Automatic Retinal Vessel Tortuosity Measurement using Curvature of Improved Chain Code

Danu Onkaew1, Rashmi Turior1, Bunyarit Uyyanonvara1
School of Information, Computer and Communication Technology
Sririndhorn International Institute of Technology, Thammasat University
Pathum Thani, Thailand
Email: {danu.onkaew,rashmi.turior,bunyarit}@siit.tu.ac.th

Nishihara Akinori2
The Center for Research and Development of Educational Technology
W9-108, 2-12-1 Ookayama, Meguro-ku, Tokyo, 152-8550, Japan
Email: aki@cradle.titech.ac.jp

Chanjira Sinthanayothin3
National Electronics and Computer Technology Center
112 Thailand Science Park, Phahon Yothin Rd., Klong I, Klong Luang,
Pathumthani, Thailand
Email: chanjira.sinthanayothin@nectec.or.th

Abstract—Measurement of blood vessel tortuosity is a useful capability for automatic ophthalmological diagnostic tools. Screening of Retinopathy of Prematurity (ROP), a disease of eye that affects premature infants, for example, depends crucially on automatic tortuosity evaluation. Quite a few techniques for tortuosity measurement and classification have been proposed, but they do not always match the clinical concept of tortuosity. In this paper, we propose the alternative method of automatic tortuosity measurement for retinal blood vessels that uses the curvature calculated from improved chain code algorithm taking the number of inflection point into account. The tortuosity calculated from the proposed method is independent of the segmentation of vessel tree. Our algorithm can automatically classify the image as tortuous or non-tortuous. The test results are verified against two expert ophthalmologists. For an optimal set of training parameters the prediction is as high as 100% on 18 images.

I. INTRODUCTION

Analyzing retinal fundus images is important for early detection of many retinal and systemic diseases. Assessment of retinal blood vessels is of immense clinical importance. Deformation in the blood vessel network of the retina are indicators of not only the retinal pathologies but also other systemic diseases coming from cardiovascular, central nervous and endocrine-metabolic systems [1]. Non-smooth appearance of vessel course is rightly termed as Tortuosity. One of the first changes in vessel morphology to occur is the increase in vessel tortuosity.

Retinopathy of Prematurity (ROP) is a disease of eye that affects premature infants. It is characterized by an increase in tortuosity and abrupt changes in the growth of blood vessels near the optic disc. Many techniques have been devised to measure vessel diameter objectively; relatively few attempted to quantify tortuosity. In order to evaluate the clinical significance of tortuosity changes with time, and to compare different levels of the same retinopathy, there is a strong need to devise a new approach for tortuosity evaluation that matches the clinical perception of ophthalmologists. Several possible measures of tortuosity have been proposed, but none of them has gained universal acceptance.

Hart et al. [2] created the automated measurement using seven integral estimates of tortuosity based on the curvature of vessels. However, it failed in differentiating the tortuosity of structures that visually appear to be different in tortuosity. Dougherty and Varro [3] calculated the tortuosity using second derivatives along central axis of the blood vessels. Grisan et al. [4] - [5] proposed alternative method called Measures involving curvature. The idea behind, is to use the points of changing curvature sign. However, this algorithm required manual vessel extraction and inflection point placement. Sukkaew et al. [6] applied the method called Arc length over Chord length ratio, which used the length of a straight line over considered part of the vessel. But this method required proper partitioning values for each part of the blood vessel to avoid significant error.

Curvature estimation is a crucial task in shape analysis in general and tortuosity evaluation in particular. One such application is the detection of high curvature points, referred to as corners or dominant points [7]. Several works have come up recently, which exploit curvature information to solve various problems. Hence, an improved algorithm for estimating k-curvature [8] is proposed.

This paper is organized in four sections. In section II, a schematic overview of our methodology is demonstrated
and the techniques that required for tortuosity measurement is also explained. Experimental results and evaluation of the proposed algorithm are given in section III. Finally, section IV is dedicated to the discussion and conclusion.

II. METHODOLOGY

The implementation methodologies can be schematically described in Fig. 1. The proposed method is divided into two main parts. The first part is the vessel segmentation and the second is tortuosity measurement.

A. Extraction of Vessel Centerline

To extract centerline of blood vessel, we applied the Laplacian of Gaussian (LOG) to gray scale of an RGB image followed by Otsu thresholding. Then, a set of morphological operation was used following to the technique by Sukkaew et al. [6] to eliminate noise and get only centerline of vessel as shown in Fig. 2.

![Fig. 2. (a): The original image (b): detected vessel centerline.](image)

B. Vessel Partitioning

Any tortuosity measure requires vessel segmentation as an initial step. Vessel partitioning can be done by using branching and ending point. We track every vessel pixel and count the number n of pixel around the eight neighborhood of a current location that has the same intensity as vessel pixel, and use this number to classify the point as ending point (n = 1), non-significant point (n = 2) and candidate for branching point (n ≥ 3).

In [9], they defined branching point as n more than or equal to 3. We found that sometimes it give a wrong results. For example, the value of n corresponding to the point a, b and c in Fig. 3 is 3 which is considered as a branching point by definition of [9]. In this case only point b should be considered as a branching point. Based on early observations, we, therefore, compute four connectivity of each eight neighborhood of branching point candidate (ignore the branching point candidate). If there is no connectivity in each eight neighborhood, that branching point candidate is masked as a branching point. Results of branching point and ending point are shown in Fig. 4. Fig. 5 shows the result after applied vessel partitioning to skeleton vessel tree.

C. Curvature Calculation

In the Euclidean plane, curvature is defined as the rate of change of slope as a function of arc length. Given a curve y = f (x), the curvature at a point p (x, y) ∈ R^2 is expressed as

\[ \kappa = \frac{y''}{(1 + y'^2)^{3/2}} \]  

(1)

where, y' and y'' are the first and second derivative respectively. The above equation often produces errors in discrete curves. To calculate curvature at each point on curve, we applied the improved algorithm for estimating k-curvature described in Pal et al. [8]. We give a brief of improved k-curvature here and refer the reader to [8] for details. The measure of k-curvature, was first introduced in [7] to detect dominant points, has been modified in three stages as Eq. 2.

\[ \kappa(p_i, k) = \frac{1}{k} \sum_{j=1}^{k} \left\{ \min\left(f_{i+j}, 8 - f_{i+j}^{'(+1)}\right), \min\left(f_{i+j}^{'(+1)}, 8 - f_{i+j}^{(-1)}\right), \min\left(f_{i+j}^{'(-1)}, 8 - f_{i+j}^{(+1)}\right), \right\} \]  

(2)
where, $f'_{i+j} = |f_{i+j} - f_{i-j+1}|$, $f'_{i+j+1} = |f_{i+j+1} - f_{i-j+1}|$
and $f'_{i+j} = |f_{i+j} - f_{i-j}|$. $f_{i+j}$ and $f_{i-j}$ are the chain code of the $j$th leading and following point with respect to point of interest $p_i$ respectively. $k$ is the number of points used for curvature calculation. In this work, $k$ equal eight is used. The size of $k$ was determined experimentally, by observing the curvature values obtained with vessel contours over size of $k$ equal to 4, 6, 8, 10 and 12. This value of $k$ need to be changed for different image resolutions. Small size of $k$ lead to aggressively noisy measurement and large size of $k$ lean to underestimate curvature values.

D. Twists Count

In order to distinguish between smoothly curved blood vessel and vessels that make abrupt changes in direction, the number of inflection or twists points is taking into account. Having defined the curvature of a curve as in Eq. 2, inflection points of a vessel curve is defined as curvature value decrease to zero which is similar to a change in sign of the curvature for planar curves. Fig. 7 shows curvature values of each pixel on a vessel in Fig. 6. We found that when dealing with real vessels, small oscillations along vessel occur, due to the noise. These oscillations can affect the precise inflection number of the vessel. To overcome this, we set a threshold on curvature as shown in Fig. 7. Red horizontal line indicates the threshold used to deal with small oscillations that occur due to noise. Number in Fig. 8 indicates values of inflection point on each sub-vessel.

E. Tortuosity Calculation

The simplest method that used to estimate tortuosity is arc-chord ratio as shown in Eq. 3

$$\tau = \frac{L}{C}$$

where, $L$ is a length of curve and $C$ is the distance between the ends of curve. When evaluating tortuosity, ophthalmologists integrate information on how many times a vessel changes convexity and how large is the amplitude [5]. Using Eq. 3 alone is not enough to meet the requirement because this formula do nothing with number of convexity. Arc-chord ratio value is also depending on how user segments the vessel tree. So, we propose a new way to describe vessel tortuosity as

$$\tau = \frac{n_{ic} - 1}{n_{ic}} \sum_{i=1}^{n} \kappa(p_i, k)$$

where, $n_{ic}$ and $L$ are the number of inflections and arc length respectively. This measure evaluates vessel tortuosity by summing curvature at every pixels of vessel and also consider number of inflection point at each sub-vessel. This formula
has a dimension of $1/L$ and thus may be interpreted as a tortuosity density. So it can be compared on vessels that have a different length. The advantage of this formula is that it does not depend on segmentation of the vessel tree.

III. EXPERIMENTS AND RESULTS

Eighteen images were used to test the performance of the proposed method. All the images were sent to two ophthalmologists in order to classified those images as a tortuous or non-tortuous based on their experiences. Classifications are divided into two levels. The first level is vessel level. This means the doctor classified each segment of vessel from vessel tree as tortuous or non-tortuous. Another level is frame level. In this level, the doctors decided which image is tortuous by looking at the whole vessel tree as one structure. Only the agreed results from the doctors will be used as a gold standard. Ten of eighteen images were used for training set and eight images was used for test set.

We calculate tortuosity of the whole vascular structure by sum of tortuosity values of each sub-vessel if and only if the tortuosity value is higher than a specified threshold that we got from training phrase (the values is 0.03). This threshold is used to classify sub-segment as tortuous or non-tortuous. Any sub-vessel that has tortuosity value less then threshold is not considered here. We also ignore sub-vessel that has arc-length less than 20 because it is too short (almost straight) to take into account. The result from training set is shown in Table I.

From the training phrase, we obtained threshold that is used for classification of the retinal images into two classes by calculating mean of the maximum tortuosity value of normal retinal image and the minimum tortuosity value of tortuous retinal image. So this training set produced threshold equal to 1.0509. The experiment with 8 images is shown in Table II.

IV. DISCUSSION AND CONCLUSION

We have proposed a new algorithm for evaluating tortuosity of retinal vessels using curvature calculating from improved chained code. One of the strength of the proposed algorithm is that the result is independent of vessel sub-segmentation. The algorithm is verified with ground truth from ophthalmologists. It has proved to be reliable and does not suffer from drawbacks of earlier proposed tortuosity measures. However, to justify it as a valid tortuosity index, we investigate to satisfy for the requisite tortuosity properties. A more extensive evaluation, based on a larger set of images will be further performed.

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