

## Automated Detection Algorithm for Arteriolar Narrowing on Fundus Images

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**Abstract**—We have developed a computer-aided diagnosis system (CAD) to detect abnormalities in fundus images. In Japan, ophthalmologists usually detect hypertensive changes by identifying arteriolar narrowing and focal arteriolar narrowing. The purpose of this study is to develop an automated method for detecting arteriolar narrowing and focal arteriolar narrowing on fundus images. The blood vessel candidates were detected by the density analysis method. In blood vessel tracking, a local detection function was used to determine the centerline of the blood vessel. A direction comparison function using three vectors was designed to optimally estimate the next possible location of a blood vessel. After the connectivity of vessel segments was adjusted based on the recognized intersections, the true tree-like structure of the blood vessels was established. The blood vessels were recognized as arteries or veins by hue of HSV color space and their diameters. The arteriolar narrowing was detected by the ratio of diameters (artery vs. vein; A/V ratio). Focal arteriolar narrowing was detected by measuring the diameter of an artery. By applying this method to 100 fundus images, the detection sensitivity for arteriolar narrowing was found to be 76% when the specificity was 91%. Furthermore, by applying this method to 70 other different fundus images, the detection sensitivity for the focal arteriolar narrowing was 75% with 2.9 false positives per image. The number of some false positives is planned to be reduced during the next stage of development. Such an automated detection of abnormal vessels could help ophthalmologists in diagnosing ocular diseases.

### I. INTRODUCTION

The number of patients suffering from adult diseases such as cardiac and cerebrovascular diseases is currently on a rise in our country. To prevent or detect these diseases at an early stage, ophthalmologists rely on fundus images or direct ophthalmoscopy during complete health examinations or mass screenings. In recent times, ophthalmoscopy has been the third most frequently employed method in health

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examinations after sphygmomanometry and electrocardiography. Typically, ophthalmologists in Japan visually observe fundus images while diagnosing hypertension. Ophthalmoscopy is expected to be the most frequently used technique in the future. Frequent use of this technique, however, may impose a heavy burden on ophthalmologists. Therefore, several research groups have made efforts in developing their own computer-aided diagnosis (CAD) systems based on fundus images [1-7].

In our country, ophthalmologists usually evaluate hypertensive retinopathy and arteriolosclerosis based on Scheie's classification; Grades I to IV denote the severity of these conditions. In most cases, ophthalmologists diagnose these diseases by observing the condition of vessels. However, this method does not permit quantitative determination. Therefore, the objective of this study is to develop an automatic analysis method for detecting the distribution and geometries of blood vessels on fundus images.

Recently, several studies on a CAD system for analyzing fundus images have been reported [1-7]. Tolia et al. presented a method for detecting blood vessels [1]. Their fuzzy algorithm for vessel tracking was applied to the detection of ocular fundus vessels. Their main tool identifies vessel and non-vessel regions along a vessel profile if the fuzzy c-means clustering algorithm is fed with properly pre-processed data. Zana et al. presented an algorithm based on point correspondence for the temporal and/or multimodal registration of fundus images [2]. This technique uses the Hough Transform to analyze the furcations. Chaudhuri et al. presented a different method for detecting blood vessels [3]. They developed 12 different templates intended for use in searching vessel segments in all possible directions. Can et al. presented an algorithm for vessel tracking and feature extraction from fundus images [4]. Their algorithm can track vessels using a set of two-dimensional correlation kernels that act as low-pass differentiators; these kernels are perpendicular to the direction of the vessels and to the low-pass averaging filters along the vessels. Sakuma et al. presented a method for correcting colors and detecting any changes based on the values for differences in sequential ocular fundus images [5]. The method we propose detects vessel furcations [6]. Our algorithm extracts vessels through a double-ring filter. This filter enables us to extract the vessels with main focus on the irregularity; it eliminates the effect of vessel narrowing. We also propose an automated method for

detecting retinal hemorrhage and exudates in fundus images [7]. No results have so far been obtained on the method for detecting abnormal blood vessels having arteriolar narrowing and focal arteriolar narrowing. Therefore, to automate the Scheie's classification process, we have designed our study to develop an automated method for detecting abnormal vessels on fundus images.

## II. METHOD

### A. Overall scheme

Our detection scheme including the new technique consists of the following 7-step procedure: (1) Image digitization (1,600 dots per inch (dpi) and 24-bit color resolution), (2) pre-processing, (3) extraction of optic disks, (4) extraction of vessels, (5) tracking of vascular trees, (6) recognition of arteries and veins, (7) measurement of vessel diameters, and (8) detection of abnormal vessels.

### B. Image digitization, pre-processing of fundus images, and detection of optic disks

The fundus images were captured on a 35-mm positive film and digitized using the EPSON ES2000—a flatbed-type scanner with a transmissive unit. The resolution of the digitized 24-bit color images was  $1,600 \times 1,600$  pixels in the bitmap format. For better processing efficiency, the scale of the matrix was initially reduced to  $800 \times 800$  pixels by taking detailed sub samples of the original image data.

Next, the color images were converted to greyscale using only the green component; this helped in achieving a clearer contrast in comparison with the original ones that were represented using all color components (Fig. 1 (a)). Following this, as the optic disk was highlighted at a higher brightness than that used for highlighting other tissues, it was extracted by the p-tile technique, and the optic disk was eliminated from the greyscale image.

### C. Extraction of vessels

The blood vessel candidates were extracted by the threshold technique using a double-ring filter as shown in Fig. 2 [6]. Regions A and B have diameters of 3 pixels and 7 pixels, respectively. The feature value was calculated from the difference in the average value of pixels between regions A and B. The threshold for the feature value was experimentally set to 5. The fundus image is shown in Fig. 1 (a), and an example of vessel extraction is shown in Fig. 1 (b).

### D. Vascular tree tracking

In this step, the main vessels to be observed were detected by tracking the vessel candidates extending from the optic disk as shown in Fig. 3. First, the centerlines of the vessels were extracted using the thinning algorithm. Next, the extracted vessels were tracked along their centerlines extending from the optic disk. The blood vessels have several branches and furcations, which are determined by the number of neighboring

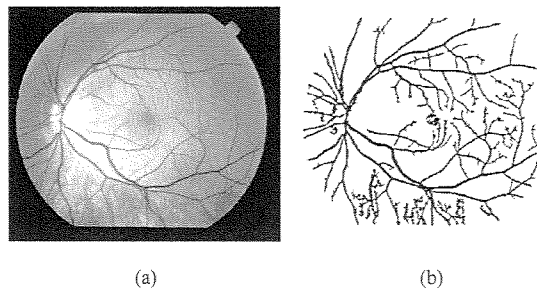


Fig. 1 An example of vessel extraction. (a) An original retinal image. (b) Black lines indicate vessels extracted using a double-ring filter.

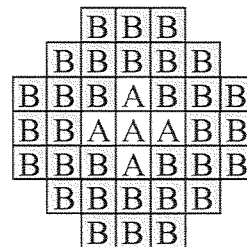


Fig. 2 A double-ring filter for extracting vessels.

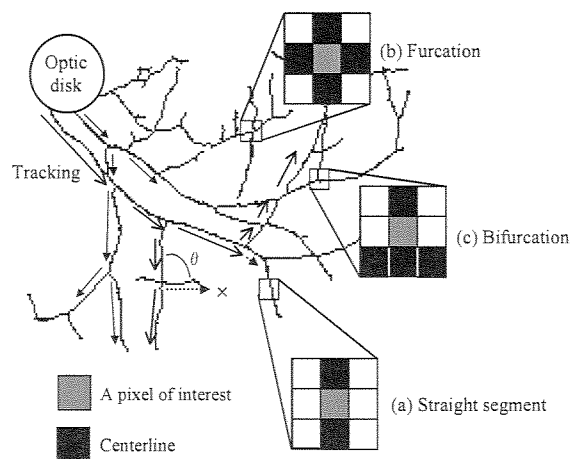


Fig. 3 Determination of furcations and branches. (a) Straight segment. (b) Furcation point. (c) Bifurcation.

pixels. A point with two neighboring pixels was defined as one of the elements of a straight line as shown in Fig. 3 (a); one with three neighboring pixels was defined as a bifurcation as shown in Fig. 3 (c); and one with four neighboring pixels was defined as a furcation as shown in Fig. 3 (b).

In the next step, the direction of a vector was determined by measuring the angle formed between a bifurcation point and a furcation. An example of vector tracking is shown in Fig. 3. Using our method, it was possible to track the vector if the internal angle of each branch was greater than 90 degrees. Since the internal angle ( $\theta$  in Fig. 3) was lesser than 90 degrees, the vessel was not tracked.

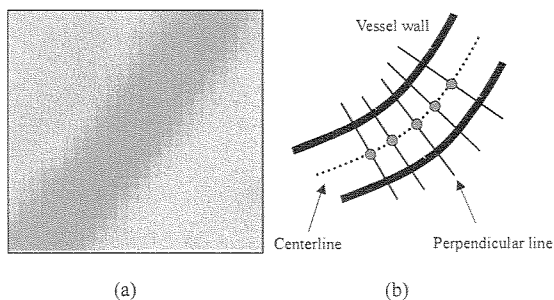


Fig 4 (a) The retinal region of interest (ROI) on a gray image. (b) Measuring vessel width. The bold black lines indicate vessel walls, the black dashed line indicates the centerline of the vessel, and the black lines are perpendicular lines.

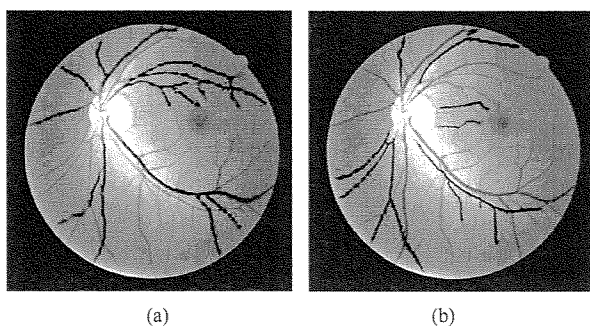


Fig. 5 (a) The result of detecting veins. (b) The result of detecting arteries

#### E. Measurement of vessel diameters

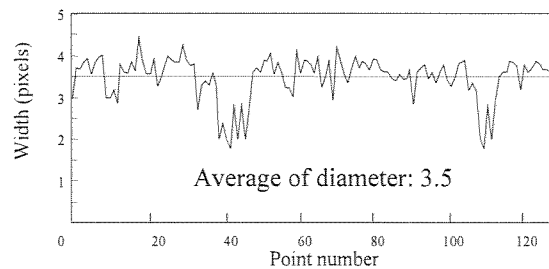
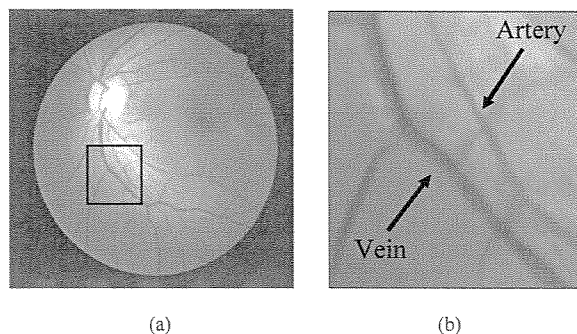
Fig. 4 shows the manner in which measurement of vessel diameter was performed. First, the straight line was perpendicular using two neighboring pixels on the centerline. In the second step, a perpendicular line was determined using the perpendicular line of the centerline (Fig. 4 (b)). In the third step, the vessel walls were determined by the zero-crossing method. It is well known that the zero-crossing method is effective in detecting the edges. Finally, the vessel diameter was measured based on the distance between the vessel walls from the approximated line.

#### F. Recognition of arteries and veins

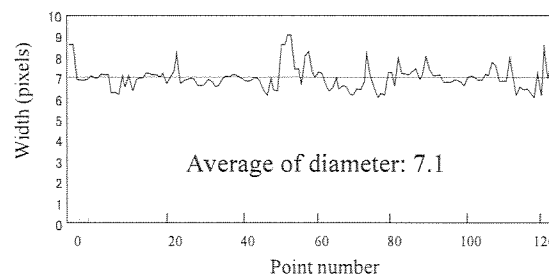
Initially, only the veins were extracted using the diameter of blood vessels and the hue angle value. The diameter and the hue angle value for veins were found to be greater when compared with that of arteries, and the veins were extracted from the blood vessels detected on the image. Next, the blood vessels that remained after extraction of veins were considered as arteries. The example in Fig. 5 shows the result of detecting veins and arteries.

#### G. Detection of arteriolar narrowing

In this step, the average vessel diameter of each branch was calculated, and the A/V (artery vs. vein) ratio was calculated. A case was considered as abnormal if the A/V ratio was less than 0.5. An example of vessel diameter measurement is shown in Fig. 6. Since the A/V ratio is 0.49, this case is considered as



(c) Diameter of artery



(d) Diameter of vein

Fig. 6 This case is abnormal because the A/V (artery vs vein) ratio is 0.49. (a) This image shows arteriolar narrowing. (b) The enlarged image of a rectangular region shown in (a). (c) The graph shows the diameter of the artery shown in (b). (d) The graph shows the diameter of the vein shown in (b).

abnormal.

#### H. Detection of focal arteriolar narrowing

In this final step, the average vessel diameter of each branch was calculated. The vessels were regarded as abnormal if their diameters in any section were narrower than two thirds of the average diameter. An example of vessel diameter measurement is shown in Fig. 7. If the diameter of the vessel was less than two thirds of the average diameter in a certain segment, the vessel including the narrow segment was regarded as abnormal.

### III. RESULTS AND DISCUSSION

To evaluate our method for detecting arteriolar narrowing, we examined 100 fundus images; among these, 96 abnormal blood vessels were detected in 50 images and no abnormal blood vessels were detected in the remaining 50 images. On comparing the results obtained by our method with the

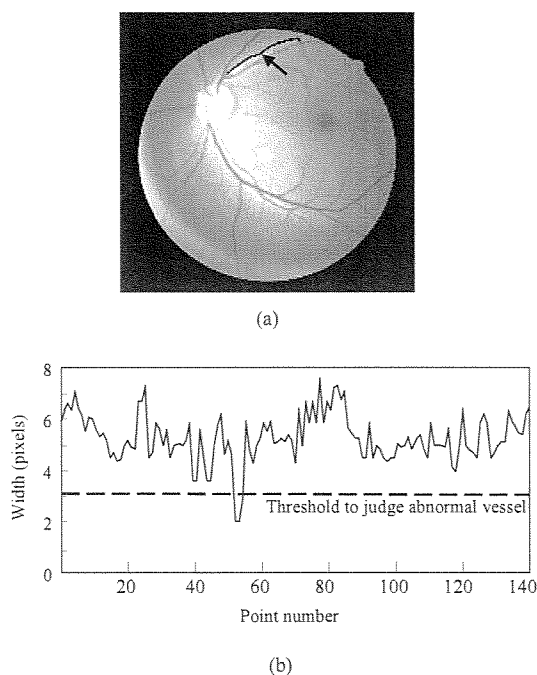


Fig. 7 (a) The detected focal arteriolar narrowing segment indicated by a black arrow on a fundus image. (b) This graph shows the diameter of the vessel segment.

diagnostic results obtained by physicians, it was demonstrated that our computerized method automatically detected the presence of any irregularity. Abnormalities were detected in 76% of the 72 abnormal blood vessels. Of the 790 blood vessels studied, 715 vessels were found to be normal.

To evaluate our method for detecting focal arteriolar narrowing, we examined 70 fundus images; among these, abnormal blood vessels were detected in 24 images. In all 24 abnormal cases, focal arteriolar narrowing was observed, and no abnormal cases were detected in the remaining 46 images. Among the 24 abnormal main blood vessels, abnormalities were detected in 75% (18 abnormal blood vessels) whereas they were not detected in the remaining 25% (6 abnormal vessels). Approximately 2.9 normal vessel segments per image were found to be abnormal.

The analysis of blood vessels on fundus images is significant for detecting abnormalities. Our scheme focuses on recognizing the complete blood vessel structure instead of partial vessel segments. Such a scheme will provide the basis for an accurate quantitative analysis of the geometric features of blood vessels.

However, we also encountered some problems in the course of testing the scheme. Some vessel segments appeared broken after the density analysis. This might adversely affect vascular tree tracking. In addition, some vessel paths were too close to each other. This could lead to errors in vascular diameter measurements. Most erroneous measurements of vessel diameters occurred in the arteries; therefore, a technique for identifying arteries and veins that is capable of

reducing errors needs to be developed.

Our system detected abnormal vessels on fundus images. Moreover, it highlighted the possibility that ophthalmologists could diagnose adult diseases at a higher sensitivity by fully utilizing image data output from a computer.

#### IV. CONCLUSION

In this study, we presented a new scheme for an automated blood vessel analysis using digitized fundus images. The results obtained from the preliminary work performed on 170 fundus images have clarified that the efficiency and accuracy of blood vessel diagnosis has considerably improved. The efficiency and accuracy of abnormal blood vessel diagnosis was improved by the recognition of vascular geometries and distributions with higher accuracy. At present, we are making an effort to modify the scheme to minimize the problems that have been previously mentioned in the discussion section. In the future, the integrated analysis scheme will be further improved, and more clinical cases will be included in the study to evaluate its accuracy. The techniques employed in our system will help in improving diagnostic accuracy as well as in reducing the workload of ophthalmologists in the future.

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