Retinal Blood Vessel Segmentation Using Minimum Spanning Superpixel Tree Detector

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Abstract- *Diabetic retinopathy (DR), also known as diabetic eye disease, 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. Ophthalmologists can effectively examine diabetic patients by checking for retinal lesions, microaneurysms, 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. In this project propose a robust and effective approach that qualitatively improves the detection of low-contrast and narrow vessels. Rather than using the pixel grid, use a superpixel as the elementary unit of our vessel segmentation scheme. Regularize this scheme by combining the geometrical structure, texture, color, and space information in the superpixel graph. And the segmentation results are then refined by employing the efficient minimum spanning superpixel 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). In addition, the tests on the challenging retinal image database have further demonstrated the effectiveness of our method.*

Keywords- Feature extraction, minimum spanning superpixel tree (MSST), retinal image, superpixel, vessel segmentation.

I. INTRODUCTION

Image preprocessing includes the image enhancement procedures such as con- trast enhancement, image sharpness enhancement, correction of non-uniform illumi- nation, standardization of the images obtained from different sources (FOV stan- dardization), FOV/background matching, and resizing of the image to a standard size. The contrast enhancement technique using adaptive histogram equalization is for low quality/degraded images due to non-uniform illumination, shade correction using average/median filter or the image restoration techniques have been proposed in Different noise removal techniques have been reported such as morphological opening or altering.

Diabetic retinopathy (DR) is the most common microvascular complication of diabetes and remains the leading cause of vision loss in the working-age population. Early diagnosis through regular screening helps prevent vision loss. In a DR screening programme, a very large number of digital retinal images need to be examined for the presence of DR by human experts. Pathological signs of DR in the digital colour fundus images are dark lesions including microaneurysms (MAs) and haemorrhages, as well as bright lesions such as exudates and cotton wool spots. An automated system for separating healthy and diseased regions in the image can efficiently reduce the workload associated with large scale screening. Color fundus images with low-cost and patient friendliness are widely used for automatic DR detection. In the color fundus images, the signs of DR contain red lesions such as Mas (Microaneurysms) and hemorrhages, bright lesions such as hard exudates and cotton wool spots. Many machine learning methods have been developed for MA detection. Generally, DR candidates are firstly indentified, and then a set of features for these candidates are extracted, finally machine learning methods are applied for candidate classification. This project unsupervised classification method based on sparse PCA for DR detection.

The retina is a multi-layered sensory tissue that lines the back of the eye. It contains millions of photoreceptors that capture light rays and convert them into electrical impulses. These impulses travel along the optic nerve to the brain where they are turned into images. There are two types of photoreceptors in the retina: rods and cones. The retina contains approximately 6 million cones. The cones are contained in the macula, the portion of the retina responsible for central vision. They are most densely packed within the fovea, the very centre portion of the macula. Cones function best in bright light and allow us to appreciate colour.

Segmentation partitions an image into its integral components to facilitate further processing. However, segmentation is an ill-posed problem because it has no unique solution; Superpixels can be regarded as a result of an unsupervised over-segmentation; they avoid under-segmentation to preserve most segment boundaries of various ground truth data. Simultaneously, superpixel algorithms preferably create a small number of superpixels to capture redundancy. Before superpixels were established, Shi and Malik had presented a Bayesian view on segmentation: The interpretation of the quality of an segmentation is based on prior knowledge. Prior knowledge comprises not only low-level cues such as coherent brightness, color or texture, but also mid- and high-level cues.

Higher-level cues combine segments obtained by low-level cues. In contrast to low-level cues, they can consider context, instead of only relying on intrinsic object information; if the context is neglected, it can result in a bad segmentation on natural images due to occlusion, bad illumination, and shadows. Therefore, a good segmentation is inherently hierarchical. This insight gave rise to superpixels, which are computed through low-level cues and enable fast higher-level processing. Accordingly, superpixel creation is a preprocessing step, reducing the complexity of an image without loosing much information. Superpixels speed up subsequent computations significantly. For example, a graph-based segmentation algorithm runs notably faster if the graph's nodes consist of several hundred superpixels instead of several hundred thousand pixels.

II. LITERATURE SURVEY

A method is presented for automated segmentation of vessels in two-dimensional color images of the retina. This method can be used in computer analyses of retinal images, e.g., in automated screening for diabetic retinopathy. The system is based on extraction of image ridges, which coincide approximately with vessel centerlines. The ridges are used to compose primitives in the form of line elements. With the line elements an image is partitioned into patches by assigning each image pixel to the closest line element. Every line element constitutes a local coordinate frame for its corresponding patch. For every pixel, feature vectors are computed that make use of properties of the patches and the line elements. The feature vectors are classified using a NN-classifier and sequential forward feature selection. The algorithm was tested on a database consisting of 40 manually labeled images. The method achieves an area under the receiver operating characteristic curve of 0.952. The method is compared with two recently published rule-based methods of Hoover et al. and Jiang et al. The results show that our method is significantly better than the two rule-based methods (0 01). The accuracy of our method is 0.944 versus 0.947 for a second observer.

In the framework of computer-aided diagnosis of eye diseases, retinal vessel segmentation based on line operators is proposed. A line detector, previously used in mammography, is applied to the green channel of the retinal image. It is based on the evaluation of the average grey level along lines of fixed length passing through the target pixel at different orientations. Two segmentation methods are considered. The first uses the basic line detector whose response is thresholded to obtain unsupervised pixel classification. As a further development, we employ two orthogonal line detectors along with the grey level of the target pixel to construct a feature vector for supervised classification using a support vector machine. The effectiveness of both methods is demonstrated through receiver operating characteristic analysis on two publicly available databases of color fundus images.

This presents an algorithm based on mathematical morphology and curvature evaluation for the detection of vessel-like patterns in a noisy environment. Such patterns are very common in medical images. Vessel detection is interesting for the computation of parameters related to blood flow. Its tree-like geometry makes it a usable feature for registration between images that can be of a different nature. In order to define vessel-like patterns, segmentation is performed with respect to a precise model. We define a vessel as a bright pattern, piece-wise connected, and locally linear, mathematical morphology is very well adapted to this description, however other patterns fit such a morphological description. In order to differentiate vessels from analogous background patterns, a cross-curvature evaluation is performed. They are separated out as they have a specific Gaussian-like profile whose curvature varies smoothly along the vessel. The detection algorithm that derives directly from this modeling is based on four steps: (1) noise reduction; (2) linear pattern with Gaussian-like profile improvement; (3) cross-curvature evaluation; (4) linear filtering. We present its theoretical background and illustrate it on real images of various natures, then evaluate its robustness and its accuracy with respect to noise.

In this project propose a general framework of adaptive local thresholding based on a verification-based multithreshold probing scheme. Object hypotheses are generated by binarization using hypothetic thresholds and accepted/rejected by a verification procedure. The application-dependent verification procedure can be designed to fully utilize all relevant informations about the objects of interest. In this sense, our approach is regarded as knowledge-guided adaptive thresholding, in contrast to most algorithms known from the literature. We apply our general framework to detect vessels in retinal images. An experimental evaluation demonstrates superior performance over global thresholding and a vessel detection method recently reported in the literature. Due to its simplicity and general nature, our novel approach is expected to be applicable to a variety of other applications.

III. PROPOSED SYSTEM

The architecture of the proposed retinal recognition framework is shown in Fig 1.1 and it is discussed in this section. The main contribution of this project is a novel superpixel-based vessel tree detector framework with the following unique characteristics. It combines the superpixel and minimum spanning tree to segment retinal vessel. It effectively addresses the detection of narrow and low contrast vessels, preventing influences from other retinal structures. It achieves satisfactory segmentation performance in comparison with state-of-the-art methods. The framework could be extended to human ID, as the retinal vessel structure is unique to each person.

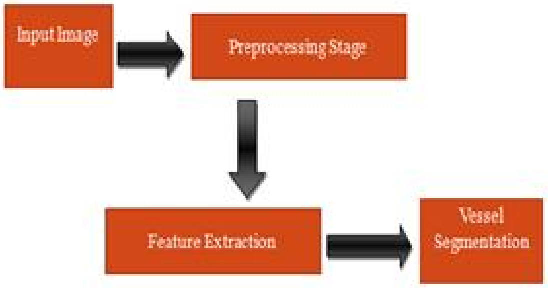

Fig 1.1 Block Diagram

Input image is taken in the .jpg format. The input image is being pre-processed i.e. Image resizing. Therefore, a preprocessing algorithm is executed to remove noise information. Preprocessing step includes contrast enhancement and retinal boundary growth. Then the image is being processed in feature extraction model. The feature extraction model consists of Illumination Layer, Reflectance layer, Texture layer. Then, a minimum superpixel tree detector is adopted to refine the segmentation results.

Pre-processing

Fundus images have a special feature of high contract in the field of view (FOV), false vessel detection may occur around the edge area of the retina image. Therefore, a preprocessing algorithm is executed to remove noise information preparing for further processing the following manipulations as shown in Fig. 2. Walter and introduced the key facts and contributions for image enhancement using different preprocessing techniques. The preprocessing step includes contrast enhancement and retinal boundary growth. The contrast limited adaptive histogram equalization (CLAHE) algorithm could generate image with the effects of local contrast enhancement. Therefore, in this work adopt CLAHE method adopted through dividing our input images with 8 × 8 = 64 areas. In addition, to further eliminate the drawbacks generated around camera aperture border through wavelet transformation, we have applied a boundary germinating method using iteration-based computing to expand the concerned area.

Feature Extraction

Illumination Layer

Inspired by the work obtain two layers from an original retinal image I, and one layer is smoother than the other 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,. The illumination layer is used for subsequent superpixel-based segmentation. The intrinsic image model is formulated as

$$I = L_1 + L_2 \tag{3.1}$$

The extraction process utilizes a gradient-based sparsity prior on reconstructed layers and an additional constraint on the smooth layer. To address layer separating, a probability-based method is adopted to obtain most-likely representation of the original image; further details can be found. The reflectance layer appears to be very bright, whereas some areas are poorly illuminated and unevenly distributed in the FOV. In contrast, the illumination layer is smoother and more consistent, guaranteeing good image quality.

Texture Layer

Textures in images play an essential place in many tools like remote sensing, environmental monitoring, and medical image processing. They usually have a natural sequence in the orientation and the multinarrow-band frequency information. This represents some fundamental features of visual appearances and is crucial in the perception of color. Retinal image textures provide us with spatial color and intensity information, and such information can be applied for superpixel-based vessel segmentation. In this paper, Gabor wavelets are employed as texture layer detectors. These wavelets have orientation selectivity, multiscale properties, a linear stage, and nice localization in spatial and frequency fields, making them proper for texture analyzing. In this section, we utilize the expressions in for the representation, and the Gabor transform is defined in the following as:

$$T_\varphi(b,\theta,a) = c_\varphi^{-1/2} a^{-1} \int \varphi^*\left(a^{-1} r_{-\theta}(x-b)\right) I(x)\, d^2x \quad (3.2)$$

Where, I is the image to be processed, $A = diag\left[\eta^{-1/2}, 1\right]$ denotes the 2 by 2 matrix that the off-diagonal entries are zero, k0 denotes a vector for frequency. ψ, ψ∗, a, and b are the given 2-D Gabor variables, more details of the wavelet expressions and processing could be found.

To obtain a good initial response from vessels orientation in different directions, the θ value of the filter is varied from 0 to 170 to generate high-quality feedback. Through all the orientations, the maximum wavelet feedback for every pixel is computed as

$$M_\varphi(a,b) = \max_\theta \; |T_\varphi(b,\theta,a)| \quad (3.3)$$

The thickness of blood vessels in the retina varies from 50 µm to 200 µm, with a median of 60 µm. Here, a is set to 1.5 experimentally for the high-quality detection of easy-missing vessels, and multiple scales wavelet could be utilized for multiscale vessel detection. The superpixel blocking result based on illumination layer and on conventional RGB layer.

Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

Minimum Spanning Superpixel Tree Detector

Superpixels are usually formed by over-segmentation. In this paper, we take illumination and texture layer information, and employ the SLIC algorithm to partition the original image as a group of superpixels. SLIC begins by sampling starting cluster centers on a regular grid spaced S = √N/K pixels apart. Next, to prevent putting these cluster centers at edges, they are moved to seed locations relate to the lowest gradient position through 3 by 3 neighborhood. Then, the clustering process is iteratively applied to give every pixel to the nearest cluster center according to color and spatial relation. At the end of this process, pixel connectivity is enhanced by relabeling disjoint segments using labels from the largest neighboring cluster. Compared with other superpixel methods, SLIC has low computational complexity and excellent boundary adherence.

In addition, SLIC is easy to use because it needs only one parameter to produce the target superpixel number. Generally, SLIC clusters image pixels using color, texture, and image plane spaces according to a weighted distance metric. Then measure the distance between a pixel i and the SLIC cluster center Ck in the illumination and texture layers, respectively and take the spatial distance is taken into consideration, as the pixel position [x,y]T may vary for different sized images. Just applying the 6D Euclidean distance in the space generated by combining information from all three layers may cause inconsistencies during clustering superpixels of different sizes. For large superpixels, spatial distances outweigh illumination information; more essentialness is given to the spatial information than to color contents. Such operations will generation superpixels which do not conform very nice to edges. While in the case of smaller superpixels, the effects are more accurate. It try to join the two distances as one metric and assign different weights to the three layers. The overall distance measure D is defined as follows:

$$d_{rgb} = \sqrt{\left(R_{k_1}-R_{k_2}\right)^2 + \left(G_{k_1}-G_{k_2}\right)^2 + \left(B_{k_1}-B_{k_2}\right)^2} \quad (3.4)$$

$$d_t = \sqrt{\left(g_{k_1}-g_{k_2}\right)^2} \quad (3.5)$$

$$d_s = \sqrt{\left(x_{k_1}-x_{k_2}\right)^2 + \left(y_{k_1}-y_{k_2}\right)^2} \quad (3.6)$$

$$D = \sqrt{m_{rgb} d_{rgb}^2 + m_t d_t^2 m_s d_s^2} \quad (3.7)$$

Where

R_k = Red Channel Illumination Layer
G_k = Green Channel Illumination Layer
B_k = Blue Channel Illumination Layer

Further, d_{rgb}, d_t, and d_s represent the illumination, texture, and spatial proximities, respectively, and mrgb, mt, and ms are the weights of the illumination distance, texture distance, and spatial distance, respectively. Illumination and texture information both help generate superpixels adaptively so that they can adhere well to boundaries. The information represents some basic characteristics that are crucial in the perception of color.

To fully utilize the illumination and texture feature, we set the weight proportional to the difference between pixel and the coordinates of the cluster center. Shows some superpixel-based fragments of a retinal image. It is clear that superpixel blocks adhere well to vessel boundaries when we combine the three layers of information, especially for some small vessels. Fundus images are known to suffer from uneven illumination noise, which can be eliminated by clustering pixels into superpixels. This in turn would enhance both big and small vessels, because inherent homogeneities are spread across their neighbors in the process of k-means clustering. When a set of superpixels is generated through k-means clustering with the distance measure defined above, the superpixel attributes can be viewed as a set of local nearby homogenous pixels. Based on our observation, vessel superpixels in fundus images are characterized as slender edge areas, which may not be comprehensively preserved by general enhancement methods, such as the well-known bilateral filter, because they deal with slender areas based on a locally averaging operator that tends to smooth out the small homogenous vessel regions. Moreover, they often suffer from severe deviation from the original sharp edges, because the geometric image structures are ignored.

To evaluate the vesselness of superpixels, a new edge preserving tree detector is employed to determine weighted average. Compared with traditional enhancements, our vessel tree detector distinguishes small connected components (details) from large connected components (major structures) in a nonlocal manner, achieving impressive results for slender areas such as retinal vessels in fundus images. The tree detector utilizes a minimum spanning tree to deal with large connected components in superpixel graph. Each superpixel represents a graph node, and superpixel-based feature differences provide edge weights between the nearest neighboring superpixels. An MSST is formed by repeatedly removing edges with large weights, such that any two close but dissimilar superpixels are automatically dragged apart.

To optimize a graph, there are many frequently used methods like normalized-cut (N-cut), max-flow min-cut, minimum spanning tree, and so on. By comparing these methods, we found that MST is the most suitable one in this situation. The N-cut method measures both the total dissimilarity between the different groups as well as the total similarity within the groups. It is an NP-complete problem and has high complexity. The graph-cut method based on max-flow min-cut theorem utilizes the property that the smallest total weight of the edges which if removed would disconnect the source from the sink. It can get the global optimal solution efficiently, and it has good noise immunity. But we have to choose the pixel inside and outside the target as seed point manually, which limit its application in image segmentation. The MST method can reserve the details inside the boundaries of vessels. Its self-adaptability when searching for minimum weight helps to get the global features, which show the perception of color that is similar to human's eye. Then apply MST to optimize a graph. Considering the important property the retinal vessels appear to be similar to vascular tree structures, it can easily connect the vessel superpixel sets by constructing the MSST. This method has low complexity.

IV. SCREEN SHOTS

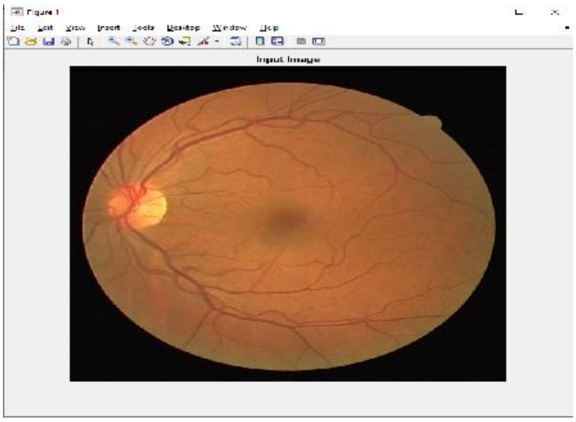

Fig 1.2 Input Image

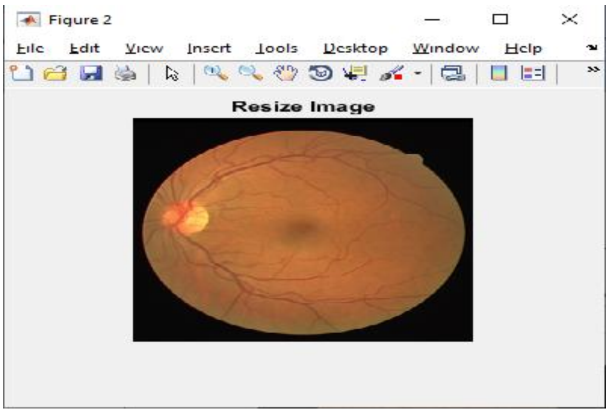

Fig 1.3 Resize Image

Fig 1.4 Green Channel Extracted Image

Fig 1.5 Contrast Enhancement Image

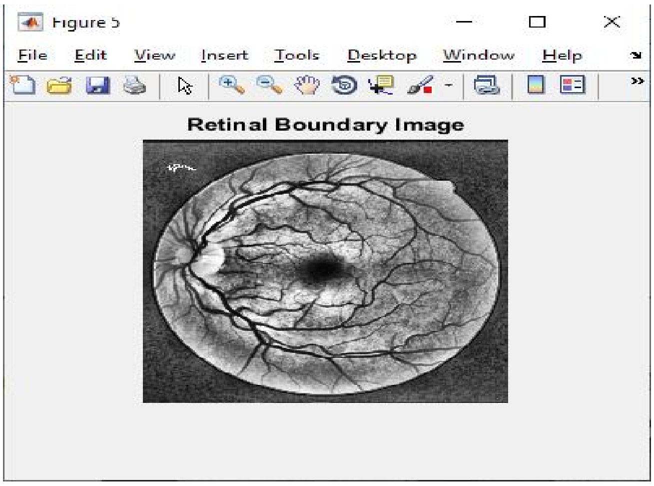

Fig 1.6 Retinal Boundary Image

Fig 1.7 Reflectance Layer

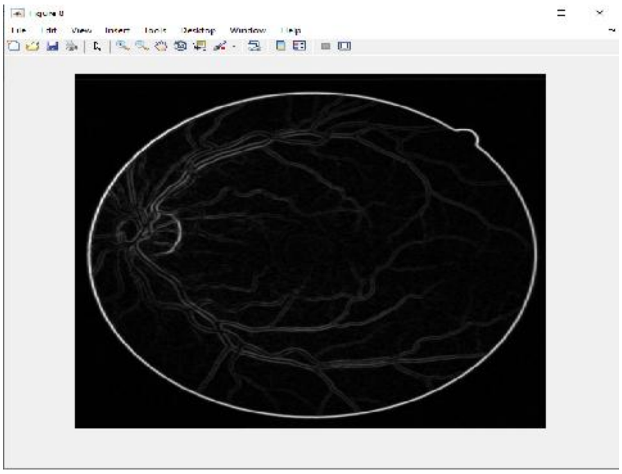

Fig 1.8 Texture Layer

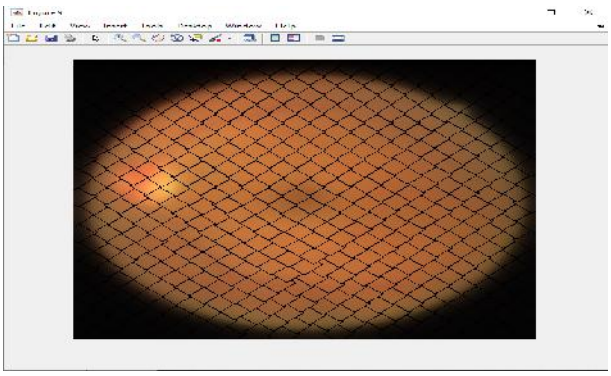

Fig 1.9 Super pixel Image

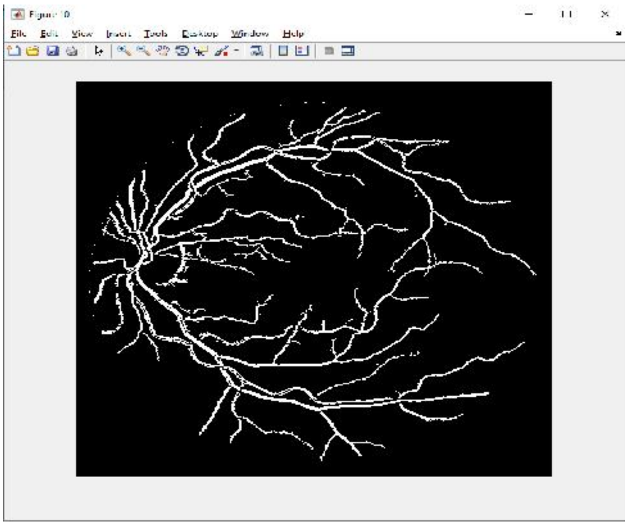

Fig 1.10 Blood Vessel Segmentation

V. CONCLUSION

Effective vessel segmentation for retinal images is a critical research domain in medical imaging. Owing to inherent nonuniform 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 implemented. Instead of operating on the pixel grid, we regularized the proposed scheme by combining global shape, texture, color, and space information in the superpixel graph. Refined our results further 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. The current SLIC method has limitations like time-consuming and unsmooth boundary.

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