A Review of Vessel Segmentation Methodologies and Algorithms: Comprehensive Review

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Chapter 9
A Review of Vessel Segmentation Methodologies and Algorithms:
Comprehensive Review

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ABSTRACT

"Prevention is better than cure", true statement which all of us neglect. One of the most reasons which cause speedy recovery from any diseases is to discover it in advanced stages. From here come the importance of computer systems which preserve time and achieve accurate results in knowing the diseases and its first symptoms.One of these systems is retinal image analysis system which considered as a key role and the first step of Computer Aided Diagnosis Systems (CAD). In addition to monitor the patient health status under different treatment methods to ensure How it effects on the disease.. In this chapter the authors examine most of approaches that are used for vessel segmentation for retinal images, and a review of techniques is presented comparing between their quality and accessibility, analyzing and catgrizing them. This chapter gives a description and highlights the key points and the performance measures of each one.

INTRODUCTION

Retinal image analysis is one of systems which help on diagnosing almost of diseases in advanced stages like (hypertension, diabetic retinopathy, hemorrhages, macular degeneration, glaucoma, neo-vascularization and vein occlusion), in addition to achieving accurate result and saving time (Bernardes, Serranho, & Lobo, 2011). It is the main first step of Computer Aided Diagnosis (CAD) systems and registration of patient images. This diagnosis done by detection of some morphological features and attributes of the

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retinal vasculature like width, length, branching pattern or tortuosity and angles. And on another level, manually detection of retinal vasculature is very difficult because of the complexity and the low contrast of blood vessels in retinal image (Asad, Azar, & Hassanien, 2014). Here come the importance of vessel segmentation as a pre-step in most of medical applications.

No specific method is existed which segments the vasculature from each retinal image modality. So on classifying the segmentation methods, we should put in our mind some important factors such as application domain, method being automated or semi-automated, imagining modality, and other factors (Miri & Mahloojifar, 2011; Fraz, Remagnino, Hoppe, & Barman, 2013). And also not lose sight of the amount of effort and time which taken in the manual manner of the retinal blood vessel segmentation, in addition to our need for training and skill.

Sometimes we may need a preprocessing step before the actual algorithm of segmentation method is executed; this is due to other factors such as noise or bad acquisition that effect on the quality of image. In the opposite some methods perform post-processing in order to treat some problems which happened after segmentation method. And there are methods which not to do neither this nor that.

In this chapter, the authors present a review about the most methodologies of blood vessel segmenttion; to provide the algorithms which employed for vessel segmentation to researchers to be considered as ready reference; to discuss the advantages and limitations of these approaches; to discuss the current trends and future challenges to be opened for solving, then it discusses the proposed approach for vessel segmentation which will be completely explained in the next sections.

BACKGROUND

Retinal Image Processing

Retinal Photography

Creating photograph of the interior surface of the eye containing the retina, macula, optic disc, and posterior pole is called fundus photography (also called fundography) (Lee, et al., 2000). A fundus camera is used in performing this fundus photograph; it consists of a specialized low power microscope with an attaching camera (Cassin & Solomon, 1990b; Saine, 2011).

Three modes the fundus camera basically operates in:

1. **Color Photography:** Examining the retina with full color under white light illumination.
2. **Red Free Photography:** Improving contrast of the vessels and other structures where the imaging light is filtered to remove red colors.
3. **Angiography Photography:** Where the vessels are brought into high contrast by intravenous injection of a fluorescent dye. The retina is illuminated with an excitation color which fluoresces light of another color where the dye is present. By filtering to exclude the excitation color and pass the fluorescent color, a very high-contrast image of the vessels is produced. Shooting a timed sequence of photographs of the progression of the dye into the vessels reveals the flow dynamics and related pathologies. Specific methods include sodiumfluorescein angiography (abbreviated FA or FAG) and indocyanine green (abbreviated ICG) angiography (Cassin & Solomon, 1990a).

Medical Image Analysis

The medical filed is a source of interest of images. Large amount of image information is generated Because of the multiplicity of imaging modalities like MRI (Magnetic Resonance Imaging), as CT (Computed Tomography), PET (Positron Emission Tomography) etc. Not only the image's resolution and size grow with new improved technology, but also the image's number of dimensions increase. In the previous, only two dimensional images in medical staff were studied which produced by X-ray. But now there is image with three dimension volumes which is common in usual practice (Läthén, 2010). In addition to four dimensional data (three dimensional images which changed with time changing) is also used. So the key technical challenges are introduced because of this huge increasing of size and dimensionality.

We really need to store, transmit, look at and find relational information between all this data. Here, we find automatic or semi-automatic algorithms as kind of interest. We want algorithms which automatically detect lesions, diseases and tumors and stand out their locations in the huge heap of images. But another problem presents itself, we also must trust in these algorithms results. This is special important issue in medical applications; we don't need to algorithms with missing fatal diseases or algorithms with false alarms. So, it is important issue to perform validation studies to make the algorithms results for medical image analysis usable. Another dimension is added to the research process which includes communication between two non-similar worlds- the medical world which focus on patient, and the technical world which focus on computer. Coexistence between these two worlds rarely found and both sides must join to make great efforts achieving a common goal.

Retinal Vessel Segmentation

One of the most popular problems of computer vision is the image segmentation (Terzopoulos, 1984). Containment effects in general images like shadows, highlights, object occlusion, and transparency is considered as so difficult problem. Segmentation may be easy task and difficult task in the same time depending on its characteristics. On the one hand, an anatomic region is the most popular thing which the imaging is focused on (Asad, Azar, & Hassanien, 2012). Context may be provide some scope in general images segmenting (e.g., indoor vs. outdoor, people vs. animals, city vs. nature), it is more accurate in a medical imaging task where method, conditions, and organ identity of the imaging is known. In addition, there are limitations in the pose variations, and a prior knowledge of the Region of Interest (ROI) and tissue's number (Deserno & Thomas, 2010).

On the other hand, producing the images in the medical field is one of the challenges because of the imaging poor quality, based on that; we find it is difficult to segment the anatomical region from the background. To discriminate between the foreground and background, we depend on not only the intensity variations but also additional cues to isolate ROIs. Summarizing for the above, in medical imaging, segmentation is used as essential tool for many reasons, one of them is detection process or diagnosis such as segmentation of anatomical surfaces for blood vessels and this what we will discuss in the next paragraph in more details about the anatomic of the retina.

The retinal vasculature consists of both arteries and veins which appearing as outspread fea-tures, with visible tributaries within the retinal medical image. Vessel widths vary depending on both the image resolution and the vessel's width ranging from one pixel to twenty pixels. Ocular fundus image shown other structures including the optic disc, the retina boundary, and pathologies which take the form of bright and dark lesions, cotton wool spots, and exudates. If we take a cross-sectional intensity of vessel retinal medical image, we will note approximation to gaussian shape. The intensity of the grey level and orientation of a vessel is gradually changing along their lengths. From other aspect about vessels shape it seems to take the structure of connected treelike (Emary E., Zawbaa, Hassanien, Tolba, & Sansel, 2014). However, there are huge varying in the shape, local grey level, and size. However, there are huge varying in the shape, local grey level, and size and, on the other hand some features of background may have similar attributes to vessels.

Vessel crossing and branching can further complicate the profile model. As with the pro-cessing of most medical images, signal noise, drift in image intensity and lack of image contrast pose significant challenges to the extraction of blood vessels. A central vessel reflex which is con-sidered as indicator of a presence of strongly reflection along retinal vessels centerline, this reflec-tion is more clear in arteries than veins, we can see it more stronger at images which taken at long wave-lengths in the retinal images of younger patients.

There are some characteristics of vessel segmentation depending on different aims, contrary to classical segmentation, such as:

1. Complex topologies and branches which should be correctly detected,
2. Vessels should be detected with different thickness (ranging from very thick to very thin),
3. Small occlusions should be repaired (false disconnections),
4. Noise which is incorrectly segmented should be removed, and
5. The vessel's minimum thickness should be put under control. Moreover, it must take into account robust, automatic, and efficient methods when we use vessel segmentation in a medical real-time environment (Emary E., Zawbaa, Hassanien, Schaefer, & Azar, 2014), so we find very challenging problems in this domain in return for all these requirements.

CLASSIFICATION OF RETINAL VESSEL SEGMENTATION APPROACHES

The authors have divided the retinal vessel segmentation algorithms into seven main categories:

- Pattern recognition techniques.
- Matched filtering.
- Vessel tracking/tracing.
- Mathematical morphology.
- Multiscale approaches.
- Model based approaches.
- Parallel/hardware based approaches.

Some of these categories are further divided into subcategories.

PATTERN CLASSIFICATION AND MACHINE LEARNING

Pattern recognition algorithms handle with the automatic detection or blood vessel features which classified on retinal images and other non-vessel objects one main object of them is background. To perform pattern recognition tasks, humans are adapted. There are two main vessel segmentation categories of patern recognition techniques:

1. **Supervised Approaches:** In this method it should be decided if a pixel is a vessel or non-vessel depending on some prior labeling information which is exploited to make this decision.
2. **Unsupervised Approaches:** The vessel segmentation is performed with no any prior labeling knowledge.

Supervised Approaches

The gold standard of vessel extraction in this method is about the training set basis of reference images which is manually processed and segmented. Ophthalmologist is doing this by precisely marking the gold standard images. In a supervised method, the algorithm performs its classification according to a given features. Therefore the classified ground truth data have to be available because in some real life applications, it is not available and this is the main condition of the classification. Usually In healthy retinal images, a supervised method produce good results more than unsupervised method because of its dependability on pre-classified data.

As we said before that supervised method classify each pixel if it is vessel or not. In (Niemeijer, Staal, Van Ginneken, Loog, & Abramoff, 2004) 31- feature sets are extracted by Gaussians and their derivatives through the k-Nearest Neighbor (kNN) classifier. Then in (Staal, Abramoff, Niemeijer, Viergever, & Van Ginneken, 2004) the algorithm was improved using ridge-based detection. The image should be parttioned by assigning each pixel to its nearest ridge element. So a 27 feature set is computed for each pixel which KNN classifier uses. But these methods have two main disadvantages. Firstly the large size of the features sets and thus the algorithm becomes slow down, and secondly the dependency of the training data and its sensitivity to false edges. Another method presented in (Soares, Leandro, Cesar, Jelinek, & Cree, 2006) performs Gaussan Mixture Model (GMM) classifier which extracts a 6-feature set using Gabor-wavelets. This method also is characterized by the dependency of its training data and requires more hours to train GMM models with a mixture of 20 Gaussians.

The method in (Ricci & Perfetti, 2007) performs line operators and support vector machine (SVM) classifier, a 3-feature set is extracted per each pixel. But this method characterized by its sensitivity to the training data, and it’s intensively computation because it uses the SVM classifier. Boosting and bagging strategies is applied in (Fraz, et al., 2012b) with vessel classification of 200 decision trees with Gabor filters which extracts 9-feature set. And because of using boosting strategy, this method has high computational complexity. And about method that has independent training data set is produced in (Marin, Aquino, Gegundez-Arias, & Bra, 2011). It extracts 7-features set using moment invariants-based method and neighborhood parameters with neural network as classifier. The motivation of this method is to design an algorithm with low dependence on training data and with quickly computation.

The part of computational complexity has been proposed in (Perfetti, Ricci, Casali, & Costantin, 2007) and (Lam, Gao, & Liew, 2010). In (Roychowdhury, Koozekanani, & Parhi, 2014) Gaussian Mixture Model (GMM) classifier is used with 8-features which extracted using pixel neighborhood with first and second-order gradient images. This method has good consistency in the accuracy of vessel segmentation because it reduces the number of pixels which classified and identifies an optimal feature set, but on the other hand it has low computational complexity. The performance measures adopted for evaluating the efficiency of supervised classification of retinal vessels are illustrated in Table 1.

Table 1. Performance measures for supervised methods

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Niemeijer, Staal, Van Ginneken, Loog, & Abramoff, 2004)	0.942	0.969	0.689	_	_	_
(Staal, Abramoff, Niemeijer, Viergever, & Van Ginneken, 2004)	0.944	0.977	0.719	0.952	0.981	0.697
(Soares, Leandro, Cesar, Jelinek, & Cree, 2006)	0.946	0.978	0.733	0.948	0.975	0.72
(Ricci & Perfetti, 2007)	0.959	0.972	0.775	0.965	0.939	0.903
(Fraz, et al., 2012b)	0.948	0.981	0.74	0.953	0.976	0.755
(Marin, Aquino, Gegundez-Arias, & Bra, 2011)	0.945	0.98	0.706	0.952	0.982	0.694
(Lam, Gao, & Liew, 2010)	0.947	_	_	0.957	_	_
(Roychowdhury, Koozekanani, & Parhi, 2014)	0.952	0.983	0.725	0.951	0.973	0.772

Unsupervised Approaches

Unsupervised classification approaches aim to find inherent patterns of blood vessels, and then uses these patterns to determine if a particular pixel is classified as a vessel or not. The training data do not directly contribute to the design of the algorithm in these unsupervised approaches.

An unsupervised approach, presented in (Kande, Subbaiah, & Savithri, 2010), corrects non-uniform illumination of color fundus images by using the intensity information of red and green channels on the same retinal image. Then matched filtering is used to enhance blood vessels contrast against the background. Finally, identifying the vascular tree structure of the retinal images by applying connected component labeling after weighted fuzzy C-means clustering is performed. In (Ng, Clay, Barman, & Feilde, 2010) a vessel detection system presented using the idea of maximum likelihood inversion of a model of image formation. Second derivative Gaussian filters are applied on images at several scales, and from the outputs of these filters, it is inferred the presence of vessels and their properties. For blood vessels detection, a generative model is proposed using a Gaussian-profiled valley and their corresponding filter outputs are calculated. The Gaussian model of noise is performed, and then the filter outputs covariance is calculated to the isotropic. To estimate the image and noise models parameters, these models are incorporated into a maximum likelihood estimator. The contrast, width, and direction of the blood vessel at every point in the image are estimated by the system. It also produces likelihoods of the model with additive noise. Likelihoods with additive noise are produced. Then the vessel centerline is detected by using these likelihoods in conjunction with vessel parameters which were estimated previously. Finally the model marks the vessel by combining the estimated width parameter and this centerline.

The Gray-Level Co-occurrence Matrix (GLCM) in combination with The local entropy information is performed in (Castaldi, Fabiola, & River, 2010) for vessel segmentation. To enhance the vessels structure, a matched filter is performed, then GLCM is computed, from the calculations of a statistical feature, and this calculated value is considered as threshold. Another method is presented in (Zhang, Cui, Jiang, & Wang, 2015), it aims to construct multidimensional feature vector with the green channel intensity as first step. Also the vessel intensity is enhanced using morphological operation. As second step, they perform pixel clustering by constructing Self-Organizing Map (SOM) which considered as unsupervised neural network. In the last stage by using Otsu's method, each neuron is classified as neuron or non-vessel neuron in the output layer of SOM. Finally, in order to segment the vessel network, local entropy thresholding is applied.The performance measures adopted for evaluating the efficiency of unsupervised classification of retinal vessels are illustrated in Table 2.

MATCHED FILTERING

In this approach, 2-D kernel is convolved with the retinal image to detect the vasculature. A feature in the image is modeled by the kernel at some orientation and position, and also the matched filter response (MFR) is used as indicator of the presence of the feature (Sreejini & Govindan, 2015). The following properties are used to design the matched filter kernel:

1. Vessels usually characterized by a limiting on its curvature and it may be approached by piecewise linear segments.
2. The farther the vessels move radially outward from the optic disc, the less the diameter of the vessels.
3. The line segment on its cross-sectional intensity of the pixel approximately takes a Gaussian curve shape.

The convolution kernel is large and should be applied in a computational head at several rotations resulting. and also to confirm investigating the optimal responding for the kernel, the underlying Gaussian function which specified by the kernel must be have the same standard deviation for most vessels. So it is possible that the kernel do not respond to the vessels with a different profile. Another reason for false response, it is the variation of background and existence of pathologies. in the retinal image, this in turn increase the number of false responses because the pathologies and the vessels may have the same local attributes. A matched filter achieves good effective response when it applied with other processing techniques.

Matched filter approach is used in (Cinsdikici & Aydin, 2009), firstly the image is preprocessed, and then the matched filter and ANT algorithm is performed on the image in parallel manner. To completely extract the vasculature, the results are combined followed by length filtering. In (Zhang, Zhang, Zhang, & karray, 2010) the method exploits that the classical matched filter is generalized and extended with the first-order derivative of the Gaussian (MF-FDOG) to exploit the property of the blood vessel which is the symmetric Gaussian shaped cross section with respect to its peak position, on the other hand the

Table 2. Performance measures for unsupervised methods

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Kande, Subbaiah, & Savithri, 2010)	0.891	_	_	0.898	_	_
(Ng, Clay, Barman, & Feilde, 2010)	_	0.953	0.700	_	_	_
(Castaldi, Fabiola, & River, 2010)	0.976	0.948	0.9648	0.948	0.975	0.72
(Zhang, Cui, Jiang, & Wang, 2015)	0.940	_	_	_	_	_

nonvessel edges - e.g. the step edge for lesions- are asymmetric. For detecting the vessels in this method, the zero-mean Gaussian filter (MF) and the first-order derivative of the Gaussian (FDOG) are used. For vessel structure, there will be a high response for the MF around shape's peak position, while the value of the local mean to the FDOG will be close to zero around position of the peak. In contrast, for non-vessel, the response of both the MF and the local mean to the FDOG will be high. The advantage of this method is that many vessels which are missed by MF are fine detected, so in this methodology, the false detections produced by the original MF are reduced.

Phase congruency is used in (Amin & Yan, 2011) to detect the retinal blood vessels. Firstly phase congruency is performed on the retinal image. This classification features by its soft and invariant because both luminosity and contrast of the image change. Then to measure phase congruency, a log-Gabor filters are applied, finally binary vessel tree is extracted by thresholding. The performance measures adopted for evaluating the efficiency of unsupervised classification of retinal vessels are illustrated in Table 3.

MORPHOLOGICAL PREPROCESSING

The term morphology is a branch of biology, its basics are the structures and the form of animals and plants. As for the mathematical morphology, it is a tool which extracts the image components that are forms a good data in the description and representation of region shapes such as boundaries, features, skeletons and convex hulls. The mathematical morphology produces a powerful and unified approach to a huge image processing problems. Morphological image processing (Serra, 1982), (Hassan, Elbendary, Hassanien, Shoeb, & Snasel, 2015) is a collection of techniques for digital image processing based on mathematical morphology. Structuring elements (SE) are applied to images by morphological operators, and specially are applied to binary images or to gray level images. There are two main operators (dilation and erosion). In dilation, objects are expanded by a structuring element, holes will be filled, and the disjoint regions will be connected. In erosion the objects are shrunk by a structuring element. There are two other compound operations which are closing and opening. Closing is a combination of dilation and erosion respectively, opening is a combination of erosion and dilation, respectively.

In medical image segmentation, there are two algorithms that used as enhancement tool. Top-hat transformation performs morphology opening operation to estimate the local background, and then subtracts it from the original image, this in turn leads to enhance in vessels to perform high results later in segmentation process. If we look at the vasculature from the point of view the morphology, it will show that the vasculature is a collection of linear segments which are connected together to form the final shape. If we reviewed the advantages and disadvantages of identifying shapes with morphological

Table 3. Performance measures for matched filtering methods

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Cinsdikici & Aydin, 2009)	0.929	_	_	_	_	_
(Zhang, Zhang, Zhang, & karray, 2010)	0.938	0.972	0.712	0.948	0.975	0.718
(Amin & Yan, 2011)	0.920	_	_	_	_	_

processing, we will find that noise resistance and speed are from its main advantages. from the other hand morphological processing use long structure element which makes fitting highly tortuous vessels difficult, also the known vessel cross-sectional shape isn't exploited in this method.

Mathematical morphology and a fuzzy clustering algorithm are proposed in (Yang, Huang, & Rao, 2008). Top-hat morphological operation enhances the blood vessels and removes the background, then by using fuzzy clusltering, the vessels are extracted. Morphological multi-scale enhancement method is also presented in (Sun, Chen, Jiang, & Wang, 2011). For the extraction of the blood vessels in the angiogram, fuzzy filter and watershed transformation are used. Multi-scale non-linear morphology opening operators with structuring element which vary in size is used to estimate the background, and then the background is subtracted from the image to achieve the contrast normalization. A combined fuzzy morphological operation is applied on the normalized angiogram with twelve linear structuring elements with nine pixels length, the structuring element rotated every 15° between zero and 180°. Thresholding the filtered image to obtain the vessel region, then for approximating the vessels centerlines, thinning operation is applied. Finally watershed techniques are applied on vessel centerline to detect the vessel boundaries.

Another method is presented in (Fraz, et al., 2012a) which is a combined unique vessel centerlines detection with morphological bit plane slicing. The first order derivative of a Gaussian filter is used in four directions to extract the centerlines, and then performing an average derivative and derivative signs with the extracted centerlines. Mathematical morphology has proven their worth as a brilliant technique for the blood vessels segmentation in the retina. Morphological multidirectional top-hat operation is applied on blood vessels gray-scale image with linear structure element to obtain the orientation map and shape, and then the enhanced vessels are subject to bit plane slicing. For obtaining the vessel tree, these maps are combined with the centerlines.

In (Miri & Mahloojifar, 2011) fast discrete curvelet transform with multi-structure mathematical morphology is proposed. For contrast enhancement, FDCT is performed. For detecting the blood vessels edges, multi-structure morphological transformation is applied. Then morphological opening is applied on the result image to remove the false edges. Finally for obtaining the complete final vascular tree, a connected adaptive component analysis is applied.

Another automated enhancement and segmentation method for blood vessels is presented in (Hou, 2014). This method decreases the optic disc influence and emphasizes the vessels by applying a morphological multidirectional top-hat transform with rotating structuring elements to the background of the retinal image. For producing a vessel response image and the final blood vessel tree, an improved multi-scale line detector is applied. As line detectors in the multi-scale detector have different line responses, the longer line detectors produce more vessel responses than the shorter line detectors. To set different weights for different scales, all the responses are combined by the improved multi-scale detector at different scales. The performance measures adopted for evaluating the efficiency of morphological processing methods of retinal vessels are illustrated in Table 4.

MULTI-SCALE APPROACHES

The width of a vessel decreases as it travels radially outward from the optic disk and such a change in vessel caliber is a gradual one. The farther the vessel travels from the optic disc, the smaller the vessels

Table 4. Performance measures for morphological processing methods

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Fraz, et al., 2012a)	0.943	0.977	0.715	0.944	0.968	0.731
(Miri & Mahloojifar, 2011)	0.946	0. 979	0. 735	_	_	_
(Hou, 2014)	0.942	0.969	0.735	0.934	0.965	0.735

width will be. Depending on this property, we can define a vessel as contrasted pattern with a Gaussian such as piecewise connected, shape cross-section profile, and locally linear, with a decreasing gradually vessel width. So to extract the complete vascular of retinal image in this method, some information which is related to the blood vessels with varying different scales is separated out.

A proposed supervised method for red-free vessel segmentation retinal images is presented in (Anzalone, Bizzarri, Parodi, & Storace, 2008). Normalization of the background of retinal image is performed for uneven illumination, and then enhancement of the vessels via scale space theory. For determining the optimal scale factor and also the threshold to binarize the segmented image, an optimization supervised algorithm is performed, and then cleaning operation is done to ensure completely super removal.

Another blood vessel segmentation method is investigated in (Farnell, et al., 2008) whose idea depends on the multi-scale line operator (MSLO).By using Gaussian sampling on a series of images at respectively coarser length scales with respect to the original image, sub-sampled images Gaussian pyramid- are constructed. Then the line operator is performed to the images on every level of this Gaussian pyramid in a separate manner. By using a cubic spline, the result image of the previous stage was mapped to the original level of scale. The final image is the addition of all images of the Gaussian pyramid. For each length scale in the MSLO image, the weight is obtained, and then a threshold is calculated to produce a binary segmented image. Finally By using a region simple growing algorithm, all remaining noise should be removed.

In (Vlachos & Dermatas, 2010) a multi-scale line tracking algorithm for blood vessel segmentation is proposed. Firstly both contrast normalization and luminosity are performed, and then based on normalized histogram; brightness selection rule is obtained to derive the seeds of the line tracking. We get varying widths of the vessel via initialization of the line tracking at multiple scaled. Many cross sectional conditions are constructed as a termination condition of line tracking. The result of all multi-scale line tracking is combined to get the confidence image map which quantized in order to derive the initial vessel network. And because of the disconnected vessel lines and the remaining noise, Median filter is performed for restoration. Finally by performing morphological reconstruction, the fault artifacts are removed.

In (Hou, 2014) another proposed vascular segmentation is presented as we explain before in section 3 morphological processing. This method combines between morphological processing to enhance the influence of optic disc and the multi-scale line detector to produce the final vascular tree of the retinal image.The performance measures adopted for evaluating the efficiency of multi-scale approaches of retinal vessels are illustrated in Table 5.

Table 5. Performance measures for multiscale approaches

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Anzalone, Bizzarri, Parodi et al., 2008)	0.942	_	_	_	_	_
(Vlachos & Dermatas, 2010)	0.929	0.955	0.747	_	_	_
(Hou, 2014)	0.942	0.969	0.735	0.934	0.965	0.735

MODEL BASED APPROACHES

In these approaches, an explicit vessel models are applied in order to extract the vascular. In (Vermeer, Vos, Lemij, & Vossepoel, 2004) a proposed segmentation method is presented which extracts the blood vessels by convolving with a Laplacian kernel, and then a threshold is calculated to segment the vessels. Finally the broken lines are connected. In (Lam & Yan, 2008) some improvement is performed on the previous methodology. The Laplacian operator is used to extract the vascular and pruning is performed for objects with noise according to center lines. Some advantage of this methodology is that it can extract the vessels from images with bright abnormalities, but in contrast it can't work with red lesions in retinal images (like microaneurysms or hemorrhages).

The method in (Lam, Gao, & Liew, 2010) proposed perceptive transformation approaches for segmenting vascular in retinal images with both bright and red lesions. A model-based method in (Jiang & Mojon, 2003) performs adaptive locally thresholding. In the verification process, vessel information is integrated. And because this method has an overall low accuracy, it is more generalizable than matched filter methods. Another approach for vessel segmentation presented in (Al-Diri, Hunter, & Steel, 2009). Active contour models are used, but it has computational complexity.The performance measures adopted for evaluating the efficiency of model based methods of retinal vessels are illustrated in Table 6.

PARALLEL HARDWARE BASED IMPLEMENTATIONS

The Parallel hardware based implementation addresses the high computational cost of vascular segmentation algorithms, and also addresses the real-time performance requirements. Cellular neural networks

Table 6. Performance measures for model based approaches

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Vermeer, Vos, Lemij, & Vossepoel, 2004)	0.929	_	_	_	_	_
(Lam & Yan, 2008)	_	_	_	0.965	_	_
(Lam, Gao, & Liew, 2010)	0.947	_	_	0.957	_	_
(Jiang & Mojon, 2003)	0.891	0.900	0.830	0.901	0.900	0.857
(Al-Diri, Hunter, & Steel, 2009)	_	0.955	0.728		0.968	0.752

represent one appealing paradigm for image processing of parallel real-time (Manganaro, Arena, & Fortuna, 1999), (Roska & Chua, 1993), which VLSI chips are used to implement on. For parallel implementation for vascular segmentation algorithms, the registration ToolKit and insight segmentation are also used in high resolution images (Ibanez, Schroeder, Ng, & Cates, 2003). An approach is presented in (Alonso-Montes, Vilario, Dudek, & Penedo, 2008) which is pixel-parallel based method to confirm fast vascular extraction. In fact this method is an improvement of the original proposal (Alonso-Montes, Vilarino, & Penedo, CNN-based automatic retinal vascular tree extraction, 2005) which implements and tests morphological operations and local dynamic convolutions together with logical and arithmetic operations in parallel processor array (a fine-grain single instruction multiple data (SIMD)).

ITK parallel based implementation is presented in (Palomera-perez, Martinez-Peez, Benitez-Perez, & Ortega-Arhona, 2010). It ensures achieving accuracy similar to its serial counterpart. In addition to its quick processing time (8-10 times faster), and that make it possible to handle high resolution images and large datasets. The image should be divided into sub-images which have overlapped regions. Then these sub images is distributed across computers. Each computer calculates the feature extraction and region growing and finally combining the segmentation results from different computers. But there are no guidelines to tune its design parameters (the neighborhood size, scaling factors of variance and local mean, and the structuring element for morphological operations), so they must be empirically tuned. In addition, for local variance estimation in the image, nonlinear CNN templates are required. (Costantini, Casali, & Todisco, 2010) overcomes the drawbacks of previous approach by exploiting the blood vessels geometrical properties. The line strength measures is calculated for the blood vessels on the level of green plane in the colored retinal image. Linear space-invariant 3×3 templates are required for the CNN algorithm, so by using one existing CNN chips, it could be implemented. The performance measures adopted for evaluating the efficiency of Parallel hardware based implementations of retinal vessels are illustrated in Table 7.

FUTURE RESEARCH DIRECTIONS

The future direction of vessel segmentation research is to develop more accurate, faster automatic techniques. The segmentation accuracy is a critical and essential point in the research because of the nature of work that dealing with a part of human which is dealing with a part of the human body which must stop in front of him and do the best of ours. In order to achieve high accuracy we must focus on two important factors which are the acquisition phase to get images with high resolution with perfect

Table 7. Performance measures for parallel hardware implementation based methods

Test Data	Drive Test			Stare Test		
	Acc	Specificity	Sensitivity	Acc	Specificity	Sensitivity
(Alonso-Montes, Vilario, Dudek, & Penedo, 2008)	0.919	_	_	_	_	_
(Palomera-perez, Martinez-Peez, Benitez-Perez, & Ortega-Arhona, 2010)	0.925	0.967	0.64	0.926	0.945	0.769

brightness and these will help in the processing phase, and developing hybrid approach with optimization techniques which achieve faster and accurate results. In the end, we must not forget that we are dealing with human nature, so we must investigate precision to handle with.

CONCLUSION

Segmentation algorithms are the heart of medical image applications like multimodal image registration, radiological diagnostic systems, visualization, creating anatomical atlases, and computer-aided diagnosis systems. There is different and large number of techniques on this area, however it is still having an areas which needs more research. In the future, the authors aim to develop more accurate automated segmentation techniques. The quick progress in radiological imaging systems lead to increase in volume patient images. Based on that, image processing in radiological diagnostic systems will require more fast segmentation algorithms. Developing parallel algorithms is one of the ways of achieving faster segmentation results. Cronemeyer is one of the people who relied on the exploitation of the nature of parallel hardware to achieve faster skeleton algorithm. Also from other approaches which achieve faster segmentation is neural network-based approaches because of their parallel nature. Also multi-scale approach is considered as faster segmentation approach because it can extract major structures in low resolution images and fine structures in high resolution images. The authors proposed a survey of current vessel segmentation algorithms. The authors tried to cover both old and new researches related to vessel segmentation approaches and techniques. The authors aimed to introduce the current vessel segmentation methods and also to give the researcher a base line and a framework for the existing research.

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KEY TERMS AND DEFINITIONS

Blood Vessel Extraction: An automatic processing step to extract vessels away from image to investigate the existence on some disease.

Blood Vessel: A tubular channel that is characterized as flexible like a vein, an artery, and a capillary, and the blood passes through it to the eye.

Hemorrhages: Secretions and ample blood as a result of a ruptured blood vessel.

Lesions: A pathologic change in the tissues and individual points of multifocal disease.

Macular Degeneration: A disease happened in the eye, especially destroys the macula and caues blindness because it effects on the center of vision.

Magnetic Resonance Imaging: A method which used to obtain images of the interiors of objects, as humans and animals, it uses radio-frequency waves on its caption.

Neural Network: A Deep learning technology depends on simulating the nature of brain to solve pattern recognition problems.