Retinal Fundus Biometric Analysis for Personal Identifications

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Abstract. In this paper a biometric system for personal identification, realized through the manipulation of retinal fundus images and the detection of its bifurcation points, is described. In the image pre-processing step, a strong contrast exaltation between blood vessels and the background in retinal image is carried out; then blood vessels are extracted and next the vasculature bifurcation and crossover points are identified within squared shaped regions used to window the image. Finally the features sets are compared with a pattern recognition algorithm and a novel formulation is introduced to evaluate a similarity score and to obtain the personal identification.

Keywords: personal identification; retinal fundus; blood vessels detection; vasculature bifurcation and crossover points extraction; clustering algorithm; Naka-Rushton filter; Generalized Hough Transform; pattern recognition.

1 Introduction

The retina is located inside the eyeball on its back wall (Fig.1). Blood reaches the retina through vessels coming from the optic nerve. Just behind the retina is a matting of vessels called the choroidal vasculature. The mat of vessels of the choroid just behind the retina reflect most of the useful information used to identify individuals. This area of the eye is also referred to, by medical doctors, as the retinal fundus [1].

The retinal pattern capturing process can be summarized as follows this: the user looks 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

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centre of the retina, is then scanned by an infrared beam [2]. Due to its internal location, retina is protected from variations caused by exposure to the external environment (as in the case of other physical characteristics used in personal identification like fingerprints, palm-prints etc.).

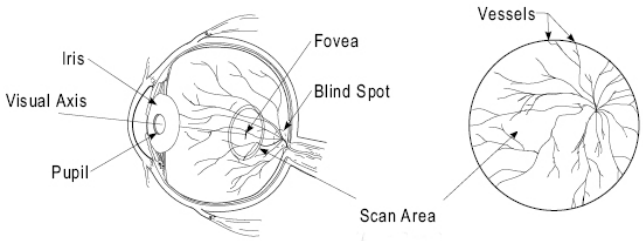


Fig. 1. Eye and scan area

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: every eye has its own totally unique pattern of blood vessels. They subsequently published a paper on the use of retinal photographs for people identification based on blood vessel patterns [3]. Later in the 1950's, their conclusions were supported by Dr. Tower in the course of his study of identical twins [4]. He noted that, considering a couple of persons, identical twins would be the most likely to have similar retinal vascular patterns. However, Tower's study showed that, among resemblance factors typical of twins, retinal vascular patterns are the one that have the least similarity. Besides, among human physical features, none is longer lasting than retinal fundus. Consequently, a retinal image offers an extremely accurate personal identification tool [5].

This paper describes a methodology to perform personal identification by detecting bifurcation points of retinal fundus vasculature. The process consists of three phases: at first each retinal image is handled by pre-processing operations aiming to reduce its intrinsic noise; than, blood vessels are extracted to allow, subsequently, the detection of the bifurcation points necessary to personal identification.

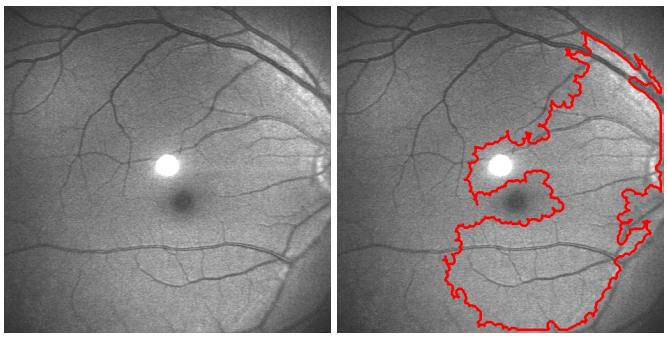
A database of 12 images containing 256 grey levels obtained by the ophthalmic clinic of a local hospital, has been used for testing the algorithm. The digital medical images constituting this database, where acquired by fluorescent angiography and, moreover, have a resolution of 512 x 512 pixels and a quantization of 8 bit per pixel.

2 Pre-processing

Through the pre-processing stage, two goals are to be reached: in primis a reduction of image noise, coming both from the disuniformity of light radiation on retinal fundus and from image acquisition hardware itself, and in secundis, a contrast enhancement of the lines that describe blood vessels, to semplify the successive vasculature extraction.

2.1 Noise Reduction

The first target has been successfully achieved by clustering the hole image in regions depending on the mean grey value of each area with a binarization operation (Fig. 2). Binarization is performed using two different selection criteria, the first one based upon a numeric approach, that considers the percentage of bright pixel of the image, and a second one based upon chromatic informations that considers, also, the gray value of the pixels previously calculated. The selection criterion based on the percentage of bright pixel allows to improve the determination of bright areas in case of overexposed images during the data capture step. The lower threshold, that shows the lowest gray value represented in a bright region, used in the second criterion, has been located considering the shift that afflicts the histogram of images acquired under different illumination conditions. Finally, the 40% of bright pixels of the images, belonging to the range [160, 255], will be selected. At this point, the necessity of applying the Naka-Rushton filter to every single region reveals clear. The use of this filter, in fact, allows to obtain a strong contrast enhancement between blood vessels and background, since each pixel belonging to areas under different illumination condition will be processed after being weighted by the average of pixels having the same brightness level, decreasing considerably the noise.



(a) (b)

Fig. 2. Retinal Fundus (*a*), Bright Region (*b*)

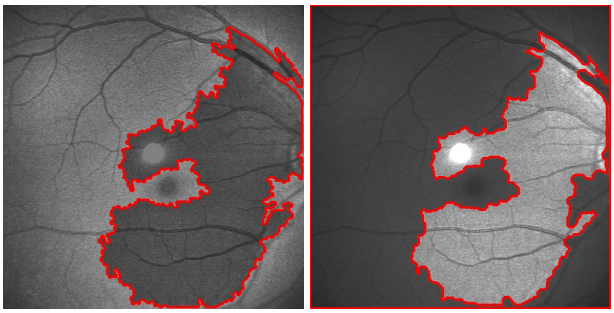
2.2 Contrast Enhancement

The second goal, as introduced before, has been accomplished by applying Naka-Rushton filter to both the regions defined in the previously step. The Naka-Rushton technique, that consists of a strong compactness operation of grey levels [6] [7], is regulated by the law:

$$O(i,j) = \frac{I(i,j)}{I(i,j) + \mu_{window}} \tag{1}$$

where O(i,j) is the output matrix, that is the transformation result, I(i,j) is the elaborated image matrix and μ_{window} is the mean gray value of the pixels in the exploration window.

The result of this process is an image with a greater contrast between background and objects, as depicted in Figure 3.



(a) (b)

Fig. 3. Bright region after Naka - Rushton filtering (*a*), dark region after Naka - Rushton filtering (*b*)

3 Blood Vessel Detection

A blood vessel appears, as a line that is darkner then the background, within the image.

The lines estraction algorithm, developed to find out blood vessels, is based on the image filtering, by means of a gaussian mask that allows the enhancement of the points of discontinuity within the image. The reason beneath the choice of a kernel of Gauss resides in the necessity of performing a smooth operation on the image in order to reduce noise [8].

The image has been derived by convolving it with gaussian kernels and with the first and second derivative of the same kernel, and the position of the line crests has been determined thanks to a sub pixeling algorithm. This algorithm discovers the direction that is orthogonal to the line by calculating the first derivative of image, and the exact position of the center of the line by determining the maximum value for the second derivative in that area.

Analitically, each line can be described as follows:

$$r(x) = \begin{cases} a, x < -\omega \\ h, |x| \leq \omega \\ b, x < \omega \end{cases} \tag{2}$$

where:

- $(a,b) \in [0,h]$ are coefficients representing the cromatic differences on the edge of a generic line;
- $h \in [0,255]$ is the maximum grey value that the line assumes in the image;
- 2ω represents the line thickness.

The existence of the line is determined by studying the first spatial derivative of the image. The pixels where the first derivative has a null value are considered as belonging to the border of a line. But this is not enough: the noise that affects the pictures of retinal fundus creates false positives making, for this reason, impossible the extraction of lines by means of a bare calculation of the first derivative. The adopted criterion to overcome this disavantage, is based upon the study of the second derivative behaviour in the region laying around the points where the first derivative is zero. The exact position of the line center is determined searching for the second derivative maximum value in that area, with a sub pixel precision.

The operation of image derivation is computed as the result of the convolution of the image itself with Gauss kernel built as in Figure 4.

$$\begin{matrix} -1 & -1 & 0 & 1 & 1 \\ -1 & -1 & 0 & 1 & 1 \\ -1 & -1 & 0 & 1 & 1 \\ -1 & -1 & 0 & 1 & 1 \\ -1 & -1 & 0 & 1 & 1 \end{matrix} \qquad \begin{matrix} -1 & -1 & 0 & -1 & -1 \\ -1 & -1 & 0 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 \end{matrix} \qquad \begin{matrix} 0 & 1 & 1 & 1 & 1 \\ -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & 0 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 \\ -1 & -1 & -1 & -1 & 0 \end{matrix}$$

Fig. 4. The used Gauss Kernel

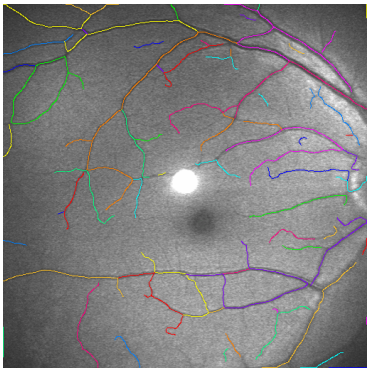


Fig. 5. Detected blood vessels

The gaussian filter will be more efficient while increasing the dimensions of the convolution matrix. The dimension of the used filter has been determined considering the dimension of the thinnest blood vessel to be detected (Fig. 5).

4 Bifurcation Points Extraction

The research of blood vessels crossing points has been developed studying of intersections of lines extracted in the previous phase, within squared shaped regions used to window the image.

In fact the image has been windowed by using squares with 8 pixel side, that moves along the principal axis of the image so that two consecutives squares overlap for the half of their area (Fig. 6).

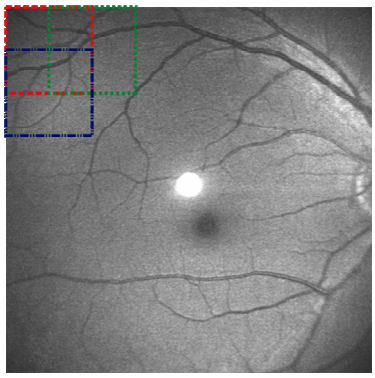
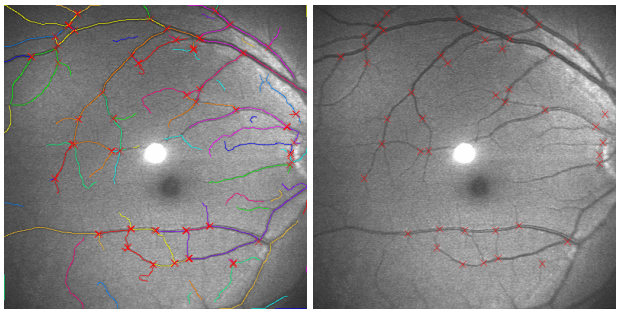


Fig. 6. Squared shaped regions used to window the image

The study of map of extracted lines has been limited to the area enclosed inside the window. Segments within each window are considered as straight lines and their intersection is geometrically computed. The risk of loosing intersection points eventually located on the boundary of the region is avoided by choosing windows that partially overlap. Within each region only the points which falls inside the window baundaries are considered. All the intersection points falling outside the window will be computed and stored when the algorithm will investigate the region to which they belong.

The windows positioning criterion brings to overlap of solutions: the same intersection point can be determined more than once, i.e. one time for each window positioned in that area.

The result is that we have more points that represent the same intersection of vessels, positioned around the real intersection point (Fig. 7 (a)). To calculate the exact coordinates of the intersection points, the average value for both the coordinates x and y, has been calculated (Fig. 7 (b)). Another error is introduced where interpolating curves with straight lines. The interpolation error has been reduced by considering smaller windowings squares.



(a) (b)

Fig. 7. The extracted cloud of points (*a*); the final extracted blood vessels crossing points (*b*)

5 Personal Identification

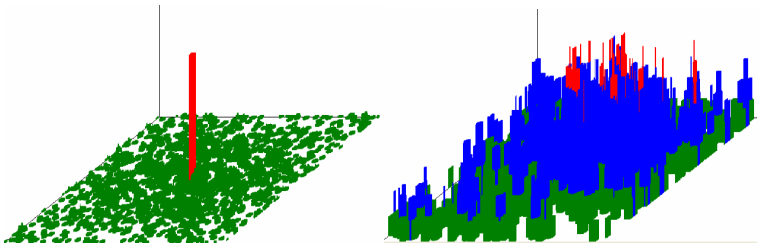
The cloud of points, extracted as described, represents a feature set which identifies each retina (i.e. each subject). In this step the goal is to use a matching algorithm which provides a score of correlation between two clouds of points (i.e. our features sets). Each feature is represented by a couple of coordinates, hence a simplified version of the Generalized Hough Transform [9] has been tested. The Generalized Hough Transform is an effective way to recognize shapes: it makes a comparison between two set of connected points by means of an accumulation matrix (AM). Each couple of connected points of one set is compared with each couple which shows the same inclination on the other set. Since the used set does not consist of connected points, we use a simplified algorithm which can be described as follows:

```
Calculate RA and RB (reference points for features set A and B. It
can be arbitrary set)

Refer all points of each features set to their own reference point

For each point Pa of set A
     For each point Pb of set B
         Calculate distance between Pa and Pb and add contribute in
         the accumulation matrix
```

A peak in the AM will represent a high factor of similarity (Fig. 8 (a)). Of course noise can cause a random displacement of each feature point of two sets related to the same subject, with a consequent lowering of the peak in the AM. In order to make the algorithm noise tolerant, the way to add the contribution in the AM has been changed: instead of adding a single contribution at the calculated coordinates, we add contribution in an area all around it. The area is user defined and it corresponds to a circular Roberts Window [10] which allows to choose how many points will carry contribution, with a fine step of variation. The area chosen for the Roberts Window gives a measure of the tolerance to noise.

When the AM is calculated, a similarity score has been extracted. Two identical features sets produce an AM with an absolute maximum value placed in the middle and various multiple local maxima of lower value. Local maxima usually have much lower values than the peak, but their difference depends on the Roberts Window chosen for the accumulation process. Differences in the two sets cause a decrease of the absolute maximum and an increase of the other values. Sets of points with no correlation can also produce multiple absolute maxima and multiple local maxima of high value (Fig. 8 (b)). We use this behaviour to extract a similarity score. Our algorithm can be described as follows:

- Calculate the absolute maximum value of the accumulation matrix;
- Calculate the gravitational center (C) of all absolute maxima positions (in case of high similarity, it will be coincident with the singular absolute maximum position);
- Calculate the mean value (HV) inside the Roberts Window centered in C;
- Calculate the mean value (LV) outside the Roberts Window centered in C;
- Normalize value LV: LV’ = LV/HV;



(a) (b)

Fig. 8. 3D representation of the Accumulation Matrix. (*a*) Case of identity between clouds of points; (*b*) Case of clouds of points with no correlation.

The Roberts Window used for the mean calculation has the same order of that used for the accumulation process. The identified similarity score is proportional to the difference between values HV and LV. Since HV and LV depend also on the Roberts Windows, their difference have been related with the value obtained in case of perfect coincidence. Hence:

$$\text{Similarity score} = (1 - LV') / (1 - LVi') \tag{3}$$

Where LV' is the normalized mean value outside the Roberts Window and LVi' is the normalized mean value outside the Roberts Window calculated in case of identical features sets.

6 Experimental Results

The algorithm has been run on a database of 12 images, 512 x 512 pixel, of 10 different persons where two couple of images belongs to the same person. Figure 9 shows the mean trend of the similarity score relative to the order of the Roberts Window.

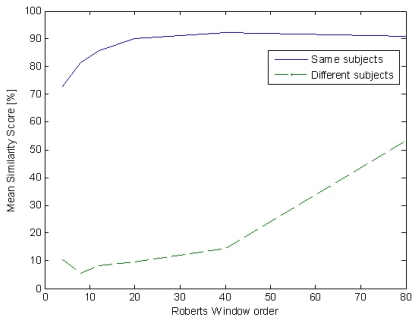


Fig. 9. Mean Similarity Score vs Roberts Window Order

Even though mean results reveal a good performance of the algorithm for a wide range of the order of the Roberts Window, in tests, an order of 8, which corresponds to a Window comparable to a circle of radius 3 pixel, minimizes best the score for different subjects.

Experimental evidence shows also that a threshold equal to 70% would bring both False Acceptance Rate and False Rejection Rate to a value of 0%.

7 Conclusions

In this paper is described a biometric system for personal identification, realized through the manipulation of retinal fundus images and the detection of its bifurcation points. The process consists of three phases: at first each retinal image is handled by pre-processing operations aiming to reduce its intrinsic noise; than, blood vessels are extracted to allow, subsequently, the detection of the bifurcation points necessary to personal identification. The satisfactory results of experimental encourage the authors to continue the studies in this direction.

References

1. Jain, A., Bolle, R., Pankanti, S.: Biometrics: Personal Identification in Networked Society, p. 123. Springer Science/Business Media, New York (1996)
2. Wilson, C.L., McCabe, R.M.: Simple Test Procedure for Image-based Biometric Verification Systems. NISTIR 6336, National Institute of Standards and Technology (1999), `http://www.itl.nist.gov/iaui/894.03/pubs.htm`
3. Tower, P.: The Fundus Oculi in Monozygotic Twins: Report of Six Pairs of Identical Twins. Archives of Ophthalmology 54, 225–239 (1955)
4. Simon, C., Goldstein, I.: A New Scientific Method of Identification. New York State Journal of Medicine 35(18), 901–906 (1935)
5. Kresimir, D.I., Mislav, G.: A Survey of Biometric Recognition Methods. In: 46th International SyrnPoSium Electronics in Marine, ELMAR-2004, Zadar, Croatia (2004)
6. Naka, K.I., Rushton, W.A.: S-potentials from Luminosity Units in the Retina of fish (Cyprinidae). Journal of Physiology 185, 587–599 (1966)
7. Bevilacqua, V., Cariello, L., Cambò, S., Daleno, D., Mastronardi, G.: Retinal Fundus Features Hybrid Detection based on a Genetic Algorithm. In: Proceedings of the Workshop on Medical Applications of Genetic and Evolutionary Computation (MedGEC), Seattle (USA) (2005)
8. Steger, C.: An Unbiased Detector of Curvilinear Structures. Proceedings of IEEE Transactions on Pattern Analysis and Machine Intelligence 20(2) (1998)
9. Ballard, D.H.: Generalizing the Hough Transform to detect arbitrary shapes. Pattern Recognition 13, 111–122 (1981)
10. Mastronardi, G., Daleno, D., Bevilacqua, V., Chiaia, G.: Tecniche di identificazione personale basate sulla trasformata generalizzata di Hough applicata a nuvole di punti. In: Proceedings of National Conf. AICA 2007 (Associazione italiana per l'informatica ed il calcolo distribuito), Milano (Italy) (2007) ISBN 88-901620-3-1