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Energy Feature Extraction Using Wavelet Transform for Glaucomatous Image Classification

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Abstract -Wavelet Transforms is a part of large community of mathematical function approximation method, they are being increasing and being deployed in image processing for segmentation, filtering, classification etc. This work is based on image classification with the use of single level Discrete Wavelet Transform (DWT). Wavelets have been employed in many applications of signal processing. Thetexture features within images are extracted for accurate and efficient Glaucoma Classification. Energy is distributed over the wavelet sub-bands to find these important texture features. The discriminatory potential of wavelet features obtained from the daubechies (db3), symlets (sym3), and reverse biorthogonal (rbio3.3, rbio3.5, and rbio3.7) wavelet filters. We propose a technique to extract energy features obtained using 2-D discrete wavelet transform. The energy features obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy. The effectiveness is evaluated using K-NN classifier by taking 30 normal and glaucoma images, 15 images are used for training and 15 images for testing.

I. INTRODUCTION

Glaucoma is the second leading cause of blindness worldwide. Glaucoma is caused due to the increase in intraocular pressure of the eye. The intraocular pressure increases due to malfunction or malformation of the drainage system of the eye. The anterior chamber of the eye is the small space in the front portion of the eye. A clear liquid flow in and out of the chamber and this fluid is called aqueous humor. The fluid, aqueous humor nourishes and bathes nearby tissues. The intraocular pressure of the eye is maintained by the aqueous humor. The pressure within the eye is maintained by producing a small amount of aqueous humor while an equal amount flows out of the eye through a microscopic drainage system called trabecular meshwork. Glaucoma is mainly caused due to increase in intraocular pressure. Increased intraocular pressure results from either increased production or decreased drainage of aqueous humor.

The increased intraocular pressure within the eye damages the optic nerve through which retina sends light to the brain where they are recognized as images and makes vision possible. Hence elevated intraocular pressure is considered a major risk factor for Glaucoma. The prevalence of Glaucoma in worldwide is increasing rapidly .This is due in part to the rapidly aging population. Blindness due to Glaucoma greatly impacts the independence of many people who are part of this aging population. A prevalent model estimates that at the current time, there are about 60 million people worldwide with Glaucoma. Thus Glaucoma has become the second leading cause of blindness worldwide. Thus it becomes necessary to detect Glaucoma earlier and can provide better treatment. In this paper, we proposed a novel method to detect Glaucoma at an early stage by differentiating Glaucoma affected retinal images from normal retinal images by extracting the energy signatures from the provided dataset using two dimensional discrete wavelet transform and subject them to classification process. In this paper, we propose the use of 3 different wavelet filters such as daubechies, symlets and reverse biorthogonal on a set of fundus images by employing 2-DDWT. The texture features using wavelet transforms in image processing are often employed to overcome the generalization of features. We calculate the averages of the detailed horizontal and vertical coefficients and wavelet energy signatures obtained by wavelet decomposition. The extracted features are subjected to feature selection procedure to determine the combination of relevant features to maximize the class similarity.

II. RELATED WORKS

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 [1] and multifocal electro retinograph (mfERG) [2] are prominent methods employed in order to analyse functional abnormalities of the eye especially glaucoma. The mfERG gives detailed topographical information of each zone and can therefore detect small-area local lesions in the retina and even in its central region (fovea). The discrete wavelet transform (DWT) [3] analyses mfERG signals and detect glaucoma. In ophthalmology, CDSS [4] [5] are used efficiently to create a decision support system that identifies disease pathology in human eyes.

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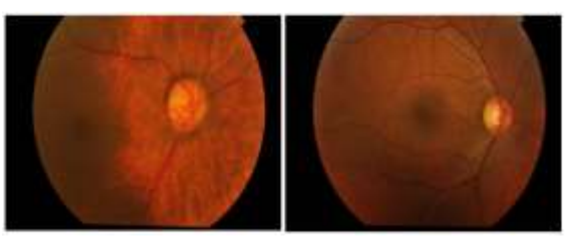
In CDSS, both structural and texture features of images are extracted. The extracted structural features mainly include disk area, rim area, cup to disc ratio and topographical features. Automatic glaucoma diagnosis can be done by calculating cup to disc ratio (6). The CDR (Cup-to-Disc Ratio) is defined as the ratio of the vertical cup height divided by the vertical disc height. A CDR value that is greater than 0.65 indicates high glaucoma risk. The glaucoma diagnosis can be improved by the enhancement of optic cup to disc ratio [7].The enhancement is done such that the least square fitting is used to determine boundary of cup and disc. The glaucoma progression can be identified from textural features using a method called POD [8]. Glaucoma often damages the optic nerve head (ONH) and ONH changes occur prior to visual field loss. Thus, digital image analysis is a promising choice for detecting the onset and/or 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 (or) baseline condition using proper orthogonal decomposition. If there is any glaucomatous changes in the optic nerve head 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 [9] [10] can also be used for glaucomatous image classification. The wavelet decomposition is used for feature extraction and the classification is done using sequential minimal optimization, support vector machine, random-forest classifier and naive Bayesian Classifiers.

III. DATASET

The retinal images used for this study were collected from the Aravindar Eye Hospital, Pondicherry, India. The doctors in the ophthalmology department of the hospital manually curated the images based on the quality and usability of samples. All the images are stored in lossless JPEG format. The dataset contains 30 fundus images. The 30 fundus images consist of 15normal and 15 glaucomatous images collected from 20 to 70 year-old subjects. The fundus camera, a microscope, and a light source are used to acquire the retinal images to diagnose diseases.



(a) **(b)**

Fig. 1. Shows typical fundus images (a) normal (b) glaucoma respectively.

In glaucoma, the pressure within the eye's vitreous chamber rises and compromises the blood vessels of the optic nerve head, leading to eventual permanent loss of axons of the vital ganglion cells.

IV. METHODOLOGY

The retinal images in the dataset are subjected to discrete wavelet transform. The following detailed procedure was then employed in order to classify glaucomatous image.

A. Image Decomposition

The wavelet features of an image are obtained by undergoing wavelet decomposition. Here the wavelet decomposition is done by using 2-D discrete wavelet transform which captures both spatial and frequency information's of a signal. DWT analyses the image by decomposing the given image into coarse approximation and detail information.

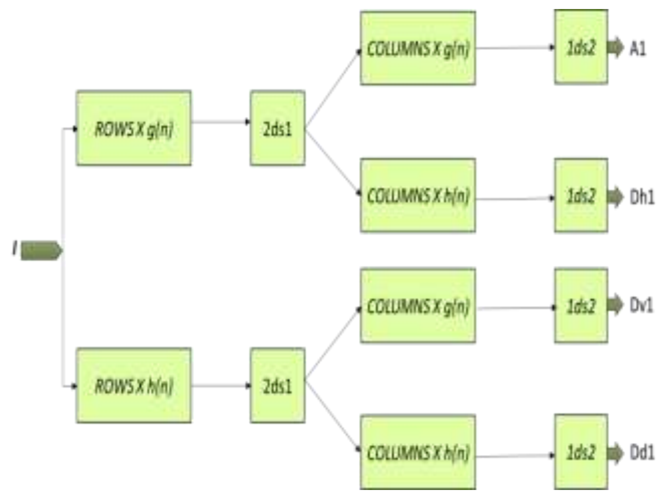


Fig.. 2. Shows 2-D-DWT decomposition, here 2ds1 indicates that rows are down sampled by two and columns by one. 1ds2 indicates that rows are down sampled by one and columns by two. The "×" operator indicates convolution operation.

The coarse approximation is done by low pass filtering and detail information via high pass filtering. Consider the image is represented as m*n matrix[10], it is subjected to four decomposition directions corresponding to 0 degree (horizontal, cH), 45 degree (diagonal, cD), 90 degree (vertical, cV) and 135 degree (diagonal, cD). Each element of the matrix represents the gray scale intensity of one pixel of the image thereby resulting in four coefficient matrices. The first level of decomposition results in four coefficient matrices, namely, A1, Dh1, Dv1, and Dd1. The decomposition structure for one level is illustrated in Fig. 2. In this figure, I is the image, g[n] and h[n] are the low-pass and high-pass filters, respectively, and A is the approximation coefficient. In this study, the results from level 1 are found to yield significant features.As is evident from Fig. 2, the first level of decomposition results in four coefficient matrices, namely, $A1$, $Dh1$, $Dv1$, and$Dd1$. Since the number of elements in these matrices is high, and since we only need a single number as a representative feature, the averaging methods were employed to find such single valued features. Using the DWT coefficients the definitions of the three features were determined

B. Feature Extraction

The 2-D DWT [10] is used in order to extract the energy signatures. The DWT is applied to three different filters namely daubechies (db3), symlets (sym3) and reverse biorthogonal (rbio3.3, rbio3.5, rbio3.7). With the help of these filters, we obtain the wavelet coefficients. Since the number of elements in these matrices is high, and we only need a single number as a representative feature, we employ averaging methods to determine such single valued features. The definitions of the three features that were determined using the DWT coefficients are in order. Equations (1) and (2) determine the averages of the corresponding intensity values, whereas (3) is an averaging of the energy of the intensity values. Thus wavelet coefficients which are subjected to average and energy calculation results in feature extraction.

$$AverageDh1 = \frac{1}{pXq} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dh1(x,y)| \quad ..(1)$$

$$AverageDv1 = \frac{1}{pXq} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x,y)| \quad ..(2)$$

$$Energy = \frac{1}{p^2Xq^2} \sum_{x=\{p\}} \sum_{y=\{q\}} (Dv1(x,y))^2 \quad ..(3)$$

C. Dataset Classification

The classification process is done using K-NN classifier. In this paper, classifier mainly performs two functions such as training the classifier and testing the images.

K Nearest Neighbour (KNN) is one of those algorithms that are very simple to understand but works incredibly well in practice. KNN is also surprisingly versatile and its applications range from vision to proteins to computational geometry to graphs and so on. Most people learn the algorithm and do not use it much which is a pity as a clever use of KNN can make things very simple. It also surprises many to know that KNN is one of the top 10 data mining algorithms. Instance-based classifiers such as the KNN classifier operate on the premises that classification of unknown instances can be done by relating the unknown to the known according to some distance (or) similarity function. The perception is that two instances far apart in the instance space defined by the appropriate distance function are less likely than two closely situated instances to belong to the same class.

KNN is a non-parametric lazy learning algorithm. That is a pretty crisp statement. The word non-parametric, it means that it does not make any assumptions on the underlying data distributions. This technique is pretty useful, as in the real world, most of the practical data does not obey the typical theoretical assumptions made (e.g. Gaussian mixtures, linearly separable etc.). Non parametric algorithms like KNN come to the rescue here.

(a) Training the classifier

Unlike many artificial learners, instance based training do not abstract any information from the training data during the training phase. Training the classifier is merely a question of encapsulating the training data. The process of generalization is postponed until it is absolutely unavoidable, that is, at the time of classification. This property has led to the referring to instance based learners as lazy learners, where as classifiers such as feed forward neural networks, where proper abstraction is done during the training phase, often are entitled eager learners.

(b) Classification process

Classification using an instance-based classifier can be a simple matter of locating the nearest neighbour in instance space and labelling the unknown instance with the same class label as that of the located neighbour. This approach is referred to as a nearest neighbour classifier. The downside of this approach is the lack of robustness that characterizes the resulting classifiers. The high degree of local sensitivity makes nearest neighbour classifiers highly inclined to noise in the training data. Most robust models can be achieved by locating k, where $k > 1$, neighbours and letting the majority vote decide the outcome of the class labelling. When the value of k is higher, it results in a smoother, less locally sensitive, function. The nearest neighbour classifier can be regarded as a special case of the more general K-nearest neighbour's classifier; hereafter it is referred to as a KNN classifier. The problem of increasing the value of K is of course that as K approaches n, where n is the size of the instance base, the performance of the classifier will approach that of the most straight forward statistical baseline, the assumption that all unknown instances belong to the class most frequently represented in the training data. This difficulty can be avoided by limiting the influence of distant instances. One way of doing so is to assign a weight to each vote, where the weight is a function of the distance between the unknown and the known instance. By letting each weight be defined by the inversed squared distance between the known and unknown instances votes cast by distant instances will have very little influence on the decision process compared to instances in the near neighbourhood. Distance weighted voting usually serves as a good middle ground as far as local sensitivity is concerned.

V.SOFTWARE REQUIREMENT AND DESCRIPTION

The operating system used is Windows 7 and the tool used is Matlab of version 7.10. MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numerical computation. Matlab is a data analysis and visualization tool which has been designed with powerful support for matrices and matrix operations. As well as this, Matlab has excellent graphics capabilities, and its own powerful programming language. One of the reasons that Matlab has become such an important tool is through the use of sets of Matlab programs designed to support a particular task.

VI. RESULTS AND DISCUSSION

In this work, first the colour fundus image is taken as input and it is converted to gray-level images. Then, the feature extraction process is done for all input images. The classifier will get trained for normal and abnormal features. Then the classification of images is done to find normal and glaucoma affected images.

Fig. 3. Shows the normal fundus image after classification process. There will be a small screen displayed as “Normal Image”

Fig. 4. Shows the Glaucoma affected image after classification process. There will be a small screen displayed as “Abnormal Image”.

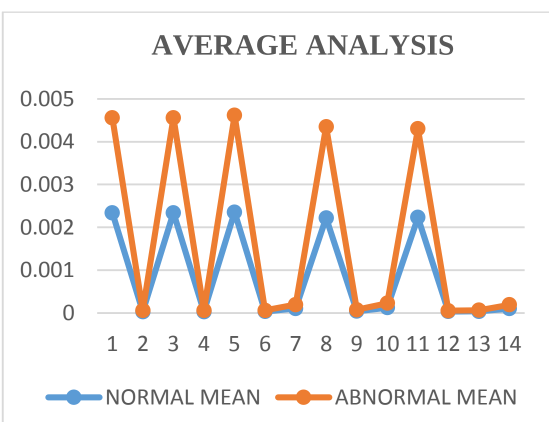


Fig. 5. Shows the graph plotted between normal and abnormal average values.

The output is obtained by subjecting the testing image to the K-NN classifier. Then, the classifier will show normal and glaucoma images.

After the feature extraction process is done. The values are obtained by applying the image to wavelet filters. The average is taken for all wavelet filter coefficients.

VII. CONCLUSION

This paper demonstrates the feature extraction process using three wavelet filters. The daubechies, symlets and reverse biorthogonal are the wavelet filters used. The wavelet coefficients obtained are then subjected to average and energy calculation resulting in feature extraction. The classification is done using K-Nearest Neighbour classifier which provides higher accuracy. 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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