case for actual microaneurysms. This is also accounted in the diagnostics layer in the system.

Object characteristics that include area, eccentricity, intensity, edge intensity, and distance from the fovea are part of the evaluation process. Object criticality weighting is inversely proportional to their distance from the fovea. A single, small, suspicious object at a large distance from the fovea will not return a level 3 or level 4 diagnose.

4. RESULTS AND DISCUSSIONS

Two databases were used to design and test the work presented here. One database provides high-resolution images and the other lower resolution ones. Twenty images were utilized for the design and training phase and the other twenty images for testing. The high-resolution database was provided by the Jules Stein Institute, UCLA and the other database was downloaded from the www.ces.clemson.edu/~ahoover/stare website. Ten images from each database were selected for training and testing

respectively. Of the 20 images tested, we were only able to diagnose 18 images. In two cases the system failed to detect the fovea and therefore no diagnose was obtained. Sixteen out of the 18 images were correctly diagnosed. In one of the misdiagnosed cases, the system incorrectly detected the fovea region causing the diagnostics layer to misclassify the level of DR (severe instead of moderate). On the other misdiagnosed case, the system erroneously classified an object as an abnormality inside the fovea region generating a misclassification of the level of DR from severe to moderate. Considering only the images that were diagnosed by the system, we obtain correct diagnoses 90% of the time.

It is worth mentioning that the system's performance is also dependant on image resolution. As pointed out in [9], successful detection of small lesions is directly related to resolution. Further testing is required to better understand the system capabilities and required improvements.

5. REFERENCES

[1] National Society to Prevent Blindness. *Vision problems in the U.S.: a statistical analysis*. New York: National Society to Prevent Blindness, 1980.

[2] K. Estabridis, and R. Defigueiredo, "Blood Vessel Detection via a Multi-window Parameter Transform," *Proc. IEEE Symp. Computer-Based Medical Systems*, June 2006.

[3] K. Estabridis, and R. Defigueiredo, "Fovea and Vessel Detection via a Multi-resolution Parameter Transform," *Proc. SPIE Conf. Medical Imaging*, February 2007.

[4] P. Kahai, K. R. Namudiri, and H. Thompson, "Decision Support for Automated Screening of Diabetic Retinopathy," *Proc. IEEE Conf. Signals*, *Systems and Computers,* Nov. 2004.

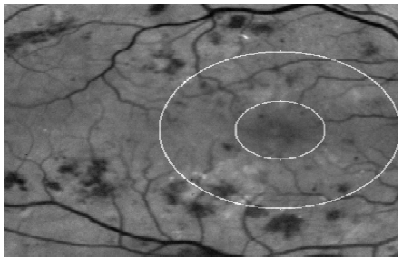
[5] C. I. Sanchez, R. Hornero, M. I. Lopez, and J. Poza, , "Retinal Image Analysis to Detect and Quantify Lesions Associated with Diabetic Retinopathy," *Proc. IEEE Conf. EMBS*, Sep. 2004.

[6] R. A. Simandjuntak, A. B. Suksmono, T. L. R. Mengko, and I. Sovani, "Development of Computer-Aided Diagnosis System for Early Diabetic Retinopathy based on Micro Aneurysms Detection from Retinal Images," *Proc. Int. Workshop Enterprise Networking and Computing in Healthcare Industry,* June 2005.

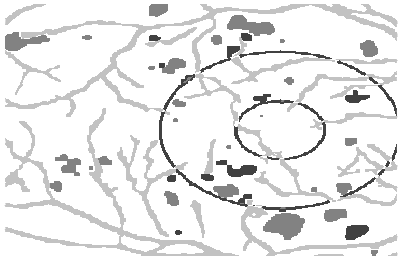
[7] X. Zhang, and O. Chutatape, "Top-down and Bottom-up Strategies in Lesion Detection of Background Diabetic Retinopathy," *Proc. IEEE Conf. CVPR*, June 2005.

[8] N. Hamadani, "Automatic target cueing in IR imagery", *Master's thesis, Air Force IT*, WPAFB, Ohio, Dec. 1981.

[9] B. Raman, E. S. Bursell, M. Wilson, G. Zamora, I. Benche, S. C. Nemeth and P. Soliz, "The Effects of Spatial Resolution on an Automated Diabetic Retinopathy Screening System's Performance in Detecting Microaneurysms for Diabetic Retinopathy," *Proc. IEEE Symp. Computer- Based Medical Systems*, June 2004.

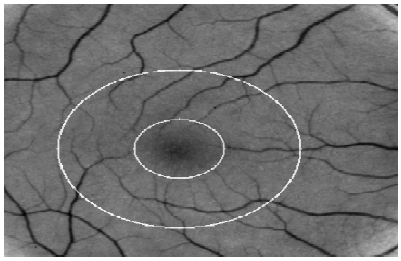


(a)



(b)

Figure 3. a) Input image. Inner circle indicates fovea / critical region. Outer circle indicates macular region. b) Light gray traces the vessel detected network, dark gray indicates bright lesions, and lighter gray indicates dark lesions. Classified as level 4 (severe DR).



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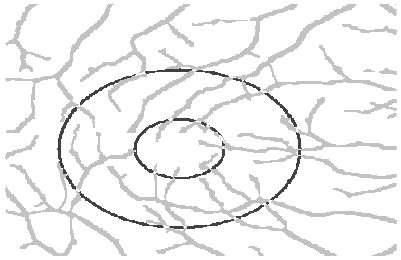

(b)

Figure 4. a) Original Image. b) Processed image, classified as level 1 (no DR).