SEGMENTATION OF OPTIC DISC IN FUNDUS IMAGES

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Abstract

Glaucoma is one of the leading eye diseases that cause blindness. Early detection of glaucoma is essential to minimize the risk of visual loss of diabetic patients. A standard procedure that is used for the detection of glaucoma and other eye diseases is done by manual examination of the optic disc by an ophthalmologist. The proposed work implements automatic optic disc segmentation of fundus images of the eye. Automatic retinal image analysis is emerging as an important screening tool for early detection of eye diseases. This method better captures the boundary of a non-homogeneous object such as the optic disc (OD). Depending on the shape of this boundary, one can find whether the person is affected by glaucoma or not. Active contour models like Gradient Vector Flow model and Chan-Vese model fail to localize disc boundaries due to gradient and global information (gray level intensities, contour lengths, region areas). The proposed region-based active contour model utilizes local image information around each point of interest in multi-dimensional feature space to provide robustness against variations found in and around the OD region. This model defines a local energy functional to achieve desired OD segmentation. This energy is minimized to OD boundary using level set method.

Keywords: Image Segmentation, Optic Disk, Active Contour Model

1. Introduction

Glaucoma is an eye disease that causes blindness in humans. It is mostly seen or observed among diabetic patients. It occurs mainly due to the degeneration of the optic nerve fibers and leads to structural changes of the optic nerve head, which is commonly referred to as optic disc. When the intensity of glaucoma in an OD increases, it becomes the villain for complete blindness or vision loss. So the only way to escape from the bad effects of glaucoma is early detection and prevention. The detection processes of glaucoma, involves OD segmentation [1] in which the defective input image (Fig. 1) is partitioned into regions or sub images. Then, the defective portion is identified from the segmented image.

Optic disc is an important structure in human retina. Ophthalmologists manually assess various retinal pathologies by observing the changes in the shape, depth or color in the OD. The tests were done through ophthalmoscopy and tomography.

After the observation of the patient, the defected parts of retinal images are drawn and the cup to disc ratio (CDR) is determined. This is the traditional method used by the ophthalmologists. However, the method is not compatible in explaining the OD damage caused by glaucoma.

Fig. 1. Original Color Retinal Image

The proposed work presents an automated glaucoma detection method known as color fundus imaging (CFI). A monocular CFI gives a 2-D projection of retinal structures, where the OD segmentation gives better results against pathological changes. Gradient Vector Flow (GVF) model is used to extract OD boundary. This model fails because of its incompatibility to capture irregular OD shapes. Recently, region based active contour models are proposed for object segmentation. The basic model employed is the Mumford-Shah model, where the foreground and background regions are separated easily using energy functions. This model is also used to segment images with complex intensity variations. However, in case of global statistics, region based approaches give erroneous segmentations. To overcome such over segmentation, Chan-Vese (C-V) model [2] is proposed including local image information. This model does not impose any circularity constraint and is a good solution for OD segmentation.

OD Segmentation

2.1. *Preprocessing*

Preprocessing is a method to provide improvement in an image data that suppresses undesired distortions or enhances the image features for further processing. It does not increase image information content. This method uses the considerable redundancy in images. Neighboring pixels corresponding to one object in real images have the same or similar brightness value and if a distorted pixel can be picked out from the image, it can be restored as an average value of neighboring pixels. Image pre-processing tool, created in MATLAB, realizes many brightness transformations and local pre-processing methods. Shape-based models [3, 4] also require initial preprocessing in extracting the disk features from the fundus images.

2.2. *OD Localization and Contour Initialization*

The second step in GVF model and C-V model is to localize OD region and define region of interest for further processing. The red color plane of CFI gives good definition of OD region thus a good choice for the OD localization task [5]. The contour initialization is the next essential step to initiate active contour evolution. The method performs localization and initialization steps together by performing circular Hough transform on the gradient map. Hough transform is a shape based approach in which shape of the OD is compared with a Hough circle. Hough transform is used here for region identification.

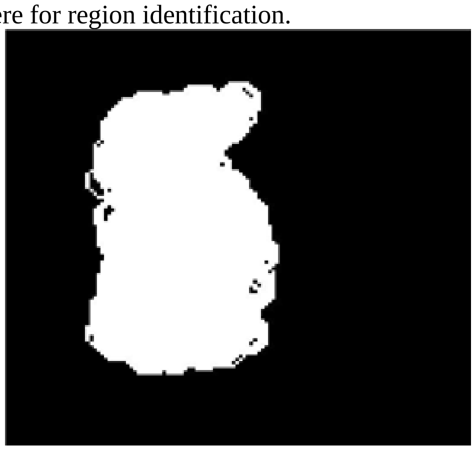

Fig. 2. Hough Space

2.3. *GVF Model*

The gradient based active contour model is used for disk boundary detection. The algorithm retains the shape feature of the desired object and its performance relies on contour initialization. Its advantage over many other methods is that it integrates shape feature into snake evolution. Before applying this method, Gaussian filter is used to remove possible noise. After applying the Gaussian derivates, the desired output of the model is obtained as shown in (Fig. 5).

2.3.1. *Magnitude and Orientation of Gradient Vector*

After performing the Hough transform, the magnitude components of the image (Fig. 3) is found, which gives the pixel information in X and Y coordinates.

The orientation of gradient vectors is obtained from canny edge detection. This detection is done by using the principles of RGB color format. The edges in the defective part of the image is detected and segmented with the help of canny edge detector. In addition to that, it gives a clear distinction of the defected boundary with the background image. Orientation of gradient vectors (Fig. 4) is resolved in four directions like top, down, left and right.

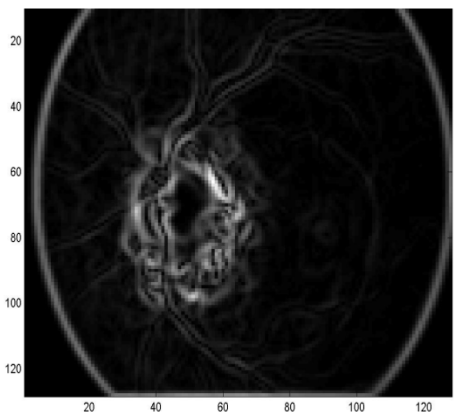

Fig. 3. Magnitude of Gradient Vectors

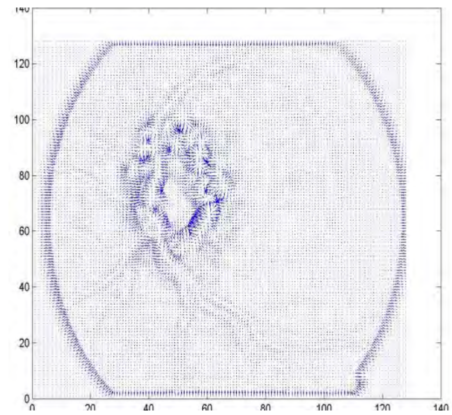

Fig. 4. Orientation of Gradient Vectors

2.4 *Chan Vese Model*

CV model is also an active contour model. This is a powerful, flexible method that can successfully segment many types of images, including some that would be difficult or impossible to segment with classical thresholding or gradient- based methods. The scope is extended by including local image information at the support domain around each point of interest in multi dimensional feature space. The model is further redefined to differentiate the OD region from the similar characteristic regions around it by integrating information from the multiple image feature channels. This method does not impose any shape constraint to the underlying model and hence makes a good choice for OD segmentation as shown in (Fig. 6).

The goal of this method is to evolve the contour in such a way that it stops on the boundaries of the foreground region. The algorithm evolves the contour via a level set method [6].

2.4.1. *Level Set Method*

Level set methods are a powerful tool for performing contour evolution. The function φ (i, j, t) (level set function) is defined where (i, j) are coordinates in the image plane and t is an artificial "time." At any given time, the level set function simultaneously defines an edge contour and a segmentation of the image. The edge contour is taken to be the zero level set {(i, j) s. t. φ (i, j, t) = 0}, and the segmentation is given by the two regions {φ≥0} and {φ<0}. The level set function will be evolved according to some partial differential equation. If the foreground is defined to be in the region where φ<0, then the background found by this segmentation would be the region inside the circle. Level set methods are especially useful because they can easily handle topological changes in the edge contour that would be difficult to handle with a model that directly evolves the contour.

2.4.2. *Fitting Energy Functional*

The goal of the segmentation algorithm will be to minimize this fitting energy for a given image, and the minimizing level set function φ will define the segmentation. In its most general form, the fitting energy is

$$F(\emptyset) = \mu(\ _{\Omega}|\nabla H(\emptyset)|dx)^{p} + v\ \ _{\Omega} H(\emptyset)\, dx + \lambda_1\ \ _{\Omega}|I - c1|^{2}\, H(\emptyset)dx + \lambda_2 |I - c2|^{2}\, (1\text{-}H(\emptyset))\, dx \qquad (1)$$

μ, v, $\lambda 1$, $\lambda 2$ and p are parameters selected by the user to fit a particular class of images. Here H is the Heaviside function, I is the image to be segmented, and **Ω** is the domain of that image. $C1$ and $C2$ are the averages of the image I in the regions where $\varphi \geq 0$ and $\varphi < 0$, respectively, given by Eq. (2) and Eq. (3).

$$C_1 = \frac{\Omega\, I.H(\emptyset)dxdy}{\Omega\, H(\emptyset)dxdy} \qquad (2)$$

$$C_2 = \frac{\Omega\, I.(1-H(\emptyset))dxdy}{\Omega(1-H(\emptyset))dxdy} \qquad (3)$$

In Eq. (1), the first term, $\mu(\ _{\Omega}|\nabla H(\emptyset)|)^{p}$ is a penalty on the total length of the edge contour for a given segmentation. Similarly, the term $v\ \ _{\Omega} H(\emptyset)dx$ is a penalty on the total area of the foreground region found by the segmentation. The third term $\lambda_1\ \ _{\Omega}|I - c1|^{2}H(\emptyset)dx$ is proportional to the variance of the image gray level in the foreground region and measures the uniformity of the region in terms of pixel intensity. The fourth term does the same for the background region. Minimizing the sum of these two terms leads to segmentation.

2.4.3. *Color Segmentation*

Color image segmentation is done by initializing window size, bit depth and colors for segmentation. This yields coarse segmented results of the image (Fig. 1), from which clusters are formed by using k-means [7] algorithm which classify pixels in an extracted feature space. Finally, these clusters are grouped using segmentation map function.

3. Results

Fig. 5. GVF output

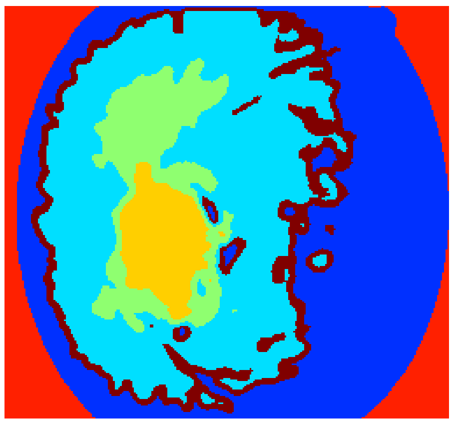

Fig. 6. Segmented Maps of C-V Model

The image shown in (Fig. 5) is the output obtained as a result of segmenting input image (Fig. 1) using Gradient Vector Flow model. In this image, the defective part of the retinal image is obtained and this output is compared with the segmented output (Fig. 6) of modified Chan-Vese model. It is clearly seen that the result is more accurate in C-V model than that of GVF model. C-V model overcomes the disadvantages of GVF model. It segments images with complex intensity variations and removes over-segmentation [8] caused by region based approaches.

4. Conclusion

In the proposed work, an active contour model is presented to achieve OD segmentation. The scope of C-V model has been extended by including local image information around each point of interest. This model has been further strengthened by the integration of information from the multiple image feature channels. The method yielded a solution for glaucoma assessment which allows derivation of various geometric parameters of the OD. This is in contrast to earlier approaches which have largely focused on the estimation of CDR which varies considerably within normal. It is also well recognized that there is significant intra and inter observer error in manual assessment with this parameter.

The proposed method captures OD boundary in a unified manner for both normal and challenging cases without imposing any shape constraint on the segmentation result unlike the GVF model. The comparison results show that the method is more robust and accurate than the other model, particularly in the cases of atrophy.

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