Evaluating the Accuracy of Optic Nerve Detections in Retina Imaging Using Complementary Methods

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Abstract— **The detection of the optic nerve in retina images is a key element of detecting the anatomical structure of the retina. In this work we report on the fusion of two complementary optic nerve detection methods. The methods are complementary in the sense that they use different fundamental queues for locating the optic nerve. By fusing the methods through applying simple distance-based threshold, a confidence level may be assigned to the quality of the optic nerve detection. In a practical screening system this metric can be used to determine if the images should be immediately reviewed by a physician or if further automatic processing is feasible. We report on the results for two different data sets and show that the use of the threshold improves detection quality.**

Keywords— **Retina, optic disk, optic nerve, telemedicine**

I. Introduction

The World Health Organization estimates that 135 million people have diabetes mellitus worldwide and that this number will increase to 300 million by the year 2025 [1]. More than 18 million Americans currently have diabetes and the number of adults with the disease is projected to more than double by the year 2050 [2]. Visual disability and blindness have a profound socioeconomic impact upon the diabetic population and diabetic retinopathy (DR) is the leading cause of new blindness in working-age adults in the industrialized world [3]. Thus, there is a significant need to develop inexpensive, broad-based screening programs for DR.

In an overview of computer aided diagnosis of retina images [4], identifying the expected physiological features of the retina is a common initial step in automatic processing, as this helps to eliminate systematic structures in the imagery and also establishes a coordinate system for further analysis. In this paper we are concerned with the expected physiological features of the retina. The detection of anatomic structures is fundamental to the subsequent characterization of the normal or disease states that may exist in the retina. A critical structure in images of the human retina is the optic nerve (ON) which is also known as the "optic disk" due to its characteristic circular shape. An example of a retina image with the ON highlighted in black is shown in Figure 1.

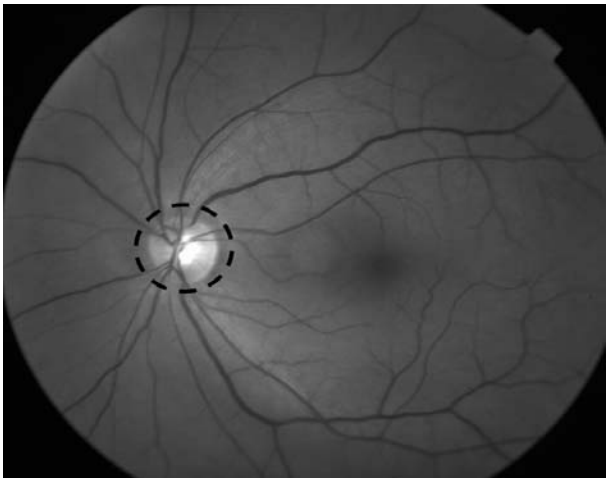

Fig. 1 Example retina image. The optic nerve is shown circled in black. The optic nerve is a key landmark in identifying the retinal structures.

In a practical computer-assisted diagnostic system as shown in Figure 2, after image capture a quality assessment [9] is undertaken followed by the location of anatomic structures, lesion detection and population description then automatic diagnosis using an image database as shown by the lower right pathway [11,12]. Physician diagnosis is crucial when initially populating the database, but even after full training, a level of physician oversight will be required. By controlling the quality of the image and the quality of the location of the anatomic structures, the performance of the overall system should be improved. In particular, in this paper we are concerned with detecting when automatic anatomic location methods are less reliable. Images where the quality of the anatomic detection is in question will

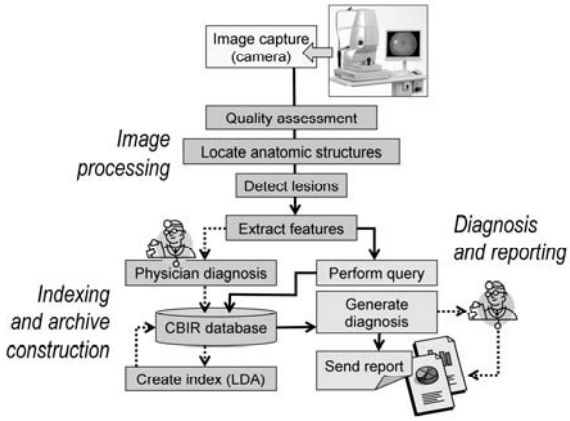

Fig. 2. Overview of system for retina screening. After image acquisition, a quality check is conducted followed by detection of physiological structures. In this work we are focused on estimating the accuracy of the detection of the optic disk.

require physician attention and thus should be rejected from further automatic processing.

In this work, we begin by reviewing the two optic disk detection methods which were discussed previously in [6,10]. We then discuss a simple strategy for fusing their results based on the Euclidean distance of their estimates. In the results section we discuss the data sets tested and the performance of the optic disk location algorithms with the fusion distance parameter. We conclude with some observations about the performance and expected future development.

II. Approach

A. Overview of optic nerve detection methods

The literature contains many examples of ON detection in retinal imagery. Many methods analyze the vasculature structure using techniques such as point distribution models of image structures [14], convergence of the vasculature [15], geometric models [16], and matched filters for the vessel direction [17]. Other methods (such as [13]) use models of the optic disk itself. In past work [6] we compared the model-based method of [13] to the likelihood-ratio based method of [10] (discussed below) and offered improvements to the former by using linear discriminant analysis or LDA. As a result of our comparison, we developed improvements to the model-based method that use additional information about the ON regions and non-ON regions of the training images to improve accuracy.

In this work we use the likelihood based method of [10] and the LDA method. Both methods have strengths in their approach. The method of [13] and by extension that of [6] uses principal component analysis to embody the main structure of the ON and does not require vasculature segmentation, but is more dependent on intensity variations in the image. The method of [10], which we identify as the FBLR for feature-based likelihood ratio, uses well-known classical Bayesian pattern recognition techniques [18]. The method requires a successful segmentation of the vasculature in the image, but is less dependent on intensity variations in the image.

B. Feature-Based Likelihood Ratio (FBLR) method

In the FBLR method of [10], the retinal image is processed by segmenting the vasculature with morphological reconstruction. Next, a set of four features are generated at each pixel. These features are the brightness of the pixel region, the thickness of the vasculature, the orientation of the vasculature, and the density of the vasculature. Optic nerve regions are labeled using the ON center and a surrounding area based on an estimate of the ON radius. A training set of data (with the optic disk hand-segmented by a non-clinical researcher) is analyzed to estimate the parameters of a Gaussian distribution describing the ON regions and the non-ON regions. We also use the hand-segmented training set to estimate the ON center probability density function (pdf). The pdf was estimated by summing the ON locations of the training set and convolving them with an averaging window whose size is set to the average ON diameter. This approximates the pdf of the ON location using Parzen windows [18]. The Gaussian parameters and the pdf are used to compute a likelihood ratio function using maximum a posteriori (MAP) estimation.

C. PCA-LDA-LR method

The model-based method of [13] uses principal component analysis (PCA) to capture the information content of a training set of optic nerve images. In this method, “candidate regions” of a retina image that may contain the ON are projected to PCA space, then the PCA coefficients are used to reconstruct the region and the residual error is measured. This process is repeated for all pixels in the candidate and the pixel with the smallest residual error is chosen as the ON location. In [6], we extended the method to include linear discriminant analysis (LDA). After generating the PCA coefficients for the training set, the reconstruction distances were calculated for the entire image of all training images. Twenty different pixels (the number is somewhat arbitrary) were chosen to comprise a data set in PCA space. We first selected the ON and masked it with a region the size of the average ON. We repeated this process on the five smallest reconstruction distances, which comprise a set

of training examples which are non-ON but score low on the reconstruction distance. Finally, we chose the remaining 14 vectors by randomly selecting pixels in the candidate region. The vectors corresponding to these twenty pixels were projected back to PCA space. After repeating this process for all images in the training set, LDA was employed to compute a transform to a one-dimensional space. This feature was then used to formulate a MAP likelihood ratio modelling the feature as a Gaussian random process. We call this method the PCA-LDA Likelihood Ratio method or PCA-LDA-LR.

D. Fusion methodology

In our past experiments with these and other methods, failures were typically due to large lesions that are roughly circular, or fall at the convergence of vertical vessels, or are near striations or other textural characteristics that are confused with the vasculature tree. In many cases where one method failed, the other would succeed. This suggests complementary methods could be used to test the effectiveness of a measurement. There are many potential means of comparison possible for the optic disk estimate. Determining the metric itself is still a topic of research, but for this work a very simple estimate of the position error was used: the distance between the two individual method estimates.

III. EXPERIMENTS

A. Data sets

In this study, two data sets were used. The first was composed of 370 retinal images representing 18 different retinal pathologies and normal (non-diseased) retina. These images were originally captured at a resolution of 12 microns per pixel. However, we processed at a smaller scale (roughly 100 microns per pixel) to improve speed of performance which will be essential for automatic screening purposes. Note that this image set (supplied by E. Chaum) represents an actual population from an ophthalmology practice and has a large number of abnormal retinas (326 abnormal or 88%) and also has large variability in the physiological structure of the ON. This set, which we will call Chaum370, represents individuals who have sought medical attention and are more advanced with respect to their DR variability than real broad-based screening data may encompass. The second dataset, dubbed Abramoff748, is composed of 748 images from a much larger data set supplied by Dr. M. Abramoff [7,8]. We selected a subset captured at 45 degree field of view, a common resolution of roughly 200 microns per pixel and macula-centered. This set represents a broad-based screening effort and is more representative of the type of set automatic screening would encounter in practice. All images in this set were rescaled so that the distance from macula to optic nerve was roughly the same scale as Chaum370. In both data sets, we processed only the green channel, and aligned the images so that the manually segmented ON was on the left side of the image. This was justified because in the type of system shown in Figure 2, the camera identifies the image as OD or OS. Both data sets were randomly separated into two equal sets for a 2-fold validation study. All experiments were performed using software created in the MATLAB programming environment on a standard desktop PC.

B. Feasibility of detection accuracy estimate

The testing portion of the 2-fold validation consists of computing the estimated location for both methods. The mean is taken as the final estimate, but the distance between the estimates is recorded as well, normalized to one ON radius. We then evaluate the performance as we increase the threshold for the distance between the original estimates from 0.1 ON radii to 4 ON radii in steps of 0.1.

In Figure 3 we show the results of the automatic detection of the optic disk. As the threshold is decreased between the individual method's estimates, the number of estimates within 1 ON radius increases, but the total images that pass the threshold test decreases (requiring more manual intervention). For Chaum370, screening 85% of the data allows 99% successful location of the optic disk location. When 100% of the images were screened, the location was found successfully 92% of the time. In 3b we show the results of the Abramoff748 data set. This data set is more representative of a broad-based screening population and shows better overall performance. Roughly 99% of the images have correct ON location estimate when screening 98% of the data (threshold 1.5 ON Radii). When performing 100% screening, the location was found successfully 98.5% of the time.

IV. CONCLUSIONS

In this work we examined how two complementary methods of optic disk detection can be used to estimate the quality or confidence of the accuracy of the optic disk detection. While we have shown empirically that the two complementary methods can be used to act as a screening mechanism for the ON detection accuracy, the larger issue is determining when the ON location estimate is correct. Excellent performance is obtained on the Abramoff748 data while the decrease in performance on the Chaum370 data set is due to its higher prevalence of diseased retinas.

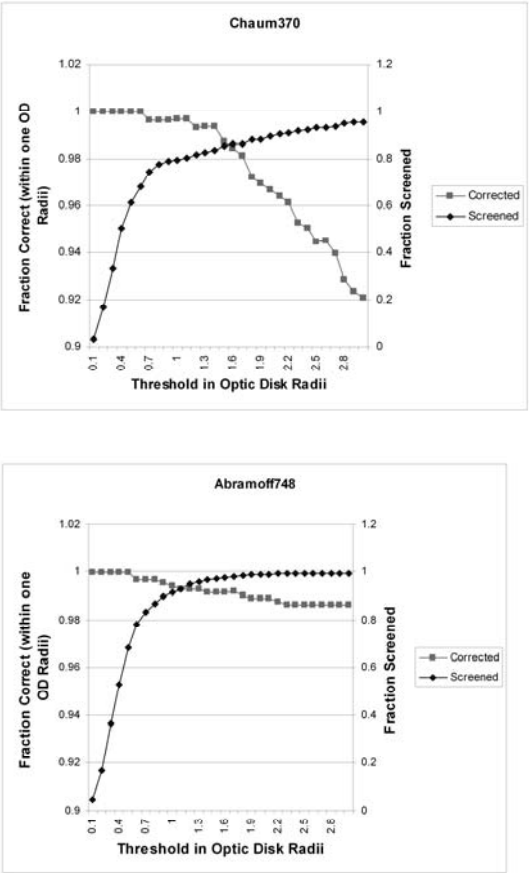

Fig. 3. Results of optic disk detection on (top) Chaum370 and (bottom) Abramoff748 data set. As the threshold increases between the individual method estimates, the number of images screened increases but the number that are correct (mean estimate within 1 ON radius) decreases.

Empirically a threshold of 1.5 gives good results, but this is may change with other data sets. Other methods of verification will be the subject of future investigations, as well as tests on additional data sets.

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