Edge Complement of the Cornea's Endothelial Cell Using Energy Function

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Abstract—An area distribution of Corneal Endothelial Cell(CEC) include important clinical information. In this paper, we present a two-step processing method of contour complement for the CEC. In the first step; we apply not only conventional Laplasian Gaussian filters(LGF) but also three-arrow-shaped LGFs which is newly developed to extract vertices of hexagonal shapes. In the second step; we complement the lacking part of CEC by using an energy minimum algorithm. Using the results, we measure areas of CEC.

Index Terms—Hexagonal contour, CEC, Energy function, LGF.

I. INTRODUCTION

Corneal Endothelial Cell (CEC) takes charge of refraction in image formation system of eyeball and plays a most important roll of keeping the eyeball's transparency. Each CEC usually has regular hexagonal form. Being damaged by e.g. inner operation, some cells die and surrounding cells become large to compensate them. These cause irregularity in the form and the size. Measuring and quantifying the shape of CEC automatically by in vivo image is important for clinical diagnosis. We present an approach of extracting and complementing the contour for CEC image.

The contour extraction processing of the CEC includes the following problems: (I)much additional noise, (II)low image contrast, (III)low resolution, (IV)position dependent variation of gray level, etc. Therefore, it is difficult to extract the contour extraction by only simple algorithm. T. Saga presented a method [1]; there, enhancing the image by combining FIR and smoothing filters, extraction of the contour extraction for CEC are carried out by discriminating the vertical angle information of hexagon.

In this paper, we present a two-step processing method of contour extraction and complement for the CEC. In the first step; (1)We apply not only conventional Laplasian Gaussian filters (LGF) but also three-arrow-shaped LGFs (TAS-LGF) which is newly developed to extract vertices of hexagonal shapes[2, 3]. Thus, we enhance and extract contour lines including vertices by the LGF's[4, 5]. In the second step; we complement the lacking part of CEC by using an energy minimum algorithm.

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II. PRE-PROCESSING

A. Contour enhancement using three-arrow-shaped LGF

An original image of CEC is shown in Fig. 1. One directional LGF are used for vertical line extraction. Here, the filter is composed of stepwise weight of Fig. 2 affecting second-order differential operation. Therefore, the shape is not a pure LGF. However, the original image is degraded and has few high frequency component. Stepwise shape will affect only high frequency component. Therefore, this approximation gives no effective difference to the output shape. This situation is the same as the following TAS-LGF. The image is faded naturally. However, the vertex of the CEC hexagon is difficult to extract by the 1D-LGF, since the 1D-LGF is fitted only to extract the simple edge. Therefore, it causes the missing vertices sometimes. Therefore, we specially devised the TAS-LGF to extract the crossing parts. TAS-LGF and oblique one-directional LGF are shown in Fig. 3 and Fig. 4 respectively. Four types of vertical, horizontal, left, and right LGF's and two types of TAS-LGF's are applied to the original image, their six output are summed up to extract contours irrelevant to edge direction. Outputs of LGF, TAS-LGF are shown in Fig. 5, Fig. 6 respectively.

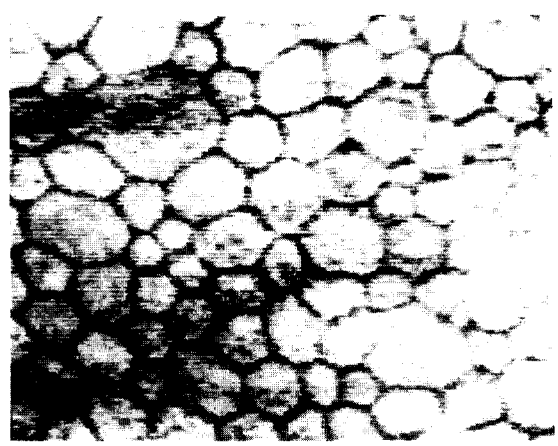


Fig. 1 Original Image

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

Fig. 2 One-directional Laplasian Gaussian filter for vertical line extraction

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

Fig.3 Three-Arrow-Shapped Laplasian Gaussian filter

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

Fig. 4 Oblique one-directional Laplasian Gaussian filter

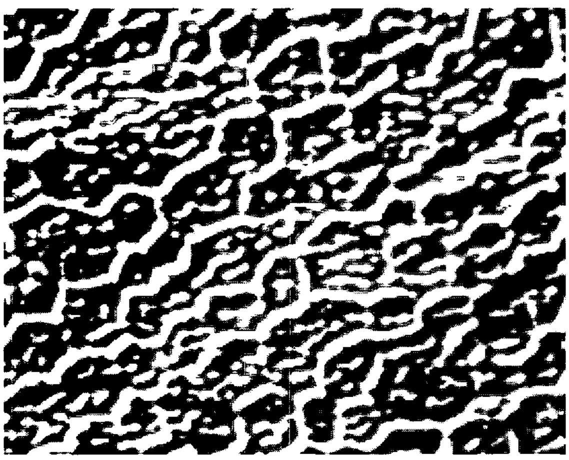


Fig. 5 Output of Oblique LGF

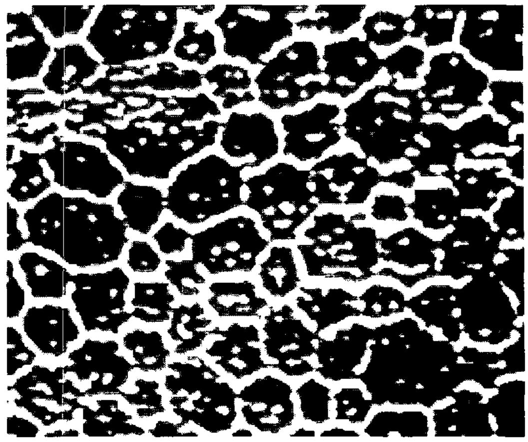


Fig. 6 Output of Three-arrow-Shaped LGF

B. Contour extraction

Automatic binarization processing is applied to the results of 2-1. In order to eliminate the noise, we repeat the expansion and shrink processing. After then we make their thinning. A result is shown in Fig. 7.

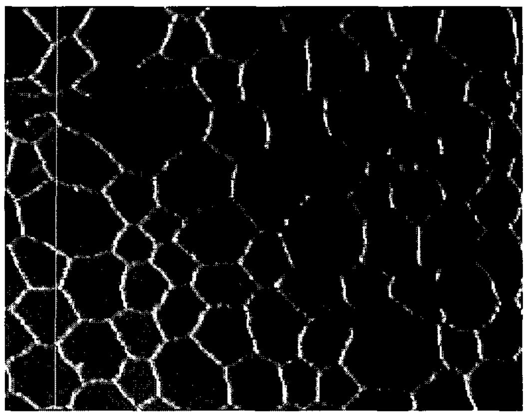


Fig. 7 Thin lined Image

III. COMPLEMENT OF MISSING CONTOUR USING ENERGY FUNCTION

Contour extraction of a lip image causes many breaks because of noise and ambiguity. H. Mitsumoto et al. have shown the effectiveness of energy function method, to complement the lip contour. We also found many breaks in the extracted cell contour of CEC. However, the shape has the fundamental characterstic of hexagon distinctly. Therefore, we define a evaluation (energy) function with respect to the objective cell contour. The algorithm using the energy function is shown below. First, CEC is approximated by closed loop spline curve. Next, the nodes are moved to minimize the energy function. These algorithms complement the break contour.

A. Pixel energy **:** E_l

The estimated contour line being the closed loop curve which complement the breaks of point sequence. The energy to suit to this estimated contour curve to the contour data extracted practically is the pixel energy. Search for energy minimum is done by moving the nodes within the ten pixels upward, downward, left, or right direction; the cost (energy) is given by the square of the distance from the curve to the pixel if exist, and some fixed cost is given if not exist. And the energy is given by eq. (1) if the gradient is less than 45 degrees, and else eq. (2).

Suppose a pixel on obtained contour image axis is to be (x_i, y_j) and the complement axis to be (x_i, y_j) .

$$E_l = \frac{\sum_{i=0}^{n} \min\{\sum_{-10}^{10}(my_i - Y_i)^2\}}{\sum_{i=0}^{n} 1} \qquad (1)$$

$$my_i = \{(x_i, y_i - 10), (x_i, y_i - 9), \cdots (x_i, y_i + 9), (x_i, y_i + 10)\}$$

$$E_l = \frac{\sum_{i=0}^{n} \min\{\sum_{-10}^{10}(mx_i - X_i)^2\}}{\sum_{i=0}^{n} 1} \qquad (2)$$

$$mx_i = \{(x_i - 10, y_i), (x_i - 9, y_i), \cdots (x_i + 9, y_i), (x_i + 10, y_i)\}$$

B. Energy for circularity : E_c

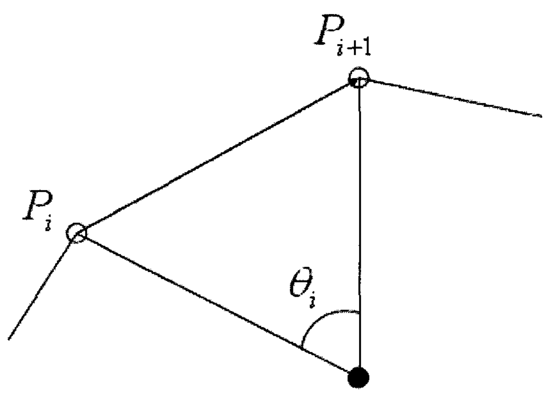


Fig. 8 Energy for Circularity

Energy for circularity E_c means the energy of similarity to a circle. E_c is defined to be the square of difference; the distance length between each node and the average length. The center of the estimated contour circle is obtained by averaging the axis of pixels. Let E_{c1} and E_{c2} as Eq. (3), (4), respectively ; where θ_i is the angle between i-th node, the adjacent node and the center, and $\bar{\theta}$ is the average of angles (36 degrees for ten nodes) as shown in Fig. 8. We define the energy for circularity as the summation of E_{c1} and E_{c2}.

$$E_{c1} = \sum^{k}(\theta_i - \bar{\theta})^2 \qquad (3)$$

$$E_{c2} = \sum^{k}(|P_i P_{i+1}| - \bar{l})^2 \qquad (4)$$

where P_i is the i-th node and $\bar{l}$ is the average length.

C. Mutual crossing energy : E_M

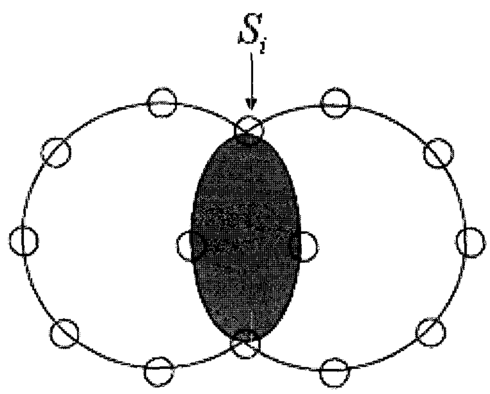


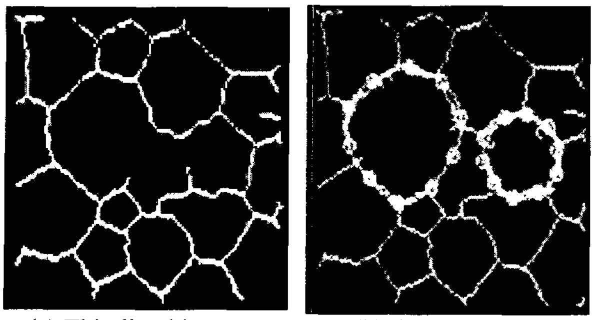
Fig. 9 Mutual Crossing Energy

Mutual crossing energy (MCE) is the interaction energy for adjacent cells and the cost for the overlapping. After extracting cells, the processing is carried out locally with respect to each cell. As the results, two adjacent cell region often overlaps each other. To cope with the overlapping, MCE E_M is introduced and the MCE is varied in proportion to the overlapping area S_i (Fig. 9).

The evaluation function used for experiment is shown below. The total energy function is the weighted summation of these energy function.

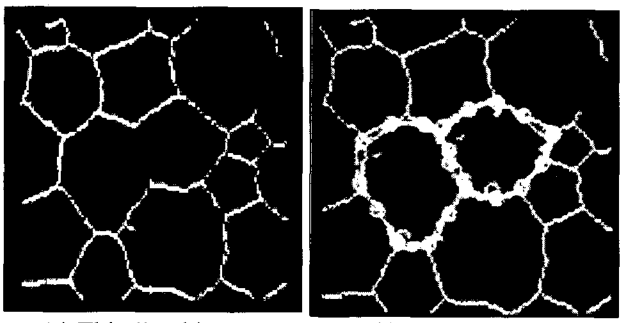
IV. EXPERIMENTAL RESULTS

The results of complement processing for image with many breaking contour parts are shown in Fig. 10, Fig. 11, and Fig. 12. (a) is an image after the thinning. (b) is after the complement and a small circle mark indicates the node position. Processing the contour extraction for two non-adjacent cells independently (Fig. 10), the breaking parts are complemented so far (in outline) even if the estimated contour invade into the neighboring region because of being expanded by E_c processing.



(a) Thin lined image (b) Complement

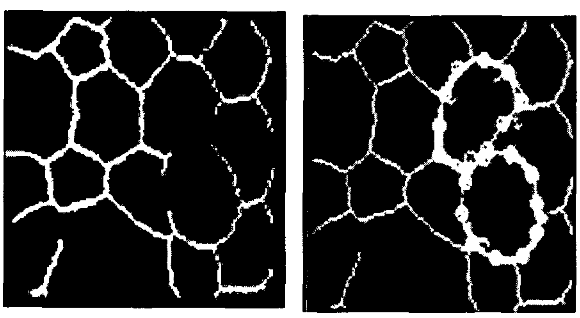
Fig.10 Defected Contours and their independent complements



(a) Thin lined image (b) Complement

Fig.11 Defected Contours and their independent complements

In Fig. 11 the boundary contour between two adjacent cells are obtained almost correctly. However, the convergence positions of nodes cause small gaps (space). To cope with this, an algorithm of many contour extraction processing run at the same time should be introduced. Missing so many contour segments near vertex, e.g., Fig. 12, better complement can be carried out by the energy function method. Observing the results as a whole, the energy function method used have an ability of complement the partially breakings of cell contour in the image.



(a)Thin lined image (b)Complement

Fig.12 Largely Defected Contours and its complements results

V. CONCLUSIONS

We have enhanced the contour of CEC image which is in low resolution, with low image contrast, and with additional noise using three-arrow-shaped Gaussian filter. In addition, we have presented an algorithm to complement the contours with many breaks, defining an energy function conforming to the characteristics of the image and minimizing the energy function. The data applied in this experiment, has relatively well enhanced and complemented sufficiently. However, the images obtained in daily clinical diagnosis, are with less contrast and often include more noise. To cope with such situations the algorithm should be reformed to more generalized form. Algorithms of estimating how many cells a contour with breaks and irregular shape is composed of, i.e., wether a contour should be separated into two cells or to be unified as one cell, is a remaining problem to be solved.

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