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Automatic cataract detection and classification systems: A survey

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Abstract: The human eye is an organ that reacts to light and has several purposes. As a sense organ, it allows vision. Cataract is a leading cause of blindness worldwide. It is caused by clouding of lens, which is painless and developed gradually over a long period. Cataract will slowly reduce the vision and leads to blindness. There are various Automatic cataract detection and classification methods available today. In this paper we compare recent methods. All the cataract detection and classification systems have 3 basic steps: Pre-processing, Feature extraction and Classification.

Keywords: Cataract, Blindness

1 Introduction

Cataract is an eye disorder which occur when there is a build up of protein at lens that makes it cloudy. This prevents light from passing clearly through the lens, causing some loss of vision. Depending on the area where cataract develops, it can be classified into three: *nuclear cataract*, *cortical cataract* and *posterior sub capsular cataract*. Nuclear cataract is the most common type of cataract. It forms deep in the central zone (nucleus) of the lens. It is usually associated with aging. Cortical cataract is due to the lens cortex (outer layer) becoming opaque. It occurs when changes in the water content of the periphery of the lens causes fissuring. Posterior sub capsular cataract occurs at the back of the lens. People with diabetes or those who are taking high doses of steroid medications have a greater risk of developing this type of cataract. Most of the aged people suffer from any one of these three types of cataract. So it is convenient for the ophthalmologist if the eye diseases are mass screened out. So it is very relevant if there is an automatic filtering system. Automatic filtering can be performed in different ways. In the first criteria, cataract is classified according to its position of occurrence in the eye. There is also another classification among the fundus images which classifies the images into *normal cataract* and *post cataract*.

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2 Overview

All the cataract detection and classification systems have three basic steps.

1. **Pre-processing**

   First the images are pre-processed. At this stage all the unwanted data are removed and the images are made more suitable for further steps.

2. **Feature extraction**

   The second step is feature extraction. It is the most important step and useful features are extracted. Depending on these features the classification is done. The features should be extracted from all the images and for different classes they should be different. For these two steps the different image processing techniques are used.

3. **Classification**

   The next and last step is classification: according to the features extracted the classifier classifies the images in to different classes. For that different artificial intelligence and neural network techniques are used.

3 Different types of automatic systems for cataract classification

In [1], automated classification of normal, cataract and post-cataract optical eye images using *SVM classifier* is implemented. In this work author uses image processing techniques to detect the features in the three classes of optical eye images such as normal, cataract and post-cataract images. The features of the optical eye images such as big ring area (BRA), small ring area (SRA), edge pixel count (EPC) and object perimeter are extracted. These features are statistically analyzed and found to be significant for the automatic classification. Based on these features SVM classifier is used to classify the optical images.

In [2], an automatic approach to grade cortical and posterior sub-capsular (PSC) cataracts using *retro-illumination images* has been proposed. This classification is based on the region where the cataract is affected. To characterize the photometric appearances and geometric structures of cortical and PSC cataracts in retro-illumination images, low-level vision features like intensity, texture, and homogeneity is used. Then SVR classifier is used to classify the images in to cortical cataract and PSC cataract.

In [3], the author introduces a new feature for cataract grading together with a group sparsity-based constraint for linear regression, which performs feature selection, parameter selection and regression model training simultaneously. The system consists of three components: *region of interest (ROI) and structure detection, feature extraction, and prediction*.

In [4], a method to classify cataract lens from the non-cataract lens is introduced. The *enhanced texture feature* is proposed based on the graders expertise of cataract and the characteristics of the retro-illumination lens images. Here anterior image and posterior image of the eye is used to extract the features. The statistics of the enhanced texture feature is used to train the linear discriminant analysis (LDA) to detect the cataract.

In [5], a system for detection of the cataract and to test for the efficacy of the post-cataract surgery using *optical images* is proposed using *artificial intelligence techniques*. Image processing and *fuzzy K-means clustering algorithm* is applied on the raw optical images to detect the features. Then the *back propagation algorithm* (BPA) is used for the classification.

In [6], two separate automatic grading systems are presented for nuclear cataract and cortical cataract diagnosis respectively. In the former system, features were extracted based on the lens structure. Then, severity of nuclear cataract was predicted using *support vector machines (SVM) regression*. For cortical cataract grading, the opacity was detected using region growing. The seeds were selected by local thresholding and edge detection in radial direction. Cortical cataract was graded based on the area of cortical opacity.

4 Methodology of automatic cataract detection

4.1 Pre-processing

The *pre-processing* is the process of manipulating the image in such a way that the images become more suitable for a particular application. That is, the pre-processed images are used for feature extraction and classification. So in every system, pre-processing of images is done in different ways appropriate for their processing.

- In [1], pre-processing is done to reduce the contrast and to normalize the mean intensity. The intensities of the three colour bands were transformed to an intensity-hue-saturation representation [7]. It allows the intensity to be processed without affecting the perceived relative colour values of the pixels.

- In [2], during pre-processing step the images are converted into gray channel, so as to help feature extraction.

- In [3], firstly each lens image is separated into three sections: nucleus, anterior cortex, and posterior cortex. After obtaining the lens structure of each image, the central part of the lens along the visual axis is extracted and resized to 128×512. Features are extracted from each of the resized sections.

- In [4], the texture filter is applied to suppress the non-uniformity and artifacts while highlighting the cataract. Then for the anterior and posterior image pair, ellipse fitting method is applied to get the ROI of the lens images [8].

- In [5] the pre-processing step involves histogram equalization and fuzzy K-means algorithm.

- In [6] two computer-aided diagnosis systems for cataract grading are used.

Pre-processing in automatic grading system for nuclear cataract is lens localization. The lens is located using thresholding, horizontal and vertical profile clustering for ellipse estimation. Active shape model is further applied to extract the contour of lens. The shape of the lens is denoted by twenty-four landmark points.

A statistical description of the shape and its variations was obtained using *principal component analysis* (PCA) on the training shapes. The *learnt shape model* is able to deform in a way that reflects the variations in the training set. *Active shape model* (ASM) method is an iterative searching procedure to fit the shape model in a new image to find the contour of lens. In automatic grading system for cortical cataract, first canny edge detection and Laplacian edge detection were employed to detect the region of interest (ROI). The edges detected on the convex hull by both detectors were selected and fitted to an ellipse for ROI detection.

4.2 Features extraction

Transforming the input data into the set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

In [1], mainly the features of the optical eye image such as *big ring area*, *small ring area*, *edge pixel count* and *object perimeter* are extracted. The features are statistically analyzed and found to be significant for the automatic classification. The colour at the inner surface of the cornea is not the same in all the three kinds of images. In cataract images, the inner surface of the cornea images is more whitish as compared to that of normal and post-cataract images. It is the basis for calculating small ring area. The color at the outer surface of the cornea is not the same in all the three classes. In cataract images, the outer surface of the cornea images is bright in colour as compared to that of the normal and post-cataract images. It is basis of finding big ring area. Then using Cannys edge detection method EPC (edge pixel count) is computed. By the computation of EPC, the number of white pixels in the output of the edge detection is counted. For normal image, the count is very few and in post cataract image it is more than the normal where as in the cataract image it is very high. The next feature extracted is object perimeter, for that erosion is performed. The normal, cataract and post-cataract images have too many sudden changes in the gray levels. Hence, there will be many edges in these images which can be used as a feature to reflect normality and abnormalities in the eye images. So, performing erosion provides the best result.

In [2], mainly *intensity*, *texture*, and *homogeneity* features are extracted. The intensity histogram serves as an important feature to distinguish opacity from transparency. The histogram of a clear lens generally has narrow width at bright intensity level, while the histogram of a lens with cataracts has wider width and the tail extends to the darker side. Next important feature extracted is *fused texture information*. Here the wavelet coefficients are efficient to characterize such texture information. The results from both anterior and posterior images, indicating a fused wavelet map shall be more suitable to characterize cortical and PSC cataracts. Last and final feature extracted is *spatial distribution of intensity* and *texture features*. One challenge of automatic cataract detection is the variety of the opacities and the variance of the illuminations in the images. Statistics of the whole lens image may show similar values for clear lens images and lens images with severe cataracts. To characterize the different spatial variance between them, lens is equally divided into twenty-four subfields. Then, extract the above intensity and wavelet statistics within each subfield.

In [3], *bag-of-features (BOF) extraction* is performed. It is also known as the *bag-of-words model* [9]. The BOF model provides a location-independent global representation of local features in which properties such as intensity, rotation, scale or affine invariance can be preserved. Here, the local features in BOF model are image patches that represent intensity and texture information. Each section of the resized lens image is divided into a grid of half-overlapping $s \times s$ patches each represented as an s^2-dimensional vector. After obtaining all the local patches from a set of training images, k-means clustering is used to generate the codebook from randomly selected samples, and then the BOF is obtained in a binning procedure. For each slit-lamp image, here obtain its image feature representation 'fi' by concatenating the BOFs extracted in its three sections $S = \{S_a, S_n, S_p\}$ (i.e., anterior cortex, nucleus, and posterior cortex), computed for each of six colour channels $C = \{Ch, Cs, Cv, Cr, Cg, Cb\}$ (i.e., HSV and RGB colour channels),with a fixed patch size $s = 8$ and various bin numbers $K = \{100, 200, 400\}$. This leads to a feature dimension of

$$|fi| = |S| \times |C| \times \sum_{n=1}^{|K|} K_n = 12600.$$

Here, each BOF extracted for a given section of the lens, colour channel, patch size and bin number is referred as a group feature. L^1-normalization is performed such that the sum of each group feature is equal to 1, and a truncation similar to that used in SIFT feature extraction [10] is applied to reduce feature bias and noise, that is, if a bin is greater than 0.2, it is set to 0.2 and the L^1-norm is recomputed.

In [4], the texture of the ROI image pair is computed first through local entropy filtering. Then compensate the window processing of the local entropy filtering, smooth the posterior image with a Gaussian low pass filter. Then, get the inverse intensity of the smoothed image as the weight image. For the posterior image, multiply the texture with the weight of the posterior image to get the enhanced texture measurement. Divide the lens region into central part and outer part. Normalize and enhance the texture measurement and compute the statistics of these measurements in the central part of the posterior enhanced texture image and the outer part of the anterior texture image, respectively. Calculate the mean, standard deviation, skewness and kurtosis as the final features.

In [5], *probability density function* (PDF) and six clusters are main features for classification. The PDF is found from the histogram equalization. Then, the fuzzy K-means clustering algorithm is applied. K-means clustering is used to group regions within each image using the RGB vector as an input [11]. Depending up on the K-means clustering, the cluster centroids are found.

In [6], *automatic grading system* for nuclear cataract based on the landmark detection using ASM method is used. Features were extracted using previously published clinical work [12, 13]. Six-dimensional feature was selected and they are: *mean intensity inside* *lens, colour on posterior reflex (HSV colour space), mean intensity of sulcus, and intensity ratio between anterior lentils to posterior lentil*. The last two features were obtained using visual axis profile analysis, which is the intensity distribution on a horizontal line through central posterior reflex. In automatic grading system for cortical, to detect the cortical opacities in ROI, spoke-like features were utilized to distinguish cortical opacities from the posterior sub-capsular opacities. An original image is converted to polar coordinate first. Local thresholding and edge detection were applied in both radial and angular directions. Angular opacities were subtracted from radial opacities to retain only the cortical opacities as cortical seeds. Region growing was then applied to detect the cortical opacities. Spatial and size filters were used to remove noises as a post- processing step.

4.3 Classification

In [1], *SVM classifier* is used. It is a very good supervised classifier proposed by Vapnik et al [14]. It minimizes the empirical training error. SVMs aim at minimizing an upper bound of the generalization error through maximizing the margin between the separating hyper planes and the data [15]. SVMs have been successfully applied in various fields like classification, regression etc[16].

In [2], *SVR classifier* is used to classify the cortical and PSC cataract. It is a supervised learning method, used to train the regression model. When the feature dimension is much higher than the number of samples (434), then apply a linear kernel in SVR. The scortical opacities are coupled with PSC opacities on the retro illumination images, then use two types of opacities graded by the professional grader as the ground truth. The prediction provides an estimation of the levels of opacities in the lens images.

In [3], a *regression model* is used to grade nuclear cataract. With the image feature representation, a regression model is trained for the nuclear cataract grading task. A reduced representation could potentially be used, but it is unclear which colour channels are most informative for each section of the lens, and how many bins is optimal for a given channel. To address this problem, a group sparsity constraint in the regression is applied to select an effective subset of the extracted features for nuclear cataract grading.

In [4], *linear-discriminant-analysis* (LDA) classifier is used. It uses the statistics as the input features to classify the images. The basic idea of LDA is simple, for each class to be identified, calculate a (different) linear function of the attributes. The class function yielding the highest score represents the predicted class.

In [5], *back propagation* (BP) classifier is used for classification of images. The cluster centroids are fed into a BPA that bonds inputs from the same class so as to distinguish them from the other classes. The BPA is a supervised learning algorithm, aims at reducing the overall system error to a minimum.

In [6], *support vector machines* (SVM) regression was employed to train a grading model and predict the grade for a testing image. One hundred images were selected as the training set. Twenty images from each grading group (0-1, 1-2, 2-3, 3-4, 4-5) were selected as the training set.

5 Conclusion

All automatic detection systems use slit lamp direct images or retro illumination images. The advantage of these systems is mass screening. The disadvantage is that these systems cannot handle exceptions.

- In [1], the system is able to detect the early stage of cataract and classify normal, cataract and post-cataract eye images. The disadvantage is that Normal and post cataract image classification have less accuracy than classification of cataract images.
- In [2] system the important advantage is the ability to avoid over-detection for clear lenses and under-detection for lenses with high opacities.
- In [3]Author introduces a new feature for cataract grading together with a group sparcity-based constraint for linear regression, which performs feature selection, parameter selection and regression model training simultaneously. By using this, the feature noise can be reduced as suitable for low dimensional feature extraction for classification.
- In [4], the enhanced texture feature is proposed based on the graders expertise of cataract and the characteristics of the retro-illumination lens images. The statistics of the enhanced texture feature is used to train the linear discriminant analysis to detect the cataract. This is more suitable for mass screening.
- In [5], a system for detection of the cataract and to test for the efficiency of the post- cataract surgery using optical images is proposed using artificial intelligence techniques. The importance of this system is that it can help to detect the outcome of the cataract operation.
- In [6] two separate automatic grading systems are presented for nuclear cataract and cortical cataract diagnosis respectively. It is a novel approach for cataract detection; since it uses separate methods it provides more accuracy in detection.

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