



Glaucomatous Image Classification Based On Wavelet Features

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Abstract: Glaucoma is one of the second largest diseases caused in human eye that may results in the sightlessness or even blindness. Texture features within images are effectively used for accurate and efficient glaucoma classification. Energy distribution over wavelet features are applied to find these important texture features. In this paper several wavelet filters are used in order obtain energy signatures. Most commonly used wavelets are Harr wavelet, May also called daubechies (db1), symlets (sym3), and biorthogonal (bio3.1, bio3.4, and bio3.5) wavelet filters. Then the feature ranking and feature selection process are carried out before the wavelet features are introduced to the classifier network. We have gauged the effectiveness of the resultant ranked and selected subsets of features using a support vector machine, sequential minimal optimization, random forest, and naive Bayes classification strategies. Based on certain action caused by the classifier to these features, the selected candidates will produce effective glaucoma classification. And the proposed system will have an accuracy more than the existing system i.e., above 95%.

Keywords: Glaucoma, wavelet filters, SMO, SVM, random forest, naive Bayes

I. Introduction

Glaucoma is the second leading cause of blindness worldwide. Glaucoma is a condition that causes damage to your eye's optic nerve and gets worse over time. It may be due to the buildup of pressure inside the eye. Effect of glaucoma increases with increase in the age of human and may not show up until later in life. The increased pressure, called intraocular pressure, can damage the optic nerve, which transmits images to the brain. If damage to the optic nerve from high eye pressure continues, glaucoma will cause permanent loss of vision. Without treatment, glaucoma can cause total permanent blindness within a few years. Before years this disease was only shown in elder people, but because of some biological reason this symptoms has been shown in younger people also. This can happen when eye fluid isn't circulating normally in the front part of the eye. Normally, this fluid, called aqueous humor, flows out of the eye through a mesh-like channel. If this channel becomes blocked, fluid builds up, causing glaucoma. The direct cause of this blockage is unknown, but doctors do know that it can be transferred parents to children. So better treatment should be given at the earliest.

A number of techniques have been developed in order to detect the glaucoma at the earliest. Here the proposed system also deals with the detection of glaucoma which is having several advantages than the previous techniques. One the main advantage of this paper is that, it has a better accuracy compared with the previous.

Now a days we know that, in the field of diagnostic several new diagnostic methods has been arised in order for detection and management of glaucoma. Several imaging modalities and their enhancements, including optical coherence tomography and multifocal electroretinograph are prominent techniques employed to quantitatively analyze structural and functional abnormalities in the eye both to observe variability and to quantify the progression of the disease objectively. Glaucoma diagnosis usually follows an investigation of the retina using the Heidelberg Retina Tomograph (HRT), here the HRT is a confocal laser scanning system developed by Heidelberg Engineering. It allows 3-dimension images of the retina to be obtained and analyzed. This way the topography of the optical nerve head, called papilla, can be followed over time and any changes made is quantitatively characterized. In this paper we investigate intends to improve on this side by proposing a systematic and automatic investigation of 2-dimendional level images. Pre-processing is the first step in automatic diagnosis of retinal images. The quality of image is usually not good. Hence, Z- Score Normalization is used, which improves the quality of the retinal image. The two issues for the automatic glaucoma recognition are: 1) feature extraction from the retinal images and 2) classification based on the chosen feature extracted. Features extracted from the images are categorized as either structural features or texture features. Commonly categorized structural features include disk area, disk diameter, rim area, cup area, cup diameter, cup-to-disk ratio, and topological features extracted from the image.

Here, in this paper the texture features with in the images are actually mend for the efficient glaucoma classification. Here we use wavelet based features of that glaucoma image and after analyzing the energy features from the wavelet, these are introduced into certain classifier for the accurate glaucoma classification. Here accuracy is one of the important features of this paper which crosses about 95%. Previous techniques are

not as accurate as the proposed technique. We propose to use five well-known wavelet filters, the Haar or daubechies (db1), the symlets (sym3), biorthogonal (bio3.1, bio3.5, and bio3.7) filter wavelet filters. We calculate the averages of the detailed horizontal and vertical coefficients and wavelet energy signature from the detailed vertical coefficients. We subject the extracted features to four different classifications. We have gauged the effectiveness of the resultant ranked and selected subsets of features using a support vector machine, sequential minimal optimization, random forest, and naive Bayes classification strategies. This approach includes classification with huge scale of data and consuming times and energy, if done manually.

II. Related works

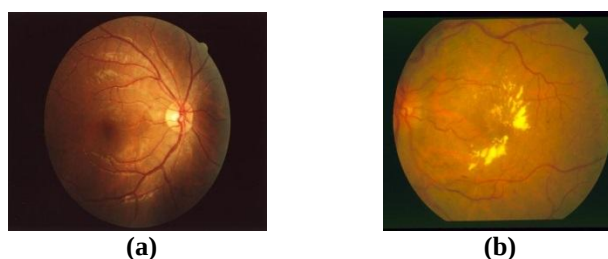
A number of works has been developed in order to detect the glaucoma with in the human eye. Many more efforts are made for several years to detect or diagnosis the disease, glaucoma, so that the sufferings caused by the disease can be reduced or even fully cured. The optical coherence tomography and multifocal electroretinograph (mfERG) are some prominent methods employed in order to find out and analyze the functional abnormalities of the eye especially glaucoma. Electroretinography measures the electrical responses of various cell types in the retina, including the photoreceptors (rods and cones), inner retinal cells (bipolar and amacrine cells), and the ganglion cells. The mfERG gives detailed idea regarding the topographical information of each zone of our retina and can therefore detect small-area local lesions in the retina and even in its central region (fovea). And several other abnormalities can also be detected with the help of multi focal electroretinograph. Optical coherence tomography (OCT) is an optical signal acquisition and processing method. This technique, typically employing near-infrared light. Diseases affected in in the internal tissues and muscles can be detected with the help of optical coherence tomography. This disease may affect the internal parts of eye which may leads to the loss of vision of eye. The discrete transform (DWT) analyses mfERG signals and detect glaucoma. In ophthalmology, CDSS are used efficiently to create a decision support system that identifies disease pathology in human eyes. In CDSS, both structural and texture features of images are extracted. The extracted structural features mainly include disk area, rim area, cup to disc ratio and topographical features. Automatic glaucoma diagnosis can be done by calculating cup to disc ratio.

The glaucoma progression can be identified from textural features using a method called POD. Glaucoma often damages the optic nerve head (ONH) and ONH changes occur prior to visual field loss. Thus, digital image analysis is extremely good choice for detecting the disease related to glaucoma and onset and progression of glaucoma by using the method of proper orthogonal decomposition (POD). A baseline topography subspace was constructed for each eye to describe the structure of the ONH of the eye at a reference/baseline condition using POD. Any glaucomatous changes in the ONH of the eye present during a follow-up exam were estimated by comparing the follow-up ONH topography with its baseline topography subspace representation. The texture features and higher order spectra can also be used for glaucomatous image classification. The wavelet decomposition is used for feature extraction, and they uses three well-known wavelet filters, the daubechies (db1) also called haar filter, the symlets (sym3), and the biorthogonal (bio3.1, bio3.5, and bio3.7) filters and then the classification is done using support vector machine, sequential minimal optimization, naive Bayesian, and random-forest classifiers.

III. Data set

The retinal images used for this study were collected from the Kasturba Medical College, Manipal, India (<http://www.manipal.edu>). The doctors in the ophthalmology department of the hospital manually curated the images based on the quality and usability of samples. The ethics committee, consisting of senior doctors, approved the use of the images for this research. All the images were taken with a resolution of 560×720 pixels and stored in lossless JPEG format. The dataset contains 60 fundus images: 30 normal and 30 open angle glaucomatous images from 20 to 70 year-old subjects. The fundus camera, a microscope, and a light source were used to acquire the retinal images to diagnose diseases. Fig. 1(a) and (b) presents typical normal and glaucoma fundus images, respectively.

Figure 1 data set (a) Normal image (b) Glaucoma image



IV. Methodology

The images in the dataset were subjected to standard histogram equalization. Evaluation of histogram provides the efficient classification of glaucoma. The objective of applying histogram equalization was twofold. The first

one to assign the intensity values of pixels in the input image, such that the output image contained a uniform distribution of intensities, and the second one is to increase the dynamic range of the histogram of an image. The following detailed procedure was then employed as the feature extraction procedure on all the images before proceeding to the feature ranking and feature selection schemes

A. Image Decomposition

For the classification of glaucoma from several data sets, the decomposition of data set is necessary. Here the decomposition is done with help of transform called discrete wavelet transform (DWT). A discrete wavelet transform is any wavelet transform for which the wavelets are discretely sampled. This transforms captures both frequency and location information. The DWT captures both the spatial and frequency information of a signal. DWT analyzes the image by decomposing the specified image in to a coarse approximation through low-pass filtering and then the image information is subjected to high-pass filtering. Such decomposition is performed recursively on low-pass approximation coefficients obtained at each level, until the necessary iterations are reached. While taking the DWT of the data set, each image from the data set are converted to four parts based on their intensity of frequency and there directions. They may be of 0 degree (horizontal, cH), 45 degree (diagonal, cD), 90 degree (vertical, CV) and 135 degree (diagonal, cD). As the image itself is considered to be a matrix with dimension $m \times n$, after decomposition they are converted to four coefficient matrices. The first level of decomposition results in four coefficient matrices, namely, A1, Dh1, Dv1, and Dd1

B. Feature Extraction

After image decomposition certain features are extracted from decomposed image. Here 2D-DWT is used for the feature extraction procedure. The DWT is applied to three different filters namely daubechies (db1) also called haar filter, symlets (sym3) and biorthogonal (bio3.1, bio3.5, bio3.7). From these filters certain filter coefficients are extracted. With the help of these filter coefficients feature extraction is carried out. The extraction is possible with those three equations mentioned below. Equations (1) and (2) represents the average of the corresponding intensity values and equation (3) represents the average of energy of intensity values.

$$\text{Average Dh1} = 1/(p \times q) \sum_{x=\{p\}} \sum_{y=\{q\}} |Dh1(x, y)| \quad (1)$$

$$\text{Average Dv1} = 1/(p \times q) \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x, y)| \quad (2)$$

$$\text{Energy} = 1/(p^2 \times q^2) \sum_{x=\{p\}} \sum_{y=\{q\}} (Dh1(x, y))^2 \quad (3)$$

C. Normalisation of Features

The next step after feature extraction is normalization of these features. From each data set given, 14 features are extracted out. These features are then z-score normalized with the help of given equation. For the normalization of old features mean and the standard deviation of these 14 features should be determined.

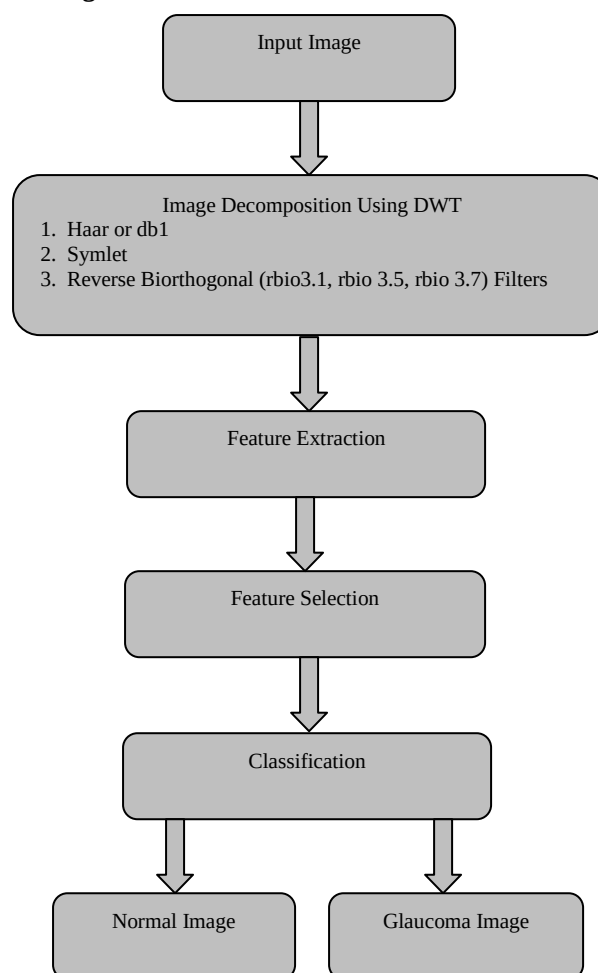
$$Y_{\text{new}} = (Y_{\text{old}} - \text{mean})/\text{std}$$

Where Y_{old} is the original value, Y_{new} is the new value, and the mean and std are the mean and standard deviation of the original data range, respectively.

V. Data set classification

We performed the validation of the ranked features and feature subsets using the standard C-SVC implementation of SVM, SMO, random forest, and naive Bayes. Here support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification of given data set and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. In SVM model, it represents the given images as points in space, mapped so that the images of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Sequential minimal optimization (SMO) is an algorithm for solving the quadratic programming (QP) problem that arises during the training of support vector machines. SMO is widely used for training support vector machines. Here the data set given as input is classified accordingly. Naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong independence assumptions between the features. Here assumptions between the features are taken from the data set. It is a popular method for text categorization, the problem of judging documents as belonging to one category or the other, with word frequencies as the features. Random forests are ensemble learning method for classification and regression of data set given as input, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees. The method combines Breiman's bagging idea and the random selection of features of the given data set, in order to construct a collection of decision trees with controlled variance.

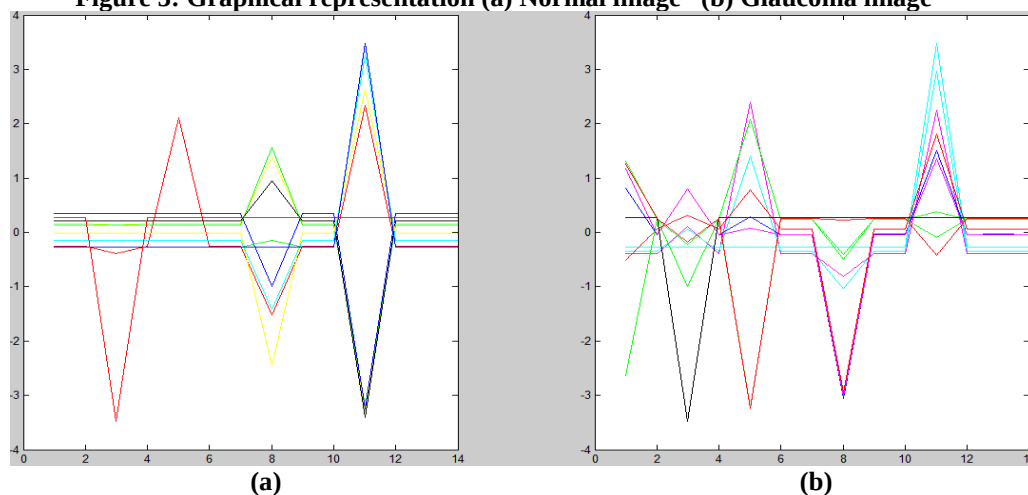
Figure 2 Data set classification flow chart.



VI. Experimental Result

The program code is generated using Matlab and the result is analyzed. The output is such that it classifies the dataset into normal and glaucomatous images. We performed the validation of the ranked features and feature subsets using the standard C-SVC implementation of SVM, SMO, random forest, and naive Bayes. Below mentioned is the graphical representation of feature extraxtion. The first figure is the graph showing tested images that contains glaucoma and the second graph that does not contain glaucoma. The different colour representation in the graphs shows the 14 features that has been extracted from different discrete wavelet transform filters.

Figure 3: Graphical representation (a) Normal image (b) Glaucoma image



VII. Conclusion

This paper demonstrates the feature extraction process using three wavelet filters. The daubechies (db1) or also represented as haar filter, symlets (sym3) and three biorthogonal wavelet filters such as rbio3.1, rbio3.5, rbio3.7 are used. From these five filters 14 wavelet coefficients are extracted. The wavelet coefficients obtained are then subjected to average and energy calculation resulting in feature extraction. The sequential feature selection algorithm is then used for selecting the most appropriate features for classification. The classification is done using four different classifiers that provides higher accuracy. The classifiers used here in this paper constitute SMO, SVM, Naïve bayes and Random Forest classifiers. We can conclude that the energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy.

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