# A COMBINED METHOD TO DETECT RETINAL FUNDUS FEATURES

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## ABSTRACT

This paper presents a computational model to extract, from eye fundus images, the retinal vasculature and then to detect its features such as bifurcations and crossover points of retinal vessels. In particular, our approach can be articulated in six steps. The first five steps are represented by a combined application of five operators: Naka-Rushton filter, cluster filter, hyperbole filter, median filter and a skeleton process. These computational steps process retinal images in order to remove noise and then they can produce an optimised skeleton version of the vessels. Last step consists of detecting bifurcation and crossover points of the retinal vessels. These extracted features are a powerful tool for medical and biological evaluations of ocular and non-ocular illness diagnoses.

**Keywords:** retinal vessels analysis, image filtering, clinical diagnoses, bifurcation and crossover points detection, personal identification.

## INTRODUCTION

In the last years the ophthalmology is always more heavily driven by image analysis. In fact, a number of image analysis tools has been developed for tracing vasculature, identifing key structures, segmenting pathologies and comparing several morphologies to normal ones.
In particular, the retinal fundus image analysis allows phisicians to detect in more robust and automatic way pathologies as macular degeneration, diabetic retinopathy, glaucoma, retinopathy of prematurity and so on.
Moreover these kind of applications can be divided into off-line and real-time ones (1-2). For example off-line applications are:

- early change-based detection/diagnosis,
- disease and treatment monitoring,
- mass screening to detect onset of disease conditions,
- scoring clinical trials for decision making diagnostic support,
- retinal image understanding for basic research, mass screening, population studies, and education.

Instead, real time applications are:

- control and guidance for positioning of instrumentation,
- tracing the vasculature and various pathologies,
- on-line treatment monitoring during laser retinal surgery,
- alarms and safety cutoffs in change detecting,
- patient/eye authentication.

As a matter of fact, the patient/eye authentication can be regarded as real-time and off-line as well. The real-time case concerns the mass classification, while the off-line concerns the fine personal identification. In particular, the bifurcations and crossover points detection in retinal images is of main interest in several areas of ophthalmology. It allows at the same time the personal identification and an optimised support during the phase of clinical diagnosis because of their structures (3).
In fact, they have some properties that allow the retina to be a sure instrument for clinical evaluations and also for personal identification:

- they are present in fixed locations on the patient retina,
- they are present in sufficient numbers into all retina areas, in function of their effective localization,
- they are detectable in the same area of a retina even when these ones are different for magnitude, focus and brightness, in different images,
- they are quickly detectable.

The changes in the retinal vasculature are a sure signal of an illness in progress (4). So, studying the retinal bifurcation and crossover points, it’s possible to diagnose not only the ocular but also the non-ocular diseases.
For example, retinal central vena occlusion produces more tortuous and larger venae; a hyper-tensive problem causes a reduction of the arteries; diabetes instead generates new blood vessels.
The mentioned cases carry out a modification to the retinal fundus, in terms of bifurcations and crossover points. So, by controlling periodically the retinal fundus of a vulnerable individual, it’s possible to detect anomalies in the retinal vasculature and consequently to diagnose prematurely an illness.
The aim of this work is to define a method, opportunely combined, in order to detect the retinal features with a good accuracy.

## IMAGE PREPROCESSING

The retinal fundus images present a structural and impulsive noise. The first one is due to anatomic shape of the retina, and the second one is caused by the acquisitions tools. For these motivations a characteristic of retinal image is to have the same grey levels both for background and the vascular system (see Fig. 1). So, in order to extract the desired retinal features, it's necessary a good image pre-processing.

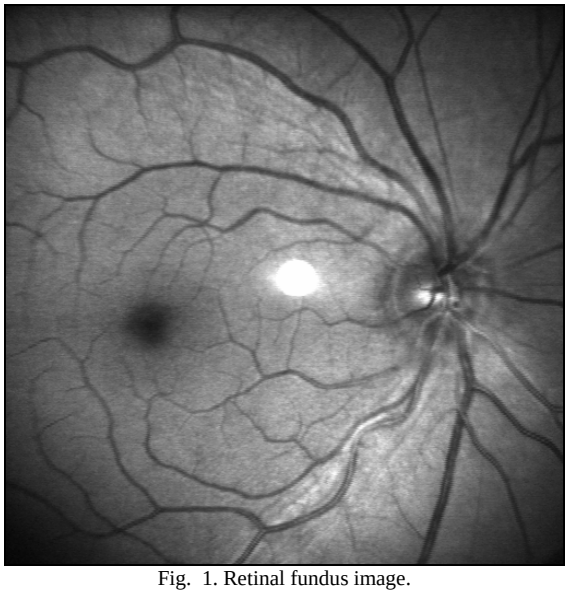


Fig. 1. Retinal fundus image.

In a first time we tried out several smoothing filters, but we obtained high loss of details.
Thus, we thought to take advantage of the same eye main characteristic: it's a filter itself. In this way, we used the retinal non-linear features to make uniform the image. The filter that provided satisfactory results has been the one based on the Naka-Rushton law:

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

where $O(i,j)$ is the output matrix, that is the transformation result, $I(i,j)$ is the original image matrix and $\mu_{window}$ is the average of pixels in the chosen exploration window.
By using this filter we obtained a grey level equalization, in other words the Naka-Rushton filter produces a grey level compression of the image. The obtained results are in terms of higher contrast between background and objects in the image (see Fig. 2).
We can understand the obtained improvement by comparing the histogram, respectively, of the original image (see Fig. 3) and the filtered image (see Fig. 4).
We can notice that the grey levels represented in Fig. 4, are compressed respect to the ones of the original image (see histogram in Fig. 3): the range which the grey levels are distributed, has constricted.

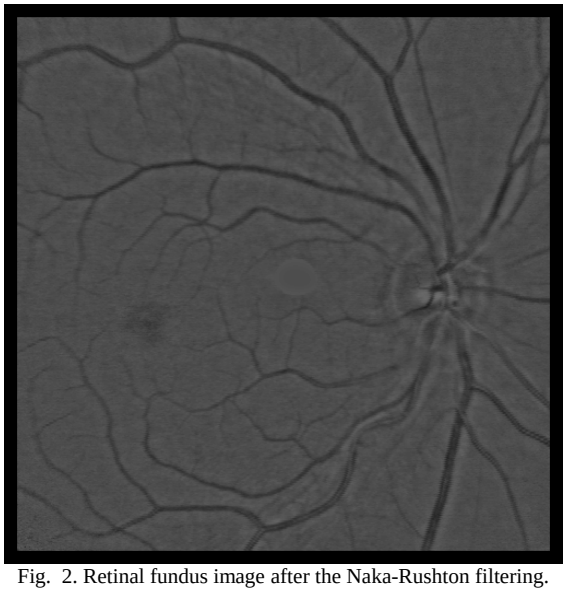


Fig. 2. Retinal fundus image after the Naka-Rushton filtering.

Now the processed image can be used with a filter that divides the objects from the image background.

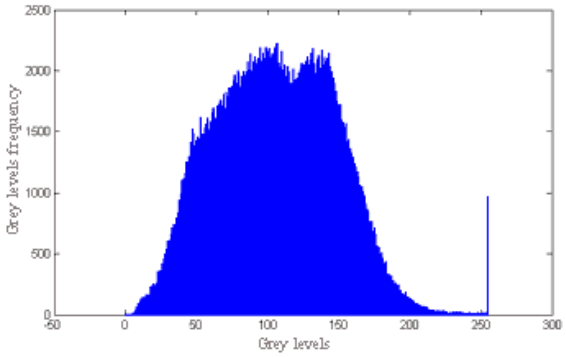



Fig. 3. Original image histogram.

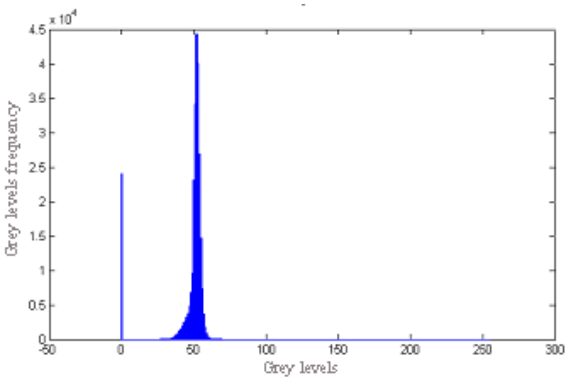



Fig. 4. Retinal fundus image histogram after the Naka-Rushton filtering.

## BLOOD VESSEL BIFURCATION EXTRACTION

In this step, it's processed the image with uniform grey levels: the blood vessels are extracted using a cluster filter. The last one splits in two different clusters the blood vessels and the image background (5).
If we indicate with $\text{CLUSTER}(q)_{\text{blood vessels}}$ and with

CLUSTER(q) $_{\text{background}}$ as the cluster that will embrace the blood vessels and the image background respectively, the employed algorithm can be divided into five phases:

1. calculate the average and standard deviation of the image;

2. set
   q = 1,
   $\text{CLUSTER}(q)_{\text{blood vessels}}$ = average – std_dev,
   $\text{CLUSTER}(q)_{\text{background}}$ = average + std_dev;

3. estimate the Minkowski distance between the pixel i-th and the parallel cluster value to q-th iteration:

$$d_{ij}(X_i, X_j, r) = \left\{ \sum_{K=1}^{n} \left| X_{ik} - X_{jk} \right|^{r} \right\}^{1/r}$$

for i from 1 up to the image dimension; so we obtain two distances:

$$D_1 = distance(X_i, CLUSTER(q)_{\text{blood vessels}})$$

$$D_2 = distance(X_i, CLUSTER(q)_{\text{background}})$$

   if $D_1 < D_2$ than the i-th pixel is assigned to blood vessels cluster, otherwise it is assigned to background cluster;

4. update the clusters centers in this way:

$$CLUSTER(q+1)_{\text{blood vessels}} = \frac{1}{\left| CLUSTER(q)_{\text{blood vessels}} \right|} \sum_{i \in \text{blood vessels}} X_i$$

$$CLUSTER(q+1)_{\text{background}} = \frac{1}{\left| CLUSTER(q)_{\text{background}} \right|} \sum_{i \in \text{background}} X_i$$

5. increase the value q and repeat phases 4 and 5.

The outcome image has only two grey levels: black and white (see Fig. 5).

## IMPULSIVE NOISE REMOVAL

In the clustering process all the vascular system has been preserved, but at the same time also the impulsive noise has been conserved. For this reason we have used the hyperbole filter (6-7).
Firstly it has been used on a negative image, like a morphological erosion operator; while, in a second moment, it has been used like a dilatation operator, on the image with white background and black objects (8).
In the first case the image has been processed by a window of 17 x 17 pixels (see Fig. 6).

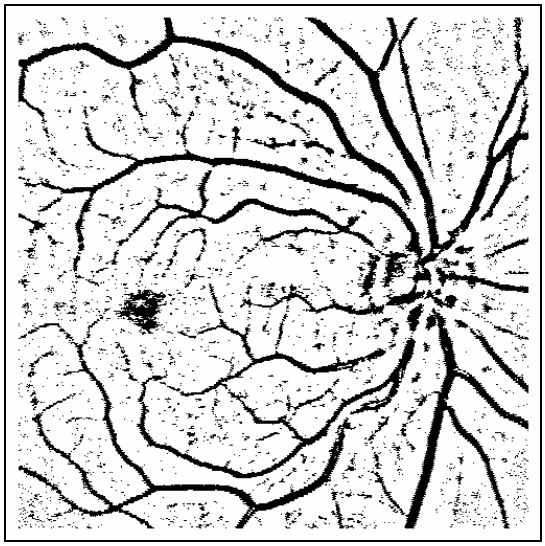


Fig. 5. Clusterised image.

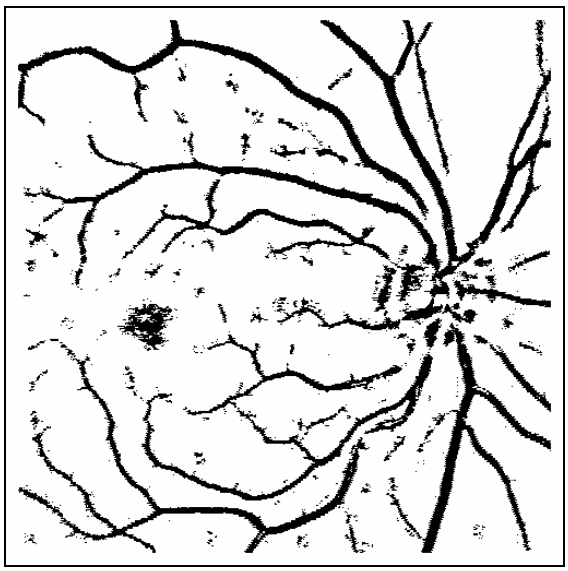


Fig. 6. Image after the hyperbole filtering (erosion operator).

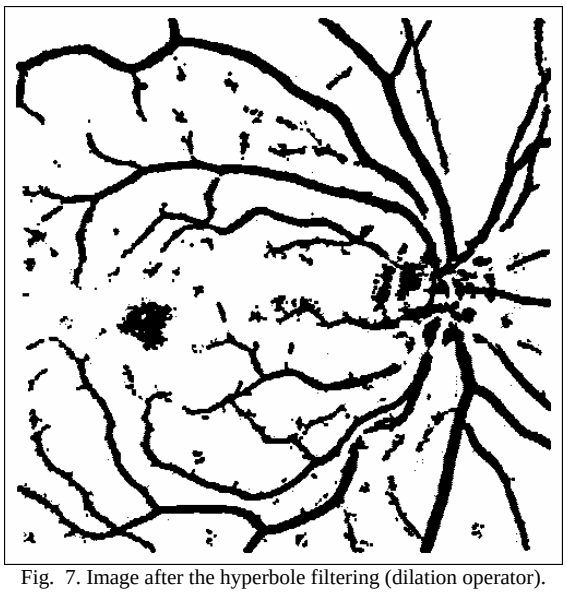


Fig. 7. Image after the hyperbole filtering (dilation operator).

In the second case the hyperbole filter has been applied using a more little exploration window (3 x 3 pixels) in order to hold blood vessels dimensions (see Fig. 7).
But the obtained image still presents noise. From this reason a median filter is applied to regularize the image. The choice has fallen on the median filter because it has the ability to reduce noise and to preserve image features (see Fig. 8).

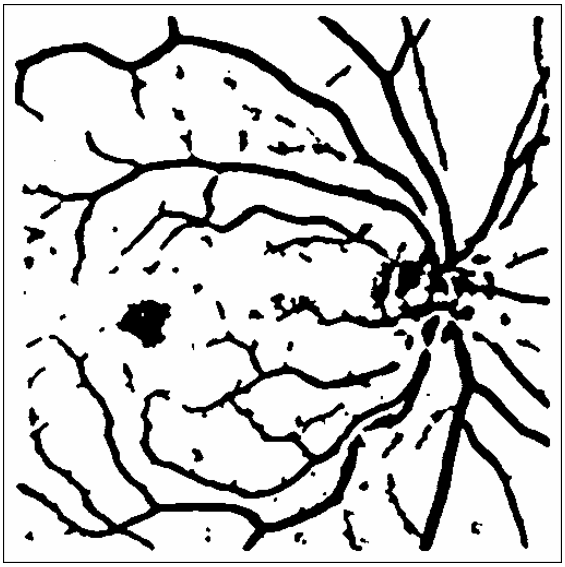


Fig. 8. Image after the median filtering.

## SKELETON PROCESS

Only after the regolarisation algorithm the image is ready for the application of the skeleton process, to extrapolate the retinal bifurcation and crossover points. In fact this method provides good results if input image has a little noise and if the objects are clearly defined.
The skeleton algorithm is based on the Zhang-Suen method (9). The pixels, to be removed from the image, must satisfy two sub-conditions.
In the first one the pixel *I(i,j)* is removed if the following conditions are satisfied:

1. the connectivity number (the number of pixels connected with the one considered) must be equal to 1 pixel;
2. it must have at least two near pixels and at the latest six;
3. the pixels in position *(i,j+1)*, *(i-1,j)* and *(i+1,j)* must be white;
4. the pixels in position *(i-1,j)*, *(i+1,j)* and *(i,j-1)* must be white.

In the second one the pixel *I(i,j)* is removed if the following conditions are satisfied:

1. the connectivity number must be equal to 1 pixel;
2. it must have at least two near pixels and at the most six;
3. the pixels in position *(i-1,j)*, *(i+1,j)* and *(i,j-1)* must be white;
4. the pixels in position *(i,j+1)*, *(i-1,j)* and *(i+1,j)* must be white.

At the end if there aren't pixels that verify the two conditions, the algorithm will be stopped (see Fig. 9).

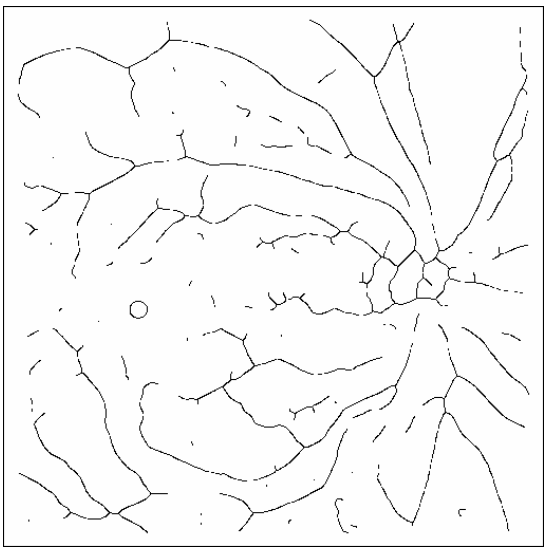


Fig. 9. Skeleton image.

## EXPERIMENTAL RESULTS

Now we have all the instruments that allow to detect the retinal blood vessels bifurcation and crossover points that are the aim of this paper. In fact, starting from the skeleton image it's possible to extract the retinal vessel features, exploiting the skeleton unitary depth (10).
Initially we must calculate the intersection number around the point *p(i,j)* by means of equation:

$$cnp = \frac{1}{2}\left(\sum_{i=1}^{8}|P_i - P_{i+1}|\right)$$

where $P_9 = P_1$ according to the used window structure (see Fig.10):

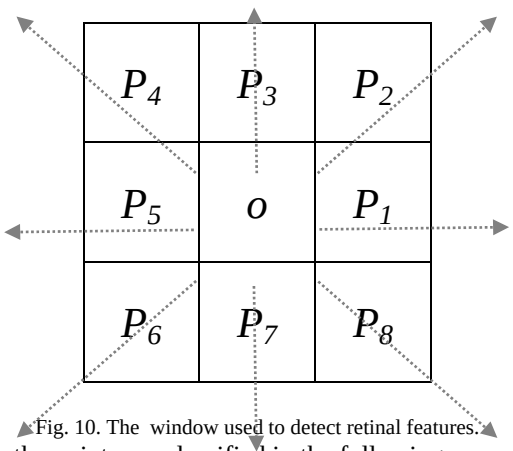



Fig. 10. The window used to detect retinal features.

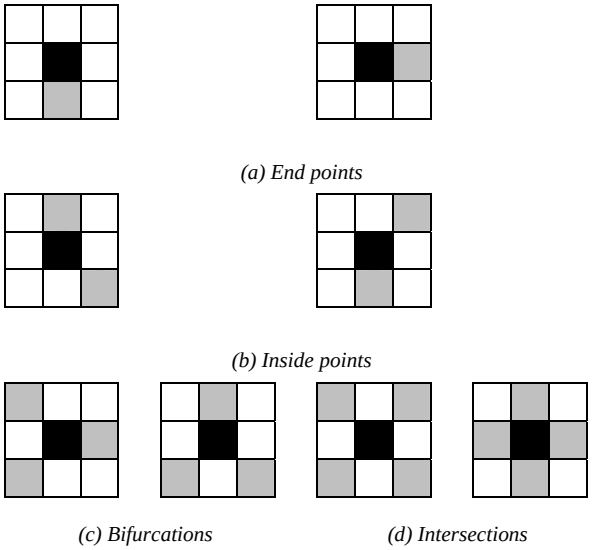
Now the points are classified in the following way:

if *cnp* = 1, it is an end point (see Fig. 11(a));

if *cnp* = 2, it is an inside point (see Fig. 11(b));

if *cnp* = 3, it is a bifurcation point (see Fig. 11(c));

if *cnp* = 4, it is a crossover point (see Fig. 11(d)).



*(a) End points*

*(b) Inside points*

*(c) Bifurcations* *(d) Intersections*

Fig. 11. Classification of points.

In Fig. 12 the cloud of retinal bifurcations and crossover points, obtained after the six steps of the method shown in this paper, has been overlapped to the image of Fig. 1, in order to make them more visible.

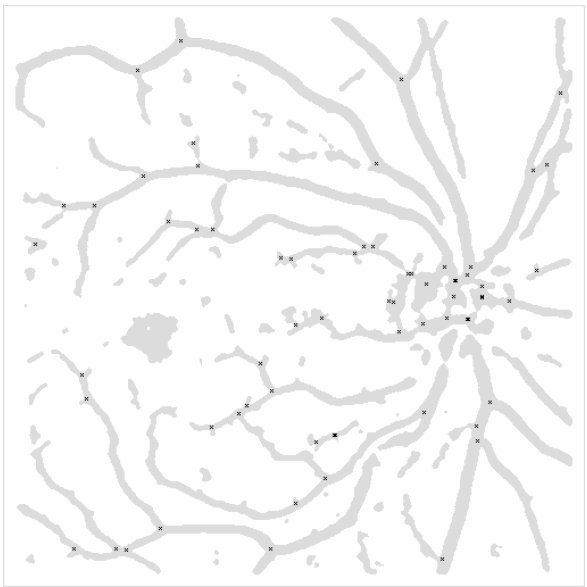


Fig. 12. Cloud of bifurcations and crossover points, extracted by the original image shown in Fig. 1.

## CONCLUSIONS

The results obtained by means of the combined method presented in this work, applied to extract the blood vessels features on a set of twelve different images of retinal fundus belonging to ten right eyes of ten different persons, are to be considered of good accuracy. In fact, these results have been compared with others obtained applying, in pervasive way, genetic algorithms (11-12), in all the steps discussed in the present paper showing a better representation of the cloud of retinal vessel bifurcations and crossover points. Of course, an hybrid approach (genetic and heuristic) can produce significant results, that can be applied not only to clinical environments, for detecting more pathologies, but also in biometry as personal identification tools.

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