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# Localisation of the optic disc by means of GA-optimised Topological Active Nets

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ABSTRACT

In this paper we propose a new approach to the optic disc localisation process in digital retinal images by means of Topological Active Nets (TAN). This is a deformable model used for image segmentation that integrates features of region-based and edge-based segmentation techniques, being able to fit the edges of the objects and model their inner topology. In this paper the active nets incorporate new energy terms for the optic disc localisation and their optimisation is performed with a genetic algorithm, with adapted or new ad hoc genetic operators. There is no need of any pre-processing of the images, which allows a quasi automatic localisation of the optic disc. This process also provides a simultaneous segmentation of the disc. We present representative results of optic disc localisations showing the advantages of the approach, with images focusing on the optic disc or on the macula, and with images with different levels of noise and lesion areas.



## 1. Introduction

The retinal fundus photographs are widely used in the diagnosis of eye, cerebrovascular and other diseases. Automatically processing a large number of retinal images can help ophthalmologists to increase the efficiency in the medical environment. The optic disc is the entrance region of the vessels and also where the nerve axons enter and leave the eye. It is the brightest area in the image, it is a slightly oval disc and its detection is very important since it is used for blood vessel tracking and it works as a landmark to measure distances and identifying anatomical parts in the retina like the fovea.

The localisation and segmentation have been previously performed through several approaches, as we will explain in the next section. Some methods are focused on the localisation of the optic disc centre and others additionally segment the disc. Deformable models, concretely different snake models, have also been used in this application. The main problems are the noise presence in the areas in which the optic disc is located, the presence of blood vessels that cross the optic disc and that greatly difficult the segmentation, and the possible presence of lesions that could be associated with the optic disc.

In this paper an alternative methodology is proposed. A Topological Active Net (TAN) is used to locate the optic disc at the same time that performs its segmentation. The active net model was proposed by Tsumiyama and Yamamoto [1] as a variant of the deformable models that integrates features of region-based and boundary-based segmentation techniques. To this end, active nets contain two kinds of nodes: internal nodes, related to the region-based information, and external nodes, related to the boundary-based information. The former model the inner topology of the objects whereas the latter fit the edges of the objects. The Topological Active Net model [2] was developed as an extension of the original active net model, solving some intrinsic problems to the deformable models such as the initialisation problem.

The TAN model is optimised by means of a genetic algorithm (GA) adapted to the current application. The global search of the GA, together with new energy terms useful to the problem, allow reducing the commented problems such as the noise presence or the blood vessels internal to the disc. The methodology does not need pre-processing for the localisation of the optic disc. Moreover, a segmentation of the boundary can be performed.

This paper is organised as follows. Section 2 summarises previous work about the optic disc localisation and segmentation. Section 3 introduces the bases of the TAN model whereas Section 4 explains the domain characteristics incorporated in the TAN model. Section 5 explains the main aspects of the genetic algorithm we have used. Section 6 shows representative results of the approach. Finally, Section 7 exposes the conclusions.

## 2. Previous work

There are several previous works on optic disc localisation. Lalonde et al. [3] use pyramidal decomposition on the green channel to identify the potential regions containing the optic disc, and then extract possible optic discs using Hausdorff-based template matching, deleting the wrong results according to a confidence level. The algorithm provides good results but depends on the com-

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pleteness of the thresholded edge map. This task is accomplished by removing noisy edges and preserving the optic disc contour.

In the work of Li and Chutatape [4] the authors propose a new method to automatically locate the optic disc. The candidate regions are first determined by clustering the brightest pixels in intensity image. For instance, if the number of pixels in a cluster is less than 100, the cluster is abandoned. Principal component analysis (PCA) is then applied to the remaining candidate regions. The minimum distance between the original retinal image and its projection onto disc space is located as the centre of the optic disc. There are other works that perform optic disc localisation based on the use of vessel cues with proven robust methods. Niemeijer et al. [5] present an automatic system to find the localisation of the major anatomical structures: the optic disc, the macula and the vascular arch. The structures are found by fitting a single point-distribution model to the image which contains points on each structure. The method of Foracchia et al. [6] is based on a geometrical model of the direction of main retinal vessels (two parabolas with a common vertex). Hoover and Goldbaum [7] use a novel algorithm they call fuzzy convergence to determine the origination of the blood vessel network. Their method uses brightness as a secondary feature for optic nerve detection. Using the results provided by ophthalmologists as the testing criterion, the authors reported a 100% of correct localisations in a set of 31 healthy retinas and 82% of correct detections in a set of 50 diseased retinas. The method of Tobin et al. [8] relies on the accurate segmentation of the vasculature of the retina followed by the determination of spatial features describing the density, average thickness and average orientation of the vasculature in relation to the position of the optic nerve. These features are used to train and apply a Bayesian classifier which determines the likelihood of an image location being associated with the optic nerve.

Regarding segmentation, Chrástek et al. [9] use an automated method for the optic disc segmentation which consists of four steps: localisation of the optic disc, nonlinear filtering, Canny edge detection and Hough transform. The nonlinear filtering is used as a method for noise reduction, which at the same time preserves the edges. Since the optic disc is a circular structure, the authors used the Hough transform as a method of circle detection. The transform gives them the centre and radius of a circle approximating the border of the optic disc. The authors report results with 97% successful localisation and 82% successful segmentation. The criterion of correctness was visual inspection in both cases. In the work of Abdel-Ghafar and Morris [10] the boundary of the optic disc was also estimated using a simple edge detector and the circular Hough transform. To simplify the detection, the blood vessels in the image were previously suppressed by morphological methods. A 24 radial vector set is defined to approximate the centre of the optic disc as their origin, and then the image is resampled along these vectors to form a good representation.

The difficulty of the problem can be summarised in the work of Jelinek et al. [11]. The authors apply different steps for an integrated automated analyser of the retinal blood vessels in the vicinity of the optic disc. First, they detect the optic disc using a combination of Butterworth filtering, Canny edge detection and morphological filters. The initial red plane image is first reduced in size using bilinear interpolation for efficiency. The image is then normalised using a high pass Butterworth filter. The local intensity standard deviation filter is then used to locate the optic disc as the region of greatest variation. In the next step the authors apply a greyscale morphological closing with a flat, disc-shaped structuring element to remove the edge of the blood vessels. Canny edge detection is then applied followed by a morphological closing with a disc structuring element to close any gaps in the perimeter of the optic disc. With this methodology the optic disc was well located in 13 of 20 images.

There are fewer works that have used active contours in the segmentation of the optic disc. Mendels et al. [12] used a two stage method. In a first stage, the image was processed using grey-level mathematical morphology to remove blood vessels regions, replacing them by pixels representative of the optic disc background. Then, a snake was manually placed around the optic disc and allowed to evolve onto its boundary. This snake is an improved version including a Gradient Vector Flow (GVF) external energy force, which is calculated as a diffusion of the gradient vectors of a grey-level or a binary edge map derived from the image [13]. The authors indicate that the accuracy of the method is highly sensitive to initialisation together with the sensitivity of the snake to energy minima.

Osareh et al. [14] report improvements on this previous work. They use a simple template matching approach to estimate the position of the disc centre, which allows the initialisation of a snake automatically. First, they pre-process the image through a closing operation (a dilation to remove the blood vessels followed by an erosion to restore the boundaries to their former position) to create a fairly constant region before applying a snake method. Then, a GVF-based snake is used to perform the segmentation. Moreover, the authors show how the boundary localisation can be drastically improved using colour mathematical morphology on the original colour image.

Chanwimaluang and Fan [15] introduce methods for the automatic detection and extraction of blood vessels and the optic disc. The optic disc detection is performed with a two-step initialisation for a snake active model. The authors use the local window based variance to select the initial centre of the disc. Then they initialise the size and the number of contour points by estimating the local contrast and variance around the centre. The authors also indicate that the initialisation of size and shape of the snake model is critical to the final result. In the work of Lowell et al. [16] the optic disc localisation is achieved using template matching (a specialised correlation filter) whereas the segmentation is performed with a snake model. According to the authors, no intervention is required as the algorithm automatically selects the general location of the centre of the optic nerve head, and then fits a contour to the optic nerve head rim. Comparing their results with the localisations obtained by ophthalmologists, they reported a 96% of correct localisations in a set of 100 fundus images.

As indicated by Xu et al. [17], deformable models can be roughly classified into free-form deformable models (snakes) and parametrically deformable models (ASM). The latter was used by Li and Chutatape [18], since they first used the previously mentioned PCA method to locate the optic disc and then a modified active shape model (ASM) to refine the optic disc boundary based on the point distribution model defined from the training sets.

In [17,19], the authors use a deformable model which is modified and extended in two aspects. First, after each deformation, the contour points are classified into edge-point cluster or uncertain-point cluster by unsupervised learning, *k*-means algorithm. Second, the contour is updated by variable updating sample numbers. The clustering process self-extracts the uncertain contour points (typically points belonging to noise or vessels) from the correct edge points. The variable updating sample number combines global and local information of only the correct edge points to update the contour points after each radial deformation. The authors report a better success rate of 94% on 100 testing images when compared to the results obtained by GVF-snake and modified ASM method. For the calculation of this rate, the ground truth of the boundary is manually labelled under the supervision of ophthalmologists.

With a similar philosophy of detecting contour points, Carmona et al. [20] propose a method which consists on three stages. In the first phase the eye fundus image is pre-processed. After that, they obtain a set of hypothesis points, which are candidates to be in the