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A Review of Methods for Blood Vessel Segmentation in Retinal images

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Abstract

An automated blood vessel segmentation method can be integrated into a pre-screening system for early eye disease detection. Blood vessel segmentation involves a huge challenge as images present inadequate contrast, lighting variations, noise influence and anatomic variability, affecting retinal background texture and the blood vessels structure. This paper does a detail survey and comparative study of various blood vessel segmentation methods in literature.

Keywords: Medical imaging, Image segmentation, Blood vessel segmentation, Diabetic Retinopathy.

1. Introduction

Diabetic retinopathy (DR) is one of the leading causes of blindness among people suffering from diabetes. It is observed that about 2% of the patients affected by this disorder are blind and 10% undergo vision degradation after 15 years of diabetes. [1] DR patients perceive no symptoms until visual loss develops which happens usually in the later disease stages, when the treatment is less effective. DR is not a curable disease, but laser treatment can prevent major vision loss if detected in the early stages. So, diabetic patients need frequent eye-fundus examination.

Recent advances in digital imaging and computing power have made it possible to use data provided from medical images in new and revolutionary ways. This has also led to considerable interest in the development of automatic medical diagnosis systems to improve the services provided by the medical community. The automatic diagnosis systems relieve physicians of repetitive work, increases efficiency and provide remarkable cost savings [2]. An automated blood vessel segmentation method can be a suitable tool for being integrated into a complete pre-screening system for early DR detection. It is useful for other clinical purposes as vessel diameter measurement to diagnose hypertension and cardiovascular diseases, and computer-assisted laser surgery.

This kind of systems should require no user interaction, and be robust enough to analyze different kinds of images. It is a huge challenge, since large variability is observed in the image acquisition process and a natural variation is reported in the appearance of the retina. The eye fundus photographs present inadequate contrast, lighting variations, noise influence and anatomic variability affecting both the retinal background texture and the blood vessels structure. Blood vessels particular features make them complex structures to detect as the color of vascular structures is not constant even along the same vessel. Their complex tree-like geometry includes bifurcations and overlaps that may mix up the detection system. As blood vessels segmentation becomes essential for several medical diagnostic systems, numerous research efforts have been done in this field.

The rest of the paper is structured as; In Section 2 is Related Work. In Section 3 we describe different Blood Vessel Segmentation Algorithms. In Section 4 we give a Comparative Study finally in Section 5 we give Conclusion to paper.

2. Related Work

The retinal vessel segmentation methods are rule-based and supervised methods.

The tracking based methods start from an initial set of points established automatically or by manual labelling; the vessels are traced by deciding most appropriate candidate pixel close to the pixels under evaluation. A fuzzy approach [3] halts when the

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response to a 1D matched filter falls below a given threshold. The method is dependent upon locating the starting points. A recursive dual edge tracking and connectivity recovering technique [4] uses image edge map computed by the canny edge operator and monitors the connectivity of its twin border. It shows robustness against visual quality of the images.

The mathematical morphology methods use the knowledge of vessel shape features such as piecewise linear and connected. Then, applying morphological operators vessel structure is filtered from the background for final segmentation. The top-hat-transform [5] causes vessel pixels to darken; border pixels take the value of the closing. For other patterns which fit such a morphological description. So evaluate the cross curvature using the Laplacian filter [6] as vessels curvature is linearly coherent.

The matched filter uses a 2-D linear structuring element with a Gaussian cross section for vessel identification. In [8] 12 templates kernel as, $K(x,y)=-\exp(-x^2/2\sigma^2)$ where, σ-intensity spread, L- segment length with fixed orientation are rotated and for each pixel maximum response is selected. The convolution kernel size affects the computational load The thin vessels might not match. The response to the detection of blood vessels is increased by optimising parameters [9].

The model-based locally adaptive thresholding [10], is verification-based multithreshold probing scheme that includes vessels information into the verification process. The deformable or snake models [11], [12] evolve to fit the shape of the desired vessel structure by an iterative adaption. A multiscale feature extraction method [13] employs a multiple pass region growing procedure. Growth progressively segmented the blood vessels by using both feature and spatial information. Isodata [15] technique provides automatic threshold value to get a binary image. The processing time is less compared neural networks and region-growing algorithms.

The supervised methods are based on pixel classification into two classes, vessel and non-vessel. The classifiers are trained by learning from manually-labelled images. The classifiers are the Bayesian classifier [17], kNN method [18], support vector machines [19] and neural networks [20]. This paper provides a comparative study of various vessel segmentation algorithms.

3. Segmentation Methods

3.1. Pre-processing

Depending on the image quality some segmentation methods may require image preprocessing prior to the segmentation algorithm. In Adaptive Histogram Equalization method [16] original RGB image is transformed into Gaussian and *Lxaxb* color space. The two components of Gaussian color space, Luminance L and Green channel G are taken due to the higher contrast of vessel and background. The histogram equalization is applied only on small non-overlapping regions. Then neighboring tiles are combined using bilinear interpolation to reduce induced boundaries. This method gives best contrast enhancement for texture feature extraction.

Ridges are defined as points where the image has an extremum in the direction of the largest surface curvature. In [18] a ridge is detected from the green channel. The ridges are used to form line elements by region growing algorithm. With line elements an image is partitioned into patches by assigning each image pixel to the closest line element. Detection induces blurring hence high probability for vessel being found around while there are no vessels; no ridge is detected at the location of a vessel, which can happen for very small vessels.

The normalization [19] of green plane is done by subtracting an approximate background estimated using a median filter on the original retinal image. Thereby blood vessels are brighter after normalization. The gradient images are convoluted with Sobel operators along horizontal and vertical directions. The optic disk is located as it corresponds to a single local maximum or minimum. Large vessels are extracted as corresponds to a pair of local gradient maximum and minimum on both sides the optic disk. The method extracts thin and large vessels separately.

In another algorithm vessel central light reflex removal involves employing morphological opening, background homogenization uses mean filters of varied dimensions and vessel enhancement uses tophat transformation [20]. This method suits intensity and shape based features.

3.2. Feature Extraction

The aim of the feature extraction stage is pixel characterization by means of a feature vector. Gabor filters [16] with twenty-four orientations and three wavelengths are used for texture feature extraction for each of the color channels. Twelve texture images are constructed for each original retinal image considering the maximum response. These are used to analyze the number of clusters which are classifier input. The 12 length feature vector is constructed for every pixel mapping each pixel position of all the texture images. The method is very efficient in detecting both major and minor blood vessels.

In ridge based segmentation method [18], feature vectors are computed that make use of properties of the patches and the line elements like height, width of vessel profile etc. 18 features are taken. The sequential forward selection method starts with a null feature set and, for each step; the best feature that satisfies a criterion function i.e. area under curve is included with the current feature set. Scale as a feature can improve performance of detecting small vessels.

The curvelet transforms [19] detect line features. It decomposes the gray image at scale 2 and angle 8, and produces one approximate subband and eight detailed coefficient blocks. Each detailed coefficient block is selected to reconstruct image, and calculate the modulus image. The large vessels are extracted by adaptive local thresholding. Then a 12 dimensional feature vector is constructed for each residual pixel in the binary retinal image excluding the large vessels. The thin vessel segments are identified by SVM, and lengthened by tracking. The accuracy is highest but is dataset sensitive.

The Gray-level-based features [20] are based on differences between gray-level in the candidate pixel and a value representative of its surroundings. A set of gray-level-based descriptors are derived from homogenized images considering a small pixel region centered on the described pixel. For detecting the shapes not all equally wide and oriented at any angle, shape descriptors invariant to translation, rotation and scale change i.e. Moment invariants-based features are considered. Discriminative power increases when feature types are jointly considered.

3.3. Classification

The classifier assigns one of the classes (vessel) or (nonvessel) to each candidate pixel when its representation is known. In FCM clustering algorithm [16] each data point belongs to a cluster specified by a membership grade. The number of clusters is assigned after analyzing the histogram of the texture image. From output of algorithm a 2D matrix is constructed with cluster numbers which have the highest membership values (for each position). The segmented image is obtained by converting the cluster numbers into binary values considering the cluster centroid values. The method is very efficient in detecting both major and minor blood vessels.

A GMM classifier [17] is a Bayesian classifier in which each class-conditional probability density function is a linear combination of Gaussian functions. Gaussian parameters and weights are determined with the Expectation-Maximization(EM) algorithm. GMM classifier has a computationally demanding training phase, but guarantees a fast classification phase and better performance. Feature vectors from a particular class (vessel or nonvessel) cluster together in the feature space. kNN-classifier [18] determines a decision boundary between the different classes. Classification is by determining on which side of the decision boundary feature vector is situated. Using k neighbours of which n are labelled as vessel, the posterior probability for being part of a vessel is approximated as p(vessel)=n/k. Method is sensitive to feature scaling. Feature dependence is not a issue.

The Support Vector Machines [19] have high performance in higher dimensional spaces. Binary SVM is used to find the hyper-plane that best separates vectors from both classes in feature space while maximizing the distance from each class to the hyper-plane. The radial basis function is used to map input vector to a high dimensional features space. The classifier gives highest accuracy but is dataset sensitive. A multilayer feedforward neural network [20], consist of an input layer, three hidden layers and an output layer. NN is trained by back-propagation training algorithm. Performance is enhanced by the inclusion of a two step post processing stage: filling pixel gaps in detected blood vessels, and removing falsely detected isolated vessel pixels. The neural network classifier provides high accuracy.

4. Comparative Analysis

Table 1: Comparison among various Blood Vessel segmentation methods

Sr No	Algorithm	Advantages	Limitations
1	Morphological Top Hat transform[5]	Acceptable in low contrast images.	Prefiltering step required.
2	Morphological Top Hat transform along with curvature evaluation[6]	Generates clean but not always connected structure.	False detection when black zone next to a brighter zone

3	2D matched filter[8]	Efficient for poor local contrast. Better performance over other edge detection algorithms.	Post processing required. L must be larger to reduce noise but the thin vessels missed.
4	Improved 2D matched filter [9]	Results are comparable in r, g, and b channels.	Requires better hardware support
5	2D Gabor Wavelet & Gaussian Mixture Model Bayesian Classifier [17]	Robust against varied types of images.	Fails for large variations in lighting. Ignores information from shapes and structures.
6	Feature vectors based on properties of patches & line segments ,KNN classifier [18]	Feature selection strategy increases performance.	Blurring occurs in the detection of ridges. Vessel found while there are no vessels; no ridge is detected at the location of a vessel.
7	Line operators & SVM classifier[19]	Highest accuracy in all methods over the used dataset.	Dataset sensitive.
8	Gray level & moment invariant based features & NN classifier[20]	Discriminative power increases when both feature sets are jointly taken. Robust regarding the dataset used.	

5. Conclusion

This paper provides a detailed review and comparative analysis of the various vessel segmentation methods.

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