Retinal Blood Vessel Detection in Fundus Image of Eye

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***Abstract*— Diabetic Retinopathy is globally the primary cause of visual impairment and blindness in diabetic patients. An algorithm to detect the retinal blood vessels effectively is proposed here. The proposed work uses an Extreme Learning Machine (ELM) approach for blood vessel detection in digital retinal images. This approach is based on pixel classification using a 7-D feature vector obtained from pre-processed retinal images and given as input to an ELM. It results in the detection of blood vessels in the retinal image. ELMs parameters can be analytically determined rather than being tuned.. The green channel will be selected for image analysis to extract vessels accurately. The discrete curvelet transform is used to enhance the image contrast for effective vessels detection. Morphology operators using multi structure elements are applied to the enhanced image in order to find the retinal image ridges. A simple thresholding method along opening and closing indicates the remained ridges belonging to vessels. Simulated results will be shows that the blood vessels can be effectively detected from retina images with parametric evaluation to measure the algorithm efficiency.**

Keywords*— *Diabetic Retinopathy, Retinal Blood Vessel, Extreme Learning Machine.

I. Introduction

Diabetic Retinopathy (DR) is a vascular disorder affecting the retina due to prolonged diabetes. Diabetic retinopathy is one of the leading causes of visual impairment [1]. The risk of blindness can be reduced by 50% in patients by early screening of diabetic patients for the development of diabetic retinopathy. Diabetic retinopathy causes several types of retinal lesions. As the disease progresses to its proliferative stage retinal ischemia can trigger abnormal vessel changes, such as venous beading, intra-retinal microvascular abnormalities (IRMA) and new vessel growth.

To build an expert system that is able to perform the diagnosis task needed to use digital retinal images. By imaging the retina of a person with a special camera, then using image processing and pattern recognition technique to analyses that retina make a specific diagnoses decision. One of the important procedures performed on the digital retina is the edge detection of blood vessels of the retina. Proliferative retinopathy is a more serious condition as it involves the development of new vessels which are prone to bleed. The differences between normal and abnormal vessels are usually subtle, due to the limits of the spatial and contrast resolution of the photograph. Vessels which grow out of the focal plane of the photograph can be particularly difficult to identify. Accurate vasculature segmentation is a difficult task for several reasons like the presence of noise, the low contrast between vessels and background, the variability of vessels width, brightness, shape, reflection on the tiny uneven surface of the soft tissue in the image and pathological variations [3].

Many methods have been used for retinal vessel segmentation. These can be divided into two groups: rule-based methods and supervised method. Supervised methods are based on pixel classification, which consists on classifying each pixel into two classes, vessel and non-vessel. Considering rule-based methods, vessel tracking method can obtain the vasculature structure by following vessel centerlines. The segmentation of vessels can be represented in two ways: One method is to mark out all vessel pixels. The other method is to find the vessel centerlines and the radius at each pixel of the centerlines.

In this paper a method for automatic detection of blood vessels in retinal image is described. Here a method for blood vessel detection based on pixel classification using a 7-D feature vector extracted from pre-processed retinal images [3]. With the use of pixels, an image is divided into many parts by declaring each image pixel to the nearest pixels [12]. Every line element contains a local coordinate frame for its corresponding pixels. For every pixel, feature vectors are calculated that make use of various properties of the pixel representation of the images specifically retinal vessels [11]-[13]. The evaluation is based on using labeled segmentations of several images. The necessary feature vector is computed from pre-processed retinal images in the neighbourhood of the pixel under consideration. It is then given as input to a neural network [3].

II. PROPOSED SYSTEM

This paper proposes a supervised approach for retinal blood vessel detection based on an Extreme Learning Machine (ELM) for pixel classification [1]. Extreme learning machine (ELM) for single-hidden layer feed forward neural networks (SLFNs) randomly chooses hidden nodes and analytically determines the output weights of SLFNs.

The following processes takes place to detect retinal blood vessels (1)Green channel extraction from RGB image, 2)Discrete Curvelet Transform based Feature extraction for numerical representation of pixels,(3)Classification of pixels as vessel or non-vessel.

Sequence of steps for the detection of blood vessels in digital retinal image as shown in Fig.1.

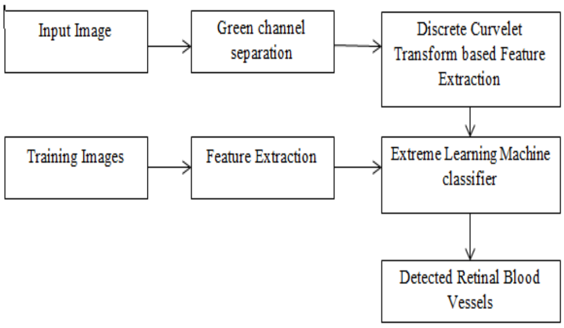

Fig. 1. Block diagram of retinal blood vessel detection

A. Green Channel Separation

Each and every color images will be having its own characteristics based on the primary color representation specifically termed to be RGB analysis. Each plane can be separated alone such that this type of function is called as planar separation. All the color images will be decomposed initially into gray scale image, such that then only the desired feature can be extracted drastically.

From original RGB retinal image, the green band is extracted so that the input image is monochrome. The green channel provides the best vessel-background contrast of the RGB representation, while the red channel is the brightest color channel and has low contrast, and the blue one offers poor dynamic range. Thus, blood containing elements in the retinal layer (such as vessels) are best represented and reach higher contrast in the green channel. As this system has to be applied on retinal images of different sizes, input image has to be resized.

B. Discrete Curvelet Transform based Feature Extraction

The goal of the feature extraction stage is pixel characterization by means of identification of a feature vector which may be easily used in the classification stage to resolve whether pixels belong to a real blood vessel or not.

Feature extraction in retinal image is done by applying Curvelet transform. Curvelet is a non-adaptive technique for multi-scale object representation [8]. Basis with large coefficient contain features of the image and thus used for feature extraction. Checking those basis is useful in pattern recognition. The basis of curvelet function has high sensitivity to directional image and edge. Curvelets is an appropriate basis for representing retinal images where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. As one zooms in on such images, the edges they contain appear increasingly straight.

Discrete Curvelet Transform (DCT): A curvelet transform gets varied from other directional wavelet decomposition technique in that the degree of localization in predilection differs with respect to the transformation that is implemented. Curvelet are a non-adaptive algorithm for multi-scale object delegacy.

There are two methods to implement the second-generation DCT: Wrapping method and Unequispaced Fast Fourier Transform (USFFT) method [8]. Here we are using wrapping around method because it is faster, accurate and easier to implement than USFFT.

The architecture of Fast Discrete Curvelet Transform (FDCT) via wrapping is as follows:

Initial data: Cartesian array $f(i1, i2)$, $0 \leq i1, i2 \leq N-1$

1. Apply the 2D FFT and obtain Fourier samples

2. For each scale j and l, angle form the product

3. Wrap this product around the origin and obtain

where the range for n1 and n2 is now $0 \leq n1 < L1,j$ and $0 \leq n2 < L2,j$ (for θ in the range

4. Apply the inverse 2D FFT to each hence collecting the discrete coefficients.

C. Classification

A classification procedure assigns one of the classes: vessel or nonvessel to each candidate pixel when its representation is known. For vasculature segmentation in retinal images, use of a nonlinear classifier is necessary for better accuracy. The kNN method, support vector machines, Bayesian classifier or neural networks comes under non-linear classifier [7]. Extreme Learning Machine classifier is proposed in this paper.

a) Extreme Learning Machine

Extreme learning machine (ELM) is a simple learning algorithm for Single Layer Feed forward Neural networks [4]. ELM will randomly select the input weights and analytically determines the output weights of SLFNs. The learning speed of ELM is thousands of times faster than traditional feed forward network learning algorithms like back-propagation (BP) algorithm while obtaining better generalization performance [7]. All the parameters can be analytically determined rather than being tuned. The hidden node parameters are completely independent from the training data. ELM can approximate any target continuous function and classify any disjoint regions.

The main features of ELM are minimum training errors, smallest norm of weights, best generalization performance and the minimum norm least-square solution is unique [4]. The structure of ELM network contains an input layer, hidden layer and an output layer.

Extreme Learning Machine Training Algorithm is as follows:

Given a training set N, activation function g(x) and hidden neuron Ñ. Assign random value to the input weight wi and the bias, bi=1 ,…., Ñ.

1. Find the hidden layer output matrix H.

2. Then find the output weight β^ = H+T

Where β, H and T are defined in the same way they were defined in the SLFN.

III. RESULTS

Extreme Learning Machine approach is implemented to detect retinal blood vessels by applying Discrete Curvelet Transform (DCT). For a given input retinal image, first the green plane extracted image is obtained. The application of Discrete Curvelet Transformation gives a segmented image. The output image shows blood vessels in the given input retinal image. Analyzing of the fundus images based on the retinal images can be mentioned as the enhancement factor over here. Thus the overall work flow is carried out with the initial extraction of the input image and the feature extraction with the vessel separation as R, G, B separation which is termed to be the channel separation. The feature vectors have been diagnosed with the use of 7D-vector analysis. Input retinal image given to proposed system is shown in Fig.2. Retinal blood vessels detected for a given input image is shown in Fig.3.

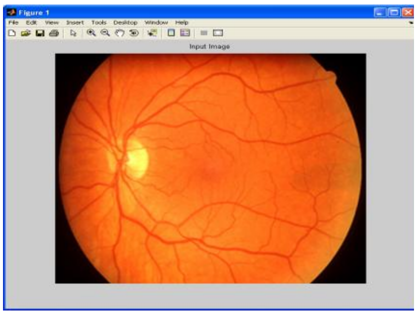

Fig. 2. Input Image

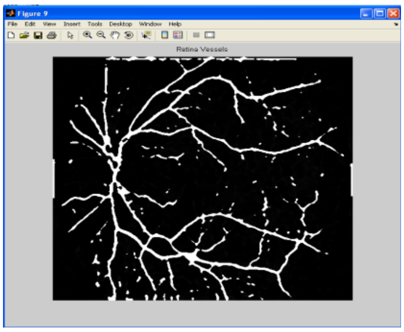

Fig. 3. Retinal Blood Vessels after Classification

IV. CONCLUSION

The overall work flow is carried out with the initial extraction of the input image and the feature extraction The feature vectors have been diagnosed with the use of 7D-vector analysis. The contrast enhanced image has been termed out the image can be reconstructed using the step of morphological processing. Extreme Learning Machine approach is used to diagnose the retinal cells by using the training samples. Training samples will be having both normal and abnormal retinal image with affected blood vessels.

The proposed ELM will produce the most accurate classifier than a model built with Multilayered Feed forward Neural Network (MLFNN) technique. The proposed ELM technique performs well in huge datasets but the existing MLFNN technique does not perform well in huge dataset. Our results demonstrate that the system is well suited to complement the screening of DR and may be used to help the ophthalmologists in their daily practice.

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