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Cornea Contour Extraction from OCT Radial Images

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1. Introduction

Contour detection is part of a segmentation process. We describe a cornea contour detection approach on images from Optical Coherence Tomography (OCT). These scans present some noise due to the acquisition means. This causes the segmentation to be more difficult. OCT usually provides high-resolution images, but these pictures suffer from speckle. This multiplicative type of noise is common on such images. The elimination of this noise is thus essential before analyzing any features on the image.
The Optical Coherence Tomography is an interferometric, non-invasive optical tomographic imaging technique Huang et al (1991). Nowadays, OCT is well known, especially in ophthalmology and dermatology. This technique enables a medical examination without danger for the tissues. It is particularly used with visual examination and diagnoses. OCT approximately offers a 2-3 millimeters penetration in the tissue, which is compatible with a correct visualization of ocular tissues like retina or cornea. This technique offers live sub-surface images at near-microscopic resolution.
We study corneal images acquired by OCT. It renders radial section including iris and cornea. The cornea contour detection on this section allows ophthalmologists to measure the corneal thickness or the radius of curvature. These measurements are useful for diagnoses and for refractive surgery. Therefore the segmentation from many radial sections permits the creation of a corneal model.

2. Previous Work

Many techniques exist in order to detect contour on digital images. The goal of segmentation is to partition an image into sub-regions. This operation is processed according to the properties of the picture like intensity or texture. The image segmentation is typically used to locate objects or boundaries. We present in the following sections two dual methods: the edge-based segmentation and the region-based segmentation. We also analyze two others approaches: the

Active Contours and the Level Set which are continuous edge contour detector. In a last section we study the Markov models which are traditionally used for a robust-to-noise image segmentation.

2.1 Edge-based Segmentation

The edge-based segmentation is a first approach of image segmentation. This method seeks for variations of the intensity in an image. Thus it assumes that the sub-sections are sufficiently uniform in order to detect discontinuities.
A first approach to segment images by edge is the gradient vector. This vector gives for each pixel the difference between the pixel above and below (vertical vector), and the difference between the left and the right side of the current pixel (horizontal vector) (see Fig.1). Weight of these vectors gives the presence of edge on the pixel. The laplacian uses the derivate of this gradient to determine the location of the edge Marr & Hildreth (1980). A significant noise sensibility is the main drawback of laplacian method.

-1	0	1

-1
0
1

Fig. 1. Gradient kernel in horizontal direction on the left and vertical direction on the right. Kernel center is marked with grey color.

Other operations give better results with larger kernel. We can cite Marr, Prewitt (Fig.2) or Sobel. For example, Sobel Sobel & Feldman (1968) is a gaussian filtering (see Fig.3) which has a double advantage: it provides derivate like the gradient vector and a smoothing effect. This smoothing effect brings fewer noise sensibility.

-1	0	1
-1	0	1
-1	0	1

-1	-1	-1
0	0	0
1	1	1

Fig. 2. Prewitt kernel in horizontal direction on left and vertical direction on right. Kernel center is marked in grey.

-1	0	1
-2	0	2
-1	0	1

-1	-2	-1
0	0	0
1	2	1

Fig. 3. Sobel kernel in horizontal direction on left and vertical direction on right. Kernel center is marked in grey.

The Canny edge detector Canny (1986) is a two-pass process based on this Sobel operator.

The second pass uses two thresholds to determine a non-closed contour in image. In the first pass, a Sobel kernel is performed through the image. This step attenuates the most important variation in pixels intensity. After this process, the thresholding is most effective for contour detection. The Canny algorithm uses specific thresholding: hysteresis. The thresholding with hysteresis requires high and low thresholds. The high thresholding marks pixels along the contour. The hysteresis approach considers pixels with intensity between two thresholds like edge pixels in the case they are close to other edge contour pixels (superior of high threshold). Canny method and other optimal edge detectors need parameters that are unknown when dealing with OCT scans. Moreover for the specific cornea segmentation, these algorithms do not use knowledge about the cornea. Thus this method is not relevant for the OCT scans. However the hysteresis filtering is a good starting point for the elaboration of an efficient algorithm. Indeed, adding a corneal knowledge and taking into account a larger area could increase the efficiency of contour detection.
Other edge-based method uses entirely the knowledge about segmented object. The Hough transform Hough (1962) is an algorithm used for the image segmentation. The purpose of this technique is to find known shape (like line or circle) by a voting procedure. The main drawback of this method is the limited shapes it can detect. The classical Hough transform detects line and circle, and a generalized Hough detects curves and parameterized shapes. However, the cornea region has not a well known structure.

2.2 Region-based Segmentation

The region-based segmentation methods are dual approach of edge-based methods. In this kind of algorithms, we try to find and fix the uniform regions on the picture.
The region growing Brice & Fennema (1970), and its simplified version the pixel aggregation Gonzales & Woods (1993) are methods that merge sub-regions according to similarity in texture, color, or intensity. The pixel aggregation method is initialized with seed pixels. The algorithm merges two sub-regions (or pixels) and appends neighboring if they satisfy some user criterion. The method stops when any near regions are similar. Some important improvements of the region growing algorithm can enhance merging and segmentation result Zhu & Yuille (1995) Zhu & Yuille (1996).
The main drawback of these region-based segmentation methods in OCT scans is their incompatibility with an important noise. The region uniformity, used by segmentation methods, is broken by a significant speckle.

2.3 Active Contour

An efficient continuous edge detection technique is the Active Contour model, also called *snakes* Kass et al (1988). It is a framework to detect object contours from a 2D image. The aim of this algorithm is to minimize an energy associated to the current contour. This energy depends on the value of gradient (external energy) and shape-dependent parameters like curvature or elasticity (internal energy). The sum of both energies gives the edge score. With small modifications, the algorithm tries to minimize this score. The algorithm stops when a local minimum is reached, and any modification can reduce the total energy.
However, some problems occur in these methods. The main drawback is that this approach requires a good initialization. This method provides a precise contour detection only if the initialized curve is sufficiently near from the edges. Only local information along the edges are used to detect the minimum energy. In the OCT scans this initialization is relatively difficult without an a priori about the thickness and the radius of curvature of the cornea (related to the

image resolution). A class of Active Contours with shape a priori is an interesting approach to add knowledge in the detection process Gastaud et al (2004). However, the adjustments are difficult to put into practice for such specific images.
Active Contours are autonomous and self-adapting in their search for a minimal energy state. In spite of these advantages, the main drawback of these methods is the initialization of seed pixels or seed regions. In the cornea segmentation process, the Active Contour method assumes that we know the initial position of the cornea in the scan, but this is not the case for us. In the frame of a custom-built contour detection algorithm, we would like to take into account some guidance dedicated to corneal data: the stability of the thickness and the radius of curvature along the cornea.

2.4 Level Sets

Osher and Sethian propose Level set theory that is a formulation to implement the Active Contours Osher & Sethian (1988)Malladi et al (1995). A known limitation of the classic snakes is the use of continuous curves, without topological modifications. Level Set avoid this restriction with a two-dimensional Lipschitz-continuous function. This function has multiple level, and the evolution of level set are equivalent to the evolution of the contour. With this kind of function, the Level Set method can detect more than one boundary simultaneously, and user can initialize the algorithm with multiple contours.
The Active Contour models give fair results in boundary detection with important noise. However the same difficulties appear for Level Set with OCT scans.

2.5 Markov models

Koozekanani et al. proposed a Markov boundary model to extract retinal contours from radial scans of the macula Koozekanani et al (2000)Boyer et al (2000). Although scans come from OCT, this method is not applicable in the corneal region because of significant anatomical differences. It is difficult to train a new Markov model because both cornea and iris are on the scans. Moreover it could be interesting to add a priori about the cornea to the detection method, which is not possible with the proposed model. The solution proposed in this chapter is a specific algorithm, considering a priori cornea informations.

This section introduces most of the contour detection methods which bring piece of specific algorithm for OCT images. These scans have two particularities: we have some a priori information of the segmented cornea but the scans have a strong noise that complicates the majority of segmentation algorithms. Thus our specific method uses these notable characteristics with a filtering pass which minimizes the noise. We present this contour detection approach in the following section.

3. Contour Detection Approach

The contour detection algorithm requires three successive steps. In a first step we detect two points, which initialize the detection contour. Then some filters are applied for a noise reduction and a contrast enhancement. And finally the three-components contour detection can begin.

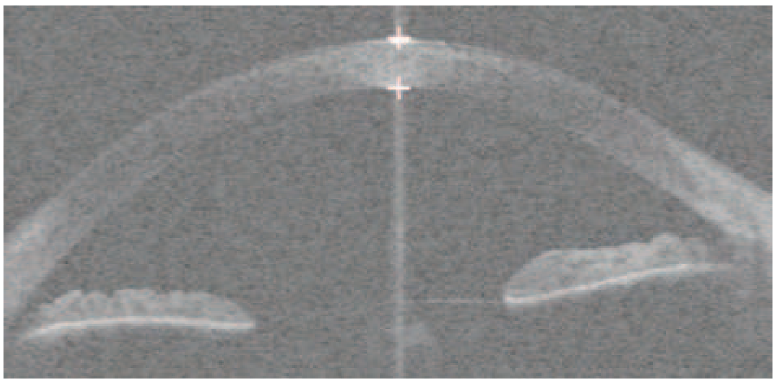


Fig. 4. A typical OCT scan. The markers show both anchor points A (the top cross) and B (the bottom cross).

3.1 Detection of the Top Points of Corneal Epithelium and Endothelium

The contour detection algorithm works pixel by pixel on the x-coordinate. Every pixel is found with the pixel on the left or on the right (according to the search direction). Therefore the detection of the initialization points is very important (we call them *anchor point*). The top points of corneal epithelium and endothelium are the best points to optimize the next step of the algorithm. Fig. 1 shows the two anchor points.

We conceive a robust method for the anchor points' detection. We call the top point of the corneal epithelium (the top cross in Fig. 4) the anchor point A and the top point of the corneal endothelium (the bottom cross in Fig. 4) the anchor point B. Firstly, the image is preprocessed. The aim of this operation is to obtain a better contrast and a reduction of the noise, particularly on the top of the cornea. We apply a Wiener filter to reduce the noise regions. This adaptive filter is used to reduce the background noise Lim (1990). It uses a comparison between a local variance and the background variance (noise variance). The Wiener filter moves a box over the image, and finds the local variance of each box. If the local variance is close to the background variance, a mean filter averages the box region, otherwise the filter does not blur the region (see Fig. 7). Next we apply a threshold with the maximum brightness value from background region. Finally we apply a dynamic range expansion to the image. Fig. 5 shows the result of this preprocess.

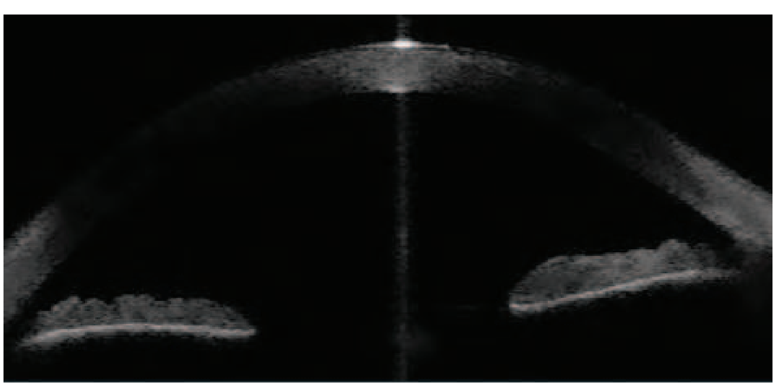
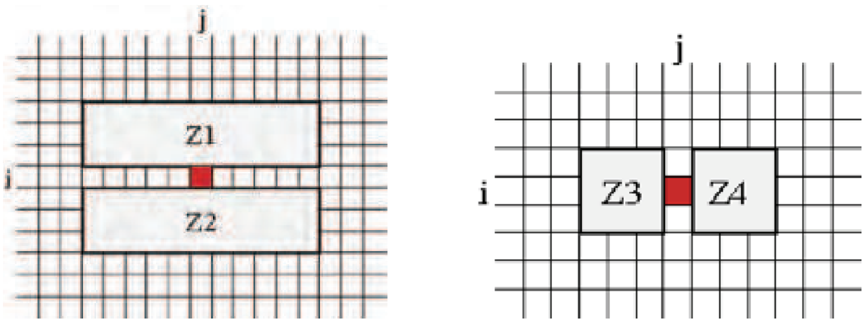


Fig. 5. The resulting image after preprocessing.

After this process, we search the y-coordinate of the anchor point A. We then compute the difference between the average of the area Z1 and the average of the area Z2, as shown on Fig. 6.



(a) Two rectangles used to compute the variation between the top and bottom areas.

(b) Two squares used to compute the horizontal variation.

Fig. 6. Both structures used to compute variations.

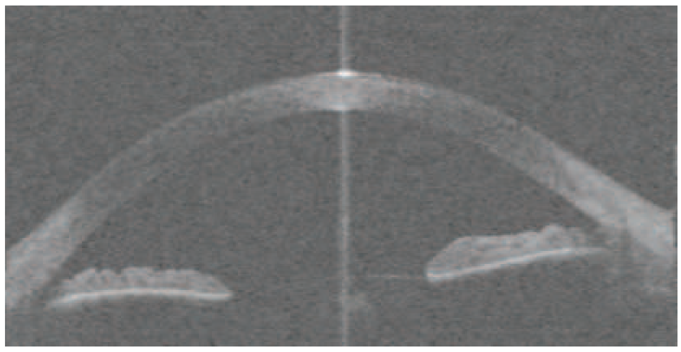
Then we apply this computation column by column, and we keep for every column the y-coordinate of the maximum difference. The highest y-coordinate of these maxima indicates the ordinate of the anchor point A. We now find the x-coordinate of both anchor points: we compute the difference between Z3 area and Z4 area in the y-axis corresponding to the point A ordinate (see Fig. 6). The middle of the x-coordinates upper and lower value of this difference is equal to the x-coordinate of the anchor points. In the last step, we find the y-coordinate of the anchor point B. For this, we apply the difference between Z1 and Z2 and repeat the same process as the point A. After this process we have the coordinates of both anchor points.

3.2 Preprocessing Functions

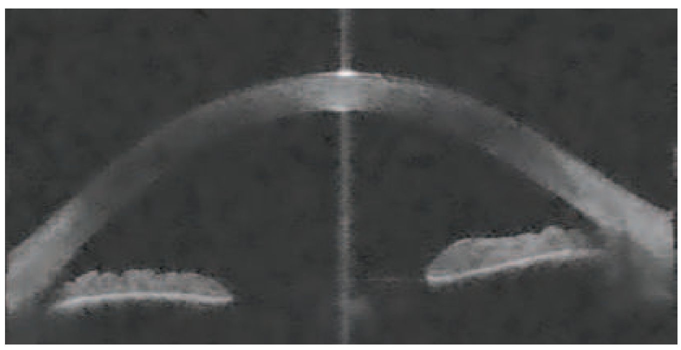
A strong multiplicative noise always comes with OCT scans. The speckle reduction is an important step for the quality of the contour detection algorithm. In fact this noise type creates a big luminance variation in each pixel decreasing the algorithm's quality. To obtain a correct result in the noise reduction, we apply a succession of simple filters to the image.
The results obtained by Wiener filter for the noise reduction are similar to a classic average filter. Yet the Wiener filter has an important advantage: it keeps the contour of the image intact. Fig. 7 shows an example of the application of a Wiener filter.
This filter reduces the background noise. However this noise has to be eliminated in the contour region. To do this, a sequence of classic median filters gives fair results. Contrary to average filter, the median filter preserves a precise contour, without spreading it. Thus many median filters are applied sequentially on the image after the Wiener filter, as shown in the final result on Fig. 8.

3.3 Contour Detection

The contour detection algorithm consists of three parts. Firstly the algorithm detects the contour pixel by pixel with the image information only. The posterior and the anterior corneal contours are detected simultaneously. Then the algorithm checks the coherence of the corneal thickness and the radius of curvature for each double pixel found. According to the relevance of the image information in an area, the contour can be more or less adjusted by these parameters.



(a) Original scan.



(b) Filtered scan.

Fig. 7. The result obtained with a Wiener filter 10X10.

Fig. 8. Result of the preprocessing on a typical OCT scan.

Maximization of a Difference of Luminance.

This part is an incremental method that progresses pixel by pixel along the x-axis. The anchor points are the initial points of the first contour. The algorithm searches the left corneal contour, and then the right part. When a pixel belongs to the contour, the algorithm applies a high-pass filter on the points nearest to the contour pixel. The filter is focused on the neighborhood of the contour point. A sized neighborhood is required: five pixels above and below the contour pixel is a correct size. Then the algorithm uses two triangular areas to compute the best contour points. Fig. 9 shows the regions of interest. The next contour point is the one maximizing the difference between the mean of the upper area (Z5) and the mean of the lower area (Z6). For each pixel this difference is called *score*.

This contour detection algorithm proceeds pixel by pixel strictly with the image information.

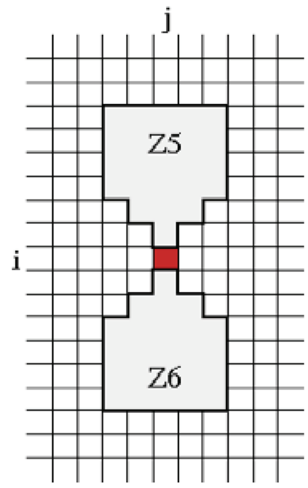


Fig. 9. The score of a pixel is equal to the difference of both shapes Z5 and Z6.

Nevertheless the OCT radial scans are of poor quality. The difference of luminance between the cornea and the background is low for many reasons. The optical coherence tomography renders a poor scan quality and the preprocessing decreases the contrast quality. For these reasons, searching the corneal contour in these scans with only the image information gives a low-quality contour. Therefore knowledge is added to the algorithm to enhance its quality.

Variation of the Curvature.
This step is based on the low variation of the curvature along the cornea. This global parameter influences the curve when the scores of pixels are weak. For each pixel, the contour detection algorithm mixes the pixel value obtained by the image information and an extrapolation of the previous pixels' curvature. This combination is a function of the score of the pixel.
The extrapolation of the new pixel location requires a significant number of contour pixels. Each triplet gives a contribution to a y-coordinate of the new pixel. At the end of this phase, the algorithm keeps the y-coordinate chosen by a majority of triplets.

Variation of the Thickness.
Like the curvature, this step is based on the low variation of the thickness along the cornea. Physiologically this thickness increases from center to periphery. However this increase is sufficiently low to consider the thickness invariant on a small length.
For each contour pixel, the algorithm sets the pixel location according to the vertical deviation of the previous contour point. This vertical deviation does not correspond to the corneal thickness (due to contours angle from x-axis), however the extrapolation is sufficient to obtain a correct result.

4. Results and Discussion

This original segmentation method gives significant results: the recognition phase of anchor points is robust as well as the contour detection.
The initialization of corneal epithelium and endothelium points is an essential process for the method to work correctly. A failure in this process leads to a collapse in the entire algorithm. Therefore the robustness of this step is very important in the process. On all the radial scans

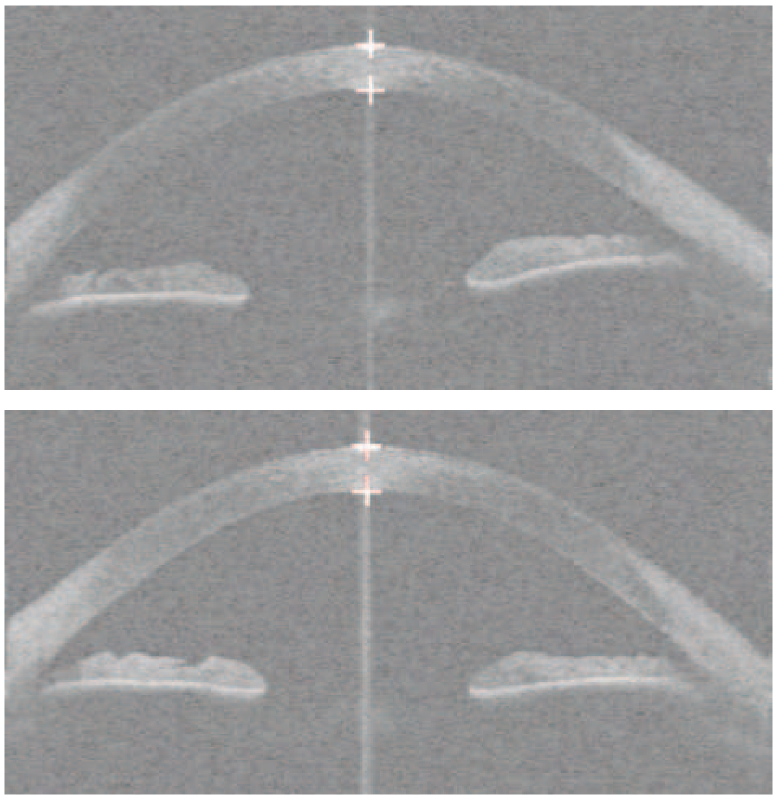


Fig. 10. Anchor points on two typical OCT scans.

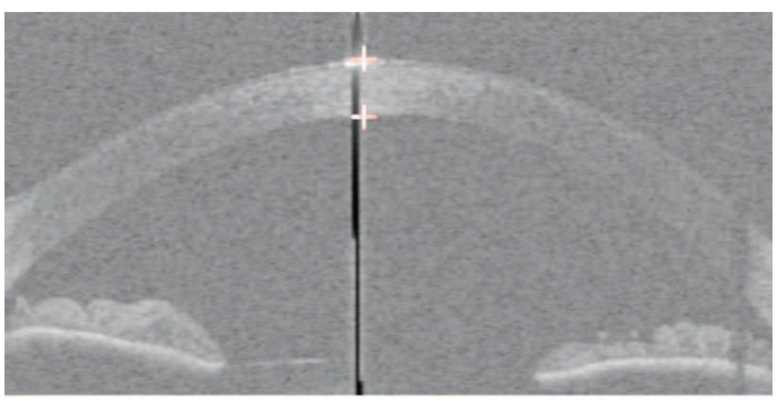
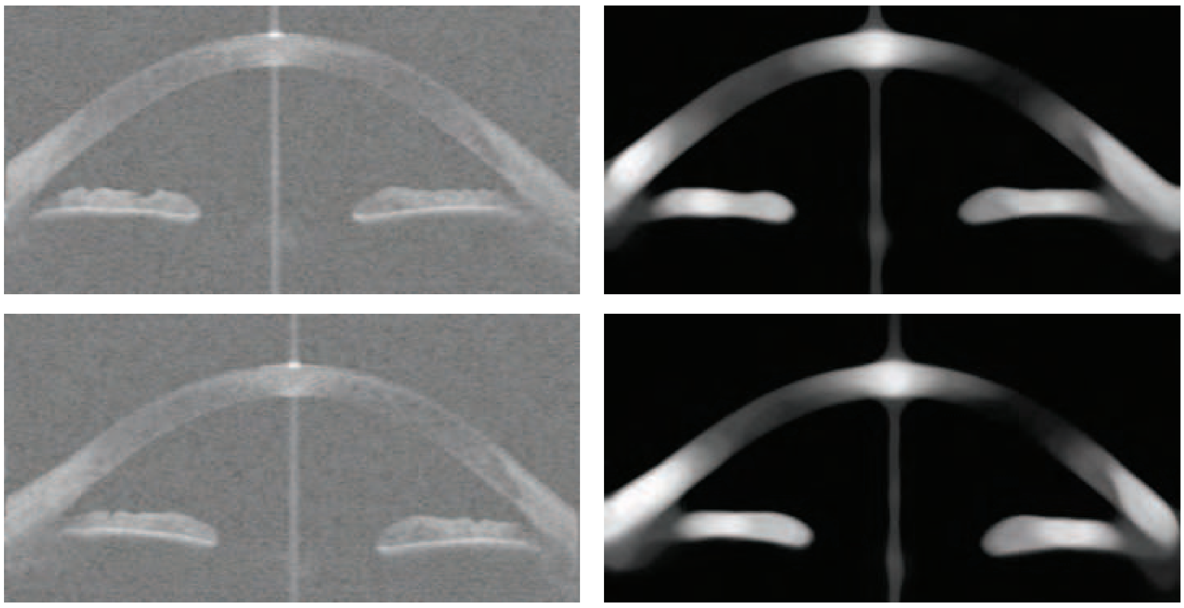


Fig. 11. Anchor points on an OCT scan with some important defects.

that have been tested, the anchor points were correctly detected. Fig. 10 shows the results for two typical scans from OCT.
Several causes (like high local saturation, eyelashes, strong noise) can degrade input images. Fig. 11 shows that the detection of anchor points succeeds even on such a deteriorated example.
Before detecting the boundaries, the noise on the images has to be reduced. This step is realized by a sequence composed of one Wiener filter and several median filters (see Fig 12).
As soon as the anchor points are correctly detected and the noise reduced, the corneal boundary detection algorithm has to go through several steps for every pixel. The first step consists in maximizing the difference between both the higher and lower zone of the pixel. This only step allows an efficient detection on most images. Fig. 13 presents two examples.



(a) Original scans. (b) Scans after preprocessing.

Fig. 12. Two examples resulting from preprocessing.

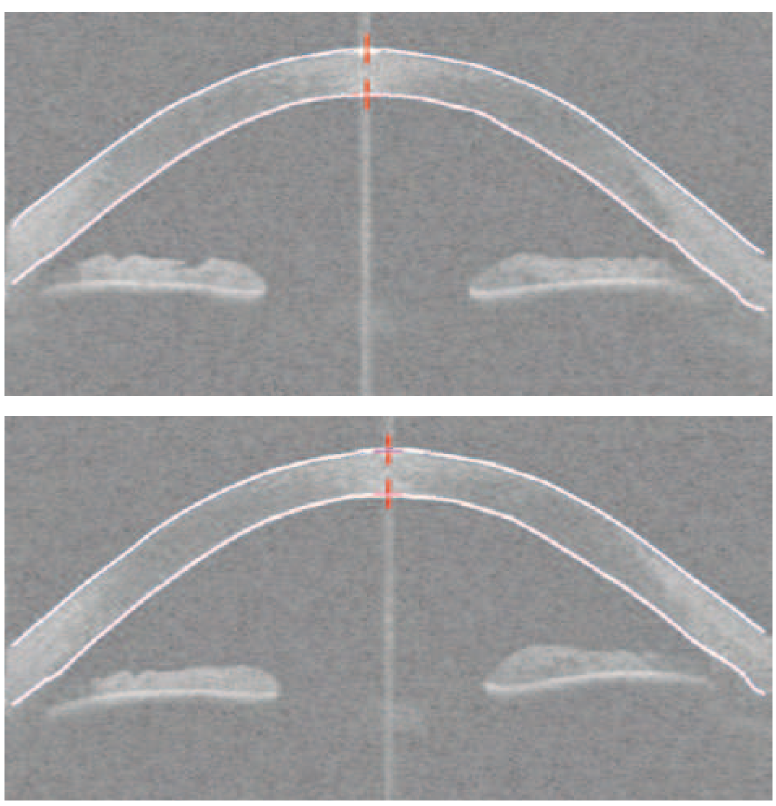


Fig. 13. Two examples of a cornea contour detected by the algorithmÕs first step.

This detection is correct for strong contrast images. However some images as shown in Fig. 14 have a lack of information at the posterior corneal level. Preprocessing allows the recovering of most image defects. For example, it is the case for the central zone of the images on

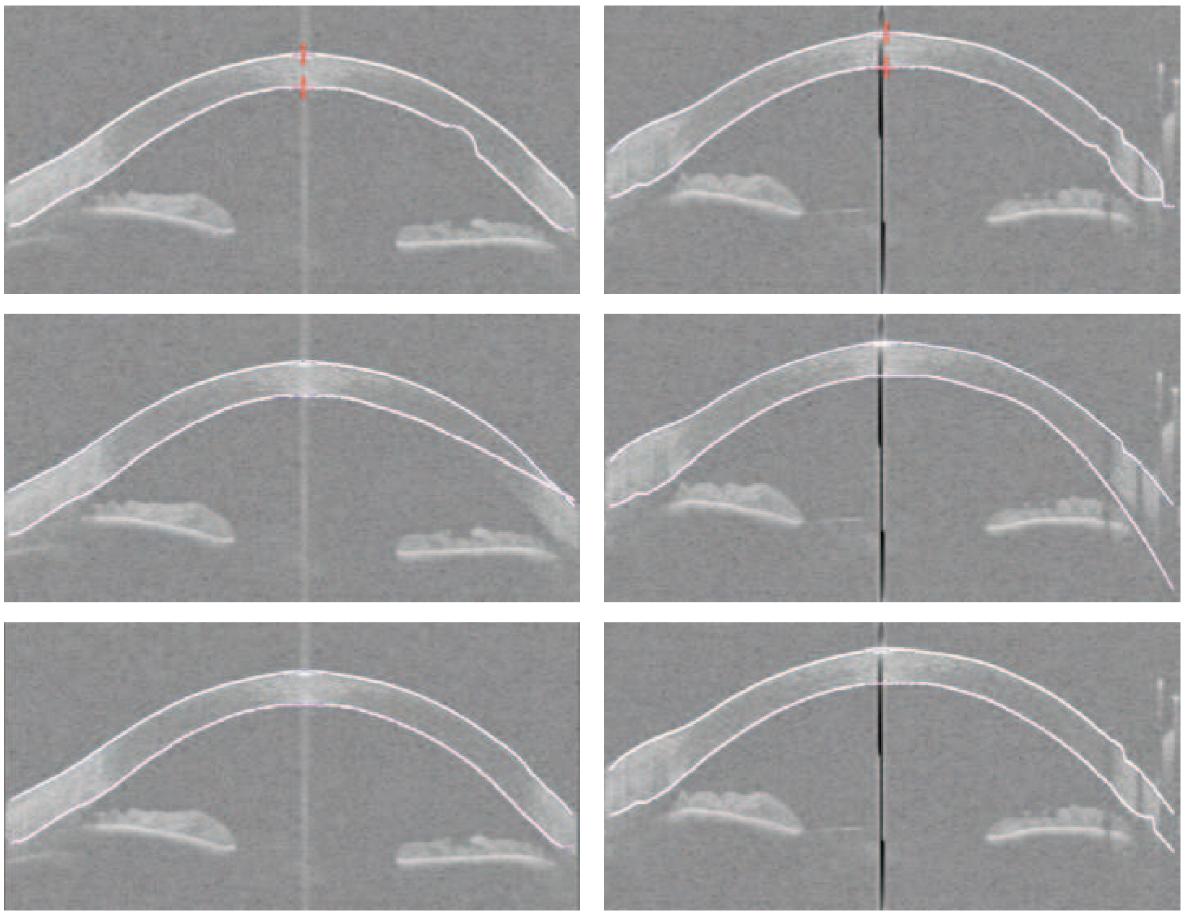


Fig. 14. Two examples (one per column) of a corneal contour. The first row shows the result of the first step: maximization of difference of luminance. The curvature guides the contours (on the second row) and the thickness refines it (on the third row).

Fig. 14. However, following the algorithm's first step we can notice sharp edges due to the presence of eyelashes.
Therefore, this step only based on the image is not enough for a correct segmentation. It is necessary to take into account some other parameters related to the cornea. The radius of curvature is the first parameter used. When the information on the image is incorrect, it is the radius of curvature that guides the detection of the corneal contour.
However Fig. 14 shows that the radius of curvature is not sufficient for a relevant contour detection. A second parameter is used for the contour detection: the corneal thickness.

5. Conclusion

This algorithm is an original method of contour detection using two kinds of information: local values from the image pixels, and global parameters from the contours already found. This contour detection uses a specific and robust algorithm composed of three steps: top and bottom key-vertices detection, speckle reduction and contour recognition using geometrical features of the cornea.
Ophthalmologists can use the resulting contour for visual examinations and diagnoses. As future work, we plan on developing a 3D interface based on such contours to build a 3D

geometrical model of the cornea. Such a mathematical model could contribute to computer-aided measurements for prostheses design.

6. References

S. Osher and J. Sethian. Fronts propagating with curvature dependent speed: Algorithms based on hamilton-jacobi formulations *Journal of Computational Physics*, pp. 12-49, 1988.

S. Zhu and A. Yuille. Region competition and its analysis: a unified theory for image segmentation *Tech. Rep. 7*, Robotics Lab, Havard University, 1995.

S. Zhu and A. Yuille. Region competition: Unifying snakes, region growing, and bayes/MDL for multiband image segmentation *IEEE Transactions on Pattern Analysis and Machine Intelligence*, no. 9, pp. 884-200, 1996.

P. Hough. A method and means for recognizing complex patterns *US Patent 3,069,654*, 1962.

C. Brice & C. Fennema. Scene Analysis Using Regions *Artificial Intelligence*, pp. 205-226, 1970.

R. Gonzales & R. Woods. Addison-Wesley Publishing, 1st ed *Digital Image Processing*, 1993.

I. Sobel & G. Feldman. A 3x3 Isotropic Gradient Operator for Image Processing *Stanford Artificial Project*, 1968.

D. Marr & E. Hildreth. Theory of edge detection *Proc. of Roy. Soc.*, pp. 187-217, 1980.

J. Canny. A computational approach to edge detection *IEEE Transactions on Pattern Analysis and Machine Intelligence*, no. 8, p. 769, 1986.

Huang D; Swanson EA; Liu CR; Schuman JS; Stinson WG; Chang W; Hee MR; Flotte T; Gregory K; Puliafito CA & Fujimoto JG. Optical Coherence Tomography *Science*, Vol. 254, pp. 1178-1181, 1991.

M. Kass; A. Witkin & D. Terzopoulos. Snakes: Active Contour Models *IJCV*, pp. 321-331, 1988.

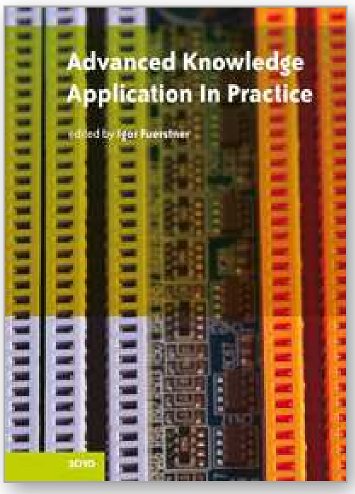
R. Malladi, J. Sethian, and B. Vemuri. Shape modeling with front propagation: A level set approach *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 17, pp. 158-175, 1995.

M. Gastaud; M. Barlaud & G. Aubert. Combining shape prior and statistical features for active contour segmentation *IEEE Transactions on Circuits and Systems for Video Technology*, Vol. 14, pp. 726-734, 2004.

D. Koozekanani; K. Boyer & C. Roberts. Retinal Thickness Measurements from Optical Coherence Tomography Using a Markov Boundary Model *IEEE Transactions on Medical Imaging*, Vol. 20, No 9, pp. 900-916, 2000.

D. Koozekanani; K. Boyer & C. Roberts. Retinal Thickness Measurements in Optical Coherence Tomography Using a Markov Boundary Model *IEEE Compter Society Conf. Computer Vision and Pattern Recognition*, Vol. 2, pp. 363-370, 2000.

J, S. Lim. Two-Dimensional Signal and Image Processing, Englewood Cliffs, NJ, Prentice Hall, p. 548, 1990.



Advanced Knowledge Application in Practice
Edited by Igor Fuerstner

ISBN 978-953-307-141-1
Hard cover, 378 pages
Publisher Sciyo
Published online 02, November, 2010
Published in print edition November, 2010

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How to reference

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Florian Graglia, Jean-Luc Mari and Jean Sequeira (2010). Cornea Contour Extraction from OCT Radial Images, Advanced Knowledge Application in Practice, Igor Fuerstner (Ed.), ISBN: 978-953-307-141-1, InTech, Available from: http://www.intechopen.com/books/advanced-knowledge-application-in-practice/cornea-contour-extraction-from-oct-radial-images

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