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RETINAL FUNDUS HYBRID ANALYSIS BASED ON SOFT COMPUTING ALGORITHMS

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Abstract.

In this paper, an analysis of images of the retinal fundus by means of a combination of soft-computing techniques is carried out, in order to extract from blood vessels their bifurcation and crossover points. These retinal features are unique for each individual and therefore they are useful for a successive process of personal identification. In particular, the implemented method is constituted of four steps. In the first step, a pre-processing of the input image by using, in sequence, several filters, is carried out: the retinal image is processed by means of pixel to pixel elaboration algorithms to obtain a black and white image representing the template of retinal veins and arteries. In the second step, applying to the so obtained image a genetic algorithm, it is extracted the edges' template. To this point, in the third step, the method continues with a skeleton process of the contours making use of an empirical algorithm. Finally, in the last step, the objective is caught up by characterising the searched points by means of a tracking algorithm.

Keywords: Medical imaging; Biometrics; Identification points; Retinal fundus; Vessel bifurcation and crossover detection; Genetic algorithm; Edge detection; Skeleton extraction; Tracking algorithm.

1. Introduction

Biometric technology improves the accuracy which systems can identify individuals with. Personal identification involves a very large type of life situations and this is the reason for the high interest given, in the last years, to the biometric methods.[7] Biometric security technologies, in fact, are being incorporated into many applications for improving airport security, preventing business theft, strengthening our national borders, into travel documents, visas and in preventing ID theft. This technology relies on measurements of physical characteristics unique to an individual such as fingerprints, facial features, retinal fundus, iris, hand geometry, or behavioural characteristics such as voice, handwritten signature. 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. One technology has emerged in the biometric area: *retinal recognition*. The retina, a layer of blood vessels located at the back of the eye, forms an identity card for the individual under

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investigation. In particular retinal recognition creates an "eye signature" from its vascular configuration and its artificial duplication is thought to be virtually impossible. For all these reasons, the retinal image offers a personal identification method of acceptable accuracy.[8] The retinal recognition process can be so summarized: the user views 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 center of the retina, is then scanned by an infrared beam. The retina pattern is captured, its features are extracted and then they are compared to previously-stored patterns for identification. If there is a match that meets a preset recognition threshold, the identification is accepted as valid.[11] This paper is dipped in this scenario. In fact this work is interposed between the image capture process and the comparison process: it consists of a method of features extraction. In other words a map of main bifurcation and crossover points are extracted from a retinal fundus image for a successive process of personal identification.



Fig. 1. Retinal fundus image.

A database of 12 images containing 256 grey levels, obtained by an oculistic clinic of a local hospital, has been used for elaborations. The retinal experimental images are been acquired with fluorescent angiography. The digital medical images have a resolution of 512 x 512 pixels and a quantization of 8 bit per pixel. An example of used images is depicted in Fig. 1.

2. Vasculature Extraction

In the first step of this process is used a combination of algorithms, existing in literature[1] , for retinal features extraction. The output of this stage is a correct representation of vasculature without loss or alteration of particulars of the image.

2.1. *Preprocessing*

The characteristic of retinal fundus images is to have the same grey levels both for backgrounds and vasculature. This problem is due to the presence of impulsive noise given by the acquisition tools and of structural noise given by the anatomic shape of the retinal fundus. For these reasons, to characterise the searched retinal features, it is necessary a good image preprocessing. It is realised making uniform the image by using the same retinal no-linear features. This preprocessing technique consists of a strong compactness operation of grey levels where classic thresholds systems fail because of loss

of a large number of important particulars. The applied filter answering to our necessity, famous in literature with the name of Naka-Rushton filter[10] 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 media of pixels in the choice exploration window. The result of this process, an image with a greater contrast between background and objects, is depicted in Fig. 1.

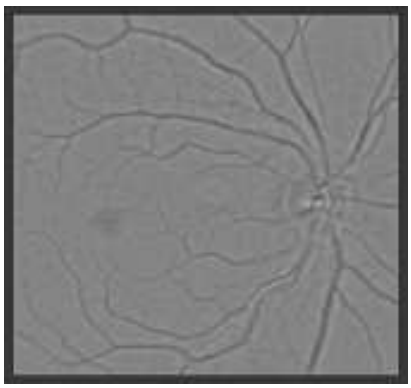


Fig. 1. Image after Naka-Rushton filtering.

2.2. *Vasculature identification*

The image, after preprocessing, is filtered to extract vasculature with a clustering of image.[6] The two clusters in which image is splitted on, are vasculature cluster and background cluster. It is an iterative method that uses average and standard deviation to start and Mikowski distance to distinguish pixels of vasculature from background. The output image has two levels: black pixels and white pixels that are respectively the vasculature and background. In the image, now, it is present an impulsive noise. By a successive application of morphological operators of erosion and dilation, and median filtering (see Fig. 2), it is obtained an image in which noise is reduced and features are preserved. In particular, the operations of erosion and dilation use hyperbole filter[3,4,9] , in the first case on negative image with a window of 17x17 pixels and in the second on image with a window of 3x3 pixels.

3. Genetic Algorithm for Edge Extraction

The vessel edge detection, existing in literature[2,3] , is performed by using a genetic approach in which the problem is formulated as one of function cost minimization. In particular has been chosen an edge detection algorithm by which it is possible to preserve some properties of the vessels edges looked for. The semantic interpretation and recognition of the observed object have found on the edge detection, understanding the sequences of disposed edges so that to form closed lines with this term, possibly deprived of gaps and blind ramifications. The search of the optimal solution to the objective function, is performed through an iterative procedure applied to a population of chromosome

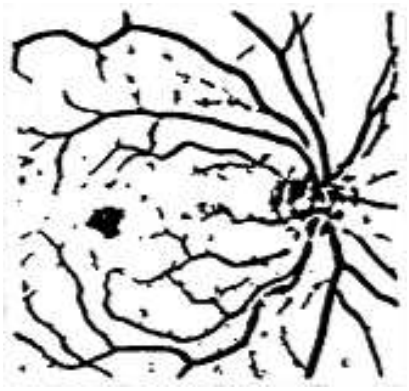


Fig. 2. Image after median filtering.

corresponding to feasible solutions to the problem. The genetic algorithm implements multi-directional search maintaining a population of potential solutions and encouraging the exchange of information between themselves. The adopted cost function is that proposed by Tan for the measure of edge fitness from real images. It introduces a cost factor related to the correct localization of edges based on a criterion of difference between adjacent regions.[5] The point cost of a binary edges image S at the position $p=(i,j)$ is obtained like weighted sum of opportune cost factors:

$$F(S,p) = \sum_i W_i C_i(S,p) \tag{1}$$

The total cost $F(S)$ of an edges image S is given by adding of the point cost at each pixel of the image:

$$F(S) = \sum_p F(S,p) \tag{2}$$

Therefore, considering two edge images S_a and S_b identical everywhere less that in a 3x3 pixel region centred on the p position, a comparative cost function could be defined as follows:

$$\Delta F = (S_a, S_b, p) = \sum_{I(p)} \sum_k W_k [C_k(S_a,p) - C_k(S_b,p)] = \sum_{I(p)} \sum_k \Delta C_k(S_a, S_b, p) \tag{3}$$

where $0 <= C_k <= 1$. The C_k terms are the factors of cost and the W_k terms the relative weights. With these positions, if $F(S_a, S_b, p) < 0$, Sa corresponds to a configuration of edges better than S_b, while it is the contrary when $F(S_a, S_b, p) > 0$. If $F(S_a, S_b, p) = 0$ the two configurations are equivalent in terms of cost. The C_t cost has been introduced to emphasize the contours locally thin, making a penalty for those locally thick. A pixel of contour has to be considered when it involves the existence of multiple connections between two or other pixels in the surrounding about 3x3. The C_t cost of a point of edge will come therefore engaged equal to 1 if such point is thick according to the preceding definition, or equal to 0 in contrary case. The C_c cost has been introduced to improve

the structures of contour locally linear in spite of those locally curve. An edge pixel has to be considered locally not bend, curved or very curved on the average if, always in the window 3x3 surrounding, you have the presence respectively of the 4 linear structures, or of the 8 structures with angle of bending of 45°, or of any other structures. The C_c cost is set to 0 for a pixel not curved, 0.5 for a pixel curved on the average, 1 for a very curved pixel. The C_f cost has been introduced to improve the structures of contour locally continuous in spite of those bended. An edge pixel has to be considered locally not bended, bended on the average, or much bended if, always in the surrounding about 3x3, it has respectively more than a pixel of adjacent contour, an only pixel of adjacent contour, or no pixel of adjacent contour. The C_f cost is therefore set to 0 for a pixel not bended, 0.5 for a pixel bended on the average fragmented, 1 for a pixel much bended. The C_e cost has been introduced to contain the number of pixel labeled like contour, balancing the opposite inherent tendency in the C_d cost. The C_e is set to 0 for a pixel not labeled like contour, to 1 for a pixel labeled like contour.

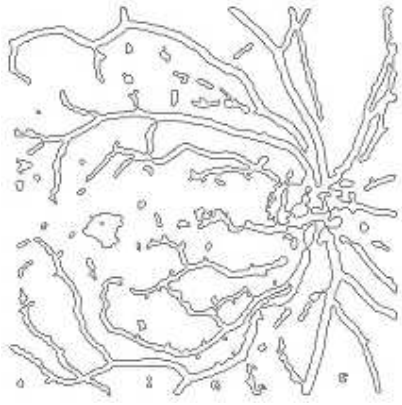


Fig. 1. The final edge image.

Concerning the weights attributed to the costs, Tan suggests a series of values generally valid, but to adapt however of time in time on heuristic base; set $C_e = 1.00$ follows W_d= 2.00, W_c ={0.25, 0.50, 0.75}, W_f ={2.00, 3.00, 4.00} and, in the case in which you want that to the local minima of the cost function corresponds configurations of contours not thick, W_t is set $= 2W_f + W_d - W_c - W_e$. This algorithm, using an opportune code for the solutions and, above all, thanks to a very efficient pair of mutation strategies, has produced the final edge image depicted in Fig. 1.

4. Skeleton Process

The next step consists to realise the skeleton of the blood vessels from the template edges image obtained in the previous phase. The skeleton process is divided into two moments: the edges image is processed in the first time in horizontal direction and in the second time in vertical direction. In a few words, considering the images like a matrix of 512 rows and 512 columns, for each row and each column that are met in the vertical and horizontal scansion respectively, all couples of points with a sufficient distance to be considered to belong to the edge of the same vessel, are individuated and for each of them is traced the median point in a output image. So the complete skeleton is produced. At

the end the two images so obtained are fused and the final image is processed in order to clean and eliminate the isolated points.

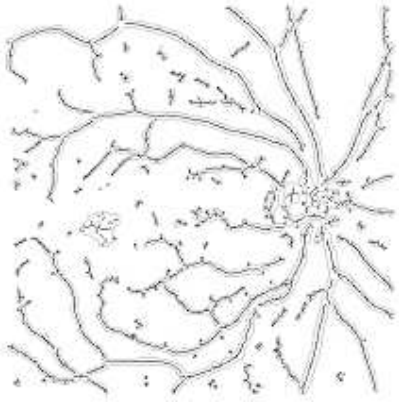


Fig. 1. The edge image fused with skeleton image.

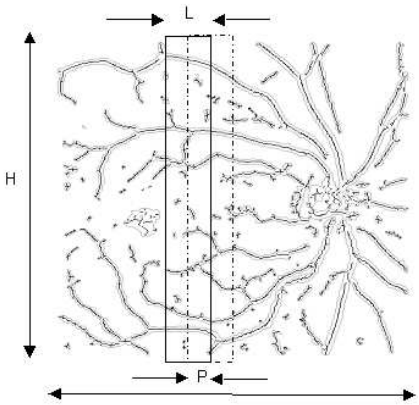


Fig. 2. Retinal image parametrization and blocks extraction.

5. Experimental Results

After having obtained the blood vessels skeleton, both the image of the edges and skeleton, have been merged in an unique one to exploit at the same time, the advantages of the information supplied from both the images (Fig. 1). At this point it proceeds with the application of a tracking algorithm that has allowed to characterise the bifurcation points.

In the tracking process the images of width 512 (W in Fig. 2) pixels and height 512 (H in Fig. 2) pixels, is divided into overlapping blocks of height 32 (L in Fig. 2) and width 512 (W in Fig. 2). The amount of overlap between consecutives blocks is 16 pixels (P in Fig. 2).

The idea of the algorithm is to start from the skeleton and to consider all the couples of points belonging to two parallel vessels that, at the end of their way, could converge forward a bifurcation point. When a couple of this type is characterised, the tracking process starts with the pursuit of the points of the vessels contour under examination

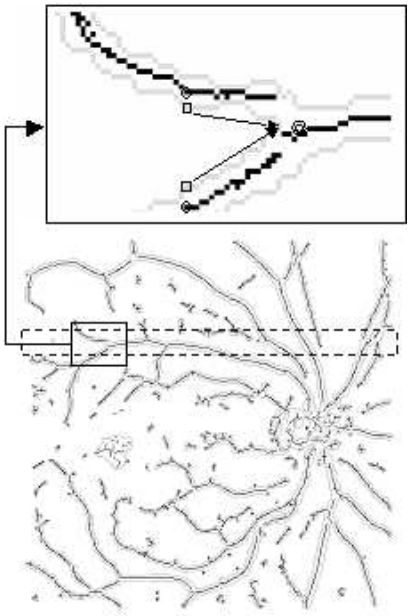


Fig. 1. Tracking algorithm process.

and, in particular, it is followed the way covered by those edge points that are between the two skeleton points (Fig. 1). Because of the different forms of blood vessels, it has been necessary to repropose previous process, analyzing the image in all the four directions: from left to right, from right to left, from top to down, from bottom to up, in order to cover all the bifurcation and crossover points characterised by two vessels coming from different directions. The path of edge points is tracked by matching it, step by step, with preset schemas of routes, that are different for each of four scanning directions (Fig. 2).

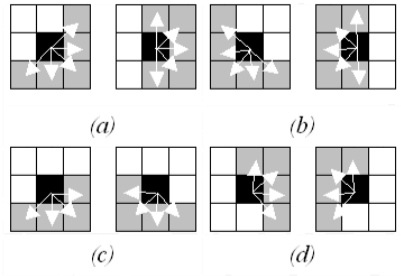


Fig. 2. Possible routes of the two edge points considered in scanning (a) from left to right, (b) from right to left, (c) from top to down, (d) from bottom to up.

When these tracked ways join, then a bifurcation point is characterised. The obtained bifurcation and crossover points are depicted in Fig. 3. The number of points, achieved by this features extraction process, is not complete, however, this is in a satisfactory amount to allow an efficient and sure personal identification process.

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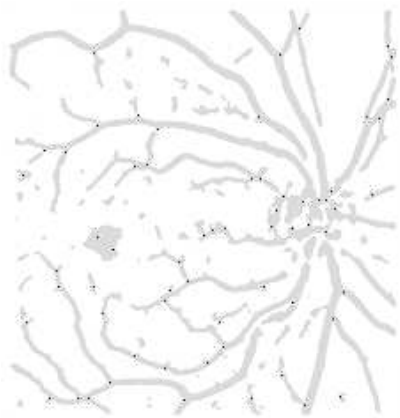


Fig. 3. Vessel entities, bifurcation and crossover points in superimposition.

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