Cost Function Selection for a Graph-Based Segmentation in OCT Retinal Images

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Abstract. This paper is based on a methodology for segmentation of the main retinal layers in Optical Coherence Tomography (OCT) images. The input image is transformed into a geometric graph and the layers to be detected will be given by its minimum-cost closed set. The main problem in this method is the selection of the appropriate cost functions associated to the graph, because of the variety of anomalies that images from patients might have.

Keywords: image segmentation, OCT retinal image, cost function, minimum closed set, graph.

1 Introduction

Several diseases, such as hypertension or diabetes, cause changes on the retina, like the apparition of pathological structures or alterations on the retinal layers [1][2]: thickening, thinning, detachment... Detection of these anomalies is possible in OCT retinal images, which are used by experts to make a diagnose and determine the appropriate treatment, since they are captured in a non-invasive, contactless method in a real time fashion[3].

An automatic processing to detect the area of interest where critical features will be searched in the future is possible, with the purpose of assessing experts in their diagnosis. Considering that the retina is composed by different layers, the first step is the automatic segmentation of the first and the sixth layers, that is to say, the top boundary of the Internal Limiting Membrane (ILM) and the bottom boundary of the Retinal Pigment Epithelial (RPE), which are presented in detail in Fig 1.

This work is based on the methodology proposed in [4], which consist on transforming the segmentation task into that of finding a minimum-cost closed set in a geometric graph [5], which is built from edge and regional information, considering some surface smoothness and interaction constraints. The main objective of this work is designing the suitable cost functions to be used in this method in order to detect the first and the sixth retinal layers.

This paper is organized as follows: Section 2 details the methodology used to segment the boundary layers mentioned before. In Section 3 results are presented and, finally, the conclusions obtained and the future lines of work are exposed in Section 4.

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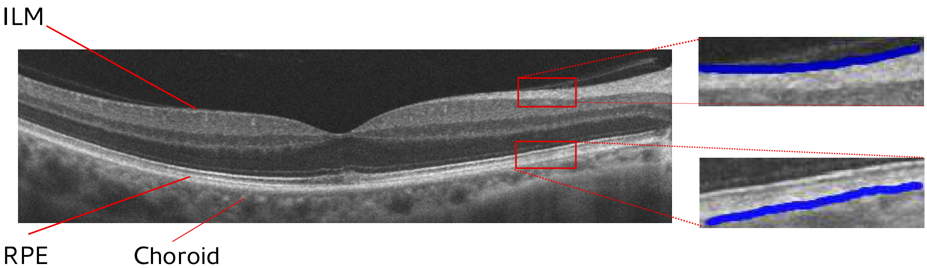


Fig. 1. Sample OCT image with main layers identified and zoom applied over a portion of the first (above) and the sixth (below) layers, both highlighted in blue

2 Methodology

In the methodology presented in [4] a graph is built based on the input image. Thus, each node in this graph represents a pixel in the image, and the arcs between them are given by the connectivity of the pixels in the image, satisfying some constraints of smoothness and interaction. Additionally edges are included to connect nodes to the source or the sink in the graph. Cost functions must be designed to obtain the minimum closed set of the graph, which will be computed based on the minimum-cut of the graph. In order to detect the layers of interest, the cost functions should maximize the capacity of the nodes representing pixels in the image associated to the layers that are searched.

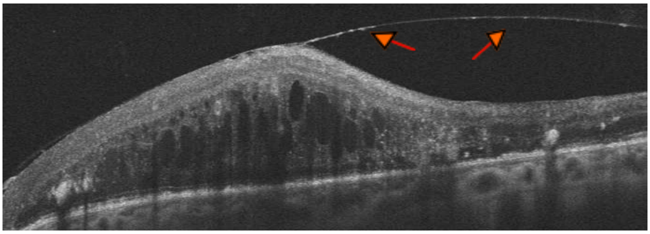
The main factor to take into account in the designing of the cost functions used to compute the minimum closed for each layer segmentation is the signed edge image, which gives an idea of where the more abrupt transitions are located. But also some anomalies in the images, caused by the capture process or derived from the patient disease, have to be considered, given that they affect in a way to the signed edge term extracted from the images.

In order to obtain the appropriate cost functions to segment each layer, it is necessary to examine separately those anomalies or difficulties. Regarding the first layer, the main problems, shown in Figure 2, are the following:

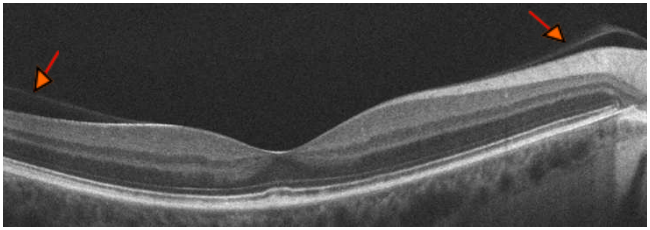
- The intensity transition in the top part of the RPE, very similar to the first layer one.
- Some anomalous structures can be present in the top part of the image.
- Posterior Hyaloide and Epiretinal Membrane (ERM) can be present, making difficult the detection of the real layer.
- Noise and small changes in the image intensity, which can produce the cost function varying.

Considering the sixth layer, the problems found on the images are exposed in Figure 3 and detailed as follows:

- Bright intensity above and below the sixth layer area: the RPE is a bright layer, as well as the Choroid, located below it. Although the choroid counts,



(a)



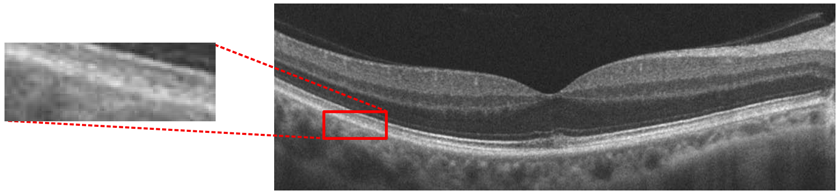
(b)

Fig. 2. Presence of problematic alterations in the detection of the first layer: (a) Posterior Hyaloide (b) ERM, both marked with red arrows

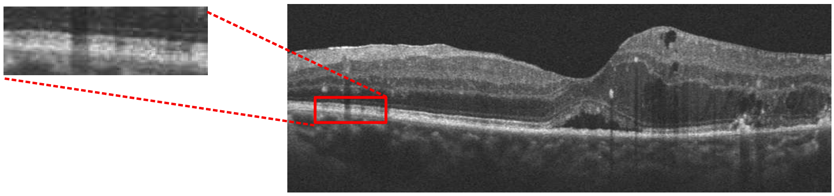
in general, with a bit lower intensity, it is not immediate establishing the separation between them.
- Noise and small changes in the image intensity, as it occurs for the first layer.
- Ruptures and discontinuities in the RPE can make the cost function varying.

The cost functions to segment these layers, in addition to the edge image, should include these kind of information to avoid wrong segmentations. Firstly, for the first layer, the cost function is given by the addition of the terms detailed below. A weight has been given to each term, in order to encourage some characteristics in front of other ones:

- Signed edge image will be process to erase all edges excepting the first ones in each column, considering a flexibility threshold t_{first}. The weight for this term is given by wa_1.
- Odd structures in the top part of the image has usually a linear shape, therefore pixels in the signed edge image near enough (regarding threshold t_{linear}) pixels belonging to the signed edge image with opposite direction are penalized. wa_2 is the weight associated to this term.
- To discard the thin bright area just above the first layer, pixels in the signed edge image with neighbors with the same edge direction, in a distance of t_{thin} pixels below, are penalized. The weight wa_3 control this term.
- Last edges at each column are erased: For all the edges found on the same column, a percent p_{last} are erased. Its weight is given by wa_4.



(a)



(b)

Fig. 3. Problematic situations in the detection of the sixth layer: (a) Similar intensity between regions above and below the layer. (b) Discontinuity in the layers.

- Any detected edge might pull the graph to wrong areas, so the gradient distance of the image is included to penalize abrupt transitions in the graph, as follows: the distance d between two adjacent pixels, considering 8-connectivity, is given by factor f_d. Therefore, gradient distance for a pixel connected to an edge ($d = 1$) is f_d and, in general, for a pixel in a distance d, the gradient distance is $d * f_d$. The importance of these term is controlled by weight wa_5.

For graph computation, minimizing the cost of a path in the graph is equivalent to maximizing its capacity, so the cost function in a pixel can be understood as the opposite of the capacity that each node has in the graph. Therefore, emphasizing areas in the image is equivalent to give them a higher capacity and cost functions will be built in this way. An example of all these terms that compose the cost function for the first layer is shown in Figure 4. In this case, the Posterior Hyaloide is present on the image (a). The preprocessing consist in a close operator and a blurring step applied to (b). All emphasized and erased edges are shown in the following subfigures. The inverse of the gradient distance (pixels near edges must have more capacity in the graph than those that are far) is presented in (g). The combination of all these terms, each one with a weight factor, is the cost function to be used.

Considering the sixth layer, the cost function includes the terms described as follows:

- Edges corresponding bright-to-dark transitions, with weight wb_1, since the sixth layer is characterized by this kind of regions, are emphasized. Also pixels in the image with bright areas above and below, as happens with the sixth layer: for each pixel on the image, the addition of the intensities of the n_1 pixels above and the addition of the intensities of n_2 pixels below are considered. The weights for these terms are defined as wb_2 and wb_3;

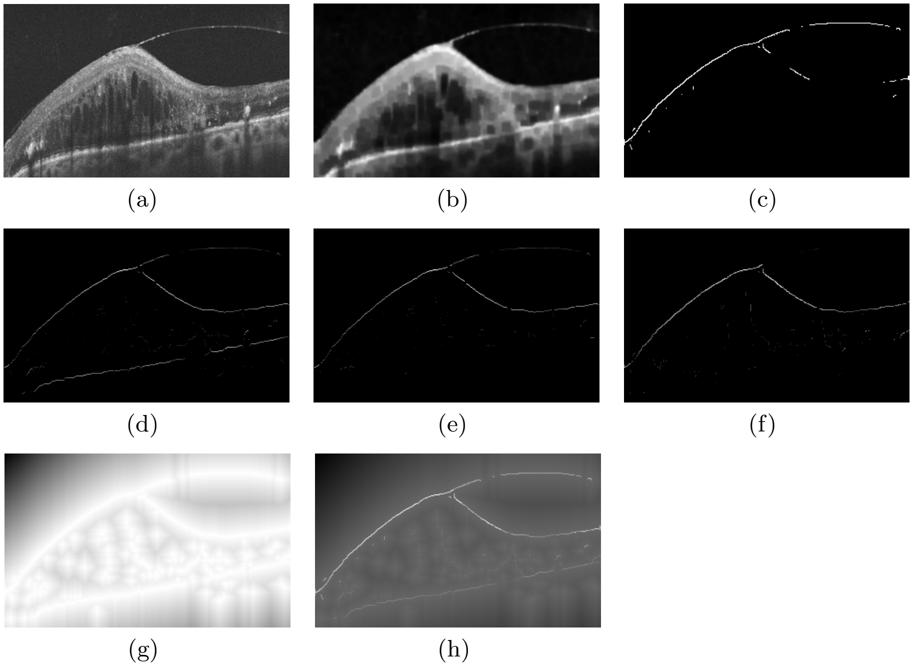


Fig. 4. Terms considered in the cost function to segment the first layer: (a) Original image; (b) Preprocessed image; (c)(d) Edges remained after erasing the first ones at each column and discard those corresponding to linear shapes, respectively; (e) Edges after discard those with neighbors below that count with same direction; (f) Edges after erasing last edges at each column; (g) Inverse of the gradient distance computed over the combination of (c-f); (h) Final cost function, combination of these all terms

– In the same way that for the first layer, the gradient distance of the image is included. In this case, it is very important to avoid the influence of the ruptures present in the layer and get a precise segmentation. Its importance is controlled by weight wb_4.

An example of the cost function used to guide the graph in the computation of the minimum closed set is shown in Figure 5. The preprocessing consist in a close operator and a strong blurring step.

3 Results

The methodology exposed here has been tested over a data set containing 142 images, which 16 are from healthy people and the rest from patient with diabetic retinopathy. These images were captured using Cirrus HD-OCT, with Spectral Domain Technology (Zeiss), at a resolution of 924x616 pixels.

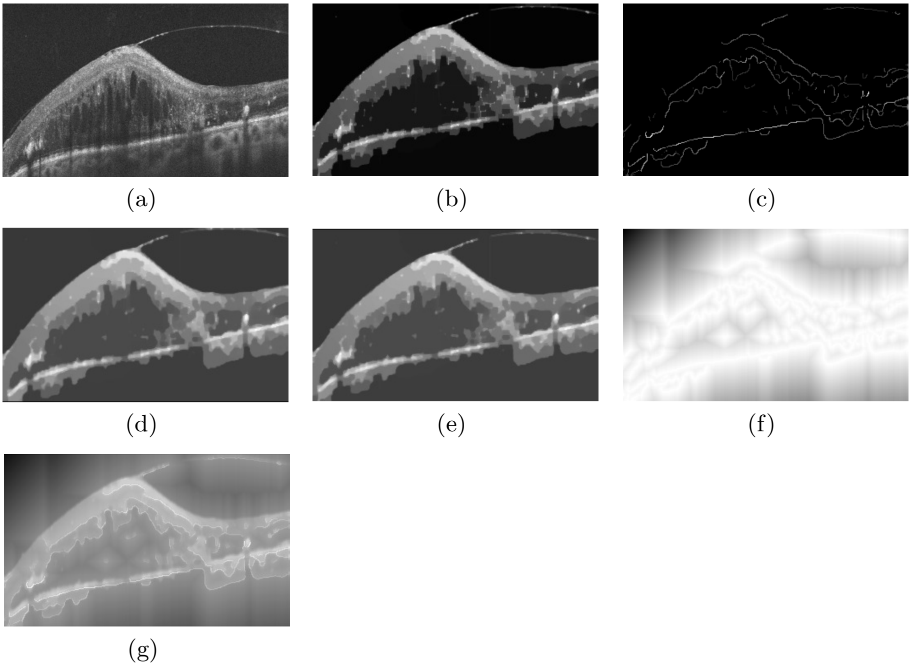


Fig. 5. Terms considered in the cost function to segment the sixth layer: (a) Original image; (b) Preprocessed image; (c) Edges associated to light-to-dark transitions; (d, e) Images representing, for each pixel, the addition of the intensities of the n_1 pixels above and n_2 pixels below, respectively; (f) Inverse of the gradient distance computed over the combination of (c); (g) Final cost function, combination of these all terms

Parameters have been obtained empirically and their values are the following: Firstly, regarding the first layer, $t_{first} = 5$, $t_{linear} = 10$ and $t_{thin} = 5$ while $p_{last} = 50\%$. Values for the all the different weights for this layer are set to 1000, excepting wa_5, which takes value of 2000. For the sixth layer, $n_1 = 2$ and $n_2 = 1$. Factor f_d used in the gradient distance for cost functions in both layers is 20. Regarding the weights for each term for these layer, $wb_1 = 1000$, $wb_2 = 500$, $wb_3 = 1000$ and $wb_4 = 2000$.

The minimum closed set of the graph has been computed using the Ford–Fulkersson algorithm implemented in [6] and the success rate is 98.9%, that can be analyzed based on the two layers that have been segmented. Regarding the first layer, the segmentation obtained was successful in the 99.29% of the images, while for the sixth layer, this percentage is 98.59%. Figure 6 shows some segmentation examples.

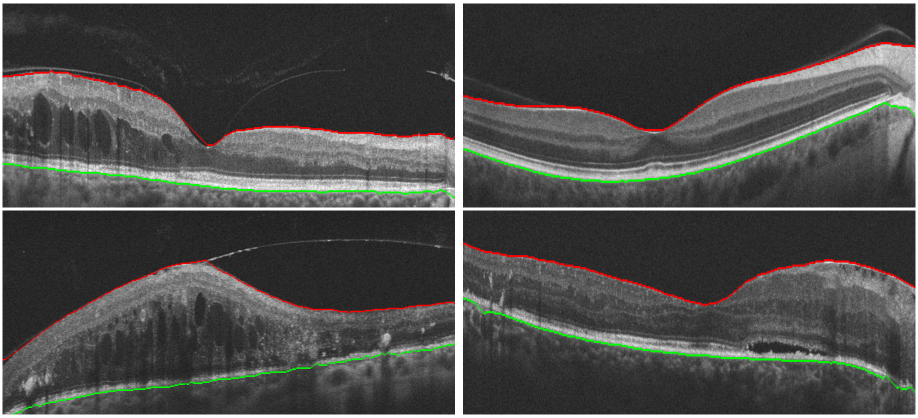


Fig. 6. Sample result images: first layer in red, sixth layer in green

4 Conclusions

Establishing the cost functions to segment retinal layers is necessary but they must cover all the problematic features on these images. The proposal method provides an appropriate segmentation of the retinal layers, even in images with pathological alterations, therefore, it is possible to affirm that the segmentation achieved is closed to that made by the expert. After the segmentation of these layers, the area where future features will be searched is bounded, which is a first step to tackle a wide variety of problematics. Future work includes the measurement of different indicators between layers and searching for pathological structures in the retina area.

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