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Automated Segmentation of Retinal Blood Vessels

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ABSTRACT
Digital image processing and the image analysis technology based on the advances in microelectronics and computer have many applications in biology. In clinical ophthalmology, study of blood vessels in retina is important for detection of the diseases. Diabetic retinopathy is one of the diseases which damages the retina and leads to blindness. Manual diagnosis of analyzing images from a patient with Diabetic Retinopathy increases the time. Automatic segmentation of retinal blood vessels could save workload of the ophthalmologists and may assist in characterizing the defected lesions and to identify false positives with high accuracy. The proposed algorithm uses optimized Gabor filter with local entropy thresholding. The blood vessel detection and segmentation is important for diabetic retinopathy diagnosis at earlier stage. The proposed method detects blood vessels with higher accuracy and sensitivity in the retinal images. The DRIVE database has been used to enable comparative studies on segmentation of blood vessels in retinal images.

Keywords
Retinal image, Blood vessels, Diabetic retinopathy, Optimized Gabor filter, Local entropy thresholding, DRIVE database

1. INTRODUCTION

Retinal blood vessel segmentation using fundus photographs plays a vital role in assessing the severity of retinal pathologies that can lead to acquired blindness such as retinopathy of prematurity, glaucoma, vein occlusions and diabetic retinopathy (DR). Automated blood vessel segmentation algorithms can be very useful in screening patients that are affected by such retinal complications and require regular follow-up by automated blood vessel segmentation systems. Thus, an accurate vessel segmentation algorithm that is robust to image variability and that has low computational complexity is desirable for such automated real-time detection and screening systems.

All existing algorithms for automated segmentation of blood vessels using fundus images can be broadly categorized as supervised and unsupervised. In the supervised category of algorithms, classifiers such as the k-Nearest Neighbor, Gaussian Mixture Model (GMM), Support Vector Machine (SVM), Neural Networks, Decision Trees and Ada-Boost have been applied to classify vessel pixels from the non-vessels. The unsupervised algorithms mostly apply matched filtering, line detectors, morphological transformations, model-based methods, or multi-scale vessel segmentation methods. While most supervised vessel classification methods are dependent on the training data and sensitive to false edges, the existing unsupervised methods are computationally complex and hence they are not viable for real-time portable DR screening systems.
Diabetic retinopathy (DR) is the result of damage caused by diabetes to the small blood vessels located in the retina. Blood vessels damaged from diabetic retinopathy can cause vision loss.

Computer based analysis for automated segmentation of blood vessels in retinal images will help ophthalmologists screen larger populations for vessel abnormalities. A wide variety of approaches have been proposed for retina blood vessels segmentation [1] [2] [3] [4] [5] [6] [7]. This paper is based on optimized Gabor filter with local entropy thresholding. Gabor filters have been widely applied to image processing and computer vision application problems such as face recognition and texture segmentation.

Optimized Gabor filter methods often produce false positive detections and fail to detect vessel of different widths. Also detection process is much more complicated when retinal image is in abnormal condition. This paper has been proposed a much robust and fast method of retinal blood vessels extraction using optimized Gabor filter with local entropy thresholding.

2. PROPOSED METHOD

The proposed method is one of the several ways of implementing the vasculature detection using fundus images. In this method, the green plane image is extracted from the fundus image which is the green color values from the fundus image obtained. The color image obtained from the

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funduscopy camera is an RGB image. It contains pixel information of red, green, blue colors. Generally the blood present in the eye and the tissues present in the eye reflect the red color image. It reflects the red color from the RGB spectrum. On the other hand; the blood and the tissues cells in the eye absorb blue light. So one can't differentiate the output using blue light, but green light is absorbed by blood completely and is reflected by the tissue cells. Thus using green spectrum we can distinguish between blood and adjacent tissue cells. Thus, instead of converting the entire image into gray scale, we can obtain the green plane image from the existing RGB image and apply the algorithm.

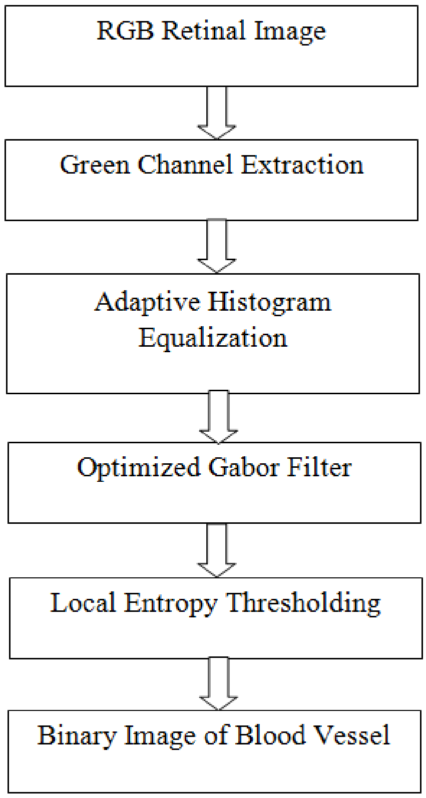

Fig 1: Flow chart of the proposed method

After obtaining the green plane image, we have to normalize its data to remove the noise present and to smooth the data. This data can be used to obtain the residual from the original image to obtain the connected vasculature.

2.1 RGB Retinal Image

An RGB image, sometimes referred to as a true color image is stored in MATLAB as an m-by-n by 3 data array that defines red, green and blue color components for each individual pixel. RGB image doesn't use a palette. The color of each pixel is determined by the combination of red, green and blue intensities stored in each color plane at the pixel's location. An RGB MATLAB array can be of class double, unit8 or unit16. In an RGB array of class double each color component is value between 0 and 1. A pixel whose color components are (0, 0, 0) displays as black, and a pixel whose color components are (1, 1, 1) displays as white. The three color components for each pixel are stored along the third dimension of the data array. With the help of Fundus camera, here we capture an RGB image of retina which is more likely in red in color as it is captured by passing IR rays.

2.2 Green Channel Extraction

Regarding the acquisition process, retinal images have often low contrast that cause to hardly detect the blood vessels. This method is to improve the image dynamic range to prepare images for next step, detection the blood vessels, and attain to higher accuracy and precision of segmentation. Concerning our purpose, contrast enhancement, the green channel of colored retinal images is used, because compared to other channels it has the highest contrast about 59%. Combining advantages of brightness in red channel decreasing the contrast between the abnormalities and the retinal background; this helps to reduce some responses from abnormalities which do not resemble any blood vessels that would otherwise decrease the performance of blood vessels segmentation methods.

2.3 Adaptive Histogram Equalization

Adaptive Histogram Equalization is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called Contrast Limited Adaptive Histogram Equalization (CLAHE) prevents this by limiting the amplification.

Ordinary histogram equalization uses the same transformation derived from the image histogram to transform all pixels. This works well when the distribution of pixel values is similar throughout the image. However, when the image contains regions that are significantly lighter or darker than most of the image, the contrast in those regions will not be sufficiently enhanced.

Adaptive histogram equalization (AHE) improves on this by transforming each pixel with a transformation function derived from a neighbourhood region. In its simplest form, each pixel is transformed based on the histogram of a square surrounding the pixel, as in the figure below. The derivation of the transformation functions from the histograms is exactly the same as for ordinary histogram equalization: The transformation function is proportional to the cumulative distribution function (CDF) of pixel values in the neighbourhood.

Pixels near the image boundary have to be treated specially, because their neighborhood would not lie completely within the image. This applies for example to the pixels to the left or above the blue pixel in the figure. This can be solved by extending the image by mirroring pixel lines and columns with respect to the image boundary. Simply copying the pixel lines on the border is not appropriate, as it would lead to a highly peaked neighborhood histogram. The size of the neighborhood region is a parameter of the method. It constitutes a characteristic length scale: contrast at smaller scales is enhanced, while contrast at larger scales is reduced.

Due to the nature of histogram equalization, the result value of a pixel under AHE is proportional to its rank among the pixels in its neighborhood. This allows an efficient implementation on specialist hardware that can compare the center pixel with all other pixels in the neighborhood. An un normalized result value can be computed by adding 2 for each pixel with a smaller value than the center pixel, and adding 1 for each pixel with equal value. When the image region containing a pixel's neighborhood is fairly homogeneous, its histogram will be strongly peaked, and the transformation function will map a narrow range of pixel values to the whole range of the result image. This causes AHE to over amplify small amounts of noise in largely homogeneous regions of the image.

2.4 Gabor Filter

In image processing, a Gabor filter is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

Its impulse response is defined by a sinusoidal wave (a plane wave for 2D Gabor filters) multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually.

2.4.1 Extraction of Features from Images

A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. In the discrete domain, two-dimensional Gabor filters are given by,

$$G_\theta(x,y) = \exp\left\{-\frac{1}{2}\left(\frac{\mathrm{x_\theta}^2}{\sigma_\mathrm{x}} + \frac{(\gamma^2 \mathrm{y}_\theta^2)}{\sigma_\mathrm{y}}\right)\right\}\cos\left(2\pi\frac{x_\theta}{\lambda}+\varphi\right)$$

$$x_\theta = x\cos\theta + y\sin\theta$$

$$y_\theta = -x\sin\theta + y\cos\theta$$

Where,

σ_x: Standard deviation of Gaussian in x direction along the filter that determine the bandwidth of the filter.

σ_y: Standard deviation of Gaussian filter that control the orientation selectivity of the filter.

Θ: Orientation of the filter, an angle of zero gives a filter responds to vertical feature.

λ: Wavelength of the cosine factor of the Gabor filter kernel i.e., preferred wavelength of this filter.

Γ: Spatial aspect ratio, specifies the ellipticity of the support of the Gabor function

Ψ: Phase offset

2.5 Local Entropy Thresholding

An image can be viewed as an information source with a probability vector described by its gray-level image histogram, the entropy of the histogram can be used to represent a certain level of information contained in the image. In the proposed method the gray-level co-occurrence matrix [8] is used to derive the texture feature for retinal image segmentation. The texture feature chosen is the entropy of the retinal image. In order to perform proper extraction of the enhanced segments from the Gabor filter response images, an effective thresholding method is used.

2.6 Binary Image of the Retinal Blood Vessel

The final image is the output of local entropy thresholding consists of 0's & 1's which resembles as a black and white image where white resembles 1's in the foreground and black resembles 0's in the background. The white pixels that are detected in the foreground are true to be known as blood vessels which we need to be acquired.

3. RESULTS AND DISCUSSIONS

In this work, extensive experimentations are performed on the publicly available retinal image database, namely, DRIVE [9]. In the retinal blood vessels detection process, the outcome is the entropy of the retinal image.Any pixel is classified either as vessel or non-vessel. Then, we compare every resulting binary image with the corresponding ground truth by computing the following four performance measurements the pixels that belong to a vessel in the ground truth image and that are classified as vessels are counted as: True positives (TP), otherwise they are counted as false negatives (FN). The pixels that belong to the background and that are classified as non-vessels, are counted as true negatives (TN), otherwise they are counted as false positives (FP). In order to compare the performance of the proposed method with other state-of-the-art algorithms, we compute the accuracy (ACC) and sensitivity index (SI). The proposed method achieved an Average Accuracy of 94.80% and Sensitivity Index 69.14% on DRIVE dataset.

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