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Optic Disc Boundary and Vessel Origin Segmentation of Fundus Images

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Abstract*—This paper presents a novel classification-based optic disc (OD) segmentation algorithm that detects the OD boundary and the location of vessel origin (VO) pixel. First, the green plane of each fundus image is resized and morphologically reconstructed using a circular structuring element. Bright regions are then extracted from the morphologically reconstructed image that lie in close vicinity of the major blood vessels. Next, the bright regions are classified as bright probable OD regions and non-OD regions using 6 region-based features and a Gaussian Mixture Model classifier. The classified bright probable OD region with maximum Vessel-Sum and Solidity is detected as the best candidate region for the OD. Other bright probable OD regions within 1-disc diameter from the centroid of the best candidate OD region are then detected as remaining candidate regions for the OD. A convex hull containing all the candidate OD regions is then estimated, and a best-fit ellipse across the convex hull becomes the segmented OD boundary. Finally, the centroid of major blood vessels within the segmented OD boundary is detected.

I. INTRODUCTION

The retinal fundus photograph is widely used in the diagnosis and treatment of various eye diseases such as diabetic retinopathy and glaucoma. Medical image analysis and processing has great significance in the field of medicine, especially in non-invasive treatment and clinical study. Normally fundus images are manually graded by specially trained clinicians in a time-consuming and resource-intensive process. A computer-aided fundus image analysis could provide an immediate detection and characterization of retinal features prior to specialist inspection. With the increasing size and number of medical images of eye, the use of computers in facilitating their processing and analysis has become necessary. In particular, computer algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks. These algorithms, called image segmentation algorithms, play a vital role in numerous biomedical imaging applications such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data, and computer integrated surgery. Image segmentation remains a difficult task, due to both the tremendous variability of object shapes and the variation in image quality. In particular, medical images are often corrupted by noise, which can cause considerable difficulties when applying classical segmentation techniques. As a result, these techniques either fail completely or require some kind of post processing step to remove invalid object boundaries in the segmentation results. And problem is to tune or optimize the segmentation methods by changing its topology.

II. MATERIALS AND METHOD

Several general-purpose algorithms and techniques have been developed for image segmentation. These are listed below:

- Clustering methods
- Compression-based methods
- Histogram-based methods
- Edge detection methods
- Region growing methods
- Split-and-merge methods
- Partial differential equation-based methods
  1. Parametric methods
  2. Level set methods
  3. Fast Marching methods
- Graph partitioning methods
- Watershed transformation
- Model based segmentation
- Semi-automatic segmentation
- Segmentation Benchmarking
- Neural networks segmentation

which is obtained when the points no longer switch clusters (or alternatively centroids are no longer changed). Lloyd's algorithm and k-means are often used synonymously, but in reality Lloyd's algorithm is a heuristic for solving the k-means problem, as with certain combinations of starting points and centroids, Lloyd's algorithm can in fact converge to the wrong answer. Other variations exist, but Lloyd's algorithm has remained popular, because it converges extremely quickly in practice. In terms of performance the algorithm is not guaranteed to return a global optimum. The quality of the final solution depends largely on the initial set of clusters, and may, in practice, be much poorer than the global optimum. Since the algorithm is extremely fast, a common method is to run the algorithm several times and return the best clustering found. A drawback of the k-means algorithm is that the number of clusters k is an input parameter. An inappropriate choice of k may yield poor results. The algorithm also assumes that the variance is an appropriate measure of cluster scatter.

TECHNIQUES USED

This chapter discusses the various techniques employed for the purpose of detection of optic disc in retinal imaging.

- Level Set Method of Segmentation
- Eye Imaging
- Morphology

Traditional level set method

In level set formulation of active contours, the active contour is denoted by C, are represented by the zero level set of a level set function $\varphi(t, x, y)$.

The evolution equation of the level set function φ can be written in the following form:

which is called level set equation. The function F is called the speed function. For image segmentation, the function F depends on the image data and the level set function φ . In this method of level set problems are the level set function can develop shocks, very sharp and flat shape during the evolution, To avoid these problems, a common numerical scheme is used that is to initialize the function φ as a signed distance function before the evolution, and then reshape the function φ to be a signed distance function periodically during the evolution.

Color Fundus (Retinal) Photography (CFP)

The Fundus, or inner lining, of the eye is photographed with specially designed cameras through the dilated pupil of the patient. The painless procedure produces a sharp view of the retina, the retinal vasculature, and the optic nerve head (optic disc) from which the retinal vessels enter the eye. Color Fundus Photography is used to record the condition of these structures in order to document the presence of disorders and monitor their change over time.

Anatomy of eye

The human eye is the organ which gives us the sense of sight. The eye allows us to see and interpret the shapes, colors, and dimensions of

objects by processing the light they reflect or emit. The eye is able to detect bright light or dim light, but it cannot sense an object when light is absent. Several structures compose the human eye. Among the most important anatomical components are the following components.

Aqueous Humour: The aqueous humour is a jelly-like substance located in the anterior chamber of the eye

Choroid: The choroid layer is located behind the retina and absorbs unused radiation.

Ciliary Muscle: The ciliary muscle is a ring-shaped muscle attached to the iris. It is important becausecontraction and relaxation of the ciliary muscle controls the shape of the lens.

Cornea: The cornea is a strong clear bulge located at the front of the eye (where it replaces thesclera - that forms the outside surface of the rest of the eye). The front surface of the adult cornea has a radius of approximately 8mm. The cornea contributes to the image-forming process by refracting light entering the eye.

Fovea: The fovea is a small depression (approx. 1.5 mm in diameter) in the retina. This is the part ofthe retina in which high-resolution vision of fine detail is possible.

Hyaloid: The hyaloid diaphragm divides the aqueous humour from the vitreous humour.

Iris: The iris is a diaphragm of variable size whose function is to adjust the size of the pupil toregulate the amount of light admitted into the eye. The iris is the coloured part of the eye (illustrated in blue above but in nature may be any of many shades of blue, green, brown, hazel, or grey).

Lens: The lens of the eye is a flexible unit that consists of layers of tissue enclosed in a tough capsule.It is suspended from the ciliary muscles by the zonule fibers.

Optic Nerve: The optic nerve is the second cranial nerve and is responsible for vision. Each nervecontains approx. one million fibers transmitting information from the rod and cone cells of the retina.

Papilla: The papilla is also known as the "blind spot" and is located at the position from which theoptic nerve leaves the retina.

Pupil: The pupil is the aperture through which light - and hence the images we "see" and "perceive" - enters the eye. This is formed by the iris. As the size of the iris increases (or decreases) the size of the pupil decreases (or increases) correspondingly.

Retina: The retina may be described as the "screen" on which an image is formed by light that haspassed into the eye via the cornea, aqueous humour, pupil, lens, then the hyaloid and finally the vitreous humour before reaching the retina. The retina contains photosensitive elements (called rods and cones) that convert the light they detect into nerve impulses that are then sent onto the brain along the optic nerve.

Sclera: The sclera is a tough white sheath around the outside of the eye-ball. This is the part of theeye that is referred to by the colloquial terms "white of the eye".

Visual Axis: A simple definition of the visual axis is a straight line that passes through both the centreof the pupil and the centre of the fovea. However, there is also a stricter definition (in terms of nodal points) which is important for specialists in optics and related subjects.

Vitreous Humour: The vitreous humour (also known as the "vitreous body") is a jelly-like substance.

Zonules: The zonules (or "zonule fibers") attach the lens to the ciliary muscles.

Reconstruction

Morphological reconstruction can be thought of conceptually as repeated dilations of an image, called the marker image, until the contour of the marker image fits under a second image, called the mask image. In morphological reconstruction, the peaks in the marker image spread out or dilate. Morphological reconstruction processes one image, called the marker, based on the characteristics of another image, called the mask. The high points, or peaks, in the marker image specify where processing begins. The processing continues until the image values stop changing.

Opening

The definition of a morphological opening of an image is erosion followed by dilation, using the same structuring element for both operations. Morphological opening is used to remove small objects from an image while preserving the shape and size of larger objects in the image.

Closing

The morphological closing of an image is the reverse: it consists of dilation followed by erosion with the same structuring element.

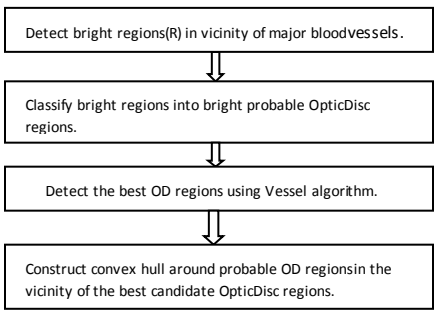


fig :The proposed 3-step automated Optic Disc and Vessel Origin algorithm

Process for level set evolution

The process employed for Level Set evolution without Re-intialization is as follows.

Step 1:- Firstly the image was read with help of imread command. This command is inbuilt command in matlab processing toolbox. The image to be read should not be of compressed .tiff file format because it is not acceptable in matlab.

Step 2:- Now the matrix values are converted into more uniform and simple form so as to make further calculation easy by using following mathematical formula

$$f = I_{x}.^{\wedge} 2 + I_{y}.^{\wedge} 2 \qquad (1)$$

Step 3:- After this image is filtered with the help of Gaussian filter. The Gaussian filter is the basicfilter. Generally Gaussian filter is used to remove the noise from the image so as to make the image more sharp and smooth. The Gaussian filter smoothens or blurs an image by performing a convolution operation with a Gaussian filter kernel is shown by

$$I_{V=abs\{I-LPF(I)<0\}>0.2} \qquad (2)$$

Step 4:- Now preprocessed image is further processed and its gradient is calculated. Now thisgradient image is used to calculate the edges of the image. For calculation of edges, function defined below is used

$$g = 1/1+f \qquad (3)$$

Step 5:- In this step all Parameters are defined which change the topology of the contour. Bytopology of contour we mean speed, stability etc.

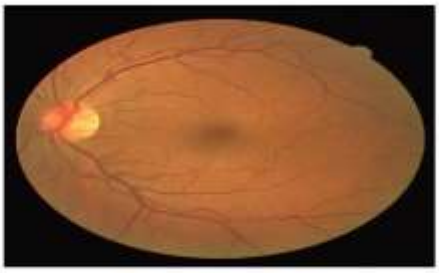
Step 6:- Initialization of contour, means starting shape of contour which depends upon the region.Mainly we can start it from the centre of optic disc in retinal image because in retinal images nerve of retina make many edges so if we start from outside of optic disc then it might stop on other edges while not on edges of optic disc. So in this we can start from center by making a polygon by mouse click inside the optic disc using this command. It creates a polygon and it is this value that is given to contour function.

Step 7:-. In this step we give all parameters and the initial contour to the evolution function. Thisevolution function updates the level set function according to the level set evolution equation given in Equation 2.2. The simple idea of the curve evolution is to reduce the set of vertices of the polygon to a subset of vertices containing important information about the original contour.

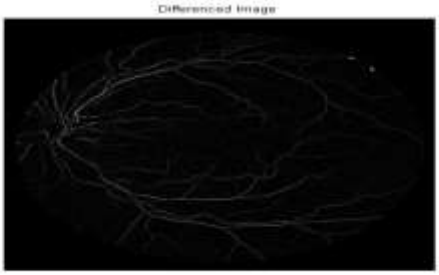
Step 8:- The step 7 repeats until we do not get final contour. The repetition depends on the number of iterations given.

Step 9:- In the last step, final contour will display after all iterations. The updated value fromevolution function is given to the function contour and at end of the iterations it gives us final contour.

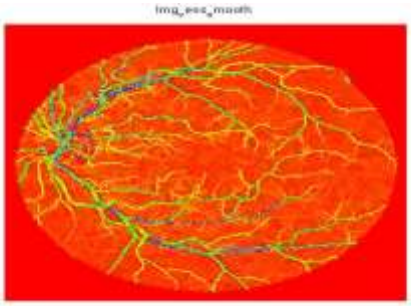
RESULTS



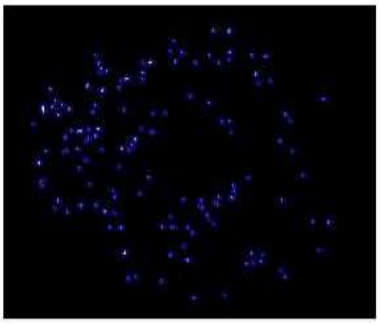
(a)original image



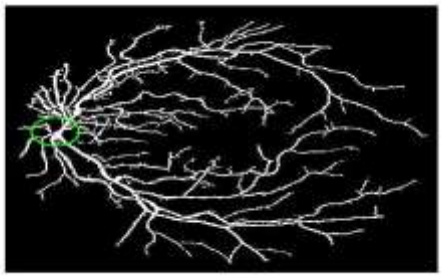
(b)High-pass filter image



(c)Morphologically reconstructed image



(d)Bright optics disc regions



(e)Location of optics disc boundary

CONCLUSION

In this paper, we propose a novel three-step classification based OD segmentation algorithm that is robust to fundus images with varying FOV, illuminations and pathologies. For the first step, circular structuring elements are found to be preferable over the linear structuring elements for extracting bright regions after morphological reconstruction. In the second step, double cross validation with feature ranking leads to feature reduction for classification of the bright probable OD regions from the non-OD regions. We observe that the bright OD regions comprise 11-18% of all the bright regions extracted per image. The GMM classifier is successful in reducing the number of false positive bright regions but it is not sufficient for detecting only the bright OD regions. Therefore, classification followed by maximization of the major vessel pixels and bright region solidity (*MaxVeSS*) detects a best bright candidate region for the OD. This method of detecting the bright candidate region for OD is analogous to the method of detecting a pixel within the OD neighbourhood region in Lu [10], Lu et, al. [9] and Mendonca et. al. [14]. Also, the 6 features identified for bright OD region classification are successful in locating the OD candidate region in images with atrophy to the optic nerve, thereby resulting in 100% success on the MESSIDOR data set. These features are more effective than the methods that remove the vessels and rely on inpainted retinal images for OD segmentation [21] [19].And also gets the results of analysis as shown in the fig .In this we observe average best performance metrics and their standard deviation per imageusing proposed method on drive data sets as shown below:

Mean=2.1203

Sensitivity=0.3895

False positive ratio=0.0105

Accuracy=0.290

Radius=42.8267

Origin at X=478.88 Y=350.40

Future Scope

Automated analysis of fundus images requires segmentation of the image into regions such as optic disk, fovea, vessels, and background retina. The technique described here can form part of this segmentation process.The success of the proposed algorithms can be accredited to the employment of the morphological operations for preprocessing of retinal images. Further pre-processing techniques should be used on the proposed algorithms. Such techniques could contribute to further improvements on the algorithms, resulting in more robust and more precise detection that eventually can be accepted for the clinical purposes.

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