Fast Automatic Retinal Blood Vessel Segmentation and Vascular Landmarks Extraction Method for Biometric Applications

Fabiola M. Villalobos-Castaldi[1], Edgardo M. Felipe-Riverón[2]

[1, 2] Center for Computing Research, National Polytechnic Institute,
Av. Juan de Dios Batiz and Miguel Othon de Mendizabal, Mexico,
D.F., P. O. 07738. Mexico, Phone: 5729 6000/56515.
[1]fvillalobosb07@sagitario.cic.ipn.mx,
[2]edgardo@cic.ipn.mx

Abstract. The retina has many desirable characteristics as the basis of authentication. Retinal blood vessel patterns are known to be very distinctive, even between identical twins. The blood vessel structure is very stable over time, well shielded from outside environmental impacts, and believed to be difficult to spoof. Retinal Identification seeks to identify a person by comparing images of the blood vessels in the back of the eye, the retinal vasculature. This method takes advantage of the fact that of all human physiological features, the retinal image is the best identifying characteristic. This article describes a fast, efficient and automatic algorithm for segmenting retinal blood vessels and for extracting vascular landmarks from these vessels as a unique representation used for biometrical applications. The proposed segmentation method is based on the second local entropy and on the gray-level co-occurrence matrix (GLCM). The algorithm is designed to have flexibility in the definition of the blood vessel contours. Using information from the GLCM, a statistic feature is calculated to act as a threshold value. After the segmentation stage, a morphological thinning process is applied and the landmarks are detected and their attributes are extracted. Finally the "eye print" representation is constructed using this salient features. The results obtained show the effectiveness and accuracy of the proposed method to detect and extract information from a retinal fundus images. The elapsed time for the proposed segmentation method is 3.2 seconds.

Keywords: Biometric identification; Retinal recognition; Retinal vessel tree; Bifurcation and ending points; Image segmentation; Co-occurrence matrix; Entropy thresholding.

1 Introduction

The terms *Biometric"* and *"Biometry"* have been used since early in the 20th century referring to the field of development of statistical and mathematical methods applicable to data analysis problems in the biological sciences [1]. For a layman, it

Advances in Computer Science and Engineering.
Research Computing Science 45, 2010, pp. 303-316

Received 30/04/10
Final version 19/05/10
Accepted 14/05/10

could be said that Biometry is the science of measuring physical and/or behavioral characteristics that are unique to each individual and could be used to verify that an individual is who he or she claims to be. Since these characteristics are unique to each individual, biometrics are believed to effectively combat theft and fraud in a wide variety of industries and applications. Notably, the recent advances of information technology and the increasing requirement for security have led to a rapid development of intelligent personal identification system based on biometrics [12].

The retina has many desirable characteristics as the basis of authentication. Retinal blood vessel patterns are known to be very distinctive [2], even between identical twins [3]. The blood vessel structure is very stable over time, well shielded from outside environmental impacts, and believed to be difficult to spoof [6]. Retina-based identification has long been perceived as a robust biometric solution but very few practical applications or commercially viable products have been demonstrated. However, it suffered from a human interface perceived as intrusive and unfriendly. The genesis of the retinal identification technology lies in the medical imaging field. Retinal imaging devices and automated diagnostic tools were developed for a range of retinal disease states. This led to an understanding of imaging the retinal blood vessel network and an interest in developing automated tools for its analysis [9].

2 Retinal blood vessels as a biometric

Retinal identification (RI) is an automatic method that provides true identification of persons by acquiring an internal body image, the retina of a willing person, who must cooperate in a way that would be difficult to counterfeit [6]. Awareness of the uniqueness of the retinal vascular pattern dates back to 1935 when two ophthalmologists, Drs. Carleton Simon and Isodore Goldstein, while studying eye disease, noted that every eye has its own totally unique pattern of blood vessels. They subsequently published a paper on the use of retinal photographs for identifying people based on blood vessel patterns [2]. Later in the 1950s, their conclusions were supported by Dr. Paul Tower in the course of his study of identical twins. He noted that, of any two persons, identical twins would be the most likely to have similar retinal vascular patterns. However, Tower's study showed that of all the factors compared between twins, retinal vascular patterns showed the least similarities [3].

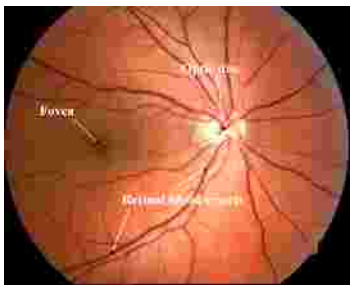


Fig. 1. Retinal blood vessels appearance.

2.1 Retinal Blood Vessels Characteristics

It is the blood vessel pattern in the retina (Figure 1) that forms the foundation for the science and technology of the RI [6]. This method takes advantage of the fact that of all human physiological features, the retinal image is the best identifying characteristic [5]. Because of the complex structure of the vessels that supply the retina with blood, each person's retina and also each person's eye is unique.

The blood vessels of the vascular network of the retina have the following characteristics:

a) Uniqueness. It is unique in:

- The number of major blood vessels that are located in the area of the optic nerve [5], [9]. [25]. The biometric systems that detect a vascular pattern of an individual's retina to identify it use the vascular structure outside of the optic disc because it was thought that only this area of the retina contained enough information to distinguish one individual from another [7].
- The relative angle of these major blood vessels as they emerge from the optic disc. The central retinal artery and vein can be seen to bifurcate rapidly at the optic disc [9].
- The branching characteristics of the blood vessels. Among all features, bifurcation points are the most reliable and abundant features in the fundus images. It has been suggested that non-equilibrium Laplacian process could be involved in retinal angiogenesis and that fluctuations in the distribution of embryonic cell-free spaces provides the randomness needed for fractal behavior and for the uniqueness of each individual's retinal vascular pattern [9].
- The position and size of the optic disc. The optic disc, seen as the bright spots in Figure 1, is the point where the optic nerve breaks out into the retina. This disc is approximately 15.5º ±1.1º nasals and 1.5º ± 0.9º superior to the fovea [32].
- The pigments or coloring patterns of the retina and of the retinal vasculature.
- The infinite variability that exists with respect to certain anatomical landmarks of the retinal vasculature [4]. Its detailed final structure is mostly stochastic and thus its uniqueness stands of reasons [8].

Also, the retinal image has some other characteristics that place it as the best biometric identification option.

b) Permanence. The retinal image does not change significantly with time. Other than cases of significant trauma, pathology, or biochemical interference, spontaneous adult ocular vasculogenesis and angiogenesis usually do not occur [8]. Age or disease may change the characteristics of the eye blood vessels, but not their position in the retina [11].

c) Reliability. It is impossible to counterfeit the retinal image. The fine, multi-surface structure of the ocular vessels makes them hard to reproduce as a physical artifact [8]. Fraud-proof, that is, it is virtually impossible to replicate the image produced by a human retina for unauthorized access to computer networks, medical records or physical facilities [10]. Moreover, imaging the retinal vasculature may be done to the eyes of living persons. Therefore, by accurately recording and analyzing the

configuration of the blood vessels, the subject can be positively being identified. Since the configuration of retinal blood vessels of an eye can not be falsified or altered, it offers an incredibly, accurate, inalterability, and unchanging characteristic of the subject [4].

d) Universality. A holangiotic eye is an eye having vasculature on the ocular fundus, with the vasculature entering the eye, primarily, through the optic nerve head. Humans, as well as virtually all domestic animal species and many game animal species, including deer and elk, have holangiotic eyes. Based on this, it is possible to identify an individual using the image that is acquired of an eye of the animal (human or non-human) and the retinal vasculature is extracted from that image [4]. In humans, the retinal vasculature disappears within seconds of the cessation of life, thereby insuring that the captured image was obtained from a living subject.

e) Safety. The eye shares the same stable environment as the brain and among physical features unique to individuals; none is more stable than the retinal vascular pattern. Because of its internal location, the retina is protected from variations caused by exposure to the external environment (as in the case of fingerprints, palm prints, etc.).

f) Representative. By targeting common structures such as the optic disc and the retinal vascular branches, a consistent source of readily identifiable, yet contrasting structures are available for digital imaging and processing.

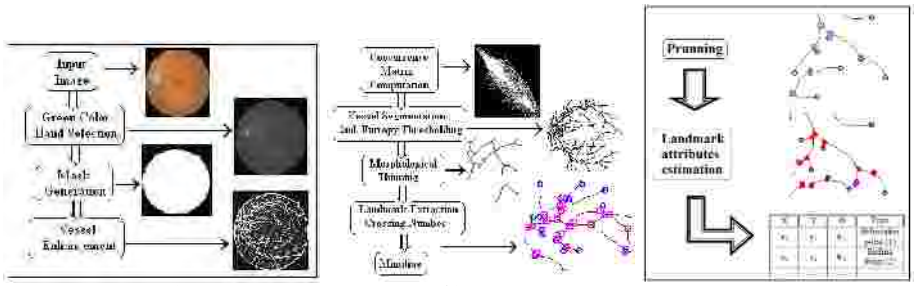
g) Certainty. Unlike passwords, a retina cannot be forgotten; unlike plastic cards, a retina cannot be lost or loaned by someone else.

The majority of the disadvantages that owns the biometric identification based on the vascular network of the retina are inherent to the user interface.

As mention before, retinal based recognition for personal identification has desirable properties such as uniqueness, stability, permanence, etc. However, research on retinal vessel structure for biometric applications, has not revealed its full potential. Retinal vessel structure has extraordinary structures and provides many interlacing characteristics, which are unique for each person, so it will be one of the most reliable and accurate biometric [12].

3 The proposed method

As depicted in Figure 2 the proposed method is composed of 3 main processing stages: 1) a pre-processing step, 2) a main process step, and 3) a post-processing step. The pre-processing step consists of the following 3 stages: a) green-color band selection, b) mask generation, and c) image enhancement for vessel network detection. The main process consists of 4 stages: a) co-occurrence matrix computation, b) vessel segmentation by the second entropy thresholding technique, c) morphological thinning, and d) landmarks detection. Finally, the post-processing step contains 2 stages: a) pruning and b) landmark attributes estimation.



a) b) c)

Fig. 2 a) Block diagram of the proposed method; a) Pre-processing step, b) Main process stage, and c) post-processing step.

3.1 Green color band selection

A gray-level image is produced by extracting the green layer of the original RGB image. The green component of color image gives the blood vessels on a highly contrasted background (dark blood vessels on a bright background). Hence, the green channel of image is employed in the retinal vasculature detection [12].

3.2 Mask generation

Mask generation aims at labeling pixels belonging to the fundus Region of Interest (ROI) in the entire image [31]. Pixels outside that ROI are those belonging to the dark surrounding region in the image.

3.3 Image enhancement

Denoising, correction of the brightness and contrast enhancement are applied in this pre-processing step [13]. Therefore, the proposed enhancement method detects vessels using the knowledge of their known gray level profile and the concept of the matched filter detection, which is used to detect piecewise linear segments of blood vessels in retinal images.

3.3.1 Bell-Shaped Gaussian Matcher Filter (BSGMF)

It can be noted that the retinal vessels can be represented by piecewise linear segments with Gaussian-shaped cross sections. A matched filter is constructed for the detection of the vessel edge segments searching in all possible directions. A Bell-Shaped Gaussian matched filter (BSGMF) was developed to cover all 12 orientations where designed kernel was given by Eq. 1 [16].

$$K(x,y) = \pm \exp\left(-\frac{x^2 + y^2}{2s^2}\right) \qquad \text{(Eq. 1)}$$

With the tail truncated at $x^2 + y^2 = 3s^2$. The application of this method enhances individual vessels segments in the image. A proper thresholding scheme must be used to distinguish between the enhanced vessel segments and the background.

3.4 Computation of the co-occurrence matrix

A co-occurrence matrix of an image is an L x L square matrix, denoted by **W** = $[t_{ij}]_{\text{L x L}}$ whose elements are specified by the numbers of transitions between all pairs of gray-levels in $G = \{0, 1, \ldots, L-1\}$ in a particular way [33], [34]. Each entry in the matrix t_{ij} gives the number of times the pixel gray-level j follows the gray-level i in some pattern [17], [18].

3.4.1 Quadrants of the co-occurrence matrix

Let t be a value used to threshold a gray-level image. It partitions a co-occurrence matrix into four quadrants, namely, A, B, C and D. We assume that pixels with levels above the threshold are assigned to the foreground (corresponding to vessels), and those equal to or below the threshold are assigned to the background. Then, quadrants A and C correspond to local transitions within foreground and background, respectively, whereas quadrants B and D are joint quadrants which represent joint transitions across boundaries between background and foreground. The probabilities of the gray-level transition within each particular quadrant can be by the so called 'cell probabilities' (Eq. 2):

$$P^t_{ij|A} = \frac{P_{ij}}{P^t_A} \qquad P^t_{ij|B} = \frac{P_{ij}}{P^t_B} \qquad P^t_{ij|C} = \frac{P_{ij}}{P^t_C} \qquad P^t_{ij|D} = \frac{P_{ij}}{P^t_D} \qquad \text{(Eq. 2)}$$

3.5 Blood vessel segmentation

The objective of retinal vessel segmentation is to decide which part of the image belongs to the foreground (which is of our interest for extracting features for recognition and identification), and which part belongs to the background (which is the noisy area around the boundary of the image) [14]. Reliable vessel extraction is a pre-requisite for subsequent retinal image analysis and processing because vessels are the predominant and most stable structures appearing in image [12]. Accurate segmentation of retinal images influences directly the performance of minutiae extraction. If more background areas are included in the segmented retinal image, more false features are introduced; if some parts of the foreground are excluded, useful feature points may be missed [14]. The first step of 2-D segmentation is to build the 2-D histogram, which can be commonly established by using the gray-level co-occurrence matrix [19].

3.5.1 Gray-level co-occurrence matrix used for relative entropic thresholding

Relative entropy has been used to measure the information distance between two information sources. The smaller the relative entropy is, the closer the two sources are in terms of their probability distributions. The transition probabilities defined by the co-occurrence matrix contain the spatial information that reflects homogeneity of local gray-level transitions in quadrants A and C, and joint gray-level transitions across boundaries in joint quadrants B and D [20], [21].

Let the second-order relative entropy of the gray-level transition probabilities $\{p_{ij}\}_{i=0,j=0}^{L-1,L-1}$ and $\{h_{ij}{}^{t}\}_{i=0,j=0}^{L-1,L-1}$ be defined by:

$$J(\{p_{ij}\};\{h_{ij}{}^{t}\}) = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij} \log \frac{p_{ij}}{h_{ij}{}^{t}} \qquad \text{(Eq. 3)}$$

Where p_{ij} are the transition probabilities from gray level i to gray level j of the original image and h_{ij}^{t} is the transition probability generated by the thresholded binary image in response to p_{ij}. Using Eq. 3 as a thresholding criterion to minimize $J(\{p_{ij}\};\{h_{ij}^{t}\})$ over t generally renders the thresholded binary image that best matches the original image.

3.5.2 Local Relative Entropy (LRE) thresholding

If we define $P_{ij|AC}^{t} = \frac{P_{ij}}{(P_A^t + P_C^t)}$, and normalize the probabilities in the local quadrants A and C, then we get:

$$J_{LRE}(\{p_{ij|AC}\};h_{ij}^{t}) = H_{BB+FF}(t) - \sum_{(i,j)\in BB\cup FF} p_{ij|AC} \log h_{ij}^{t} \qquad \text{(Eq. 4)}$$

Where

$$H_{BB+FF}(t) = -\sum_{(i,j)\in BB\cup FF} p_{ij|AC} \log p_{ij|AC} \qquad \text{(Eq. 5)}$$

is the entropy of local quadrants A and C in the co-occurrence matrix $\boldsymbol{W}$. The second term in Eq. 5 can be further reduced to:

$$\sum_{(i,j)\in BB\cup FF} P_{ij|AC}^{t} \log h_{ij}{}^{t} = \frac{P_A^t}{P_A^t + P_C^t}\log\left(\frac{q_A^t}{P_A^t + P_C^t}\right) + \frac{P_C^t}{P_A^t + P_C^t}\log\left(\frac{q_C^t}{P_A^t + P_C^t}\right) \qquad \text{(Eq. 6)}$$

Substituting Eq. 6 into Eq. 4 results in:

$$J_{LRE}(\{P_{ij|AC}^{t}\};h_{ij}{}^{t}) = -H_{BB+FF}(t)\left[\frac{P_A^t}{P_A^t + P_C^t}\log\left(\frac{q_A^t}{P_A^t + P_C^t}\right) + \frac{P_C^t}{P_A^t + P_C^t}\log\left(\frac{q_C^t}{P_A^t + P_C^t}\right)\right] \qquad \text{(Eq. 7)}$$

The LRE thresholding method aims to find a threshold value t_{LRE} that minimizes $J_{LRE}(\{P_{ij|AC}^{t}\};h_{ij}^{t})$, that is:

$$t_{LRE} = \arg\left\{\min_{t\in G} J_{LRE}(\{p_{ij|AC}\};h_{ij}^{t})\right\} \qquad \text{(Eq. 8)}$$

3.6 DRIVE database

In this paper we used the images included in the well-known DRIVE database (http://www.isi.uu.nl/Research/Databases) to implement the proposed segmentation method and to assess its performance. The DRIVE database contains 40 color retinal images of size 565 × 584 pixels. The images have been divided into 2 sets, a training set and a test set. Each one contains 20 color retina images. Each set also contains the corresponding segmented images, which were graded by two experts, resulting in sets A and B.

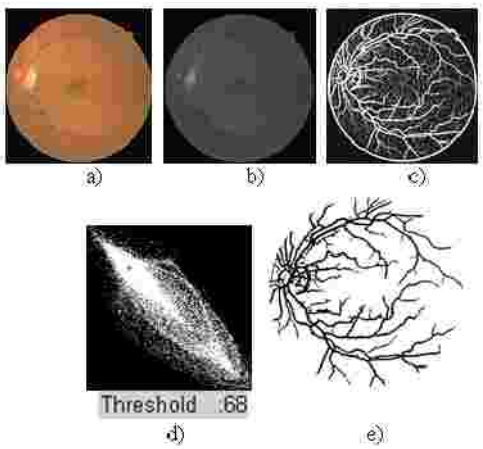


Fig. 3. Steps of the segmentation process for a typical image.

Figure 3 illustrates the results of each step of the pre-processing stage. In figure 3 b) the green color band extracted from the figure 3 a) is shown. The enhanced vessel after applying the BSGMF is presented in figure 3 c). Figure 3 d) illustrates the corresponding co-occurrence matrix and the threshold value obtained for this image depicted as a red cross overlapped in the co-occurrence matrix. Finally, in figure 3 e) the segmented blood vessels using the 2nd local entropy thresholding method is presented. The experimental results show that the proposed segmentation method performs well in extracting vessels, achieving the highest score from all the methods that where compared. There are several parameters of the algorithm that have effects in the performance of the vessel segmentation method. The most significant parameter is the thresholding value. Since the proposed segmentation method obtains automatically this value for each image, it is not necessary to establish a range of thresholding values, and also, it is not necessary the interaction of the user that adjust this value depending on the image case.

3.7 Feature extraction

There are two types of features used for biometric coding, i.e., block features and point wise features [14]. The American National Standards Institute-National Institute

of Standard and Technology (ANSI-NIST) proposed a minutiae-based biometric representation. It includes minutiae location and orientation. Minutia orientation is defined as the direction of the underlying segment at the minutia location. Retinal vessel landmarks are bifurcation**,** crossings and ending points. Among these features, bifurcations are the most reliable and abundant feature in fundus images [22]. The retinal bifurcations and ending points are unique for each individual and therefore they are useful for a successive process of personal identification [13].

3.7.1.1. Extracting vasculature skeleton image of vessel structure

As can be seen in figure 4 e), the width of the extracted blood vessels is not the same for the entire vasculature. To overcome this, retinal vessel thinning is usually implemented via morphological operation which reduces the width of vessels to a single pixel width line while preserving the extent and connectivity of the original shape. After the skeleton of the retinal image is computed, extracting the minutiae from the one-pixel-wide vessel tree is a trivial task.

3.7.2. Minutiae detection

Minutiae detection in a retinal vessel skeleton is implemented by scanning the thinned vasculature and counting the *crossing number (cn) between veins and arteries* [14]. The *cn* can be defined as follows:

$$cn(P) = \frac{1}{2}\left(\sum_{i=1}^{8}\left|val(P_{i \bmod 8}) - val(P_{i-1})\right|\right) \quad \text{(Eq. 9)}$$

Where $P_0, P_1, \ldots, P_7$ are neighbors of p, $val(p) \in (0,1)$.
Based on the calculated cross number *cn* it is possible to classify the point according to the following (Table 1):

Table 1. Classification of landmarks according to the *cn* value.

if *cn* = 1, it is an ending point	Ending points as vascular landmarks is defined by one connection of the pixel with its eight connected neighbors.
if *cn* = 2, it is an inner point	A segment is a vessel between 2 successive points of bifurcation or between a bifurcation and an ending point. Generally, the continuous blood vessel without vascular landmarks has two connections of its eight connected neighbors [32].
if *cn* = 3, it is a bifurcation point	Bifurcations consist of a center location that is met by three blood vessel branches [32].
if *cn* = 4, it is a crossover point	A crossing is an image point which is the intersection of four line segments. Crossings of vessel segments are, for practical purposes, always between a vein and an artery (i.e., crossing between arteries and arteries or between veins and veins are, for practical purposes, non-existent).

3.8. Pruning

Although there are a lot of minutiae detection algorithms available in the literature, minutiae detection accuracy can not reach 100%. In this work it is used a set of simple heuristic rules to eliminate false minutiae.

3.9. Minutiae attribute estimation

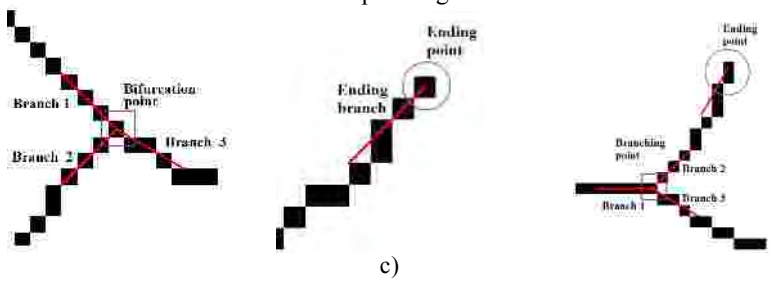
As stated before, most common features in biometric applications are minutiae. A retinal image is pre-processed and minutiae of the vascular tree are extracted and coded using their attributes like location and orientation of the vessel they are located on. Then, a list or a graph of minutiae is formed. For each detected minutiae, the following parameters are recorded:

1) ***Location attributes****:* x-coordinate, y-coordinate.
2) ***Angular attributes****:* Orientation, which is defined as the local vessel orientation of the associated vessel.
3) ***The minutiae type***, i.e., bifurcation point (1) or ending point (2).

The machine representation of a biometric is critical to the success of the matching algorithm. A minimal representation of a processed retinal image is a set $\{(x_i, y_i, ?_i)\}$ of minutiae, i.e., a set of points (x_i, y_i) expressed in some coordinate systems with a vessel direction at this point $?_i$.

4 Experimental results

Figure 4 shows the results of the minutiae attribute estimation stage illustrated for each kind of minutia. In figure 4a) the location of the final detected bifurcation points is indicated using magenta square overlapped to the skelettonized vessel tree, and the corresponding orientation of its three connected segment vessels that conform the bifurcation are indicated using a red line going from the center of the bifurcation point through its three surrounding branches. In figure 4b) the position of the ending points are indicated using blue circles overlapped to the one-pixel-wide vessel tree, and its corresponding orientation are also presented using a red line overlapped to the ending neighbor vessel. Finally, the figure 4c) illustrates the cloud of the entire vascular landmarks and its estimated attributes using the same color code described before for each kind of landmark and for the corresponding orientation attribute.



c)

Fig. 4 Landmarks attribute detected in a zoomed zone for a particular minutiae point.

Finally, the characteristic vector can be constructed using all this information, i.e., the landmark position (x, y), the angular landmark attribute (branch orientation) and landmark type (bifurcation point or ending point). All this information integrates the representation used in biometric applications.

4.1. Execution time

How fast the system takes a decision about the claimed identity is of course an important parameter of a biometric system. For this reason, in this work we also analyze the time that the proposed algorithm takes for complete the blood vessel segmentation and the vascular landmarks extraction. On a Pentium (R) Dual-Core T4200 @ 2GHz and 4 GB of internal memory, and with a MATLAB 7.4.0 (R2007a) implementation, it takes in an image of size 565×584 pixels, an average of 4 seconds to obtain the "eye print" from the retinal input image.

5 Conclusions

In this paper it is presented a fast, efficient and automatic minutiae-based algorithm for segmenting retinal vessel tree and extracting its vascular landmarks to use this information as a unique feature for biometrical applications. The proposed method consists of three main steps.

For the pre-processing step we can conclude that:

a) The extraction of the green color band let us to process more efficiently the information contained in the image and thus reduces the noise effects. The required time is also reduced because only one band is processed.
b) The mask generation stage uses a thresholding with a free parameter empirically chosen such that pixels with intensity value above that threshold are considered to belong to the Region of Interest (ROI). The threshold is applied to the selected green color band of the image.
c) Image denoising, correction of uneven illumination and contrast enhancement are needed before applying the vessel segmentation method for landmarks extraction. Uneven illumination (also called shading) is presented in retinal images and must be suppressed in order to achieve more accurate segmentation of the blood vessels. Normalization, correction of the brightness and contrast enhancement are applied in this preprocessing step. Higher contrast between background and vessels in the image, and the small bright noise is removed while most of the capillaries are preserved.

For the main processing step the conclusions are:

d) The co-occurrence matrix computation gives a powerful tool to obtain an automatic threshold value to segment the vessel tree depending only on the information contained in the image.
e) Accurate segmentation of retinal images influences directly the performance of minutiae extraction. If more background areas are included in the segmented

retinal image, more false features are introduced; if some parts of the foreground are excluded, useful feature points may be missed. The method is non-supervised, fast and offers high segmentation accuracy.

f) It is usually desirable to reduce the images to thin representations located along the approximated middle of the original curve or line. Thinning is the process of reducing a shape to its core components while retaining the essential features of the original object.

g) For the landmarks extraction stage and based on the skeleton image it is possible to extract the retinal vessel landmarks, exploiting the skeleton unitary depth. Using a window of 3 x 3 with 8 neighbor pixels to the central pixel, it is calculated the cross number around the central point.

And, for the post-processing step it is possible to conclude that:

h) The presence of undesired segment and broken vessels present in a thinned vessel tree may lead to detect many false positive minutiae. Therefore some heuristics rules are used to pre-process the vascular tree.

i) For each kind of minutia some attributes are estimated. These are: landmark position, orientation and type. Using these features it is possible to create the retinal feature vector.

The average time required to segment and extracts the vascular landmarks information is 4 seconds. Based on these results we consider that our method offers a good alternative for biometrics applications where the time of analysis plays an important role.

References

1. Jain A., Bolle R. and Pankanti S., (2004), Introduction To Biometric Recognition, Michigan State University, East Lansing, MI, IBM T. J. Watson Research Center, Yorktown Heights, NY.
2. Simon C., and Goldstein I., (1935), A new scientific method of identification. New York State. J. Medicine, 35(18):901-906.
3. Tower, P., (1955), The fundus oculi in monozygotic twins: Report of six pairs of identical twins. Arch. Ophthalmol., 54:225-239.
4. Bruce L. Golden, Bernard E. Rollin, Ralph V. Switzer JR., (2004), Apparatus and method for creating a record using biometric information, U.S. Patent No. 028343.
5. Hill R. B., (1978), Apparatus and method for identifying individuals through their retinal vasculature patterns, U.S. Patent No. 4109237.
6. Hill R. B., (1992), Retina Identification, Portland, OR, USA.
7. Marshall J. and Usher D., (2006), Method for generating a unique and consistent signal pattern for identification of an individual, U.S. patent No. 6993161.
8. Derakhshani R. and Ross A., (2007), A Texture-Based Neural Network Classifier for Biometric Identification using Ocular Surface Vasculature, Appeared in Proc. Of International Joint Conference on Neural Networks (IJCNN), Orlando, USA.
9. Usher D., Tosa Y. and Friedman M., (2007), Ocular Biometrics: Simultaneous Capture and Analysis of the Retina and Iris, Advances in Biometrics Sensors, Algorithms and Systems, pp. 133-155.

10.http://www.absoluteastronomy.com/topics/Retinal_scan.
11.Usher D. B., (2003), Image analysis for the screening of diabetic retinopathy. PhD thesis, University of London.
12.Jung E. and Hong K., (2006), Automatic Retinal Vasculature Structure Tracing and Vascular Landmark Extraction from Human Eye Image, Proceedings of the International Conference on Hybrid Information Technology, IEEE Computer Society.
13.Bevilacqua V., Cambó S., Cariello L. and Mastronardi G., (2007), Retinal Fundus Hybrid Analysis Based on Soft Computing Algorithms, Communications To Simai Congress, ISSN 1827-9015, Vol. 2.
14.Wu C., (2007), Advanced Feature Extraction Algorithms for Automatic Fingerprint Recognition Systems, a Dissertation submitted to the Faculty of the Graduate School of State University of New York at Buffalo in Particular fulfillment of the requirements for the degree of Doctor of Philosophy.
15.Chaudhuri S., Chatterjee S., Katz N., Nelson N. and Goldbaum M., (1989), Detection of Blood Vessels in Retinal Images Using Two-Dimensional Matched Filters, IEEE Transactions on Medical Imaging, 8(3):263–269.
16.Zhang Y. F, and Zhang Y, (2006), Another Method of Building 2D Entropy to Realize Automatic Segmentation, International Symposium on Instrumentation Science and Technology; Journal of Physics: Conference Series 48, 303–307.
17.Haralick, R.M., Shanmugam, K., and Dinstein, I., (2008), Textural features for image segmentation, IEEE Trans. Syst. Man Cybern., 973, SMC-3, (6), pp. 610–621, 1973.
18.Gonzalez, R., and Woods, J., (2004), Digital image processing, Addison-Wesley.
19.Kullback, S., Information theory and statistics, Communications and Information Theory, Vol. 1, Issue 4, Pp. 417 – 528.
20.Pal N.R. and Pal S.K., (1989), Entropic thresholding, Signal Process 16, 97-10.
21.Zana F. and Klein J. C., (1997), Robust Segmentation of Vessels from Retinal Angiography. In International Conference on Digital Signal Processing, pages 1087–1091, Santorini, Greece.
22.Choe T. E., Cohen I., Lee M. and Medioni G., (2006), Optimal Global Mosaic Generation from Retinal Images, the 18th International Conference on Pattern Recognition.
23.M. Martinez M. , Hughes A., Stanton A., Thom S., Bharath A., and Parker K., (1999), Scale-space analysis for the characterization of retinal blood vessels, Medical Image computing and Computer-Assisted Intervention-MICCAI'99, C. Taylor and A. Colchester, eds., pp. 90-97.
24.Staal J., Abramoff M., Niemeijer M., Viergever M. and van Ginneken B., (2004), Ridge-based Vessel segmentation in color images of the retina, IEEE Trans. Med. Imag. 23, 501-509.
25.Nagasubramanian S. and Weale R. A., (2004), Ethnic variability of the vasculature of the optic disc in normal and in glaucomatous eyes. Eur. J. Ophthalmol. 14,(6) pp. 501–507.
A. Arakala A., Horadam K. J. and Boztas S., (2008), Practical Considerations for Secure Minutiae Based Templates", Proc. 2008 Biometrics Symposium, Tampa, Florida, 23-25, IEEE Press.
26.Soares J.V.B., Leandro J.J.G., Cesar R.M., Jelinek H.F. and Cree M.J., (2006), Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification, IEEE Transactions on Medical Imaging, 25:1214–1222.
27.Wang L. and Bhalerao A., (2003), Model Based Segmentation for Retinal Fundus Images. In Proc. of Scandinavian Conference on Image Analysis (SCIA).
28.Chanwimaluang T. and Fan G., (2003), An efficient blood vessel detection algorithm for retinal images using local entropy thresholding. In: Proc. of the IEEE Intl. Symp. on Circuits and Systems.

29. Jiang X. and Mojon D., (2003), Adaptive local thresholding y verification-based multi-threshold probing with application to vessel detection in retinal images. IEEE Trans. Pattern Recogn. Anal. Mach. Intell. 25, 131-137.
30. Siddalingaswamy P.C. and Prabhu G.K., (2007), Automated Detection of Anatomical Structures in Retinal Images, International Conference on Computational Intelligence and Multimedia Applications vol. 3, pp.164-168.
31. Rohrschneider K., (2004), Determination of the location of the fovea on the fundus. Invest. Ophthalmol. Vis. Sci. 45, 9 pp. 3257–8.
32. Srivastavas V., (2005), Performance of micro-calcification detection algorithms, Master Thesis, Department of Electrical and Computer Engineering.
33. Yang C.W., Dye M., Shuenn C., Chuin W., Chia W., Chien L., Pau C. and Chein C., (2000), Computer-aided diagnostic detection system of venous beading in retinal images, Society of Photo-Optical Instrumentation Engineers. 39(5): 1293–1303.