

An Overview of Glaucoma Segmentation using Watershed Transformation

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ABSTRACT

Glaucoma is an eye disease that can steal sight without any kind of symptoms. It can lead to permanent vision loss if left untreated. Nearly half of those with Glaucoma do not know they have the disease. However, the early detection of Glaucoma can limit the disease progression. Automatic analysis of retina images is becoming an important screening tool now days. Glaucoma happens due to the increase of Intraocular Pressure. Early detection of this disease is essential to prevent the permanent blindness. The main idea behind this paper is to describe a system which is mainly based on image processing segmentation techniques for detection of glaucoma by Watershed Transformation.

Keywords: Watershed Transformation, Marker Based Watershed Transformation, Glaucoma Segmentation, Image Processing

1.INTRODUCTION

The recent rapid advances in medical imaging and automated image analysis allow us to make significant advances in our understanding of life and disease processes, and our ability to deliver quality healthcare. Fundus eye image processing is now a core field of research for diagnosis of various eye disorders. Glaucoma assessment is one of the applications of fundus image processing. Glaucoma is a chronic and irreversible neurodegenerative disease in which the nerve that connects the eye to the brain is progressively damaged. Progression of the disease leads to loss of vision, which occurs gradually over a long period of time. Unawareness about the disease until it reaches the advanced stage is a major problem as it cannot be cured. According to World Health Organization, glaucoma is the leading cause of blindness that contributes to approximately 5.2 million cases of blindness and will increase to 11.2 million people by 2020[1]. So detecting the disease in time is critical and population based glaucoma assessment is very relevant to save the vision of millions.

Glaucoma assessment performed by trained ophthalmologists limits its potential for population based glaucoma screening. There comes the need for an efficient automatic glaucoma assessment technique. There are several automated glaucoma detection techniques available in image processing. In Watershed Transformation, the morphological gray level images are considered as topographic reliefs, each relief is flooded from its minima based on their gradient levels formed in an image and when two lakes merge, a dam is built, the set of all dams

define the so called watershed and it is also called as Catchment basin [2]. In this paper, we propose the methodology of glaucoma segmentation using watershed transformation techniques.

II. WATERSHED TRANSFORMATION

The watershed transform is a popular segmentation method coming from the field of mathematical morphology. The intuitive description of this transform is quite simple. If we consider the image as a topographic relief, where the height of each point is directly related to its gray level, and consider rain gradually falling on the terrain, then the watersheds are the lines that separate the “lakes” (actually called catchment basins. Generally, the watershed transform is computed on the gradient of the original image, so that the catchment basin boundaries are located at high gradient points [3]. To start with the image is filtered and watershed transformation is applied to locate the optic Cup boundaries. Since the optic Cup represents a bright area, and as blood vessels emerge dark in gray level retinal images, the gray level variation within the optic Cup region is very high. This variation is first removed using a closing morphological operation to facilitate later watershed operation [4].

Particularly, we show how the watershed transformation contributes to improve the numerical results for optic Cup segmentation problems. Let $f(x, y)$ with $(x, y) \in \mathbb{R}^2$, be a scalar function describing an image I . The morphological gradient of I is defined by

$$g = (f \oplus b) - (f \ominus b)$$

Where $(f \oplus b)$ and $(f \ominus b)$ are respectively the elementary dilation and erosion of f by the structuring element b . The morphological Laplacian is given by

$$G_L = (f \oplus b) - 2f + (f \ominus b)$$

We note here that this morphological Laplacian allows us to distinguish influence zones of minima and suprema: regions with $GL < 0$ are considered as influence zones of suprema, while regions with $GL > 0$ are influence zones of minima. Then $GL = 0$ allows us to interpret edge locations, and will represent an essential property for the construction of morphological filters. The basic idea is to apply either dilation or erosion to the image I , depending on whether the pixel is located within the influence zone of a minimum or a maximum [4].

The retinal image contains many objects of different sizes that are touching each other. Object detection in an image is an example of image segmentation. To segment touching objects, the watershed transform is often used. If we view an image as a surface, with mountains (high intensity) and valleys (low intensity), the watershed transform finds intensity valleys in an image. Fig.1 illustrates this approach. We have considered the same original image as previously. Fig. 1(a) shows the watershed of the image and Fig.1 (b) shows the watershed of its gradient and Fig.1(c) shows the segmentation results of the filtered image and finally Fig.1 (d) shows the segmented image.

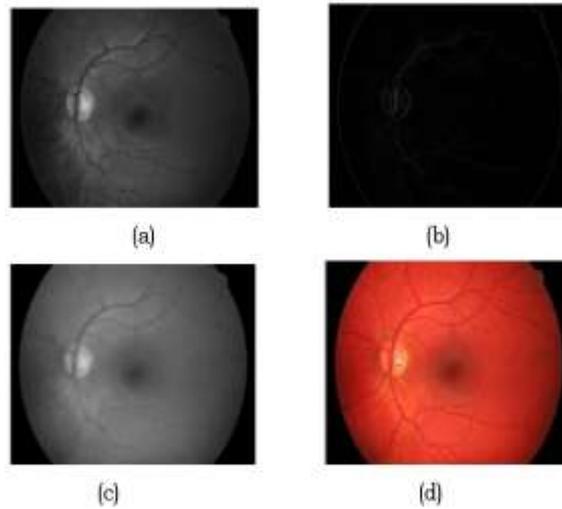


Fig1. Sample Images

As a first step, we eliminate large gray level variations within the papillary region by filtering the image using morphological closing operator. The removal of large peaks involves opening operator with large structuring element which alters the shape of the papillary region. So calculate the morphological reconstruction by dilation. Before we apply the watershed transformation to the morphological gradient, we impose internal and external markers. We use the locus of optic Cup, $f(x, y)$ as an internal marker that has been calculated and a square containing the optic Cup with center at (x, y) as an external marker.

The Catchment basin $C(M)$ associated to a minimum M is the set of pixels p of Ω such that a water drop falling at p flows down along the relief, following a certain descending path, and eventually reaches M . The catchment basins of an image I correspond then to the influence zones of its minima, and the watershed will be defined by the lines that separate adjacent catchment basins [4].

Several algorithms have been proposed for the computation of watersheds and the most commonly used are based on an immersion process analogy. Let us express this immersion process more formally according to Soille (1992): we consider k_{min} and k_{max} the smallest and the largest values taken by f . Let $T_k = \{p \in \Omega, f(p) \leq k\}$ be the threshold set of f at level k . We define a recursion with the gray level k increasing from k_{min} to k_{max} , in which the basins associated with the minimum of f are successively expanded. We consider X_k the union of the set of basins computed at level k . A connected component of the threshold set T_{k+1} at level $k+1$ can be either a new minimum, or an extension of a basin in X_k . Finally, by denoting by min_k the union of all regional minima at level k , we obtain the following recursion which defines the watershed by immersion,

$$\begin{cases} X_{k_{min}} = T_{k_{min}} \\ \forall k \in [k_{min}, k_{max} - 1], X_{k+1} = min_{k+1} \cup IZ_{T_{k+1}}(X_k) \end{cases}$$

With $IZ_{\Omega}(Y_l) = \{z \in \Omega, \forall n \neq l, d_{\Omega}(z, Y_l) \leq d_{\Omega}(z, Y_n)\}$

Where k is the number of minima of I and $iZT_{k+1}(X_{k_i})$ is defined by the set of the catchment basins of a gray level image I is equal to the set $X_{k_{max}}$. At the end of this process, the watershed of the image I is the complement of $X_{k_{max}}$ in Ω .

Watershed segmentation of the imposed minima image is accomplished with the watershed function. The watershed function returns a label matrix containing nonnegative numbers that corresponds to watershed regions. Pixels that do not fall into any watershed region are given a pixel value of 0. This technique modifies a gray-scale image so that regional minima occur only in marked locations. Other pixel values are pushed up as necessary to remove all other regional minima. Thus the optic Cup is segmented by mathematical morphology and watershed transform. The extracted image by watershed transformation method is as shown in fig 2,

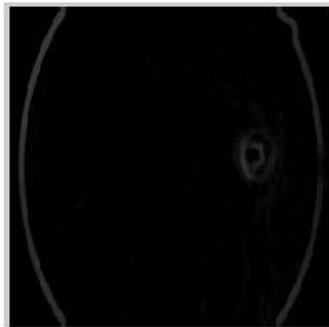


Fig 2. Segmentation result

The advantages of the watershed transformation are that it is simple, instinctive knowledge, and can be parallelized. The main drawback of this method is the over-segmentation due to the presence of many local minima. To decrease the effect of severe over-segmentation, marker-controlled watershed transformations have been proposed [5].

III.MARKER BASED WATERSHED TRANSFORMATION

These are robust and flexible methods for segmenting objects with closed contours. The internal marker and external marker are initially defined. The boundaries, even if not clearly defined, are expressed as ridges between two markers and located. In marker-controlled watershed method to segment the image the external marker is obtained manually by drawing a circle enclosing object of our interest. The internal market is determined automatically by combining techniques including canny edge detection, thresholding and morphological operation. Modify the segmentation function so that it only has minima at the foreground and background marker locations [6]. Compute the watershed transform of the modified segmentation function

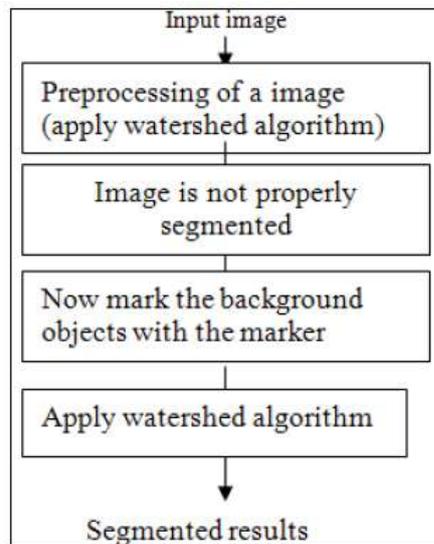


Fig3. Flowchart for Marker-Controlled Watershed Segmentation

IV.LITERATURE SURVEY

Boren Li, Mao Pan and Zixing Wu (2012) [7] has presented an approach to reduce over segmentation using both pre- and post-processing for watershed segmentation. They have used more prior knowledge in pre processing and merge the redundant minimal regions in post processing. In the initial stage of the watershed transform produces a gradient image from the original image, but also introduces the texture gradient. The texture gradient can be extracted using a gray -level co-occurrence matrix. Then, both gradient images are fused to give the final gradient image. After the initial results of segmentation, we use the merging region technique to remove small regions.

Xiaoyan Zhang, Lichao Chen, Lihu Pan and LizhiXiong (2012) [8] has presented an image segmentation approach based on independent component analysis (ICA) and watershed algorithm is proposed. ICA is a method of image filtering for its characteristics.ICA can effectively remove the noises and maintain a clear image texture. Using independent component analysis algorithm can eliminate wavebands redundancy and extract the image signal components from source signal for image segmentation. Results showed that this method can process image segmentation effectively and identify features accurately.

ZhonglinXia ,Danfeng Hu and Xueyan Hu (2011) [9] has presented watershed algorithm is introduced based on image processing technology for the contamination of insulator. This algorithm can be used to obtain the size of contamination area of the insulator, and follow the following steps. Firstly segment the insulator image with watershed algorithm, and then the region growing algorithm is used to process the segmented image, which can guarantee the segmentation effectiveness and reduce the number of segmented regions so as to enhance the segmentation results of the insulator image.

V.CONCLUSION

Glaucoma is a silent disease that comes with no symptoms and warning. Initially no one can say that the patient is having any sort of problem either by looking and touching the eye. When Glaucoma increases, the pressure

inside the eye increases which makes the patient feel uncomfortable and needs to consult a doctor. An algorithm is proposed in this paper focuses on watershed segmentation algorithm. The watershed transformation is a powerful tool for image segmentation based on mathematical morphology. The watershed transformation has segmented the exact circular area of the optic disc in retinal images.

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