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Detection of Grading Diabetics in Retina Using Wavelet Transforms

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Abstract: Detection of grading diabetics in retina has been developed to classify the retinal images using wavelet transform has been presented in this paper. . These weakened blood vessels will leak blood to spread over the retina, which in turn forms micro aneurysms, hemorrhages, hard exudates, cotton wool spots and Large Plaque Hard Exudates (LPHE). Severe stage of diabetic retinopathy leads to blindness. The goal of this project is, thus to automatically classify normal eye images and diseased diabetic retinopathy eye images based on the distribution of average texture features obtained from three prominent wavelet families. Hence, the objective is to evaluate and select prominent features for enhanced specificity and sensitivity of retinal image classification. For this purpose, the DWT is applied to the input images. In this project, the effectiveness of different wavelet filters on a set of diabetic retinopathy images by employing the standard 2-D-DWT is examined. The use of three well-known wavelet filters such as the daubechies filter (db3), the symlets filter (sym3) and the bi orthogonal filters (bio3.3, bio3.5, and bio3.7) are proposed.

Keywords: DWT discrete wavelet transform, symlets filter, orthogonal fiters

I. Introduction

Diabetic retinopathy is found to be a leading cause of blindness in the recent past. In general, the blood vessels of retina are affected in the person with diabetic. The weakening of retinal blood vessels leads to leakage of the blood in to the retina which causes visual impairment for permanent blindness. The increase in number of diabetic victims and the need for developing advanced measurement techniques of various retina parameters have been motivated by many researchers in the past few decades.

Non-Insulin Dependent Diabetes Mellitus (NIDDM) is found as the most rapidly growing chronic disease and its long-term complications includes retinopathy, nephropathy, neuropathy and accelerated macro vascular disease which cause major morbidity and mortality. Electrophysiological tests reveal the abnormal function of the visual system in patients with diabetic retinopathy. The structure of retinal vessels is a well-known feature that explains further information on the state of diseases that are reflected in the form of measurable abnormalities in diameter, color and tortuosity. Hence consistent methods of vessel detection and various vessels measurements are needed for extensive analysis and decision making. Wu et al. have developed the method to detect the ridges by checking the zero-crossing of the gradients and the curvature. The edge constraints were used to suppress the response of spurious boundary. Edges and the center lines of vessels have been tracked from seeds obtained using multiple thresholds of the enhanced image. Since we have developed a system for ratite diabetic Retinopathy based on the bright lesion of the retinal image. In this method a rule based classifier has been used for the decision making. Later have demonstrated that the curve let transform can enhance and prepare the retinal image vessel detection. The simple thresholding method along with Connected Components Analysis (CCA) indicates the remaining ridges belonging to vessels. S.Supot et al.have developed an automatic fuzzy K-mean clustering segmentation scheme for blood vessel in retinal image and extracted features were given to the classifier. Then we have proposed a tracking-based method using a probabilistic approach. The statistical segmentation scheme was associated with the Maximum Posteriori (MAP) as criterion to estimate local vessel edges.

Recently, al has developed the methodology for obtaining the Fractal Dimension (FD) of retinal images. This includes the image enhancement using wavelet transforms, the implementation of Fourier Fractal Dimension (FFD) computation, testing the robustness (re-peat ability and reliability) of the technique and validating the results by evaluating its associations with age, a well-known association found with FD in biological organs and systems. Benson S. Y. Lam et al. have developed regularization-based multi concavity approach for segmenting blood vessels in both normal and pathological retinas with bright and dark lesions in a single system. The perceptive transform derived from Weber's law was used to map an input image into a perceptive space for robust vessel segmentation.

The blood vessel detection by extracting 7-D feature vectors has been presented by Diego Marin et al.. Classification results (real values between 0 and 1) were considered as threshold to classify each pixel into two classes namely vessel and non vessel region. They developed a method to estimate the blood vessel diameter. The vessel intensity profile model was used to make the vessel geometry.

They have developed the method for an efficient detection of Optic disc in color retinal images. The geometric model based implicit active contour model was used to find the exact boundary of the optic disc. Also the method has been evaluated for a selected database of 148 retinal images and compared with the human expert. The Topographic measurements of the optic disc were reported. The Retinal Thickness Analyzer (RTA) and the Heidelberg Retina Tomography II (HRT II) were used to determine the mean values of the optic disc.

Di Wu and Ming Zhang have developed an adaptive detection scheme for large and small blood vessels in color retinal images. It was suggested that three methods can be used for the blood vessels analysis of retinal images such as adaptive contrast enhancement, feature extraction of blood vessels and tracing. Retinal and Nerve Fiber Layer (NFL) thickness, Retinal Pigment Epithelium Layer (RPEL) especially sub foveal area, Presence of maculopathy (atrophic, cystoid, cellophane) and Optic disc changes have been developed et al. In this measurement technique it was noticed that the Retinal thickness reduced in the cases with pronounced waxy yellow optic disc color, generalized attenuation of blood vessels, heavier pigmentation and more RPE atrophy.

The Transient Visual Evoked Potential (TVEP) has been used in the clinical environment as a diagnostic tool for a long period. It is one of the non-invasive tools used in analyzing the diabetic retinopathy. Very few researchers have focused on identifying the effect of retinopathy in the optical response and the variation in the functioning of the optic nerve. Analysis of the evoked potential response may pave the way for early diagnosis of diabetic retinopathy and prognosis during the treatment process been used. During the thresh holding process, individual pixels in an image are marked as object pixels if their value is greater than sum of three components of RGB threshold value (assuming an object to be brighter than the back-ground) and as background pixels otherwise. Typically, an object pixel is given a value of "1" while a back-ground pixel is given a value of "0". Finally, a binary image is created by coloring each pixel as white or black, depending on a pixel's labels. In the present work, the RGB values as assigned as r 0>200, g 0>200 and b00 to 50.The equation is written and have developed the retinal blood vessel segmentation scheme using line operators and support vector classification. The computer-aided diagnosis based on line operators have been proposed and applied to the green channel of the retinal image. Artificial Neural Network (ANN) has also been used extensively in medical fields to accurately classify the images. The advantages of artificial neural net-works include ability to generalize and adapt to the signal distortion and noise without loss of robustness.

In the present work, the classification of retina is done using different ANN classifiers. The features extracted are optic disc measurement, blood vessel thickness and vein diameter. This proposed method can be used as second reader for retinal image analysis.

II. Proposed System

The flow diagram of the proposed medical decision support system for classifying diabetic retina is shown in Fig. 1. The proposed method consists of Image Preprocessing, Segmentation, Feature Extraction, Classification and decision making.

PROPOSED SYSTEM

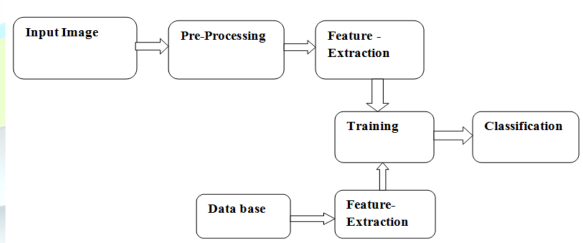

Fig.1 Block diagram for Classification

The retinal image can be acquired with the dedicated fundus camera and digitized with a laser film scanner [ZEISS STRA-TUS OCT, Modern 3000]. In the development of automated diabetic retinal image classification system, the analysis of diabetic retina detection depends on the region of interest such as optic disc, vascular thickness and the vein diameter. Hence the image de noising

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and enhancement techniques are required to highlight the image features. In general, the Gabor filtering can be used for preprocessing to obtain the sharp edges. The retina edges can be detected using

$$G(x,y,f,\vartheta)=\exp\left\{-\frac{1}{2}\left[\frac{x'^2}{\delta_{x''}{}^2}+\frac{y'^2}{\delta_{y'}{}^2}\right]\right\}\cos(2\pi f x')$$

Where,

$$y' = x\cos\vartheta + y\sin\vartheta$$

$$x' = x\sin\vartheta + y\cos\vartheta$$

Here θ is the orientation of the Gabor filter.

Then the adaptive histogram equalization can be done to improve the images local contrast to bring out more details in the image. Then the features can be extracted to classify using various artificial intelligence techniques.

A. Segmentation And Feature Extraction

The DWT captures both the spatial and frequency information of a signal. DWT analyzes the image by decomposing it into a coarse approximation via low-pass filtering and into detail information via high-pass filtering. Such decomposition is performed recursively on low-pass approximation coefficients obtained at each level, until the necessary iterations are reached. Let each image be represented as a $p \times q$ gray-scale matrix $I\,[i,j]$, where each element of the matrix represents the gray scale intensity of one pixel of the image. Each non border pixel has eight adjacent neighboring pixel intensities. These eight neighbors can be used to traverse the matrix. The resultant 2-DDWTcoefficients are the same irrespective of whether the matrix is traversed right-to-left or left-to-right.

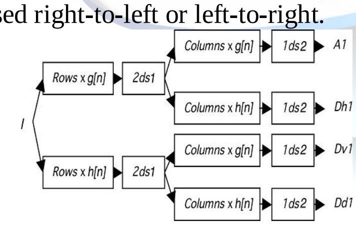


Fig. 2: 2-D DWT Decomposition: 2ds1 indicates that rows are down sample

B. Segmentation

The segmentation is to distinguish one or more Regions of Interest (ROI) from the selected image after pre processing. The segmentation is done by partitioning an image into homogeneous regions (Spatially converted groups of pixels called classes, or subsets) with respect to one or more characteristics or features such that the union of any two neighboring regions yields heterogeneous features. Segmentation techniques can be classified into two main categories: edge based segmentation and region based segmentation techniques. The region based techniques such as region growing, water shed algorithm and thresholding have been more commonly used algorithms. In the present work, RGB based thresholding method is used for segmentation, In this segmentation, the images size of M×N pixel has been used. During the thresholding process, individual pix-els in an image are marked as object pixels if their value is greater than sum of three components of RGB threshold value (assuming an object to be brighter than the back-ground) and as background pixels otherwise. 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.

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

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

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

Where, Dh1- Horizontal orientation
Dv1- Vertical orientation
p&q- Number of rows and columns in an image

C. Measurement of optic disc parameters

The optic disc is brighter than all other features in the retinal image and it is approximately circular and measures around 1800 µm. Retinal vasculature originates in optic disc. Since the optic disc has characteristics similar to those of exudates, it is vulnerable to detect as a false acceptance rate. In this work, optic disc measurement is done by an application of morphological operations such as dilation and area opening. After doing morpho-logical operations filtering is done for locating the optic disc.

In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, mor-phological operation can be done which is sensitive to specific shapes in the input image. The two morphological operations such as dilation and area opening are discussed below.

D. Dilation

In dilation, the value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1. It is used to increase the object in the image. It has the following equation:

$$\delta_B(X) = \{x | B_x \cap X \neq \phi\}$$

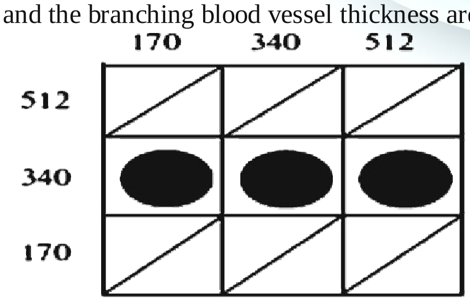
Where B_x means B translated with x, X is the image and B is the structure element.

E. Classification

Probabilistic Neural Network (PNNs) is a relatively new learning process influenced highly by advances in statistical learning theory and a sufficient increase in computer processing power in recent years. PNN is a useful technique for data classification. It is easier than other neural networks like back propagation network, Learning vector quantization. The hyper plane optimally separates the vectors with maximal distance and reduced errors. To construct an optimal hyper plane, PNN employs an iterative training algorithm. It is used to minimize an error function. Since it provides localized and finite responses across the entire range of the real x-axis, PNNs are effective in a wide range of bio informatics problems. According to the features that are extracted, retinal image can be classified as normal and abnormal diabetic retina.

F. Optical coherence tomography (OCT)

Optical Coherence Tomography (OCT) is a non invasive, high-resolution imaging technique to measure total retinal thickness, Retinal Nerve Fiber Layer (RNFL) thickness and optic nerve head morphology. In the present work the vascular network or retinal blood vessel thickness is consid-ered. The blood vessel thickness is detected using vessel segmentation algorithm. First the captured image is binarized to get the blood vessel structure clearly, and then it is ske-letonised to get the overall structure of all the terminal and branching nodes of the blood vessels. By identifying the terminal node and the branching points automatically, the main and the branching blood vessel thickness are estimated.



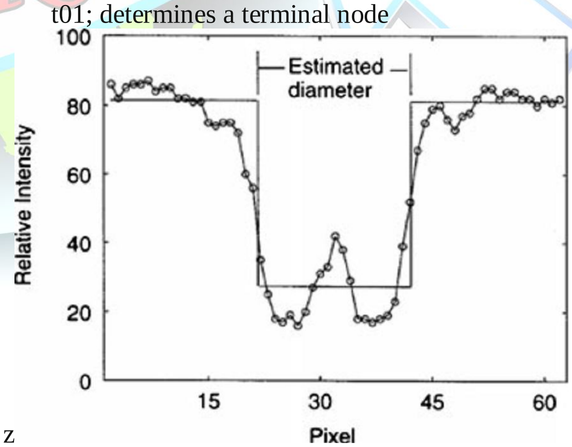
Vessel segmentation binarisiation technique is mainly used for segmentation thickness measurement of the blood vessel. To get an exact blood vessel structure and shape of the retina image, this technique is used. If any small varia-tion occurs in a vessel structure of the retina it can be magnified. The histogram of a digital image with gray levels in the range [0,L-1] is a discrete function $h(r_k)0n_k$, where r_k the k^{th} gray level and n_k is the number of pixels in the image having gray level r_k. A histogram is normalized by dividing each of its values by the total number of pixels in the image, denoted by n. Thus, a normalized histogram is given byPð r_k Þ ¼ n_k =n, fork ¼ 0; 1; L_1. Histogram manipulationcan be used effectively for image enhancement. The hori-zontal axis of each histogram plot corresponds to gray level values, r_k. The vertical axis corresponds to values of h (r_k) 0n_k or P (r_k) 0nk / n if the values are normalized. The histogram plots are simple plots of h (r_k) 0nk versus r_k or P (r_k) 0nk / n versus r_k.

The gray level histogram corresponds to an image f(x, y), composed of light objects on a dark background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a thresh-old T that seperates the background from the fore ground modes. Then any point (x, y) for which f(x, y)>T is called an object point. Otherwise, the point is called a background point.

G. Vessel Thickness Measurement

The vessel width can be measured by from black to white moving clockwise around the eight neighborhood point is counted which is classified as follows:

t01; determines a terminal node



z

t00, 2; determines a non significant node

t>0 3; determines a branching point

H. Vein Diameter

Measurement of vein diameter can be done in many ways. Vein diameter is measured perpendicular to the vein centerline at each point. The local direction is taken as the average of the directions of the branch element from the preceding pixel to the current one and the current pixel to the next one. Since the chain code restricts branch element angles to integer multiples of 45^0, this averaging procedure results in effectively quantiz-ing branch direction in increments of 22.5^0. Thus, the magni-tude of the maximum error in centerline direction is $\pm 11.25^0$ and it is due to centerline quantization. With this error, the maximum error e_θ in estimation of vein diameter due to centerline direction quantization can be shown to be,

$$e_\vartheta = \frac{d}{\cos 11.25} - d$$
$$= 0.0196d$$

Where, d is the actual vein diameter.

Vein diameter may be estimated with sub pixel resolution, considering two basic assumptions. Initially the vein is signif-icantly larger than the diagonal measurement of a pixel, there-by insisting that a pixel can straddle at most one vein edge. Then the inner regions of the vein and the background have relatively constant (but significantly different) intensities. With these assumptions, the diameter of the vein is estimated by the width of the rectangular profile shown with heavy lines.

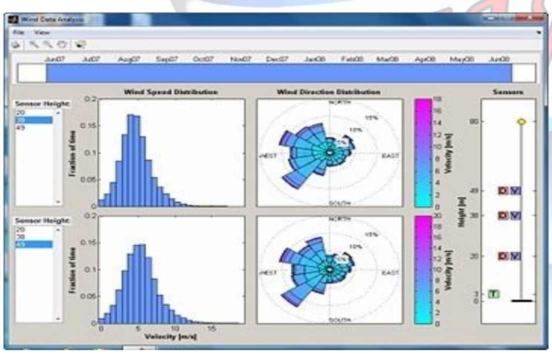


Fig. 3 A Custom GUI built using MATLAB

These, having the same area as the spatially and intensity-quantized vein profile. Separating data into training and testing sets. Each instance in the training set contains one target value and several attributes. The goal of SVM is to produce a model based on the training data which predicts the target values of the test data given only the test data attributes. The Hyper plane optimally separates the vectors with maximal distance and reduced errors. To construct an optimal hyper plane, The handles structure is created by guide and the elements are named the same as the tag you specified. Set up the figures and Enter the message loop are taken care of by using the matlab gui editor (guide). The important thing is that we should give control of the program flow over to the message loop. In order to get things done, we can tell the message loop to call a function whenever something happens. In the gui editor, right click the pushbutton and select "View Callbacks -> Callback". This will automatically create such a function in you file where we can specify what happens when we push the button. For a better understanding take a look at the Callback property of the pushbutton. Guide will have entered somethinglike add('push_calc_Callback',hObject,eventdata,guidata(hObject)) which calls the main function (add) as a wrapper for the new callback function.

I. Dataset

The retinal images used for this project were collected from two publicly available data bases of DRIVE and STARE for developing the decision support system. The database is loaded in MATLAB.

III. RESULT AND DISCUSSION

In the present work, the features of the retinal images such as optic disc area, cup area and thickness of the blood vessels, main vessel and branch vessel and vein diameter have been extracted. The images have been obtained from STARE and DRIVE database for developing the decision support system. Then the system is validated considering the real time image obtained from various eye hospitals. The performance of various classification techniques have been analyzed and compared by using extracted features. The step by step process of the proposed method described as follows. The pro-posed system considered for Normal and Abnormal retinal image is shown in Figures

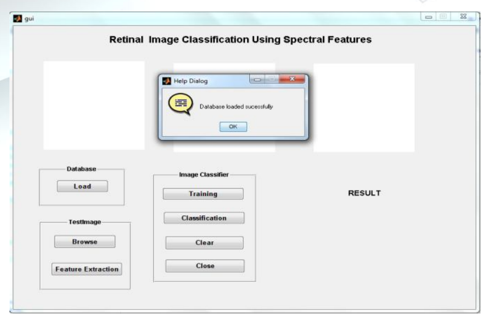


Fig. 4 Loading the Database

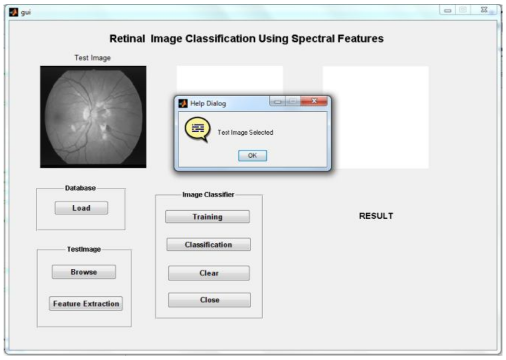


Fig. 5 Abnormal Retinal Image

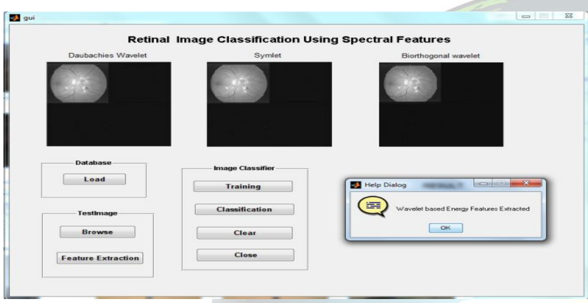


Fig. 6 Extraction of Wavelet based Energy Features

The Analysis is applied to all the 120 sample with age group varying 26–65.As a first step, measurements have been made on the normal subjects (Free from diabetics). Same procedure is repeated for abnormal images such as diabetic affected patients.

A. Comparative Analysis

This sub section presents the comparative analysis of the proposed approach. FAR is the percentage of incorrect acceptances. FRR is the percentage of incorrect rejection. The following,

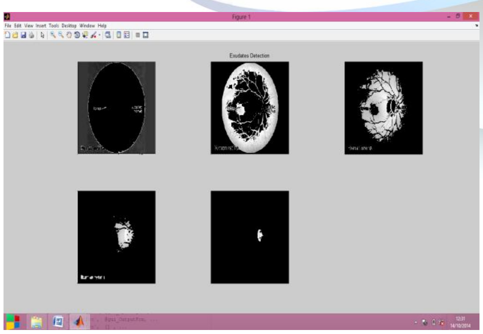


Fig. 7 Training process

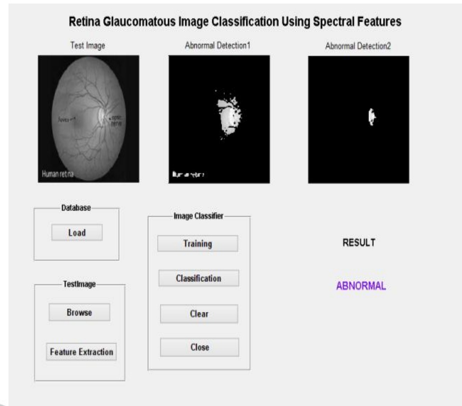


Fig. 8 Classification of images

Genuine Acceptance Rate (GAR) is an overall accuracy measurement of the approach. The following Table 2 gives the percentage of the recognition rates and the accuracy rates. From the Fig. 7, it can be observed that the percentage of the False Acceptance Rate of the SVM classifier is less than that of the other classifiers. Similarly from the Fig. 8, the percentage of False Rejection Rate of the SVM classifier is less than that of the other classifiers. These FAR and FRR have been used for classifying normal and abnormality of retinal images (Fig. 9).

The proposed system has a higher accuracy compared to the other methods by feature extraction techniques such as optic disc measurement of the disc area and cup area, blood vessel thickness, main vessel thickness and branch vessel. thickness and vein diameter of the retinal images of both normal and abnormal.

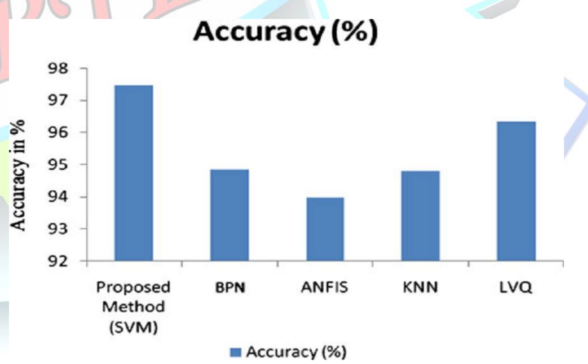


Fig. 9 Accuracy (%)

IV. CONCLUSION

The computer aided diagnostic system to classify the retinal images using neural network has been developed and validated with various samples and experts. It is concluded from the analysis that the multiple features and the selection of the SVM classifier enhance the classification of retinal as Normal or Abnormal. The proposed system can be used as secondary observer in clinical decision making.

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