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Automatic Detection of Cortical and PSC Cataracts Using Texture and Intensity Analysis on Retro-illumination Lens Images

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Abstract— **Cataract remains a leading cause for blindness worldwide. Cataract diagnosis via human grading is subjective and time-consuming. Several methods of automatic grading are currently available, but each of them suffers from some drawbacks. In this paper, a new approach for automatic detection based on texture and intensity analysis is proposed to address the problems of existing methods and improve the performance from three aspects, namely ROI detection, lens mask generation and opacity detection. In the detection method, image clipping and texture analysis are applied to overcome the over-detection problem for clear lens images and global thresholding is exploited to solve the under-detection problem for severe cataract images. The proposed method is tested on 725 retro-illumination lens images randomly selected from a database of a community study. Experiments show improved performance compared with the state-of-the-art method.**

I. INTRODUCTION

Cataracts are clouds in the lens, causing opacities that obstruct the passage of light which gradually impairs vision, and may lead to total blindness if untreated. Cataracts reduce the sharpness of the images perceived by the eye and color perception may be hindered [1]. It is the leading cause of blindness in most regions of the world except for the most developed countries [2].

The three most common types of cataracts are nuclear cataract, cortical cataract and posterior subcapsular (PSC) cataract. Nuclear cataract is diagnosed using slit-lamp images while cortical and PSC cataracts are detected on retro-illumination images. In this paper, we focus on the detection of the opacity of both cortical and PSC cataracts using retro-illumination images. A retro-illumination lens image with presence of both cortical and PSC cataracts is shown in Fig. 1.

There are a few clinical cataract classification systems. For Lens Opacities Classification System III (LOCS III) [3], a set of standard images with different degrees of opacity is provided. The subject's retro-illumination lens image is compared with the set of standard images and a grade is assigned accordingly. Another system uses the Wisconsin grading protocol, and assigns grades based on the percentage coverage of cataracts on the lens [4].

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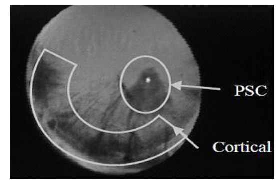

Fig. 1. Retro-illumination image with presence of cortical and PSC opacity.

There are several problems associated with manual grading that are difficult to overcome if not impossible. Human error arises from estimations, making the process highly subjective. The process is also time-consuming as it takes five to ten minutes to grade one image by a trained grader. The experience of the graders also plays a role in the accuracy of the grading. Lastly, manual grading is highly inconsistent as it has been shown that the same grader cannot give exactly the same grade at two different time instances [4].

Several existing methods are available to diagnose cataracts automatically. The Nidek EAS-1000 software [5] uses global thresholding. The method has inherent limitation as uneven illumination is common for retro-illumination lens image. An improvement method using contrast-based thresholding is proposed in [6]. Research efforts had also been made to give a better detection, extending their work to detect only cortical cataracts [7] and PSC cataracts [8]. The latter two methods demonstrate very promising results. However, the under-detection of severe cataract and over-detection of mild cataract or clear lens are unsolved, which decreases the performance.

In this paper, we proposed a new method which makes no distinction between cataract types. The proposed method investigates a more accurate and precise detection and improves the performance from three aspects compared to [7] and [8]. Firstly, texture-based ROI (Region Of Interest) detection is proposed, which is more robust to reflective noise than the edge-based method. Secondly, the boundary of the lens is approximated as a circle curve only locally to give a more accurate mask compared to a global fitting of an ellipse. Thirdly, a more effective method is proposed to achieve better performance of cataract detection. In [7], cortical cataract is detected by using a combination of radial edge detection and local thresholding along angular direction, followed by region growing. In [8], global thresholding is used to classify the image into either a clear lens or one with opacity. For a lens with opacity, the angular edge detection and local thresholding along radial direction is applied to detect PSC. Edge filtering detects the boundary

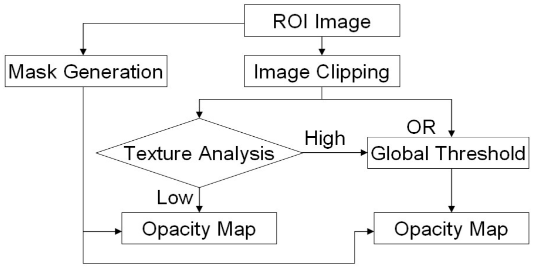

Fig. 2. Flowchart of the cataract detection method.

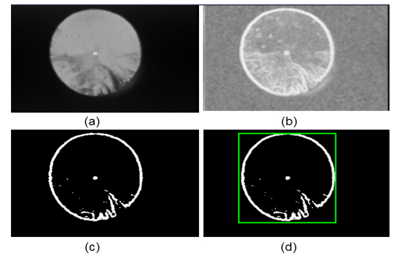

Fig. 3. Processing steps of ROI detection. (a) Original Image. (b) After local entropy filtering. (c) After global thresholding. (d) Cropped ROI based on the outline of the result in (c).

of the opacities that correspond to high gradient region and local thresholding detects the inner patch of the opacities based on the local contrast along certain direction. Although the method can differentiate the cortical cataract from PSC cataract to some extent, the method suffers over-detection for clear lens with uneven illumination or white artifact, and under-detection for severe cataract wherein the boundary of opacity is blur and the local thresholding also fails for the large patch of dense opacity. To overcome the over-detection issue, the proposed system applies image clipping method to remove the white artifact and texture filtering that is robust to uneven illumination. Texture analysis has a good performance for clear lens, lens with moderate cataract and PSC opacities with lacy structures. However, it fails for large patch of dense opacities which results in under-detection for severe cataract. To solve the under-detection issue, the proposed system exploits both global thresholding and texture analysis techniques. Global thresholding works well for dense opacity patch wherein the local thresholding, edge detection and texture analysis fail.

II. METHODOLOGY

Fig. 2 illustrates the procedure of the proposed cataract detection method. The proposed method has three major parts, i.e., pupil extraction (ROI detection), lens mask generation and cataract detection. The pupil is firstly extracted to obtain the ROI image. To exclude the four corner regions of the ROI image as shown in the lower left image in Fig. 4, a lens mask is generated. The opacity is detected on the ROI image through texture and intensity analysis. The lens mask is applied to the opacity map to exclude the background and the grade of the cataract is computed within the lens area. The details of each part will be presented in the following subsections.

A. Pupil Extraction (ROI Detection) Using Texture Analysis

The first step is to extract the ROI which is the pupil area. In the works of [7] and [8], the pupil region is detected in three steps. Firstly, Laplacian and Canny edge detectors are applied to the image. Then, the detected edge is filtered based on the convex hull. A non-linear least square fitting method is finally used to fit an ellipse mathematically to the edge points on the convex hull. Investigations show that ellipse fitting is not robust to irregularly shaped lens, and Laplacian and Canny edge detections are susceptible to noise.

To improve the robustness, the proposed method applies texture analysis to detect the ROI. More specifically, local entropy filtering is used to measure the texture of the image. Local entropy filtering is a statistical measure of randomness in a local window that is defined in Eq. (1) [9].

$$H = -\sum_{i} p_i \log_2 p_i, \tag{1}$$

where i represents the intensity value and p_i is the probability distribution of the intensity i of the pixels within the local window. As edges correspond to regions of rapid change of intensities, they tend to have high entropy values. On the other hand, background pixels of constant intensity correspond to regions of low texture, hence they have lower entropy values. Global thresholding is performed to convert the entropy profile into a binary image which defines the outline of the pupil region well. Cropping is then done based on the pupil outline defined by global thresholding. Fig. 3 illustrates the procedure of the proposed ROI detection method.

B. Lens Mask Detection and Reconstruction in Polar Coordinates

The next step involves obtaining the mask of the lens which gives us a binary image with the white pixels representing the lens area. In the works of [7] and [8], the mask is obtained using ellipse fitting, and the problems are similar to that in the pupil extraction whereby the masks of irregularly shaped lens will be poorly defined. Fig. 4 illustrates the procedure of the proposed mask detection and the details of the processing steps are described as follows.

1) Starting from the pupil region, an approximate outline of the lens is obtained using a combination of texture analysis, global thresholding and thinning the result to one pixel thick.
2) The approximate lens outline is transformed into the polar coordinates. As circles and ellipses in the Cartesian coordinate system are transformed into lines in the polar coordinates if the centers of the circles or ellipses are taken as the origin of the Cartesian system, the outline of the lens should approximate a line in the lower part of the polar image. Due to the reflective noise on the background or the inaccurate detection caused by opacity, e.g. in Fig. 3 (c), the outline of the lens is rugged.

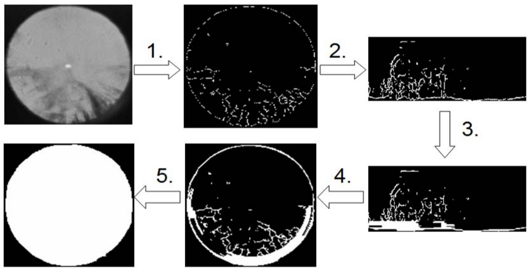

Fig. 4. Diagram to illustrate the processing steps of lens mask generation.

3) Assume that the local region of the lens boundary can be approximated by a circle segment which corresponds to a horizontal segment in the polar image, the lower part of the polar image is smoothed to enclose the outline of the lens.
4) The polar image of the lens outline is converted back to Cartesian coordinates, and the outcome is a smoother and enclosed lens outline. Canny edge detection is added to the lens outline to improve edge localization.
5) Region filling of enclosed areas with white pixels to complete the mask.

The proposed method obtains more accurate boundary of the lens mask since it is only locally approximated to a circle segment. Fig. 5 shows some examples of the masks generated by the proposed method.

C. Cataract Detection

As mentioned in section I, to overcome the over-detection and under-detection problems, image clipping is applied first to remove the bright spots in the retro-illumination image. Then the proposed method uses texture analysis to classify the image into two categories. One category is clear lens or lens with light opacity. The other category is lens with moderate or severe opacity. For clear lens, only texture filtering is applied to obtain the final result. While for non-clear lens, both global thresholding and texture analysis using local entropy are exploited to detect the opacity. Fig. 2 illustrates the procedure of the proposed cataract detection. The steps are described in detail as follows.

1) Image Clipping: This is a pre-processing method performed on the pupil image to remove the bright spots on the lens caused by either unusual artifacts present or a small white spot usually located at the center of the lens. This central white spot is caused by light reflecting off the cornea.
2) Texture Analysis: From the texture analysis, images can be classified into either a clear/light opacity lens or a lens with moderate/severve opacities. The difference in textures of a clear lens and a lens with cataracts makes texture analysis suitable for lens classification.
3) Detection of Clear Lens: Texture analysis is utilized for the clear lens. Local entropy filtering is robust to uneven illumination which is commonly found in clear lens. Thus, the uneven illumination will not be detected as cataracts using local entropy filtering.
4) Detection of Cataracts in a Non-clear Lens: For the non-clear lens, both texture filtering and global thresholding are applied. The logical OR operator is used between the two results. Texture analysis enables good detection of cataract edges, while global intensity thresholding enables the detection of the darker regions within the cataracts.

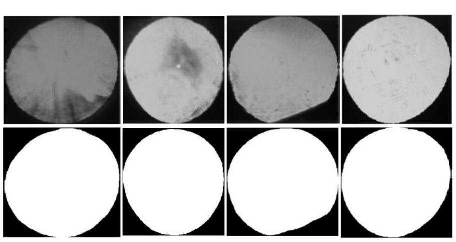

Fig. 5. Examples of masks generated by the proposed method.

III. RESULTS AND DISCUSSIONS

A. Data Description

Both the proposed and existing algorithms [7], [8] are tested using retro-illumination images obtained from a population-based study, the Singapore Malay Eye Study (SiMES), which comprises of 3280 Malays aged 40 to 80 in Singapore, and 6526 lens images. To reduce the evaluation work load, a small database of 2500 lens images is randomly selected to evaluate the ROI detection method, and another small database of 725 lens images randomly selected is used to test the effectiveness of mask generation and cataract detection. To make the small database a good representation of the original large database, we keep the ratio between the different degrees of cataracts according to graders' grading results based on Wisconsin Protocol.

B. Pupil Extraction (ROI Detection)

Subjective evaluation is used to evaluate the effective of both pupil extraction methods. A range of 4 scores are given, with 4 denoting a perfect ROI and 1 representing the poorest detection. Table I shows the distribution of scores for both algorithms tested on 2500 images. It can be seen that the proposed algorithm is significantly more robust than the existing method. This is because the existing method uses edge detection and ellipse fitting. The edge detection is sensitive to the reflective noise and ellipse fitting performs poorly for the irregularly shaped lens.

TABLE I

MANUAL EVALUATION RESULTS FOR PUPIL EXTRACTION

	Proposed Method	Ellipse Fitting
Score 1	0(0%)	1(0.04%)
Score 2	11(0.44%)	35(1.4%)
Score 3	48(1.92%)	215(8.5%)
Score 4	2441(97.64%)	2249(90.0%)

TABLE II

MANUAL EVALUATION RESULTS FOR MASK DETECTION

Methods	Perfect	Minimal Misfit	Significant Misfit
Proposed	670(92.5%)	35(4.8%)	20(2.7%)
Existing	610(84.1%)	85(11.7%)	30(4.1%)

TABLE III

MANUAL EVALUATION RESULTS FOR IMAGE CLIPPING

Passed Image Clipping	711 (98.1%)
Failed Image Clipping	14 (1.9%)
Total Number of Test Images	725

C. Mask Detection

Subjective evaluation is used for both the proposed method and the existing method [7], [8] by overlaying the lens image with its mask (draw the boundary of the mask using a color line). A perfect mask fits the lens exactly, and a minimal misfit occurs if the absolute difference between the mask and lens is within a few pixels wide, and a significant misfit if the absolute difference is beyond a few pixels wide. Table II summarizes the mask detection results from both methods. The results show that the proposed method is much more effective than the existing method. The proposed method is more robust because the masks can be generated accurately for cut-off lens and irregularly shaped lens while the existing method's performance is limited to circular or elliptical lens.

D. Cataract Detection

The image clipping algorithm is first evaluated manually. It is considered to have passed the evaluation if it retains all cataract information while removing the bright pixels. A failure occurs if cataract information is lost. A batch processing is then implemented to obtain the percentage of cataracts using both the proposed and existing methods, and the percentages are compared objectively with human grading results by taking the absolute difference between them. Table III shows the results of the effectiveness of the image clipping algorithm, and Table IV shows the results of cataract detection by both proposed and existing algorithms.

From Table III, it is evident that the image clipping method is robust with a success rate of 98.1%. Most of the failure cases are those that are poorly illuminated or contain high amounts of cataracts. Table IV further shows that the proposed method agrees with human grader more often. Fig. 6 shows some examples of the detection results using the proposed method and the existing method, respectively.

TABLE IV

OBJECTIVE EVALUATION RESULTS FOR CATARACT DETECTION

Differences	Proposed Method	Existing Method
Less than 2%	306 (42.2%)	266 (36.7%)
Between 2% to 5%	102 (14.1%)	152 (21.0%)
Between 5% to 10%	90 (12.4%)	84 (11.6%)
More than 10%	227 (31.3%)	223 (30.7%)

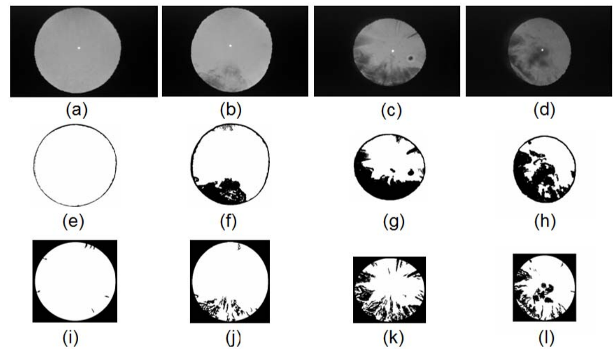

Fig. 6. Examples of cataract detection. (a) - (d) Original images. (e) - (h) Results detected by the proposed method. (i) - (l) Results detected by existing method [7], [8].

IV. CONCLUSION

A new approach to detect cortical and PSC cataracts has been proposed on retro-illumination images. Experiment demonstrates that the proposed method is more accurate and robust compared to the state-of-the-art method. The analysis also shows the pros and cons of different techniques when applying to the cataract detection.

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