Focal Edge Association to Glaucoma Diagnosis

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Abstract-Glaucoma is an optic nerve disease resulting in the loss of vision. There are two common types of glaucoma: open angle glaucoma and angle closure glaucoma. Glaucoma type classification is important in glaucoma diagnosis. Clinically, ophthalmologists examine the iridocorneal angle between iris and cornea to determine the glaucoma type as well as the degree of closure. However, manual grading of the iridocorneal angle images is subjective and often time consuming. In this paper, we propose focal edge for automated iridocorneal angle grading. The iris surface is located to determine focal region and focal edges. The association between focal edges and angle grades is built through machine learning. A modified grading system with three grades is adopted. The experimental results show that the proposed method can correctly classify 87.3% open angle and 88.4% closed angle. Moreover, it can correctly classify 75.0% grade 1 and 77.4% grade 0 for angle closure cases.

I. INTRODUCTION

Glaucoma is an optic nerve disease resulting in loss of vision. It is often associated with increased pressure of fluid inside the eye. Two common types of glaucoma are open angle glaucoma (OAG) and angle closure glaucoma (ACG). Ophthalmologists examine the iridocorneal angle between iris and cornea to determine OAG and ACG. When the angle is open, it is OAG, otherwise, ACG. A detailed description of the angle structures can be found in [1]. Here we briefly explain why the iridocorneal angle is important. The iris, cornea, and lens are bathed in aqueous humor, which is continually produced by nearby tissues. The fluid moves out of the eye via the trabecular meshwork drainage. Blockage in the trabecular meshwork would lead to increased pressure in the eye. The trabecular meshwork is associated with the angle, thus, the iridocorneal angle is important. Because of different causes and specific treatments for different types of glaucoma as well as the necessity of urgent treatment of ACG, it is important to determine the glaucoma type early [2], which implies that it is essential to visualize the iridocorneal angle to make a correct diagnosis of the disease.

Gonioscopy is an eye examination that looks at the front part of the eye between the cornea and the iris. The drawback of this examination is that it requires considerable clinical expertise and effort as well as a full knowledge of the angle structures [3]. A new option with much more convenience is the RetCam (Clarity Medical Systems, Inc., Pleasanton, CA) camera, which is explored to capture the image of iridocorneal angle [3]. Ophthalmologists often examine four quadrants





(a) Original Image

(b) Iris Surface and angle structures

Fig. 1. Sample Iridocorneal Angle Image

including inferior, superior, nasal and temporal of an eye [4]. Fig. 1(a) shows a typical iridocorneal angle image from inferior quadrant of an eye. The angle which is of our interest is located at the boundary between the iris and the cornea. The arcuate line in Fig. 1(b) indicates the iris surface which is part of angle boundary. When there are other edges on the corneal side of the iris surface, as indicated by the black arrow in Fig. 1(b), it is an open angle, otherwise, closed.

Shaffer grading system [2] is widely used in gonioscopy to evaluate the angle status. Based on the visibility of the angle structures, the system assigns a numerical grade (0-4) to each angle with associated anatomical description and implied clinical interpretations [1]. In this paper, a modified grading system is adopted. Since the anterior trabecular meshwork cannot be identified through the angle images captured by the RetCam, grade 2 cannot be differentiated from grade 1 according to [1]. Thus, grade 2 is merged into grade 1. Moreover, as the clinical interpretation for grade 3 and 4 are the same: 'Closure Impossible', it is not important to differentiate them. In summary, the modified Shaffer grading system contains three grades: 1) Open for 'Closure Impossible', 2) Grade 1 for 'Eventual Closure Probable' and 'Closure Possible', 3) Grade 0 for 'Closure Present or Imminent'. This is a three-class classification problem. Manual grading is currently adopted clinically. However, it is subjective and time consuming due to ambiguous angle structures. Thus, an automated system for angle grading is beneficial to save workload of ophthalmologists.

Limited work has been done for automated angle image grading as the imaging modality appears only recently. In [4], the edges around strongest arc are used to determine ACG or OAG without estimating the degree of closure for ACG. One limitation of the approach is that some edges from inner iris are mistaken as edges from angle structures. In this paper, we propose to first locate the iris surface. The edges on the cornea side of the iris surface are then used. Besides the differentiation between ACG and OAG, we further tell the degree (grade 1 or 0) of closure for ACG. The rest of paper is organized as

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Fig. 2. Architecture of the Angle Image Analysis System

follows. In Section II, we introduce the system and methods in details. Section III shows the experimental results, followed by the conclusions in the last section.

II. METHODOLOGY

A system for automatic grading of the angle images is proposed. In the proposed system, focal edge is used for angle evaluation and the association between focal edge and the angle grades is built. Fig. 2 shows the architecture of the system. It contains the following main steps: quadrant determination, focal edge extraction, and grading.

A. Quadrant Determination

As the images can be from the inferior, superior, nasal and temporal quadrants of the eye, one important step for the automated diagnosis is to determine the quadrant. In order to do so, we make use of the strongest arc. The background is removed first by a threshold empirically remove background and selected to segment the effective image area. Then, Canny edge [5] followed by circular Hough transform [6] similar to that in [4] is used to obtain the strongest arc. Assuming $(x_i, y_i), i = 1, 2, \dots, N$, are the coordinates of all points from the arc, where top-left corner is defined as (1, 1) and bottom-right corner as (m, n), N is the number of points. The function to determine the quadrant Q is given as ¹:

$$Q = \begin{cases} \text{Superior, if } x_c - \bar{x}_i \ge |y_c - \bar{y}_i| \\ \text{Inferior, if } \bar{x}_i - x_c \ge |y_c - \bar{y}_i| \\ \text{Nasal, if } y_c - \bar{y}_i > |x_c - \bar{x}_i| \\ \text{Temporal, if } \bar{y}_i - y_c > |x_c - \bar{x}_i| \end{cases}$$
(1)

where $(\bar{x}_i, \bar{y}_i) = (\frac{1}{N} \sum_{i=1}^N x_i, \frac{1}{N} \sum_{i=1}^N y_i)$ is the mean of the coordinates, (x_c, y_c) is the center of the detected strongest arc.

B. Focal Edge

Focal edge refers to edges associated with certain objects or structures. In this paper, it refers to edges associated with angle structures. In order to find the focal edges, the strongest arc from the circular Hough transform is first obtained. Then we locate the iris surface, i.e., the arcuate line in Fig. 1(b), as it is visible in both open angle and angle closure. For angle closure, the iris surface is normally the strongest edge in the nearby area of the strongest arc. However, for open angle, edges from other angles structures can be stronger. In this paper, the iris surface is located as follows.

Without losing generality, assuming that the image is from inferior side of an eye as in Fig. 3(a). Given $L_j(x) = I(x, j)$, $x = 1, 2, \dots, M$, from the j^{th} column of the image I. Assuming L_j crosses with the strongest arc at x_j . Inspired





Fig. 3. Focal edge: Red: strongest arc, Blue: Canny edge

by the observations on iris surface, we search for the point with strongest ascending edge (from iris to cornea) from pixels around x_i in L_i (the pixels between the two white arrows in Fig. 3(a)) and get its coordinate x_k . Among all ascending Canny edge within $(x_k - w, x_k)$ as well as x_k itself, the point closest to the pupil is used as the candidate iris surface point in this column. Here, w is set to be the estimated maximum angle width. Finally, curve fitting is applied based on all candidate points located in the last step. In this paper, the iris surface is modelled as part of circle and a circular Hough transform is applied again to find the fitted curve with circular center (x_c, y_c) and radius r. After obtaining the estimation of iris surface highlighted in green as shown in Fig. 3(b), another circular arc can be determined based on the same circular center (x_c, y_c) with a larger radius $r + \delta r$. The parameter δr is set to be slightly larger than w. The region in between is the focal region and the edges within the region is the focal edge.

C. Grading

In manual grading, the ophthalmologists examine the structures seen and then convert to grades (0, 1, or Open). In the automated grading, we use the estimated iris surface as the start point of the angle. In the following, we estimate the end point of the angle and the distance between them is computed as the width of the angle.

1) Angle Width Profile Computation: As mentioned in [4], the angle width is a critical measurement. The angle width is the distance between two imaginary tangent lines constructed to the inner surface of the trabecular meshwork and the anterior iris surface, respectively. In last section, we have estimated the iris surface. However, identification of trabecular meshwork requires much efforts especially in the presence of other angle structures. In this paper, we use the Canny edge as well as the iris surface in the focal region as possible angle boundary. For images taken from the superior and inferior quadrants, we take the top and bottom edges from each column as borders of angle area. The distance in between is the computed angle width in this column. The distance values from all columns form the width profile. For columns without Canny edges within the focal region, the angle width is zero. For images from the nasal and temporal quadrants, the computation is similar except that we process on each row and we take the leftmost and rightmost edges in rows. As the width



Fig. 4. Strongest arc and estimated iris surface for some iridocorneal angle images: Red: strongest arc, Green: estimated iris surface, Blue: ground truth points. The first and second rows are from eyes with OAG and the last row is from an eye with ACG.

profiles from different quadrant often have different lengths, the profile cannot be compared directly. In order to get unified feature with same dimension, we use same amount of widths sampled from the width profile. Moreover, as the blur happens often in two sides of the image, we use central portion only. By doing so, we extract an unified feature from the image.

One major difference between the approach here and the approach in [4] is that the strongest arc from previous approach can be any part from the angle structures. Thus, edges from both sides of the strongest arc are used previously. When iris surface is located, only the edges on the corneal side need to be considered. Thus, the chance of false detection of the edges from inner iris as angle structures is reduced.

2) Classification: Recall in the threshold approach in [4], the mean angle width is computed and a threshold T_1 is used to differentiate open angle from angle closure. As mentioned earlier in the introduction, we further tell the degree of closure for angle closure glaucoma. For the threshold approach, we can introduce another threshold T_2 to differentiate grade 1 from grade 0. We compute the mean width \overline{w} as in [4]. For an image with mean width \overline{w} , its grade $G(\overline{w})$ is computed as:

$$G(\overline{w}) = \begin{cases} Open & \overline{w} \ge T_1 \\ 1 & T_1 > \overline{w} > T_2 \\ 0 & \overline{w} \le T_2 \end{cases}$$
(2)

Although the threshold approach is simple and straightforward, the computing of the mean angle width may overlook some information, e.g., the width distribution, and etc. In practice, some angles can be partially closed. In this paper, we propose to use the width profile as the feature instead of its mean. Machine learning is applied for the classification of images with different grades.

We use support vector machines as the optimization tools for solving machine learning problems. The LIBSVM [7] is used in our experiments as a powerful classifier. In our method, we implement a three-class classifier using a two-tier system with two sub-classifiers. Classifier one is trained to get the classification between angle closure and open angle. Classifier two is trained to differentiate grade 0 from grade 1. In the testing, classifier one is applied first to differentiate angle closure from open angle. For angle closure, it would be further classified to grade 1 or grade 0 using classifier two.

III. EXPERIMENTAL RESULTS

A total of 1866 images as in [4] are used. The images are graded by ophthalmologists manually. The breakdown of the images are as follows: 1149 images are graded as open, 421 images are graded as 1, and 296 images are graded as 0. The above grading is used as the ground truth. The results by the proposed method as well as prior method are compared using this ground truth.

Locating the iris surface is a critical step. Fig. 4 shows results from some sample images. The lines in red are the strongest arcs obtained by method as in [4]. The lines in green are the estimated iris surface by the proposed method. Although ground truth is difficult to obtain for all points in all images, we manually mark three points evenly along the iris surface as ground truth points, as shown by the crosses in blue.



Fig. 5. Accuracies of gradings by two classifiers at different thresholds

Method		Prior [4]	Proposed
Classifier	Open	80.3%	87.3%
One	Close	80.3%	88.4%
Classifier	1	70.6%	75.0%
Two	0	71.3%	77.4%

 TABLE I

 Performance of the two-class classifiers

The distances between these points and the two lines in green and red (not visible if it overlaps with the green line) are the localization errors. The first two rows are from patients with OAG. The third row is from patients with ACG. Comparing the lines in green with the stars in blue, the proposed method estimates the iris surface well while the strongest arc does not work well for most OAG examples. However, it is too tedious to manually mark the ground truth for all images. Instead, the grading accuracy is used as the measurement.

In the threshold based approach, the selection of the two thresholds are critical. In order to select them properly to have best performance, we look into how the threshold selection affects the classifications, as shown in Fig. 5. Two thresholds T_1 and T_2 are determined to maximize the total accuracies in the classification between grade open vs. closed and grade 1 vs. grade 0, respectively.

In the machine learning approach, two classifiers are trained. In the first classifier for classification between open and angle closure, half of the images from all grades are used as set one and the other half are used as set two. The images from same eye quadrants are either in set one or set two, but not both. In the training, same number of images from angle closure and open angle from set one are used. A cross-validation is used in the training to determine parameters for the LIBSVM [7]. The trained model is used to test on set two. After that we swop the two sets and applied the training and testing again to get the performance on set one. Finally, the accuracy is computed as the average of the two testing. In the second classifier for grade 1 and grade 0, a similar procedure is done. It should be noted that we achieve the three-class classification through a two-tier system instead of one against one or one against all as in [8] as the classification between angle closure and open angle is more important than that of grade 1 and grade 0.

Table I shows the results of the two-class classifiers in comparison with prior method [4]. As shown in Table I, the proposed method improves the accuracies by 7.0% and 8.1% compared prior method for classification between open and closed angle. For classification between grade 1 and grade 0, it improves by 4.4% and 6.1%.

		Predicted		
	Grading	Open	1	0
Actual	Open	80.3%	14.5%	5.2%
	1	29.5%	43.2%	27.3%
	0	8.8%	19.9%	71.3%

TABLE II Confusion matrix by prior method

		Predicted		
	Grading	Open	1	0
Actual	Open	87.3%	6.8%	5.9%
	1	13.8%	64.6%	21.6%
	0	8.5%	18.9%	72.6%

TABLE III Confusion matrix by proposed method

We then compute the confusion matrices of the three-class classifiers. Table II shows the results by the mean angle width approach as similar in [4], extended to three-class. Table III shows the results by the proposed method. Comparing them, we can see that the machine learning approach improves the accuracies by 7.0%, 23.4%, and 1.3% for open, 1, and 0, respectively. The improvement for grade 0 is minimal as the width distribution does not provide much more information.

IV. CONCLUSION

In this paper, we propose a new system for automated iridocorneal angle image grading. The proposed method uses focal edge via locating the iris surface. The association between focal edge and angle grades is built through machine learning. Experimental results show good agreement with manual grading in ACG and OAG classification. It provides an automatic classification of angle closure and open angle. Moreover, for angle closure, it tells the degree of closure by grading 1 or 0. Automatic grading of the iridocorneal images is a challenging work due to ambiguous angle structures in some images. Further analysis of the angle would be done to improve the grading accuracy. More images from new patients would be included to evaluate the performance of the system.

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