31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

An Automatic Diagnosis System of Nuclear Cataract Using Slit-lamp Images

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***Abstract*—An automatic diagnosis system of nuclear cataract is presented in this paper. Nuclear cataract is graded according to the severity of opacity using slit-lamp lens images. Anatomical structure in the lens image is detected using a modified active shape model (ASM). Based on the anatomical landmark, local features are extracted according to clinical grading protocol. Support vector machine (SVM) regression is employed to train a grading model for grade prediction. The system is tested using clinical images and clinical ground truth. More than five thousands slit-lamp images were tested. The success rate of feature extraction is 95% and the mean grading difference is 0.36. The automatic diagnosis system can help to improve the grading objectivity and save the workload of ophthalmologists.**

I. Introduction

THE number of blind people worldwide has been projected to 76 million by 2020 [1]. Statistics show that cataract causes half of blindness throughout the world [2]. Some possible risk factors for cataract development have been suggested, but there is no confirmed prevention of cataract [3]. Nearly normal visual function can be restored by cataract surgery with the use of an intraocular lens. Accurate diagnosis and timely treatment of cataract are essential to prevent vision loss.

The normally transparent lens is located immediately behind the iris in the human eye. It is an oval structure with three layers from center to surface: the nucleus, the cortex and the capsule. The clouding or opacity of the lens is called cataract. There are mainly three types of age-related (senile) cataract defined by their clinical appearance: nuclear, cortical, and posterior subcapsular [4]. Nuclear cataract, the commonest among the three types, is the focus of this paper. Clinically, cataract is diagnosed via slit-lamp assessment where a grade is assigned to provide a quantitative record of cataract severity by comparison with standard photos [5]. These clinical classification systems are subjective and they are also time-consuming for population study.

Computer-aided diagnosis has the advantage of objectivity and reproducibility. Automatic diagnosis of nuclear cataract using slit-lamp images has been investigated by several research groups. The Wisconsin group [6-7] extracted anatomical structure on the visual axis. Sulcus intensity and intensity ratio between anterior and posterior lentil were selected as features and linear regression was performed for automatic grading. The Johns Hopkins group [8] analyzed the intensity profile on visual axis and three features were extracted: nuclear mean gray level, slope at the posterior point of profile, and the fractional residual of the least-square fit. Neural network was trained to determine the grade of nuclear opacification. All these studies only utilized the features on the visual axis, whereas the whole area of lens nucleus is analyzed in the clinical diagnosis [5]. Also none of these systems was validated by a large amount of clinical data.

An automatic diagnosis system of nuclear cataract is described in this paper. Compared with the available work, more meaningful features are extracted in our system. The proposed automatic diagnosis system has been validated using more than five thousands clinical images with their clinical grading results.

II. Approach

The flowchart of our automatic diagnosis system is shown in Fig.1. Some initial work of the system has been published in [9-10]. The improvement of the system includes the following aspects: (1) A new thirty-eight point shape model is proposed to include the structure of the nucleus in the lens; (2) More features are extracted for the grading; (3) The system is validated using a large amount of clinical data.

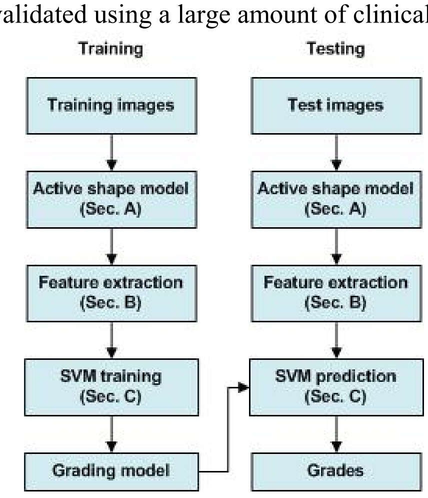

Fig. 1. Flowchart of the system

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A. Anatomical Lens Structure Detection via a Modified ASM Method

In the lens structure detection, the first step is to locate lens position. The corneal bow is identified using thresholding and clustering. The corneal bow is the leftmost (for right eye) or rightmost (for left eye) bright vertical curve in the slit-lamp image. The lens center and radius are further detected using horizontal profile and vertical profile clustering. The lens is thus estimated as an ellipse. This localization is utilized to initialize the active shape model (ASM) for lens structure detection because ASM is a local searching method.

The contour of lens and its nucleus are detected using a modified ASM method [11]. The shape of the lens structure is described by a thirty-eight point distribution model as shown in Fig.2. Besides the lens contour described in the previous model [9-10], the contour of the lens nucleus is added in this new model. The opacity in the nucleus region is the main area in the assessment of nuclear cataract. Therefore the new model is more meaningful for feature extraction.

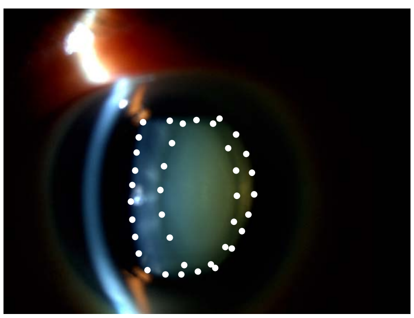

Fig. 2. The shape model on a slit-lamp image

Ten images were selected as the training set and the landmark points of the shape model were annotated manually. Principal component analysis (PCA) is applied to the aligned training shape to get the shape model. For a test image, ASM method [12] can fit the non-rigid shape in a new image. Two improvements were proposed in the modified ASM method to fit the shape model in a new image more robustly. The improvement includes adding the self-adjusting weight in the transform between shape space and image space and excluding the outlier in the projection of shape parameter. The main purpose of these improvements is to avoid the influence of the misplaced matching points in the detection. The details of the modified ASM method can be found in [11].

The modified ASM method is an iterative searching procedure and convergence of the shape is evaluated to stop the iteration. The final shape of the lens can be obtained using the method and the regions inside the lens and inside the nucleus can be defined using the landmark points. The location of visual axis and posterior subcapsular reflex can also be obtained using the related landmark points.

B. Feature Extraction

Based on the detection of anatomical lens structure, features are extracted for diagnosis. The features were selected according to clinical lens grading protocol [5, 13]. The feature description is listed in Table 1.

Table 1 Feature table for nuclear cataract diagnosis

Feature	Description
1	Mean intensity inside lens contour
2-4	Mean color inside lens contour
5	Mean entropy inside lens contour
6	Mean neighborhood standard deviation inside lens contour
7	Mean intensity inside nucleus contour
8-10	Mean color inside nucleus contour
11	Mean entropy inside nucleus contour
12	Mean neighborhood standard deviation inside nucleus contour
13	Intensity ratio between nucleus and lens
14	Intensity of sulcus
15	Intensity ratio between sulcus and nucleus
16	Intensity ratio between anterior lentil and posterior lentil
17-18	Strength of nucleus edge
19-21	Color on posterior reflex

For all the features related to color, the HSV color space is selected to represent the color information. For feature 1~6, the measurement is averaged within the lens contour detected by the modified ASM method. Similarly, the measurement is averaged within the region of lens nucleus for feature 7~12.

The intensity distribution on a horizontal line through central posterior reflex is obtained to analyze visual axis profile. Low-pass Chebyshev filter is applied to smooth the profile. The positions of anterior lentil edge and posterior lentil edge are identified by edge detection. The intensity ratio between anterior lentil and posterior lentil and the strength of nucleus edge are calculated based on the visual axis profile. The horizontal position of sulcus is defined as the median point of nucleus edges. The intensity of sulcus is calculated, which is a very important feature to decide the grade of nuclear cataract clinically.

Other features such as intensity ratio between sulcus to nucleus and the ratio between nucleus to lens are measured for grading the severity of lens opacity. The color information on the posterior reflex is extracted as well.

C. Automatic Grading via SVM Regression

Support Vector Machines (SVM) regression [14], a supervised learning scheme, is employed here for the purpose of grade prediction. The training procedure of SVM can be described as the following optimization problem:

$$\min \quad \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i + C \sum_{i=1}^{N} \xi_i^* \qquad (1)$$

with the condition of

$$\begin{aligned} & y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i \\ & \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0 \end{aligned} \qquad (2)$$

where x_i denotes the feature vector of training sample i and y_i represents its associated grade (label), < , > denotes the dot product, w is the vector of coefficients, C > 0 is a regularization constant, b is an offset value, and ξ_i, ξ_i^* are the slack-variables for pattern x_i.

In testing, the features x are extracted first for a testing image. Then the grade of the testing image is predicted by

$$f(x) = \langle w, x \rangle + b \qquad (3)$$

III. Results

A. System Interface

The user interface of our system is illustrated in Fig.3. The main menu includes: Load Image, Feature Extraction and Predict Grade. The interface is simple and straightforward for usage in clinics. For a large amount of images, the system has a batch processing mode to process all the testing images together.

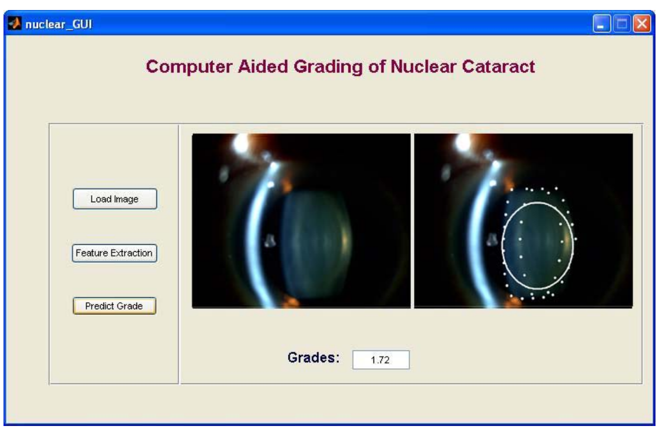

Fig.3. The user interface of the automatic diagnosis system

B. Data Description

The system was tested using the slit-lamp images from a population-based study, the Singapore Malay Eye Study [15]. The sampling frame consisted of all Malays aged 40-79 living in designated study areas in South-West of Singapore. A digital slit-lamp camera (Topcon DC-1) was used to photograph the lens through dilated pupil. The images were saves as 24 bit color images with the size of 1536 *2048 pixels. Totally 5820 images from 3280 subjects were tested.

The ground truth of clinical diagnosis of nuclear cataract is provided which followed the Wisconsin cataract grading system [13]. The range of the grade is from 0.1 to 5, in which the grade of 5 indicates the most serious case of nuclear cataract.

C. Experimental Result and Discussion

Our approach of lens estimation and lens structure detection was tested using 5820 slit-lamp images. Some examples of the detection results are shown in Fig.4. From these examples, it can be noted that the lens localization and structure detection are satisfactory though the size and location of lens may vary.

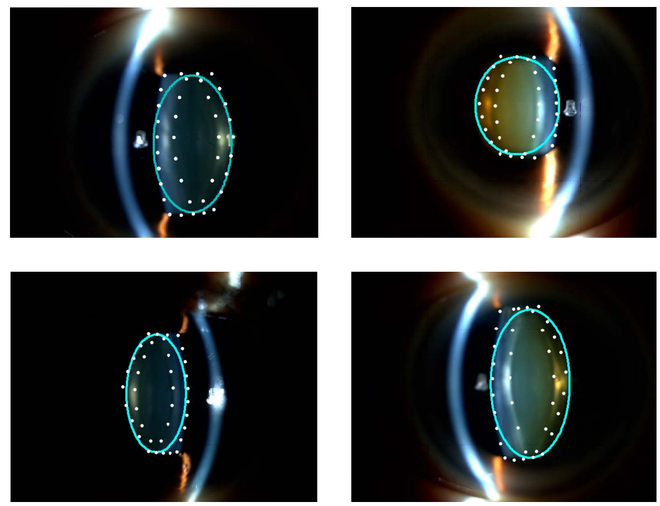

Fig.4. Examples of lens estimation and structure detection. The ellipse represents the estimation of lens localization and the white dots stand for the detected contour of lens and nucleus.

Table 2 Statistical analysis of feature extraction

	Lens Localization	Lens Structure Detection
Testing images	5820	5820
Wrong detection	23	69
Partial detection	161	222
Success detection	5636	5529
Success rate	96.8%	95%

The statistics of the feature extraction is shown in Table 2. The overlap between the automatic detection and the real lens structure is evaluated visually. The success detection is defined if the automatic detection matches the lens structure well. When the overlap is between 80%~100%, the detection is categorized as partial detection. The detection is categorized into wrong detection if the overlap is less than 80%. As ASM is a local searching method, all the wrong localization of lens will lead to wrong structure detection. For some images with the slightly deviated lens estimation, the modified ASM method can converge to the contour of lens structure. Our system can achieve 95% success rate for feature extraction. Currently the images with wrong detection of lens structure (69 images) were excluded in the automatic grading. The user interface can be improved later to include user interaction function so that any wrong detection or partial detection can be corrected.

There are 161 images marked by the clinical grader as not gradable and these images were excluded in the evaluation of automatic grading. One hundred images were used as the training set in the SVM regression. The images were classified into five group according their clinical grading (0-1, 1-2, 2-3, 3-4, 4-5) and twenty images from each group were selected as the training set. The rest images (5490 images) were used as test set and their severity of nuclear opacity is automatically diagnosed using the SVM regression to predict the grades. The comparison between the automatic grades and clinical grading results were performed. The comparison results were illustrated in Fig. 5. Taking the clinical grading as ground truth, the mean error of the automatic grades is 0.36. The errors were further analyzed as shown in table 3. It can be seen that the grading errors for 96.63% of the test images were less than one grade difference, which is the acceptable difference in clinical diagnosis.

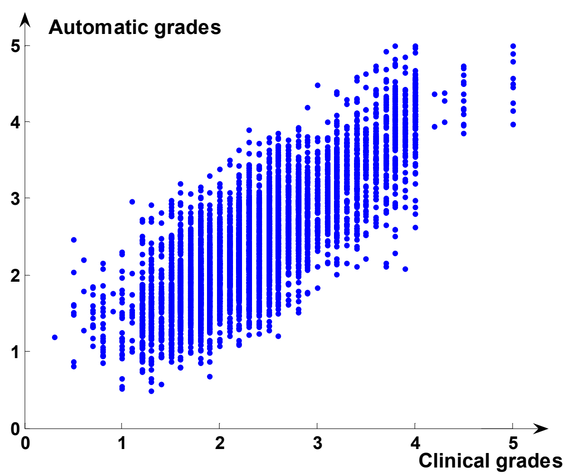

Fig.5. Evaluation of automatic diagnosis (5490 images)

Table 3 Statistics of grading error (5490 images)

Error	No. of Images	Percentage
0~0.5	4062	73.99%
0.5~1	1243	22.64%
>1	185	3.37%

IV. Conclusion

An automatic diagnosis system is presented in this paper to diagnose nuclear cataract. Novel feature extraction scheme is proposed and the system is tested using clinical images and clinical grading results. Over five thousands slit-lamp images were tested. The success rate of feature extraction is 95% and the mean error of automatic grading is 0.36. This is the first automatic nuclear cataract diagnosis system that have been tested and evaluated using a large amount of clinical data. The promising experimental results show that the system can be utilized to facilitate clinical diagnosis.

Acknowledgment

We would like to acknowledge Singapore A*STAR SBIC grant of “Singapore Retinal Image Archival and Analysis Network (SiRIAN) for Disease Prediction” for providing clinical data. We want to express our gratitude to Prof. Paul Mitchell, Prof. Jie Jin Wang and Ms Ava Tan from the University of Sydney, Australia for providing technical inputs and providing the ground truth of cataract grading.

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