An Overview of Retinal Blood Vessels Segmentation

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Abstract In the recent past, the application of image processing in the fields of medicine and ophthalmology was widely used. Retina blood vessels are the only part of the human body that can be directly visualized non-invasively in vivo. Retina segmentation is important to help ophthalmologists detect various eyes diseases such as diabetic retinopathy, glaucoma, and age macular degeneration. Consequently, vessel segmentation is an important step in image analysis used to assess retinal abnormality. Vessel segmentation must be completed accurately to obtain good results for further image analysis. This paper reviews the algorithms used in previous studies on retinal vessel segmentation and discusses the problems associated with retina analysis.

1 Introduction

Medical imaging rose to prominence due to the advancement of computer and image technology [1, 2]. In early the 1960s, optical imaging played a significant role in clinical medicine. Developing technology in optical imaging was crucial to

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advances in optics, data acquisition, and image processing [3]. In 1891, German ophthalmologist, Gerloff was the first to discover photographic retina images that showed blood vessels. The fundus camera was first developed by Gullstrand in 1910 [4].

Herbert and Michael [5] stated that the development of optical imaging and increasing research in retinal image analysis might be due to the needs of clinical practice to find better and cheaper ways of identifying, managing, and treating retinal disease. Interest and developments in this field may be the result of a desire on the part of clinical practitioners and the research community for a better understanding of the causes of retinal disease and disease progression that require detailed analysis.

Image segmentation of the morphological features of retinal blood vessel can be used in diagnosis, screening and for treatment purposes. The extracted features of blood vessel such as width, tortuosity, and bifurcation are used in image analysis to detect various eye diseases that may cause blindness [6–8]. Image analysis of retina vessels such as changes in diameter is used to diagnose hypertension, whereas, bifurcation angles, and tortuosity can assist in the detection of cardiovascular diseases and diabetic retinopathy [6, 7, 9]. Accurate detection of retinal vascular is crucial and can be a valuable aid for diagnosing ophthalmologic diseases [8, 10, 11]. In addition, retinal vascular has a unique structure for each person and blood vessel can be visualize non-invasive directly in vivo [6–8, 10, 12, 13]. Thus, the extracted retinal blood vessel is not only useful for diagnosis purposes, but also in the registration of retinal images and for biometrics applications [8, 9, 14].

Vascular networks are traditionally mapped by hand, which is a time-consuming process that requires both training and skill [13, 15]. The variety of vascular networks that have been recorded in retinal images and the irregularity of the image acquisition process makes retinal blood vessel segmentation a challenging task [16]. The segmentation of blood vessels is an important preprocessing step for the early detection of retinal diseases [13, 15]. According to [10], the measurements of blood vessel features are open to user-bias as they are obtained using semi-automated methods. Automated vessel segmentation algorithms have been introduced by researchers. These algorithms are categorized as being supervised or unsupervised methods [17]. Figure 1 provides an example of retinal images before and after the blood vessels was segmented.

This paper will use information from publicly available datasets for retina images (Sect. 2) and previous studies that examined blood vessel segmentation algorithms (Sect. 3). Further discussion is provided in Sect. 4 and the conclusion is covered in Sect. 5.

Fig. 1 Retinal image: before and after vessel segmentation

2 Retinal Image Dataset

Most of the retinal vessel segmentation methodologies were evaluated using two public databases known as DRIVE and STARE. Using the same retinal image dataset make it easier to compare results with the results of other studies. However, there are several others public database that contain retinal image such as the MESSIDOR database.

The photographs in the DRIVE database [18] were obtained from a diabetic retinopathy screening program in the Netherlands. Each image is a compressed JPEG. The DRIVE database was established to enable comparative studies on segmentation of blood vessels in retinal images. The retinal images were captured using 8 bits per color plane at 768 by 584 pixels and collected using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). The FOV of each image is circular with a diameter of approximately 540 pixels. Retinal images in the database have been cropped around the FOV. For each image, a mask image was provided that delineated the FOV.

The STARE database [19] contains 20 images for blood vessel segmentation; ten of these images contain pathology. The images were acquired using a TopCon TRV-50 fundus camera with a 35 degree field of view and the images captured were 8 bits per color plane by 605×700 pixels. The images were manually segmented by two observers. The first observer segmented 10.4 % of the pixels as vessels and the second observer segmented 14.9 % of the pixels as vessels. This indicates that the second observer may have segmented more of the thinner vessels.

The MESSIDOR database [20] is the largest database and it contains 1200 retinal images acquired by three ophthalmologic departments using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field of view. The images were captured using 8 bits per color plane at 1440×960, 2240×1488, or 2304×1536 pixels. Eight hundred images were acquired with pupil dilation (one drop of Tropicamide at 0.5 %) and 400 without dilation.

3   Previous Studies on Retinal Segmentation Algorithm

Many different approaches for automated vessel segmentation have been proposed. Vessel tracking, matched filter responses, and morphological processing are categorized as unsupervised methods. Whereas, segmentation based on pixel classification is categorized as a supervised method. Supervised methods require a feature vector for each pixel and manually labelled images to train the algorithm [10, 14, 17, 21]. According to Patton et al. [7], four techniques that are commonly used in vascular segmentation are matched filter, vessel tracking, morphological processing, and neural networks.

Matched filter involves filtering the image using kernel and Gaussian functions to extract the linear segment of retinal blood vessels [7, 10, 13, 22]. Many improvements have been made on matched filtering approaches, including using global or local thresholding strategies [19, 23, 24]. The vessel tracking method is based on the continuity property of blood vessels that tracks each vessel from the initial point. According to [25], the vessel tracking approach can identify each vessel and provide more significant vessel structures than the pixel-based methods. Morphological methods have two main processes, namely dilation and erosion. In image processing, morphological methods are appropriate for analyzing shapes in images that use a priori feature of the vascular shape such as linear continuity. When segmenting blood vessels, the algorithms that extract linear shapes are useful [7]. Kee [26] stated that statistical parameters for each pattern class are estimated using a sample pattern in the neural network method. Neural networks consist of layers and units. Units are also known as neurons, which take an input and pass the output to the next layer. Neural networks are commonly designed to be fed-forward, in which a unit gives the output to all the units in the next layer, and the previous layer does not receive any feedback from next layer [27].

Based on previous studies on retinal blood vessel segmentation (Table 1), various techniques have been introduced for the efficient detection of retinal vessel that lead to highly accuracy results. These proposed algorithms were tested using the public retinal datasets DRIVE and STARE. Manoj et al. [27] also used the MESSIDOR dataset in addition to DRIVE and STARE.

Fraz et al. [28] proposed a supervised method for segmenting blood vessels using an ensemble classifier of bagged decision tree that used nine dimensional feature vectors based on gradient orientation analysis, morphological linear transformation, line strength measure, and Gabor filter response. The approach proposed by Fraz was fast and required fewer samples in the training phase.

A method proposed by Yin et al. [29] was an automatic tracking method based statistical Bayesian. The tracking process started with seed points and detected vessel edge points iteratively using the proposed Bayesian method.

Asad et al. [15] proposed an approach for retinal vessel segmentation using a stand-alone bio-inspired algorithm, Ant Colony System (ACS) without coalition with others method. Eight features were used in this study; however, the results of Asad's proposed method did not reveal the best segmentation approach. The performance of

Table 1 Previous studies on retinal blood vessel segmentation

Technique	Accuracy result		
Ensemble classifier (decision tree and bootstrap) [28]	DRIVE: 0.9480; STARE: 0.9534		
Tracking method based statistical Bayesian method [29]	STARE: 0.9290		
Ant colony system [15]	DRIVE: 0.9028		
Self-organizing map, K-means clustering [14]	DRIVE: 0.9459		
Neural network [30]	DRIVE: 0.9503		
Neural network [27]:	DRIVE:	STARE:	MESSIDOR:
(a) Feed forward back propagation neural network (FFBNN)	0.9623	0.9583	0.9541
(b) Radial basis function (RBF)	0.8995	0.8929	0.9061
(c) Multi-layer perceptron (MLP)	0.9007	0.8485	0.8276
Matched filtering [31]	DRIVE: 0.9340; STARE: 0.9341		
Matched filtering [32]	DRIVE: 0.9461; STARE: 0.9521		
Multi-scale line-tracking [33]	DRIVE: 0.9285		
2-D gabor wavelet and sharpening filters [34]	STARE: 0.9439		

the proposed approach was also considered as it depended on simple and fast computed features.

An automatic unsupervised method was introduced by Lupaşcu and Tegolo [14] and it was based on Self-Organizing Maps (SOM) and K-means clustering. SOM was trained using images that were divided equally between the training and testing phases. The map units were divided into two classes by K-means clustering. Similar to the most accurate supervised methods, the proposed unsupervised method did not have any a priori knowledge in pixel labels because it relied on knowledge of vessel network morphology. Compared to supervised methods, which are computationally more expensive, the proposed method is computationally fast.

Franklin and Rajan [30] used a back propagation algorithm in the neural network for vessel segmentation. Back propagation is a systematic method for training multi-layer artificial neural networks. This method could assure efficiency in the classification phase and resulted in excellent performance, even though it needed a training phase.

A supervised method proposed by Manoj et al. [27] employed nine dimensional feature vector based on the orientation analysis of a gradient vector field, morphological transformation, line strength measures, and Gabor filter responses. The pixels were classified using three neural network classifier techniques, which were a Feed Forward Back propagation Neural Network (FFBNN), Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP). The effectiveness and its speed of classification made the method proposed by Manoj et al. appropriate for retina image analysis.

The approach proposed by Odstrcilik et al. [31] utilized Matched Filtering and minimum error thresholding technique to extract a binary blood vessel tree. The method was improved to segment blood vessel with variations of vessel diameter.

By considering five width classes of retinal vessels, five different kernels were designed according to regular blood vessel cross-sectional profiles.

Wang et al. [32] proposed a novel vessel enhancement technique based on a matched filter with multiwavelet kernels. This method generated very competitive results and did not require a training phase. No thresholds were manually adjusted as the system depended on adaptive thresholding.

An algorithm based on a novel seeded multi-scale line-tracking procedure and morphological post-processing was proposed by Vlachos and Dermatas [33]. The tracking process started with an estimation of the confidence matrix obtained from a group of seeds that were extracted from an image's histogram. This tracking process terminated when a specific condition of cross sectional profile became invalid.

Thin and less visible vessel patterns were enhanced using 2-D Gabor wavelets in a study conducted by Akram et al. [34]. Blood vessels were sharpened using a sharpening filter before the vessel was extracted. Vessels edges were detected in sharpened images and the vessels segmentation binary mask was created by assigning a value of one to the pixels that belong to blood vessels and a value of zero for non-vessels pixels. Lastly, morphological dilation was applied to refine the vessel segmentation mask.

4   Discussion

Vessel tracking is efficient as it analyses a smaller number of pixels than the image dimension [35]. Patton et al. [7] stated that vessel tracking can provide very accurate measurements of vessel widths and tortuosity, but it may be confuse by the vessel crossings and bifurcations. When the contrast between the vessels and background is weak, tracking may be terminated. Human intervention is needed when the automatic detection for initial points is unavailable [25]. Morphological processing methods that use a priori features of the vasculature shape have the advantage of speed and noise resistance [28]. Neural network methods are efficient but their accuracy depends on the quality of the image [26]. However, with the accuracy for predictive inference, neural network methods have a potential to support clinical decision-making [27].

Supervised schemes result in better segmentation, however, they require a training procedure that depends on hand-labeled vessel segmentation, which is very time consuming. By contrast, unsupervised methods do not require a training set and they are usually faster and better suited to automatic vessel segmentation [10, 25]. Nonetheless, Bankhead et al. [10] stated that unsupervised methods require slight modifications according to image properties such as quality, type, and size, before they can be used. Unsupervised methods require these modifications because they often use a filter and operations that are only suitable for particular types of images. However, perfect segmentation is impossible if the quality of the image is poor or images with pathologies are analyzed, regardless all the algorithms [16, 35].

5 Conclusion

This paper provides a review on retinal vessel segmentation. Vessel segmentation is completed before further image analysis to detect any retinal abnormalities. Therefore, developing an efficient and fast algorithm that can achieve a high level of accuracy is important. The DRIVE and STARE datasets were used to evaluate the proposed algorithm. Retinal blood vessel segmentation can be completed using either a supervised or unsupervised method. Supervised method required training images that need difficult manual segmentation but they provide better segmentation results. By contrast, unsupervised methods are faster and do not require a training image. Future work should focus on improving the literature review regarding the details of the methods used in vessel segmentation and further analysis of retina vessels, such as changes in diameter, bifurcation angles, and tortuosity, should be included.

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