ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Blood Vessel Segmentation from Retina Images Using Curvelet Transform and Multi-Structure Elements Morphology



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ABSTRACT

Retinal images play vital role in several applications such as disease diagnosis and human recognition. They also play a major role in early detection of diabetics by comparing the states of the retinal blood vessels. The detection of blood vessels from the retinal images is a tedious process. In this work a new algorithm to detect the blood vessels effectively has been proposed. Initially enhancement of the image is carried out using curvelet transform and modification of the curvelet coefficients. Since the blood vessels are distributed in various directions, morphology processing with multidirectional structuring elements are used to extract the blood vessel from the retinal images. Afterwards, morphological operator by reconstruction using multistructure elements eliminates the ridges not belonging to the vessel tree.

A simple thresholding along with connected component analysis (CCA) indicates the remained ridges belonging to vessel tree. Finally applying length filter on the connected components all residual ridges are refined from the images. Experimental results show that the blood vessels are extracted from the retinal images with better PSNR and 96% accuracy than enhancement using other techniques

INTRODUCTION

One of the most important internal components in eye is called retina, covering all posterior compartment, on which all optic receptors are distributed. Disorders in retina resulted from special diseases are diagnosed by special images from retina, which are obtained by using optic imaging called fundus. Blood vessel is one of the most important features in retina consisting of arteries and arterioles for detecting retinal vein occlusion, grading the tortuosity for hypertension and early diagnosis of glaucoma . Checking the obtained changes in retinal images in an especial period can help the physician to diagnose the disease.

Applications of retinal images are diagnosing the progress of some cardiovascular diseases, diagnosing the region with no blood vessels (Macula), using such images in helping automatic laser surgery on eye, and using such images in biometric applications, etc. On the other hand, extracting the retinal blood vessels is done in some cases by physician manually, which is difficult and time consuming and is accompanied by high mistakes due to much dependence on the physician's skill level. So, the exact extraction of the blood vessels from the retinal images necessitates using algorithm and instruments which reduce the dependency on the functor and eliminate the error factors.

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Diabetes is a disease that affects about 5.5% of the population world wide, a number that can be expected to increase significantly in the coming years. About 10% of all diabetic patients have diabetic retinopathy, which is the primary cause of blindness in the Western World. Early detection and prevention of these diseases are crucial to avoid preventable vision loss, the World Health Organization advises yearly ocular screening of patients. Automation will facilitate this screening.Diabetes mellitus is a chronic, systemic, life-threatening disease characterized by disordered metabolism and abnormally high blood sugar (hyperglycemia) results from low levels of the hormone insulin within or without abnormal resistance to insulin's effects. Through computer simulations it is possible to demonstrate that prevention and treatments are relatively inexpensive compared to healthcare and rehabilitation costs incurred by vision loss or blindness. Vessels, fovea and optic disks in the human retina are most widely used in several applications. The extraction of blood vessels from the retinal image can be difficult for a number of reasons. Some of the corrupting sources are related to acquisition process and kind of imagery, and others are intrinsic features of retinal images. The two most tedious 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 papers has deficiency of missing some thin vessels because of the simple thresholding technique. In this paper, a method based on Curvelet transform is used to enhance the retinal images and makes it better prepare for segmentation part. Curvelet transform coefficients are modified to enhance the week edges. Mathematical morphology approach to retinal vessel segmentation, which uses the top-hat transform calculated from the supremum of openings with large linear structuring elements in different directions. Then morphological opening by reconstruction used to remove the ridges not belonging to the vessel tree. The morphological opening by reconstruction benefits from using multistructure elements, which helps to improve the performance of this step. There is restriction on the size of the structuring elements (SEs) concerning the blood vessels diameter. Therefore the remaining false edges are removed by means of connected component analysis (CCA) along with length filtering. Results show a promising performance in the segmentation of blood vessels

Related Work

Optic fundus assessment is widely used for diagnosing vascular and non-vascular pathology. Inspection of the retinal vasculature may reveal hypertension, diabetes, cardiovascular disease. In many imaging applications, imaging conditions are often not favourable 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 no uniform 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: matched filters, intensity edges, adaptive thresholding, intensity ridges, and wavelets. Many efforts have been introduced in order to segment retinal images. The algorithms in this field fall in three groups: tracking based, window-based and classifier-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 modelled 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 steps along and segments 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

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utilize a profile model to incrementally step along classifier. The final result is produced by length filtering. Tracking-based methods utilize a profile model to the 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 labour intensive 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.

Curvelet Transform

The edge plays an important role in image identifying. So it is no doubt that the enhancements of the edges can efficiently helping the image identifying. The traditional edge enhancements are "High pass filtering" and "basis enhancement", but the performance is not as well as expect. The wavelet transform is useful for this work, but it is not proper to the image with directional element. Besides, the wavelet approach image enhancement will smooth the detail of the image. On the contrary, the basis of curvelet function has high sensitivity to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law. This makes it own the advantage of image enhancement. The approach of image enhancement is describe as follows: First, apply the curvelet transform to the image. Then, according to noise ratio of each sub band, enforce sectional nonlinear enhancement to the coefficients. At last, apply the inverse curvelet transform to the coefficients and come out the image with image enhancement on edge. Since the curvelet transform is well-adapted to represent images containing edges, it is a good candidate for edge enhancement. Curvelet 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. There are two approaches to implement fast discrete curvelet transform (FDCT): wrapping method and unequispaced fast discrete fast fourier transform (USFFT) method. The wrapping method is faster to implement than the USFFT method, while having the same result as USFFT method. Since the curvelet transform is well adopted 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 is then improves the image contrast. To this end we improve the nonlinear function to modify the representation coefficients in such a way that the details of the smaller amplitude are enhanced at the expense of the larger ones and perform this uniformly over all scales. Definition of the function Parameters are based on some statistical features of curvelet coefficients of the input image is very beneficial to adopt the function better with every input image. Therefore, there is a need for a nonlinear function, such as y, to multiply against the transform coefficients. The function is defined as follows:

$$y(x) = \begin{cases} k_1 \left(\frac{m}{c}\right)^p, & \text{if } |x| < ac \\ k_2 \left(\frac{m}{|x|}\right)^p, & \text{if } ac \le |x| < m \\ k_3, & \text{if } |x| \ge m \end{cases}$$

where x is the curvelet coefficient, $0 < p < 1$ determines the degree of nonlinearity.$k1$, $k2$ and $k3$ are assigned weights to each function part to allow us to control the modification of coefficients. Due to the assigned weights, we can indicate how much the coefficients became magnified or reduced or even be unchanged. The adjustment parameter makes it possible to determine and regulate the coefficients

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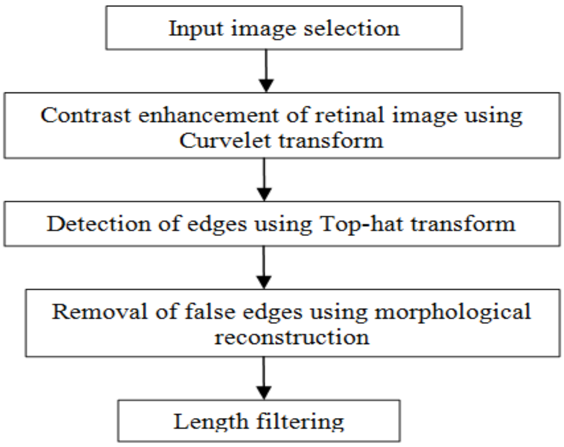
modification interval. Parameters *c* and *m* are involved in determining the coefficients modification interval as well as the amplitude of corresponding multiplying *y*. These parameters are defined according to two statistical features of coefficients. The first one is the noise standard deviation, with the aim of preventing the noise amplification, and the Second one is the maximum value of coefficients in each band. We choose $c = \sigma ji$, where σji is the noise standard deviation of coefficients being in the same direction and same scale. *m* can be derived from maximum curvelet coefficients of the relative and *MC* ($m = kMC$). *k* is an additional and independent parameter from the curvelet coefficient values, and therefore, much easier for a user to set. The assigned weights and adjustment parameter are experimentally tuned based on intrinsic characteristics of the input image and the goal of work.

Proposed Method

In this proposed method, the algorithm consists of six steps. They are

1) Image representation selection
2) Retinal image Contrast enhancement using Curvelet transform
3) Edge detection using morphological processing
4) False edges removal using morphological operation by reconstruction
5) Length filtering .The steps are described in detail as follows



Design method

A. Input image selection:

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.

B. Contrast enhancement of retinal image using Curvelet transform:

Curvelet transform is well adopted to represent the image containing edges; it is a good candidate for edge enhancement. Enhancing the retinal image using curvelet transform consists of following steps:

1) Applying FDCT via wrapping method, we get a set of scales *sj*, each scale consists of a set of directional bands containing coefficients.
2) For each directional band in each scale *Di*, do the following:
a) Calculate the noise standard deviation σji;
b) Determine the value of *m*.
3) Multiply each coefficient individually by corresponding *y*.
4) Reconstruct the enhanced image using modified curvelet coefficients.

C. Detection of edges using Top-hat transform:

The edges of an image can be found by applying a morphological edge detector named the modified top-hat transformation. A modified top-hat used which involves 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:

$$Top - hat(I) = I - min((I \bullet S_C) o S_O; I)$$

where *SC* and *SO* stands for the SEs for closing (•) and opening (◦) operators, respectively. The closing operation is used to generate a smoothed version of the original data, where the details smaller than the SEs are replaced by higher nearby intensities. The opened image essentially maintains the pixel values, while

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eliminating more intense image regions with sizes smaller than the SEs size. The final result of the comparison and subtraction is an edge detected image that mostly retains the original image regions with size smaller than the structuring element which show significant local intensity variations.

D. Removal of false edges using morphological reconstruction:

Edge detection step results few edges there are not belonging to vessel tree because of uneven background illumination. Morphological opening by reconstruction using multistructure elements are used to eliminate this undesired object.

This technique includes two steps are Conventional morphological opening and reconstruction by dilation. Since the multistructure elements are highly sensitive to edges in all directions, it helps to accurately eliminate the false edges.

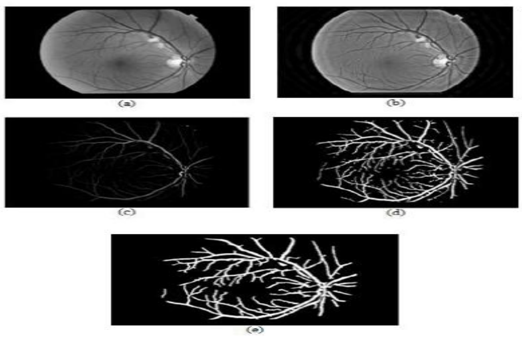
E. Length filtering:

Final step is length filtering that helps in the removal of small pixel blocks that do not belong to vessel tree. In this method, the concept of CCA is used where connected components pixels which are identified above a specific threshold and labelled using eight connected neighborhood and are considered as a single object. 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.

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.



Green channel image (b) curvelet transform enhancement (c) edge detection (d) morphological reconstruction (e) length filtering

CONCLUSION

From the above result it is shown that the blood vessels are segmented with better PSNR and accuracy. Here, a new method for the retinal vessel segmentation has been presented. The retinal image contrast was improved using curvelet transform and prepared better for segmentation. Due to high sensitivity of multistructure elements to edges in all directions, multistructure elements morphology was capable of detecting the blood vessel edges successfully. Morphological opening by reconstruction using multistructure elements removed the 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

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results of both segmentation and enhancement steps show that our method effectively detects the thin blood vessels. The segmented blood vessels can be used for diagnosis of diseases like diabetic, glaucoma and blind spot. For diseased persons the diameter of the blood vessels may vary or otherwise there is a possibility for growth of new vessels when compared with normal persons blood vessels. The blood vessels get swallowed for diabetic patients and it gets narrower for glaucoma diseased patients. This research work can be extended with the segmented blood vessels for differentiating diseased persons from the normal persons.

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