

TOWARDS UNDERSTANDING COLOR OCULAR FUNDUS IMAGES

Koichiro Akita

Hideki Kuga

Central Research Laboratory
Mitsubishi Electric Corporation
80 Nakano, Minamishimizu,
Amagasaki, Japan 661

We have studied some fundamental problems on the way of understanding color ocular fundus images by computer. They are the extraction of blood vessels from the retinal background and labeling them arteries and veins. We analyze the chromatic characteristics of color ocular fundus images to get the signal level knowledge on them which is used in the stages of extracting blood vessels and most reliable labeling of initial line segments. We propose a dynamic threshold selection scheme for binarization of gray images that have an amount of shadings or unevenness of gray values. In the labeling stage we use a deterministic procedure which takes into account the physical level knowledge on blood vessels. Some other methods are also discussed.

1. INTRODUCTION

Color ocular fundus images are used in the mass diagnosis of adult diseases such as hypertension and diabetes. Since the photographing system of them is simple and cheap, if the automatic understanding system of them is realized, the mass health management by them together with chest X-ray images will be much more popularized. There are a few examples of computer analysis of ocular fundus images [1],[2],[3],[4],[5].

For color ocular fundus photographs, as far as we know, there has been only one example of computer analysis. It is the pattern recognition of color fundus images by Yokouchi et al. [4],[5]. They investigated the possibility of automatic diagnosis of arterio-venous crossing phenomena. But their method is interactive in the sense that they indicate the cross points manually before the computer analysis. The change of venous caliber before and after its crossing was measured along its course and the minimum value of each normalized caliber measurement was utilized to grade the crossing signs. The researches mentioned above stay in the phase of analysis. The objective of our research is the understanding

of color ocular fundus images by computer, which is inevitable for the automatic mass diagnosis of hypertension and diabetes. The theme in this paper is to locate blood vessels and identify arteries and veins automatically. This process is fundamental for the analyses of not only arterio-venous crossing phenomena but also other symptoms of adult diseases [9].

We have to make clear the levels of knowledge [10] that can be used in each stage of the process.

For the first step we analyze the chromatic characteristics of color ocular fundus images. We get the signal level knowledge on them which is utilized in the stages of extracting blood vessels and most reliable labeling of initial line segments.

We propose a dynamic thresholding scheme for the extraction of blood vessels. It is very effective against images which have shadings or unevenness of light intensities. Thirdly a deterministic labeling algorithm of blood vessels is proposed in which the physical level knowledge on them is implemented. The labels of some vessel segments from which the labeling starts are determined by the signal level knowledge and some positional constraints.

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2. CHARACTERISTICS OF COLOR FUNDUS IMAGES

The first step of understanding color ocular fundus images is the analysis of their photographic and chromatic properties. They are taken on the 35 mm color reversal films by the fundus camera. It requires some skill to take the fundus photos of good quality. Since the state of fundus is individually different, they have some variation of color tone. More specifically, there are two main causes of the variation--the photographic system and the individual. The former involves the spectral characteristics of color films, the condition of photo processing, the optical property of the fundus camera and the amount of light. It is comparatively easy to prescribe these conditions and they do not have so much influence on changing color tone. The latter comes from the age, the size of pupil and other conditions of a person [1]. It changes color tone of photos remarkably. Therefore, it is very important to select parameters that are not influenced by each photograph, in other words we should use relative (not absolute) color information.

2-1. Digitization of Film Images

In our experiment we used a high-speed drum scanner which had the Wratten No.25, No. 47B, and No.58 filters for tricolor decomposition. The photo density was quantized to 256 levels.

The color fundus images on films were scanned by the drum scanner with the sampling pitch of 50 μ m, and digitized to 256 x 256 pixels (i.e. 12.8mm x 12.8mm on film).

2-2. Chromatic Analysis of Digitized Fundus Images

A fundus image consists of four portions; Retina, Disc, Artery, and Vein. We plotted the chromatic information of the digitized data in the sample areas of each portion onto the UCS color coordinate system (u, v, V).

The distribution in u-v plane shows that it is parallel to the u-axis, which means the chromatic information of this sample fundus image is approximately represented by the u-coordinate. Furthermore the distribution of retina is roughly separated from that of blood vessels. But the distributions of artery and vein can't be distinguished.

From the distribution of those data in V-u coordinates we see that arteries can't be

completely separated from veins also in this case.

Certainly some confirmed artery or vein pixels are determined by (u, v, V) values.

The analysis tells us that the labeling of blood vessels requires not only signal level knowledge mentioned above, but also physical level knowledge which will be introduced in section 4.

3. A DYNAMIC THRESHOLD SELECTION FOR EXTRACTING BLOOD VESSELS

The extraction or distinction of blood vessels from the retinal background is a milestone of understanding fundus images.

Color ocular fundus images contain an amount of shading or unevenness of light intensity. So the ordinary global threshold selection methods fail to extract blood vessels. Dynamic threshold selection schemes are desirable in such circumstances. Chow and Kaneko's method [6] is a well-known one which has been applied to the extraction of blood vessels in fluorescence fundus images with some modification by some researchers [3] with fairly good results.

The contrasts of fluorescence fundus images are much higher than those of color fundus images. The shortcomings of this method when applied to the extraction of low contrast blood vessels are as follows. The thresholds of all subimages cannot necessarily be obtained and the distribution of them is non-uniform in the image because of the irregular pattern of blood vessels. Therefore, the error of interpolating the threshold at each pixel is often bigger than the contrast between blood vessels and the retinal background, resulting in noisy binary images. We abandoned applying Chow and Kaneko's method to color fundus images because of their low contrasts and unevenness of light intensity. We have developed our own method.

3-1. A Dynamic Threshold Selection Scheme

The gray image is splitted into a set of blocks (subimages) as in the case of Chow and Kaneko's method to eliminate the influence of shading. In each block it is examined whether the boundary of blood vessels and the background is included or not by taking the derivative and binarizing it with variable thresholds. When boundaries are detected in a block, the histogram of pixels only around boundaries is made to determine the threshold for this block. If a block does not include any boundary, It is

classified into the background. The size of a block which is given in advance is large enough to contain full width of a vein or an artery. The flow of this scheme is the following.

- (1) Split the image into N blocks. For each block, do the next steps.
- (2) Apply the Laplacian operator to the block. The result will be called the Laplacian subimage.
- (3) Binarize the Laplacian subimage by varying the threshold and check whether there is a connected component whose size satisfies some conditions. If not, then set the flag of this block to 0 representing that it belongs to the background. If it exists, the flag is set to 1 showing that this block includes some parts of vessels.
- (4) For each block whose flag is equal to 1, the histogram of pixels only around boundaries is made to determine the threshold by Otsu's method [7] and the block is binarized. In the binary block the size of each connected component is measured and if it is less than a given value, the component is eliminated as a noise.

We should add some words on step (3). When the Laplacian subimage is binarized, the threshold is decremented first from the given upper value until the size of maximum connected component satisfies a certain condition. If any line segment which corresponds to a part of a boundary exists, then the threshold is incremented next from the given lower value until the size of maximum connected component satisfies another condition. This procedure is important in order not to miss low contrast boundaries which also exist in the block.

For the conditions mentioned above we can set some constraints on the size and the shape of the extracted boundary in the subimage.

4. LABELING BLOOD VESSELS

The second stage of fundus image understanding is the labeling of blood vessels. There are two kind of vessels; arteries and veins. Our aim here is to locate them, which leads to the detection of crossing points and to the measurement of arterio-venous crossing phenomena such as tapering, banking, Salus' sign, S-shaped bend and parallel-Gunn [9].

The physical level knowledge on blood vessels that can be used at this stage is as

follows.

- (i) Arteries (Veins) do not intersect each other. In other words arteries (veins) intersect only veins (arteries).
- (ii) Arteries (Veins) branch off only from arteries (veins).

In order to use this knowledge positively we have adopted the following procedure for locating arteries and veins.

- (1) Make the thinned image from the binary vessel image.
- (2) Detect characteristic points in the thinned image and make the line segments list.
- (3) Label each line segment, namely determine whether it is a part of an artery or a vein.

4-1. Skeleton Patterns of Binary Blood Vessels

The state of blood vessels such as branching, crossing and meandering is simply represented by that of their medial axes or skeletons. The direct results of thinning binary blood vessel images contain small circles, isolated points and prickles that act as noises. We first eliminate them and start with thinned images. In order to analyze blood vessel networks we detect characteristic points and list up line segments. We define three kinds of characteristic points: end point, branch point and cross point. A line segment is defined as a segment of medial axis whose head and tail are characteristic points. Therefore, there are nine situations of a line segment. Several parameters on a characteristic point and a line segment are measured and are written into the characteristic points list (CP-LIST) and the line segments list (LS-LIST), respectively. These lists are very useful to activate the physical level knowledge mentioned above.

* Characteristic Points List (CP-LIST)

It includes several parameters of each characteristic point. They are the (x, y) coordinate, the characteristic index which represents whether the point is an end Pt. or a branch Pt. or a cross Pt., the numbers of the line segments which meet at this point, and so forth.

* Line Segments List (LS-LIST)

The parameters of each line segment in the LS-LIST are the characteristic point numbers of the head Pt. and the tail Pt., the length, the directions of this line segment at the head Pt. and the tail Pt., the chain code and others.

4-2. Labeling Algorithm

The goal of labeling is to decide that each line segment belongs to an artery or a vein or the retinal background. The labeling starts with some line segments that have most reliable initial labels determined by the signal level knowledge.

4-2-1. Initial Labeling

The gray values of arteries are smaller than those of veins in a broad sense. If we limit the area in the V-image and set two thresholds θ_L , θ_U in the gray levels, we can expect with certainty that the pixels whose gray values are less than θ_L belong to arteries and the pixels whose gray values are greater than θ_U belong to veins. θ_U and θ_L may be settled by some clustering approaches. The most reliable line segments with which the labeling starts are determined as follows. On every line segment of the skeleton pattern in the certain limited area the number of pixels with a certain label (or no label) is counted and divided by the line length. There are three ratios, P_A , P_V , and P_N which represent the probabilities that the line segment is a part of artery, vein and unknown, respectively. Hence $P_A + P_V + P_N = 1.0$. If a line segment has the probability of P_A or P_V higher than a given value, it is chosen as one of the most reliable line segments.

4-2-2. Labeling Procedure

The labeling starts from the line segments which have the most reliable initial labels. If a non-labeled line segment is connected to other labeled line segments, it will be labeled as follows using the physical level knowledge mentioned before. The procedure also takes into account the natural directions of blood streams.

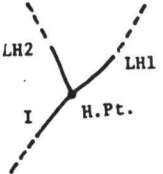
Since the full program structure of the procedure is lengthy to be described here, only the essence of it is presented.

At the head point (H.Pt.) and the tail point (T.Pt.) of a non-labeled and non-isolated

line segment I, the next steps are taken.

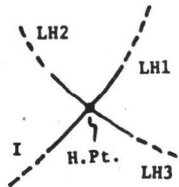
- 1) When the H.Pt. is a branching Pt., let the other two line segments be LH1 and LH2.

- ① Label(LH1) = Label(LH2)
= C $\neq$ 0
→ Label(I) = C, go to 3).
- ② Label(LH1) $\neq$ 0,
Label(LH2) $\neq$ 0 and
Label(LH1) $\neq$ Label(LH2)
→ Select the line segment whose angle between I is nearest to 180° and call it LH1. Let Label(I) = Label(LH1), and Conflict-Flag(I) is incremented by one. Go to 3).
- ③ Label(LH1) $\neq$ 0 or Label(LH2) $\neq$ 0
→ Label(I) = Label(LH1) or Label(LH2), go to 3).
- ④ Otherwise, go to 3).



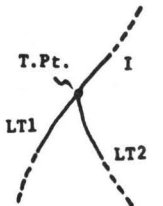
- 2) When the H.Pt. is a crossing Pt., let the other three line segments be LH1, LH2 and LH3.

- ① Choose the line segment whose angle between I is nearest to 180° and call it LH1. If Label(LH1) $\neq$ 0, then let Label(I) = Label(LH1) and go to 3). Otherwise do the next steps.
- ② Label(LH2) = Label(LH3) = artery (vein)
→ Label(I) = vein (artery), go to 3).
Label(LH2) $\neq$ 0, Label(LH3) $\neq$ 0 and
Label(LH2) $\neq$ Label(LH3)
→ Conflict Flag(I) is incremented by one and no label is given to I. Go to 3).
- ③ Label(LH2) = artery (vein) or Label(LH3) = artery (vein)
→ Label(I) = vein (artery), go to 3).
- ④ Otherwise go to 3).



- 3) When the T.Pt. is a branching Pt., let the other two line segments be LT1 and LT2.

- ① Label(LT1) = Label(LT2)
= C $\neq$ 0
→ If Label(I) = 0, then let Label(I) = C.
If Label(I) $\neq$ 0 and
Label(I) $\neq$ C, Conflict Flag(I) is incremented. Exit.
- ② Label(LT1) $\neq$ 0, Label(LT2) $\neq$ 0 and Label(LT1) $\neq$ Label(LT2)
→ If Label(I) = 0, then choose the line



segment whose angle between I is nearest to 180° and call it LT1. Label(I) = Label(LT1). Exit.

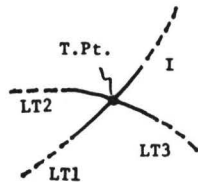
If Label(I) $\neq$ 0, increment Conflict Flag(I) by one and exit.

- ③ Label(LT1) $\neq$ 0 or Label(LT2) $\neq$ 0
 → If Label(I) = 0, then let Label(I) = Label(LT1) or Label(LT2), and exit.
 If Label(I) $\neq$ 0 and $\neq$ Label(LT1) and $\neq$ Label(LT2), increment Conflict Flag(I) by one and exit.

- ④ Otherwise, exit.

- 4) When the T.Pt. is a crossing Pt., let the other three line segments be LT1, LT2, and LT3.

- ① Choose the line segment whose angle between I is nearest to 180° and call it LT1.
 If Label(LT1) $\neq$ 0, and Label(I) = 0, then Label(I) = Label(LT1) and exit.
 If Label(LT1) $\neq$ 0 and Label(I) $\neq$ 0 and $\neq$ Label(LT1), increment Conflict Flag(I) by one and exit. Otherwise do the next steps.
- ② Label(LT2) = Label(LT3) = artery (vein)
 → If Label(I) = 0, then let Label(I) = vein (artery).
 If Label(I) = artery (vein), increment Conflict Flag by one. Exit.
- ③ Label(LT2) $\neq$ 0, Label(LT3) $\neq$ 0 and Label(LT2) $\neq$ Label(LT3)
 → Increment Conflict Flag(I) by one and exit.
- ④ Label(LT2) = artery (vein) or Label(LT3) = artery (vein)
 → If Label(I) = 0, then let Label(I) = vein (artery).
 If Label(I) $\neq$ 0 and Label(I) = artery (vein), increment Conflict Flag by one. Exit.



The labeling procedure terminates when the number of non-labeled line segments does not decrease anymore by iteration.

The isolated line segments which have no reliable initial labels are left to be non-labeled. They need another analysis. The conflicts are caused by artifactitious line segments or by disappearance of true blood vessel line segments. Since the binary blood vessels before thinning have widths at cross points, artifacts are made after thinning. In other words a cross point before thinning is splitted into two branch points after thinning.

Another example of artifacts is a bridge caused by noise. The disappearance of a true vessel line segment has the same effect as a bridge. We need more details of the image in order to distinguish the disappearance from noise. From this analysis we know that the conflict flag gives us very important information on crossings, noises and disappearance of true vessel segments.

Another useful physical level knowledge which was not taken into account in our experiment is that there should be no isolated blood vessel pieces except concealments. This tells us that the interpolation of line segments could be done before labeling.

5. DISCUSSION

Here we consider some additional methods that might be useful for our problems.

- 1) On the extraction of blood vessels:

Another approach is to apply line detection or ridge following algorithms which are often used to find linear features in LANDSAT images. We have applied one of them to our case and got some promising results.

- 2) On the labeling of blood vessels:

The relaxation labeling [8] might be applied to our case. Since the pixelwise relaxation spends a great amount of time, we should use it in the stage of line segment labeling. We have to define neighbor relationships of line segments, compatibility functions, and weights. The arithmetic updating rule may be used.

- 3) From the view point of diagnosis:

In case of the analysis of arterial-venous crossing phenomena, some specified retinal areas are inspected. The area around the fovea which includes only very thin vessels and the area within some radius of the disc are outside the inspection. This will go a long way in overcoming the difficulty of noise elimination.

On the other hand there are important phenomena on arteries which might be neglected or erased by careless noise elimination. They are light streaks on arteries (copper wire arteries) which serves much for the diagnosis of arteriosclerosis but often acts as obstacles to labeling. This problem was not dealt with in our experiment.

6. CONCLUSIONS

The difficulty of understanding color fundus images lies on the fact that the image qualities are not so good as those of other medical images and the variety of colors and blood vessel shapes is very large. There is still a long distance to get the full automatic understanding of color ocular fundus images. We did not discuss the automatic diagnosis of arterio-venous crossing phenomena. In that process we will have to implement semantic level knowledge on symptoms of them into diagnostic algorithms.

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An example of color ocular fundus image

left : u-component
right: V-component