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Review on Segmentation Techniques used in Optic Disc and Blood Vessel Segmentation

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Abstract—

The analysis of the Retinal images is done through different diagnosis methods in this modern Ophthalmology. There are different novel methods available for segmentation of the blood vessel and optic disc in the fundus retinal images. These methods are used for non-intrusive diagnosis for the eye diseases. The morphology of the blood vessel and optic disc is an important indicator for some of the diseases like diabetic retinopathy, glaucoma and hypertension. These retinal elements are landmark for the segmentation. The aim of this review paper is to describe the various blood vessel and optic disc segmentation techniques, highlighting their key points. Accordingly this review firstly overview the different key elements of the retina along with their properties and function and also describe the various image segmentation methodology for the blood vessel and optic disc.

Index Terms— retina, macula & fovea, retinal images, optic disc segmentation, blood vessel segmentation.

I. INTRODUCTION

VISISUAL perception plays very important role in one's existence. There are various diseases which affect the vision of the person, so early detection of such problem can prevent the person from the vision loss. Therefore, experts have been applying the digital image processing techniques to retinal images for identifying, locating, and analyzing the retinal landmarks which are nothing but blood vessel, optic disc, and macula. This computer-aided image analysis, in turn, facilitates the detection of the retinal lesions and abnormalities which significantly affect the general appearance of the retinal landmarks.

Fundus is nothing but the part of hollow organ that is furthest from the opening. Hence the fundus is inner portion of the eye which contains the blood vessels, optic disc, macula and fovea. Some of the retinal elements are described below with their functionality and their characteristics.

Retina: the retina is the fundus area of the eye which contains the light sensitive cells called cones and rods, the retina is the tissue where the image is projected since it receive image formed by the lens and convert these image into the signals. These signals are then forwarded to the brain through the optic nerve [1].

Optic Disc: the optic disc is also known as optic nerve head or papilla. This is a circular area with bright white portion from where the optic nerve and major blood vessel is enter in the retina. The diameter of the optic disc is near about 2mm, 1.76mm horizontally and 1.92mm vertically. The optic disc does not contain any receptors itself, thus it is the blind spot of the eye [1].

Macula & Fovea: the macula is located near the center of the retina which allows us to see object with great details. The fovea is a depression in the retina that contains only cons (not rods), and which provide accurate focused eyesight's. The fovea is located as center area of the macula area is an oval-shaped, blood vessel free reddish spot. It is approximately 5mm from the center of the optic disc [1].

Blood Vessels: there is 2 types of the blood vessels like arteries and veins. The arteries carry the fresh blood from the lungs and hearts to the eye and veins are responsible to away the use blood from the retina to the heart and lungs for refreshing the use blood by the oxygen and other nutrients.

II. BLOOD VESSEL SEGMENTATION TECHNIQUES

This topic contents the detail review of the vessel segmentation techniques also includes various vessel extraction approaches and techniques in perspective by means of classification of the existing research. The vessel segmentation algorithm and techniques are divided into six main categories.

(1) Pattern recognition techniques,
(2) Model-based approaches,
(3) Tracking-based approaches,
(4) Artificial intelligence-based approaches,
(5) Neural network-based approaches; and
(6) Miscellaneous tube-like object detection approaches.

A. Pattern Recognition Techniques

Basically, the pattern recognition techniques are used to automatically detect the object or features. In concerned with the blood vessel segmentation the pattern recognition techniques are used for the automatically detect the blood vessel structures and features. This techniques gives multiple approaches for the automatically detection of the blood vessels like (1) multi-scale approaches, (2) skeleton-based approaches, (3) ridge-based approaches, (4) region growing approaches, (5) matching filter approaches and (6) mathematical morphology schemes.

A.1 Multi-scale Approaches (MSA): This approach performs the segmentation at varying image resolutions. In this, the major structures like large blood vessels are extracted from the low resolution images while fine structures are extracted from the high resolution images. The main benefit of using this Approach is its high processing speed as it is also provide robustness by segmenting the strong structure from low resolution images and the small components such as branches presents in the neighborhood of the strong structures from the high resolution images.

A.2 Skelton-based Approaches (SBA): The main aim of Skelton-based Approaches in concerned with the blood vessels is to extract the centerlines from the blood vessels. And these centerlines are connected to form the blood vessel tree. Different approaches are used for the extraction of the centerlines from the blood vessels. Minor reduction in size should not have an adverse effect the quality of the image.

A.3 Ridge-based Approaches (RBA): Ridge-based methods treat grayscale images as 3D elevation maps in which intensity ridges approximate the skeleton of the tubular objects. Ridge points are local peaks in the direction of maximal surface gradient; and can be obtained by tracing the intensity map from an arbitrary point along the steepest ascent direction. The Ridges are invariant to affine transformations and can be detected in different image modalities. These properties are exploited in medical image registration. Since RBA detect skeleton of tubular objects; it can be thought of as a specialized SBA.

A.4 Region Growing Approaches (RGA): The region growing Approaches segment the image using seed points by incrementally recruiting the pixels to a region based on some predefined criteria and these segmentation criteria's are value similarity and spatial proximity. The pixels which are close to each other and have similar intensity values are more likely belong to the same object. The main disadvantage of this method is it required the user-specified seed points. Due to the variations in image intensities and noise, RG can result in holes and over segmentation. Thus, it requires post processing of the segmentation result.

A.5 matching filter approaches (MFA): Matching filters (MF) approach convolves the image with multiple matched filters for the extraction of objects of interest. Thus in extracting vessel contours; designing different filters to detect the vessels with different orientation and size plays a crucial role. The convolution kernel size affects the computational load. The MF are usually followed with some other image processing operations like thresholding and CCA to get the final vessel contours. CCA is preceded by a thinning process to detect vessel centerlines.

A.6 Mathematical Morphology Schemes: In this approach two important morphological operations are used, dilation and erosion morphological operation respectively. The dilation operation expands the object by SE, filling holes, and connecting disjoint regions. Thus erosion operation is used to shrinks the object by a SE. Closing; dilation followed by erosion; and opening; erosion followed by dilation, are two other operations. The two algorithm are used for the medical applications are top hat and watershed transformation.

B. Model-Based (MB) Approaches

The MB is further categorized in (1) Deformable models, (2) Parametric models, (3) Template matching, and (4) Generalized cylinders.

B. 1 Deformable Model (DM): DM are MB techniques find object contours using parametric curves that deform under the influence of internal and external forces.

B. 2 Parametric Models (PM): PM approaches define objects of interest parametrically. Thus in tubular object segmentation, objects are described as a set of overlapping ellipsoids. Some applications use a circular vessel model. The parameters of the model used are estimated from the image. While an elliptic PM can approximate healthy vessels, it fails to approximate pathological irregular shapes and vessel bifurcations.

B.3 Template Matching: Template matching tries to recognize a structure model (template) in an image. The method uses the template as a context; which is a priori model. It is a contextual method and a top-down approach. In arterial extraction applications; the arterial tree template is usually represented in the form of a series of nodes connected in segments. Thus template is then deformed to fit the structures in the scene optimally. The stochastic deformation process described by a Hidden Markov Mode l (HMM) is a method to achieve template deformation. Thus dynamic programming is an effective method employed in recognition process.

B.4 Generalized Cylinders Model: Generalized cylinders (GC) are used to represent cylindrical objects.

C. Tracking-Based Approaches

The tracking-based approaches included semi-automated tracing and automated tracing. In the semi-automated tracing methods, the user manually selects the initial vessel seed point. These methods are generally used in quantitative coronary angiography analysis and they generally provide accurate segmentation of the vessels. In fully automated tracing, the algorithms automatically select the initial vessel points and most methods use Gaussian functions to characterize a vessel profile model, which locates a vessel point for the vessel tracing.

D. Artificial Intelligence-Based Approaches

The artificial intelligence-based approaches uses knowledge to guide the segmentation process for extracting the blood vessel trees. The source of this knowledge is the properties of the image acquisition techniques, such as MRI, MRA, cine-angiography, DSA, computed tomography (CT). Some of the application uses general blood vessel model as its knowledge source.

E. Neural Network-Based Approaches

Neural nets are basically a classification approach. The network is a collection of elementary processor (nodes). Each node takes a number of inputs, performs elementary computations; and generates a single output. Therefore 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. One of the advantages that make neural networks attractive in medical image segmentation is their ability to use nonlinear classification boundaries obtained during the training of the network. There is necessity for the selection of the good training sets which includes the all possible features and objects through these training sets the neural network learns the classification boundaries in its feature space. The major disadvantage of the neural network is that every time when new feature is introduced the network need to train and another disadvantage is difficult to debug the network performance.

F. Miscellaneous Tube-Like Object Detection

These approach is basically used for the extraction of the tubular structure from the images. This is “miscellaneous” class basically and may be applied to the vessel extraction purpose because vessels are also nearly like tubular form, but these approaches are not designed for the blood vessel extraction.

III. OPTIC DISC SEGMENTATION TECHNIQUES

The main reason for segmentation of the optic disc is to developing the better screening system for eye diseases such as glaucoma, diabetic retinopathy. The detecting and locating the main anatomical structure such as optic disc is considered as an essential step towards detecting abnormalities and finding lesions in the retinal images. The live example for the reason why the optic disc detection is necessary is as because of the similarity between the exudates and optic disc create confusion for detecting the optic disc amongst the exudates. So in this case it is necessary to detect the optic disc and isolate it for better identification of the exudates within retinal fundus images [2] & [3].

Fig 1 Normal Retina

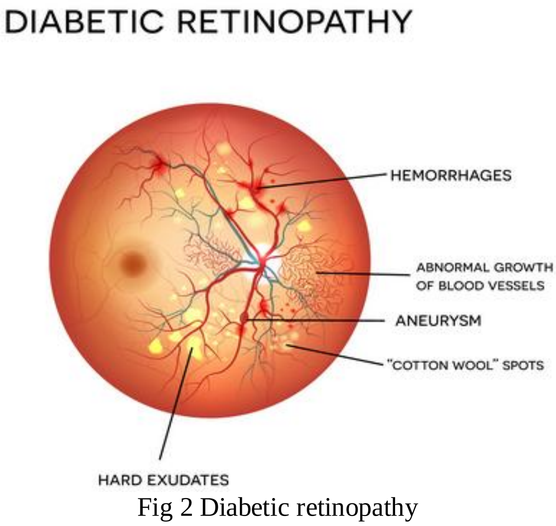

Fig 2 Diabetic retinopathy

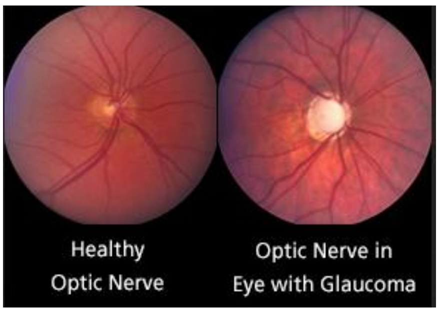

Fig 3 Glaucoma affected Retina

The important method for optic disc detection reviewed in the literature are as follows

A. Property-based methods

This method is purely based on the properties of the optic disc (e.g. location, size, color, shape).Goldbaum et al. use the properties of the optic disc to jointly locate the optic disc. They normally uses the three properties of the optic disc: the convergence of the blood vessels at the optic disc, the appearance of the optic disc as a bright region, and entrance of large vessels above and below the optic disc.

Sinthanayothin et al [4]. Use the approach in which the optic disc area is identified by the highest variation in intensity of adjacent pixels using window size equal to that of the optic disc. These approach correctly detect the optic disc with the sensitivity and specificity of 99.1% on a local dataset composed of 112 TIFF fundus images.

Similarly, based on the brightness and roundness of the optic disc, Park et al. [5] also presented a method with a successful detection percentage of 90.25% using an approach that included thresholding, detection of object roundness, and detection of circles.

A circular transformation was designed by Lu [6] to capture both the circular shape of the optic disc as well as the image variation across the optic disc boundary, simultaneously. The variation of each pixel within the retinal image was measured along multiple evenly-oriented radial line segments of specific length. The pixels with the maximum variation along all radial line segments were determined, which were then exploited to locate both the center and the boundary of the optic disc. Experimental results showed that the center of the optic disc was accurately detected in 99.75%, 97.5%, and 98.77% of the STARE, ARIA and MESSIDOR datasets, respectively. Also, the boundary of the optic disc was accurately segmented in 93.4% and 91.7% of the STARE dataset and the ARIA dataset, respectively.

Also, Chrástek et al. [7] applied an averaging filter to the green-band image, and roughly located the optic disc at the point with the highest average intensity with a success rate of 97.3% on a local dataset.

Yu and Yu [8] localized the optic disc through a method based on extracting the brightest pixels, iteratively, in order to overcome the presence of any other bright artifacts such as large exudates. Initially, the image was smoothened via the Gaussian filter and then the blood vessels were removed from the image using the closing operator. Then, at each round in the iterative algorithm, the brightest pixels were extracted and a binary candidate map was constructed. Both, the thresholds for the area and the circular degree were employed in order to select and identify the optic disc region among other candidates. The proposed method successfully localized the optic disc in 95% of only 40 images from the STARE dataset. Walter and Klein [9] approximated the centroid of the optic disc as the center of the largest and brightest connected object in the fundus. Their method successfully detected optic disc in all images of a local dataset composed of 30 images, and achieved a success rate of 58% on the STARE dataset.

Carmona et al. [10] proposed a genetic algorithm in order to obtain an ellipse that approximated the optic disc. First, they obtained a set of hypothesis points that exhibited the geometric properties and intensity levels similar to the optic disc contour pixels. The genetic algorithm was used next to find an ellipse containing the maximum number of hypothesis points in an offset of its perimeter. The results of their algorithm showed that 96% of the 110 retinal images had less than five pixels of discrepancy.

Zubair et al. [11] detected the optic disc by increasing its contrast using preprocessing techniques such as CLAHE, contrast stretching transformation, and extended minima transformation. Using the contrasted image, the optic disc was localized by using morphological erosion and dilation in order to remove all non-optic disc regions that are not of the size of the optic disc. Finally, after taking negative of the image, the resultant image obtained was subtracted from the resized green-channel component to get an optic disc free image, with an accuracy of 98.65% on the MESSIDOR dataset.

Using the Circular Hough Transform, Abdel-Ghafar et al. [12] were able to detect the optic disc by finding the largest circular object. Similarly, Zhu et al. [13], [14] also used the Hough Transform to detect the circles in which the best-fitting circle for the optic disc was chosen by using a method of intensity-based selection. They achieved a successful detection rate of 90% on the DRIVE dataset and 44.4% on the STARE dataset.

B. Convergence of blood vessels

This method uses the optic disc as vessels convergence point and uses the information provided by the vascular tree instead, depends on the properties of the optic disc.

The Hough Transform was utilized by ter Haar [15] two different ways. In the first method, the Hough Transform was applied only to the pixels on or close to the binary image of the retinal vasculature obtained by Staal et al. [16], in which the binary image was dilated on order to increase the number of optic disc candidates. This approach achieved a success rate of 96.3% on a local dataset and 71.6% on the STARE dataset. In the second alternative method, the Hough Transform was applied only to the brightest 0.35% of the fuzzy convergence image obtained by Hoover and Goldbaum [17], in which dilation was applied again to the convergence image to fill the gaps created by small vessels. This approach achieved a success rate of 97.4% on a local dataset and 65.4% on the STARE dataset.

Fleming et al. [18] detected the approximate region of the optic disc using an elliptical shape of the major retinal vessels which was formed using the Generalized Hough Transform. The approximate location of the optic disc was then refined via the Circular Hough Transform achieving a success rate of 98.4% of the 1056 retinal images, in which the positional accuracy was better than 50% of the diameter of the optic disc.

Ying et al. [19] proposed an algorithm that differentiates the optic disc from other bright regions such as hard exudates, in which the optic disc was detected based on its high fractal dimension of the converging pattern of blood vessels. With its location known, the optic disc was correctly segmented via local histogram analysis in 97.5% of the images of the DRIVE dataset.

Based on tensor voting for analyzing vessel structures, Park et al. [20] proposed a method to identify the location of the optic disc. The vessel patterns were first extracted by tensor voting in equalized images, and then the position of the optic disc was identified by mode detection which was based on mean-shift procedure. Their approach was tested with 90 images from the STARE dataset, which achieved 100% success rate on 40 normal images and 84% on pathological images.

Taking advantage of this spatial relationship between the optic disc and blood vessels, Hoover and Goldbaum [21] developed a voting-type algorithm called fuzzy convergence in order to detect the origination of the blood-vessel network (i.e. convergence point) which was considered as the center of the optic disc in a fundus image. The input to their algorithm was a binary segmentation of the blood vessels, in which each vessel was modeled by a fuzzy segment that contributed to a cumulative voting image. The output of the algorithm was a convergence image which was threshold to identify the strongest point(s) of convergence. This technique successfully detected 89% of the normal and abnormal images in the STARE dataset.

In the work of Rangayyan et al. [22], [14], the blood vessels were first detected using Gabor filters, and then phase portrait modeling was applied to detect the convergence points of the vessels, in which the best-fitting circle for the optic disc was chosen by using an intensity-based condition. This approach achieved success rates of 100% and 69.1% for the DRIVE and STARE datasets, respectively.

C. Model-based methods (template-matching)

This is the template matching method in this, the template is compare with the set of candidates to determine the best-matching candidates.

Model-based approach was proposed by Osareh et al. [23] who created a gray-level template image by averaging the optic disc region of 25 images whose colors were normalized using histogram specification. The center of the optic disc was located by using the generated template along with gray-scale morphological filtering and active contour modeling in which the normalized correlation coefficient was used to find the most similar match between the template and all the candidate pixels, with an average accuracy of 90.32% in detecting the boundary of the optic disc of 75 images of the retina.

Also, Li and Chutatape [24] created an optic disc model (disc-space) by applying Principal Component Analysis (PCA) to a training set of 10 intensity normalized images that were manually cropped around the optic disc. The candidate regions with the highest 1% gray-level were selected and matched to the disc-space, in which the optic disc was successfully detected in 99% of the images as the region with the smallest Euclidean distance to its projection onto the disc-space.

Lu [25] used another technique for the detection of the optic disc in a way different than the one he used in [6]. In the proposed technique, the retinal background surface was first estimated through an iterative Savitzky-Golay smoothing procedure. Afterwards, multiple optic disc candidates were detected through the difference between the retinal image and the estimated retinal background surface. Finally, the real optic disc was selected through the combination of the difference image and the directional retinal blood vessel which was based on the observation that the retinal blood vessels were mostly oriented vertically as they exit the optic disc. The proposed technique was evaluated over four datasets DIARETDB0, DIARETDB1, DRIVE and STARE giving an accuracy of 98.88%, 99.23%, 97.50% and 95.06%, respectively.

Instead of creating an image and using it as a template, Dehghani et al. [26] constructed three histograms as a template for localizing the center of the optic disc using four retinal images from the DRIVE dataset, in which each histogram represented one color channel. Then, an 80×80 window was moved through the retinal image to obtain the histogram of each channel. Finally, they calculated the correlation between the histogram of each channel in the moving window and the histograms of its corresponding channel in the template. The DRIVE, STARE, and a local dataset composed of 273 images were used to evaluate their proposed algorithm, in which the success rate was 100%, 91.36% and 98.9%, respectively.

Lately, [27] proposed a method for detecting the optic disc accurately in an efficient way. First, the algorithm identified a number of possible vertical windows (x-coordinates) for the optic disc according to three characteristics of retinal vessels, which are: (1) the high density of vessels at optic disc vicinity, (2) compactness of the vertical vascular segments around the optic disc center, and (3) the uniform distribution of vessels. Consequently, the y-coordinate of the optic disc is identified according to the vessels direction via parabola curve fitting using the General Hough Transform. The proposed method was tested on four datasets: DIARETDB0, DIARETDB1, DRIVE and STARE, in which the optic disc was correctly detected in all images of each dataset, except only one image in the STARE dataset.

IV. CONCLUSION

This survey first contains the different approaches for the blood vessel segmentation. The next section represent different approaches for optic disc localization and segmentation purpose. The first approach is property based approach relays on the size, shape, color and location of the optic disc which is moderate level approach for optic disc detection. Amongst these different approaches convergence of the blood vessel does not rely on the properties of the optic disc but it uses the information provided by the vascular tree which is generated due to the blood vessel segmentation. But the response time of this approach is more than the property based method and model based method. As more processing required in the convergence of the blood vessel the property based method is faster than this method.

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