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Detection of Glaucoma using Optic Disk and Incremental Cup Segmentation from Retinal Image

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ABSTRACT

Medical researchers, detection of eye disease is very important because it may causes blindness. Glaucoma is one of the diseases that cause blindness. Standard procedure for detection glaucoma is to analysis of optic disk (OD) and cup region in retinal image. In this paper, introduce an automatic OD parameterized technique which is based on segmentation and Incremental Cup segmentation. The incremental cup segmentation method is based on anatomical evidence such as vessel bends at the cup boundary, considered relevant by glaucoma experts. Bends in a vessel are robustly detected using a region of support concept, which automatically selects the right scale for analysis. A multi-stage strategy is applied to derive a reliable subset of vessel bends called r-bends followed by a local 2-D spline fitting to derive the desired cup boundary. The results are compared with existing methods using different retinal images.

INDEX TERMS -*Active contour, cup, cup-to-disk ratio (CDR), glaucoma, neuroretinal rim, optic disk (OD), retinal images, segmentation, vessel bend.*

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I. INTRODUCTION

In the industrial countries sixty seven million individuals suffer from eye disease, that represents the third commonest reason behind sightlessness and therefore incorporates a high economic impact. Early designation of eye disease, that doesn't essentially involve raised pressure, is important as a result of by the time the patient notices practical impairment the harm is irreversible. Glaucoma could be a serious worldwide UN wellness whose treatment will be improved by early detection. The point (OD) is that the location wherever neural structure cell axons exit the attention to make the nerves optics through that visual data of the photo-receptors is transmitted to the brain. The OD will be divided into 2 distinct zones, namely, a central bright zone known as the cup and a peripheral region known as the neuroretinal rim wherever the nerve fibers bend into the cup region [3]. The loss in optic nerve fibers ends up in an amendment within the structural look of the OD, namely, the enlargement of cup region (thinning of neuroretinal rim) known as bloodletting. Eye disease detection usually considers the case history, intra-ocular pressure and visual field loss tests of a patient at the side of a manual assessment of the OD, through ophthalmoscope. Since enlargement of the cup with relation to OD is a vital indicator of eye disease progression, numerous parameters area unit calculable and recorded to assess the eye disease stage. These embody the diameter and space of OD, cup diameter, rim area, mean cup depth, etc. The sound judgments in the manual estimation of cup parameters is overcome, when attainable, by mistreatment advanced modalities like optical coherence tomography and Heidelberg tissue layer imaging. These provide the 3-D depth data either within the kind of a colorless or pseudo-color image. The disk boundaries on the 3-D image area unit then manually marked by the specialists to extract the desired disk parameters. Color structure imaging (CFI) is another modality which will be used for eye disease assessment. It’s emerged as a most popular modality for large-scale retinal sickness screening and has already been established for large-scale diabetic retinopathy screening. It’s attainable to accumulate structure pictures in an exceedingly noninvasive manner that is appropriate for big scale screening. In such programs, an automatic system which will decide whether or not or not any signs of suspicious for a sickness area unit gift in a picture can improve efficiency; solely those pictures deemed suspect by the system would need examination by Associate in nursing eye doctor. There are efforts to mechanically sight eye disease from 3-D pictures [4]. However, attributable to their high price they are typically out of stock at medical care centers and hence an answer engineered around these imaging equipments isn't appropriate for a large-scale screening program. The work is aimed at developing a prescreening system to alter eye disease detection for large-scale screening programs mistreatment CFI. In this paper, introducing partial results of this work. In next section II , presenting the literature survey over the various methods presented for Glaucoma Detection. In section III, the proposed approach and its proposed system block diagram is depicted. In section IV, presenting the current state of implementation and results achieved. Finally conclusion and future work is predicted in section V.

II. LITERATURE SURVEY

The previous method’s introduces in this section.

G. Michelso et al. discuss in the article, papilla as screening parameter for early diagnosis of glaucoma,[2] that, the current situation with regard to early diagnosis of glaucoma and the available investigative methods, that assess the medical quality of screening examinations for the detection of glaucoma. Limitations are no study has far investigated Heidelberg retina tomography under screening conditions. The results of the studies that investigated several approaches showed unambiguously that sensitivity, specificity, and receiver operating characteristic (ROC) curves – a method used to optimize threshold values was improved by combining investigative methods and using appropriate algorithms.

R. bock et al. [3] proposes a novel automatic acquisition of glaucoma detection system is inexpensive and widely circulated on digital color fundus images using a cataract after preprocessing, various specific generic feature types a narrowed decrease presence-based technology dimension. Subsequently, a potential two-stage classification plan novel glaucoma risk index (an appropriate cataract detection performance shows GRI) combines these features remove types. But damage optic in odd nerve fibers, called area enlargement cupping Cup appearance leads to structural changes.

M. L. Huang et al. Adaptive neuron-fuzzy inference system (ANFIS) normal and glaucomatous eyes optical coherence tomography in Chinese Taiwan Stratus (OCT) summary data report quantitative assessment on the basis of the difference between developing an automatic classifier, Adaptive neuron-fuzzy inference system using glaucoma screening [4] introduced populations.

J. Meier et al. [5] a novel automatic classification system based on image features of fundus photographs which do not depend on expert knowledge structure partition or focused on.

H. Ohwada et al. [6] a robust, automated data-driven way glaucoma detection system color fundus images using construction. provided that the cataract detection are new in the domain, therefore, the image-based features, the so-called presence, based approach to object and facial recognition is famous.

R. Bock et al. A novel, automatic, see base don't trust that partition based mostly eye disease organization most measurement approaches the mass screening examination. Approach applied purely data-driven is a customary pattern recognition classification with a 2-stage pipeline steps. Many types of image-based options analyzed and field unit

Glaucomatous structures to capture United make sure UN wellness in homogeneities, size variations and variations in illumination free ship structures within the field unit eliminated the preprocessing section.

L. G. Nyl [8] analyze concentrated on a completely unique automatic classification system for eye disease, supported image options from anatomical structure images. Their new data-driven approach needs no manual help and doesn't depend upon express structure segmentation and measurements. First, disease independent variations, like heterogeneous illumination, size variations, and blood vessels area unit eliminated from the images. Then, the extracted high-dimensional feature vectors area unit compressed via PCA and combined before classification with SVMs takes place.

III. PROPOSED APPROACH FRAMEWORK AND DESIGN

3.1 Problem Definition

There are a few attempts at automated OD and cup segmentation from monocular images for structure segmentation as well glaucoma detection point of view. It is note that works related to glaucoma detection focus only on the estimation of cup-to-disk diameter ratio (CDR) which has been traditionally used to detect glaucomatous cases. However, CDR has been found to be inconsistent in explaining the amount of OD damage caused by glaucoma. Thus, an accurate segmentation of OD and cup is essential to get better localization of neuroretinal rim to enable new glaucoma evaluation methodologies which consider other factors in addition to CDR.

3.2 Proposed Architecture

To overcome above discussed issues; in this paper introduced a navel approach for glaucoma detection. As in existing paper, uses automatic OD parameterized technique for optic segmentation. The proposed OD segmentation is robust to image variations within and near an OD region. The cup is modelled as a region enclosing pallor region and defined by a boundary passing through a sparse set of vessel bends called relevant bends (*r-bends*). And introduce an Incremental Cup segmentation method which includes 3-D spline interpolation. Thus appearance and anatomical knowledge are considered by the glaucoma experts to determine cup region. Hence, the propose a method that integrates both these information under a common framework.

As shown in figure 1.

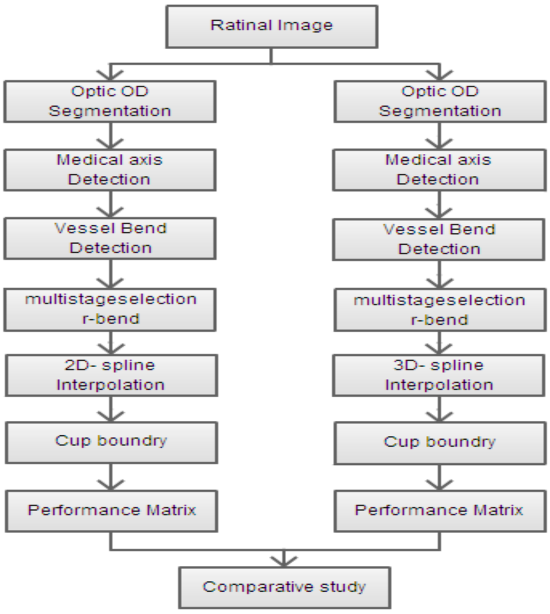

Figure 1: Proposed architecture diagram.

IV. ACTIVE CONTOURS

The earliest and best known active contour approach is *snakes*: deformable splines that are acted upon by image, internal, and user-defined "forces" and deform to minimize the "energy" they exert in resisting these forces. Notice that the general form of a snake follows the idea introduced graph-based approaches:

1. Establish the problem as the minimization of some cost function.
2. Use established optimization techniques to find the optimal (minimum cost) solution.

In the case of a snake, the cost function is the "energy" exerted by the snake in resisting the forces put upon it. The original formulation of this "energy" was

$$\text{Esnake} = w_{int}E_{int} + w_{image}E_{image} + w_{con}E_{con}$$

where each term is as follows:

E_{int} Internal Energy Keeps the snake from bending too much
E_{image} Image Energy Guides the snake along important image features
E_{con} Constraint Energy Pushes or pulls the snake away from or towards user-defined positions

The total energy for the snake is the integral of the energy at each point:

$$E_{snake} = \int_0^1 Esnake(s)ds$$

4.1 Internal Energy

The *internal energy* term tries to keep the snake smooth. Such smoothness constraints are also a common theme in computer vision, occurring in such approaches as

- Bayesian reconstruction
- Shape from shading
- Stereo correspondence
- and many others . . .

The internal energy term in general keeps the model relatively close to its original *a priori* shape. In this case, we explicitly assume that the contour we want is generally smooth but otherwise unconstrained. Other models might start with an approximation of a brain, a heart, a kidney, a lung, a house, a chair, a person, etc.orm this model—in all cases, the internal energy term constrains the deformation. One has to be careful with the weighting given to internal energy terms, though: too much weight means the model stays too "rigid" and the system "sees what it wants to see", too little weight means the model is too flexible and can pretty much match up to anything. In the original snakes implementation, they used two terms to define the internal energy: one to keep the snake from stretching or contracting along its length (elasticity) and another to keep the snake from bending (curvature):

$$Eint(s) = \alpha(s) \parallel \frac{d\bar{v}}{ds}(s) \parallel^2 + \beta(s) \parallel \frac{d^2\bar{v}}{ds^2}(s) \parallel^2$$

That both $\alpha(s)$ and $\beta(s)$ are functions of the arc length along the snake. This means that we can (perhaps interactively), keep the snake more rigid in some segments and more flexible in others.

4.2 Image energy

The *image energy* term is what drives the model towards matching the image. It is usually inversely based on image intensity (bright curve finding), gradient magnitude (edge finding), or similar image features. Make sure to note the inverse relationship: strong features are *low* energy, and weak features (or no features) are *high* energy. An interesting image energy term used in the original snakes paper also tracked *line terminations*. These are useful in analyzing visual illusions such as the Kinisa and Ehringhaus illusions illustrated.

4.3 Constraint Energy

Some systems, including the original snakes implementation, allowed for user interaction to guide the snakes, not only in initial placement but also in their energy terms. Such *constraint energy* can be used to interactively guide the snakes towards or away from particular features.

V. WORK DONE

5.1 Input:

Retinal images collected from an ongoing pilot study in collaboration with a local eye hospital.

5.2 Matrix Computation

Precision and recall values are computed to assess the overlap area between computed region and ground truth and for better results; we compute a single performance measure called F-score (F).

$$\text{Precision} = \frac{\text{tp}}{\text{tp} + \text{fp}} \qquad \text{Recall} = \frac{\text{tp}}{\text{tp} + \text{fn}}$$

where tp = True Positive,
fp = False Positive,
fn = False Negative

$$\text{F} = 2\frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.3 Results of work done

The results of work done are shown in figures given below.

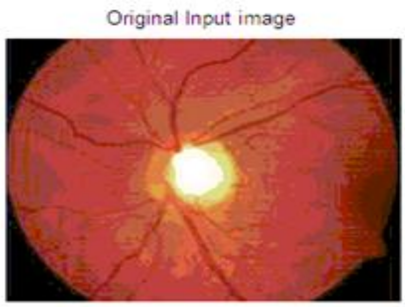

Figure 2: Input image.

Figure 3: ROI image result.

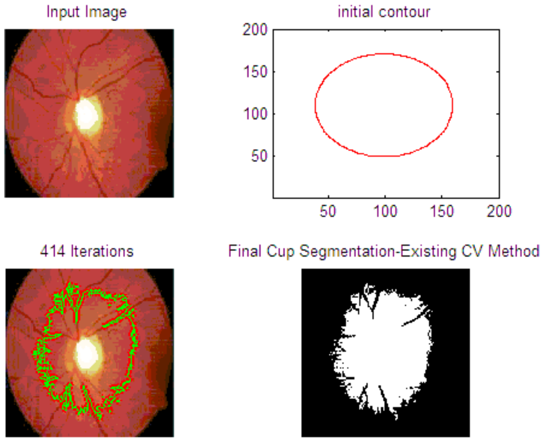

Figure 4: Result of Existing method.

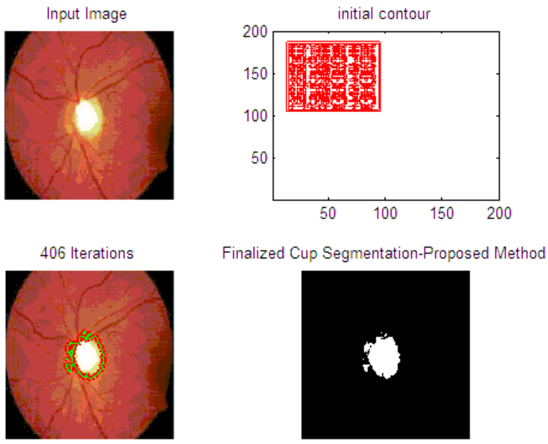

Figure 5: Result of Proposed method.

The Original image i.e the image to be segmented is taken as a input image to be segmented is taken as a input image is shown in fig.2, then pre processing is done to remove noise and to get the noise free image which further use in the process [as shown in fig.3], then contour initialization is done to decide the optic disk region[as shown in fig.4]. Then cup segmentation method is implemented to get the optimized result [as shown in fig.5].

VI. CONCLUSION AND FUTURE WORK

In this paper, presenting a solution for glaucoma assessment which allows derivation of various geometric parameters of the OD and Incremental cup segmentation method using 3D interpolation. The bestowed answer for eye disease assessment was within the form of 2 segmentation strategies for OD and cup. A novel, active contour model is bestowed to urge strong OD segmentation. This has been achieved by enhancing the C-V model by together with image info at the support domain around each contour purpose. A horny facet of the extension is the strengthening of region-based active contour model by the integration of data from multiple image feature channels. The obtained results will show that technique captures OD boundary during a unified manner for each traditional and difficult cases while not imposing any form constraint on the segmentation result, in contrast to the sooner strategies. In cup segmentation, it's observed that boundary estimation errors area unit principally in regions with no depth cues that is in keeping with the high inter-observer variability in these regions.

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