CPCO: Contourlet based PCO Quantification System

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***Abstract*— Nowadays, Posterior Capsule Opacification (PCO) is a common postoperative complication of cataract surgery. The rate of incidence and the intensity of PCO are affected by factors such as type and shape of implanted intraocular lens (IOL), cataract surgical techniques and etc. Clinical quantification of PCO is so subjective that evaluating the effects of these factors on PCO are varying among studies. The need for a reliable and efficient automated PCO quantification system is highly desired and many researchers tried to design such a system till now. In this paper a new fully automated Contourlet based PCO quantification system (CPCO) is presented. Comparing this system with other subjective and objective systems shows the reliability and correctness of CPCO system.**

***Keywords-component;* Posterior Capsule Opacification (PCO), quantification, Contourlet transform**

I. INTRODUCTION

Posterior capsule opacification (PCO) is a common postoperative complication of cataract surgery. The rate of incidence and the intensity of PCO depend on parameters such as type and shape of implanted intraocular lens (IOL), cataract surgical techniques and etc. PCO quantification plays an important role for estimating the effects of these parameters on PCO. PCO quantification is a subjective process. As a result, studies show different rates of PCO incidence and intensity, even with the same surgical technique and IOL. PCO quantification criteria have an important role in these variations. Subjectiveness of clinical quantification of PCO has a major role. In order to quantify PCO in a standard way, an objective quantification system is so desirable. The average of subjectively quantified PCO scores determined by expert clinicians can be used as a norm for specifying the correctness of such automated systems.

The need for an automated PCO quantification system is so eligible that researchers tried to design such a system till now. There are several implementations for PCO quantification systems. Friedman et al [1] designed a PCO quantification system based on image processing techniques. 4-mm-diameter region of interest (ROI) is extracted manually. After preprocessing stage, regions of opacification are identified by thresholding operation. The percent area covered by opacity and density of opacification are two values that are computed. Barman et al [2] designed a system named POCO. ROI is determined manually using a mouse. After preprocessing, the image is segmented into areas of opacity and transparency using a directional bow-tie-shaped variance filter and co-occurrence matrix. The percentage area of opacification within the ROI is considered as PCO value. Siegl et al [3, 7] presented a system named AQUA. Semi-automated ROI definition is performed by drawing manually a circle or a freehand shape surrounding ROI and applying radial filtering on this defined area. Purkinje spots (artifacts resulted from reflectance of light while photography) removal is carried out using fusion process consists of registration and fusion modules. Entropy calculated from gray level co-occurrence matrix is considered as PCO score. Aslam et al [4] designed a system named OSCA. Two PCO images obtained from different angles are aligned using image registration technique. Flash-spoiled areas in one image are replaced by exact corresponding unspoiled areas in other image. Size of capsular area to be analyzed is specified by user. Entropy as a texture measure is used to state PCO score. Tetz et al [5] have designed a subjective system named EPCO. ROI is marked by a circle. Different opacification areas are marked interactively and color coded to their density (0 to 4) then multiplied by the fractional area involved.

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What emerges from a review of investigations carried out so far into PCO quantification systems is that the system presented in this paper is the first fully automated PCO quantification system. The input of this system is a colored retro illuminated PCO image, and the output of this system is its related PCO score without any manually contribution. This system comprises preprocessing and feature extraction stages that are explained at the rest of this paper.

II. PREPROCESSING

Preprocessing stage plays an important role for extracting valuable features that will be used in feature extraction stage. Determining the region of interest (ROI) automatically and Purkinje spots deletion are two important tasks performed in preprocessing stage. Color image processing is used for determining ROI of PCO images. Purkinje spots deletion is performed with the aid of their neighboring pixels.

A. Digital Image Dataset

By taking permission from the AQUA [3, 7] patent holders, a dataset containing 50 digital retroilluminated PCO images of varying scores has been provided from dataset used in AQUA. AQUA imaging system consists of a Zeiss 30 slitlamp, Zeiss retrolux illumination module and a Kodak NC2000 digital camera in order to acquire such high signal-to-noise ratio images. Geometric resolution of CCD is set to 1268×1012 pixels and radiometric resolution is set to 36 bits.

B. ROI Detection

An instance raw PCO image is depicted in Fig. 1. Red region can be considered as ROI. At first, RGB color space is converted to YCbCr color space. The smallest rectangular area surrounding ROI has been determined with multiplying horizontal projection by vertical projection, of binary image, of Cr component. Cr component binarization has been done using Otsu binarization method. (Fig. 1)

Rectangular area surrounding ROI has been extracted and its related gray level image has been obtained as depicted in Fig. 2. Corner regions surrounding ROI has been removed. The largest inner rectangular area including ROI has been extracted as shown in Fig. 2. Afterward, the ROI image resizes to 1024×1024.

C. Purkinje Spots Removal

Purkinje spots (artifacts resulted from reflectance of light while photography) detection has been performed easily using thresholding operations (Fig. 3). Purkinje spots appear as black holes in ROI images. The information of these regions has been lost through photography, but considering the small area of these regions, intensities of pixels in these black holes can be predicted using neighboring pixels information (Fig. 3). Now ROI image has been ready for feature extraction phase.

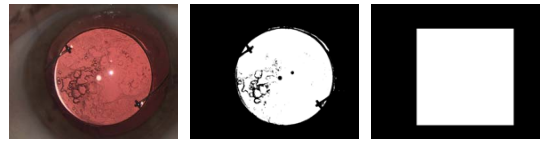

Figure 1. Instance raw PCO image, Binary image of Cr component, Smallest rectangular area surrounding ROI (left to right)

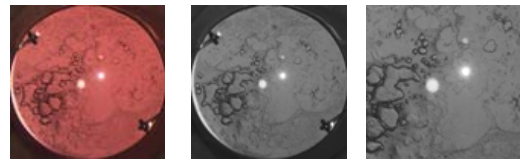

Figure 2. Rectangular area surrounding ROI, its graylevel image, the largest inner rectangular area (left to right)

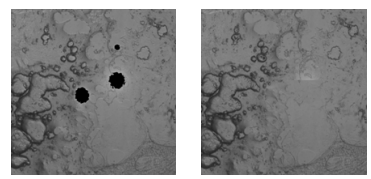

Figure 3. Purkinje spots detection, predicting their pixels (left to right)

III. FEATURE EXTRACTION

With consideration of the type of PCO images that contain a lot of contours, Contourlet transform [6] for feature extraction stage has been used.

A. Contourlet Transform

Smooth contours can be captured efficiently using Contourlet transform introduced by Do and Vetterli [6]. Multiresolution, localization, critical sampling, directionality and anisotropy are five important features for an effective image representation tool, that all of them are satisfied using Contourlet transform. Contourlet transform is a double filter bank named pyramidal directional filter bank (PDFB). Contourlet transform consists of Laplacian Pyramid (LP) followed by a Directional Filter Bank (DFB). LP decomposes input image into two parts: downsampled lowpass sub-band (coarse image) and bandpass sub-band. DFB is applied to bandpass part. By applying this scheme iteratively on the coarse image resulted from LP at each level, a fine to coarse representation of input image will be obtained according to Fig. 4.

Considering $x = a_0[n]$ is the input image. The output after one level of the LP is a lowpass sub-band $a_1[n]$ and one bandpass sub-band $b_1[n]$. After J levels of the LP, there are J bandpass images $b_j[n],\ \ j = 1,\ 2,...,\ J$ ψ (fine-to-coarse) and a lowpass image $a_J[n]$. Then each bandpass image $b_j[n]$ is decomposed by an l_j-level DFB

into 2^{l_j} bandpass directional images $C_{j,k}[n],\ k=1,\ 2,\ \ldots,\ 2^{l_j}-1$.

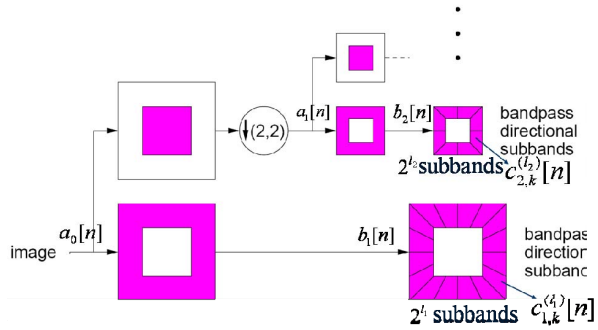

Figure 4. Contourlet transform: Laplacian Pyramid (LP) followed by a Directional Filter Bank (DFB)[6]

In Fig. 5, the analysis part of contourlet transform is shown as a block diagram.

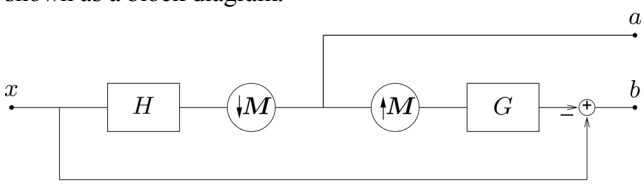

Figure 5. The analysis part of contourlet transform

Feature vector comprises two parts. As approximation sub-band contains overall information of an image, all of the coefficients in this sub-band are considered as one part of feature vector. Besides this overall information the need for detail information is necessary. All other sub-bands convert to binary ones using Otsu method. The number of white pixels in each of these binary sub-bands is computed. The second part of feature vector including these numbers.

The significance of central regions of PCO images for determining PCO intensity is often stated in PCO related researches. So in feature extraction stage the system should be designed in a way that the attention is more given to these regions. Considering five PCO classes with crisp integer scores (0 to 4), a training PCO database has been obtained. This training database has limited numbers of 128×128 pixels size PCO sub-images (about 20 sub-images per class). Because of the texture type of selected PCO sub-images and small size of them, their corresponding PCO scores can be surely determined subjectively by an expert. So, the PCO sub-images have been displayed on a 17-inch monitor and have been graded subjectively by an expert three times with weekly intervals. If a PCO sub-image has the same score in all of these three steps, it is considered as one of the training database sub-images. Fig. 6, shows some PCO sub-images of this training database with their related PCO scores.

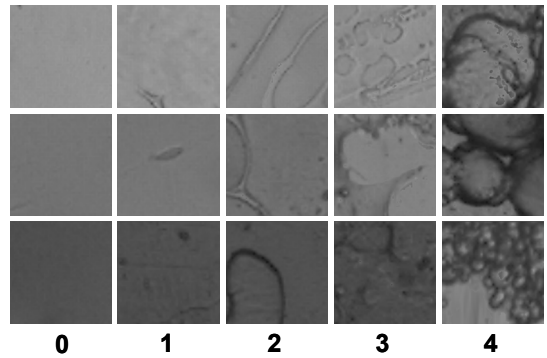

Figure 6. Training set containing 128×128 pixels size PCO sub images with known intensities

For each of these sub-images, feature vector is created. All feature vectors with their related scores are stored. Furthermore each preprocessed PCO images with unknown scores is divided into 64 equally area regions (Fig. 7). As the size of the preprocessed PCO image is 1024×1024, the size of every region in Fig. 7, is 128×128 pixels.

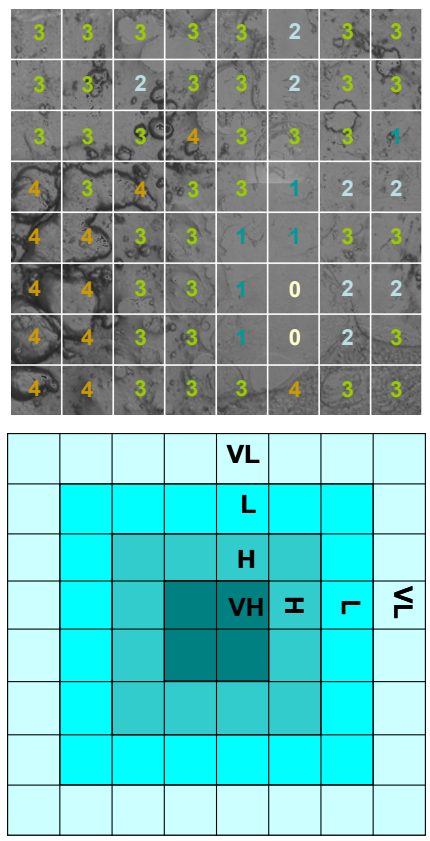

Figure 7. PCO scores of all regions (up), Coefficients (VL, L, H and VH) assigned to every regions (down)

For each of 64 regions of PCO image, the feature vector is created. By comparing the feature vector of one region with stored feature vectors of said training database using Euclidian distance, the most similar feature vector with its

related PCO intensity is revealed. This procedure is applied on every regions of PCO image and related PCO scores are specified as depicted in Fig. 7.

For highlighting the significance of central regions of PCO images, a coefficient (VL, L, H and VH) is assigned to each 64 regions according to Fig. 7. In Fig. 7, VL, L, H and VH regions are abbreviated for very low, low, high and very high significant region respectively. Each revealed scores is multiplied by its related coefficient and weighted average is computed as the PCO score.

In Fig. 8, PCO quantification system is shown as a block diagram.

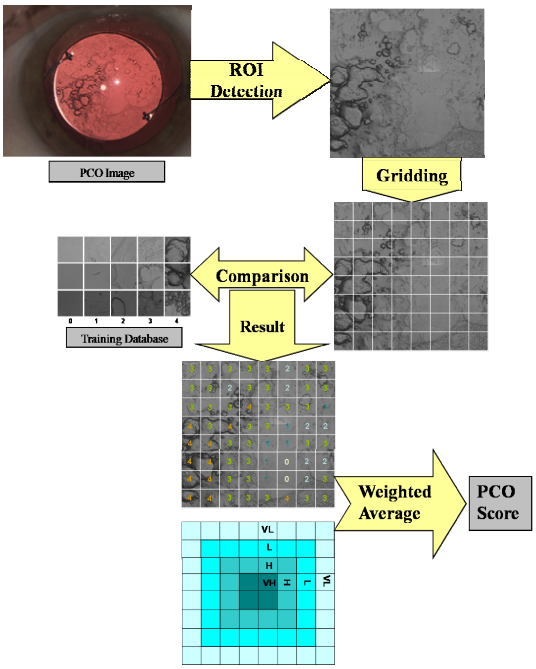

Figure 8. PCO quantification system block diagram

B. System Parameters

Pyramidal filter type, directional filter type, number of scales, directions per scales, and regions' coefficients values are system parameters. Forty different cases have been tested. It was found from the test results that assigning '9-7' filter to pyramidal and directional filtering, considering 2 scales with 8 and 4 directions in each scale (fine to coarse) and selecting [1,2,4,8] as regions' coefficients are the best selective system parameters' types and values.

IV. EXPERIMENTAL RESULTS

In order to evaluate CPCO reliability and efficiency, it has been compared with two subjective methods 'mean subjective' and '3 experts' performed as follows:

All of the PCO images have been graded subjectively and independently by four experienced examiners from Vienna University Department of Ophthalmology two times with one week interval. The grading process has been carried out in a dark room where the PCO images have been displayed on a 19-inch monitor. The scores are between 0 (completely clear) and 10 (completely covered with opacity). One month later, three experts determine a common score for each PCO images by consulting with each other. The mean score between all of determined PCO scores in three cases stated above have been considered as 'mean subjective' method and the scores specified by three experts have been considered as '3 experts' method.

CPCO has been also compared with two famous quantification systems: subjective EPCO and objective AQUA. In order to compare PCO scores resulted from each of the systems, all of the scores were converted to the range of [0, 4].

Fig. 9, show the linear regression lines and scatter plot between CPCO and other four methods. Correlation coefficients between CPCO and other four methods were also computed and shown in Table I. As a result of these comparisons, it is obvious that CPCO is highly correlated with 'mean subjective' and '3 Experts' methods. Correlation coefficients are 0.95 and 0.93 respectively. It implies that CPCO system determines PCO scores reliably and properly. CPCO exhibits the similar results in comparison with AQUA system. The correlation coefficient in this case is 0.96. CPCO is correlated well with EPCO system. The correlation coefficient is 0.88.

CPCO software has been written in MATLAB version 7.6.0.324(R2008a) environment and has been run on an AMD Athlon(tm) 64 X2 Dual Core processor 5600+, 2.9 GHz, 2048 MB of RAM system. In CPCO software, the mean processing time for determining the score of one PCO image is approximately 12 seconds while this time is about 25 seconds in subjective method and about 144 seconds in subjective EPCO [7].

V. DISCUSSION

In this paper, a new fully automated Contourlet based PCO quantification system (CPCO) was introduced. The input of CPCO system is a color PCO image and the output is its PCO score.

CPCO shows excellent performance for determining PCO scores. CPCO is highly correlated with two subjective methods as norm methods. This shows the reliability and correctness of CPCO system.

TABLE I. CORRELATION COEFFICIENTS

	CPCO	***Subj.***	***3Experts***	***AQUA***	***EPCO***
CPCO	*1*	*0.95*	*0.93*	*0.96*	*0.88*
Subj.	*0.95*	*1*	*0.98*	*0.94*	*0.94*
3Experts	*0.93*	*0.98*	*1*	*0.92*	*0.96*
AQUA	*0.96*	*0.94*	*0.92*	*1*	*0.88*
EPCO	*0.88*	*0.94*	*0.96*	*0.88*	*1*

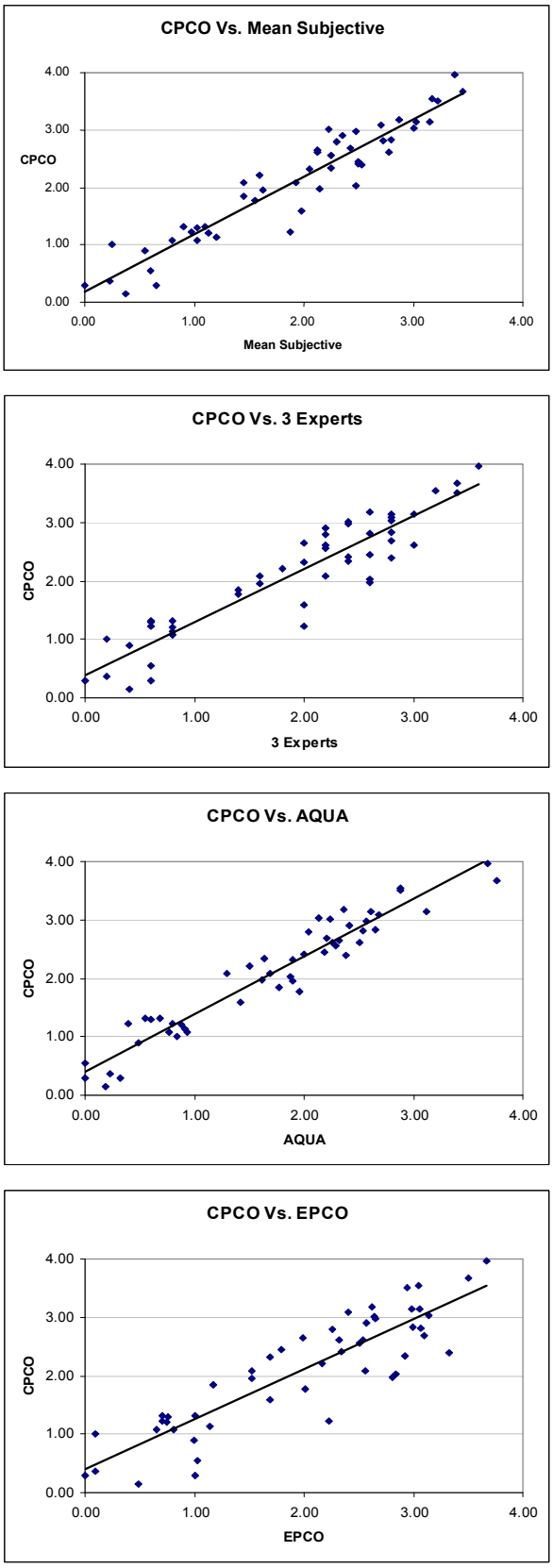

Figure 9. CPCO Scores Vs. other four methods linear regression lines

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