

A Review of Retinal Vessel Segmentation Techniques And Algorithms

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Abstract-

Retinal vessel segmentation algorithms are the critical components of circulatory blood vessel Analysis systems. We present a survey of vessel segmentation techniques and algorithms. We put the various vessel segmentation approaches and techniques in perspective by means of a classification of the existing research. While we have mainly targeted the segmentation of blood vessels, neurovascular structure in particular. We have divided vessel segmentation algorithms and techniques into six main categories: (1) Parallel Multiscale Feature Extraction and Region Growing, (2) a hybrid filtering, (3) Ridge-Based Vessel Segmentation, (4) artificial intelligence-based approaches, (5) neural network-based approaches, and (6) miscellaneous tubelike object detection approaches. Some of these categories are further divided into subcategories.

Keywords: Vessel segmentation, retinal image, Parallel Multiscale Feature Extraction

I.INTRODUCTION

Assessment of the characteristics of vessels plays an important role in a variety of medical diagnoses. For these tasks measurements are needed of e.g., vessel width, color, reflectivity, tortuosity, abnormal branching, or the occurrence of vessels of a certain width. When the number of vessels in an image is large, or when a large number of images is acquired, manual delineation of the vessels becomes tedious or even Impossible [16]. While increased size and volume in medical images required the automation of the diagnosis process, the latest advances in computer technology and reduced costs have made it possible to develop such systems. Blood vessel delineation on medical images forms an essential step in solving several practical applications such as diagnosis of the vessels (e.g. stenosis or malformations) and registration of patient images obtained at different times. Vessel segmentation algorithms are the key components of automated radiological diagnostic systems. Segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors. There is no single segmentation method that can extract vasculature from every medical image modality. While some methods employ pure intensity-based pattern recognition techniques such as thresholding followed by connected component analysis [1], [2], some other methods apply explicit vessel models to extract the vessel contours [3], [4], and [5]. Depending on the image quality and the general image artifacts such as noise, some segmentation methods

may Require image pre-processing prior to the segmentation algorithm [6], [7]. On the other hand, some methods apply post-processing to overcome the problems arising from over segmentation we divide vessel segmentation algorithms and techniques into six main categories: (1) Parallel Multiscale Feature Extraction and Region Growing, (2) a hybrid filtering, (3)Ridge-Based Vessel Segmentation,(4)artificial intelligence-based approaches, (5) neural network-based approaches, and (6) miscellaneous tubelike object detection approaches. Pattern recognition techniques are further divided into seven categories: (1) multi-scale approaches, (2) skeleton- based approaches, (3) region growing approaches, (4) ridge- based approaches, (5) differential geometry-based approaches, (6) matching filters approaches, and (7) mathematical morphology schemes. Model-based approaches are also further divided into four categories: (1) deformable models, (2) parametric models, (3) template matching approaches, and (4) generalized cylinders approaches. Although we divide segmentation methods in different categories, sometimes multiple techniques are used together to solve different segmentation problems. We,therefore, cross-listed the methods that fall into multiple segmentation category. Such methods are reviewed in one section and mentioned in the other section with a pointer referencing to the section in which it is reviewed This paper provides a survey of current vessel segmentation methods. We have tried to cover both early and recent literature related to vessel segmentation algorithms and techniques. After a short introduction to each segmentation method category, papers fall in that category are summarized briefly. This paper is organized as follows. In Section II, Parallel Multiscale Feature Extraction and Region Growing are defined and reviewed. a hybrid filtering are discussed in Section III. In Section IV, Ridge-Based Vessel Segmentation. Methods based on artificial intelligence are discussed in Section V. In section VI conclusion and future work

II PARALLEL MULTISCALE FEATURE EXTRACTION ANDREGION GROWING

The purpose of parallelizing the segmentation algorithm described earlier is to process larger data sets of images, whose resolution varies from low to high, in an acceptable time. The main problem for processing such images (particularly high-resolution ones) is the available local memory. Even though the trivial solution may be increasing the amount of memory per processor, the essential problem is not truly solved. Parallelism is applied so the solution is developed by partitioning the images, so each sub image can be partially processed within the available memory per processor.

This kind of parallelism is known as domain partitioning, and it is considered for both stages of the segmentation algorithm, FE and RG

1) FE in Parallel

The multiscale process of FE is a local process for both, gradient magnitude and maximum eigenvalue. Thus, for a current pixel, the feature value does not depend on its neighbouring pixels. Considering this, the parallel implementation consists of partitioning the image into equal size sub images, so each sub image is processed by each processor. After parallel FE, the resulting image is then compound by all resulting sub images. However, this procedure yields some false vessel edges for boundary pixels of each sub image. In order to avoid this problem, the original image is divided so that neighbouring sub images contain certain overlapping between each other.

Fig. 1 shows an example of partitioning an image into five sub images. Fig.1(a) shows the simple division into R_i ($i = 5$) sub images. Fig.1(b) depicts the overlapping needed to process each sub image. Each pixel region to be processed is then the composition of an overlapping T region (defined by a number of extra pixels from the neighbouring sub images) along with the pixels belonging to the R_i sub image. Hence, the pixel region for a particular sub image is $R_i + 2T$. Nevertheless, topmost and bottommost sub images have a size of $R_i + T$. The particular value of T used in this parallel implementation will be described

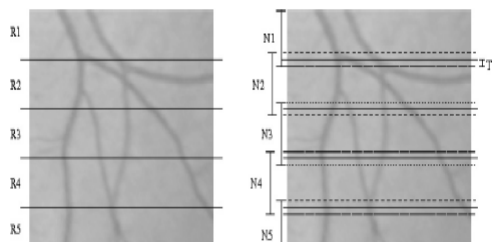


Fig. 1. Partitioning: (a) into sub images (R_i), and (b) considering pixel regions ($R_i + 2T$).

2) RG in Parallel

Since the RG algorithm depends on the iteration stage and on the processing of neighbour pixels, the parallelizing of this algorithm is not straightforward. In the current RG a global statistic defines where pixel seeds are planted. The position of these pixel seeds depends on the gradient magnitude and the maximum eigen value. Starting from each seed, each pixel class grows by iteratively classifying each pixel as vessel or background. The growing rules for a given pixel considers the pixels classified in the previous iteration along with the current class of its 8-neighboring pixels. Thus, dividing the image into sub images is not enough to address the growing

problem. This is a challenging problem. Suppose, for example, that an image is divided into two sub images, as shown in Fig. 2. If the image is horizontally divided [as shown in Fig. 2(a)], vessels horizontally growing have no problem. Nevertheless, vessels vertically growing may go across the sub image borders, and therefore, the algorithm cannot find a direction to grow giving truncated vessels. This also occurs when the image is vertically divided, as it is shown in Fig. 2(b). A possible solution to the problem of truncated vessels is to allow communication between sub images that share an overlapping, at each iteration. However, this approach may produce an excessive number of communications, so it is not recommended. Another effective solution is to divide the image into sub images in both directions, horizontal and vertical, as shown in Fig. 2. The resulting image then is obtained by combining both sets of sub images (horizontal and vertical), as shown in Fig. 2(c). In summary, the parallel RG algorithm takes an initial empty image, plants the seeds in it, and divides it into two sets of sub images: horizontal and vertical. Then, each sub image is processed, performing the growing algorithm on it. Since vessel and background classes grow in any direction, it is likely that some vessels would appear in the vertical sub image but would not appear in the horizontal sub image and vice versa. Therefore, the use of an OR operator applied to all pixels of the image corrects this situation.

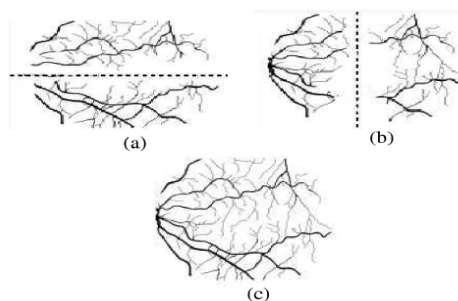


Fig. 2. Process with two nodes. (a) Horizontal. (b) Vertical. (c) Combined Results

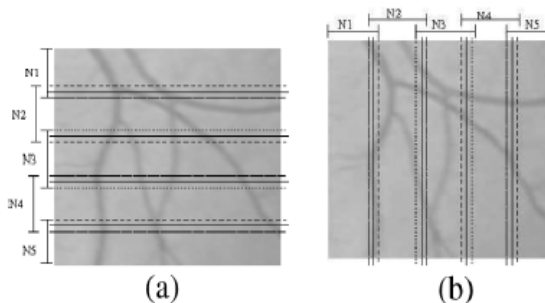


Fig. 3. Partition scheme: (a) horizontal and (b) vertical subimages.

The image is put back together at the end of the growth, considering vessel with value 1 and 0 for background. Although each sub image is represented twice (one vertical

and one horizontal) instead of only once, this partitioning scheme does not imply communications, which normally may represent a bottleneck for any parallel application. Fig. 3 shows an example of this kind of partitioning. The image is divided into five horizontal and five vertical sub images. This partitioning scheme makes easy to collect the final results, allowing to load-balance the process. Once again, this partitioning scheme can be generalized for any number of sub images.

III A HYBRID FILTER

Hessian-based filters can enhance vessels of various size and estimate their directions at the same time. However, Hessian-based filters can not distinguish step edges from vessels effectively. Matched filters can distinguish step edges from vessels more effectively. Matched filters are normally applied at multiple scales, whereas at each scale multiple kernels are used to enhance vessels in different directions. Consequently, the computational cost of matched filters is higher than that of Hessian-based filters. To solve the problem of false detection of edges, Sofka [13] proposed using the edge information at the boundary of vessels. A vessel should have two edges on each side of it which can be used to effectively distinguish between vessels and edges in the image. The proposed enhancement filter combines the advantages of Hessian based filters, matched filters, and edge information. The proposed filter is parametric and is simple to implement. We assume that vessels in retinal images have the following three properties: the profile in the cross section is Gaussian, the intensity changes little along the center line of vessels, and there are two edges at the boundary of vessels. Similar to Hessian-based filters, we compute the Hessian matrix at each pixel of the image on multiple scales by convolving the image with Gaussian kernels of multiple sizes

IV RIDGE-BASED VESSEL SEGMENTATION

A method is presented for automated segmentation of vessels in two-dimensional color images of the retina. This method can be used in computer analyses of retinal images, e.g., in automated screening for diabetic retinopathy. Since image ridges are natural indicators of vessels, we start our analysis with a short overview of ridge detection for two-dimensional gray value images. For a more extensive discussion on this subject, see [15] and [26]. The ridge detection method used in this paper is described in full detail in [16]. Because the green channel of color fundus images formatted as an RGB image gives the highest contrast between vessel and background [1], this channel is used for extraction of the image ridges. The next step in forming primitives for the vessels is a grouping of ridge pixels which belong to the same ridge. The aim is to obtain primitives which represent approximately straight line elements. The grouping method is a simple region growing algorithm which compares an already grouped ridge pixel with ungrouped pixels in a neighbourhood of radius r , where the subscript c stands for connectivity. If no grouped pixel is available, a new one is selected randomly as seed from the remaining ungrouped ridge pixels. The comparison between the grouped and a candidate pixel within the neighbourhood is based on two conditions: 1) The eigenvector directions of the ridge pixels should be similar and 2) If condition 1) is met, the pixels should be on the same ridge (and not on parallel ridges). The first condition can be checked by

taking the scalar product of the eigenvectors at the location of the pixels. If the pixels have similar orientation the scalar product will be close to 1. The second condition can be checked by computing the unit-length normalized vector between the locations of the two pixels under consideration and taking the vector product between and of the grouped pixel. If the pixels are on the same segment, the vector product will be close to 1. The goal of this work is to classify every pixel in an image as vessel or nonvessel. For this purpose labelled examples or training sets, features and a classifier are needed. From the training sets feature vectors are constructed that can be labelled as vessel or nonvessel, so every feature vector belongs to one of two classes. The idea is that feature vectors from a particular class cluster together in the feature space and that a classifier can be designed that determines a decision boundary between the different classes. After the training, a nonlabelled feature vector can be classified by determining on which side of the decision boundary it is situated. With some classifiers it is possible to approximate the chance, given the features, that a pixel is vessel or not. This is called soft classification [17]

V METHODS BASED ON ARTIFICIAL INTELLIGENCE

Artificial Intelligence-based approaches utilize knowledge to guide the segmentation process and to delineate vessel structures. Different types of knowledge are employed in different systems from various sources. One knowledge source is the properties of the image acquisition technique, such as cine-angiography, digital subtraction angiography (DSA), computer tomography (CT), magnetic resonance imaging (MRI), and magnetic resonance angiography (MRA). Some applications utilize a general blood vessel model as a knowledge source. Smets et al [14] encode general knowledge about appearance of blood vessels in the form of 11 rules (e.g. that vessels have high intensity centre lines, comprise high intensity regions bordered by parallel edges etc.). The work of Stansfield [7] applies a domain-dependent knowledge of anatomy to interpret cardiac angiograms in the high-level stages. According to Stansfield, "Anatomical knowledge is embodied within the system in the form of spatial relations between objects and the expected characteristics of the objects themselves. Knowledge-based systems exploit a priori knowledge of the anatomical structure. These systems employ some low-level image processing algorithms, such as thresholding, thinning, and linking, while guiding the segmentation process using high-level knowledge. Artificial Intelligence-based methods perform well in term of accuracy, but the computational complexity is much larger than some other methods. Rost et al [14] describe their knowledge-based system, called SOLUTION (Solution for a Learning Configuration System for Image Processing), designed to automatically adopt low-level image processing algorithms to the needs of the application. It aims to overcome the problem of extensive change requirement in the existing system to perform in a different environment. The system accepts task descriptions in high-level natural spoken terms and configures the appropriate sequence of image processing operators by using expert knowledge formulated explicitly by rules. In the present implementation, extraction process is limited to contours. Smets et al [7] present a knowledge-based system for the delineation of blood vessels on subtracted angiograms. The system encodes general knowledge about appearance of blood vessels in these images in the form of 11 rules (e.g. that

vessels have high intensity centre lines, comprise high intensity regions bordered by parallel edges etc.). These rules facilitate the formulation of a 4-level hierarchy (pixels, centre lines, bars, segments) each of which is derived from the preceding level by a subset of the 11 rules. The main stages in the algorithm are: First, obtain the centre lines of the vessels by an adaptive maximum intensity detector. Second, apply thresholding, thinning, and linking operations to get the final centre lines segments. Third, construct bar-like primitives using region growing algorithm on the center lines detected. Finally, combine bar-like structures into blood vessel segments using geometrical and topological knowledge of the blood vessels. They show results of their system that indicate that the system is successful where the image contains high contrast between the vessel and the background, and that the system has considerable problems at vessel bifurcations and self-occlusions. Stansfield [6] describes a rule-based expert system, called ANGY, to segment coronary vessels from digital subtracted angiograms. There are three main stages in the ANGY system: a pre-processing stage which contains low-level image processing routines written in C and a rule-based expert system with two stages: a low-level image processing stage and a high-level medical stage. The former stage embodies domain-independent knowledge of segmentation, grouping, and shape analysis while the latter stage embodies a domain-dependent knowledge of cardiac anatomy and physiology. The system extracts vessel segments as trapezoidal units using an OPS5 production system. The rule set is used to determine which edge segments may participate the formation of these trapezoidal strips and which segments arise from image noise. The system does not combine these units to form an extended vascular structure. Goldbaum et al [2] describe their STARE (Structural Analysis of the Retina) image management system for the automatic diagnosis and analysis of the retinal images. Their system is designed to automatically diagnose images, compare sequential images to find the changes, extract and measure key objects, and find images that have similar features from large databases. The 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 inferencing about the image content is accomplished with Bayesian network which learns from sample images of the diseases. Due to the rotated matched filters used in the segmentation process, this work can also be classified.

VI CONCLUSION AND FUTURE WORK

Vessel segmentation methods have been a heavily researched area in recent years. Segmentation algorithms form the essence of medical image applications such as radiological diagnostic systems, multimodal image registration, creating anatomical atlases, visualization surgery. Even though many promising techniques and algorithms have been developed, it is still an open area for more research. The future direction of segmentation research will be towards developing faster, more accurate, and more automated techniques. Accuracy of the segmentation technique is a crucial criteria due to the nature

of the work. Accuracy of the segmentation process is essential to achieve more precise and repeatable radiological diagnostic systems. Accuracy can be improved by incorporating a priori information on vessel anatomy and let high level knowledge guide the segmentation algorithm this paper provides a survey of current vessel segmentation methods. We have tried to cover both early and recent all literature related to vessel segmentation algorithms and techniques. Our aim was to introduce the current segmentation techniques. This paper is intended to give the practitioner a framework for the existing research and to introduce interested parties to the panoply of vessel segmentation literature.

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