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A Comparison Between a Geometrical and an ANN Based Method for Retinal Bifurcation Points Extraction

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Abstract: This paper describes a comparative study between an Artificial Neural Network (ANN) and a geometric technique to detect for biometric applications,the bifurcation points of blood vessels in the retinal fundus. The first step is an image preprocessing phase to extract retina blood vessels. The contrast of the blood vessels from the retinal image background is enhanced in order to extract the blood vessels skeleton. Successively, candidate points of bifurcation are individualized by approximating the skeleton lines in segments. The distinction between bifurcations and vessel bends is carried out through the employment of two methods: geometric (through the study of intersections within the region obtained thresholding the image portion inside a circle centered around the junctions point and the circumference of the same circle) and an ANN. The results obtained are compared and discussed.
Key Words: personal identification, retinal fundus, blood vessels detection, preprocessing, gaussian derivation, crossover points extraction, blood vessels skeleton, ANN.
Category: D.0, G.1.10, G.3, J.3

1 Introduction

The identity verification in computer systems is done based, usually, on measures like keys, cards, passwords, PIN and so forth. Unfortunately, these may often be forgotten, disclosed or changed. A reliable and accurate identification/verification technique may be designed using biometric technologies. A biometric system can be defined as a automated method of identifying or authenticating the identity of a living person by an his physiological or behavioral characteristic. Commonly used biometric information is based on the face, fingerprints, hand shape, palm print, voice, iris, retina, and so on [Jain (1999)] [Zhang (2000)]. But the following properties are required to biometric characteristics:

– Universal: everyone must have the attribute.

– Invariance of properties: they should be constant over a long period of time.

– Singularity: each expression of the attribute must be unique to the individual.

– Privacy: the process should not violate the privacy of the person.

– Comparable: the attribute should be able to be reduced to a state that makes it digitally comparable to others.

– Inimitable: the attribute must be irreproducible by other means.

Among the various biometric technologies, historically, retinal identification has been cited as being one of the most accurate biometrics. The fundamental advantages of the technology are its reliance on the unique characteristics of each person's retina, as well as the human retinal vasculature is located inside the eye, so it is protected from intentional or accidental tampering and it is not exposed to threats posed by the external environment: it is stable from birth to death. In additional, it also disappears within seconds of a person's death, so helping to ensure that a captured image is obtained only from a living user. For other biometrics, such as fingerprints, hand geometry, etc., the opposite holds true. Awareness of the uniqueness of the retinal vascular pattern dates back to 1935 when two ophthalmologists, Drs. Carleton and Goldstein, while studying eye disease, made a startling discovery: each eye has its own totally unique pattern of blood vessels. They published a paper on the use of retinal photographs for people identification based on blood vessel patterns [Tower (1955)]. Later in the 1950's, their conclusions were supported by Dr. Tower in the course of his study of identical twins [Simon (1935)]. He assumed that, in comparing two subjects, identical twins would be the most likely to have similar retinal vascular patterns. However, Tower's study showed that among typical twin resemblance factors, retinal vascular patterns are those that have the least similarity and moreover, among human physical features, none is less subject to change than the retinal fundus. Furthermore, another retina advantage is the average feature vector size is much smaller compared to other biometric feature vectors, (i.e. iris recognition), so the identification process is faster [Goh (2000)]. Consequently, a retinal image offers a rather accurate personal identification tool [Kresimir (2004)]. For all these reasons, retina biometrics systems are suited for environments requiring maximum security, such as Government, military and banking. In fact they have been in use for military applications since the early seventies. In spite of this feature, the retina has not been used frequently in common biometric systems mainly because of technological limitations in manufacturing low-cost scanners [Hill (1983)][Hill (1999)]. However, recent progress in retinal scanner technology has brought low-cost retinal scanners onto the market [Hill (1999)][Farzin (2008)]. On the contrary, the retinal recognition system possesses some weaknesses such as:

– the retina image acquisition process, requires the cooperation of the subject;

– diseases such as glaucoma, cataracts, may affect retina blood vessels [Farzin (2008)].

It is said that the retina ïs to the eye as film is to a camera̋: it consists of multiple layers of sensory tissue and millions of photoreceptors whose function is to transform light rays into electrical impulses that arrive to the brain via the optic nerve, where they are converted to images. The retina is approximately 0.5mm thick and is located on the back wall of the eyeball [Fig.1]. In the center of the retina there is the optical nerve or optical disk (OD), an elliptic white area measuring from 1.5mm to 2mm across (about 1/30th of retina diameter). Blood reaches the retina through vessels coming from the optic nerve. Just behind the retina is a matting of vessels called the choroidal vasculature which contains the majority of the information used to identify individuals. This area of the eye is also referred to by medical doctors, as the retinal fundus [Jain (1999)] [Tabatabaee (2006)][Goh (2000)].

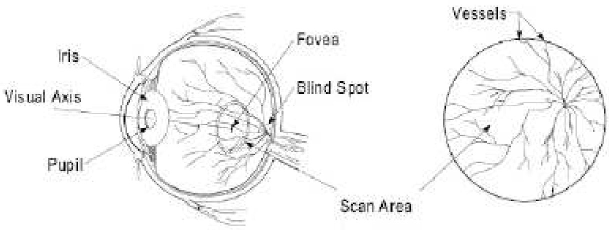

Figure 1: Eye and scan area.

Retina scans require that the person removes their glasses and place their eye close to the scanner. Then, retinal pattern capturing process can be summarized as follows: the user stares at a green dot for a few seconds until the eye is sufficiently focused for a scanner to capture the blood vessel pattern. An area, known as the fovea, located in the centre of the retina, is then scanned by an infra-red beam [Wilson (1999)]. In this way is possible to have a retinal fundus digital image. Then, the detected bifurcations and crossovers points of retinal vasculature in retinal blood vessels, are used with successful as biometric features for a personal identification process by a comparison of input fundus image characteristic points with reference fundus images in the database. In this paper, a personal identification technique by detecting bifurcation points of retinal fundus vasculature is described. In literature, methods for retinal vessel image segmentation can be divided into two groups [Staal (2004)]. The first group consists of supervised methods, which require manually labeled images for training [Sinthanayothin(2002)], [Bevilacqua(2005)]. The second group consists of rule-based methods and comprises vessel tracking [Bevilacqua,Cariello(2005)], [Chutatape (1998)], matched filter responses [Chaudhuri (1989)], [Gang (2002)], grouping of edge pixels [Pinz (1998)], model based locally adaptive thresholding [Jiang (2003)], topology adaptive snakes [McInerney (2000)] and morphology-based techniques [Zana (2001)]. In particular, the process described in this paper can be classified as belonging to both groups as matched filter responses and model-based locally adaptive thresholding techniques (second group) together with manual labeled images (first group) have been implemented.

1.1 Previous Paper

In [Bevilacqua(2005)], a genetic algorithm approach for feature recognition in fundus retinal images is presented. In particular, different genetic algorithms, each with its fitness function and its chromosome structure, are proposed for segmentation, vessel edge detection and bifurcation points identification in retinal images. An improvement of this method is provided in [Bevilacqua,Cariello(2005)]. In this paper, the analysis of retinal fundus images by means of a four step algorithm is described. A combination of soft-computing techniques is carried out in order to extract blood vessel bifurcation and crossover points. In the first step, the input image is preprocessed using in sequence, Naka-Rushton filter, clustering process, erosion and dilation operators, median filtering. The retinal image is processed pixel by pixel to obtain a black and white image representing the template of retinal veins and arteries. In the second step, the edges template is extracted by applying a genetic algorithm to the preprocessed image. Then, in the third step, the method continues with a skeleton process of the contours. Finally, the goal is reached by characterizing the searched points by means of a tracking algorithm. Nevertheless, the true imperfection of the above mentioned techniques and the others implemented from the same authors is that, through an algorithmic approach, it is impossible to obtain only bifurcation points as the results also include false positives. Thus, the basic idea of this paper is to compare two methods: a neural network approach versus to a geometric method, to discriminate the true bifurcation and cross-over points from false positives. Starting from preprocessing operation finalized in the reduction of noise from the retinal image, the process continues through the extraction of the blood vessel skeleton and detection of bifurcation points. At this point, the two techniques described above are employed to obtain the true bifurcation and cross-over points, whose results are compared. A database of 20 jpg retinal color images of 768x576 pixels (provided by the Ospedali Riuniti of Foggia), has been used. An example of input images is depicted in [Fig. 2].

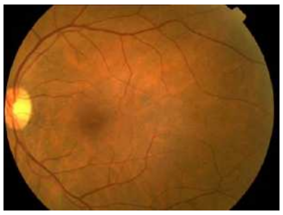

Figure 2: Input image.

1.2 Artificial Neural Netkork

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way the biological nervous systems processes information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) cooperating to solve specific problems. All connections among neurons are characterized by numeric values (weights) that are updated during training. If we consider n to be the number of neurons in the input layer, m as the number of neurons in the output layer, Nl as the number of neurons belonging to the l^{th} layer and $o_k^{(l)}$ to be the output of the k^{th} neuron of the l^{th} layer, then the computation performed by each neuron can be expressed as:

$$net_k^l = \sum_{l=1}^{N_{l-1}} w_{kj}^{(l)} o_j^{(l-1)}$$

$$o_k^l = f(net_k^l)$$

where $net_k^{(l)}$ is the weighted sum of the k neurons of the $l^{(th)}$ layer, $w_{kj}^{(l)}$ is the weight by which the same neuron multiplies the output $o_j^{(l-1)}$ of the j^{th} neuron of the previous layer and f() is a nonlinear bounded function (typically a sigmoid function). The ANN is trained by a supervised learning process: in the training phase the network processes all the pairs of input-output presented by the user, learning how to associate a particular input to a specific output trying to extend the information acquired also for cases that do not belong to the training set spectrum. Each data pair in the training set is presented to the system for a quantity of time determined by the user a priori.

2 Pre-Processing and Skeleton and bifurcation points Extraction

The preprocessing stage performs a color transformation to convert the colored input image to the scale of gray and a contrast enhancement to simplify vein extraction.

2.1 Color Transformation

As the color itself does not contain any useful information to distinguish veins from the background, it was therefore, deemed efficient to decompose the image in its three channels (each of them represented in the scale of gray), thus reducing threefold the computational cost of the algorithm. The resulting blue, green and red images show different brightness [Fig.3]: the green channel was chosen for successive elaboration.

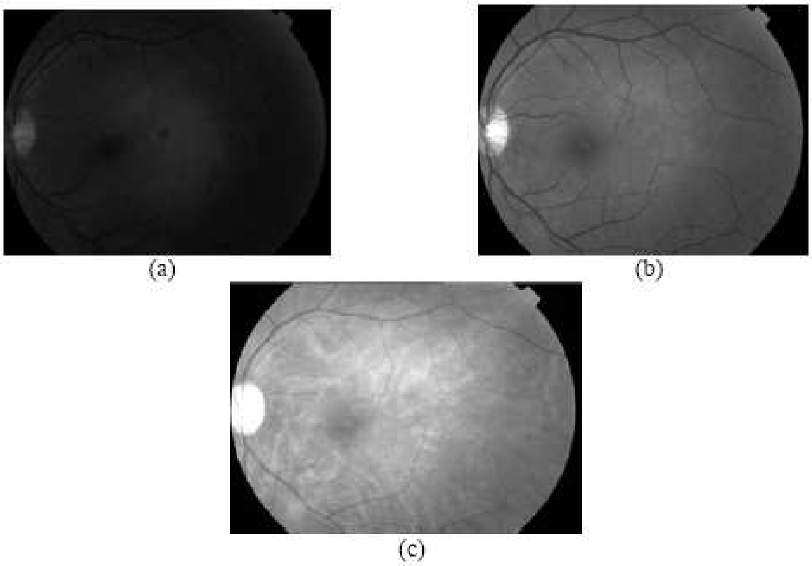

Figure 3 : Images of Blue (a), Green (b), and Red (c) channels.

The rectangular image (768x576 pixels), reproduces centrally the circular area of the retina, while the corners are black. Using a thresholding operation, the corners have been removed from the area of interest to avoid further manipulation. Observing the image, three concepts clearly appear:

1. all the veins start from the optic nerve;
2. the optic nerve is much brighter than the rest of the retina;
3. the optic nerve, for this reason, cannot be studied with the same algorithms that will be used for the whole image. For this reason, the region containing the nerve has been deleted from the region of interest [Fig. 4].

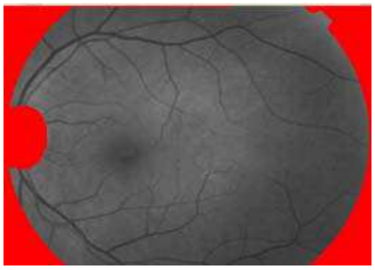

Figure 4 : The ROI (Region Of Interest).

2.2 Contrast Enhancement

The green image channel was considered to provide more contrast. Nonetheless, it was still necessary to increase the contrast between the background and the region of interest. The first step was the Gauss derivation of the image along the x-axis, and its convolution with the previously processed image [Steger (1998)]. This operation leads to the recognition of veins as those points of the image where the gray level changes from bright to dark. In order to increase the scale of gray values representing the image, a function that rates the histogram of the absolute frequencies of the gray values was used, followed by a function that scanned the histogram determining the smallest and the highest gray value. The highest one was then divided by 255 to determine the scale factor. The obtained image is depicted in [Fig. 5].

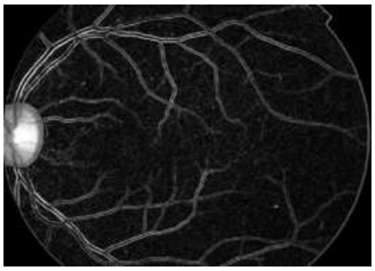

Figure 5 The image normalized after Gauss derivation along the x-axis.

2.3 Extracting Skeleton and Bifurcation Points

The next objective consisted in calculating the histogram threshold that had 80 % of its pixels located on its right. In order to do this, the absolute and the relative histogram of the gray values of the image was computed [Eckardt (1998)]. Both histograms were tuples of 256 values, from 0 to 255, containing the occurencies of the individual gray values of the image. Twenty percent of the image pixels represent veins, as they are darker than the background. The threshold level was determined summing the relative frequencies one by one until the value 0.8 was obtained. In [Fig. 6] we can observe the detected blood vessels.

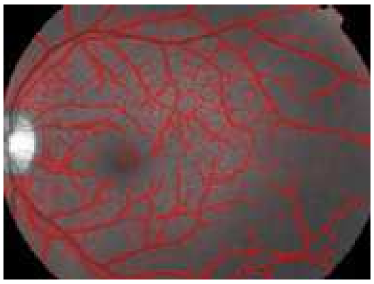

Figure 6 : Detected blood vessels.

The blobs generated by thresholding were selected by means of dimensional criteria, based on their size, in order to reduce the image noise [Fig. 7].

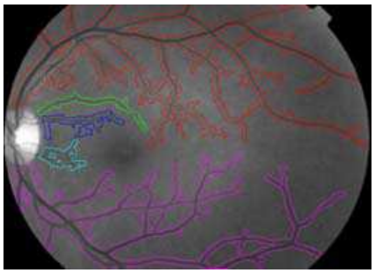

Figure 7 : Detected blood vessels without noise.

Subsequently, the median axis of the input regions was computed. The skeleton operation was carried out selecting those points within the region which corresponded to the center of the largest circle inscribed in the region itself.

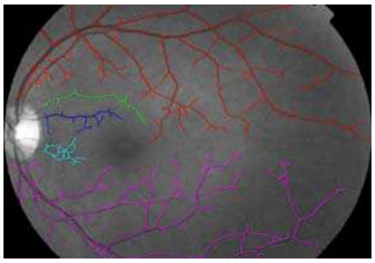

Figure 8 : The skeleton image.

The idenitification of blood vessel bifurcation and cross-over points was developed by studying intersetcions of the previously extracted skeleton. After approximating the skeleton lines with segments, bifurcation points and cross-over points were identified as those points from which two or more segments branched out.

3 Bifurcation Points Extraction by Geometrical Approach

For each point determined through the described algorithm, a circumference (radius = 9 pixel) was generated. The area encircled was studied selecting 35darkest pixels as vein representative. After simple noise reduction operations, the region of the vein was intersected by the ring [Fig. 9]. Whenever the intersection consisted of two points, it was classified as an inflection point [Fig. 10]. While, on the contrary, intersections of three or four points, were classified as vein intersections [Fig.11]. Following this, the number of candidate points were counted and a routine to individualize true intersection points was initiated.

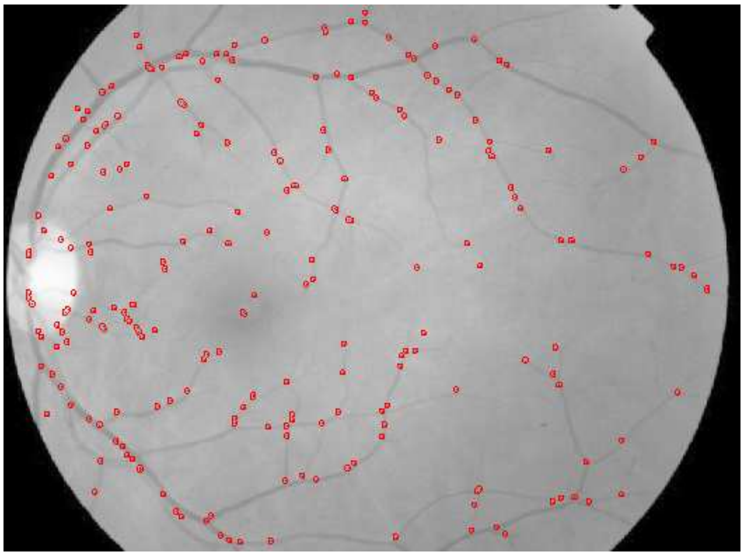

Figure 9 : Bifurcation candidate points.

Figure 10 : Bifurcation points defined as vein inflection.

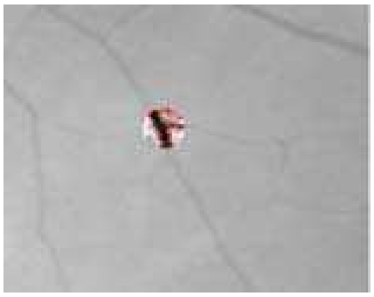

Figure 11 : Bifurcation point defined as vein junction.

For each candidate, a circle region (radius = 10 pixel) was created and the image reduced to that area. The histogram of the reduced image was then linearized to enhance the contrast. The starting point was the histogram of the reduced image. The following simple gray value transformation, f(g), was carried out:

h(x) describes the relative frequency of the occurrence of the gray level value x. The maximum value of the histogram was calculated and then, through a threshold operation, the darkest area was extracted. The relative histogram of the gray values was determined and the relative minima were taken and set as threshold values. In order to reduce the number of minima, the histogram was smoothed with a Gauss filter. The mask size was enlarged until there the smoothed histogram contained just one minimum. The selected region contains those pixels having gray values ranging from 0 to the minimum. After thresholding, it was possible to count the number of intersections between the ring and the selected area. If the resulting number was greater than 2, the point under test was defined as a junction point. The detected retinal blood vessel intersections are shown in [Fig. 12].

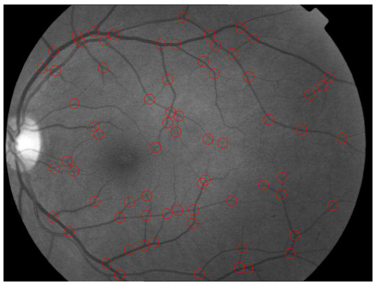

Figure 12 : The extracted blood vessel bifurcation and cross-over points.

4 Bifurcation Points Extraction by ANN Approach

The other approach consists in the use of a EBP Neural Network. The synthesized NN has 225 inputs, a first layer of 15 input neurons, a hidden layer with 5 neurons, and 1 output neuron. The developed training set is constituted by 24 patterns, divided in 12 correct examples and 12 wrong ones. The validation set is constituted by 6 patterns, divided in 3 correct examples and 3 wrong ones. The synthesized NN presents the following parameters : 40000 epochs, 0.02 Learning Rate, 0.02 Momentum and logsig functions for each layer. Best performances were obtained choosing a threshold equal to 0.20 .

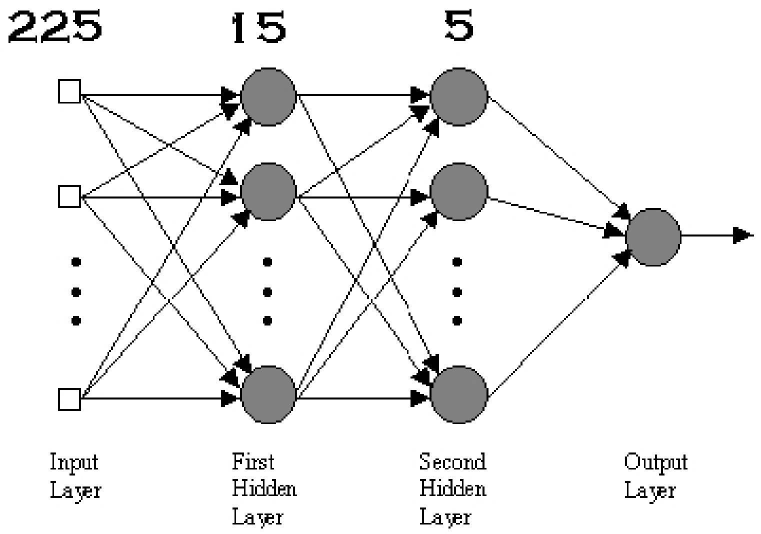

Figure 13 : Neural Network

5 Comparison of ANN and Geometric Method Results

In order to validate the efficiency of the forementioned methods, we tested them on three standard images [Fig. 15] and compared the obtained results. [Fig. 14] shows the outcome of the two algorithms in comparison with the manual classification of the same points performed by an operator.

Tot	Positive	False Positive	Geometric Method %	ANN %
134	76	58	77.6	80.26
122	54	68	68.5	77.78
113	68	45	72.0	77.94

Figure 14 : Experimental Results.

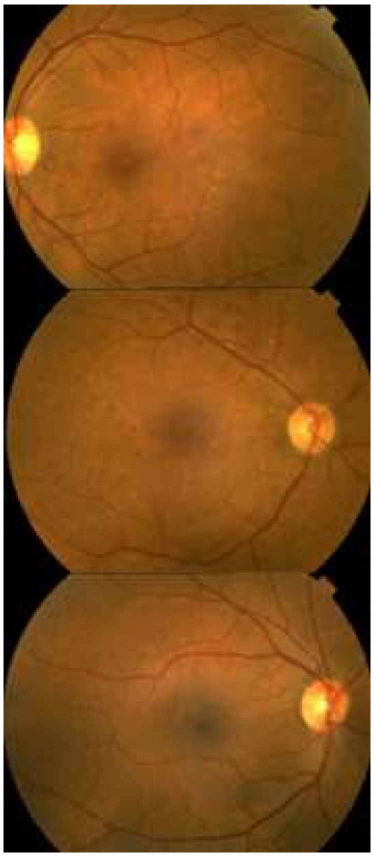

Figure 15 : The three input images.

6 Conclusions

In this paper a method to detect retinal blood vessels bifurcation and cross-over points is described. It consists of a first step in which, retinal image is pre-processed to reduce the noise, the skeleton of blood vessels is extracted and bifurcation and crossover points are detected. Then a geometric method and ANN approach are used to exclude false positives. The ANN method provides ,of course, best performance on the first image which the NN was trained on (see percentage greater than 80 shown in Table1), but it is relevant in terms of generalization the fact that performances on the two other images not used for training reach approximately 78%. These results encourage the authors to continue their study in this direction, considering the identification of bifurcation and cross-over points to have a relevant role in people recognition.

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