Automatic Segmentation of the Papilla in a Fundus Image Based on the C-V Model and a Shape Restraint

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Abstract

For computer aided Glaucoma diagnostics it is essential to robustly and automatically detect and segment the main regions, e.g. the papilla (optic nerve head), in a fundus image. In this paper an effective method for automatic papilla segmentation based on the C-V model and a shape restraint is proposed. The method is a combination between the C-V model using level sets and the elliptic shape restraint for papilla segmentation. The combination of the level set framework with a shape restraint ensures that the evolving curve stays an ellipse. Experiments verify that the method shows a good performance in detecting the papilla shapes and computing the shape feature parameters within a broad variety of fundus images. The experiment results also show that the method is robust to noise and object deformity.

1. Introduction

With the advancement of medical imaging and computer vision technology, the effective use of image-guided diagnostics and treatment has been a focus of research in image processing and computer vision. The application of digital fundus imaging provides ophthalmologists with digitized data that could be exploited for computerized detection of eye diseases based on image processing and pattern recognition technologies [1].

For the diagnosis of eye diseases, such as glaucoma, the ophthalmologists concentrate on the area around the papilla and pay most of their attention to changes in this region (see Figure 1.). Therefore, both the identification and automatic calculation of shape feature parameters, such as disc radius, cup radius and shape variations of the papilla within a sequence of fundus images of one eye are very important. By these quantitative features the early detection and grading of glaucoma might be greatly facilitated. For this purpose the method of papilla detection and segmentation should be robust against varying image qualities and resolutions as well as be able to automatically provide shape feature parameters.

Figure 1. A fundus image. Zone 1 represents the cup, 2 is the optic disc (papilla), 3 is the black mask area.

Several methods based on Hough transform [2], mathematical morphology [3], snake model [4] etc. have been developed for the automatic detection of the papilla within a fundus image. In [2] an area threshold is used to locate the papilla. The contours are detected by means of the Hough transform. This method relies on conditions about the shape of the papilla that are not always met. In [4] a two-stage method was reported. In the first stage, the fundus image is processed using grey-level mathematical morphology to remove the blood vessel region. Then, a closed curve as an initial condition is manually placed around the papilla. A snake model allows it to evolve onto the papilla boundary. This method was improved in [5] by a simple template matching to locate the center of the papilla for the automatic initialization of the snake curve. In [6] a method with binarization of a fundus image by means of an adaptive threshold and a linear gradient compensation was presented to detect the...
contour of the papilla. The results rely on the image contrast and the image quality. In [3] the contour of the papilla is detected by means of the Watershed transformation. In this method the large grey level variation within the papilla region that is usually caused by dark blood vessels must be eliminated and smoothed for the effective detection of the papilla contour. In processing images with low contrast, varying image qualities and different resolutions these algorithms are not always effective and sometimes the results are not acceptable. There are more than 16000 fundus images in the database that were taken in different clinics with different cameras within the European Glaucoma Prevention Study. For processing this large amount of fundus images, the method of automatic papilla segmentation based on the C-V model and a shape restraint was proposed. Experimental tests with the broad variety of images showed that the method presented in this paper is very effective for automatic papilla shape detection compared to other methods, especially for low contrasts and noisy images.

The outline of this paper is as follows. In the second section the active contour C-V model is shortly introduced. In section 3 the new method based on the C-V model and a shape restraint is presented. The procedure of papilla detection using this method within fundus images is introduced and some experimental results are shown in section 4. This paper ends with a brief discussion and conclusion in section 5.

2. Active contour model based on region [7]

In [7] Tony Chan and Luminita Vese proposed an active contour model to detect objects in an image, based on techniques of curve evolution, Mumford-Shah function for segmentation and level sets. Unlike the classic active contour based on the gradient of a given image, the C-V model can detect the contours both with and without gradient. In addition, the model has a level set formulation, interior contours are automatically detected, and the initial curve can be anywhere in the image.

Let \( \Omega \) be a bounded open subset of \( \mathbb{R}^2 \) and \( C \) be an evolving curve denoting the boundary of the open subset \( \omega \) of \( \Omega \). Let \( u_0 : \Omega \rightarrow \mathbb{R} \) be a given image. In the level set method, the curve \( C \) is represented implicitly by the zero level set of a Lipschitz function \( \phi : \Omega \rightarrow \mathbb{R} \), such that:

\[
\begin{align*}
C &= \partial \omega = \{(x, y) \in \Omega : \phi(x, y) = 0\} \\
\text{inside}(C) &= \omega = \{(x, y) \in \Omega : \phi(x, y) > 0\} \\
\text{outside}(C) &= \Omega \setminus \omega = \{(x, y) \in \Omega : \phi(x, y) < 0\}
\end{align*}
\]

Here \( x \) and \( y \) are image co-ordinates. Assume that the image \( u_0 \) is formed by two regions of approximatively piecewise-constant intensities. Assume further that the object to be detected is one of two regions. The C-V model is formulated by the minimizer of the following “fitting energy” function \( E \) [7]:

\[
\inf_{c_1, c_2, \phi} E(c_1, c_2, \phi) = \mu \int_{\Omega} \nabla H(\phi(x, y)) dxdy + \lambda_1 \int_{\Omega} [u_0(x, y) - c_1] H(\phi(x, y)) dxdy + \lambda_2 \int_{\Omega} [u_0(x, y) - c_2]^2 (1 - H(\phi(x, y))) dxdy
\]  

(2)

Where \( \mu, \lambda_1, \lambda_2 \) are fixed parameters, \( c_1 \) and \( c_2 \) are the average intensities of \( \omega \) and \( \Omega \setminus \omega \) respectively, and \( H(\cdot) \) denotes the Heaviside function. With the level set formulation the associated Euler-Lagrange equation can be deduced from the equation (2). Then, the zero-level curve of its steady solution is the contour of the object to be detected.

3. The method of elliptic object detection based on the C-V model and a shape restraint

In fundus images the papilla appears as a bright or yellowish region (see Fig. 1). Its shape appears more or less like a circle or an ellipse. Its size and shape vary from image to image. Based on the shape feature, an elliptic shape restraint is imposed on the zero level set of a Lipschitz function in C-V model. The C-V model with an elliptic shape restraint can be written as follows:

\[
\inf_{c_1, c_2, \phi} \{E[c_1, c_2, \phi | u_0] = \\
\alpha \int_{\Omega} (u_0 - c_1)^2 H(\phi) + (1 - \alpha) \int_{\Omega} (u_0 - c_2)^2 (1 - H(\phi)) \}
\]

subject to

\[
\phi = 1 - \left[\frac{((x-x_0) \cos \theta + (y-y_0) \sin \theta)^2}{a^2} + \frac{(-(x-x_0) \sin \theta + (y-y_0) \cos \theta)^2}{b^2}\right]^{1/2}
\]

(4)

where \( \alpha>0 \) are fixed parameters and \( H(\cdot) \) is the Heaviside function. Here, \( x_0, y_0, \theta, a, b \) are the parameters of the ellipse: \( \phi = 0 \). Using the following denotations:

\[
\begin{align*}
A &= (x - x_0) \cos \theta + (y - y_0) \sin \theta \\
B &= -(x - x_0) \sin \theta + (y - y_0) \cos \theta \\
L &= A \cos \theta / a^2 - B \sin \theta / (b^2) \\
M &= A \sin \theta / a^2 + B \cos \theta / (b^2) \\
N &= AB \left[1 / b^2 - 1 / a^2\right]
\end{align*}
\]

(5)
the evolution equations related to the Euler-Lagrange equations for (3) and (4) (parameterizing the descent direction by a time variant t) are:

\[
\frac{da(t)}{dt} = \frac{-1}{\gamma} \int [\alpha(u_i - c_i)^3 - (1 - \alpha)(u_i - c_i)^4] \delta(x) \, dx \, dy
\]

\[
\frac{db(t)}{dt} = \frac{-1}{\gamma} \int [\alpha(u_i - c_i)^3 - (1 - \alpha)(u_i - c_i)^4] \delta(y) \, dx \, dy
\]

\[
\frac{dc_i(t)}{dt} = \frac{-1}{\gamma} \int [\alpha(u_i - c_i)^3 - (1 - \alpha)(u_i - c_i)^4] \delta(x) \, dx \, dy
\]

\[
\frac{dy_i(t)}{dt} = \frac{-1}{\gamma} \int [\alpha(u_i - c_i)^3 - (1 - \alpha)(u_i - c_i)^4] \delta(y) \, dx \, dy
\]

\[
\frac{d\theta(t)}{dt} = \frac{-1}{\gamma} \int [\alpha(u_i - c_i)^3 - (1 - \alpha)(u_i - c_i)^4] \delta(\theta) \, dx \, dy
\]

(6)

Here, \(\delta(x)\) is the Dirac function and

\[
c_1 = \left( \int u_i H(\phi) \, dx \, dy \right) / \left( \int H(\phi) \, dx \, dy \right)
\]

\[
c_2 = \left( \int u_i (1 - H(\phi)) \, dx \, dy \right) / \left( \int (1 - H(\phi)) \, dx \, dy \right)
\]

With

\[
\phi_0(x, y) = 1 - \left( (x - x_c)^2 + (y - y_c)^2 \right) / R
\]

the initial conditions for the equation (6) can be given as follows:

\[
\left\{ \begin{array}{l}
a(t) \big|_{t=0} = R, \\
b(t) \big|_{t=0} = R, \\
x_i(t) \big|_{t=0} = x_c, \\
y_i(t) \big|_{t=0} = y_c, \\
\theta(t) \big|_{t=0} = 0
\end{array} \right.
\]

(8)

where \(R > 0\) is a constant. The steady solutions of the equation (6), \(a(T), b(T), x_c(T), y_c(T), \) and \(\theta(T)\), determine the ellipse equation:

\[
\frac{((x - x_c(T)) \cos(\theta(T)) + (y - y_c(T)) \sin(\theta(T)))^2}{(a(T))^2} + \frac{(-(x - x_c(T)) \sin(\theta(T)) + (y - y_c(T)) \cos(\theta(T)))^2}{(b(T))^2} = 1
\]

(9)

It is namely the contour of the elliptic object to be detected, i.e. the contour of the papilla. The explicit finite difference scheme leads to the numerical solution of equation (6). Compared to other methods, including C-V method, for papilla segmentation in a fundus image, this method does not need to smooth the original image for eliminating the vessel, even for a noisy image. Additionally, the post-processing of the segmentation result, such as ellipse approximation and mathematical morphology operations, is also not necessary. The example in Figure 2 shows the papilla detection in a fundus image with C-V model and the new method respectively. From the Figure 2 one can see that the segmentation result with C-V model needs further processing for papilla shape detection.

4. The procedure of papilla shape detection in a fundus image

The procedure of papilla shape detection within a fundus image, in practice, includes two steps: 1) automatic localization of the papilla center; 2) the automatic shape detection of the papilla. From the color fundus images it can be found that the contour of the papilla appears more continuous and less disturbed by the dark vessels in the red channel of the RGB color space. As in this channel the papilla belongs to the brighter parts and has better region features, it is more reliable to use the red channel to find its contour (see images in Fig. 2). In numerical experiments the parameter \(\alpha\) in equation (6) was chosen as \(\alpha = 0.6\). The time step is \(\Delta t = 0.1\), the intensity range of the input image is limited to \([0, 1]\). The discrete time step of the equation for \(\theta(t)\) in (6) is 0.01\(\Delta t\) for the stability of the finite difference scheme.

As mentioned in section 2 and 3, in both the C-V model and the new method the initial curve can be anywhere in the image and it evolves and stops on the boundary of the object. In this way, preprocessing, such as choosing the initial curve, is not necessary. In practice, the initial curve should be near to the desired boundary of the object for fast and accurate object detection. For this purpose an automatic location of the papilla center in a fundus image was implemented. The method applied for localizing papilla center was proposed in [8]. In this method the papilla center is located using high grey level variation on the point in the variance image that has the absolute grey maximum value (see Fig. 3). More details are given in [8]. This approach has been proved to work very well, if no or only low level noise appears in an image. For some noisy images, although the papilla center can not be correctly localized, the new method can also detect the papilla shape, because in the original C-V model the initial curve can be anywhere in an image. It affects only the convergence speed of the numerical solution.
Figure 3. Papilla location in a fundus image. a) the original fundus image. b) the variance image of the red channel in the original image (+: center of the papilla).

Let \((x_c, y_c)\) be the detected papilla center, the initial function in equation (3) is chosen as

\[
\phi_0(x, y) = 1 - \left(\sqrt{(x-x_c)^2 + (y-y_c)^2} / R\right)
\]

where \(R\) is the estimating radius of the papilla in fundus images or simply taken as:

\[
R = \min\{\min h/2, (w-x_c)/2\}, \min\{y_c/2, (h-y_c)/2\}\}
\]

Here, \(h\) and \(w\) are the height and width of an image respectively. By the equation (7), the initial condition of equation (6) can be determined as stated in equation (8). Three examples of papilla detection with the new method are shown in Fig.4.

Figure 4. Examples of papilla contour detection. a) to c): original fundus images. d) to f): detected contours on the image.

5. Conclusion and discussion

The method in this paper for an automatic papilla detection based on the C-V model and an elliptic shape restraint has three advantages. Firstly, it can not only give satisfactory segmentation results but also directly provides the shape feature parameters of the papilla region, such as the lengths of the major and minor axes and centre location. Secondly, it is not necessary to smooth the original image and to eliminate the vessels. Lastly, it is not based on the gradient of a given image and independent of image size, resolution and image contrast. The new method was tested with the 50 color fundus images, including 20 low contrast images. 47 results are fully satisfactory like the results shown in this paper. For color fundus images only the red channel is applied to detect the contour of the papilla in our method. If the red channel of a fundus image can not reflect the papilla region feature, this method failed to detect the papilla shape. The drawback may be improved by the image fusion method with red, green and blue channels, or the combination between the gradient of a given image and region features in a new model.

6. References


