

Retinal Image Analysis for Exudates Detection

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ABSTRACT

This project proposes a glaucomatous image classification using texture features within images and it will be classified effectively based on feature ranking and neural network. In addition with, an efficient detection of exudates for retinal vasculature disorder analysis performed. The states of retinal blood vessels can be used to detect some diseases like diabetes. The important texture features can be found by using the Energy distributions over wavelet subbands. This system uses different wavelet features obtained from the daubechies (db3), symlets (sym3), and bi-orthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. The energy signatures obtained from 2-D discrete wavelet transform subjected to different feature ranking and feature selection strategies. The energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy. This performance will be done by artificial neural network model. The exudates are also detected effectively from the retina fundus image using segmentation algorithms. Finally the segmented defect region will be post processed by morphological processing technique for smoothing operation.

Keywords-Feature extraction, glaucoma, image texture, neural network, wavelet transforms.

1. Introduction

Glaucoma is an eye disease and is the leading causes of blindness. In Glaucoma the optic nerve is damaged. This damages vision in the affected eye(s) and lead to blindness if not treated. It is normally associated with increased fluid pressure in the eye. Glaucoma is divided into two types, "open-angle" and "closed-angle" glaucoma. Closed-angle glaucoma appears suddenly and is painful and also visual loss progresses quickly. Open-angle, chronic glaucoma progresses at a slower rate and patients may not notice they have lost vision until the disease has progressed significantly. In closed angled Glaucoma, fluid pressure in the eye increases because of inadequate fluid flow between the iris and the cornea.

For the detection and management of glaucoma recent advances in biomedical imaging offers effective quantitative imaging alternatives. Manual

analysis of eye images is fairly time consuming, and the accuracy of parameter measurements varies between experts. Automated clinical decision support systems (CDSSs) are used to get effective decision support systems for the identification of disease in human eyes. In CDSS, features extracted from the images are structural features or texture features. Proper orthogonal decomposition (POD) is a technique that uses structural features for the identification of glaucomatous progression. Wavelet transforms (WT) in image processing are used to obtain the texture features. In WT, the content of the image is represented in frequency domain. The goal of this paper is to develop an algorithm which automatically analyze eye ultrasound images and classify normal eye images and diseased glaucoma eye images and also finds the exudates present in the diseased eye image. Here, discrete wavelet transform (DWT) using daubechies wavelet, symlets wavelet and biorthogonal wavelet are used to extract features. Wavelet Energy signatures are calculated from these extracted features. Probabilistic Neural Network is used to automatically analyse and classify the images as normal or abnormal eye images. K-means Clustering technique is applied lastly to find the exudates present in the abnormal eye images. This scheme will reduce the processing time currently taken by the technologist to analyze patient images.

2. SYSTEM ANALYSIS

2.1. Existing System

2.1.1. Threshold based Segmentation

A simple method of image segmentation is the thresholding method. Thresholding is used to extract a part of the image. Thresholding is classified into Hard thresholding and Soft thresholding. Thresholding is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value. In hard thresholding, pixel having intensity lower than threshold are set to zero and the pixels having intensity greater than the threshold are set to 255 or left at their original intensity. As the value of the threshold is increased, the image becomes too dark. Several popular methods are used in industry like the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods are developed for thresholding computed tomography (CT) images, in which the

thresholds are derived from the radiographs instead of the (reconstructed) image.

2.1.2. Design Steps

- (1) Set the initial threshold $T = (\text{the maximum value of the image brightness} + \text{the minimum value of the image brightness})/2$.
- (2) Using T segment the image to get two sets of pixels B (all the pixel values are less than T) and N (all the pixel values are greater than T);
- (3) Calculate the average value of B and N separately, mean u_b and u_n .
- (4) Calculate the new threshold: $T = (u_b + u_n)/2$
- (5) Repeat Second steps to fourth steps upto iterative conditions are met and get necessary region from the brain image.

The method fails to produce accurate result and provide optimal threshold for accurate image segmentation.

2.1.3. Proper orthogonal decomposition (POD)

In this method, pixel-level information is used to gauge significant changes across samples that are location or region specific. The measurement of texture features, on the other hand, is roughly defined as the spatial variation of pixel intensity (gray-scale values) across the image. Textural features are, thus, not bound to specific locations on the image techniques, including spectral techniques, are available to determine texture features.

2.2. Proposed System

Automatic glaucomatous image classification using wavelet based energy features followed by neural network classifier and fundus exudates detection through clustering model. These Modules includes the following methodologies,

- Discrete wavelet transforms
- Energy feature Extraction
- Artificial Neural Network Training and Classification
- Segmentation using clustering model
- Morphological Process

2.2.1. Requirement Specification

2.2.1.1. Software Requirement

- MATLAB 7.5 and above versions
- Image Processing Toolbox

2.2.1.2 Hardware Requirements

- Pentium(R) D CPU 3GHZ
- 1 GB of RAM
- 500 GB of Hard disk

2.3. System Implementation

2.3.1. Discrete Wavelet Transform

Wavelet transform is an efficient tool to represent an image. The wavelet transform allows multi-resolution analysis of an image. The wavelet transform has received attention in image processing due to its flexibility in representing non-stationary image signals. Wavelet transforms are the most powerful and widely used tool in image processing. The

applications of Wavelet transforms are Image compression, such as still image compression, image denoising and watermarking. Wavelet-coding schemes at higher compression ratios avoid blocking artifacts. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable degradation are important.

Wavelet Transform (WT) are used to analyze non-stationary signals, i.e., signals whose frequency response varies in time, as Fourier Transform (FT) is not suitable for such signals.

To overcome the limitation of FT, Short Time Fourier Transform (STFT) was proposed. In STFT, the signal is divided into small segments, where these segments (portions) of the signal are assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window in time must be equal to the segment of the signal. By STFT, one can get time-frequency response of a signal simultaneously, which can't be obtained by FT. Where the length of the window is $(t-\tau)$ in time such that we can shift the window by changing value of t , and by varying the value τ we get different frequency response of the signal segments. Multi-resolution is not possible with STFT.

The wavelet transform (WT) is developed as an alternate approach to STFT to overcome the resolution problem. The wavelet is not having a fixed-width sampling window. The transform is computed separately for different segments of the time-domain signal at different frequencies. This approach is called Multi-resolution Analysis (MRA), as it analyzes the signal at different frequencies giving different resolutions.

Discrete Wavelet transforms are implemented through sub-band coding. By using DWT we can avoid time complexity. The DWT is useful in image processing because it simultaneously localise signals in time and scale.

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. The four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

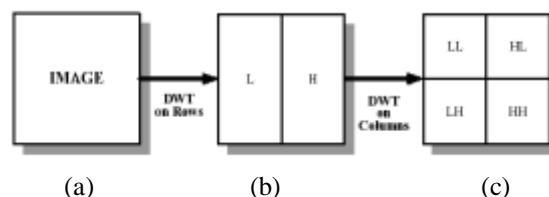


Figure 1 Block Diagram of DWT (a) Original Image (b) Output image after the 1-D applied on Row input

(c) Output image after the second 1-D applied on column input.

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, known as sub bands. The upper and lower areas of Fig. 1 respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image is shown in Fig.1.

We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. The straight forward convolution implementation of 1D-DWT requires a large amount of memory and large computation complexity. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity. Lifting also allows in-place computation of the wavelet coefficients. The lifting approach computes the same coefficients as the direct filter-bank convolution.

2.3.2. Energy Features

The wavelet filters decomposed the image into approximation and detailed coefficients in the horizontal, vertical and diagonal orientation. The features averaging coefficient and energy are extracted and it is determined by:

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

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

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

2.3.3. Probabilistic Neural Networks

Neural networks are predictive models which are based on the action of biological neurons.

The neural network used to refer to a network or circuit of neurons. A biological neural network is made up of a group or groups of chemically connected or functionally associated neurons. A single neuron in a network is connected to many other neurons. The number of neurons and the connections in a neural network are extensible. Artificial Neural Networks are composed of interconnecting artificial neurons. This uses a computational or mathematical model for information processing. Artificial Neural networks are simple compared to biological neural network and these networks have good predictive ability and low

generalization error. The original "Perceptron" model was developed by Frank Rosenblatt in 1958. Rosenblatt's model has three layers, (1) a "retina" that supplies inputs to the second layer, (2) "association units" that combine the inputs with weights and trigger a threshold step function which feeds to the output layer, (3) the output layer which combines the values.

The training of a neural network is performed by a particular function by adjusting the values of the connections between elements. Neural Networks are used in various fields like Pattern recognition, Identification, Classification, Speech, Vision and Control systems. Neural networks are used to solve problems which are difficult for conventional computers and human beings.

Probabilistic Neural Network (PNN) is a feed forward network. It is designed from the Bayesian network and a algorithm called Kernel Fisher discriminant analysis. Probabilistic networks perform classification where the target variable is categorical. In PNN, the operations are done in four stages: (1) Input layer: Each neuron in this layer represents a predictor variable. (2) Pattern layer: It contains neurons that stores the value of the variable and the target value. A hidden neuron calculates Euclidean distance. (3) Summation layer: This layer has pattern neurons. The pattern neurons add value for the class. (4) Output layer: The output layer compares the weighted votes of the target and uses the largest vote for the prediction of target category.

PNNs are used for classification problems. When an input is applied, the first layer computes distances from the input vector to the training input vectors and produces a vector. The second layer sums these contributions for each class of inputs and produces a vector of probabilities. Transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. The PNN classifier presented good accuracy, very small training time, robustness to weight changes, and negligible retraining time.

2.3.4. Image Segmentation

Segmentation is the process of partitioning a digital image into groups of pixels which are homogeneous with respect to some criterion. Different groups must not intersect with each other, and adjacent groups must be heterogeneous. Segmentation algorithms are area oriented instead of pixel-oriented. The result of segmentation is the splitting up of the image into connected areas. The segmentation is concerned with dividing an image into meaningful regions. Image segmentation can be done in three different philosophical perspectives. Regions in an image are a group of connected pixels with similar properties. In the region approach, each pixel is assigned to a particular object or region. In the boundary approach, the attempt is to locate directly the boundaries that

exist between the regions. In the edge approach, the edges are identified first and then they are linked together to form required boundaries. The result of image segmentation is a set of segments that collectively cover the entire image.

2.3.5. Clustering methods

The K-means algorithm is the simplest method in unsupervised classification. It is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1. Choose K initial cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center.
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

Distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic.

The drawback of the K-means algorithm is the number of clusters is fixed. Once K is chosen, it returns K clustercenters. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K .

3. Conclusion

This project implemented a glaucomatous image classification using texture features and it will be classified effectively based on artificial neural network. Here, probabilistic neural network was used for classification based on unsupervised leaning using wavelet energy features and target vectors. In addition with, an efficient detection of exudates for retinal vasculature disorder analysis was performed. This abnormal region detection was successfully done by using clustering algorithm which is used to provide better segmentation result and performance accuracy. Finally this system is very useful to diagnose the retinal diseases for early detection vision loss and diabetics.

3.1. Advantages

- Accurate image classification
- Accurate executes detection
- It is useful in diabetic diagnosis
- Better performance compared to previous methods.

3.2. Result

- Automatic Image Classification categorized into
 - Normal

- Abnormal(Glaucomatous and exudates)
- Image Segmentation for exudates detection

3.3. Snapshots



Figure 1.GUI output



Figure 2.GUI output after selecting test image



Figure 3.Feature extraction of test imsgge using Daubachies, Symlet and Bio-orthogonal Wavelet filters



Figure 4. GUI output classifying the test image as ABNORMAL and also it shows the exudates present in that abnormal image

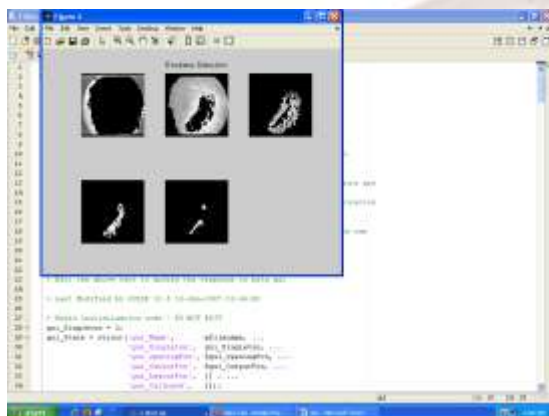


Figure 5. Exudates present in the abnormal image



Figure 6. GUI output classifying the test image as NORMAL image

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