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Research Article

Segmentation Methodologies for Retinal Structures: A Review

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Abstract

Segmentation techniques of retinal anatomical structures (blood vessel and optic disc) aid during mass screening for retinal diseases. This review paper describes the blood vessel segmentation techniques and optic disc segmentation techniques. The aim of this paper is to review, analyse and categorize the retinal vessel and optic disc extraction techniques, giving a brief description, highlighting the key points and the performance measures. Performance measures include accuracy, true positive rate, false positive rate which is plotted on chart for comparative analysis of the results for blood vessel segmentation and overlap ratio, success rate for optic disc segmentation.

Keywords: *Retinal structures, Blood vessel segmentation, Optic disc segmentation, Review*

1. Introduction

In ophthalmology, retinal images acquired are used for the detection and diagnosis of retinal diseases, vascular disorders. Retinal images are helpful to aid in anatomical structure analysis and locate abnormalities. Extraction of retinal blood vessels forms an essential step in ophthalmology. Morphological features of retinal blood vessels have pertinence with the disease diagnose and can be used to predict the stages of diseases (M. E. Martinez-Perez *et al,* 2002). But in some medical applications like detection of pathological elements like haemorrhages, neovascularization the vascular structure and optic disc must be excluded to ease the analysis (M. Niemeijer *et al,* 2005). Consequently there is a need for exact segmentation of blood vessels as shown in Fig.2, as well as optic disc from retinal images to aid ophthalmologists during mass screening for the detection and diagnosis of diabetic retinopathy, glaucoma and haemorrhages.

Manual delineation of retinal structures is a highly skilled task, time-consuming and is even susceptible to errors. To overcome this problem large number of automatic segmentation techniques, algorithms have been proposed in the literature. This paper provides a survey of algorithms focussing on segmentation of blood vessels and optic disc. The objective of this paper is to review retinal segmentation techniques also provide a performance measures for comparative study of segmentation techniques.

Blood vessels constitute obstruction for the optic disc segmentation breaking the continuity of the disc. Optic Disc (OD) processing in eye fundus images is a two-step approach: localization and segmentation. The former step finds an OD pixel (generally a centre). The latter step estimates the OD boundary. At this step, a general distinction can be made between template-based methods which obtain OD boundary approximations and deformable model methods which extract the OD boundary as exactly as possible. Retinal optic disc segmentation methods can be represented as shown in 0.

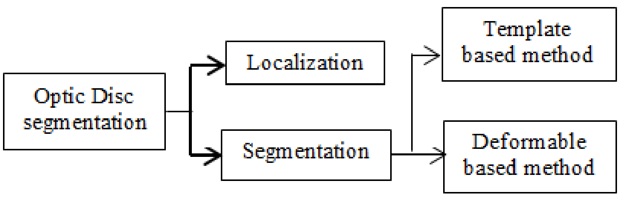

Fig.1 Optic disc segmentation

1.1. Classification of retinal vessel segmentation approaches

1.1.1. Classification of retinal blood vessel segmentation

We categorize retinal blood vessel segmentation methods as follows:

i. Pattern recognition techniques
a. Multi-scale approaches
b. Skeleton (centerline)-based approaches
c. Ridge-based approaches
d. Region growing approaches
e. Matching filters approaches
f. Mathematical morphology schemes

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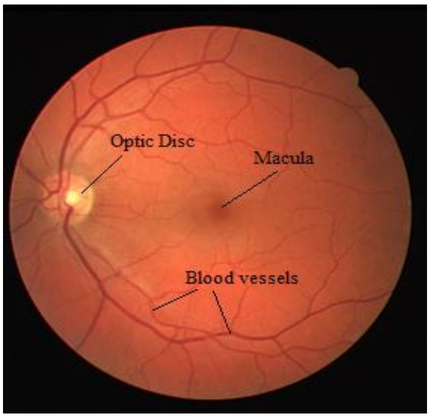
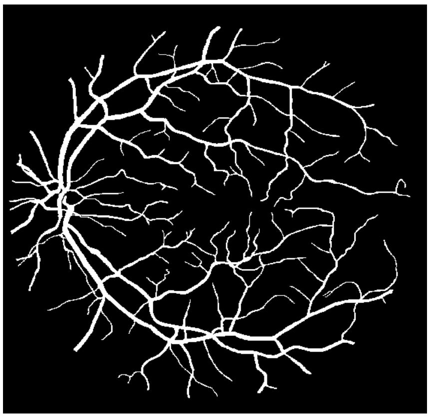
ii. Model-based approaches
iii. Artificial Intelligence and Neural Network based approaches
iv. Graph-cut based approaches
v. Edge detection approaches
vi. Thresholding based approaches
vii. Wavelet based approaches
viii. Tracking-based approaches



(a)



(b)

Fig. 2 (a) Retinal structure, (b) Segmented retinal blood vessels

Each segmentation method category is introduced, discussed and the papers of this category are summarized. The performance measures used by the segmentation algorithms are tabulated at the end of each section. Fig.3 shows the frequency of the distribution of articles to various segmentation approaches. It illustrates that of these reviewed articles, 55.2% use pattern recognition techniques, 13.6% employ Model-based approaches, 4.8% use Artificial Intelligence and Neural Network based approaches, 6.4% employ Graph-cut based approaches, 17.6% use Edge detection approaches, 3.2% employ Thresholding based approaches, 2.4% use Wavelet based approaches.

Although we divide segmentation methods in different categories, sometimes multiple techniques are used together to solve different segmentation problems. Therefore, methods that fall into multiple segmentation categories are described in the Table 4.

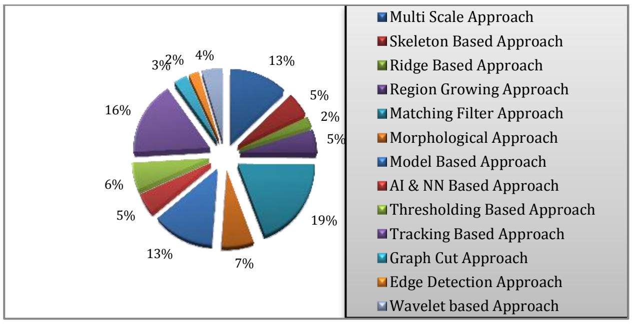


Fig. 3 Category wise decomposition of reviewed articles

1.1.2 Classification of retinal optic disc segmentation

Following the optic disc localization, segmentation algorithms are divided into two main categories: Template based methods, Deformable based methods or snakes. The main advantage of using a deformable model instead of a template-based model for OD segmentation is that, theoretically, 100% of overlapping areas between the automated segmentation and the ground truth may be achieved. Deformable models have much more degrees-of freedom than template-based models to fit to desired shape. In this paper six papers from each category are reviewed, summarized. The performance measures used by the segmentation algorithms are tabulated at the end of section.

This paper is organized as follows. In Section1, the classification of the segmentation methods, definitions of performance measures are given. Other segmentation methods are discussed in section2. In Section 3, blood vessel segmentation techniques which include pattern recognition techniques, Model-based approaches, artificial intelligence-based approaches, neural network-based approaches, tracking-based methods are reviewed along with their performance measures. In section 0, optic disc segmentation techniques that include template matching methods, deformable based methods are reviewed along with their performance measures. We conclude with discussion on the retinal structure segmentation reviews and its applications in Section 5 and section6.

1.2 Performance measures

The true positive rate (TPR) represents the fraction of pixels correctly detected as vessel pixels. The false positive rate (FPR) is the fraction of pixels erroneously detected as vessel pixels. The accuracy (Acc) is measured by the ratio of the total number of correctly classified pixels (sum of true positives and true negatives) to the number of pixels in the image field of view. It is denoted that TP and TN illustrate the blood vessel pixels and background pixels, which properly identified. FP demonstrates that the pixels are not fit in to a vessel, but is known as blood vessel pixels and FN shows the pixels belonging to a vessel, but is recognized as background pixels.

i. $$TPR = \frac{\text{TP}}{\text{TP+FN}} \quad (1)$$

ii. $$FPR = \frac{\text{FP}}{\text{FP+TN}} \quad (2)$$

iii. $$ACC = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad (3)$$

Success rate of localization method is location success rate. Ratio of overlap or common area between segmented region and true optic disc region is overlap percentage. Mean area overlap error is average error for the overlapping area.

2. Other Segmentation methods

Classification schemes proposed in the literature can be a combination of above mentioned approaches. There are two main approaches considered for retinal vasculature segmentation in the literature:

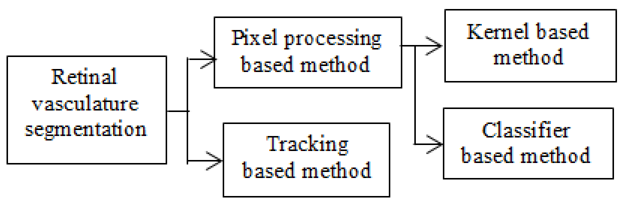


Fig.4 Classification of retinal vascular segmentation

Retinal vasculature segmentation is classified as Pixel processing-based methods and Tracking methods. The former class is divided by some authors as kernel and classifier based methods (K. A. Vermeer *et al,* 2004) as shown in Fig.4 Pixel processing based methods use a two-step approach. The first step is an enhancement procedure, where filters are used to enhance the appearance of the blood vessels in the image. The second step is validation of vessel pixels, where thinning or branching techniques are applied to classify the pixel as either belonging to vessels or not. Kernel-based methods convolute the image on a predefined model. A Gaussian shaped curve is used to model the cross-section of a vessel and a matched filter is used for detection in (S. Chaudhuri *et al,* 1989). Classifier-based methods use a two-step approach. They start with a segmentation step by employing one of the kernel-based methods and next the regions are classified according to many features.

In 2004, Niemeijer *et al.* presented a vessel segmentation algorithm based on pixel classification using a simple feature vector. In 2005, Cree *et al.* proposed Comparison of various methods to delineate blood vessels in retinal images. In 2006, Soares *et al.* proposed the Feature vectors are composed of the pixel's intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales.

Retinal vasculature segmentation is classified as Rule-based methods and supervised methods as shown in Fig.5.

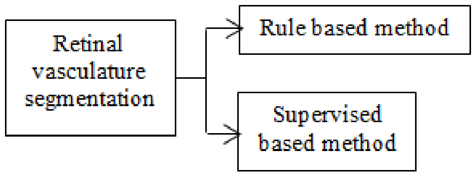


Fig. 5 Classification of retinal vascular segmentation

The former group consists of rule-based methods and comprises vessel tracking, matched filter responses, model based techniques and morphology-based techniques. The latter group requires manually labelled images for training, it comprises of neural network based approaches.

Selected performance measures: True Positive Rate (TPR), False Positive Rate (FPR), Accuracy is tabulated in 0, where high accuracy of 0.9480 is achieved by a method proposed by Soarse *et al* in 2006.

Table 1 Performance measure of other segmentation methods

Methodology	TPR	FPR	Accuracy
Niemeijer *et al.*	0.7068	0.0305	0.9452
Soares *et al.*	-	-	0.9480

3. Blood Vessel Segmentation techniques

3.1 Pattern recognition techniques

3.1.1 Multi-scale approaches

Multi-scale approaches perform segmentation at varying image resolutions. The main advantage of this technique is increased processing speed. Major structures (vessels in our application domain) are extracted from low resolution images while fine structures are extracted at high resolution. Another advantage is increased robustness.

In 1998, Frangi *et al.* examined multiscale second order local structure of an image (Hessian) in developing vessel enhancement filter. In 1999, Martinez-Perez *et al*, proposed a method where image derivatives are obtained at multiple scales. The features derived from image derivatives are then used in a two-stage region growing procedure which segments the retinal vessels progressively. In 2004, Wink *et al.* have developed a method for central axis extraction that finds a minimum cost path using the Vector valued multiscale representation. In 2004, kondo *et al.* employed a multi-scale approach to detect various sizes of features, especially blood vessels with varying diameters. The blood vessel network is finally extracted from the detected features by global thresholding with some morphological operations. In 2006, Sofka and Stewart used for vessel centreline extraction that combines matched filter response, confidence measures and vessel boundary measures. In 2007, Elena *et al*. have used the multiscale feature extraction principle for retinal vessel segmentation. The advantage of this approach is that it is able to detect the blood vessels with different widths, lengths and orientations. In 2007, Perez *et al*. used insight segmentation and registration toolkit ITK. In 2008, Anzalone *et al*. proposed a modular supervised algorithm for vessel segmentation in red-free retinal images. The image background is normalized for uneven illumination conditions followed by vessel enhancement using scale space theory. In 2008, Farnell *et al*. investigated multiscale Line Operator and region growing for segmentation of retinal vessels. In 2008, Rezatofighi *et al*. employed a combination of feature extraction approach which utilizes Local Binary Pattern (LBP), morphological method and spatial image processing for segmenting the retinal blood vessels in optic fundus images. In 2009, Vlachos *et al* proposed multiscale line tracking for vasculature segmentation. The methodology is very much dependent upon initial selection of seeds for line tracking.

In 2010, Martinez-Perez *et al*. exploits the observation that the intensity of image is proportional to the amount of blood in the light patch corresponding to particular pixel during image capture. In 2010, Moghimirad *et al*. proposed a multi-scale method based on a weighted 2D medians function. Then extracted the centrelines of vessels and estimated radius of vessels, to segment retinal vessels. In 2013, Quinn *et al*. proposed a multi-scale method for retinal image contrast enhancement based on the curvelet transform on the contrast adjusted image. Then morphological operators are used to smoothen the background, allowing vessels, to be seen clearly and to eliminate the non-vessel pixels. In 2013, Nguyen *et al*. extracted vascular network using a method based on multi-scale line detection. A trimming process is then performed to isolate the main vessels from unnecessary structures such as small branches or imaging artefact.

3.1.2 Skeleton-based (centreline detection) approaches

Skeleton-based methods extract blood vessel centerlines. These methods apply thresholding, object connectivity, thresholding followed by thinning procedure, and extraction based on graph description. The resulting centreline structure is used for image reconstruction.

In 1998, Pinz *et al*. proposed identification of the candidates for vessel cross sections, by combining edge information producing the final centreline segments. A major feature of the method is its adaptability to particular image intensity properties, as most algorithm settings are based on threshold values computed from local or global image information. In 2002, Conor *et al* have used the skeleton operations to determine the change in retinal anatomy for DR detection in abnormal images. The features used in this work are vessel width and tortuosity. The experiment is analysed in terms of accuracy. In 2006, Mendonca *et al*. presented a method to extract a vessel centreline undergoing vessel segmentation phase, which involves vessel enhancement, reconstruction by multi-scale approach and vessel filling by region growing approach.

In 2008, Salem *et al*. employed larger eigenvalue of the Hessian matrix is used for vessel centrelines detection, while vessel orientations are estimated from the eigenvectors corresponding to the smaller eigen value. The vesselness measure combines information from vessel centrelines and orientations over scales to segment retinal blood vessels from colour fundus images. In 2010, Quinmu *et al*. proposed radial projection method to locate the vessel centrelines. Then the supervised classification is used for extracting the major structures of vessels.

The final segmentation is obtained by the union of the two types of vessels after removal schemes. In 2012, Baisheng *et al*. extracted Vessel centrelines by using a set of directional line detectors. Next an Iterative Geodesic Time Transform (ItGTT) is designed to segment the entire vessel network. In 2014, Panda *et al*. presented a novel method of Hausdorff symmetry operator for automatic centreline pixel selection towards retinal blood vessel segmentation. Centreline pixels are determined by considering geometrical symmetry (distance and orientation) and Hausdorff distance based point set matching at the centreline pixel.

3.1.3 Ridge based approaches

This approach is based on intrinsic property that the vessels are elongated structures. Algorithm uses image primitives formed from image ridges, which are grouped into sets that approximate straight line elements. Ridge detection is based on the observation that the vessels can be modelled as ridges, where for each pixel a gradient is determined based on the intensity of that pixel and surrounding pixels. Once the ridges have been highlighted further processing is done to link ridges and classifies pixels based on their gradients and that of neighbouring vessel pixels.

In 2004, Staal *et al*. presented a method for automated segmentation of vessels in two-dimensional colour images of the retina. In 2011, Miri and Mahloojifar employed Curvelet transform and multi-structure elements morphology. In 2014, Karthik *et al*. proposed Contourlet Transform to detect the blood vessels efficiently. But it has disadvantages that is directional specificity of the image is less owing to that the effectiveness is poor. Therefore, morphology operators by means of multi structure elements are given to the enhanced image in order to locate the retinal image ridges.

3.1.4 Region growing approaches

Region growing technique is a bottom up method that, segment images by recruiting pixels to a region based on some predefined criteria, starting from some seed point. It is assumed that pixels that are close to each other and have similar intensity values are likely to belong to the same object. When the growth of one region stops, another seed pixel is chosen which does not yet belong to any region and start again until all pixels belong to some region. The main disadvantage of region growing approach is that it often requires user-supplied seed points. Due to the variations in image intensities and noise, region growing can result in holes and over-segmentation. Hence, it requires post-processing of the segmentation result.

In 1999, Martinez-Perez *et al*. employed the minimum eigenvalue and the magnitude of its gradient as features for a region growing procedure which is defined in two stages. For the first stage, growth is restricted to regions with low gradients, allowing vessels to grow where the values of the minimum eigenvalue lie within a wide interval and allowing rapid growth of background regions outside of the vessel boundaries. For the second stage, the algorithm grows vessel and background classes simultaneously without the gradient restriction. In 2004, Wang *et al*. proposed a method as a fast solution for automated detection of retinal blood vessels, which is a combination of edge detection, matched filtering, and region growing. In 2007, Garg *et al*. presented an unsupervised, curvature-based method for segmenting the complete vessel tree from colour retinal images. The vessels are modelled as trenches and the medial lines of the trenches are extracted using the curvature information derived from a novel curvature estimate. The complete vessel structure is then extracted using a modified region growing method. In 2010, Perez *et al*. presented multi-scale feature extraction and region growing algorithm for retinal blood vessels segmentation. This implementation allowed a faster processing of these images and was based on a data partitioning.

3.1.5 Matching filters (MF) approaches

Matching filters approach convolves the image with multiple matched filters for the image segmentation. The convolution kernel size affects the computational load. MF are often used in image enhancement step, so this method is usually followed with some other image processing operations like thresholding and thinning or branching process to validate the pixel as of vessel.

The concept of matched filter detection was proposed by Chaudhuri *et al*. in the year 1989. In this method, the authors use 12 rotated versions of a 2-D Gaussian shaped template for searching vessel segments along all possible directions. For every pixel, the maximum response to these kernels is retained. Other matched filtering approaches using local or global thresholding strategies have been reported for the segmentation of retinal vessels. In 1994, Cote *et al*. proposed a method which classifies the segments as vessel or not vessel according to many properties, including their response to a classic operator. In 1995, Wood *et al* equalizes image variability as a pre-processing step to segment retinal vessels. Image equalization is achieved by computing a local two dimensional average and subtracting from each pixel. This procedure normalizes the variation in the background level before edge detection. Then, a nonlinear morphological filtering method is used to locate the vessel segments. In 1997, Hart *et al*. describe an automated tortuosity measurement technique for blood vessel segments in retinal images. They use a filter developed by Chaudhuri *et al*. in the vessel extraction process. Then, a thresholding and thinning processes are applied to get the binary image containing the vessel segments. The final set of vessel segments is obtained by applying a linear classifier algorithm, described by Cote *et al*. In 1998, Kochner *et al*. utilized steerable filters.

In 2000, Hoover *et al*. proposed a framework to extract blood vessel from retinal images using a set of twelve directional kernels to enhance the vessels before applying threshold-probing technique for segmentation. Gaussian filter approach is used for retinal vessel detection by Luo *et al* in the year 2002. The vessel width measurement is incorporated in this technique which yields superior results than the matched filter approach. In 2002, Gang *et al*. proposed the amplitude-modified second order Gaussian filter for vessel detection. In 2003, Xiaoyi and Mojon proposed an adaptive local thresholding framework based on a verification-based multi-threshold probing scheme. A general framework of adaptive local thresholding based on the use of a multithreshold scheme, combined with a classification procedure to verify each resulting binary object, was presented in the year 2003 by Jiang *et al*. Matched filtering approaches may use global or local thresholding strategies, derivative of Gaussian function or dual-Gaussian model are used to detect the blood vessels. In 2003, Chanwimaluang *et al*. proposed global thresholding strategies. In 2007, Al-Rawi *et al*. improved Gaussian matched filter by using an exhaustive search optimization procedure. In 2007, Sukkaew *et al*. statistically optimized Laplacian of Gaussian, skeletonization followed by pruning, and edge thinning for vessel segmentation. In 2007, Yao and Chen employed Gaussian MF and Pulse coupled neural network to segment the blood vessels by firing neighbourhood neurons.

In 2009, Cinsdikici and Aydin employed Matched filter and ANT colony algorithm for vessel segmentation. A high speed detection of retinal blood vessels using phase congruency has been proposed by Amin and Yan in the year 2010. Gaussian function and dual-Gaussian model approaches were proposed respectively in 2008 by Narasimha *et al* and in 2010 by Zhang *et al*. In 2012, Oliveira *et al*. develops an unsupervised segmentation procedure for the segmentation of retinal vessels images using a combined matched filter, Frangi filter and Gabor Wavelet Filter. In 2012, Kuri *et al*. used optimized matched filter response to enhance the blood vessel followed by local entropy thresholding used to segment the vessels automatically. In 2013, Fazil *et al*. focus on two methods of retinal vessel segmentation including first derivative of Gaussian matched filter and Gaussian matched filter and make use of adaptive histogram equalization. In 2014, Sil kar *et al*. used Curvelet transform to enhance the finest details along the vessels followed by matched filtering to intensify the blood vessel's response. The conditional fuzzy entropy is then maximized to find the set of optimal thresholds. Thresholds thus obtained extract the thin, the medium and the thick vessels from the enhanced image which are then logically OR-ed to obtain the entire vascular tree.

3.1.6 Morphology based approaches

Morphology relates to the study of object forms or shapes. Morphological operators (MO) apply structuring elements (SE) to images, and are typically applied to binary images but can be extended to the gray-level images. The use of morphological operations in image segmentation typically uses combinations of the opening and closing operations to select for features, which may not necessarily be entire objects but components of the object being sought. These operations can repeatedly enlarge and reduce the size of features, allowing the elimination of noise and smaller details by shrinking them to such a point that they are removed from the image, while simultaneously retaining and potentially emphasizing the larger elements. These operations are built up from erosions and dilations, which are conceptually straight forward filters, applied to an image that contract or expand the borders of regions, restricting their actions to those that are above or below some threshold of intensity or other criteria. Two algorithms used in medical image segmentation and related to mathematical morphology are top hat and watershed transformations (E. Ardizzone *et al*, 2009).

In 1997, Zana and Klein present a vessel segmentation algorithm from retinal angiography images based on mathematical morphology and linear processing. A unique feature of the algorithm is that it uses a geometric model of all possible undesirable patterns that could be confused with vessels in order to separate vessels from them. Vessels are extracted using curvature differentiation in the final step. In 2001, Zana *et al*. proposed an algorithm that combines morphological filters and cross- curvature evaluation to segment vessel-like patterns in retinal images. In 2005, Ayala *et al*. defines Fuzzy mathematical morphology then threshold is applied to generate binary vessel tree. In 2011, Fraz *et al*. have proposed a unique combination of Vessel centreline detection and morphological bit-plane slicing. In 2010, Fabilo *et al*. constructed a 7-D feature vector by computing the outputs of morphological linear operators, line strengths and oriented Gabor filters at multiple scales for retinal blood vessel segmentation. In 2013, Betaouaf *et al* evaluated a retinal identification algorithm based on fundus images mainly on retinal vascular network that is a characteristic of the most reliable biometric identification. In order to extract the features, a segmentation of the vascular network is performed using a powerful morphological technique called watershed. In 2014, Mehrotra *et al*. employed a combination of morphological operations like top- hat and bottom-hat transformations on the pre-processed image to highlight the blood vessels.

The comparison of selected performance measures for the pattern recognition methodologies is tabulated, where the highest accuracy of 0.96 is achieved by the ridge based method (RBA) proposed by Karthik *et al*.

3.2 Model based approaches

Model-based approaches apply explicit vessel models to extract the vasculature.

In 2004, Vermer *et al*. proposed a method, which involves vessel detection by thresholding, after the convolution of the image with a 2-D Laplacian kernel. In 2004, Mahadevan *et al*. presented a set of algorithms for a robust and modular framework for vessel detection in noisy images using Vessel profile model. The advantages of using structural features are demonstrated by Harihar *et al* in the year 2007. In this algorithm, the dual-Gaussian model is used to estimate the cross sectional intensity profile of retinal vessels. But the system failed in case of thin blood vessels.

In 2007, Li *et al*. employed Multiresolution Hermite intensity model over spatial resolutions. In 2007, *Lam et al* proposed a novel vessel segmentation algorithm for pathological retinal images based on divergence of vector fields. Algorithm is based on regularization based Multi concavity modelling which is able able to handle both normal and pathological retinas with bright and dark lesions simultaneously. A universal representation of vessel cross-sectional profiles in the Fourier domain, utilizing phase congruency to characterize this representation is proposed by Zhu *et al* in 2007. In 2007, Espona *et al*. use Snakes in combination with blood vessel topological properties to extract vasculature from retinal image. In 2008, Espona *et al* proposed improvement in the algorithm by introducing Snakes in combination with morphological processing. In 2008, Sum and Cheung incorporated local image contrast into a level-set-based active contour to handle non-uniform illumination. An algorithm for the extraction of segment profiles of blood vessels which integrates vessel segmentation and width measurement based on the Ribbon of Twin active contour model is presented by Al-Diri *et al*. in the year 2009. In 2009, Zhang *et al*. proposed a methodology based on nonlinear projections, variational calculus to capture the texture structures in retinal images.

In 2010, Narasimha-Iyer *et al*. employed Dual Gaussian profile model to estimate the cross sectional intensity profile of retinal vessels. In 2012, Fraz *et al.* estimated the diameter of retinal blood vessels based on the detection of the centreline pixels from a vessel probability map image, determining the vessel orientation at these pixels, extracting the vessel segments and later using a two dimensional model, which is optimized to fit various types of intensity profiles of vessel segments. In 2014, *Qureshi et al.* aimed to reconstruct retinal vessel trees from the broken vessel segments in fund us images for clinical studies and early diagnosis of systemic diseases including diabetic retinopathy, atherosclerosis, and hypertension using Naive Bayes model.

Performance of model based approaches is illustrated. The highest accuracy is achieved by an algorithm based on divergence of vector fields of Lam and Hong (B.S.Y. Lam *et al,* 2007).

3.3 Artificial intelligence and Neural network approaches

Artificial Intelligence-based approaches (AIBA) utilize knowledge to guide the segmentation process and to delineate vessel structures. Different types of knowledge are employed in different systems from various sources.

In 1996, Goldbaum *et al* describe their STARE (Structural Analysis of the Retina) image management system for the diagnosis and analysis of the retinal images. Segmentation of the images is achieved by employing rotating matched filters. After the extraction of the objects of interests, the classification is performed using one of the linear discrimination function, quadratic discrimination function, logic classifier, and back propagation artificial neural networks with balanced accuracy and computation cost. Finally, the inference about the image content is accomplished with Bayesian network which learns from sample images of the diseases.

Neural networks (NN) are used to simulate biological learning and widely used in pattern recognition. The network is a collection of elementary processor (nodes). Each node takes a number of inputs, performs elementary computations, and generates a single output. Each node is assigned a weight and the output is a function of weighted sum of the inputs. These weights are learned through training and then used in the recognition. Back-propagation algorithm is a widely used learning algorithm. One problem associated to learning is that, learning depends on the training data set. The size of the training data set affects the learning process. The training procedure should be rerun each time new training data is added to the set. Since the aforementioned neural networks require a training data set, the learning process is a supervised learning. A different class of NN are self-teaching and do not depend on training data set for the learning.

Work of Sinthanayothin et al. in the year 1999 described, identification of retinal vessels using a neural network whose inputs are derived from principal component analysis of the image and edge detection of the first principal component. In 2005, Alonso *et al.*extracted retinal vascular tree using cellular neural networks (CNNs), aim of which is to improve computational time in order to achieve real-time requirements. In 2011, Marin et al. presented a neural network based supervised methodology for the segmentation of retinal vessels. A multilayer feed forward neural network is utilized for training and classification. The method proves to be effective and robust with different image conditions and on multiple images. In 2012, Holbura *et al* proposed a new approach, combining powerful Machine learning classifiers: support vector machines and neural networks over the same feature set, to improve the classification accuracy by a weighted decision fusion. In 2014, Chen *et al*. proposed a neural network based supervised segmentation algorithm for retinal vessel delineation. Test image can be segmented by using a number of local thresholds that are predicted by the trained the neural network according the histograms of image patches.

Depicts the performance measures of artificial intelligence and neural network based methods, with the highest accuracy of 0.9526 reported by a supervised method of Marin *et al*.

3.4 Graph-cut based approaches

The segmentation energies optimized by graph cuts combine boundary regularization with region-based properties. The graph cut is an energy based object segmentation approach. The technique is characterised by an optimisation operation designed to minimise the energy generated from a given image data. This energy defines the relationship between neighbourhood pixel elements in an image. It allows the incorporation of prior knowledge into the graph formulation in order to guide the model and find the optimal segmentation.

In 2011, Xu *et al*. proposed a reliable and accurate method to measure the width of retinal blood vessel in fundus photography is proposed in this paper. Our approach is based on a graph-theoretic algorithm. In 2012, Xinjian *et al*. reported an automated method is reported for segmenting 3-D fluid-associated abnormalities in the retina, so-called symptomatic exudate-associated derangements (SEAD). Initially retinal layers are segmented, candidate SEAD regions identified, then probability constrained combined graph search-graph cut method refines the candidate SEADs by integrating the candidate volumes into the graph cut cost function as probability constraints. In 2014, Salazar *et al*. presented an automated and unsupervised method for retinal blood vessels segmentation using the graph cut technique. The graph is constructed using a rough segmentation from a pre-processed image together with spatial pixel connection. It takes as first step the extraction of the retina vascular tree using the graph cut technique. The blood vessel information is then used to estimate the location of the optic disc. It employs graph formulation technique.

3.5 Edge Detection Methods

These use standard image-processing techniques such as the Canny, Sobel and Laplacian operators to extract lines from within the image. While they are appropriate for many applications in computer vision, generic edge detection operators are less appropriate for the task of retinal vessel segmentation due to the fact that most vessels have boundaries that are blurred or indistinct, and very fine vessels are often only two or three pixels wide, which are not picked up, instead being seen as part of the background. In addition to this, the edge detection operations do not distinguish between vasculature and pathologies within the eye. They can falsely despite the fact that in isolation they are not adequate for the entire task at hand.

In 2010, Xiaolin *et al*. proposed a method is based on a modified canny edge detection method with a bilateral filter. The bilateral filter is used to remove the vessel background noises, and then the Canny detector is used to detect all vessel edges, vessel sample profiles crossed vessel boundaries are obtain based on Canny edges. Then the new vessel positions are measured from the Gaussian fits of the sample profiles. In 2013, Prasanna *et al*. described the algorithm for integrating edges and regions. Initially, the edge map of image is obtained by using kirsch edge operator. The result demonstrates that the algorithm is robust, satisfying and work well for images with non-uniform illumination. In 2014, Dhar *et al*. proposed an analysis of performance of Canny and Laplacian of Gaussian filter in edge detection of retinal images. Comparative analysis of the aforesaid filters is done and found that canny edge operator performs better than Laplacian of Gaussian filter in most of the varieties of retinal images under various conditions.

3.6 Thresholding based methods

The readers are referred to (B. Sankur *et al*) for a most recent review. Only very few adaptive local approaches (Y. Nakagawa *et al*, 1979) are known in the literature. In 1994, O'Gorman bases his approach on a histogram of the number of horizontal and vertical runs that result from thresholding the input image at a series of thresholds. Alternatively, in 1996, Pikaz *et al*. investigate the histogram of the number of objects of some minimum size by applying binarization at different thresholds. It is important to mention that both approaches (L. O'Gorman *et al*, 1994 : A. Pikaz *et al*, 1996) intend to determine a single global threshold, while our work leads to an adaptive local thresholding framework. In (Yong Yang *et al*, 2012), a new method that combines the adaptive thresholding and local entropy thresholding for blood vessel extraction is proposed. In 2009, Zhang *et al*. proposed adaptive thresholding to extract vessels from fundus images. In 2010, Akram *et al*. proposed a wavelet based method for vessel enhancement, piecewise threshold probing and adaptive thresholding for vessel localization and segmentation respectively.

3.7 Wavelet based Methods

Previously, we have shown promising preliminary results using the wavelet transform (H. F. Jelinek *et al*, 2003) and integration of multiscale information through supervised classification (J. J. G. Leandro *et al*, 2001). Many different approaches for automated vessel segmentation have been reported. The usage of blood vessel extraction technique for Diabetic Retinopathy detection is demonstrated by Cornforth *et al* in the year 2005. The concept of wavelet transforms is used in this work for segmentation. But this approach is not applicable for images with noisy background.

3.8 Tracking based methods

Tracking or Tracing based methods use a single step approach. It starts by locating the vessel points for tracing the vascular network, by assessing image properties. The extraction of image features and the recognition of the vasculature are simultaneously executed. Localization of the initial vessel point can be manual or automatic. In the manual tracing, the user selects the initial vessel point, which is mostly used in coronary angiography analysis and they generally provide accurate vessel segmentation. In the automatic tracing, the initial vessel point is automatically selected by algorithm, which utilizes a Gaussian function to characterise a vessel profile model to head forward and segment a vessel.

Sun *et al*. in 1989, proposed the classification of regions segmented by user-assisted thresholding as blood vessel or leakage according to their length to width ratio. In 1994, Zhou *et al*., the authors report an algorithm that is initiated by the definition of the starting and ending points and is automatically followed by a matched filter for locating the vessel boundaries, tracking the midline and extracting parameters of clinical interest. This methodology is extended by Frame *et al*. in 1997 with the objective of detecting the end of the vessels, and successfully tracking down new vessels at bifurcations. In 1998, Chutatape *et al*. proposed that, the tracking process begins from the circumference of the optic disc, being a Kalman filter the base to estimate the next search location. The method proposed by Tolis *et al*. in 1998, overcomes the problem of initialization, but does not require vessel profile modelling. Initial points are detected on the bounding circle of the optic nerve and the determination of vessel and non-vessel regions along the vessel profile is done using a fuzzy C -means clustering algorithm.

Table 2 Performance measures for blood vessel segmentation techniques

Approaches	Methodology	TPR	FPR	Accuracy
Multi-scale approaches	Martinez *et al.*	0.6389	-	0.9181
	Martinez *et al.*	0.7506	0.0431	0.941
	Elena *et al.*	0.7246	0.0345	0.9344
	Perez *et al.*	0.779	0.0591	0.924
Multi-scale approaches	Anzalone *et al.*	0.7286	0.019	0.9419
	Vlachos *et al.*	0.747	0.0455	0.929
Skeleton-based approach	Mendonca *et al.*	0.7334	0.0236	0.9452
Ridge based approach	Staal *et al.* in	-	-	0.9516
	Miri *et al.*	0.7352	0.0205	0.9458
	Karthik *et al.*	-	-	0.96
Matching filters approaches	Chaudhuri *et al.*	-	-	0.8773
	Hoover *et al.*	0.6751	0.0433	0.9267
	Xiaoyi *et al.*	-	-	0.9337
	Jiang *et al*	-	-	0.9009
	Al-Rawi *et al.*	-	-	0.9535
	Yao and Chen	0.8035	0.028	-
	Zhang *et al.*	0.7177	0.0247	0.9484
	Amin *et al.*	-	-	0.92
	Cinsdikici *et al.*	-	-	0.9293
	Kuri *et al.*	-	-	0.9586
	Fazil *et al.*	-	-	0.9353
Morphology based approaches	Zana and Klein	0.6971	-	0.9377
	Fraz *et al.*	0.7311	0.032	0.9442
Model based approaches	Vermer *et al.*	0.924	0.079	0.9187
	Li *et al.*	0.752	0.02	-
	Lam and Hong	-	-	0.9474
	Espona *et al.*	0.6634	0.0318	0.9316
	Espona *et al.*	0.7436	0.0385	0.9352
	Al-Diri *et al.*	0.7521	0.0319	-
	Zhang *et al.*	0.754	0.0228	0.961
	Qureshi *et al.*	-	-	0.933
Artificial intelligence, Neural network based approach	Sinthanayothin *et al.*	0.833	0.09	-
	Marin *et al.*	0.6944	0.0181	0.9526
	Holbura *et al.*	-	-	0.94
Graph-cut based approach	Xinjian *et al.*	0.865	0.017	-
Tracking based approach	Elisa Ricci *et al.*	-	-	0.9584
	Xu *et al.*	0.776	-	0.9328

In 1998, Chandrinos *et al* extract vessels in fundus images for the examination of atherosclerotic changes due to hypertension. The method utilizes the idea that each vessel presents a ridge in cross sectional intensity profiles. Ridge detection process starts with a Gaussian smoothing to handle the variations in image intensity. After the extraction process, the method employs some image-based measuring techniques to obtain vessel calibre, wall thickness, and tortuosity.

The tracing method described by Can *et al* in 1999, automatically detects seed-tracking points, defined as local grey-level minima along a grid of one-pixel wide lines. In 1999, Ali *et al* describes real time algorithm which is based on Recursive tracking with directional templates. Lalonde *et al*. in 2000 and Tamura *et al* in 1988 presents vessel tracking methods to obtain the vasculature structure, along with vessel diameters and branching points. Vessel network tracking using recursive dual edge tracking and connectivity recovering. To deal with the problem of the central light reflex area, Goa *et al*. in 2001 modelled vessel intensity profiles using twin Gaussian functions. Vessel network tracking using recursive dual edge tracking and connectivity recovering was proposed by Gagnon *et al*. in 2001. There are methods based on active contours (L. Espona *et al*, 2007 : B. Al-Diri *et al*, 2009) matched filters (A. Can *et al*, 1999), and probabilistic models among others (E. Poletti *et al*, 2011 : Y. Yin *et al*, 2012) Among the techniques compared, we select the line operator introduced in (R. Dixon *et al*, 1979), which has been modified to take into account the peculiarities of retinal vessel structure. In 2007, Elisa Ricci *et al*. introduced a method for segmentation of blood vessels in retinal images using line operators and support vector machine classifier. Incapability of thin vessel detection and lack of a proper performance measure are the demerits of this approach. A semi-automated method for segmentation of vascular images is proposed by Kelvin *et al* in the year 2007. Line tracking based retinal vessel segmentation is implemented by Marios *et al* in 2010. The major drawback of the proposed algorithm is the high misclassification rate of the optic disk. In 2010, Xu *et al* combined the adaptive local thresholding method and the tracking growth technique to segment retinal blood vessels. In 2010, Delibasis *et al*. proposed Model based tracing algorithm for vessel segmentation and diameter estimation. It utilizes parametric model of a vessel. In 2010, Bhuuiyan *et al*. employed new technique vessel edge tracking method which combines the method of finding pattern of vessel start point and pixel grouping and profiling techniques for segmentation. Experimental results have shown that 92.4% success rate in the identification of vessel start-points and 82.01% success rate in tracking the major vessels.

In 2011, Quek and Kirbas proposed Wave propagation and trace back for the extraction of the vasculature from retinal angiography images. In 2012,

Salazar *et al* used an adaptive histogram equalisation and the distance transform algorithm to enhance the vessels appearance, then applied the graph cut technique to segment vessels. In 2013, Malek *et al* proposed a method is based on a tracking strategy where centreline extraction is done by an iterative prediction estimation tracking technique based on a multi-scale analysis of image moments and on a shape model close to snakes. In 2014, Hatanaka *et al* previously proposed a method to determine cup edge by analysing a vertical profile of pixel values, but this method provided a cup edge smaller than that of an ophthalmologist. Then it was an improved method using the locations of the blood vessel bends. The blood vessel bends were detected by tracking the blood vessels from the disc edge to the primary cup edge.

The comparison of selected performance measures for Tracking based methods is summarized, where the highest accuracy of 0.9584 is achieved by the method proposed by Elisa Ricci *et al*.

4. Optic Disc Segmentation

4.1 Optic disc localization

With regard to algorithms for optic disc localization, Synthanayothin *et al*. in 1999, presented a method where the images were pre-processed by applying an adaptive local contrast enhancement to the intensity channel of the HSI colour space. In 1998, Goldbaum and Hoover in 2003, located the centre of the OD using the vasculature origin. It achieved 89% correct detection. The method that uses the convergence of the vessels to detect the OD centre by employing geometrical parametric model was proposed by Foracchia *et al*. in 2004. In 2008, Youssif *et al*. presented an OD location method based on matching the retinal vessel's directional pattern.

4.2 Optic disc segmentation

With regard to template matching methods, lalonde *et al*. proposed two modifications to the geometrically deformable template model. First, the optimization stage originally based on simulated annealing is replaced with a meta-heuristic called Variable Neighbourhood Search that treats simulated annealing as a local search tool. Second, affine deformation energy is introduced to improve the quality of the search. In 2002, Ardizzone *et al*. presented two methods aimed to the optic disc positioning based on a template of the entire image on the retinal images. In 2010, Aquino *et al*. presented a new template-based methodology for segmenting the OD from digital retinal images. This methodology uses morphological and edge detection techniques followed by the Circular Hough Transform to obtain a circular OD boundary approximation. In 2012, Yu *et al*. presented a new, fast, and fully automatic OD localization and segmentation algorithm developed for retinal disease screening. OD location candidates are identified using template matching. Then, vessel characteristics on the OD are used to determine OD location. Initialized by the detected OD centre and estimated OD radius, a fast, hybrid level-set model, which combines region and local gradient information, is applied to the segmentation of the disk boundary. In 2013, Mohammad *et al*. described ongoing work on the segmentation of the optic disc in retinal images using pixel classification and circular template matching. In 2014, Saleh *et al*. proposed method that comprises three major stages, namely optic disc localization, pre-processing and segmentation. Localization is performed using the fast Fourier transform based template matching to obtain a seed point located on the optic disc which is then used as an input to the region growing technique for the purpose of segmentation.

With regard to deformable methods, in 2004, Lowell *et al*. in 2004 localized the OD by means of template matching and selected a deformable contour model for its segmentation. In 2008, Espona *et al*. presented an improved version of specific methodology to detect the vessel tree in retinal angiographies. In 2010, Joshi *et al*. estimated relevant disk parameters using the OD and cup boundaries. A deformable model guided by regional statistics is used to detect the OD boundary. In 2012, Jun *et al*. proposed a superpixel classification based method for the initialization in deformable model based optic disc segmentation.

The comparison of selected performance measures for the methodologies based on optic disc segmentation techniques is tabulated in Table 3.

Table 3 Performance measures of optic disc segmentation techniques

Methodologies	Algorithms	Location success rate (%)	Overlap percentage (%)	Accuracy (%)	Mean area overlap error (%)
Template matching methods	Aquino *et al.*	99	86	-	-
	Yu *et al.*	99	-	-	-
	Mohammad *et al.*	-	81	-	-
	Saleh *et al.*	100	87.16	98.68	-
Deformable methods	Jun *et al.*	-	-	-	10

5. Discussion

Accuracy, TPR, FPR of reviewed retinal blood vessel segmentation techniques are plotted in Fig.6. 7 and 8 respectively. Karthik *et al.* and Vermer *et al.* outperform all other reviewed segmentation techniques in terms of accuracy and TPR respectively.

Although retinal vessel segmentation techniques are categorized, few authors employ combination of multiple segmentation techniques to improve the accuracies. Few articles that fall into multiple segmentation techniques are described with a brief description in the Table 4.

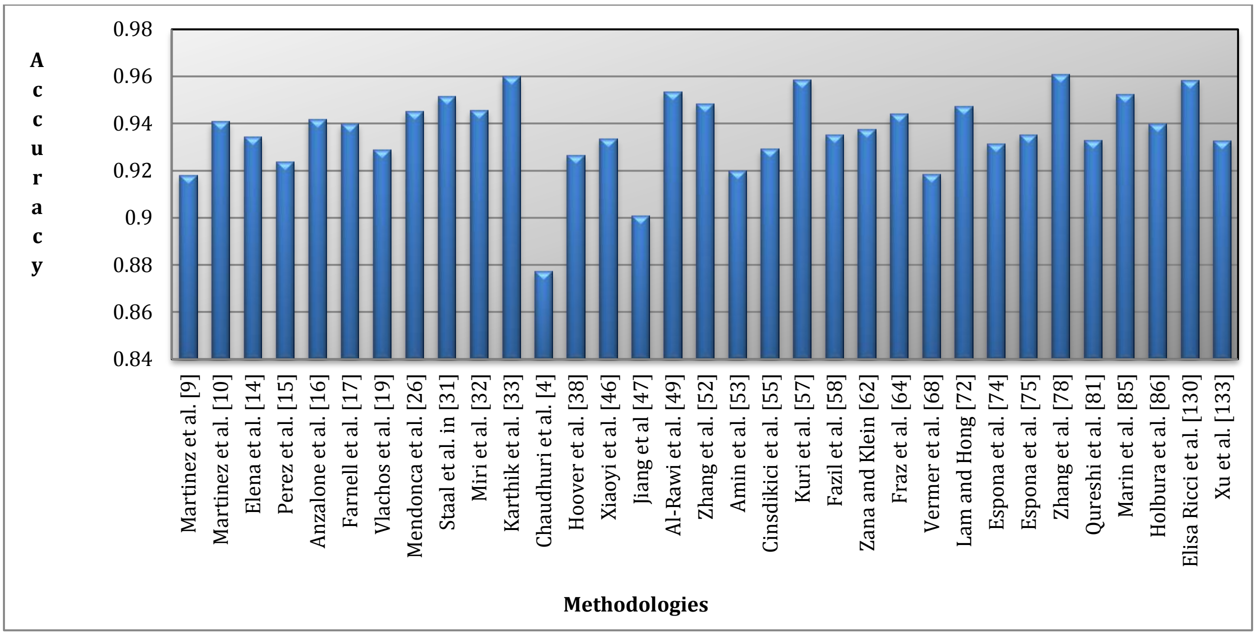


Fig. 5 Accuracies of blood vessel segmentation techniques

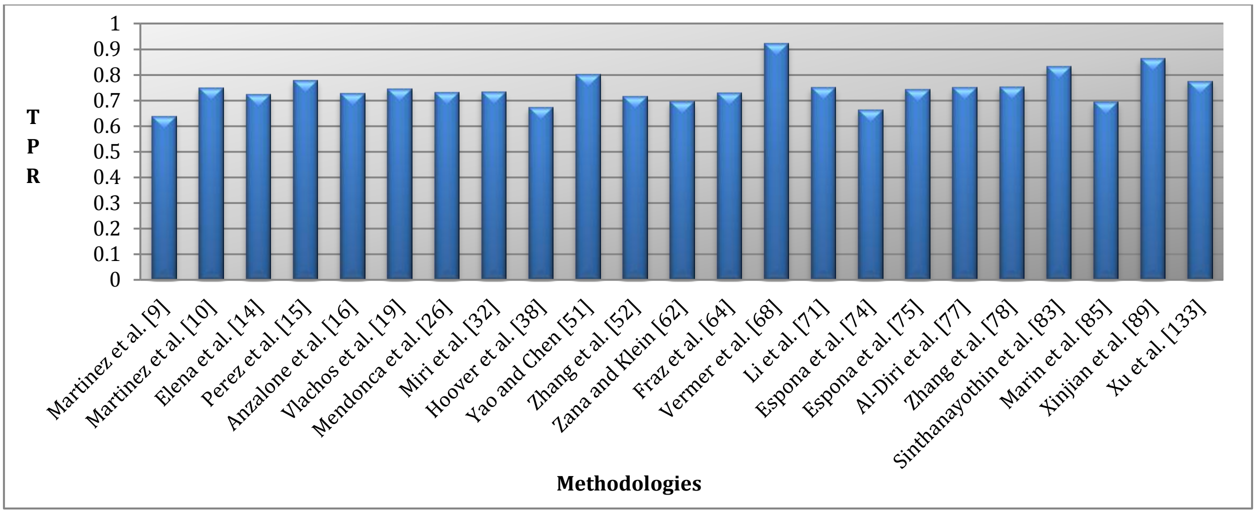


Fig. 6 True Positive Rate of blood vessel segmentation techniques

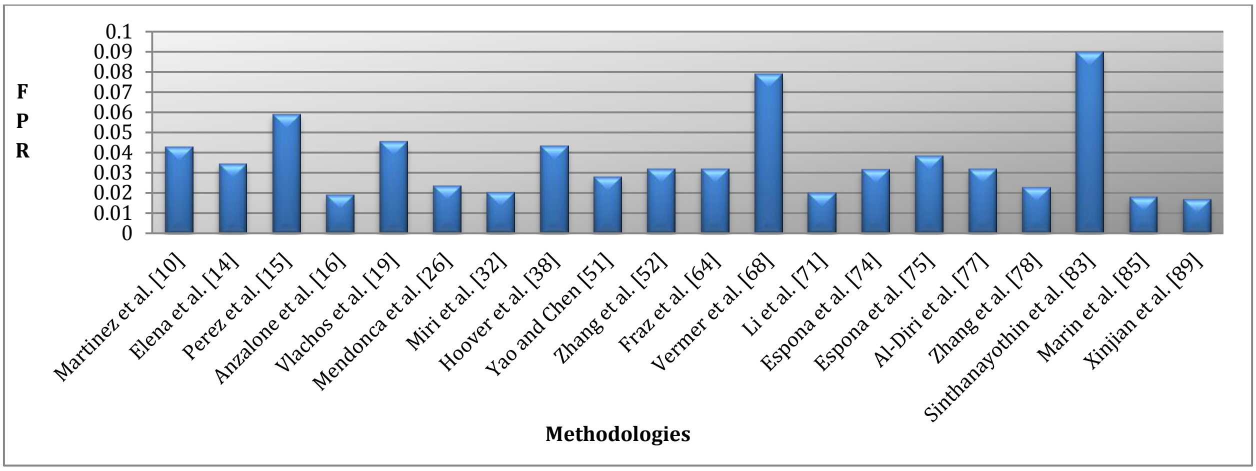


Fig. 7 False Positive Rate of blood vessel segmentation techniques

Table 4 Articles with combination of segmentation techniques

Algorithm	Year	Classification	Description
Goldbaum *et al*	1996	ANNBA	Refer 3.3
		MSA	Rotated matched filters are used in segmentation process.
		MBA	Deformable contour model is used in the segmentation process
Perez *et al.*	1999	MSA	Refer 3.1.1
		RGA	Features derived from image derivatives are used in a two-stage region growing procedure of segmentation process.
Miri *et al.*	2003	RBA	Refer 3.1.3
		MBA	Morphological operations applied to find ridges
Wang *et al.*	2004	RGA	Refer 3.1.4
		MSA	Employed MSA along with edge detection, matched filtering
Mendonca *et al.*	2006	SBA	Refer 3.1.2
		MSA	Employed MSA in the segmentation process.
		MBA	Morphological operations are involved in the segmentation process.
		RGA	Employed RGA in the segmentation process (vessel filling).
Panda *et al.*	2007	SBA	Refer 3.1.2
		RGA	Centreline pixels act as seed points to be used in region growing for segmentation
Narasimha *et al.*	2008	MFA	Refer 3.1.5
		MBA	Employed Gaussian function based model.
Kuri *et al.*	2008	MFA	Refer 3.1.5
		TA	Employed in the segmentation process of vessels
Zhang *et al.*	2010	MFA	Refer 3.1.5
		MBA	Employed dual-Gaussian model based approaches.
Moghimirad *et al.*	2010	MSA	Refer 3.1.1
		SBA	Extracted the centrelines of vessels to estimated radius of vessels
Fraz *et al.*	2011	MBA	Refer 3.2
		MSA	Computes output of Gabor filters at multiple scales
Quinn *et al.*	2013	MSA	Refer 3.1.1
		MBA	Morphological operators are used to smoothen the background
Karthik *et al.*	2014	RBA	Refer 3.1.3
		MBA	Morphology operators are applied in order to locate the retinal image ridges

SBA – skeleton based approach, MSA – multi-scale approach, RGA – region growing approach, A NNBA – artificial intelligence and neural network based approach, MBA – model based approach, MFA – matching filter approach, RBA – ridge based approach, TA – tracking approach

Conclusion

Accuracy and robustness of the segmentation process is essential to achieve a more precise and efficient computer aided diagnostic system as in ophthalmology, acquired retinal images are used for the detection and diagnosis of diseases related to eye, vascular disorders. It is not expected that the vessel segmentation systems will replace the human experts in diagnosis; rather they will reduce stress and workload of the experts in examining the large volume of retinal images. This could save time and assist ophthalmologist to analyse large database of retinal images in a systematic manner with the high accuracy within a short span. Although many promising segmentation techniques have been developed, it is still an open area for research. As the future direction of segmentation research will be towards developing faster, accurate and automated techniques.

This paper provides a survey of current segmentation methods for retinal structures (blood vessels and optic disc) with a theoretical background. Aim of this paper is to present insights of the various retinal segmentation techniques along with the performance measures, give the reader a framework for the existing research and to introduce various segmentation algorithms of retinal structures found in literature.

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