www.ijprems.com
editor@ijprems.com

INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
Vol. 02, Issue 05, May 2022, pp : 300-304

e-ISSN : 2583-1062

Impact Factor : 2.205

AN ANALYSIS OF OPTIC DISC AND CUP SEGMENTATION FOR DETECTION OF GLAUCOMA IN EYE

A. Vetrivel Murugan [1], P. Stella Rosemalar [2]

[1,2]Assistant Professor, Department of CSE, JP College of Engineering, Agarkattu,Tenkasi, Tamil Nadu

ABSTRACT

Diagnosing the abnormal regions in retinal image is one of the critical issues because these images contain different types of minute nerves and attenuation artifacts. This paper proposes an optic cup segmentation using Pixel Classification and Feature Extraction of cup disc for diabetic retinopathy and glaucoma screening. In optic disc segmentation, histograms, and center surround statistics are used to classify each pixel as disc. A self assessment reliability score is computed to evaluate the quality of the automated optic disc segmentation. For optic cup segmentation, in addition to the histograms and center surround statistics, the location information is also included into the feature space to boost the performance. The methods can be used for segmentation and glaucoma screening. The self assessment will be used as an indicator of cases with large errors and enhance the clinical deployment of the automatic segmentation and screening. This paper proposes an automatic morphological segmentation method to change the representation of an image into something that is more meaningful and easier to analyze the interested object. There are several methods that intend to perform segmentation, but it is difficult to adapt easily and detect the very small nerves accurately. To resolve this problem, this paper aims to present an adaptable automatic morphological segmentation method that can be applied to any type of retinal images which is exactly diagnosed even with the small changes that occur in the image.

Keywords: Cup Disc Ratio, Feature Extraction, Pixel Classification, Segmentation

1. INTRODUCTION

The optic disc is the location where ganglion cell axons exit the eye to form the optic nerve. There are no light sensitive rods or cones to respond to a light stimulus at this point. This causes a break in the visual field called blind spot. The optic disc represents the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together. The optic disc is also the entry point for the major blood vessels that supply the retina. The optic nerve head in a normal human eye carries from 1 to 1.2 million neurons from the eye towards the brain. The cup-to-disc ratio is a measurement used in ophthalmology [1] and optometry to assess the progression of glaucoma. The optic disc is the anatomical location of the eye's "blind spot", the area where the optic nerve and blood vessels enter the retina. The optic disc can be flat or it can have a certain amount of normal cupping. But glaucoma, which is due to an increase in intra-ocular pressure, produces additional pathological cupping of the optic disc. The pink rim of disc contains nerve fibers. The white cup is a pit with no nerve fibers. As glaucoma advances, the cup enlarges until it occupies most of the disc area. The cup-to-disc ratio compares the diameter of the "cup" portion of the optic disc with the total diameter of the optic disc. The hole represents the cup and the surrounding area the disc. A large cup-to-disc ratio may imply glaucoma or other pathology. Retina is a light sensitive tissue lining the inner surface of the eye. The optics of the eye creates an image of the visual world on the retina, which serves much the same function as the film in a camera.

2. DETERMINATION OF OPTIC DISC

Morphological image processing operations reveal the underlying structures and shapes within binary and grayscale images, clarifying basic image features. While individual morphological operations perform simple functions, they can be combined to extract specific information from an image. Morphological operations often precede more advanced pattern recognition and image analysis operations such as segmentation. Shape recognition routines commonly include image thresholding or stretching to separate foreground and background image features [3][4]. A new morphological gradient operator for colour images is introduced that can be viewed as a direct extension of the well known morphological gradient.To overcome any sensitivity to noise a robust colour morphological gradient operator is proposed that rejects outlying vector pairs before determining the maximum distance. Results show the effectiveness of the techniques. Detecting edges of image object by using Morph Gradient function applies the gradient operation to a grayscale image. This operation highlights object edges by subtracting an eroded version of the original image from a dilated version. Repeatedly applying the gradient operator or increasing the size of the structuring element results in wider edges. The image gradient is to find edge strength and direction at location (x,y) of image, and defines as the vector. The image gradient is to find edge strength and direction at location (x,y) of image, and defines as the vector.

$$\nabla f \equiv \mathrm{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix}$$

The magnitude (length) of vector ∇f , denoted as M(x,y)

$$\mathrm{mag}(\nabla f) = \sqrt{g_x + g_y}$$

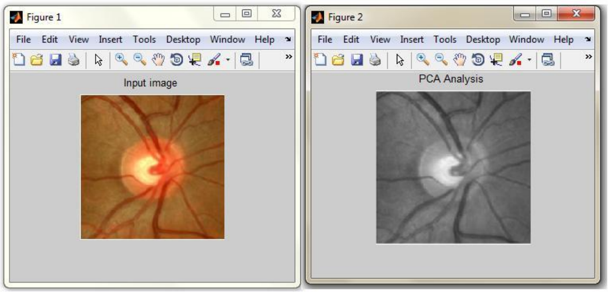

Fig 1. Input and PCA Analysis

Structuring Element

The basic idea in binary morphology is to probe an image with a simple, pre-defined shape, drawing conclusions on how this shape fits or misses the shapes in the image. the structuring element B is defined by: When the structuring element B has center is located on the origin of E, then the erosion of A by B can be understood as the points reached by the center of B when B moves inside A. In this process, the use of a new grey-scale image is proposed. Specifically, it is calculated by means of PCA because this type of analysis maximizes the separation of the different objects that compose an image so that the structures of the retina are better valued. The non uniform illumination of this grey image is also corrected and its contrast is increased through a local transformation [5].

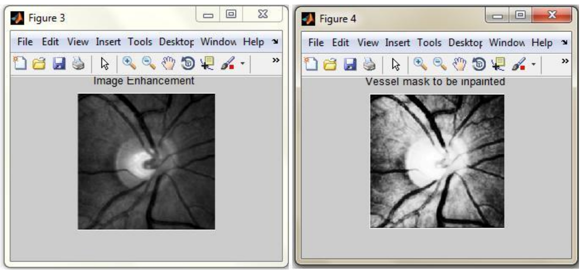

Fig 2. Image Enhancement and Vessel Mask

The dilation of *A* by the structuring element *B* is defined by:

$$A \oplus B = \bigcup_{b \in B} A_b \, .$$

The dilation is commutative, also given by:

$$A \oplus B = B \oplus A = \bigcup_{a \in A} B_a \, .$$

If *B* has a center on the origin, as before, then the dilation of *A* by *B* can be understood as the locus of the points covered by *B* when the center of *B* moves inside *A*.

$$A \oplus B = \{z \in E \mid (B^s)_z \cap A \neq \varnothing\},$$

Where B^s denotes the symmetric of *B*, that is,

$$B^s = \{x \in E \mid -x \in B\}.$$

Dilation is the dual operation of the erosion. Figures that are very lightly drawn get thick when "dilated". The opening of the dark-blue square by a disk, resulting in the light-blue square with round corners. The opening of A by B is obtained by the erosion of A by B, followed by dilation of the resulting image by B:

$$A \circ B = (A \ominus B) \oplus B.$$

The closing of *A* by *B* is obtained by the dilation of *A* by *B*, followed by erosion of the resulting structure by *B*:

$A \bullet B = (A \oplus B) \ominus B$.

The closing can also be obtained by

$A \bullet B = (A^c \circ B^s)^c$,

Where X^c denotes the complement of X relative to E.

3. DETECTION OF OPTIC CUP

Image classification uses the quantitative spectral data contained in a picture that is expounded to the composition or condition of the target surface. There are many core principles of image analysis that pertain specifically to the extraction and options from remotely detected data. Spectral completely differentiation relies on the principle that objects of various composition or condition seem as different colors in an exceedingly multispectral image. Radiometric differentiation is that the detection of variations in brightness, which can insure cases, be wont to inform the image analyst on the character or condition of the remotely detected object. Spatial differentiation is expounded to the thought of spatial resolution. To analyze the spectral content of a specific pel or cluster of pixels in an exceedingly digital image once those pixels comprise one homogenous material or object. it's conjointly vital to grasp the potential for compounding of the spectral signatures of multiple objects into the recorded spectral values for one pel.

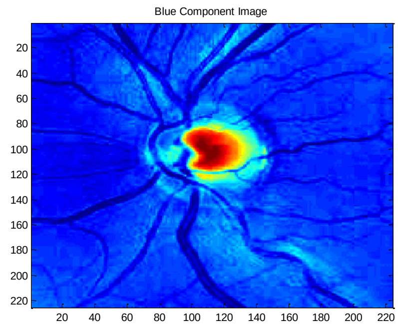

Fig 3.Pixel Classification

The image analyst should choose a sufficient variety of coaching sites in every category to represent the variation gift at intervals every category within the image. The classification rule then uses spectral characteristics of the coaching sites to classify the rest of the image. Coaching sites developed in one scene might or might not be transferable to a whole study space. If ground conditions, lighting conditions, or region effects modification from scene to a different, then coaching sites should be developed severally for every scene. moreover, coaching sites might not be transferable across time; additionally to the conditions noted on top of that modification over time also as house, real changes within the land cowl occurring at a coaching web site location over time can cause incorrect classification ends up in the second image. Correct supervised classification results rely entirely on the analyst’s ability to gather a sufficient variety sites and to acknowledge once training sites will be transferred from one image to a different. Unattended classification needs less input from the analyst before process.

4. FEATURE EXTRACTION

Feature extraction involves simplifying the number of resources needed to explain an outsized set of knowledge accurately. Once acting analysis of complicated knowledge one among the foremost issues stems from the quantity of variables concerned. Analysis with an outsized variety of variables usually needs an outsized quantity of memory and computation power or a classification algorithmic rule that over fits the coaching sample and generalizes poorly to new samples. Feature extraction may be a general term for strategies of constructing combos of the variables to urge around these issues whereas still describing the info with adequate accuracy.

Suppose that each training class is represented by a prototype vector:

$$m_j = 1/N_j \sum_{x \epsilon \omega_j} x \text{ for } j = 1, 2, \ldots, M$$

Where Nj is the number of training pattern vectors from class Wj.

Based on this, we can assign any given pattern x to the class of its closest prototype by determining its proximity to each mj.

$$D_j(x) = \|x - m_j\| \text{ for } j = 1, 2, \ldots, M$$

It is not difficult to show that this is equivalent to computing

$$d_j(x) = x^T m_j - 1/2(m_j^T m_j) \text{ for } j = 1, 2, \ldots, M$$

and assign ‘x’ to class Wj if dj(Z) yields the largest value.

5. EXPERIENTAL RESULTS

In this section, our experimental results of applying to infected image to detect the glaucoma affected region. Our results shows our method is easy to diagnose the infected region compare to other techniques. Calculating the grey-image centroid combines the centrality of the image with respect to edge distance but penalizing this distance in relation to the intensities.

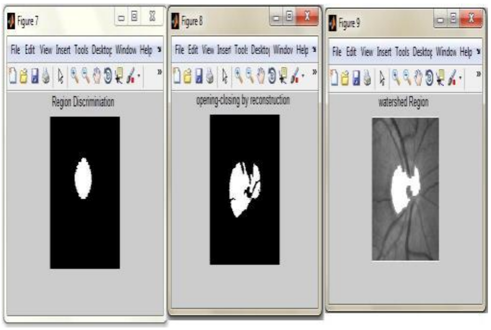

Fig 4. Region Discrimination

Segmentation method makes use of the stochastic watershed. This transformation uses random markers to build a probability density function of contours, segmented by volume watershed for defining the most significant regions. Discrimination between the significant and non significant regions is based on the average intensity of the region.

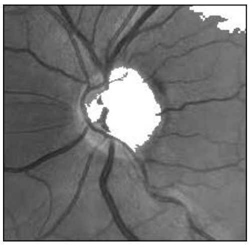

Fig: 5. Proposed method of Cup Disc Ratio

The regions belonging to the optic disc will be light regions around darker regions therefore the residue of a close-hole operator is calculated.

5. CONCLUSION

This paper proposes an automatic detection of the optic cup disc ratio has been presented. First, it is focused on the use of a new grey image as input obtained through PCA which combines the most significant information of the three RGB components. The goal of the proposed method is to make easier the early detection of diseases related to the fundus. Its main advantage is the full automation of the algorithm since it does not require any intervention by clinicians, which releases necessary resources and reduces the consultation time. Hence its use in primary care is facilitated. This project results show that diseases recognition based on the advanced image processing diagnosing has comparable.

6. REFERENCES

[1] Ajay K. Mishra, Yiannis Aloimonos, Loong-Fah Cheong, And Ashraf A. Kassim, “Active Visual Segmentation”,IEEE Transactions Pattern Analysis And Machine Intelligence, Vol. 34, No. 4, April 2012.

[2] Diego Marín, Arturo Aquino, M.E.G.Arias, and J.M Bravo , “A New Supervised Method for Blood Vessel Segmentation in Retinal Images by Using Gray-Level and Moment Invariants-Based Features”, IEEE Transactions On Medical Imaging , Vol. 23,N0.11, April 2011.

[3] M. Foracchia, E. Grisan, And A. Ruggeri, “Detection Of Optic Disc In Retinal Images By Means Of A Geometrical Model Of Vessel Structure”,IEEE Transactions On Medical Imaging, Vol. 23, No. 10, October 2004

[4] A. Hoover and M. Goldbaum, "Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels," IEEE Trans. Med. Image, vol. 22, no. 8, pp. 951–958, Aug. 2003.

[5] Joes Staal, Michael D. Abràmoff, Meindert Niemeijer, Max A. Viergever, and Bram van Ginneken, "Ridge-Based Vessel Segmentation in Colour Images of the Retina", IEEE Transactions On Medical Imaging, Vol. 23, No. 4, April 2004

[6] H. Li and O. Chutatape, "Automated feature extraction in colour retinal images by a model based approach," IEEE Trans. Biomed. Eng., vol. 51, no. 2, pp. 246–254, Feb. 2004.

[7] J. Lowell, A. Hunter, D. Steel, A. Basu, R. Ryder, E. Fletcher, and L.Kennedy, "Optic nerve head segmentation," IEEE Trans. Med. Image, vol. 23, no. 2, pp. 256–264, Feb. 2004.

[8] M. Park, J. S. Jin, and S. Luo, "Locating the optic disc in retinal images," in Proc. IEEE Int. Conf. Computer Graph. Image Visualisation, pp. 141–145 Oct 2006,

[9] Sandra Morales, Valery Naranjo, Jesus Angulo, And Mariano Alcaniz, "Automatic Detection Of Optic Disc Based On PCA And Mathematical Morphology", IEEE Transactions on Medical Imaging, Vol. 32, No. 4, April 2013.

[10] Sivaswamy, and S. R. Krishnadas "Optic Disk and Cup Segmentation from Monocular Colour Retinal Images for Glaucoma Assessment" in IEEE Transactions on Medical Imaging, vol.30, no. 6, June 2011.