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Dear Researcher,

Greetings!

Articles in this issue discusses about study endeavors to recent trends in segmentation.

We look forward many more new technologies in the next month.

Thanks,
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A Comparative Study on Optic Disc Segmentation in Retinal Fundus Images

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Abstract- Optic Disc Segmentation (ODS) is a crucial part of fundus image diagnosis. The centre and boundary of the optic disc are often required features in providing a frame of reference for diagnosing retinal defects. Automatic eye disease screening relies on accurate and efficient Optic Disc (OD) segmentation. In the literature, many research methods are published in account of optic disc segmentation. This paper analyzes eight latest papers related to optic disc segmentation, namely, ODS-DMF-LS, ODS-SPC, ODS-PT, ODS-MLDN-PT, ODS-pOSAL, ODS-SD, ODS-MLSACM-AS and ODS-RCNN. The performance qualities of these methods are analyzed based on segmentation accuracy. The working process of these methods is deeply explained to understand the pros and cons.

Keywords--Optic disc, OD segmentation, medical segmentation, Fundus image processing.

I. INTRODUCTION

Human eyes are camera-type eyes which mean they focus light onto film in the same way as camera lenses do. The principal aspects of the human eye include the retina, iris, optic nerve, vitreous humour, lens, and cornea, etc. The lens and cornea of the eye are nearly identical to camera lenses, while the retina is similar to film.

The retina is the tissue covering the back of the human eye. Light activates two types of cells in the retina when it strikes it. In low-light circumstances, rods sense light and dark and assist in the production of images. Cones are the cells in the eye that regulate color vision. Color perception is controlled by the cones in the retina. Cones come in three different varieties, each of which can only take up one color: red, green, or blue. When you focus clearly on an object, light hits a region known as the fovea. Cones are densely packed in the fovea, which allows for clear vision. Outside of the fovea, rods are in charge of peripheral vision.

One of the most crucial tasks in ocular image analysis and computer-aided diagnosis of numerous forms of eye diseases [2] is automatic Optic Disc [1] recognition from retinal images.

Axons from 1.2 million neural structural cells make up the optic disc, which transmits visual information to the brain [3] by penetrating the retina of the eye and emerging through the scleral canal. Neural structure cell axons leave the eye to form the OD, which eventually develops into the optic nerve. There are hardly any luminous rods or cones that could really respond to light stimulation at this stage. The optic disc is actually where the axons of retinal neural structure cells interact to form the optic nerve. It also serves as the site of entrance for the retina's major blood veins.

OD is one amongst the foremost vital components of a retinal fundus image [4]. The FUNDUS is the inner, back surface of the eye. The term "bottom" is referred to as "fundus" in Latin. The bottom or base of an organ is referred to as the fundus in medicine. The retinal fundus which contains the retina optic disc and macula is the internal portion of the eyeball against the lens. The fundus has been the only part of the inner eye that can be viewed via the pupil throughout an imaging test, and it can be inspected with an ophthalmoscope or fundus photography.

A complicated microscope coupled to a camera with a flash is used in fundus photography, which is a specialized technique for photographing the fundus, the rear of the eye. On the basis of the monocular indirect ophthalmoscope [5] principle, fundus cameras' optics is designed.

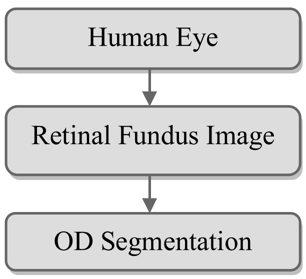

Fig.1. OD Segmentation

II. SURVEY METHODS

This paper makes a survey with the following eight recent papers in retinal optic disc segmentation.

- OD Segmentation using Directional Matched Filtering and Level Sets (ODS-DMF-LS) [6].
- OD Segmentation using Superpixel Classification (ODS-SPC) [7].
- OD Segmentation using Polar Transform (ODS-PT) [8].
- OD Segmentation using Multi-Label Deep Network and Polar Transformation (ODS-MLDN-PT) [9].
- OD Segmentation using patch-Based Output Space Adversarial Learning (ODS-pOSAL) [10].
- OD Segmentation using Salency Detection (ODS-SD) [11].
- OD Segmentation using Modified Locally Statistical Active Contour Model with the Information of Appearance and Shape (ODS-MLSACM-AS) [12].
- OD Segmentation using Region-Based Convolutional Neural Network (ODS-RCNN) [13].

A. OD Segmentation using Directional Matched Filtering and Level Sets (ODS-DMF-LS)

Barriga et al. [6] reported a rapid and entirely automatic OD localization and segmentation methodology is developed for retinal illness screening. Template matching is used to identify applicants for OD location. The template has been created to operate with a variety of image resolutions. The steps involved in these methods are, OD Detection and OD Segmentation.

There are three main processing processes in OD localization and segmentation: 1) Adaptive OD size estimation for varied image resolutions 2) OD localization, which determines the disc center's location, and 3) OD boundary segmentation.

Candidates for OD detection are discovered using template matching, with the template designed to adapt to various image resolutions. The location of the OD is then determined using the blood vessel features on the optic disc. It uses a rapid, hybrid level set model that combines region and native gradient data to segment the disc border, which is initialized by the detected OD center and predicted OD radius.

The optic disc segmentation process employs morphological filtering to exclude the ocular blood vessels and other lucid areas outside of the optic disc that interfere with segmentation in the peripapillary region.

The accuracy and speed of this technology are good enough for heavy workloads in automatic eye screening. Additionally, it improves the reliability and precision of OD detection. The segmentation accuracy is inadequate to competitive with recent techniques.

B. OD Segmentation using Superpixel Classification (ODS-SPC)

The author Jun Cheng et al. [7] described an effective method for classification and OD segmentation. This approach uses Superpixel classification to segment the optic disc and the optic cup (OC) for glaucoma screening. Superpixel Classification [15], [16] is used for image segmentation in different images of scenes, animals, humans, etc. The Simple Linear Iterative Clustering algorithm (SLIC) [17] is also used in this technique.

Here, two types of segmentation methods are followed, they are, Optic Disc segmentation and Optic Cup segmentation.

Histograms and center surround statistics are used in OD segmentation to classify each Superpixel as an optic disc or an optic non-disc, and a self-assessment reliability score is produced to assess the quality of the automated OD segmentation. In OC segmentation, location data is included in the feature area in addition to histograms and center surround statistics to boost performance. Segmentation method is mainly focuses on automatic glaucoma screening from retina using Cup to Disc Ratio (CDR) from 2D retinal fundus images. Accurate segmentations of disc and cup are essential for CDR measurement; during this technique achieves areas under curve of 0.800 and 0.822 in two datasets, which is larger than other methods.

According to discussions with physicians and ophthalmologists, the benefit is high classification accuracy, and this method is sufficient for screening purposes in polyclinics and eye facilities.

The modelling may not include some morphologies, such as a quick change in disc or cup boundary, and CDR-based screening from 2D images also has limits. Another issue is that a weak color modification would make cup segmentation more difficult.

C. OD Segmentation using Polar Transform (ODS-PT)

Muhammad Nauman Zahoor et al. [8] presented a novel hierarchical method for fast and accurate OD localization and OD segmentation. In this technique demonstrated a hybrid approach for fast and accurate localization and segmentation of optic disc based on Circular Hough Transform (CHT) [18] and Polar Transformation (PT) algorithm [19].

The Polar Transformation algorithm has been used in many applications relating to image segmentation and it has been utilized for the first time in the precise segmentation of OD in eye retinal images. This work described two techniques; they are Optic Disc Detection/Localization and Optic Disc Segmentation.

Using morphological operations, this methodology preprocesses the image to reduce retinal blood vessels and enhance the OD boundary. For OD localization, CHT is applied. To convert the circular region of interest into a rectangle, the spatial to polar transform is used. The OD boundary is also identified by using adaptive thresholding.

OD Localization requires a radius search range of min and max radius. This radius is approximated to be 1/30th to 1/10th of the image width. OD segmentation uses the polar transform. Polar transform is a 2D coordinate system where each point's location in relation to a reference point and its angle from it are determined. For OD segmentation the Region of Interest (ROI) image is calculated and Region of Interest pixel co-ordinates are converted from Cartesian to polar co-ordinates.

Herein, the datasets such as MESSIDOR, DIARETDB1, DRIONS-DB, HRF, DRIVE and RIM-ONE are used for performance evaluation. The merit of this paper is the time efficiency and the negative side is the semi automatic process.

D. OD Segmentation using Multi-Label Deep Network and Polar Transformation (ODS-MLDN-PT)

Jun Cheng et al. [9] provided a deep learning architecture, named M-Net, which solves the Optic Disc and Optic Cup segmentation. M-Net is an end to end multi-label deep network that consists of 4 main parts.

A multi-scale layer is used to construct an image pyramid input and reach multi-level receptive field fusion.

U-shape convolutional network (U-Net) [20], [21] that is employed as the main body structure to learn a rich hierarchical representation.

Side-output layer, which works on the early convolutional layers to support deep layer supervision.

Finally, a multi-label loss function is proposed to guarantee optic disc segmentation and optic cup segmentation jointly.

The positive side of this method is improving the segmentation result and the negative side is the high learning time.

E. OD Segmentation using patch-Based Output Space Adversarial Learning (ODS-pOSAL)

Chi-Wing Fu et al. [10] exposed a patch-based Output Space Adversarial Learning (pOSAL) framework to segment the OD and OC. In this pOSAL framework demonstrates its effectiveness in developing the segmentation performance on three public retinal fundus image datasets namely Drishti-GS, RIM-ONE-r3, and REFUGE. This framework has three modules, ROI extraction, Segmentation network and Patch-level discriminator.

ROI extraction is done to perform accurate segmentation. Segmentation network follows the spirit of DeepLabv3+ architecture [22]. To further decrease the no. of parameters and the computation cost and it replace the backbone network Xception with the lightweight and handy MobileNetV2 [23].

A patch discriminator is used to conduct the adversarial learning. A patch-level discriminator employs the adversarial learning technique to train the whole framework. The worth of this technique is better and smooth prediction. The imperfection is dependency of illumination variation.

F. OD Segmentation using Saliency Detection (ODS-SD)

Chen Jie et al. [11] reported an optic disc segmentation method based on the saliency. This method includes two stages, they are OD Location and Saliency based segmentation

The OD is recognized using a matching template and the density of the eye blood vessels in the localization step. The optic disc is treated as the salient object in the saliency based segmentation stage, and the task is formulated as a saliency detection problem. Accurate OD segmentation is complicated by the presence of blood vessels. Using group based sparse representation [24] and two close-open filtering the vessels in the OD window are eliminated before OD segmentation.

This method is carried out on two datasets: DRISONS [25] and MESSIDOR. On the DRISONS dataset, it takes the OD mask labeled by the first specialist as ground truth, and the segmentations by the second specialist are also compared with the ground truth to obtain inter-expert differences. MESSIDOR has 1200 images of the retinal fundus, including both normal and diabetic retinopathy images.

Quality of this technique is the simple and effective segmentation. The complication is that it is not suitable for segmenting highly diseased OD.

G. OD Segmentation using Modified Locally Statistical Active Contour Model with the Information of Appearance and Shape (ODS-MLSACM-AS)

Yuan Gao et al. [12] demonstrated an automated detection scheme for glaucoma in terms of different evaluation parameters. These parameters necessitate appropriate OD and OC segmentation information.

There are two sorts of segmentation methods used in this procedure, Locally Statistical Active Contour Model with the Information of Appearance and Shape (LSACM-AS) [26] and Modified Locally Statistical Active Contour Model with the Information of Appearance and Shape (MLSACM-AS)

The LSAM model is used to address the common occurrence of intensity inhomogeneity induced by lighting variations that are imprecise. The OC border is extracted using the Modified LSACM, which includes multi-view information regarding the appearance and shape of the OC. The public dataset of retinal images namely DRISHTI-GS [27] is used for testing purpose.

Positive side of this method is that it achieves a better segmentation. The negative side is the intolerance of noisy environment.

H. OD Segmentation using Region-Based Convolutional Neural Network (ODS-RCNN)

Yuming Jiang et al. [13] presented a joint optic disc and cup segmentation end-to-end region-based convolutional neural network. Joint RCNN is the name of this technique. It is a detection approach that is based on objects. The steps in this procedure are Feature Extraction module, Disc Proposal Network (DPN), Cup Proposal Network (CPN) and Disc attention module

Methods Name	Segmentation technique	Segmentation Accuracy
ODS-DMF-LS	Directional Matched Filtering and Level Set method	0.76
ODS-SPC	super-pixel classification	0.78
ODS-PT	Circular Hough Transform (CHT)	0.79
ODS-MLDN-PT	Multi Label Deep Network and Polar Transformation	0.81
ODS-pOSAL	patch-based Output Space Adversarial Learning framework	0.89
ODS-SD	Saliency-Based Segmentation	0.90
ODS-MLSACM-AS	Locally Statistical Active Contour Model	0.92
ODS-RCNN	End-to-end region-based convolutional neural network	0.93

Table I. Segmentation Accuracy Analysis

The feature extraction module is made up of deep convolutional layers. It also consists of convolutional layers, pooling layers and Atrous convolutional. The Atrous convolutional is used for dense segmentation [28]. DPN and CPN are used to detect OD and OC in retinal fundus images. Faster RCNN [29] can be used to detect OD and OC in retinal fundus image directly. Optic Disc attention module is used to connect DPN and CPN.

The outstanding factors is improved FScore in segmentation of OD. In addition, it gives an inaccurate OD segmentation for highly affected retina in case of glaucoma.

III. ANALYSIS AND DISCUSSION

This survey analyzes the optic disc segmentation methods such as ODS-DMF-LS, ODS-SPC, ODS-PT, ODS-MLDN-PT, ODS-pOSAL, ODS-SD, ODS-MLSACM-AS and ODS-RCNN using the analysis metrics segmentation accuracy. Herein, the segmentation accuracy is calculated by using equation (1).

$$SA = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

Where,

TP - True Positive Count
FP - False Positive Count
TN - True Negative Count
FN - False Negative Count

Below the Table 1 and Fig. 2 shows the segmentation accuracy values of the eight methods. From that, it can be proved that the ODS-RCNN method achieves the OD segmentation than the others. The higher segmentation accuracy achieved by the ODS-RCNN method is 0.93. The second best method is ODS-MLSACM-AS which has the segmentation accuracy value of 0.92. The least performance method is ODS-DMF-LS.

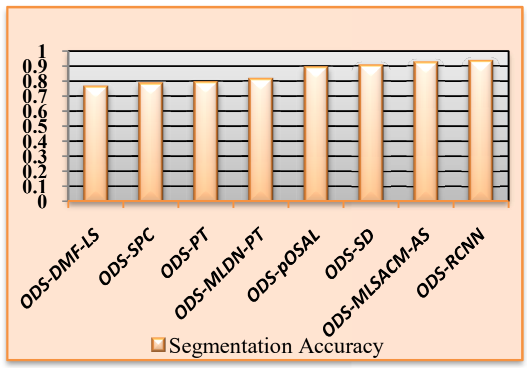

Fig.2. Chart for OD Segmentation Accuracy analysis

Methods	Merits	Demerits
ODS-DMF-LS	Speedy execution for high workloads	Segmentation accuracy is inadequate
ODS-SPC	High classification accuracy	A weak color change is appeared
ODS-PT	Better time efficiency	Semi automatic process
ODS-MLDN-PT	Improved segmentation	High learning time
ODS-pOSAL	Better and smooth prediction	Dependency of illumination variation
ODS-SD	Simple and effective segmentation	Not suitable for segmenting highly diseased OD
ODS-MLSACM-AS	Better OD segmentation	Intolerance of noisy environment
ODS-RCNN	Improved FScore in segmentation of OD	Inaccurate OD segmentation for highly affected retina

Table II. Analysis on Merits and Demerits

IV. CONCLUSION

This work is a comparative analysis for optic disc segmentation in fundus images. It evaluates and analyses the eight methods related to optic disc segmentation viz. ODS-DMF-LS, ODS-SPC, ODS-PT, ODS-MLDN-PT, ODS-pOSAL, ODS-SD, ODS-MLSACM-AS and ODS-RCNN. This research declares that the ODS-RCNN method is the best one according to segmentation accuracy. This research can be used as a better guideline for new researchers for choosing the best method for optic disc segmentation.

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