RETINAL BLOOD VESSEL SEGMENTATION ALGORITHM FOR DIABETIC RETINOPATHY AND ABNORMALITY CLASSIFICATION BY SUPERVISED MACHINE LEARNING

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Abstract: The field of medical imaging gains its importance with increase in the need of accurate and efficient diagnosis over a short period of time. Since manual processes are tedious, time consuming and impractical for large data there is a need for automatic processing that helps community health workers. Retinal blood vessel segmentation in diabetic retinopathy plays an important role in diagnosing the pathologies, which occur as swelling in parts of the vasculature, changing of width along blood vessels, and tortuosity that later on may cause blindness. A method is presented in this work for an automated segmentation of blood vessels in the fundus images using texture, thresholding and morphological operation (combined approach) and classification by artificial neural networks. The distinct invariant features are used features for classification. Our method gives clearer and more accurate output for ophthalmologists. The implementation is observed on various types of normal and abnormal retinal images are used for the prediction of diabetes retinopathy in a given retinal image.

Index Terms: Retinal fundus images, segmentation, neural network training algorithm

I. INTRODUCTION

Digital fundus imaging in ophthalmology plays an important role in medical diagnosis of several pathologies like hypertension, cardiovascular disease and diabetes[1]. Retinal vessel segmentation is a primary step towards automated analysis of the retina for anomaly and also image registration. Automated assessment of the retinal vasculature morphology can be used in screening tool for early detection of diabetic retinopathy. The retinal vasculature is comprised of two complex networks – veins and arteries that spread out from the optic disk branch successively to occupy different regions of the fundus. Many kinds of methodologies and algorithms have been proposed to segment blood vessels utilizing an adaptive local threshold [2, 3, 4]. This method has less accuracy because of non-illumination and less color contrast. After the color enhancement operation, we applied first a texture for obtaining more color contrast between the blood vessels and fundus background, and then segmentation using the threshold for binary image output. We apply morphological operations with an implemented mask for tracking along the vasculatures and filling the unwanted gaps of the binary image. These operations included dilation, filling and thinning with median filter, executed in much iteration.

Texture features are extracted and applied to neural networks for further classification.

Figure 1: Abnormal Retinal Image

II. PROPOSED METHODOLOGY

The method proposed is image filtration by applying an adaptive median filter, and then color enhancement using histogram equalisation. After that image segmentation and classification utilising texture and morphological operators. The texture features are derived from retinal images are trained by neural networks using back propagation algorithm.
A. Preprocessing operation: Image quality is of central importance to the success of retinal examination. Hence noise suppression by means of digital image processing should improve image quality and diagnostic potential of fundus images. Images are filtered to remove some noise using the adaptive median filter. The adaptive filter can vary its behaviour based on the image location characteristics. But the result of this filter is identical to the original image size and shape of the object. The main purpose is to remove salt and pepper noises, smooth the image and reduce the distortion. It utilizes an adaptive window which changes its size based on certain circumstances.

B. Image enhancement: The histogram of an image represents the relative frequency of occurrence of various gray levels in the image. Histogram modelling techniques provide a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. The acquired image needs to be enhanced in order to make distinctions between its features such as blood vessels, retina fundus foreground color and image background color. The histogram measures the intensity of the gray level of the image and plot its gray level versus the number of pixels can be used for this mission. A dark image has the majority of histogram components are closed to 255 in gray level.

III. MORPHOLOGICAL OPERATIONS

Morphological operations are used to understand the structure or form of an image. This usually means identifying objects or boundaries within an image. Morphological operations play a key role in applications such as machine vision and automatic object detection. Morphological operations apply a structuring element to an input image, creating an output image of the same size. 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 neighbours. By choosing the size and shape of the neighbourhood, a morphological operation can be created that is sensitive to specific shapes in the input image. There are many types of morphological operations such as dilation, erosion, opening and closing.

Dilation and Erosion

Dilation and erosion are basic morphological processing operations. They are defined in terms of more elementary set operations, but are employed as the basic elements of many algorithms. Both dilation and erosion are produced by the interaction of structuring element with a set of pixels of interest of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbours in the input image. The rule used to process the pixels defines the operation as a dilation or an erosion.

**DILATION:** Suppose $A$ and $B$ are sets of pixels. Then the dilation of $A$ by $B$, denoted $A \oplus B$, is defined as $A \oplus B = \bigcup_{x \in B} A_x$. This means that for every point $x \in B$, $A_x$ is translated by those coordinates. An equivalent definition is that $A \oplus B = \{(x, y) + (u, v); (x, y) \in A, (u, v) \in B\}$.
Dilation is seen to be commutative, that \( A \oplus B = B \oplus A \).

\[
A_{\text{matrix calculated for each sub-image, then the features are given as follows.}}
\]

1. Maximum probability
   \[
f^1 = \max_{i,j} p(i, j)
   \]
2. Contrast
   \[
f^2 = \sum_{i,j=0}^{N-1} P_i, j(i - j)^2
   \]
3. Inverse difference moment (homogeneity)
   \[
f^3 = \sum_{i,j=0}^{N-1} [P_i, j]/[1 + (i - j)^2]
   \]
4. Angular second moment
   \[
f^4 = \sum_{i,j=0}^{N-1} P^2 i, j
   \]
5. Gray level co-occurrence mean
   \[
f^6 = \sum_{i,j=0}^{N-1} i(P_{i,j}) = u_i
   \]
6. Variance
   \[
f^7 = \sum_{i,j=0}^{N-1} (P_{i,j}(i - \mu_i))^2
   \]
7. Entropy
   \[
f^8 = \sum_{i,j} P_{i,j}(-\ln p_{i,j})
   \]
8. Standard deviation
   \[
f^9 = \text{std} (\text{std}(I))
   \]

IV. NN TRAINING AND CLASSIFICATION OF NORMAL AND ABNORMAL RETINAL IMAGES

The commonest type of artificial neural network consists of three groups, layers of units: a layer of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weight between the hidden and output units. The behavior of an ANN depends on both the weights and input output function that is specified for the units. Here back propagation neural network is used for classification. During back propagation additional neurons are added to a hidden layer as needed to improve classification. The three main approaches for feature extraction and classification based on the type of features are as follows:

- Statistical approach
- Syntactic or structural approach
- Spectral approach

In case of statistical approach, pattern is defined by a set of statistically extracted features represented as vector

**3. FEATURES EXTRACTION**

The feature extraction extracts the features of importance for image recognition. The feature extracted gives the property of the text character, which can be used for training in the data base. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted character. Let \( P \) be the \( N \times N \) co-occurrence matrix calculated for each sub-image, then the features are given as follows.

- Statistical approach
- Syntactic or structural approach
- Spectral approach

In case of statistical approach, pattern is defined by a set of statistically extracted features represented as vector
in multidimensional feature space. The statistical features could be based on first-order, second-order, or higher order statistics of gray level of an image. In case of syntactic approach, texture is defined by texture primitives, which are spatially organized according to placement rules to generate complete pattern. In case of spectral approach, textures are defined by spatial frequencies and are evaluated by autocorrelation function of a texture.

\[
\text{trainParam} = 100; \\
\text{Lr} = 0.04; \\
\text{Maximum epochs} = 7000; \\
\text{goal} = 1e-5;
\]

Simulation results and discussion:

**References**


