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Bifurcation Structures for Retinal Image Registration & Vessel Extraction

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ABSTRACT - *Exact extraction of the blood vessels of the retina is an important task in computer-aided diagnosis of retinopathy. This paper describes the development of an automatic image processing fundus and the analytical system to facilitate the diagnosis. The algorithm for the detection of the optical disc, blood vessels and exudates are investigated. The optical disc is identified by the method of the Sobel edge detector and LSR in the candidate area. Blood vessels and exudates are extracted by the method of Kirsch in different color components of the color image of the fundus. The processing results of the implemented methods are also presented.*
This paper also presents a new structural feature based registration function in the retinal image. The point coincident conventional methods depend largely branching angles single branching point. The feature correspondence through two images may not be unique because of the angle values like. In view of this, the record matching structure is favored. The branch structure comprises a branch point and its three neighbors master connected. The feature vector of each branch structure consists normalized angle and length of branching, that is invariant against translation, rotation, scaling, and distortion and even modest. This may considerably reduce the ill-posed nature of the pairing process, provided that the vascular pattern may be segmented. The simplicity and efficiency of the proposed method make it easy to apply alone or incorporated with other existing methods for formulating a hybrid or hierarchy scheme.
Keywords - *Bifurcation structure, Feature extraction, Image registration, optic disk, Retinal image.*

I. Introduction

The automated extraction of blood vessels in the retinal images is an important step in the computer assisted diagnosis and treatment of diabetic retinopathy, hypertension, glaucoma, obesity, arteriosclerosis and retinal artery occlusion, extraction, etc. is basically a boat type of line detection problem, and many methods have been proposed. A class of popular approaches for vessel segmentation is based filtering methods [2], which work by maximizing response as ship-structures. Mathematical morphology [3] is another approach by applying morphological operators. Trace-based methods [14] to map out the global network of blood vessels after edge detection by tracing the centerlines of vessels. Such methods are highly dependent on the result of edge detection. Machine learning based methods [1, 4-5] have also been proposed and can be divided into two groups: supervised methods [1, 5] and unsupervised methods [4]. Supervised methods exploit some labeling information before deciding whether a pixel belongs to a ship or not, while unsupervised methods do vessel segmentation without any prior knowledge of labeling.

Image registration is the process of establishing one pixel correspondence between two images of the same scene. Registration methods can be classified into several categories including feature-based techniques, approaches and methods of gradient correlation [6]. Depending based methods, objects and distinguishing protrusions (eg, edges and corners) manually or automatically selected for estimating the transformation between pairs of images, such as translation, rotation, scale and distortion. Approaches degraded originated from optical flow, estimating the translation parameters using linear partial differential equations. The idea behind correlation methods is quite simple as the cross-correlation between the delayed signal and the reference peak will have a time delay. According to the change of property Fourier transform of a function shifted Fourier transform is a function-multiplied by the phase shifted. Therefore, the phase correlation method identifies the translation of the normalized cross-spectrum. Similarly, rotation and scaling can be estimated with the aid of Fourier representation polar. Retinal image registration is challenging because of the difficulties of the method and time varying intensities of retinal images. The first difficulty concerns the multimodal registration means medical images with different modalities, such as Angiograhy fluorescein angiography, indocyanine green, red and free. The second is the temporary registration of images taken at different times. These properties justify the operation of vasculature and robust as optical disk instead of the intensity in the retinal image registration [7] - [9]. In general, feature-based techniques can be classified in each region and the matching point categories. The region-matching approaches consider all the characteristics of a region as a whole and identify the transformation parameters by minimizing similarity measures. For example, the cost function in [10] is defined as the error between two binary images the test vessel with affine transformation models, bilinear, and projective. The similarity measure is formulated as the mutual information based on the entropy. Deficiencies of matching methods of the region are at their huge search space and local convergence when modeling involves higher order processing and inconsistent features.

Methods correspond points, moreover, are based on matched features in both images. The technique consists of two stages: estimation comparison function and transformation. The characteristic adaptation process establishes the correspondence between the two groups of functions. Once the pairs of matching features are reliable, the transformation parameters can be easily and accurately identified. Most point matching method using historical point of bifurcation, as it is an important indicator of the vasculature. Branching angles each branching point are used to produce a probability for each pair of points. Since some bifurcation points can have more than one paired homolog, a hierarchical method is proposed to solve this dilemma [11]. The correspondences are refined gradually from the translation model from coarse to fine the quadratic model. This idea spread to dual boot iterative closest point (ICP) algorithm [12]. The location, the branching angle and width of reference points is taken as the similarity metric. Based on initial estimates lower order are accurate only in small regions boot, dual boot PCI iteratively decides the optimal transformation model from simple to complex, and boot area extends from the local to the global. Another way is to find the minimum error by imposing transform any combination of function points [13]. This search requires large stones exhausted when the number of feature points increases. The self-organizing maps (SOM), an unsupervised neural network that can train, offer promising results for multimodal registration [14]. It is well known that when more robust signal can be achieved with less computational complexity, the performance characteristics based methods will be enhanced greatly. However, the aforementioned methods rely heavily branch angles single branching point. As such angles are accurate thickness leading to similar bifurcation points, the correspondence cannot be unique and reliable for registration purposes. In view of this, we present a new structural feature for feature based registration retinal image. Different from the point-matching techniques, the proposed method is a structure matching approach. The branch structure comprises a branch point and its three neighbors master connected. The feature vector of each branch structure is the branching angle, and the normalized length, is invariant against translation, rotation, scaling, and even modest distortion. More analysis and simulation show that it can greatly reduce the ill-posed nature of the matching process.

2. Detection Techniques

2.1. Detection of optic disk

The optical disk is the most obvious feature n the view of the fundus image. It is the brightest part of the normal retinal magician that can be seen as a pale, well-defined round or slightly oval disk vertically. The optical disk is the inlet region of the blood vessels and the optic nerves to the retina and often serves as a reference for other characteristics. The detection is performed on the red component in three steps: identifying candidate area, Sobel edge detection and phase estimation. The candidate area is defined as an area of 200 x 200 pixels. The pixels of the highest levels of gray 2% in the red component is selected and a clustering algorithm is applied to gather in groups neighboring pixels. The center of gravity of the largest group s defined as the center of the candidate area.

Sobel edge detector is applied in the area of the candidate contour for the optical disk. This is the convolution of the image with 3 x 3 matrix of impulse response in the column direction and the row. The detection limit obtained Sobel edge is not met due to noise. Since the optical disc form a closed circle, LSR (least squares regression) is applied to obtain the estimated circle based on the result of the Sobel edge detection.

2.2. Detection of Blood Vessels

The retinal vessels are usually referred to, arteries and veins. The artery and central vein normally appear near each other in the nasal side of the optical disc center. Blood vessels are clearer in the green component. Information about the structure of the blood vessels can help to classify the severity of the disease and may also serve as a reference during operation. Two strategies have been used for the detection of blood vessels in fundus image. One is the detection of edges, and the other is monitoring that requires a priori knowledge of the position from the image. The first method is applied in this project.

Kirsch method [16] is used in the detection of blood vessels. Gradient is calculated by convolving the image with eight arrays template impulse response (H1 ~ H8) as shown in Fig.2.1. The scale factor is 1/15.

5	-3	-3
5	0	-3
5	-3	-3

H_1 East

-3	-3	-3
-3	0	-3
5	5	5

H_5 North

-3	-3	5
-3	0	5
-3	-3	5

H_2 West

5	5	5
-3	0	-3
-3	-3	-3

H_6 South

-3	-3	-3
5	0	-3
5	5	-3

H_3 Northeast

-3	-3	-3
-3	0	5
-3	5	5

H_7 Northwest

-3	5	5
-3	0	5
-3	-3	-3

H_4 Southwest

5	5	-3
5	0	-3
-3	-3	-3

H_8 Southeast

Fig.2.1. Impulse response arrays of Kirsch's method

The slopes of the different directions are obtained by convolving the image with eight impulse response matrices. The final gradient is established in the largest among different directions. Thus, the edge is reinforced by the method of Kirsch. A threshold is set after edge enhancement to determine whether a pixel belongs to the edge or not.

3. Bifurcation Structure for Retinal Image Registration

3.1 Bifurcation Point Matching

Consider imaging of the retina in a stage 3-D machine vision and optical axis of the camera as the coordinate reference, the main factors causing the difference between the images are: (1) change eye position, including movements along X, Y and Z axes (horizontal and vertical translation, and scale), (2) the change in position of the eye including rotations around X , Y and Z-axis (horizontal and vertical quadratic spherical distortion, and rotation), (3) the change of the inner chamber parameters, such as focal length and resolution, (4) a change in form of image, and (5) the change of tissue retinal disease progression. It is assumed that certain limitations are imposed on (1) - (3) to restrict the misalignment in a controlled condition. It is a way to explore the nature and establishing the relationship between the image pair vasculature because the blood vessels are robust to the geometric transformation and the intensity of the changes. In most retinal images, branching points are prominent visual features can be recognized by their T-shaped surrounding Braches 3, as shown in Fig. 3.1. Assuming that the centerlines of vessels listed, bifurcation points can be detected if 3 neighbors in a 3 × 3 window belong to the foreground. Other types of points in the vasculature for example, endpoints and trifurcation are characterized by their neighbors 1 and 4 in the foreground. The fictitious bifurcation points are defined as points with a short branch bifurcation or too close to another characteristic point. At the point of coincidence of the methods, the characteristic vector of each point of bifurcation is mainly composed of the three angles of branching. The search process will seek the best similarities between all pairs of feature vectors. However, branching angles are accurately calculated thickness of about 100 ~ 200, the correspondence cannot

Be unique because similar bifurcation angles. To analyze this problem multiple correspondence misconceived, 3 branching angles of each branching point are assumed to be randomly distributed on a scale of 1 ~ M, where each scale 150 represents the precision and the corresponding M is 3600/150 = 24. It is worth mentioning that the number of combinations to satisfy p $+q$ $+r = M$, subject to $p, q, r > 0$ is$\sum_{i=1}^{|M/3|}[(M-3i+1)/2]$. Thus, the number is 48 for all possible combinations of 3 branching angles. In other words, each point of bifurcation has, on average, two counterparts with the same angles as each image contains 100 bifurcation points.

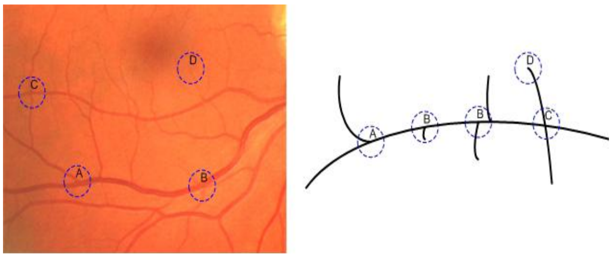


Fig.3.1. The illustration of different point types in retinal images. A: Bifurcation point; B: Dummy Bifurcation point; C: Trifurcation point; D: Terminal point. (a) Real-life retinal vasculature. (b) Vessel centerlines.

3.2. Bifurcation Structure Matching

In feature-based registration, the problem of the adaptation function and the estimation of the transformation is the chicken and egg dilemma. Both problems can be solved gradually by trial and error. The basic idea is simply that one imposes a processing model obtained from the matched features in the image pair. If this does not work, another solution must be sought to minimize the error. This iterative scheme can be trapped by local minima when only depends on the angles of bifurcation for matching features. Furthermore, it is well known that performance is greatly improved registration when more robust features are adopted. The best solution for matching feature will provide a solid foundation for the subsequent transformation model estimation. Moreover, a good characteristic should be invariant to different processing models and robust under noisy conditions.

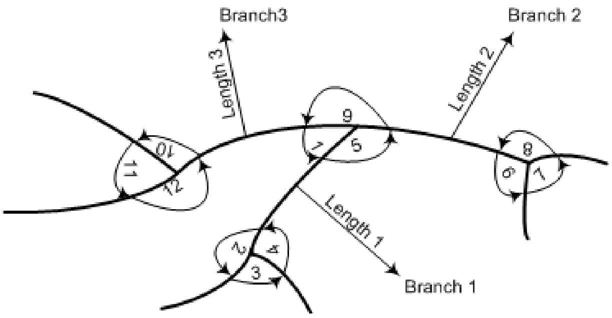


Fig. 3.2. Bifurcation structure is composed of a master bifurcation point and its three connected neighbors.

As shown in the fig. 3.2, a branch structure composed of a branch point and its three neighbors master connected proposed for recording characteristics of the retinal image basis. The master branch point has three branches surrounding lengths numbered 1, 2, 3 and angles numbered 1, 5, 9, wherein each branch is connected to a neighboring branching point. The characteristic vector for each bifurcation structure is:

$$\tilde{x} = \{\text{lengths, angles}\} = [l_1, l_2, l_3, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11}, \theta_{12},] \quad (1)$$

where l_i and θ_i represent the normalized length and angle, respectively:

l_i= *i-th branch length / sum {length 1, length 2, length 3}*

θ_i = *i-th branch angle in degree/360^0* (2)

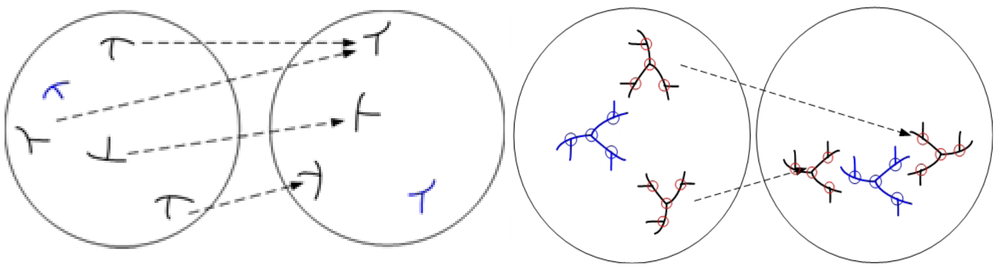
Since there are some redundant elements in (1) as the summation of branching angels and length will be 1, we use a simplified characteristic vector in this work:

$$x = [l_1, l_2, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11}] \quad (3)$$

It is worth mentioning that x must be provided that the longest branch is taken as the first element. This mechanism ensures that the feature vector is invariant to translation and scaling. The process of adapting the search feature similarity between all pairs of good structure. Let X and Y represent groups of features of the two images containing the number of branch structures N1 and N2, respectively. The similarity measure $s_{i,j}$ for any pair of fork structure is

$$s_{i,j} = d(x_i ,y_j) \quad (4)$$

where x_i and y_j feature vectors denote the i-th and j-th branch structure in two images. The term d (·) denotes the measure of the distance between the feature vectors. In contrast with the single point of bifurcation of 3 angles, the eigenvector for the proposed branch structure containing ordered length and angular elements. The extended function facilitates the matching process in which multiple occurrences of correspondence can be reduced as shown in Fig. 3.3 It is important to mention that branching structures proposed fictitious bifurcation points, trifurcation and terminal are excluded because they cannot be consistent and be more easily prone to errors in practical situations. Other minor technical point is that only connected neighbors are considered instead of the nearest neighbors in space. The online branch points indicate the physical relationship of the vessels when many points of bifurcation point surrounded the teacher or geometric distortion is present.



(a) (b)

Fig.3.3. The illustration of feature-based method. (a) Point-matching based on branching angles. (b) Structure matching based on bifurcation structures.

3.3 Correspondence Verification

Associating features across two images is critical to image registration, where features may be matched With One-none-, or multiple-correspondence. To verify and correct the initial correspondence, the eigen decomposition methods exploit spatial relations Between features With The aid of the coordinate proximity matrices. The technique works well on a simple shape matching, but Suffers from the spurious feature points in the inexact matching. Several Approaches are proposed to correctly resolve the ambiguous matches, Such as Bayesian framework [15], region-based cross-correlation, and intensity profile. In the Following part, we are interested in correspondence developing an efficient verification scheme. It Is Well Known That the minimum points requirement for linear transformation is 2 pairs, and affine is 3 pairs. Therefore, one matched pair bifurcation structure is enough to estimate the parameters of low-order model transformation for it Provide 4 point pairs. The correspondence refinement and transformation estimation simultaneously can Be Achieved by:

$$e_{(pq,mn)} = d\left(N\left(x_p, y_q\right), N(x_m, y_n)\right) \quad (5)$$

Here $N\left(x_p, y_q\right)$ and $N(x_m, y_n)$ transformation models are estimated from the matched pair $x_p$andy_q, x_m and y_n respectively. In this verification step, structure candidates should be those with good similarity in (4). Through this way, we can eliminate the false match when yields different model to others. In the final stage, the refined branching structures can be used together to estimate transformation models, such as spherical quadratic transformation [11], [12].

4. Results

Kirch method [16] is applied in red and green components of the image. The different parts of the processing results of the two components are detected as blood vessels. Morphological operators are applied to the post-processing. Fig. 4.1 shows extraction of blood vessels. The dataset contains images of the retina with various pathologies, where each FOV image is approximately 1024 × 1024. First, trees crest veins are segmented based segmentation using vascular tree [21]. Secondly, the matching method is performed using structure (3) and (4) to find the initial correspondence. These initial candidates matching are used to estimate the transformation model and refine the correspondence retrospective. Fig. 4.2 (a) and (b) represents a pair of retinal images taken at different times. For this image pair, 107 and 77 branch structures are detected and give good

matched pairs 8. Top 3 matching structures are highlighted in Fig. 4.2 (d) and (e) use the square box. We discussed the linear transformation, affine and quadratic and found that the affine model is robust enough to describe the transformation. The mosaic image aligned by the affine model shown in Fig. 4.2 (c) and (f). It is

observed that most vessels align well except a few local vessel centerlines with 1-pixel displacement. By contrast, the method of matching point pairs produces 797 points coinciding with the angle difference of less than 1% between 145 and 136 branch points. They need additional constraints, such as the location or width container to filter the results of [11] - [13].

(a) (b)

Fig.4.1. (a) Input image, (b) Extracted Blood Vessels .

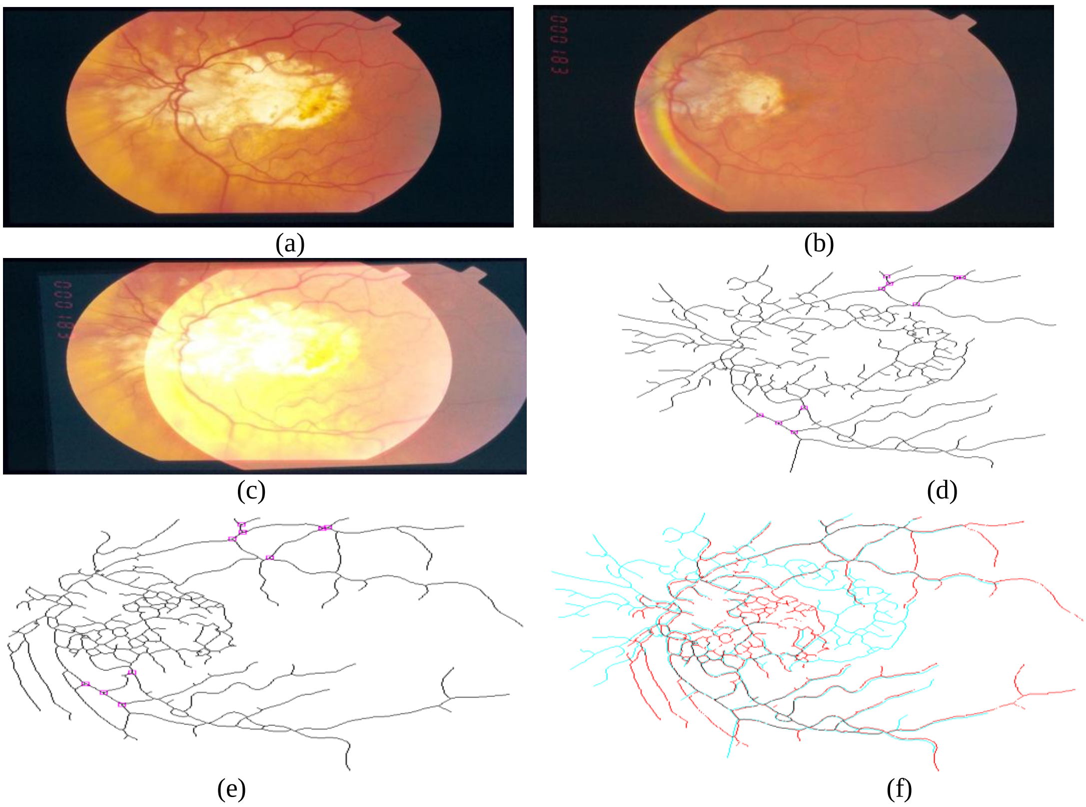


Fig 4.2. Image registration results. (a) One retinal image. (b) Another retinal image captured at different time. (c) The mosaic retinal image. (d) Vascular tree and matched bifurcation structures of (a). (e) Vascular tree and matched bifurcation structurs of (b). (f) The mosaic vessel image. (g) One vessel image. (h) The mosaic vessel image.

5. Conclusion

This paper presents a feature-based method of retinal image registration based on the bifurcation structure matching and extraction of blood vessels based in diabetic retinopathy. The branch structure comprises a branch point and its three neighbors master connected. It is invariant against translation, rotation, scaling, and even modest distortion. You can deal with the registration of retinal images when-like vascular pattern is identifiable, even partially. The simplicity and effectiveness of the proposed methods can be easily applied alone or incorporated with other existing methods to develop a hybrid or hierarchy scheme.

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