Fundus Image Based Cataract Classification

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***Abstract*—Cataract is one of the leading causes of visual impairment worldwide. People with cataracts often suffer a lot in many aspects of daily life. Although early treatment can reduce the sufferings of cataract patients and prevent visual impairment turning to blindness, people in less developed areas still can't get timely treatment because of poor eye care services or lack of professional ophthalmologists. Besides, the present commonly used methods for cataract diagnosis, clinical assessment and photographic grading, need to be operated at a slit lamp by ophthalmologists, which are complicated and expensive for many patients. So reducing the cost and simplifying the process of early cataract diagnosis is of great importance. In this paper, we proposed a fundus image based cataract classification method by using pattern recognition, which can be used in early screening of cataract. By calculating the 2-dimensional discrete Fourier transform of a fundus image and using the calculated spectrum as features, a cataract classification and grading method is carried out by using the linear discriminant analysis promoted with the AdaBoost algorithm as the classifier. A preliminary test is implemented on an image sample set including 460 fundus images that normal, mild, moderate and severe cataract images are 158, 137, 86 and 79 respectively. Correspondingly, the two-class and four-class classification accuracy for our proposed method are 95.22% and 81.52%. We believe that our proposed method has a great potential in practical applications.**

Keywords—cataract; classification; fundus image; 2-dimensional discrete Fourier transform; Principle Component Analysis; Linear Discriminant Analysis; AdaBoost

I. Introduction

Cataract is one of the leading causes of visual impairment worldwide. According to a WHO report [1], the estimated number of people visually impaired in the world is 285 million: 39 million blind and 246 million having low vision; 33% of visual impairment and 51% of all blindness are caused by cataract. In low and middle income counties and regions the prevalence of cataract is even higher because of lower investments in health [1].

In general, the term "cataract" refers to lens opacities that interfere with vision function [2]. People with cataracts often suffer difficulties in reading, driving, appreciating colors, recognizing faces and objects, and coping with glare from bright lights [3]. Although early treatment can reduce the sufferings of cataract patients and prevent visual impairment turning to blindness, people in less developed areas still can't get timely treatment because of poor eye care services or lack of professional ophthalmologists. On the other hand, the present commonly used methods for cataract diagnosis, i.e., clinical assessment, such as the lens opacity classification system (LOCS III) [4], and photographic grading, such as the Wisconsin cataract grading system (Wisconsin System) [5], need to be operated at a slit lamp by ophthalmologists, which are complicated and expensive for many patients.

Faced with the above reasons, reducing the cost and simplifying the process of early cataract diagnosis is of great importance. It is also one of the ways to improve the eye care service in less developed areas and bring light to cataract patients. Modern medical science benefits much from the combination of medical image analysis and computer technology, so we can see the potential to use these techniques in cataract diagnosis.

Fundus image of the eye, also known as a kind of retinal image [17], can be easily obtained with low cost. It is widely used in cataract diagnosis and can provide sufficient information of the retina. Fundus based automatic detection of diabetic retinopathy [6], age-related macular degeneration [7] and other ophthalmic diseases, shows the great prospect on automatic diagnosis using fundus image in ophthalmology, especially in cataract screening.

In the related previous studies, Yitao Liang et al. found that the green component image holds the basic feature of the original color fundus image [8]. Michael Goldbaum et al. segmented objects in fundus image and tested linear discriminant function, quadratic discriminant function, logistic

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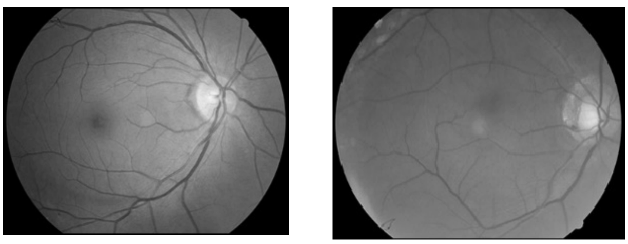
regression discrimination classifier, and back propagation artificial neural networks as classifier for the objects [9]. Meimei Yang et al. used an improved Top-bottom hat transformation to pre-process the retinal image and extracted the luminance and texture message as features, then constructed the classifier by two-layered back propagation neural network [10]. Their work was the first reported literature on the automatic cataract retinal image classification through IT technology. However, all of the present classifiers are complicated with too much computation cost, and as for early screening, we just need to distinguish the obvious characteristics of cataract, so it is unnecessary to pay too much attention on recognizing subtle details of fundus image.

In this paper, we propose a fundus image based cataract classification method by using pattern recognition. After pre-processing, we calculate the 2-dimensional discrete Fourier transform (DFT) [11] of a fundus images and use the obtained spectrum as the features, followed by principle component analysis (PCA) [12] to reduce dimensions. We use linear discriminant analysis (LDA) [13] as classifier, with the promotion by AdaBoost algorithm [14]. Since fundus image is widely used in automatic diagnosis of other ophthalmic diseases, while there is hardly no similar work on automatic classification and grading of cataract, our fundus image based cataract classification method has a great potential in practical applications, which can reduce the cost and simplify the process of early cataract screening.

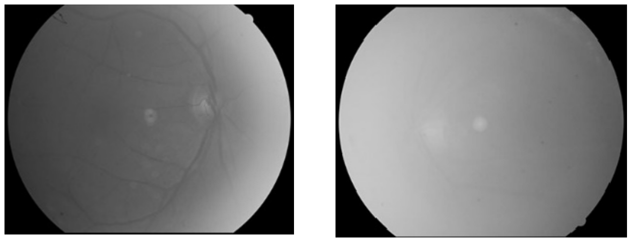
II. Feature Extraction

A. *The fundus image database and pre-processing*

In this paper, we use a fundus image database selected by professional ophthalmologists. It contains 460 fundus images in total, and the number of normal, mild, moderate and severe cataract images are 158, 137, 86 and 79 respectively. All of these images are not in the same size, so we resize them into 300×242 ones before using. Because the green component image keeps the most details of the original color fundus image [8], we extract the green channel of the fundus images as the data set. Besides, we erase the patients' personal information on these images for the protection of their privacy and the subsequent process. The example fundus images (the green channel) of every class are shown in Fig. 1.



(a) (b)



(c) (d)

Fig. 1. Fundus images without and with different levels of cataract. (a) normal; (b) mild; (c) moderate; (d) severe.

It can be seen that in a normal fundus image, the retinal arterioles and venules in the nerve fiber layer of the retina [15] can be observed clearly, whereas the cataract fundus images are misty and lack of details. As the degree of the cataract getting more severe, there will be more opacifications in the eye lens, resulting in fewer vessels observed in fundus images. In the mild cataract fundus image, it seems there is a veil before the retina leading to most micro-vessels and other details can't be observed. As to the moderate cataract ones', we can only distinguish the most thick trunk vessels, while as for the severe cataract ones', there is nearly nothing can be seen.

The direct impress of cataracts above is exactly the most prominent characteristic of cataract fundus images. With this characteristic, we explore our methods below.

B. *2-Dimensional Discrete Fourier Transform*

Physically, when light propagate in the lens of a cataract patient, it will be absorbed and scattered by opacifications. Under this consideration, the opacifications in the lens can be regarded as a low-pass filter. The more severe the cataract is, the more opacifications will be in the lens, thus the more light will be absorbed and scattered and the less light will reach to the fundus. It shows out the fundus image is mistier, that is, the proportion of low frequency components will take more place.

By calculating the 2-dimensional discrete Fourier transform of an input image, we can get the spectrogram of it. The spectrogram of the image is in the Fourier or frequency domain, where each point represents a particular frequency contained in the spatial domain image, i.e. the original input image. The images in the spatial and Fourier domain are of the same size. For an image of size M×N, the 2-dimensional DFT is given by:

$$F(k,l)=\sum_{i=0}^{N-1}\sum_{j=0}^{M-1} f(i,j)e^{-i2\pi(\frac{ki}{N}+\frac{lj}{M})} \quad (1)$$

where $f(i,j)$ is the image in the spatial domain and the exponential term is the basis function corresponding to each point $F(k,l)$ in the Fourier space [11].

The base functions are sine and cosine waves with increasing frequencies, that means $F(0,0)$ represents the DCcomponent of the image which corresponds to the average brightness and $F(M,N)$ represents the highest frequency.

The Fourier images of each class are shown in Fig.2. They are shifted in a way that the DC-value (i.e. the image mean) $F(0,0)$ is displayed in the center of the image. The further away from the center an image point is, the higher its corresponding frequency is. We can find that as the increase of the cataract degree, the shape of the spectrogram is getting more regular, the high frequency components are fewer and the low frequency components are more. We use these Fourier images as features of the fundus images.

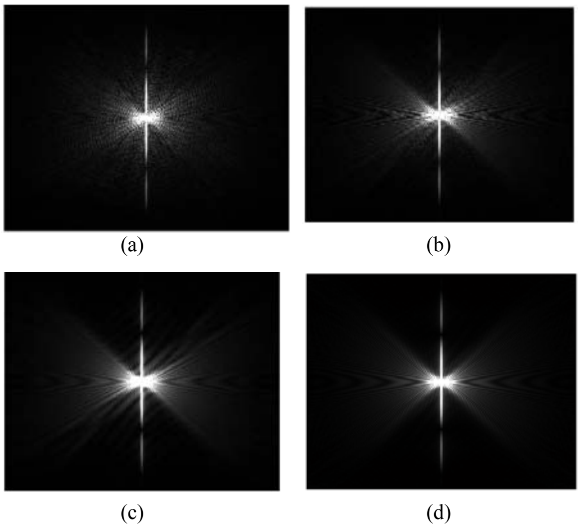


Fig. 2. The Fourier transform of fundus images without and with different levels of cataract. (a) normal; (b) mild; (c) moderate; (d) severe.

C. Dimension reduction

However, the Fourier images we get are the same size as the original fundus images, i.e. 300×242 pixels. It's still in so high dimension that will cost too much on computation, thus we use Principle component analysis to reduce the dimensions.

PCA is a common method for dimension reduction by seeking a projection that best represents the data in a least-squares sense [16]. The scatter matrix $\mathbf{S}$ is defined by:

$$\mathbf{S}=\sum_{k=1}^{n}(\mathbf{x}_k-\mathbf{m})(\mathbf{x}_k-\mathbf{m})^T \quad (2)$$

where $\mathbf{x}_k$ is the data vector, $\mathbf{m}$ is the mean vector of all data vectors. If we reduce the number of dimension to d, then the projecting direction vectors $\mathbf{e}_i$ are the eigenvectors of the scatter matrix $\mathbf{S}$, corresponding to the largest d eigenvalues λ_i, $i=1,2,\ldots,d$. The squared error of the projection is:

$$\xi=\sum_{j=d+1}^{\infty}\lambda_j \quad (3)$$

We choose $d=300$ in this paper, that is, we reduce the dimension of the features to 300. The error after dimension reduction computed by (3) is 0.36%, which means the squared error of data before and after PCA is 0.36%.

III. Design of Classifier

In the previous section, we extract features of the fundus images and reduce the features to 300-dimension, the next work is the design of classifier. We choose Linear discrimination analysis as classifier, with the promotion by AdaBoost.

A. The classifier and its promotion

Linear discrimination analysis, also known as Fisher linear discrimination, is another projecting method, whose purpose is to find a projection that best separates the data in a least-squares sense [16]. For LDA, the scatter matrices $\mathbf{S}_i$ and $\mathbf{S}_{Wij}$ are defined by:

$$\mathbf{S}_i=\sum_{\mathbf{x}\in\omega_i}(\mathbf{x}-\mathbf{m}_i)(\mathbf{x}-\mathbf{m}_i)^T \quad (4)$$

and

$$\mathbf{S}_{Wij}=\mathbf{S}_i+\mathbf{S}_j \quad (5)$$

where $\mathbf{m}_i$ is the mean vector of class ω_i. The weight vector is defined by:

$$\mathbf{w}_{ij}=\mathbf{S}_{Wij}^{-1}(\mathbf{m}_i-\mathbf{m}_j) \quad (6)$$

then we can project a data vector $\mathbf{x}$ to the direction of $\mathbf{w}_{ij}$ and get the 1-dimension projection:

$$y=\mathbf{w}_{ij}^T\mathbf{x} \quad (7)$$

The classification criterion is, if $y>y_0$, decide $\mathbf{x}\in\omega_i$, otherwise decide $\mathbf{x}\in\omega_j$. In this paper, y_0 is defined as:

$$y_0=\frac{\tilde{m}_i+\tilde{m}_j}{2}+\frac{\ln(P(\omega_i)+P(\omega_j))}{n_i+n_j-1} \quad (8)$$

where $\tilde{m}_i=\frac{1}{n_i}\sum_{y\in\omega_i}y$, $\tilde{m}_j=\frac{1}{n_j}\sum_{y\in\omega_j}y$, $P(\omega_i)$ and $P(\omega_j)$ are the prior probabilities of class ω_i and ω_j separately.

In order to verify that the 300-dimensional features are pairwise 1-dimensional separable after LDA, we visualize them in one dimension, see Fig. 3.

As shown in Fig. 3, it can be found that in one dimension after LDA, every two classes are separable, and the difference in degrees of two classes is obvious, the distance between two median points is far. The four classes are pairwise 1-dimensional separable, which supports the application of LDA and shows that we can reduce the features to just one dimension.

For classification of four classes, we use “one vs one” strategy. It means every time we choose two classes in the training set and train the classifier, then decide samples in the testing set into these two classes. For four classes we will classify 6 times and get 6 decisions, afterwards we vote the most decision as the classification result.

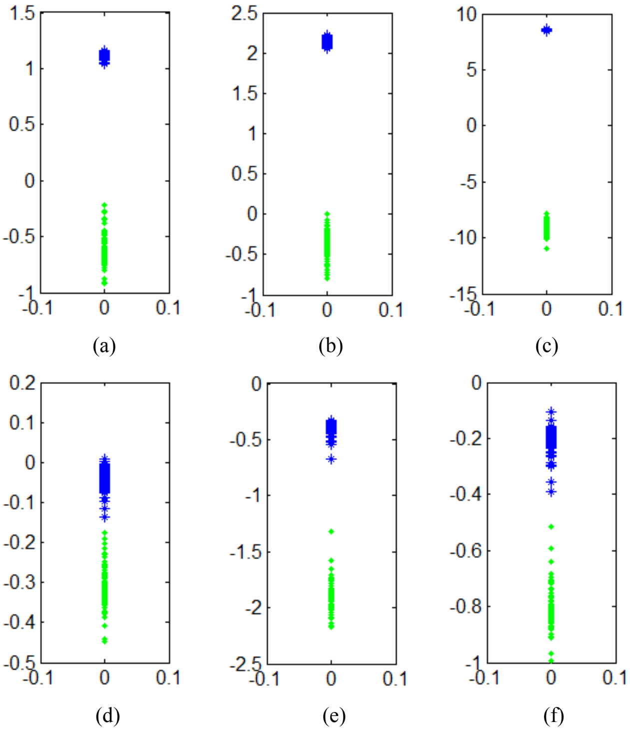


Fig. 3. Visualization of pairwise 1-dimensional seperability of fundus images with different levels of cataract. (a) normal vs mild; (b) normal vs moderate; (c) normal vs severe; (d) mild vs moderate; (e) mild vs severe; (f) moderate vs severe.

To promote the performance of the classifier, AdaBoost algorithm is chosen to be used. The main idea of AdaBoost is to train many individual component classifiers using just a part of training samples by resampling then vote for the final decision [14]. A weight is given to each training sample, which determines the probability of the sample being selected for a component classifier. If a training sample is misclassified, its weight will increase, thus the chance of this sample to be chosen for a component classifier is raised. In this paper, the iteration times is set to be 100, balancing the accuracy of the classifier and the computation cost, and then the classification result in the iteration with the highest classification accuracy is used as the final classification result.

Since there are just 460 labeled samples, we use 10-fold cross validation method to evaluate the performance of the classifier. All Fourier images are equally divided into 10 subsets, thus there are 46 images in one subset. In each fold we choose one subset as testing set and another nine subsets as training set, execute PCA and LDA with AdaBoost, then get the classification accuracy of this fold. The average of 10 accuracies is regarded as the classification accuracy of our classifier.

So far, we can summarize the procedure of the classification as is illustrated below.

1) Pre-processing: resize all fundus images and extract the green channel images.

2) 2-Dimensional DFT: execute 2-dimensional DFT on all images and get Fourier images.

3) Divide10 subsets: arrange all Fourier iamges with their labels in random permutation, equally divide all these Fourier images into 10 subsets.

4) Dimension reduction: choose one subset as testing set and another nine subsets as training set, execute PCA on training set and testing set, get 300-dimensional features.

5) LDA with AdaBoost: use LDA as basic classifier, execute 100 times AdaBoost iteration, i.e. train 100 component classifiers, choose the best result with highest accuracy as the classification result.

6) Classification of another fold: go back to step 4) for classification of another fold.

7) Get the result: use the average accuracy as the classification accuracy of this classifier.

B. The classification results

To evaluate our cataract classification method, we use the procedures above to carry out two-class classification (i.e. normal and cataract) and four-class classification (i.e. normal, mild, moderate and severe) separately. Table I shows the classification accuracy of two-class and four-class classification.

TABLE I. ACCURACY OF TWO-CLASS AND FOUR-CLASS CATARACT CLASSIFICATION

Dimension number after PCA	**AdaBoost iteration times**	**Two-class accuracy**	**Four-class accuracy**
300	100	95.22%	81.52%

As is shown in Table I, the accuracy of two-class cataract classification is satisfactory, which means our classification method can recognize normal and cataract fundus images in a relatively high accuracy; however the accuracy of four-class classification seems a bit lower and still has the space for improvement.

IV. CONCLUSION

In this paper, we proposed a fundus image based cataract classification method by using pattern recognition. We considered opacifications in the eye lens as a low-pass filter, which filters the details of the eye fundus. According to this understanding and by observing fundus images in different degrees of cataract, we found that the most prominent characteristic of a cataract fundus image is the mist of it and as the degree of cataract increase, the mist gets thicker and the details get fewer, in other words, the low-frequency components get more and the high-frequency components get less. Thus we calculated 2-dimensional discrete Fourier transform of fundus images, by which we can exactly obtain the frequency spectrum of the images. Since the dimension of the Fourier image was still too high, we then used PCA to reduce the dimension. LDA was used as basic classifier with AdaBoost improving the performance of it.

The final two-class and four-class classification accuracy of our method are 95.22% and 81.52% respectively. We can see the great prospect of our fundus image based cataract classification method in early cataract screening and diagnosis, and we believe our method can be helpful in reducing the cost and simplifying the procedure of cataract diagnosis.

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