Automated Classification of Glaucoma Images by Wavelet Energy Features

N.Annu[1], Judith Justin[2]
[1]PG Scholar, Dept. of Biomedical Instrumentation Engg, Avinashilingam University, Coimbatore, India
Email:annunatarajan1@gmail.com
[2]Faculty, Dept of Biomedical Instrumentation Engg, Avinashilingam University, Coimbatore, India
Email:judithvjn@yahoo.co.in

***Abstract*—Glaucoma is the second leading cause of blindness worldwide. As glaucoma progresses, more optic nerve tissue is lost and the optic cup grows which leads to vision loss. This paper compiles a system that could be used by non-experts to filtrate cases of patients not affected by the disease. This work proposes glaucomatous image classification using texture features within images and efficient glaucoma classification based on Probabilistic Neural Network (PNN). Energy distribution over wavelet sub bands is applied to compute these texture features. Wavelet features were obtained from the daubechies (db3), symlets (sym3), and biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. It uses a technique to extract energy signatures obtained using 2-D discrete wavelet transform and the energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images. We observed an accuracy of around 95%, this demonstrates the effectiveness of these methods**.

Keywords- Wavelet transform, Glaucoma, Image texture, Feature extraction, PNN.

I.INTRODUCTION

Glaucoma is caused by increased intraocular pressure (IOP) due to the malfunction of the drainage structure of the eyes [1]. It is the second leading cause of peripheral blindness worldwide and results in the neurodegenerationof the optic nerve. As the revitalization of the degenerated optic nerve fibers is not viable medically, glaucoma often goes undetected in its patients until later stages. Unfortunately, glaucoma symptoms are painless and the brain compensates gradual vision impairment to a considerable extent. The prevalent model estimates that approximately 11.1million patients worldwide will suffer from glaucoma induced bilateral blindness in 2020 [2]-[3]. Most people are not aware of such blind areas until the optic nerve has been destroyed substantially already. If the entire nerve is destroyed blindness results.

Glaucoma diagnosis usually follows an investigation of the retina using the Heidelberg Retina Tomograph (HRT), which

is a confocal laser scanning system developed by Heidelberg Engineering. It allows 3-dim 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 be quantitatively characterized [4]. The current investigation intends to improve on this side by proposing a systematic and automatic investigation of 2-dim 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 central issues to 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.

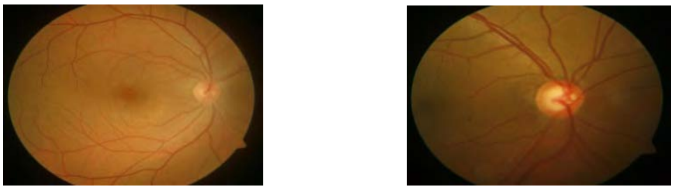
At this point, it is important to make a distinction between wavelet feature selection and the general feature selection discussed in pattern recognition. Both selection methods aim at obtaining a compact representation of the image for classification. However, the two techniques are not exactly the same. First, for general feature selection methods, the explicit knowledge of the feature extraction process may not always be available. The input to the general feature selection process is usually a vector of values representing the different features without any *a* priori information about how these features were obtained [5]. On the other hand, the wavelet feature selection methods can take advantage of the tree structure of the wavelet decomposition for the selection process.

Texture features using wavelet transforms (WTs) [12] in image processing are often employed to overcome the generalization of features. We propose to use three well-known wavelet filters, the daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) filters [2].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 Probabilistic Neural Network (PNN) classification. A PNN is a multilayered feed forward network with four layers namely input layer, pattern layer, summation layer and output layer[6]. This approach includes classification with huge scale of data and consuming times and energy, if done manually.

The rest of this paper is organized as follows. Section I presents about the data base. Section II describes our proposed feature extraction method. The classification of glaucoma and normal fundus images using PNN is shown in section IV. Its experimental results and comparisons are given in Section V. Finally, we conclude briefly in Section VI.

II.MATERIAL USED

The digital retinal images were collected from the ophthalmology department of a hospital, which manually curated the images based on the quality and usability of samples. The images were grouped into a set of normal retina images and a set of images clinically diagnosed with glaucoma. All the images were taken and stored in JPEG format.



(a) (b)

Fig.1. Typical fundus images (a) normal (b) glaucoma. In glaucoma, the optic nerve damages by the elevation in the intraocular pressure inside the eye, causing irreversible damage to the optic nerve and to the retina.

III.IMAGE PREPROCESSING

Differences in luminosity, contrast and brightness inside retinal images make it complex to extort retinal features and make a distinction of exudates from other bright features in images. Hence image pre-processing is required in equalization of the irregular illumination associated with retinal images. Each image is subject to z-score normalization [2],[1]. Z-score normalization converts to common scale with an average of zero and standard deviation of one.

$$y_{new} = \frac{y_{old} - mean}{std} \qquad (1)$$

Average of zero shows that it avoids introducing aggregation distortion. Here y_{old}, is the original value and y_{new} is the new value and the mean and std are the mean and standard deviation of the original data range, respectively.

IV.I LEVEL 2D DWT – BASED FEATURES

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved [3]. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training. Feature extraction is a general term which depicts to extract only valuable information from given raw data. The main objective of feature extraction is to represent raw image in its reduced form and also to reduce the original dataset by measuring certain properties to make decision process easier during classification. A feature is nothing but the significant representative of an image which can be used for classification, since it has a property which distinguishes one class from other. The extracted features provide characteristics of input pixel to the classifier [8].The spatial features can be extracted by statistical and co-occurrence methods.

It is a well-known fact that Fourier Transforms (FT) can be useful for extracting frequency contents of a stationary signal.

However, it cannot provide time-evolving effects of frequencies in non-stationary signals. STFT suffers from the limitation that it employs a fixed width of window function, chosen a priori, and hence it creates a problem for simultaneous analysis of high frequency and low frequency non-stationary signals.

Table I.
Results of Texture Features for Normal and Glaucoma Classes

Feature	Normal	Glaucoma	P-Value
Energy	8.0830E-004 ± 4.1659E-005	3.9611E-004 ± 3.7244E-004	≤ 0.0001

Hence, wavelet transform arose as an effective tool for those situations where one needs multi resolution analysis, providing short windows at high frequencies and long windows at low frequencies[7].Here each image is represented as a $p \times q$ gray-scale matrix $I[i,j]$. The resultant 2-DDWTcoefficients are the same irrespective of whether the matrix is traversed top-to-bottom or bottom-to-top. Hence, it is sufficient that we consider four decomposition directions corresponding to 0◦ (horizontal, *Dh*), 45◦ (diagonal, *Dd*), 90◦ (vertical, *Dv*), and 135◦ (diagonal, *Dd*) orientations. 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. Where, 2ds1 indicates that rows are

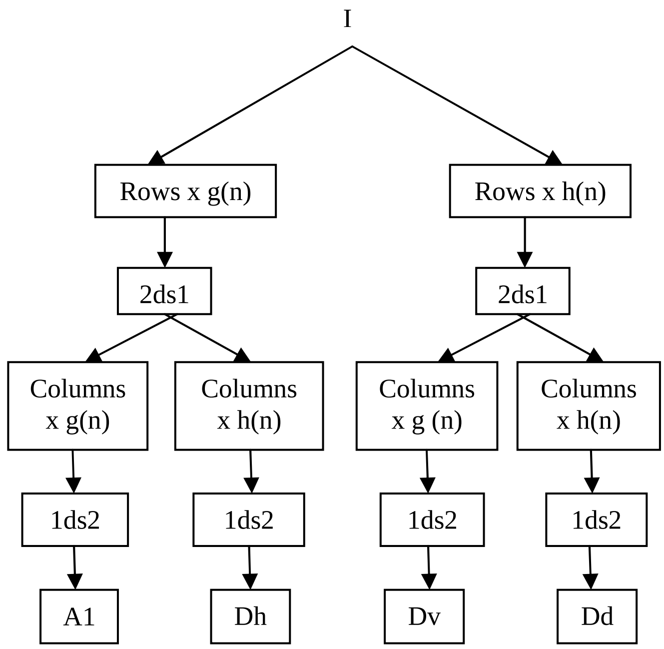


Fig.2. 2-Dimention Discrete Wavelet Transform decomposition

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. Since the number of elements in these matrices is high, and since we only need a single number as a representative feature, [2] we employed averaging methods to determine such single valued features. These are obtained by the following equations,

$$Average\ Dh1 = \frac{1}{p\times q}\sum_{x=\{p\}}\sum_{y=\{q\}}|Dh1(x,y)| \qquad (2)$$

$$Average\ Dv1 = \frac{1}{p\times q}\sum_{x=\{p\}}\sum_{y=\{q\}}|Dv1(x,y)| \qquad (3)$$

$$Energy = \frac{1}{p^2\times q^2}\sum_{x=\{p\}}\sum_{y=\{q\}}\big(Dv1(x,y)\big)^2 \qquad (4)$$

Energy signatures provide a good indication of the total energy contained at specific spatial frequency levels and orientations [9].The energy based approach assumes that different texture patterns have different energy distribution in the space-frequency domain. The energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy. Hence these energy features are highly discriminatory. This approach is very appealing due to its low computational complexity involving mainly the calculation of first and second order moments of transform coefficients.

V. CLASSIFIER USED

The Probabilistic Neural Network was developed by Donald Specht. Classification refers to the analysis of the properties of an image. Depending upon the analysis, the dataset is further referred into different classes. Input features are categorized as 0 and 1.The classification process is divided into two phases: training phase and testing phase [15]. In the training phase, known data is given and in the testing phase, an unknown data is given. Classification is done by using classifier after the training phase [14].The Probabilistic Neural Network provides a general solution to pattern classification problems.

PNN is adopted for it has many advantages. Its training speed is many times faster than a BP network. Additionally, it is robust to noise examples. However, we choose a basic Matlab PNN for its simple structure and training manner. The most important advantage of PNN is that training is easy and instantaneous. Weights are not “trained” but assigned. Existing weights will never be alternated but only new vectors are inserted into weight matrices during training. So it can be used in real-time [11]. Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast. The network classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input layer, Radial Basis function Layer and the Competitive Layer. Equation (5) determines the Probabilistic Neural Network process.

$$output = f^{\Sigma Woli} + BIAS \qquad (5)$$

Where, Wo is Weight, li is Input, BIAS is called activation function. The training set of PNN must be done through representative of the actual population of effective classification and it is characterized by the following, more demanding than most NN's, sparse set sufficient and erroneous samples and outliers tolerable. Adding and removing training samples simply involves adding or removing "neurons" in the pattern layer. The training of PNN is fast as orders of magnitude faster than backpropagation. Fig.3 represents the basic operations of the process for classification of normal retinal eye images and glaucomatous retinal eye images.

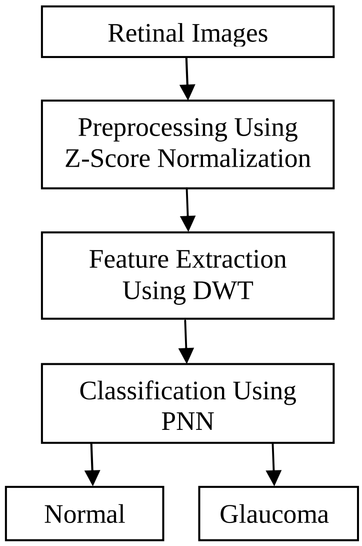


Fig.3.Block diagram of Classification as Glaucoma and Normal Retinal Image.

VI.IMAGE QUALITY EVALUATION METRICS

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert which is complicated and does not give the exact quality. There are various metrics used for objective evaluation of an image.

Sensitivity is the probability of an abnormal class being classified as abnormal.

$$sensitivity = \left(\frac{TP}{TP+FN}\right) \times 100\% \qquad (6)$$

Specificity is defined as the probability of a normal class being identified as normal.

$$specificity = \left(\frac{TN}{TN+FP}\right) \times 100\% \qquad (7)$$

The Positive Predictive Accuracy (PPV) shows the accuracy of detecting the normal and abnormal cases.

$$PPV = \left(\frac{TP}{TP+FP}\right) \times 100\% \qquad (8)$$

The accuracy shows quality or ability of the performance.

$$accuracy = \frac{TP+TN}{TP+FP+FN+TN} \qquad (9)$$

Where, True Negative (TN) is the number of normal images classified as normal images, False Negative (FN) is the number of glaucomatous images classified as normal, True Positive (TP) is the number of glaucoma images classified as glaucoma and False Positive (FP) is the number of normal images classified as glaucomatous.

VII.EXPERIMENTAL RESULTS AND DISCUSSION

The following section provides a detailed description of the results obtained from our pre processing, feature ranking and Classification.

A . Z-SCORE NORMALIZATION

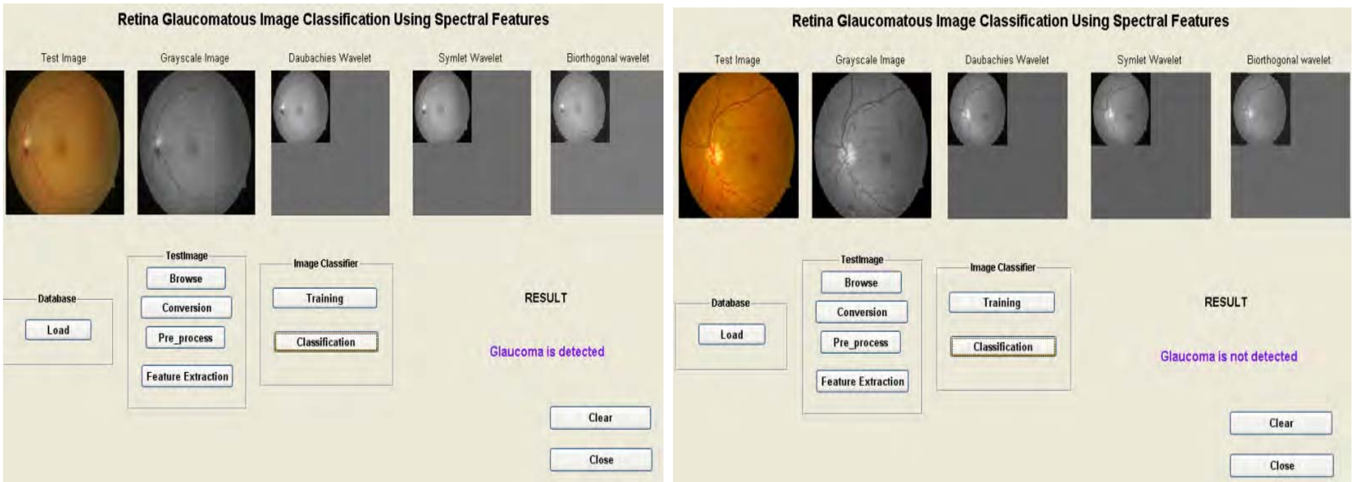
Figure.4. shows the resulting retinal images obtained after preprocessing. Figure.4. (a) shows the image before z-score normalization and (b) shows the image after z-score normalization.

(a) (b)

Fig.4 (a) and (b). Shows the difference between before and after process of Z-Score Normalization

B . FEATURE EXTRACTION

The energy based approach assumes that different texture patterns have different energy distributions in the space-frequency domain. This approach is very appealing due to its low computational complexity involving mainly the calculation of first and second order moments of transform coefficients [12]. Figure 5 provides a snapshot of the results obtained from Feature extraction described in the methodology section. Figure 5 shows the energy feature extraction using Discrete Wavelet Transform.



(a) (b)

Fig. 5(a) and (b) shows the energy feature extraction using 2D-DWT and Classification of glaucoma images.

Here one level Wavelet decomposition is done, and the wavelet filters used here were, the daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) filters. The extracted features were used for Classification [2].

C . CLASSIFICATION USING PNN

Probabilistic Neural Network (PNN) is a kind of supervised neural network that is widely used for pattern recognition [14]. The PNN is applicable to the same class of problems for which the back propagation neural network BPNN is typically used. Experimental results indicate that PNN has a number of major advantages over other traditional neural networks. Figure 5 shows classification result using PNN, the retinal images are classified as 'glaucoma is detected' or 'glaucoma is not detected'. First, the Wavelet transform technique is employed to extract the energy distribution features of the distorted signal at one level decomposition. Then, the PNN classifies these extracted features to identify the normal and abnormal retinal images according to the energy features. Experiments have been carried out to verify the ability of the PNN in achieving good classification rate. In this approach, we have considered 20 retinal images both normal and glaucoma eye. Out of 20 images taken for classification, 10 were normal retinal images and the remaining 10 were glaucomatous images and 15 images were used for training. Results are presented in Table II.

Table III

Classification Accuracies (%) of Classifier after Normalization and Feature Extraction

Classifier	Sensitivity	Specificity	Positive Predictive Accuracy	Accuracy
PNN	100%	90%	90%	95%

Table II summarizes the classification accuracy obtained by the classifier used. Here the number of normal images classified as normal is 9 which is True Negative, the number of glaucoma images classified as normal is zero which is called False Negative, the number of glaucoma images classified as glaucoma is called True Positive which is 10 here and the number of normal images classified as glaucoma is 1 which is called False Positive. Thus the Sensitivity, Specificity, Positive Prediction Accuracy and Accuracy using the Probabilistic Neural Network were 100%, 90%, 90% and 95% respectively.

VIII.CONCLUTION

In this paper, a wavelet-based texture feature set has been used. The texture feature set is made up of the energy of sub images. Wavelet transform are very efficient tools for feature extraction and they are very successfully used in biomedical image processing. Classification technique is developed to automatically detect whether glaucoma is present or not. Features by DWT give maximum classification accuracy of 95% and it is rapid, easy to operate, non-invasive and inexpensive.

We have carried out the classification by Probabilistic Neural Network for the purpose of examining the efficiency of the features extracted. If more powerful classifiers used, classification accuracy may further be improved. The approach will be left as a future work.

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