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Insight To Glaucomatous Image Classification Using Probabilistic Neural Network

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Abstract— **Features within retina images has been analysed to identify efficiently glaucoma in its early stages. Image features like average and energy were used to classify glaucoma. In this paper we extracted the image features using daubechies (db3), symlets (sym3), and biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters and then classified the images using PNN (Probabilistic neural network Algorithm) and Structural Similarity Measurement. The classified glaucomatous image was later processed using Fuzzy C means and K means algorithm to get exudates of the image. We observed high efficiency glaucomatic feature extraction from the images with high accuracy. Further analysis is underway to propose a method to identify initial phases of glaucoma and the percentage of accuracy.**

Keywords— **daubechies; biorthogonal; glaucomatous image.**

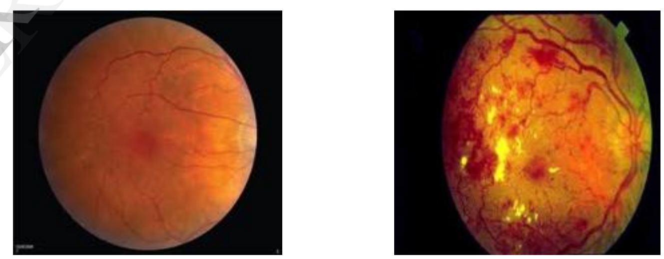
I. INTRODUCTION

World wide, Glaucoma is one of the most common causes of blindness. Glaucoma is a disease of the optic nerve caused by the increased pressure inside the eye. Glaucoma mainly affects the optic disc by increasing the cup size. It can lead to the blindness if it is not detected and treated in correct time. In other words glaucoma means it is a" silent thief of sight" because the loss of vision occurs gradually over a long period of time. The detection of glaucoma through Optical Coherence Tomography (OCT) [2] and Heidelberg Retinal Tomography (HRT) is very expensive. In this paper a new method will be introduced namely PNN (Probabilistic Neural Network) algorithm, for the detection of glaucoma.

Optical coherence tomography and multifocal electro-retinograph (mfERG) [3] are two different techniques used for the detection of glaucoma. These two methods analyse structural and functional abnormalities in the eye, both to observe variability and to quantify the progression of the disease objectively [4]. These two methods have some drawbacks like feature extraction using any method, its output efficiency is very low. These methods are not bound to specific location on original image. In this paper, the features can be extracted by using five different wavelet filters i.e, daubechies (db3), symlets (sym3), and biorthogonal (bio3.3, bio3.5, and bio3.7) [5].These five wavelet filters extract features very efficiently. Then classified normal and abnormal images by using PNN algorithm. The segmentation of the abnormal images are done using FCM and K-means algorithms while the optical disc of normal images are obtained using morphological operators.

II. METHODOLOGY

The retina images used in the study were collected from reputed ophthalmologist in Kerala. We had a set of 20 images of which 10 were normal and 10 were glaucomatic images. The images were in JPEG format [10]. Fig 1 (a) and (b) represents typical normal and glaucomatic images.



(a) (b)

Fig.1 Retina images (a) normal (b) glaucoma.

Histogram equalization was applied on the images [1,9] for increasing the dynamic range and for image enhancement. In general it makes the details in the image more visible.

Here the features of images obtained from test images and features of images in the data set are compared by using PNN algorithm and images can be classified into normal and abnormal images (glaucomatous image). If the image is glaucomatous then it is segmented. Here, we used two types of clustering methods i.e., k-means and Fuzzy c means. Fuzzy c means results faster and reliably good clustering when compared to k-means.

A. Discrete Wavelet Transform Features

Wavelet transforms has gained widespread acceptance in signal processing and image compression. In dwt, this transforms a discrete time signal to a discrete wavelet representation. In numerical studies and functional analysis, a discrete wavelet transform (DWT) can be defined as any wavelet transform in which the wavelets are discretely sampled. Comparing with other wavelet transforms, a key advantage it has over Fourier Transform is temporal resolution. In two dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain.DWT analyzes the image by decomposing it into a coarse approximation via low pass filtering and into detail information via high pass filtering [1]. Such decomposition is performed continuously on low pass approximation co-efficient obtained at each stage, until its necessary iterations are achieved.

Let each image be represented by pxq gray scale matrix, in which each element of the matrix represents the gray scale intensity of one pixel of the image. It has to be noted that each non border pixel has eight adjacent neighboring pixel intensities. The eight neighbors are used to traverse the matrix. The resultant 2D-DWT coefficients are the same irrespective of the directions in which the matrix is traversed. Hence, it is important to consider four decomposition directions corresponding to 0◦ (horizontal, *Dh*), 45◦ (diagonal, *Dd*), 90◦ (vertical, *Dv*), and 135◦ (diagonal, *Dd*) orientations [1]]. The decomposition structure for one level is illustrated in fig.2

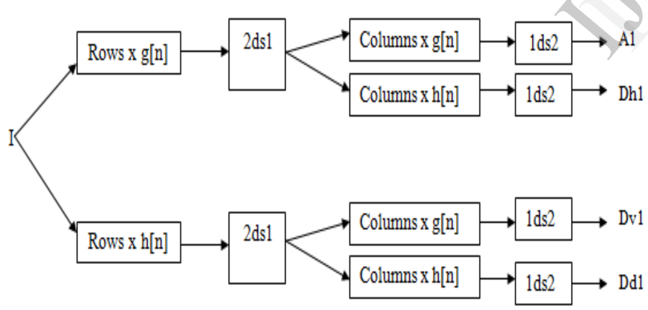


Fig.2 -D-DWT decomposition: 2ds1 indicates that rows are down sampled by two and columns by one. 1ds2 indicates that rows are down sampled by one and columns by two. The "×" operator indicates convolution operation

In this figure, I is the input image, g(n) and h(n) are the low pass and high pass filters respectively, and A is the approximation coefficient for filtering. The first level of decomposition gives four coefficient matrices, namely, A1, Dh1, Dv1 and Dd1. Averaging methods are employed to determine single valued features.The first two following equations determines the average of the corresponding intensity values ,whereas the last equation is an averaging of the energy of the intensity values[1].

$$AverageDh1 = \frac{1}{pxq} \sum_{x=\{p\}} \sum_{y=\{q\}} \left| Dh1(x,y) \right| \qquad (1)$$

$$AverageDv1 = \frac{1}{pxq} \sum_{x=\{p\}} \sum_{y=\{q\}} \left| Dv1(x,y) \right| \qquad (2)$$

$$Energy = \frac{1}{p^2 xq^2} \sum_{x=\{p\}} \sum_{y=\{q\}} \left(Dv1(x,y) \right)^2 \qquad (3)$$

B. Classification

Probabilistic Neural Network Algorithm(PNN)

Probabilistic Neural Network is a feed forward neural network; it performs classification where the target variable is categorical. PNN is efficient network architecture with slightly difference in fundamentals from back propagation. The architecture is feed forward in nature which has similarity to back propagation, but differ in the way that learning occurs. PNN is often used in classification problem. When an input is present, the first layer calculates the distance from the input vector to training input vector. PNN is supervised learning algorithm without including any weights in its hidden layer. Here each hidden node represents an example vector, with the example itself act as a weight to the hidden node which are not adjusted at all.

Basically, PNN consists of an input layer, which represents the input pattern feature or vector. The input layer is fully interconnected with the hidden layer, which consists of the example vectors (the training set for the PNN).The actual example vector serves as the weights as applied to the input layer. The output layer represents each of the possible classes for which the input data can be classified and hidden layer is not fully interconnected to the output layer. The example nodes for a given class connect only to that class's output node and none other.

Another important element of the PNN is the output layer and the determination of the class for which the input layer fits. This is done through a winner-takes-all approach. The output class node with the largest activation represents the winning class. While the class nodes are connected only to the example hidden nodes for their class, the input node feature vector connect to all examples and therefore influences their activation. Its therefore the sum of the example vector activations that determines the class of the input feature vector. PNN algorithm, calculates the class node activation through a simple process. For each class node, the example vector activations are summed which are the sum of the product of the example vector and the input vector. The hidden node activation, shown in the following equations, is simply the product of the two vectors,

$$h_i = E_i F$$

Where E is the example vector F is the output feature vector. The class output activations are then defined as

$$c_j = \frac{\sum_{i=1}^{N} e^{\frac{(h_i - 1)}{\gamma^2}}}{N}$$

Where N is the total number of example vectors for their class h_i is the hidden node activation and γ is the smoothing factor. The smoothing factor is chosen through experimentation If the smoothing factor is too large, details can be lost, but if the smoothing factor is too small, the classification may not be generalize well. Then classified normal and abnormal images by using PNN algorithm. The segmentation of the abnormal images are done using FCM and K-means algorithms. If the image is normal, find optical disc by using morphological operators.

K-means clustering algorithm:

It is a technique of vector quantization originally from signal processing, that is known for cluster analysis in data mining. k-means clustering aims to partition ' n' number of observations into k cluster in which each observations belongs to the cluster with the nearest mean, which serves as a prototype of the cluster. This results in a partitioning of the data space into voronoi cells. The main idea is to define k-centroids one for each cluster.

The centroids are placed proper way because different location can cause different result. The best choice is to place hem far away as possible from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k- new centroids as barycentre of the cluster resulting from the previous step.

After having new centroid,a new binding is done between the same data set points and the nearest new centroid. A loop has been generated in which we can notice the k centroids change their location step by step until no more changes are done. In other words centroids do not moving any more. Finally this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$$

Where $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, is an indicator of the distance of the n data points from their respective cluster centres. The algorithm is composed of the following steps:

Step1: Place k points into the space represented by the objects that are being clustered. This points represent initial group centroids.

Step2: Assign each object to the group that has the closest centroid.

Step3: When all objects have been assigned, recalculate the position of the k centroids.

Step4: Repeat step 2 and 3 until the centroids no longer move.

Fuzzy C- Means clustering algorithm:

Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is used in pattern recognition and is based on minimization of following objective function [7,8],

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2, \quad 1 \le m < \infty$$

Where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j x_i is the *i*th of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}}, \qquad c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

This iteration will stop when $\max_{ij} \left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{(k)} \right| \right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas *k* are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m. The algorithm is composed of the following steps:

1. Initialize U=[u_{ij}] matrix, $U^{(0)}$
2. At k-step: calculate the centers vectors $C^{(k)}$=[c_j] with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

3. Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

4. If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then STOP; otherwise return to step 2.

III. EXPERIMENTAL RESULTS

The images in the dataset were subjected to standard histogram equalization. The table I shows the maximum correlation values obtained from 5 wavelet transforms of five different images [6]. What we observe is that Db3 and Sym 3 transforms results in the maximum correlation values and they match. Since both the wavelets show the maximum correlation value, we can conclude that these wavelets are better than the others for providing structural similarity result. The table II shows the wavelet features. Figure3 shows the result of normal image.. Figure 4 shows the result of glaucomatic image where we find the exudates from segmentation. From the results we can infer that fuzzy c-mean clustering is much better than k-mean clustering.

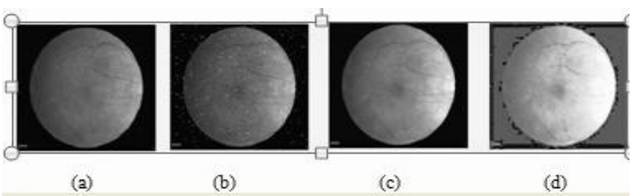
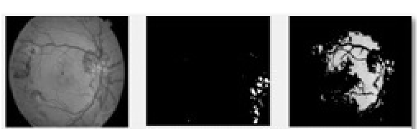


Fig.4.Result of a normal image (a) input image (b) image with salt and pepper (c) filtered image (d) adaptive histogram equalization.



(a) (b) (c)

Fig.5.Result of a abnormal image (a) input image (b) k-means (c) fuzzy c-means

Table I

INPUT	MAX CORRELATION VALUES FOR DIFFERENT WAVELET				
	DB3	SYM3	BIOR3.3	BIOR3.5	BIOR3.7
INPUT 1	0.8161	0.8161	0.7873	0.7964	0.8037
INPUT2	0.7696	0.7696	0.7581	0.7630	0.7656
INPUT3	0.8257	0.8257	0.8062	0.8161	0.8239
INPUT4	0.8557	0.8557	0.8298	0.8346	0.8388
INPUT5	0.9952	0.9952	0.9830	0.9837	0.9844

Table II
WAVELET FEATURES

Wavelet	Feature	Normal	Glaucoma
Db3	Average	0.0035	0.0165
	Energy	5.6124e-005	4.7414 e-004
Sym3	Average	0.0035	0.0165
	Energy	5.6785e-005	4.7132 e-004
Bior3.3	Average	0.0046	0.0126
	Energy	2.8124e-004	6.2124 e-004
	Energy	4.6743e-004	5.3007e-004
Bior3.5	Average	0.0092	0.0080
	Energy	2.1428e-004	3.2123 e-004
	Energy	7.9124e-005	6.4374e-004
Bior3.7	Average	0.0093	0.0133
	Energy	3.4154 e-004	4.9137 e-004
	Energy	8.7941e-005	1.6075 e-004
	Energy	7.9124e-005	6.4374e-004

IV CONCLUSION

In our study we extracted the image features using the five transformations and classified the image using PNN algorithm. The exudates of the image was obtained by processing the glaucomatic image using Fuzzy C means and K means algorithm. From the images we studied using this process method, we conclude that glaucomatic feature extraction from the images can be carried out with high efficiency. We need to process large number of retina images to quantify the actual accuracy of this method.

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