Optic Disk Segmentation for Glaucoma Detection in Retinal Images

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Abstract Segmentation of optical disk and optical cup from retinal fundus images help to diagnose the abnormalities such as Glaucoma and can help to create awareness among the common man to plan for proper treatment plan in order to avoid complete visual morbidity. The original input image is at first filtered by means of histogram processing and further subjected to morphological image processing in order to classify the positions of optic cup and optic disk. This complete computation procedure is simulated using Matlab technical computing language.

Keywords Recognition of the features · Graphic retinal fundus · Morphological closure · Optical disk and cup · Segmentation

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1 Introduction

Thanks to the efficient use of retinal image by biomarkers in early detection of many conditions such as cardiovascular disease, asthma, glaucoma and diabetic retinopathy (DR), etc., the automated retinal image analysis has gained considerable research attention in recent years, the automated retinal image analysis has gained considerable interest in recent years. Glaucoma is associated with leading causes of blindness, with suffering globally affecting around 415 million people. Glaucoma is an eye abnormality that can affect human vision, or even cause irreversible loss of vision. However, the patient can't recognize visual impairment at the early Glaucoma stage, which can result in loss of vision for a long life. A patient also needs a route examination which will help him/her delay the onset of vision loss or blindness. Through careful analysis of the patient's retinal image, Glaucoma can also detect its early stages through trained ophthalmologists. This will help in the proper use of preventive drugs and successful therapies to reduce life losses. The small number of ophthalmologist's specialists, however, can't keep up with the drastic rise in the number of patients suffering from Glaucoma. Therefore, the development of an automatic Glaucoma detection system based on the digital retinal fundus photograph is impending and urgent [1].

Optical disk segmentation is also important to the automated detection of other ophthalmic pathologies. Glaucoma is one of them, and perhaps the most notable. It is the world's second most severe cause of blindness by identifying the form, color, or depth changes it causes in the OD. Hence its segmentation and analysis may be used to reliably diagnose glaucoma signs.

This work introduces the development of a new Optical Disk (OD) segmentation technique based on OD's statistic properties. This strategy initially centered on the location of the OD's theme pixel, which can also be called Optic Disk Pixel (ODP). When extracting the ODP from the retinal image, the sub-image is filtered and processed for blood vessel removal. Circular Hough Transform (CHT) is in fact implementing a new approach for segmentation of OD [2].

2 Need and Importance

Optical disk (OD) is considered to be one of the most important aspects of retinal fundus image detection OD in many retinal structure automated image segmentation systems, a typical stage in most retinopathy screening procedures. The OD has a vertical oval outline (elliptical) separating the central region or cup and the peripheral zone or neuroretinal field into two distinct regions. In this post, we use Optical Disk segmentation strategy technique that is based on OD's statistical properties.

The need for this model is to segment the optic disk (OD) and create a standard framework for treating pathologies of the optic nerve head, such as glaucoma.

Therefore a robust OD segmentation technique is necessary for the automatic detection of abnormalities in the head of the optic nerve [3].

The purpose of this model is to define the outer boundary of the optic disk which may enable ophthalmologists to measure changes in the optic disk quantitatively over time. Segmentation of the OD is required in order to establish a frame of reference within the retinal image and is therefore important for any interpretation of the picture analysis.

3 Literature Review

The ratio of optic cup to disk (CDR) in retinal fundus images is one of the key physiological features for the diagnosis of ocular disease, glaucoma. The CDR is currently measured manually, and can be arbitrary, thus preventing its use in mask screening. The algorithm for climbing the Hill extracts values from k, the cluster tool used to remove the optical disc. A sample of 50 retinal images is used to test the CDR output decided on the clinical CDR and 90% accuracy is derived from the CRD-decided tests [3]. The results show the potential applicability of the approaches in automated and objective mass screening for early glaucoma detection.

This [4] paper suggests a computer-aided decision support framework for the automated identification of monocular images of the glaucoma background. Detection of Glaucoma using fundus images involves calculation of the size, shape of the Optic Cup and the surface of the Neuro retinal. Identification of the Optical Cup is a challenging task because of the cup's interweaving with the blood vessels. Using K- means clustering, a new color model technique is used to differentiate the boundary between the Optical cup and the disk, based on the pallor of the fundus images. The procedure varies according to the original measurement of the optic cup area accompanied by the blood vessel erasure.

In addition to the shape-based features, textural features are extracted to better define pathological subjects, the optimal set of features chosen by the Genetic algorithm are fedas input to the Adaptive Neuro-Fuzzy inference method for classifying images into regular, suspected and abnormal categories. 55 photographs combined with normal and glaucoma pictures tested the method. In terms of classification accuracy and convergence time the performance of the proposed approach is contrasted with that of the Neural Network and SVM Classifier. Experimental studies indicate that the functions used are clinically relevant to good glaucoma diagnosis [6].

The texture features of the glaucoma picture are evaluated based on the probabilistic neural network [7]. The extracted features are correct and the Glaucoma is graded based on energy transfer and the study of the key components. The PCA-PNN and DWT-PNN have reached 90 percent and 95 percent respectively strong classification. This demonstrates the effectiveness of wavelet as an extractor feature and PNN as a classifier-relative to another recent study [5.]

Provide a phase method-by-phase analysis of the correct evolution of the optical coherence tomography(OCT) photos and the morphology of the Retinal Nerve Fiber Layer (RNFL). RNFL thickness decreases as the pressure increases which contributes to glaucoma. Using Entropy equation, the RNFL is segmented. The segmented RNFL is has been smoothed with Bezier curve technique. The lower-superior temporal nasal (ISNT) ratio experiences variations in glaucoma status. The algorithm is verified by means of 12 standard RNFL images and 45 RNFL images collected from patients with glaucoma [8].

In this [9] paper it is suggested that glaucoma detection be detected by separate segmentation algorithm from the fundus picture and the spectral scope of optical coherence tomography is proposed. Specific segmentation algorithms are introduced to separate areas of discs and cups. Algorithms are Otsu, a clustering the field, c-means and climbing up the hill. The retinal nerve segmentation Fiber helps to assess disk and cup thickness [5].

4 Existing Method

The purpose of this analysis is to first segment the disk. The test images from DRISHTI-GS dataset are regarded as feedback for the current method.

Otsu thresholding is the process that already exists. In this step, the retinal image is first pre-processed by adding equalization to the histogram. The spherical optic disk is segmented by the adding of the circular detector Hough transform. The optical cup is just separated from the retinal image's green channel. Measurements of results including dice coefficient, average boundary location and error in the cup-disk ratio. RGB (red, green, and blue) refers to a color representation scheme that will be displayed on a computer monitor. To achieve some color red, green, and blue should be mixed in various quantities in the visual spectrum. R, G and B concentrations should range from 0 to 100 percent of the maximal resistance. The set of decimal numbers from 0 to 255 (256 levels for each color) is specified for each level, similar to the set of binary numbers from 00000000 to 11111111 or hexadecimal 00 to FF. The total number of available colors is 256 x 256 x 256, or possible colors are 16,777,216. The planes red (R), green (G) and blue (B) are divided and strengthened by an equalization of histograms. Histogram Equalization is a digital image analysis tool used to improve image contrast. This is done by transmitting the most frequently used strength values efficiently, i.e. by extending the range of the image. This method typically enhances total image contrasts as accessible data is represented as by near-contrast values. It results in a stronger contrast for low-spatial-contrast regions.

5 Proposed Method

MESSIDOR offers methods for testing the Retinal Ophthalmology segmentation and indexing process. The primary goal of the MESSIDOR project in the sense of Diabetic Retinopathy and Diabetic Maculopathy is to compare and assess:

- Different segmentation algorithms build for the identification of lesions present in color retinal images;
- Tools for indexing and maintaining image repositories.

The suggested approach called gray level thresholding is to eliminate certain pixels representing an object from the image. Objects are often descriptions of text or other line images (graphs, maps). All target pixels have a gray level after thresholding the image, and the background pixels have a different color. The highest threshold is the one that selects all entity pixels the black and maps it. Unfortunately, constructing a specific threshold that is 'efficient' for an arbitrary gray-level image is not generally feasible, while creating an image that cannot be a good threshold for a specific value is a straight forward matter. In actual photos, this sort of condition may also occur due to noise or non-uniform lighting.

Gray Level Co-Occurrence Matrix
Texture analysis Using the Gray-Level Co-Occurrence Matrix (GLCM) The Gray-Level Co-Occurrence Matrix (GLCM), also known as the Gray-Level Spatial Dependency Matrix, is a mathematical method for texture analysis that recognizes the spatial relation between pixels Abstract- Feature Extraction is a process of gathering the visual quality of photographs for indexing and retrieval. Gray-Level Co-occurrence Matrix (GLCM) method is a means of eliminating second order statistical texture features. The GLCM functions define the texture of an image by calculating how often pixel pairs of different values occur in an image, producing a GLCM, and then extracting statistical measurements from the matrix.

Support Vector Machine
Support Vector Machines (SVM): A simple and efficient classification algorithm with a limited amount of data that performs very well. The Support Vector Machine (SVM) is a supervised learning model with related learning algorithms in machine learning which analyzes the data used for classification and regression analysis. This is used mainly in classification problems. The data object is plotted as a point in n-dimensional space in this method (where n is number of features), with the value of each element being the value of a particular coordinate. The distinction is then made by determining the hyper-plane which distinguishes the two groups better. Besides performing linear classification, SVMs can effectively perform non-linear classification by mapping their inputs indirectly into high-dimensional spaces of attributes.

6 Methodology

Algorithm for image segmentation using Gaussian mixture models

Step1: Image acquisition from data base.
Step2: Applying gray thresholding.
Step3: Removal of the inappropriate edges by filling and deleting process.
Step4: Repeat the step3 to remove two large blobs.
Step5: Circles are drawn on the basis of the centroid, the major axis length and the board axis length.
Step6: Displaying the display picture of the disk and cup boarder.
Step7: Obtain Cup-disk ratio and Rim-disk ratio.
Step8: Classification of the issue of the patient's symptoms.
Step9: Using Gray level co-occurrence matrix (GLCM) to remove various parameters.
Step10: Using Support vector machine (SVM) to identify the final diabetic retinopathy (or) diabetic maculopathy.

Optic disk (optical nerve head) is the circular cup region, where the ganglion cell axons detach from the body. Although the optic disk has no rods or cones, each pupil leads to a small blind spot. The optic disk is often an entrance point for large blood vessels that supply the retina. The area between the cup border and the disk border is considered the surface layer of the neuroretinal. The boundary segmentation was centered at the boundary between the disk and the retina (Fig. 1).

7 Results and Analysis

The database reference picture of the retina is represented using two blobs, i.e. disks and cup circles, to be repeated over two periods. Gray limits are eliminated and the edges formed by the filling and dilation operations. The performance photographs collected are also categorized on the basis of characterized such as patient age, diabetes and glaucoma. Depending on the signs and combination of Gray Level Co-occurrence Matrix and Support Vector Machine, if glaucoma is observed, it helps to assess whether the current glaucoma is converted to diabetic retinopathy (or) diabetic maculopathy; Within this relationship, five photos were considered for scientific research, and their respective disk and cup pictures and boundaries can be seen in Figs. 2, 3, 4, 5 and 6

A comparison table is then defined for parameters such as centroid, length of main axis, length of small axis, CDR, RDR [9] along with comments about whether glaucoma is present or not. Besides the tabular chart, it can be observed that the specific age groups were specified for the analysis of the proposed program. Depending on the age, records of diabetes and glaucoma such as 'No Glaucoma,'

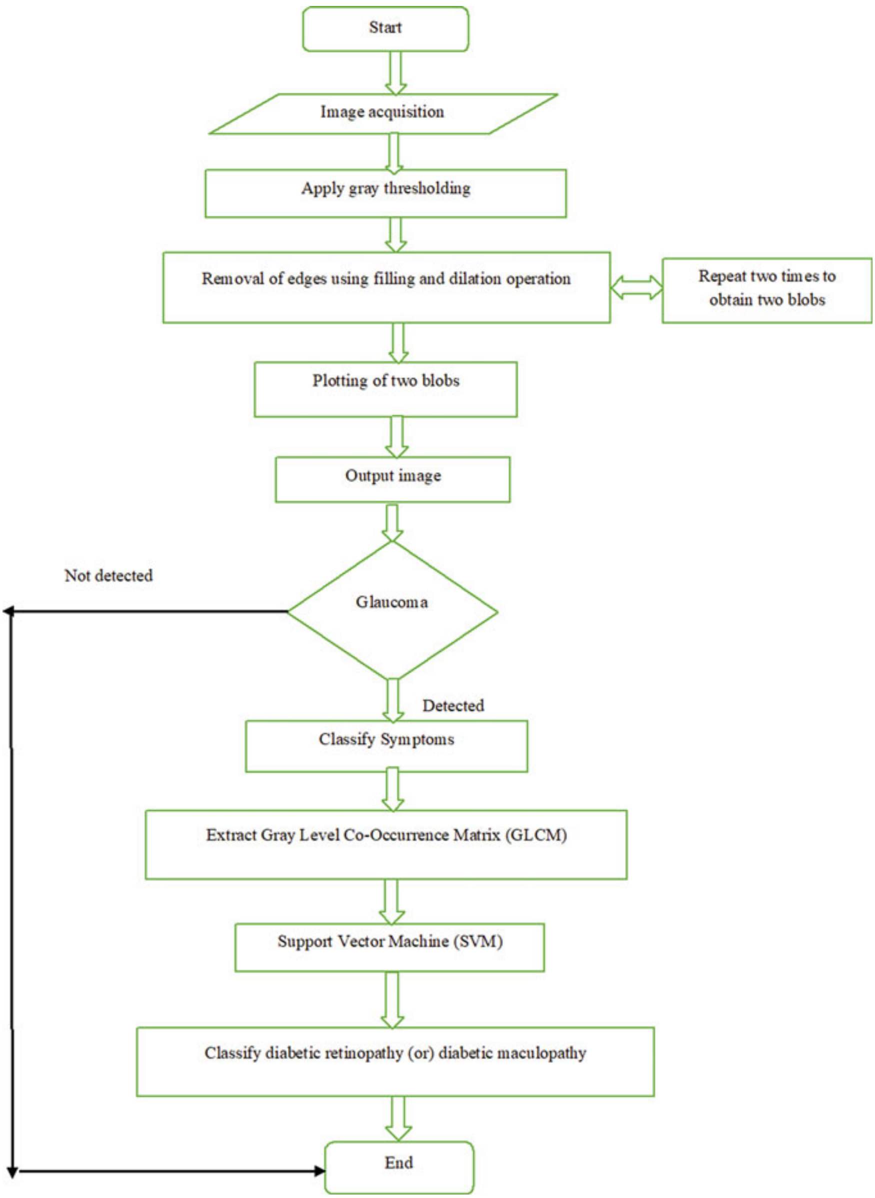

Fig. 1 Proposed process flow

2-month check-up alert of the individual's impending glaucoma, 'Glaucoma chance' and circumstances of 'Glaucoma risk' (Table 1).

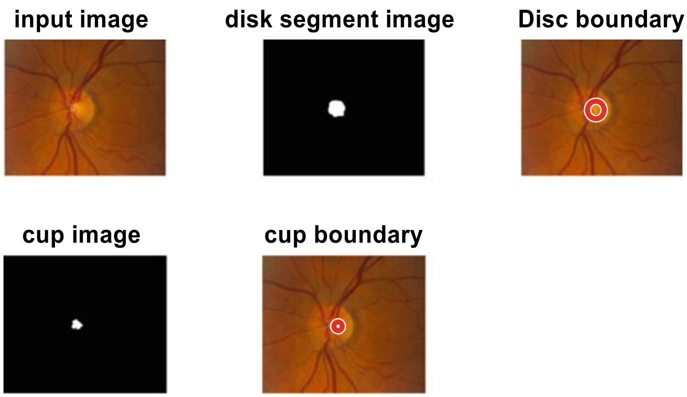

Fig. 2 Disc and cup extraction of 1st image

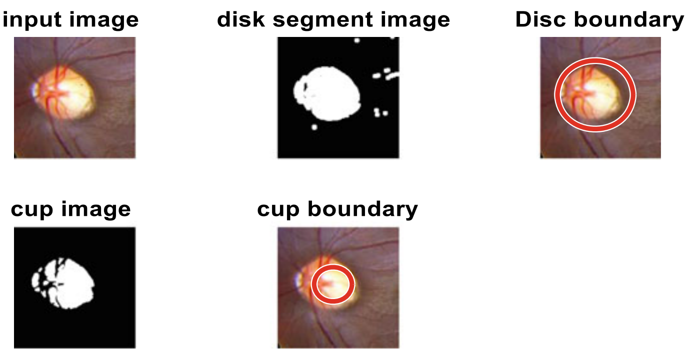

Fig. 3 Disc and cup extraction of 2nd image

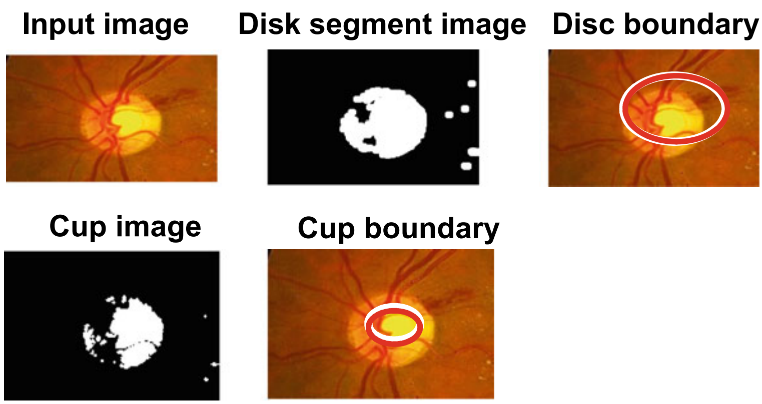

Fig. 4 Disc and cup extraction of 3rd image

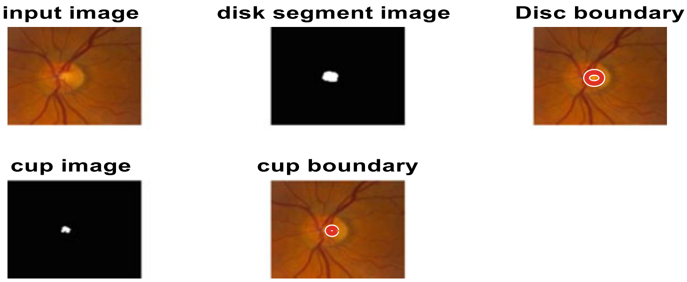

Fig. 5 Disc and cup extraction of 4th image

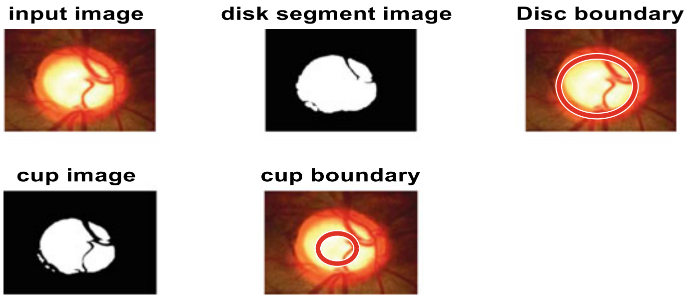

Fig. 6 Disc and cup extraction of 5th image

Table 1 Comparison of parameters

S. no	Attributes (age, diabetics, glaucoma)	Centroid	Major axis length	Minor axis length	CDR	RDR	Remarks
1.	30,4.4,13	[134.3295 120.4711]	31.1875	28.5086	0.315231	1.106104	No glaucoma
2.	36,7,25	[126.8268 143.5169]	192.1792	149.7244	0.256474	0.66664	Very high risk
3.	37,5.5,22	[167.2276 121.4413]	150.8038	119.4714	0.39059	0.568217	Risk glaucoma
4.	40,5,15	[137.3227 155.3978]	36.4336	32.1224	0.329069	1.033654	No glaucoma
5.	47,8,26	[232.8340 236.0730]	259.5391	234.1010	0.826816	0.106892	Very high risk

8 Conclusion

This paper is used to diagnose the detections of glaucoma from the images of the fundus and OCT. We need human comprehension of the optical disks and cups portion. Computer algorithms are used to classify the optical disk and cup to avoid duplication and to get right results. The cups are defined using the Gray Thresholding type. The form and scale of the structuring element as well as the boundary processes are used to learn the value of the Cup-Disk and Rim-Disk ratio using a statistical morphological method. Glaucoma is done for a diabetic patient because of the combination of the boundaries between the cup and the disc. Patients of diabetes get exudates in their plasma.

References

1. Muramathsu C, Nakagawa T, Sawada A, Hatanaka Y, Yamamoto, Fujita H (2011) Automatic measurement of cup to disc ratio based on line profile analysis in retinal images. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp 3387–3390
2. Yin F, Liu J, Wong DWK, Tan,NM, Cheung C, Bascaran, WTY (2012) Automatic separate of an optical disk & optical cup in glaucoma diagnostic picture. In: 25th IEEE international symposium on software-based medical applications
3. Ho MH, Chutatape O (2003) limitation of optical disc using the improve ASM process. Pattern Recogn 36(9):1993–2004
4. Ho C, et al (2013) Identification of Superpixel-centric optical disk and optical cup segmentation for glaucoma safeguard. Uh. IEEE Def IEEE Trans Med Oh Imaging 32(6), 1019–1032
5. Tan NM, Xu Y, Goh WB, Liu J (2015) Reliable multi-scale super pixel labeling for optical cup location. This is programing U. Pharm Man Oh Med Imaging 40:182–193
6. Almazroa, man, man (2015) Optical disk and optical cup segmentation methodologies for the identification of glaucoma picture: study. L Ophthalmol. 189972-1–180972-28
7. Shaik F, Sharma AK, Ahmed SM, Gunjan VK, Naik C (2016) An improved model for analysis of Diabetic Retinopathy related imagery. Indian J Sci Technol 9(44). (ISSN: 0974-6846)
8. Mathworks I (2014) MATLAB: R2014a. Math works Inc., Natick
9. Sivaswamy J, Krishnadas SR, Joshi GD, Jain M, Tabish AUS (April 2014) DRISHTI-GS: retinal picture dataset for segmentation of the optical nerve head (ONH). In: IEEE 11th international symposium on biomedical imaging, pp 53–56