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Review of Retinal Blood Vessel Segmentation Techniques

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Abstract—**Vessel segmentation algorithms are critical components of circulatory blood vessel analysis systems. We present a survey of vessel extraction techniques, putting the various approaches and techniques in perspective by means of a classification of the existing research. We review some of the segmentation methods shows characteristics of vessels. We divide vessel segmentation algorithms and techniques into three main categories: (1) Pattern Classification and Machine Learning (2) Matched Filtering, (3) Multi-scale Techniques, Some of these categories are further divided into different sub-categories.**

Index Terms — **Retinal blood vessel segmentation, Review.**

I. INTRODUCTION

Retinal Vascular disorders refer to a range of eye diseases that affect the blood vessels in eye. These conditions are linked to common vascular diseases, such as artherosclerosis (thickening of artery walls) and high blood pressure. The most commonly found Retinal Vascular Disorders are hypertensive retinopathy, retinal vein occlusion, diabetic retinopathy

High blood pressures (hypertension) causes the narrowing of blood vessels in the eye which may leak and harden over time as these vessels are subjected to continued excessive blood pressure.

Retinal Vein Occlusion (RVO) is a most common vascular disorder where the vein becomes narrowed or obstructed. RVO is one of the most frequent causes of blindness after Diabetic Retinopathy. RVO can be classified into two main types which are Central Retinal Vein Occlusion (CRVO) and Branch Retinal Vein Occlusion (BRVO).CRVO happens in the retinal vein at the optic nerve. Mostly 90 per cent of CRVO occurs in those people whose age is more than 50. The second is Branch Retinal Vein Occlusion (BRVO) which causes obstruction at a branch of the retinal vein. Nearly 30% of all vein blockages are due to BRVO.

A Diabetic Retinopathy is disease related to retina which affects blood vessels in patients with diabetes mellitus. In developed countries, it is the leading cause of blindness in working adults. About 60% of patients with diabetes for 15 years or more will have some blood vessel damage in their eyes. Out of these some patients have probability of developing blindness.

Retinal vessel segmentation and delineation of morphological attributes of retinal blood vessels, such as length, width, tortuosity or branching pattern and angles are utilized for diagnosis, treatment, screening, and evaluation of various cardiovascular and ophthalmologic diseases. Automatic detection and analysis of the vasculature can assist in foveal a vascular region detection, the implementation of screening programs for diabetic retinopathy, arteriolar narrowing, evaluation of retinopathy of prematurity, the relationship between vessel tortuosity and hypertensive retinopathy, vessel diameter measurement in relation with diagnosis of hypertension and computer assisted laser surgery. Automatic generation of retinal maps and extraction of branch points have been used for retinal image mosaic synthesis, temporal or multimodal image registration, fovea localization and optic disk identification. Besides the retinal vascular tree for each individual is found to be unique and thus can be used for biometric identification. Manual segmentation of retinal blood vessels is a prolong and tiresome task which also requires skill and training. Thus the automatic detection of blood vessels in the retina is the first step in the development of a computer-assisted diagnostic system for ophthalmic disorders. A large number of algorithms and techniques have been published relating to the segmentation of retinal blood vessels. This paper gives a brief review of some of the previously proposed methods for the detection of blood vessels in the retina.

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II. RETINAL BLOOD VESSEL SEGMENTATION TECHNIQUES

We have done survey on current vessel segmentation methods, covering both earlier and recent literature related to vessel segmentation algorithms and techniques. The various retinal blood vessel segmentation techniques can be broadly divided into pattern classification and machine learning, matched filtering, and multiscale techniques. In this paper, all segmentation technique are divided into these categories and are briefly summarized under the respective categories.

A. Pattern Classification and Machine Learning

The algorithms based on pattern recognition concern with the automatic detection or classification of retinal blood vessel features and other non vessel objects including background. Pattern recognition techniques for blood vessel segmentation are classified into two categories; supervised methods and unsupervised methods. Supervised methods utilize some preliminary labelling knowledge to decide whether a pixel belongs to a blood vessel or not whereas unsupervised methods perform the vessel segmentation of blood vessel without any preliminary labelling information.

1) Supervised Methods: In supervised methods the rule for vessel extraction is learned by the algorithm on the basis of a segmented reference images and training set of manually processed. The reference image is generally termed as the gold standard. The vascular structure in these ground truth or gold standard images is precisely marked by an ophthalmologist. But there is significant disagreement in the identification of vessels even amongst expert observers. In a supervised method the rules for evaluation of result are determined by the ground truth data. Therefore the prior requirement is the availability of the already classified ground truth data which may not be available in real life applications. These supervised methods are designed based on pre-classified data their performance is usually better than that of unsupervised ones and can produce very good results for healthy retinal images.

The assumption that vessels are elongated structures is the basis for the supervised method of ridge-based vessel detection and segmentation which was introduced by Staal *et al.* [1]. The image ridges which roughly coincide with the vessel center lines are extracted by this algorithm. After this image primitives are obtained by grouping image ridges into sets that model straight-line elements. These sets are used to partition the image by assigning each pixel to the closest primitive set. For every partition a local coordinate is defined by the corresponding line element. At last feature vectors are computed for every pixel using the characteristics of the partitions and their line elements and classified using sequential forward feature selection and a *k*-nearest neighbour classifier. This method achieves an area under the receiver operating characteristic curve of 0.952 and accuracy of 0.944 for Utrecht database.

Soares et al. [2] applied complex Gabor filters for feature extraction and supervised classification for the detection of blood vessels in retinal fundus images. In this method the magnitude outputs at several scales obtained from 2D complex Gabor filters were assigned to each pixel as a feature vector. Then a Bayesian classifier was applied for classification of the results into vessel or no vessel pixels. It achieves an area under the receiver operating characteristic curve of 0.9614 on DRIVE database.

Marin et al. [3] presented a supervised method for blood vessel detection in digital retinal images. This method uses a neural ntwork (NN) scheme for classification of pixels and computes a 7-D vector composed of gray-level and moment invariants-based features for pixel representation. The method was estimated on the publicly available DRIVE and STARE databases since they contain retinal images where the vascular structure has been precisely marked by experts. The method proves especially accurate for vessel detection in STARE images. Its application to STARE database (even when the NN was trained on the DRIVE database) outperforms all analyzed segmentation approaches. Its robustness and effectiveness with different image conditions, together with its fast implementation and simplicity makes this blood vessel segmentation proposal convenient for retinal image computer analyses such as automated screening for early diabetic retinopathy detection. In this paper, the sensitivity was 0.7067, specificity was 0.9801 whereas accuracy was upto 0.9552 for DRIVE database. For STARE database sensitivity was 0.6944, specificity was 0.9819 and accuracy was 0.9526

2) Unsupervised methods: The techniques based on unsupervised classification seeks to find inherent patterns of blood vessels in retinal images that can then be used to decide that a particular pixel belongs to vessel or not. The training data or hand labelled ground truths do not contribute directly to the design of the algorithm in these techniques.

Salem et al. [4] proposed a Radius based Clustering Algorithm (RACAL) which uses a distance based principle to represent the distributions of the image pixels. A partial supervision strategy is combined with the clustering algorithm. The features used are the local maxima of the gradient magnitude, the local maxima of the large eigenvalues calculated from Hessian matrix and the green channel intensity. The performance of this algorithm is compared with *k*-NN and found to be better in order to detect small vessels. Experimental results had shown that a true positive rate (TPR) of 81% at false positive rate (FPR) of 4.5% is achieved here.

G. Robertson et al. [5] explored post-processing of scanning laser ophthalmoscope (SLO) images for the automatic detection of retinal blood vessels. The retinal vasculature was first enhanced using Gaussian matched filters and morphological before a thresholding technique produces a binary vessel map. Such permutations of post-processing techniques were commonly used to achieve unsupervised classification of the vasculature in fundus images. The purpose of their study was to investigate the applicability of these methods to SLO imaging. The results of vascular detection on SLO images were compared with the results on fundus images. They reported the TPR of 54.6% with 0.3% FPR and an accuracy of 95.7% on SLO images.

Unsupervised methods for automatic vessel segmentation from retinal images are attractive when only small datasets with associated ground truth markings are available. Garg et al. [6] proposed an unsupervised curvature-based method for segmenting the complete vessel tree from colour retinal images was presented. The vessels were modeled as trenches and the medial lines of the trenches were extracted using the curvature information derived from a novel estimation of curvature. The complete vessel structure was extracted using a modified region growing method. It achieves an area under the receiver operating characteristic curve of 0.9271 on DRIVE database.

B. Matched Filtering

When Matched filtering for the detection of the vascular structure convolves a 2-D kernel with the retinal image. The kernel is designed to model a feature in the image at some unknown orientation and position. The matched filter response (MFR) indicates the presence of the feature. The following three properties are utilized in order to design the matched filter kernel: (i) the diameter of the vessels decreases as they move radially outward from the optic disk; (ii) the cross-sectional pixel intensity profile of these line segments approximates a Gaussian curve; (iii) vessels usually have a limited curvature and may be approximated by piecewise linear segments. The convolution kernel may be large. It needs to be applied at several rotations resulting in a computational overhead. Besides, the kernel responds excellent to vessels that have the same standard deviation of the underlying Gaussian function stated by the kernel. As a result, the kernel may not respond to those vessels which have a different profile. The retinal background variation and presence of pathologies in the retinal image increase the number of false responses because the pathologies can model the same local attributes as the vessels. A matched filter response method is found effective when used in parallel with additional processing techniques.

Chaudhuri et al. [7] proposed an algorithm based on two dimensional (2D) matched filters for vessel detection. Their method is based on three assumptions: (i) the intensity profile of a vessel can be approximated by a Gaussian function, (ii) vessels can be approximated by piecewise linear segments, and (iii) the width of vessels is relatively constant. Detection of blood vessels is performed by convolving the given image with the matched filter rotated in several orientations. The maximum filter response over all orientations is assigned to each pixel.

Hoover et al. [8] describe an automated method to locate and outline blood vessels of the ocular fundus images. Such a tool should prove useful to eyecare specialists for purposes of treatment evaluation, clinical study and patient screening. This method differs from previously known methods in that it uses local and global vessel features cooperatively to segment the vessel network. This method against hand-labeled ground truth segmentations of five images yielded 65% sensitivity and 81% specificity. For a baseline, the ground truth against a second hand labeling was compared, yielding 80% sensitivity and 90% specificity.

Al-Rawi et al. [9] proposed better filter parameters to increase the matched filter response for the detection of blood vessels. These filter parameters are found by using an optimization procedure on 20 retina images of the DRIVE database. Compared with other approaches, the matched filter that uses the newly found parameters outperforms the matched filter that uses the classical filter parameters. A technique is also discussed to find the best threshold value for the continuous matched filter output image and hence the best segmented vessel image. It achieves an area under the receiver operating characteristic curve of 0.9352 on DRIVE database and Maximum Average Accuracy(MAA) of 0.9458.

Zhang et al. [10] proposed a novel extension of the MF approach namely the MF-FDOG to detect retinal blood vessels. The MF-FDOG is composed of the first-order derivative of Gaussian (FDOG) and original MF which is a zero-mean Gaussian function. The vessels are detected by thresholding the retinal image's response to the MF and the threshold is adjusted by the image's response to the FDOG. The MF-FDOG achieves accuracy upto 0.9382 and 0.9484 for DRIVE and STARE respectively.

C. Multi-scale Techniques

The width of a vessel decreases as it travels radially outward from the optic disk and such a change in vessel calibre is a gradual one. Therefore, a vessel is defined as contrasted pattern with a Gaussian like shape cross-section profile, locally linear and piecewise connected with a gradually decreasing vessel width. Thus, the idea behind scale-space representation for vascular extraction is to separate out information related to the blood vessel having varying width at different scales.

Frangi et al. [11] examined the multiscale second order local structure of an image (Hessian) for developing a vessel enhancement filter. Gray-level invariant geometric ratios are defined on the basis of eigenvalues and the Frobenius norm matrix is computed. A vesselness measure is obtained on the basis of the eigenvalue analysis of the Hessian which finds out the principal directions in which the local second order structure of the image can be decomposed which directly gives the direction of smallest curvature along the vessel. The final vesselness measure is defined using the geometric ratios, the eigenvalues and the Frobenius norm matrix. This measure is tested on cerebral magnetic resonance angiography (MRA) data, two dimensional Digital Subtractions Angiography (DSA) and three dimensional aortoiliac. Many of the multiscale algorithms are based on this vessel enhancement filter. Its clinical utility is shown by the simultaneous noise and background suppression.

Salem et al.[4] proposed a method which is based on extracting vessel centerlines and orientation in scale space. Different scales are used to calculate the eigenvalues as vessels are of different diameters and then keeping the maximum response at each image pixel over scales. Based on this vesselness measure a generated ground truth (GGT) image is acquired by thresholding and removing segments of small sizes. The segmentation is obtained by using this GGT image in combination with a Radius-based Clustering Algorithm (RACAL).

Rangayyan et al. [12] performed multiscale analysis for the detection of blood vessels using Gabor filters and classified pixels using multilayer perceptron (MLP) neural networks and Artificial Neural Networks (ANNs) with Radial-Basis Functions (RBF).High efficiency in the detection of blood vessels with the area under the receiver operating characteristics curve of up to 0.96.

Nguyen et al. [13] proposed method based on the fact that line detectors at varying scales are achieved by changing the length of a basic line detector. The line responses at varying scales are linearly combined to produce the final segmentation for each retinal image. This eliminate the drawbacks and maintain the strength of each individual line detector. The performance of the proposed method was evaluated both quantitatively and qualitatively on three publicly available DRIVE, REVIEW and STARE datasets. Visual inspection on the segmentation results shows that the proposed method produces accurate segmentation on central reflex vessels while keeping close vessels well separated. On DRIVE and STARE datasets, the proposed method achieves high local accuracy (a measure to assess the accuracy at regions around the vessels) of 0.7883 and 0.7630 respectively while retaining comparable accuracy of 0.9407 and 0.9324 for DRIVE and STARE datasets respectively compared to other existing methods. On REVIEW dataset, the vessel width measurements obtained using the segmentations produced by the proposed method are highly accurate and close to the measurements provided by the experts. This shows applicability for automatic vascular calibre measurement and the high segmentation accuracy of the proposed method. Other advantages of the proposed method include its efficiency with fast segmentation time, its scalability and simplicity to deal with high resolution retinal images.

III. Discussion

The performance of algorithms based on supervised classification [1]-[3] is better in general than their counterparts [4]-[6]. However, these methods do not work very well on the images with non uniform illumination as they produce false detection in some images on the border of the optic disc, hemorrhages and other types of pathologies that present strong contrast.

Matched filtering has been extensively used for automated retinal vessel segmentation. Many improvements and modifications are proposed since the introduction of the Gaussian matched filter by Chaudhuri et al. [7]. The parametric optimization of the matched filter using exhaustive search and optimization resulted in an improvement of segmentation accuracy. Compared with the MF, the

MF-FDOG [10] can better distinguish the true vessel structures from non-vessel structures such as blobs and lesions. The experimental results demonstrated that it significantly reduces the false detections generated by the MF and detects many fine vessels that the MF will miss. In particular, the MF-FDOG can extract effectively the vessels in pathological images, leading to competitive results as compared with state-of-the-art schemes; at the same time it has much lower complexity and is much easier to implement. The matched filtering alone cannot handle vessel segmentation in pathological retinal images; therefore it is often employed in combination with other image processing techniques.

Methods to address the issue of retinal blood vessel detection may take advantage of the fact that blood vessels are elongated, piecewise-linear, or curvilinear structures with a preferred orientation. However, most of the directional, fan, and sector filters that have been applied to extract directional elements are not analytic functions; such filters tend to possess poor spectral response and yield images with not only the desired directional elements but also artifacts. The Gabor function provides a solution to the above mentioned problem [12]. High efficiency in the detection of blood vessels with the area under the receiver operating characteristics curve of up to 0.96.

The Gabor Wavelets are very useful in retinal image analysis [2]. Besides vessel segmentation and optic disk detection , the Gabor wavelet transform has also been utilized for the robust fractal analysis of the retinal vasculature.

IV. CONCLUSION

The blood vessel segmentation algorithms are very important in medical image processing applications like automated computer aided systems for diagnosing ophthalmologic and cardiovascular diseases. Although many reliable algorithms and techniques exist but still there is some scope for improvement in order to get better results for vessel segmentation.

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