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A Review on Blood Vessel Segmentation Algorithm

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Abstract—Retinal vessel segmentation algorithms are important in automatic retinal disease screening systems. Images captured from fundus camera are useful in screening various diseases affecting retina by processing the images for better diagnosis and planning of treatment. Ophthalmology is a branch of biomedical field which requires computer aided automated techniques for pathology identification in human eyes. Many automatic segmentation techniques are available but it is difficult to achieve the concept of generalization among these techniques. These automated techniques must be highly accurate and should process a quick convergence rate. Hence there is a significant necessity to analyze these techniques to highlight their suitability for retinal disease identification applications.

Keywords- Ophthalmology, retinal vessels, segmentation algorithms, disease diagnosis.

I. INTRODUCTION

Retinal disease identification techniques are highly important in the field of ophthalmology. Conventional techniques for retinal disease identification are based on manual observation, which may not produce accurate results. Also the time required for segmenting the retinal blood vessels manually is significantly high and requires training and skills. Hence, there is a need of automated techniques to eliminate the drawbacks of the conventional techniques which is significant in the medical field [12][14]. The automated disease identification techniques should be highly accurate. Besides being accurate, the techniques also should possess a quick convergence rate to be suitable for real-time applications. Based on these two performance measures, several automated techniques are developed and implemented successfully for retinal disease identification. Segmentation methods vary depending on whether the method is automatic or semiautomatic, imaging modality, application domain and other specific factors.
Inspection of retinal vasculature may reveal early signs of diabetes, hypertension [1][5][6][7][12][13], arteriosclerosis, cardio-vascular disease and stroke[1][3-9][12]. It also plays an important role in diagnosis and study of diseases such as choroidal neo-vascularization, dystrophy age related macular degeneration (AMD), diabetic retinopathy [1][4][5][7][12][13], retinopathy of prematurity (ROP), glaucoma [1][3][4][6]. For diagnosis, screening, treatment and evaluation of retinal diseases features such as length, width, tortuosity, angles, branching pattern [2][3][6-10][12][13] vessel diameters, Bifurcations [6][7] are taken into account. However there are various challenges faced during segmentation of retinal vasculature that includes high noise levels, drift in image intensity, lack of image contrast, reflection along central lines (Central vessel reflex) [8-10], wide range of vessel widths [7]. Presence of hemorrhages, angiogenesis, blockages and arteriolar-venular diameter ratios [1], projected neural canal opening, low visibility in optic nerve head (ONH) center [3] also affect segmenting the images. Image resolution, overlap and crossing of arterial and

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venous network [5] low contrast of thin vessels to background, non-uniform illumination, central light reflex in wide vessels and presence of pathological lesions [6-10] are also some of the challenges faced. This paper presents review of various algorithms for retinal blood vessel segmentation from two dimensional, colored, non-dilated retinal images acquired from a fundus camera or from fluorescein angiography.

II. RELATED WORK

A method for automated segmentation of vessels in color images of retina to be used in computer analysis of retinal images for automated screening of diabetic retinopathy is proposed by Staal *et al.* [3]. Image ridges that coincide approximately with vessel centerlines are extracted to compose primitives in form of line elements. Images were partitioned into patches and each image pixel was assigned to closest line element that constitutes a local coordinate frame for its corresponding patch. Using the properties of the patches and line elements, feature vectors were calculated and classified using a k-NN classifier and sequential forward feature selection. The methodology was tested on publically available DRIVE and STARE database and achieved an average accuracy of 0.9442 and 0.9516 respectively and area under ROC curve 0.952 and 0.9614 on DRIVE and STARE database respectively.

Zhihong *et al.* [4] proposed two approaches for segmenting optic nerve head spectral domain optical coherence tomography (SD-OCT) volumes where segmentation was a challenge due to projected neural canal opening and low visibility in optic nerve head. In registered fundus vessel segmentation approach, vessels segmented on fundus photographs using a k-NN classifier were mapped on SD-OCT volumes through registration. In multi-modal vessel segmentation approach, after registration of vessels from fundus to SD-OCT, they were segmented simultaneously using features from both modalities. Features were generated from the 3-D structural information obtained through graph theoretic segmentation methods, intra-retinal layers and neural canal opening from SD-OCT volumes with Gaussian filter banks and Gabor wavelets. The method gave area under ROC of 0.85 and 0.89 for both the approaches when tested on images collected from a few subjects.

A method for automatic segmentation of retinal vasculature that classifies each image pixel as vessel or non-vessel based on feature vectors was presented by Soares *et al.* [5]. Responses from 2D Gabor wavelet at multiple scales and pixel intensities form the feature vectors. Noise filtering and vessel enhancement is achieved by use of Gabor wavelet that can tune to variable frequencies. For classification of vessel pixels a Baysien classifier with class conditional probability density functions as Gaussian mixtures was used. The performance of the method evaluated on DRIVE and STARE database showed an area under ROC to be 0.9614 and 0.9671 respectively.

An unsupervised method for retinal vessel segmentation using combined matched filters, Frangi filters and Gabor wavelet was proposed by Oliveira *et al.* [6]. Approach based on deformable models that are flexible and used for complex operations and which works well with non-homogeneous feature images and fuzzy c-means approach used for clustering and pattern recognition segmentation methods were implemented after vessel enhancement on the images from DRIVE and STARE database. The combined filters gave the highest accuracy of 0.9607 and 0.9613 on the images from the database as compared to the individual filters.

A principal curve based segmentation approach to segment retinal vessels accurately for extraction of features for disease diagnosis was presented by You *et al.* [7]. Retinal vessels were enhanced and their diameters were measured using an isotropic Gaussian kernel Frangi filter and the centerlines of the vessels were identified using a multi-scale principal curve projection and tracing algorithm using underlying kernel smoothing interpolation of intensities. The principal curve projection and tracing

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step used the estimated radius of the Frangi filter as the bandwidth of the kernel interpolation. Segmentation was done on images from the publically available DRIVE database and the results were used in diagnosis of various diseases.

A segmentation method based on ridge descriptors for vessel centerlines as explained by Wu *et al.* [8] states that the second order derivatives of the Gaussian kernel for matched filters are appropriate for the vessel center only and that the ridge descriptor in the local neighborhood has the normalized largest curvature and the orientations of the gradients. A relation between the vessel radius and the Gaussian kernels scale in estimation method based on normalized largest curvature shows the distribution of the descriptors to be normal for vessels of a certain scale. Based on the distance between the ridge descriptor at candidate pixel and the learned model, vessel centerline segmentation was performed on images from both DRIVE and STARE database and the area under ROC was calculated to be 0.95848 and 0.9421 respectively.

Li *et al.* [9] proposed a multi-resolution Hermite model employing a 2-D Hermite function intensity model over a range of spatial resolutions in quadtree structure for vascular segmentation. To incorporate central light reflex, vessel modeling and estimation technique uses multi-resolution Hermite model instead of Gaussian mixture. A local model incorporating estimation for a piece-wise linear background variation segments vessels along their widths, local directions, amplitude and bifurcations. Local model parameters are fitted with combination of block based multi-resolution approach and expectation maximization optimization scheme. A stochastic Bayesian approach links local models of vessel segments and bifurcations to infer global vascular structure on STARE and DRIVE database images.

Ricci *et al.* [10] proposed application of line operators as feature vector and SVM for pixel classification where the green channel of an RGB image is applied with a line detector based on evaluation of average gray level along lines of fixed length passing through target pixel at different orientations. A feature vector for supervised classification is constructed using a support vector machine by employing two orthogonal vectors with the gray level of the target pixel. Using local computational differentiation of line strength the line detector becomes robust with respect to non-uniform illumination and contrast and the performance is evaluated on DRIVE and STARE database for accuracy as 0.9562 and 0.9584.

Lam and Yan [11] based on divergence of vector fields proposed a novel based segmentation algorithm for pathological retinal images. A normalized gradient vector field detects centerlines and gradient vector field of a pixel detects blood vessel like objects. The detected blood vessel like objects are pruned according to distance from detected centerlines. Accuracy and area under curve for pathological images from STARE database are found to be 0.9474 and 0.9392 respectively when evaluated by this algorithm.

Parallel implementation of multi-scale vessel implementation algorithm by Palomera-Perez *et al.* [12] based on ITK provides 8-10 times faster processing comparable to its serial counterpart with much accuracy which is much useful for handling high resolution images and large datasets. Images are divided into sub-images having overlapping regions and distributed for feature extraction and region growing and the segmentation results are combined. The implementation tested on DRIVE and STARE database gave accuracy of 0.925 and 0.926 respectively.

Regularization based multiconcavity model able to handle both normal and pathological retinas with bright and dark lesions presented by Lam *et al.* [13] shows three different concavity measures proposed to detect blood vessels each designed to address the negative impact produced by the lesions to identify the normal vessels. A steep intensity transition pattern of bright lesion is distinguished from vessels with differential concavity measures by a line shape concavity measure. Noise is filtered out by a locally normalized concavity measure and these measures are combined

according to their statistical and geometrical properties to obtain features and a lifting technique optimizes the regularized solution towards the ideal vessel shape. The effectiveness of the method evaluated on DRIVE and STARE database gave accuracy and area under ROC as 0.9567 and 0.9739 on STARE database and 0.9472 and 0.9614 on DRIVE database respectively.
A supervised approach to partition retinal color images into non-overlapping segments covering the entire image such that each segment (splat) contains pixels with same color and spatial location is explained by Tang *et al.* [14] to detect retinal hemorrhages. Characteristics of each segment relative to its surroundings are described by the features extracted from each splat taking into account responses from a variety of filter banks, shape and texture information and interaction with neighboring splats. A classifier with splat based approach is tested on publically available Messidor database yielding area under ROC as 0.96 and the approach is tested for detection of similar other objects.

The performance measures of various algorithms with respect to sensitivity, specificity, accuracy and area under ROC are compared in the Table 1.

Table 1. Performance measures for segmentation approaches

Author	**Image processing Technique**	**Database**	**Sensitivity**	**Specificity**	**Accuracy**	**Area under ROC**
Staal *et al.* [3] 2004	Image ridges and kNN classifier	DRIVE STARE	- -	- -	0.9442 0.9516	0.952 0.9614
Zhihong Hu *et al.* [4] 2012	Registered fundus vessel segmentation Multi-modal vessel segmentation	STARE	- -	- -	- -	0.85 0.89
Soares *et al.* [5] 2006	Pixel classification based on feature vector and 2D Gabor wavelet transform	DRIVE STARE	-	-	0.94	0.9614 0.9671
Oliveira *et al.* [6] 2012	Deformable model based approach and fuzzy c-means approach	DRIVE STARE	- -	- -	0.9607 0.9613	- -
You *et al.* [7] 2011	Principal curve based segmentation approach	DRIVE	0.8033	0.9594	0.9456	-
Wu *et al.* [8] 2008	Vessel centerline segmentation based on ridge descriptor	DRIVE STARE	- -	- -	- -	0.95848 0.9421
Li *et al.* [9] 2007	Multi-resolution Hermite model	DRIVE STARE	0.780 0.752	0.978 0.980	- -	- -
Ricci *et al.* [10] 2007	Line operator and support vector machine	DRIVE STARE	- -	- -	0.9563 0.9584	0.9558 0.9602

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Lam *et al.* [11] 2008	Divergence of vector fields	STARE	-	-	0.9474	0.9392
Palomera-Perez *et al.* [12] 2010	ITK parallel implementation	DRIVE STARE	0.64 0.769	0.967 0.9449	0.9250 0.926	- -
Lam et al. [13] 2012	Regularization based multi-concavity model	DRIVE STARE	- -	- -	0.9472 0.9567	0.9614 0.9739
Tang et al. [14] 2013	Splat based feature classification approach	Messidor				0.96

III. CONCLUSION

The paper presents a survey of segmentation algorithms applied for blood vessel segmentation that proved to be an assisting tool in the diagnosis and treatment of various diseases. Most of the techniques available in the literature have been evaluated on a few of the images from the publically available datasets *i.e.* images from DRIVE and STARE datasets. The development of techniques which works for images acquired from various imaging modalities under various environmental conditions is an open area of research in vessel segmentation algorithms. There is a requirement of solutions for screening programs where large image datasets can be evaluated and the collaboration between the experts and the healthcare centers is needed. Processing of these images in computer aided diagnostic systems requires segmentation algorithms that are robust and fast enough to process the images acquired from various image capture systems and imaging conditions. It is not expected that these automated systems will replace the experts in diagnosis but will reduce the peer pressure on them due to large imaging volumes. The current trends in segmentation and the future directions are an open area of research in automatic segmentation of these images.

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