Journal of Engineering Sciences

Vol 11, Issue 4 , April/2020

ISSN NO:0377-9254

RETINAL VESSEL SEGMENTATION USING MINIMUM SPANNING SUPERPIXEL TREE DETECTOR

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Abstract— The retinal vessel is one of the determining factors in an ophthalmic examination. Automatic extraction of retinal vessels from low-quality retinal images still remains a challenging problem. In this paper, we propose a robust and effective approach that qualitatively improves the detection of low-contrast and narrow vessels. Rather than using the pixel grid, we use a super pixel as the elementary unit of our vessel segmentation scheme. We regularize this scheme by combining the geometrical structure, texture, colour, and space information in the super pixel graph and the segmentation results are then refined by employing the efficient minimum spanning super pixel tree to detect and capture both global and local structure of the retinal images. Such an effective and structure-aware tree detector significantly improves the detection around the pathologic area. Experimental results have shown that the proposed technique achieves advantageous connectivity-area-length (CAL) scores of 80.92% and 69.06% on two public datasets, namely, DRIVE and STARE, thereby outperforming state-of-the-art segmentation methods. In addition, the tests on the challenging retinal image database have further demonstrated the effectiveness of our method. Our approach achieves satisfactory segmentation performance in comparison with state-of-the-art methods. Our technique provides an automated method for effectively extracting the vessel from fund us images.

I. INTRODUCTION

DIABETIC RETINOPATHY also known as diabetic eye, refers to the progressive retinal damage occurring in people suffering from diabetes. This disease causes a narrowing of the small retinal vessels and often shows no symptoms in its early stages. However, it can progress rapidly and cause vision loss through several pathways. Diabetic retinopathy affects up to 80 percent of those who have had diabetes for 20 years or more. At least 90% of new cases could be reduced with proper treatment and monitoring of the eyes. The longer a person has diabetes, the higher his or her chances of developing diabetic retinopathy. Each year in the United States, diabetic retinopathy accounts for 12% of all new cases of blindness. It is also the leading cause of blindness in people aged 20 to 64.

Ophthalmologists can effectively examine diabetic patients by checking for retinal lesions, micro aneurysms, and abnormal/fragile blood vessels. However, owing to the high prevalence of diabetes and shortage of human experts, screening programs are costly and time-consuming for clinics. A reliable automatic retinal image examination method would significantly reduce the workload of ophthalmologists and facilitate a more effective screening process.

The motivation of this method is to develop an automatic and effective retinal vessel extraction from fundus images. It enhance both the low-level feature estimation process and the subsequent vessel extraction process by using an efficient minimum spanning superpixel tree (MSST) detector that can accurately capture both global and local structure features for retinal vessel segmentation. Furthermore, it could be extended to human identification (ID), as the retinal vessel structure is unique to each person. It is believed that in real-life applications, some bio-metrical features would be more applicable than others in certain cases. For example, human ID was achieved based on a new biometrical method: sclera recognition, which was based on a Gabor wavelet-based sclera vessel patterns detection. And their experimental results have shown comparable recognizing rate to iris recognition in visible wavelengths.

Numerous methods have been proposed for vessel extraction. These methods can be broadly categorized into three types: 1) the machine-learning-based classifications; 2) the tracking-based approaches; and 3) the enhancement/thresholding methods. Among these methods, machine-learning-based classifications usually obtain the best segmentation accuracy, and such a strategy can provide satisfactory results for healthy retinal images. However, these methods usually require the ground-truth segmentations for model training, however, these ground truth image labels are difficult to generate in practice. Meanwhile, another problem for these methods is that they often require a time-consuming retraining process when applied to a new image set. On the other hand, most of the tracking-based approaches are interactive, requiring a lot of user interactions which will significantly increase the workload of ophthalmologists. Although it is as-automated-as-possible algorithm needs limited initial inputs and user interaction, the method requires a given scale tube diameter for processing. Thus, our technique pursues fast, robust, automatic, and accurate vessel segmentation.

II. EXISTING SYSTEM

In general, traditional vessel extraction algorithms (such as the thresholding methods) consist of four steps. First, a preprocessing step aims to remove illumination noise and enhance specific features in the original retinal images. Second, the "vesselness" (likelihood of being a vessel) of each image pixel is computed using approaches, such as matched filtering and Hessian-based filtering. Third, vessel/non-vessel areas are classified on the basis of the vesselness measurement; in this paper, a threshold is used for the classification. Finally, false vessel pixels are removed by examining certain properties, such as connectivity and have categorized vessel segmentations into six major types:

1) pattern recognitions
2) model-based methods
3) tracking-based methods
4) AI-based methods
5) neural network-based methods
6) tube-like object detections

The concept of a matched filter (MF) for improve vessel detection in eyes was first adopted in "Detection of blood vessels in retinal images using two-dimensional matched filters". In that method, 12 different templates are constructed on the basis of a 2-D design MF, which uses intersectional vessel information and minimum changes in distance. " Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response" presented a method using the threshold for area-based vessel classification and improved the response and performance of a Gaussian MF by proposing a general-purpose optimization technique to determine better filter parameters. A revised MF for enhancing the vessel detection processing in the case of non-vessel structures is introduced. However, a major drawback of MF-based approaches is the ambiguous assumption that the intensity distribution of a vessel cross section obeys a Gaussian function, which is not always the case.

The line operator in "Finding orientated line patterns in digital mammographic images," is a useful method for detecting linear structures in mammographic photos. Given a target pixel and multiple lines passing through the pixel, the method selects the largest gray-level value as the line strength of the target pixel. The basic line operator to detect retinal vessels along all directions was introduced, as vessels can have different orientations, widths, and intensities. It isgeneralized that the basic line operator and combined various scales to produce a satisfactory segmentation result. Although the basic line operator is effective for vessels with a central reflex (a bright strip that is sometimes present along the center of wider vessels).

DRAWBACK OF EXISTING SYSTEM:

The first is its ineffectiveness in detecting small vessels owing to illumination noise and extremely small gray-level variance in the neighborhood of small vessels. The line operator mainly distinguishes vessels from the background according to their gray levels. However, the gray levels of thin and low-contrast vessels are similar to those of the background. Therefore, it is extremely difficult to set a threshold for discrimination. The second limitation is the spurious response to nonvascular structures, such as the optic disc boundary and pathologic area, which commonly have a strong boundary and tend to be falsely detected as vessel boundaries by the line operator.

III. PROPOSED SYSTEM

The supervised method is trained with the marked dataset. Then, the method is applied to classify retinal pixels, and gave the overview of some blood vessel segmentation methods. Supervised classifications are discussed both the unsupervised and supervised methods for blood vessel detections "Blood vessel segmentation methodologies in retinal images" introduced the supervised methods in detail. But supervised methods require manually segmented results as a training set. They will be inconvenient without the training set. Recently, there are several new methods to handle retinal vessel extraction. Filtering-based method using 3-D rotation is applied a left-invariant rotating derivative frame, and a locally adaptive derivative frame. An image inpainting method is applied to enhance the vessel detection rate during enhancement processing. A new formulation of deep convolutional neural networks was used, that allows simple and accurate segmentation of the retinal vessels using classification. Various color channels combination to improve vessel segmentation with the fine color fusion method was investigated.

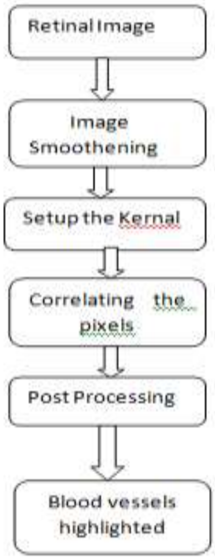
In addition, there are some novel image segmentation methods. Song applied regularized gradient flux flows for an accurate extraction of object boundary and contour, which not only reduce noise information but also keep nice edge information presented a method to estimate bias field and segment images with intensity inhomogeneity at the same time. It is introduced that a level set approach to segment the images with intensity in-homogeneity. Experimental

Journal of Engineering Sciences
Vol 11, Issue 4 , April/2020
ISSN NO:0377-9254

results on different types of images have shown the effectiveness of the learning-based approachfor enhancing objects segmentation with the information of boundary cues. The result is favorable when applying to cell segmentation. It has a certain reference to vessel segmentation. These new methods are valuable for vessel segmentation.

Many existing methods for vessel segmentation use pixel grid as underlying representation. Image grid with local neighborhood pixels are used and distinguishedthe value difference in image intensities for neighbors. For vessel segmentation, using pixel grid is not accurate enough. It is believed that a pixel form is not good enough for vessel structures, whereas superpixels provide a more natural and efficient way to compute local image features and distinguish vessels from other retinal structures. The superpixel method, which is becoming increasingly common in the field of image processing, can group pixels using the degree of feature similarity, thereby allowing for redundant information about the image to be acquired. This method fully utilizes spatial information and thus provides excellent anti-noise performance. In addition, it can retain the edge information of the original image while enhancing the local consistency. Super pixel and bottom-hat filtering are to segment retinal vessel, but the characteristic of super pixel is not utilized when using bottom-hat filtering. Super pixel-based method instead of pixel-based method is needed to detect vessel super pixels. Effective and simple linear iterative clustering (SLIC) algorithm to segment a retinal image into a set of super pixels using a feature combination of spatial distance, color distance, and texture distance.

BLOCK DIAGRAM:



ALGORITHM:

STEP 1: Obtain the Input Image.
STEP 2: Perform the Image smoothening operation.
STEP 3: Setting up the Kernal for zero degree orientation.
STEP 4: Perform the correlation operation in between the pixels.
STEP 5: Post Processing is performed by using median filter.
STEP 6: Obtain the blood vessel highlighted image.

WORKING PROCESS:

The features are computed for two aims. First, features are computed within a super pixel to determine the probability that the super pixel is part of a vessel. Second, the sets divide the input image into patches by distributing each pixel to the nearest primitive. The minimum-spanning tree structure constructed based on these super pixels, called MSST. Such structure-preserving MSST-based detector is employed to evaluate the vesselness of each super pixel and determine pixels in a patch as either vessel pixels or non-vessel pixels. Finally, segmentation results are refined further by applying a path-opening processing to reduce negative feedback for detection and to avoid nonvascular structures.

To evaluate this method, a database of manually labeled images is constructed. The dataset is referred as NIVE dataset. It consists of totally 40 fundus images. For comparison, our method is also evaluated using the digital retinal images for vessel extraction (DRIVE) and structured analysis of the retina (STARE) databases. The results indicate that despites its simplicity, the proposed approach matches or outperforms state-of-the-art methods. The main contribution is a novel super pixel-based vessel tree detector framework with the following unique characteristics.

1) It combines the super pixel and minimum spanning tree to segment retinal vessel.
2) It effectively addresses the detection of narrow and low-contrast vessels, preventing influences from other retinal structures.
3) It achieves satisfactory segmentation performance in comparison with state-of-the-art methods.
4) The framework could be extended to human ID, as the retinal vessel structure is unique to each person.

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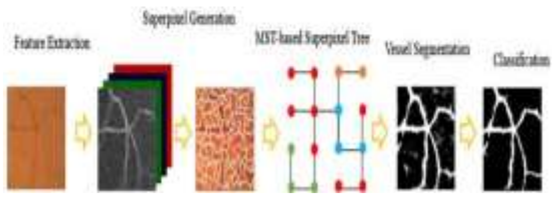

Figure: Overview of the proposed minimum spanning super pixel-based tree detector for retinal vessels.

IV. EXPERIMENTAL RESULTS

Figure: Original image and extracted green channel

Preprocessing algorithm is executed to remove noise includes contrast enhancement and retinal boundary growth on extracted green channel.

Figure: Enhanced image and illumination layer

The smoother layer is referred to as the illumination layer L_1, and the other layer is referred to as the reflectance layer L_2. It is more consistent, guaranteeing good image quality.

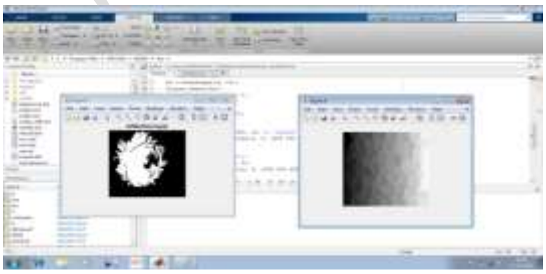

Figure: Reflection layer and Super pixel blocking on conventional RGB layer

Above figure gives the reflectance layer appears to be very bright.

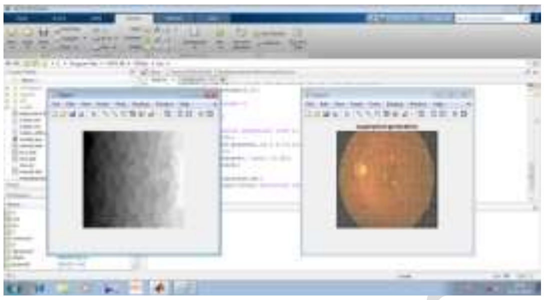

Figure: Superpixel blocking on illumination layer and Superpixel generation

Above figure gives the superpixel blocking result based on illumination layer and on conventional RGB layer. It is obvious that illumination and texture information help generate superpixels adaptively so that they can adhere well to boundaries. Illumination and texture layer information are taken to employ the SLIC algorithm to partition the original image as a group of superpixels.

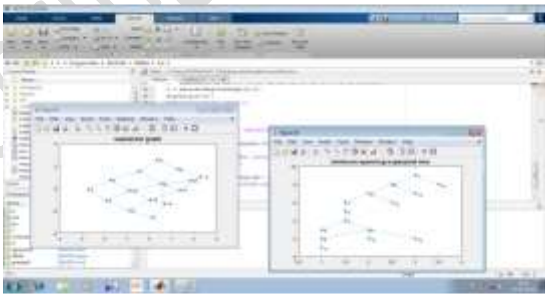

Figure: Superpixel graph and Minimum spanning Superpixel Tree

Above Figure the tree detector utilizes a minimum spanning tree to deal with large connected components in super pixel graph. Each super pixel represents a graph node, and super pixel-based feature differences provide edge weights between the nearest neighboring super pixels. An MSST is formed by repeatedly removing edges with large weights, such that any two close but dissimilar super pixels are automatically dragged apart.

Figure: Final extracted output vessel

Applying the method of path opening processing, undesired information like image noise could be filtered out, while vessels with thin structures could be retained.

CONCLUSION

Effective vessel segmentation for retinal images is a critical research domain in medical imaging. Owing to inherent non uniform illumination artifacts and complicated neighboring pathologies, existing methods have achieved reliable results for wide vessels, but they have failed to adequately segment thin and low-contrast vessels. A new ID scheme for retinal vessel segmentation using superpixel-based tree structure is introduced. Instead of operating on the pixel grid, the proposed scheme is regularised by combining global shape, texture, color, and space information in the superpixel graph. Results are further refined by employing an MSST-based vessel tree detector to evaluate the vesselness for each superpixel. Furthermore, path-opening filters are employed to enhance the effectiveness for more accurate extraction of retinal blood vessels avoiding unnecessary nonvascular influences, further will work to 3-D images, and investigate techniques for classifying different categories of retina-related disease and avoiding inaccurate placement of vessel structures for different pathologies.

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