Curvelet Transform and Multi Structure Elements Morphology by Reconstruction based Retinal Image Analysis

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Abstract: Curvelet transform is a multi scale transform that can represent the edges along curves much more efficiently.Retinal images play important roles in finding of some diseases in early stages, such as diabetes, which can be performed by comparison of the states of retinal blood vessels. Automated image processing has the potential to support in the early detection of diabetes, by detecting changes in blood vessel diameter and patterns in the retina. Proposed paper describes the development of segmentation methodology in the processing of retinal blood vessel images obtained using non-mydriatic color photography. Highly accurate identification of blood vessels for the purpose of studying changes in the vessel network that can be utilized for detecting blood vessel diameter changes associated with the path physiology of diabetes. There is a deficiency of missing some thin vessels is because of utilizing a simple thresholding method. My contribution is to implement a technique that will also be applicable for small length blood vessels.

***Keywords*: Blood vessel segmentation,curvelet transform,multistructure elements morphology, morphological operators by reconstruction,retinal image.**

I. INTRODUCTION

Digital fundus imaging in ophthalmology plays an important role in medical diagnosis of primary levels of diabetes and blood pressure as well as cardiovascular disease .Some of the main clinical objectives reported in the literature for retinal vessel segmentation are the implementation of screening programs for diabetic retinopathy, evaluation of the retinopathy of prematurity, cardiovascular diseases, and computer-assisted laser surgery.

Diabetes is a disease that affects about 5.5% of the population worldwide, a number that can be expected to increase significantly in the coming years. About 10% of all diabetic patients have diabetic [1]retinopathy, which is the primary cause of blindness in the Western World. Since this type of blindness can be prevented with treatment at an early stage, the WHO advises yearly ocular screening of patients. Automation will facilitate this screening .Knowledge about the location of the vessels can aid in screening of diabetic retinopathy, e.g., to reduce the number of false positives in the detection of microaneurysms , to serve as a means for registration of images taken at different time instants or at different locations of the retina , or to find the location of the optic disc and the fovea .

Vessels, fovea, and optical disk are the three most important structures of the human retina and are mostly used for several applications.Detection of these important structures manually is time consuming and depends on the expertise of the user. The segmentation of blood vessels from fundus photographs can be difficult for a number of reasons. Some of the corrupting sources are related to the acquisition process and kind of imagery, and others are intrinsic features of retinal images. The two most influential factors that make the segmentation difficult are the improper retinal image contrast and the uneven background illumination In other words, arteries have higher contrast than veins. Existing paper also has a deficiency of missing some thin blood vessels because of the simple thresholding method.

In this paper, a method based on using curvelet transform is proposed to enhance and prepare the retinal image for better vessel detection. In the past decade, introduced the curvelet transform, a new multi scale transform.The second generation of curvelet transform, is faster and simpler than the first version. Therefore, the second generation of curvelet transform, discrete curvelet transform (DCT), and modified the DCT coefficients by a suitable nonlinear function are used. One way to increase the image contrast is to enhance the image ridges, which play an important role in enhancing image contrast.

In order to simultaneously enhance the weak edges and eliminate the noise, the modifying function parameters are defined based on some statistic features of fast DCT (FDCT) coefficients.

Mathematical morphology using multi structure elements are applied to obtain the image ridges. Then, morphological opening by reconstruction helps to remove the detected ridges not belonging to the vessel tree while preserving the thin vessel edges. The morphological opening by reconstruction benefits from using multistructure elements, which helps to improve the performance of this step. There is a restriction on size of structure elements (SEs) concerning the blood vessels diameter. Therefore, the remaining false edges will be removed by means of connected components analysis (CCA) along with length filtering. In order to act locally, image is decomposed to several tiles and CCA, and length filtering is individually applied to each tile. Modified CCA is proposed to predict the length of the blood vessels dynamically. Results shows a promising performance in segmentation of the blood vessels.

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II. RELATED WORK

Optic fundus assessment is widely used for diagnosing vascular and non-vascular pathology. Inspection of the retinal vasculature may reveal hypertension, diabetes, arteriosclerosis, cardiovascular disease and stroke. In many in vivo imaging applications, such as image-guided therapy, imaging conditions are often not favorable and each image frame must be processed with the presence of noise, clutter, texture and low contrast. Recorded images are often photon-limited and noisy. Furthermore, they are frequently subject to nonuniform illumination, glare, fadeout, and loss of focus. Consequently, there have been significant efforts aimed at tracking and segmentation of vascular structures in retinal images. Existing methods for vessel segmentation in retinal images are based on various features such as: intensity edges, matched filters, adaptive thresholding, intensity ridges, and wavelets.

Many efforts have been made and various methods have been introduced in order to segment retinal images. The algorithms in this field fall in three groups: window-based, classifier-based, and tracking-based approaches. The Window-based methods, such as edge detection, estimate a match at each pixel for a given model against the pixel's surrounding window. The cross section of a vessel in a retinal image was modeled by a Gaussian-shaped curve in and then detected using rotated matched filters.

Classifier-based methods perform in two stages. First, a low-level algorithm produces a segmentation of spatially connected regions. These candidate regions are then classified as being vessel or not vessel. The method incrementally step along and segment a vessel. In order to start tracking, there is a need for seed points proposed in is based on fuzzy K-median clustering, where the connected regions are detected by applying 12 rotating 16 × 15 matched filters, and the results go into classifier.The final result is produced by length filtering. Tracking-based methods utilize a profile model to incrementally step along and segment a vessel. In order to start tracking, there is a need for seed points.

Generally, there are two approaches to select the seed points: manually selecting seeds, which is labor intensive classifier.The final result is produced by length filtering. Tracking-based methods utilize a profile model to the

The architecture of the FDCT via wrapping is as following

1. Apply the 2D FFT and obtain Fourier samples
$$\hat{f}[n1, n2], -\frac{n}{2} < n1 \ \ and \ n2 < \frac{n}{2}$$
2. For each scale j and angle l, form the product
$$\widehat{U}j, l[n1, n2]\hat{f}[\mathrm{n1,n2}]$$
where $\widehat{U}j, l[n1, n2]$is the discrete localizing window.
3. Wrap this product around the origin and obtain
$$\hat{f}j, l[n1, n2] = W\left(\widehat{U}j, l \quad \hat{f}\right)[n1, n2]$$
where the range for n1 and n2 is now
$0 \leq$ n1 < L1,j and $0 \leq$ n2 < L2,j (for φ in

and depends on the expertise of the user, and automatically selecting seeds. A previous proposed method in which the ridges are detected by checking the zero-crossing of the gradients and the curvature; tracking starts from the seed with the highest intensity. Vessel segments, which are shorter than a given threshold or shorter than 30 pixels and with a height-to-width ratio bigger than a given threshold, are removed.

III. CURVELET TRANSFORM

A. Motivation

A special member of this emerging family of multiscale geometric transforms is the curvelet transform which was developed in the last few years in an attempt to overcome inherent limitations of traditional multiscale representations such as wavelets.

The idea of curvelet is to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law . This can be done by first decomposing the image into sub bands i.e., separating the object into a series of disjoint scales. Each scale is then analyzed by mean of a local ridgelet transform.

Since the curvelet transform is well-adapted to represent images containing edges, it is a good candidate for edge enhancement. Curvelets are based on multiscale ridgelets combined with a spatial band pass filtering operation to isolate different scales. This spatial band pass filter nearly kills all multiscale ridgelets which are not in the frequency range of the filter. In other words a curvelet is a multiscale ridgelet which lives in a prescribed frequency band. The band pass is set so that the curvelet length and width at fine scales are related by a scaling law and so the anisotropy increases with decreasing scale like a power law.

B. Discrete Curvelet Transform (DCT)

There are two approaches to implement the so-called second generation DCT: Wrapping method and unequispaced fast Fourier transform (USFFT) method. The wrapping method is faster and easier to implement than the USFFT method. Hence, wrapping method is used in this paper.

the range $(-\frac{\pi}{4}, \frac{\pi}{4})$)

4. Apply the inverse 2D FFT to each $\hat{f}j, l$,hence collecting the discrete coefficients c^D(j, l, k)

The FDCT via wrapping: first and unlike earlier discrete transforms, this implementation is a numerical isometry; second, its effective computational complexity is 6 to 10 times that of an FFT operating on an array of the same size, making it ideal for deployment in large scale scientific applications. The wrapping method assumes a regular rectangular grid to wrap the object. The idea is to first decompose the image into a set of frequency bands, and to analyze each band by a curvelet transform. The block size can be changed at each scale level.

IV. MATHEMATICAL MORPHOLOGY

A. Theory

Mathematical morphology is a powerful tool in dealing with various problems in image processing and computer vision. Mathematical morphology is composed of a series of morphological algebraic arithmetic operators. The shape and the size of SE play crucial roles in such type of processing and are, therefore, selected according to the need and purpose of the associated application.

In the 2-D Euclidean space Z2 , assume $I(x, y)$ as a gray-scale 2-D image and S as a defined SE. The edges of an image can be found by applying a morphological edge detector named the top-hat transformation described as follows:

$$\text{top-hat}(I) = I - (I \circ S)$$

where ($\circ$) denotes the opening operator. There is a problem in utilizing the top-hat, because pixels in opened image have smaller or equal gray-level values than those in the original image; therefore, the result of top-hat operator includes all the small ordinary intensity fluctuations that can be found in the data such as noise. In addition, the uneven background illumination of the fundus images aggravates this problem severely. To overcome this drawback, a modification was proposed. In the modified top-hat, a closing operator that proceeds by an opening is applied to the original image; the result will be compared to the original image using a minimum operator to attain an image equal to original image except in edges. The modified top-hat transformation is represented as follows:

$$\text{top-hat}(I) = I - \min((I \bullet Sc) \circ So; I)$$

where Sc and So stand for the SEs for closing ($\bullet$) and opening ($\circ$) operators, respectively.

B. Multistructure Elements Morphology

The choosing of SE is a key factor in morphological image processing. Single and symmetrical SEs are normally selected in order to perform the morphological processing; such SEs are successful in detecting ordinary, simple, and straight edges of an image. The basis of the multistructure elements morphology theory relies on gathering several SEs in one square window. In other words, decomposing an SE produces the *si*. Therefore, such SE is capable of detecting different edges with different directions, efficiently.

C. Morphological Operators by Reconstruction

Both morphology closing and opening leave the features larger than SE unchanged. However, the main drawback of conventional opening and closing is that they don not preserve edge information perfectly. Bangham *et al.* introduced a new operator to address this defect, called *M*- and *N*-sieves. The new operator emphasizes only on the size of the features, but rejects the shape completely. Morphological operators by reconstruction are designed to address this problem and consider both the shape and size of the features.

Basic morphological operators by reconstruction are erosion, dilation, opening and closing.The geodesic dilation of the marker image is defined as the pointwise minimum between the mask image and the elementary dilation of the marker image.

The geodesic erosion which is the dual transformation of geodesic dilation *is* defined as the pointwise maximum between the mask image and the elementary erosion of the marker image.

The morphological opening by reconstruction in its first step eliminates bright features smaller than the SE. in the next step, it dilates iteratively to restore the contours of components that have not been completely removed by opening and it is performed by considering the original image as the reference. In a similar manner, closing by reconstruction is accomplished in case of dark features. Therefore, as a valuable result, producing new edges, edge drift and deforming the contours and edges, which often occur by applying conventional morphological opening and closing will not appear by applying opening and closing by reconstruction.

V . PROPOSED METHOD

In this section, the proposed method is illustrated and the algorithm is described in detail.

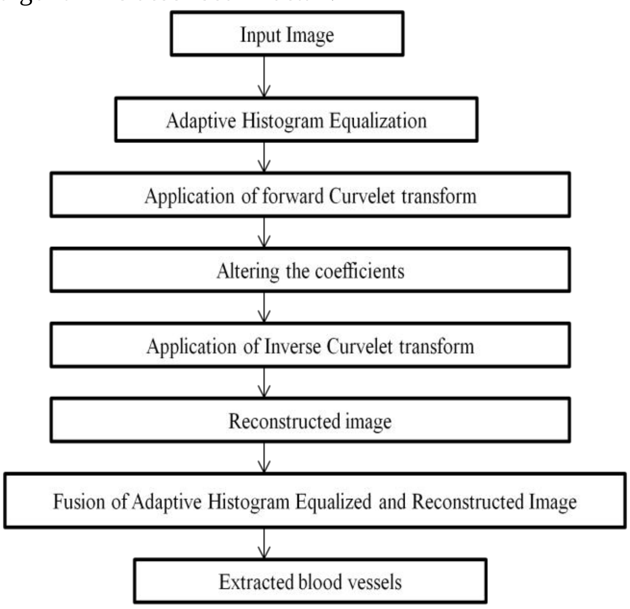

Fig.1. Design Model

A. Image Representation Selection

Since the blood vessels in the green channel image of the original colored retinal image have the highest contrast with the background, this channel is chosen to apply the proposed algorithm. The blue channel tends to be empty and the red channel tends to be saturated.

The green channel image is suitable for images of DRIVE database.

B. Retinal Image Contrast Enhancement Using FDCT

The curvelet transform is well adapted to represent the images containing edges, it is a good candidate for edge enhancement. Curvelet coefficients can be modified to enhance the edges in an image, which improves the image contrast.

The aim of enhancement step is enhancing the thin vessels having low contrast to detect better in the edge detection step.

Here contrast enhancement is carried out by means of Adaptive Histogram Equalization. It is a technique by which image brightness changes sharply.

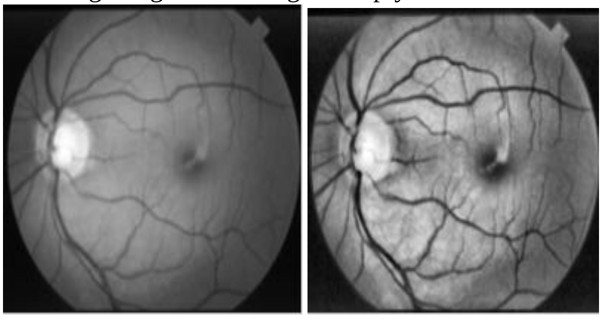

Fig.2. (a) Sample Retinal image (b) Result after enhancement

C. Edge Detection & Reconstruction

Edge detection is a fundamental tool in image processing which aim at identifying points in a digital image at which the image brightness changes sharply. In order to perform edge detection using multi structure elements morphology, the earlier SE of morphological edge detector should be replaced by new introduced SE and follow the following algorithm.

1) Produce the proposed SEs *Si* with regard to the required directional resolution.
2) Apply the selected edge detector function *F* on the original image using the achieved SEs in 1 and get the sub edge image *F*(I)*i* .
3) Put the *F*(I)*i* obtained in the following equation to achieve the whole of detected edges:

$$F(I)\sum_{i=o}^{M-1} wi\, F(I)i$$

where *F*(*I*) is the total edge image, $M = 180/\alpha$ is the number of *Si* and *ωi* is the assigned weight to each of sub edge image. In order to have the same effect of each *F*(I)*i* , the assigned weight can be defined as $\omega i = 1/M$, or they can be calculated by other methods as well. Also, if any information about the processed image exists, the weights can be assigned according to the degree of importance of information that may exist in each of *F*(I)*i*

D. False-Edges Removal Using Morphological Operators by Reconstruction

In the result image of edge detection step, there are edges not belonging to blood vessels but that arise from uneven background illumination. A simple method to eliminate these undesired objects is using morphological opening by reconstruction. Opening by reconstruction includes two steps: conventional morphological opening and reconstruction by dilation. In order to improve the performance of the morphological opening by reconstruction, the opening using multi structure elements is performed. Since the multi structure elements are highly sensitive to edges in all directions, it helps to accurately eliminate the false edges.

E. Length Filtering

In order to obtain a clear final result without presence of pixels that do not belong to vessel tree, we use length filtering with the aim of removing the small pixel blocks. In this case, the concept of modified CCA is used where connected components pixels which are identified above a specific threshold and labeled using eight connected neighborhood and are considered as a single object. Modified CCA is used to predict the length of the blood vessels dynamically here the threshold value is automatically calculated.

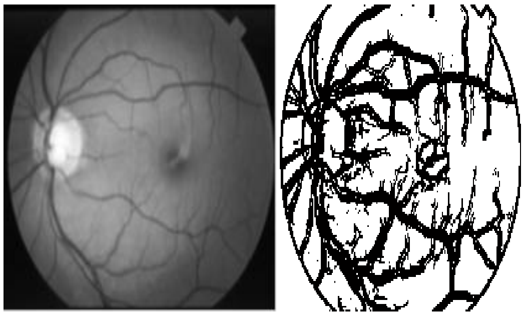

Fig.3.a) Input Retinal image b) Extracted blood vessels

Considering the entire image in CCA and length filtering leads to inferior results. This is because the input gray-scale image of this step contains thick vessels having high gray levels in contrary to thin vessels, which hold low gray levels that are close to gray levels of false edges. A kind of adaptive CCA, that is consider images in separate tiles and apply CCA and length filtering to each tile, individually. By this means, there is no large range of gray levels in each block, and a proper threshold can be chosen which separates the false edges from vessel edges efficiently. After applying modified CCA, all the small length blood vessels are identified. Finally, all of the results are integrated in a single image as the final blood vessel detection result.

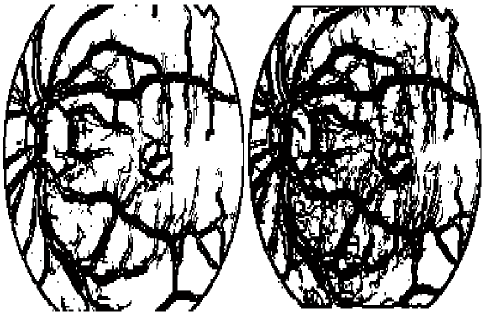

Fig.3.a) Extracted blood vessels b)Extracted blood vessels using Modified CCA

Therefore, the algorithm is as follows.

1) Partition image into tiles of $N \times N$ pixels with 50% interpolation to avoid windowing effect.
2) Apply the described thresholding algorithm to each part individually and obtain the desired threshold of each tile.
3) Apply CCA to each tile with considering only the pixels whose gray levels are more than the corresponding threshold.
4) Apply length filtering to each tile individually and retain the components having length larger than the elements morphology was capable of detecting the corresponding threshold
5) Gather all the results in one image.

V. CONCLUSION AND FURTHER WORK

In this paper, a new method for the retinal vessel segmentation has been presented. The retinal image contrast was improved and prepared better for segmentation step.

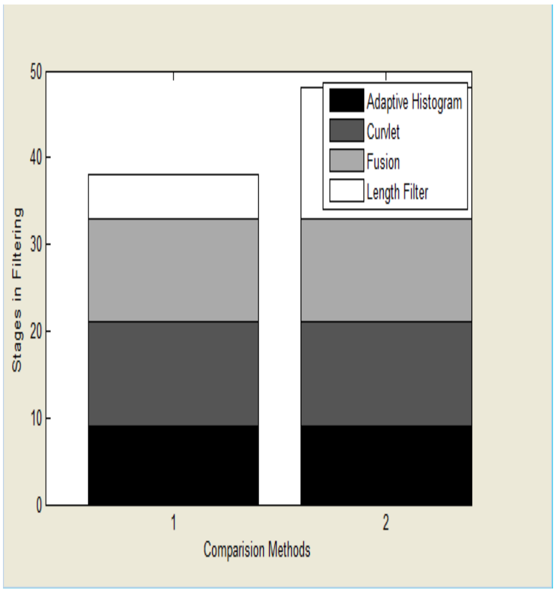

Fig.4.Comparision graph

The graph shows the comparison of the existing system with proposed system. Bar 1 represents existing system and bar 2 represents proposed system. The four different colors indicate that 4 different types of important operations used in the project. The Y axis represents the MSE (Mean Square Error) values in different steps.From the comparison graph it is clear that the proposed system's length filtering has high Error Rate value when compares to existing method.

Due to high sensitivity of multistructure elements to edges in all directions, multistructure false edges, while preserved the thin vessel edges perfectly. By applying the modified CCA and length filtering locally, helped to remove the remained false edges more accurately. Modified CCA predicted all the small length blood vessels dynamically. The quantitative performance results of both segmentation and enhancement steps show that our method effectively detects the thin blood vessels . Hence, my future work is to replace the simple threshold method with a more proper approach to increase the accuracy of the method.

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