MRF Reconstruction of Retinal Images for the Optic Disc Segmentation

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Abstract. The retinal image analysis has been of great interest because of its efficiency and reliability for optical diagnosis. Different techniques have been designed for the segmentation of the eye structures and lesions. In this paper we present an unsupervised method for the segmentation of the optic disc. Blood vessels represent the main obstruction in the optic disc segmentation process. We made use of our previous work in blood vessel segmentation to perform an image reconstruction using the Markov Random Field formulation (MRF). As a result the optic disc appears as a well defined structure. A traditional graph is then constructed using spatial pixel connections as boundary term and the likelihood of the pixels belonging to the foreground and background seeds as regional term. Our algorithm was implemented and tested on two public data sets, DIARETDB1 and DRIVE. The results are evaluated and compared with other methods in the literature.

Keywords: Retinal image, segmentation, optic disc, retinal lesions.

1 Introduction

The segmentation of medical images constitutes the first step for different analyses such as anatomical structures, tissues and computer assisted diagnosis. Due to poor contrast, weak boundary definition and inconsistent elements, medical images are challenging to analyse and require further studies.

The optic disc can be described as the brightest round area where the blood vessels converge. This convergence feature is often used to localize the optic disc. At the same time blood vessels constitute the first obstruction for the optic disc segmentation breaking the continuity of the object to segment. Some techniques have addressed the vessels intrusion using morphological operations as preprocessing [5, 11].

In this paper we present an unsupervised method for the segmentation of the optic disc. The main contribution of this paper is the use of prior segmented vessel to perform the reconstruction of the retinal image, as a result the optic

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disc appears as a well defined structure. Assuming the blood vessel pixels as unknown, the retinal image is reconstructed using MRF formulation. The reconstructed image presents better edge definition of the optic disc improving the segmentation results. Later the Graph Cut technique is used to segment the optic disc on the reconstructed image. The graph is initialized automatically using the MRF reconstructed image.

The rest of the paper is organised as follows. Section 2 makes a review of the current methods for the location and segmentation of the optic disc in the literature. Section 3 is dedicated to describe our method. We have included details about the MRF reconstruction performed on the retinal image by using prior segmented vessels. Finally experimental results are presented in section 4.

2 Background

In [3] a combination of morphological operations, Hough transform and an anchored active contour model is used to segment the optic disc. The blood vessels are removed by using a distance map; each pixel is assigned a value equal to its distance from the nearest boundary. This distance map is then thresholded and all pixels with a distance of six or less are removed. The method assumes a maximum vessel diameter of ten pixels, which produce a distance of five, but this is not always the case for all retinal images datasets. A deformable contour model is used to segment the optic disc in [7]. The model makes use of a direction-sensitive gradient which try to ignore vessel edges distraction. The watershed transform form markers is used to find the optic disc boundary in [11]. A first boundary is found by using initial makers, later by using an iterative process markers are updated and new boundary is defined. In order to minimize the vessel obstruction in the internal marker the method performs morphological erosion. In [5] the optic disc boundary is localized by using morphological and edges detection techniques followed by a Circular Hough Transform. The authors consider the blood vessels within the optic disc as a strong distracter and indicate that they should be erased. The method makes use of morphological processing to eliminate vessels.

In [12] blood vessels are used to estimate the location of the optic disc. The retinal vessels are segmented by using a 2-D Gaussian matched filter and a vessel direction map is created. The vessels are then thinned, and filtered using local intensity, to finally represent the optic disc centre candidates. The minimum difference between the matched filter result and the vessel direction around each candidate provides an estimation of the optic disc location. The method just localize the optic disc, but it does not perform its segmentation.

In [9] the histogram of the enhanced retinal image is modelled using a mixture model. From the histogram shape, two heavy tails are distinguished and assumed as foreground area (vessels, optic disc and lesions). It is assumed that the high intensity tail includes the optic disc. From the high intensity tail optic disc is segmented. The segmentation is performed by using mathematical morphology to select candidate pixels; this selection is then prune by restricting the selection

to the pixels in the neighbourhood of the main vessels. The main vessels are detected by using a two dimensional vertical oriented filter. The method assumes that the primary four vessels normally emanate near vertically from the optic disc. This assumption limited the performance of this method to the type of retinal images where the optic disc has been captured under the exact conditions to clearly display the four main vessels crossing vertically the optic disc.

Morphological operations are a recursive element to eliminate vessels from the retinal image beforehand [11, 5]. But this type of processing operates not only on vessels, the modification is extended to the rest of the image and some important information can be corrupted. This issue has been pointed out in [5], which declares that as a consequence of this processing the optic disc is enlarged by a fixed length in all directions.

In our discrimination of vessels method we remove vessels from the ROI by using prior vessel segmentation to perform the reconstruction of the image. The reconstruction is performed only on the vessel pixels (unknown pixels) to avoid the modification of other structures. Our proposed methods were designed as unsupervised methods, and they can perform on images with different characteristics. In the next section the process to localize the optic disc is explained. Next, the problem of segmenting overlapping tissues is presented and the methods to explore the opposing research lines are detailed.

3 Our Method

The retinal blood vessels have two roles in the optic disc segmentation. On one hand they are the main obstruction when segmenting the optic disc; and on the other hand blood vessels inside the optic disc are part of the object to segment. We start a MRF reconstruction of the retinal image from a previous blood vessel segmentation. Blood vessel pixels are considered as unknown and the surrounded pixels are used to fill these vacancies. We have selected a Markov Random Field based reconstruction technique. The general idea is to find the best matching for the missing pixels. One of the disadvantages of this approach is the intensive time consumption. We address this problem by limiting the reconstruction to a smaller area of the image that contains the region of interest. The method is described in Table 1.

Table 1. The optic disc segmentation

Input: Colour retinal image I_{in}
1. Segment the blood vessels from I_{in} [8];
2. I_c = Localize the optic disc and constrain the image;
3. I_r = Perform the MRF reconstruction of I_c;
4. Initialize Fg_s and Bg_s in I_r;
5. I_{out} = Construct graph for I_r and resolve;
Output: Optic disc segmented I_{out}

In the first stage blood vessels are segmented from the retinal colour image. The blood vessels convergence is localized and assumed as the center of the optic disc. The retinal image is then constrained to the region of interest and the MRF reconstruction is performed using the prior blood vessel segmentation. Foreground Fg_s and background Bg_s seeds are initialized in the reconstructed image and used to construct the graph. Finally the graph is cut by minimizing the energy function and producing the optimal segmentation of the image.

3.1 Blood Vessels Segmentation

As a first step eye structures are segmented. We have selected the graph cut technique for this purpose. Graph cut is an interactive image segmentation technique in computer vision and medical image analysis [1]. Graph cut methods have been used widely in image segmentation due to its ability to compute globally optimal solutions. The general idea is to map an image onto a graph with weighted connections. The graph is then cut (separating foreground and background), minimizing the energy function and producing the optimal segmentation for the image.

The graph cut based method [8] is adopted in this work. First the green channel of the retinal colour image is enhanced. An improved adaptive histogram equalization is applied to the image, followed by a pruning stage in order to obtain a rough segmentation of the vessels. The distant transform is calculated from the binary resultant image. The flux of the vectors in the distant map along with regional boundaries terms are used to construct a graph. Finally the graph is cut, resulting in the segmentation of the blood vessels.

3.2 Optic Disc Location

Once the vessel network is segmented, the image is pruned using a morphologic open operation in order to keep the main arcade of the vessels. Inspired by the work presented in [11] the centroid of the arcade is calculated using:

$$C_x = \sum_{i=1}^{K} \frac{x_i}{K} \qquad C_y = \sum_{i=1}^{K} \frac{y_i}{K} \tag{1}$$

where x_i and y_i are the coordinates of the pixel in the binary image and K is the number of pixels set to "1", which is the pixels marked as blood vessels in the binary image.

Using the blue channel of the RGB retinal image, the 1% of the brigthest pixels are marked. The algorithm detects the brightest area in the image in order to determine the position of the optic disc with respect to the centroid. This is followed by a pruning to eliminate the group of pixels with fewer elements. In order to find the most likely center of the optic disc our algorithm finds the way from the centroid to the vessels convergence by adjusting the point while

approaching. Considering that the main arcade is narrowing until the vessels converge, the algorithm adjusts the centroid point by reducing the distance with the optic disc and keeping the same distance with the vessel on the main arcade. Figure 1 shows an example of optic disc detection.

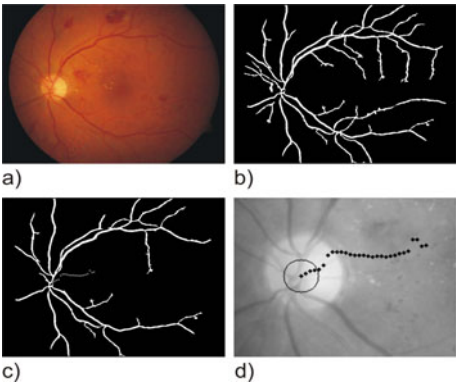

Fig. 1. Optic disc detection. a) retinal image, b) blood vessel segmentation, c) blood vessel segmentation after pruning and d) sequence of points from the centroid to the vessels convergence.

Our algorithm detected successfully 96.7% of the DIARETDB1 [6] data set images and in 97.5% of the images in DRIVE [10]. We constrain the image to a smaller area in order to minimize processing time. The region of interest is constrained to a square of 200 by 200 pixels concentric with the optic disc.

3.3 Optic Disc Segmentation

In order to produce an image with a well defined optic disc, the retinal image is reconstructed using a prior blood vessel segmentation. We have selected a Markov Random Field based method to perform the reconstruction [4]. Blood vessel pixels are considered as unknown. The general idea is to find a collection of patches statistically similar to the patch where a pixel p ($p = 0$) is missed. Then we create a histogram of the pixels that are in the same position as p in the collection of patches and obtain the best approximate value to substitute the missing pixel.

A pixel neighborhood $w(p)$ is defined as a square window of size W, with center on pixel p. The image that is going to be reconstructed is I. Some of the pixels in I are missing and the objective is to find the best approximate value for them. Let $d(w1, w2)$ indicate a perceptual distance between two patches that indicate how likely they are. The exact matching patch would be the one that $d(w', w(p)) = 0$. If we define a set of these patches as $\Omega(p) = \{\omega' \subset I : d(\omega', \omega(p)) = 0\}$ the probability density function of p can be estimated with a histogram of all center pixel values in $\Omega(p)$. But owing to the fact that we are considering a finite

neighborhood for p and the searching is limited to the image area, there might not be any exact matches for the patch. For this reason in our implementation we find a collection of patches whose match falls between the best match and a threshold. The closest match is calculated as $\omega_{best} = argmin_{\omega} d(\omega(p), \omega) \subset I$. And all the patches ω with $d(\omega(p), \omega) < (1 + \epsilon) d(\omega(p), \omega_{best})$ are included in the collection ω'. In our implementation $d(w', w(p))$ is defined as the sum of the absolute differences of the intensities between patches, so identical patches will result in $d(w', w(p)) = 0$. We have set $\epsilon = 0.1$ and $W = 5$. Using the collection of patches we create a histogram and select the one with highest mode. The reconstruction process is summarized in Table 2 and Figure 2 shows some examples of reconstructed images.

Table 2. Pseudo function for the MRF image reconstruction in the constrained retinal image

Inputs: Retinal gray scale image I_g and binary blood vessel image I_{bv}.
1. If $I_{bv}(p) = vessel$ then $I_g(p) = 0$; 2. Create a list of unknown pixels p in I_g, $I_g(p) = 0$ and their neighborhood $w(p)$; 3. Sort out the list according with the number of unknown pixels included as part of the neighborhood $w(p)$; 4. for $i = 0$ to $i = W - 1$; for each element in the list; $patch$ = w(p) if unknown neighbors number is equal to i; find $\omega_{best} = argmin_{\omega} d(\omega(p), \omega) \subset I$; collection of patches $d(\omega(p), \omega) < (1 + \epsilon) d(\omega(p), \omega_{best})$; create a histogram of collection of patches; Substitute p in I_g by the intensity with highest mode; $i++$ end for end for

Foreground and Background Seeds Initialization. Using the retinal reconstructed image, the foreground Fg_s and background Bg_s seeds are initialized. A neighborhood of 20 pixels of radius around the centre of the optic disc is marked as Fg_s pixels, while a band of pixels around the perimeter of the image are taken as Bg_s.

Graph for Optic Disc Segmentation. Graph cut is a well known technique used for interactive image segmentation in computer vision and more specific in medical image analysis [2, 14]. The general idea is to map the image into a graph with weighted connections. The graph is then cut (separating foreground and background) by minimizing the energy function and producing the optimal segmentation for the image. For the optic disc segmentation we have selected the traditional edge weight assignment method as presented in [1]. The energy function consists of regional and boundary terms. Regional term is calculated

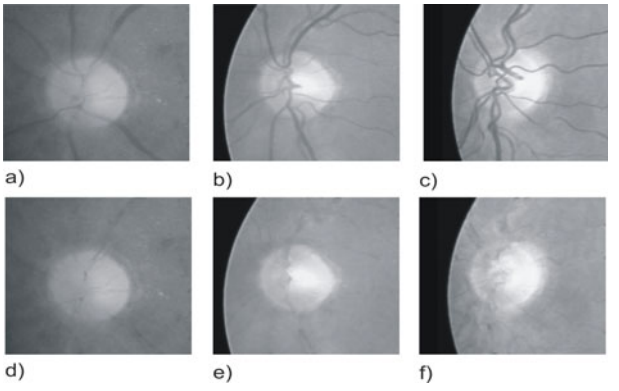

Fig. 2. MRF reconstruction applied to retinal images. (Top) original gray scale images. (Bottom) reconstructed images using the MRF based method.

from the likelihood of a pixel p belonging to the foreground and background, generating the t-links weight. The boundary term is based on the own pixel properties (i.e. intensity) which is used to assign weight to the n-links.

A grid of 16 neighbors N is selected to create links between pixels in the image Im. The n-links and t-links weights are assigned according to Table 3. lik_{Fg} and lik_{Bg} represent the negative log-likelihood of the pixel p with respect to the prior information of the foreground and background. The distance $dist(p, q)$ is defined by the Euclidean distance between p and q. Max-Flow[1] is used to cut the graph and find the optimal segmentation.

Table 3. Link weight assignment for the graph of the optic disc segmentation process

link	weight	for
n-link	$B_{p,q}$	$p, q \in N$
t-link (Foreground)	$\lambda \cdot lik_{Fg}$	$p \in Im, p \notin F \cup B$
	K	$p \in F$
	0	$p \in B$
t-link (Background)	$\lambda \cdot lik_{Bg}$	$p \in Im, p \notin F \cup B$
	0	$p \in F$
	K	$p \in B$

where $B_{p,q} = exp(-\frac{(I_p - Iq)^2}{2\sigma^2}) \cdot \frac{1}{dist(p,q)}$
$K = 1 + max_{p \in Im} \sum_q B_{p,q}$

4 Results

Our method was tested on two public data sets, DIARETDB1 (89 images) [6] and DRIVE (40 images) [10]. We created hand labeled sets for DIARETDB1 and

[1] maxflow-v3.01 is available at http://www.cs.ucl.ac.uk/staff/V.Kolmogorov/software.html.

DRIVE in order to have a ground truth to compare our results. The performance of the methods was evaluated by the overlapping ratio ($Oratio$) and the mean absolute distance(MAD). The overlapping ratio is defined as:

$$Oratio = \frac{G \bigcap S}{G \bigcup S}$$

where G represents the manually segmented area and S is the area as result of the algorithm segmentation. MAD is defined as:

$$MAD(G_c, S_c) = \frac{1}{2}\left\{ \frac{1}{n}\sum_{i=1}^{n} d(g_{c_i}, S) + \frac{1}{m}\sum_{i=1}^{m} d(s_{c_i}, G) \right\}$$

where G_c and S_c are the contour of the segmented area in the ground truth and the resulting images, and $d(a_i, B)$ is the minimum distance from the position of the pixel a_i on the contour A to the contour B. A good segmentation implies a high overlapping ratio and a low MAD value.

We calculated the sensitivity of the methods when they are applied to DIARETDB1 and DRIVE, which is defined as:

$$Sensitivity = \frac{Tp}{Tp \ + \ Fn}$$

where Tp and Fn are the number of true positives and the number of false negatives respectively. Sensitivity is an indicator of the foreground pixels detected by the segmentation method.

Our results are compared to those provided in [11]. This method was tested on the same datasets (DIARETDB1 and DRIVE) and results were measured under the same parameters. Also we have included the results of our experiments using the traditional graph cut technique without compensation and the ones using the topology cut technique [13].

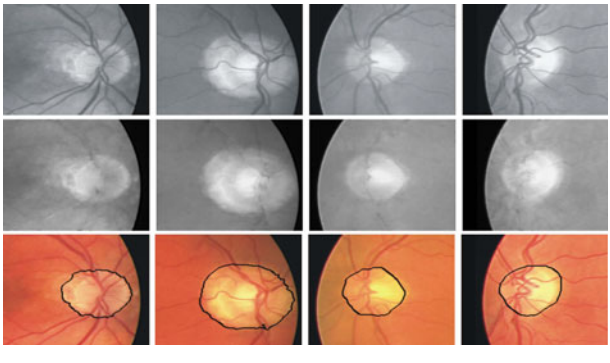

Fig. 3. Optic disc segmentation results. First row: original image, second row: MRF reconstructed image, third row: optic disc segmentation.

Unfortunately most of the methods do not use a unique ground truth to measure the results of the optic disc segmentation, so this makes the comparison of the results difficult.

Figure 3 shows the segmentation results on images with and without reconstruction. We have included sample images of both data sets with different *Oratio* measures. It is clear that a significant improvement has been achieved when the images have been reconstructed previously using the MRF formulation.

Figures 4, 5 and 6 show the segmentation results on the DIARETDB1 and DRIVE datasets by using three different methods, traditional graph cut technique, topology cut technique and our method. The segmentation results are evaluated in terms of the *Oratio* by using the ground truth images. The graph cut segmentation improves considerably when it is applied to a well defined optic disc. When the MRF reconstruction was applied the segmentation improved in 95% of the images on DRIVE, and 80% of the images on DIARETDB1.

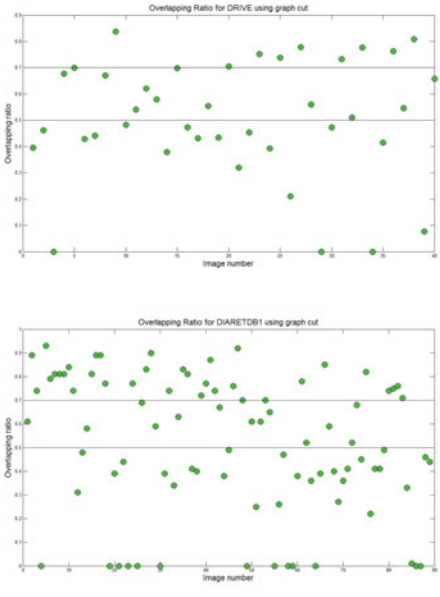

Fig. 4. Optic disc segmentation results on the DIARETDB1 and DRIVE datasets by using Graph Cut technique

There are few specific cases where the segmentation of the optic disc resulted in null. This cases are shared by the other methods as well. The characteristic of these images is the poor contrast, as a consequence all the pixels are linked with strong weight and is not possible to find a cut to segment it. This is an indication of the challenge of analyzing those specific images.

Table 4 and Table 5 show the comparison with different methods in terms of *Oratio*, *MAD* and *Sensitivity*. Our method achieved the highest overlapping

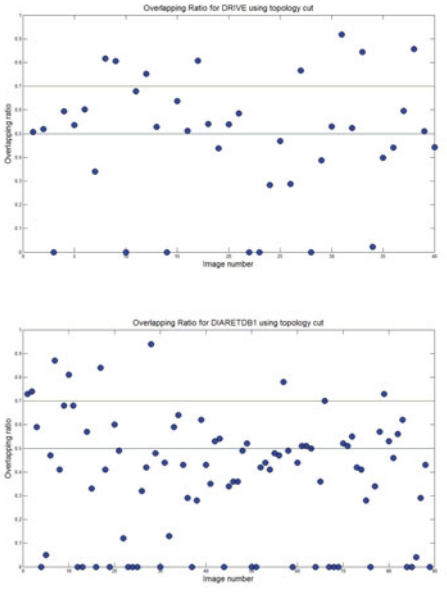

Fig. 5. Optic disc segmentation results on the DIARETDB1 and DRIVE datasets by using Topology Cut technique

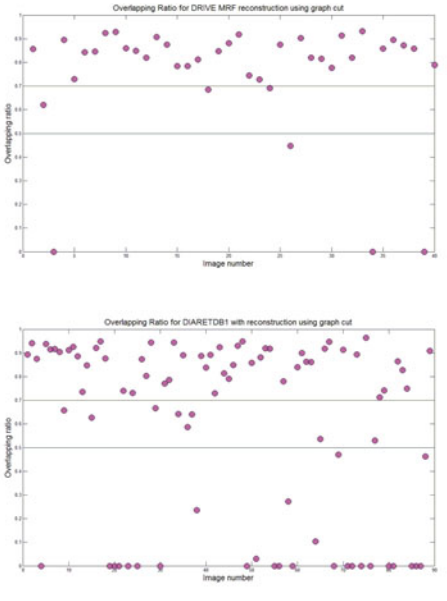

Fig. 6. Optic disc segmentation results on the DIARETDB1 and DRIVE datasets by using our method

ratio with the minimum MAD value. It can be seen that an increase in the overlapping ratio does not mean a decrease on MAD value necessarily. MAD value does not represent the best way to measure the segmentation results, but it provides a good reference of the contour matching with the ground truth contour reference.

Table 4. Performance comparison on the DIARETDB1 dataset

Method	Average ORatio	Average MAD	Average Sensitivity
Topoly Cut	38.43%	17.49	55.30%
Adaptive morphologic [11]	43.65%	8.31	—
Graph Cut	54.03%	10.74	76.35%
MRF + Graph Cut	78.3%	6.75	87.3%

Table 5. Performance comparison on the DRIVE dataset

Method	Average ORatio	Average MAD	Average Sensitivity
Topoly Cut	55.91%	10.24	65.12%
Adaptive morphologic [11]	41.47%	5.74	—
Graph Cut	55.32%	9.97	73.98%
MRF + Graph Cut	82.2%	3.59	97.99%

It is possible appreciate that our method performs better on the DRIVE dataset. The 95.5% of the images in DIARETDB1 dataset are characterized by contain at least one type of retinal lesion. In general, a healthy retinal image is easier to analyse than a image with some type of retinopathy.

5 Conclusions

Optic disc segmentation is an important process in the analysis of retinal images. The analysis of optic disc morphology is part of the retinal screen process. Retinal Blood vessel network requires special attention due to its overlapping with the optic disc.

In this paper we have presented an unsupervised method for the segmentation of the optic disc. Our method performs MRF reconstruction by using prior segmented vessels. Vessels are masked out and a well defined optic disc is created.

Our method was tested on two public data sets: DIARETDB1 and DRIVE. Experimental results were compared with other methods, including the traditional formulation of the graph cut and the topology cut techniques. The results comparison shows the outperformance of our method.

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